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Fit between humanitarian professionals and project requirements: Hybrid group decision procedure to reduce uncertainty in decision-making.

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Abstract

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Keywords: Expert selection; humanitarian projects; multi-criteria decision making; Fuzzy Analytic Hierarchy Process, Technique for Order Preference by Similarity to Ideal Solution.

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1. Introduction

There exist many different kinds of humanitarian projects with different objectives and aims. Humanitarian development projects are intended to enhance the well-being of population such as ensuring a health program, developing awareness, etc. Humanitarian development projects within different countries require inputs from the experts' experience and different types of skill and knowledge related to specific scientific and industrial fields. In fact, a good implementation depends on the experts selected for this purpose and is one of the key success factors. In the fields of health and education for instance, experts can be appointed to work on large variety of purposes: improving hygienic circumstances in health care facilities or on a broader basis, educating people on health subjects or convey school knowledge, or instruct on behavioural subjects, leading community empowerment projects, enhancing the self-empowerment of specific groups, or work on a preventive approach of health in communities. On another side, experts can also be appointed to technical or infrastructural projects like construction, transportation systems, implementation of renewable energy, etc. The requirements of ability of experts are multi-fold and it varies with respect to humanitarian development projects. Beside the required specific knowledge and experience, experts nevertheless often need to be versatile and have to deal with different situations, which have potentially different cultural and linguistic backgrounds. All those factors lead to a bunch of criteria that needs to be taken into account when evaluating the expert's candidatures for specific position linked to a humanitarian development project. Although the importance of each criterion may also vary under different requirements and situations, it is easier for a decision maker to describe his/her desired value, and the importance of a criterion, by using common language. The decision makers have also the possibility to add or remove some criteria depending on the situation and the project under consideration.

On the other side, as far as it is considered as strategic, in many cases, the decision to selection a specific expert for a humanitarian development project is taken by a group of people involved in implementing the programme or the institution in which they evolve. This is generally the case of non-governmental organisations (NGO's), where the management board is in charge of selecting and appointing experts for its projects. The situation is then a group decision making rather than a single decision making problem. The group is constituted of different decision makers with different field expertise. Each one has unique characteristics with regard to the criteria, which implies that for a considered situation, the decision makers usually have diverging decisions due to their different perceptions and opinions. This situation applies for the selection of criteria that need matching with the requirements of the humanitarian projects as well as for the assessment of the criteria themselves with respect to the experts/consultants. To the best of the knowledge of the authors, there are no studies dealing with the match between expert and the humanitarian development projects. The objective of this paper is developing a group decision making approach to select experts for humanitarian development projects based on subjective and objective multiple criteria.

The remaining part of the paper is organized as follows. Literature related to expert selection and methodologies employed by various researchers is explained in Section 2. The scientific background and the methodology developed are extensively presented in Section 3. Section 4 provides a real application of the approach with the experimental results for a case of four decision makers with six criteria in order to choose one of the five experts proposed. The sensitivity analysis and comparison of the obtained result is discussed in Section 5. Finally, the paper closes with a conclusion and future research developments.

2. Literature review

Expert selection is an unstructured decision problem due to the non-availability of exact definition of the complicated processes and rules that are linked to. The process itself involves subjectivity, validity and criteria fixing (Canós and Liern 2008; Tavares 1994). The general problem of selection decision, where some or all the information are subjective, is addressed by Zahedi (1987), and a substantial amount of information regarding the personnel selection problem and the techniques used to solve it is developed by Liang and Wang (1992). In the humanitairian field, decision-making has always been considered as a tricky issue, where research directions have been suggested in (Benini et al. 2009; Peng and Yu 2014). Through the existing studies, humanitarian operations are receiving high attention by researchers with many aspects to be explored, such as the disaster operations management reviewed by (Altay and Green 2006; Galindo and Batta 2013) and development of humanitarian projects. In this realm, to the knowledge of the authors, there is no work dealing with the selection of experts for the development of projects in the humanitarian field. However, several multi-criteria decision making (MCDM) models are developed in order to provide decision makers (DMs) in humanitarian aid with suitable decision support. A large variety of optimization criteria have been employed in the literature on operations-research approaches to humanitarian aid, such as (I) efficiency criteria, (II) effectiveness criteria, and (III) equity criteria (Gralla et al. 2014). Several papers propose general MCDM processes to assist the evaluation of suitable alternative solutions to humanitarian operations management problems such as the work of Sgarbossa et al. (2015). Recent literature review on the application of multi-criteria optimization to the management of humanitarian aid is proposed by Gutjahr and Nolz (2016).

Regarding the inherent complexity of the humanitarian field, the final hierarchical objectives are usually linked to several factors, which may not be easily evaluated such as the availability of capital and humanitarian resources, the number and role of the beneficiaries, as well as cultural and social aspects included in humanitarian development projects. Expert selection is discussed in few studies, and several different MCDM methods are suggested to tackle this problem. Several case studies are documented. On the other hand, staff selection is discussed in some studies (e.g., Smith et al. 2002; Rouyendegh and Erkan 2013) dealing with actual application of academic staff selection using the opinion of experts to be applied into a model of group decision. In particular, very few studies offer a coherent comparison between the different methods in the field of staff or personnel selection. Furthermore, these studies concentrate on staff recruitment in the absence of standards, and consist of process-oriented descriptions. Additionally, for humanitarian development and aid purposes, the focus of those papers is on the selection of facilities and tangible assets, and not on the experts that may help in the development of the project itself, such as the development and implementation of healthcare facilities and hospitals (Brent et al. 2007; Tsai and Chou 2009; Karagiannidis et al. 2010; Lu et al. 2016), emergency shelters location (Trivedi and Singh 2017; Xu et al. 2016), corresponding funding models (Tavana 2007) or locating refugees camps proposed by Çetinkaya et al. (2016).

In terms of methodology, fuzzy approaches are applied satisfactorily for personnel selection problems. In fact, fuzzy set theory appears as an essential tool to provide a decision method, which incorporates imprecise judgment inherent to the personnel selection process (Karsak 2001). Expert selection for humanitarian development projects has imprecise or vague elements both in evaluating the experts as well as their fit to the humanitarian projects. For that reason, many traditional MCDM techniques are combined with fuzzy logic techniques as an answer to the ambiguity and the impreciseness that raise up in these problems. However, the degree of uncertainty, or level of fuzziness, is almost never justified nor investigated. Saad et al. (2013) review the most widely used fuzzy techniques for solving staff selection processes. These techniques exist in many different variations and combinations. Moreover, they identify the criteria relevant to the selection process such as experience, certification, acclamation, consistency, reliability, ability, behavioral characteristics, knowledge sets and training. Both crisp and fuzzy analytical hierarchy processes (AHP) have often been suggested to deal with the personnel selection problem (e.g., Güngör et al. 2009; Özcan et al. 2011; Özdağoğlu & Özdağoğlu 2007). Petrovic-Lazarevic (2001) present a two-level personnel selection fuzzy model with a short list and hiring decision in order to minimize subjective judgment in the process of distinguishing between an appropriate/inappropriate employee for a job vacancy. The model proposed by the authors is composed of an AHP of three levels where the lowest one relates to the preliminary selection or shortlist procedure, the second level relates to the hiring decision or selection of a final candidate, and the top level is the expected utility of hiring the successful candidate. A comparison of crisp AHP and fuzzy AHP (FAHP) with a case study dealing with the selection of shop floor workers is documented in (Özdağoğlu & Özdağoğlu 2007). Chandran et al. (2005) estimate the weights in the AHP using linear programming models, but also outline the limitations of AHP in the evaluation of criteria weights. The main limitation being that the criteria are considered as independent. Huang et al. (2008) suggest using analytical network process (ANP) to deal with dependencies. In fact, ANP can accommodate for the interrelationships that exist among criteria (Huang et al. 2011). ANP is used by Lin (2010) to deal with personnel selection for an electric and machinery company in Taiwan. The work deals with the inner dependences among the criteria in the ANP phase using pairwise comparison matrices. A methodology for sniper selection using a combination of fuzzy ANP, fuzzy TOPSIS (technique for order preference by similarity to the ideal solution) and fuzzy ELECTRE (elimination and choice expressing reality) techniques is proposed by Kabak et al. (2012).

Researchers also drew attention to the problems associated with the way traditional fuzzy ANP deal with dependences. First, establishing a suitable network structure can be very difficult. Second, the process of constructing pairwise comparison deriving the dependences between the criteria is unnatural and cumbersome, as there are more than four criteria, and thus it can lead to inconsistencies for group decision-making processes as shown by Limayem and Yannou (2007). Modeling dependences and feedback in ANP with fuzzy cognitive maps is suggested in (Mazurek & Kisová 2012) to solve this problem. Karsak (2001) proposes a fuzzy MCDM framework based on the concepts of ideal and anti-ideal solutions for the personnel selection process. The authors' proposed method incorporates data in the forms of linguistic variables, triangular fuzzy numbers and crisp numbers into the personnel selection decision analysis. Chen and Cheng (2005) proposes a new approach to rank fuzzy numbers by metric distance for selecting information system personnel.

For the evaluation of alternatives against criteria, TOPSIS is extensively used for the personnel selection problem (Dursun and Karsak 2010, Polychroniou and Giannikos 2009). A fuzzy TOPSIS approach to managers' selection with three new concepts (namely, relative importance of DMs per criterion, similarity-proximity degree among the decision makers, and veto thresholds) is proposed by Kelemenis et al. (2011). Interestingly, it was also shown that using different distance measurements, such as Yager's Sign distance in TOPSIS, can change the ranking of the alternatives (Kelemenis and Askounis 2010). Liu et al. (2015) suggested an extended VIKOR method, combined with interval 2-tuple linguistic variables, to choose appropriate individuals among candidates in a group decision-making environment under uncertain and incomplete linguistic information. In the evaluation process, the ratings of the candidates are represented as interval 2-tuple linguistic variables. The VIKOR method is used to obtain the ranking of candidates and to find an optimal individual for personnel selection. Finally, the authors provide a numerical example of personnel selection in a tertiary care hospital. In the same context, Boran et al. (2011) present a multi-criteria group decision-making process using the intuitionistic fuzzy TOPSIS method to select appropriate personnel among candidates to a sales manager position in a manufacturing company. In the evaluation process, the ratings of the candidates are represented as intuitionistic fuzzy numbers.

In the context of employee evaluation and selection system, Haghighi et al. (2012) propose an employee evaluation and selection approach, based on fuzzy multiple attribute decision making through triangular fuzzy numbers, to evaluate the most adequate employee dealing with the rating of both qualitative and quantitative criteria. Canos and Liern (2008) develop a flexible decision support system simulating experts evaluations using ordered, weighted average aggregation operators, which assign different weights to different selection criteria to help managers in their decision making for personnel selection. Kelemenis and Askounis (2010) propose a new TOPSIS based multi-criteria approach to personnel selection, incorporating a new measurement for the ranking of the alternatives, based on the veto concept, a critical characteristic of the main outranking methods. The authors presented an empirical application of the proposed approach for the selection of a senior IT officer to illustrate the use of the suggested method. Chen et al. (2016) propose a decision-making model to deal with the personnel selection effectively and efficiently using TOPSIS and entropy methods to calculate closeness coefficient of each applicant in order to reduce the number of candidates. Qualitative information of each suitable candidate is expressed by a 2-tuple linguistic variable. Dursun and Karsak (2010) propose a MDCM algorithm using the principles of fusion of fuzzy information, 2-tuple linguistic representation model, and TOPSIS technique in order to manage information assessed using both linguistic and numerical scales.

In terms of applications, the existing research is scattered in different domains regarding the importance of personnel and expert selection, which represent one of the organizations' success factors. Several applications are found in the literature. Sadatrasool et al. (2016) develop a MCDM and statistical model for the selection of project manager for petroleum industry. Chaghooshi et al (2016) propose a VIKOR and DEMATEL (decision making trial and evaluation laboratory) based hybrid fuzzy approach for the selection of a project manager for an Iranian food company. For personnel selection in IT companies, Erdem (2016) proposes a fuzzy hierarchy process method and Aggarwal (2013) proposes a new AHP weighted fuzzy linear programming model. Bose and Chadtterjee (2016) propose a fuzzy hybrid MCDM approach for the selection of wind turbine service technicians. Dadelo et al. (2012) offer a model for selection of elite security personnel, based on expert evaluation method, to determine criteria weights known as Dadelo's methodology, and on ARAS (additive ratio assessment) method to aggregate criteria values. Capaldo and Zollo (2001) propose a fuzzy model to improve the effectiveness of personnel assessment within a large Italian company. Golec and Kahya (2007) propose a competency-based fuzzy model to minimize subjective judgment in multifactor, competency-based measures in a hierarchical structure. Canos and Liern (2008) develop a flexible decision support system simulating experts' evaluations using ordered, weighted average aggregation operators, which assign different weights to different selection criteria, to help managers in their decision making for personnel selection. Gungor et al. (2009) propose a personnel selection system where

FAHP is applied to evaluate the most adequate personnel dealing with the rating of both qualitative and quantitative criteria, and the result is compared by Yager's weighted goals method.

In most of the situations related to expert selection for humanitairian development projects where a decision must be taken, it is rare for the DMs to have in mind a clear single criterion. Thus, when a DM is part of a group descion making process, it is even rarer to be a priori a single, well-defined criterion deemed acceptable by all actors to guide the process (Figueira et al. 2005). Such situations refer to the group MCDM problems. The present paper is then dealing with innovative aspects of expert selection for humanitarian development projects, characterized by specific criteria that have to be considered to comply with the requirements of most funding humanitarian organizations and agencies.

3. Hybrid methodology and theoretical background

Since multiple criteria and decision makers are involved in the process of expert selection for humanitarian development projects, a four-step group-based methodology is designed and developed to tackle the complexity of the problem. The proposed methodology uses the concepts of multiple-criteria group decision making and fuzzy sets theory. The approach takes advantage of fuzzy Analytic Hierarchic Process (FAHP) for weighting the decision makers as well as the criteria considered and of Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) in ranking the alternatives. Indeed, since criteria and experts weighting is a process based on subjective assessments, an adequate way to obtain decision-maker's judgments is to perform pairwise comparison, which is one of the most important features of AHP. Moreover, due to the quantitative and the qualitative natures of the criteria, fuzzy formulations of AHP are more adequate than crisp AHP. Furthermore, the technique for order performance by similarity to ideal solution (TOPSIS) (Hwang and Yoon 2012) is a widely accepted multi-attribute decision-making technique for ranking different alternatives for a considered problem. Among the advantages of TOPSIS are logically representing the rational of human choice by considering both the best and the worst attributes of alternatives simultaneously (represented by a scalar value), and the simplicity on computation and presentation (Shih et al. 2007). The number of attributes does not influence the number of steps, thus it offers a faster solution (Ic 2012). In recent years, TOPSIS has been successfully applied as decision-making tools to different areas, including water management (Srdjevic et al. 2004), transportation planning (Janic 2003), human resource (Shih et al. 2007), mechanical engineering (Milani et al. 2005), manufacturing engineering (Kwong and Tam 2002) and policies development (Qin et al. 2008). In the chemical engineering field, this technique has been combined with optimization procedures to identify the best options considering economic and environment factor (Li et al. 2009). For all these reasons, TOPSIS is chosen in the evaluation of the alternatives. The overall computational procedure consists of four steps as follows.

- Step 1: Pre-research phase.
- Step 2: Fuzzy AHP phase for decision-makers' weights.
- Step 3: Fuzzy AHP phase for criteria weights.
- Step 4: TOPSIS phase.

The above four steps are now detailed in the next subsections.

3.1. Step 1: Pre-research Phase

In the pre-research phase, a list of the criteria used to select an expert for humanitarian projects is established. Indeed, from humanitarian organisations point of view, the expert has the decision-making power regarding the field work and the responsibility of reaching the project objectives (Krause 2014). Thus, the selection is based on the concordance and the coherence of the criteria with the requirements of humanitarian and social development projects (Bierschenk and Olivier de Sardan 2003; Rondinelli 2013). Six criteria are identified as follows:

- C1: *Work experience*: the experience that a person has accumulated in working in a specific field. In fact, it concludes the previously accomplished jobs and the experience obtained from these jobs. In many cases, a certain degree of work experience is a prerequisite for the assignment of an expert to a humanitarian development project.
- C2: *Education*: a process in which a person accumulates knowledge, skills and values out of the given context. The criterion evaluates the educational level and diplomas obtained by the different experts.
- C3: *Satisfaction from past projects*: experts who had already been assigned to projects in the past can be evaluated through the level of their employers' satisfaction or can provide proof of success. It is closely linked to the way earlier projects have been conducted and managed until their success.
- C4: *Motivation*: a kind of energy that enables the expert to achieve her/his goals, to which we can add the willingness to engage oneself in a project and the interest in the project. It partially provides answers to questions like "why a person applies for a specific project". By analysing the motivation, we can also take into account further social commitment of the expert, which has not been considered in the experience criterion. Due the nature of the job, some examples can be cited such as working as a volunteer, participation in humanitarian and social associations, NGOs or NPOs.
- C5: *Compensation*: one of the basic criteria used to make a choice. Humanitarian and social projects are often bound to a limited budget. The funding is often composed by donations or directly allocated by non-governmental, governmental or industrial organizations. Therefore, the remuneration of the experts, in particular the salary asked by an expert, can become an important criterion.
- C6: *Capacity of integration*: the capacity to adapt someone's behaviour, language, appearance to the host country or region, and the interest towards the social and cultural issues. Indeed, transmitting ideas and managing projects requires a certain degree of acceptance among the host community.

At a first glance, these six criteria are considered as independent. However, since the work deals with humans considering their complexity and diversity, it may be interesting as well to consider these criteria as dependent. For the first assumption, fuzzy AHP is adapted to deal with independent criteria with ambiguity in their evaluation, where for the second assumption, ANP seems to be a good technique to be used for the criteria weight evaluation.

3.2. Step 2: Fuzzy AHP Phase for Decision Makers' weights

The group consists of four decision makers, denoted as DM_1, DM_2, DM_3 and DM_4. A decision maker who knows all the other ones is appointed to assess each one's importance and expertise level, and makes a pairwise comparison between decision makers on a linguistic scale basis. The linguistic assessments are then converted into triangular fuzzy numbers for Fuzzy AHP evaluations. AHP technique essays the qualitative and the quantitative indices efficiently (Rao and Davim 2008). The advantages of this method include formulating the problem in question, improving the consistency of judgments, handling and solving the various problems, obtaining the opinions of members for making decision, aggregating the judgments of experts to determine the best alternative, and prioritizing through the pairwise comparisons of criteria. The other advantage of AHP is the use of qualitative criteria for decision-making and expressing the results quantitatively by mathematical techniques.

The combination of AHP and fuzzy logic, and the use of fuzzy numbers, is designed to obtain more decisive judgments by prioritizing the expert selection criteria and weighting them in the presence of vagueness. There are various fuzzy AHP applications in the literature that propose systematic approaches for selection of alternatives, and justification of problem by using fuzzy set theory and hierarchical structure analysis. Decision makers usually find it more convenient to express interval judgments than fixed value judgments due to the fuzzy nature of the comparison process. This work focuses on a fuzzy AHP approach introduced by Chang (1992), in which triangular fuzzy numbers are preferred for pairwise comparison scale. Extent analysis method is selected for the synthetic extent values of the pairwise comparisons as follows.

A fuzzy number is a special fuzzy set $F = \{(x, \mu_F(x), x \in R\}$, where x takes its values on the real line, R: $-\infty \leq x \leq \infty$, and $\mu_F(x)$ is a continuous mapping from R to the closed interval [0, 1], called membership function. A triangular fuzzy number (TFN) expresses the relative strength of each pair of elements in the same hierarchy and can be denoted as M = (l, m, u), where $l \leq m \leq u$. The parameters l, m and u indicate, respectively, the smallest possible value, the most promising value, and the largest possible value in a fuzzy event. Triangular type membership function of M fuzzy number can be described as in Equation (1). When l = m = u, it is a non-fuzzy number by convention.

$$\text{MM}(x) = \begin{cases} 0 & x < l \\ (x-l)/(m-l) & l \leq x \leq m \\ (u-x)/(u-m) & m \leq x \leq u \\ 0 & x > u \end{cases} \tag{1}$$

A linguistic variable is a variable whose values are expressed in linguistic terms. The concept of a linguistic variable is very useful in dealing with situations, which are too complex or not well defined to be reasonably described in conventional quantitative expressions (Zadie 1965, Zimmermann 2011, Kaufmann and Gupta 1991, Sonner et al. 2012). In this study, the linguistic variables used in the model can be expressed in positive TFNs for each criterion as shown in Figure 1. The linguistic variables matching TFNs and the corresponding membership functions are provided in Table 1. The proposed methodology employs a scale of fuzzy numbers from $\tilde{1}$ to $\tilde{9}$ symbolize with tilde (~) as triangular fuzzy numbers. Table 1 depicts AHP and fuzzy AHP comparison scale considering the linguistic variables that describes the importance of attributes and alternatives to improve the scaling scheme for the judgment matrices.

Linguistic scale for importance	Fuzzy numbers for fuzzy AHP	Membership function	Domain	Triangular fuzzy scale (***l*, *m*, *u***)
Equal importance	$\tilde{1}$	$\mu_M(x) = (x - \frac{1}{3}) \Big/ (1 - \frac{1}{3})$	$\frac{1}{3} \le x \le 3$	(0.33, 1.0, 3.0)
		$\mu_M(x) = (3 - x)/(3 - 1)$	$1 \le x \le 3$	
Weak importance of one over another	$\tilde{3}$	$\mu_M(x) = (x - 1)/(3 - 1)$	$1 \le x \le 3$	(1.0, 3.0, 5.0)
		$\mu_M(x) = (5 - x)/(5 - 3)$	$3 \le x \le 5$	
Essential or strong importance	$\tilde{5}$	$\mu_M(x) = (x - 3)/(5 - 3)$	3	(3.0, 5.0, 7.0)
		$\mu_M(x) = (7 - x)/(7 - 5)$	$5 \le x \le 7$	
Very strong importance	$\tilde{7}$	$\mu_M(x) = (x - 5)/(7 - 5)$	$5 \le x \le 7$	(5.0, 7.0, 9.0)
		$\mu_M(x) = (9 - x)/(9 - 7)$	$7 \le x \le 9$	
Extremely preferred	$\tilde{9}$	$\mu_M(x) = (x - 7)/(9 - 7)$	$7 \le x \le 9$	(7.0, 9.0, 9.0)
Intermediate values between the two adjacent judgments.				
If factor *I* has one of the above numbers assigned to it when compared to factor *j*, then *j* has the reciprocal value when compared with *I*				Reciprocals of above $M_1^{-1} \approx (1/u_1, 1/m_1, 1/l_1)$

Table 1. Linguistic variables describing weights of attributes and values of ratings.

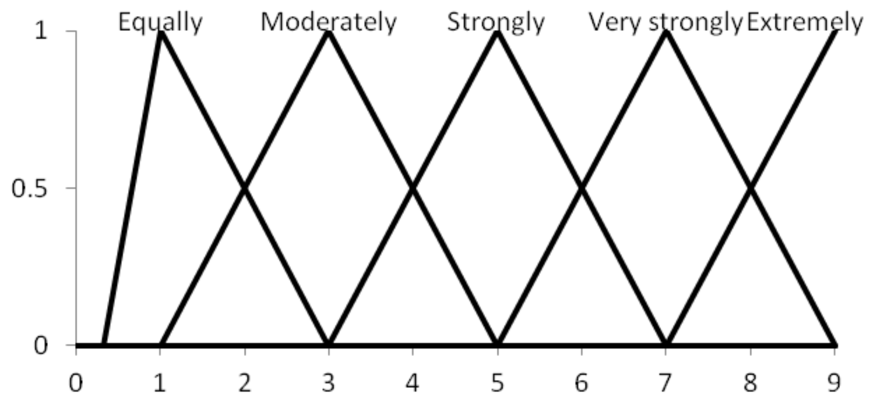

Figure 1. Linguistic variables and membership function of each criterion.

By using triangular fuzzy numbers via pairwise comparison, the fuzzy judgment matrix $\tilde{A}\,(a_{ij})$ can be expressed mathematically as in Equation (2).

$$\tilde{A} = \begin{cases} 1 & \tilde{a}_{12} & \tilde{a}_{13} & \cdots & \tilde{a}_{1(n-1)} & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \tilde{a}_{23} & \cdots & \tilde{a}_{2(n-1)} & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ \tilde{a}_{(n-1)1} & \tilde{a}_{(n-1)2} & \tilde{a}_{(n-1)3} & \cdots & 1 & \tilde{a}_{(n-1)n} \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \tilde{a}_{n3} & \cdots & \tilde{a}_{n(n-1)} & 1 \end{cases} \tag{2}$$

The judgment matrix $\tilde{A}$ is (n x n) fuzzy matrix containing fuzzy numbers $\tilde{a}_{ij}$ as shown in Equation (3).

$$\tilde{a}_{ij} = \begin{cases} 1, & i = j \\ \tilde{1},\tilde{3},\tilde{5},\tilde{7},\tilde{9} \; or \ldots \; \tilde{1}^{-1},\tilde{3}^{-1},\tilde{5}^{-1},\tilde{7}^{-1},\tilde{9}^{-1}, & i \neq j \end{cases} \tag{3}$$

Let X = { $x_1, x_2, \ldots, x_n$ } be an object set, whereas U = { u_1, u_2, … , u_n } is a goal set. According to fuzzy extent analysis, the method can be performed with respect to each object for each corresponding goal, resulting in m extent analysis values for each object, given as M_{gi}^{1}, M_{gi}^{2}, … , M_{gi}^{m} (for i = 1, 2, … , n), where all the M_{gi}^{j} (for j = 1, 2, … , m) are triangular fuzzy numbers representing the performance of the object x_i with regard to each goal u_j. The steps of Chang's extent analysis (1992) can be detailed as follows (Kahraman et al., 2003; Bozbura et al., 2007):

Step 1: The fuzzy synthetic extent value with respect to the ith object is defined as:

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} \tag{4}$$

Where $\otimes$ is a fuzzy multiplication operator? To obtain $\sum_{j=1}^{m} M_{g_i}^{j}$, perform the fuzzy addition operation m extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \tag{5}$$

And obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$, perform the fuzzy addition operation of $M_{g_i}^{j}$ ($j = |1,2,...,m$) values such that

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \tag{6}$$

and then compute the inverse of the vector in Equation (6) such that

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{7}$$

Step 2: The degree of possibility of $M_2 \geq M_1$ is defined as:

$$V\ (M_2 \geq M_1) = \sup_{y \geq x}[\min(\mu_{M_1}(x), \mu_{M_2}(y))] \tag{8}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & if \quad m_2 \geq m_1, \\ 0, & if \quad l_1 \geq u_2, \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise, \end{cases} \tag{9}$$

where *hgt* is the height of the intersection of M_1 and M_2, d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} (see Figure 2). To compare M_1 and M_2, both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are required.

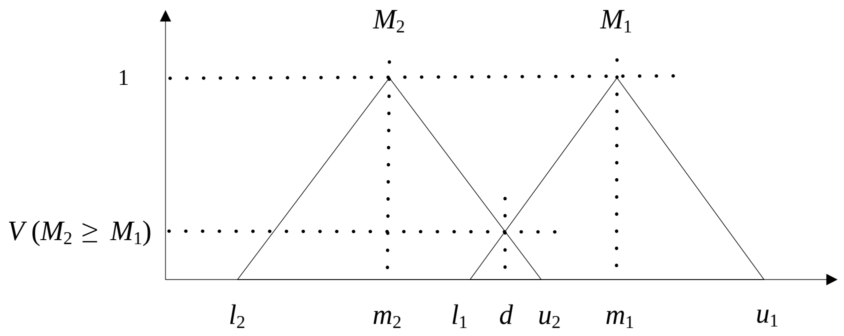

Figure 2. Intersection point “d” between two fuzzy numbers M_1 and M_2.

Step 3: The degree possibility of a convex fuzzy number to be greater than k convex fuzzy numbers M_i (for i = 1, 2, …, k) can be defined by Equation (10).

$$V(M \geq M_1, M_2, ..., M_k) = V[(M \geq M_1) \text{ and } V[(M \geq M_2) \text{ and } \ldots \text{ and } (M \geq M_k)] = \min V(M \geq M_i), \quad \mathbf{i = 1, 2, 3, \ldots, k.} \tag{10}$$

Assume that:

$$d'(A_i) = \min V\ (S_i \geq S_k) \tag{11}$$

For k = 1, 2,…,n; k ≠ i. Next, the weight vector is given by Equation (12).

$$W' = (d'(A_1), d'(A_2), ..., d'(A_n))^T \tag{12}$$

where A_i (i = 1, 2, … , n) has n elements.

Step 4: The normalized weight vectors are defined as:

$$W = (d(A_1), d(A_2), ..., d(A_n))^T \tag{13}$$

where W is a non-fuzzy number.

3.3. Step 3: Fuzzy AHP Phase for criteria weights

At the third step, the decision makers do pairwise comparisons in a linguistic form in order to obtain criteria weights. The linguistic forms are converted into triangular fuzzy numbers for Fuzzy AHP evaluations that uses the same procedure as presented in step 2. Fuzzy comparisons are defuzzified with Chang’s extent analysis (1992) and the criteria weights are obtained by the Fuzzy AHP phase. Table 1 is used for pairwise comparisons as in step 2. Next, the fuzzy values of paired comparison are converted into crisp values via the Chang’s extent analysis (1992). The overall weight are calculated using the Additive Weighted Aggregation (AWA) operator (Xu 2009) as shown in Equation (14).

$$g_i = \lambda_k * g_{ik} \tag{14}$$

where $i = 1,....I$ represents the criteria, $k = 1,....K$ represents the decision makers, λ_k is the weight of the k^{th} decision maker, and g_i is an aggregated group decision value of the i^{th} criterion function. After this aggregation phase, a unique matrix is obtained for criteria weights.

3.4. Step 4: TOPSIS phase

TOPSIS, one of the classical MCDM methods, was proposed by Hwang and Yoon (2012). TOPSIS is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution (PIS), and the farthest from the negative ideal solution (NIS), for solving a multiple criteria decision-making problem. The various J alternatives are denoted as $A_1, A_2, . . . , A_J$. For the alternative A_j, the rating of the i^{th} aspect is denoted by f_{ij} as the value of the i^{th} criterion function for the alternative A_j. Assuming that n is the number of criteria, the TOPSIS procedure consists of the following steps.

Step 1: calculation of the normalised decision matrix**.**

The normalized decision matrix r_{ij} is calculated as:

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{J} f_{ij}^{2}}} \quad j=1, 2, 3,\ldots, J \quad i=1, 2, 3,\ldots,n \tag{15}$$

Step 2: calculation of the weighted normalized decision matrix.

The weighted normalized decision matrix v_{ij} is calculated as:

$$v_{ij} = w_i * r_{ij} \quad j=1, 2, 3,\ldots, J \quad i=1, 2, 3,\ldots,n \tag{16}$$

where w_i is the weight of the i^{th} attribute or criterion, and $\sum_{i=1}^{n} w_i = 1$

Step 3: determination of the ideal and negative-ideal solutions.

The ideal and negative-ideal solutions, respectively A^* and A^-, are determined as follows:

$$A^* = \{v_1^*, ..., v_i^*\} = \left\{\left(\max_j v_{ij} \mid i \in I'\right), \left(\min_j v_{ij} \mid i \in I''\right)\right\} \tag{17}$$

$$A^- = \{v_1^-, ..., v_i^-\} = \left\{\left(\min_j v_{ij} \mid i \in I'\right), \left(\max_j v_{ij} \mid i \in I''\right)\right\} \tag{18}$$

where I' is associated with the benefit criteria, and I'' is associated with the cost criteria.

Step 4: calculation of the separation from the ideal solution. The separation measures are calculated using the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is given as follows:

$$D_j^* = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_i^{\;*}\right)^2} \qquad \text{j=1, 2, 3,…, J.} \tag{19}$$

Similarly, the separation from the negative ideal solution is given as:

$$D_j^- = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_i^{\;-}\right)^2} \qquad \text{j=1, 2, 3,…, J.} \tag{20}$$

Step 5: calculation of the relative closeness to the ideal solution.

The relative closeness of the alternative a_j is defined as:

$$CC_j^* = \frac{D_j^-}{D_j^* + D_j^-} \qquad \text{j=1, 2, 3…, J.} \tag{21}$$

Step 6: ranking of the preference order. The preference order is simply ranked according to the work of (Opricovic and Tzeng 2004).

Step 7: Application of TOPSIS

This step starts by establishing fuzzy evaluations of the alternatives with respect to the individual criteria by using TFNs. A decision matrix indicating the performance ratings of the alternatives according to the criteria is then obtained. The linguistic scales and their corresponding fuzzy numbers are used as follows: (1,1,1)-very poor, (2,3,4)-poor, (4,5,6)-fair, (6,7,8)-good, (8,9,10)-very good. Each decision-maker achieves the evaluation in a linguistic form and obtains the alternatives' performances. A defuzzification is then done using the formula in Equation (22) (Xu & Chen, 2007)

$$\bar{f}_{ijk} = \frac{1}{2}\left[f_{ijk}^{\,l} * (1-\eta_{ijk}) + f_{ijk}^{\,m} + f_{ijk}^{\,u} * \eta_{ijk} \right] \tag{22}$$

where f_{ijk} is the fuzzy value of i[th] criterion function for the alternative A_j for the k[th] decision maker, $f_{ijk}^{\,l}$ represents the lower value, $f_{ijk}^{\,m}$ represents the medium value, $f_{ijk}^{\,u}$ represents the upper value of f_{ijk} and $\bar{f}_{ijk}$ is the defuzzified value of f_{ijk}. A new way is proposed here to calculate the coefficient η_{ijk} for the k[th] decision maker of the i[th] criterion for the alternative A_j. The idea is inspired from the calculation of the relative degree of similarity adapted from Olcer and Odabasi (2005). The principle is to determine this value regarding to the distance between the decision-makers' evaluations. If a decision-maker's evaluation is closer to the group evaluation, then her/his upper fuzzy value has a higher impact. On the other hand, if a decision-maker's evaluation is far from the group evaluation, then her/his upper fuzzy value has lower impact. This calculation procedure makes the proposed methodology more realistic. For calculating the relative degree of similarity, the degrees of similarity, the similarity matrix, and the average degree of similarity have to be calculated respectively. To obtain the degree of similarity value of the p^th^ decision maker to the r^th^ decision maker, S_{pr} is calculated as in Equation (23)

$$S_{pr} = 1 - \frac{\left| f^{l}_{ijp} - f^{l}_{ijr} \right| + \left| f^{m}_{ijp} - f^{m}_{ijr} \right| + \left| f^{u}_{ijp} - f^{u}_{ijr} \right|}{3} \tag{23}$$

which forms the agreement matrix *AM* as shown in Equation (24)

$$AM = \begin{bmatrix} 1 & S_{12} & .... & S_{1K} \\ : & 1 & : & S_{2k} \\ : & : & 1 & : \\ S_{K1} & S_{K2} & .... & 1 \end{bmatrix} \quad \forall i, j \tag{24}$$

To obtain the average degree of similarity, AA_p is calculated using Equation (25).

$$AA_p = \frac{1}{K-1} \sum_{\substack{r=1 \\ p \neq r}}^{K} S_{pr} \quad p = \{1,........., K\} \ \forall i, j \tag{25}$$

Last, the relative degree of similarity η_{ijk} is calculated as shown in Equation (26).

$$\eta_{ijk} = \frac{AA_p}{\sum_{p=1}^{K} AA_p} \text{ where p=k } \forall i, j \tag{26}$$

In calculating η_{ijk} in this way, the degree of similarity of each decision maker is included in the defuzzification step. These individual decision matrices are aggregated into a group decision matrix by using the AWA operator (Xu 2009) using Equation (27)

$$f_{ij} = \lambda_k * \bar{f}_{ijk} \tag{27}$$

where $i = 1,....I$ represents the criteria, $j = 1,....J$ represents the alternatives, $k = 1,....K$ represents the decision makers, λ_k is the weight of the k^{th} decision maker and f_{ij} is the aggregated group decision value of i^{th} criterion function for the alternative A_j. Following this aggregation phase, only one group decision matrix is obtained.

4. Application for the selection of experts for humanitarian development projects

4.1. Weights of the decision makers

The case discussed in this paper is related to the evaluation and selection of experts for a humanitarian development project in Africa proposed by one of the several United Nations offices. The consultancy concerns the reduction of poverty in a rural area, in accompanying and coaching a group of women, producing handmade embroideries. The project is devoted to build up and structure complete value chains that could help this specific population to provide their products on the market and manage them using the most adequate business development techniques. Four decision makers participate to the humanitarian expert selection procedure from the same department according to the rules specified by the United Nations (United Nations 2010). The office is in charge of funding, hiring the expert and controlling the execution of the project. Five candidates considered as alternatives apply for the job. The decision maker who has a better knowledge of all the others is asked objectively to assess each one's importance according to their respective levels of expertise and to make a pairwise comparison between the decision makers (DMi, i=1…4) on a linguistic scale basis. The linguistic assessments are then converted into triangular fuzzy numbers for Fuzzy AHP (FAHP) evaluations, using the transformation procedure in Table 2. The results are shown in Table 3, where each 3-uplet is a triangular fuzzy number. By applying FAHP, the different weights of the decision makers in the selection process are obtained in Table 4. This process reaches a situation where the weights of the decision makers have different values. In that case, DM2 is taking almost half of the decision importance in the selection process with a weight equal to 0.449.

Equal Importance	0.33	1,00	3,00	**1~ = (1/3, 1, 3)**
Weak Importance	1,00	3,00	5,00	**3~ = (1, 3, 5)**
Strong importance	3,00	5,00	7,00	**5~ = (3, 5, 7)**
Very strong importance	5,00	7,00	9,00	**7~ = (5, 7, 9)**
Extremely preferred	7,00	9,00	9,00	**9~ = (7, 9, 9)**

Table 2. Representation of triangular fuzzy numbers.

	DM 1			**DM 2**			**DM 3**			**DM 4**		
DM 1	1	1	1	0.20	0.33	1.00	1.00	3.00	5.00	3.00	5.00	7.00
DM 2	1.00	3.00	5.00	1	1	1	3.00	5.00	7.00	3.00	5.00	7.00
DM 3	0.20	0.33	1.00	0.14	0.20	0.33	1	1	1	0.20	0.33	1.00
DM 4	0.14	0.20	0.33	0.14	0.20	0.33	1.00	3.00	5.00	1	1	1

Table 3. Pairwise comparisons of the expertise of the decision makers.

DM 1	0.360
DM 2	0.449
DM 3	0.015
DM 4	0.176

Table 4. Final weights of the decision makers.

Similarly to the process providing the weights of the decision makers, the criteria weights are calculated. It is done when all the decision makers complete the tables comparing the different criteria. Each decision maker assesses the importance of each criterion compared to the others and fills in the corresponding table. By comparing the criteria and after the application of FAHP, we obtain the weight of each criterion. The different criteria weights are illustrated in Table 5:

- C3: Satisfaction with past projects: This criterion has the highest weight (0.264) and corresponds to the objective of giving a maximum insurance to achieve the humanitarian development project objectives through qualified experts, who were successful in achieving their previous assignments.
- C1: Work experience: The second highest weight is given to the criterion 'Work experience' (0.251), which is too close to the weight of C3 (0.264). This is because those two criteria represent complementary concepts linked to the satisfaction with past work in which the expert was involved.
- C4: Motivation: Motivation is an important criterion (equal to 0.237) in the selection of experts involved in humanitarian projects due to the nature of the job, where the expert can be granted a limited budget and has to face difficult working conditions.
- C6: Integration capacity: This criterion is ranked fourth with an important weigh of (0.171). Thus, the expert ability of integrating and leading a team in such a job of a delicate nature is a key factor in the selection process.
- C2: Education: Related to the educational level and diplomas obtained by the expert, this criterion has a weight of (0.077).
- C5: Compensation: Surprisingly, the results show a null weight for the criterion C5 'Compensation' (financial remuneration). This is explained by the fact that on the one hand, the office offers remuneration on the basis of a predefined fixed scale with limited reimbursement of the travel and subsistence expenses. On the other hand, the office limits the time schedule within which the project has to be developed and implemented. Thus, the remuneration is more or less the same for all candidates and has no significant influence on the selection process.

The TOPSIS phase consists of evaluating the experts by each decision maker according to the six criteria. For this evaluation, the fuzzy linguistic variables shown in Table 6 are used.

C1	Work experience	0.251
C2	Education	0.077
C3	Satisfaction with past projects	0.264
C4	Motivation	0.237
C5	Compensation	0.000
C6	Integration capacity	0.171

Table 5. Defuzzified criteria weights.

Very good	0.8	1	1
Good	0.6	0.8	1
fair	0.4	0.6	0.8
Poor	0.2	0.4	0.6
Very poor	0	0.2	0.4

Table 6. Definition of triangular fuzzy numbers for TOPSIS.

The process is based on the calculation of the degree of similarity for the five experts (step2), the matrix of degree of similarity (step3), the deffuzified matrix (step4), the aggregated and defuzzified matrix which takes into account the Decision Makers' weights (step5) and the normalized matrix (step6), the weighted normalized matrix which takes into account the Criteria's weights (step7). Finally, we are able to find the Ideal-solution (A*) and the Negative-Ideal-Solution (A-) that are addressed in Table 7 for each criterion.

	A*	A-
C1	0.138	0.064
C2	0.047	0.010
C3	0.148	0.065
C4	0.141	0.065
C5	0.000	0.000
C6	0.108	0.034

Table 7. Ideal-solution (A*) and Negative-Ideal-Solution (A-) for each criterion.

As a result, the highest value related to the relative closeness to the ideal solution defines the best adequate expert for the considered activity, taking into account all the criteria and all the evaluations of the decision makers. According to the relative closeness to the ideal solution, the experts are ranked as shown in Table 8. The results shows the superiority of Expert 3 with a CC* equal to 0.878. We can also notice that Expert 3 is far away from the second best expert, *Expert 1* (0.878 vs 0.557).

	D*	D-	CC*	Ranking
Expert 1	0.093	0.117	0.557	2
Expert 2	0.106	0.114	0.519	3
Expert 3	0.017	0.125	0.878	1
Expert 4	0.104	0.077	0.426	5
Expert 5	0.111	0.089	0.445	4

Table 8. Final ranking of the experts.

5. Sensitivity analysis

5.1. Sensitivity analysis of Decision Makers weights

To analyse the quality of the methodology in reaching a good solution under different conditions, a sensitivity analysis is conducted. Two different situations are investigated. In the first situation, the defuzzification phase is addressed to identify the impact of the relative degree of similarities (η_{ijk}) on the results. In this investigation, each relative degree of similarity of the decision maker *i* is increased respectively by 25 %, 50%, 100% and 200% for each alternative and criterion and noted respectively Ei-25, Ei-50, Ei-100 and Ei-200. While one decision maker's value is increased, the remaining values of the decision makers are decreased such that the total of the relative degree of similarities is equal to one for each alternative and criterion. The result of this test is given in the Figure 3. The x-axis represents the increase in the decision maker i (i= 1...4) assessment's values in percentage and the y-axis represents the new relative closeness CC_j* values of the expert *j*, *j=1…5*.

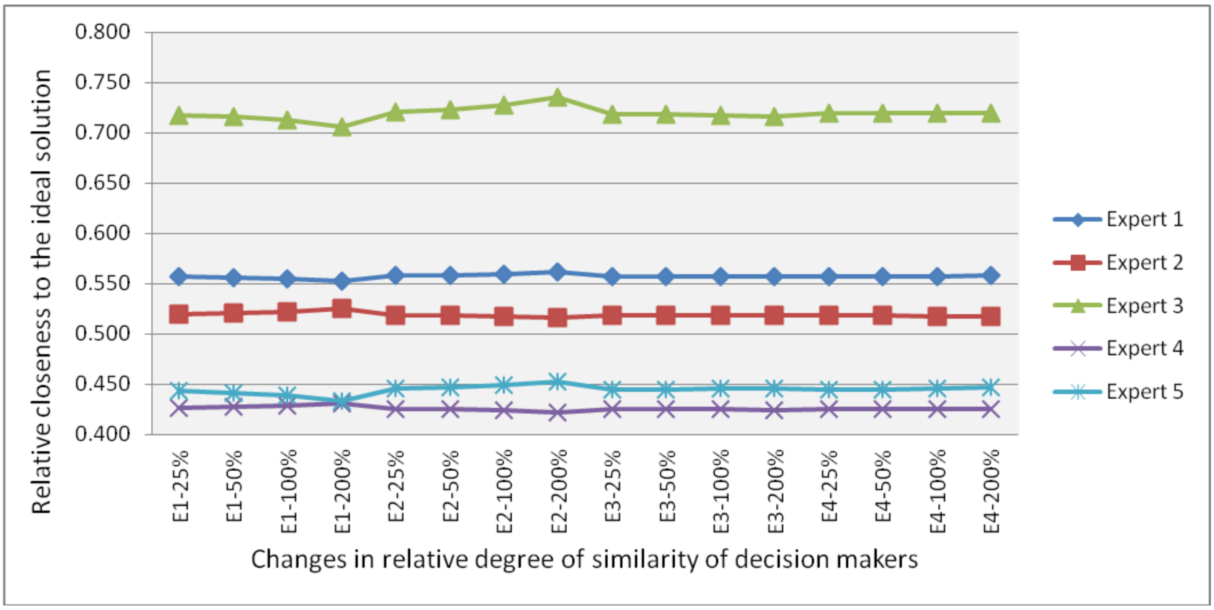

Figure 3. Sensitivity analysis of the decision maker's relative degree of similarity.

As shown in Figure 3, *Expert 3* remains the best candidate for the humanitarian development project in all calculations and cases. Even if there are small deviations in the calculations, the results are still consistent. Indeed, *Expert 3* has the highest CC_j* value with 0.735, reached when the second Decision Maker's relative degree of similarity value is increased by 200% (E2-200 in Figure 3). Furthermore, the lowest CC_j* value for the *Expert 3* is 0.706 calculated comparing all the tests. This value is obtained when the first Decision Maker's relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The second best expert is *Expert* 1 with a highest CC_j* value of 0.561 obtained when the second Decision Maker's relative degree of similarity value is increased by 200% (E2-200 in Figure 3). The lowest CC_j* value obtained by *Expert 1* is 0.553 when the first Decision Maker's relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The third best candidate is *Expert 2* with the highest CC_j* value of 0.525 reached when the first Decision Maker's relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The lowest CC_j* value obtained by *Expert 2* is 0.516 when the second Decision Maker's relative degree of similarity value is increased by 200% (E2-200 in Figure 3). The fourth best candidate is *Expert 5* where the highest CC_j* value is 0.453 reached when the second Decision Maker's relative degree of similarity value is increased by 200% (E2-200 in Figure 3). The lowest CC_j* value obtained by *Expert 5* is 0.433 in the calculation obtained when the first Decision Maker's relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The last candidate *Expert 4* reached its highest CC_j* value of 0.431 when the first Decision Maker's relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The lowest CC_j* value obtained by *Expert 4 is* 0.422 in the calculation obtained when the second Decision Maker's relative degree of similarity value is increased by 200% (E2-200 in Figure 3)

From the results in Figure 3, we notice that the only change in ranking occurs when the first Decision Maker's relative degree of similarity value is increased by 200%. *Expert 4* (originally the last one) in this context reaches the fourth place as same as *Expert 5*. As a consequence, the ranking obtained by this approach is not significantly affected by the variation related to the degree of similarity of Decision Makers. Thus, we can conclude that in one hand, the proposed approach is robust since the similarity of the obtained ranking with the original one especially for *Expert 1*, *Expert 2*, and *Expert 3*

In the second series of test, the focus is put on the investigation of the effect of the Decision Maker's weights on the results. The tests are designed by increasing each original Decision Maker weight by 25%, 50%, 100% and 200%. While one Decision Maker's weight is increased, the remaining values of Decision Makers are decreased in certain amount such that the total of the Decision Maker weights is equal to one. The result of this sensitivity analysis is given in Figure 4. The x-axis represents the relative increase of the ith Decision Maker's weight E_i (i= 1...4) and the y-axis represents the new relative closeness CC_j* values of the expert *j, j=1…5*.

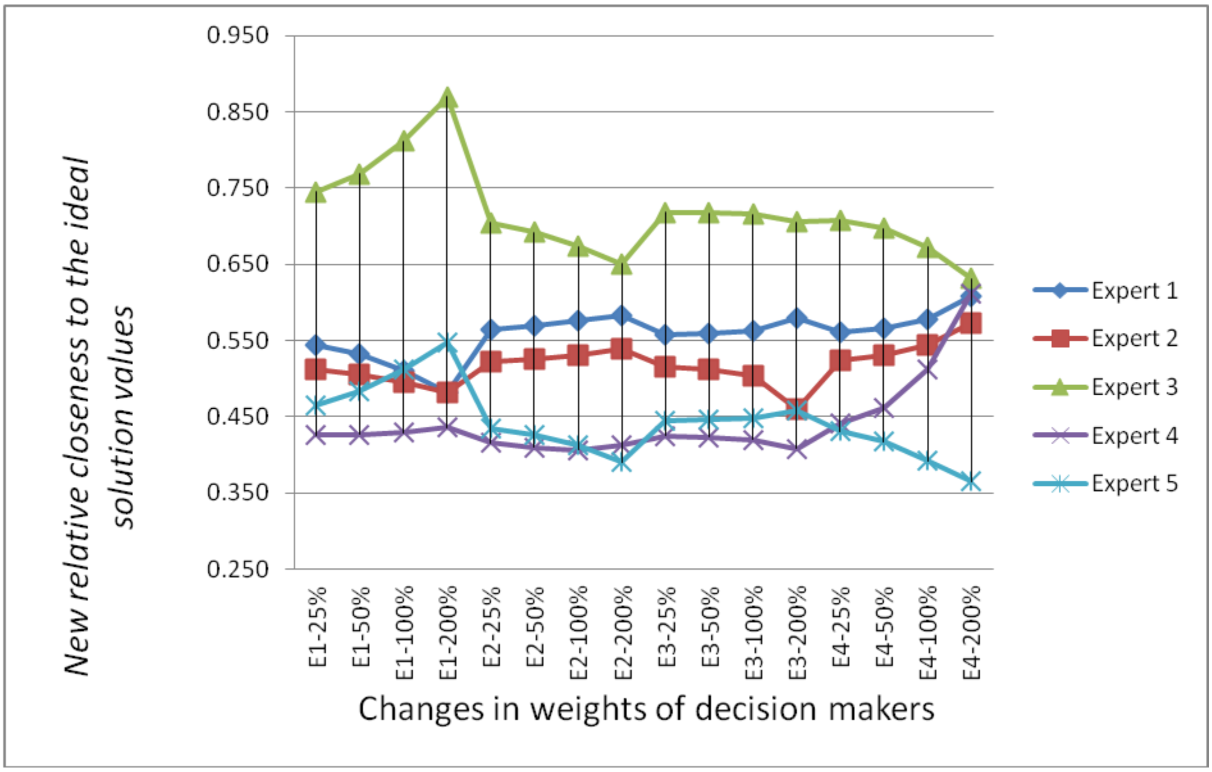

Figure 4. Sensitivity analysis of the Decision Maker weights.

Similar to the variation of Decision Makers degree of similarity and as shown in Figure 4, *Expert 3* remains the best candidate for the project in all calculations and cases. Even if there are small deviations in the calculations, the results are still consistent. Indeed. *Expert 3* has the highest CC_j* value of 0.870, reached when the first Decision Maker's weight value is increased by 200% (E1-200 in Figure 4). Moreover, the lowest CC_j* value of the *Expert 3* in all the tests performed is 0.631, obtained when the fourth Decision Maker's weight value is increased by 200% (E4-200). The highest CC_j* value for *Expert 1 is* 0.608, reached when the fourth Decision Maker's weight is increased by 200% (E4-200), while the lowest CC_j* value is 0.482, obtained when the first Decision Maker's weight is increased by 200% (E1-200). The highest CC_j* value for the *Expert 2* is 0.574, reached when the fourth Decision maker's weight value is increased by 200% (E4-200), while his lowest CC_j* value is 0.460 when the third Decision Maker's weight value is increased by 200% (E3-200). The highest CC_j* value for the *Expert 5* is 0.548, reached when the first Decision Maker's weight value is increased by 200% (E1-200), while his lowest value is 0.366 obtained when the fourth Decision Maker's weight is increased by 200% (E4-200). The highest CC_j* value for the *Expert 4* is 0.611, reached when the fourth Decision Maker's weight value is increased by 200% (E4-200), while the lowest CC_j* value is 0.407, obtained if the weight of the third Decision Maker's increases by 100% (E3-200).

Moreover, it is possible to observe what follows:

– When the first Decision Maker's weight value is increased by 200% (E1-200%), *Expert 5* becomes the second best expert instead of the fourth place.

– When the second Decision Maker's weight value is increased by 200% (E2-200%), *Expert 4* becomes the fourth best expert instead of the last place.

– When the third Decision Maker's weight value is increased by 200% (E3-200%), *Experts 2* and 5 are on the equal level and both take the third place.

– When the fourth Decision Maker's weight value is increased by 25%, 50%, 100% and 200%, *Expert 5* (originally the 4rth place) changes significantly his rank; he/she leaves the 4^{th} position and reaches the last one. We can also notice that for E4-200, the difference between *Expert 4*, *Expert2* and *Expert 3* is very small. Thus, the fourth Decision Maker has the most important influences on the ranking of the expert's selection.

5.2. Sensitivity analysis of criteria weights

The experiments are based on the increase of each original criterion weight respectively by 25%, 50%, 100% and 200%. While one criterion's value is increased, the remaining values of criteria are decreased in certain amount such that the total of the criteria weights is equal to one. The result of this sensitivity analysis is given in Figure 5. The x-axis represents the increase in criteria weight's values in percentage with respect to the criteria itself *Ci* (i= 1...6) and the y-axis represents the new relative closeness to the ideal solution CC_j* related to the *Expert j*, j=1…5.

As shown in Figure 5, an expert rank changes according to the different criteria weights. Indeed, the best candidate depends on the criterion selected to be changed and on its variation. The results are not consistent in this case and they are very sensitive to the variation of criteria weights except for the criterion C5 which is the remuneration of the expert (see the data set C5-25%, C5-50%, C5-100%, C5-200% in Figure 5). In this case, the best candidate remains the *Expert 3*. This is due to the weight of the criterion 'Remuneration' that is originally null as provided by the fuzzy AHP evaluation done by the decision makers. In the variations context, we can notice through Figure 5 that *Expert 3* (originally the best expert) highest CC_j* value is given by (C3-200%) representing the increasing of weight related to satisfaction from past projects while the lowest CC_j value is given by (C6-200%) corresponding to the integration capacity weight increasing. *Expert 1* (originally second ranked expert) highest CC_j* value is given by (C1-200%) related to work experience weight. The lowest CC_j* value of *Expert 1* is obtained when the weight of the criteria related to satisfaction from past projects is increased by 200% (C3-200%)). The highest CC_j* value for *Exper*t 2 is also given by (C3-200%) while the lowest CC_j* value is given by the increasing of the weight related to motivation criteria (C4-200%). *Expert 4* highest CC_j* value is obtained by (C6-200%) while the lowest CCj* value is given by (C1-200%) related to work experience criteria weight which is the same case of *Expert 5*. Thus, care should be given to weighting the different criteria, since this step may influence significantly the final rank.

Figure 5. Sensitivity analysis of the criteria weights.

5.3. Comparison of the obtained criteria weights (FAHP) with ANP technique result

As mentioned above, we used in this paper Fuzzy AHP for criteria weights (Step 3) assuming that the six criteria are independent. However, since the work deals with experts, taking into account their complexity and diversity, Analytic Network Process (ANP) seems to be a good technique to be used for the criteria weight evaluation for comparison purposes. The advantage of ANP is the capability of solving the problems in which alternatives and criteria have such interactions that cannot be shown in a hierarchy. When decision makers decide to model a problem as a network, it is not necessary for them to specify the levels (Bauyaukyazici and Sucu, 2003). Indeed, in this case we assume that the six criteria for the humanitarian expert selection are dependent and affect each other, which is referred to as inner dependency (Saaty and Takizawa, 1986).

The different criteria weights obtained by ANP technique are illustrated in Table 9, where we notice that the ranking remains the same as the results obtained by our hybrid approach. C3 (Satisfaction with past projects) and C1 (Work experience) have more than half of the total criteria weights. C4 (motivation) comes in the 3rd place with an important weight equal to 0.128 (vs 0.237). C6 (Integration capacity) in the 4th place with a weigh of 0.088 (vs 0.171). C2 (education) comes in the 5th place with a weight of 0.061 (vs 0.77). Unlike the result obtained by our approach C5 (compensation) comes with a weight of 0.043 (vs 0.000).

From ranking point of view, this comparison validate our adopted approach and we can also notice that the fuzzy hybrid approach pushes the criteria values towards limits by increasing those having the highest ranking such as C3 and C1 (0.345 vs 0.264 and 0.332 vs 0.251) and decreasing the lowest ranking values like C2 and C5 (0.077 vs 0.061 and 0.043 vs 0.000) which allows to reduce the uncertainty for the decision makers.

C1	Work experience	0.332
C2	Education	0.061
C3	Satisfaction with past projects	0.345
C4	Motivation	0.128
C5	Compensation	0.043
C6	Integration capacity	0.088

Table 9. ANP criteria weights.

6. Conclusion

In this paper, a multi-criteria group decision making approach is designed and applied to the selection of experts for humanitarian development projects due to the imprecise or vague elements in evaluating the experts as well as their fit to the humanitarian projects. The hybrid approach is based on two stages: the first one consists of fuzzy AHP for the criteria and decision makers' weights, and the second stage is based on TOPSIS to rank the candidates according to the relative closeness to the ideal solution. The present paper is then dealing with innovative aspects of expert selection in the humanitarian field, characterized by specific criteria that have to be considered to comply with the requirements of most funding humanitarian organizations and agencies. In this work, we identify six criteria to be considered in the selection of experts and consultants for humanitarian projects development: Work experience, Education, Satisfaction from past projects, Motivation, Compensation and Capacity of integration. In this regard, one of the major contributions of our work is the ability to take into account both quantitative and qualitative evaluations for the different criteria, thanks to the use of fuzzy concepts.

The real case considered shows that for all cases where the decision makers' weights or the relative degree of similarity vary, the best candidate to be selected remains the same. This conclusion applies as well for most of the cases where there is an increase of the weights of the different criteria, even if in some extreme cases (an increase by 200%), there could be a change in the final candidates' ranks. Furthermore, in order to validate the approach used to weight the different criteria, we assumed the existence of dependency between those elements. As a comparison, an ANP technique is developed and the result shows that the ranking of criteria remains the same. This shows the robustness of the solutions provided by the approach that makes the decisions made valid for different cases and configurations taking into account changes in weights of the decision makers and the criteria. As the methodology chosen shows a high rank for *Expert 3*, the decision makers decided to select the *Expert 3* for a deep interview, confirming the results of the study. The interview shows that the *Expert 3* fulfils the requirements of the job, with respect to the six criteria selected, ensuring an optimal achievement of the humanitarian development project. Moreover, the democratization of the selection process through integration of the opinions of all decision makers, independently from their areas of expertise or their roles, allowed to put a common responsibility and commitment in controlling the tasks and the funds allocated during the execution of the project. Thus, such an approach can easily increase the objectivity and awareness in the recruitment processes of experts for humanitarian development projects and help to ensure a fair and equal treatment for the candidates applying for this type of job.

Although it is noted that the different decision makers' contributions have been evaluated by a unique decision maker with a prior knowledge of the expertise and skills of all other decision makers, it is not possible to always find such a situation. A possible future research direction consists of the use of a cross evaluation process, where each decision maker evaluates the others and where the final weight of each decision maker takes into account all the evaluations made.

References

Aggarwal, R. (2013). Selection of IT Personnel through Hybrid Multi-attribute AHP-FLP approach. *International Journal of Soft Computing and Engineering*, *2*(6), 11-17.

Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. *European journal of operational research*, *175*(1), 475-493.

Benini, A., Conley, C., Dittemore, B., & Waksman, Z. (2009). Survivor needs or logistical convenience? Factors shaping decisions to deliver relief to earthquake-affected communities, Pakistan 2005–06. *Disasters*, *33*(1), 110-131.

Bierschenk, T., & de Sardan, J. P. O. (2003). Powers in the village: Rural Benin between democratisation and decentralisation. *Africa*, *73*(02), 145-173.

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.

Bose, G., & Chatterjee, N. (2016). Fuzzy hybrid MCDM approach for selection of wind turbine service technicians. *Management Science Letters*, *6*(1), 1-18.

Bozbura, F. T., Beskese, A., & Kahraman, C. (2007). Prioritization of human capital measurement indicators using fuzzy AHP. *Expert Systems with Applications*, *32*(4), 1100-1112.

Brent, A. C., Rogers, D. E., Ramabitsa-Siimane, T. S., & Rohwer, M. B. (2007). Application of the analytical hierarchy process to establish health care waste management systems that minimise infection risks in developing countries. *European Journal of Operational Research*, *181*(1), 403-424.

Büyükyazıcı, M., & Sucu, M. (2003). The analytic hierarchy and analytic network processes. *CRITERION*, *1*, c1.

Canós, L., & Liern, V. (2008). Soft computing-based aggregation methods for human resource management. *European Journal of Operational Research*, *189*(3), 669-681.

Capaldo, G., & Zollo, G. (2001). Applying fuzzy logic to personnel assessment: a case study. *Omega*, *29*(6), 585-597.

Chaghooshi, A., Arab, A., & Dehshiri, S. (2016). A fuzzy hybrid approach for project manager selection. *Decision Science Letters*, *5*(3), 447-460.

Chandran, B., Golden, B., & Wasil, E. (2005). Linear programming models for estimating weights in the analytic hierarchy process. *Computers & Operations Research*, *32*(9), 2235-2254.

Chang, D. Y. (1992). Extent analysis and synthetic decision. *Optimization techniques and applications*, *1*(1), 352-355.

Chen, C. T., Cheng, H. L., & Hung, W. Z. (2016, August). A two-phase decision-making method for handling personnel selection problem. In *Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), 2016 12th International Conference on* (pp. 1021-1026). IEEE.

Chen, L. S., & Cheng, C. H. (2005). Selecting IS personnel use fuzzy GDSS based on metric distance method. *European Journal of Operational Research*, *160*(3), 803-820.

Çetinkaya, C., Özceylan, E., Erbaş, M., & Kabak, M. (2016). GIS-based fuzzy MCDA approach for siting refugee camp: A case study for southeastern Turkey. *International Journal of Disaster Risk Reduction*, *18*, 218-231.

Dadelo, S., Turskis, Z., Zavadskas, E. K., & Dadeliene, R. (2012). Multiple criteria assessment of elite security personal on the basis of aras and expert methods. *Economic Computation and Economic Cybernetics Studies and Research*, *46*(4), 65-87.

Dursun, M., & Karsak, E. E. (2010). A fuzzy MCDM approach for personnel selection. *Expert Systems with applications*, *37*(6), 4324-4330.

Erdem, M. B. (2016). A Fuzzy Analytical Hierarchy Process Application in Personnel Selection in IT Companies: A Case Study in a Spin-off Company. *Acta Physica Polonica A, 130*(1), 331-334.

Figueira, J., Mousseau, V., & Roy, B. (2005). ELECTRE methods. In *Multiple criteria decision analysis: State of the art surveys* (pp. 133-153). Springer New York.

Galindo, G., & Batta, R. (2013). Review of recent developments in OR/MS research in disaster operations management. *European Journal of Operational Research*, *230*(2), 201-211.

Golec, A., & Kahya, E. (2007). A fuzzy model for competency-based employee evaluation and selection. *Computers & Industrial Engineering*, *52*(1), 143-161.

Gralla, E., Goentzel, J., & Fine, C. (2014). Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. *Production and Operations Management, 23,* 978–989.

Güngör, Z., Serhadlıoğlu, G., & Kesen, S. E. (2009). A fuzzy AHP approach to personnel selection problem. *Applied Soft Computing*, *9*(2), 641-646.

Haghighi, M., Zowghi, M., & Ansari, M. (2012). A fuzzy multiple attribute decision making (MADM) approach for employee evaluation and selection process. *American Journal of Scientific Research ISSN*, 75-84.

Huang, C. C., Chu, P. Y., & Chiang, Y. H. (2008). A fuzzy AHP application in government-sponsored R&D project selection. *Omega*, *36*(6), 1038-1052.

Huang, C. Y., Wan, C. W., & Tzeng, G. H. (2011, June). Expatriate manager selection for an overseas manufacturing site by using FMCDM methods. In *Fuzzy Systems (FUZZ), 2011 IEEE International Conference on* (pp. 2401-2406). IEEE.

Hwang, C. L., & Yoon, K. (2012). *Multiple attribute decision making: methods and applications a state-of-the-art survey* (Vol. 186). Springer Science & Business Media.

Janic, M. (2003). Multicriteria evaluation of high-speed rail, transrapid maglev and air passenger transport in Europe. *Transportation Planning and Technology*, *26*(6), 491-512.

Kabak, M., Burmaoğlu, S., & Kazançoğlu, Y. (2012). A fuzzy hybrid MCDM approach for professional selection. *Expert Systems with Applications*, *39*(3), 3516-3525.

Kahraman, C., Ruan, D., & Doğan, I. (2003). Fuzzy group decision-making for facility location selection. *Information Sciences*, *157*, 135-153.

Karagiannidis, A., Papageorgiou, A., Perkoulidis, G., Sanida, G., & Samaras, P. (2010). A multi-criteria assessment of scenarios on thermal processing of infectious hospital wastes: a case study for Central Macedonia. *Waste management*, *30*(2), 251-262.

Karsak, E. E. (2001). Personnel selection using a fuzzy MCDM approach based on ideal and anti-ideal solutions. In *Multiple criteria decision making in the new millennium* (pp. 393-402). Springer Berlin Heidelberg.

Kauffman, A., & Gupta, M. M. (1991). Introduction to Fuzzy Arithmetic, Theory and Application.

Kelemenis, A., & Askounis, D. (2010). A new TOPSIS-based multi-criteria approach to personnel selection. *Expert systems with applications*, *37*(7), 4999-5008.

Kelemenis, A., Ergazakis, K., & Askounis, D. (2011). Support managers' selection using an extension of fuzzy TOPSIS. *Expert Systems with Applications*, *38*(3), 2774-2782.

Kwong, C. K., & Tam, S. M. (2002). Case-based reasoning approach to concurrent design of low power transformers. *Journal of Materials Processing Technology*, *128*(1), 136-141.

Li, C., Zhang, X., Zhang, S., & Suzuki, K. (2009). Environmentally conscious design of chemical processes and products: Multi-optimization method. *Chemical engineering research and design*, *87*(2), 233-243.

Liang, G. S., & Wang, M. J. J. (1992). Personnel placement in a fuzzy environment. *Computers & Operations Research*, *19*(2), 107-121.

Lin, H. T. (2010). Personnel selection using analytic network process and fuzzy data envelopment analysis approaches. *Computers & Industrial Engineering*, *59*(4), 937-944.

Liu, H. C., Qin, J. T., Mao, L. X., & Zhang, Z. Y. (2015). Personnel Selection Using Interval 2-Tuple Linguistic VIKOR Method. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *25*(3), 370-384.

Lu, C., You, J. X., Liu, H. C., & Li, P. (2016). Health-care waste treatment technology selection using the interval 2-tuple induced TOPSIS method. *International journal of environmental research and public health*, *13*(6), 562.

Mazurek, J., & Kiszová, Z. (2012). Modeling dependence and feedback in ANP with fuzzy cognitive maps. In *Proceedings of the 30th international conference Mathematical methods in Economics* (pp. 558-563).

Md Saad, R., Ahmad, M. Z., Abu, M. S., & Jusoh, M. S. (2013, April). Some fuzzy techniques for staff selection process: A survey. In A. Ishak, I. Hashim, E. S. Ismail, & R. Nazar (Eds.), *AIP Conference Proceedings* (Vol. 1522, No. 1, pp. 462-469). AIP.

Milani, A. S., Shanian, A., Madoliat, R., & Nemes, J. A. (2005). The effect of normalization norms in multiple attribute decision making models: a case study in gear material selection. *Structural and multidisciplinary optimization*, *29*(4), 312-318.

Ölçer, A. I., & Odabaşi, A. Y. (2005). A new fuzzy multiple attributive group decision making methodology and its application to propulsion/manoeuvring system selection problem. *European Journal of Operational Research*, *166*(1), 93-114.

Özcan, T., Çelebi, N., & Esnaf, Ş. (2011). Comparative analysis of multi-criteria decision making methodologies and implementation of a warehouse location selection problem. *Expert Systems with Applications*, *38*(8), 9773-9779.

Özdağoğlu, A., & Özdağoğlu, G. (2007). Comparison of AHP and fuzzy AHP for the multi-criteria decision making processes with linguistic evaluations.

Peng, Y., & Yu, L. (2014). Multiple criteria decision making in emergency management. *Computers and Operations Research*, (42), 1-2.

Petrovic‐Lazarevic, S. (2001). Personnel selection fuzzy model. *International Transactions in Operational Research*, *8*(1), 89-105.

Polychroniou, P. V., & Giannikos, I. (2009). A fuzzy multicriteria decision-making methodology for selection of human resources in a Greek private bank. *Career Development International*, *14*(4), 372-387.

Qin, X. S., Huang, G. H., Chakma, A., Nie, X. H., & Lin, Q. G. (2008). A MCDM-based expert system for climate-change impact assessment and adaptation planning–A case study for the Georgia Basin, Canada. *Expert Systems with Applications*, *34*(3), 2164-2179.

Rao, R. V., & Davim, J. P. (2008). A decision-making framework model for material selection using a combined multiple attribute decision-making method. *The International Journal of Advanced Manufacturing Technology*, *35*(7), 751-760.

Rondinelli, D. A. (2013). *Development projects as policy experiments: An adaptive approach to development administration*. Routledge.

Rouyendegh, B. D., & Erkan, T. E. (2013). An application of the fuzzy electre method for academic staff selection. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *23*(2), 107-115.

Saaty, T. L., & Takizawa, M. (1986). Dependence and independence: From linear hierarchies to nonlinear networks. *European Journal of Operational Research*, *26*(2), 229-237.

Sadatrasool, M., Bozorgi-Amiri, A., & Yousefi-Babadi, A. (2016). Project manager selection based on project manager competency model: PCA–MCDM Approach. *Journal of Project Management*, *1*(1), 7-20.

Sgarbossa, F., Peretti, U., Persona, A., & Tatham, P. (2015). Multi-criteria decision-making in the management of humanitarian operations. *International Journal of Services and Operations Management*, *22*(4), 413-441.

Srdjevic, B., Medeiros, Y. D. P., & Faria, A. S. (2004). An objective multi-criteria evaluation of water management scenarios. *Water resources management*, *18*(1), 35-54.

Shih, H. S., Shyur, H. J., & Lee, E. S. (2007). An extension of TOPSIS for group decision making. *Mathematical and Computer Modelling*, *45*(7), 801-813

Smith, L. D., Nauss, R. M., Banis, R. J., & Beck, R. (2002). Staffing geographically distributed service facilities with itinerant personnel. *Computers & Operations Research*, *29*(14), 2023-2041.

Soner, S., Ayadi, O., & Cheikhrouhou, N. (2012). An extensive group decision methodology for alliance partner selection problem in collaborative networked organisations. *International Journal of Applied Logistics*, *3*(EPFL-ARTICLE-176266), 1-19.

Tavana, M. (2007). A threat–response multi-criteria funding model for homeland security grant programs. *International Transactions in Operational Research*, *14*(4), 267-290.

Trivedi, A., & Singh, A. (2017). A hybrid multi-objective decision model for emergency shelter location-relocation projects using fuzzy analytic hierarchy process and goal programming approach. *International Journal of Project Management*.

Tavares, L. V. (1994). The strategic development of human resources: the challenge of OR. *International Transactions in Operational Research*, *1*(4), 463-477.

Gutjahr, W. J., & Nolz, P. C. (2016). Multicriteria optimization in humanitarian aid. *European Journal of Operational Research*, *252*(2), 351-366.

Tsai, W. H., & Chou, W. C. (2009). Selecting management systems for sustainable development in SMEs: A novel hybrid model based on DEMATEL, ANP, and ZOGP. *Expert systems with applications*, *36*(2), 1444-1458.

Xu, J., Yin, X., Chen, D., An, J., & Nie, G. (2016). Multi-criteria location model of earthquake evacuation shelters to aid in urban planning. *International Journal of Disaster Risk Reduction*, *20*, 51-62.

Xu, Z. (2009). An automatic approach to reaching consensus in multiple attribute group decision making. *Computers & Industrial Engineering*, *56*(4), 1369-1374.

Xu, Z. S., & Chen, J. (2007). An interactive method for fuzzy multiple attribute group decision making. *Information Sciences*, *177*(1), 248-263.

Limayem, F., & Yannou, B. (2007). Selective assessment of judgmental inconsistencies in pairwise comparisons for group decision rating. *Computers & operations research*, *34*(6), 1824-1841.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, *8*(3), 338-353.

Zahedi, F. (1987). Qualitative programming for selection decisions. *Computers & operations research*, *14*(5), 395-407.

Zimmermann, H. J. (2011). *Fuzzy set theory—and its applications*. Springer Science & Business Media.