MCDM Methods: Practical Difficulties and Future Directions for Improvement

Abstract

This paper critically reviews practical difficulties inherent in some of the existing multi-criteria decision-making methods. The paper also emphasizes why a benchmark decision situation is essential in assessing the capabilities of any multi-criteria decision-making method. The capability is in terms of accuracy in modeling the human decision-making process. Most multi-criteria decision-making methods consist of two important steps. The first step involves elicitation of preferences from the decision-maker on various criteria and alternatives of the problem. In the second step, the preferences defined by the decision-maker are aggregated. The overall score generated after aggregation is used in rank order calculation and final selection. However, if the prescriptions of multi-criteria decision-making method do not resemble actual or real decision of the very same decision-maker, then multi-criteria decision-making method failed in either capturing the true preferences of the decision-maker or in aggregating these preferences as per the expectations of the decision-maker. This paper discusses some of the latest theories of decision-making and provides three important directions to improve the descriptive aspects of multi-criteria decision analysis.

Keywords: Multi-Criteria Decision Analysis, Behavioral Decision Making, Prospect Theory, Complexity Theory, Range Sensitivity

1. Introduction

Decision analysis is primarily a prescriptive discipline built upon normative and descriptive foundations. Multiple criteria are used to analyze and assess discrete alternatives. Multi-Criteria Decision Analysis (MCDA) provides a framework and procedure to systematically deal with

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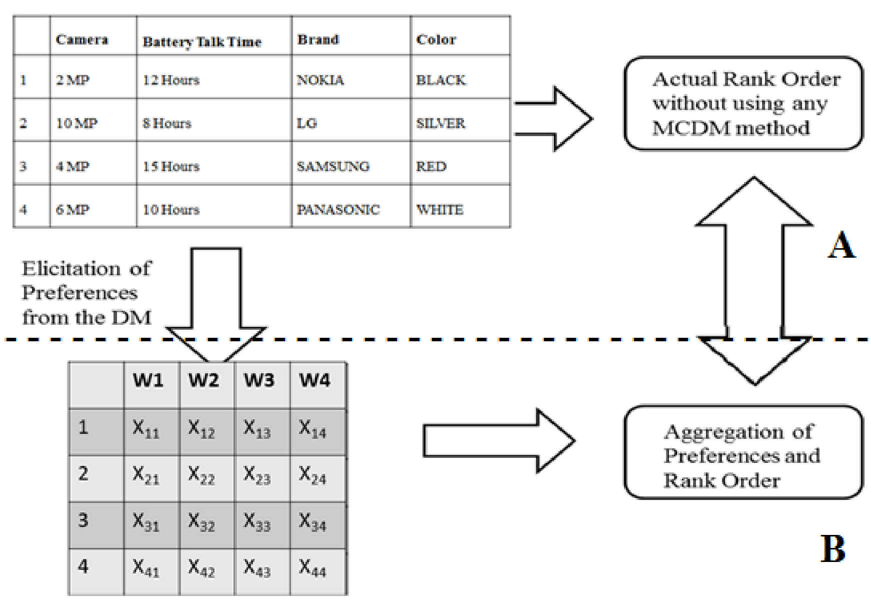
Multi-Criteria Decision (MCD) problems. There are two broad categories of MCD problems: the multi-criteria discrete alternative problem and the multi-criteria optimization problem (Wallenius et al., 2008). The former has a limited number of feasible alternatives while the latter has, sometimes, many feasible alternatives. The presence of many feasible alternatives in a multi-criteria optimization problem creates ample scope for optimization because the alternatives are generated and evaluated during the course of problem-solving. However, the complex feasible region of optimization problems makes them more computationally intensive. Contrary to this, the alternatives and criteria are identified a priori in the discrete category of MCD problems. Subsequently, the alternatives are evaluated using the preference structure defined by the decision-maker (DM). Normally, in most discrete alternative Multi-Criteria Decision Making (MCDM) methods, the decision-making process relies on the DM's judgment on the objective values of the alternatives, often independently on each criterion. Since the role of the DM is important in discrete alternatives MCDA, it is necessary that it abide by the cognitive capabilities of the DM and the descriptive realities of decision-making.

MCDA has been extensively researched in the last few decades (Jacquet-Lagreze & Siskos, 2001; Köksalan, Wallenius & Zionts, 2011; Mardani et al., 2015; Figueira, Greco & Ehrgott, 2016). Several methods have been proposed to solve a variety of MCD problems. For instance, ELECTRE (ÉLimination et Choix Traduisant la REalité) by Roy (1968, 1996), MAVT/MAUT (Multi-attribute Value/Utility Theory) (Keeney & Raiffa, 1976), AHP (Analytic Hierarchy Process), ANP (Analytic Network Process) (Saaty, 1977), TOPSIS (Technique for Order Preferences by Similarity to Ideal Solutions) (Hwang & Yoon, 1981), and PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) (Brans & Mareschal, 2005; Behzadian et al., 2010). Considerable progress has been made in the field of theory, algorithms, and tools to improve the capabilities of the DM. ELECTRE and PROMETHEE are the outranking methods and represent the European school of thought whereas the MAVT/MAUT, AHP, ANP, TOPSIS, and Choquet Integral methods are their American counterparts. The European school of thought is focused mainly upon helping a DM to identify his/her preferences (Roy, 1976; Wierzbicki, 1980) without making any assumptions on preference structures. On the other hand, the American school takes many presumptions in deriving DM's preferences in terms of a value function. Because of unique axiomatic foundations, MCDM methods also differ in terms of complexity involved in eliciting preferences from the DM and, thereafter, processing them. The number of preferences or judgments required from the DM affects the complexity of the MCDM methodology. The preference elicitation and processing largely depend upon how the problem is structured. In addition, the solution prescribed by an MCDM method relies heavily on the procedure used for preferences elicitation and processing. Based upon the kind of information required from the DM, Hwang and Yoon (1981) classified various MCDM methods into 17 groups.

The majority of MCDM methods are complex in terms of the number of preferences required from the DM and the cognitive burden on the DM to remain consistent in defining his/her preferences. This complexity increases drastically with the size of the MCD problem. Many of these MCDM methods are based upon normative foundation and consider the DM a rational individual with unlimited cognitive capacity. These methods are also designed with a tendency to prescribe optimal decisions. However, it is likely that the prescribed decision is optimal but may be far from reality. The foremost objective of MCDA is to reduce the complexity of the MCD problem by breaking it into multiple and single-criterion problems. These problems are approached independently and the solutions are aggregated to produce an overall solution to the MCD problem.

Moreover, sometimes, these single-criterion problems become complex to the extent that the DM finds it difficult in coping with the cognitive requirements of dealing with these single-criterion problems. Therefore, it is highly desirable that the MCDM method must not exceed the capabilities of the human information processing system. Rather, it must boost the confidence of the DM in making a truly informed decision and justifying the choice. In addition, when the DM has full information about the criteria and the alternatives of the problem and associated consequences, it is highly desirable that the prescribed decisions should resemble actual and/or known decisions. If it does not, then the MCDM method failed in either capturing true preferences from the DM or processing them according to DM's expectations. For example, the upper left table in Figure 1 represents a set of alternatives profiled on various criteria. The lower left table in Figure 1 represents the preferences defined by the DM using the objective value of alternatives provided in the upper left table. These preferences are aggregated to produce an overall score for each alternative, which is then used to rank the alternatives. Ideally, the computed rank order should

Figure 1: MCDA Prescriptions and Actual Decisions



resemble actual decision, at least in situations where the actual decision is known or can be arrived at with ease. The upper part (marked as “A”) in Figure 1 exhibits actual decisions made by the DM and the lower part (marked as “B”) represents the computed decisions using an MCDM method.

Is it possible to explain the mismatch (if any) between the computed and actual decisions? For example, Analytic Hierarchy Process (AHP) is one of the popular MCDM methods but most of its applications are limited to problems that are difficult to solve directly without the help of computing machines. Similarly, very few studies have used any MCDM method for rank order calculation in an informed multi-criteria decision situation. For example, Dhurkari and Swain (2013) and Dhurkari (2019) proposed new MCDM methods and compared the effectiveness of proposed methods against AHP in resembling actual decisions. Pereira, Figueira, and Marques (2020) reported considerable similarity between the criteria weight defined by the DM and the one computed using the proposed method. Wang and Triantaphylloub (2008) raised concerns on the accuracy of the rank order of alternatives computed using the ELECTRE II and III methods. They compared the rank order generated before and after adding a new alternative into the problem. Other studies have mostly been conducted either in single-criterion decision situations or using preferences of the DM on the profile of an alternative (Novemsky & Kahneman, 2005; Devers, Wiseman & Holmes, 2007; Gächter, Johnson & Herrmann, 2021), sometimes using prospect theory (for a review, refer to Barberis, 2013).

In the case of an informed decision situation, the DM generally possesses complete information on the consequences associated with different alternatives and criteria. The actual decision can be arrived at without using any MCDM method. However, it is necessary to explore whether the prescriptions of the MCDM method and the actual decision are similar?” If not, can there be an explanation for this? Though the role of the DM is important in MCDA, the behavioral and the psychological phenomena of decision-making have not found much use in MCDA except in a few studies like investigation of possible biases in elicitation of weights (Delquié, 1993, 1997; Keeney, 2002; Pöyhönen & Hämäläinen, 2001; Pereira, Figueira & Marques 2020) and issues related to design of value trees and selection of attributes (e.g., Hämäläinen & Alaja, 2003). An adequate representation of the human decision-making process in MCDA can reduce the mismatch between the computed and actual decisions.

For example, the simple additive weighting (SAW) method is the most widely used method to aggregate the preferences of the DM defined over various criteria. This method assumes that the criteria are mutually independent. The preferences of the DM are defined based on the performance score of an alternative for each criterion, which is weighted by the respective criterion weight. The DM also defines the criterion weight. The overall evaluation score of an alternative is computed by adding the weighted score of that alternative on various criteria, as represented in equation 1.

$$\boldsymbol{V_i = \sum_{j=1}^{m} w_j X_{\mathrm{ij}}} \tag{1}$$

$$\forall\, i = 1\ to\ n\,, j = 1\ to\ m$$

where V_i is the aggregated value of i^{th} alternative, w_j is the weight of j^{th} criterion such that $\sum_{j=1}^{m} \boldsymbol{w_j = 1}$, m is the number of criteria, n is the number of alternatives, and X_{ij} is the utility or preference of the DM for objective value of i^{th} alternative on j^{th} criterion. The underlying assumption in equation 1 is that all the criteria are preferentially independent (Keeney & Raiffa, 1976) and can compensate equally for each other in proportion to the criteria weight. Further, another prerequisite condition of the SAW method is that the X_{ij} values should be on a common scale across all criteria. However, this is not necessary for the weighted product model (WPM) (Bridgman, 1922), shown in equation 2. In WPM, the weights become exponents of X_{ij}, a positive power for the benefit criterion (advantages) and a negative power for the cost criterion (disadvantages). The only condition that requires attention is that X_{ij} should be numeric and positive.

$$\boldsymbol{V_i} = \prod_{j=1}^{m} (X_{ij})^{w_j} \tag{2}$$

$$\forall\; i = 1 \; to \; n \,, j = 1 \; to \; m$$

Some of the popular MCDM methods that use the SAW model (Equation 1) are MAUT, AHP, ANP, and TOPSIS. All these methods belong to the American school of thought. This paper questions the presumptions of the methods originating from the American school. It explores how the elicitation and processing of preferences defined by the DM in MCDA can be enriched using descriptive realities of decision-making. The paper highlights some of the descriptive theories of decision-making, particularly originating from the field of psychology and behavioral sciences, that may explain the mismatch between decisions prescribed by an MCDM method and the actual decision. The paper critically examines the widely accepted SAW model and suggests directions for improvement. Using some of the descriptive theories of decision-making, this paper provides three possible directions to improve the prescriptive power of MCDA. These directions are based upon the consideration that the normative MCDM framework is oversimplified to address the complex, real-world decision-making processes (Wallenius et al., 2008). The directions include 1) preference elicitation and the scale of measurement, 2) sensitivity of the criteria weight on the range of alternatives and 3) context-dependent aggregation of preferences. Further, this paper focuses only on the discrete categories of the MCD problems under certainty where the objective value associated with an alternative is certain. For example, if the DM is considering choosing a 21-inch color television, it is certain that he/she will receive the product with the same specification. There is no uncertainty involved, for example, 0.5 probability of receiving a 21-inch color television and 0.5 probability of receiving x or y inch color television. In this paper, all subsequent use of the term "Multi-Criteria Decision" (MCD) refers to the discrete category of MCD problems under certainty, unless explicitly mentioned. The rest of the paper is organized as follows. Section 2 discusses some of the inherent practical difficulties of various MCDM methods. Section 3 provides a summary of descriptive theories of decision-making and how they can be used to enrich the prescriptions of MCDM methods. Finally, Section 4 concludes the paper.

2. Practical Difficulties in MCDM methods

The early days of research in MCDA witnessed success in situations where the objectives were precise and the criteria for evaluation were quantifiable. Over the years, the sphere of application moved from operational decisions to more subjective, semi-structured, and higher-level managerial decisions. In such new situations, the prescription of MCDM methods relied more on human preferences. A preference elicitation scale is used to help the DM in defining his/her preferences across different criteria, which are aggregated subsequently. As a result, a variety of MCDM methods were developed and proposed using different axiomatic foundations.

When criteria do not conflict with each other, the solution is straightforward i.e. prescribing the alternative that is performing better on all criteria. However, the complexity increases when the DM has to make trade-offs before a rank order of alternatives can be generated. It should be noted that the objective of MCDA is to reduce the complexity of the decision problem, which generally increases with the size of the problem (number of criteria and/or number of alternatives). This is because as the size increases, the cognitive burden on the DM to remain consistent in judgment and decision-making also increases. Even though the role of the DM is critical in the discrete alternative MCDM methods, research has made very few attempts to manage the complexity of MCDM methods and level it with the capabilities and descriptive realities of human decision-making processes. The mismatch sometimes leads to a disparity between solutions prescribed by an MCDM method and actual decisions. For example, using the measures of distance from the reference objects, Shekhovtsov and Sałabun (2020) found different rankings of alternatives generated using two different methods. They reported that the mismatch was mainly because of the size of the problem (complexity) and the task characteristics. Dehe and Bamford (2015) compared the prescriptions of AHP and Evidential Reasoning (ER) in a healthcare infrastructure location decision situation. They found that the prescribed rank order was almost similar but the scores between the alternatives were significantly different. Wątróbski et al. (2019) analyzed 56 MCDM methods in reference to nine problem characteristics structured into three levels. They developed a hierarchy to obtain a rule base that could serve as an input to choose an MCDM method suitable in a given context. According to Watróbski (2019), different MCDM methods deliver different results, and therefore it is necessary to have a methodological and practical framework to choose a suitable MCDM method for a particular decision situation. However, the mismatch can be partially attributed to the inability of various MCDM methods in resembling actual decision-making processes. The inherent complexity of extant MCDM methods creates a gap between normative requirements of the MCDM method and the descriptive realities of decision-making. A brief summary of the existing MCDM methods is provided in Table 1. The next section covers some of the descriptive theories of decision-making that can be used to enrich MCDA.

Table 1: Summary of MCDM methods

MCDM Method	Key Postulates	Shortcoming and Difficulties
ELECTRE (election et choix traduisant la realite)	Type of Information from the DM: Information between Criteria, Threshold Values Salient Feature of Information: Cardinal (Interval) Aggregation of Information: Weighing of Threshold Preferences (Non-Compensatory, Linear)	Use of threshold values that are arbitrary, although their impact on the final solution may be significant.
PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations)	Type of Information from the DM: Information between Criteria, Preference Functions, and Parameters Salient Feature of Information: Cardinal (Ratio) Aggregation of Information: Weighing of Preference Functions on Pairwise Differences (Non-Compensatory, Linear)	Use of preference function overrides the preferences of the DM. Lack in providing a structure to the decision problem. In the case of many criteria and alternatives, it becomes difficult for the DM to obtain a clear view of the problem and evaluate results. The way in which the preference information is processed is complicated and hard to explain to non−specialists.
MAVT/MAUT (Multi-attribute Value/Utility Theory)	Type of Information from the DM: Information between Criteria, Information within Criteria Salient Feature of Information: Cardinal (Ratio and Interval) Aggregation of Information: Simple Additive Weighting (SAW) method (Compensatory, Linear)	Uses iterative, complicated, and unreliable utility estimation methods that use hypothetical lotteries. Interaction between alternatives within a criterion and across criteria is not captured.
AHP (Analytic Hierarchy Process) and ANP (Analytic Network Process)	Type of Information from the DM: Information between Criteria, Information within Criteria Salient Feature of Information: Ordinal Pair wise Comparison converted to Cardinal (Ratio) Aggregation of Information: Simple Additive Weighting (SAW) method (Compensatory, Linear)	The complexity is in the order of n^2. Do not capture the interaction between alternatives within a criterion and across criteria. ANP does capture the interactions but it is biased by the DM.
TOPSIS (Technique for Order Preferences by Similarity to Ideal Solutions)	Type of Information from the DM: Information between Criteria Salient Feature of Information: Cardinal (Ratio) Aggregation of Information: Simple Additive Weighting (SAW) method (Compensatory, Linear)	Lack in providing any formal guidelines to define criteria weights, but assumes that the DM is able to weigh the criteria appropriately. Preference elicitation procedure not provided.
Choquet Integral	Type of Information from the DM: Information on Attribute Salient Feature of Information: Cardinal (Ratio and Interval) Aggregation of Information: Simple Additive Weighting (SAW) method (Non-Compensatory, Non-Linear)	Difficult for the DM to give a precise weight estimate to every possible subset of criteria. Preference elicitation procedure or scale not provided.

3. Future Directions for Improvement

Most MCDM methods consider the DM a rational individual with unlimited cognitive capacity and a tendency to optimize his/her decisions. However, there are instances where the actual decision differs from the optimal one. For example, suppose a customer wishes to purchase a mobile phone from a given choice set consisting of three brands (A, B, and C). The customer uses an MCDM method to arrive at a decision. Based upon the preferences, suppose the MCDM method prescribes brand A as the preferred choice. However, if the customer finds brand B more attractive, it is likely that the MCDM method failed to either capture the true preferences of the DM or process them as per the expectations of the DM (the customer in this case). The complexity does not end here. Suppose the customer notices another brand D that is different from brands A, B, and C. On comparing the features of brand D, the customer finds brand C as the most attractive option. It is paradoxical. How the introduction of a new and a different alternative can cause rank reversal? Surprisingly, many studies have reported such rank reversal phenomena (Belton & Gear, 1983; Dyer & Wendell, 1985; Triantaphyllou, 2000; Triantaphyllou, 2001; Wang & Triantaphylloub, 2008). To understand and explain such phenomena, it is necessary that the MCDM methods connect the objective measures of alternatives on various attributes to the observed choices. Various descriptive theories of decision-making, primarily from the fields of economics and psychology, can be used to understand the choice behavior of individuals.

A typical decision-making process consists of problem recognition, profiling of alternatives on various criteria, evaluation of alternatives, and post-decision assessment. Cinelli et al. (2020) provided a high-level representation of MCDA research. Their work is helpful in defining how the MCDA process should be organized. They presented a decision support system to recommend relevant MCDM methods. It is important that the preference elicitation process is appropriately designed in order to capture the true preferences of the DM. This is because the preference structure forms the basis for the solution prescribed by an MCDM method. Here, the judgment of the DM involves assessing the alternatives in terms of degree of goodness, which is closely related to estimation of utilities (Schoemaker, 1982). If the judgments are flawed, the prescribed solutions are likely to differ from the actual decisions or choices. In traditional MCDA, the alternatives are evaluated using prior assessment of beliefs and values followed by their aggregation. On the other hand, the rule-following cases involve the application of rules, heuristics, and principles specific to a given context. Therefore, this paper suggests three possible directions to improve the prescriptive power of MCDA, namely, 1) preference elicitation and the scale of measurement, 2) sensitivity of criteria weight on the range of alternatives, and 3) context-dependent aggregation of preferences.

3.1 Preference Elicitation and the Scale of Measurement

Most MCDM methods rely on a unipolar scale to elicit preference from the DM with a 0 (interval scale) or a 1 (ratio scale) as the starting point. However, scholars have shown that the decision-making involves bipolar measures separated by a neutral level (often having a reference point), separating good or positive attitude from the bad or negative attitude of the DM towards alternatives (Grabisch & Labreuche, 2010). The existence of this neutral level is supported by many applications (Bana e Costa & Vansnick, 1997), and has deep roots in the field of psychology (Slovic, Finucane, Peters, & MacGregor, 2002) and the theory of bounded rationality (Simon, 1956). These theoretical developments can help in improving the fundamental operation of preference elicitation in an MCDM method, thereby, improving its prescriptive power.

3.2 Sensitivity of Criteria Weight on Range of Alternatives

In any MCDM method, the two most fundamental operations are valuation and integration. Valuation involves elicitation of preferences from the DM for the criteria weight and on the performance of alternatives on various criteria. The integration involves combining these sets of information to arrive at an overall score for each alternative. If the context or the choice set is irrelevant, these two elementary operations can remain independent of each other. However, when the overall score of alternatives depends on each other, the process of valuation and integration must be interlinked (Anderson, 1971). In most MCDM methods, the criterion weight and the preference score of each alternative on various criteria are elicited assuming that they are independent of each other. Scholars have discovered various phenomena that do not favor the idea of independence. For instance, primacy effects (Anderson, 1965; Asch, 1946), positive context effects (Anderson, 1966; Kaplan, 1971), discounting effects (Anderson & Jacobson, 1965; Lampel & Anderson, 1968; Schumer & Cohen, 1968) and differential weighting (Oden & Anderson, 1971). To resemble the choice behavior of the DM, any MCDM method should incorporate possible biases that creep into the decision-making process.

For example, Zeleny (1976) proposed to record contrast intensities (λ) of attributes or criteria indicating the prominence of various attribute levels. A combination of λ and w can model the DM's context-dependent preference. If the DM is asked to select an alternative without using any MCDM method, the general tendency of the DM will be to analyze which alternative performs better in a given choice set which means that the choice process involves analyzing the performance of alternatives across attributes and alternatives. This does not happen in existing MCDM methods because of the principle of preference independence and additivity. Contrary to Luce's (1959) axiom of regularity, Meyer and Johnson (1995) describe that the probability that an alternative is selected from a given choice set is not only a function of its attractiveness relative to the others but also its attribute-wise proximity or similarity with other alternatives. The choice made by the DM is also influenced by the implied trade-offs in the given choice set. Tsetsos, Usher, and Chater (2010) recently conducted a simulation study that used the decision field theory (DFT) (Roe, Busemeyer & Townsend, 2001) and leaky competing accumulators (LCA) (Usher & McClelland, 2004) to explain several effects contributing to the preference reversal. Their model makes parametric predictions for choices by capturing how various alternatives are placed in a multi-attribute space for a given choice set. The DFT and LCA are computational models of multi-attribute decision-making. They use a similar connectionist framework but differ in accounting for the contextual preference reversal effects, mainly the attraction effect and the compromise effect.

3.3 Context-Dependent Aggregation of Preferences

A fundamental characteristic of all choice-based models is that they view choice as a constructive process where the attitude of the DM is altered by the addition or deletion of alternatives in a choice set (Bettman, Luce & Payne, 1998; Payne, Bettman & Johnson, 1992). It is also found that the decision-making process is shaped by the interaction between the properties of human information processing system and task environment (Simon, 1990). Therefore, in addition to valuation and integration, an MCDM method should also attempt to capture and measure the interactions across attributes and alternatives. Such additional measurements can be used to either adjust the attribute weights or directly be included in the integration process. This requires an understanding of how the DM assesses the two-way interaction (across the attribute and across the alternatives) in the choice processes.

The descriptive theories of decision-making provide ample evidence to improve the preference elicitation and aggregation procedures. For example, even though it is known that a person follows non-linear and non-compensatory strategies during choice processes, much of the existing research on human judgment and decision-making supports the notion that the DM processes information in a linear rather than in a configural manner (Dawes & Carrigan, 1974; Payne, 1976; Slovic, Fischhoff & Lichtenstein, 1977). This notion pre-empts all non-linear and non-compensatory cognitive processes (Einhorn, 1971; Payne, 1976; Payne, Braunstein & Carroll, 1978; Slovic, 1969; Slovic et al., 1977; Tversky, 1969; Valenzi & Andrews, 1973). The problem formulation is important because, when the axiomatic rules or the principles of the MCDM method are not attuned to the DM's psychology, the prescriptions will diverge. Thus, there is a need to revisit the current MCDM methods and question its assumptions of normality. This possibly may help in reducing the gap between the normative and descriptive aspects of decision-making.

In this direction, Dhurkari and Swain (2013) proposed a novel MCDM method using the prospect theory, norm theory, and a few context-dependent theories. Their method, known as the Multi-Criteria Gain Loss (MCGL) method, proposes a novel non-compensatory and non-linear way of aggregating the DM's preferences. Dhurkari (2019) tested a vanilla linear version of the MCGL method against AHP in resembling actual decisions. Fan et al. (2013) also proposed a prospect theory based method to solve the MCDM problem, considering the aspiration levels of the criterion. They represented the criterion values and aspiration levels in two different formats viz. crisp numbers and interval numbers. The overall value of an alternative is computed using prospect theory's value function and the SAW method. Recently, the TODIM (an acronym in Portuguese for Iterative multi-criteria decision-making) method, along with its extensions (Gomes & Lima, 1992; Gomes & Rangel, 2009; Gomes & Gonzalez 2012), was used to pairwise compute the dominance of an alternative over another in an attribute using the prospect theory value function. The generalized version of TODIM adopts the standard values of the parameters used by the prospect theory value function. The overall performance of an alternative is computed by the additive function. A few more attempts were made to extend the application of the prospect theory into a multi-criteria setting (Bleichrodt, Schmidt & Zank, 2009; Lahdelma & Salminen, 2009; Salminen & Wallenius, 1993; Zank, 2001) and using the standard parametric values of the prospect theory value function, independent of the choice set or the context in place. It is likely that if the descriptive realities of decision-making are hybridized with the normative frameworks used to support MCDA, the quality of prescriptions of MCDM methods will improve in terms of their resemblance with actual or real decisions.

In addition, there is also a lack of work describing the means to verify the potential of an MCDM method using simple decision-making problems where the DM can make decisions with relative ease and without using any MCDM method. The development of simple decision-making problems will enable a direct comparison between the prescriptions of MCDM methods with the actual decisions. In spite of this, AHP-based methods are being extensively used across applications in various industries. The philosophy of MCDM methods is to split the MCDM problem into multiple single-criterion problems. The final solution is obtained by combining the solution to each of these single criterion problems. When the DM is fully informed, the solution prescribed by the MCDM method should resemble actual decisions of the very same DM. This resemblance can easily be verified for small-scale problems. If an MCDM method does not incorporate the decision-making style of the DM, it is very likely that the solution will not resemble actual decisions. This necessitates the establishment of a standard suite of applications in which the DM is able to make decisions a priori without using any MCDM method. This will help in testing the effectiveness of the MCDM method in resembling actual decisions.

Table 2: Descriptive Theories of Decision Making

Theory/Concept	Highlights
Prospect Theory	• Carrier of value for alternatives are gains and losses with respect to a fixed reference point. • The reference point could be DM's current status quo, aspiration level, or norms for choices. • The gains are associated with positive outcomes and the losses with negative outcomes. • Since the value function does not depend upon the probability (Abdellaoui, Bleidhrodt & L'Haridon, 2008), prospect theory has also been applied to understand the choice behaviour in riskless environments (Tversky & Kahneman, 1991). • Losses (outcomes below the reference point) loom larger than gains of the same magnitude (outcomes above the reference point). • Pope and Schweitzer (2011) have shown that the prospect theory can very well be used to model the behaviour of an informed DM.
Bipolarity in Preferences	• The concept of bipolarity refers to the existence of information along positive and negative dimensions. • A bipolar scale consists of two unipolar scales separated by a neutral point. • The neutral point separates the zone of acceptable performance from the zone of unacceptable performance. • Grabisch and Labreuche (2010) proposed an MCDM framework considering a bipolar scale for preference elicitation, assuming that the positive and the negative part of preferences can be combined and processed jointly once the DM specifies them. • However, the separate treatment of these preferences is necessary, assuming that one cannot be retrieved from the other (Benferhat, Dubois, Kaci & Prade, 2008). • The studies in cognitive psychology show that the positive and the negative information is processed differently by the human brain and often assessed on distinct dimensions (Cacioppo & Bernston, 1999; Cacioppo, Gardner & Bernston, 1997). • When preferences are elicited using a bipolar scale, positive preferences indicate the DM's satisfaction levels, hence playing a role of criteria for the selection of an alternative. Negative preferences, on the other hand, indicate acceptability levels, and hence play a role of a constraint (Kaci, 2008).
Norm Theory	• When the DM is asked to evaluate an alternative in a given choice set, the elements of the choice set evoke or provide a set of norms for evaluation. The norms are either constructed by recruiting similar alternatives belonging to the category (category norm) or from the given choice set. • The former is a category norm (category-centered norm) which is evoked by references to categories, while the latter is a stimulus norm (stimulus-centered norm) evoked by experience of objects and events. • The alternatives are compared and evaluated by consulting pre-computed schemas and frames of reference (Kahneman & Miller, 1986). • These schemas and frames of reference provide benchmarks for evaluating the alternative in the sense of what it could have been, might have been, or should have been.
Theories on Range Sensitivity of Attribute Weights	• When the performance of alternatives in an attribute is highly variable or largely scattered, that attribute should receive more importance in comparison to any other attribute on which almost all the alternatives are performing equally well. • The range sensitivity is reflected in a choice process but not in judgment processes. • The weights assigned during the judgment process may remain fixed or constant but get stretched or skewed in the process of choice as per the given choice set or stimuli involved. • Any change in weight has power to change the evaluation of alternatives and subsequently the rank order of all the alternatives. Any reversal in order also implies a change in weight.

	• Without violating the concept of true weights, Beattie and Baron (1991) suggested keeping the true weight constant at all time but adjusting it with respect to the context in place. • In order to make attribute weights range sensitive, Forman and Gass (2001) suggested following a bottom-up approach in the preference elicitation process. • According to Fischer (1995), "*The greater the degree to which a weight assessment task requires cross attribute comparisons of value differences, the more sensitive the evoked weights will be to the range of attribute values in the local decision context*". • Fischer (1995) in his empirical work found that the weight elicited using the direct weight method is range insensitive, while weight elicited using the swing method and trade-off methods is significantly range sensitive. • Zeleny (1976) proposed Attribute Dynamic Attitude Model using the concept of entropy of information according to which the influence of an attribute on the overall evaluation of an alternative can be a function of intrinsic information generated by all the alternatives in that attribute. Zeleny's model is an attempt to operationalize the context-dependency of preferences.
Kauffman's Complexity Theory	• According to Kauffman's (1993) complexity theory (NK Landscape), the fitness contribution of an attribute on the overall evaluation of an alternative also depends upon that alternative's performance on all other attributes. • In Kauffman's NK model, N is the number of attributes under consideration in the evaluation of a set of alternatives while K is the level of interaction of one attribute with every other attribute. • If K = 0, the landscape is considered to be smooth meaning there is no interaction and the fitness contribution of one attribute on the overall evaluation of an alternative is independent of that alternative's performance on other attributes. • However, when K = N - 1, the landscape is rugged and the fitness contribution of one attribute on the overall evaluation of an alternative depends upon that alternative's performance on all the other N - 1 attributes.
Context-Dependent Choice Theories	• The psychological demands of the judgment process and the choice process are different (Bettman & Park, 1980; Huber & Klein, 1991; Payne, 1976, 1982; Tversky, Sattath & Slovic, 1988). • Choice processes follow a maze of heuristics through cut-off strategies and other non-compensatory processes (Johnson & Russo, 1984) • The choices are found to be more lexicographic (more prominent dimension looms larger) (Tversky et al., 1988). • Choices involve a commitment to a course of action while the judgment does not (for example, see Beach & Mitchell 1978; Einhorn & Hogarth 1981; Janis & Mann, 1977). • People are stricter in the process of choice than in judgment and this strictness is associated with increased reliance on a conjunctive strategy (Ganzach, 1995). • The use of conjunctive strategy implies extremeness aversion of the DM where the DM is ready for compromise rather than polarization (Tversky & Simonson 1993). • In addition, the choice process focuses more on negative attribute levels and the DM instantly screens out or quickly devalues an alternative performing below their expectations or reference point, especially if an attribute is very important. • Moore (2004) hypothesized systematic differences in utility weights estimated from rating-based and choice-based conjoint methods. This bias is due to the presence of prominence effect, compatibility effect, and level focusing effect in the choice processes. • In the utility-dependent cut-off mechanism proposed by Klein and Bither (1987), a different form of level focusing is reported in which individuals ignore lesser-valued attribute differences and focus on larger utility differences. • The prominence effect reflects the empirical generalization that people are more likely to prefer an alternative that is superior on the more prominent attribute when making choices than when making a judgment (Tversky, Sattath & Slovic, 1988; Fischer & Hawkins 1993, Hawkins, 1994).

	• According to the "elimination by aspects" model of Tversky (1972), "*probability of selection of an alternative not only depends upon its overall value but also on its relations to other available alternatives*". • According to the trade-off contrast hypothesis (Simonson & Tversky, 1992), "*the tendency to prefer an alternative is enhanced or hindered depending on whether the trade-offs within the set under consideration are favorable or unfavourable to that option*". This means that the effect of contrast not only applies to a specific criterion or attribute (a circle appears larger (smaller) when surrounded by smaller (larger) circles) but also to the trade-off offered by the choice set. • Consumer choice theories proposed psychological phenomena like attraction effect (Huber, Payne & Puto, 1982), substitution effect (Tversky, 1972), compromise effect (Simonson, 1989), extremeness aversion (Simonson & Tversky, 1992), and loss aversion (Tversky & Kahneman, 1991) that play an active role in various choice processes. • A preference reversal effect recently observed in problems involving choices is the phantom decoy effect (Choplin & Hummel, 2005; Dhar & Glazer, 1996; Pettibone & Wedell, 2000, 2007; Pratkanis & Farquhar, 1992).

4. Conclusion

The inherent complexity in extant MCDM methods creates a gap between the cognitive requirements of these decision-making methods (normative) and the possibilities of human information processing systems (descriptive). This can be attributed to some of the inherent limitations of the human information processing system, for instance, a limited span of working memory (Solso, 1988); limited exactness in quantitative measurements (Tversky, 1969); and human errors and contradictions. Larichev (1999) also highlighted this mismatch. Many of the extant MCDM methods have normative foundations leading to rational decision-making, which often differs from the actual decision. Theories that have evolved from the field of psychology and behavioral sciences can explain these departures. Recent developments propose new models and concepts that can better explain the decision-making process in individuals.

In this paper, the author recommends use of descriptive theories of decision-making to improve the effectiveness of MCDA. The disparity between the actual decision and the one prescribed by the MCDM method can be addressed using various descriptive theories of decision-making. Since descriptive theories have widely been applied to describe human choices in single-criterion decision-making situations under uncertainty, this paper provides three possible directions on how these theories can be used to improve the prescriptive power of MCDA under certainty. This paper is an attempt to explore the connection between the findings of descriptive theories of decision-making and the MCDA methodologies. Exploring the missing links can help in the development of an MCDM method that is simple to use, less complex, and, at the same time, resembles the human decision-making process. The recommendations can help in developing mechanisms to incorporate diverse behavioral and psychological phenomena into the MCDA, in order to make them more practical and their prescriptions more realistic.

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