Expert Systems with Applications 40 (2013) 5694–5702

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

# A novel hybrid social media platform selection model using fuzzy ANP and COPRAS-G

Madjid Tavana [a,*], Ehsan Momeni [b], Nahid Rezaeiniya [b], Seyed Mostafa Mirhedayatian [c], Hamidreza Rezaeiniya [b]

[a] Business Systems and Analytics Department, Lindback Distinguished Chair of Information Systems and Decision Sciences, La Salle University, Philadelphia, PA 19141, USA
[b] Department of Industrial Engineering, Islamic Azad University, Firoozkooh, Iran
[c] Young Researchers Club, Islamic Azad University, Amol, Iran

ARTICLE INFO

*Keywords:*
Social media
Analytic Network Process
Fuzzy set theory
COPRAS-G

ABSTRACT

The growing popularity of social media platforms has sparked new marketing opportunities for companies. Marketers have turned to social media campaigns as a means to build brand loyalty, exposure, and engagement. While social media has evolved into a powerful marketing tool, marketers must carefully choose the most suitable social media platform. Improper selection of the social media platform can be costly and can be detrimental to the brand. Despite all of the supposed benefits, selecting the right social media platform has been a daunting task for corporate marketers. The social media platform selection problems are inherently complex problems with multiple and often conflicting criteria. We propose a novel analytical framework for social media platform selection. The proposed hybrid framework integrates the Analytic Network Process (ANP) with fuzzy set theory and the COmplex PRoportional ASsessment of alternatives with Grey relations (COPRAS-G) method. The ANP and fuzzy set theory are used to determine the importance weight of the social media platform selection criteria in a fuzzy environment. The COPRAS-G method is used to rank and select the most suitable social media platform. A case study is presented to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms.



## 1. Introduction

The World Wide Web, described by Sir Tim Berners-Lee as "an interactive sea of shared knowledge.....made of the things we and our friends have seen, heard, believe or have figured out," has drastically changed traditional marketing (Evans & McKee, 2010, p. xvii). Traditional marketing involves an information exchange in a one-way direction (e.g., television and radio commercials). On the contrary, web-based marketing involves two-way communication with customers while maintaining the push-messaging (Trusov, Bucklin, & Pauwels, 2009). Social media facilitate two-way communication and connect people on a mass scale. The collaborative technologies that now define contemporary marketplaces provide tremendous opportunities for new business initiatives across a wide range of applications. These social media technologies allow savvy businesses to connect with their customers and prosper through a two-way collaborating relationship. Social media sites are leveraging direct selling to reach social networks of family, friends, and co-workers, thus extending the reach of direct selling (Glenn, 2011). Social media comprise both the conduits and the content disseminated through interactions between individuals and organizations (Kietzman, Hermkens, McCarthy, & Silvestre, 2011).

Despite all of the supposed benefits, selecting the right social media platform has been a daunting task for corporate marketers. This difficulty is due to: (i) the optimal frequency of posting; (ii) the fixed cost of establishing a social media presence; (iii) the average cost of creating a typical 'engagement entry' (e.g., a Facebook posting, a YouTube video, a tweet, etc.) on a social media site; and (iv) the expected cost of building a reasonable follower audience or fan base. Although the social media platform selection problems are inherently complex problems with multiple and often conflicting criteria, no analytical social media platform evaluation and selection model has been proposed in the literature. Most existing models are limited to simple classification charts categorizing the different types of social media engagements (McLellan, 2010). There is a need for a more systematic and analytical framework for social media platform evaluation and selection.

* Corresponding author. Tel.: +1 215 951 1129; fax: +1 367 295 2854.
*E-mail addresses:* tavana@lasalle.edu (M. Tavana), ehs_momeni@yahoo.com (E. Momeni), nah.rezaeiniya@gmail.com (N. Rezaeiniya), mstf.mirhedayatian@yahoo.com (S.M. Mirhedayatian), h_rezaeiniya121@yahoo.com (H. Rezaeiniya).
*URL:* http://tavana.us/ (M. Tavana).

0957-4174/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2013.05.015

We propose a novel analytical framework for social media platform selection. The proposed hybrid framework integrates the Analytic Network Process (ANP) with fuzzy set theory and the COmplex PRoportional ASsessment of alternatives with Grey relations (COPRAS-G) method. The ANP and fuzzy set theory are used to determine the importance weight of the social media platform selection criteria in a fuzzy environment. The COPRAS-G method is used to rank and select the most suitable social media platform.

The remainder of this paper is organized as follows. In Section 2 we review the relevant literature on social media marketing, Multi-Attribute Decision Making (MADM) and the Analytic Network Process (ANP), fuzzy set theory and the COmplex PRoportional ASsessment of alternatives with Grey relations (COPRAS-G) method. In Section 3 we provide the details of the hybrid method proposed in this study. In Section 4 we present a real-world case study to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms. In Section 5 we present our conclusions and future research directions.

## 2. Literature review

Social media are Internet platforms used to disseminate information through social interactions that provide decentralized user level content and public membership (Abrahams, Jiao, Wang, & Fan, 2012). Most social media are highly accessible and scalable and allow for a variety of social interactions such as social viral activity and intimate community engagement (Li & Shiu, 2012). The most widely used social media mechanisms are online forums such as product or service review websites, blogs, chat rooms, discussion boards, and social networking websites like Facebook, Twitter, LinkedIn, Google+, and YouTube (Kaplan & Haenlein, 2010; Mangold & Faulds, 2009). Social media marketing addresses people as part of a social network and uses social relations and social influences between people to sell products or services (Wang, Wang, & Farn, 2009).

Five distinct properties make social media a powerful marketing tool: (1) participation: social media encourages contributions and feedback (Durugbo, 2012); (2) openness: most social media services are open to feedback and participation by encouraging voting, commenting and the sharing of information (Bertot, Jaeger, & Grimes, 2010); (3) conversation: traditional media is about broadcasting a message while social media is a two-way conversation (Özyurt & Köse, 2010); (4) community: communities can form quickly and converse effectively through social media (Kim & Ahmad, 2013); and (5) connectedness: social media thrives on connections by making use of links to other sites, resources and people (Grieve, Indian, Witteveen, Tolan, & Marrington, 2013). Possessed with these distinct features, social media marketing provide several practical advantages. Social media marketing helps companies boost their brand awareness (Qualman, 2009), reach millions of audience across the globe (Trusov et al., 2009), and save in marketing costs (Michaelidou, Siamagka, & Christodoulides, 2011; Weber, 2007).

The social media platform selection problems are complex problems with multiple criteria. MADM methods are commonly used to solve multi-criteria problems. Each MADM method provides a different approach for selecting the best among several preselected alternatives (Janic & Reggiani, 2002). The MADM methods help Decision Makers (DMs) learn about the issues they face, the value systems of their own and other parties, and the organizational values and objectives that will consequently guide them in identifying a preferred course of action. The primary goal in MADM is to provide a set of attribute-aggregation methodologies for considering the preferences and judgments of DMs (Doumpos & Zopounidis, 2002). Roy (1990) argues that solving MADM problems is not searching for an optimal solution, but rather helping DMs master the complex judgments and data involved in their problems and advance towards an acceptable solution. Multi-attributes analysis is not an off-the-shelf recipe that can be applied to every problem and situation. The development of MADM models has often been dictated by real-life problems. Therefore, it is not surprising that methods have appeared in a rather diffuse way, without any clear general methodology or basic theory (Vincke, 1992). The selection of a MADM framework or method should be done carefully according to the nature of the problem, types of choices, measurement scales, dependency among the attributes, type of uncertainty, expectations of the DMs, and quantity and quality of the available data and judgments (Vincke, 1992). ANP is a popular MADM method used for solving multi-criteria problems with interdependencies. We use fuzzy ANP to determine the importance weight of the social media platform selection criteria.

The ANP, introduced by Saaty (1996), is a generalization of the Analytic Hierarchy Process (AHP). AHP models are represented with unidirectional hierarchical relationships. However, ANP models allow for complex inter-relationships among the decision levels and the attributes. The feedback mechanism in AHP replaces the hierarchical structure with a network structure where the relationships between levels are not simply represented as higher or lower, dominant or subordinate, direct or indirect (Meade & Sarkis, 1999). In other words, while the importance of the criteria determines the importance of the alternatives in a hierarchy, the importance of the alternatives may also have an impact on the importance of the criteria. AHP solves the problem of independence among the alternatives or criteria and ANP solves the problem of dependence among the alternatives or criteria by obtaining the composite weights through the development of a "supermatrix" (Shyur, 2006). The supermatrix is actually a partitioned matrix, where each matrix segment represents a relationship between two components or clusters in a system (Saaty, 2005).

The inability of ANP to deal with the imprecise or uncertain judgments has been remedied in fuzzy ANP. Instead of a crisp value, fuzzy ANP applies a range of values to incorporate the DM's imprecise or uncertain judgments in the pairwise comparison process. Recent applications of the fuzzy ANP are, transportation-mode selection (Tuzkaya & Önüt, 2008); faulty behavior risk assessment in work systems (Dağdeviren, Yuksel, & Kurt, 2008); shipyard location selection (Guneri, Cengiz, & Seker, 2009); evaluation of high-speed public transportation (Gumus & Yilmaz, 2010); selecting container ports (Önüt, Tuzkaya, & Torun, 2011); agricultural drought risk assessment (Chen & Yang, 2011); evaluation of the airline industry (Sevkli et al., 2012); professional selection (Kabak, Burmaoğlu, & Kazançoğlu, 2012) and strategy prioritization (Babaesmailli, Arbabshirani, & Golmah, 2012), amongst others. Once the importance weights of the social media platform selection criteria are determined we use COPRA-G to rank and select the most suitable social media platform.

The COPRAS-G method (Zavadskas, Kaklauskas, Turskis, & Tamošaitienė, 2008; Zavadskas, Kaklauskas, Turskis, & Tamošaitienė, 2009) uses a stepwise evaluation procedure to rank the alternatives in terms of their significance and utility degree. In this method, the parameters of the alternatives are determined with the grey relational grade and expressed in terms of intervals. The grey systems theory, established by Deng (1982), Deng (1988), focuses on the study of problems involving small samples and poor information. It deals with uncertain systems with partially known information. Grey analysis defines situations with no information as black, and those with perfect information as white. However, real-world problems do not generally involve these idealized situations. The situations between these extremes are described as being grey, hazy or fuzzy. Therefore, a grey system represents a system in which part of the information is known and part of the information is unknown. Since uncertainty always exists, one is always somewhere in the middle, somewhere between the back and white extremes (i.e., somewhere in the grey area).

Recent applications of COPRAS-G are, bank evaluation (Ginevičius & Podvezko, 2008), employee selection (Datta, Beriha, Patnaik, & Mahapatra, 2009; Zolfani, Rezaeiniya, Aghdaie, & Zavadskas, 2012b), website evaluation (Bindu Madhuri, Anand Chandulal, & Padmaja, 2010), material selection for engineering applications (Chatterjee, Athawale, & Chakraborty, 2011), building renovation and construction (Bitarafan, Zolfani, Arefi, & Zavadskas, 2012; Medineckiene & Björk, 2011), location planning (Rezaeiniya, Zolfani, & Zavadskas, 2012; Zolfani, Rezaeiniya, Zavadskas, & Turskis, 2011), university evaluation (Das, Sarkar, & Ray, 2012), container terminal technology assessment (Barysiene, 2012), supplier evaluation and selection (Sahu, Datta, & Mahapatra, 2012; Zolfani, Chen, Rezaeiniya, & Tamosaitiene, 2012a), and market segment evaluation and selection (Aghdaie, Zolfani, & Zavadskas, 2013).

## 3. The proposed hybrid method

The hybrid model depicted in Fig. 1 integrates the ANP method with fuzzy set theory and the COPRAS-G method to assess the alternative social media markets.

### 3.1. The ANP method

The ANP method (Saaty, 2001) is comprised of the following four steps:

#### 3.1.1. Step 1: Form the network structure

In the first step, the criteria, the sub-criteria and the alternatives are identified. Then, the clusters of the elements are determined and a network is formed based on the relationship among the clusters and within the elements in each cluster. Several different relationships could be found in a network. Direct relationship is a regular dependency in a standard hierarchy. Indirect relationship is a relationship that flows through another criteria or alternative. The direct relationship between a criterion and itself is characterized by "self-interacting" criteria. Finally, interdependencies are relationships among criteria which form a mutual effect.

#### 3.1.2. Step 2: Form the pairwise comparison matrices

In the second step, pairwise comparisons are performed on the elements within the clusters as they influence each cluster and on those that it influences, with respect to that criterion. The pairwise comparisons are made with respect to a criterion or sub-criterion of the control hierarchy. Thus, the importance weights of the factors are determined. In pairwise comparison, decision makers compare two elements. Then, they determine the contribution of the factors to the result (Saaty, 2001). In ANP, similar to AHP, pairwise comparison matrices are formed using the 1–9 scale of relative importance proposed by Saaty (1996). The values of the pairwise comparisons are assigned to a comparison matrix and a local priority vector is obtained from the eigenvector which is calculated as follows:

$$Aw = \lambda_{enb} w \tag{1}$$

In this equation, $A$, $w$ and $\lambda_{enb}$ represent the pairwise comparison matrix, the eigenvector, and the eigenvalue, respectively. Saaty and Takizawa (1986) has proposed a normalization algorithm for the approximate solution of $w$ (Saaty & Takizawa, 1986). The matrix which shows the comparison between the factors is obtained as follows:

$$A = [a_{ij}]_{n \times n}, \quad i = \overline{1,n}; \ j = \overline{1,n} \tag{2}$$

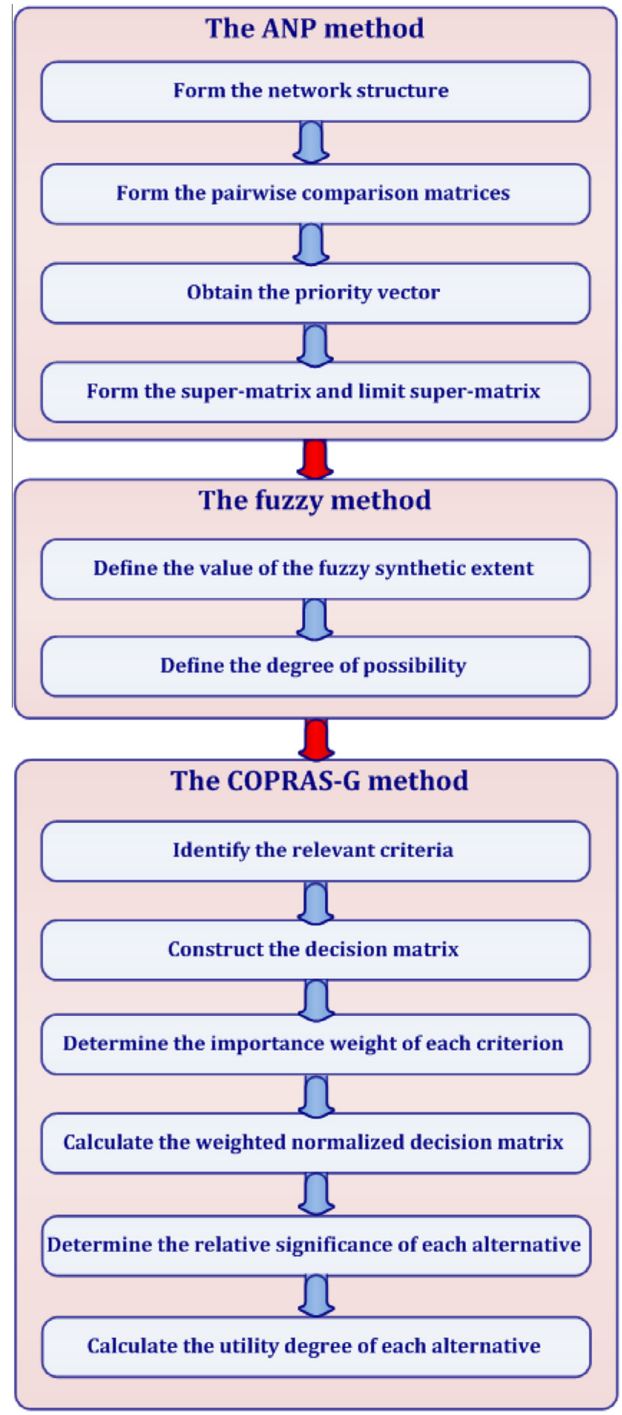


**Fig. 1.** The proposed hybrid model.

#### 3.1.3. Step 3: Obtain the priority vector

The significance distribution of the factors as a percentage is obtained as follows:

$$B_i = [b_{ij}]_{n \times 1}, \quad i = \overline{1,n} \tag{3}$$

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{4}$$

$$C = [b_{ij}]_{n \times n}, \quad i = \overline{1,n}; \ j = \overline{1,n} \tag{5}$$

$$w_i = \frac{\sum_{j=1}^{n} c_{ij}}{n} W = [w_i]_{n \times 1} \tag{6}$$

*3.1.4. Step 4: Form the super-matrix and limit super-matrix*

The overall structure of the super-matrix is similar to the Markov chain process (Saaty, 1996, 2005). To obtain the global priority in a system that has interdependent effects, all local priority vectors are allocated to the relevant columns of the super-matrix. Consequently, the super-matrix is a limited matrix and every part of it shows the relationship between two elements in the system. The long-term relative impacts of the elements to each other are obtained by raising the super-matrix to a power. To equalize the importance weights, the matrix is raised to the $(2k+1)th$ power, where $k$ is an arbitrary large number (Saaty, 2001). As noted by Lee, Kim, Cho, and Park (2009, p. 897) "Raising the weighted super-matrix to the power $2k+1$, where $k$ is an arbitrarily large number, allow convergence of the matrix, which means the row values converge to the same value for each column of the matrix." The new matrix is called the limited Super-matrix (Saaty, 1996). The consistency of the pairwise comparison matrix is checked with the consistency index (CI). For accepted consistency, CI must be smaller than 0.10 (Saaty & Takizawa, 1986).

## 3.2. The fuzzy method

Let the universe of discourse $X$ be the subset of real numbers $R$. The fuzzy number $M$ on R is a triangular fuzzy number if its membership function $\mu_M(x)$:$R \to [0, 1]$ is equal to:

$$\mu_M(x) = \begin{cases} \frac{x}{b-a} - \frac{a}{b-a}, & x \in [a,b] \\ \frac{x}{b-c} - \frac{c}{b-c}, & x \in [b,c] \\ 0 & otherwise \end{cases} \quad (7)$$

where $a \leqslant b \leqslant c$, $a$ and $c$ are the lower and upper bound values of the support of $M$, respectively; and $b$ is the peak or center. The triangular number is denoted by $(a, b, c)$. If $a = b = c$, the number is an ordinary (non-fuzzy) number.The support of $M$ is the set $\{x \in R | a < x < c\}$.

Consider two triangular fuzzy numbers $M_1 = (a_1, b_1, c_1)$ and $M_2 = (a_2, b_2, c_2)$. The following describes the addition, multiplication and inverse of the two fuzzy numbers $M_1$ and $M_2$, respectively:

$$(a_1, b_1, c_1) \oplus (a_2, b_2, c_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (8)$$

$$(a_1, b_1, c_1) \otimes (a_2, b_2, c_2) = (a_1 a_2 + b_2 b_2 + c_1 c_2) \quad (9)$$

$$(a_1, b_1, c_1)^{-1} \approx \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}\right) \quad (10)$$

The triangular fuzzy numbers used in this model are suggested by Önüt, Karar, and Tugba (2008) to represent the subjective pair-wise comparisons of the experts' judgments. Table 1 presents the triangular fuzzy scale used to convert the linguistic values into fuzzy scales.

We use the extent analysis method proposed by Chang (1996) to consider the extent to which an object can satisfy the goal (or the satisfaction extent). In this method, the extent is quantified with a fuzzy number. Based on the fuzzy values for the extent analysis of each object, a fuzzy synthetic degree value is obtained using the following two steps:

*3.2.1. Step 1: Define the value of the fuzzy synthetic extent*

The value of the fuzzy synthetic extent is defined using the standard fuzzy arithmetic as follows:

$$S_i = \sum_{j=1}^{m} M_i^j \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_i^j\right]^{-1} \quad (11)$$

where $S_i$ is the fuzzy extent value and $\otimes$ is defined as the multiplication fuzzy operation. $M_i^j$ is a triangular fuzzy number representing the extent analysis value of the decision element $i$ with respect to the goal $j$. $M_i^j$ is the generic element of the fuzzy pair-wise comparison matrix. To obtain $\sum_{j=1}^{m} M_i^j$, we perform the fuzzy addition operation of $m$ extent analysis values for a particular matrix as follows:

$$\sum_{j=1}^{m} M_i^j = \left(\sum_{j=1}^{m} a_j, \sum_{j=1}^{m} b_j, \sum_{j=1}^{m} c_j\right) \quad (12)$$

In order to obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_i^j\right]^{-1}$, we perform the fuzzy addition operation on $M_i^j (j = 1, 2, \ldots, m)$ values as follows:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_i^j = \left(\sum_{i=1}^{n} a_i, \sum_{i=1}^{n} b_i, \sum_{i=1}^{n} c_i\right) \quad (13)$$

We then compute the inverse of the vector as follows:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_i^j\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} c_i}, \frac{1}{\sum_{i=1}^{n} b_i}, \frac{1}{\sum_{i=1}^{n} a_i}\right) \quad (14)$$

*3.2.2. Step 2: Define the degree of possibility*

The degree of possibility of $M_2 = (a_2, b_2, c_2) \geqslant M_1 = (a_1, b_1, c_1)$ is defined as:

$$V(M_2 \geqslant M_1) = \sup_{x \geqslant y}[\min(\mu_{M_1}(x), \mu_{M_2}(y))] \quad (15)$$

and can be equivalently expressed as follows:

$$V(M_2 \geqslant M_1) = \text{hgt}(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & if\ b_1 \geqslant b_2 \\ 0, & if\ a_1 \geqslant c_2 \\ \frac{a_1 - c_2}{(b_2 - c_2) - (b_1 - a_1)}, & otherwise \end{cases} \quad (16)$$

where $d$ is the ordinate of the highest intersection point $D$ between $\mu_{M_1}$ and $\mu_{M_2}$. To compare $M_1$ and $M_2$, we need both the values of $V(M_1 \geqslant M_2)$ and $V(M_2 \geqslant M_1)$ given in Fig. 2.

The degree of possibility for a convex fuzzy number to be greater than $k$ convex fuzzy numbers $M_i (i = 1, 2, \ldots, k)$ can be defined by:

$$V(M \geqslant M_1, M_2, \ldots, M_k) = V[(M \geqslant M_1), (M \geqslant M_2), \ldots, (M \geqslant M_k)] = \min\ V(M \geqslant M_i) \quad (17)$$

where $i = 1, 2, \ldots, k$. Assume that:

$$d'(A_i) = \min\ V(M \geqslant M_i) \quad (18)$$

**Table 1**
The triangular fuzzy conversion.

| Linguistic scale for importance | Triangular fuzzy scale $(a,b,c)$ |
|---|---|
| Just equal | (1.0,1.0,1.0) |
| Equal importance | (1.0,1.0,3.0) |
| Weak importance of one over another | (1.0,3.0,5.0) |
| Essential or strong importance | (3.0,5.0,7.0) |
| Very strong importance | (5.0,7.0,9.0) |
| Extremely preferred | (7.0,9.0,9.0) |

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 $i$: $M_1^{-1} \approx \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}\right)$

where $k = 1, 2, \ldots, n$; $k \neq i$. Then, the weight vector is given by:

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^T \tag{19}$$

where $A_i (i = 1, 2, \ldots, n)$ are $n$ decisions elements.

The normalized weight vectors are:

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \tag{20}$$

where $W$ is a non-fuzzy number.

### 3.3. The COPRAS-G method

We use the COPRAS-G method proposed by Zavadskas et al. (2009) to calculate the utility degree and priority order of the alternative social media markets. This method works on a stepwise ranking and evaluation procedure of the alternatives in terms of their significance and utility degree as follows:

#### 3.3.1. Step 1: Identify the relevant criteria

We first identify the criteria relevant to the social media platform selection problem.

#### 3.3.2. Step 2: Construct the decision matrix

We then construct the decision matrix $\otimes X$ as follows:

$$\otimes X = \begin{bmatrix} [\otimes x_{11}] & [\otimes x_{12}] & \ldots & [\otimes x_{1m}] \\ [\otimes x_{21}] & [\otimes x_{22}] & \ldots & [\otimes x_{2m}] \\ \ldots & \ldots & \ldots & \ldots \\ [\otimes x_{n1}] & [\otimes x_{n2}] & \ldots & [\otimes x_{nm}] \end{bmatrix} = \begin{bmatrix} [\underline{x}_{11}; \bar{x}_{11}] & [\underline{x}_{12}; \bar{x}_{12}] & \ldots & [\underline{x}_{1m}; \bar{x}_{1m}] \\ [\underline{x}_{21}; \bar{x}_{21}] & [\underline{x}_{22}; \bar{x}_{22}] & \ldots & [\underline{x}_{1m}; \bar{x}_{1m}] \\ \ldots & \ldots & \ldots & \ldots \\ [\underline{x}_{n1}; \bar{x}_{n1}] & [\underline{x}_{n2}; \bar{x}_{n2}] & \ldots & [\underline{x}_{nm}; \bar{x}_{nm}] \end{bmatrix}; \quad j = \overline{1,n}; \overline{1,m} \tag{21}$$

where $\otimes x_{ji}$ is determined by $\underline{x}_{ji}$ (the smallest value, i.e., the lower limit) and $\bar{x}_{ji}$ (the biggest value, i.e., the upper limit).

#### 3.3.3. Step 3: Determine the importance weight of each criterion

We then determine the relative importance of each criterion ($q_i$) by using the ANP.

#### 3.3.4. Step 4: Calculate the weighted normalized decision matrix

In this step we first normalize the decision-making matrix $\otimes X$ in order to determine the importance weight of the selection criteria:

$$\tilde{\underline{x}}_{ij} = \frac{\underline{x}_{ji} - 2\underline{x}_{ji}}{\frac{1}{2}\left(\sum_{j=1}^{n}\underline{x}_{ji} + \sum_{j=1}^{n}\bar{x}_{ji}\right)\left(\sum_{j=1}^{n}\underline{x}_{ji} + \sum_{j=1}^{n}\bar{x}_{ji}\right)},$$
$$\tilde{\bar{x}}_{ji} = \frac{\bar{x}_{ji} - 2\bar{x}_{ji}}{\frac{1}{2}\left(\sum_{j=1}^{n}\underline{x}_{ji} + \sum_{j=1}^{n}\bar{x}_{ji}\right)\left(\sum_{j=1}^{n}\underline{x}_{ji} + \sum_{j=1}^{n}\bar{x}_{ji}\right)}, \quad j = \overline{1,n}; \overline{1,m} \tag{22}$$

where $\underline{x}_{ji}$ is the lowest value of criterion $i$ for alternative $j$; $\bar{x}_{ji}$ is the highest value of criterion $i$ for alternative $j$; $m$ is the number of criteria; and $n$ is the number of alternatives under consideration. The normalization process results in the following normalized decision matrix:

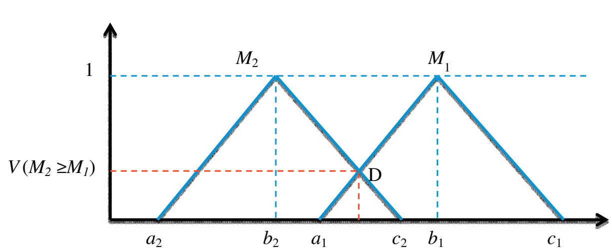


**Fig. 2.** Highest intersection point D between $M_1$ and $M_2$.

$$\otimes \tilde{X} = \begin{bmatrix} [\tilde{\underline{x}}_{11}; \tilde{\bar{x}}_{11}] & [\tilde{\underline{x}}_{12}; \tilde{\bar{x}}_{12}] & \ldots & [\tilde{\underline{x}}_{1m}; \tilde{\bar{x}}_{1m}] \\ [\tilde{\underline{x}}_{21}; \tilde{\bar{x}}_{21}] & [\tilde{\underline{x}}_{22}; \tilde{\bar{x}}_{22}] & \ldots & [\tilde{\underline{x}}_{1m}; \tilde{\bar{x}}_{1m}] \\ \ldots & \ldots & \ldots & \ldots \\ [\tilde{\underline{x}}_{n1}; \tilde{\bar{x}}_{n1}] & [\tilde{\underline{x}}_{n2}; \tilde{\bar{x}}_{n2}] & \ldots & [\tilde{\underline{x}}_{nm}; \tilde{\bar{x}}_{nm}] \end{bmatrix} \tag{23}$$

In order to construct the weighted normalized decision matrix, we first calculate the weighted normalized values $\otimes \hat{x}_{ji}$ as follows:

$$\otimes \hat{x}_{ji} = \otimes \tilde{x}_{ji} \cdot q_i \quad \text{or } \hat{\underline{x}}_{ji} = \tilde{\underline{x}}_{ji} \cdot q_i \quad \text{and } \hat{\bar{x}}_{ji} = \tilde{\bar{x}}_{ji} \cdot q_i \tag{24}$$

where $q_i$ is the relative importance of the $i$th criterion determined by using the ANP.

We then construct the weighted normalized decision matrix $\otimes \hat{X}$ as follows:

$$\otimes \hat{X} = \begin{bmatrix} [\otimes \hat{x}_{11}] & [\otimes \hat{x}_{12}] & \ldots & [\otimes \hat{x}_{1m}] \\ [\otimes \hat{x}_{21}] & [\otimes \hat{x}_{22}] & \ldots & [\otimes \hat{x}_{2m}] \\ \ldots & \ldots & \ldots & \ldots \\ [\otimes \hat{x}_{n1}] & [\otimes \hat{x}_{n2}] & \ldots & [\otimes \hat{x}_{nm}] \end{bmatrix} = \begin{bmatrix} [\hat{\underline{x}}_{11}; \hat{\bar{x}}_{11}] & [\hat{\underline{x}}_{12}; \hat{\bar{x}}_{12}] & \ldots & [\hat{\underline{x}}_{1m}; \hat{\bar{x}}_{1m}] \\ [\hat{\underline{x}}_{21}; \hat{\bar{x}}_{21}] & [\hat{\underline{x}}_{22}; \hat{\bar{x}}_{22}] & \ldots & [\hat{\underline{x}}_{1m}; \hat{\bar{x}}_{1m}] \\ \ldots & \ldots & \ldots & \ldots \\ [\hat{\underline{x}}_{n1}; \hat{\bar{x}}_{n1}] & [\hat{\underline{x}}_{n2}; \hat{\bar{x}}_{n2}] & \ldots & [\hat{\underline{x}}_{nm}; \hat{\bar{x}}_{nm}] \end{bmatrix} \tag{25}$$

#### 3.3.5. Step 5: Determine the relative significance of each alternative

We first calculate the sums $P_j$ of the criterion values (whose larger values are more preferable) as follows:

$$P_j = \frac{1}{2}\sum_{i=1}^{k}(\hat{\underline{x}}_{ji} + \tilde{\bar{x}}_{ji}) \tag{26}$$

We then calculate the sums $R_j$ of the criterion values (whose smaller values are more preferable) as follows:

$$R_j = \frac{1}{2}\sum_{i=k+1}^{m}(\hat{\underline{x}}_{ji} + \tilde{\bar{x}}_{ji}); \quad i = \overline{k,m} \tag{27}$$

where $(m - k)$ is the number of criteria which must be minimized.

We then determine the minimum value of $R_j$ as follows:

$$R_{\min} = \min_j R_j; \quad j = \overline{1,n} \tag{28}$$

The relative significance of each alternative is then calculated as follows:

$$Q_j = P_j + \frac{\sum_{j=1}^{n} R_j}{R_j \sum_{j=1}^{n} \frac{1}{R_j}} \tag{29}$$

#### 3.3.6. Step 6: Calculate the utility degree of each alternative

In order to calculate the utility degree of each alternative, we first determine the optimally criterion $K$ as follows:

$$K = \max_j Q_j; \quad j = \overline{1,n} \tag{30}$$

The degree of project utility is determined by comparing the alternatives under consideration with the best alternative. The values of the utility degree range from 0% (for the worst alternative) to 100% (for the best alternative). The utility degree of each alternative $j$ is calculated as follows:

$$N_j = \frac{Q_j}{Q_{\max}} \times 100\% \tag{31}$$

where $Q_j$ and $Q_{\max}$ are the significances of the alternatives obtained from Eq. (29).

**Table 2**
Social media selection criteria.

| Criterion | Sub-Criterion |
|---|---|
| Content ($\otimes X_1$) | |
| Impression Score ($\otimes X_2$) | |
| Cost ($\otimes X_3$) | |
| Look and feel ($\otimes X_4$) | User friendliness ($\otimes X_{4.1}$) |
| | Design ($\otimes X_{4.2}$) |
| Audience fit ($\otimes X_5$) | Educational level ($\otimes X_{5.1}$) |
| | Age ($\otimes X_{5.2}$) |

## 4. Case study

This study was conducted for one of the largest airlines in the Middle East, Trans-Gulf Airline[1], which was considering social marketing to convert "likes" into paying customers. Part of their marketing strategy was to choose the best social media platform money could buy. While social media may have a low financial cost, it can take a tremendous amount of time, an asset that's often scarce in many organizations. The main financial costs of social media marketing are content production and editing, strategy execution, and impact analysis among others. To achieve this goal, Trans-Gulf was considering five social media platforms including: Facebook ($A_1$), Twitter ($A_2$), LinkedIn ($A_3$), Google + ($A_4$), and YouTube ($A_5$). A team of five marketing managers at Trans-Gulf participated in the evaluation process. The team carefully reviewed a large number of social marketing platform assessment criteria. After several rounds of brainstorming sessions, the assessment team at Trans-Gulf selected the five criteria presented in Table 2 to evaluate these five social media platforms.

The content score is a subjective score, used to capture the amount of relevant information provided by a social media site. Visitors to a website scan content and often decide within a few seconds if they want to read more or switch over to another site. The impression score is a subjective score used to capture this behavior. Cost is a subjective score used to estimate the financial costs of a social media marketing including content production and editing, strategy execution, and impact analysis. Some social media websites are very basic and some are pretty sophisticated in design and layout. The look and feel score is a subjective score used to measure the look and feel of a social media site in terms of user friendliness and design. Finally, the audience fit is a subjective score given to a social media website in terms of the educational level and age of its visitors. The linguistic variables that were used by the marketing managers were expressed in positive triangular fuzzy numbers for each criterion. The linguistic variables matching the triangular fuzzy numbers and the corresponding membership functions were provided earlier in Table 1. We employed a Likert Scale of fuzzy numbers starting from 1 to 9. The fuzzy comparison scale with respect to the linguistic variables that describes the importance of criteria was also provided earlier in Table 1. The team studied the criteria and sub-criteria presented in Table 2 and determined a maximizing optimization direction for factors $x_1$, $x_2$, $x_{4.1}$, $x_{4.2}$, $x_{5.1}$, $x_{5.2}$ and a minimization optimization direction for factor $x_3$. The team also studied the relationship and interrelationships among the criteria and sub-criteria and developed the network diagram presented in Fig. 3.

The relationships presented in Fig. 3 were used to make pairwise comparisons among the criteria. Using the extent analysis method proposed by Chang (1996), the team considered the extent to which a criterion (or sub-criterion) could satisfy the overall social marketing goal. The triangular fuzzy scale presented in Table 1 was used to quantify the fuzzy numbers. In Table 3 we present an example pairwise comparison matrix for the "Look & Feel" ($X_4$).

We used Eqs. (11)–(20) to define the values of the fuzzy synthetic extents and the degrees of possibilities. As an example, the values of the fuzzy synthetic extents for the "Look & Feel" criteria are calculated as follows:

$$S_{x_1} = (0.0209, 0.0337, 0.0564) \otimes (5.5709, 9.9816, 16.0094) = (0.1162, 0.3392, 0.9032)$$

The minimum the degrees of possibility is calculated as follows:

$$Min\ V(S_{x_1} \geqslant S_{x_2}) = 0.8200$$

Similar calculations performed on the remaining criteria and sub-criteria produced the following weight vector:

$$W' = (1.0000, 0.8200, 0.5647, 0.5082, 0.6983)^T$$

The following normalized weights are calculated by dividing each weight into the total weight:

$$W = (0.2785, 0.2283, 0.1572, 0.1415, 0.1944)$$

where $W$ is a non-fuzzy number.

In Table 4 we present an example of a pairwise comparison matrix for the elements of "Audience Fit" ($X_{5.1}$ and $X_{5.2}$) on the design component of the "Look & Feel" cluster calculated using Eq. (11)–(20).

After all comparisons and weighting processes were completed, we obtained the overall priority weights of the criteria and sub-criteria shown in the initial matrix presented in Table 5.

In order to find the weighted super matrix, we first had to normalize and cluster the initial matrix presented in Table 5. The clustering and normalization process resulted in the weighted super matrix presented in Table 6.

We then constructed the limit super matrix presented in Table 7 by finding the power of the weighted super matrix according to Markov's Eq. (32). According to the ANP, the power calculation process is completed when the consecutive powers become equal.

$$\text{limit super matrix} = (\text{weighted super matrix})^{2k+1} \quad (32)$$

The criteria and sub-criteria values shown in the rows of the limit super matrix were the used in the COPRAS-G method. As shown in Table 7, the "Content" criterion ($X_1$), was the most important criterion for selecting the most suitable social media platform.

Next, the COPRAS-G method and the importance weights found with the fuzzy ANP method were used to evaluate the five social media platforms of Facebook ($A_1$), Twitter ($A_2$), LinkedIn ($A_3$), Google + ($A_4$), and YouTube ($A_5$). The initial decision making matrix

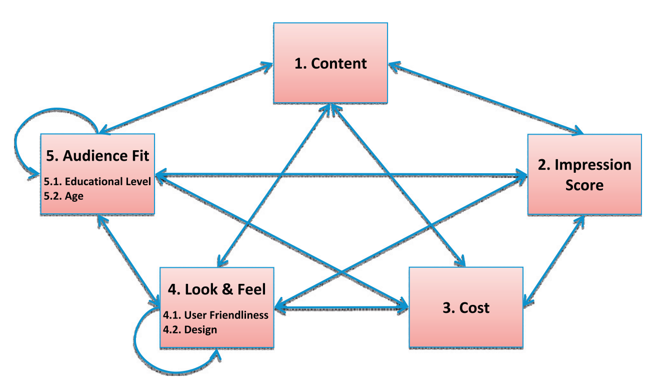


**Fig. 3.** The network structure.

[1] The name is changed to protect the anonymity of the airline.

**Table 3**
The "Look & Feel" ($X_4$) pairwise comparison matrix.

| | $X_1$ | | | $X_2$ | | | $X_3$ | | | $X_4$ | | | $X_5$ | | | $W$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $X_1$ | 1.0000 | 1.0000 | 1.0000 | 0.8209 | 1.5254 | 2.3650 | 1.4422 | 2.9618 | 5.1369 | 1.3077 | 2.6085 | 4.0964 | 1.0000 | 1.8860 | 3.4110 | 0.2785 |
| $X_2$ | 0.4228 | 0.6555 | 1.2181 | 1.0000 | 1.0000 | 1.0000 | 0.7974 | 1.3077 | 2.5015 | 1.3077 | 2.6085 | 4.0964 | 0.5529 | 1.2009 | 1.9693 | .02283 |
| $X_3$ | 0.1947 | 0.3376 | 0.6934 | 0.3998 | 0.7647 | 1.2540 | 1.0000 | 1.0000 | 1.0000 | 0.5078 | 0.6934 | 1.6610 | 0.5848 | 1.0889 | 2.1720 | 0.1572 |
| $X_4$ | 0.2441 | 0.3834 | 0.7647 | 0.2441 | 0.3834 | 0.7647 | 0.6020 | 1.4422 | 1.9693 | 1.0000 | 1.0000 | 1.0000 | 0.3420 | 0.4807 | 1.4422 | 0.1415 |
| $X_5$ | 0.2932 | 0.5302 | 1.0000 | 0.5078 | 0.8327 | 1.8086 | 0.4604 | 0.9184 | 1.7100 | 0.6934 | 2.0801 | 2.9240 | 1.0000 | 1.0000 | 1.0000 | 0.1944 |

**Table 4**
The "Design" ($X_{4.2}$) pairwise comparison matrix.

| | $X_{5.1}$ | | | $X_{5.2}$ | | | $W$ |
|---|---|---|---|---|---|---|---|
| $X_{5.1}$ | 1.0000 | 1.0000 | 1.0000 | 0.6098 | 1.0889 | 2.0829 | 0.7868 |
| $X_{5.2}$ | 0.4801 | 0.9184 | 1.6398 | 1.0000 | 1.0000 | 1.0000 | 0.2132 |

**Table 5**
The initial super-matrix.

| | $X_1$ | $X_2$ | $X_3$ | $X_{4.1}$ | $X_{4.2}$ | $X_{5.1}$ | $X_{5.2}$ |
|---|---|---|---|---|---|---|---|
| $X_1$ | 0.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| $X_2$ | 1.0000 | 0.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| $X_3$ | 1.0000 | 1.0000 | 0.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| $X_{4.1}$ | 0.6831 | 0.4097 | 0.2132 | 0.0000 | 1.0000 | 0.3873 | 0.5903 |
| $X_{4.2}$ | 0.3169 | 0.5903 | 0.7868 | 1.0000 | 0.0000 | 0.6128 | 0.4097 |
| $X_{5.1}$ | 0.3873 | 0.3271 | 0.6557 | 0.0000 | 0.7868 | 0.0000 | 0.0000 |
| $X_{5.2}$ | 0.6127 | 0.6729 | 0.3443 | 0.0000 | 0.2132 | 1.0000 | 0.0000 |

**Table 6**
The weighted super-matrix.

| | $X_1$ | $X_2$ | $X_3$ | $X_{4.1}$ | $X_{4.2}$ | $X_{5.1}$ | $X_{5.2}$ |
|---|---|---|---|---|---|---|---|
| $X_1$ | 0.0000 | 0.3009 | 0.3643 | 0.3457 | 0.2785 | 0.2045 | 0.2444 |
| $X_2$ | 0.1950 | 0.0000 | 0.1319 | 0.2834 | 0.2283 | 0.2476 | 0.2960 |
| $X_3$ | 0.2933 | 0.1601 | 0.0000 | 0.1952 | 0.1572 | 0.2070 | 0.2474 |
| $X_{4.1}$ | 0.1783 | 0.1057 | 0.0432 | 0.0000 | 0.1415 | 0.0687 | 0.1252 |
| $X_{4.2}$ | 0.0827 | 0.1522 | 0.1594 | 0.1757 | 0.0000 | 0.1088 | 0.0869 |
| $X_{5.1}$ | 0.0971 | 0.0919 | 0.1976 | 0.0000 | 0.1530 | 0.0000 | 0.0000 |
| $X_{5.2}$ | 0.1536 | 0.1892 | 0.1037 | 0.0000 | 0.0414 | 0.1634 | 0.0000 |

**Table 7**
The limit super-matrix.

| | $X_1$ | $X_2$ | $X_3$ | $X_{4.1}$ | $X_{4.2}$ | $X_{5.1}$ | $X_{5.2}$ |
|---|---|---|---|---|---|---|---|
| $X_1$ | 0.2370 | 0.2370 | 0.2370 | 0.2370 | 0.2370 | 0.2370 | 0.2370 |
| $X_2$ | 0.1818 | 0.1818 | 0.1818 | 0.1818 | 0.1818 | 0.1818 | 0.1818 |
| $X_3$ | 0.1738 | 0.1738 | 0.1738 | 0.1738 | 0.1738 | 0.1738 | 0.1738 |
| $X_{4.1}$ | 0.1002 | 0.1002 | 0.1002 | 0.1002 | 0.1002 | 0.1002 | 0.1002 |
| $X_{4.2}$ | 0.1132 | 0.1132 | 0.1132 | 0.1132 | 0.1132 | 0.1132 | 0.1132 |
| $X_{5.1}$ | 0.0934 | 0.0934 | 0.0934 | 0.0934 | 0.0934 | 0.0934 | 0.0934 |
| $X_{5.2}$ | 0.1007 | 0.1007 | 0.1007 | 0.1007 | 0.1007 | 0.1007 | 0.1007 |

$\otimes X$ is presented in Table 8. The relevant information for the seven criteria and sub-criteria are presented in this table. All criteria are maximizing criteria with the exception of $\otimes X_3$ which is a minimizing criterion. The weights presented in this table are the importance weights determined through the fuzzy ANP process. The values presented for the initial decision matrix are all interval values.

The initial decision matrix with interval values was then normalized. The normalized decision matrix ($\otimes\tilde{X}$) is presented in Table 9. The weighted decision matrix ($\otimes\hat{X}$) presented in Table 10 was constructed next.

We then followed the procedure described earlier and determined the relative significance of each alternative by calculating $P_j$ using Eq. (26), $R_j$ using Eq. (27), and $Q_j$ using Eq. (29). Following this step, we determined the utility degree of each alternative ($N_j$) using Eq. (29). Table 11 presents the $P_j$, $R_j$, $Q_j$, and $N_j$ for the five social media platforms under consideration.

As shown in Table 11, Facebook ($A_1$) with a utility degree of 100% was selected as the most suitable social media platform for Trans-Gulf Airline. LinkedIn ($A_3$) with a utility degree of 99.1% was selected as the second most suitable social media platform. YouTube ($A_5$) with a utility degree of 94.0% was the third ranking social media platform. Twitter ($A_2$) and Google + ($A_4$) with utility degrees of 82.8% and 80.4%, respectively, were selected as the fourth and fifth choices for social media at Trans-Gulf. In summary, $A_1 > A_3 > A_5 > A_2 > A_4$. While platforms such as Facebook, Twitter, LinkedIn, Google+, and YouTube have emerged as top social media sites for most companies, these too often are treated as stand-alone marketing tools rather than as an integrated part of the sales strategy (Hanna, Rohm, & Crittenden, 2011). To this end, Trans-Gulf management decided to choose the top two platforms of Facebook (to reach out networks of family and friends) and LinkedIn (to reach out network of co-workers).

## 5. Conclusions and future research directions

The recent developments in computers and information technology have brought both opportunities and challenges in the global and boundary-less world. Marketing managers are faced with a dynamic and interconnected international environment and social media sites have become important tools for businesses. Many organizations now actively use social media platforms to promote and market their products and services. Unlike conventional marketing tools, social media applications allow users to have more control of their choices by posting comments, sharing information, or praising or criticizing products and services. Although traditional media are not disappearing, it is clear that major marketers are shifting their budgets into new social media marketing opportunities and applications. Traditional marketing, involving exchange of information in one direction, can no longer help companies introduce all aspects of their products and show customers that their needs are important. Social media facilitate two-way communication and connect customers on a mass scale.

Despite these benefits, selecting the right social media platform has been a difficult task because these problems are complex with multiple and often conflicting criteria. Most existing social media selection models are limited to simple classification charts categorizing the different types of social media engagements or simple decision trees highlighting the key decisions one must make when choosing the right platform.

We proposed a novel analytical framework for social media platform selection. The proposed hybrid framework integrates the ANP with fuzzy set theory and the COPRAS-G method. The ANP and fuzzy set theory were used to determine the importance weight of the social media platform selection criteria. The COPRAS-G method was used to rank and select the most suitable social media platform. We presented a real-world case study and demonstrated the applicability of the proposed framework.

The proposed framework is: (1) structured and systematic with step-by-step and well-defined procedures; (2) simple and

**Table 8**
The initial decision matrix.

| Criterion | Optimal | Weight | Initial decision matrix | | | | |
|---|---|---|---|---|---|---|---|
| | | | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
| $\otimes X_1$ | *Max* | 0.2370 | [70;80] | [50;60] | [80;90] | [50;60] | [60;70] |
| $\otimes X_2$ | *Max* | 0.1818 | [90;95] | [60;70] | [60;70] | [40;50] | [60;70] |
| $\otimes X_3$ | *Min* | 0.1738 | [80;90] | [60;70] | [45;55] | [40;50] | [50;60] |
| $\otimes X_{4.1}$ | *Max* | 0.1002 | [60;70] | [40;50] | [60;70] | [30;40] | [50;60] |
| $\otimes X_{4.2}$ | *Max* | 0.1132 | [70;80] | [40;50] | [50;60] | [30;40] | [60;70] |
| $\otimes X_{5.1}$ | *Max* | 0.0934 | [50;60] | [60;70] | [70;80] | [60;70] | [70;80] |
| $\otimes X_{5.2}$ | *Max* | 0.1007 | [65;75] | [70;80] | [40;50] | [70;80] | [60;70] |

**Table 9**
The normalized decision matrix.

| Criterion | Normalized decision matrix | | | | |
|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
| $\underline{\hat{X}}_{1n};\hat{\overline{X}}_{1n}$ | [0.209;0.239] | [0.149;0.179] | [0.239;0.269] | [0.149;0.179] | [0.179;0.209] |
| $\underline{\hat{X}}_{2n};\hat{\overline{X}}_{2n}$ | [0.271;0.286] | [0.180;0.211] | [0.180;0.211] | [0.120;0.150] | [0.180;0.211] |
| $\underline{\hat{X}}_{3n};\hat{\overline{X}}_{3n}$ | [0.267;0.300] | [0.200;0.233] | [0.150;0.183] | [0.133;0.167] | [0.167;0.200] |
| $\underline{\hat{X}}_{4.1n};\hat{\overline{X}}_{4.1n}$ | [0.226;0.264] | [0.151;0.189] | [0.226;0.264] | [0.113;0.151] | [0.189;0.226] |
| $\underline{\hat{X}}_{4.2n};\hat{\overline{X}}_{4.2n}$ | [0.255;0.291] | [0.145;0.182] | [0.182;0.218] | [0.109;0.145] | [0.218;0.255] |
| $\underline{\hat{X}}_{5.1n};\hat{\overline{X}}_{5.1n}$ | [0.149;0.179] | [0.179;0.209] | [0.209;0.239] | [0.179;0.209] | [0.209;0.239] |
| $\underline{\hat{X}}_{5.2n};\hat{\overline{X}}_{5.2n}$ | [0.197;0.227] | [0.212;0.242] | [0.121;0.152] | [0.212;0.242] | [0.182;0.212] |

**Table 10**
The weighted decision matrix.

| Criterion | Weighted decision matrix | | | | |
|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
| $\underline{\hat{X}}_{1n};\hat{\overline{X}}_{1n}$ | [0.050;0.057] | [0.035;0.042] | [0.057;0.064] | [0.035;0.042] | [0.042;0.050] |
| $\underline{\hat{X}}_{2n};\hat{\overline{X}}_{2n}$ | [0.049;0.052] | [0.033;0.038] | [0.033;0.038] | [0.022;0.027] | [0.033;0.038] |
| $\underline{\hat{X}}_{3n};\hat{\overline{X}}_{3n}$ | [0.046;0.052] | [0.035;0.041] | [0.026;0.032] | [0.023;0.029] | [0.029;0.035] |
| $\underline{\hat{X}}_{4.1n};\hat{\overline{X}}_{4.1n}$ | [0.023;0.026] | [0.015;0.019] | [0.023;0.026] | [0.011;0.015] | [0.019;0.023] |
| $\underline{\hat{X}}_{4.2n};\hat{\overline{X}}_{4.2n}$ | [0.029;0.033] | [0.016;0.021] | [0.021;0.025] | [0.012;0.016] | [0.025;0.029] |
| $\underline{\hat{X}}_{5.1n};\hat{\overline{X}}_{5.1n}$ | [0.014;0.017] | [0.017;0.020] | [0.020;0.022] | [0.017;0.020] | [0.020;0.022] |
| $\underline{\hat{X}}_{5.2n};\hat{\overline{X}}_{5.2n}$ | [0.020;0.023] | [0.021;0.024] | [0.012;0.015] | [0.021;0.024] | [0.018;0.021] |

**Table 11**
The evaluation of the utility degree.

| | $P_j$ | $R_j$ | $Q_j$ | $N_j$ (%) |
|---|---|---|---|---|
| $A_1$ | 0.196 | 0.049 | 0.219 | 100.0 |
| $A_2$ | 0.151 | 0.038 | 0.182 | 82.8 |
| $A_3$ | 0.178 | 0.029 | 0.217 | 99.1 |
| $A_4$ | 0.132 | 0.026 | 0.176 | 80.4 |
| $A_5$ | 0.170 | 0.032 | 0.206 | 94.0 |

transparent with a straightforward computation process; (3) rational and logical with a sound mathematical and theoretical foundation; (4) supportive and informative with a scalar value that identifies both the best and worst social media platform simultaneously; (5) realistic and practical with the ability to deal with impreciseness and vagueness in real-world social media platform assessment problems; and (6) versatility and flexibility with the ability to be applied to other multi-criteria prioritization problems. A stream of future research can extend our method by developing other hybrid approaches for the integrated use of our distance measure, not only for hybrids of different MADM methods but also for hybrids of multi-attribute value theory and numerical optimization.

## References


Abrahams, A. S., Jiao, J., Wang, G. A., & Fan, W. (2012). Vehicle defect discovery from social media. *Decision Support Systems, 54*, 87–97.

Aghdaie, M. H., Zolfani, S. H., & Zavadskas, E. K. (2013). Market segment evaluation and selection based on application of fuzzy AHP and COPRAS-G methods. *Journal of Business Economics and Management, 14*(1), 213–233.

Babaesmailli, M., Arbabshirani, B., & Golmah, V. (2012). Integrating analytical network process and fuzzy logic to prioritize the strategies – A case study for tile manufacturing firm. *Expert Systems with Applications, 39*(1), 925–935.

Barysiene, J. (2012). A multi-criteria evaluation of container terminal technologies applying the COPRAS-G method. *Transport, 27*(4), 364–372.

Bertot, J. C., Jaeger, P. T., & Grimes, J. M. (2010). Using ICTs to create a culture of transparency: E-government and social media as openness and anti-corruption tools for societies. *Government Information Quarterly, 27*(3), 264–271.

Bindu Madhuri, Ch., Anand Chandulal, J., & Padmaja, M. (2010). Selection of best web site by applying COPRAS-G method. *International Journal of Computer Science and Information Technologies, 1*(2), 138–146.

Bitarafan, M., Zolfani, S. H., Arefi, S. L., & Zavadskas, E. K. (2012). Evaluating the construction methods of cold-formed steel structures in reconstructing the areas damaged in natural crises, using the methods AHP and COPRAS-G. *Archives of Civil and Mechanical Engineering, 12*(3), 360–367.

Chang, D. Y. (1996). Applications of extent analysis method on fuzzy AHP. *European Journal of Operational Research, 95*(3), 649–655.

Chatterjee, P., Athawale, V. M., & Chakraborty, S. (2011). Materials selection using complex proportional assessment and evaluation of mixed data methods. *Materials & Design, 32*(2), 851–860.

Chen, J., & Yang, Y. (2011). A fuzzy ANP-based approach to evaluate region agricultural drought risk. *Procedia Engineering, 23*, 822–827.

Das, M. C., Sarkar, B., & Ray, S. (2012). A framework to measure relative performance of Indian technical institutions using integrated fuzzy AHP and COPRAS methodology. *Socio-Economic Planning Sciences, 46*(3), 230–241.
Datta, S., Beriha, G. S., Patnaik, B., & Mahapatra, S. S. (2009). Use of compromise ranking method for supervisor selection: A multi criteria decision making (MCDM) approach. *International Journal of Vocational and Technical Education, 1*(1), 7–13.
Dağdeviren, M., Yuksel, I., & Kurt, M. (2008). A fuzzy analytic network process (ANP) model to identify faulty behavior risk (FBR) in work system. *Safety Science, 46*(5), 771–783.
Deng, J. L. (1982). Control problems of grey systems. *Systems and Control, 1*(5), 288–294.
Deng, J. L. (1988). Introduction to grey system theory. *The Journal of Grey Theory, 1*(1), 1–24.
Doumpos, M., & Zopounidis, C. (2002). *Multicriteria decision aid classification methods*. Boston, MA: Kluwer Academic Publishers.
Durugbo, C. (2012). Modelling user participation in organisations as networks. *Expert Systems with Applications, 39*(10), 9230–9245.
Evans, D., & McKee, J. (2010). *Social media marketing: The next generation of business engagement*. Indianapolis, IN: Wiley Publishing, Inc.
Ginevičius, R., & Podvezko, V. (2008). Multi-criteria evaluation of Lithuanian banks from the perspective of their reliability for clients. *Journal of Business Economics and Management, 9*(4), 257–267.
Grieve, R., Indian, M., Witteveen, K., Tolan, G. A., & Marrington, J. (2013). Face-to-face or Facebook: Can social connectedness be derived online? *Computers in Human Behavior, 29*(3), 604–609.
Glenn, B. (2011). The social media phenomenon. *Direct Selling News, 7*(9), 11–18.
Gumus, A. T., & Yilmaz, G. (2010). Sea vessel type selection via an integrated VAHP–ANP methodology for high-speed public transportation in Bosphorus. *Expert Systems with Applications, 37*(6), 4182–4189.
Guneri, A. F., Cengiz, M., & Seker, S. (2009). A fuzzy ANP approach to shipyard location selection. *Expert Systems with Applications, 36*(4), 7992–7999.
Hanna, R., Rohm, A., & Crittenden, V. L. (2011). We're all connected: The power of the social media ecosystem. *Business Horizons, 54*(3), 265–273.
Janic, M., & Reggiani, A. (2002). An application of the multiple criteria decision making (MCDM) analysis to the selection of a new hub airport. *European Journal of Transport and Infrastructure Research, 2*(2), 113–141.
Kabak, M., Burmaoğlu & Kazançoğlu, Y. (2012). A fuzzy hybrid MCDM approach for professional selection. *Expert Systems with Applications, 39*(3), 3516–3525.
Kaplan, A. M., & Haenlein, M. (2010). Users of the world unite! The challenges and opportunities of social media. *Business Horizons, 53*, 59–68.
Kietzman, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons, 54*(3), 241–251.
Kim, Y. A., & Ahmad, M. A. (2013). Trust, distrust and lack of confidence of users in online social media-sharing communities. *Knowledge-Based Systems, 37*, 438–450.
Lee, H., Kim, C., Cho, H., & Park, Y. (2009). An ANP-based technology network for identification of core technologies: A case of telecommunication technologies. *Expert Systems with Applications, 36*(1), 894–908.
Li, Y. M., & Shiu, Y. L. (2012). A diffusion mechanism for social advertising over micro-blogs. *Decision Support Systems, 54*, 9–22.
Mangold, G., & Faulds, D. (2009). Social media: the new hybrid element of the promotion mix. *Business Horizons, 52*, 357–365.
McLellan, D. (2010). Social Media Cheat Sheet. http://www.drewsmarketingminute.com/2010/03/social-media-cheat-sheet.html.
Meade, L. M., & Sarkis, J. (1999). Analyzing organizational project alternatives for agile manufacturing processes: An analytical network approach. *International Journal of Production Research, 37*(2), 241–261.
Medineckiene, M., & Björk, F. (2011). Owner preferences regarding renovation measures – the demonstration of using multi-criteria decision making. *Journal of Civil Engineering and Management, 17*(2), 284–295.
Michaelidou, N., Siamagka, N. T., & Christodoulides, G. (2011). Usage, barriers and measurement of social media marketing: An exploratory investigation of small and medium B2B brands. *Industrial Marketing Management, 40*(4), 1153–1159.
Önüt, S., Karar, S., & Tugba, E. (2008). A hybrid fuzzy MCDM approach to machine tool selection. *Journal of Intelligent Manufacturing, 19*(4), 443–453.
Önüt, S., Tuzkaya, U. R., & Torun, E. (2011). Selecting container port via a fuzzy ANP-based approach: A case study in the Marmara Region, Turkey. *Transport Policy, 18*(1), 182–193.
Özyurt, Ö., & Köse, C. (2010). Chat mining: Automatically determination of chat conversations' topic in Turkish text based chat mediums. *Expert Systems with Applications, 37*(12), 8705–8710.
Qualman, E. (2009). *Socialnomics: How Social media transforms the way we live and do business*. Hoboken, New Jersey: John Wiley & Sons.
Rezaeiniya, N., Zolfani, S. H., & Zavadskas, E. K. (2012). Greenhouse locating based on ANP-COPRAS-G methods - an empirical study based on Iran. *International Journal of Strategic Property Management, 16*(2), 188–200.
Roy, B. (1990). Decision-aid and decision making. *European Journal of Operational Research, 45*, 324–331.
Saaty, T. L. (2001). *Decision making with dependence and feedback* (2nd Edition). Pittsburg: RWS Publication.
Saaty, T. L. (1996). *Decision making with dependence and feedback: The analytic network process*. Pittsburgh: RWS Publications.
Saaty, T. L. (2005). *Theory and applications of the analytic network process: Decision making with benefits, opportunities, costs, and risks*. Pittsburg: RWS Publications.
Saaty, T. L., & Takizawa, M. (1986). Dependence and independence from linear hierarchies to nonlinear Networks. *European Journal of Operational Research, 26*(2), 229–237.
Sevkli, M., Oztekin, A., Uysal, O., Torlak, G., Turkyilmaz, A., & Delen, D. (2012). Development of a fuzzy ANP based SWOT analysis for the airline industry in Turkey. *Expert Systems with Applications, 39*(1), 14–24.
Sahu, N. K., Datta, S., & Mahapatra, S. S. (2012). Establishing green supplier appraisement platform using grey concepts. *Grey Systems, 2*(3), 395–418.
Shyur, H. J. (2006). COTS evaluation using modified TOPSIS and ANP. *Applied Mathematics and Computation, 177*(1), 251–259.
Trusov, M., Bucklin, R., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an Internet social networking site. *Journal of Marketing, 73*(5), 90–102.
Tuzkaya, U. R., & Önüt, S. (2008). A fuzzy analytic network process based approach to transportation-mode selection between Turkey and Germany: A case study. *Information Sciences, 178*(15), 3133–3146.
Vincke, P. (1992). *Multicriteria decision aid*. New York: Wiley.
Wang, K., Wang, E. T. G., & Farn, C. K. (2009). Influence of Web advertising strategies, consumer goal-directedness, and consumer involvement on Web advertising effectiveness. *International Journal of Electronic Commerce, 13*(4), 67–96.
Weber, L. (2007). *Marketing to the social web: How digital customer communities build your business*. Hoboken, New Jersey: John Wiley & Sons.
Zavadskas, E. K., Kaklauskas, A., Turskis, Z., & Tamošaitienė, J. (2008). Selection of the effective dwelling house walls by applying attributes values determined at intervals. *Journal of Civil Engineering and Management, 14*(2), 85–93.
Zavadskas, E. K., Kaklauskas, A., Turskis, Z., & Tamošaitienė, J. (2009). Multi-attribute decision- making model by applying grey numbers. *Informatica, 20*(2), 305–320.
Zolfani, S. H., Chen, I. S., Rezaeiniya, N., & Tamosaitiene, J. (2012a). A hybrid MCDM model encompassing AHP and COPRAS-G methods for selecting company supplier in Iran. *Technological and Economic Development of Economy, 18*(3), 529–543.
Zolfani, S. H., Rezaeiniya, N., Aghdaie, M. H., & Zavadskas, E. K. (2012b). Quality control manager selection based on AHP-COPRAS-G methods: A case in Iran. *Ekonomska istraživanja – Economic Research, 25*(1), 88–104.
Zolfani, S. H., Rezaeiniya, N., Zavadskas, E. K., & Turskis, Z. (2011). Forest roads locating based on AHP and COPRAS-G methods: An empirical study based on Iran. *E&M Ekonomie a Management, 4*, 6–21.