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A New Aggregation Model for TOPSIS Multi-Criteria Group Decision-Making Environment: Competitive Marketing Strategy

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ABSTRACT

In recent years, moving from single criterion to multi-criteria, as well as decision-making from one person to multi-person, has led to the challenge on how to reach a consensus group views in Multiple Criteria Group Decision-Making/Multiple Attribute Group Decision-Making (MCGDM/MAGDM) environment. In Group Decision-Making (GDM) literature, two main categories of aggregation techniques can be distinguished: (1) aggregation of individual judgments (or internal/first aggregation) and (2) aggregation of individual priorities (or external/last aggregation). Theoretically, there is no reason to be restricted to these methods. Therefore, in this article, the extended TOPSIS method is used which was originally introduced by Hwang and Yoon (1981), but unlike from Hwang and Yoon's approach, different relative closeness method is proposed for the calculation of the relative closeness to the ideal solution. We shall call this type of aggregation as 'middle aggregation' method. In addition, a new chi-square-based approach introduced to determine the importance of decision-makers (DMs) in GDM process. Then, by using the weights of DMs, all individual decision is aggregated into a collective decision. Finally, a numerical example (to determine a unique competitive marketing strategy) is used to test the proposed approach, and results show the advantage of our extended model over previous one.

Keywords: Multiple criteria group decision-making, group decision-making, TOPSIS, aggregation method, chi-square, marketing strategy selection problem

INTRODUCTION

Due to the ever-increasing complexity of socioeconomic environments, it is very difficult for only one decision-maker (DM) to consider all the important aspects of a problem. Thus, most decisions in an organisation, whether public or private, are made by a group of people. This change of who to focus on the problem, that is, the focus moves from that of one DM to that of a group of people, introduces the important issue of how best to aggregate the DMs preference structures (Alencar *et al.*, 2010). Therefore, aggregation is important in the decision-making problem because it is used to derive a collective decision made by the DMs by representing in the individual opinions (Mohd and Abdullah, 2017).

A collective decision-making process can be defined as a decision situation in which (1) there are two or more persons, each of them characterised by his or her own perceptions, attitudes, motivations and personalities, (2) who recognise the existence of a common problem and (3) attempt to reach a collective decision (Bui, 1987). Therefore, Aggregation is easily defined as the process of combining several numerical scores with respect to each criterion by using an aggregation operator in order to produce a global score (Mohd and Abdullah, 2017).

Historically, the first papers, which tackled this problem, were by Borda and by Condorcet (Alencar *et al*., 2010). Nevertheless, there are several possible ways to aggregate various opinions from several viewpoints in a decision process. Theoretically, there is no reason to be restricted to these methods. This article addresses this problem.

On the other side, according to Furrer (2006), the study and practice of marketing have broadened considerably, from an emphasis on marketing as a functional management issue, to a wider focus on the strategic role of marketing in overall corporate strategy. This broadening of the marketing concept, to include strategic as well as operational decisions, has resulted in an overlap between marketing and strategic management. Thus, market(ing) strategy, in fact, translates the business objective and strategy into market terms and market(ing) activity (Fifield, 2007).

Marketing strategy is on organisation's integrated pattern of decisions that specify its crucial choices concerning products, markets, marketing activities and marketing resources in the creation, communication and/or delivery of products that offer value to customers in exchanges with the organisation and thereby enables the organisation to achieve specific objectives (Morgan *et al*., 2018). In other words, market(ing) strategy is the process by which the organisation aligns itself with the market it has decided to serve (Fifield, 2007). According to Azadfallah (2016a), there are many definitions of marketing strategy in the marketing literature, reflecting differing points of view. However, most of the definitions agree that marketing strategy provides the means of utilising the company's skills and resources to achieve marketing objectives. Hence, proper and strong marketing strategy is essential for the survival and success of any business in the increasing complex, competitive environment of organisations (Yousefi, 2016). Further, marketing strategy must focus on delivering greater value to customers and the firm at a lower cost (Gbolagade *et al*., 2013).

According to Mohaghar *et al*. (2012), marketing strategists should consider a large number of complex factors while evaluating and selecting marketing strategies. Therefore, a marketing strategy decision can be classified as a Multi-Criteria Decision-Making (MCDM) problem. Lin *et al.* (2009); Wu *et al.* (2010); and Azadfallah (2016a) could be referred to as an example.

MCDM has been one of the fastest-growing areas during the last decades depending on the changings in the business sector (Jahanshahloo *et al*., 2006). In sum, MCDM is all about making choices in the presence of multiple, generally conflicting criteria. Many real-life problems are multi-objective by nature that requires evaluation of more than one criterion. Therefore, MCDM has become an important issue and many researches are devoted to help people make better decision (Sabokbar *et al*., 2016). Since criteria are often conflicting there may be no solution satisfying all criteria simultaneously. Consequently, result of this process is often a compromise solution, which is obtained according to DMs preferences (Nenad and Zoran, 2017). The problems of MCDM can be broadly classified into two categories, Multiple Attribute Decision-Making (MADM) and Multiple Objective Decision-Making (MODM), depending on whether the problem is a selection problem or a design problem. MODM methods have decision variable values that are determined in a continuous or integer domain, with either an infinitive or a large number of choices, the best of which should satisfy the DM's constraints and preference priorities. MADM methods, on the contrary, are generally discrete, with a limited number of predetermined alternatives (Rao, 2007) (in this article, we will use the terms MADM and MCDM to denote the same concept).

According to Falsafi *et al*. (2011), several methods exist for MCDM. The decision method used in this study is the TOPSIS (the Technique for Order Preference by Similarity to Ideal Solution) method. Furthermore, this method was established by Hwang and Yoon (1981). Dizaji and Khanmohammadi (2016) believe that one of the most common ways of MCDM is TOPSIS. It is based on the idea, that the chosen alternative should have the shortest distance from the positive ideal solution and, on the other side, the farthest distance of the negative ideal solution (Jahanshahloo *et al*., 2006).

In general, the process for the TOPSIS algorithm starts with forming the decision matrix representing the satisfaction value of each criterion with each alternative. Next, the matrix is normalised with a desired normalising scheme, and the values are multiplied by the criteria weights. Subsequently, the positive-ideal and negative-ideal solutions are calculated, and the distance of each alternative to these solutions is calculated with a distance measure. Finally, the alternatives are ranked based on their relative closeness to the ideal solution (Roszkowska, 2011).

On the other side, according to Buyukozkan and Ozturk (2019), in organisations, generally, many strategic decisions are made after a group decision-making (GDM) process where the alternatives are assessed, and the solutions are discussed. Anisseh *et al*. (2012) believe that disagreement always happens in GDM as members in a group generally do not come to the same decision. Solving disagreement is a significant matter in GDM, which requires methods of aggregating preferences and setting differences. In such a situation, we need to aggregate all group members' opinions on all alternatives under all criteria, which are called Multi-Criteria Group Decision-Making (MCGDM) (Zhang *et al*., 2015). From this perspective, the competitive marketing strategy selection is an MCGDM problem.

In general, GDM problem can be defined as a decision problem with several alternatives and DMs (DMs) that try to obtain the best solution(s) taking into account their opinions or preferences. As an important branch of GDM problems, Multiple Attribute (also often called criteria) GDM (MAGDM/MCGDM) is commonly encountered in the real world and plays a key role especially in engineering and economy fields (Azadfallah, 2017). According to Azadfallah (2016b), the definition of MAGDM is described specially as follow, multi DMs make judgments or evaluations by virtue of respective knowledge, experience and preference for a decision space (i.e. a finite set of alternatives) under multi attributes to rank all the alternatives or give evaluation information of each alternative, and then decision results from each DM are aggregated to form an overall ranking result for all the alternatives. Furthermore, according to Yue (2013a), MAGDM problems may be defined as decision situations where: (1) there are two or more experts, who are characterised by their own ideas, attitudes, motivations and knowledge. (2) There is a problem to be solved and (3) they try to achieve a common solution. More specifically, a MAGDM problem with (t e" 1) DMs, m alternatives and n attributes can be expressed in matrices format as follows:

$$X_k = (x_{ij}^k)_{m.n} = \begin{array}{c|cccc} & U_1 & U_2 & \dots & U_n \\ A_1 & x_{11}^k & x_{12}^k & \dots & x_{1n}^k \\ A_2 & x_{21}^k & x_{22}^k & \dots & x_{2n}^k \\ \vdots & \vdots & \vdots & & \vdots \\ A_m & x_{m1}^k & x_{m2}^k & \dots & x_{mn}^k \end{array}$$

$$W = (w_1^k, w_2^k, \dots, w_n^k),\ k = 1, 2 \dots, t,$$

where x_k and w_k ($k = 1, 2, \dots, t$), respectively, are the decision matrix and weight vector of attributes, which are provided by k_{th} DM.

According to the viewpoint proposed by Ossadnik *et al*. (2016), in some decision settings, it is appropriate to waive the assumption of equivalent group members in favour of a differentiated, relative weighting of votes. Marked differences in knowledge, experience, management level or competence between the DMs should be reflected in their respective influences on the overall ranking of the alternatives. It is the aim of this article. So, the relative weight of DMs is determined using chi-square-based method.

Chi-square test is a non-parametric test used for two specific purposes: (1) to test the hypothesis of no association between two or more groups, population or criteria (i.e. to check independence between two variables); (2) and to test how likely the observed distribution of data fits with the distribution that is expected (i.e. to test the goodness-of-fit) (Rana and Singhal, 2015).

Up to now, many methods have been proposed to aggregating the individual pre-order in a single collective pre-order (in literature, two main categories of aggregation techniques can be distinguished: (1) aggregation of individual judgments [in other words, internal or first aggregation] and (2) aggregation of individual priorities [in other words, external or last aggregation]). However, in this article to solve this problem, a novel aggregation procedure is used (we shall call this type of aggregation as 'middle aggregation' method) to derive the collective choice from the individual preferences. Further, in this article, the extended TOPSIS method is used which was originally introduced by Hwang and Yoon (1981), but unlike from Hwang and Yoon's approach, different relative closeness method is proposed for the calculation of the relative closeness to the ideal solution. In addition, a new chi-square-based approach introduced to determine the importance of DMs in GDM process. Then, by using the weights of DMs, all individual decision is aggregated into a collective decision.

In sum, the contribution of this article is to use a numerical example to illustrate the process of the proposed MCGDM/MAGDM method in marketing strategy selection context.

The article is organised as follows. In Section 2, the literature is discussed. In Sections 3 and 4, the research design, and the proposed approach is discussed. Experimental results are provided in Section 5. The findings and the conclusion of the article are presented in Sections 6 and 7.

LITERATURE REVIEW

In this section, we review previous related works and to integrate the research in various aspects, we divided it into two parts: preference aggregation and multi-criteria marketing strategy selection methods.

The aggregation problem of the individual preferences in order to establish a collective preference has been widely studied in GDM literature. The social choice theory is considered to be the first theory that tackled through Borda's (1781) and Condorcet's (1785) works—this aggregation problem when individual preferences are expressed by rankings (total pre-orders). Since then several studies have been directed towards the research of a mathematical formalism which can determine from the different individual opinions a collective opinion which respects a set of 'desirable' conditions (Jabeur and Martel, 2007). According to Jabeur *et al*. (2004), it was only in 1951 that Arrow proposed an axiomatic theory in which he showed through his impossibility theorem that there exists no function allowing to aggregate individual preorders into a collective preorder, which respects the conditions of rationality, freedom of choice, sovereignty, independence with respect to irrelevant alternatives and non-dictatorship. Since the Arrow theorem statement, several studies have proposed different ways to avoid this impossibility by determining a collective preorder which minimises the distance between the different individual preorders. Nevertheless, the problem of aggregating the individual pre-orders of DMs in a single collective pre-order has been the target of several studies in the literature on GDM (Alencar *et al*., 2010). For instance, Bui (1987) suggest the following categories: (1) the group can interact simultaneously, (i.e. pooled-interdependent mode) and (2) make individual decisions separately and then collectively confront and discuss the results (i.e. sequential-interdependent mode). Forman and Peniwati (1998) observed that the two most appropriate methods to aggregating individual preferences (particularly, in Analytic Hierarchy Process [AHP] context) are (1) the aggregation of individual judgments (AIJ) and (2) the aggregation of individual priorities (AIP). Shih *et al*. (2007) classify these methods into the two distinct groups (particularly, in TOPSIS environment): (1) external aggregation (involve) (i) pre-operation (i.e. mathematical operations for cardinal information) and (ii) post-operation (i.e. Borda's count or function for ordinal information) and (2) internal aggregation (involve; utilise some operations to manipulate the alternative ratings and weight ratings to obtain a final ranking from individual DMs of the group) rules. In addition, following Roghanian *et al*. (2010), we can classify these works as (particularly, in fuzzy TOPSIS area) first aggregation and last aggregation methods. During recent years, various studies have been undertaken. Here, we will mention some of them. Perez and Romero (1995) attempted to complete a framework for systematic comparison among ordinal preference aggregating methods. Jabeur *et al.* (2004) proposed an aggregation procedure, which includes two steps. In the first one, the group's members elaborate individually a pre-order on the alternatives set. In the second step, these individual pre-orders are aggregated into a collective pre-order, which take into account the relative importance of the members. Wang *et al.* (2005) extended a preference aggregation model for ranking alternative courses of actions by combining preference rankings of alternatives given on individual criteria or by individual DMs. Escobar and Jimenez (2007) developed a structure for aggregating individual preferences in AHP GDM environment. Jabeur and Martel (2007) suggested a method which would determine from individual preferences relational systems at least one collective subset containing the 'best' alternatives. Finally, a collective preferences relational system obtained from the aggregation of the individual preferences relational systems. Luo and Jennings (2007) employed a framework for identifying various types of compromise operators that decision-making agents might adopt when aggregating opinions. Wang *et al*. (2007) developed three new models for preference voting and aggregation. Alfares and Duffuaa (2008) presented an empirical methodology to determine aggregate numerical criteria weights from group ordinal ranks of multiple decision criteria. Fu (2008) developed three extended TOPSIS models. The pre-model, post-model and inter-model, associated with three approaches to aggregating group performances (the pre-operation, post-operation and inter-operation), which depends on Dempster's rule or its modifications, some social choice functions (i.e. Borda's function and some mean approaches). Alencar *et al*. (2010) proposed an MCGDM model aggregating performance of DMs based on ELECTRE methods. Jabeur and Martel (2010) applied an index to measure the agreement level of an individual pre-order with respect to a collective pre-order (or reference pre-order). Deng *et al*. (2011) extended a simple method to aggregate interval numbers. Kang *et al.* (2011) suggested a new optimal aggregation method to combine interval data based on genetic algorithm. Huang and Li (2012) studied on aggregation of TOPSIS ideal solutions for GDM. Qu *et al*. (2012) presented a hybrid particle SWARM optimisation algorithm with evolutionary strategies for aggregation of interval numbers in group decision context. Carmo *et al*. (2013) aggregated the individual priorities in incomplete hierarchies. Mousavi and Moghadam (2015) provided a new last aggregation compromise solution approach based on TOPSIS method with hesitant fuzzy setting to energy policy evaluation. Azadfallah (2015, 2016c) focused on the application of MAGDM/MCGDM models, more specifically, TOPSIS and Borda's function approach for solving the supplier selection problem. Further, in the present model, first TOPSIS is used to find the individual preference ordering (with same criteria set for each DMs) and while each expert has own criteria set, respectively. Then, Borda's function is used to find the collective preference orderings. Zahir (2016) identified the deficiency of the traditional weighted sum aggregation rule used in the AHP and possibly in the Multiple Attribute Value Theory (MAVT) with the prior normalisation as the cause for rank reversals and proposed a modified aggregation rule as a remedy. Srdjevic *et al*. (2017) used multi-criteria and social choice methods for aggregating results in assessing water management plan. Finally, Sodenkamp *et al*. (2018) proposed an aggregation method for solving group MCDM problems with single-valued neutrosophic sets.

On the other side, Tang *et al*. (1999) presented a hierarchy fuzzy MCDM method for evaluating the propagating Electronic Commerce (EC) market strategies. Lin *et al*. (2009) provided a five-step decision-making process to enable careful marketing strategy assessment, and contribute to practical implementation for fuzzy Analytic Network Process (ANP) utilisation by marketing experts, in a real industry. Abdolvand and Najafizadeh (2011) evaluated the standardisation/adoption of international marketing strategy in IRAN multinational companies (MNCs) based on hybrid MCDM model (particularly, Decision Making Trial Evaluation Laboratory [DEMATEL] and ANP) in which the impact of external environments variables on the marketing mix internal variables is considered. Mohaghar *et al*. (2012) proposed an integrated fuzzy approach (more specifically, fuzzy AHP and VIKOR) for selecting a marketing strategy. Gorecka and Szaluka (2013) applied Multi-Criteria decision Aiding (MCDA) methods to country market selection in international expansion. Wieloch (2014) suggested two procedures in MCDM environment under complete uncertainty. Further, the application of the suggested tool is illustrated with an example of marketing strategy selection. Jandaghi and Aziziyan (2015) tried to select the optimum marketing strategy for privileged deposits of Maskan bank by using combined two MCDM (more specifically, ANP and DEMATEL) techniques. Azadfallah (2016a) focused on the application of the TOPSIS with interval data method in combination with mathematical approach for solving a marketing strategy problem under incomplete preference information. Yousefi (2016) proposed a suitable MCDM model (particularly, AHP and TOPSIS) method for determining the appropriate marketing strategy. Anna *et al*. (2017) employed an integrated approach based on ANP and TOPSIS to determine the best strategy for Batik Madura Industry marketing problems. Carillo *et al*. (2018) used the MCDM approach to identify the suitable marketing mix strategy. In addition, Cahyadi and Anna (2019) developed a multi-criteria model for selecting the best marketing strategy in the Batik Fashion Industry (in Indonesia). MAGDM/MCGDM has also been employed in marketing strategy selection problem. Lin *et al*. (2010) applied the fuzzy AHP method as an analytical tool to determine a unique competitive marketing strategy for a small tourism venture such as a privately owned hotel.

In sum, in this study, an extension of TOPSIS MCDM technique, to a group decision environment is investigated. Further, we modify the conventional TOPSIS algorithm by changing the closeness to the ideal solution definition. In addition, comparisons with other existing technique will also be made. In the next section, the research design will be considered.

RESEARCH DESIGN

According to Azadfallah (2016a), an organisations marketing strategy describes how the firm will fulfil the needs and wants of its customers. Since, marketing activities to succeed in business is so important. On the other side, at the same time, Buyukozkan and Ozturk (2019) believe that many strategic decisions are made after a GDM process where the alternatives are assessed, and the solutions are discussed on the one hand. And a marketing strategy decision can be classified as an MCDM problem (Yousefi, 2016), on the other hand. From this perspective, the marketing strategy selection problem is an MCGDM/MAGDM problem. Nevertheless, there are several techniques for this decision-making problem. The decision method used in this study is the TOPSIS method. Because, according to Shih (2015), TOPSIS is deemed as a major analytic technique and has been successfully applied in numerous areas. Further, Shih *et al.* (2007) believe that the high flexibility of this concept is able to accommodate further extension to make better choices in various situations. In addition, some of the advantages of TOPSIS methods are simplicity, rationality, comprehensibility's, good computational efficiency and ability to measure the relative performance for each alternative in a simple mathematical form (Roszkowska, 2011). In continuation, based on modifying conventional relative closeness definition in TOPSIS algorithm, this article proposed a new approach to the MCGDM/MAGDM problem. In other words, the novelty of this study is that the conventional TOPSIS method is employed in MCDM/MADM problem. The proposed TOPSIS-based method is employed in MCGDM/MAGDM problem.

PROPOSED APPROACH

In this section, brief description presented as follows.

Conventional Version of the TOPSIS Method

According to Huang and Li (2012), TOPSIS has become a popular MCDM technique; since it has a comprehensible theoretical structure and is able to provide an exact model for decision-making. Yue (2013b) believe that the underlying logic of TOPSIS is to define an ideal solution and negative ideal solution. Then, the optimal alternative is the one, which has the shortest distance from the ideal solution and the farthest distance from the negative ideal solution. The idea of TOPSIS can be expressed in a series of steps (Tayeb *et al*., 2007):

Step 1*:* Obtain performance data for *n* alternatives over *k* criteria. Raw measurements are usually standardised; converting raw measures x_{ij} into standardised measures s_{ij}. Construct normalised decision matrix. This step transforms various attribute dimensions into non-dimensional attributes, which allows comparisons across criteria. Normalise scores or data as follows:

$$r_{ij} = X_{ij} / \sqrt{\Sigma X_{ij}^2} \text{ for } i = 1, \ldots, m;\ j = 1, \ldots, n. \qquad \ldots (1)$$

Step 2*:* Develop a set of importance weights w_k, for each of the criteria. The basis for these weights can be anything, but usually, is ad hoc reflective of relative importance. Scale is not an issue if standardising was accomplished in Step 1. Construct the weighted normalised decision matrix. Assume we have a set of weights for each criteria w_j for j = 1, …, n. multiplies each column of the normalised decision matrix by its associated weight. An element of the new matrix is:

$$V_{ij} = w_j r_{ij} \quad \text{... (2)}$$

Step 3: Determine the ideal and negative ideal solutions.

Positive ideal solutions:

$$A^* = \{v_1^*, \dots, v_n^*\}, \text{ where} \quad \text{... (3)}$$

$$V_j^* = \{\max (v_{ij}) \text{ if } j \,\varepsilon\, J; \min (v_{ij}) \text{ if } j \,\varepsilon\, J'\}$$

Negative ideal solutions:

$$A^- = \{v_1^-, \dots, v_n^-\}, \text{ where} \quad \text{... (4)}$$

$$V_j^* = \{\min (v_{ij}) \text{ if } j \,\varepsilon\, J; \max (v_{ij}) \text{ if } j \,\varepsilon\, J^-\}$$

Step 4*:* Calculate the separation measures for each alternative. The separation from the ideal alternative is:

$$S_i^* = [\Sigma (v_j^* - v_{ij})^2] \wedge^{1/2} \quad i = 1, \dots, m. \quad \text{... (5)}$$

Similarly, the separation from the negative ideal alternative is:

$$S_i^- = [\Sigma (v_j^- - v_{ij})^2] \wedge^{1/2} \quad i = 1, \dots, m. \quad \text{... (6)}$$

Step 5*:* Calculate the relative closeness to the ideal solution Ci*:

$$C_i^* = S_i^{"} / S_i^* + S_i^{"}, \quad 0<C_i^*<1 \quad (7)$$

Step 6*:* Rank order alternatives by maximising the ratio in Step 5. Select the option with Ci* closest to 1.

Group Version of the TOPSIS Method (the Proposed Approach)

According to Pedrycz *et al.* (2011), there are many situations, for instance, at the high managerial levels of organisations, when the decision problems involve wide domains of knowledge which are beyond a single individual (this is particularly true when the decision environment becomes more complex and multifaceted). As a consequence, it is usually necessary to allocate more than one professional to the decision process. This is particularly valid in environments with a diverse workforce, where decisions require multiple perspectives and different areas of expertise of the individuals represented in the group. Thus, how to obtain the maximum degree of consensus or agreement from these experts for the given alternatives is an interesting and important research topic (Li and Sun, 2012). This is the problem we wish to address here.

The proposed procedure in this article can be expressed in the following steps:

Step 1*:* Construct the decision matrixes for k-DMs

In the process of GDM under multiple criteria, each DM provides his/her preferences over the alternatives with respect to each criterion and constructs an individual decision matrix as discussed earlier).

Step 2*:* Calculate the normalised decision matrix $X = (x_{ij})_{m.n}$ for each DM.

Step 3*:* Calculate the weighted normalised decision matrix for each DMs, by Equation (2).

In sum, the two of fundamentally accepted criteria weighting in MCDM context are the subjective (the criteria weight can be determined independently by a supra DM. according to Pate-Cornell, 1984, the supra DM is one person has the role to make final decisions for the group, taking into account the preferences of the individual DMs) and the objective approach (the criteria weights is calculated mathematically). The concern here is with the first type of criteria weighting.

Step 4*:* Determine the positive ideal and negative ideal solutions for each DMs, by Equations (3) and (4).

Step 5*:* Calculate the separation measures from the ideal solution and the negative ideal solution for each DMs, by Equations (5) and (6).

***Step 6**:* Calculate the relative closeness to the ideal solution.

6.1. Determine the weights of DMs (as discussed latter in this article),

6.2. Calculate the relative closeness for the group, by Equation (9).

$C_i^{*Group} = ((S^-_{iE1} \times W_{E1}) + (S^-_{iE2} \times W_{E2}) + \ldots + (S^-_{iEk} \times W_{Ek})) /$ ...(8)

$(((S^-_{iE1} \times W_{E1}) + (S^-_{iE2} \times W_{E2}) + \ldots + (S^-_{iEk} \times W_{Ek})) +$

$((S^*_{iE1} \times W_{E1}) + (S^*_{iE2} \times W_{E2}) + \ldots + (S^*_{iEk} \times W_{Ek}))),$

$= \Sigma^t_{k=1} (S^-_{iEk} \times W_{Ek}) / (\Sigma^t_{k=1} (S^-_{iEk} \times W_{Ek}) + \Sigma^t_{k=1} (S^*_{iEk} \times W_{Ek}))$ ...(9)

, i=1, 2, …, m; j=1, 2, …, n; k=1, 2, …, t.

where,

C_i^{*Group}: The relative closeness of group decision of each alternative

W_{Ek}: The weights of DM k

S_i^*: The separation of each alternative from the positive ideal solution

S_i^-: The separation of each alternative from the negative ideal solution.

***Step 7**:* Rank the preference order

Rank alternatives in terms of their relative closeness.

As can be seen, the major difference from conventional TOPSIS technique is in Step 6.2.; in other words, moving from relative closeness for each DM to relative closeness for the group.

Chi-Square Test

Historically, the logic of hypothesis testing was first invented by Karl Pearson (1857–1936), a renaissance scientist, in Victoria London in 1900 (Rana and Singhal, 2015). According to Dunn (2001), the chi-square, which compares observed frequencies against expected frequencies, is such a tool. Nevertheless, the omnibus of all three tests in the Karl Pearson family of chi-square tests—goodness of fit, independence and homogeneity—use essentially the same formula. Each of these three tests is, in fact, distinct with specific hypothesis, interpretations and options following rejection of the null hypothesis. The main difference across each of the three chi-square tests relates to the appropriate situations for which each should be used.

- The chi-square goodness of fit test is used when a sample is compared on a variable of interest against a population with known parameters.
- The chi-square test of independence determines whether two categorical variables in a single sample are independent from or associated with each other.
- Finally, the chi-square test of homogeneity is used to determine whether two or independent samples differ in their distributions on a single variable of interest (Franke *et al*., 2012).

On the other side, according to Dunn (2001), given its non-parametric nature, the chi-square test need not be applied to data that conform to any particular shape (i.e. normal distribution), though the observations must be nominal. The data are usually organised as frequencies placed within a relatively small range of categories. As a result, the shape of the data's distribution is unlikely to resemble the familiar bell-shaped curve. The formula for calculating a chi-square statistic is (Rana and Singhal, 2015):

$$X^2 = \Sigma^n_{i=1} (O_i \Sigma E_i)^2 / E_i \qquad \text{... (10)}$$

where,

O stands for the observed frequency

E stands for the expected frequency.

Expected count is subtracted from the observed count to find the difference between the two. Then the square of the difference is calculated to get rid of the negative values. Then the square of the difference is divided by the expected count to normalise bigger and smaller values.

The Extended Chi-Square-Based Method for DM Weighting in GDM Process

According to Ossadnik *et al*. (2016), in some decision settings, it is appropriate to waive the assumption of equivalent group members in favour of a differentiated, relative weighting of votes. Marked differences in knowledge, experience, management level of or competence between the DMs should be reflected in their respective influences on the overall ranking of the alternatives. This is the problem we wish to address here.

The proposed procedure in this article can be expressed in the following steps:

Step1. Identify the group ideal solution

Determine the group ideal solution, by Equation (11).

$$A^{*Group} = \{x^{*1}_{ij}, \dots, x^{*k}_{ij}\} = \{(\max (x_{ij})^k \ \%i \ \varepsilon \ I), (\min (x_{ij})^k \ \%i \ \varepsilon \ J)\}, \quad \text{... (11)}$$

i=1, 2, …, m; j=1, 2, …, n; k=1, 2, …, t.

where, I is associated with benefit criteria and J is associated with cost criteria.

Step2. Construct the ideal decision matrices of all individual decision matrices (the group ideal decision matrix) (Equation 12), by Equation (11).

$$\begin{array}{cccccc} & C_1 & C_2 & \dots & C_n & \\ A_1 & x^{*k}_{11} & x^{*k}_{12} & \dots & x^{*k}_{1n} & \\ A_2 & x^{*k}_{21} & x^{*k}_{22} & \dots & x^{*k}_{2n} & \\ . & . & . & . & . & \\ . & . & . & . & . & \\ . & . & . & . & . & \\ A_m & x^{*k}_{m1} & x^{*k}_{m2} & \dots & x^{*k}_{mn} & \end{array} \quad (12)$$

Step3. Conducted the modify chi-square-based approach

Conducted the modify chi-square-based method ($X^{2'}$), by Equation (13).

As noted earlier, Pearson proposed the chi-square test for calculating the goodness of fit, independence and homogeneity. We use Pearson's method to calculate DMs weight. Further, we modify the conventional chi-square test by changing the formula parameters definition. So, in the proposed method, individual preferences and group ideal preference play the role of observed frequency and expected frequency, respectively (Equation 13).

$$X^{2'}_k = \Sigma^m_{i=1}\Sigma^n_{j=1} (I_p \, \Sigma GI_p)^2/GI_p, \ i=1, 2, \dots, m; \ j=1, 2, \dots, n; \ k=1, 2, \dots, t. \quad \text{... (13)}$$

where,

I_p stands for the individual preferences,

GI_p stands for the group ideal preference.

Step4. Determine the weight of DM

The chi-square-base proposed model in this article is capable of being deployed as a DMs weighting calculation method, through following formula (Equation 14):

$$\text{Weight of each DM } (W_k) = [1 \, \Sigma \, (X^{2'}_k / \Sigma^t_{k=1} X^{2'}_{k)}], \ k= 1, 2, \dots, t. \quad \text{... (14)}$$

where, $0 \leq Wk \leq 1$ and $\Sigma^t_{k=1} W_k = 1$.

Generally, the expert has a large weight if his/her preference is close to the ideal preference and has a small weight if his/her preference is far from the group ideal preference.

EXPERIMENTAL RESULTS

In this section, we provide a numerical example to illustrate the implementation of the proposed methodology. Consider three committee members, who are experts (in short, E_1, E_2 and E_3), five alternatives (or marketing strategy; in short MS_1 = offering pricing and sales incentive, MS_2 = developing new product, MS_3 = modifying existing ones, MS_4 = growth through acquisition and MS_5 = new modes of distribution) and three criteria (C_1 = product positioning, C_2 = brand loyalty and C_3 = market share) MCGDM problem as follows.

Construct the Decision Matrixes for k-DMs

In the process of GDM, each committee members (or experts) provide the performance values the alternatives with respect to each attribute (Tables 1–3).

Table 1: The Performance Value for E_1

		Criteria		
		C^*_1	C^*_2	C^*_3
Alternative	MS_1	1	83	22
	MS_2	5	53	18
	MS_3	5	53	23
	MS_4	3	73	15
	MS_5	7	67	19

*Benefit-type criteria

Table 2: The Performance Value for E_2

		Criteria		
		C^*_1	C^*_2	C^*_3
Alternative	MS_1	7	84	22
	MS_2	9	61	18
	MS_3	5	99	25
	MS_4	7	79	20
	MS_5	1	70	18

*Benefit-type criteria

Table 3: The Performance Value for E_3

		Criteria		
		C^*_1	C^*_2	C^*_3
Alternative	MS_1	9	53	19
	MS_2	7	100	24
	MS_3	5	68	17
	MS_4	3	75	22
	MS_5	9	86	25

*Benefit-type criteria

In this section, we have used TOPSIS to find the relative closeness for each DM. For instance, for E_1:

Calculate the Normalised Decision Matrix (Based on Table 1)

$$r_{ij} = X_{ij} / \sqrt{\Sigma X_{ij}^2} \text{ for } i = 1, \ldots, m;\ j = 1, \ldots, n.$$

$$R_{ij} = \begin{vmatrix} 0.096 & 0.555 & 0.502 \\ 0.479 & 0.355 & 0.410 \\ 0.479 & 0.355 & 0.524 \\ 0.287 & 0.489 & 0.342 \\ 0.670 & 0.448 & 0.433 \end{vmatrix}$$

Calculate the Weighted Decision Matrix

$V_{ij} = w_j\, r_{ij}$

The given weights from the supra DM is equal weights. Thus, $E_1 = E_2 = E_3 = 0.333$.

The weighted decision matrix is then:

$$V_{ij} = \begin{vmatrix} 0.032 & 0.185 & 0.167 \\ 0.159 & 0.118 & 0.137 \\ 0.159 & 0.118 & 0.175 \\ 0.096 & 0.163 & 0.114 \\ 0.223 & 0.149 & 0.144 \end{vmatrix}$$

Determine the Positive Ideal and Negative Ideal Solutions

Positive Ideal solutions:

$A^* = \{v_1^*, \ldots, v_n^*\}$, where, $V_j^* = \{\max (v_{ij}) \text{ if } j \in J; \min (v_{ij}) \text{ if } j \in J'\}$, $A^* = (0.223, 0.185, 0.175)$.

Negative ideal solutions:

$A^- = \{v_1^-, \ldots, v_n^-\}$, where, $V_j^* = \{\min (v_{ij}) \text{ if } j \in J; \max (v_{ij}) \text{ if } j \in J^-\}$,

$A^- = (0.032, 0.118, 0.114)$

Calculated the Separation Measures

Separation from the positive ideal solution:

$S_i^* = [\Sigma (v_j^* \Sigma v_{ij})^2]$ ^1/2 $i = 1, \ldots, m$.

$S^*_1 = 0.192$, $S^*_2 = 0.100$, $S^*_3 = 0.092$, $S^*_4 = 0.143$ and $S^*_5 = 0.047$.

Separation from the negative ideal solution:

$S_i^{"} = [\text{“} (v_j^{"} \text{ “ } v_{ij})^2]$ ^1/2 $i = 1, \ldots, m$.

$S^-_1 = 0.085$, $S^-_2 = 0.130$, $S^-_3 = 0.141$, $S^-_4 = 0.078$ & $S^-_5 = 0.196$.

The computation for E_2 and E_3 is not repeated here. A comparison of the test results is given in Table 4.

Table 4: Comparison Results for Three Experts

		Separation measure					
		E_1		E_2		E_3	
		S_i^*	S_i^-	S_i^*	S_i^-	S_i^*	S_i^-
Alternative	MS_1	0.192	0.085	0.058	0.149	0.099	0.128
	MS_2	0.100	0.130	0.87	0.186	0.043	0.133
	MS_3	0.092	0.141	0.093	0.127	0.118	0.051
	MS_4	0.143	0.078	0.70	0.144	0.138	0.054
	MS_5	0.47	0.196	0.200	0.017	0.027	0.153

Calculate the Relative Closeness to the Ideal Solution

Now, to aggregate the preference ordering into consensus ordering, the extended TOPSIS method (introduced in this article) is used. As you see, the separation measures from the positive and negative ideal solution for three DMs are shown in Table 4. Moreover, as noted earlier, this model is capable of taking the experts weights into account. Therefore, the weight of each DM (by extended chi-square method, introduced in this article; Equations 11–14), in which the DMs weights are different, is set as follows, that is, for E_1:

Identify the Group Ideal Solution

We identify the group ideal solution, by using Equation (11). For instance, for x^{*1}_{11}:

$A^{*Group} = \{x^{*1}_{ij}, \ldots, x^{*k}_{ij}\} = \{(\max (x_{ij})^k \%i \in I), (\min (x_{ij})^k \%i \in J)\}$,

$x^{*1}_{11} = \{\max (1, 7, 9)\} = 9.$

o Construct the ideal decision matrices' of all individual decision matrices

By using previous step results, we construct the ideal group decision matrix, as follows (Table 5).

Table 5: The Group Ideal Decision Matrix

		Criteria		
		C_1	C_2	C_3
Alternative	MS_1	9	84	22
	MS_2	9	100	24
	MS_3	5	99	25
	MS_4	7	79	22
	MS_5	9	86	25

Construct the Modify Chi-Square Test

We conducted the modify chi-square test, by using Equation (13), for instance, for $X^{2'}_1$:

$X^{2'}_1 = ((1 - 9)^2/9 + (83 - 84)^2 / 84 + (22 - 22)^2 / 22 + (5 - 9)^2 / 9 + (53 - 100)^2 / 100 + (18 - 24)^2 / 24 + (5 - 5)^2 / 5 + (53 - 99)^2 / 99 + (23 - 25)^2 / 25 + (3 - 7)^2 / 7 + (73 - 79)^2 / 79 + (15 - 22)^2 / 22 + (7 - 9)^2 / 9 + (67 - 86)^2 / 86 + (19 - 25)^2 / 25) = 65.08$

Similarly,

$X^{2'}_2 = 29.38,$

$X^{2'}_3 = 27.05.$

Determine the Weights of DM

Finally, by using Equation (14), we have:

Weight of DM (E_1) = [1 – (65.08 / (65.08 + 29.38 + 27.05))] = 0.464,

Similarly,

Weight of DM (E_2) = 0.758,

Weight of DM (E_3) = 0.777.

Based on the $\Sigma^t_{k=1} W_k = 1$, we have:

$W_1 = W_1 / \Sigma^3_{k=1} W_k = 0.464 / (0.464 + 0.758 + 0.777) = 0.232,$

Similarly,

W_2=0.379,

W_3 =0.389.

Then, W_k = (0.232, 0.379 and 0.389).

As can be seen from the above results, the expert E_3 and E_1 who give the close and far value from the ideals decisions, are considered as the most and least important, respectively.

Calculate the Relative Closeness for the Group

Calculate the relative closeness for the group, by Equation (9). For instance, for C^*_1:

C_1^{*Group} = “$^{3}_{k=1}$ $(S^{-}_{iEk} \times W_{Ek}) / (\Sigma^{3}_{k=1} (S^{-}_{iEk} \times W_{Ek}) + \Sigma^{t}_{k=1} (S^{*}_{iEk} \times W_{Ek}))$ = ((0.085 × 0.232) + (0.149 × 0.379) + (0.128 × 0.389)) / (((0.085 × 0.232) + (0.149 × 0.379) + (0.128 × 0.389)) + ((0.192 × 0.232) + (0.058 × 0.379) + (0.099 × 0.389))) =0.545,

Similarly,

C_2^{*Group} = 0.676,

C_3^{*Group} = 0.496,

C_4^{*Group} = 0.452,

C_5^{*Group} = 0.534.

Rank the Preference Order

Finally, we rank alternatives in terms of their relative closeness, as follows.

$MS_2 \geq MS_1 \geq MS_5 \geq MS_3 \geq MS_4$

0.676 0.545 0.534 0.496 0.452

Therefore, the best alternative is MS_2 (developing new product), since it is superior to all the other alternatives. While MS_4 (growth through acquisition) have a very bad performance.

According to the viewpoint proposed by Wang (2007), ‘one intriguing problem is that often time’s different methods may yield different answers to the same decision problem. Thus, the issue of evaluating the relative performance of different MCDM method is raised. One evaluating procedure is to examine the stability of an MCDM methods mathematical process by checking the validity of its proposed rankings’. Therefore, the effectiveness of the proposed method is validated through a comparative analysis with two other previous methods including extended TOPSIS to obtain the ideal compromise solution in GDM context (Azadfallah, 2017—further, the main goal of this article is to propose a methodology for the selection of suppliers when decision has to be made by a group of DMs. With this in mind the authors build on the popular TOPSIS method (often used to find individual preference order), extending it to accommodate multiple DMs as in a conventional TOPSIS analysis. The proposed approach works on an alternative-criteria matrix. However, in this case, the criteria are given by each DM and the entries represent the priorities obtained for each DM from a conventional TOPSIS analysis. This approach not only allows the use of a well-defined framework to consider collective preference orderings but also it provides a way to handle different weights on DMs], and TOPSIS and Borda’s function approach (Hwang and Lin, 1987—in this method, the conventional TOPSIS method can be used to find the individual preference ordering. Then Borda’s function can be used to find the collective preference orderings]. With no intention to describe the whole procedure, we shall only point to the final results (Table 6).

FINDINGS

In summary, the main findings of this study are as follows.

The proposed method with extended TOPSIS approach

According to the results of Table 6, the proposed method rank order $MS_2 \geq MS_1 \geq MS_5 \geq MS_3 \geq MS_4$ can be said to be consistent with respect to the extended TOPSIS rank orders ($MS_2 \geq MS_1 \geq MS_5 \geq MS_4 \geq MS_3$). As can be seen, the three best-ranked alternatives (MS_2, MS_1 and MS_5) are same. However, it is clear that there exist some differences (particularly, MS_3 and MS_4).

Table 6: Comparison with Other Models

PreferenceDM	Priorities
E_1 (Individual)	$MS_5 \geq MS_3 \geq MS_2 \geq MS_4 \geq MS_1$ 0.807 0.605 0.565 0.352 0.308
E_2 (Individual)	$MS_1 \geq MS_2 \geq MS_4 \geq MS_3 \geq MS_5$ 0.718 0.681 0.647 0.578 0.078
E_3 (Individual)	$MS_5 \geq MS_2 \geq MS_1 \geq MS_3 \geq MS_4$ 0.851 0.755 0.565 0.302 0.283
Collective (proposed method)*	$MS_2 \geq MS_1 \geq MS_5 \geq MS_3 \geq MS_4$ 0.676 0.545 0.534 0.496 0.452
Collective (extended TOPSIS method, Azadfallah, 2017)*	$MS_2 \geq MS_1 \geq MS_5 \geq MS_4 \geq MS_3$ 0.806 0.616 0.509 0.478 0.476
Collective (proposed method)**	$MS_2 \geq MS_5 \geq MS_3 \geq MS_1 \geq MS_4$ 0.661 0.572 0.513 0.509 0.440
Collective (TOPSIS and Borda's method, Hwang and Lin, 1987)**	$MS_2 \approx MS_5 \geq MS_1 \geq MS_3 \geq MS_4$

*The same problem (Tables 1–3), W_j = (0.333, 0.333 and 0.333) and W_k= (0.232, 0.379 and 0.389).
**Notice: here, due to the comparison capability between TOPSIS and Borda's function approach and the proposed method, equal weights for experts are used.

The proposed method with TOPSIS and Borda's function approach

According to the results of Table 6, we can find the priority (for proposed method) is $MS_2 \geq MS_5 \geq MS_3 \geq MS_1 \geq MS_4$. This priority is different from that the TOPSIS and Borda's function approach ($MS_2 \approx MS_5 \geq MS_1 \geq MS_3 \geq MS_4$). As can be seen, the two best-ranked alternatives (MS_2 and MS_5) are closeness (in other words, $MS_2 \approx MS_5$). However, the proposed method introduced only one of them (MS_2) as the best alternative. As compared results show our model is better than the previous ones. Because our model is capable of considering the preference intensities. In addition, there is no tie between the ranks in the proposed model.

The proposed method with equal/unequal DM weights

According to the results of Table 6, we can find the priority (for unequal DM weights, W_k= [0.232, 0.379 and 0.389]) is $MS_2 \geq MS_1 \geq MS_5 \geq MS_3 \geq MS_4$. This priority is different from that of the other method (in other words, for equal DM weights, W_k= [0.333, 0.333 and 0.333]), $MS_2 \geq MS_5 \geq MS_3 \geq MS_1 \geq MS_4$). Because, the DM weights are considered into the proposed method.

In general, the results are easily acceptable for all experts. Because, they are based on his/her giving preference information. On the other side, can more assurance to the results by applying a systematic model.

CONCLUSION

The problem of aggregating the individual decisions in a single collective decision is the main challenge to the GDM. However, in the literature, several ways to aggregate the individual pre-order in a single collective pre-order in a GDM process are proposed. More specifically, in the case of the TOPSIS the two approaches systematically employed to deal with GDM: 1. the external aggregation and 2. The internal aggregation rules. Theoretically, there is no reason to be restricted to these methods. Therefore, in this article, different aggregation method is discussed. We shall call this type of aggregation as 'middle aggregation' method. Further, in this article, the extended TOPSIS method is used which was originally introduced by Hwang and Yoon (1981), but unlike from Hwang and Yoon's approach, different relative closeness method is proposed for the calculation of the relative closeness to the ideal solution. In addition, a new chi-square-based approach introduced to determine the importance of DMs in GDM process. Finally, a numerical example in marketing strategy selection environment is given to illustrate the feasibility and practicability of the proposed multiple attribute GDM/multiple criteria GDM (MAGDM/ MCGDM) method. According to the results (Table 6), we can find the priority $MS_2 \geq MS_1 \geq MS_5 \geq MS_3 \geq MS_4$ and $MS_2 \geq MS_5 \geq MS_3 \geq MS_1 \geq MS_4$. This priority is different from that the existing approaches (extended TOPSIS approach, proposed by Azadfallah, 2017; and Borda's function approach) $MS_2 \geq MS_1 \geq MS_5 \geq MS_4 \geq MS_3$ and $MS_2 \approx MS_5 \geq MS_1 \geq MS_3 \geq MS_4$, respectively. However, as can be seen, three best-ranked alternatives ((MS_2, MS_1 and MS_5) and two best and worst ranked alternatives (MS_2 and MS_4), are closeness, respectively. It is clear that there exist some differences. But, in sum, these analyses show that the proposed method is efficient and the result is consistent. In addition, according to the results, we can find changing the weight of expert in decision-making process has a significant effect in ranking results ($MS_2 \geq MS_1 \geq MS_5 \geq MS_3 \geq MS_4$, versus $MS_2 \geq MS_5 \geq MS_3 \geq MS_1$ e" MS_4 for equal/unequal DM weights, respectively).

The merits and advantages of the proposed approach are shown as follows:

- The attractiveness of this approach is that we do not have to modify the conventional TOPSIS and chi-square methods and does not cause more computational burden than the conventional method.
- The proposed method makes full use of decision information and does not require the extra data from experts.
- Support the GDM and avoid groupthink.
- The proposed method (particularly, TOPSIS –based approach), used the results of one, as input of another, then the output is considered reliable.

In sum, the proposed method is straightforward and the algorithm is clear (for both TOPSIS and chi-square-based approach). Hence, we believe that the mechanisms of proposed methods are reasonable. Finally, future research can apply this proposed approach to other managerial issue or compare it with another existing model (internal and external aggregation mode for TOPSIS method). On the other side, it is expected that the methods developed in this article may have more potential applications in the future works.

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REFERENCES

Abdolvand MA and Najafizadeh NS, 2011. "A model for standardization/adaptation strategy selection in the Iran's multinational companies (MNCs)", *International Journal of Management and Business Research*, Vol. 1, No. 1, pp. 25–34.

Alencar LH, Almedia ATD and Morais CC, 2010. "A multi criteria group decision model aggregating the preferences of decision makers based on ELECTRE methods", *Pesquisa Operacional*, Vol. 30, No. 3, pp. 687–702.

Alfares HK and Duffuaa SO, 2008. "Determining aggregate criteria weights from criteria rankings by a group of decision makers", *International Journal of Information Technology & Decision Making*, Vol. 7, No. 4, pp. 1–13.

Anisseh M, Piri F, Shahraki MR and Aghamohamadi F, 2012. "Fuzzy extension of TOPSIS model for group decision making under multiple criteria", *Artificial Intelligence Review*, Vol. 38, No. 12, pp. 325–338.

Anna ID, Cahyadi I and Yakin A, 2017. "Model for marketing strategy decision based on multi criteria decision making: a case study in Batik Madura industry", *Journal of Physics Conference Series*, Vol. 953, No. 17, pp. 1–7. doi: 10.1088/1742-6596/953/1/012135.

Azadfallah M, 2015. "A multiple attribute group decision making model for selecting the best supplier", *International Journal of Business Analytics and Intelligence*, Vol. 3, No. 2, pp. 13–19.

Azadfallah M, 2016a. "Marketing strategy selection by interval TOPSIS under incomplete data", *XIBA Business Review*, Vol. 2, No. 2, pp. 29–38.

Azadfallah M, 2016b. "A new aggregation rule for ranking suppliers in group decision making under multiple criteria", *Journal of Supply Chain Management Systems*, Vol. 5, No. 4, pp. 38–48.

Azadfallah M, 2016c. "A supplier selection using a group decision making under multi criteria by considering individual criteria set", *Journal of Supply Chain Management Systems*, Vol. 5, No. 2, pp. 38–45.

Azadfallah M, 2017. "Supplier selection by extended TOPSIS to obtain the ideal compromise solution in group decision making", *International Journal of Business Analytics*, Vol. 4, No. 3, pp. 71–85.

Bui TX, 1987. *A group decision support system for cooperative multi criteria group decision making*, Springer-Verlag, Berlin Heidelberg.

Buyukozkan G and Ozturk D, 2019. "2-tuple linguistic integrated group decision making methodology for E-commerce strategy selection", *11th conference of the European Society for fuzzy logic and technology* (EUSFLAT 2019), Atlantis Studies in uncertainty Modelling, Vol. 1, No. 2, pp. 706–713.

Cahyadi I and Anna ID, 2019. "A multi-criteria model for marketing strategy selection for Batik fashion creative industry in Indonesia", *International Journal of Advances in Scientific Research and Engineering*, Vol. 5, No. 1, pp. 74–84.

Carillo CJB, Hernandez HG and Redondo RP, 2018. "Decision making under the multi criteria approach to identify marketing mix strategies", *Contemporary Engineering Science*, Vol. 11, No. 52, pp. 2581–2589.

Carmo DKDS, Marins FAS, Salomon VAP and Mello CHP, 2013. "On the aggregation of individual priorities in incomplete hierarchies", *Proceedings of the international symposium on the Analytic Hierarchy Process*, Vol. 20, No. 13, pp. 1–9.

Deng Y, Wu J, Sun X, Xu P and Zhang Y, 2011. "Aggregation of interval numbers in group decision making", *ICIC Express Letters*, Vol. 5, No. 4, pp. 1057–1062.

Dizaji LY and Khanmohammadi S, 2016. "A new multi-criteria decision making based on fuzzy-TOPSIS theory", *Journal of Advances in Computer Engineering and Technology*, Vol. 2, No. 4, pp. 39–48.

Dunn DS, 2001. *Statistics and data analysis for the behavioral sciences*, McGraw-Hill companies, Inc., New York.

Escobar MT and Jimenez JMM, 2007. "Aggregation of individual preferences structures in AHP-group decision making", *Group Decision and Negotiation*, Vol. 16, No. 20, pp. 287–301.

Falsafi N, Zenouz RY and Mozaffari MM, 2011. "Employees performance appraisal with TOPSIS under fuzzy environment", *International Journal of Society Systems Science*, Vol. 3, No. 3, pp. 272–290.

Fifield P, 2007. Marketing strategy the difference between marketing and markets, Third edition, Elsevier Ltd.UK

Forman E and Peniwati K, 1998. "Aggregating individual judgments and priorities with the Analytic Hierarchy Process", *European Journal of Operational Research*, Vol. 108, No. 1, pp. 165–169.

Franke TM, Ho T and Christie CA, 2012. "The chi-square test: often used and more often misinterpreted", *American Journal of Evaluation*, Vol. 33, No. 3, pp. 448–458.

Fu C, 2008. "Extended TOPSIS for belief group decision making", *Journal of Service Science & Management*, Vol. 1, No. 1, pp. 11–20.

Furrer O, 2006. Marketing strategies, In: *Marketing management: international perspectives*, M. East, pp. 81–98.

Gbolagade A, Adesola MA and Oyewale IO, 2013. "Impact of marketing strategy on business performance a study of selected small and medium enterprise (SMEs) in Oluyole local government, IBADAN, Nigeria", *IOSR Journal of Business and Management*, Vol. 11, No. 4, pp. 59–66.

Gorecka D and Szaluka M, 2013. "Country market selection in international expansion using multi criteria decision aiding methods", *Multiple Criteria Decision Making*, Vol. 8, No. 2013, pp. 31–55.

Huang YS and Li WH, 2012. "A study on aggregation of TOPSIS ideal solutions for group decision making", *Group Decision and Negotiation*, Vol. 21, No. 2012, pp. 461–473.

Hwang CL and Lin MJ, 1987. *Group decision making under multiple criteria: methods and applications*, Springer-Verlag, Berlin Heidelberg.

Hwang CL and Yoon K, 1981. *Multiple attribute decision making*, Springer Verlag. US.

Jabeur K and Martel JM, 2010. "An agreement index with respect to a consensus preorder", *Group Decision and Negotiation*, Vol. 19, No. 10, pp. 571–590.

Jabeur K and Martel JM, 2007. "A collective choice method based on individual preferences relational systems (P.R.S.)", *European Journal of Operational Research*, Vol. 177, No. 7, pp. 1549–1565.

Jabeur K, Martel JM and Khelifa, 2004. "A distance-based collective preorder integrating the relative importance of the group members", *Group Decision and Negotiation*, Vol. 13, No. 20 pp. 327–349.

Jahanshahloo GR, Lotfi FH and Izadkhah M, 2006. "Extension of the TOPSIS method for decision making problems with fuzzy data", *Applied Mathematics and Computation*, Vol. 181, No. 6, pp. 1544–1551.

Jandaghi G and Aziziyan B, 2015. "Formulating and selecting optimum marketing strategy for privileged deposits of Maskan bank by combined DEMATEL and ANP approach", *Indian Journal of Fundamental and Applied Sciences*, Vol. 5, No. S4, pp. 1358–1375.

Kang BY, Zhang Y, Deng X, Wu J, Sun X, Li Y and Deng Y, 2011. "Optimal aggregation of interval numbers based on genetic algorithm in group decision", *Journal of Information & Computational Science*, Vol. 8, No. 5, pp. 842–849.

Li F and Sun M, 2012. "Approach to reaching consensus in triangular fuzzy multiple attribute group decision making", *Journal of Information and Computational Science*, Vol. 9, No. 12, pp. 3557–3567.

Lin CT, Lee C and Wu CS, 2009. "Optimizing a marketing expert decision process for the private hotel", *Experts Systems with Applications*, Vol. 36, No. 3, pp. 5613–5619.

Lin CT, Lee C and Wu CS, 2010. "Fuzzy group decision making in pursuit of a competitive marketing strategy", *International Journal of Information Technology & Decision Making*, Vol. 9, No. 2, pp. 281–300.

Luo X and Jennings NR, 2007. "A spectrum of compromise aggregation operators for multiple attribute decision making", *Artificial Intelligence*, Vol. 171, No. 7, pp. 161–184.

Mohaghar A, Fathi MR, Zarchi MK and Omidian A, 2012. "A combined VIKOR-Fuzzy AHP approach to marketing strategy selection", *Business Management and Strategy*, Vol. 3, No. 1, pp. 13–27.

Mohd VRW and Abdullah L, 2017. "Aggregation methods in group decision making: a decade survey", *Informatica,* Vol. 41, No. 2017, pp. 71–86.

Morgan NA, Whitler KA, Feng H and Chari S, 2018. "Research in marketing strategy", *Journal of the Academy of Marketing Science*. Vol. 20, No. 2, pp. 156-175

Mousavi M and Moghadam RT, 2015. "A new last aggregation compromise solution approach based on TOPSIS method with hesitant fuzzy setting to energy policy evaluation", *Journal of Industrial and Systems Engineering*, Vol. 8, No. 2, pp. 54–66.

Nenad M and Zoran A, 2017. "Multi-criteria decision making methods: comparative analysis of PROMETHEE and VIKOR", *XVII International scientific conference on Industrial Systems* (IS'17), Novisad, Serbis, 4–6 October 2017, pp. 284–287.

Ossadnik W, Schinke S and Kaspar H, 2016. "Group aggregation techniques for analytic hierarchy process and analytic network process: a comparative analysis", *Group Decision and Negotiation*, Vol. 25, No. 16, pp. 421–457.

Pate-Cornell ME, 1984. "Aggregation of opinions and preferences in decision problems, In: Waller RA and Covello VT (eds)", *Low-probability, high-consequence risk analysis*, section 7, pp. 493–505, Springer Science Business Media, LLC.

Pedrycz W, Ekel P and Perreiras R, 2011. *Fuzzy multi criteria decision making models, methods and applications*, John Wiley & Sons, Ltd. UK.

Perez J and Romero SB, 1995. "Theory and methodology three practical criteria of comparison among ordinal preference aggregation rules", *European Journal of Operational Research*, Vol. 85, No. 95, pp. 433–487.

Qu L, He D and Wu J, 2012. "Hybrid particle SWARM optimization algorithm for aggregation in interval numbers in group decision", *Journal of Information and Computational Science*, Vol. 9, No. 6, pp. 1437–1445.

Rana R and Singhal R, 2015. "Chi-square test and its application in hypothesis testing", *Journal of the Practice of Cardiovascular Sciences*, Vol. 1, No. 1, pp. 69–71.

Rao RV, 2007. *Decision making in the manufacturing environment, using graph theory and fuzzy multi attribute decision making methods*, Springer-Verlag, London.

Roghanian E, Rahimi J and Ansari A, 2010. "Comparison of first aggregation and last aggregation in fuzzy group TOPSIS", *Applied Mathematical Modelling*, Vol. 34, No. 20, pp. 3754–3766.

Roszkowska E, 2011. *Multi-criteria decision making models by applying the TOPSIS method to crisp and interval data*. Multiple Criteria Decision Making/University of Economics in Katowice, pp. 200–230.

Sabokbar HF, Hosseini A, Banaitis A and Banaitiene N, 2016. "A novel sorting method TOPSIS-Sort: an application for Tehran environmental quality evaluation", *Business*

Administration and Management, Vol. 2, No. 19, pp. 56-65 doi: 10.15240/tul/001/2016-2-006.

Shih HS, 2015. "A mixed-data evaluation in group TOPSIS with differentiated decision power", *Group Decision and Negotiation*. Vol. 25, No. 3, pp. 537-565,

Shih HS, Shyur HJ and Lee ES, 2007. "An extension of TOPSIS for group decision making", *Mathematical and Computer Modelling*, Vol. 45, No. 20, pp. 801–813.

Sodenkamp MA, Tavana M and Caprio DD, 2018. "An aggregation method for solving group multi-criteria decision making problems with single-valued neutrosophic sets", *Applied Soft Computing*, Vol. 71, No. 18, pp. 715–727.

Srdjevic B, Srdjevic Z and Medeiros YDP, 2017. "Multi-criteria and social choice methods in assessing water management plan", *Proceedings of the 8th international conference on information and communication technologies in agriculture, food and environment* (HAICTA 2017), Chania, Greece, 21–24 September, 2017, pp. 541–553.

Tang MT, Tzeng GH and Wang SW, 1999. "A hierarchy fuzzy MCDM method for studying electronic marketing strategy in the information service industry", *Journal of International Information Management*, Vol. 8, No. 1, pp. 1–22.

Tayeb S, Ahcene B, Omar PJS and Mouloud BK, 2007. "Equipment selection by numerical resolution of the Hessian matrix and Topsis algorithm", *Asian Journal of Information Technology*, Vol. 6, No. 1, pp. 81–88.

Wang X, 2007. Study of ranking irregularities when evaluating alternatives by using some ELECTRE methods and proposed new MCDM method based on Regret and Rejoicing. MSc Thesis, supervisor: E. Triantaphyllou, Louisiana State University, USA.

Wang YM, Chin KS and Yang JB, 2007. "Three new models for preference voting and aggregation", *Journal of the Operational Research Society*, Vol. 58, No. 7, pp. 1389–1393.

Wang YM, Yang JB and Xu DL, 2005. "A preference aggregation method through the estimation of utility intervals", *Computers & Operation Research*, Vol. 32, No. 5, pp. 2027–2049.

Wieloch HG, 2014. "The use of a modification of the Hurwicz's decision rule in multi-criteria decision making under complete uncertainty", *Business, Management and Education*, Vol. 12, No. 2, pp. 283–302.

Wu CS, Lin CT and Lee C, 2010. "Optimal marketing strategy: a decision making with ANP and TOPSIS", *International Journal of production Economics*, Vol. 127, No. 10, pp. 190–196.

Yousefi R, 2016. "An integration of MCDM methods for marketing strategy selection", *Global Journal of Management Studies and Researches*, Vol. 3, No. 3, pp. 96–101.

Yue Z, 2013a. "Group decision making with multi attribute interval data", *Information Fusion*, Vol. 14, No. 13, pp. 551–561.

Yue Z, 2013b. "An avoiding information loss approach to group decision making", *Applied Mathematical Modeling*, Vol. 37, No. 1–2, pp. 112–126.

Zahir S, 2016. "Aggregation of priorities in multi criteria decision analysis (MCDA): connecting decision spaces in the cognitive space", *American Journal of Operations Research*, Vol. 6, No. 4, pp. 317–333.

Zhang G, Lu J and Gao Y, 2015. *Multi-level decision making models, methods, and applications*, Springer-Verlag, Berlin Heidelberg.

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