Updated discussions on ‘Hybrid multiple criteria decision-making methods: a review of applications for sustainability issues’

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ABSTRACT
A recent review discussed a variety of hybrid multiple criteria decision-making (HMCDM) methods on the subject of sustainability issues. Some soft computing techniques, such as the fuzzy set, have contributed significantly to HMCDM studies, emulating the imprecise or uncertain judgments of experts/decision makers in a complex environment. Nevertheless, a new rising trend in HMCDM, known as multiple rule-based decision-making (MRDM), which has the advantage of revealing understandable knowledge for supporting systematic improvements based on influential network relation maps (INRM), was not discussed in the review. This study therefore attempts to extend the review by introducing recent developments and the associated work on MRDM for solving practical problems, updating the discussion.

1. Introduction

In a recent review (Zavadskas, Govindan, Antucheviciene, & Turskis, 2016), the necessity for and reasoning, why multiple methods or techniques are required, to be combined or integrated to form hybrid multiple criteria decision-making (HMCDM) models for solving various real-world problems, were broadly discussed. One of the key reasons is that the complexity of obstacles confronted by decision makers (DMs) or practitioners has grown dramatically in recent years. A single MCDM method might not be sufficient to tackle an issue with interrelated criteria and identify the relative importance of each involved criterion (Liou & Tzeng, 2012; Shen, Yan, & Tzeng, 2014; Tzeng & Huang, 2011; Zavadskas et al., 2016) simultaneously. A rising trend of adopting HMCDM for solving practical problems was discussed in another review by Zavadskas and colleagues (Zavadskas, Antucheviciene, Turskis, & Adeli, 2016), co-written with Hojjat Adeli, one of the most cited scientists in this field.
Conventional MCDM research comprises two major fields: multiple attribute decision-making (MADM) and multiple objective decision-making (MODM), as suggested by previous work (Hwang & Yoon, 1981; Liou & Tzeng, 2012; Zavadskas, Turskis, & Kildienė, 2014; Zavadskas et al., 2016; Zeleny, 1982). Both MADM and MODM (or HMCDM) have enticed numerous researchers to employ suitable methods for solving problems in fields like economics (Zavadskas & Turskis, 2011), marketing (Kumar, Rahman, & Kazmi, 2013), e-learning (Zare et al., 2016), finance (Spronk, Steuer, & Zopounidis, 2016; Zopounidis, Galariotis, Doumpos, Sarri, & Andriosopoulos, 2015), construction site selection (Turskis, Zavadskas, Antucheviciene, & Kosareva, 2015), engineering (Zavadskas et al., 2016), supplier evaluation and selection (Keshavarz Ghorabaee, Amiri, Zavadskas, & Antucheviciene, 2017), supply-chain management (Ansari & Kant, 2017; Soheilirad et al., 2017) and green energy (Kumar et al., 2017). Although those studies have shown various MCDM or HMCDM approaches to decision support, three crucial issues deserve more attention.

First, how to form an adequate MCDM model by selecting the minimum but critical criteria (attributes) is overlooked. Most MCDM studies use the three commonly observed approaches to constructing their models: (1) literature review; (2) the Delphi method (Adler & Ziglio, 1996; Linstone & Turoff, 1975); and (3) statistical analysis (e.g., principal component analysis). The literature review approach stands on the grounds of previous research, and might reproduce similar models for different cases. The Delphi (Adler & Ziglio, 1996) or fuzzy Delphi methods (Chang, Tsujimura, Gen, & Tozawa, 1995) rely on seasoned experts’ opinions. Nevertheless, when regarding a particular problem, even qualified experts might have diverse opinions; once the involved dimensionalities are large, the consistency of their judgments may be a concern. The statistical approach might overcome the issue of high dimensionalities by analysing historical data; nevertheless, the statistical method is constrained by some unrealistic assumptions (Berk & Adler, 2003) on modelling social problems. For example, the examined data set has to follow a particular probabilistic distribution. Moreover, variables (or attributes) are usually presumed to be independent, which might not apply to those MCDM problems that have an interdependent relationship among the criteria in practical applications (Zavadskas, STEVIĆ, Tanackov, & Prentkovskis, 2018).

Second, the previous review (Zavadskas et al., 2016) categorised HMCDM research as classical and non-classical, where only the combinations of the fuzzy set technique (Zadeh, 1965) and MCDM methods (i.e., fuzzy MCDM or FMCDM) are classified as non-classical. FMCDM has the advantages of dealing with imprecise judgments and reasoning (Keshavarz Ghorabaee et al., 2017; Liu & Liao, 2016; Mardani, Jusoh, & Zavadskas, 2015), which facilitates the understanding of a complex problem in a more natural way (such as using linguistic terms or degrees of membership), to interact with DMs (Hu & Tzeng, 2017). Owing to the prominent role of fuzzy set theory in dealing with uncertain information to support decisions, the journal Technological and Economic Development of Economy organised a special issue in 2015 to commemorate the 50th anniversary of the debut of the theory. An editorial introduction by a renowned scholar from the Granada University in Spain (Herrera-Viedma, 2015) systematically discussed fuzzy sets and fuzzy logic in multi-criteria decision making. In the following year, the journal provided another special issue on the applications of intuitionistic fuzzy set (IFS) theory (Atanassov, 1986) in economics, technology and management. The IFS technique extends the degree of classical fuzzy membership into membership, non-membership and hesitation degrees, which provides more flexibility for researchers modelling uncertainty. The various advantages or
new developments of IFS regarding uncertain knowledge representation were discussed in this special issue (Liu, 2016).

As also highlighted by Govindan, Diabat, and Shankar (2015) and Zavadskas et al. (2016), the integration of fuzzy logic (or fuzzy inference) with MCDM has gained growing attention. According to discussions of fuzzy set theory (FST) applied to supplier selection (Simić, Kovačević, Srircević, & Simić, 2016), there are two main streams: the fuzzy inference system (FIS; Amindoust, Ahmed, Saghafinia, & Bahreininejad, 2012) and the adaptive-network-based fuzzy inference system (ANFIS; Jang, 1993). ANFIS also has the capability of machine learning to adjust the fuzzy parameters of a FIS system/model by minimising the overall fitting errors. Again, an issue would be generating adequate and essential rules – a knowledge base (Magdalena, 2015) – for FIS or ANFIS models, which is similar to the first point on selecting the minimal criteria to form an MCDM/HMCDM model.

Third, on the subject of sustainability, DMs often require guidance on how to overcome a predicament or improve the alternatives on hand (Shen, 2017). To pursue sustainability, even without having to consider stable growth in profits or superior results for green energy policy, business or government have only limited resources when making decisions (e.g., improving financial performance (Shen et al., 2014) or selecting the location of a technology park (Lin & Tzeng, 2009) for sustainable industrial growth). In practice, a systematic guidance, considering the resource constraints, is required to fulfil this mission (Liou & Tzeng, 2012; Peng & Tzeng, 2013; Shen, Hu, & Tzeng, 2017).

The three issues mentioned above were not highlighted in previous reviews (Zavadskas & Turskis, 2011; Zavadskas et al., 2016, 2016; Zavadskas, Antucheviciene, Vilutiene, & Adeli, 2017), and one of the plausible approaches to resolving these issues would be multiple rule-based decision-making (MRDM), an emerging but promising field in HMCDM (Tzeng & Shen, 2017). Although there are several existing approaches that may support decision-making by using decision rules (e.g., expert systems (Liao, 2005), case-based reasoning (Kolodner, 1992) and decision trees (Safavian & Landgrebe, 1991)), the MRDM in HMCDM discussed here is mainly based on the theoretical foundation of the rough set theory (RST) (Pawlak, 1982, 2002; Pawlak & Skowron, 2007; Pawlak & Słowiński, 1994).

The ensuing dominance-based rough set approach (DRSA) (Greco, Matarazzo, & Słowiński, 1997, 1999, 2001, 2002, 2005, 2016), developed by the eminent Laboratory of Intelligent Decision Support Systems (IDSS) research group from Poznań University of Technology, led by the influential Polish scholar R. Słowiński, has contributed significantly to rule-based decision-making. The contributions from the IDSS group inspired many aspects of the studies in MRDM described below. The fundamentals of DRSA and MRDM will be briefly introduced in the following sections.

2. Theoretical background

The essential foundations of MRDM discussed here are based on RST (Pawlak, 1982), which can be categorised into fields like applied mathematics, soft computing and machine learning. RST deals with the inconsistencies among the objects of a data set with multiple attributes, and those attributes are expected to be discretised before approximation. In RST these discretised values can be termed ‘granules of knowledge.’ Some researchers have attempted to extend the capability of rough set theory for dealing with continuous numeric attributes; this idea leads to the emergence of fuzzy-rough set theory. In the latest review
regarding this theory (Mardani et al., 2017), 132 articles from the Web of Science from 2010 to 2016 were selected and indexed. The papers were categorised into six application areas (i.e., information systems, decision-making, approximation operators, feature and attribute selection, fuzzy set theories and other areas of application). Nine articles (8.33%) were classified in the decision-making area. It is interesting to find that the previous article (Zavadskas et al., 2016) classified MCDM research into discrete MADM and continuous MODM methods, whereas the fuzzy-rough set theory seems to blur this boundary.

Although both FST and RST were devised to model impreciseness, RST is more information-oriented, which is suitable for resolving data-centric problems by considering the indiscernibility relations among alternatives (also termed as objects or observations) for different attributes (Dubois & Prade, 1987; Pawlak & Skowron, 2007; Stević, Pamučar, Kazimieras Zavadskas, Ćirović, & Prentkovskis, 2017; Tzeng & Shen, 2017). RST has the advantage of generating or inducing understandable rules during the learning phase, which is beneficial for DMs to discern the ambiguous or hidden patterns (or logic) of a complicated problem. The classical RST does not, however, consider the preferential characteristic of attributes, which is often required to tackle MCDM problems. Consequently, the ‘dominance relation’ has been broadly discussed in previous work (Greco et al., 1997, 1999, 2001, 2002, 2005, 2016), termed the decision rule approach or DRSA related/extended approach, for resolving MCDM problems.

### 2.1. Dominance-based rough set approach (DRSA) for decision aids

The adoption of DRSA (Greco et al., 2005, 2016) often begins by organising data as an information table, in the form of a four-tuple information system (IS), where the attributes (called criteria in MCDM) and alternatives are arranged in rows and columns, respectively. The DRSA IS = (U, Q, V, f), where U is a finite state of the universe and Q = \{q_1, q_2, ..., q_p\} is a finite set of p attributes. For making decision aids, Q usually comprises a set C of condition attributes and a decision attribute D (i.e., two sets, where \(C \cup D = Q \text{ and } C \cap D = \emptyset\)), V is the value domain of attribute q (V is the union of all value domains of \(q_i\) for \(i = 1, ..., p\)), f is a total function, such that \(f: U \times Q \rightarrow V\), where \(f(x, q) \in V_q\) for each \(x \in U\) and \(q \in Q\). In typical MADM applications of DRSA, only a single decision attribute exists in D (i.e., \(D = \{d\}\)) with multiple decision classes (DCs), and DCs can be denoted as \(Cl = \{Cl_t, t = 1, ..., n\}\) in a general case, with a monotonic preference order.

Next, \(\succeq_q\) is defined as a weak preference relation on U when considering a criterion q (for \(q \in Q\)) to compare any two alternatives (objects) in U. For objects \(x, y \in U\), if \(x \succeq_q y\), which denotes that ‘x is at least as good as y regarding attribute q’, and the weak preference relation implies that x and y are comparable on attribute q. Assume that DCs are all preference-ordered, which has n DCs; for all \(r, s = 1, ..., n\); if \(r \succeq s\), then \(Cl_r\) is preferred to \(Cl_s\).

Subsequently, given a set of DCs, the upward and downward unions of DCs can be defined as follows: \(Cl^+ = \bigcup_{s \geq r} Cl_s\) and \(Cl^- = \bigcup_{s \leq r} Cl_s\). The abovementioned ‘dominance relation’ can thus be defined for any set \(H \subseteq C\). Taking the upward union of DCs for an illustration in this section, \(D_H^+\) denotes the dominance relation considering a subset H in C. For any \(x\) and \(y\) in U, \(xD_H^+y\) denotes that x ‘dominates’ y on any subset of criteria in \(H (H \subseteq C)\). Using this predefined dominance relation \(D_H\), the H-dominating and H-dominated sets can be defined as: \(D_H^+(x) = \{y \in U : yD_H^+x\}\) and \(D_H^-(x) = \{y \in U : xD_H^-y\}\), respectively. Using \(D_H^-(x)\)
and $D_H^-(x)$, the $H$-lower (i.e., the certain region) and $H$-upper (i.e., the uncertain region) approximations can thus be defined as Equations (1) and (2)

$$\overline{H}(C_l^x) = \{ x \in U: D_H^+(x) \subseteq C_l^x \}$$

$$\tilde{H}(C_l^x) = \{ x \in U: D_H^-(x) \cap C_l^x \neq \emptyset \}$$

The boundary region can be defined by $B_{nH}(C_l^x) = \overline{H}(C_l^x) - \tilde{H}(C_l^x)$, which denotes the doubtful regions. For any $H \subseteq C$, the $H$-consistency (termed the quality of approximation) regarding the ‘dominance relation’ is defined in Equation (3) (Greco et al., 2005, 2016)

$$\gamma_H(C_l) = \frac{|U - \bigcup_{r \in \{2, \ldots , n\}} B_{nH}(C_l^x)|}{|U|}$$

The quality of approximation $\gamma_H(C_l)$ denotes the ratio of objects that are $H$-consistent with the dominance relationship in $U$. The DRSA algorithm can leverage the dominance approximation capability to induce a set of rough decision rules; the general form of a DRSA decision rule would be like ‘if antecedents hold, then consequence.’ A DRSA decision rule can be indicated as: $r \equiv$ if $f_1(x) \geq r_1 \land \ldots \land f_h(x) \geq r_h$ (antecedents), then $x \in C_l^x$ (consequence). The ratio $\gamma_H(C_l)$ expresses the ratio of $H$-consistently classified alternatives. Each minimal subset $H \subseteq C$ that can satisfy $\gamma_H(C_l) = \gamma_C(C_l)$ is called a REDUCT of a set $C$ regarding $C_l$, and the intersection of all REDUCTs is the core set of attributes in $C$ (i.e., $\text{CORE}_C$). The core attributes denote the indispensable condition attributes to maintain the same level of approximation quality of an $IS$.

The use of those lower/upper approximations of upward and downward unions of DCs can induce five types of decision rules: (1) certain $D^\geq$-; (2) possible $D^\geq$-; (3) certain $D^\leq$-; (4) possible $D^\leq$-; and (5) approximate $D^\leq \geq$-decision rules. The fifth type of rules is not usually used in practice, which is questionable. On the one hand, certain rules (the first and third types) comply with the dominance relations in both the antecedents and consequence, denoting certain knowledge. On the other hand, the possible rules (the second and fourth types), that at least comply with the antecedents, express possible knowledge. Several papers (mainly from the IDSS group) have introduced algorithms (Błaszczyński, Greco, Matarazzo, Slowiński, & Szeląg, 2013; Błaszczyński, Slowiński, & Szeląg, 2011; Susmaga, Slowiński, Greco, & Matarazzo, 2000) to generate decision rules by DRSA or DRSA extended approaches, and the details of DRSA can be found in previous work (Greco et al., 1999, 2001, 2005).

### 2.2. Net flow score (NFS) and reference-point-based outranking approach by DRSA

DRSA was initially applied for classification, as are most of the machine learning techniques. To the best of our knowledge, it was the IDSS research group, as a pioneer in this field, that first proposed DRSA for resolving MCDM ranking and choice problems (Greco et al., 1997, 1999). The initial idea was based on collecting certain reference objects (i.e., a partial preorder of the available alternatives in which a DM has confidence, termed a reference set $\mathbb{R}$) and forming a pairwise comparison table (PCT), as proposed by Greco et al. (1999). This approach does not analyse the raw $IS$ table directly. Instead, it has to begin with a set
of preference functions $P(x, y)$ for each pair (i.e., any two objects from the reference set) that denotes a degree of net preference or outranking of $x$ over $y$ (Greco et al., 2016) for a particular attribute.

Using the preference function $P(x, y)$, a PCT can be transformed from the raw IS into a new table, where rows denote pairs of objects (alternatives) with the associated evaluations on all attributes, and a PCT is supposed to capture the pairwise comparisons between each pair of objects for each attribute for forming multi-graded dominance relations. Suppose that a DM wants to buy a house considering six alternatives $\{A, B, C, D, E, F\} = \mathbb{N}$ and four criteria, namely price ($C_1$), location ($C_2$), neighbourhood environment ($C_3$), and space ($C_4$). The DM only has confidence on the pairwise comparisons between pairs among $\{A, B, F\}$, then $\{A, B, F\} = \mathbb{R}$ is here called the reference set $\mathbb{R}$. The degree of preference of alternative can be denoted as $d(\cdot)$, and the following preferential degrees are assumed for a simple illustration: ‘Dislike = −1’, ‘Neutral = 0’ and ‘Like = +1’. If $d_{C_1}(A) = 1$ and $d_{C_2}(B) = −1$ then the value of the preferential function would be $P_{C_1}(A, B) = 1 − (−1) = 2 > 0$ to indicate the preferential degree of $A$ over $B$ on the criterion $C_1$; in which, $P_{C_1}(A, B)$ can be interpreted as an outranking relation. If $P(A, B) > 0$, it can be denoted as $A \succ B$; on the other hand, if $P(A, B) < 0$, it is shown as $A \prec B$.

In addition, the overall preferences of those reference objects need to be identified (e.g., $A \succ F \succ B$). The $P$-upper and $P$-lower approximations of each pair of alternatives regarding the criteria can thus form the boundary approximations. After multi-graded dominance relations are obtained from a PCT, the abovementioned five types of DRSA decision rules (see the previous section) can be induced by adopting a DRSA or DRSA-extended algorithm.

In this case, any pair of objects (e.g., $(B, F)$ or $(A, B)$) that belongs to $\mathbb{R}$ can match the decision rules that have been obtained in four situations of outranking, termed four-value outranking (Greco, Matarazzo, Slowinski, & Tsoukiàs, 1998). The final evaluation of the objects can then be assessed by exploring the preference structure from the obtained rules by various measures; one well-known way is the net flow score (NFS) (Greco et al., 2005, 2016) for any object in $\mathbb{R}$ (e.g., $A \in \mathbb{R}$) as in Equation (4)

$$NFS(A) = S^{++}(A) - S^{+-}(A) + S^{-+}(A) - S^{--}(A)$$

where

$S^{++}(A) =$ cardinality (\{any object $O \in \mathbb{R}$: at least one decision rule affirms $A \succ O\}$) \\
$S^{+-}(A) =$ cardinality (\{any object $O \in \mathbb{R}$: at least one decision rule affirms $A \succ O$\}) \\
$S^{-+}(A) =$ cardinality (\{any object $O \in \mathbb{R}$: at least one decision rule affirms $A \prec O$\}) \\
$S^{--}(A) =$ cardinality (\{any object $O \in \mathbb{R}$: at least one decision rule affirms $A \prec O$\})

With the aggregated (summed) NFS for each objective in $\mathbb{N}$, the preferential ranking order can be obtained, from high to low NFSs for all of the objectives, with the presumption that the preferential structure induced from $\mathbb{R}$ could be applied to $\mathbb{N}$. As for the choice problem, a DM is merely required to choose the alternative/object with the highest NFS.

## 3. New concepts and recent developments in MRDM

The DRSA or reference-point-based approach (by NFS index) that utilises DRSA approximations has exhibited a solid theoretical foundation from the outranking theories in MCDM (Greco et al., 1997, 1999), which also inspires many aspects of research in MRDM. Nevertheless, to solve practical problems in business (e.g., marketing (Liou, 2009; Liou...
& Tzeng, 2010) or finance (Geng, Bose, & Chen, 2015; Greco, Matarazzo, & Słowiński, 2013)), DRSA or DRSA-extended methods seem to prevail much more than the reference-point-based approach. To delve into this phenomenon, several limitations of the reference-point-based approach for resolving practical problems might be as listed below:

1. DRSA has the advantage of dealing with a large number of condition attributes (e.g., >20) for a complicated problem. While facing such a complex issue, however, it would be difficult for a DM to make an overall evaluation or give a precise preferential order for certain reference objects (i.e., \( \mathbb{R} \)) with high confidence (Tzeng & Shen, 2017). This constraint seems to be in line with the theory of bounded rationality (Simon, 1972, 2000) for human beings.

2. MCDM studies often rely on several domain experts’ opinions or knowledge to construct an evaluation model for a practical subject. If multiple DMs (say 10 experts) were involved in forming different PCT tables, the decision rules obtained and NFSs might comprise many contradictory preferential orders or rules. It would be difficult to convince the users (or DMs) to adopt these different sets of rules and aggregate them together for evaluation or understanding of the other objects in \( \mathbb{N} \). Therefore, the reference-point-based approach might be more suitable for supporting a single DM when making a decision, based on their preferences.

The two limitations mentioned above have raised interest and the need for combining or integrating DRSA with the other MCDM methods for forming new HMCDM models, which is the central theme of this updated discussion: hybrid MRDM

### 4. Core-attribute-based hybrid MRDM model

In the background introduction to DRSA, one specific valuable outcome of the approximations, using dominance relations, is a new set (i.e., a subset of \( C \)), termed \( \text{CORE}_C \). All of the condition attributes in this \( \text{CORE}_C \) are those that are minimal and indispensable for maintaining the same level of approximation quality of an \( IS \). In other words, if hidden patterns or logics of a complex problem can be discovered using DRSA or DRSA-extended algorithms by reaching an acceptable level of approximation quality, the \( \text{CORE}_C \) should comprise the minimal number of indispensable attributes (criteria) for evaluating this problem. It may resolve the first issue mentioned in the Introduction: how to choose the minimal and critical criteria for forming an MCDM or hybrid MCDM model objectively.

Inspired by this new concept, several studies have been published in recent years, which adopt the attributes in a \( \text{CORE}_C \) set to form hybrid MCDM models. This approach is also termed the CORE-attribute-based approach, which has been applied in financial fields like the banking (Shen & Tzeng, 2014, 2015a) and life insurance (Shen, Hu & Tzeng, 2017) sectors. The conceptual framework for new hybrid MRDM research can be separated into three (only ranking or selection decision) or four stages (include improvement planning based on various analytics) as in Figure 1.

The retrieved CORE attributes are regarded in the studies mentioned above (Tzeng & Shen, 2017; Shen, Hu, & Tzeng, 2017) as the criteria for evaluating a particular problem. The other MADM methods (such as the Decision-Making Trial and Evaluation Laboratory (DEMATEL; Fontela & Gabus, 1974, 1976), Analytic Network Process (ANP; Saaty, 1996, 2004) or DEMATEL-based ANP (DANP; OuYang, Shieh, Leu, & Tzeng, 2008; OuYang,
Shieh, & Tzeng, 2013) can then be incorporated into exploring the influential relationship or interrelationship among criteria. Moreover, ANP or DANP could analyse the relative weight of each core attribute (i.e., criterion) of a given problem. In other words, the first and second stages in Figure 1 could achieve a hybrid MCDM model with weighted criteria in a hierarchical structure. Compared with the conventional hybrid MCDM models, however, the fundamental differences are twofold: (1) the involved criteria are induced from data with the minimal number of indispensable ones; and (2) the directional influences among dimensions and criteria can be identified by the DEMATEL technique, which can depict the directional relationship among dimensions and criteria, termed the internetwork relationship map (INRM). The second point supports conducting systematic improvement planning by highlighting the sources that would influence the underperforming criterion of a hybrid model.

At Stage 3, there are various methods – include additive (e.g., simple additive weight, SAW or fuzzy SAW), semi-additive (e.g., modified VIKOR [VIseKriterijumska Optimizacija I Kompromisno Resenje] method; Opricović & Tzeng, 2004, 2007) and nonadditive type aggregators (e.g., fuzzy integral technique (Sugeno, 1974) and Choquet integral (Sugeno, Narukawa, & Murofushi, 1998) – based on the DM’s assumptions or understanding of a problem. For example, Shen and Tzeng (2014, 2015a) adopted this MRDM framework with the modified VIKOR method to identify the performance gaps of each criterion for a group of commercial banks; in addition, the ANFIS technique was incorporated, using the strong rules induced by DRSA, to enhance the understanding of their model (Shen & Tzeng, 2014). The nonadditive type aggregator (fuzzy integral and fuzzy measurement techniques) has also recently been adopted for modelling life insurance companies (Shen, Hu & Tzeng, 2017). The nonadditive type aggregator has led to growing interest in HMCDM; applications include supplier selection (Liou, Chuang, & Tzeng, 2014), city sustainability evaluation (Zhang, Xu, Yeh, Liu, & Zhou, 2016) and green supply chain management (Liou, Tamošaitienė, Zavadskas, & Tzeng, 2016).

As mentioned above, improvement planning should be more valuable than merely making ranking or choice decisions in MCDM, which belongs to Stage 4 in Figure 1. The idea

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**Figure 1.** Framework of CORE-attribute-based hybrid MRDM research. Source: Author.
may have been highlighted by Liou and Tzeng (2012), in the comments for a comprehensive review by Zavadskas and Turskis (2011). To accomplish this goal, guiding a systematic improvement could be achieved by several new concepts and techniques in HMCDM. One likely way, the modified-VIKOR method, is an aggregation method that synthesises an alternative's performance gaps for all criteria. The conventional VIKOR method is only applied for ranking and the selection of alternatives, and there must be at least two (or more) alternatives as the given options (to decide minimum–maximum values for all criteria). The modified-VIKOR method emphasises performance improvement, however, by analysing the cause–effect interrelationship among criteria (based on INRM), which can even be applied to improving a single alternative for systematic and continuous enhancements towards long-term sustainable development.

The modified-VIKOR method suggests using the aspiration levels and the worst values (a new concept in MCDM methods that uses ‘aspired-worst’ as benchmarks), for all criteria, replacing the relative best and worst ones from the alternatives on hand (the conventional ways, using ‘max–min’ as benchmarks). This new concept may encourage and guide DMs to pursue continuous improvement for achieving the aspired levels in all aspects and criteria (Tzeng & Shen, 2017). To enhance this idea, Shen and Tzeng (2016a) used not only the core-attribute-based approach to select the critical criteria with cause–effect analyses for evaluating the financial performance (FP) of semiconductor companies, they also incorporated formal concept analysis (FCA) to infer the associated attributes that may contribute to the FP improvement of the top priority criterion. The combination of DRSA, DANP and FCA is another type of hybrid MCDM model.

Another enticing field that has high potential for being supported by MRDM relies heavily on data analytics is making investment decisions in financial markets. Taking the equity market as an example, the stock selection problem can be solved by analysing the changes of financial fundamentals (e.g., key ratios from financial statements), which is widely adopted in practice by analysts. Shen and Tzeng (2015b) adopted the MRDM framework (see Figure 1) to select the essential financial indicators at time period $t$ (as condition attributes) to associate with the ensuing financial outcomes at $t + 1$ (i.e., decision attribute), in accordance with the philosophy of fundamental analysis (Greenwald, Kahn, Sonkin, & Van Biema, 2004). The selected stocks outperformed the market index during the experiments, which also revealed valuable financial patterns from the historical data.

Another type of investment decision (i.e., timing decisions), is broadly embraced by professional investors using technical analysis (TA), which includes various technical indicators, pattern analyses and the technical signals from the trading records of stocks (Menkhoff, 2010). Nevertheless, how to select and jointly consider several technical indicators is still a challenging and valuable task in practice. Shen and Tzeng (2015c) applied variable-consistency DRSA (VC-DRSA; Błaszczyński et al., 2013) to analyse the trading information of the weighted average stock market index of Taiwan for about 3000 daily trading data, and a group of frequently used technical indicators (suggested by seasoned investors) were extracted to form a decision support system. Certain technical signals that require imprecise judgments were handled by the fuzzy set technique, and the strong rules also formed a FIS to generate buy-in decisions. In their experiments, this hybrid approach outperformed the use of a single technical indicator and the buy-and-hold strategy, after considering the estimated transaction costs.
5. Bipolar hybrid decision model

In addition to the core-attribute-based approach, a novel hybrid bipolar decision model was proposed by Shen and Tzeng (2016b,c). The bipolar model also leverages the dominance approximation and rule induction capabilities of DRSA or DRSA related algorithms, and the key difference begins by categorising the initial data into three DCs: (1) positive (POS); (2) neutral or others (NEU/OTR); and (3) negative (NEG). The strong and certain rules associated with the POS and NEG objects are further filtered by a DM assigned threshold \( \Theta \) (0 \( \leq \Theta \leq 100 \)), to cover the required percentage of objects (alternatives) in these two groups of rules. For example, if there were \( \alpha \) and \( \beta \) alternatives classified as POS and NEG from an IS, then Equations (5)–(8) must be satisfied for a bipolar model.

\[
|O_{POS}| / \alpha \geq \Theta \tag{5}
\]

\[
|O_{NEG}| / \beta \geq \Theta \tag{6}
\]

\[
\sum_{i=1}^{p-th} S^POS_{i-th} \geq |O_{POS}|
\]

\[
\sum_{j=1}^{q-th} S^{NEG}_{j-th} \geq |O_{NEG}|
\tag{8}
\]

In Equations (5) and (6), \(|-|\) denotes the cardinality. \( |O_{POS}| \) and \( |O_{NEG}| \) denote the minimal number of alternatives that should be covered in these certain positive and negative rules, respectively. The two groups can be ranked from high to low supports, denoted as \( R^POS_i \) (for \( i = 1,...,\alpha \)) and \( R^{NEG}_j \) (for \( j = 1,...,\beta \)). The support numbers for the two groups of rules are denoted as \( S^POS_{i-th} \) and \( S^{NEG}_{j-th} \). In the next, \( R^{POS}_{1-th} \) (i.e., the positive certain rule with the highest supports) to \( R^{POS}_{p-th} \) should be included if Equation (7) can be satisfied. Similarly, \( R^{NEG}_{1-th} \) to \( R^{NEG}_{q-th} \) would be kept in the model once Equation (8) can be satisfied. In other words, the numbers of the positive and negative rules (included in this bipolar model) would be \( p \) and \( q \), respectively.

The original idea for the bipolar model is similar to one MADM method: Technique for Order Preference by Similarity to Ideal Solution (TOPSIS (Opricović & Tzeng, 2004, 2007)), which aims to select the best one to be closer to the positive ideal point and far from the negative ideal point. Nevertheless, in a bipolar model, it turns out to be more similar to the strong positive rules and more dissimilar to the negative ones (Shen & Tzeng, 2016b; Tzeng & Shen, 2017). The stability of the rules included in a bipolar model (while non-deterministic attributes exist) has also recently been examined (Shen, Sakai, & Tzeng, 2017), based on the work of Sakai, Okuma, Nakata, and Ślęzak (2011).
The bipolar approach adopts those strong and certain positive or negative rules as the new criteria; these new criteria have, however, the contextual characteristic that contains granules of knowledge. In other words, several requirements of a rule (new criteria) should be jointly satisfied contextually. Also, regarding the improvement planning of sustainability, the status change of one requirement (attribute) might influence multiple rules (i.e., new criteria) that include this attribute (Shen, 2017). This type of interrelationship among criteria (i.e., strong positive and negative rules) suggests a plausible chain reaction in a contextual way, which has been underexplored in previous research. Only limited studies were found in this direction (Gao & Yao, 2017; Shen & Tzeng, 2016b). The bipolar approach can also be applied to pursuing the aspired levels on all rules for continuous improvements; the idea is inspired by the previously discussed modified-VIKOR method (Opricović & Tzeng, 2004, 2007).

6. Concluding remarks

The review by Zavadskas et al. (2016) addressed the importance of sustainability issues, which were resolved by various hybrid MCDM methods with in-depth discussion and publication analyses. Many widely adopted MCDM methods were mentioned, such as ANP, DEMATEL, VIKOR, multiple criteria complex proportional assessment (COPRAS), COPRAS in an interval-valued intuitionistic fuzzy environment (COPRAS-IVIF) (Hajiagha, Hashemi, & Zavadskas, 2013), COPRAS with single value neutrosophic sets (COPRAS-SVNS) (Bausys, Zavadskas, & Kaklauskas, 2015) and several COPRAS extended hybrid methods (Beheshti, Mahdiraji, & Zavadskas, 2016; Liou et al., 2016; Rabbani, Zamani, Yazdani-Chamzini, & Zavadskas, 2014; Yazdani, Jahan, & Zavadskas, 2017). One field of MCDM research, however, – the emerging trend of MRDM – deserves more attention. Therefore, the present work highlights the importance of RST as a foundation for revealing the complex logical relations of a problem and discusses several recent approaches of MRDM and related applications.

It can be observed that data-centric problems are gaining interest in various fields in this big data era, such as the use of advanced statistical models (e.g., structural equation modelling (SEM)) to solve environmental sustainability problems (Mardani et al., 2017). The integration or combination of fuzzy set, rough-set-based machine learning and specific MCDM methods not only illustrates the logical relations or patterns of a problem, but can also be applied to the support of continuous improvement with a directional guidance. DMs should be able to make superior decisions by comprehending the complicated logic behind a problem while dealing with extensive historical data (Shen, Yan, & Tzeng, 2017; Shen & Tzeng, 2018). Therefore, it is our hope to see the rapid growth of research in the field of MRDM to solve practical problems for crucial sustainability issues in future studies.

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