Applying Linguistic VIKOR and Knowledge Map in Personnel Selection

Chen-Tung Chen a,*, Ping-Feng Pai b, Wei-Zhan Hung c

a Department of Information Management, National United University, Taiwan
b Department of Information Management, National Chi Nan University, Taiwan
c Department of International Business Studies, National Chi Nan University, Taiwan

Received 21 May 2010; Received in revised form 18 October 2011; Accepted 9 November 2011

Abstract

In the high competitive environment, both core knowledge of business and intelligent employee are important assets of a company. Personnel selection is a very important issue for the enterprises because most of the enterprises’ activities need the right person to handle it. In order to choose the suitable employee for the company to compete with other competitors, it needs a suitable method to deal with the problem of personnel selection based on the knowledge map of company and capability of each employee. In fact, many factors will influence the personnel selection problem such as language ability, work experience, communication ability, and so on. By considering general criteria and knowledge criteria simultaneously, a linguistic VIKOR method is proposed in this paper to deal with personnel selection problem. Finally, an example is implemented to demonstrate the practicability of the proposed method.

Keywords: Knowledge map, fuzzy set, personnel selection, MCDM

1. Introduction

In the knowledge economy age, a knowledgeable and talented employee is the company’s asset (Wei, 2007). Personnel selection is a very important issue for the enterprises because most of the enterprises’ activities need the right person to handle it (Caligiuri et al., 2009). On the contrary, the person in the wrong position will reduce the company’s competitiveness. Moreover, Stein and Zwass (1995) stated that enterprise can aggregate organization memory (Intelligent Capital) to create competitiveness. So, knowledge had been considered as a crucial asset for companies to survive in a highly competitive environment (Lai et al., 2008). It is important for identifying, disseminating, categorizing, retrieving and sharing information assets (knowledge) throughout the organization (Taft, 2000). There are two kinds of knowledge such as explicit and tacit. Explicit knowledge refers to codified knowledge that is transmittable in formal, systematic language and is easily transferred by using information technology (IT) (Woo et al., 2004). Tacit knowledge is knowledge housed in the human brain, such as expertise, understanding, or professional insight formed as a result of experience (Polanyi, 1996). However, most of the competitive knowledge is tacit knowledge. Knowledge map is a tool or technique for visualizing knowledge and relationship that the relevant features of the knowledge can be clearly highlighted (Vail, 1999). The function of knowledge map is to record the person who possess the special knowledge in the company. So, knowledge map is also called “yellow pages”. The goal of knowledge map is to make sure that manager or relative workers can find employee who possess the relative knowledge in special case (Earl, 2001). Hence, manager can save the resource and reduce the operation time to record tacit knowledge which is difficult to express clearly.

* Corresponding author. Email: ctchen@nuu.edu.tw
literatures, knowledge map has been used in many situations. Woo et al., (2004) used software (such as Dynamic Knowledge Map) to improve the job performance in Architecture, Engineering and Construction (AEC) company. Pyo (2005) compared four tourism destination types of knowledge maps in tourism industry and suggested different mapping schemes to let traveler find useful travel information. Rouse et al., (1998) developed a six-step knowledge mining methodology according to user-oriented knowledge maps to judge knowledge available in a R&D project. Shaw (2010) proved that the application of knowledge maps in e-learning materials design can improve workers’ learning performance. It is essential to choose employee which can provide the relative knowledge and experience based on company’s knowledge requirement in accordance with company’s knowledge map.

There are some literatures about dealing with personnel selection problem. Ertugrul Karsak (2000) used fuzzy objective programming to select personnel. Korvin et al., (2002) used the fuzzy construct of compatibility to measure the fitness degree of a person’s skill set. It combined levels of compatibility with acceptable levels of quality to deal with multiple phase project personnel selection problem. Chien and Chen (2007) developed an effective data mining approach based on rough set theory to analyze human resource data for personnel selection. Chien and Chen (2008) developed a data mining framework based on decision tree and association rules to generate useful rules for personnel selection. Gungor et al., (2009) used fuzzy AHP to cope with personnel selection problem by considering both quantitative and qualitative criteria. Celik et al., (2009) used fuzzy AHP and Fuzzy TOPSIS to recruit academic personnel in maritime human resources. Fan et al., (2009) used a bi-objective 0-1 programming model to select desired members by considering individual information of members and the collaborative information between members. Feng et al., (2010) built a multi-objective 0–1 programming model and improved non-dominated sorting genetic algorithm II (NSGA-II) based on the individual and collaborative performances of candidate to deal with the problem of project member selection. Although the knowledge map is an important tool for selecting personnel, a few of above literatures considered about this issue. Furthermore, there are several conflicting criteria (such as experience and age) need to be considered in choosing the suitable employee. Therefore, multi-criteria decision making method is suitable to deal with the personnel selection problems.

In multi-criteria analysis, it is difficult to obtain a solution to satisfy all criteria simultaneously (Chang and Hsu, 2009). A compromise solution for a problem with conflicting criteria can help decision-makers identify an acceptable answer (Opricovic, 1998). VIKOR (ViseKriterijumska Optimizacija I Kompromisno Resenje) is a multi criteria decision making method which developed by Opricovic (1998). VIKOR determines a compromise solution that provides the maximum group utility for the majority and a minimum of individual regret for the opponent (Chen and Wang, 2009). So, VIKOR can find a compromise priority ranking of alternatives according to the evaluation criteria (Opricovic and Tzeng, 2002, 2003). According to the VIKOR method, the compromise ranking order could be performed by comparing the measure of closeness to the ideal alternative through the process of ranking and selecting a set of alternatives in the presence of conflicting criteria (Chen and Wang, 2009). Because imprecise and subjective information that often appears in personnel evaluation process, crisp values are inadequate for solving the problems. A more realistic approach may be to use linguistic assessments instead of numerical values (Chen, 2000; Herrera and Herrera-Viedma, 2000). The 2-tuple linguistic representation model is based on the concept of symbolic translation (Herrera and Martinez, 2000; Xu, 2005). Decision makers can apply 2-tuple linguistic variables to express their opinions and obtain the final evaluation result with appropriate linguistic variable. It is an effective method to reduce the mistakes of information translation and avoid information loss through computing with words (Herrera-Viedma, 2003). Therefore, a linguistic VIKOR method is proposed to
evaluate employee by both considering general criteria and knowledge criteria based on knowledge map in the company. Linguistic VIKOR method not only let experts flexibly use different kind of linguistic variables to express their opinions but also obtain a compromise solution which take account of the maximum group utility for the majority and a minimum of individual regret for the opponent simultaneously.

This paper is organized as follows. In section 2, we present the definition and operation of 2-tuple linguistic variables. In section 3, we describe the detail of the proposed method. In section 4, an example is implemented to demonstrate the procedure for the proposed method. Finally, the conclusion is discussed at the end of this paper.

2. 2-Tuple Linguistic Variable

Let \( S = \{s_0, s_1, s_2, \ldots, s_g\} \) be a finite and totally ordered linguistic term set. A 2-tuple linguistic variable can be expressed as \((s_i, \alpha_i)\), where \( s_i \) is the central value of \( i \)-th linguistic term in \( S \) and \( \alpha_i \) is a numerical value representing the difference between calculated linguistic term and the closest index label in the initial linguistic term set. The symbolic translation function \( \Delta \) is used to translate \( \beta \) into a 2-tuple linguistic variable (Herrera and Martinez, 2001). Then, the symbolic translation process is applied to translate \( \beta \) (\( \beta \in [0, 1] \)) into a 2-tuple linguistic variable. The generalized translation function can be represented as (Tai and Chen, 2009):

\[
\Delta: [0,1] \rightarrow S \times [-\frac{1}{2g}, \frac{1}{2g}] \quad \text{and} \quad \Delta(\beta) = (s_i, \alpha_i) \quad \text{where} \quad i = \text{round}(\beta \times g), \; \alpha_i = \beta - \frac{i}{g} \quad \text{and} \quad \alpha_i \in [-\frac{1}{2g}, \frac{1}{2g}].
\]

A reverse function \( \Delta^{-1} \) is defined to return an equivalent numerical value \( \beta \) from 2-tuple linguistic information \((s_i, \alpha_i)\). According to the symbolic translation, an equivalent numerical value \( \beta \) is obtained as follow (Tai and Chen, 2009).

\[
\Delta^{-1}(s_i, \alpha_i) = \frac{i}{g} + \alpha_i = \beta \quad \text{(1)}
\]

Let \( x = \{(r_1, \alpha_1), (r_2, \alpha_2), \ldots, (r_n, \alpha_n)\} \) be a 2-tuple linguistic variable set. The arithmetic mean \( \bar{X} \) is computed as (Herrera-Viedma et al., 2004)

\[
\bar{X} = \Delta \left( \frac{1}{n} \sum_{i=1}^{n} \Delta^{-1}(r_i, \alpha_i) \right) = (s_m, \alpha_m) \quad \text{(2)}
\]

In general, decision makers would use the different 2-tuple linguistic variables based on their knowledge or experiences to express their opinions (Herrera et al., 2005). A transformation function is needed to transfer these 2-tuple linguistic variables from different linguistic sets to a standard linguistic set at unique domain. However, the domain of the linguistic variables will increase as the number of linguistic variable is increased in the method of Herrera and Martinez (Goumas and Lygerou, 2000). To overcome this drawback, a new translation function is proposed here to transfer a crisp number or 2-tuple linguistic variable to a standard linguistic term at the unique domain (Tai and Chen, 2009). Suppose that the interval \([0, 1]\) is the unique domain. The linguistic variable sets with different semantics (or types) will be defined by partitioning the interval \([0, 1]\). Transforming a crisp number \( \beta \) (\( \beta \in [0, 1] \)) into \( i \)-th linguistic term \((s_i, \alpha_i)\) of type \( t \) as \( \Delta(\beta) = (s_i, \alpha_i) \) where \( i = \text{round}(\beta \times g), \; \alpha_i = \beta - \frac{i}{g} \quad \text{and} \quad g = n(t) - 1 \) and \( n(t) \) is the number of linguistic variable of type \( t \).
Transforming \(i\)-th linguistic term of type \(t\) into a crisp number \(\beta\) (\(\beta \in [0, 1]\)) as

\[
\Delta_t^{-1}(s_i^{n(t)}, \alpha_i^{n(t)}) = \frac{i}{g_t} + \alpha_i^{n(t)} = \beta
\]

where \(g_t = n(t) - 1\) and \(\alpha_i^{n(t)} \in [-\frac{1}{2g_t}, \frac{1}{2g_t}]\).

Therefore, the transformation from \(i\)-th linguistic term \((s_i^{n(t)}, \alpha_i^{n(t)})\) of type \(t\) to \(k\)-th linguistic term \((s_k^{n(t)}, \alpha_k^{n(t)})\) of type \(t+1\) at interval \([0, 1]\) can be expressed as

\[
\Delta_{t+1}(\Delta_t^{-1}(s_i^{n(t)}, \alpha_i^{n(t)})) = (s_k^{n(t+1)}, \alpha_k^{n(t+1)})
\]

where \(g_{t+1} = n(t+1) - 1\) and \(\alpha_k^{n(t+1)} \in [-\frac{1}{2g_{t+1}}, \frac{1}{2g_{t+1}}]\).

3. Proposed Method

In fact, a personnel selection problem may be described by means of the following sets:

(a) A set of decision-makers is called \(D = \{D_1, D_2, \ldots, D_K\}\);

(b) A set of candidates (alternatives) is called \(A = \{A_1, A_2, \ldots, A_m\}\);

(c) A set of general criteria \(C = \{C_1, C_2, \ldots, C_n\}\) with which candidates’ performances are measured;

(d) A set of performance ratings of candidates with respect to general criteria is called \(x_{ij}\), \(i = 1, 2, \ldots, m\), \(j = 1, 2, \ldots, n\).

(e) A set of knowledge criteria \(F = \{F_1, F_2, \ldots, F_y\}\) based on company’s knowledge map with which candidates’ professional knowledge are measured;

(f) A set of professional ratings of candidates with respect to knowledge criteria is called \(z_{id}\), \(i = 1, 2, \ldots, m\), \(d = 1, 2, \ldots, y\).

The performance of the \(i\)-th candidate with respect to the \(j\)-th general criterion decided by the \(k\)-th expert can be represented as a 2-tuple linguistic variable \(F_j(A_k) = (s_j^k, \alpha_j^k)\). The aggregated linguistic ratings \(F_j(A)\) of the \(i\)-th alternative with respect to the \(j\)-th general criterion can be calculated as

\[
F_j(A_i) = \Delta \left( \frac{1}{K} \sum_{k=1}^{K} \Delta^{-1}(s_j^k, \alpha_j^k) \right) = (s_j^i, \alpha_j^i)
\]

The aggregated linguistic weights \((\bar{\omega}_j)\) of each general criterion can be calculated as

\[
\bar{\omega}_j = \Delta \left( \frac{1}{K} \sum_{k=1}^{K} \Delta^{-1}(s_j^w, \alpha_j^w) \right) = (s_j^w, \alpha_j^w)
\]

The linguistic positive-ideal solution \((F_j^+)\) of each general criterion can be calculated as

\[
F_j^+ = \Delta \left( \max_i \Delta^{-1}(F_j(A_i)) \right), \forall A_i \in A
\]

The linguistic negative-ideal solution \((F_j^-)\) of each general criterion can be calculated as

\[
F_j^- = \Delta \left( \min_i \Delta^{-1}(F_j(A_i)) \right), \forall A_i \in A
\]

The group utility for the majority \((S_i)\) of each candidate can be calculated as

\[
S_i = \sum_{j=1}^{n} \Delta^{-1}(\bar{\omega}_j) \frac{\Delta^{-1}(F_j^+ - F_j^-)}{\Delta^{-1}(F_j^+ - F_j^-)}, \forall i
\]
where $S_i$ represents as the relative competitive ability of $i$-th candidate by weighted average the relative position $\frac{\Delta^{-1}(F_i^*) - \Delta^{-1}(F_j(A_i))}{\Delta^{-1}(F_i^*) - \Delta^{-1}(F_j^*)}$ of each general criterion.

The individual regret rating for the opponent $R_i$ of each candidate can be calculated as

$$R_i = \max \left( \Delta^{-1}(F_i^*) \cdot \frac{\Delta^{-1}(F_j^*) - \Delta^{-1}(F_j(A_i))}{\Delta^{-1}(F_i^*) - \Delta^{-1}(F_j^*)} \right), \forall i$$

(10)

where $R_i$ represents as the maximum regret by choosing $i$-th candidate as solution according to choose the worst performance in general criteria.

The value $(Q_i)$ of each candidate can be calculated as

$$Q_i = v \cdot \frac{S_i - S^*}{S^* - S^*} + (1 - v) \cdot \frac{R_i - R^*}{R^* - R^*}, \forall i$$

(11)

$$S^* = \min_i S_i, \quad S^- = \max_i S_i, \quad R^* = \max_i R_i, \quad R^- = \min_i R_i$$

(12)

where $S^*$ represents the positive-ideal solution of $S_i$, $S^-$ represents the negative-ideal solution of $S_i$, $R^*$ represents the positive-ideal solution of $R_i$, $R^-$ represents the negative-ideal solution of $R_i$. The $v$ value represents the decision making coefficient and $v$ is between 0 and 1. When $v$ is closed to 1 represents that decision maker chooses the candidate who mainly considers maximize group utility for the majority. On the other hand, when $v$ is closed to 0 represents that decision maker chooses the candidate who mainly considers minimize individual regret for the opponent. The smaller $Q_i$ represents $i$-th candidate is better with respect to general criteria.

In this paper, the performances of candidates’ knowledge are measured according to professional ratings of candidates with respect to knowledge criteria based on knowledge map. The weight of knowledge criteria is according to the scarceness in the company. The weight vector can be represented as $Fw = \{Fw_1, Fw_2, \cdots, Fw_y\}$ where $Fw_d = \frac{1}{FN_d + 1}, \forall Fw_d \in F$, $FN_d$ is the number of personnel in the company who possess the knowledge in knowledge criteria $F_d$.

The $z_{id}$ is professional rating of $i$-th candidate with respect to knowledge criteria $d$. The $z_{id}$ can be represented by 2-tuple linguistic variable. For example, the $F_k^k(A_i) = (S_{id}, \alpha_{id})$ can be represented as the opinion of $k$-th expert. The aggregated linguistic rating $F_d(A_i)$ of the $i$-th alternative with respect to the $d$-th knowledge criterion can be calculated as

$$F_d(A_i) = \Delta \left( \frac{1}{K} \sum_{k=1}^{K} \Delta^{-1}(S_{id}^k, \alpha_{id}^k) \right) = (S_{id}, \alpha_{id})$$

(13)

We determine the threshold $Ft = \{Ft_1, Ft_2, \cdots, Ft_y\}$ in each knowledge criterion to judge that $i$-th candidate possesses the knowledge. The knowledge rating $K_{id}$ of $i$-th candidate with respect to the $d$-th knowledge criterion can be calculated as

$$K_{id} = \begin{cases} 1, & \Delta^{-1}(F_d(A_i)) \geq Ft_d \\ 0, & \Delta^{-1}(F_d(A_i)) < Ft_d \end{cases}$$

(14)

If $F_d(A_i)$ is equal to or larger than threshold $Ft_d$, than we set $K_{id}$ to 1 and represent $i$-th candidate possesses the knowledge in $d$-th knowledge criterion. Otherwise, we set $K_{id}$ to 0.

The performance of knowledge $PK_i$ of each candidate can be calculated as
The $PK_i$ represents the weighted average of the knowledge performance of $i$-th candidate. The relative knowledge $RK_i$ of each candidate can be calculated as

$$RK_i = \frac{\max(PK_i) - PK_i}{\max(PK_i) - \min(PK_i)}$$

The $RK_i$ value represents the knowledge competitiveness of each candidate. $RK_i$ is between 0 and 1. The higher $PK_i$, the lower $RK_i$ represents $i$-th candidate is more closed to ideal-candidate with respect to knowledge criteria.

Considering general criteria and knowledge criteria simultaneously, the value $RQ_i$ of each candidate can be calculated as

$$RQ_i = u * Q_i + (1 - u) * RK_i, \quad \forall i, A_i \in A$$

The $u$ value represents the decision making coefficient and $u$ is between 0 and 1. When $u$ is closed to 1 represents that decision maker chooses the candidate who mainly considers the competitive ability of each candidate according to general criteria. On the other hand, when $u$ is closed to 0 represents that decision maker chooses the candidate who mainly considers knowledge know-how of each candidate according to knowledge criteria based on company’s knowledge map. According to the equation (17), the smaller $RQ_i$ represents $i$-th candidate is better than other candidates with respect to all criteria.

4. Numerical Example

Suppose that a semi-conduct industry company desires to select an engineer. In the company, three experts are formed a evaluation team to choose the best engineer from four candidates in accordance with four general criteria and six knowledge expertise criteria based on knowledge map. General criteria include English ability, work experience, communication ability and emotional steadiness. Professional knowledge criteria include Japanese language ability, product knowledge, market knowledge, accounting knowledge, law knowledge and mechanism knowledge.

According to the proposed method, the computational procedures of the problem are summarized as follows.

Step 1. Each expert will choose the linguistic variable type to express his opinion. Expert $D_1$ chooses type 1, $D_2$ chooses type 2, and $D_3$ chooses type 3 (refer to Table 1). Then, each expert uses the linguistic variables to evaluate weights of each general criterion as Table 2 and performance ratings of each candidate with respect to general criteria as Table 3.
### Table 1. Different types of linguistic variables.

<table>
<thead>
<tr>
<th>Type</th>
<th>Linguistic variable</th>
<th>Figure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td><strong>performance</strong>&lt;br&gt;Extremely Poor ($s_0^5$), Poor ($s_1^5$), Fair ($s_2^5$), Good ($s_3^5$), Extremely Good ($s_4^5$)&lt;br&gt;<strong>weight</strong>&lt;br&gt;Extremely Low ($s_0^5$), Low ($s_1^5$), Fair ($s_2^5$), High ($s_3^5$), Extremely High ($s_4^5$)</td>
<td>Fig. 1</td>
</tr>
<tr>
<td>2</td>
<td><strong>performance</strong>&lt;br&gt;Extremely Poor ($s_0^5$), Poor ($s_1^5$), Medium Poor ($s_2^5$), Fair ($s_3^5$), Medium Good ($s_4^5$), Good ($s_5^5$), Extremely Good ($s_6^5$)&lt;br&gt;<strong>weight</strong>&lt;br&gt;Extremely Low ($s_0^5$), Low ($s_1^5$), Medium Low ($s_2^5$), Fair ($s_3^5$), Medium High ($s_4^5$), High ($s_5^5$), Extremely High ($s_6^5$)</td>
<td>Fig. 2</td>
</tr>
<tr>
<td>3</td>
<td><strong>performance</strong>&lt;br&gt;Extremely Poor ($s_0^5$), Very Poor ($s_1^5$), Poor ($s_2^5$), Medium Poor ($s_3^5$), Fair ($s_4^5$), Medium Good ($s_5^5$), Good ($s_6^5$), Very Good ($s_7^5$), Extremely Good ($s_8^5$)&lt;br&gt;<strong>weight</strong>&lt;br&gt;Extremely Low ($s_0^5$), Very Low ($s_1^5$), Low ($s_2^5$), Medium Low ($s_3^5$), Fair ($s_4^5$), Medium High ($s_5^5$), High ($s_6^5$), Very High ($s_7^5$), Extremely High ($s_8^5$)</td>
<td>Fig. 3</td>
</tr>
</tbody>
</table>

Figure 1. Membership functions of linguistic variables at type 1 ($t=1$).

Figure 2. Membership functions of linguistic variables at type 2 ($t=2$).
Step 2. Transform the linguistic evaluations of weight of each general criterion into the linguistic variables of type 2 and aggregate the linguistic weight of each general criterion.

Step 3. Transform the linguistic ratings into the linguistic variables of type 2 and aggregate the linguistic ratings of each candidate with respect to general criteria.

Step 4. Determine the linguistic positive-ideal solution $\tilde{F}^+$ and the linguistic negative-ideal solution $\tilde{F}^-$ of each general criterion as Table 4.

Step 5. Compute the group utility for the majority $S$, the individual regret rating for the opponent $R_i$ and $Q_i$ when we set decision making coefficient $\nu=0.5$ as Table 5.

Step 6. Each expert uses the linguistic variables to evaluate the performance ratings of each knowledge criterion as Table 6.

Step 7. Transform the linguistic ratings into the linguistic variables of type 2 and aggregate the linguistic ratings of each candidate with respect to knowledge criteria.
Step 8. Collect data about the number of personnel who possess knowledge in each knowledge criterion as Table 7.
Step 9. Determine the threshold values of each knowledge criterion as Table 7.
Step 10. Calculate the performance of knowledge $PK_i$, the relative knowledge $RK_i$ and $RQ_i$ when we set decision making coefficient $u=0.5$ as Table 8. Finally, the ranking order of all candidates according to $RQ_i$ is $A_1 > A_2 > A_4 > A_3$.

Table 4. The values $F^*_j$ and $F^-_j$ of general criteria.

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F^*_j$</td>
<td>$(s^2_5,0.063)$</td>
<td>$(s^4_4,-0.021)$</td>
<td>$(s^2_3,0.056)$</td>
<td>$(s^4_2,-0.083)$</td>
</tr>
<tr>
<td>$F^-_j$</td>
<td>$(s^2_5,0.073)$</td>
<td>$(s^4_4,-0.042)$</td>
<td>$(s^2_3,0.056)$</td>
<td>$(s^4_2,-0.056)$</td>
</tr>
</tbody>
</table>

Table 5. The values $S_i$, $R_i$ and $Q_i$ of each candidate.

<table>
<thead>
<tr>
<th></th>
<th>$A_1$</th>
<th>$A_2$</th>
<th>$A_3$</th>
<th>$A_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_i$</td>
<td>0.973</td>
<td>1.580</td>
<td>1.653</td>
<td>1.605</td>
</tr>
<tr>
<td>$R_i$</td>
<td>0.639</td>
<td>0.736</td>
<td>0.903</td>
<td>0.833</td>
</tr>
<tr>
<td>$Q_i$</td>
<td>0.000</td>
<td>0.631</td>
<td>1.000</td>
<td>0.834</td>
</tr>
</tbody>
</table>

Table 6. The rating of linguistic variables of each expert with respect to knowledge criteria.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Alternative</th>
<th>$D_1$</th>
<th>$D_2$</th>
<th>$D_3$</th>
<th>Criterion</th>
<th>Alternative</th>
<th>$D_1$</th>
<th>$D_2$</th>
<th>$D_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_1$</td>
<td>$A_1$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$F_4$</td>
<td>$A_1$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_2$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_2$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_3$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_3$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_4$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_4$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td>$F_2$</td>
<td>$A_1$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$F_5$</td>
<td>$A_1$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_2$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_2$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_3$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_3$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_4$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_4$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td>$F_3$</td>
<td>$A_1$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$F_6$</td>
<td>$A_1$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_2$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_2$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_3$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_3$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
<tr>
<td></td>
<td>$A_4$</td>
<td>$(s^5_5,0)$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td></td>
<td>$A_4$</td>
<td>$(s^4_4,0)$</td>
<td>$(s^2_3,0)$</td>
<td>$(s^2_3,0)$</td>
</tr>
</tbody>
</table>
Table 7. The number and threshold values of knowledge criteria.

<table>
<thead>
<tr>
<th></th>
<th>F₁</th>
<th>F₂</th>
<th>F₃</th>
<th>F₄</th>
<th>F₅</th>
<th>F₆</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>11</td>
<td>8</td>
<td>4</td>
<td>7</td>
<td>14</td>
<td>4</td>
</tr>
<tr>
<td>Threshold</td>
<td>0.667</td>
<td>0.667</td>
<td>0.667</td>
<td>0.667</td>
<td>0.667</td>
<td>0.667</td>
</tr>
</tbody>
</table>

Table 8. The values $PK_i$, $RK_i$ and $RQ_i$ of each candidate.

<table>
<thead>
<tr>
<th></th>
<th>A₁</th>
<th>A₂</th>
<th>A₃</th>
<th>A₄</th>
</tr>
</thead>
<tbody>
<tr>
<td>PKᵢ</td>
<td>0.703</td>
<td>0.519</td>
<td>0.200</td>
<td>0.503</td>
</tr>
<tr>
<td>RKᵢ</td>
<td>0.000</td>
<td>0.365</td>
<td>1.000</td>
<td>0.398</td>
</tr>
<tr>
<td>RQᵢ</td>
<td>0.000</td>
<td>0.498</td>
<td>1.000</td>
<td>0.616</td>
</tr>
</tbody>
</table>

5. Conclusion

In the proposed method, experts can flexibly use their preferable linguistic variable to express their opinions about the performance of each candidate which includes general criteria and knowledge criteria. General criteria can be used to evaluate the competitive ability of each candidate. Knowledge criteria are according to company’s knowledge map and considering the scarceness of the knowledge. The linguistic VIKOR method not only can deal with conflicting criteria but also can determine a compromise solution that considers the maximum group utility for the majority and a minimum of individual regret for the opponent simultaneously. The personnel selection problem is suitable to be dealt with by the linguistic VIKOR method because it includes some conflicting criteria and needs to consider the relative competitiveness of each candidate. In fact, we will combine knowledge map with new methodology such as social network to improve the linguistic VIKOR method as our next research topics. A computerized system will be designed based on linguistic VIKOR method to deal with personnel promotion selection and other decision-making problems.

References


