International Journal of
Information
and
Management
Sciences

International Journal of Information and Management Sciences
30 (2019), 57-71. DOI:10.6186/IJIMS.201903_30(1).0004

A Dynamic MADM Method for the Selection of a Big Data Service Provider

Liang Yin and Huan-Jyh Shyur

Tamkang University

Abstract

The decision making process for selection of a proper Big Data service platform can be complex and dynamic. The bidding process can occur multiple times, the assessment criteria vary each time and they may conflict with each other. Most existing multiple attribute decision-making (MADM) methods are unable to take into account such dynamic process. This paper presents a new dynamic decision making method for the selection of a big data service provider. The dynamic nature of such process is addressed by means of a feedback mechanism. The final decision is taken at the end of a series of exploratory processes. The ranking algorithm for the proposed method uses prospect theory to reflect the decision maker's behavior in the face of risk. A case study shows the actual bidding process and proves the proposed method is able to guide and support a decision team to efficiently aggregate their preferences dynamically.

Keywords: Dynamic decision making, MADM, prospect theory, big data.

1. Introduction

The speed of the growth of data is very fast nowadays: about 2.5 Quintillion bytes of data are generated daily and this value doubles every 1.2 years (see James et al. [24]). For example, in the financial industry, where e-banks are replacing actual banking branches in towns, money transfers, bill payments and currency exchanges are performed online and on smart phones. These banking activities produce a lot of activity logs and transaction data daily, which is measured in terabytes or even in petabytes (see Logothetis et al. [22]). It is impossible to analyze these data sets instantly using traditional data processing application software because of the sheer amount of data, but this is a clear need for banks.

Big data technology supports search, development, governance and analytics services for all data types. However, incorporating big data technology in organizations to manage and make the best use of business data is a big challenge. This requires a proper infrastructure that can manage and process rapidly increasing volumes of structured and unstructured data and at the same time protect data privacy and security. Unlike a single software or hardware project, a big data solution often involves a full set of services, from the base platform (e.g., Apache Hadoop, Spark) and a distributed file system, batch processing tools, stream processing tools and interactive analysis tools. There are plenty of tools and service providers, but often it is difficult for a customer who is new to this area and lacks the required knowledge and experience to make a decision and determine the most suitable service provider (see Chen and Zhang [4]). To address this need, this paper develops a methodology for the selection of big data solution providers in a dynamic group decision environment.

Many studies have developed methods for structuring and solving multiple attribute decision problems, since the 1970s (see Hwang and Yoon [15], Opricovic [25], Roy [26] and Saaty [27]). These methods have also been widely used for software selection (see Zaidan et al. [39], Yazgan et al. [36] and Shyur [28]). Traditional MADM (multiple attribute decision making) involves finding the most preferred solution of many usually conflicting decision attributes in a single decision process (see Cheng et al. [5]). A finite set of alternatives is assumed and the related attribute vectors are given explicitly. However, due to the ambiguity of a decision problem, the potential effects of environmental change and a lack of knowledge, the traditional MADM method may not provide an outcome that satisfies the decision maker. In the case study, the decision involves more than one round of choices and events. Due to the longer decision time horizon, the decision makers change their evaluation criteria and their relative importance in the decision process. This is beneficial because it gives decision makers the opportunity to discover previously unconsidered criteria or alternatives. According to the concept of temporal construal theory, temporal distance changes a decision maker's responses to future events by changing the way in which people mentally represent those events. Trope et al. [30] also noted that the greater the temporal distance, the more likely are events to be represented in terms of a few abstract criteria that are used to evaluate alternatives, rather than in terms of more concrete and incidental details of the events. This paper presents a new dynamic decision making method to evaluate a big data solution, which involves making optimal decisions for an N-stage horizon before uncertain events are discovered. The final decision is taken at the end of a series of exploratory processes.

Most traditional MADM methods use expected utility theory. However, Kahneman and Tversky [17] provided evidence that most decision makers systematically violate the basic axioms of subjective expected utility theory in their decision-making behavior. In response to these findings, prospect theory (see Kahneman and Tversky [17]), which is an alternative theory of choice, was proposed. The theory accurately reflects the decision makers' subjective risk preference. It has been applied to multiple attribute decision-making problems in recent years (see Gomes and Lima [9], Gomes and Rangel [10], Hu et al. [13], Lahdelma and Salminen [19], Shyur et al. [29] and Wang and Zhou [34]). Meanwhile, Wu and Tiao [35] developed an operational validation schema to compare the effectiveness of MCDM methods including TOPSIS, VIKOR, ELECTRE, PLP, and AHP and warned that these methods perform less effectively when the decision-maker's preference is not risk-neutral. To deal with that, in the proposed method, human preferences and risk behavior are taken into consideration to evaluate the alternatives. Utility functions are replaced by value functions that describe and explain user behavior in the decision making process.

Unlike a single stage decision, the proposed method is useful in a dynamic decision environment, because it can discover previously unconsidered alternatives or criteria from previous decisions and abandon some of the unnecessary criteria. The remainder of this paper is organized as follows. Section 2 details related works. Section 3 describes the proposed dynamic MADM methods. The use of the method to evaluate big data solutions for a bank are described in section 4. Conclusions are presented in Section 5.

2. Related Work

MADM is a procedure that involves finding the best alternative from a set of feasible alternatives. Most traditional MADM methods assume that the decision makers have identified fixed sets of alternatives and criteria before proceeding with the selection. Usually, an MADM problem with m alternatives, $A_1, \ldots, A_m$, and n decision criteria, $C_1, \ldots, C_n$, can be expressed in the following matrix format:

$$\begin{array}{cc} & \begin{array}{cccc} w_1 & w_2 & \cdots & w_n \\ C_1 & C_2 & \cdots & C_n \end{array} \\ A = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \end{array}$$

where d_{ij} represents the rating of alternative A_i under criterion C_j and w_j is the relative weight of criterion C_j.

There have been many studies of methods for structuring and solving multiple criteria decision problems since the 1970s. When there is a non-dominant set of solutions to be compared and ranked, methods such as TOPSIS (technique for order performance by similarity to ideal solution), VIKOR (Serbian phrase for multi-criteria optimization and compromise solution), AHP (analytical hierarchical process) or ELECTRE (ELimination and Choice Expressing Reality) are often used. However, some real word decision problems are dynamic. The decision makers may change the attributes to be considered or the potential alternatives in a series of exploratory processes. Traditional MADM methods cannot address this problem. Lin et al. [20] integrated the concepts of grey theory and the Minkowski distance function into the TOPSIS method to evaluate multi-period alternatives. Campanella and Ribeiro [3] used aggregation functions and provided a framework to integrate the ranking results from multiple decision groups. Yu and Chen [38] studied dynamic decision making from the viewpoint of Habitual Domains (HD). Alanazi et al. [1] considered time as a significant factor that influences decisions and presented a mathematical model that used a Dynamic Weighted Sum Method (DWSM). Jassbi et al. [16] studied dynamic decision making models for the selection of suppliers, taking into consideration not only the historical performance data, but also future knowledge, for tactical or strategic decisions in particular. Most of these dynamic MADM methods use aggregation functions to aggregate the decision matrices and to calculate the final ranking using an aggregated decision matrix (see Lin et al. [20]) (e.g. Jassbi et al. [16]), or use an aggregation function to directly aggregate the rating results that are calculated using different decision matrices (e.g. Campanella and Ribeiro [3]). These methods are easy and straightforward. However, some methods do not take into account the importance of different decision matrices and some methods do not allow any changes to alternatives and decision attributes in an evaluation process.

Kahnema and Tversky [17] discovered that human decision behavior when there is uncertainty is actually relative, in the sense that some individuals are risk-seeking and some are risk-averse. In most situations, risk is to be avoided. Prospect theory (see Kahnema and Tversky [17]) is a descriptive model of individual decision making when there is risk. In 1992, Tversky and Kahneman [32] developed the cumulative prospect theory, which takes account of the psychological aspects of decision-making when there is risk.

Prospect theory is widely used as a behavioral model for decision-making when there is risk, mainly in economics and finance (see Edwards [6], Gurevich et al. [12], Hu et al. [14]). In traditional MADM studies, the attitude towards risk is seldom taken into consideration. One of the first MADM methods to use prospect theory was TODIM (an acronym in Portuguese for iterative multi-criteria decision making), which was proposed by Gomes and Lima [9].

According to prospect theory, decision makers decide which outcomes they consider equivalent, set a reference point and then consider lesser outcomes as losses and greater outcomes as gains. TODIM, however, uses a pairwise comparison between decision criteria and the reference points are not determined initially. When comparing alternative Ai with alternative Aj using criterion c, there is a gain if the outcome of alternative Ai is greater than that for alternative Aj and there is a loss if the outcome of alternative Ai is smaller than that of alternative Aj. Although TODIM does not deal with risk directly, it deals with the attitude to risk of the decision maker (see Gomes et al. [11]). Wang et al. [33] extended TOPSIS and the TODIM method using hesitant fuzzy linguistic numbers to describe the preferences of decision makers. They found that the TODIM method is more practical than the TOPSIS method for solving practical decision-making problems. Lourenzutti and Krohling [22] used the Hellinger distance in the context of MCDM (multiple criteria decision making) to allow TOPSIS and TODIM to deal with ratings for alternatives that are not real numbers. Khamseh and Mahmoodi [18] used fuzzy TOPSIS to evaluate the initial weight for each criterion and then used TODIM to evaluate the final weight of each criterion against alternatives and the relationship between criteria. Liu et al. [21] and Fan et al. [7] also developed MADM methods that used prospect theory. In contrast to TODIM, the gains and losses for alternatives are calculated by measuring the perceived differences between attribute values and reference points. The overall prospect value for the alternative is calculated using a simple additive weighting method. Bai et al. [2] combined the neighborhood rough set theory, fuzzy cluster means and cumulative prospect theory to create a three-step hybrid multiple criteria decision process to help evaluate green product deletion decisions.

3. The Dynamic EBVD (Election Based on Value Distances) Model

In a dynamic decision problem, different decision matrices are received from different decision groups at different time points. Jassbi et al. [16] aggregated all decision matrices to determine the final decision matrix using the geometric mean. A ranking algorithm was then applied to the aggregated decision matrix to determine the priorities for the alternatives. This method requires that all decision matrices have the same alternatives (technique for order performance by similarity to ideal solution) and decision attributes. Campanella and Ribeiro [3] presented a different framework to aggregate multiple ranking results that are provided by a series of exploratory processes. Using the aggregation function, the current ranking result is aggregated with the historical value. The final decision is taken at the end of several decision iterations. However, the importance of the different decision outcomes has not been explicitly considered. The Dynamic EBVD (election based on value distances) is a dynamic decision making method. Given a number of exploratory processes to make a final decision, decision makers can update their potential alternatives and the attributes to be considered in a dynamic process. The method is an extension of our previous proposed single stage MADM approach - EBVD (see Yin and Shyur [37]). Compared with TOPSIS and TODIM methods, the EBVD provides a more efficient and robust ranking results in numerical examples and practical examination. The new model uses a more flexible way to support decision makers in a multiple-stage decision making process. Figure 1 illustrates the proposed dynamic framework. Firstly, the available alternatives and attributes to be considered are determined. Secondly, the weight of each considered attribute us identified using methods such as AHP or ANP (analytical network process). The decision matrix is then created and the ranking outcomes for alternatives is determined using ranking algorithms. The ranking outcome is then passed on to the next iteration of the decision-making process as an additional attribute to be considered, if the final decision is not confirmed. The weight of the ranking outcome is identified in the next iteration, which determines the importance of previous decision's outcome.

The ranking algorithm, EBVD, used in each iteration is a multi-attribute decision making method that incorporates prospect theory to reflect the decision behavior of a decision maker when there is risk. The EBVD replaces the traditional expected utility function with a value function to express the outcome of a preference. This function is constructed in parts, whose mathematical descriptions reproduce the gain/loss function of prospect theory. The basic concept for the proposed ranking algorithm is that the chosen alternative must have the shortest value distance from the absolute positive ideal solution (APIS) and the farthest value distance from the absolute negative ideal solution (ANIS). To prevent the valuations for the alternatives for each of the attributes depend on the rest of the alternatives, the APIS (absolute positive ideal solution) and ANIS (absolute negative ideal solution) are fixed for each iteration. The APIS and the ANIS represent the "ideal" and "worst" feasible solutions, which are based on the decision maker's knowledge and experience. The detailed steps for the EBVD are described as follows.

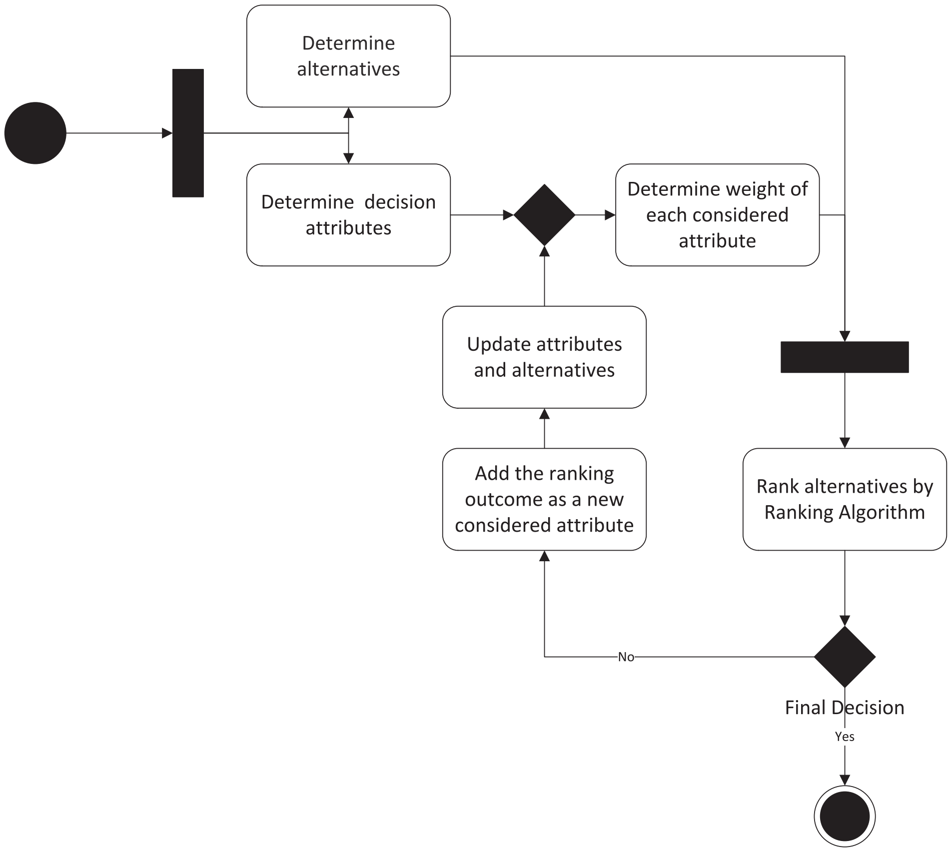

Figure 1: The framework for a Dynamic EBVD.

Step 1. Determine the APIS and ANIS:

To determine the APIS and ANIS, the feasible range of values for each attribute must be agreed by the decision maker. The range depends upon decision maker's experience with or knowledge of the particular attribute. The APIS (I^+) and ANIS (I^-) are determined as follows:

$$I^+ = \{D_1^+, \dots, D_n^+\}, \qquad I^- = \{D_1^-, \dots, D_n^-\} \tag{3.1}$$

where D_j^+ and D_j^- are the "ideal" and "worst feasible" values that are assigned to attribute j.

Step 2. Construct the normalized decision matrix, R:

To compare the alternatives for each attribute, an interval scale transformation is used to transform the various attribute scales into a comparable scale. It should be noted that the norm that the TOPSIS approach establishes can result in rank reversal, because after normalization, the new scale depends not only on the initial value, but also on the valuation that is obtained by the other alternatives (see Garca-Cascales and Lamata [8]).

In this circumstance, the new scale depends only on the initial value and the feasible range of each attribute. The value, r_{ij}, in the normalized decision matrix, $R = [r_{ij}]_{m\times n}$, is obtained by the following equations:

$$\begin{aligned} r_{ij} &= \frac{d_{ij}^{-} D_j^{-}}{D_j^{+} - D_j^{-}}, \qquad j \in \text{benefit criteria}, \\ r_{ij} &= \frac{D_j^{-} - d_{ij}}{D_j^{-} - D_j^{+}}, \qquad j \in \text{cost criteria}. \end{aligned} \tag{3.2}$$

Note that it is presumed that the available data is completed in the given decision matrix, including quantitative and qualitative information. Qualitative data or linguistic data is normalized by first transforming to a linear scale, e.g., 1−10. The above method is then applicable. Since the APIS $A^{+} = \{D_1^{+}, \ldots, D_n^{+}\}$ and the ANIS $A^{-} = \{D_1^{-}, \ldots, D_n^{-}\}$ the vectors for the normalized values are $\{1, 1, \ldots, 1\}$ and $\{0, 0, \ldots, 0\}$, respectively.

Step 3. Calculate the separation measures:

Prospect theory states that people make decisions based on the potential value of losses and gains, rather than the final outcome. The basic principle of the proposed model is that the chosen alternative must have the shortest value distance from the APIS and the farthest distance from the ANIS. Instead of using Euclidean distances, value distances are used to represent the separation measures for alternative A_i from the APIS and ANIS. The following expression is used to calculate the value distance from alternative A_i to the APIS:

$$S_i^{+} = \sum_{j=1}^{n} w_j \cdot (1 - r_{ij})^{\alpha}, \qquad i = 1, \ldots, m. \tag{3.3}$$

This is a weighted value function. Compared with A_i, the ideal solution, I^{+}, is of more value to the decision maker. The value distance represents the dominance of the ideal solution I^{+} over alternative A_i. The concave function implies that decision maker is risk-averse in a domain of gain. This estimates the extra value that the ideal solution gives to the decision maker when alternative A_i is selected.

A different function (Eq.12) is used to measure the value distance from alternative A_i to the ANIS.

$$S_i^{-} = \sum_{j=1}^{n} w_j \cdot (-\lambda \cdot (r_{ij})^{\alpha}), \qquad i = 1, \ldots, m. \tag{3.4}$$

This function is a convex function, which implies that decision maker is risk-seeking in a domain of loss. It is used to estimate the loss when the worst feasible solution, I^{-}, is selected to replace A_i. It is noted that the output value of S_i^{-} is negative.

Step 4. Calculate the relative proximity of each alternative to the ideal solution:

Since S_i^- is a negative number, the proximity coefficient for each alternative is calculated as:

$$\phi_i = \frac{|S_i^-|}{|S_i^+| + |S_i^-|}, \qquad i = 1, \ldots, m. \tag{3.5}$$

ϕ_i is a number between 0 and 1. The larger this value, the greater is the prospect value for alternative i compared to ANIS, when alternative i is selected. However, if the APIS replaces alternative I, the prospect lacks value. Therefore, an alternative with a higher ranking index must have a higher priority order. The separations of each alternative from the APIS and the ANIS are calculated using an s-shaped value function. The measures are related to the behavior of a decision maker who has nonlinear preferences and who takes risks to avoid losses. The EBVD has been evaluated in our previous study (see Yin and Shyur [37]). Compared with TOPSIS and TODIM methods, the ranking algorithm provides a more efficient and robust ranking results in numerical examples and practical examination.

The proposed dynamic framework allows decision makers to make multiple decisions over time. For each iteration, the decision matrix is recreated. The attributes to be considered and the potential alternatives can be reviewed and modified. The previous ranking result is added to the current decision matrix as a special attribute. In this way the previous ranking results are accumulated continuously. The current framework easily deals with the problem of adding new attributes or removing the previous ones by adding new columns or removing columns from the previous decision matrix. However, if a new alternative is added to the current decision iteration, the separation measure and the proximity coefficient for the new decision must be calculated separately with other alternatives because it lacks the ranking result from the previous iteration. Except for the special attribute of the previous ranking results, only other attributes that are defined in this iteration are used to calculate the separation measure and the proximity coefficient for the new alternative. The weight of each attribute (not including the special attribute) must be determined again to ensure that the sum of the weights is equal to 1.

4. Case Study

The study case involves one of the largest banks in China. Its call center is located in Beijing and has over 300 employees who serve over 4,000,000 credit card and debit card customers. On a daily basis, reports on information management and employee performance are generated using a tool that was developed by company A. The outcomes that are generated using this tool allow managers to identify areas where there is scope for improvement or corrective actions. The important data that is provided by the current system is described as follows:

(1) The average handling time indicates the resource utilization; (2) the schedule adherence indicates the service level; (3) the transfer percentage indicates the cost per call; (4) the quality score indicates the revenue per call; (5) Customer satisfaction scores and (6) the resolution rate indicates the quality measurements.

Table 1: Assessment criteria for the first round of decision-making.

Category	Criterion	Description
Efficiency and Reliability	Response speed (C_1)	The response time to create a report.
	Stability (C_2)	The degree to which erroneous situations are handled effectively.
	Error rate (C_3)	The frequency and criticality of software failure.
Usability	Comprehensibility (C_4)	Ease with which the interface is understood.
	Ease of learning (C_5)	The ease with which users can learn how to use the system.
	Identity (C_6)	Software identity is clear and unique.
Ease of construction, installation and maintenance	Time, budget, and maintenance effort (C_7)	Ease building, installing and maintaining the system.

To measure these, the bank must establish a Big Data application server to read call log data and generate reports. The information system department organized the bidding for service providers. Four Information Technology companies competed to bid. The goal was to retrieve and clean the data that is produced by the CSR (customer service record) system, the IVR (interactive voice response) system, the CTI (computer telephony integration) system and the PBX (private branch exchange) system. The service providers must use Big Data technology because of the huge amount of historical data, run reports and analytical services that are required to optimize the internal processes, production operation management and the service quality.

One of the competing companies was the current statistical reporting tool provider and the current reports system developer, company A. The other three were all IT (information technology) companies that provide Big Data solutions.

A group of individuals from the bank's call center and the MIS (management information system) department, each of whom had an average of 10 years system operation and development experience, participated in the study to resolve the decision for the selection of a Big Data solutions provider. The participants agreed that it a fair competition would be impossible without a formal evaluation process. The decision group planned the evaluation date and decided the assessment criteria. Seven criteria were identified in the first round of decision-making process and these are listed in Table 1. Prior to the evaluation process, the relative weights of the 7 criteria were identified using the AHP method. The decision group also identified the judgment standard, the APIS, and the ANIS for each assessment criterion. Table 2 shows all of the required parameters

Table 2: The parameters for the first round decision.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Weight	0.066	0.196	0.066	0.130	0.130	0.216	0.196
Type	Benefit	Benefit	Cost	Benefit	Benefit	Benefit	Cost
APIS	95.00	95.00	10.00	88.00	88.00	85.00	20.00
ANIS	70.00	66.00	40.00	60.00	70.00	50.00	50.00
α	0.88						
β	0.88						
λ	2.25						

Table 3: The decision matrix for the first round.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Provider 1	83	75	20	77	80	83	25
Provider 2	85	69	39	80	75	65	46
Provider 3	78	80	23	80	76	82	23
Provider 4	72	84	34	85	72	65	45

for the ranking process. The evaluation process was performed in October 201X, after three weeks of preparation. Firstly the vendors demonstrated the data cleaning process. They then published the efficiency with which data was read from the operation database and transferred into the analysis database. The reported data was displayed on the UI (user interface). The competitors used different approaches to accomplish the goal, but the bidding demonstration steps were similar. Firstly, there was an introductory presentation to the decision group and then the participants tried the tools that were developed and viewed the report outputs.

After the demonstration, the decision group initiated an NGT (nominal group technique) type discussion to identify the decision matrix. The decision group assigned scores to each provider using each assessment criterion. If a consensus was not achieved, the geometric mean of the individuals' judgments was calculated. The group decision matrix is shown in Table 3. Finally, using the proposed ranking algorithm, the separation measures and proximity coefficients were calculated and these are listed in Table 4.

After the first round of decision-making, the decision group decided that providers 2 and 4 were no longer potential candidates. One had very high error rate and the other had a data transfer speed that was too slow. The judges could not reach a consensus as to which of the two remaining vendors were most suitable because their results were

Table 4: Ranking results for the first round.

	S^+	S^-	ϕ	Rank
Provider 1	0.3798	-1.5450	0.8027	2
Provider 2	0.7172	-0.7798	0.5209	4
Provider 3	0.3732	-1.5568	0.8066	1
Provider 4	0.6334	-0.9707	0.6051	3

similar. The users then made some new suggestions for the reporting tool, based on their experience. A second round of evaluation was instigated, to give a greater understanding of big data technology. A senior manager from the MIS department joined this decision group. He proposed customization as an assessment criterion for software selection so customization (C_8) was included as a new assessment criterion and a second round of evaluation began. As shown in Table 5, the ranking results for the previous round of decision were imported and treated as one of the criteria. The dynamic nature of the decision process was addressed by means of a feedback mechanism. The new relative weights for the nine criteria were also identified using the AHP method. Since both service providers were allowed to modify their systems based on the evaluation that had been made in previous round and the evaluators also gained more experience, the performance of the two service providers improved, so the APIS's and ANIS's were modified by the new decision group. Table 6 shows the new decision matrix that was created by the new decision group. The evaluations at the end of the second round of decision-making are shown in Table 7. The best ranked alternative for the second round of evaluation was provider 3. This result was confirmed by the decision group. The decision group also agreed that the proposed method was able to guide and support the

Table 5: Parameters used in the second round of decision-making.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	Previous Results
Weight	0.028	0.096	0.076	0.087	0.054	0.098	0.116	0.146	0.299
Type	Benefit	Benefit	Cost	Benefit	Benefit	Benefit	Cost	Benefit	Benefit
APIS	95.00	95.00	5.00	95.00	90.00	90.00	10.00	99.00	0.90
ANIS	80.00	75.00	30.00	70.00	70.00	60.00	30.00	75.00	0.70
α	0.88								
β	0.88								
λ	2.25								

decision team in aggregating the decision makers' preferences as the evaluation process progressed over time.

Table 6: Decision matrix for the second round.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Provider 1 89	82	15	80	80	83	15	90	0.8027	
Provider 3 85	90	10	88	84	84	14	87	0.8066	

Table 7: Results for the second round.

	S^+	S^-	ϕ	Rank
Provider 1	0.2585	-0.7656	0.7476	2
Provider 3	0.1654	-0.9632	0.8534	1

5. Conclusions

Choosing the right service provider is the first step in constructing a big data platform as the base for all other high-level human decision auxiliary tools, such as Artificial Intelligence tools. The bidding process can last for several months and new technologies are evolving constantly, so the decision-making problem is dynamic. The decision makers require a dynamic multiple-attribute decision-making framework. This paper proposes a dynamic EBVD method that determines a solution for multiple decisions over time and provides the potential decision attributes for the problem of big data provider selection. It is proven to be efficient and helpful in a dynamic environment in our practical case study. The advantages of the proposed method over traditional MADM methods are:

- The decision makers can add or remove criteria, eliminate unwanted alternatives and start the next round multiple times. Time is considered as an important factor, which can affect the decision makers' preferences.
- The feedback mechanism ensures that all previous rounds are meaningful and can shape the final outcome with the algorithm, to reflect human preferences when there is risk. The results of the previous round are included in the next iteration of the decision-making process as a special attribute. Its weight represents the importance of the previous decision round, as defined by the decision makers.

The case study shows how this approach can effectively guide and support decision makers to integrate their preferences in multiple stages of decision-making.

There are other types of dynamic decision making processes to consider, for example, new alternatives may be added into the bidding process. And there can be different set of decision criteria for different groups of decision makers. More studies can be carried out to handle scenario like that. Also, it is sometimes difficult to objectively determine the quality of soft computing solutions (see Tseng et al. [31]). We may consider comparing the effectiveness of this method with more other MADM methods for future enhancement.

References

[1] Alanazi, H. O., Abdullah, A. H. and Larbani, M. (2013). *Dynamic weighted sum multi-criteria decision making: mathematical model*, International Journal of Mathematics and Statistics Invention, Vol.2, 16-18.

[2] Bai, C., Shah, P., Zhu, Q. and Sarkis, J. (2018). *Green product deletion decisions: An integrated sustainable production and consumption approach*, Industrial Management & Data Systems, Vol.118, No.2, 349-389.

[3] Campanella, G. and Ribeiro, A. R. (2011). *A framework for dynamic multiple-criteria decision making*, Decision Support Systems, Vol.52, 52-60.

[4] Chen, C. L. P. and Zhang, C. Y. (2014). *Data-intensive applications, challenges, techniques and technologies: a survey on big data*, Information Sciences, Vol.275, 314-347.

[5] Cheng, S., Chan, C. W. and Huang, G. H. (2002). *Using multiple criteria decision analysis for supporting decision of solid waste management*, Journal of Environmental Science and Health, Vol.37, No.6, 975-990.

[6] Edwards, K. D. (1996). *Prospect theory: a literature review*, International Review of Financial Analysis, Vol.5, No.1, 19-38.

[7] Fan, Z. P., Zhang, X., Chen, F. D. and Liu, Y. (2013). *Extended TODIM method for hybrid multiple attribute decision making problems*, Knowledge-Based Systems, Vol.42, 40-48.

[8] Garca-Cascales, M. S. and Lamata, M. T. (2012). *On rank reversal and TOPSIS method*, Mathematical and Computer Modelling, Vol.56, 123-132.

[9] Gomes, L. F. A. M. and Lima, M. M. P. P. (1992). *TODIM: basics and application to multicriteria ranking of projects with environmental impacts*, Foundations of Computing and Decision Sciences, Vol.16, No.4, 113-127.

[10] Gomes, L. F. A. M. and Rangel, L. A. D. (2009). *An application of the TODIM method to the multicriteria rental evaluation of residential properties*, European Journal of Operational Research, Vol.193, 204-211.

[11] Gomes, L. F. A. M., Machado, M. A. S. and Rangel, L. A. D. (2013). *Behavioral multi-criteria decision analysis: the TODIM method with criteria interactions*, Annals of Operations Research, Vol.211, 531-548.

[12] Gurevich, G., Kliger, D. and Levy, O. (2009). *Decision-making under uncertainty - a field study of cumulative prospect theory*, Journal of Banking & Finance, Vol.33, No.7, 1221-1229.

[13] Hu, J. H., Chen, X. H. and Liu, Y. M. (2009). *Multi-criteria making method based on linguistic evaluation and prospect theory*, Control and Decision, Vol.24, No.10, 1477-1482.

[14] Hu, J., Chen, P. and Yang, L. (2013). *Dynamic stochastic multi-criteria decision making method based on prospect theory and conjoint analysis*, Management Science and Engineering, Vol.8, 65-71.

[15] Hwang, C. L. and Yoon, K. (1981). Multiple Attribute Decision Making: Methods and Applications, Springer-Verlag, New York.

[16] Jassbi, J. J., Ribeiro, R. A. and Varela, L. R. (2014). *Dynamic MCDM with future knowledge for supplier selection*, Journal of Decision Systems, Vol.23, No.3, 232-248.

[17] Kahneman, D. and Tversky, A. (1979). *Prospect theory: an analysis of decision under risk*, Econometrica, Vol.47, 263-292.

[18] Khamseh, A. A. and Mahmoodi, M. (2014). *A new fuzzy TOPSIS-TODIM hybrid method for green supplier selection using fuzzy time function*, Advances in Fuzzy Systems, http://dx.doi.org/10.1155/2014/841405.

[19] Lahdelma, R. and Salminen, P. (2009). *Prospect theory and stochastic multicriteria acceptability analysis*, Omega, Vol.37, 961-971.

[20] Lin, Y. H., Lee, P. C., and Ting, H. I. (2008). *Dynamic multi-attribute decision making model with grey number evaluations*, Expert Systems with Applications, Vol.35, No.4, 1638-1644.

[21] Liu, P., Jin, F., Zhang, X., Su, Y. and Wang, M. H. (2011). *Research on the multi-attribute decision-making under risk with interval probability based on prospect theory and the uncertain linguistic variables*, Knowledge-Based Systems, Vol.24, No.4, 554-561.

[22] Logothetis, D., Olston, C., Reed, B., Webb, C. K. and Yocum, K. (2010). *Stateful Bulk Processing for Incremental Analytics*, SoCC 10 Proceedings of the 1st ACM symposium on Cloud computing, 51-62.

[23] Lourenzutti, R., and Krohling, R. A. (2014). *The hellinger distance in multicriteria decision making: an illustration to the TOPSIS and TODIM methods*, Expert Systems with Applications, Vol.41, No.9, 4414-4421.

[24] James, M., Michael, C., Brad, B., Jacques, B., Richard, D., Charles, R. and Angela, H. B. (2012). Big data: The next frontier for innovation, competition, and productivity, McKinsey Global Institute.

[25] Opricovic, S. (1998). Multicriteria Optimization of Civil Engineering Systems, Faculty of Civil Engineering, Belgrade.

[26] Roy, B. (1991). *The outranking approach and the foundations of ELECTRE methods*, Theory and Decision, Vol.31, 49-73.

[27] Saaty, T. L. (1980). The Analytic Hierarchy Process, McGraw-Hill, New York.

[28] Shyur, H. J. (2006). *COTS evaluation using modified TOPSIS and ANP*, Applied Mathematics and Computation, Vol.177, 251-259.

[29] Shyur, H. J., Yin, L., Shih, H. S. and Cheng, C. B. (2015). *A multiple criteria decision making method based on relative value distances*, Foundations of Computing and Decision Sciences, Vol.40, No.4, 299-315.

[30] Trope, Y. and Liberman, N. (2010). *Construal-level theory of psychological distance*, Psychological Review, Vol.117, No.2, 440-463.

[31] Tseng, M. L., Zhu, Q., Sarkis, J. and Chiu, A. S. F. (2018). *Responsible consumption and production (RCP) in corporate decision-making models using soft computation*, Industrial Management & Data Systems, Vol.118, No.2, 322-329.

[32] Tversky, A. and Kahneman, D. (1992). *Advances in prospect theory: cumulative representation of uncertainty*, Journal of Risk and Uncertainty, Vol.5, No.4, 297-323.

[33] Wang, J. Q., Wu, J. T., Wang, J., Zhang, H. U. and Chen, X. H. (2016). *Multi-criteria decision-making methods based on the Hausdorff distance of hesitant fuzzy linguistic numbers*, Soft Computing, Vol.20, No.4, 1621-1633.

[34] Wang, J. Q. and Zhou, L. (2010). *Grey-stochastic multi-criteria decision-making approach based on prospect theory*, Systems Engineering-theory & Practice, Vol.30, No.9, 1658-1664.

[35] Wu, J. Z. and Tiao, P. J. (2018). *A validation scheme for intelligent and effective multiple criteria decision-making*, Applied Soft Computing, Vol.68, 866-872.

[36] Yazgan, H. R., Boran, S. and Goztepe, K. (2009). *An ERP software selection process with using artificial neural network based on analytic network process approach*, Expert Systems With Applications, Vol.36, No.5, 9214-9222.

[37] Yin, L. and Shyur, H. J. (2017). *A robust group multiple attributes decision-making method based on risk preferences of the decision makers*, International Journal of Applied Science and Engineering, Vol.15, No.1, 33-46.

[38] Yu, P. L. and Chen, Y. C. (2012). *Dynamic multiple criteria decision making in changeable spaces: from habitual domains to innovation dynamics*, Annals of Operations Research, Vol.197, No.1, 201-220.

[39] Zaidan, A. A., Zaidan, B. B., Hussain, M., Haiqi, A., Mat Kiah, M. L. and Abdulnabi, M. (2015). *Multi-criteria analysis for OS-EMR software selection problem: A comparative study*, Decision Support Systems, Vol.78, 15-27.

Department of Management Sciences, Tamkang University, Taiwan.

E-mail: sherryyin@gmail.com

Major area(s): MCDM, database management, decision support system.

Department of Information Management, Tamkang University, Taiwan.

E-mail: shyur@mail.im.tku.edu.tw

Major area(s): Soft computing, decision support system, software reliability.

(Received October 2017; accepted December 2018)