Technological Forecasting & Social Change 146 (2019) 366–379

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

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

Grey-based Multi-Criteria Decision Analysis approach: Addressing uncertainty at complex decision problems

Hesham F. Maghrabie[a,*], Yvan Beauregard[b], Andrea Schiffauerova[a]

[a] Concordia Institute for Information Systems Eng., Concordia University, Montreal, Quebec, Canada
[b] Département de génie mécanique, École de technologie supérieure, Université du Québec, Montréal, Québec, Canada

ARTICLE INFO

Keywords:
MCDA
Uncertainty
Grey systems theory
ANP
PROMETHEE II
Decision support systems

ABSTRACT

In complex systems, decision makers encounter uncertainty from various sources. In this paper, a new hybrid grey-based Multi-Criteria Decision Analysis (MCDA) approach is proposed to optimize the evaluation space in decision problems that are subject to subjective and objective uncertainty over different types of interrelated criteria. The four-phase methodology begins with the formulation of a decision problem through the analysis of the system of concern, its functionality, and substantial connections among evaluation criteria. The second phase involves the development of grey linguistic scales to handle the uncertainty of human judgements. The third phase integrates the grey linguistic scale, concepts of grey systems theory, and principles of Analytical Network Process to prioritize criteria. Finally, to evaluate and rank alternatives in such a complex setting, Preference Ranking Organization METHod for Enrichment Evaluation II is extended using a grey linguistic scale to articulate subjective uncertainty, grey numbers to account for objective uncertainty, grey operating rules to normalize evaluation measures, and the proposed approach of prioritizing evaluation criteria to establish relative preferences. To demonstrate the viability of the methodology, a case study is presented, in which a strategic decision is made within the context of innovation. To validate the methodology, a comparative analysis is provided.

1. Introduction

Decision makers usually encounter large amount of complex information. The complexity of decision problems increases when different evaluation criteria of different nature (e.g., qualitative and quantitative), different scales, and different values (e.g., continuous, discrete, and linguistic) are involved.

Multi-Criteria Decision Analysis (MCDA) is therefore considered one of the most fruitful sub-disciplines of operations research. The main role of MCDA is to aid Decision Makers (DMs) in establishing a coherent picture about complex decision problems (Kurka and Blackwood, 2013). However, in many cases uncertainty-related aspects (i.e., uncertainty associated with limited objective information and uncertainty associated with subjective expert knowledge) are present. This adds to the complexity of analyzing the decision problems as the conventional MCDA approaches presume the availability of precise information (Kuang et al., 2015; Li et al., 2007).

Various methods have been proposed to deal with different types of uncertainty-related aspects. Grey systems theory is recommended for decision problems with a relatively small amount of data (i.e., small samples) and poor information, which cannot be described by a probability distribution (Li et al., 2012; Li and Yuan, 2017; Liu and Lin, 2006). Accordingly, different researchers, which are presented in the next section, have considered the grey systems theory to address uncertainty in decision problems. The existing approaches assumed that DMs are able to assign the weights of the evaluation criteria precisely, did not consider the interrelationships among evaluation criteria, or did not consider the relations among evaluation criteria of different clusters, hence a better method is needed to address the existing research gaps.

The ultimate goal of this research is to enhance DMs abilities of handling multi-criteria decision problems under uncertainty. To this end, the main objective of this manuscript is to establish a structured methodology, which are able to carry on MCDA under uncertainty, by integrating the grey systems theory with a distinctive combination of MCDA techniques (i.e., Analytical Network Process (ANP) (Saaty, 1996) and Preference Ranking Organization METHod for Enrichment Evaluation II (PROMETHEE II) (Brans and De Smet, 2016a). The hybrid methodology uses the grey systems theory as the key element for tackling uncertainty aspects; the principles of ANP to handle the

* Corresponding author.
E-mail address: hesham.maghrabie@gmail.com (H.F. Maghrabie).

https://doi.org/10.1016/j.techfore.2019.05.031
Received 22 October 2017; Received in revised form 21 February 2019; Accepted 28 May 2019
Available online 26 June 2019

complexity of the decision structure; the extended PROMETHEE II approach to evaluate feasible alternatives.

The contributions of this paper are as follows: (1) Establishing priorities among sub-criteria within a complex structure under uncertain subjective judgments using the combination of linguistic expression, grey systems theory, and the principles of ANP; (2) Extending PROMETHEE II, such that potential alternatives can be evaluated and ranked in such a complicated decision structure by integrating the linguistic expressions and grey systems theory to address subjective and objective uncertainty related measures of potential alternatives over different types of criteria; (3) Improving the evaluation space in a complex decision problems under uncertainty by utilizing the emergent strengths of the integrated approach, which would enhance the evaluation of a DM.

This paper is organized as follows: first, a brief background on related subject matters is provided to identify the research problems and to establish the direction of the current research; next, the proposed methodology is discussed and explained; afterwards, a case study is presented to demonstrate the viability of the methodology; then, a comparative analysis with an existing approach is performed for the validation purpose; finally, the conclusion is put forward.

2. Research background

2.1. Multi-Criteria Decision Analysis

Despite the diversity of MCDA approaches, at the most primitive level, MCDA can be demonstrated by a set of alternatives, at least two evaluation criteria, and minimally one decision maker (Greco et al., 2016). Accordingly, MCDA can be described as a systematic methodology that helps in making decisions by evaluating a number of alternatives over a set of criteria according to the preferences of the involved decision maker(s).

There is no optimal MCDA's approach that would fit perfectly with every decision problem. Therefore, understanding a decision problem's nature is a critical step to identify the suitable approach for it (Jaini and Utyuzhnikov, 2017; Wątróbski and Jankowski, 2016). The various approaches of MCDA can be classified into three main categories (Belton and Stewart, 2002):

- **Value measurement models**: Approaches that belong to this category are value-focused, where the utility value of each alternative is being recognized based on its overall performance over the evaluation criteria. Among the most common approaches within this category are Analytic Hierarchy Process (AHP) (Saaty, 1988), Analytic Network Process (ANP) (Saaty, 1996), Multi-Attribute Value Theory (MAVT) (Stefanopoulos et al., 2014), Multi-Attribute Utility Theory (MAUT) (Dyer, 2005), and Weighted Sum Method (Triantaphyllou, 2000).
- **Goal, aspiration, or reference-level models**: In this set of approaches, alternatives are evaluated with respect to a targeted level of performance over a particular goal, aspiration, or reference levels, e.g., goal programming and heuristic algorithms. An example of this category is Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Behzadian et al., 2012).
- **Outranking methods**: A typical outranking approach performs pairwise comparisons between alternatives across a specified set of evaluation criteria. Subsequently, the resulting comparisons are aggregated and analyzed in accordance with the designated approach to favor one alternative over another. Outranking methods include ELimination and Choice Expressing REality (ELECTRE) (Govindan and Jepsen, 2016), and Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE) family of methods (Brans and De Smet, 2016a).

These conventional approaches of MCDA have an implicit assumption, which presumes the availability and accuracy of information that is required for analyzing decision problems. However, in real world applications, DMs encounter uncertainty from various sources, such as limited human cognition, lack of understanding for interrelationships among decision criteria, and limited input data (Belton and Stewart, 2002; Durbach and Stewart, 2012).

2.2. Handling uncertainty in MCDA

While the presence of uncertainty would limit the utilization of the MCDA approaches, differentiating among two types of uncertainty would be useful to properly address the associated uncertainty in a decision problem: (i) uncertainty associated with limited objective information, e.g., quantitative (interval scales) and stochastic (probability distribution) data, and (ii) uncertainty associated with subjective expert knowledge (i.e., ambiguous concepts and semantic meanings) (Ben Amor et al., 2015; Moretti et al., 2016). Different approaches have been proposed to handle different types of uncertainty in MCDA:

- **Probabilistic models**: A DM can assign probability distribution based on relative experiences and beliefs to describe uncertainty (i.e., imperfect information) of a decision parameter. Consequently, comparisons can be established among feasible alternatives and probabilistic statements can be made to describe the probability of occurrence for each outcome, which can be achieved through different means (e.g., Stochastic multi-objective acceptability analysis (SMAA)) (Durbach and Stewart, 2012; Lahdelma et al., 1998).
- **Fuzzy set theory**: Zadeh (1965) introduced this theory to handle the associated vagueness and imprecision with human judgments (i.e., ambiguous concepts and semantic meanings). Within the context of MCDA, fuzzy numbers are utilized to map linguistic expressions that would express human opinions using the concept of the membership function, such that by assigning a value between 0 and 1 the linguistic term can be stated more precisely, where 0 indicates no membership and 1 indicates full membership to a given set (Zadeh, 1965).
- **Grey systems theory**: Ju-long (1982) introduced the grey systems theory as a methodology to handle data imprecision or insufficiency in a system. It is intended for problems that involve a relatively small amount of data and poor information, which cannot be described by a probability distribution. Thus, a better understanding for such a system can be achieved through partially known information using grey systems theory (Liu et al., 2015). Similar to fuzzy set theory, grey systems theory can handle associated vagueness with verbal statements (linguistic expressions) using grey numbers (Broekhuizen et al., 2015), which is denoted by $\otimes$ (Liu and Lin, 2006). More on grey systems theory is given in the Appendix A.

Although probabilistic models and fuzzy set theory are intended to investigate uncertain systems, grey systems theory is preferred when it comes to problems with a relatively small amount of data and poor information, which cannot be described by a probability distribution (Li et al., 2012; Li and Yuan, 2017; Liu and Lin, 2006) due to its less restricted procedure that neither requires any robust membership function, nor a probability distribution (Memon et al., 2015).

2.3. The use of grey systems theory in Multi-Criteria Decision Analysis

As mentioned earlier, conventional MCDA approaches do not mimic the functional reality of the human cognitive system in decision problems. Therefore, several research papers have proposed grey systems theory to supplement the deficiencies that exist in MCDA as a result of poor information. The rest of this section deliberates on existing methods to solve multi-criteria decision problems under uncertainty using grey systems theory, and the reasoning behind the proposed methodology.

Grey systems theory has been integrated with PROMETHEE II to evaluate performance of available alternatives on certain criteria where uncertainty aspects are involved (Kuang et al., 2015). However, the weights of evaluation criteria are assumed to be given by DMs precisely, which is hardly the case in complex decision problems under uncertainty. Some other works have tried to address this issue by integrating the grey systems theory with Analytic Hierarchy Process (AHP) to prioritize evaluation criteria and to evaluate potential alternatives under uncertainty (Jianbo et al., 2016; Thakur and Ramesh, 2017). Also, Grey Relational Analysis (GRA), which is a branch of grey systems theory, has been combined with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach to better rank feasible alternatives, using fuzzy analytic hierarchy process (FAHP) to evaluate the criteria weights (Celik et al., 2016; Sakthivel et al., 2014). Nevertheless, one of the underlying assumptions of AHP is the independency (Ishizaka and Labib, 2011), which implies that elements of a hierarchal structure are independent but in reality a complex system usually involves interactions and dependencies among the system's elements.

To tackle the problem of dependencies in a complex system, grey systems theory has been used with ANP. This combination has been proposed in different areas such as, green supplier development programs (Dou et al., 2014), R&D system development for a home appliances company (Tuzkaya and Yolver, 2015), and early evaluation model for storm tide risk (Zhang et al., 2009). However, the relations between sub-criteria of different clusters have not been considered. Accordingly, a better method is needed to bridge the existing research gaps.

In this paper, a new hybrid grey-based MCDA approach is proposed to enhance DMs abilities of handling multi-criteria decision problems under uncertainty. The proposed approach integrates the grey systems theory with a distinctive combination of MCDA (i.e., ANP and PROMETHEE II). The combination of the proposed methodology has been considered for the following reasons:

When it comes to performance evaluation of feasible alternatives, outranking approaches outperform other MCDA methodologies, as other methodologies are designed to enrich the dominance graph by reducing the incomparability cases and allocating an absolute utility to each alternative. Consequently, the original structure of a multi-criteria decision problem would be reduced to a single criterion problem for which an optimal solution exists (Maity and Chakraborty, 2015). In contrast, outranking methods preserve the structure of multi-criteria decision problems by considering the deviation between the evaluations of feasible alternatives over each criterion (Andreopoulou et al., 2017; Maity and Chakraborty, 2015; Segura and Maroto, 2017). Moreover, this category of MCDA can handle quantitative and qualitative criteria. Furthermore, it requires a relatively small amount of information from DMs (Malczewski and Rinner, 2015). Among the outranking methods, PROMETHEE is preferred due to its mathematical properties and simplicity (Brans and De Smet, 2016b; Kilic et al., 2015; Malczewski and Rinner, 2015). Among the PROMETHEE family of methods, PROMETHEE II is preferred due to its ability of providing a complete ranking for available alternatives based on outranking relations (Sen et al., 2015). However, PROMETHEE II requires the weights of the evaluation criteria (Brans and De Smet, 2016b; Segura and Maroto, 2017).

To estimate criteria weights, ANP is preferred over other MCDA approaches due to its superiority in addressing different types of interrelationships (e.g., interactions and interdependencies) within and between different evaluation clusters of a complex system (Tuzkaya and Yolver, 2015).

While the presence of uncertainty would limit the utilization of the conventional approaches of MCDA, grey systems theory would perfectly bridge this limitation (Dou et al., 2014; Kuang et al., 2015). In particular, when it comes to address decision problems with a relatively small amount of data and poor information, which cannot be described by a probability distribution (Li et al., 2012; Liu and Lin, 2006).

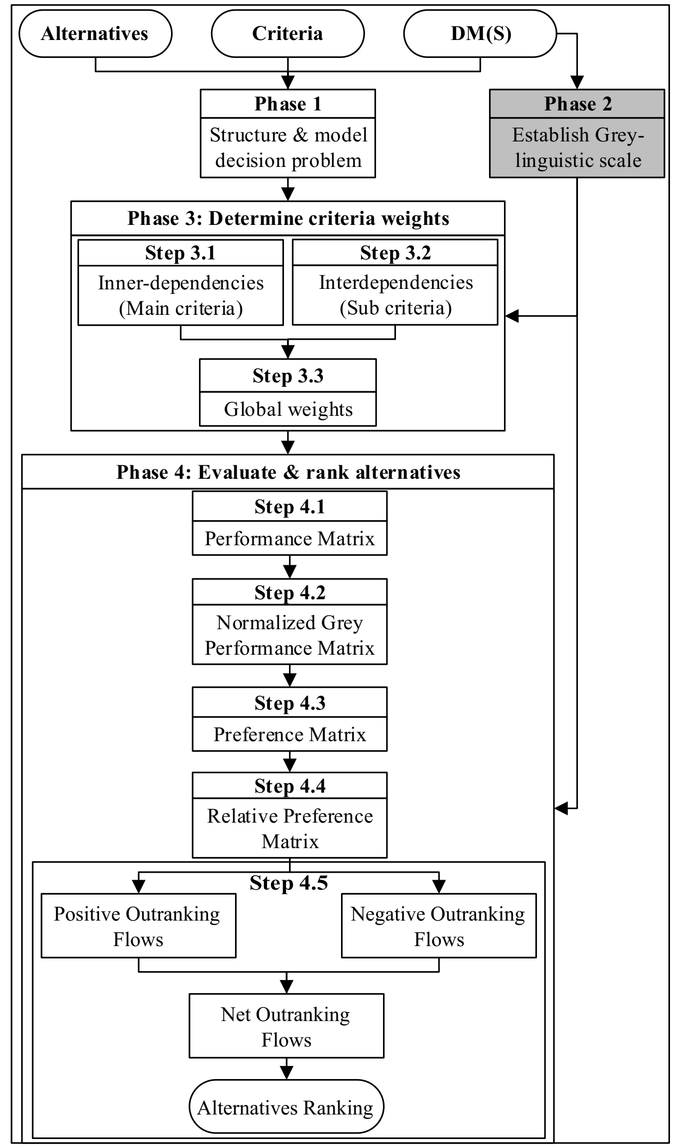

Fig. 1. Analytic framework of G-ANP-PROMETHEE II.

3. Grey-based MCDA methodology (G-ANP-PROMETHEE II)

The proposed decision analysis process (G-ANP-PROMETHEE II) is consisted of four phases: (1) structure and model the decision problem, (2) establish grey linguistic scales, (3) determine the weights of evaluation criteria, and (4) evaluate and rank feasible alternatives. The framework of the proposed methodology is illustrated in Fig. 1. The procedural steps of G-ANP-PROMETHEE II are explained in the following subsections.

3.1. Structure and model the decision problem

The first phase of the methodology is formulating the problem, which requires analysis for the system of concern, its functionality, and substantial connections (i.e., connections within and between the various elements of the system; or between the system, relevant factors, and its environment). Accordingly, the network structure can be used to model the decision problem. Fig. 2 depicts a general representation of the network structure.

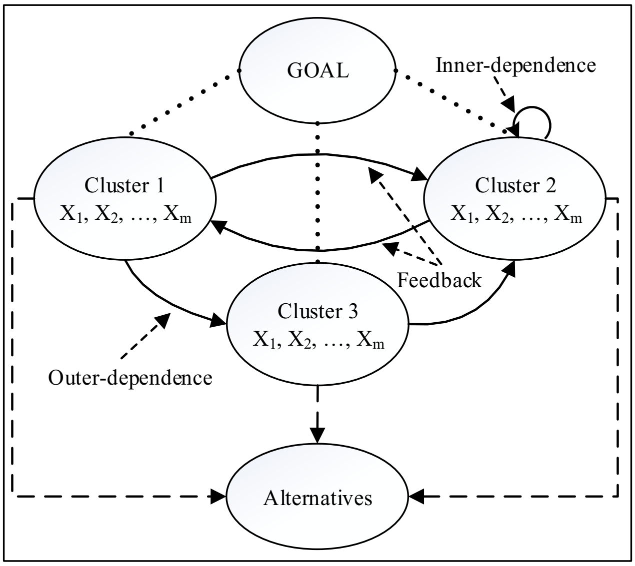

Fig. 2. Network structure model (Görener, 2012).

3.2. Establish grey linguistic scales

Multi-criteria decision problems involve some uncertainty because they are unlikely to fully satisfy decision criteria. Also, it is difficult for DMs to precisely express preferences due to information limitations and the uncertainty of human judgment. Therefore, linguistic expressions are more often used in MCDA to articulate DMs' preferences between evaluation criteria, and to evaluate available alternatives over qualitative criteria (Kuang et al., 2015; Merigó et al., 2016).

In this research, the concepts of grey systems theory and linguistic expressions provide the basis for the proposed approach, in which linguistic expressions (e.g., low, medium, and high) are used to express DMs judgments and the grey systems theory is used to handle the associated vagueness with verbal statements through the operating rules of grey numbers. To express preferences of DMs between evaluation criteria with respect to the system of concern, a grey linguistic scale of six levels is proposed, as illustrated in Table 1 (Ertay et al., 2005). When it comes to the assessment of feasible alternatives over qualitative criteria, it is also expressed in linguistic values using a five-level scale as shown in Table 2.

3.3. Determine the weights of evaluation criteria

For a complex multi-criteria decision problem (i.e., decision problems that involve interrelationships between evaluation criteria), ANP provides a structured procedure to analyze such complexity in decision problems (Zaim et al., 2014). However, ANP cannot effectively address uncertainty-related issues (Nguyen et al., 2014), which are usually present in real world applications. To overcome this limitation, linguistic expressions and concepts of grey systems theory are integrated with ANP to establish the set of weights for evaluation criteria. The procedural steps are as follows: (1) determine inner-dependencies among main criteria, (2) examine interdependencies among sub-criteria, and (3) Estimate global weights for sub-criteria using the outputs of steps 1 and 2.

Table 2
Performance evaluation scale over qualitative criteria.

Performance evaluation linguistic scale	Grey evaluation scale
Low (L)	[0,0.2]
Less than moderate (LM)	[0.2,0.4]
Moderate (M)	[0.4,0.6]
More than moderate (MM)	[0.6,0.8]
High (H)	[0.8,1.0]

3.3.1. Determine inner-dependencies among main criteria

The purpose of inner-dependencies evaluation is to detect the relative importance among various elements of the same level or cluster. This could be achieved by analyzing the influence of an evaluation criterion over other elements of the same level/cluster using linguistic expressions and relative grey numbers, as in Table 1, to articulate DMs' preferences between evaluation criteria.

3.3.1.1. Establish grey-based pairwise comparison matrices for main criteria.
Definition 3.1. Let a set of criteria within a cluster be represented by $C = \{C_1, C_2, \ldots, C_m\}$, where m is the number of criteria. Let a_{ij} indicate the existence of an influence relation of criterion C_i over C_j, where

$$a_{ij} = \begin{cases} 1 \leftrightarrow C_i \text{ influences } C_j \vee (\mathrm{i} = \mathrm{j}) \\ 0 \leftrightarrow C_i \textbf{ does not} \text{ influence } C_j \end{cases}, \ i, j = 1, 2, \ldots m \quad (1)$$

Definition 3.2. Let I_k represent a set of evaluation criteria that influence a criterion C_k, where $I_k \subset C$ and $C_k \notin I_k$. Let $R[\otimes]$ represent the set of grey numbers and $T_{k\otimes}$ denote a grey description function that describes the grey-based pairwise comparisons between elements of I_k with respect to C_k, such that

$$T_{k\otimes}: (I_k \times I_k) \to R[\otimes], \ \forall\ k = 1, 2, \ldots m \quad (2)$$

Definition 3.3. Let $\otimes k_{ij} \in T_{k\otimes}$ denote a grey number that articulates DMs' verbal preference of C_i over C_j with respect to a control criterion C_k, where both C_i and C_j influence C_k and $k \neq i, j$. Thus,

$$\exists \otimes \ k_{ij} \leftrightarrow (a_{ik}, a_{jk} = 1), \ \forall\ T_{k\otimes}(C_i, C_j), \quad (3)$$

where $k_{ij}(\bigotimes) = \begin{cases} k_{ji}(\bigotimes)^{-1} \leftrightarrow i \neq j \\ [1,1], \text{otherwise} \end{cases}, \ i, j, k = 1, 2, \ldots m.$

3.3.1.2. Estimate inner-dependence weights. To estimate the inner-dependence weights among evaluation criteria, the grey numbers at the grey-based pairwise comparisons matrices need to be transformed to white numbers (i.e., single values). To do this, the whitenization process should be performed.

The weight function of the whitenization process is decided based on the available information of the relative grey numbers (e.g., distribution information), knowledge, and experience of decision makers

Table 1
Pairwise preference scale (Ertay et al., 2005).

Pairwise linguistic scale	Grey preference scale	Reciprocal grey preference scale
Just equal	(Kurka and Blackwood, 2013)	(Kurka and Blackwood, 2013)
Equally important	[1/2,3/2]	[2/3,2]
Weakly more important	(Kuang et al., 2015; Kurka and Blackwood, 2013)	[1/2,1]
Moderately more important	[3/2,5/2]	[2/5,2/3]
Strongly more important	(Kuang et al., 2015; Li et al., 2007)	[1/3,1/2]
Extremely more important	[5/2,7/2]	[2/7,2/5]

(Liu and Lin, 2006).

Definition 3.4. Assume that a whitenization function for a relative grey number $x(\otimes)$ is $f(x_i)$, then the whitenization value $x_i(\widetilde{\otimes})$ can be defined as (Shi et al., 2013):

$$x(\widetilde{\otimes}) = x.\, f(x) \tag{4}$$

In many practical applications, the weight function of the whitenization process is unknown (Liu and Lin, 2006), which adds complexity to decision problems. Therefore, Liu and Lin (2006) proposed the equal weight mean whitenization function to establish the associated white values of interval grey numbers.

In this research, the interval grey numbers is used and it is assumed that the weight function of the whitenization process is unknown due to the lack of information. Therefore, the equal weight mean whitenization function is considered for the whitenization process as follows:

Definition 3.5. Let $x(\otimes) \in [a, b]$ be a general interval grey number, where $a < b$ and the distribution information for the grey number is unknown. Let α denote the weight coefficient. The whitenization value $x(\widetilde{\otimes})$ can be obtained using the equal weight mean whitenization, such that

$$x(\widetilde{\otimes}) = \alpha a + (1 - \alpha)b, \text{ where } \alpha = \frac{1}{2}. \tag{5}$$

Once the inner-dependence grey matrices have been transformed to fixed number matrices through the whitenization process, the inner-dependence weighs of the evaluation criteria can be estimated using the computation of the eigenvector method (Saaty, 2013). However, the resultant weights should be consistent relatively. In other words, if a criterion $C_a \succ C_b$, and $C_b \succ C_d$, the following can be inferred $C_a \succ C_d$; this is called "transitive law". To this end consistence test should be applied as follows:

Definition 3.6. Suppose the number of compared elements is m. Let a_{ij} denote the preference of C_i over C_j, $i, j = (1, 2, \ldots m)$. Let s_j denote the sum of the corresponding column element a_{ij}. Let $w = (w_1, w_2, \ldots w_m)$ represent the eigenvector (priority vector). Let λ_{max} represent the largest eigenvalue. Let CI denote consistency index of a pairwise comparison matrix and *RI* represent the consistency index of a random-like matrix using the scale of Saaty (1996) (Table 3), in which RI represents the average of consistency indices of 500 randomly filled matrices of a similar size (Mu and Pereyra-Rojas, 2017). Let *CR* reflect a consistency ratio that compare *CI* versus RI, such that

$$CR = \frac{CI}{RI} \tag{6}$$

where $CI = \frac{\lambda_{max} - m}{m-1}$, $\lambda_{max} = \sum_{j=1}^{m} \sum_{i=1}^{m} \frac{a_{ij} w_j}{s_j}$, $i, j = (1, 2, \ldots m)$

Using the values in Table 3, the estimated weight (priority) vector is considered acceptable for a consistency ration of 0.10 or less (Mu and Pereyra-Rojas, 2017).

3.3.2. Examine interdependencies among sub-criteria

Different types of interdependencies exist in complex decision problems, as depicted in Fig. 2. Therefore, these interdependencies should be considered for making better decisions.

To identify the relative importance among sub-criteria with respect to the system of concern, different types of interdependencies (i.e., inner-dependencies within each cluster and outer-dependencies between different clusters) should be identified using the network structure (Fig. 2) or the influence matrix (Table 4), which is explained by **Definition 3.7**.

Table 3
Consistency indices for a randomly generated matrix (Saaty, 1996).

m	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Table 4
Influence matrix.

		C_j			
		sc_{j1}	sc_{j2}	…	sc_{jz}
C_i	sc_{i1}	$a_{i1,\,j1}$	$a_{i1,\,j2}$	…	$a_{i1,\,jz}$
	sc_{i2}	$a_{i2,\,j1}$	$a_{i2,\,j2}$	…	$a_{i2,\,jz}$
	…	…	…	…	…
	sc_{ir}	$a_{ir,\,j1}$	$a_{i1,\,j2}$	…	$a_{ir,\,jz}$

Definition 3.7. Let the set of sub-criteria for a criterion C_i be represented by $\{sc_{i1}, sc_{i2}, \ldots, sc_{ir}\}$ and the set of sub-criteria for criterion C_j denoted by $\{sc_{j1}, sc_{j2}, \ldots, sc_{jz}\}$, where $i, j = 1, 2, \ldots, m$, and m is the number of the evaluation criteria. Let r represent the number of sub-criteria for C_i, such that $f = 1, 2, \ldots, r$; and z denote the number of sub-criteria for C_j, where $h = 1, 2, \ldots, z$. Let $C_i \times C_j$ denote the Cartesian product of two sets of evaluation criteria; and let B represent a collection of influence relations between the elements of the two sets, where $a_{if,\ jh} \in B$ represent the influence of $sc_{if} \in C_i$ over $sc_{jh} \in C_j$. Accordingly, an influence relation from C_i to C_j can be represented by

$$\exists\ B(sc_{if}, sc_{jh}) = a_{if,jh},\ \forall\ (C_i \times C_j) \to B, \tag{7}$$

such that

$$a_{if,jh} = \begin{cases} 1 \leftrightarrow sc_{if} \text{ influences } sc_{jh} \\ 0 \text{ if } sc_{if}\ \textbf{\textit{does not}} \text{ influence } sc_{jh}\ \vee\ [(i = j) \wedge (f = h)] \end{cases}$$

Once all interdependencies among the sub-criteria have been identified, the grey-based pairwise comparisons should be utilized to examine the influences among sub-criteria. To examine the inner-dependence relations among sub-criteria of the same cluster, the same procedures for determining the inner-dependence weights among the main criteria (i.e., **Definitions 3.2 and 3.3**) are used. However, for the outer-dependence weights estimation, the following subsection describes the associated procedures.

3.3.2.1. Estimate outer-dependence weights

Definition 3.8. Let $f_{jh\otimes}$ denote a grey description function that describes grey preference relations between elements of a criterion C_i over a sub-criterion $sc_{jh} \in C_j$, where $i \neq j$; and let $\otimes jh_{if,\ if*} \in f_{jh\otimes}$ represent a relative grey number that articulates DMs' verbal preference of $sc_{if} \in C_i$in comparison to $sc_{if*} \in C_i$with respect to sc_{jh}. Accordingly, the grey description function $f_{jh\otimes}$ can be defined as follows:

$$f_{jh\otimes}\colon (C_i \times C_i) \to R[\otimes], \tag{8}$$

such that

$$\exists\ jh_{if,if*}(\otimes) \leftrightarrow (a_{if,jh}, a_{if*,jh} = 1),\ \forall\ f_{jh\otimes}(sc_{if}, sc_{if*}),$$

where

$$jh_{if,if*}(\otimes) = \begin{cases} jh_{if*,if}(\otimes)^{-1} \leftrightarrow f \neq f* \\ [1, 1], \text{otherwise} \end{cases}$$

Once the levels of outer-dependence influences over the identified sub-criteria have been estimated using the grey-based pairwise comparisons approach, the outer-dependence weights over each sub-criterion can be established by applying eigenvector computations on the qualifying whitened values of the resultant grey numbers using Eq. (5). However, the consistence test should be applied using Eq. (6) to assure the consistency among the resultant weights. Consequently, the resultant interdependence matrices are the compositions of the unweighted supermatrix.

3.3.3. Estimate global weights of sub-criteria

The first step to estimate global weights of sub-criteria is to evaluate the relative importance among sub-criteria with respect to a final decision goal. To this end, the determined unweighted supermatrix is weighted using the computed inner-dependence weights of the main criteria.

Note: it is assumed that the self-influence of a main criterion is the highest, which represents one half of the total weight.

Definition 3.9. Let W_c denote inner-dependence weights matrix for main criteria, where $W_{ij} \in W_c$ indicate the influence of C_i over C_j; let w_{sc} represent the unweighted supermatrix, where $[w_{i.\ ,\ j.}] \subset w_{sc}$ represent the interdependence unweighted matrix between the elements of C_i over the elements of C_j; and let Q_w denote weighted supermatrix, where $[Q_{i.\ ,\ j.}] \subset Q_w$ represent the relevant interdependence weighted matrix of $[w_{i.\ ,\ j.}]$. The function of the weighted supermatrix is

$$f: (W_c \times w_{sc}) \rightarrow Q_w$$
$$\exists\ [Q_{i.,j.}] \in Q_w,\ \forall f\,(W_{ij} \in W_c, [w_{i.,j.}] \in w_{sc}) \tag{9}$$

Once the weighted supermatrix has been calculated, it should be normalized to obtain synthesized results for the elements of the weighted supermatrix. To establish the normalized supermatrix, the linear normalization approach is utilized: elements of each column are divided by the column sum.

Subsequently, global weights of sub-criteria can be established by obtaining the limited supermatrix. To this end, the normalized supermatrix should be raised to powers (i.e., exponentiation) until it converges into a stable matrix, where the elements of each row converge (Hosseini et al., 2013). Thus, the overall priority across the identified sub-criteria can be established using the proposed Grey-based ANP (G-ANP) approach.

3.4. Evaluate and rank feasible alternatives

When it comes to performance evaluations and alternatives ranking with respect to the system of concern, the following procedural steps are used: (1) Assess alternatives performance over the evaluation criteria and establish performance matrix; (2) Normalize relative performance measures of feasible alternatives to establish a comparison ground; (3) Evaluate preferences between alternatives over each criterion by measuring the deviation between the evaluations of the alternatives; (4) Calculate the relative preferences between alternatives across the evaluation criteria; (5) Estimate the global preference of each alternative using the net outranking flow computations, and rank available alternatives accordingly.

3.4.1. Establish performance matrix

The system of concern involves different types of criteria (e.g., quantitative and qualitative), which require different assessment approaches. Moreover, the involvement of uncertainty adds to the complexity of the system. Accordingly, to establish the performance matrix for available alternatives within the context of the system at hand, each alternative should be evaluated over the sets of criteria. While the performance over quantitative criteria is represented in numerical values; the performance over qualitative criteria is articulated in linguistic expressions, in accordance with the judgments of the involved DMs.

Definition 3.10. Let the set of alternatives be represented by $A = \{A_1, A_2, \dots, A_n\}$, where n is the number of the feasible alternatives and $t = 1, 2, \dots, n$. Let $SC = \{sc_1, sc_2, \dots, sc_{im}\}$ denote the set of evaluation criteria, where "im" is the number of evaluation criteria, and $g = 1, 2, \dots, im$. Let $A \times SC$ be the Cartesian product of the set of alternatives and the set of criteria and let $R[\otimes]$ denote the set of grey numbers. Let $y_{tg}(\otimes)$ represent the relative grey number that reflect the performance of an alternative A_t over an evaluation criterion sc_g; where sc_g is a qualitative criterion, or a quantitative criterion with uncertain data. Thus, the grey description function for the performance matrix, as defined by Kuang et al. (2015), is

$$f_{\otimes}: A \times SC \rightarrow R[\otimes],\ thus$$
$$\forall f_{\otimes}(A_t \in A, sc_g \in SC): y_{tg}(\otimes) \in R[\otimes] \tag{10}$$

Note that for performance assessment over qualitative criteria, $y_{tg}(\otimes)$ articulates DMs' verbal statements (i.e., linguistic expression) regarding the performance of A_t over the criterion sc_g; in this paper, the maps between linguistic expressions and grey numbers are identified in Table 2. However, to measure alternatives performance over quantitative criteria where uncertainty exists (e.g., imperfect numerical information), $y_{tg}(\otimes)$ would take its values from either a discrete set of values or an interval.

3.4.2. Normalize performance matrix

Once the performance matrix has been determined, consistency among performance measures should be established to draw proper comparisons. To this end, a normalization process is applied to adjust the performance matrix, wherein the following condition should be valid (Bai et al., 2012)

$$[0, 0] \le y_{tg}(\otimes) \le [1, 1] \tag{11}$$

The normalization process is done in two steps: first, transform all non-grey values in the performance matrix into general grey numbers; second, normalize all the values.

Definition 3.11. Let y_{tg} denote a white number that represents the performance of alternative A_t on a quantitative criterion sc_g, the relative grey number of the white number (y_{tg}) is

$$y_{tg}(\otimes) = \left[\underline{y}_{tg}, \overline{y}_{tg}\right],\ where\ \underline{y}_{tg} = y_{tg} = \overline{y}_{tg} \tag{12}$$

Note that although some evaluations would be expressed by interval grey numbers, a normalized scale over the criteria is not guaranteed. To establish a normalized scale for the evaluations of feasible alternatives over different types of criteria, **Algorithm 1**, which is explained by **Definition 3.12**, is proposed.

Algorithm 1. Normalize alternatives performance based on grey systems theory.

Definition 3.12. Let $y_{tg}(\otimes)$ represent a general grey number that reflects the performance of alternative A_t over a criterion sc_g; let min(y_{kg}) and max(y_{kg}) denote the lower and upper bounds of $y_{tg}(\otimes)$, respectively. Let y_g^* represent a given optimal performance value over a targeted criterion sc_g. Let $\otimes\ \tilde{y}_{tg}$ denote the relative normalized value of the general grey number $y_{tg}(\otimes)$, such that $y_{tg}(\widetilde{\otimes})$ is determined based on criteria type, i.e., increasing, decreasing, and targeted.

3.4.3. Establish preference matrix

The differences of performance measures explain the preferences between feasible alternatives. Thus, the larger the difference, the larger the preference is. In order to establish the preference matrix, the deviation between the evaluations of the feasible alternatives on each criterion should be determined, based on the definition of Xu and Da (2002).

Definition 3.13. Let $y_{ag}(\otimes) = \left[\underset{-ag}{\tilde{y}}, \tilde{\bar{y}}_{ag}\right]$ and $y_{bg}(\otimes) = \left[\underset{-bg}{\tilde{y}}, \tilde{\bar{y}}_{bg}\right]$ represent general grey numbers that reflect the normalized performance values of alternatives A_a and A_b over sc_g, respectively. Let l_{ag} and l_{bg} denote the difference between the upper and lower limits of $y_{ag}(\otimes)$ and $y_{bg}(\otimes)$, respectively, such that

$$l_{ag} = \tilde{\bar{y}}_{ag} - \underset{-ag}{\tilde{y}}$$
$$l_{bg} = \tilde{\bar{y}}_{bg} - \underset{-bg}{\tilde{y}} \tag{13}$$

Definition 3.14. Let $\tilde{d}_g(A_a, A_b)$ denote the deviation between the performance of alternative A_a with respect to the performance of alternative A_b over sub-criterion sc_g, in which the function to obtain the deviation can be defined as

$$\tilde{d}_g(A_a, A_b) = \frac{\tilde{\bar{y}}_{ag} - \underset{-bg}{\tilde{y}}}{l_{ag} + l_{bg}} \tag{14}$$

Once the deviation between the evaluations of feasible alternatives over each of the evaluation criteria have been determined, preference degrees can be established as follows.

Definition 3.15. Let $\tilde{P}_g(A_a, A_b)$ represent the preference degree of alternative A_a over A_b with respect to sc_g. Let the degree of preference vary between 0 and 1, where 0 indicates no preference and 1 indicates full preference, such that (Kuang et al., 2015)

$$\tilde{P}_g(A_a, A_b) = \begin{cases} 0, \ \tilde{d}_g(A_a, A_b) \le 0 \\ \tilde{d}_g(A_a, A_b), \ 0 < \tilde{d}_g(A_a, A_b) < 1 \\ 1, \ \tilde{d}_g(A_a, A_b) \ge 1 \end{cases} \tag{15}$$

3.4.4. Determine relative preference matrix

To determine the overall preferences between alternatives with respect to the given system, the overall priority across the identified sets of the evaluation criteria (i.e., global weights) should be considered.

Definition 3.16. Let $\tilde{\pi}(A_a, A_b)$ denote the relative preference of alternative A_a over A_b across the set of evaluation criteria SC, where $SC = \{sc_1, sc_2, \ldots, sc_{im}\}$. Let the global weight of each criterion be represented by w_g, where $\sum_{g=1}^{im} w_g = 1$, $g = 1, 2, \ldots, im$, and im is the number of evaluation criteria. Accordingly, the relative preference of A_a over A_b can be calculated using the following function (Kuang et al., 2015).

$$\tilde{\pi}(A_a, A_b) = \sum_{g=1}^{im} w_g \tilde{P}_g(A_a, A_b), \ where \ g = (1, 2, \ldots, im) \tag{16}$$

3.4.5. Estimate global preferences and rank available alternatives

Once the relative preferences have been determined for each pair of alternatives, the global preference among feasible alternatives can be estimated. To this end, the net outranking flow should be calculated using the outranking flows measures, which determine the superiority (i.e., positive outranking flow) and inferiority (i.e., negative outranking flow) levels of a given alternative over others.

Definition 3.17. Let $\tilde{\phi}^+(A_a)$ denote the positive outranking flow of alterative A_a, which indicates the preference of A_a over all other alternatives. Let $\tilde{\pi}(A_a, A_b)$ represent the extent to which alternative A_a is preferred over A_b. The positive outranking flow can be defined as (Kuang et al., 2015)

$$\tilde{\phi}^+(A_a) = \frac{1}{n-1} \sum_{b=1}^{n} \tilde{\pi}(A_a, A_b), \ a \ne b \tag{17}$$

Definition 3.18. Let $\tilde{\phi}^-(A_a)$ represent the negative outranking flow of alterative A_a, which indicates the preference of other alternatives over A_a. Let $\tilde{\pi}(A_b, A_a)$ represent the extent to which alternative A_a is outranked by A_b. The function to obtain $\tilde{\phi}^-(A_a)$ can be written as (Kuang et al., 2015)

$$\tilde{\phi}^-(A_a) = \frac{1}{n-1} \sum_{b=1}^{n} \tilde{\pi}(A_b, A_a), \ a \ne b \tag{18}$$

Definition 3.19. Let $\tilde{\phi}(A_a)$ denote the global preference (i.e., net outranking flow) of alternative A_a, which can be obtained by measuring the difference between $\tilde{\phi}^+(A_a)$ and $\tilde{\phi}^-(A_a)$. Thus, $\tilde{\phi}(A_a)$ can be determined as follows (Kuang et al., 2015):

$$\tilde{\phi}(A_a) = \tilde{\phi}^+(A_a) - \tilde{\phi}^-(A_a) \tag{19}$$

Once the net outranking flow has been estimated for all feasible alternatives, a complete ranking index can be established based on the values of global preferences, wherein the higher the value of $\tilde{\phi}(A_a)$, the better is the alternative. Thus, the best alternative is the one with the highest global preference value.

4. Case illustration of strategic decision making in FEI for a Small to Medium-sized Enterprise (SME) within the Canadian quaternary sector

The given company is suffering from a low level of formalization, when it comes to making strategic decisions with respect to innovation activities, which would jeopardize innovation success. Consequently, the company is looking for a more systematic approach to identify, characterize, evaluate, and respond better to potential opportunities for innovation. The proposed methodology would be implemented on the framework of the case to bridge deficiencies of the current process, thereby enhancing DMs' abilities in making strategic decisions.

In this case study, three different innovation projects have been reported for study. Abductive reasoning has been utilized to provide reasonable explanations about the different components of the problem at hand, and the existing interrelationships among evaluation criteria.

In order to establish a coherent understanding about the current practice of FEI within the firm, a triangulation technique has been used, which increases the validity of the data (Schweizer, 2015). The three different techniques for data collection process were semi-structured interviews (e.g., senior managers, systems engineers, and marketing personnel); on site observations to gain first-hand knowledge on innovation activities for the company; and reviewing the available archival data, including internal norms and strategies relevant to the innovation process.

4.1. Structure and model the decision problem

The first step of the proposed methodology is to formulate the decision problem. To this end, the different components of the decision problem (i.e., alternatives, criteria, and sub-criteria) should be identified. Afterwards, essential connections among the evaluation criteria would be modeled.

4.1.1. Identify feasible alternatives

As mentioned earlier, three innovation projects have been reported for the study, each of which aims to create a competitive advantage for the company. However, each project has different set of characteristics, which would make a difference in the evaluation process.

To differentiate between the potential alternatives, the type of the relative innovation strategy would be considered. Thus, the potential alternatives are alternative 1 (A_1): Radical Diversification; alternative 2 (A_2): Market Development; and alternative 3 (A_3): Product/Service Development.

Table 5
Evaluation criteria.

Evaluation criteria	Description	Reference
	Market (C1)	
Market insight (M1) (sc11)	Market related knowledge (e.g., ability to discover unfulfilled needs).	(Reid and De Brentani, 2015)
Growth rate (M2) (sc12)	Potential increases in a market size (i.e., demand growth).	(Baker et al., 2016)
Competitive degree (M3) (sc13)	Competition level indicator in a given market.	(Mendi and Costamagna, 2017)
	Technology (C2)	
Sustainable competitive advantage (T1) (sc21)	Ability to sustain advantage(s) over competitors.	(Saeidi et al., 2015)
Specification fuzziness (T2) (sc22)	Lack of clarity with respect to process functions, technical specifications, or technical requirements.	(Moos et al., 2013)
	Financial (C3)	
Revenue stream (F1) (sc31)	Potential earning from a given investment.	(Gebauer et al., 2012)
Cost structure (F2) (sc32)	Delivery cost estimation.	(Onetti et al., 2012)
Potential sources of funding (F3) (sc33)	Potential sources of funding (e.g., R&D subsidy).	(Bronzini and Piselli, 2016)
	Organizational (C4)	
Familiarity with targeted market (O1) (sc41)	Level of familiarity with a targeted market: new market, adjacent, or existing market.	(Tzokas et al., 2015)
Current development capability (O2) (sc42)	E.g., technological capability, whether the targeted innovation project is fully applicable, require significant adaptation, or not applicable.	(Martín-de Castro, 2015)

4.1.2. Establish evaluation criteria

In this study, the evaluation aspects for the decision problem at hand have been established based on the knowledge acquired from the case study and by building on the literature of the relevant subject matter. Four main sets of criteria are proposed to evaluate feasible alternatives from different perspectives. Table 5 shows the main criteria and the associated sub-criteria with a brief description for each sub-criterion.

4.1.3. Establish various types of links and model the problem

To illustrate the different types of connections within the system of concern, a network structure model has been utilized to demonstrate the general framework of the existing interrelationships within and between the different evaluation clusters, as shown in Fig. 3. However, the influence matrix has been used to give the detailed view of the interdependencies between the sub-criteria, as shown in Table 6; where 1 indicates the presence of influence relation between the associated pair of sub-criteria.

4.2. Establish grey linguistic scales

The system at hand is regarded as a complex system under uncertainty. The complexity of the decision problem could be handled by conventional MCDA approaches. However, the involved uncertainty, due to the nature of FEI (e.g., limited input data), would limit the outcomes of using MCDA solely. Therefore, the proposed methodology integrates grey systems theory with ANP and PROMETHEE II to overcome the uncertainty-related aspects as follows: firstly, grey systems theory would be utilized along with the principles of ANP to establish the set of weights for evaluation criteria with respect to the system of concern; secondly, grey systems theory would be integrated with PROMETHEE II to help measuring the performance of the alternatives over the evaluation criteria that involve uncertain evaluations.

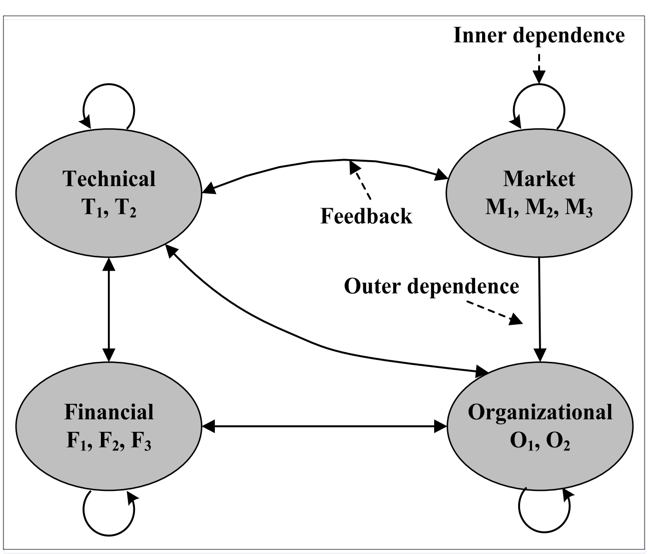

Fig. 3. Network structure of the evaluation criteria within the context of FEI.

Table 6
Interdependencies between sub-criteria.

Sub criteria	M_1	M_2	M_3	T_1	T_2	F_1	F_2	F_3	O_1	O_2
M_1	0	1	1	1	1	1	1	1	1	1
M_2	1	0	1	1	1	1	1	1	1	1
M_3	1	1	0	1	1	1	1	1	1	1
T_1	0	1	1	0	1	1	1	1	1	1
T_2	1	1	1	1	0	1	1	1	1	1
F_1	1	1	1	1	1	0	1	1	1	1
F_2	1	1	1	1	1	1	0	1	1	1
F_3	1	1	1	1	1	1	1	0	1	1
O_1	1	1	1	1	1	1	1	1	0	1
O_2	1	1	1	1	1	1	1	1	1	0

In this case study, the type of the decision problem is considered as single participant-multiple criteria, which is the general case for MCDA. To express preferences of the involved DMs regarding the evaluation criteria, Table 1 has been utilized. When it comes to the performance evaluation stage, Table 2 has been applied to assess the performance of prospective projects over qualitative measures.

4.3. Establish the priority level across criteria

After identifying the different components of the system of concern and modeling substantial connections within the FEI, the next step is to establish the level of importance among the evaluation criteria by estimating the weights of each criterion. To this end, different types of interdependencies among evaluation criteria would be considered and analyzed using the proposed G-ANP approach.

4.3.1. Determine inner-dependence weights among main criteria

Interdependence weights among the main criteria (i.e., market, technology, financial, and organizational) are estimated by analyzing

Table 7
Inner-dependencies among main criteria with respect to Market.

Market	Technical	Financial	Organizational
Technical	(Kurka and Blackwood, 2013)	(Kuang et al., 2015; Kurka and Blackwood, 2013)	[3/2, 5/2]
Financial	[1/2, 1]	(Kurka and Blackwood, 2013)	(Kuang et al., 2015; Kurka and Blackwood, 2013)
Organizational	[2/5, 2/3]	[1/2, 1]	(Kurka and Blackwood, 2013)

Table 8
Inner-dependence weights matrix of the main criteria.

Main criteria	Market	Technical	Financial	Organizational
Market	1	0.2268	0.5111	0.3527
Technical	0.4480	1	0.3067	0.4442
Financial	0.3232	0.4872	1	0.2031
Organizational	0.2289	0.2860	0.1821	1

the influence of each criterion on other criteria, using the linguistic expressions and the relative grey numbers in Table 1 in accordance with Eq. (3) of the proposed methodology. Table 7 shows the grey-based pairwise comparison matrix between the main criteria with respect to Market factor, which represents the control criterion of this matrix.

Once all the inner-dependence relations among criteria have been established, the grey values would be transformed into fixed numbers (Table 8), using the whitenization process, Eq. (5), to estimate relative inner-dependencies through eigenvector computations.

4.3.2. Examine interdependence weights among sub-criteria

The complex interdependencies (i.e., inner-dependencies and outer-dependencies) among the identified sub-criteria have been examined according to section 3.3.2 of the proposed methodology. Note that Table 1 has been used to articulate DMs' preferences between the sub-criteria.

As mentioned in section 3.3.2, the estimated priority matrices, which demonstrate the level of influence among the identified sub-criteria, are the compositions of the unweighted supermatrix (Table 9). Note that the shaded areas of Table 9 represent the inner-dependence weights among sub-criteria of the same cluster.

4.3.3. Estimate global weights of sub-criteria

To estimate the relative importance of each sub-criterion with respect to the decision problem at hand, the constructed unweighted supermatrix has been weighted, as shown in Table 10, in accordance with Eq. (9) using the computed inner-dependence weights matrix of the main criteria (Table 8). Accordingly, each element of the unweighted supermatrix (Table 9) is multiplied with the associated element in Table 8. For example, the influence of "competitive degree" (M_3), which is a sub-criterion of "Market" (C_1) cluster; on "sustainable competitive advantage" (F_1), which is a sub-criterion of "Technology" (C_2) cluster, is 0.2268. However, the associated inner-dependence weight in Table 8 is 0.4833. Consequently, the relevant value within the weighted supermatrix would be 0.1096.

In order to determine the global weights, the elements of the weighted supermatrix results (Table 10) have been normalized to obtain synthesized results. Subsequently, the global weights of the sub-criteria can be obtained by raising the normalized supermatrix to powers until it converges into a stable matrix (i.e., the limited supermatrix). In this study, the limited supermatrix has been achieved at $[\widetilde{Q}_w]^{15}$. As a result, the global weights of the sub-criteria are: $\mathbf{M_1}$ (0.0842), $\mathbf{M_2}$ (0.1095), $\mathbf{M_3}$ (0.0714), $\mathbf{T_1}$ (0.1282), $\mathbf{T_2}$ (0.1551), $\mathbf{F_1}$ (0.11), $\mathbf{F_2}$ (0.0745), $\mathbf{F_3}$ (0.0776), $\mathbf{O_1}$ (0.0865), and $\mathbf{O_2}$ (0.103).

4.4. Evaluate and rank feasible alternatives

Once the evaluation criteria have been analyzed, feasible alternatives can be ranked. The detailed procedure is explained in the following subsections.

4.4.1. Establish performance matrix

To evaluate feasible alternatives, the performance of each alternative should be assessed across the evaluation criteria. Different types of criteria are involved in the decision problem at hand, i.e., quantitative and qualitative criteria, in which the sub-elements of the financial cluster (i.e., revenue stream, cost, structure, and potential sources of funding) are quantitative, while all others are qualitative.

Due to the presence of uncertainty within the context of FEI, grey numbers have been used to express the performance of feasible alternatives in which the performance over the quantitative sub-criteria has been estimated using intervals, while the performance over the qualitative sub-criteria has been evaluated based on DMs' verbal judgments using the linguistic expressions and the grey numbers in Table 2. Alternatives' performances over the qualitative and quantitative criteria are presented in Tables 11 and 12, respectively. Note that the performance estimations over the quantitative criteria are in thousands.

4.4.2. Normalized performance matrix

To assure consistency over the preference evaluation process, the resultant performance matrices have been normalized using **Algorithm 1**. The normalized performance matrix is shown in Table 13.

4.4.3. Establish preference matrix

To establish the preference degree between the prospective projects, the deviation between the evaluations of potential alternatives over each criterion has been evaluated using Eq. (14). Afterwards, the

Table 9
Supermatrix.

Sub criteria	M_1	M_2	M_3	T_1	T_2	F_1	F_2	F_3	O_1	O_2
M_1	0	0.5857	0.3406	0.2289	0.2289	0.4442	0.2289	0.2860	0.3232	0.2860
M_2	0.6594	0	0.6594	0.4480	0.4480	0.3527	0.4480	0.4872	0.4480	0.4872
M_3	0.3406	0.4143	0	0.3232	0.3232	0.2031	0.3232	0.2268	0.2289	0.2268
T_1	0	0.4143	0.3406	0	1	0.5857	0.3406	0.5857	0.3406	0.3406
T_2	1	0.5857	0.6594	1	0	0.4143	0.6594	0.4143	0.6594	0.6594
F_1	0.4442	0.4480	0.4872	0.4872	0.4872	0	0.5857	0.6594	0.4872	0.4872
F_2	0.3527	0.3232	0.2860	0.2860	0.2860	0.4143	0	0.3406	0.2268	0.2860
F_3	0.2031	0.2289	0.2268	0.2268	0.2268	0.5857	0.4143	0	0.2860	0.2268
O_1	0.4143	0.4143	0.3810	0.4143	0.2899	0.3406	0.3406	0.4143	0	1
O_2	0.5857	0.5857	0.6190	0.5857	0.7101	0.6594	0.6594	0.5857	1	0

Table 10
Weighted supermatrix.

Sub criteria	M_1	M_2	M_3	T_1	T_2	F_1	F_2	F_3	O_1	O_2
M_1	0	0.5857	0.3406	0.0519	0.0519	0.2270	0.1170	0.1462	0.1140	0.1009
M_2	0.6594	0	0.6594	0.1016	0.1016	0.1803	0.2290	0.2490	0.1580	0.1718
M_3	0.3406	0.4143	0	0.0733	0.0733	0.1038	0.1652	0.1159	0.0807	0.0800
T_1	0	0.1856	0.1526	0	1	0.1797	0.1045	0.1797	0.1513	0.1513
T_2	0.4480	0.2624	0.2954	1	0	0.1271	0.2023	0.1271	0.2929	0.2929
F_1	0.1435	0.1448	0.1575	0.2374	0.2374	0	0.5857	0.6594	0.0990	0.0990
F_2	0.1140	0.1044	0.0924	0.1394	0.1394	0.4143	0	0.3406	0.0461	0.0581
F_3	0.0656	0.0740	0.0733	0.1105	0.1105	0.5857	0.4143	0	0.0581	0.0461
O_1	0.0948	0.0948	0.0872	0.1185	0.0829	0.0620	0.0620	0.0755	0	1
O_2	0.1340	0.1340	0.1417	0.1675	0.2031	0.1201	0.1201	0.1067	1	0

Table 11
Evaluation of potential innovation projects on qualitative criteria.

Performance matrix	Alternatives		
Qualitative criteria	A_1	A_2	A_3
Market insight (M_1)	L	MM	M
Growth rate (M_2)	H	LM	MM
Competitive degree (M_3)	L	LM	M
Sustainable competitive advantage (T_1)	H	M	MM
Specification fuzziness (T_2)	MM	LM	M
Familiarity with targeted market (O_1)	L	MM	LM
Current development capability (O_2)	L	H	LM

preference degree between the projects over each criterion has been estimated in accordance with Eq. (15). Accordingly, the resultant preferences of A1 over other alternatives are shown in Table 14.

4.4.4. Determine relative preference matrix

To determine the overall preferences between the prospective projects, the relative preferences between the projects should be determined by weighting the resultant preference measures (Table 14) using the global weights of the evaluation criteria in accordance with Eq. (16). Accordingly, the relative preference measures between alternatives are depicted in Table 15.

4.4.5. Estimate global preferences and rank feasible alternatives

To prioritize the prospective projects, the global preference measures should be established in accordance with Eqs. (17), (18), and (19). Table 16 presents: outflows (positive outranking flow), inflows (negative outranking flow), and the net-flows (global preferences). Consequently, the three projects have been ranked based on the resultant net outranking flows, wherein the higher the value of the net-flow, the better is the alternative. Thus, $\mathbf{A_2}$ is the most preferred project and the ranking order of the prospective innovation projects according to the proposed methodology is $\mathbf{A_2 \succ A_1 \succ A_3}$.

5. Comparative analysis

To validate the proposed methodology, an existing case study (Kuo et al., 2015) in the literature is used, where a framework has been developed, by integrating fuzzy ANP and fuzzy TOPSIS approaches, to evaluate carbon performance of suppliers. Table 17 shows the grey paired comparison matrix between criteria (dimensions), and the estimated weights.

The main criteria are: Organizational management (C1); Process management (C2); Procurement management (C3); R&D management (C4). Table 18 illustrates the estimated criteria weights using both methodologies, by looking at the results, the proposed methodology reflects similar priority order among the criteria.

Table 12
Evaluation of potential innovation projects on quantitative criteria.

Performance matrix	Alternatives		
Quantitative criteria	A_1	A_2	A_3
Revenue stream (F_1)	[150, 350]	[70, 200]	[85, 250]
Cost structure (F_2)	(Ertay et al., 2005; Gebauer et al., 2012)	(Dyer, 2005; Liu et al., 2015)	(Mu and Pereyra-Rojas, 2017; Zhang et al., 2009)
Potential sources of funding (F_3)	(Brans and De Smet, 2016b; Moretti et al., 2016)	(Li et al., 2012; Wątróbski and Jankowski, 2016)	(Liu et al., 2015; Wątróbski and Jankowski, 2016)

Table 13
Normalized performance matrix.

Performance matrix	Alternatives		
Qualitative criteria	A_1	A_2	A_3
Market insight (M_1)	[0, 0.25]	[0.75, 1]	[0.5, 0.75]
Growth rate (M_2)	[0.75, 1]	[0, 0.25]	[0.5, 0.75]
Competitive degree (M_3)	[0.67, 1]	[0.33, 0.67]	[0, 0.33]
Sustainable competitive advantage (T_1)	[0.67, 1]	[0, 0.33]	[0.33, 0.67]
Specification fuzziness (T_2)	[0, 0.33]	[0.67, 1]	[0.33, 0.67]
Familiarity with targeted market (O_1)	[0, 25]	[0.75, 1]	[0.25, 0.5]
Current development capability (O_2)	[0, 2]	[0.8, 1]	[0.2, 0.4]
Revenue stream (F_1)	[0.286, 1]	[0, 0.464]	[0.054, 0.643]
Cost structure (F_2)	[0, 0.333]	[0.778, 1]	[0.222, 0.556]
Potential sources of funding (F_3)	[0.429, 1]	[0, 0.143]	[0.143, 0.571]

Table 14
Multi-criteria preference matrix of A_1.

Multi-criteria preference matrix		Alternatives		
Alternative	Criteria	A_1	A_2	A_3
A_1	Market insight (M_1)	0.5	0	0
	Growth rate (M_2)	0.5	1	1
	Competitive degree (M_3)	0.5	1	1
	Sustainable competitive advantage (T_1)	0.5	1	1
	Specification fuzziness (T_2)	0.5	0	0
	Familiarity with targeted market (O_1)	0.5	0	0
	Current development capability (O_2)	0.5	0	0
	Revenue stream (F_1)	0.5	0.8485	0.726
	Cost structure (F_2)	0.5	0	0.1667
	Potential sources of funding (F_3)	0.5	1	0.8571

Table 15
Relative preference matrix.

Alternatives	A_1	A_2	A_3
A_1	0.5	0.48	0.4679
A_2	0.52	0.5	0.6176
A_3	0.5321	0.3824	0.5

Table 16
Global preference matrix - outranking flows computations.

Outranking flows	Alternatives		
	A_1	A_2	A_3
Outflow	0.7240	0.8188	0.7073
Inflow	0.7760	0.6812	0.7927
Net flow	−0.0521	0.1375	−0.0855

Due to the shortage of provided data with respect to sub-criteria in the case study, the final weights of the sub-criteria, which is provided in the existing research, will be considered for evaluating the performance of potential suppliers (S_n, where n = 1, 2, …7) using the extended grey PROMETHEE II methodology. Table 19 demonstrates the sub-criteria and the associated weights. The grey decision matrix for suppliers' performance evaluations over the sub-criteria is demonstrated in Table 20.

By utilizing alternatives evaluation procedures of the proposed methodology and the sub-criteria weights in Table 19, the overall preferences between alternatives are reflected in Table 21. Accordingly, the global preferences among alternatives are demonstrated in Table 22, in which $\mathbf{S_1}$ is the most preferred supplier, and the ranking order of the potential suppliers is $\mathbf{S_1 \succ S_4 \succ S_2 \succ S_3 \succ S_7 \succ S_6 \succ S_5}$, which is similar to the ranking order of the exiting methodology.

Although both methodologies provide the same conclusion in this example, yet grey systems theory is considered more suitable for decision problems with a relatively small amount of data and poor information, which cannot be described by a probability distribution; as it offers simpler procedure, which does not require a robust membership function as in fuzzy theory (Memon et al., 2015).

Table 19
Sub-criteria weights.

Sub-criteria	Weights
Carbon governance (sc_1)	0.229
Carbon policy (sc_2)	0.188
Carbon reduction targets (sc_3)	0.174
GHG verification (ISO 14064) (sc_4)	0.003
Risk assessment for low carbon requirement (sc_5)	0.125
Training-related carbon management (sc_6)	0.073
Availability and use of low carbon technologies (sc_7)	0.015
Energy efficiency (sc_8)	0.014
Measures of carbon reduction (sc_9)	0.018
Availability of a carbon supplier selection system (sc_{10})	0.070
Requirement of low carbon purchasing (sc_{11})	0.052
Capability of low carbon design of product (sc_{12})	0.029
Inventory of carbon footprint of product (sc_{13})	0.009

6. Conclusion

Although different methods are used to handle uncertainty-related aspects (i.e., subjective and objective uncertainty), grey systems theory is preferred when it comes to decision problems with a relatively small amount of data and poor information, which cannot be described by a probability distribution. Different researchers proposed grey systems theory to deal with uncertainty in decision problems. However, a number of shortcomings has been observed in the existing approaches with respect to the influence of the interdependencies among the evaluation criteria of different clusters on the evaluation process. As a result, a new hybrid grey-based MCDA approach is developed to better handle complex decision problems that are subject to different types of interrelated criteria (i.e., evaluation criteria with different nature, different scales, and different values) and different types of uncertainty-related aspects. The intended purpose of integrating the grey systems theory with a distinctive combinations of MCDA approaches (i.e., ANP

Table 17
Grey paired comparison matrix between dimensions.

Main criteria	C1	C2	C3	C4
C1	(Kurka and Blackwood, 2013)	(Kurka and Blackwood, 2013; Li et al., 2007)	(Li et al., 2007; Li et al., 2012)	(Brans and De Smet, 2016a; Li and Yuan, 2017)
C2	(Li and Yuan, 2017; Liu and Lin, 2006)	(Kurka and Blackwood, 2013)	(Kurka and Blackwood, 2013; Li et al., 2007)	(Li and Yuan, 2017; Liu and Lin, 2006)
C3	[0.2,0.333]	[0.333,1]	(Kurka and Blackwood, 2013)	(Kuang et al., 2015; Liu and Lin, 2006)
C4	[0.125,0.167]	[0.167,0.25]	[0.25,0.5]	(Kurka and Blackwood, 2013)

Table 18
Criteria weights of the proposed methodology and the existing methodology.

Criteria	Proposed methodology	Fuzzy ANP and fuzzy TOPSIS (Kuo et al., 2015)
Organizational management (c_1)	0.413	0.494
Process management (c_2)	0.405	0.272
Procurement management (c_3)	0.134	0.141
R&D management (c_4)	0.047	0.099

Table 20
Grey decision matrix of supplier selection.

Sub criteria	S_1	S_2	S_3	S_4	S_5	S_6	S_7
sc_1	[6.35, 8.36]	[4.98, 7.03]	[4.70, 6.87]	[6.20, 8.25]	[3.56, 5.72]	[4.09, 6.35]	[3.56, 8.36]
sc_2	[6.73, 8.74]	[5.72, 7.79]	[5.10, 7.13]	[5.86, 7.89]	[3.56, 5.72]	[3.77, 5.86]	[4.44, 6.57]
sc_3	[5.10, 7.28]	[4.70, 6.87]	[4.98, 7.03]	[5.86, 7.89]	[3.56, 5.72]	[3.77, 5.86]	[5.72, 7.79]
sc_4	[6.20, 8.25]	[6.20, 8.25]	[5.86, 7.89]	[6.73, 8.74]	[4.98, 7.03]	[4.7, 6.73]	[5.27, 7.36]
sc_5	[6.00, 8.00]	[4.33, 6.35]	[4.09, 6.20]	[5.10, 7.13]	[3.28, 5.40]	[2.49, 4.59]	[3.10, 5.27]
sc_6	[4.09, 6.20]	[4.33, 6.49]	[3.28, 5.40]	[4.70, 6.87]	[3.28, 5.40]	[2.49, 4.59]	[3.10, 5.27]
sc_7	[6.00, 8.00]	[5.40, 7.45]	[4.44, 6.57]	[5.53, 7.55]	[3.56, 5.72]	[4.09, 6.20]	[4.70, 6.73]
sc_8	[6.20, 8.25]	[4.70, 6.73]	[6.00, 8.00]	[5.40, 7.45]	[3.28, 5.40]	[3.28, 4.44]	[4.33, 6.49]
sc_9	[6.20, 8.25]	[5.10, 7.13]	[5.53, 7.55]	[5.86, 7.89]	[4.33, 6.35]	[4.09, 6.20]	[5.53, 7.55]
sc_{10}	[4.09, 6.20]	[3.48, 5.53]	[3.10, 5.27]	[3.56, 5.72]	[2.00, 3.28]	[2.29, 3.56]	[2.63, 4.70]
sc_{11}	[4.33, 6.35]	[4.98, 7.03]	[3.48, 5.53]	[4.70, 6.73]	[3.03, 5.10]	[3.48, 5.53]	[4.00, 4.00]
sc_{12}	[5.10, 7.13]	[4.70, 6.87]	[5.53, 7.55]	[5.56, 7.89]	[3.56, 5.72]	[3.03, 5.10]	[5.53, 7.55]
sc_{13}	[6.57, 8.63]	[4.98, 7.18]	[5.53, 7.55]	[6.35, 8.36]	[3.56, 5.72]	[4.09, 6.20]	[5.10, 7.13]

Table 21
Relative preference matrix.

Alternatives	S_1	S_2	S_3	S_4	S_5	S_6	S_7
S_1	0.500	0.704	0.774	0.541	0.936	0.943	0.808
S_2	0.295	0.500	0.571	0.337	0.876	0.840	0.614
S_3	0.225	0.428	0.500	0.265	0.802	0.760	0.540
S_4	0.458	0.662	0.734	0.500	0.978	0.985	0.777
S_5	0.063	0.123	0.197	0.021	0.500	0.470	0.240
S_6	0.056	0.159	0.239	0.014	0.529	0.500	0.278
S_7	0.191	0.385	0.459	0.222	0.759	0.721	0.500

Table 22
Global preference matrix - outranking flows computations.

Outranking flows	Alternatives						
	S_1	S_2	S_3	S_4	S_5	S_6	S_7
Outflow	0.868	0.672	0.587	0.849	0.269	0.296	0.540
Inflow	0.298	0.494	0.579	0.317	0.897	0.870	0.626
Net flow	0.569	0.179	0.008	0.532	−0.628	−0.574	−0.086

and PROMETHEE II) is to optimize the evaluation space in such a complex system under uncertainty by utilizing the emergent strengths of the integrated approach: the mathematical ability and the associated simplicity of PROMETHEE II in providing a complete ranking of feasible alternatives over different types of criteria (i.e., quantitative and qualitative); the superiority of ANP in establishing priorities among evaluation criteria within complex systems; and the distinctive ability of the grey systems theory in handling problems with a relatively small amount of data and poor information, which cannot be described by a probability distribution.

The proposed methodology is capable of establishing priorities among complex interrelated criteria and account for the uncertainty of subjective judgments by combining linguistic expressions, grey systems theory, and principles of ANP. Furthermore, it extends the PROMETHEE II methodology to define optimal ranking among potential alternatives in such a complicated decision problem using a combination of linguistic expressions to articulate human judgments over subjective evaluations; grey systems theory to map linguistic expressions, to deal with subjective and objective uncertainty, and to normalize performance measures over different types of criteria; and the proposed G-ANP approach to establish relative preferences among alternatives over interrelated criteria. Future work is needed to extend the applicability of the proposed methodology for more complicated cases of MCDA. In particular, MCDA with multi-participants where consensus cannot be reached.

The viability and the effectiveness of the proposed methodology have been proven through an illustrative case study, in which the process of strategic decision making with respect to innovation activities was the target to improve.

Finally, to validate the proposed methodology, an existing case study has been used, and a comparative analysis with an existing hybrid approach (i.e., fuzzy ANP and fuzzy TOPSIS) has been established.

Acknowledgement

This work was supported by the Saudi Ministry of Education and in part by Engage Grants Program from the Natural Sciences and Engineering Research Council of Canada [grant number 469739-14].

Appendix A

A.1. Grey systems theory

In grey systems theory, systems are distinguished based on the availability of information, in which a system with fully known information is called a white system, a system with partially known information is called a grey system, and a system with unknown information is called a black system. The term "system" in the given theory indicates the importance of seeing the whole picture (i.e., the structure and functions of the object of concern), in which substantial connections should be analyzed. The connections would be found within and between the various elements of the object of concern; and between the given system, relevant factors, and its environment. Grey numbers are the primitive element for grey systems (Liu et al., 2012;Liu et al., 2015; Liu and Lin, 2006).

A grey number is employed to indicate a number that its exact value is unknown; yet a range (e.g., interval or a general set of numbers) in which the value lies is known. A grey number is denoted by the symbol ⊗. However, there are several classes of grey numbers, which can be differentiated as follows (Liu et al., 2015; Liu and Lin, 2006).

Definition A.1. If a grey number has a clear lower bound $\left(\underline{a}\right)$, then the grey number is denoted by

$$\otimes \in [\underline{a}, \infty\Big) \text{ or } \otimes\Big(\underline{a}\Big)$$

Definition A.2. If a grey number has a clear upper bound $(\bar{a})$, then the grey number is written as

$$\otimes \in (-\infty, \bar{a}] \text{ or } \otimes(\bar{a})$$

Definition A.3. If a grey number has both bounds clear (i.e., a lower bound is $\left(\underline{a}\right)$ and an upper bound $(\bar{a})$), then it is called interval grey number, and it is written as

$$\otimes \in [\underline{a}, \bar{a}]$$

Definition A.4. If a grey number takes its value from a finite set or a countable number of potential values, then it is known as a discrete grey number.

Definition A.5. If a grey number can take any value that covers an interval, then it is known as a continuous grey number.

Definition A.6. If a grey number has neither a lower bound nor an upper bound clear, then it is a black number, which is denoted by

$$\otimes \in (-\infty, \infty)$$

Definition A.7. If a grey number has both bounds equal, then it becomes a white number, where

$$\otimes \in [\underline{a}, \bar{a}], \text{ and } \underline{a} = \bar{a}$$

Definition A.8. If a grey number can be represented by a white number; which can be obtained either by known information, experience, or other means; then it is called a non-essential grey number. In contrast, the essential grey number is impossible or temporarily not possible to be represented by a white number (e.g., the total energy in the universe).

References

Andreopoulou, Z., Koliouska, C., Galariotis, E., Zopounidis, C., 2017. Renewable energy sources: using PROMETHEE II for ranking websites to support market opportunities. Technol. Forecast. Soc. Change. https://doi.org/10.1016/J.TECHFORE.2017.06.007.

Bai, C., Sarkis, J., Wei, X., Koh, L., 2012. Evaluating ecological sustainable performance measures for supply chain management. Supply Chain Manag. An Int. J. 17, 78–92. https://doi.org/10.1108/13598541211212221.

Baker, W.E., Grinstein, A., Harmancioglu, N., 2016. Whose innovation performance benefits more from external networks: entrepreneurial or conservative firms? J. Prod. Innov. Manag. 33, 104–120. https://doi.org/10.1111/jpim.12263.

Behzadian, M., Otaghsara, S., Yazdani, M., Ignatius, J., 2012. A state-of the-art survey of TOPSIS applications. Expert Syst. Appl. 39, 13051–13069. https://doi.org/10.1016/j.eswa.2012.05.056.

Belton, V., Stewart, T., 2002. Multiple Criteria Decision Analysis: An Integrated Approach. Springer Science & Business Media.

Ben Amor, S., Guitouni, A., Martel, J.-M., 2015. A synthesis of information imperfection representations for decision aid. In: INFOR Inf. Syst. Oper. Res. https://doi.org/10.3138/infor.53.2.68.

Brans, J.P., De Smet, Y., 2016a. PROMETHEE methods. In: Mult. Criteria Decis. Anal. Springer, New York, pp. 187–219.

Brans, J.-P., De Smet, Y., 2016b. PROMETHEE methods. In: Mult. Criteria Decis. Anal. Springer, New York, pp. 187–219. https://doi.org/10.1007/978-1-4939-3094-4_6.

Broekhuizen, H., Groothuis-Oudshoorn, C.G.M., Til, J.A., Hummel, J.M., IJzerman, M.J., 2015. A review and classification of approaches for dealing with uncertainty in multi-criteria decision analysis for healthcare decisions. Pharmacoeconomics 33, 445–455. https://doi.org/10.1007/s40273-014-0251-x.

Bronzini, R., Piselli, P., 2016. The impact of R&D subsidies on firm innovation. Res. Policy 45, 442–457. https://doi.org/10.1016/j.respol.2015.10.008.

Celik, E., Erdogan, M., Gumus, A.T., 2016. An extended fuzzy TOPSIS–GRA method based on different separation measures for green logistics service provider selection. Int. J. Environ. Sci. Technol. 13, 1377–1392. https://doi.org/10.1007/s13762-016-0977-4.

Dou, Y., Zhu, Q., Sarkis, J., 2014. Evaluating green supplier development programs with a grey-analytical network process-based methodology. Eur. J. Oper. Res. 233, 420–431. https://doi.org/10.1016/j.ejor.2013.03.004.

Durbach, I.N., Stewart, T.J., 2012. Modeling uncertainty in multi-criteria decision analysis. Eur. J. Oper. Res. 223, 1–14. https://doi.org/10.1016/j.ejor.2012.04.038.

Dyer, J.S., 2005. MAUT - multiattribute utility theory. In: Mult. Criteria Decis. Anal. State Art Surv. Springer New York, New York, NY, pp. 265–292. https://doi.org/10.1007/0-387-23081-5_7.

Ertay, T., Büyüközkan, G., Kahraman, C., Ruan, D., 2005. Quality function deployment implementation based on analytic network process with linguistic data: an application in automotive industry. J. Intell. Fuzzy Syst. 16, 221–232.

Gebauer, H., Worch, H., Truffer, B., 2012. Absorptive capacity, learning processes and combinative capabilities as determinants of strategic innovation. Eur. Manag. J. 30, 57–73. https://doi.org/10.1016/j.emj.2011.10.004.

Görener, A., 2012. Comparing AHP and ANP: an application of strategic decisions making in a manufacturing company. Int. J. Bus. Soc. Sci. 3, 194–208.

Govindan, K., Jepsen, M.B., 2016. ELECTRE: a comprehensive literature review on methodologies and applications. Eur. J. Oper. Res. 250, 1–29. https://doi.org/10.1016/j.ejor.2015.07.019.

Greco, S., Ehrgott, M., Figueira, J.R., 2016. Multiple Criteria Decision Analysis. Springer-Verlag, New York.

Hosseini, L., Tavakkoli-Moghaddam, R., Vahdani, B., Mousavi, S.M., Kia, R., 2013. Using the analytical network process to select the best strategy for reducing risks in a supply chain. J. Eng. 2013. https://doi.org/10.1155/2013/375628.

Ishizaka, A., Labib, A., 2011. Review of the main developments in the analytic hierarchy process. Expert Syst. Appl. https://doi.org/10.1016/j.eswa.2011.04.143.

Jaini, N., Utyuzhnikov, S., 2017. Trade-off ranking method for multi-criteria decision analysis. J. Multi-Criteria Decis. Anal. 24, e1600. https://doi.org/10.1002/mcda.1600.

Jianbo, X., Suihuai, Y., Wen, F., 2016. Evaluation of man-machine system for workover rigs based on grey analytical hierarchy process. In: 2016 Eighth Int. Conf. Meas. Technol. Mechatronics Autom. IEEE, pp. 278–281. https://doi.org/10.1109/ICMTMA.2016.75.

Ju-long, D., 1982. Control problems of grey systems. Syst. Control Lett. 1, 288–294. https://doi.org/10.1016/S0167-6911(82)80025-X.

Kilic, H.S., Zaim, S., Delen, D., 2015. Selecting "the best" ERP system for SMEs using a combination of ANP and PROMETHEE methods. Expert Syst. Appl. 42, 2343–2352. https://doi.org/10.1016/j.eswa.2014.10.034.

Kuang, H., Kilgour, D.M., Hipel, K.W., 2015. Grey-based PROMETHEE II with application to evaluation of source water protection strategies. Inf. Sci. (Ny) 294, 376–389. https://doi.org/10.1016/j.ins.2014.09.035.

Kuo, R.J., Hsu, C.W., Chen, Y.L., 2015. Integration of fuzzy ANP and fuzzy TOPSIS for evaluating carbon performance of suppliers. Int. J. Environ. Sci. Technol. 12, 3863–3876. https://doi.org/10.1007/s13762-015-0819-9.

Kurka, T., Blackwood, D., 2013. Selection of MCA methods to support decision making for renewable energy developments. Renew. Sust. Energ. Rev. 27, 225–233. https://doi.org/10.1016/j.rser.2013.07.001.

Lahdelma, R., Hokkanen, J., Salminen, P., 1998. SMAA - stochastic multiobjective acceptability analysis. Eur. J. Oper. Res. https://doi.org/10.1016/S0377-2217(97)00163-X.

Li, C., Yuan, J., 2017. A new multi-attribute decision-making method with three-parameter interval grey linguistic variable. Int. J. Fuzzy Syst. 19, 292–300. https://doi.org/10.1007/s40815-016-0241-6.

Li, D.-C., Chang, C.-J., Chen, C.-C., Chen, W.-C., 2012. Forecasting short-term electricity consumption using the adaptive grey-based approach—an Asian case. Omega 40, 767–773. https://doi.org/10.1016/j.omega.2011.07.007.

Li, G., Yamaguchi, D., Nagai, M., 2007. A grey-based decision-making approach to the supplier selection problem. Math. Comput. Model. 46, 573–581. https://doi.org/10.1016/j.mcm.2006.11.021.

Liu, S., Lin, Y., 2006. Grey Information: Theory and Practical Applications. Springer-Verlag Londonhttps://doi.org/10.1007/1-84628-342-6.

Liu, S., Forrest, J., Yang, Y., 2012. A brief introduction to grey systems theory. Grey Syst. Theory Appl. 2, 89–104. https://doi.org/10.1108/20439371211260081.

Liu, S., Forrest, J.Y.L., Yang, Y., 2015. Grey system: thinking, methods, and models with applications. In: Zhou, M., Li, H.-X., Weijnen, M. (Eds.), Contemp. Issues Syst. Sci. Eng. JohnWiley & Sons, Inc, Hoboken, NJ, USA, pp. 153–224. https://doi.org/10.1002/9781119036821.ch4.

Maity, S.R., Chakraborty, S., 2015. Tool steel material selection using PROMETHEE II method. Int. J. Adv. Manuf. Technol. 78, 1537–1547. https://doi.org/10.1007/s00170-014-6760-0.

Malczewski, J., Rinner, C., 2015. Multicriteria Decision Analysis in Geographic Information Science. Springer-Verlag, Berlin Heidelberg, New York, NY, USA. https://doi.org/10.1007/978-3-540-74757-4.

Martín-de Castro, G.M., 2015. Knowledge management and innovation in knowledge-based and high-tech industrial markets: the role of openness and absorptive capacity. Ind. Mark. Manag. 47, 143–146. https://doi.org/10.1016/j.indmarman.2015.02.032.

Memon, M.S., Lee, Y.H., Mari, S.I., 2015. A combined grey system theory and uncertainty theory-based approach for supplier selection in supply chain management. In: Towar. Sustain. Oper. Supply Chain Logist. Syst. Springer International Publishing, pp. 461–473. https://doi.org/10.1007/978-3-319-19006-8.

Mendi, P., Costamagna, R., 2017. Managing innovation under competitive pressure from informal producers. Technol. Forecast. Soc. Chang. 114, 192–202. https://doi.org/10.1016/j.techfore.2016.08.013.

Merigó, J.M., Palacios-Marqués, D., Zeng, S., 2016. Subjective and objective information in linguistic multi-criteria group decision making. Eur. J. Oper. Res. 248, 522–531. https://doi.org/10.1016/j.ejor.2015.06.063.

Moos, B., Beimborn, D., Wagner, H.T., Weitzel, T., 2013. The role of knowledge management systems for innovation: an absorptive capacity perspective. Int. J. Innov. Manag. 17. https://doi.org/10.1142/S1363919613500199.

Moretti, S., Öztürk, M., Tsoukiàs, A., 2016. Preference modelling. In: Greco, S., Ehrgott, M., Figueira, J.R. (Eds.), Mult. Criteria Decis. Anal. State Art Surv. Springer New York, New York, NY, pp. 43–95. https://doi.org/10.1007/978-1-4939-3094-4_3.

Mu, E., Pereyra-Rojas, M., 2017. Understanding the analytic hierarchy process. In: Pract. Decis. Mak. Springer, Cham, pp. 7–22. https://doi.org/10.1007/978-3-319-33861-3_2.

Nguyen, H.-T., Dawal, S.Z.M., Nukman, Y., Aoyama, H., 2014. A hybrid approach for fuzzy multi-attribute decision making in machine tool selection with consideration of the interactions of attributes. Expert Syst. Appl. 41, 3078–3090. https://doi.org/10.1016/j.eswa.2013.10.039.

Onetti, A., Zucchella, A., Jones, M.V., McDougall-Covin, P.P., 2012. Internationalization, innovation and entrepreneurship: business models for new technology-based firms. J. Manag. Gov. 16, 337–368. https://doi.org/10.1007/s10997-010-9154-1.

Reid, S.E., De Brentani, U., 2015. Building a measurement model for market visioning competence and its proposed antecedents: organizational encouragement of

divergent thinking, divergent thinking attitudes, and ideational behavior. J. Prod. Innov. Manag. 32, 243–262. https://doi.org/10.1111/jpim.12232.
Saaty, R., 2013. Validation of the effectiveness of inner dependence in an ANP model. 12th Int. Symp. Anal. Hierarchy Process.
Saaty, T.L., 1988. What is the analytic hierarchy process? Math. Model. Decis. Support. 109–121. https://doi.org/10.1016/0377-2217(90)90057-I.
Saaty, T.L., 1996. The Analytic Network Process: Decision Making with Dependence and Feedback. RWS Publications, Pittsburgh, PA.
Saeidi, S.P., Sofian, S., Saeidi, P., Saeidi, S.P.S., Saaeidi, S.A., 2015. How does corporate social responsibility contribute to firm financial performance? The mediating role of competitive advantage, reputation, and customer satisfaction. J. Bus. Res. 68, 341–350. https://doi.org/10.1016/j.jbusres.2014.06.024.
Sakthivel, G., Ilangkumaran, M., Nagarajan, G., Priyadharshini, V., Kumar, S.D., Kumar, S.S., Suresh, K.S., Selvan, G.T., 2014. Multi-criteria decision modelling approach for biodiesel blend selection based on GRA – TOPSIS analysis. Int. J. Ambient Energy. 35. https://doi.org/10.1080/01430750.2013.789984.
Schweizer, L., 2015. Integrating multiple case studies with a merger and acquisition example. In: Palgrave Handb. Res. Des. Bus. Manag. Palgrave Macmillan US, New York, pp. 319–339. https://doi.org/10.1057/9781137484956.
Segura, M., Maroto, C., 2017. A multiple criteria supplier segmentation using outranking and value function methods. Expert Syst. Appl. 69, 87–100. https://doi.org/10.1016/j.eswa.2016.10.031.
Sen, D.K., Datta, S., Patel, S.K., Mahapatra, S.S., 2015. Multi-criteria decision making towards selection of industrial robot: exploration of PROMETHEE II method. Benchmarking An Int. J. 22, 465–487. https://doi.org/10.1108/BIJ-05-2014-0046.
Shi, Y., Liu, H., Sun, J., 2013. The cloud model based on grey system theory and application on effectiveness evaluation. In: Huang, D.-S., Bevilacqua, V., Figueroa, J.C., Premaratne, P. (Eds.), Intell. Comput. Theor. 9th Int. Conf. ICIC 2013, Nanning, China, July 28–31, 2013. Proc. Springer, Berlin, Heidelberg, pp. 31–38. https://doi.org/10.1007/978-3-642-39479-9_4.
Stefanopoulos, K., Yang, H., Gemitzi, A., Tsagarakis, K.P., 2014. Application of the multi-attribute value theory for engaging stakeholders in groundwater protection in the Vosvozis catchment in Greece. Sci. Total Environ. 470–471, 26–33. https://doi.org/10.1016/j.scitotenv.2013.09.008.
Thakur, V., Ramesh, A., 2017. Healthcare waste disposal strategy selection using grey-AHP approach. Benchmarking An Int. J. 24, 735–749. https://doi.org/10.1108/BIJ-09-2016-0138.
Triantaphyllou, E., 2000. Multi-criteria decision making methods. In: Multi-Criteria Decis. Mak. Methods a Comp. Study. Springer US, Boston, MA, pp. 5–21. https://doi.org/10.1007/978-1-4757-3157-6_2.
Tuzkaya, U.R., Yolver, E., 2015. R&D project selection by integrated grey analytic network process and grey relational analysis: an implementation for home appliances company. J. Aeronaut. Sp. Technol. 8, 35–41.
Tzokas, N., Ah, Y., Akbar, H., Al-dajani, H., 2015. Absorptive capacity and performance: the role of customer relationship and technological capabilities in high-tech SMEs. Ind. Mark. Manag. 47, 134–142. https://doi.org/10.1016/j.indmarman.2015.02.033.
Wątróbski, J., Jankowski, J., 2016. Guideline for MCDA method selection in production management area. In: New Front. Inf. Prod. Syst. Model. Anal. Springer International Publishing, pp. 119–138.
Xu, Z.S., Da, Q.L., 2002. The uncertain OWA operator. Int. J. Intell. Syst. 17, 569–575. https://doi.org/10.1002/int.10038.
Zadeh, L.A., 1965. Fuzzy sets. Inf. Control. 8, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.
Zaim, S., Sevkli, M., Camgöz-akdag, H., Demirel, O.F., Yayla, A.Y., Delen, D., 2014. Expert systems with applications use of ANP weighted crisp and fuzzy QFD for product development. Expert Syst. Appl. 41, 4464–4474. https://doi.org/10.1016/j.eswa.2014.01.008.
Zhang, W., Zhang, X., Fu, X., Liu, Y., 2009. A grey analytic network process (ANP) model to identify storm tide risk. In: IEEE Int. Conf. Grey Syst. Intell. Serv. IEEE, pp. 582–587. https://doi.org/10.1109/GSIS.2009.5408247.

Hesham F. Maghrabie is an experienced operations Manager with a demonstrated history of working in the transportation/trucking/aviation industry. Skilled in Strategic Planning & Management, Operation Research, Risk Assessment, Quality Management, Industrial Engineering, Lean Enterprise, Continuous Improvement, Decision Making, Product Development, and Knowledge Management. Mr. Maghrabie holds a bachelor's in industrial engineering from King Abdul-Aziz University, a master's in quality systems Engineering from Concordia University, and a PhD in information systems engineering from Concordia University. His current research interests include multi-criteria decision analysis under uncertainty, decision support systems, complex system, Grey systems theory, Fuzzy logic, and policy design.

Yvan Beauregard is a professor in the Department of Mechanical Engineering at École de technologie supérieure. Mr. Beauregard holds a bachelor's in industrial engineering from École Polytechnique de Montréal, a master's in administration from McGill University, and a PhD in Mechanical Engineering from Concordia University. He has more than thirty years of industrial experience at Pratt & Whitney and IBM Canada. His research interests include operations and risk management, as well as product development performance improvement.

Andrea Schiffauerova is an associate professor at Concordia Institute for Information Systems Engineering. Mrs. Schiffauerova holds a bachelor in Economic engineering from Silesian University, Czech Republic, and a master and a PhD in Industrial Engineering from École Polytechnique de Montréal, Canada. Her area of expertise encompasses management of knowledge, innovation and technology, new product development and quality management. She is very interested in designing effective and sustainable innovation systems. Her particular area of interest lies in the study of innovation networks and knowledge diffusion.