Supplier Selection with Interval SAW for a Group of Decision Makers When a Group Cannot Reach to Consensus

Mohammad Azadfallah

Researcher, Business Studies and Development Office, Saipayadak (Saipa after Sales Services Organisation), Islamic Republic of Iran. Email: m.azadfallah@yahoo.com

Abstract

In the present paper, we investigate the group decision-making problem when decision makers (DMs) cannot reach consensus on a single scale value to represent their joint preference. In order to reflect uncertainty of the given information, interval SAW method and interval criteria weights are applied. To do so, we propose, first the individual preferences are obtained from the respective DMs and then they are aggregated. Whilst the individual preferences are crisp, the aggregated preference is composite intervals, which contain the different views in the group. In sum, this paper focused on the application of a SAW method with interval data to reach maximum degree of consensus in the group decision-making process. Finally, a numerical example for supplier selection is given to illustrate the application of the introduced methods. In addition, the proposed method is compared with an existed method (Borda's Function approach). Comparative results indicate that results obtained by proposed method were different from those obtained using the existed method. However, the given priorities are not consistent with each other, but it seems the proposed method can more assure the results by applying a systematic model.

Keywords: Group Decision Making, SAW, Entropy, Interval Data, Supplier Selection Problem

Introduction

Today, businesses depend on strategic collaboration with their suppliers and customers to create value, develop product, and obtain better market share (Kumar, Raman, & Priya, 2015). Therefore, in today's highly competitive environment, an effective supplier selection process is very important for success of any manufacturing organisation. Selecting the right supplier is always a difficult task for the purchasing manager. Suppliers have varied strengths and weaknesses that require careful assessment by the purchasers before ranking can be given to them. Therefore, every decision needs to be integrated by trading off performances of different suppliers at each supply chain stage (Liu & Hai, 2005). In other words, selecting suitable suppliers is the cornerstone of successful purchasing. However, identifying suitable suppliers is not an easy task. One can argue that it is extremely difficult for any single supplier to excel in all criteria. An actual choice of supplier unavoidable involves trade-off among the attribute levels of different suppliers (Jounio, 2013). Therefore, supplier selection is a fundamental issue of supply chain. It is also a hard problem since supplier selection is typically a multi-criteria group decision problem (Boran, Genç Kurt, & Akay, 2009; Izadikhah, 2012). This change of how to focus on the problem, i.e. the focus moves from that on decision maker to a group of people, introduces the important issue of how best to aggregate the decision makers' preference structure (Alencar, Almeida, & Morais, 2010). So, the problem of aggregating the individual pre-orders of decision makers in a single collective pre-order has been the target of several studies in the literature on group decision making. Historically, the first papers, which tackled this problem, were by Borda and by Condorcet. In the last decade, various studies have been undertaken (Alencar *et al*., 2010). Shirouyehzad, Lotfi, & Dabestani (2013) and Yue (2013a) could be referred to as examples.

According to the viewpoint proposed by Dhingra and Singh (2015), decision problems are usually complex and involve evaluation of several conflicting criteria. Multiple criteria decision making (MCDM) is a promising field that considers the parallel influence of all criteria and aims at helping decision makers in expressing their preferences over a set of predefined alternatives, on the basis of criteria that are contradictory in nature. On the other side, generally, group decision-making (GDM) problem can be defined as a decision problem with several alternatives and decision makers (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) group decision making (MAGDM) is commonly encountered in the real world and plays a key role especially in engineering and economy fields. The definition of MAGDM is described specifically as follows. 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 multiple attributes to rank all the alternatives or give evaluation information of each alternative. Then decision results from each DM are aggregated to form an overall ranking result for all the alternatives (Pang & Liang, 2012). Generally, the MAGDM problems have three common characteristics: alternatives, attributes, and DMs. Moreover, it consists of three steps: (1) ranking phase. In this phase, each DM provides her/ his preference ranking on alternatives with respect to attributes; (2) aggregation phase. In this phase, a collective preference decision is built from the set of individual decisions; and (3) exploitation phase. A given method is applied to the collective preference decision to obtain a selection of alternatives (Yue, 2013b). On the other side of the coin, supplier selection is the process by which suppliers are reviewed, evaluated, and chosen to become part of the company's supply chain. The overall objective of supplier selection process is to reduce purchase risk, maximise overall value to the purchaser, and build the closeness and long-term relationships between buyers and suppliers (Sanayei, Mousavi, & Yazdankhah, 2010). According to Izadikhah (2012), in supplier selection process, the supplier's information and performances are usually incomplete and uncertain. Therefore, the decision makers are unable (or unwilling) to express their judgment on the suppliers with exact and crisp values. In addition, source of uncertainty are classified into two categories. These are interval uncertainties that are specific to the supplying firm (i.e. lack of adequate capacity of suppliers to produce the required amount, lack of correct and up to date information, lack of adequate financial resources, technology, commitment, and logistic capabilities, etc.), and those that come from the environment in which the firm exists (i.e. increase in the general price level of raw material, cultural barriers, etc.) (Nadeem, Xu, & Javed, 2014). Under this situation, it becomes necessary to develop such decision-making models, which can easily handle the uncertain information (Chatterjee & Chatterjee, 2012). Whether the uncertainty in the supply chain can be reduced or eliminated effectively, to a great extent, relies on our description of the uncertainty in supply chain systems. There exist lots of methods for quantitative description of supply chain uncertainty, generally involving: interval analysis, statistical method, fuzzy sets method, scenario analysis method, etc. (Xu, Jiang, Tang, & Yuan, 2013). In this paper to solve this problem, an extended SAW and Entropy method with interval data is proposed.

SAW (Simple Additive Weighting) can be considered the most intuition and easy way to deal with MCDM problems, because the linear additive function can represent the preferences of decision makers (Tzeng & Huang, 2011). This method is based on the weighted average. An evaluation score is calculated for each alternative by multiplying the scaled value given to the alternative of that attribute with the weights of relative importance directly assigned by decision maker followed by summing of the products for all criteria. The advantage of this method is that it is a proportional linear transformation of the raw data which means that the relative order of magnitude of the standardised scores remains equal (Venkateswarlu & Sarma, 2016). Salehi and Izadikhah (2014) have extended the concept of SAW and entropy to develop a methodology for solving MADM problems with interval data. Entropy has a useful meaning in information theory, where it measures the expected information content of a certain massage. Entropy in information theory is a criterion for the amount of uncertainty represented by a discrete probability distribution. Hence, the terms "entropy" and "uncertainty" are considered as synonymous (Hwang & Yoon, 1981). According to Wang and Chin (2006), crisp comparison matrices produce crisp weight estimates. It is logical for an interval or fuzzy comparison matrix to give an interval or fuzzy weight estimate. Therefore, Lotfi and Fallahnejad (2010) extended the Shannon entropy method for the imprecise data, especially interval and fuzzy data cases. Meanwhile, there is a lack of comprehensive approach to investigate effects of all factors on each other (i.e. supplier selection problem, multiple attribute group decision-making model, uncertainty and interval data). Therefore, in this paper, we have used the extended SAW and entropy method with interval data (introduced by Salehi and Izadikhah, 2014) to determine the most preferable choice out of all possible choices.

In general, this paper aims to use a numerical example to illustrate the process of the proposed MAGDM method in supplier selection context.

The paper is organised as follows. In the second section, the literature and conceptual framework and in the third section, the proposed methods, to deal with interval data is discussed. Numerical example is provided in the next section. The paper is concluded in the fifth and last section.

Literature Review

According to the viewpoint proposed by Podvezko (2011), the method SAW (Simple Additive Weighting) is one of the simplest, natural, and most widely used multi-criteria evaluation methods. Since, the proposed method was previously frequently used, in this paper, a review of the relevant literature is presented based on two main categories focusing on: I. application of SAW and its extensions in the areas other than supply chain management, and II. application of SAW methodology and its extensions in supply chain management.

I. Janic and Reggiani (2002) illustrated the application of three multi-criteria decision-making methods (particularly, SAW method) to the problem of the selection of a new hub airport for a hypothetical European Union (EU) airline. Eshlaghy, Paydar, Joda, and Paydar (2009), Memariani, Amini, and Alinezhad (2009), Alinezhad, Sarrafha, and Amini (2014), and Goodridge (2016) developed a new method for sensitivity analysis in SAW method. Afshari, Mojahed, and Yusuff (2010) considered a real application of personnel selection with using the opinion of expert by SAW method. Karami (2011) utilised and compared MADM techniques (particularly, SAW method) to re-rank Bayesian network options. Manokaran, Subhashini, Senthilvel, Muruganandha, and Ravischandran (2011) analysed the level of the students' intelligence and ranked it by TOPSIS and SAW techniques, validating by using the Artificial Neural Networks (ANN) method. Podvezko (2011) described the main features of multi-criteria evaluation methods SAW and COPRAS and their common and diverse characteristics. Chen (2012) presented SAW-based and TOPSIS-based MCDA methods and conducted a comparative study through computational experiments. ZeinEldin (2012) proposed a model-based decision support system (DSS) for performance evaluation. The proposed system is based on financial ratios and some methods such as AHP, TOPSIS, and SAW methods. Abdullah and Adawiyah (2014) presented a review of the applications of SAW and Fuzzy SAW method from 2003 to 2013. Pratiwi *et al*. (2014) developed a decision support system to majority high school student using SAW method. Adriyendi (2015) provided an overview of the analysis and implementation MADM (particularly, SAW method) models for food selection or food choice. Sorooshian (2015) used SAW method for evaluating the DaGang deep drilling applications. Moreover, Leoneti (2016) proposed an empirical experiment to evaluate the propensity for initial ranking prediction of the principal MCDM ranking methods (particularly, SAW method).

II. Asgari and Abbasi (2015) examined and introduced an appropriate method for evaluating and selecting suppliers in multiple sourcing, and compared two efficient and effective methods: 1. MADM (i.e. SAW, TOPSIS, Entropy, and AHP) and ANN (Artificial Neural Network) for selecting the suppliers. Jaberidoost, Olfat, Hosseini, Kebriaeezadeh, Abdollahi, Alaeddini, and Dinarvand (2015) identified and categorised pharmaceutical supply chain risks with perspective of local companies. The study was carried out in 4 phases: 1. risk identification through literature review, 2. risk identification in Iranian pharmaceutical companies through interview with experts, 3. risk analysis through a questionnaire and consultation with experts using group AHP method and rating scale (RS), and 4. risk evaluation with SAW method. Kaur and Kumar (2013) proposed an approach based on intuitionistic fuzzy SAW method to select an appropriate vendor (supplier). They used the simple operation of intuitionistic fuzzy arithmetic operation for calculating the aggregation score for each vendor. Finally, a score function is used to rank the vendors with largest score. Mohaghar, Kashef, and Khanmohammadi (2014) presented a novel technique to solve the supplier selection problems by combination of decision-making trial, evolution laboratory, graph theory, and matrix approach technique. Eventually, the results are compared to three common techniques: SAW, TOPSIS, and VIKOR. Sener and Ozturk (2015) proposed a decision approach based on quality function deployment (QFD) methodology for ship selection in maritime transportation industry. The proposed decision model takes into account company needs and ship attributes and also the relation between them. The SAW method is used to obtain a final score for each ship alternative. Finally, Venkateswarlu and Sarma (2016) used MCDM methods such as SAW and VIKOR to select the best supplier for implementing the spring manufacturing industry.

As noted earlier, in 2014, Salehi and Izadikhah have extended the concept of SAW and Entropy to develop a methodology for solving MADM problems with interval data. In this paper the group decision process is discussed from the scope of SAW and entropy with interval data. In other words, we used extended SAW and entropy method in MAGDM (multiple attribute group decision-making) problems. In the proposed method, first, the individual preferences are obtained from the respective DMs and then they are aggregated. While the individual preferences are crisp, the aggregated preference is composite intervals, which contain the different views in the group. Finally, application of the proposed methods is illustrated by a numerical example for the selection of a best supplier. In the next section, the conceptual framework and proposed method will be considered.

Conceptual Framework

According to the viewpoint proposed by Anisseh and Yusuff (2011), the most important decision in organisations is made by groups of managers or experts. Therefore, how to obtain the maximum degree of consensus or agreement from these experts for the given alternatives is an interesting and important topic. In addition, in the literature, supplier selection problem is typically introduced as an MAGDM problem. Boran *et al*. (2009), Izadikhah (2012), Azadfallah (2015, 2016a, 2016b), could be referred to as examples. However, it is sometimes difficult to reach a consensus among group members (Entani, 2009). Arbel and Vargas (2003) believe that when an interval may be preferred to a single values is when a group of decision makers cannot reach consensus on a single scale value to represent their joint preference. Therefore, using the SAW and entropy method with interval data (adopted for MADM environment) for MAGDM problems is the aim of this paper.

Proposed Method

In the existing literature, how to aggregate all individual decisions into a collective decision is common to MAGDM problems. The main difference between MAGDM methods appears in the aggregation approaches (Yue, 2013b). According to Alencar *et al*. (2010), Forman & Peniwati observe that the two methods that have been found to be most useful are those of aggregating, individual judgments and individual priorities. This paper focus on the former approach.

Interval Number

In the following, we describe the basic definition and operations of interval numbers.

Definition 1. Let a= $[a^l, a^u] = \{x \mid 0< a^l \leq x \leq a^u\}$, then a is called a nonnegative interval number. Especially, a is a non-negative real number, if $a^l = a^u$.

For convenience, throughout this paper, all the interval arguments are nonnegative interval numbers, and let Ω be the set of all interval numbers, M={1,2,…,m}, N= {1,2,…,n} and T = {1,2,…,t}; $i \varepsilon M$, $j \varepsilon N$, and $k \varepsilon T$.

Definition 2. Let a= $[a^l, a^u]$ and the b= $[b^l, b^u] \varepsilon \Omega$, and $\lambda \geq 0$, then:

$a+b= [a^l, a^u] + [b^l, b^u] = [a^l+ b^l, a^u+ b^u]$; ……… (1)

$a*b= [a^l, a^u] * [b^l, b^u] = [a^l b^l, a^u b^u]$; ………..... (2)

$\lambda a=\lambda [a^l, a^u] = [\lambda a^l, \lambda a^u]$. Especially, $\lambda a=0$ if $\lambda=0$. … (3)

Definition 3. If W = (W1, W2, …, Wn) is a crisp weight vector, such that:

$W_j \geq 0, \sum^n_{j=1} W_j =1, j \varepsilon N$, ……………… (4)

Then W is called normalised weight vector.

Definition 4. Let Wj= $[W_j^l, W_j^u] \varepsilon \Omega$ ($j \varepsilon N$) be non-normalised interval weights, then:

$[\hat{w}_j^{\,l}, \hat{w}_j^{\,u}] = W_j/\sum^n_{j=1} W_j = [W_j^l / \sum^n_{j=1} W_j^u, W_j^u / \sum^n_{j=1} W_j^l]$, $j \varepsilon N$, ……… (5)

Are called normalised interval weights of W_j ($j \varepsilon N$), (Yue, 2013b).

SAW Method with Interval Data

This approach may be described as follows (Salehi and Izadikhah, 2014):

Step 1. Establish decision-making matrix with interval data $[X^l_{ij}, X^u_{ij}]$.

Step 2. Determine the weights of criteria by using the interval Entropy method $[W^l_j, W^u_j]$ (as discussed latter in this paper-next section).

Step 3. Establishment of normal of decision-making matrix with interval data $[ń^l_{ij}, ń^u_{ij}]$.

For benefit type criteria:

$ń^l_{ij} = x^l_{ij}/\sum^m_{j=1} (x^l_{ij}) + (x^u_{ij})$, j=1, …,m, i=1, …, n, $j \varepsilon B$ ……. (6)

$ń^u_{ij} = x^u_{ij}/\sum^m_{j=1} (x^l_{ij}) + (x^u_{ij})$, j=1, …,m , i=1, …,n , $j \varepsilon B$ …….. (7)

For cost type criteria:

$ń^l_{ij}= (1/x^u_{ij}) /\sum^m_{j=1} (1/x^l_{ij}) + (1/x^u_{ij})$, j=1, …, m, i=1, …,n , jεC ………… (8)

$ń^u_{ij}= (1/x^l_{ij}) /\sum^m_{j=1} (1/x^l_{ij}) + (1/x^u_{ij})$, j=1, …, m, i=1, …,n , jεC ………… (9)

Step 4. The calculation of utility function for each index.

$P^l (A_i) = \sum^n_{j=1} ń^l_{ij} w^l_j / \sum^n_{j=1} (w^u_j + w^l_j)$, $P^u (A_i) = \sum^n_{j=1} ń^u_{ij} w^u_j / \sum^n_{j=1} (w^u_j + w^l_j)$, $P^l (A_i) \leq P^u (A_i)$, i=1, …, m. ………… (10)

Step 5. Ranking the alternatives

Considering there is an interval utility function $[P^l (A_i), P^u (A_i)]$ for each A_i we have to rank all the intervals. The approach (minimax regret approach) is summarised as follow.

$R_i = \max [\max_{i\neq j} (a^u_j) – a^l_i, 0] = \max [\max_{i\neq j} \{m (A_i) + w (A_i)\} – (m (A_i) - w (A_i)), 0]$; i=1, …, n ……………(11)

where

$m (A_i)$ and $w (A_i)$ is the midpoint ($m (A_i) = 1/2 (a^u_i + a^l_i)$) and widths ($w (A_i) = 1/2 (a^u_i - a^l_i)$), respectively.

It is evident that the efficiency interval with the smallest maximum loss of efficiency is the most desirable efficiency interval. Interested readers may refer to Salehi and Izadikhah (2014) for more discussion on the existing approaches.

Entropy Method with Interval Data

This approach may be described as follows (Salehi and Izadikhah, 2014):

Step 1. Suppose $A_1, A_2, …, A_m$ are m possible alternatives among which decision makers have to choose, $C_1, C_2, …, C_n$ 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 $X_{ij} \varepsilon [X^l_{ij}, X^u_{ij}]$.

Step 2. Now we calculate the normalised decision matrix as follow;

$ń^l_{ij} = x^l_{ij}/\sum^m_{j=1} (x^l_{ij}) + (x^u_{ij})$, j=1, …,m , i=1, …,n ……(12)

$ń^u_{ij} = x^u_{ij} / \sum^m_{j=1} (x^l_{ij}) + (x^u_{ij})$, j=1, …,m , i=1, …,n….. (13)

The normalisation method mentioned above is to preserve the property that the ranges of normalised interval numbers belong to [0, 1].

Step 3. Calculation of concentration index for per criteria's with interval data.

$E^l_j = (-1/ Ln (m) \sum^m_{i=1} n^u_{ij} Ln (n^u_{ij})$, …………… (14)

$E^u_j = (-1/ Ln (m) \sum^m_{i=1} n^l_{ij} Ln (n^l_{ij})$. …………… (15)

Therefore, we have $E^l_j \leq E^u_j$.

Step 4. The amount of per criteria's dispersal

$d^l_j = 1 - E^u_j$ ………………… (16)

$d^u_j = 1 – E^l_j$ ………………… (17)

Therefore, we have $d^l_j \leq d^u_j$.

Step 5. Calculation weight of criteria

$w^l_j = d^l_j / \sum^n_{j=1} (d^l_j + d^u_j)$, …………………. (18)

$w^u_j = d^u_j / \sum^n_{j=1} (d^l_j + d^u_j)$. …………………. (19)

Therefore, we $w^l_j \leq w^u_j$ and the interval weight of criterion C_j is $[w^l_j, w^u_j]$.

The following example involves a multi-attribute supplier selection problem in supply chain context, to illustrate the implementation of our proposed methods.

Numerical Example

Assume that there are three committee members, who are DMs (or experts; DM d1, d2, and d3), five alternatives (or suppliers; S1, S2, …, S5), and four criteria (C1=ordering and logistic cost, C2=lead times, C3=packing ability, and C4=performance of supplier). In the process of group decision making, each committee members provides the performance value the alternatives with respect to each attribute (Tables 1-3).

Table 1: Performance Value for E1

Criteria / Alternative	C1*	C2*	C3	C4
S1	1114	15	5	81
S2	963	14	7	61
S3	1012	23	5	96
S4	813	24	1	92
S5	833	16	5	62

*.cost type criteria

Table 2: Performance Value for E2

Alternative \ Criteria	C1*	C2*	C3	C4
S1	879	22	3	94
S2	1079	21	3	84
S3	928	17	5	60
S4	807	18	3	91
S5	915	19	1	78

*.cost type criteria

Table 3: Performance Value for E3

Alternative \ Criteria	C1*	C2*	C3	C4
S1	1153	18	7	75
S2	1093	23	3	82
S3	1162	21	7	94
S4	969	14	1	86
S5	1017	25	5	67

*.cost type criteria

Using equation 20 (it is also worth noting here that the described idea in this paper for proposed Eq. 20 is inspired from Entani (2009)), we aggregate the comparisons given by m DMs. The result is showed in Table 4.

$Aij = [a^l_{ij}, a^u_{ij}] = [\text{Min } a_{ij,k} , \text{Max } a_{ij,k}]$; i=1, 2, …, m; j=1, 2,…, n; k=1, 2, …, t. ….. (20)

i.e. for a_{11}:

S_{11} = [DM d1, $S_{11,1}$ =1114; $S_{11,2}$ =879; and $S_{11,3}$ =1153] = [Min $a_{11,1\text{-}3}$, Max $a_{11,1\text{-}3}$]=[879, 1153].

Table 4: Aggregated Comparison Matrix

Alternative \ Criteria	C1*	C2*	C3	C4
S1	[879, 1153]	[15, 22]	[3, 7]	[75, 94]
S2	[963, 1093]	[14, 23]	[3, 7]	[61, 84]
S3	[928, 1162]	[17, 23]	[5, 7]	[60, 96]
S4	[807, 969]	[14, 24]	[1, 3]	[86, 92]
S5	[833, 1017]	[16, 25]	[1, 5]	[62, 78]

*.cost type criteria

In this section, we want to get a weight for each criterion by using the proposed approach (Entropy method with interval data). So, in Table 5, the normalised rates, and in Table 6, entropy, degree of diversification and weight are presented. i.e. for a_{11}:

$ń^l_{11}$ = 879/9804 = 0.090

E^l_1=(-1/LN(5))*((0.090*Ln(0.090))+((0.098*Ln(0.098)) + ((0.095*Ln(0.095)) + ((0.082*Ln(0.082)) + ((0.085*Ln(0.085)) = 0.673

d^l_1 =1 – 0.754=0.246

w^l_1 = 0.246/ 2.403 = 0.103

Table 5: Normalised Rate ($ń^l_{ij}$)

Alternative \ Criteria	C1	C2	C3	C4
S1	[0.090, 0.118]	[0.078, 0.114]	[0.071, 0.167]	[0.095, 0.119]
S2	[0.098, 0.111]	[0.073, 0.119]	[0.071, 0.167]	[0.077, 0.107]
S3	[0.095, 0.119]	[0.088, 0.119]	[0.119, 0.167]	[0.076, 0.122]
S4	[0.082, 0.099]	[0.073, 0.124]	[0.024, 0.071]	[0.109, 0.117]
S5	[0.085, 0.104]	[0.083, 0.130]	[0.024, 0.119]	[0.079, 0.099]

Table 6: Entropy, Degree of Diversification a snd Weight

-	C1	C2	C3	C4
Entropy	[0.673, 0.754]	[0.621, 0.794]	[0.502, 0.831]	[0.658, 0.763]
degree of diversification	[0.246, 0.327]	[0.206, 0.379]	[0.169, 0.498]	[0.237, 0.342]
weight	[0.103, 0.136]	[0.086, 0.158]	[0.070, 0.207]	[0.099, 0.142]

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

W_j= ([0.103, 0.136], [0.086, 0.158], [0.070, 0.207], and [0.099, 0.142]).

When the SAW method with interval data is applied, the following values are derived (Tables 7 and 8).

i.e. for S_{11}:

$\acute{n}^{l}_{11}$=(1/1153)/(1/879+1/1153+1/963+1/1093+1/928+1/1162+1/807+1/969+1/833+1/1017)=0.084

$P^{l}_{(S1)}$ = (0.084*0.103) + (0.083*0.086) + (0.071*0.070) + (0.095*0.099)/1=0.0302

Table 7: Normalised Decision Matrix (based on Table 4)

Criteria / Alternative	C1	C2	C3	C4
S1	[0.084, 0.110]	[0.083, 0.122]	[0.071, 0.167]	[0.095, 0.119]
S2	[0.088, 0.100]	[0.080, 0.131]	[0.071, 0.167]	[0.077, 0.107]
S3	[0.083, 0.104]	[0.080, 0.108]	[0.119, 0.167]	[0.076, 0.122]
S4	[0.100, 0.120]	[0.076, 0.131]	[0.024, 0.071]	[0.109, 0.117]
S5	[0.095, 0.116]	[0.073, 0.115]	[0.024, 0.119]	[0.079, 0.099]

Table 8: Calculation of Interval Utility

-	$[P^l (A_i), P^u (A_i)]$
S1	[0.0302, 0.0781]
S2	[0.0286, 0.0764]
S3	[0.0313, 0.0732]
S4	[0.0293, 0.0625]
S5	[0.0255, 0.0663]

Using MRA method, which is introduced in step 5 (Eq. 11), we rank the suppliers. i.e. for top ranking:

R_1 = [Max (0.0764, 0.0732, 0.0625, 0.0663) – 0.0302, 0] = 0.0764-0.0302=0.0462

= [Max (0.0781, 0.0732, 0.0625, 0.0663) – 0.0286, 0] = 0.0781-0.0286=0.0495

= [Max (0.0781, 0.0764, 0.0625, 0.0663) – 0.0313, 0] = 0.0781-0.0313=0.0468

= [Max (0.0781, 0.0764, 0.0732, 0.0663) – 0.0293, 0] = 0.0781-0.0293=0.0488

= [Max (0.0781, 0.0764, 0.0732, 0.0625) – 0.0255, 0] = 0.0781-0.0255=0.0526

According to above result, supplier 1 (S1) has the best ranking. So, S1 is rated as the best supplier and eliminated from the further consideration. Repeating the above process, we fondly get the ranking order of the five suppliers as:

S1 > S2 > S3 > S4 ≈ S5

Here, more studies have been done. In order to compare this result with the Borda's function approach results, we will use the same numerical example (Tables 1-3).

According to Hwang and Lin (1987), the method Borda function is the rank-order method. With m candidates in A, assign marks of m-1, m-2, …, 1, 0 to the first ranked, second ranked, … last ranked candidate for each individual, then determine the Borda score for each candidate as the sum of the individual marks for that candidate. Then the candidate with the highest Borda score is declared as the winner. The Borda score of a candidate X is equivalent to the sum of the number of individuals that have X preferred to (P_i) Y for all Yε A / {X}.

Borda's function:

Let

$F_B (X) = \sum_{y \varepsilon A} \# (i: X\ P_i\ Y)$

And the candidates are ranked in the order of the value of F_B.

In this section, we have used interval SAW and interval Entropy method to find individual ordering. According to Wang, Greatbanks, and Yang (2005), the exact data can be viewed as a special case of interval data with the lower and upper bounds being equal. Since, the all data (notice, the individual information is crisp), are now transformed into interval data and can be evaluated using interval SAW and Entropy methods. With no intention to describe the whole procedure, we shall only point to the final result (Table 9).

Table 9: Comparison Results (individual prefer-ordering for three experts)

Expert	Ranking
E1	S2 > S1 > S5> S3 > S4
E2	S3 > S4 > S1 > S2 > S5
E3	S3 > S1 > S5 > S4 > S2

Now, to aggregate the preference orderings into a consensus ordering, the Borda method is used. So, 4, 3, 2, 1, 0 scores are assigned to the first rank, second rank, …, last rank. i.e. for S1, respectively:

S1 = 3 + 2 + 3 = 8

Similarly, S2 = 5

S3 = 9

S4 = 4

S5 = 4

From the above results, it can be easily derived that, the implied ranking is as follow.

S3 > S1 > S2 > S4 ≈ S5

Thus, the best alternative is supplier 3 (S3), since it is superior to all the other alternatives. Meanwhile, supplier S4 & S5 have bad performance.

According to the above results, we can find the priority is S3 > S1 > S2 > S4 ≈ S5. This priority is different from that of the proposed method (S1 > S2 > S3 > S4 ≈ S5). Therefore, different ranking have been obtained, but with no guidance to decide which is the optimal solution. Yue (2013b) believe that there is no one optimal method for a given MAGDM problem and the numerical comparison is not usually enough to determine which method is the most appropriate. However, it is worthwhile to examine different models from different perspectives. In sum, however, the given priorities are not consistent each other, but seems the proposed method can be more assure the results by applying a systematic model.

Conclusion

In the current literature, supplier selection is typically a multi-attribute group decision making (MAGDM) problem. How to obtain the maximum degree of consensus or agreement from these experts for the given alternatives is an interesting and important topic. In this paper, to solve this problem, interval SAW and entropy method are proposed and can provide more assurance to the results by applying a mathematical model. To do so, we propose, first the individual preferences are obtained from the respective DMs and then they are aggregated. While the individual preferences are crisp, the aggregated preference is composite intervals, which contain the different views in the group. Also, the proposed method is compared with an existed method (Borda's Function approach). Comparative results indicate that results obtained by proposed method (S1 > S2 > S3 > S4 ≈ S5) were different from those obtained using the existed method (S3 > S1 > S2 > S4 ≈ S5). However, the given priorities are not consistent with each other, but it seems that the proposed method can more assure the results by applying a systematic model. Hence, to increase your chance of finding an appropriate supplier for your companies, we suggest using the proposed models in this paper. Moreover, further research can apply this approach to other managerial issues or can compare it with other MAGDM methods.

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