Marketing Strategy Selection by Interval TOPSIS under Incomplete Data

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Abstract *The choice of suitable marketing strategy is extremely valuable for any business. Some authors claim that, marketing strategy development involves a high degree of uncertainty and ambiguity on the one hand, and can be classified as a Multi-criteria Decision Making (MCDM) problem on the other. In this paper, we try to see all aforementioned factors together. Since, in order to reflect uncertainty of the given information, interval TOPSIS, incomplete decision matrix, and interval criteria weights (instead of conventional modes, crisp data) are obtained is applied. However, in marketing strategy selection problem incomplete data is common; TOPSIS are not applicable to incomplete data. Therefore, to resolve this limitation, the Tamaddon et al. method (the mathematical formulations for finding the missing data in the Data Envelopment Analysis [DEA] environment), has introduced. In this paper, we focus our main attention on the innovative combination of TOPSIS and proposed method initiated by Tamaddon et al., and its uses in the marketing strategy selection problem under incomplete data. In the proposed method, input and output factors play the role of cost and benefit respectively. In addition, comparative analysis performed, and the proposed method seems to be more satisfactory than the traditional method in solving decision problem. The paper concludes with limitations and further research directions.*

Keywords *MCDM,, TOPSIS, Incomplete Data, Marketing Strategy Selection Problem*

INTRODUCTION

Since strategy is concerned with the future, the strategic context of a firm is always uncertain, although the degree and the source of uncertainty may be different for different firms. Facing an uncertain future, the first decision a firm has to make is when to act. The firm has the choice of acting now or waiting until after the uncertainty is resolved, or at least partly resolved. If the firm does act early while there still is uncertainly, it has to decide whether to focus its resources on several scenarios, thus maintaining flexibility (Wernerfelt and Karnani, 1987). It is important considering that marketing strategy is not a standalone endeavor and should be an integral component of functional area strategies of the firm, e.g. marketing, finance, and human resources, of the firm (Ebrahimi et al., 2015). Also, according to the viewpoint proposed by Li et al. (2000), marketing strategy involves a high degree of uncertainty and ambiguity. Therefore, uncertainty is the main challenges to the marketing strategy selection problem.

An organizations marketing strategy describes how the firm will fulfill the needs and wants of its customers (Ferrell and Hartline, 2011). Since, marketing activities to succeed in business is so important. So, organization should try its best in selecting its marketing strategies and behave rationally (Jandaghi and Aziziyan, 2015). The purpose of marketing strategy development is to establish, build, defend and maintain competitive advantage (Li et al., 2000). Therefore, proper and strong marketing strategy is essential for the survival and success of any business in the increasing complex, competitive environment of organizations (Ebrahimi et al., 2015). 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 utilizing the company's skills and resources to achieve marketing objectives. Generally, marketing strategy is concerned with the four major element of the marketing mix: product, price, place and promotion. Essentially, marketing strategy evolves as a consequences of an interplay of four major strategic inputs and the processes which act on them (Li et al., 2000). In other words, marketing strategy focuses on ways in which can differentiate itself from its competitors, investing on its distinctive strengths to deliver better value to customers. A good marketing strategy is characterized by: a) a clear market definition, b) a proper match between corporate strengths and market needs, and c) a superior performance relative to the competition, in the key success factors of the business (Ebrahimi et al., 2015). One of the greatest frustrations and opportunities in marketing is change-customers change, competitors change, and even the marketing organization changes. Strategies that are highly successful today will not work tomorrow. Customers will buy products today that they will have no interest in tomorrow. Another fact about marketing strategy is that it is inherently people driven. Marketing strategy is about people (inside and organization) trying to find ways to deliver exceptional value by fulfilling

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the needs and wants of other people (customers, shareholders, business partners, society at large), as well as the needs of the organization itself. In short, marketing strategy is about people serving people. The combination of continual change and the people-driven nature of marketing make developing and implementing marketing strategy a challenging task (Ferrell and Hartline, 2011). In other words, arriving at a sound and timely marketing strategy is not an easy task. Because of bitter competition, uncertainty, high stakes, and the complexity and fast pace of change in the environment, strategic marketing planning presents a real challenge to managers (Li et al., 2000). In addition, selecting a strategy mainly encompasses mental and qualitative judgments. Therefore, selecting marketing strategies is a strategic issue that is limited to organization resources needs, realistic support, time requirements, compliance with outcomes, or business purpose (Jandaghi and Aziziyan, 2015). So, a marketing strategy decision can be classified as a Multi Criteria Decision Making (MCDM) problem (Wu et al., 2010).

Multiple criteria decision problems are prevalent in many business fields, including marketing, operations management, finance, accounting, etc. (Javalgi and Jain, 1988). MCDM mainly consists of the following two parts: 1. Collect decision information. The decision information generally includes the attribute weights and the attribute values. In a MCDM problem, there are generally a finite set of alternatives and a collection of attributes. The attributes are the indices used to measure the given alternatives, and each attribute has its importance, which is to be determined in the process of decision-making. The attribute values are usually the measure values for the alternatives with respect to each attribute, which mainly take the form of real numbers, interval numbers, triangular fuzzy numbers, intuitionistic fuzzy numbers and linguistic variables, etc. 2. Aggregate the decision information through some proper approach and then rank or select more of the alternatives. In other words, MCDM models are used for evaluating, ranking and selecting the most appropriate alternative from among several alternatives (Azadfallah, 2016_a). In this paper an extended Technique for preference by Similarity to Ideal Solution (TOPSIS) method with interval data is proposed to solve the marketing strategy selection problem under incomplete information. TOPSIS proposed by Yoon & Hwang, is one of the widely used techniques in Multiple Attribute Decision Making (MADM / often-called MCDM). MADM models are selector models that are used for evaluating, ranking, and selecting the most appropriate alternative from among several alternatives. Moreover, TOPSIS can rank a finite number of feasible alternatives in order of preference according to the features of each attribute of every alternative and select a suitable alternative that confirms to the decision makers ideal. The basic concept of TOPSIS technique is that the selected alternative will have the shortest Euclidean distance from the ideal solution and the farthest Euclidean distance from the anti-ideal solution. In the classical TOPSIS method, the rating of alternatives and the weights of criteria are presented by real values (Azadfallah, 2016_b). According to viewpoint proposed by Stanujkic et al. (2012), in such environments classical MADM methods, which use crisp numbers to express the rating and weights, do not provide adequate and effective decision-making. So, when determining the exact values of the attributes is difficult or impossible, it is more appropriate to consider them as interval numbers. The interval numbers are more suitable to deal with the decision-making problems in the imprecise and uncertain environment, because they are the simplest form of representing uncertainty in the decision matrix (Sayadi et al., 2009). Therefore, Jahanshahloo et al. (2006) extended the concept of TOPSIS to develop a methodology for solving MADM problems with interval data. That is the problem we will wish to address here. On the other side, in 2009, Tamaddon et al., developed the mathematical formulations for finding the missing data in the case that the data are interval, in the Data Envelopment Analysis (DEA) environment. In this method, firstly, the missing amounts via the sum of other DMUs (Decision Making Units) inputs and outputs in the case that the data are interval, upper and lower bounds of the missing data via crisp processes determined, and by using convex combination of the interval beginnings and endings, we can obtain a linear function of an analogous variable with each one of the inputs and outputs components; so that we can obtain a function for the missing data via crisp process. In this paper, we focus our main attention on the innovative combination of TOPSIS with interval data and proposed method initiated by Tamaddon et al., and its uses in the marketing strategy selection problem under incomplete information. Whereas, in the proposed method, input and output factors play the role of cost and benefit respectively.

The paper is organized as follows. In the second section, the literature and in the third section, the proposed approach is discussed. Numerical example is provided in the next section. The paper is concluded in the fifth and the last section.

LITERATURE REVIEW

In sum, given the complexity and uncertainty in our environment, MCDM is a powerful decision-making tool to structure problem clearly and systematically (Clin et al., 2009). Nevertheless, in the current MCDM literature, many studies exist on missing data (or incomplete information), however, most of them are limited to Analytic hierarchy Process (AHP) method. Harker (1987), Wedley (1993), Wedley et al. (1993), Wedley (2006), Fedrizzi and Giove (2006), Gao et al. (2010), Carmo et al. (2013), Srdjevic et al. (2014), and Azadfallah (2016_c), could be referred to as an example in one hand. Many studies relate to marketing strategy and marketing resources, but few deals with criteria for MCDM marketing strategy on the other. It is also worth noting here that during our review of the current literature, no studies were found that focuses the combination of methods proposed in this paper. Nevertheless, we will mention some of them. Wind and Saaty (1980) suggested the potential application of the AHP to various marketing decision. Javalgi and Jain (1988) focused on integrating the MCDM models within the decision support system (DSS) framework to encourage greater use of these models. A DSS framework and the criteria used for choice of a model are discussed. Then, based on these MCDM models generally used in the marketing field are evaluated. Li (2005) established a web-enabled approach that combines the advantages of a web-based expert system with the benefits of the group Delphi technique and links strategic marketing planning with internet and e-commerce strategy formulation. Amir et al. (2001) analyzed the process of market selection of investment strategies in an incomplete asset market. Albadavi et al. (2007) introduced the application of PROMETHEE as a multi criteria decision-making approach for ranking preferential alternatives and for determining the best target market. Hartline et al. (2008) used of social networks in implementing viral marketing strategies. In their model, a buyer's decision to buy an item is influenced by the set of other buyers that own the item and the price at which the item is offered. They consider the incomplete information setting in which we only need to know the optimal price. Josephy et al. (2007) presented an algorithm producing a dynamic non-self-financing hedging strategy in an incomplete market corresponding to investor-relevant risk criterion. Read et al. (2008) discussed how marketing strategy decisions should be made in situations of uncertainty. So, they begin to fill the gap between existing marketing tools and the needs of managers facing uncertainty by giving a representative task to individuals with related real-world expertise, and comparing their strategies to those without such experience. Lin et al. (2009) provided a five-step decision making process to enable careful marketing strategy assessment, and contributes to practical implementation for fuzzy ANP utilization by marketing experts in a real industry. Read et al. (2009) extracted some common decision strategies of expert entrepreneurs faced with uncertain business problems and from these findings, made inferences to aid our understanding about the genesis of products, firms, and markets. Shahbandarzadeh and Haghighat (2010) considered the international marketing strategies of Boushehr province according to the variability in target markets. The marketing strategies were defined on the base of participation in six target markets of Boushehr exports. Each of the markets was investigated in terms of four general attributes of opportunities, threats, weakness and strength points, and the sub-attributes thereof by using of IFE and EFE matrixes. Then, LINAMP technique was employed for investigation and gradation of the above-mentioned strategies (separately for each level). At last, the results of each model (or level) were combined by using Borda technique and final grading was achieved. Wu et al. (2010) implemented of the integration of the ANP and TOPSIS, which can be utilized by marketing strategists in a real industry to determine the appropriate marketing strategy. Alaybeyoglu et al. (2012) studied marketing strategies and marketing decisions in the new product development process, so, the criteria that are effective in this process defined and a MCDM mode (particularly, ANP model) proposed to weight the criteria and to define the best strategic marketing scenario. Alaybeyoglu and Albayrak (2013) evaluated pricing strategies and select the pricing strategy solution while considering internal and external factors influencing the company's pricing decision associated with new product development. To reflect the decision maker's subjective preference information and to determine the weight vector of factors (attributes), the fuzzy LINMAP under intuitionistic fuzzy environments is used. Helm and Gritsch (2014) examined determinants of an international marketing mix strategy within a specific business-to-business context that includes the effects of uncertainty. Wieloch (2014) designed two new procedures (for dependent and independent criteria matrices) for multi criteria decision making with scenario planning with an example of marketing strategies selection. Ebrahimi et al. (2015) proposed a suitable model for determining the appropriate marketing strategy based on corporate resources and capabilities. In this regard, a three-step multi criteria decision-making framework is developed to determine the most appropriate marketing strategy in an efficient manner. Jandaghi and Aziziyan (2015) tried to select the optimum marketing strategy for privileged deposits of Maskan bank by purpose of selecting the optimum marketing strategy and using combined multi-criterion decision-making strategy of two ANP and DEMATEL techniques. Finally, An et al. (2007) investigated a market-based mechanism for resource allocation. This paper presents a proportional resource allocation mechanism and gives a game theoretical analysis of the optimal strategies and the analysis shows the existence of equilibrium in the incomplete information setting. In this regard, a hybrid MCDM- mathematical approach (TOPSIS-mathematical formulations for finding the missing data) is suggested to determine the most appropriate marketing strategy in effective manner.

CONCEPTUAL FRAMEWORK AND PROPOSED APPROACH

Conceptual Framework

According to the viewpoint proposed by Robinson (2006), most business decisions are made with incomplete information and in the face of an uncertain future. In other words, in reality, markets are incomplete (Staum, 2008), and uncertainty is a salient concern in many markets (Flood, 1991). At the same time, proper and strong marketing strategy is essential for the survival and success of any business, and involves a high degree of uncertainty and ambiguity (Li et al., 2000) on the one hand, and can be classified as a MCDM problem (Wu et al., 2010) on the other. Since, in this paper, TOPSIS, which is one of the widely used techniques in MCDM (Azadfallah, 2016_b) proposed. Furthermore, in order to reflect uncertainty of the given information, interval TOPSIS is applied. Because, according to Sayadi et al. (2009), the interval numbers are more suitable to deal with the decision-making problems in the imprecise and uncertain environment. However, TOPSIS with interval data method are not applicable to incomplete information. So, to overcome this drawback, this paper focuses on the application of the TOPSIS with interval data method in combination with mathematical approach (Tamaddon et al. method; the mathematical formulations for finding the missing data), for solving a marketing strategy problem, under incomplete information (Fig. 1).

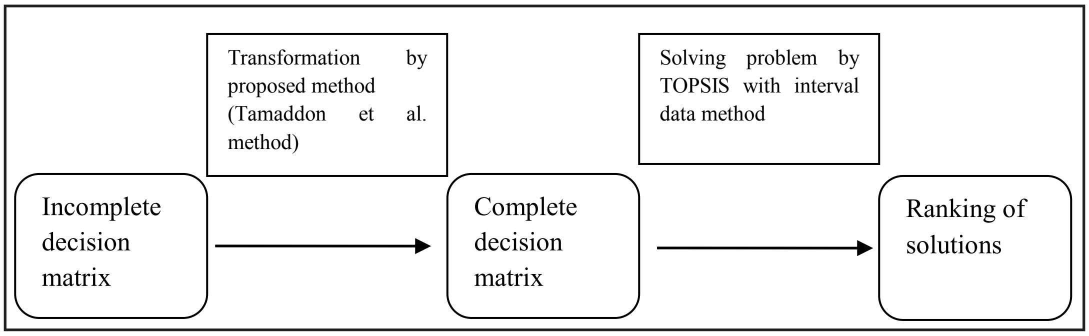

Fig. 1: The Proposed Framework

The Proposed Approach

In many real life problems, the data of the decision-making processes cannot be measured precisely and there may be some other types of data, for instance interval data and fuzzy data. In other words, the decision maker would prefer to say his/her point of view in these forms rather than a real number because of the uncertainty and the lack of certain data, especially when data are known to lie within bounded variables, or when facing missing data, judgment data, etc. (Lotfi and Fallahnejad, 2010). So, Suppose $A_1, A_2, \ldots, A_m$ are m possible alternatives among which decision makers have to choose, $C_1, C_2, \ldots, C_n$ are criteria with which alternative performance are measured, x_{ij} is the rating of alternative A_i with respect to criterion C_j and is not known exactly and only we know $x_{ij} \in [x_{ij}^l, x_{ij}^u]$. A MADM problem with interval data can be concisely expressed in matrix format as (Jahanshahloo et al., 2006):

-	C_1	C_2	C_3
A_1	$[x_{11}^l, x_{11}^u]$	$[x_{12}^l, x_{12}^u]$	$[x_{1n}^l, x_{1n}^u]$
A_2	$[x_{21}^l, x_{21}^u]$	$[x_{22}^l, x_{22}^u]$	$[x_{2n}^l, x_{2n}^u]$
A_3	$[x_{m1}^l, x_{m1}^u]$	$[x_{m2}^l, x_{m2}^u]$	$[x_{mn}^l, x_{mn}^u]$

w= $[w_1, w_2 \ldots w_n]$, where w_j is the weight of criterion C_j.

TOPSIS with Interval Data

In Jahanshahloo et al. (2006), an interval extension of original TOPSIS method was proposed. This approach may be described as follow:

1. Calculate the normalized decision matrix. The normalized value $\bar{n}_{ij}$ is calculated as:

$$\bar{n}^l_{ij} = x^l_{ij} / \sqrt{\textstyle\sum^m_{j=1} (x^l_{ij})^2 + (x^u_{ij})^2}, \quad j=1,\ldots,m, \quad i=1,\ldots,n, \quad (1)$$

$$\bar{n}^u_{ij} = x^u_{ij} / \sqrt{\textstyle\sum^m_{j=1} (x^l_{ij})^2 + (x^u_{ij})^2}, \quad j=1,\ldots,m, \quad i=1,\ldots,n, \quad (2)$$

2. Calculate the weighted normalized interval decision matrix. The weighted normalized value $\bar{v}_{ij}$ is calculated as:

$$\bar{v}^l_{ij} = w_i \bar{n}^l_{ij}, \quad j=1,\ldots,m, \quad i=1,\ldots,n, \quad (3)$$

$$\bar{v}^u_{ij} = w_i \bar{n}^u_{ij}, \quad j=1,\ldots,m, \quad i=1,\ldots,n, \quad (4)$$

Where w_i is the weight of the i_{th} attribute or criterion, and $\sum^n_{i=1}=1$.

3. Determine the positive ideal and negative ideal solution.

$$\bar{A}^+ = \{\bar{v}_1^+, \ldots, \bar{v}_n^+\} = \{(\max \bar{v}^u_{ij} / i \in I), (\min \bar{v}^l_{ij} / i \in J)\}, \quad (5)$$

$$\bar{A}^- = \{\bar{v}_1^-, \ldots, \bar{v}_n^-\} = \{(\min \bar{v}^l_{ij} / i \in I), (\max \bar{v}^u_{ij} / i \in J)\}, \quad (6)$$

Where *I* is associated with benefit criteria, and *J* is associated with cost criteria.

4. Calculate the separation measures, using the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is given as:

$$\bar{d}^+_j = \{\textstyle\sum_{i \in I} (\bar{v}^l_{ij} - \bar{v}^+_i)^2 + \sum_{i \in I} (\bar{v}^u_{ij} - \bar{v}^+_i)^2\}^{1/2}, \quad j = 1,\ldots, m. \quad (7)$$

Similarly, the separation from the negative ideal solution can be calculated as:

$$\bar{d}^-_j = \{\sum_{i \in I} (\overline{v}^u_{ij} - \bar{v}^-_i)^2 + \sum_{i \in I} (\overline{v}^l_{ij} - \bar{v}^-_i)^2\}^{1/2}, j = 1,\ldots, m. \quad (8)$$

5. Calculate the relative closeness to the ideal solution. The relative closeness of the alternative A_j with respect to $\bar{A}^+$ is defined as:

$$\bar{R}_j = \bar{d}^-_j / (\bar{d}^+_j + \bar{d}^-_j), \quad j= 1,\ldots, m. \quad (9)$$

Obviously, an alternative A_j is closer to the $\bar{A}^+$ and farther from $\bar{A}^-$ as $\bar{R}_j$ approaches to 1.

(6) Rank the preference order. Therefore, according to the closeness coefficient, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives.

Entropy with Interval Data

In Lotfi and Fallahnejad, (2010), an extended Shannon's Entropy method was proposed. This approach may be described as follow:

1. The normalized values P_{ij}^l and P_{ij}^u are calculated as:

$$P_{ij}^l = x^l_{ij} / \sum^m_{j=1} x^u_{ij}, \quad P^u_{ij} = x^u_{ij} / \sum^m_{j=1} x^u_{ij}, \quad j=1,\ldots, m, \; i = 1,\ldots, n. \quad (10)$$

2. Lower bound h^l_i and upper bound h^u_i of interval entropy can be obtained by:

$$h^l_i = \min \{- h0 \sum^m_{j=1} p^l_{ij}. \operatorname{Ln} p^l_{ij}, - h0 \sum^m_{j=1} p^u_{ij}. \operatorname{Ln} p^u_{ij}\}, \; i= 1,\ldots, n. \quad (11)$$

$$h^u_i = \max \{- h0 \sum^m_{j=1} p^l_{ij}. \operatorname{Ln} p^l_{ij}, - h0 \sum^m_{j=1} p^u_{ij}. \operatorname{Ln} p^u_{ij}\}, \; i= 1,\ldots, n. \quad (12)$$

Where h0 is equal to (Ln m)-1, and $P^l_{ij}. \operatorname{Ln} p^l_{ij}$ or $p^u_{ij}. \operatorname{Ln} p^u_{ij}$ is defined as 0 if $P^l_{ij}= 0$ or $P^u_{ij}= 0$.

3. Set the lower and the upper bound of the interval of diversification d_i^l and d_i^u as the degree of diversification as follow:

$$d^l_i= 1- h^u_i, \; d^u_i = 1- h^l_i, \quad i= 1,\ldots, n. \quad (13)$$

Set $w^l_i = d^l_i / \sum^n_{s=1} d^u_s$, $w^u_i = d^u_i / \sum^n_{s=1} d^l_s$, i=1,…, n, as the lower and upper bound of interval weight of attribute i.

Theorem. The inequality $w^l_i \leq w^u_i$, i= 1,…, n is held.

The mathematical formulations for finding the missing data (or Tamaddon et al. method).

According to the view point proposed by Tamaddon et al. (2009) for finding the missing data (or incomplete information) the following method is suggested. Suppose that n DMUs with m inputs and s outputs which are the data of interval inputs and outputs are existed, but the i_{th} input of DMU_k; that is $[X^l_{ik}, X^u_{ik}]$ is missing (as noted earlier, in this paper, input, output, and DMUs factors play the role of cost criteria, benefit criteria, and alternative respectively). In continuation, the lower bound of the missing interval is calculated as the following:

$$P^l_1=X^l_{1k}/\sum^n_{j=1,j\neq k} X^l_{1j}, \; P^l_2=X^l_{2k}/\sum^n_{j=1,j\neq k} X^l_{2j}, \ldots, P^l_i=?, \ldots, P^l_m=X^l_{mk}/\sum^n_{j=1,j\neq k} X^l_{mj} \quad (14)$$

$$P'^l_1=y^l_{1k}/\sum^n_{j=1,j\neq k} y^l_{1j}, \; P'^l_2=y^l_{2k}/\sum^n_{j=1,j\neq k} y^l_{2j}, \ldots, P'^l_s=y^l_{sk}/\sum^n_{j=1,j\neq k} y^l_{sj} \quad (15)$$

Therefore:

$$\bar{P}^l=\sum^m_{i=1} P^l_i + \sum^s_{r=1} P'^l r/m+s-1 \quad (16)$$

Finally:

$$X^l_{ik}/ \sum^n_{j=1, j\neq k} X^l_{ij}= \bar{P}^l \rightarrow X^l_{ik}= \bar{P}^l \sum^n_{j=1, j\neq k} X^l_{ij} \quad (17)$$

In addition, the upper bound of the missing data is calculated similarly:

$$\bar{P}^u=\sum^m_{i=1} P^u_i + \sum^s_{r=1} P'^u r/m+s-1 \quad (18)$$

Finally:

$$X^u_{ik}/ \sum^n_{j=1, j\neq k} X^u_{ij}= \bar{P}^u \rightarrow X^u_{ik}= \bar{P}^u \sum^n_{j=1, j\neq k} X^u_{ij} \quad (19)$$

We have,

$$[X^l_{ik}, X^u_{ik}]= [\bar{P}^l \sum^n_{j=1, j\neq k} X^l_{ij}, \bar{P}^u \sum^n_{j=1, j\neq k} X^u_{ij}] \quad (20)$$

Now, we should show that every point considered within the intervals of defined inputs and outputs and we use the suggested way for finding the missing data among crisp data. Therefore, we consider the convex combination of all inputs and outputs, which are interval.

Which $0\leq\mu\leq1$.

In order to obtain missing data, the solution for finding the missing data among crisp data should be executed:

$$P_1= \mu X^u_{1k}+ (1- \mu) X^l_{1k} / \sum^n_{j=1, j\neq k} (\mu X^u_{ij}+ (1-\mu)X^l_{1k}, \ldots, P_i=?, \ldots, P_m= \mu X^u_{mk}+ (1-\mu)X^l_{mk}/\sum^n_{j=1, j\neq k} (\mu X^u_{mj}+ (1-\mu)X^l_{mj}) \quad (21)$$

$$P'_1= \mu y^u_{1k}+ (1-\mu) y^l_{1k} / \sum^n_{j=1, j\neq k} (\mu y^u_{ij}+ (1-\mu)y^l_{1j} , \ldots, P'_s= \mu y^u_{sk}+ (1-\mu)y^l_{sk} / \sum^n_{j=1, j\neq k} (\mu y^u_{sj}+ (1-\mu)y^l_{sj}) \quad (22)$$

Therefore:

$$\bar{P} =\sum^m_{i=1} P_i + \sum^s_{r=1} P'_r / m+s-1 \quad (23)$$

And:

$$X_{ik}/ \sum^n_{j=1, j\neq k} (\mu X^u_{ij}+ (1-\mu) X^l_{ij} =\bar{P} \quad (24)$$

Finally:

$$X_{ik}= \bar{P} \sum^n_{j=1, j\neq k} (\mu X^u_{ij}+ (1-\mu) X^l_{ij}) \quad (25)$$

Therefore, by considering the convex combination of all obvious inputs and outputs, the missing data X_{ik} is obtained through a function based on μ such as f (μ).

NUMERICAL EXAMPLE

A numerical example is discussed in this section to show how to implement the proposed method. The problem is to rank alternatives by TOPSIS with interval data method according to the DMs incomplete preference information on alternatives (in other words, marketing strategy selection problem). Assume that there are five alternatives (marketing strategy; S_1= developing new product, S_2= entering new markets, S3= new modes of distribution, S4= offering pricing and sales incentive, and S5= growth through acquisition), and four criteria (C_1=required investment, C_2=sales growth, C_3=market share, and C_4=brand image). However, expert for each reason fails to make some judgments (i.e. adding new products or entering new market, etc.), thus there is empty cell in the corresponding decision matrices (table 1).

Table 1: Incomplete Decision Matrix

Criteria / Alternative	C_1	C_2	C_3	C_4
S_1	[12000,15000]	[2100,2200]	[12,14]	[3,7]
S_2	[15000,21000]	[2100,2800]	[4,9]	[5,9]
S_3	?	[2700,3300]	[10,17]	[7,9]
S_4	[14000,15000]	[2300,2900]	[13,17]	[3,5]
S_5	[14000,20000]	[2800,3800]	[14,15]	[1,3]

Where C_1 is cost type criteria, and C_2, C_3 and C_4 benefit type criteria. As noted earlier, there is incomplete information in the DMs preference judgment on alternatives (i.e. for a_{31}).

For finding the missing interval $[a^l_{31}, a^u_{31}]$, we use the process expressed in section (3.2.2.). in continuation, consider table (2), the data of this table are the convex combination of the intervals of table 1 which in this table, a_{31} is missing.

Table 2: The Convex Combination of Interval Data

Criteria / Alternative	C_1	C_2	C_3	C_4
S_1	15000μ + 12000(1-μ)	2200μ + 2100(1-μ)	14μ+12 (1-μ)	7μ + 3 (1-μ)
S_2	21000μ + 15000(1-μ)	2800μ + 2100(1-μ)	9μ + 4 (1-μ)	9μ + 5 (1-μ)
S_3	?	3300μ + 2700 (1-μ)	17μ + 10 (1-μ)	9μ + 7 (1-μ)
S_4	15000μ + 14000 (1 - μ)	2900μ + 2300 (1-μ)	17μ + 13 (1-μ)	5μ + 3 (1-μ)
S_5	20000μ + 14000 (1 - μ)	3800μ + 2800 (1-μ)	15μ + 14 (1-μ)	3μ + 1 (1-μ)

In this section, the missing value for a_{31} regards to formula number (25) can be finding and the result is as follows (table 3).

a_{31}= ((((3300 μ +2700(1- μ)/(11700 μ +9300(1- μ)) + ((17 μ +10(1- μ)/(55 μ +43(1- μ)) +((9 μ +7(1- μ)/(24 μ +12(1- μ)))/(2+2-1))*(71000 μ +55000(1- μ)

If μ=1, the amount of a_{31} is equal to 22865 which is that a^u_{31} and if μ=0, a_{31} is equal to 20281 which is that a^l_{31}. Therefore, the missing interval is obtained through [20281, 22865].

Table 3: Complete Decision Matrix

Criteria / Alternative	C_1	C_2	C_3	C_4
S_1	[12000,15000]	[2100,2200]	[12,14]	[3,7]
S_2	[15000,21000]	[2100,2800]	[4,9]	[5,9]
S_3	**[20281, 22865]**	[2700,3300]	[10,17]	[7,9]
S_4	[14000,15000]	[2300,2900]	[13,17]	[3,5]
S_5	[14000,20000]	[2800,3800]	[14,15]	[1,3]

In continuation, first, we want to get a weight for each criterion by using the proposed approach (the extended Shannon's entropy method with interval data). So, in table 4, the normalized rates, and in table 5, entropy, degree of diversification and weight are presented.

Table 4: The Normalized Rates (P_{ij})

Criteria / Alternative	C_1		C_2		C_3		C_4	
	x_{1j}^l	x_{1j}^u	x_{2j}^l	x_{2j}^u	x_{3j}^l	x_{3j}^u	x_{4j}^l	x_{4j}^u
S1	.128	.160	.140	.147	.167	.194	.091	.212
S2	.160	.226	.140	.187	.056	.125	.152	.273
S3	.216	.244	.180	.220	.139	.236	.212	.273
S4	.149	.160	.153	.193	.181	.236	.091	.152
S5	.149	.213	.187	.253	.194	.208	.030	.091

Table 5: Entropy, Degree of Diversification and Weight

-	C_1		C_2		C_3		C_4	
Entropy	.904	.991	.907	.990	.846	.986	.719	.958
degree of diversification	.009	.096	.010	.093	.014	.154	.042	.281
weight	.015	1.275	.016	1.231	.023	2.048	.068	3.729

From the above results, it can be concluded that, the criteria weights is as follows.

W_j = ([.015, 1.275]; ([.016, 1.231]; ([.023, 2.048]; ([.068, 3.729]).

Next, When the TOPSIS method with interval data is applied; the following values are derived (table 6-11).

Table 6: The Interval Normalized Decision Matrix ($\bar{n}_{ij}$)

Criteria / Alternative	C_1		C_2		C_3		C_4	
	x_{1j}^l	x_{1j}^u	x_{2j}^l	x_{2j}^u	x_{3j}^l	x_{3j}^u	x_{4j}^l	x_{4j}^u
S1	.220	.274	.241	.253	.291	.339	.163	.381
S2	.274	.384	.241	.322	.097	.218	.272	.490
S3	.371	.418	.310	.379	.242	.412	.381	.490
S4	.256	.274	.264	.333	.315	.412	.163	.272
S5	.256	.366	.322	.437	.339	.363	.054	.163

Table 7: The Interval Weighted Normalized Decision Matrix ($\bar{v}_{ij}$)*

Criteria / Alternative	C_1		C_2		C_3		C_4	
	x_{1j}^l	x_{1j}^u	x_{2j}^l	x_{2j}^u	x_{3j}^l	x_{3j}^u	x_{4j}^l	x_{4j}^u
S1	.003	.350	.004	.311	.007	.694	.011	1.420
S2	.004	.490	.004	.396	.002	.446	.018	1.825
S3	.006	.533	.005	.467	.006	.843	.026	1.825
S4	.004	.350	.004	.410	.007	.843	.011	1.014
S5	.004	.467	.005	.538	.008	.744	.004	.608

Table 8: The Positive and Negative Ideal Solution ($\bar{A}$)

-	C_1	C_2	C_3	C_4
$\bar{A}^+$	.003	.538	.843	1.825
$\bar{A}^-$	.533	.004	.002	.004

Table 9: Distance of Each Alternative from the Positive Ideal Solution ($\bar{d}^+_j$)

$\bar{d}_1^+$	$\bar{d}_2^+$	$\bar{d}_3^+$	$\bar{d}_4^+$	$\bar{d}_5^+$
2.097	2.120	2.123	2.097	2.125

Table 10: Distance of each Alternative from Negative Ideal Solution ($\bar{d}^-_j$)

$\bar{d}_1^-$	$\bar{d}_2^-$	$\bar{d}_3^-$	$\bar{d}_4^-$	$\bar{d}_5^-$
1.691	1.988	2.126	1.474	1.217

Table 11: Closeness Coefficient ($\bar{R}_j$)

$\bar{R}_1$	$\bar{R}_2$	$\bar{R}_3$	$\bar{R}_4$	$\bar{R}_5$
.446	.484	.500	.413	.364

It is also worth noting here that, as can be seen from table 5 and 7, the results are not contained in [0, 1]. Nevertheless, according to the viewpoint proposed by Yue (2012, and 2013), the property to which the ranges belong [0, 1] is not preserved for the normalized interval numbers too. Since, further transform can be done. Further investigation on this property would be investing but it is beyond the scope of this study. Therefore, interested readers may refer to aforementioned references, for more discussions on the existing approaches.

From the above results, it can be concluded that, the ranking is as follow:

$S_3>S_2>S_1>S_4>S_5$

Therefore, the best marketing strategy is S_3, since it is superior to all the other strategies. Meanwhile, S_5 have very bad performance.

Here, more studies have been done. According to the viewpoint proposed by Batista and Monard (2003), in a general way, missing data treatment methods can be divided into the following three categories: 1. ignoring and discarding data, 2. parameter estimation, and 3. imputation. In This paper, we focus on ignoring and discarding data. In other words, what happens if we drop the alternative 3 (S_3; alternative with incomplete information) and redo our assessment of alternatives? With no intension to describe the whole procedure, we shall only point to the final results. Results are shown in table 12 and 13.

Table 12: The Criteria Weights (without S_3)

Criteria / Weight	C_1	C_2	C_3	C_4
Wj	[0.015,0.915]	[0.023, 0.841]	[0.030, 1.362]	[0.090, 3.181]

Table 13: Closeness Coefficient (without S_3)

S_1	S_2	S_3	S_4	S_5
0.443	0.492	-	0.392	0.327

From the above results, it can be concluded that, the ranking is as follow:

$S_2>S_1>S_4>S_5$

Therefore, the best marketing strategy is S_2, since it is superior to all the other strategies. Meanwhile, S_5 have very bad performance.

A comparison of the test results is given in table 14, and Fig. 2.

Table 14: Comparison of Results

Model	Priority
TOPSIS with incomplete data (with S_3)	$S_3 > S_2 > S_1 > S_4 > S_5$ .500 .484 .446 .413 .364
TOPSIS with complete data (without S_3)	$S_2 > S_1 > S_4 > S_5$ .492 .443 .392 .327

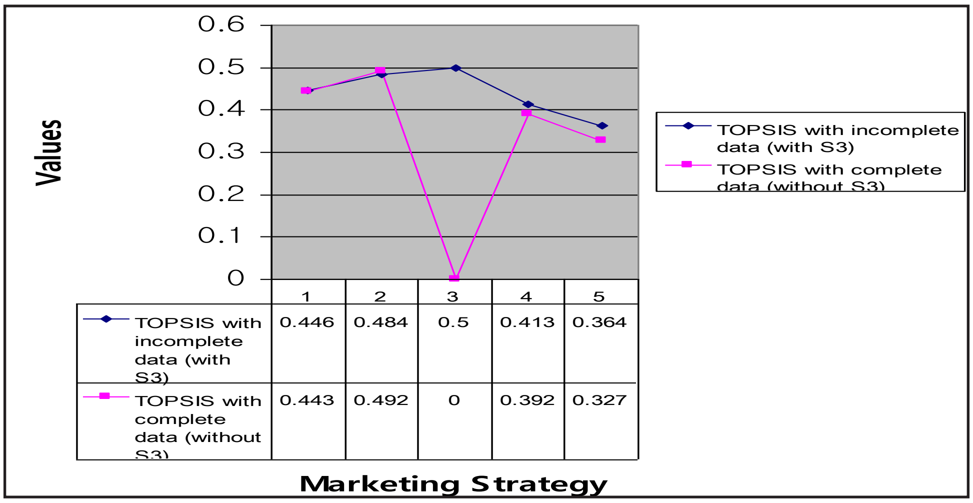

Fig. 2: Comparison of Results

As can be seen in table 14 and fig. 2, the differences between two models are clear. The current priority (TOPSIS with complete data) is $S_2 > S_1 > S_4 > S_5$. This differs from that of the TOPSIS with incomplete data [with S_3; proposed method] (S_3 > S2> S1 > S4 > S5). This difference is due to the missing value considered. In other words, missing value estimation impact could greatly improve the decision making process. So, S_3 becomes the suitable alternative instead of S_2. Therefore, findings in this paper confirm the effectiveness of proposed method.

CONCLUDING REMARKS

In this paper, we focus on the following problem: how to help the senior managers to determine the optimal marketing strategies from sets with incomplete information. Because, marketing strategy involves a high degree of uncertainty and ambiguity on the one hand, and can be classified as a Multi-Criteria Decision Making (MCDM) problem on the other. Therefore, this paper addresses the ranking strategies by using TOPSIS method with interval data. However, in marketing strategy, selection problem incomplete data is common; TOPSIS are not applicable to incomplete data. Since, in this paper, the combination of two methods: TOPSIS-Tamaddon et al. method (mathematical formulations for finding the missing data) was applied. The method has two stages: 1. finding the missing amount and 2. Rank solution. However, ignoring and discarding missing data is the default method in many decision problems, but findings in this paper show that results obtained by proposed method were significantly different from those got when conventional method was used. The alternative ranking provided by TOPSIS with complete data was $S_2 > S_1 > S_4 > S_5$ (note, S_3 is discarded), while the TOPSIS with incomplete data (with S_3; proposed method) method ranked the alternatives as S_3 > S2> S1 > S4 > S5. Moreover, proposed method (Tamaddon et al. method), has been developed for the neither DEA nor MCDM environment. Since, this could cause some bias in the final results. So, more studied are needed. In addition, further research can apply this proposed approach to other managerial issues or compare it with another existing model.

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