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Staff Selection Problem under Uncertainty Condition

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Abstract: Hiring the right person for the right position is the core to the success of an organisation. Some organizations have suggested to create an ideal candidate that fulfilled all requirements which needed for a particular job. In this case, decision makers will make comparison between a set of candidates with the ideal candidate and identify either the candidates are on the par with the ideal candidate. Hamming distance is one of the methods that is widely being used in order to compare the set of candidates with the ideal candidate. In this study, researchers extended the use of Hamming Distance Method by using weight for competence values. The decision makers will assign the weight for each competence and will determine which weight that valued most. Final result shows that the weight of each competence plays important roles to determine the best or suitable candidate when there are similarities of the competence values between different candidates.

Key words: Fuzzy Methods, staff selection, multi-criteria decision making, Hamming distance, Malaysia

INTRODUCTION

The process of staff selection usually is not an easy problem to be handled, even when it is tackled in simplified ways which consists of a homogeneous skill and a criterion (Wagner, 1975). As decision makers, they should be capable in handling unknown or unexpected condition during the decision making process. It is because during the staff selection process, sometimes the available information are not precise or exact and even worse, the imprecise information could be represented as linguistic information in terms of variables for example feelings, thoughts, beliefs and opinions (El-Hossainy, 2011). Generally, different firms come out with the different ideas in choosing the best candidate to fill the post for instance by utilizing strict and costly selection procedure. Some of the decision makers try to include personnel selection during the decision making process. Personnel selection is a process of identifying, weighting and evaluating candidates against job requirements (Khim, 2009). There are two common elements which are required in the personnel selection namely the criteria and the weight for the listed criteria. The criteria or factors will be used for evaluation and assessment. As for the weight, it should have different important or different weight for every criteria (Khim, 2009).

However, sometimes even in the fast growing and entrepreneurial firms, situations such as being biased when it comes to personnel selection could occur. For instance, the managers may reveal about their informal staffing contact such as family members, referrals and walk-ins. Besides, the decision makers cannot simply apply their personnel experiences, intuition and guesswork in order to choose the best candidates for certain post. In the existing literature, there are several methods that have been used in solving staff selection problem such as Hamming distance (Canos *et al*., 2011), correlated equilibria and Nash equilibrium (Ramsey and Szajowski, 2006), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (Dereli *et al*., 2010), linear programming techniques (Fagoyinbo and Ajibode, 2010), Analytic Hierarcy Process (AHP) (Khim, 2009) and Simple Additive Weighting (SAW) (Afshari *et al*., 2010).

Hamming distance is one of the commonly used methods in solving staff selection problem. It was proposed by Hamming (1950). He introduced this method to count the number of flipped bits in a fixed-length binary word as an estimate of error for used in telecommunication. Due to that sometimes it has been called as the signal distance (Ismail, 2012). It is a well known distance method along with the other distance methods which are Euclidean distance (Merigo and

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Casanovas, 2011) and Haousdorff Metric Method (Chaudhuri and Rosenfeld, 1999). Hamming distance is very practical for calculating the difference between two sets or elements for instance to calculate the distance between interval-valued fuzzy sets in fuzzy set theory. This method have been applied in various field such as communication (Huang *et al*., 2006), iris recognition (Ziauddin and Dailey, 2008), engineering (Morie *et al*., 2000), discrete mathematics (Shallit, 2009) and biology (He *et al*., 2004). In the earlier researches, some researchers applied the use of Hamming distance along with the fuzzy set approach. It is because during the staff selection process, sometimes the unexpected circumstances occurred such as data or information was incomplete, imprecise and vague. This approach is also applicable in handling the real world situation as some definitions or the data are performed in the qualitative and subjectivity rather than being measured in quantitative terms. Thus, linguistic information can be performed in a systematic calculus and the numerical computational can be done by using linguistic label stipulated by membership function (Daramola *et al*., 2010).

This research is an extension and improvement of the previous algorithm by Canos *et al*. (2011) by proposing Weighted Hamming Distance (WHD). It is because based on the observation and calculation, a problem has occurred during ranking the candidates. Thus, it can obstruct the decision-makers to choose the suitable candidate for the selected position. This research will be based on management by competences as it was the basis for the previous proposed personnel selection model by Canos *et al*. (2011). Each one of the competence will be assigned with different weight and comparison between ideal candidate (benchmark profile of the competence) and the candidates will be done. The evaluation of weight is based on the most required competent for the particular position.

PRELIMINARIES

A fuzzy set was proposed by Zadeh (1965). It is a multi valued logic that can define the intermediate values in conventional evaluation (Baran and Kilagiz, 2006). A fuzzy set can be represented in two ways which are a continuous membership function, $\mu_{\tilde{A}}(x)$ or by a set of discrete points (Prodanovic, 2001). A fuzzy set A in X where X is denoted as a universe of discourse is defined as:

$$\tilde{A} = \{\langle x, \mu_{\tilde{A}}(x)\rangle : x \in X\} \qquad (1)$$

where its membership function of A is:

$$\mu_{\tilde{A}}: X \to [0,1] \qquad (2)$$

that assigns to every x a degree of membership $\mu_{\tilde{A}}(x)$ in the interval [0, 1] (Baran and Kilagiz, 2006). While a fuzzy number is a fuzzy subset in the universe of discourse X that convex and normal. It should follow these conditions which are its $\mu_{\tilde{A}}(x)$ is interval continue, convex and normalize fuzzy set that $\mu_{\tilde{A}}(n) = 1$ where n is real number (Baran and Kilagiz, 2006).

Triangular fuzzy interval: The triangular fuzzy interval is specified by three parameters and can be defined as triplet $\tilde{A} = (a_1, a_2, a_3)$ where $a_1<a_2<a_3$ with the x = a_2 as the core of the triangle. Its membership function can be represented as:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & x<a_1 \\ \dfrac{(x-a_1)}{(a_2-a_1)} & a_1 \le x \le a_2 \\ \dfrac{(a_3-x)}{(a_3-a_2)} & a_2 \le x \le a_3 \\ 0 & x>a_3 \end{cases} \qquad (3)$$

The α-cuts of this fuzzy number A are denoted by:

$$[\tilde{A}]^{\alpha} = [a_1+\alpha(a_2-a_1),\ a_3-\alpha(a_3-a_2)],\ \alpha \in (0,1] \qquad (4)$$

Interval-valued fuzzy sets: Sometimes it is difficult for the experts to quantify or express their evaluation of the candidate as a number in interval [0, 1] (Ashtiani *et al*., 2009). Thus, it is applicable to use interval-valued fuzzy sets. From the definition of the fuzzy sets, the interval-valued fuzzy set can be simplified as follows (Canos *et al*., 2011). The common representation of fuzzy sets was defined as:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x), x \in X)\} \qquad (5)$$

Admitting $\mu_{\tilde{A}}(x)$ to be tolerance interval then a multi valued membership function was defined as:

$$\mu^{\Phi}: X \to P([0,1]) \qquad (6)$$

given by:

$$\mu^{\Phi}(x) = [a_x^1,\ a_x^2] \subseteq [0,1] \qquad (7)$$

Then by using the interval-valued fuzzy set definition by Gil-Aluja (1999), the interval-valued fuzzy sets is defined as:

$$\tilde{A}^{\Phi} = \{(x, \mu^{\Phi}(x), x \in X)\} \quad (8)$$

When the referential set is finite $X = \{x_1, x_2, ..., x_n\}$, it will be defined as:

$$\tilde{A}^{\Phi} = \{(x_j, \mu^{\Phi}(x_j)), j = 1,...,n\} \quad (9)$$

For this Staff Selection Model, researchers will assume that all the competence evaluations for both candidates and ideal candidate will be done in the interval-valued fuzzy sets as the experts can evaluate the candidates by giving higher and lower values.

Hamming distance: Hamming distance is used to calculate the distance between two elements and very useful in fuzzy set theory when it involved the calculation of the distance for example the distance between fuzzy sets and interval-valued sets (Lindahl and Gil-Lafuente, 2012).

Definition 1: Given a reference set, $X = \{x_1, x_2,..., x_n\}$ and two fuzzy subsets $\tilde{A}$ and $\tilde{B}$ with membership function are $\mu_{\tilde{A}}$ and $\mu_{\tilde{B}}$ (Grzegorzewski, 2004) then the Hamming distance defined as:

$$d(\tilde{A}, \tilde{B}) = \left(\sum_{i=1}^{n} \left|\mu_{\tilde{A}}(x_i) - \mu_{\tilde{B}}(x_i)\right|\right) \quad (10)$$

Then, the normalized Hamming distance is defined as:

$$d_{NHD}(\tilde{A}, \tilde{B}) = \left(\frac{1}{n}\sum_{i=1}^{n} \left|\mu_{\tilde{A}}(x_i) - \mu_{\tilde{B}}(x_i)\right|\right) \quad (11)$$

The normalized Hamming distance for two interval-valued fuzzy numbers Φ-fuzzy $\tilde{A}^{\Phi}$ and $\tilde{B}^{\Phi}$ whose membership functions are $\mu_{\tilde{A}}^{\Phi}(x_i) = \left[a_{x_i}^1, a_{x_i}^2\right]$ and $\mu_{\tilde{B}}^{\Phi}(x_i) = \left[b_{x_i}^1, b_{x_i}^2\right], i = 1, 2,...,n$ is defined as:

$$d_{NHD}(\tilde{A}, \tilde{B}) = \left(\frac{1}{2n}\sum_{i=1}^{n} \left|a_{x_i}^1 - b_{x_i}^1\right| + \left|a_{x_i}^2 - b_{x_i}^2\right|\right) \quad (12)$$

Definition 2: The weighted Hamming distance of dimension n is a mapping d_{WHD}: $[0, 1]^n \times [0, 1]^n \rightarrow [0, 1]$ that associated with weighting vector W of dimension n with $W = \Sigma_{j=1}^{n} w_j = 1$ and $w_j \in [0, 1]$ (Merigo and Gil-Lafuente, 2012). Then, the weighted Hamming distance is defined as:

$$d_{WHD}(\tilde{A}, \tilde{B}) = \left(\sum_{i=1}^{n} w_i \left|\mu_{\tilde{A}}(x_i) - \mu_{\tilde{B}}(x_i)\right|\right) \quad (13)$$

According to Merigo and Gil-Lafuente (2012), the weighted Hamming distance can become the normalized Hamming distance if $w_i = 1/n$ for all i.

WEIGHTED HAMMING DISTANCE FOR STAFF SELECTION PROBLEM

In the fuzzy set theory, Hamming distance is used to calculate the distance between the extremes of the intervals (Canos *et al*., 2011). Besides, it can be used to calculate the distance between two elements or sets. In this study, researchers will determine and compare the distance between two elements which are ideal candidate and the possible candidate. The ideal candidate is a virtual candidate that is created in order to make comparison with the candidates. The distance between the ideal candidate and the candidate will determine either the candidate is suitable to fill the vacant post or not. It means the bigger the intersection between the ideal candidate and the candidate or the less the distance between the ideal candidate and the candidate, the more suitable the candidate for the position and vice verse. Eventually, comparison with the ideal candidate is one way to order the candidates in a ranking (Canos and Liern, 2008). The evaluation of the experts for each competence is done in the interval form such that the lower and the higher value can be stated.

The main problem that may occur during this process is two or more participants may have the similar distance value for total distance values of competences that has been assigned for a selected post. When these problems occur, the decision makers cannot decide the best candidate to fill the post or to rank the candidates according to their distance value. Thus, one of the best solutions is to assign weight for each competence by determining the priority of the competence for example which competence is the most needed for a particular post. By listing the priority of weight, it will be much easier for the decision-maker to choose the candidate by looking at the distance value for the most required competence. The candidate that exhibits the small distance values for that competence should be considered as the most suited candidate for that position. Moreover, the decision-makers could choose the most suitable candidate for the selected post by looking at the distance value of certain competence and compare it with the other candidates without having to consider the distance value for all competences.

Problem definition: In this Staff Selection Model, there are two important components which are needed in order to determine the best candidate to fill the post. There are evaluation of competences on ideal candidate and possible candidates by experts and weight for each competence. First and foremost, researchers should know this selection will be based on the n necessary competences with the assign of different weight for each one of them. The evaluation of the competences will be done on the ideal candidate and the R possible candidates, Cand = $\{P_1, P_2, ..., P_R\}$ by a set of p experts, Exp = $\{E_1, E_2, ..., E_P\}$ through interval valued form. The evaluation of ideal candidate also can be done by the other experts other than p experts. The referential set for these competences will be denoted as $X = \{c_1, c_2, ..., c_n\}$. While the weight that is assigned for each competence $W = \{w_1, w_2, ..., w_n\}$ will represent the relative important of different competences that decision makers give (Filev and Yager, 1998). This weight will be applied into the classical Hamming Distance Method (definition 1). The weight values will be given by the p experts as they know which competences are most needed in the particular position. The application of weight will help the decision makers to deal with the problem that may arise later for instance the distance value for two or more candidates are same.

As these evaluations are done in the interval form for each level α requirement $\alpha\in[0, 1]$ researchers would have RΦ-fuzzy numbers such that $\tilde{P}_i^{\Phi}(\alpha), 1\le i\le R$ will represents each one of the candidates and $\tilde{I}^{\Phi}(\alpha)$ will represent the ideal candidate (Canos *et al*., 2011). In order to measure the distance between the candidates and the ideal candidate, researchers will use the weighted Hamming distance that will be simplified as:

$$d_i(\alpha) = d\left(\tilde{P}_i^{\Phi}(\alpha), \tilde{I}^{\Phi}(\alpha)\right), 1\le i\le R \tag{14}$$

where, d represents the weighted Hamming distance (definition 2). The distance values that are obtained from this calculation will be used to rank the candidate from the minimum values to maximum values. Apparently, the candidate with the minimum distance values is the most suitable candidate for the post. The candidate is order for its level α of requirement when the set of real numbers $\{d(\alpha)\}^R_{i=j}$ is ordered. When this process is repeated for the values $\alpha\in[0, 1]$, researchers will have an order of the candidates in the different α values cases. The use of the different level α requirement also can be applied to determine a final position of the candidates since the valuation of one candidate can also be changed based on level of requirement. Here, researchers present the algorithm for the staff selection problem by using weighted Hamming distance:

The algorithm

Step 1: Assign an associated weight $\{w_1, w_2, ..., w_n\}$ with the sum of weight is 1 and $w_j \in [0, 1]$ for each competence.

Step 2: Construct a fuzzy number for the ideal candidate $\{\tilde{I}_1, \tilde{I}_2, ..., \tilde{I}_n\}$ for each competence from p experts' evaluation.

Step 3: Construct a fuzzy number for the candidate $\{\tilde{c}_{i_1}, \tilde{c}_{i_2}, ..., \tilde{c}_{i_n}\}$ for each competence from p experts' evaluation.

Step 4: Construct an interval-valued fuzzy number for each competence with an exigency level, $\alpha\in[0, 1]$ for each of the candidate and the ideal candidate:

$$\begin{gathered}\tilde{P}_i^{\Phi}(\alpha) = \left\{c_{ij}, \left[c_{ij}^1(\alpha), c_{ij}^2(\alpha)\right], 1\le j\le n\right\}, i = 1, 2, ..., R \\ \tilde{I}^{\Phi}(\alpha) = \left\{c_j, \left[I_j^1(\alpha), I_j^2(\alpha)\right], 1\le j\le n\right\}\end{gathered} \tag{15}$$

Step 5: Calculate the distance value between the candidate and the ideal candidate for the chosen exigency level $\alpha\in[0, 1]$ by using:

$$d_i(\alpha) = d\left(\tilde{P}_i^{\Phi}(\alpha), \tilde{I}^{\Phi}(\alpha)\right), 1\le i\le R \tag{16}$$

Where:

$$d_{WHD}\left(\tilde{P}^{\Phi}, \tilde{I}^{\Phi}\right) = \left(\sum_{i=1}^{n} w_i^1\left|I_{x_i}^1 - c_{x_i}^1\right| + w_i^1\left|I_{x_i}^2 - c_{x_i}^2\right|\right) \tag{17}$$

Step 6: Compare each candidate for the chosen exigency level and order the candidate according to ascending distance value for the exigency level.

Step 7: Repeat step 2, 3, 4, 5 and 6 for the different values of α.

Step 8: The decision makers then will choose the exigency level and select the suitable candidate to fill the post. For this algorithm, researchers present by using $\alpha\in[0, 1]$. But for the computational proof, researchers only use level α requirement value at 0.

COMPUTATIONAL PROOFS

For this example, researchers consider there is one vacant position (T = 1) in a selected company. Overall, there will be five competences (c = 5), 20 candidates (k = 20) and four experts (p = 4). All of the competences values that have been given by the experts are the same as by Canos *et al.* (2011). The three different cases of weights for each competence will be given by the experts with the first weight cases are considered as default weight. For this calculation, researchers will only consider and use exigency level, α value at 0. Based on the end result, the comparison and discussion between the proposed method and the method by Canos *et al*. (2011) will be done especially on the rank and the distance values for selected candidate. The given weight (Table 1), competences values for the ideal candidate and the candidates (Table 2 and 3) and results (Table 4) are shown as follows:

Analysis descriptions: Table 4 showed the comparison results between three cases of weight and the resulted from Canos *et al*. (2011) without using any weight. All of these results were based on the use of level α requirement at 0. From the three cases of weight, the first weight was considered as the default weight.

Based on the result, the most prominent candidate for the selected position belonged to the candidate 4. Even with the use of different weight, the candidate 4 still maintained as he or she spotted at number one with the less distance values. If researchers looked at the Table 3, even from the 4 experts' evaluation, researchers could see that the candidate 4 had almost all of the competence values that significant with the ideal candidate competences values. The huge difference in competences values between the candidate 4 and the other candidates proved that the rank for candidate 4 was not affected even after adding the weight for each competence. On the other hand, compared to the other candidates, there were some candidates that had slightly changes on the rank after the use of different weight cases.

Table 1: Valuation of the three different cases of weights

	Weight		
Competence	1	2	3
1	0.30	0.30	0.15
2	0.25	0.20	0.10
3	0.20	0.10	0.25
4	0.10	0.25	0.20
5	0.15	0.15	0.30
Total	1.00	1.00	1.00

Table 2: Valuation of the ideal competences

	Ideal candidate	
Competence	Low value	High value
1	0.65	0.70
2	0.80	1.00
3	0.50	0.80
4	0.80	0.85
5	0.50	0.90

Table 3: Valuation of the candidates' competences

		Expert 1		Expert 2		Expert 3		Expert 4	
Candidates	Cases	Low	High	Low	High	Low	High	Low	High
1	Comp. 1	0.30	0.65	0.30	0.80	0.35	0.80	0.70	1.00
	Comp. 2	0.20	0.70	0.70	0.90	0.40	0.60	0.35	0.60
	Comp. 3	0.35	0.50	0.50	0.70	0.25	0.90	0.40	0.80
	Comp. 4	0.40	0.80	0.50	0.60	0.35	0.90	0.25	0.65
	Comp. 5	0.15	0.55	0.50	0.60	0.35	0.90	0.25	0.65
2	Comp. 1	0.25	0.60	0.25	0.70	0.40	0.80	0.35	0.70
	Comp. 2	0.35	0.80	0.35	0.60	0.30	0.60	0.70	0.80
	Comp. 3	0.40	0.60	0.40	0.50	0.70	0.80	0.35	0.70
	Comp. 4	0.45	0.75	0.50	0.80	0.35	0.80	0.40	0.60
	Comp. 5	0.50	0.70	0.50	0.80	0.35	0.80	0.40	0.60
3	Comp. 1	0.25	0.70	0.35	0.70	0.30	0.55	0.50	0.90
	Comp. 2	0.35	0.65	0.30	0.60	0.40	0.70	0.20	0.70
	Comp. 3	0.30	0.55	0.50	0.90	0.60	0.85	0.35	0.65
	Comp. 4	0.40	0.90	0.60	0.85	0.25	0.70	0.35	0.60
	Comp. 5	0.55	0.75	0.50	0.70	0.35	0.60	0.30	0.65
4	Comp. 1	0.60	0.80	0.50	0.70	0.40	0.60	0.70	0.70
	Comp. 2	0.70	0.90	0.80	1.00	0.90	0.95	0.80	1.00
	Comp. 3	0.35	0.80	0.60	0.90	0.50	0.80	0.70	0.70
	Comp. 4	0.75	0.80	0.85	0.85	0.80	0.80	0.80	0.85
	Comp. 5	0.50	0.90	0.60	0.80	0.70	0.70	0.50	0.80
5	Comp. 1	0.25	0.60	0.25	0.70	0.40	0.80	0.35	0.70
	Comp. 2	0.35	0.80	0.35	0.60	0.30	0.50	0.70	0.80
	Comp. 3	0.30	0.70	0.40	0.50	0.70	0.80	0.35	0.70
	Comp. 4	0.50	0.60	0.50	0.80	0.02	0.70	0.30	0.60
	Comp. 5	0.60	0.65	0.50	0.80	0.20	0.80	0.30	0.60
6	Comp. 1	0.25	0.55	0.30	0.70	0.20	0.90	0.50	0.70
	Comp. 2	0.35	0.70	0.50	0.60	0.35	0.70	0.20	0.80
	Comp. 3	0.50	0.65	0.35	0.50	0.35	0.90	0.35	0.55
	Comp. 4	0.50	0.60	0.30	0.45	0.30	0.50	0.30	0.70
	Comp. 5	0.45	0.90	0.40	0.55	0.40	0.50	0.40	0.70
7	Comp. 1	0.25	0.45	0.25	0.70	0.30	0.55	0.35	0.70
	Comp. 2	0.35	0.55	0.35	0.60	0.50	0.70	0.30	0.80
	Comp. 3	0.30	0.70	0.30	0.45	0.20	0.70	0.30	0.90

Table 3: Continue

		Expert 1		Expert 2		Expert 3		Expert 4	
Candidates	Cases	Low	High	Low	High	Low	High	Low	High
	Comp. 4	0.50	0.65	0.30	0.60	0.35	0.60	0.40	0.70
	Comp. 5	0.30	0.90	0.50	0.90	0.35	0.65	0.35	0.70
8	Comp. 1	0.25	0.50	0.25	0.65	0.30	0.60	0.35	0.60
	Comp. 2	0.35	0.45	0.35	0.60	0.40	0.65	0.30	0.65
	Comp. 3	0.30	0.75	0.40	0.50	0.60	0.90	0.40	0.60
	Comp. 4	0.40	0.55	0.35	0.80	0.25	0.70	0.60	0.90
	Comp. 5	0.60	0.70	0.30	0.80	0.35	0.55	0.30	0.70
9	Comp. 1	0.25	0.65	0.40	0.45	0.20	0.90	0.40	0.70
	Comp. 2	0.35	0.90	0.30	0.55	0.35	0.70	0.20	0.55
	Comp. 3	0.25	0.50	0.50	0.60	0.70	0.90	0.35	0.90
	Comp. 4	0.55	0.60	0.50	0.90	0.12	0.70	0.70	0.90
	Comp. 5	0.60	0.75	0.35	0.80	0.20	0.60	0.12	0.70
10	Comp. 1	0.50	0.50	0.30	0.30	0.55	0.55	0.70	0.70
	Comp. 2	0.35	0.65	0.40	0.45	0.50	0.70	0.30	0.80
	Comp. 3	0.30	0.70	0.60	0.85	0.65	0.65	0.70	0.70
	Comp. 4	0.60	0.60	0.70	0.70	0.35	0.60	0.30	0.55
	Comp. 5	0.35	0.50	0.50	0.65	0.35	0.80	0.40	0.70
11	Comp. 1	0.10	0.90	0.20	0.90	0.40	0.60	0.25	0.80
	Comp. 2	0.35	0.50	0.60	1.00	0.25	0.90	0.35	0.70
	Comp. 3	0.45	0.60	0.35	0.80	0.60	0.80	0.40	0.60
	Comp. 4	0.65	0.90	0.80	1.00	0.30	0.60	0.90	1.00
	Comp. 5	0.65	0.90	0.80	1.00	0.30	0.60	0.20	0.60
12	Comp. 1	0.25	0.60	0.25	0.65	0.40	0.60	0.40	0.90
	Comp. 2	0.35	0.55	0.35	0.60	0.30	0.65	0.60	0.97
	Comp. 3	0.25	0.70	0.40	0.50	0.20	0.90	0.30	0.70
	Comp. 4	0.50	0.90	0.50	0.80	0.35	0.70	0.40	0.90
	Comp. 5	0.60	0.70	0.50	0.80	0.20	0.55	0.20	0.70
13	Comp. 1	0.25	0.55	0.25	0.45	0.40	0.90	0.35	0.90
	Comp. 2	0.35	0.70	0.30	0.60	0.30	0.70	0.70	0.90
	Comp. 3	0.35	0.65	0.50	0.90	0.50	0.90	0.22	0.70
	Comp. 4	0.50	0.90	0.35	0.65	0.30	0.50	0.20	0.60
	Comp. 5	0.40	0.50	0.30	0.80	0.25	0.70	0.30	0.55
14	Comp. 1	0.40	0.55	0.40	0.70	0.35	0.60	0.50	0.70
	Comp. 2	0.35	0.70	0.60	0.65	0.20	0.70	0.30	0.70
	Comp. 3	0.30	0.90	0.40	0.45	0.35	0.65	0.40	0.90
	Comp. 4	0.40	0.50	0.50	0.55	0.60	0.65	0.35	0.70
	Comp. 5	0.60	0.65	0.50	0.70	0.25	0.80	0.30	0.60
15	Comp. 1	0.25	0.60	0.25	0.65	0.35	0.55	0.40	0.65
	Comp. 2	0.35	0.80	0.35	0.60	0.30	0.70	0.60	0.90
	Comp. 3	0.35	0.70	0.30	0.50	0.50	0.60	0.25	0.70
	Comp. 4	0.50	0.55	0.50	0.80	0.04	0.75	0.35	0.90
	Comp. 5	0.45	0.70	0.60	0.65	0.20	0.65	0.30	0.70
16	Comp. 1	0.25	0.65	0.25	0.90	0.20	0.60	0.40	0.70
	Comp. 2	0.35	0.90	0.35	0.45	0.35	0.65	0.70	0.90
	Comp. 3	0.20	0.50	0.40	0.55	0.70	0.75	0.06	0.70
	Comp. 4	0.50	0.60	0.50	0.70	0.30	0.60	0.20	0.60
	Comp. 5	0.60	0.65	0.50	0.65	0.50	0.55	0.30	0.90
17	Comp. 1	0.10	0.90	0.20	0.90	0.40	0.60	0.25	0.80
	Comp. 2	0.35	0.50	0.60	1.00	0.25	0.90	0.35	0.70
	Comp. 3	0.40	0.60	0.35	0.80	0.60	0.80	0.40	0.60
	Comp. 4	0.55	0.85	0.80	0.95	0.30	0.60	0.80	1.00
	Comp. 5	0.65	0.85	0.80	0.95	0.30	0.60	0.20	0.60
18	Comp. 1	0.25	0.50	0.60	0.70	0.60	0.75	0.40	0.90
	Comp. 2	0.35	0.80	0.35	0.65	0.25	0.70	0.60	0.70
	Comp. 3	0.25	0.70	0.40	0.60	0.35	0.60	0.25	0.60
	Comp. 4	0.50	0.60	0.50	0.90	0.04	0.60	0.35	0.65
	Comp. 5	0.60	0.90	0.30	0.80	0.20	0.80	0.20	0.90
19	Comp. 1	0.25	0.55	0.30	0.70	0.20	0.90	0.50	0.70
	Comp. 2	0.35	0.90	0.35	0.45	0.35	0.65	0.70	0.90
	Comp. 3	0.35	0.70	0.30	0.50	0.50	0.60	0.25	0.70
	Comp. 4	0.40	0.50	0.50	0.55	0.60	0.65	0.35	0.70
	Comp. 5	0.50	0.90	0.50	0.90	0.50	0.90	0.50	0.90
20	Comp. 1	0.25	0.60	0.40	0.65	0.40	0.60	0.50	0.70
	Comp. 2	0.35	0.90	0.60	0.65	0.30	0.65	0.20	0.95
	Comp. 3	0.30	0.50	0.30	0.60	0.50	0.90	0.35	0.70
	Comp. 4	0.35	0.70	0.50	0.90	0.30	0.70	0.35	0.70
	Comp. 5	0.45	0.45	0.50	0.50	0.50	0.50	0.70	0.70

Table 4: Selection of candidate using Hamming Distance Method

Ranks	Weight 1	Weight 2	Weight 3	Canos *et al*. (2011)
1	4	4	4	4
2	19	19	19	2
3	2	2	2	19
4	20	17	17	20
5	18	20	11	10
6	14	12	3	7
7	10	11	10	12
8	1	18	18	6
9	11	14	14	17
10	17	10	1	14
11	5	3	20	11
12	15	1	5	8
13	3	15	12	13
14	12	5	7	5
15	16	9	15	16
16	6	16	8	1
17	7	7	9	15
18	13	8	16	3
19	9	6	6	18
20	8	13	13	9

rank between the proposed method and the Canos *et al*. (2011). For example, at the ranked two by using the proposed method that position would belong to candidate 19 for all different weight cases while for the Canos *et al*. (2011), it would belong to candidate 2. But if researchers reviewed at the top four ranks, it showed that most of the competence values were slightly closed to the ideal candidate competence value. Therefore, the rank for the candidates did not differ much especially between the three different weight cases where the rank only started to changes at the rank 4 between the candidates 20 and 17. It proved that if the competences evaluations of the candidate by the experts were closed to the competences evaluation of the ideal candidate, the rank would not be much affected even after using different weight for the same competence. However, for some other candidates especially the candidates that ranked at the bottom, mostly the ranks were changing based on the weight that has been used.

In order to identify problems during the staff selection process; let us assume that the decision makers had to choose 9 candidates for 9 vacant positions. If that happened then the decision makers might face with unwanted consequences as the candidates with the same distance values around that rank existed. This circumstance occurred on the ranked 9 at the first weight cases as the candidates 11 and 17 actually had the same distance values. At this time, the decision makers needed to look into the most important competences with the highest weight to choose the suitable candidate. Thus, from the observation, the candidate 11 was selected to fill the spot. At this time, the decision makers should remember that sometimes there are some candidates that may perform excellently in the competence which is less needed in the specified position rather than the other candidates who purchased eligible qualification in the most wanted competence. Hence, the decision makers might want to reconsider on choosing the right candidate for the post. Eventually, this would help the decision makers to overview back the results in choosing the right candidate.

CONCLUSION

The use of mathematical model in decision making problem especially in staff selection problem will help the decision makers to make decision faster, clearer and easier to understand. The limitations of the mathematical model namely quantification and objectives can be solved by using fuzzy set theory. This is because fuzzy set theory is very suitable in handling the uncertainty and subjectivity problem. While Hamming distance is one of the distance methods and has widely been used to calculate the distance between two elements. Therefore, it can be used in searching for the best preference candidate through the distance values between the ideal and possible candidate. In this paper, the weighted Hamming distance is proposed into the previous algorithm by Canos *et al*. (2011). The use of weight for each competence can help the decision makers in selecting the right candidate effectively. It is because usually the competence has their own priority which means for a particular post, there are one or two competences that are really important. Hence, by the use of weighted Hamming distance, the decision makers can determine which candidate is more preferable for the particular post by looking at the most weighted competence if there were two or more candidates happened to have the same values. Based on the final results, the candidate 4 is the most preferably to be selected. There are also some changes on the rank between the use of three different weight cases and without the use of weight for each competence. For the future research, researchers hope to apply the real world data for the proposed method.

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