

A Decision Model for Benchmarking Knowledge Management Practices

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Abstract

This paper presents a decision model for benchmarking and evaluating organizational knowledge management (KM) practices. Linguistic variables approximated by fuzzy numbers are used for adequately handling the subjectiveness and imprecision of the evaluation process. Pairwise comparison is adopted in the evaluation process for greatly reducing the cognitive burden of the decision maker. A fuzzy multicriteria analysis algorithm is developed for generating an overall ranking of all the organizations regarding their KM practices. As a result, the relative performance of organizations in managing their knowledge can be properly assessed, and effective decisions can be made for further improving their KM practices. An empirical study in evaluating the KM practices at Victorian local governments in Australia is presented for demonstrating the applicability of the proposed decision model in real situations.

1. Introduction

Knowledge management (KM) refers to the identification, creation, distributing, utilization, and maintenance of organizational knowledge for fulfilling organizational objectives [1, 2]. Effectively managing organizational knowledge becomes increasingly important for organizations to gain competitive advantages nowadays. This is due to the increasingly competitive markets; the emergence of knowledge as the principal source of competitive advantage; a vast flood of information in both structured and unstructured formats; the continued pressures to align information flows and business processes; and the pressures of rapid technological change [2, 4].

To make full use of the potential of effective KM, organizations worldwide have adopted various

strategies and policies in implementing innovative KM initiatives. Numerous successful stories have been reported, novel KM models have been developed [1, 3, 13]. There is however no much reported research in benchmarking and evaluating the effectiveness of organizational KM practices. In particular the appropriate methodology for carrying out this kind of study is not available for practitioners in real situations.

This paper formulates the problem of benchmarking and evaluating organizational KM practices as a multicriteria analysis (MA) problem and proposes a decision model for solving the problem in a straightforward manner. Linguistic variables approximated by fuzzy numbers are used for adequately modelling the subjectiveness and imprecision of the evaluation process. Pairwise comparison is used for effectively reducing the decision maker's (DM) cognitive burden in the evaluation process. A fuzzy MA algorithm is developed for generating an overall ranking of organizations regarding their KM practices, resulting in consistent and effective decisions being made.

In what follows, we first describe the problem of benchmarking and evaluating KM practices at Victorian local governments, followed by a discussion of the concepts of fuzzy set theory, linguistic variables, fuzzy extent analysis, and fuzzy similarity. We then present a decision model for solving this problem. Finally, we provide an empirical study to illustrate the applicability of the novel decision model proposed.

2. Knowledge management practices in Victorian local governments

Australia is a multi-cultural society of more than 20 million people living mainly around the coastline and in large cities. The six states and two territories have their own elected governments. There is a nationally

elected government in Federal Parliament in Canberra. Local government in Australia is the responsibility of individual state governments. Since the 1990s, the trend has been away from prescriptive legislation in which what councils can and cannot do to the provision of enabling frameworks, within which councils have some degree of discretion in initiating their own policy directions. Following recent restructuring there are around 700 local authorities in Australia, most of them with small populations and some covering vast areas.

Local governments in Australia have a narrow range of functions. It does not take general responsibility for the provision of services. Although communities elect their own councilors, these and local mayors are essentially part-time figures. With the advent of new models of local government based on shared responsibility between a council and a professional city manager, the Mayor is no longer the Chief Executive Officer. Clearly in what is a much more business-like and indeed, entrepreneurial environment, those responsible for the administration and management of local government need access to the best information and knowledge available.

The need to respond to the challenges presented by organizational knowledge has resulted in wholesale structural and cultural changes in private sector organizations. Given the blurring of the once distinct boundaries between profit and not-for-profit operations the same need is now being felt in the public sector.

To be effective, any proposed response should avoid the temptations of *silver bullet*-type digital solutions, although a range of increasingly sophisticated information and communications technologies are available to assist in and enable the process of knowledge-based change. Within a KM architecture firmly aligned to organizational objectives, these can provide an electronic framework for capturing, codifying and distributing key information and knowledge throughout the organization.

Essentially, however, what is required is a response that promises to build the kind of capabilities likely to integrate, exploit and dynamically re-configure knowledge in order to deliver customer value. This will entail attention to those wider cultural issues identified as critical to knowledge-based change in the private sector, issues of staff collaboration, knowledge-sharing and organizational learning. This is proved to be the case at Victorian local governments in Australia in which various policies and strategies have been adopted for facilitating the organizational knowledge sharing and improving the organizational learning.

To gain insights into the extent to which the KM practice has permeated the sphere local government in Australia, in particular to identify their relative status of managing their knowledge across their peers in Victorian local governments is therefore of great significance. Such an evaluation would offer a number of benefits. First it would indicate the extent to which the concept and practice of KM are a part of the mission and strategic planning of local authorities. Second, it might indicate the extent of any differences in perception between those of top management and the people at middle and lower levels in the organizational hierarchy. Third, it could help identify any developing trends whereby local governments are becoming knowledge-based organizations.

Four evaluation criteria, including the awareness of KM value (C_1); the quality of KM (C_2), the degree of knowledge sharing (C_3); and the organizational learning ability (C_4), are used for the evaluation process. Against these evaluation criteria individual local Victorian governments are to be evaluated with respect to their relative performance in effective KM.

The awareness of KM value (C_1) refers to the recognition of an organization and its employees on the importance of KM and those innovative KM practices. This is determined by the perception of DMs with respect to the importance of KM in their organizational endeavors for excellence. The quality of KM practice (C_2) refers to the effectiveness and efficiency of KM practices in an organization, including whether there is a loss of knowledge either through staff defections or retirement or simply poor resource management.

The degree of knowledge sharing (C_3) is concerned about the ability of an organization to share knowledge and intellectual resources. A major means by which knowledge can be leveraged within organizations is through the use of mechanisms for knowledge exchange. This involves in various mechanisms such as knowledge sharing and the re-use of knowledge and learning in practice. An organization with a high level of knowledge sharing would actually decrease the possibility of people creating and recreating the same knowledge in the organization, a phenomenon commonly referred to *reinvention of the wheel*.

The organizational learning ability (C_4) is of critical importance for effective organizational KM, something that applies both to organizations and to the people within them. Learning seems to be a highly prized characteristic within local government in Australia.

Subjective assessments are made to evaluate the relative importance of the evaluation criteria and the performance of local governments with respect to each

criterion. These assessments are then aggregated so that an overall performance index for each local government can be produced.

3. Preliminary concepts

A fuzzy number is a convex fuzzy set [15], characterized by a given interval of real numbers, each with a grade of membership between 0 and 1. Its membership function $\mu_A(x)$ is piecewise continuous, and satisfies the conditions including (a) $\mu_A(x) = 0$ for each $x \in (-\infty, a_1] \cup [a_4, +\infty)$, (b) $\mu_A(x)$ is non-decreasing on $[a_1, a_2]$ and non-increasing on $[a_3, a_4]$, and $\mu_A(x) = 1$ for each $x \in [a_2, a_3]$ where $a_1 \leq a_2 \leq a_3 \leq a_4$ are real numbers in the real line R .

Triangular fuzzy numbers are a special class of fuzzy number [10], defined by three real numbers, often expressed as (a_1, a_2, a_3) . Their membership functions $\mu_A(x)$ are usually described as

$$\mu_A(x) = \begin{cases} \frac{x - a_1}{a_2 - a_1}, & a_1 \leq x \leq a_2, \\ \frac{a_3 - x}{a_3 - a_2}, & a_2 \leq x \leq a_3, \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $a_1 \leq a_2 \leq a_3$ are real numbers. In practical situations, a_2 is usually used to represent the most possible value of fuzzy number A , and a_1 and a_3 are used to respectively indicate the lower and upper bounds of fuzzy number A that are often used to illustrate the fuzziness of the data evaluated [9, 14].

Linguistic variables have been found intuitively easy to use in expressing the subjectiveness and imprecision of the DM's assessments [6, 14]. To facilitate the making of subjective assessments in the evaluation process, linguistic variables approximated by fuzzy numbers and defined as in Table 1 are used.

Table 1 Linguistic variables for making subjective pairwise assessments

Linguistic variables	Fuzzy numbers
Very Poor (VP)	$\bar{1} = (1, 1, 3)$
Poor (P)	$\bar{3} = (1, 3, 5)$
Fair (F)	$\bar{5} = (3, 5, 7)$
Good (G)	$\bar{7} = (5, 7, 9)$
Very Good (VG)	$\bar{9} = (7, 9, 9)$

Fuzzy synthetic extent analysis [5] is widely used in decision analysis when fuzzy data are present. Chang [5] applies this concept for extending the fuzzy analytic hierarchy process [12]. Zhu et al. [16] use this

concept for formulating a petroleum-prospecting problem in a fuzzy environment. These empirical studies demonstrate the effectiveness of this concept in decision analysis due to its simplicity in concept and its ease of use in practical situations.

Assume that $X = \{x_1, x_2, \dots, x_n\}$ is an object set, and $U = \{u_1, u_2, \dots, u_m\}$ is a goal set. By applying the method of fuzzy extent analysis with respect to each object for each goal respectively [5], m extent analysis values for each object can be obtained, given as $\mu_i^1, \mu_i^2, \dots, \mu_i^m$ where μ_i^j ($i = 1, 2, \dots, n; j = 1, 2, \dots, m$) are fuzzy numbers representing the performance of the object x_i with regard to goal u_j .

Aggregating these extent analysis values for each object across all goals using fuzzy synthetic extent analysis [5], the overall performance of the object across all goals can be calculated by

$$S_i = \frac{\sum_{j=1}^m \mu_i^j}{\sum_{i=1}^n \sum_{j=1}^m \mu_i^j}, \quad i = 1, 2, \dots, n. \quad (2)$$

where S_i ($i = 1, 2, \dots, n$) represents the fuzzy performance of object x_i across all goals.

Numerous measures of similarity between fuzzy numbers have been proposed [6]. These measures are used to reflect the relationships between fuzzy numbers from various dimensions. Some of these measures have been used in system analysis and linguistic approximation for solving practical problems.

A distance-based measure of two fuzzy numbers is a way to describe the closeness between two fuzzy numbers [6, 10]. It is often used to determine the degree of similarity between two fuzzy numbers. Let $A_i = (a_i, b_i, c_i)$ and $A_j = (a_j, b_j, c_j)$ be two triangular fuzzy numbers, the fuzzy similarity between these two fuzzy numbers can be defined as

$$d(A_i, A_j) = \sqrt{\frac{1}{3}((a_i - a_j)^2 + (b_i - b_j)^2 + (c_i - c_j)^2)}$$

4. The decision model

MA is widely used for ranking alternatives with respect to multiple criteria [6, 8]. Evaluating organisational KM practices obviously involves multiple criteria with subjective assessments. An overall ranking of local governments are required regarding the relative performance of their KM practices. In line with the multi-dimensional nature of the evaluation process, MA provides an effective framework for solving the problem due to its simplicity and comprehensibility in concept and its capability to handle multiple criteria. However, MA approaches are generally inadequate for dealing with

situations in which imprecision and subjectiveness are present [6, 17].

The application of fuzzy set theory in MA allows the DM to effectively formulate the decision problem in a fuzzy environment where the information available is subjective and imprecise [5, 6, 17]. The subjectiveness and imprecision of the decision process can be better modelled by fuzzy numbers with the use of linguistic variables.

To make full use of individual merits of existing MA methodologies, fuzzy set theory and linguistic variables, this section presents a decision model for evaluating and benchmarking the relative performance of KM practices at Victorian local governments. The decision model involves in (a) applying pairwise comparison for assessing the relative importance of the evaluation criteria and the performance ratings of individual alternatives with respect to each criterion, (b) using linguistic variables defined as in Table 1 to represent the subjective assessments, (c) calculating the criteria weighting and performance rating of alternatives using fuzzy synthetic analysis, (d) aggregating the fuzzy criteria weightings and performance ratings for producing a weighted fuzzy performance matrix using fuzzy arithmetic, and (e) calculating an overall performance index for each alternative across all criteria in line with the concepts of fuzzy maximum/minimum and fuzzy similarity.

The general evaluation problem usually consists of a number of alternatives A_i ($i = 1, 2, \dots, n$) to be evaluated against a set of selection criteria C_j ($j = 1, 2, \dots, m$). Subjective assessments are often required for determining the performance of each alternative A_i with respect to each criterion, denoted as x_{ij} ($i = 1, 2, \dots, n; j = 1, 2, \dots, m$), and the relative importance of the each criterion, represented as w_j ($j = 1, 2, \dots, m$), with respect to the overall objective of the problem.

The decision-making procedure starts at determining the criteria weightings and alternative performance ratings with respect to each criterion. By using the linguistic variables defined as in Table 1, a fuzzy reciprocal judgement matrix for criteria importance or for the alternative performance ratings with respect to each criterion can be determined as

$$\bar{A} = \begin{bmatrix} \bar{a}_{11} & \bar{a}_{12} & \dots & \bar{a}_{1k} \\ \bar{a}_{21} & \bar{a}_{22} & \dots & \bar{a}_{2k} \\ \dots & \dots & \dots & \dots \\ \bar{a}_{k1} & \bar{a}_{k2} & \dots & \bar{a}_{kk} \end{bmatrix} \quad (3)$$

$$\text{Where } \bar{a}_s = \begin{cases} VP, P, F, G, VG, & l < s, \\ 1, & l = s, \\ 1/\bar{a}_s, & l > s, \end{cases} \quad l, s = 1, 2, \dots, k; k = m \text{ or } n.$$

By applying (2) on (3), the corresponding criteria weightings or the alternative performance ratings with respect to criterion C_j can then be determined respectively, resulting in the decision matrix and the weight vector respectively determined as

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix} \quad (5)$$

$$W = (w_1, w_2, \dots, w_m) \quad (6)$$

where x_{ij} represents the fuzzy performance of alternative A_i ($i = 1, 2, \dots, n$) with respect to criterion C_j and w_j is the fuzzy weight of the criterion C_j ($j = 1, 2, \dots, m$).

With the decision matrix and the weighting vector as above, a fuzzy performance matrix (7) representing the weighted performance of alternatives with respect to each criterion can be determined by multiplying the weighting vector in (6) by the decision matrix in (5).

$$Z = \begin{bmatrix} w_1 x_{11} & w_2 x_{12} & \dots & w_m x_{1m} \\ w_1 x_{21} & w_2 x_{22} & \dots & w_m x_{2m} \\ \dots & \dots & \dots & \dots \\ w_1 x_{n1} & w_2 x_{n2} & \dots & w_m x_{nm} \end{bmatrix} \quad (7)$$

To avoid the complex and unreliable process of comparing fuzzy utilities [6], the concepts of fuzzy maximum and fuzzy minimum are introduced for determining the relative performance of all the alternatives with respect to each criterion represented based on the concept of fuzzy similarity. As a result, a fuzzy maximum (M_{\max}^j) and a fuzzy minimum (M_{\min}^j) are defined for each given fuzzy vector ($w_j x_{1j}, w_j x_{2j}, \dots, w_j x_{nj}$) ($j = 1, 2, \dots, m$) in (7) representing the fuzzy performance of all alternative A_i with respect to each criterion C_j . Their membership functions are determined respectively as

$$u_{M_{\max}^j}(x) = \begin{cases} \frac{x - x_{\min}^j}{x_{\max}^j - x_{\min}^j}, & x_{\min}^j \leq x \leq x_{\max}^j, \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

$$u_{M_{\min}^j}(x) = \begin{cases} \frac{x_{\max}^j - x}{x_{\max}^j - x_{\min}^j}, & x_{\min}^j \leq x \leq x_{\max}^j, \\ 0, & \text{otherwise} \end{cases}$$

where

$$x_{\max}^j = \sup \left(\text{supp} \bigcup_{i=1}^n (w_j x_{ij}) \right),$$

$$x_{\min}^j = \inf \left(\text{supp} \bigcup_{i=1}^n (w_j x_{ij}) \right).$$

Based on the concept of fuzzy similarity, the similarity between each alternative and fuzzy maximum can be calculated as follows:

$$s_i^+ = \sum_{j=1}^m d_{ij}(x_j w_j, M_{\max}^j) \quad (9)$$

By the same token, the similarity between each alternative and the fuzzy minimum is calculated as:

$$s_i^- = \sum_{j=1}^m d_{ij}(x_j w_j, M_{\min}^j) \quad (10)$$

A preferred alternative is to be as close to the fuzzy maximum as possible, and as far away from the fuzzy minimum as possible [6, 8]. Therefore, an overall performance index for each alternative A_i across all criteria can be calculated by

$$P_i = \frac{s_i^-}{s_i^+ + s_i^-}, \quad i = 1, 2, \dots, n. \quad (11)$$

The larger the performance index, the more preferred the alternative.

Summarizing the discussion as above, the decision model for determining the overall ranking of all alternatives across all criteria can be described algorithmically as follows:

- Step 1. Formulate the decision problem as a MA problem with the identification of alternatives and evaluation criteria
- Step 2. Assess alternative performance ratings with respect to each criterion using pairwise comparison with the linguistic variables defined as in Table 1, resulting in the fuzzy reciprocal judgment matrix described as in (3).
- Step 3. Apply fuzzy synthetic extent analysis on the fuzzy reciprocal judgment matrix from Step 3, resulting in the determination of the fuzzy decision matrix for all alternatives across all criteria as in (5).
- Step 4. Assess the criteria weightings using pairwise comparison with the linguistic variables defined as in Table 1, resulting in the fuzzy reciprocal judgment matrix described as in (3).
- Step 5. Apply fuzzy synthetic extent analysis on the fuzzy reciprocal judgment matrix from Step 4, resulting in the determination of the fuzzy criteria weights as in (6).
- Step 6. Calculate the weighted fuzzy performance matrix by multiplying the fuzzy decision matrix in (5) by the fuzzy weightings in (6).
- Step 7. Determine the fuzzy maximum and fuzzy minimum by (7) and (8).

Step 8. Calculate the similarity between each alternative and the fuzzy maximum or fuzzy minimum by (9) and (10).

Step 9. Determine the rankings of all alternatives by calculating their overall index values by (11).

5. An Empirical Study

This section presents an empirical study to demonstrate the applicability of the decision model for benchmarking and evaluating the KM practices. As discussed in Section 2, four evaluation criteria, the awareness of KM value (C_1); the quality of KM (C_2), the degree of knowledge sharing (C_3); and the organizational learning ability (C_4), are considered for evaluating and benchmarking three local governments (A_1, A_2, A_3) with respect to their KM practices.

Using the linguistic variables defined as in Table 1, the performance ratings of three local governments with respect to the four criteria based on pairwise comparison can be determined, resulting in the four fuzzy reciprocal judgment matrix as follows:

$$C_1 = \begin{matrix} & A_1 & A_2 & A_3 \\ A_1 & \begin{bmatrix} \bar{1} & & \\ & \bar{3} & \\ & & \bar{9} \end{bmatrix} & & \\ A_2 & \begin{bmatrix} \bar{3}^{-1} & \bar{1} & \\ & \bar{5}^{-1} & \\ & & \bar{1} \end{bmatrix} & & \\ A_3 & \begin{bmatrix} \bar{9}^{-1} & & \\ & \bar{5}^{-1} & \\ & & \bar{1} \end{bmatrix} & & \end{matrix}$$

$$C_2 = \begin{matrix} & A_1 & A_2 & A_3 \\ A_1 & \begin{bmatrix} \bar{1} & & \\ & \bar{3} & \\ & & \bar{5} \end{bmatrix} & & \\ A_2 & \begin{bmatrix} \bar{3}^{-1} & \bar{1} & \\ & \bar{9} & \\ & & \bar{1} \end{bmatrix} & & \\ A_3 & \begin{bmatrix} \bar{5} & & \\ & \bar{9} & \\ & & \bar{1} \end{bmatrix} & & \end{matrix}$$

$$C_3 = \begin{matrix} & A_1 & A_2 & A_3 \\ A_1 & \begin{bmatrix} \bar{1} & & \\ & \bar{9} & \\ & & \bar{7} \end{bmatrix} & & \\ A_2 & \begin{bmatrix} \bar{9} & \bar{1} & \\ & \bar{3} & \\ & & \bar{1} \end{bmatrix} & & \\ A_3 & \begin{bmatrix} \bar{7} & & \\ & \bar{3} & \\ & & \bar{1} \end{bmatrix} & & \end{matrix}$$

$$C_4 = \begin{matrix} & A_1 & A_2 & A_3 \\ A_1 & \begin{bmatrix} \bar{1} & & \\ & \bar{7} & \\ & & \bar{3} \end{bmatrix} & & \\ A_2 & \begin{bmatrix} \bar{7} & \bar{1} & \\ & \bar{9} & \\ & & \bar{1} \end{bmatrix} & & \\ A_3 & \begin{bmatrix} \bar{3} & & \\ & \bar{9} & \\ & & \bar{1} \end{bmatrix} & & \end{matrix}$$

Using fuzzy synthetic extent analysis, the fuzzy decision matrix for the evaluation problem can then be determined based on fuzzy arithmetic [11] as follows:

$$X = \begin{bmatrix} (0.27, 0.63 | 1.32) & (0.06, 0.12 | 0.58) & (0.17, 0.36 | 0.74) & (0.06, 0.18 | 0.50) \\ (0.13, 0.31 | 0.76) & (0.24, 0.50 | 1.04) & (0.23, 0.46 | 0.91) & (0.37, 0.75 | 1.40) \\ (0.04, 0.06 | 0.24) & (0.12, 0.30 | 0.70) & (0.06, 0.18 | 0.50) & (0.04, 0.06 | 0.25) \end{bmatrix}$$

To determine the relative importance of the evaluation criteria, fuzzy pairwise comparison process is used, resulting in a fuzzy reciprocal judgement matrix (W) as follows:

$$W = \begin{matrix} & C_1 & C_2 & C_3 & C_4 \end{matrix}$$

$$W = \begin{matrix} C_1 \\ C_2 \\ C_3 \\ C_4 \end{matrix} \begin{bmatrix} \bar{1} & \bar{3} & \bar{7} & \bar{5} \\ \bar{3}^{-1} & \bar{1} & \bar{9} & \bar{3} \\ \bar{7}^{-1} & \bar{9}^{-1} & \bar{1} & \bar{3}^{-1} \\ \bar{5}^{-1} & \bar{3}^{-1} & \bar{3} & \bar{1} \end{bmatrix}$$

Similarly, the weighting vector can be determined by (3) to (5) using fuzzy extent analysis as follows:

$$w_1 = (0.17, 0.45, 1.05), \quad w_2 = (0.16, 0.38, 0.87), \\ w_3 = (0.02, 0.04, 0.19), \quad w_4 = (0.04, 0.13, 0.41).$$

Following the procedures described as above, an overall performance index value for each local government involved across the four evaluation criteria can be determined. Table 2 shows the results.

Table 2 Performance index values and the corresponding rankings of the local governments

Alternatives	Performance index	Ranking
A_1	0.51	1
A_2	0.37	2
A_3	0.12	3

The decision model clearly has its advantages, including (a) better modeling of the subjectiveness and imprecision of the decision process and (b) cognitively less demanding on the DM. Real experience in applying the decision model for benchmarking and evaluating KM practices in Victorian local governments has reinforced these findings.

6. Conclusion

Benchmarking and evaluating the KM practices of organizations is of great significance in real world settings. This paper presents a novel decision model capable of adequately evaluating the KM practices in Victorian local governments in Australia. The subjectiveness and imprecision of the human decision-making process are properly handled using linguistic variables represented by fuzzy numbers. Pairwise comparison is used in the evaluation process for greatly reducing the cognitive burden on the DM. As a result the proposed decision model can help organisations identify their relative status in their KM practices and facilitates the pursuit of innovative KM policies and strategies for better performance.

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