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

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Multiple criteria decision-making (M.C.D.M.); multiple rule-based decision-making (M.R.D.M.); hybrid M.C.D.M. (H.M.C.D.M.); rough set theory (R.S.T.); dominance-based rough set approach (D.R.S.A.); sustainability

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C4; C44; D81

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 (H.M.C.D.M.) 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 (D.M.s) or practitioners has grown dramatically in recent years. A single M.C.D.M. 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 H.M.C.D.M. 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.

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Conventional M.C.D.M. research comprises two major fields: multiple attribute decision-making (M.A.D.M.) and multiple objective decision-making (M.O.D.M.), as suggested by previous work (Hwang & Yoon, 1981; Liou & Tzeng, 2012; Zavadskas, Turskis, & Kildienė, 2014; Zavadskas et al., 2016; Zeleny, 1982). Both M.A.D.M. and M.O.D.M. (or H.M.C.D.M.) 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 M.C.D.M. or H.M.C.D.H. approaches to decision support, three crucial issues deserve more attention.

First, how to form an adequate M.C.D.M. model by selecting the minimum but critical criteria (attributes) is overlooked. Most M.C.D.M. 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 M.C.D.M. 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 H.M.C.D.M. research as classical and non-classical, where only the combinations of the fuzzy set technique (Zadeh, 1965) and M.C.D.M. methods (i.e., fuzzy M.C.D.M. or F.M.C.D.M.) are classified as non-classical. F.M.C.D.M. 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 D.M.s (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 (I.F.S.) theory (Atanassov, 1986) in economics, technology and management. The I.F.S. 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 I.F.S. 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 M.C.D.M. has gained growing attention. According to discussions of fuzzy set theory (F.S.T.) applied to supplier selection (Simić, Kovačević, Svirčević, & Simić, 2016), there are two main streams: the fuzzy inference system (F.I.S.; Amindoust, Ahmed, Saghafinia, & Bahreininejad, 2012) and the adaptive-network-based fuzzy inference system (A.N.F.I.S.; Jang, 1993). A.N.F.I.S. also has the capability of machine learning to adjust the fuzzy parameters of a F.I.S. system/model by minimising the overall fitting errors. Again, an issue would be generating adequate and essential rules – a knowledge base (Magdalena, 2015) – for F.I.S. or A.N.F.I.S. models, which is similar to the first point on selecting the minimal criteria to form an M.C.D.M./H.M.C.D.M. model.

Third, on the subject of sustainability, D.M.s 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 (M.R.D.M.), an emerging but promising field in H.M.C.D.M. (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 M.R.D.M. in H.M.C.D.M. discussed here is mainly based on the theoretical foundation of the rough set theory (R.S.T.) (Pawlak, 1982, 2002; Pawlak & Skowron, 2007; Pawlak & Słowiński, 1994).

The ensuing dominance-based rough set approach (D.R.S.A.) (Greco, Matarazzo, & Słowiński, 1997, 1999, 2001, 2002, 2005, 2016), developed by the eminent Laboratory of Intelligent Decision Support Systems (I.D.S.S.) 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 I.D.S.S. group inspired many aspects of the studies in M.R.D.M. described below. The fundamentals of D.R.S.A. and M.R.D.M. will be briefly introduced in the following sections.

2. Theoretical background

The essential foundations of M.R.D.M. discussed here are based on R.S.T. (Pawlak, 1982), which can be categorised into fields like applied mathematics, soft computing and machine learning. R.S.T. 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 R.S.T. 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 M.C.D.M. research into *discrete* M.A.D.M. and *continuous* M.O.D.M. methods, whereas the fuzzy-rough set theory seems to blur this boundary.

Although both F.S.T. and R.S.T. were devised to model impreciseness, R.S.T. 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). R.S.T. has the advantage of generating or inducing understandable rules during the learning phase, which is beneficial for D.M.s to discern the ambiguous or hidden patterns (or logic) of a complicated problem. The classical R.S.T. does not, however, consider the preferential characteristic of attributes, which is often required to tackle M.C.D.M. 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 D.R.S.A. related/extended approach, for resolving M.C.D.M. problems.

2.1. Dominance-based rough set approach (D.R.S.A.) for decision aids

The adoption of D.R.S.A. (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 M.C.D.M.) and alternatives are arranged in rows and columns, respectively. The D.R.S.A. $IS = (U, Q, V, f)$, where U is a finite state of the universe and $Q = \{q_1, q_2, \ldots, q_p\}$ 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 $C \cup D = Q$ and $C \cap D = \emptyset$), V_q is the value domain of attribute q (V is the union of all value domains of q_i, for $i = 1,\ldots, p$), 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 M.A.D.M. applications of D.R.S.A., only a single decision attribute exists in D (i.e., $D = \{d\}$) with multiple decision classes (D.C.s), and D.C.s can be denoted as $Cl = \{Cl_t, t = 1, \ldots, n\}$ 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 D.C.s are all preference-ordered, which has n D.C.s; for all $r, s = 1,\ldots, n$; if $r \succ s$, then Cl_r is preferred to Cl_s.

Subsequently, given a set of D.C.s, the upward and downward unions of D.C.s can be defined as follows: $Cl_s^{\geq} = \bigcup_{r \geq s} Cl_r$ and $Cl_s^{\leq} = \bigcup_{r \leq s} Cl_r$. The abovementioned 'dominance relation' can thus be defined for any set $H \subseteq C$. Taking the upward union of D.C.s 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)

$$\underline{H}(Cl_r^{\geq}) = \{x \in U : D_H^+(x) \subseteq Cl_r^{\geq}\} \tag{1}$$

$$\bar{H}(Cl_r^{\geq}) = \{x \in U : D_H^-(x) \cap Cl_r^{\geq} \neq \emptyset\} \tag{2}$$

The boundary region can be defined by $Bn_H(Cl_r^{\geq}) = \bar{H}(Cl_r^{\geq}) - \underline{H}(Cl_r^{\geq})$, 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)

$$\gamma_H(Cl) = \left| U - \left(\bigcup_{r \in \{2,\ldots,n\}} Bn_H\left(Cl_r^{\geq}\right) \right) \right| \bigg/ |U| \tag{3}$$

The quality of approximation $\gamma_H(Cl)$ denotes the ratio of objects that are H-consistent with the dominance relationship in U. The D.R.S.A. algorithm can leverage the dominance approximation capability to induce a set of rough decision rules; the general form of a D.R.S.A. decision rule would be like '**if** *antecedents* hold, **then** *consequence*.' A D.R.S.A. decision rule can be indicated as: $r \equiv$ **if** $f_{i_1}(x) \geq r_{i_1} \wedge \ldots \wedge f_{ih}(x) \geq r_{ih}$ (*antecedents*), **then** $x \in Cl_t^{\geq}$ (*consequence*). The ratio $\gamma_H(Cl)$ expresses the ratio of H-consistently classified alternatives. Each minimal subset $H \subseteq C$ that can satisfy $\gamma_H(Cl) = \gamma_C(Cl)$ is called a REDUCT of a set C regarding Cl, and the intersection of all REDUCTs is the core set of attributes in C (i.e., 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 D.C.s 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 $D^{\geq\leq}$-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 I.D.S.S. group) have introduced algorithms (Błaszczyński, Greco, Matarazzo, Słowiński, & Szeląg, 2013; Błaszczyński, Słowiński, & Szeląg, 2011; Susmaga, Słowiński, Greco, & Matarazzo, 2000) to generate decision rules by D.R.S.A. or D.R.S.A. extended approaches, and the details of D.R.S.A. can be found in previous work (Greco et al., 1999, 2001, 2005).

2.2. Net flow score (N.F.S.) and reference-point-based outranking approach by D.R.S.A.

D.R.S.A. was initially applied for classification, as are most of the machine learning techniques. To the best of our knowledge, it was the I.D.S.S. research group, as a pioneer in this field, that first proposed D.R.S.A. for resolving M.C.D.M. 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 D.M. has confidence, termed a reference set $\mathbb{R}$) and forming a pairwise comparison table (P.C.T.), 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 P.C.T. 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 P.C.T. is supposed to capture the pairwise comparisons between each pair of objects for each attribute for forming multi-graded dominance relations. Suppose that a D.M. 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 D.M. 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 $d_{C_1}(B) = -1$ 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 ${}_AS_B$; on the other hand, if $P(A, B) < 0$, it is shown as ${}_AS_B^C$.

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 P.C.T., the abovementioned five types of D.R.S.A. decision rules (see the previous section) can be induced by adopting a D.R.S.A. or D.R.S.A.-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 (N.F.S.) (Greco et al., 2005, 2016) for any object in $\mathbb{R}$ (e.g., $A \in \mathbb{R}$) as in Equation (4)

$$NFS(A) = S^{++}(A) - S^{+-}(A) + S^{-+}(A) - S^{--}(A) \tag{4}$$

where

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

With the aggregated (summed) *NFS* for each objective in $\mathbb{N}$, the preferential ranking order can be obtained, from high to low *NFS*s 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 D.M. is merely required to choose the alternative/object with the highest *NFS*.

3. New concepts and recent developments in M.R.D.M.

The D.R.S.A. or reference-point-based approach (by *NFS* index) that utilises D.R.S.A. approximations has exhibited a solid theoretical foundation from the outranking theories in M.C.D.M. (Greco et al., 1997, 1999), which also inspires many aspects of research in M.R.D.M.. 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)), D.R.S.A. or D.R.S.A.-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. D.R.S.A. 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 D.M. 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. M.C.D.M. studies often rely on several domain experts' opinions or knowledge to construct an evaluation model for a practical subject. If multiple D.M.s (say 10 experts) were involved in forming different P.C.T. tables, the decision rules obtained and N.F.S.s might comprise many contradictory preferential orders or rules. It would be difficult to convince the users (or D.M.s) 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 D.M. when making a decision, based on their preferences.

The two limitations mentioned above have raised interest and the need for combining or integrating D.R.S.A. with the other M.C.D.M. methods for forming new H.M.C.D.M. models, which is the central theme of this updated discussion: hybrid M.R.D.M.

4. Core-attribute-based hybrid M.R.D.M. model

In the background introduction to D.R.S.A., one specific valuable outcome of the approximations, using dominance relations, is a new set (i.e., a subset of *C*), termed CORE_C. All of the condition attributes in this 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 D.R.S.A. or D.R.S.A.-extended algorithms by reaching an acceptable level of approximation quality, the 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 M.C.D.M. or hybrid M.C.D.M. model objectively*.

Inspired by this new concept, several studies have been published in recent years, which adopt the attributes in a CORE_C set to form hybrid M.C.D.M. 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 M.R.D.M. 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.

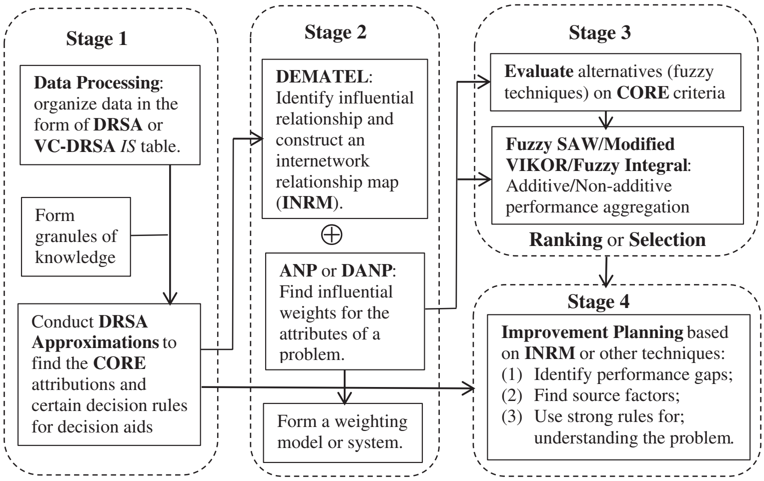

Figure 1. Framework of CORE-attribute-based hybrid M.R.D.M. research. Source: Author.

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 M.A.D.M. methods (such as the Decision-Making Trial and Evaluation Laboratory (D.E.M.A.T.E.L.; Fontela & Gabus, 1974, 1976), Analytic Network Process (A.N.P.; Saaty, 1996, 2004) or D.E.M.A.T.E.L.-based A.N.P. (D.A.N.P.; OuYang, Shieh, Leu, & Tzeng, 2008; OuYang, Shieh, & Tzeng, 2013) can then be incorporated into exploring the influential relationship or interrelationship among criteria. Moreover, A.N.P. or D.A.N.P. 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 M.C.D.M. model with weighted criteria in a hierarchical structure. Compared with the conventional hybrid M.C.D.M. 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 D.E.M.A.T.E.L. technique, which can depict the directional relationship among dimensions and criteria, termed the internetwork relationship map (I.N.R.M.). 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, S.A.W. or fuzzy S.A.W.), semi-additive (e.g., modified V.I.K.O.R. [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 D.M.'s assumptions or understanding of a problem. For example, Shen and Tzeng (2014, 2015a) adopted this M.R.D.M. framework with the modified V.I.K.O.R. method to identify the performance gaps of each criterion for a group of commercial banks; in addition, the A.N.F.I.S. technique was incorporated, using the strong rules induced by D.R.S.A., 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 H.M.C.D.M.; 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 M.C.D.M., which belongs to Stage 4 in Figure 1. The idea 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 H.M.C.D.M. One likely way, the modified-V.I.K.O.R. method, is an aggregation method that synthesises an alternative's performance gaps for all criteria. The conventional V.I.K.O.R. 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-V.I.K.O.R. method emphasises performance improvement, however, by analysing the cause–effect interrelationship among criteria (based on I.N.R.M.), which can even be applied to improving a single alternative for systematic and continuous enhancements towards long-term sustainable development.

The modified-V.I.K.O.R. method suggests using the aspiration levels and the worst values (a new concept in M.C.D.M. 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 D.M.s 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 (F.P.) of semiconductor companies, they also incorporated formal concept analysis (F.C.A.) to infer the associated attributes that may contribute to the F.P. improvement of the top priority criterion. The combination of D.R.S.A., D.A.N.P. and F.C.A. is another type of hybrid M.C.D.M. model.

Another enticing field that has high potential for being supported by M.R.D.M. 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 M.R.D.M. 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 (T.A.), 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 D.R.S.A. (V.C.-D.R.S.A.; 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 F.I.S. 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 D.R.S.A. or D.R.S.A. related algorithms, and the key difference begins by categorising the initial data into three D.C.s: (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 D.M. assigned threshold (Θ; 0\ $\leq \Theta \leq$ 100\), to cover the required percentage of objects (alternatives) in these two groups of rules. For example, if there were α and β alternatives classified as *POS* and *NEG Cl*s from an *IS*, then Equations (5)–(8) must be satisfied for a bipolar model.

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

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

$$\sum_{i=1}^{p-th} S_{i-th}^{POS} \geq |O_{POS}| \tag{7}$$

$$\sum_{j=1}^{q-th} S_{j-th}^{NEG} \geq |O_{NEG}| \tag{8}$$

In Equations (5) and (6), $|\cdot|$ 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_i^{POS} (for $i = 1,\ldots,i,\ldots,\alpha$) and R_j^{NEG}(for $j = 1,\ldots,j,\ldots,\beta$). The support numbers for the two groups of rules are denoted as S_{i-th}^{POS} and S_{j-th}^{NEG}. In the next, R_{1-st}^{POS} (i.e., the positive certain rule with the highest supports) to R_{p-th}^{POS} should be included if Equation (7) can be satisfied. Similarly, $R_{1-st}^{NEG}$to R_{q-th}^{NEG} 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 (T.O.P.S.I.S. (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-V.I.K.O.R. 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 M.C.D.M. methods with in-depth discussion and publication analyses. Many widely adopted M.C.D.M. methods were mentioned, such as A.N.P., D.E.M.A.T.E.L., V.I.K.O.R., multiple criteria complex proportional assessment (C.O.P.R.A.S.), C.O.P.R.A.S. in an interval-valued intuitionistic fuzzy environment (C.O.P.R.A.S.-I.V.I.F.) (Hajiagha, Hashemi, & Zavadskas, 2013), C.O.P.R.A.S. with single value neutrosiphic sets (C.O.P.R.A.S.-S.V.N.S.) (Bausys, Zavadskas, & Kaklauskas, 2015) and several C.O.P.R.A.S. extended hybrid methods (Beheshti, Mahdiraji, & Zavadskas, 2016; Liou et al., 2016; Rabbani, Zamani, Yazdani-Chamzini, & Zavadskas, 2014; Yazdani, Jahan, & Zavadskas, 2017). One field of M.C.D.M. research, however, – the emerging trend of M.R.D.M. – deserves more attention. Therefore, the present work highlights the importance of R.S.T. as a foundation for revealing the complex logical relations of a problem and discusses several recent approaches of M.R.D.M. 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 (S.E.M.)) to solve environmental sustainability problems (Mardani et al., 2017). The integration or combination of fuzzy set, rough-set-based machine learning and specific M.C.D.M. 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. D.M.s 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 M.R.D.M. to solve practical problems for crucial sustainability issues in future studies.

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