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An Analysis of Job Change Decision Using a Hybrid Mcdm Method: A Comparative Analysis

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ABSTRACT

This paper investigates the decision process relating to job change which mostly depends on individual's expectations about a job. Failing to fully understand the factors shaping these expectations leads to dissatisfaction and poor work performance; which produces unwanted consequences for both individuals and businesses. Since job change decision is defined as a multiple criteria decision making (MCDM) problem. This study uses a hybrid approach as a methodology combining fuzzy Analytic Hierarchy Analysis (AHP) and fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) for the job change decision of a faculty working in a university. In this approach, while the use of fuzzy AHP method helps determine the weight of the decision criteria; fuzzy TOPSIS enables the evaluation of the alternatives. In order to investigate the methods' applicability in multiple dimensions of decision problem space, a comparison analysis is conducted with the three methodologies; fuzzy AHP, fuzzy TOPSIS and the proposed hybrid approach (named fuzzy AHP-TOPSIS) in the same decision making context. Four factors are considered for the comparison: adequacy to changes of criteria or alternatives; agility in the decision process; computational complexity; and the number of criteria and alternatives. Analysis shows that three methods achieve the same results. This verifies their robustness and indicates that MCDM methods are viable in job change decisions. However; comparison analysis shows that based on the four factors; the proposed hybrid fuzzy AHP-TOPSIS method provide more consistent results than fuzzy AHP and fuzzy TOPSIS methods. Thus the proposed hybrid fuzzy AHP-TOPSIS method is more appropriate to use on a wide range of job change decision problems.

Keywords: Fuzzy AHP, Fuzzy TOPSIS, job change decision, multi criteria decision making.
JEL Codes: J24, C02, C44, C65.
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1.0 INTRODUCTION

Changing a job can be a daunting decision for any professional. However, it is a common practice in the rapidly changing competitive business environment in modern society. According to a survey by the U.S. Bureau of Labor Statistics (2015), average person born in the early 60s held 11.7 jobs from age 18 to 48.

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This creates a highly competitive job market for businesses as well for attracting and choosing the best candidate for vacant positions. However, choosing the best candidate does not guarantee an adequate performance on the job either. If the individual's expectations from the job do not meet with the business' reality, ranging from the work environment to benefits, his/her dissatisfaction and poor performance are almost inevitable. Therefore, while the business needs to make sure that the person its hiring ideally fits the requirements of the position, the individual has to be certain that with all its incentives and conditions, his/her employment will fulfill his/her needs. Thus understanding the factors effecting the job change decision can help both individuals and businesses in a better match of the right person with the right job.

By understanding factors affecting their choices, individuals assess job alternatives better and their awareness increase in making an informed decision. On the other hand, knowing the factors attracting the individual to the job position, businesses better communicate their expectations and may achieve a better match between the candidate and the job. Recruiting the right person for the job plays a considerable role in business success, and an extensive literature exists on the various aspects of employee recruitment such as recruitment methods, recruiter effects and realistic job previews (Breaugh, 2008). One of the factors that can hinder a successful recruitment process is job applicant's incorrect assessment of his/her true abilities or inability to identify exactly his/her expectations from a job; both of which received little attention in the employee recruitment literature (Breaugh, Macan, & Grambow, 2008). In order to overcome these problems and develop recruitment strategies, employer needs to better understand job applicants' decision processes. Since applicants' professional career states can be different such as the first-time, career changing or job changing; circumstances surrounding each applicants' decision making process needs to be investigated accordingly. The scope of this study covers only the job change case.

Job changes are seldom easy decision making processes. They entail internal and external challenges in terms of adjustments to new culture, changes in family and social life, relocation expenses, and potential increase in the cost of living. Groysber and Abrahams (2010) argue that it is very easy to make mistakes in the decision making process. They found that not doing enough research, overestimating oneself and thinking short term are the common mistakes. Fundamentally, decisions are based on imperfect information that individuals have about a prospective job, since it's certain properties are difficult to assess without actually experiencing the job (Halaby, 1988). Studies show that even if the job change is involuntary; individuals generally tend to have a perception of a positive outcome including better pay and benefits, opportunities for growth, job satisfaction, reduced stress and more job security (Fields et al, 2005). Furthermore, studies show that factors effecting job search and the choice process for an individual likely to vary at different stages of the process as he/she becomes more aware of other opportunities and his/her own preferences (Boswell, 2003). The mismatch between expectations and experience on the job can lead to dissatisfaction and poor work performance and initiate another job search behavior.

Job change decision involves an employee's decision to change his/her career or just to change the organization that he/she is working for. Most of the related studies in decision making are about the field of career decision making. Murtagh et al. (2011) categorize the theories explaining career decision making process into two streams of research: rational and other-than-rational perspectives. Rational decision making models explain career decision making as a systematic and objective process. Such models (i.e. Pitz & Harren, 1980) try to explain how career decisions should be made. In these models, in order to reach an optimal outcome, individuals need to consider different values of options in relation to their probabilities and select the highest valued option. However, in the applications of the rational models, individuals often fail to accomplish the correct quantification and calculation due to the limited capacity of human cognition (Murtagh et al. 2011). Following these studies in 2001, Gati and Asher proposed to enhance cognitive processes in order to overcome the problems of rational models and increase usability in applications.

In contrast, other-than-rational perspective models argue that career decision making cannot be a systematic or sequential process. The decision process is essentially an unconscious one and can be influenced by emotions and intuition (Murtagh et al. 2011). Influence of emotions in the decision making process has been acknowledged as a part of unconscious evaluation process in psychology (Johnson-Laird & Oadey, 2004). These studies are still improving our understanding and knowledge about career decision making. However there is no prescriptive model available to follow yet for all decision making cases.

These theories in the career decision making research can help understand the job change decision making process. However, in terms of the real-world applications, both rational and other-than-rational perspective models fail to offer a comprehensive solution due to the limitations of human cognition and influential mechanism shaped by emotions. Using tools and methods as decision aids could be useful in easing the cognitive burden and forming a systematic thinking process. One of the research areas that can contribute to career decisions is MCDM research. Mardani et al. (2015) describe that MCDM is concerned with designing computational and mathematical tools for supporting subjective evaluation of decision makers, offering various methods that can be applied in diverse types of decision problems. However, there is no consensus in the literature on which method to use since many MCDM methods may yield different results when they are applied on the same problem. Thus justification of results of analysis needs to always be included when comparing the results of multiple MCDM methods.

General structure of job change decision involves the evaluation of preferences of the decision maker, job alternatives, and other factors to be considered. This multi-faceted characteristic makes it a typical decision problem where various multiple criteria decision making (MCDM) methods could be employed in aiding decision making. MCDM methods are used in various decision making problems for the ranking, selection, and prioritization of alternatives. Analytic Hierarchy Process (AHP) (Saaty, 1980) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon, 1981) are the two most preferred methods in applications.

Parallel to the developments of new methods; in order to take advantage of each method's predominant features, using two or more MCDM methods and creating hybrid methods have also gained popularity. Developments have led to another stream of research called fuzzy MCDM, when various fuzzy versions of these methods have been introduced to account for the linguistic evaluation of subjective perception or preferences of individuals. A recent survey of these studies by Mardani et al. (2015) shows that interest in hybrid fuzzy MCDM methods combining different methods grown exponentially. In this study, in order to assess the applicability of MCDM methods to job change decision problems, a faculty's job change decision is modeled and evaluated using three multi criteria decision making methods namely fuzzy AHP, fuzzy TOPSIS and a proposed hybrid of fuzzy AHP-TOPSIS. Then, comparative analyses are conducted to assess the three methods' performance on the decision problem at hand.

In this paper, the researcher analyses a job change decision making process from a job applicant perspective and suggests a decision making method that enables decision maker to identify and evaluate the factors and requirements related with the job that is important to him. The purpose of this study is twofold: first to analyze job change decision making process and demonstrate the applicability of MCDM methods for job change decision problems that will help individuals to determine what he/she wants in a job and evaluate alternatives accordingly. Then, evaluate the performance of the chosen MCDM methods comparatively based on four factors named as adequacy to changes of criteria or alternatives; agility in the decision process; computational complexity; and the number of criteria and alternatives.

The paper is organized into two consecutive sections. The first section explains the methodology in four subsections, respectively; fuzzy MCDM methods, fuzzy AHP method, and fuzzy TOPSIS method and proposed hybrid fuzzy AHP-TOPSIS methodology. Next section discusses the application results of the fuzzy MCDM methods to a job change decision problem. The following subsection compares the three methods' results. The last section presents a comparative analysis of the three methods.

2.0 METHODOLOGY

2.01 FUZZY MCDM METHODS

In the applications of MCDM methods, as stated by Vasant et al. (2008), decision making is facilitated by an analysis that incorporates classification of decision makers' judgements, calculating numerical values and converting the results into a numerical evaluation of alternatives. Basically, it is about making selections among alternatives under usually conflicting multiple decision criteria. MCDM problems are expected to have a limited number of decision alternatives that need to be sorted and ranked according to their attributes (Kahraman, 2008). Liou and Tzeng (2012) categorize MCDM models into three classes; evaluating or choosing models (e.g., input-output analysis, linear structure equation models, Decision Making Trial and evaluation Laboratory (DEMATEL)), weighting models (e.g., AHP, Analytic Network Process (ANP), Entropy measure), and normalizing models (e.g., simple additive weight (SAW), TOPSIS, ELECTRE, VIKOR, PROMETHEE). Very often in real world cases, application of MCDM methods may be hindered by imprecision or vagueness inherent in the criteria or judgements of the decision maker. For these decision situations, fuzzy MCDM methods are developed. Fuzzy MCDM methods build on fuzzy sets theory (Zadeh, 1965) and first applied in decision making by the seminal work of Bellman and Zadeh (1970). Since then, fuzzy versions of various MCDM methods are proposed to tackle decision problems in ambiguous conditions (Dubois, 2011).

There are different types of fuzzy numbers (such as triangular, trapezoidal and s-functions) which are used for analyzing various conditions. Triangular fuzzy numbers are preferred the most since they sufficiently describe fuzzy information and are computationally simple (Chen and Hung 2010). A triangular fuzzy number $\widetilde{N}$ is a subset of the real numbers and defined by three numbers $a < b < c$. It's characterized by a grade of membership based on the interval [0, 1]. Triangular membership function is defined as;

$$\mu_{\widetilde{N}}(x) = \begin{cases} (x-a)/(b-a), & a \le x \le b, \\ (c-x)/(c-b), & b \le x \le c, \\ 0, & otherwise \end{cases} \quad (01)$$

Alternatively, a fuzzy number $\widetilde{N}$ can also be expressed by its intervals (Zimmermann, 2001), using α-cuts ($\widetilde{N}_\alpha$) of the fuzzy number as;

$$\widetilde{N} = \cup_\alpha \alpha \widetilde{N}_\alpha, \quad 0 < \alpha \le 1 \quad (02)$$

where, $\widetilde{N}_\alpha = [min\{x \in X | \mu_{\widetilde{N}}(x) \ge \alpha\}, max\{x \in X | \mu_{\widetilde{N}}(x) \ge \alpha\}$ (03)

Some of the fuzzy MCDM methods that have received much attention are fuzzy AHP (e.g., Cheng and Mon, 1994; Cheng, 1997; Chan and Kumar, 2007; Rajput et al., 2011; Jing et al., 2013); fuzzy TOPSIS (e.g., Chen, 2000; Wang and Elhag, 2006; Wang and Lee, 2007; Kahraman et al., 2007; Boran et al., 2011; Kilic, 2013; Zhang & Xu, 2014); fuzzy ELECTRE (e.g., Montazer et al., 2009; Vahdani & Hadipour, 2011); and fuzzy DEMATEL (e.g., Lin & Wu, 2008; Lee et al., 2011). In addition, as it is observed in classic MCDM applications; hybrid fuzzy MCDM methods combining multiple fuzzy methods are also suggested. Most of the hybrid fuzzy MCDM methods employed fuzzy AHP and combined it with other methods (e.g., Tuzkaya et al., 2010; Hadi-Vencheh & Mohamadghasemi, 2011). The second most preferred fuzzy MCDM in the hybrid models is fuzzy TOPSIS (e.g., Dursun and Karsak, 2010). By far most preferred fuzzy MCDM methods combined in hybrid models are fuzzy AHP and fuzzy TOPSIS (e.g., Ertuğrul & Karakaşoğlu, 2007; Önüt et al., 2008; Gumus, 2009; Chen & Hung, 2010; Paksoy et al., 2012; Yazdani-Chamzini, 2014).

2.02 FUZZY AHP METHOD

Saaty (1980) developed AHP based on pair-wise comparisons to derive priority scales. AHP uses nine point scale to capture decision maker's evaluations. Even though this crisp value scale has the advantage of simplicity in applications, it cannot sufficiently capture inherent uncertainty in human judgements. Scholars suggested various fuzzy AHP methods to extend the AHP's applicability in subjective and imprecise decision making cases. For example, Van Laarhoven and Pedrycz (1983) developed logarithmic least squares method and Buckley (1985) proposed a method using geometric means. Chang (1996) suggested a synthetic extent analysis. Csutora and Buckley (2001) used the lambda-max method. Each model has different characteristics and computational structure; thus adaptations of these models in applications mostly depend on their complexity. One important aspect of AHP compared to the other MCDM methods is that it offers a mechanism to measure the reliability of decision maker's judgements. Researchers suggested some methods for the fuzzy AHP in measuring consistency of pairwise comparisons. However; the idea has not been fully accepted in the applications yet, since some studies skip reporting the consistency of judgements. In this study, consistency of decision maker's judgements are measured using the widely accepted AHP method. The consistency ratio (CR) calculations are done using crisp values of the fuzzy numbers as suggested by Chen & Hung (2010). According to Saaty (1980), consistency ratio is approximated via λmax and consistency ratio of an evaluation matrix should not exceed the acceptable level of 0.1.

$$CI=(\lambda max-n)/(n-1) \quad (04)$$

$$CR=CI/RC \quad (05)$$

2.03 FUZZY TOPSIS METHOD

Hwang and Yoon (1981) suggested TOPSIS method for the ranking of alternatives in MCDM problems. The performance measure of alternatives are calculated on the basis of their relative distance from positive and negative ideal solutions. An alternative's performance increases as its distance is closer to the positive ideal solution and farther to the negative ideal solution (Abo-Sinna & Amer, 2005). TOPSIS requires precise and crisp ratings of alternatives. However, for the problems requiring uncertain or imprecise human judgement, crisp data are inadequate to model the real-life decision problems (Ertuğrul & Karakaşoğlu, 2007). In order to overcome this problem, the fuzzy TOPSIS method is proposed and used in various decision problems (e.g., Chen, 2000; Abo-Sinna & Amer, 2005; Jahanshahloo et al., 2006). Fuzzy TOPSIS uses fuzzy numbers to represent evaluations presented in linguistic terms.

2.04 HYBRID FUZZY AHP-TOPSIS METHOD

This section presents a hybrid fuzzy AHP-TOPSIS method for job change decision of a faculty. Application of MCDM methods related to job change decision problem is very limited in the literature. One related study is Alp and Özkan's (2015) study of job choice problem. They consider an individual's selection of occupation as a MCDM problem and analyze it using fuzzy TOPSIS method. Differing from their study, this research applies fuzzy AHP and fuzzy TOPSIS methods and introduces a hybrid fuzzy AHP-TOPSIS method for job change decision problem, where the evaluation of alternatives and subjective criteria are represented in linguistic terms. In the proposed hybrid method, the use of fuzzy AHP allows for evaluation of the relative importance between criteria using pairwise comparisons in linguistic terms. The use of fuzzy TOPSIS enables an efficient procedure to rank the performance of the alternatives. The method of Csutora and Buckley (2001) is chosen for the fuzzy AHP procedure and Chen's (2000) method is chosen for the fuzzy TOPSIS procedure. In both models, linguistic scales represented by triangular fuzzy numbers are preferred for criteria (Table 1) and alternatives' (Table 2) evaluations.

Table 01: Linguistic scale for importance and preferences

Linguistic scales for importance weights of criteria	**Linguistic scales for alternative preference**	Triangular Fuzzy Scale
Equally important	Equally preferred	(1, 1, 1)
Weakly important	Weakly preferred	(1, 3, 5)
Essentially important	Essentially preferred	(3, 5, 7)
Very strongly important	Very strongly preferred	(5, 7, 9)
Absolutely more important	Absolutely more preferred	(7, 9, 9)

Table 2: Linguistic scale to evaluate the ratings of the alternative jobs.

Linguistic scales for ratings of alternatives	**Triangular Fuzzy Scale**
Very Low (VL)	(0, 0, 2.5)
Low (L)	(0, 2.5, 5)
Medium (M)	(2.5, 5, 7.5)
High (H)	(5, 7.5, 10)
Very High (VH)	(7.5, 10, 10)

The proposed hybrid method consists of three main stages;
Stage 1. Identify the evaluation criteria that are important for the decision maker.
Stage 2. Calculate the weights of criteria through the application of fuzzy AHP method.
Stage 3. Conduct fuzzy TOPSIS method to achieve the final ranking results.

Although job change decision involves basic factors to consider such as wage, benefits and location; each factor may incorporate a problem or criteria that are specific to the decision maker. Thus, the first stage applying the method requires the involvement of the decision maker to identify the problem-specific criteria. In this study, a semi-structured interview is conducted with the decision maker involving a predetermined set of open-ended questions in order to determine the important decision criteria.

In the following part, stages of the proposed method are summarized in steps. The fuzzy AHP method is used for the calculation of fuzzy weights of the criteria as described by Csutora and Buckley (2001).

Step 1: Determine the fuzzy relative importance of different criteria. Construct a pairwise comparison matrix using linguistic scale, represented by triangular fuzzy numbers in Table 1. For *n* criteria, the pairwise comparison of criterion *i* with *j* yields a square matrix C as:

$$\tilde{C} = \begin{bmatrix} (1,1,1) & x_{12} & \cdots & x_{1n} \\ x_{21} & (1,1,1) & & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & (1,1,1) \end{bmatrix} \quad (06)$$

where $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $x_{ji}^{-1} = \left({}^{1}/_{c_{ji}}, {}^{1}/_{b_{ji}}, {}^{1}/_{a_{ji}} \right)$ i, j = 1, 2, …, n, i ≠ j.

Step 2: Calculate the fuzzy weights of criteria using decision maker evaluation matrix $\tilde{C}$.

a) Let α=1 then, use modal value (*b*) of the fuzzy evaluations and apply AHP to calculate the weight matrix w_b.

$$w_b = [w_{ib}], \quad i = 1,2,3 \ldots \ldots . . n \quad (07)$$

b) Let α =0 then, use lower (a) and upper (c) bounds of the fuzzy evaluations and apply AHP to calculate the weight matrices, w_a and w_c

$$w_a = [w_{ia}], \quad i = 1,2,3 \ldots \ldots . . n \quad (08)$$

$$w_c = [w_{ic}], \quad i = 1,2,3 \ldots \ldots . . n \quad (09)$$

c) In order to ensure the fuzziness of weights, calculate two constants, C_a and C_c, as follows:

$$C_a = \min \{ \frac{w_{ib}}{w_{ia}} \; where \quad 1 \leq \mathrm{i} \leq \mathrm{n} \} \quad (10)$$

$$C_c = \max \{ \frac{w_{ib}}{w_{ic}} \; where \quad 1 \leq \mathrm{i} \leq \mathrm{n} \} \quad (11)$$

d) The lower bound (w_a^*) and the upper bound (w_c^*) of the weight matrix are defined as

$$w_a^* = [\, w_{ia}^*], \; w_{ia}^* = C_a \, w_{ia} \quad i = 1,2,3 \ldots \ldots . . n \quad (12)$$

$$w_c^* = [\, w_{ic}^*], \; w_{ic}^* = C_c \, w_{ic} \quad i = 1,2,3 \ldots \ldots . . n \quad (13)$$

e) Construct the fuzzy weights of the criteria as follows:

$$w_i = (w_a^*, w_b^*, w_c^*), \quad i = 1,2,3 \ldots \ldots . . n \quad (14)$$

Step 3: Assemble the fuzzy decision matrix *D* of the alternatives and the criteria according to Eq. (15), where $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$ is the fuzzy evaluation value of decision maker of each alternatives (A_i) for each criterion (C_j):

$$D = \begin{matrix} & \begin{matrix} C_1 & C_2 & \ldots & C_n \end{matrix} \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \end{matrix} \quad (15)$$

Step 4: Establish a normalized fuzzy performance matrix R using the linear scale transformation.

$$R = [r_{ij}]_{m\times n} \quad i = 1, 2 \ldots m \quad j = 1, 2 \ldots n \qquad (16)$$

a) Eqs. (17) and (18) can be used to obtain a value $[r_{ij}]$ which is within [0, 1]. B and C are the set of benefit criteria and cost criteria respectively;

$$r_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), j \in B; \qquad (17)$$

$$r_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), j \in C; \qquad (18)$$

$$c_j^* = \max_i c_{ij} \;\; if\; j \in B; \quad a_j^- = \min_i a_{ij} \;\; if\; j \in C$$

Step 5: Calculate the weighted normalized fuzzy performance matrix using the fuzzy weight matrix of criteria $W = [w_1, w_2, \ldots, w_n]$.

$$V = [v_{ij}]_{mxn} \quad i = 1, 2 \ldots m \quad j = 1, 2 \ldots n \qquad (19)$$

where $v_{ij} = r_{ij} \otimes w_j$ and $v_{ij}, \forall\, i, j$ are normalized positive triangular fuzzy numbers and have values in the range [0, 1].

Step 6: Determine fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) as follows:

FPIS: $A^* = (v_1^*, v_2^* \ldots \; v_n^*)$ (20)

FNIS: $A^- = (v_1^-, v_2^- \ldots \; v_n^-)$

where $v^*{}_{ij} = (1, 1, 1)$ and $v^-{}_{ij} = (0, 0, 0)$

Step 7: Calculate the distance of each alternative from FPIS and FNIS. Chen (2000) used the Euclidean distance between two fuzzy numbers as a crisp value to obtain the ranking order of the decision elements:

$$d_i^-(v_{ij}, v^-{}_{ij}) = \sqrt{1/3\,[(v_{ia} - 0)^2 + ((v_{ib} - 0)^2) + ((v_{ic} - 0)^2)]} \qquad i = 1, 2 \ldots m \qquad (21)$$

$$d_i^+(v_{ij}, v^*{}_{ij}) = \sqrt{1/3\,[(v_{ia} - 1)^2 + ((v_{ib} - 1)^2) + ((v_{ic} - 1)^2)]} \qquad i = 1, 2 \ldots m \qquad (22)$$

Step 8: Define a closeness coefficient (CC_i) to rank all the alternatives as;

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad i = 1, 2 \ldots m \qquad (23)$$

where $d_i^-(v_{ij}, v^-{}_{ij})$ *and* $d_i^+(v_{ij}, v^*{}_{ij})$ are Euclidean distance of two triangular fuzzy numbers.

3.0 RESULTS

3.01 THE APPLICATION OF FUZZY MCDM METHODS TO JOB CHANGE DECISION

A job changing decision of a faculty working in a university is used as an illustrative example in the comparison of the three fuzzy MCDM methods namely; fuzzy AHP, fuzzy TOSIS, and the hybrid fuzzy AHP-TOPSIS as explained in the previous section. Buckley's (1985) method and the method of Csutora and Buckley (2001) applied for the fuzzy AHP analysis. Both methods show almost identical results. Thus, in this study, only the result of Csutora and Buckley (2001) method is reported. For the fuzzy TOPSIS analysis Chen's (2000) extension of the TOPSIS for group decision-making method is adapted for the single decision maker case. This section presents only the fuzzy AHP-TOPSIS method's steps for illustrative purposes. Final results from the three methods are used for the comparison of the methods. The job change decision at hand involves five job alternatives in different universities located in five different cities. In the first stage of the study, a semi-structured interview is conducted with the decision maker to identify the factors that he would consider in his job change decision. Five factors identified as decision criteria in the evaluation of five alternative jobs. These criteria are; salary (C1), cost of living (C2), social relations (C3), work environment (C4), and effects on the family (C5). Then, two sets of evaluation questionnaire using linguistic scale (Table 1 and 2) represented by triangular fuzzy numbers are administered to determine the importance weight of the criteria and evaluation of alternatives. One questionnaire set involves the separate fuzzy pairwise comparisons of criteria and alternatives that is required for the fuzzy AHP method. The other set includes individual evaluation of criteria and evaluation of alternatives according to each criterion which is required for the fuzzy TOPSIS method. For the fuzzy AHP-TOPSIS method, decision maker's evaluation of fuzzy pairwise comparison of criteria and evaluation of alternatives for each criterion are used in the analysis. Table 3 shows decision maker's pairwise comparison matrix of the criteria.

Table 3: Criteria pair-wise comparison matrix

	C1	C2	C3	C4	C5
C1	(1.00, 1.00, 1.00)	(3.00, 5.00, 7.00)	(3.00, 5.00, 7.00)	(1.00, 3.00, 5.00)	(0.20, 0.33, 1.00)
C2	(0.14, 0.20, 0.33)	(1.00, 1.00, 1.00)	(3.00, 5.00, 7.00)	(1.00, 1.00, 1.00)	(0.20, 0.33, 1.00)
C3	(0.14, 0.20, 0.33)	(0.14, 0.20, 0.33)	(1.00, 1.00, 1.00)	(0.14, 0.20, 0.33)	(0.11, 0.11, 0.14)
C4	(0.20, 0.33, 1.00)	(1.00, 1.00, 1.00)	(3.00, 5.00, 7.00)	(1.00, 1.00, 1.00)	(0.20, 0.33, 1.00)
C5	(1.00, 3.00, 5.00)	(1.00, 3.00, 5.00)	(7.00, 9.00, 9.00)	(1.00, 3.00, 5.00)	(1.00, 1.00, 1.00)
CR= 0.08					

Using the Eqs. (7)-(11) decision maker's weight matrix is calculated. Results are shown in Table 4.

Table 4: Weight matrix

w_a					w_b					w_c				
1	3	3	1	0.2	1	5	5	3	0.3	1	7	7	5	1
0.14	1	3	1	0.2	0.2	1	5	1	0.3	0.3	1	7	1	1
0.14	0.14	1	0.14	0.1	0.2	0.2	1	0.2	0.1	0.3	0.3	1	0.3	0.14
0.2	1	3	1	0.2	0.3	1	5	1	0.3	1	1	7	1	1
1	1	7	1	1	3	3	9	3	1	5	5	9	5	1
$C_a = 0.748$, $C_c = 1.114$														

Applying Eqs. (12)-(14) gave the fuzzy importance weights of each criterion according to the decision maker's judgment (Table 5).

Table 5: Importance measures of the criteria

Criteria	**W**
C1	(0.213, 0.285, 0.332)
C2	(0.113, 0.124, 0.147)
C3	(0.036, 0.036, 0.036)
C4	(0.116, 0.130, 0.167)
C5	(0.270, 0.425, 0.432)

Table 6 shows the decision maker's evaluation of each alternative for every criterion using the linguistic scale in Table 2. Next, the triangular fuzzy number equivalent of the linguistic ratings of the alternatives are normalized using linear scale transformation shown in Table 7.

Table 6: Linguistic ratings of the alternatives for each criterion

	C1	C2	C3	C4	C5
A1	L	L	H	H	M
A2	L	L	H	H	H
A3	VH	VH	VH	M	H
A4	H	H	H	H	H
A5	VH	VH	H	L	L

Table 7: Normalized fuzzy decision matrix

	C1	C2	C3	C4	C5
A1	(0.00, 0.25, 0.50)	(0.00, 0.25, 0.50)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
A2	(0.00, 0.25, 0.50)	(0.00, 0.25, 0.50)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
A3	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)
A4	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
A5	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.00, 0.50, 1.00)	(0.00, 0.50, 1.00)

Using the fuzzy importance weights in Table 5 and normalized fuzzy decision matrix in Table 7, the weighted normalized fuzzy performance matrix of each alternative is calculated as shown in Table 8.

Table 8: Weighted normalized fuzzy performance matrix

	C1	C2	C3	C4	C5
A1	(0.00, 0.07, 0.17)	(0.00, 0.03, 0.07)	(0.02, 0.03, 0.04)	(0.06, 0.10, 0.17)	(0.07, 0.21, 0.32)
A2	(0.00, 0.07, 0.17)	(0.00, 0.03, 0.07)	(0.02, 0.03, 0.04)	(0.06, 0.10, 0.17)	(0.14, 0.32, 0.43)
A3	(0.16, 0.29, 0.33)	(0.09, 0.12, 0.15)	(0.03, 0.04, 0.04)	(0.03, 0.07, 0.13)	(0.14, 0.32, 0.43)
A4	(0.11, 0.21, 0.33)	(0.06, 0.09, 0.15)	(0.02, 0.03, 0.04)	(0.06, 0.10, 0.17)	(0.14, 0.32, 0.43)
A5	(0.16, 0.29, 0.33)	(0.09, 0.12, 0.15)	(0.02, 0.03, 0.04)	(0.00, 0.07, 0.17)	(0.00, 0.21, 0.43)

Applying the Eqs. (21)-(23) each alternative's closeness coefficient is calculated. Table 9 shows the ranking of alternatives based on CC scores. According to the hybrid fuzzy AHP-TOSIS method's result alternatives are ranked as; A3>A4>A5>A2>A1.

Table 9: Final ranking

Alternatives	d-	d+	CC	CC Rank
A1	4.082	0.492	0.108	5th
A2	4.011	0.662	0.142	4th
A3	3.794	0.853	0.184	1st
A4	3.829	0.797	0.172	2nd
A5	3.865	0.741	0.161	3rd

3.02 COMPARISON OF THE RESULTS

In order to compare fuzzy AHP, fuzzy TOPSIS and fuzzy AHP-TOPSIS results, each method's final fuzzy performance evaluations of alternatives are defuzzified using closeness coefficient defined in Eq. (21) and Eq. (23). As seen in Table 10, all three method's final ranking of alternatives are the same. The results show that all three methods are appropriate for the job change decision problem. However, the three methods differ in terms of their usability and computation complexity. Studies show that fuzzy AHP and fuzzy TOPSIS have some fundamental limitations and advantages (Ertuğrul & Karakaşoğlu, 2007). However, there are limited number of studies on the comparison of fuzzy AHP and fuzzy TOPSIS (i.e. Ertuğrul & Karakaşoğlu, 2007; Lima Junior et al., 2014). Furthermore, there are more than one algorithm available for each method. Thus, there is a need for additional comparison studies in order to capture each method's limitations and advantages for different decision problems. Next section includes a comparative analysis of the three methods.

Table 10: Comparison of the three methods' results

	Fuzzy AHP				Fuzzy TOPSIS				Fuzzy AHP-TOPSIS			
	d-	d+	CC	CC Rank	d-	d+	CC	CC Rank	d-	d+	CC	CC Rank
A1	0.109	1.420	0.071	5th	2.690	2.035	0.431	5th	4.082	0.492	0.108	5th
A2	0.189	1.345	0.123	4th	2.547	2.298	0.474	4th	4.011	0.662	0.142	4th
A3	0.516	1.030	0.334	1st	1.609	3.015	0.652	1st	3.794	0.853	0.184	1st
A4	0.508	1.040	0.328	2nd	1.691	2.806	0.624	2nd	3.829	0.797	0.172	2nd
A5	0.332	1.203	0.216	3rd	1.870	2.741	0.594	3rd	3.865	0.741	0.161	3rd

3.03 COMPARATIVE ANALYSIS OF THREE METHODS

There are few studies available for comparative analysis of AHP and TOPSIS methods in the literature. For a facility location selection problem, Ertuğrul & Karakaşoğlu (2007) compare Chang's (1996) fuzzy AHP method and Chen's (2000) (in addition to Chen et al., 2006) fuzzy TOPSIS method and discuss similarities and differences of the two methods. Following Ertuğrul & Karakaşoğlu (2007), Lima Junior et al., (2014) conduct a comparative analysis of the same fuzzy AHP and fuzzy TOPSIS methods considering seven factors for a supplier selection process. However, Chen's (2000) method chosen in these studies deficiently calculates null weights for comparisons in some cases and there are concrete claims that this method cannot estimate the true weights from fuzzy comparison matrix (Wang, Luo and Hua, 2008). Similarly Yavuz et al. (2014) and Lima Junior et al., (2014) report cases where Chen's method fails to assign weights to some criteria. Thus, studies comparing fuzzy AHP with fuzzy TOPSIS other than Chen's are needed in order to justify the findings about the fuzzy AHP method. This part of the paper discusses a comparative analysis of the three methods namely; Csutora and Buckley's (2001) fuzzy AHP, Chen's (2000) fuzzy TOPSIS and the proposed hybrid fuzzy AHP-TOPSIS by using the four of the seven factors suggested by Lima Junior et al., (2014). In the comparison of the methods, the following factors are taken into consideration: adequacy to changes of criteria and alternatives; agility in the decision process; computational complexity; and number of criteria and alternatives.

Job change situations involves certain criteria and alternatives specific to decision maker, thus the decision making method must be chosen accordingly in order to produce a consistent preference order of alternatives. In the adequacy to changes of criteria and alternatives analysis, each model is tested for the effect of inclusion and exclusion of criteria or alternatives to the final ranking. Exclusion of a criterion or alternative from the model does not produce any change in the final ranking of the alternatives in the three models. Ten tests are performed for each inclusion of criteria and inclusion of alternatives; each test incorporating an additional criteria or alternative with rating equal to one of the existing criteria or alternative. The results demonstrate no significant changes in the final scores of alternatives and the ranking order in most of the tests, except for the inclusion of criteria for each model. In the case that the additional criterion has an importance weight equal to C5's weight, then the first and the second ranked alternatives switch places in the fuzzy AHP analysis (Figure 1a-b). The same inversion of importance order takes place in the fuzzy TOPSIS analysis (Figure 2a-b) when the additional criterion has an importance weight equal to the one of C4. This indicates that when there is a change of criteria, ranking reversal of alternatives can occur both in fuzzy AHP and fuzzy TOPSIS applications. In the fuzzy AHP-TOPSIS application, adding a new criterion causes almost no change in the order of the alternatives when the additional criterion has an importance weight equal to C1's weight. However, the rating of alternatives ranked second and third measures almost equal to each other as shown in Figure 3b.

Figure 1: Results of the changes of criteria tests for fuzzy AHP

a) shows original results

b) shows the result with additional criterion weighted same as C5

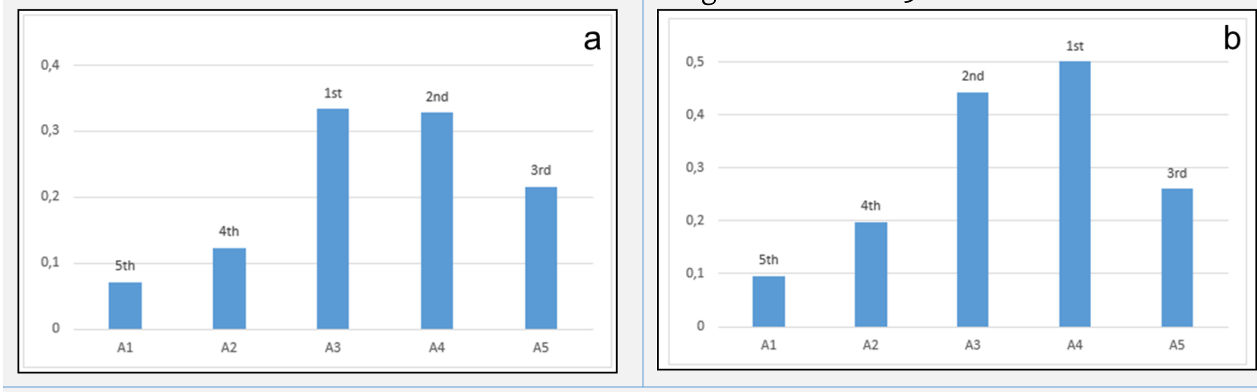


Figure 2: Results of the changes of criteria tests for fuzzy TOPSIS

a) shows original results

b) shows the result with additional criterion weighted same as C4

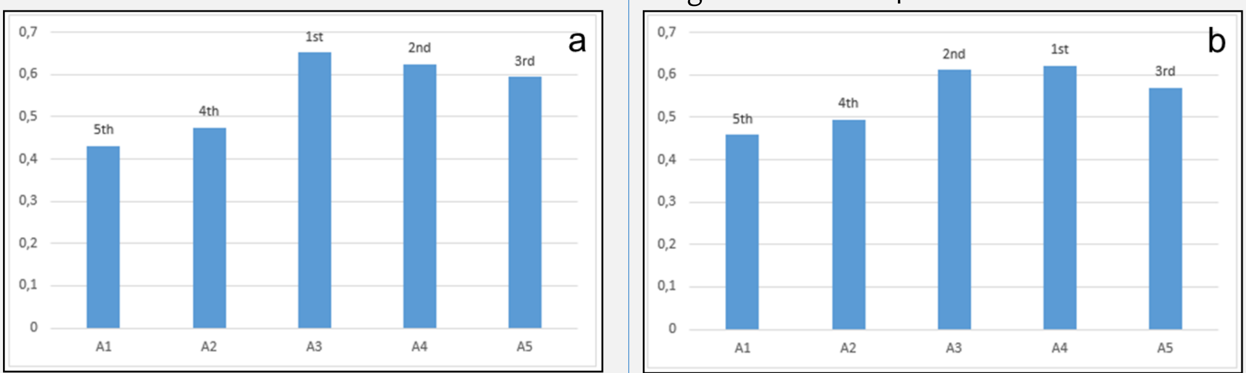
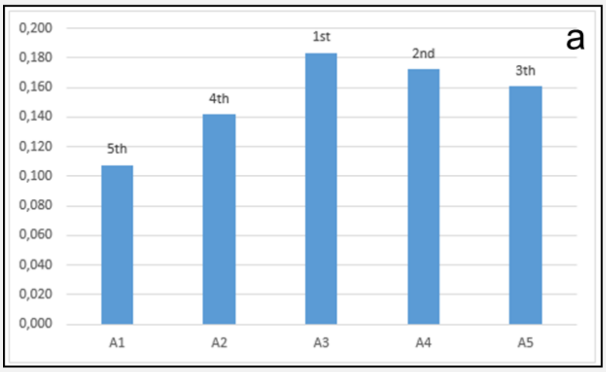
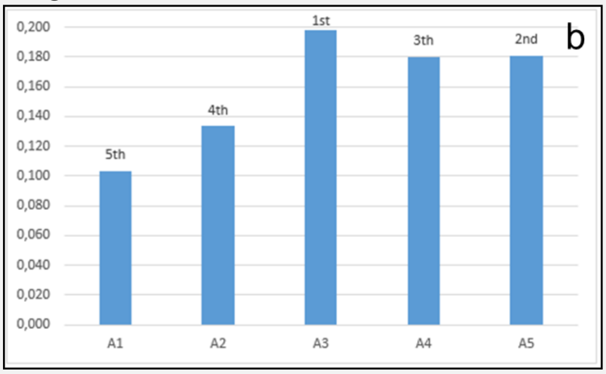


Figure 3: Results of the changes of criteria tests for fuzzy AHP-TOPSIS

a) shows original results



b) shows the result with additional criterion weighted same as C1



The second comparison is on the agility of each method in the decision process. Agility measures the amount of judgements required from the decision maker in three methods. For the *n* number of alternatives and *m* number of criteria, total number of required judgements in fuzzy AHP is expressed as (Lima Junior et al., 2014);

$$J_{n,m}^{FAHP} = m\left(\frac{m-1}{2}\right) + m\left[n\left(\frac{n-1}{2}\right)\right] \quad (24)$$

In the fuzzy TOPSIS method the total number of required judgement is (Lima Junior et al., 2014)

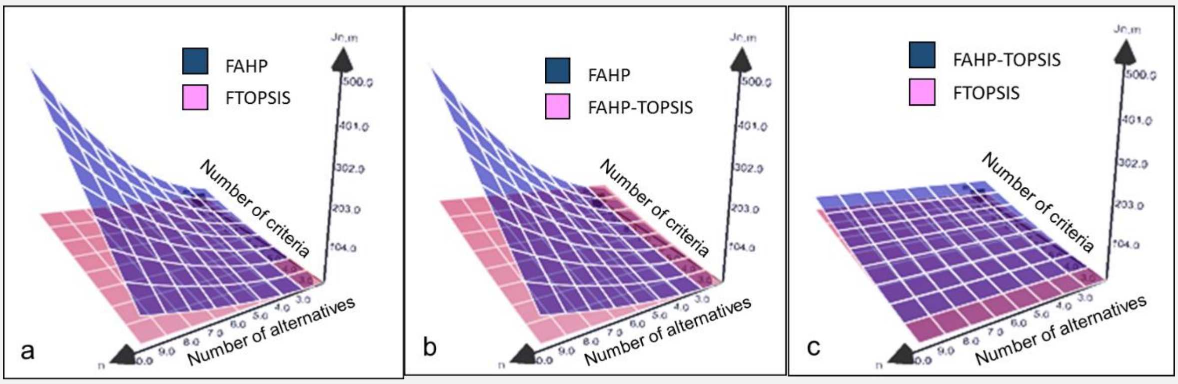
$$J_{n,m}^{FTOPSIS} = m(1+n) \quad (25)$$

In the fuzzy AHP-TOPSIS method, the total number of required judgement shows the combination of the criteria evaluation judgements of fuzzy AHP and alternative evaluation judgements of fuzzy TOPSIS methods, as shown in Eq. (26).

$$J_{n,m}^{FAHP-TOPSIS} = m\left(\frac{m-1}{2}\right) + mn = m\left[\left(\frac{m-1}{2}\right) + n\right] \quad (26)$$

Figure 4 presents the number of judgements for the three methods based on Eqs. (24)-(26) when the number of criteria and alternatives vary from 2 to 9. For example, in the current application study, fuzzy AHP requires 60 judgements, fuzzy TOPSIS requires 30 and fuzzy AHP-TOPSIS requires 35 judgements. As the number of criteria and alternatives increases the number of required judgements for the fuzzy AHP increases drastically compare to the other two methods (see Figure 4a and b). Fuzzy AHP-TOPSIS outperforms the fuzzy AHP but performs slightly worse than the fuzzy TOPSIS. Thus, fuzzy TOPSIS performs better than the two models for all cases and provides agility in the decision process.

Figure 4: Results of the agility in the decision process test



The next comparison measures the computational complexity of the three methods. Similar to the studies by Chang (1996) and Lima Junior et al., (2014), the analysis uses time complexity when comparing the computational complexity of the methods. Time complexity measures the number of times of multiplications and logical operations within the methods (Lima Junior et al., 2014). For *n* alternatives and *m* criteria, number of operations the fuzzy AHP method requires to compute is;

$$T_{n,m}^{FAHP} = n(3n+7) + nm(3m+7) + 14m \qquad (27)$$

On the other hand, fuzzy TOPSIS method requires 20*nm* operations to compute as shown in Eq. (28) (Lima Junior et al., 2014).

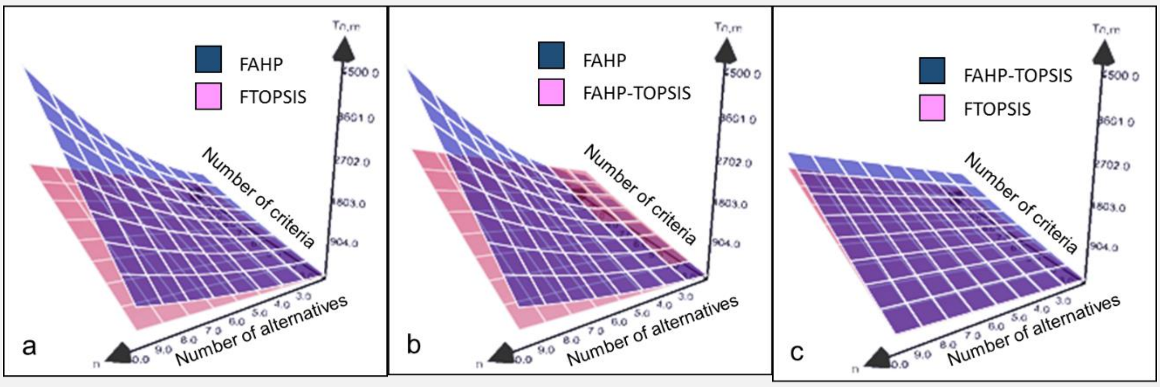
$$T_{n,m}^{FTOPSIS} = 20nm \qquad (28)$$

Since fuzzy AHP-TOPSIS method is a combination of the two methods, the operations required to compute complexity is;

$$T_{n,m}^{FAHP-TOPSIS} = n(3n+7) + 20nm \qquad (29)$$

The graphics in Figure 5 show time complexity variations depending on the number of criteria and alternatives when comparing two methods at a time. As shown in Figure 5a and 5b, fuzzy AHP performs worst compare to the other two methods. On the other hand in general fuzzy TOPSIS performs much better than the two methods. The operation requirements of fuzzy AHP-TOPSIS are better than the fuzzy AHP but slightly worse than the fuzzy TOPSIS (Figure 5b-c). In this application study, the fuzzy AHP requires 1080 operations while the fuzzy TOPSIS requires 500, and the fuzzy AHP-TOPSIS requires 610.

Figure 5: Results of time complexity tests



The last comparison is on the limitations of the number of criteria and alternatives in each method. There are no reported restrictions available on the number of criteria and alternatives for the fuzzy TOPSIS method (Lima Junior et al., 2014). However, as Saaty (1980) suggests, in order not to compromise the decision maker's judgement and its consistency, the number of criteria or alternatives to be compared needs to be limited to nine for AHP method. Since fuzzy AHP uses the same approach to capture decision maker's judgements, Saaty's (1980) suggestion about the limitation of the number of criteria and alternatives also applies to fuzzy AHP. For the fuzzy AHP-TOPSIS method, this limitation is only valid for the number of criteria, as fuzzy AHP method is employed for the importance evaluations of the criteria.

In this study a comparative analysis helps to further investigate the methods' performances. Thirty six tests with respect to changes of criteria and alternatives, agility of decision making, and computational complexity enables the comparative computational evaluation of the methods. Overall, the results of fuzzy AHP and fuzzy TOPSIS methods' comparisons confirm the findings of Lima Junior et al., (2014) study. In the adequacy to changes of alternatives tests, the three methods produce consistent results when including and excluding a new alternative. However, in the adequacy to changes of criteria, only the fuzzy AHP-TOPSIS method's results remain the same when a new criterion is included. Agility in the decision process tests show that Fuzzy AHP-TOPSIS performs better than fuzzy AHP in most cases except when there are very few alternatives. Computational complexity test indicates that, fuzzy TOPSIS performs better than fuzzy AHP and fuzzy AHP-TOPSIS in all cases. Fuzzy AHP-TOPSIS performs better than fuzzy AHP in most cases except when there are a few alternatives and many criteria.

In terms of the limitations of the number of criteria and alternatives in each method, fuzzy AHP method has some disadvantages. Although the use of pairwise comparisons enables a more natural form of evaluation that is in accord with the way human mind works, as the number of items to be compared increases, the number of comparisons increases drastically. As the number of comparisons increases to a certain number, then the consistency of judgements decline since there is a limit in human comprehension. Thus, there must be a limit in the number of criteria and alternatives for the fuzzy AHP method. This limitation is only valid for the number of criteria in fuzzy AHP-TOPSIS method where fuzzy AHP is employed for the evaluation of importance weight of criteria. On the other hand, there is no limitation on the number of criteria and alternatives in the fuzzy TOPSIS method. Nonetheless, fuzzy AHP-TOPSIS method has satisfactory performance on all fronts and it is practical for the job change decision with respect to multiple conflicting criteria.

4.0 CONCLUSION

Previous studies investigate the applicability of various fuzzy MCDM methods in different decision problems. Fuzzy AHP and fuzzy TOPSIS are the most preferred methods used in these studies. In order to overcome limitations or to use the advantages of each method, hybrid MCDM methods combining different MCDM methodologies gain popularity in application studies. In addition to the application of fuzzy AHP and fuzzy TOPSIS methods, this paper proposes a hybrid method combining the advantages of both fuzzy AHP and fuzzy TOPSIS methods with the intention of clarifying the use of fuzzy MCDM techniques and testing their applicability on a job change decision problem. Overall, in this application study, three methods provide satisfactory results for the decision maker. All three methods achieve the same performance ranking of alternatives. Thus the application contributes to the MCDM methods literature by providing evidence about the validity and robustness of the three methods.

This paper presents an analysis of a job change decision problem using three fuzzy MCDM methods. Post analysis discussion with the decision maker about the results reveals that employing fuzzy MCDM methods enable the decision maker to clearly identify the factors effecting his decision. On the contrary to his preceding judgement, he realizes that the most important factor is the effects of his decision on his family's life. This is a typical case of job applicant's incorrect assessment about his expectations as Breaugh, et al., (2008) mention. In this case, administering MCDM methods as a decision aid shows that the steps of the methods purposefully lead the decision maker into thinking about the factors separately and therefore leading him to evaluate the alternatives accordingly. It is evident from these results that using fuzzy MCDM methods ease the cognitive burden of conflicting factors effecting the decision making process that is mentioned in the studies (i.e. Murtagh et al. 2011) and help construct a systematic thinking process. In terms of the study's contribution to employee recruitment research, these results indicate that using fuzzy MCDM methods enables job applicants to truly assess their expectations from a job and therefore clearly contributes to a successful recruitment process; overcoming applicant related problems mentioned in the employee recruitment studies. Using this type of decision aid may also help businesses in identifying the applicant related factors and developing strategies that can attract the right person to the job offered. As the paper compares the methods and illustrates the reasons why the hybrid fuzzy AHP-TOPSIS approach is the most suitable and applicable to a wider range of problems compare to the other methods, it could be a more comprehensive precursor to accurate recruitment strategies.

REFERENCES

Abo-Sinna, M. A., & Amer, A. H. (2005). Extensions of TOPSIS for multi-objective large-scale nonlinear programming problems. Applied Mathematics and Computation, 162(1): 243–256. http://doi.org/10.1016/j.amc.2003.12.087

Alp, S., & Özkan, T. K. (2015). Job choice with multi-criteria decision making approach in a fuzzy environment. International Review of Management and Marketing, 5(3): 165–172.
Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. Management Science, 17(4): 141–164. http://doi.org/10.1287/mnsc.17.4.B141
Boran, F. E., Genç, S., & Akay, D. (2011). Personnel selection based on intuitionistic fuzzy sets. Human Factors and Ergonomics in Manufacturing & Service Industries, 21(5): 493–503. http://doi.org/10.1002/hfm.20252
Boswell, W. R., Roehling, M. V., LePine, M. A., & Moynihan, L. M. (2003). Individual job-choice decisions and the impact of job attributes and recruitment practices: a longitudinal field study. Human Resource Management, 42(1): 23–37.
Breaugh, J. A. (2008). Employee recruitment: current knowledge and important areas for future research. Human Resource Management Review, 18(3): 103–118. http://doi.org/10.1016/j.hrmr.2008.07.003
Breaugh, J. A., Macan, T. H., & Grambow, D. M. (2008). Employee Recruitment: Current Knowledge and Directions for Future Research. In G. P. Hodgkinson & J. K. Ford (Eds.), International Review of Industrial and Organizational Psychology. John Wiley & Sons, Ltd. pp. 45–82. http://doi.org/10.1002/9780470773277.ch2
Buckley, J. J. (1985). Fuzzy hierarchical analysis. Fuzzy Sets and Systems, 17(3): 233–247. http://doi.org/10.1016/0165-0114(85)90090-9
Chan, F. T. S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. Omega, 35(4): 417–431. http://doi.org/10.1016/j.omega.2005.08.004
Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. European Journal of Operational Research, 95(3): 649–655.
Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets and Systems, 114(1): 1–9. http://doi.org/10.1016/S0165-0114(97)00377-1
Chen, C. T., Lin, C. T., & Huang, S. F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. International Journal of Production Economics, 102(2): 289–301. http://doi.org/10.1016/j.ijpe.2005.03.009
Chen, L. H., & Hung, C. C. (2010). An integrated fuzzy approach for the selection of outsourcing manufacturing partners in pharmaceutical R&D. International Journal of Production Research, 48(24): 7483–7506. http://doi.org/10.1080/00207540903365308
Cheng, C. H. (1997). Evaluating naval tactical missile systems by fuzzy AHP based on the grade value of membership function. European Journal of Operational Research, 96(2): 343–350. http://doi.org/10.1016/S0377-2217(96)00026-4
Cheng, C. H., & Mon, D. L. (1994). Evaluating weapon system by analytical hierarchy process based on fuzzy scales. Fuzzy Sets and Systems, 63(1): 1–10. http://doi.org/10.1016/0165-0114(94)90140-6
Csutora, R., & Buckley, J. J. (2001). Fuzzy hierarchical analysis: the lambda-max method. Fuzzy Sets and System, 120(2): 181–195.
Dubois, D. (2011). The role of fuzzy sets in decision sciences: old techniques and new directions. Fuzzy Sets and Systems, 184(1): 3–28. http://doi.org/10.1016/j.fss.2011.06.003
Dursun, M., & Karsak, E. E. (2010). A fuzzy MCDM approach for personnel selection. Expert Systems with Applications, 37(6): 4324–4330. http://doi.org/10.1016/j.eswa.2009.11.067
Ertuğrul, İ., & Karakaşoğlu, N. (2007). Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. The International Journal of Advanced Manufacturing Technology, 39(7-8): 783–795. http://doi.org/10.1007/s00170-007-1249-8
Fields, D., Dingman, M. E., Roman, P. M., & Blum, T. C. (2005). Exploring predictors of alternative job changes. Journal of Occupational and Organizational Psychology, 78(1): 63–82. http://doi.org/10.1348/096317904X22719
Gati, I., & Asher, I. (2001). Prescreening, in-depth exploration, and choice: from decision theory to career counseling practice. The Career Development Quarterly, 50(2): 140–157. http://doi.org/10.1002/j.2161-0045.2001.tb00979.x
Groysberg, B., & Abrahams, R. (2010). Managing yourself: five ways to bungle a job change. Harvard Business Review, January–February. Retrieved January 16, 2015, from https://hbr.org/2010/01/managing-yourself-five-ways-to-bungle-a-job-change

Gumus, A. T. (2009). Evaluation of hazardous waste transportation firms by using a two step fuzzy-AHP and TOPSIS methodology. Expert Systems with Applications, 36(2): 4067–4074. http://doi.org/10.1016/j.eswa.2008.03.013

Hadi-Vencheh, A., & Mohamadghasemi, A. (2011). A fuzzy AHP-DEA approach for multiple criteria ABC inventory classification. Expert Systems with Applications, 38(4): 3346–3352. http://doi.org/10.1016/j.eswa.2010.08.119

Halaby, C. N. (1988). Action and information in the job mobility process: the search decision. American Sociological Review, 53(1): 9-25. http://doi.org/10.2307/2095729

Hwang, C. L., & Yoon, K. (1981). Multiple Attribute Decision Making: Methods and Applications : A State-Of-The-Art Survey. Berlin; New York: Springer-Verlag.

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. http://doi.org/10.1016/j.amc.2006.02.057

Jing, L., Chen, B., Zhang, B., Li, P. (2013). A hybrid stochastic-interval analytic hierarchy process approach for prioritizing the strategies of reusing treated wastewater. Mathematical Problems in Engineering, 2013: 1-10. http://doi.org/10.1155/2013/874805, 10.1155/2013/874805

Kahraman, C. (2008). Multi-criteria decision making methods and fuzzy sets. In C. Kahraman (Ed.), Fuzzy Multi-Criteria Decision Making. Springer US pp. 1–18. http:// doi.org/10.1007/978-0-387-76813-7_1

Kahraman, C., Ateş, N. Y., Çevik, S., Gülbay, M., & Erdoğan, S. A. (2007). Hierarchical fuzzy TOPSIS model for selection among logistics information technologies. Journal of Enterprise Information Management, 20(2): 143–168. http://doi.org/10.1108/17410390710725742

Kilic, H. S. (2013). An integrated approach for supplier selection in multi-item/multi-supplier environment. Applied Mathematical Modelling, 37(14–15): 7752–7763. http://doi.org/10.1016/j.apm.2013.03.010

Lee, Y. C., Li, M. L., Yen, T. M., & Huang, T. H. (2011). Analysis of fuzzy decision making trial and evaluation laboratory on technology acceptance model. Expert Systems with Applications, 38(12): 14407–14416. http://doi.org/10.1016/j.eswa.2011.04.088

Lima-Junior, F. R., Osiro, L., & Carpinetti, L. C. R. (2014). A comparison between fuzzy AHP and fuzzy TOPSIS methods to supplier selection. Applied Soft Computing, 21(August): 194–209. http://doi.org/10.1016/j.asoc.2014.03.014

Lin, C. J., & Wu, W. W. (2008). A causal analytical method for group decision-making under fuzzy environment. Expert Systems with Applications, 34(1): 205–213. http://doi.org/10.1016/j.eswa.2006.08.012

Liou, J. J. H., & Tzeng, G. H. (2012). Comments on "multiple criteria decision making (MCDM) methods in economics: an overview." Technological and Economic Development of Economy, 18(4): 672–695. http://doi.org/10.3846/20294913.2012.753489

Mardani, A., Jusoh, A., & Zavadskas, E. K. (2015). Fuzzy multiple criteria decision-making techniques and applications – two decades review from 1994 to 2014. Expert Systems with Applications, 42(8): 4126–4148. http://doi.org/10.1016/j.eswa.2015.01.003

Montazer, G. A., Saremi, H. Q., & Ramezani, M. (2009). Design a new mixed expert decision aiding system using fuzzy ELECTRE III method for vendor selection. Expert Systems with Applications, 36(8): 10837–10847. http://doi.org/10.1016/j.eswa.2009.01.019

Murtagh, N., Lopes, P. N., & Lyons, E. (2011). Decision making in voluntary career change: an other-than-rational perspective. Career Development Quarterly, 59(3): 249–263.

Önüt, S., Kara, S. S., & Efendigil, T. (2008). A hybrid fuzzy MCDM approach to machine tool selection. Journal of Intelligent Manufacturing, 19(4): 443–453. http://doi.org/10.1007/s10845-008-0095-3

Paksoy, T., Pehlivan, N. Y., & Kahraman, C. (2012). Organizational strategy development in distribution channel management using fuzzy AHP and hierarchical fuzzy TOPSIS. Expert Systems with Applications, 39(3): 2822–2841. http://doi.org/10.1016/j.eswa.2011.08.142

Pitz, G. F., & Harren, V. A. (1980). An analysis of career decision making from the point of view of information processing and decision theory. Journal of Vocational Behavior, 16(3): 320–342.

Rajput, H. C., Milani, A. S., & Labun, A. (2011). Including time dependency and ANOVA in decision-making using the revised fuzzy AHP: A case study on wafer fabrication process selection. Applied Soft Computing, 11(8): 5099–5109. http://doi.org/10.1016/j.asoc.2011.05.049

Saaty, T. L. (1980). The Analytic Hierarchy Process. McGraw-Hill, NewYork.

Tuzkaya, G., Gülsün, B., Kahraman, C., & Özgen, D. (2010). An integrated fuzzy multi-criteria decision making methodology for material handling equipment selection problem and an application. Expert Systems with Applications, 37(4): 2853–2863. http://doi.org/10.1016/j.eswa.2009.09.004
U.S. Bureau of Labor Statistics. (2015). Number of jobs held, labor market activity, and earnings growth among the youngest baby boomers: results from a longitudinal survey (News Release No. USDL-15-0528) p. 12. Retrieved January 25, 2016, from http://www.bls.gov/news.release/pdf/nlsoy.pdf
Vahdani, B., & Hadipour, H. (2010). Extension of the ELECTRE method based on interval-valued fuzzy sets. Soft Computing, 15(3): 569–579. http://doi.org/10.1007/s00500-010-0563-5
van Laarhoven, P. J. M., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. Fuzzy Sets and Systems, 11(1-3): 199–227. http://doi.org/10.1016/S0165-0114(83)80082-7
Vasant, P., Bhattacharya, A., & Abraham, A. (2008). Measurement of level-of-satisfaction of decision maker in intelligent fuzzy-MCDM theory: a generalized approach. In C. Kahraman (Ed.), Fuzzy Multi-Criteria Decision Making. Springer US pp. 235–261. http:// doi.org/10.1007/978-0-387-76813-7_9
Wang, Y. J., & Lee, H. S. (2007). Generalizing TOPSIS for fuzzy multiple-criteria group decision-making. Computers & Mathematics with Applications, 53(11): 1762–1772. http://doi.org/10.1016/j.camwa.2006.08.037
Wang, Y. M., & Elhag, T. M. S. (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. Expert Systems with Applications, 31(2): 309–319. http://doi.org/10.1016/j.eswa.2005.09.040
Wang, Y. M., Luo, Y., & Hua, Z. (2008). On the extent analysis method for fuzzy AHP and its applications. European Journal of Operational Research, 186(2): 735–747. http://doi.org/10.1016/j.ejor.2007.01.050
Yavuz, V. A., Pilli, R., & Pasham, P. R. (2014). A fuzzy analytic hierarchy process model for the evaluation of print advertisement designs. In K. O. Oruç & H. Demirgil (Eds.),. Proceedings of the 15th International Symposium on Econometrics, Operations Research and Statistics, Isparta, Turkey pp. 624–643. http://www.eyi2014.org/docs/Bildiriler-Kitabi.pdf
Yazdani-Chamzini, A. (2014). An integrated fuzzy multi criteria group decision making model for handling equipment selection. Journal of Civil Engineering and Management, 20(5): 660–673. http://doi.org/10.3846/13923730.2013.802714
Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3): 338–353. http://doi.org/10.1016/S0019-9958(65)90241-X
Zhang, X., & Xu, Z. (2014). Extension of TOPSIS to multiple criteria decision making with pythagorean fuzzy sets. International Journal of Intelligent Systems, 29(12): 1061–1078. http://doi.org/10.1002/int.21676
Zimmermann, H. J. (2001). Fuzzy sets-basic definitions. In Fuzzy Set Theory and Its Applications. Springer Netherlands pp. 11–21. http:// doi.org/10.1007/978-94-010-0646-0_2