Fuzzy logic decision support system for hospital employee performance evaluation with maple implementation

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ABSTRACT
In any organization, the capability, knowledge and skills play a significant role in success of an employee. For instant, in hospital management, the performance evaluation of an employee is mainly based on qualitative in nature. Evaluation of certain factors such as uncertainty, vagueness and imprecision is based on the decision making ability of the evaluator. The performance evaluation for promotion, incentives, bonuses, growth and development of any employee should be recognized in effective and efficiency manner with appropriate ratings. Therefore, this paper aims to design and implement a multi criteria performance evaluation for hospital employees to get promotion, incentives, bonus, growth and development. In this paper, we propose an Interval Valued Fuzzy Weighted Distance Algorithm (IVFWDA) for performance evaluation. The expected interval and the actual interval of the work achievement, management skill, personal quality, care, safety and risk management features are extracted by Interval Valued Fuzzy Soft Matrix (IVFSM) and it is effectively done using the proposed algorithm. An example is presented as a case study to illustrate the proposed algorithm. Implementation of the proposed algorithm in Maple is also discussed with sample computations.

1. Introduction
One of the structural factors in any organization is human resources management (HRM). Employees are one of the critical assets for organizations to sustain the competitive advantages by utilizing the specific knowledge and skills (Ahmed, Sultana, Paul, & Azeem, 2013). With the rapid development of economy, the HRM in hospital has a most significance and foundation of enterprises. Hospital staff members are interested to know the patient satisfaction and experience to improve the quality of care (Leggat, Karimi, & Bartram, 2017). In line with this, performance evaluation is an important part of HRM, and it is a system that encourages the employees, managerial areas to have a proper behavior and continuous improvement of the entire company. Furthermore, it is used to identify the weaknesses, strengths, skills to develop, opportunities to improve and create competitive advantages. Consequently, the performance of any employee will be measured based on the certain factors, such as level of commitment, precautions, attitude towards work, sense of responsibility, maintenance of discipline, communication skills, leadership qualities, capacity to work in team spirit, capacity to adhere time schedule, inter-personal skills, over all bearing and personality, etc. With certain or approximate information, the decision can be made perfectly using the applications of fuzzy logic as it resembles human decision making.

Fuzzy soft set (FSS) is one of the emerging topics to measure such type of qualitative data in the uncertain environment. In particular, dealing and measuring with such uncertainties are an application of IVFSS. The parameterization tool of IVFSS enhances the flexibility, and it is easy to apply to the real world applications.

1.1. Multi-criteria decision making
Many approaches and algorithms are available in the literature for performance evaluation, performance
appraisals and supplier selection. Some of these algorithms are analytical hierarchy process, fuzzy analytical hierarchy process, data envelopment analysis, multi-criteria decision-making, multi-attribution decision-making, and multi-objective decision-making models. The most reputed and powerful technique of multi-attribution decision-making models is TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). TOPSIS is a combination of quantitative attributions and qualitative attributions. 

1.3. Fuzzy approach

In this paper, we consider eight significant criteria of performance evaluation that enhance the safety through situational awareness (Iflaifel, Lim, Ryan, & Crowley, 2020). Wang et al. developed fuzzy hierarchical TOPSIS method (Wang, Cheng, & Huang, 2009). Rodriguez Lima Junior et al. showed that Fuzzy TOPSIS method performs better than fuzzy analytical hierarchy process method (Rodriguez Lima Junior, Osiro, & Cesar Ribeiro Carpinetti, 2014).

1.2. Criteria of performance evaluation

Quality of patient care is the responsibility of all workers within a health service center (Berry, Carbone, & Haeckel, 2002; Powell, Davies, & Thomson, 2003). In this paper, we consider eight significant criteria, which are closely related to the employee’s promotion grades. The main criteria communication includes the sub criteria like communication with respect, communicating with co-workers, providing an environment suitable for expression of opinions, knowledge and mutual respect, motivation, etc. These qualities enable the health care professionals to easily interact and commit to each other, interactive discussion between incoming and outgoing health care professionals that enhance the safety through situational awareness (Iflaifel, Lim, Ryan, & Crowley, 2020).

1.3. Fuzzy approach

In real-world applications, the personal judgment of decision makers undergo from subjectivity, vagueness and ambiguity of human judgment. To resolve this, Zadeh (1965) introduced the linguistic terms in decision-making process. In addition, Bellman and Zadeh developed fuzzy multi-criteria decision-making methodology (Bellman & Zadeh, 1970) to resolve the lack of precision in the assignment of weights and the ratings evaluation. In fuzzy sets theory, it is often difficult to quantify his or her opinion as a number in interval $[0,1]$. Since the decision makers and personal judgment are different, the fuzzy sets cannot provide sufficient explanations because the evaluation criteria are different. To resolve this, Zadeh (1965) introduced IVFSS. The parameterization tool of IVFSS enhances the flexibility, and this theory is quite convenient and easy to apply in practical problems. Decision makers express the opinion in terms of linguistic scales and converted the opinion into interval valued fuzzy numbers with the help of different membership functions. Many researchers, scientists and engineers have been applied the concept of FSS relations, composition relations, soft matrices and their applications (Carlo, et al., 2020; Hwang & Yoon, 1981; Leggat et al., 2017; Rodrigues Lima Junior et al., 2014; Wang et al., 2009; Zadeh, 1965; Zimmermann, 2010; Calik, 2019). This proposed algorithm gives improvement/better result in the performance evaluation using IVFSS. While finding the distance between two FSSs, we want to analyze the factor/skill values, which are more similar or more dissimilar to each other. The proposed fuzzy weighted distance algorithm gives equal weight for the required factor/skill, and the selection is based on the numbers of factors/skills that are positively skewed but not on the higher values in any factor/skills.

1.4. Preliminaries

**Definition 1** (Zadeh, 1965). A fuzzy set $A$ is an universe of discourse $X$ characterized by a membership function $\mu_A(x) \rightarrow [0,1]$, where $\mu_A(x)$ represents the degree of truth of $x$ in fuzzy set $A$, for all $x \in X$.

**Definition 2** (Maji, Biswas, & Roy, 2004). Let $U$ be the universe of discourse and $E$ be a set of parameters. Then the pair $(F, E)$ is called a soft set over $U$, where $F : E \rightarrow P(U)$ and $P(U)$ is the power set of $U$.

In Definition 2, it is clear that a soft set is a mapping from parameters to $P(U)$, and it is not a set, but a parameterized family of subsets of the universe of discourse.

**Definition 3** (Park, Lim, Park, & Kwun, 2008). Let $U$ be the universe of discourse and $E$ be a set of parameters. Let $A \subset E$. Then the pair $(F, A)$ is called FSS over $U$, where $F$ is a mapping given by $F : A \rightarrow I^U$ and $I^U$ denotes the collection of all fuzzy subsets of $U$.

**Definition 4** (Zimmermann, 2010). Let $(f_u, E)$ be a FSS over $U$. Then a subset of $U \times E$ defined uniquely by $R_a = \{(u, e) | e \in A, u \in F_A(e)\}$ is called a relation form of the fuzzy soft set $(f_u, E)$. The characteristic function of $R_a$ is given by $\mu_R_a : U \times E \rightarrow [0,1]$, where $\mu_R_a(u, e) \in [0,1]$ is the membership value of $u \in U$ for each $e \in E$. If $\mu_y = \mu_R(a(u, e))$, an $m \times n$ fuzzy soft
matrix of the FSS \((f_A, E)\) over \(U\) is defined as
\[
[H]_{m \times n} = \begin{pmatrix}
\mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\
\mu_{21} & \mu_{22} & \cdots & \mu_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\mu_{m1} & \mu_{m2} & \cdots & \mu_{mn}
\end{pmatrix}
\]
Thus a FSS \((f_A, E)\) is uniquely characterized by the matrix \([H]_{m \times n}\) and both concepts are interchangeable. The set of all \(m \times n\) fuzzy soft matrices over \(U\) is denoted by \(FSM_{m \times n}\).

**Definition 5** (Atanassov & Gargov, 1989). Let \(X\) be an universal set with cardinality \(n\). Let \(M\) be the set of all closed sub intervals of the interval \([0, 1]\) and elements of this set are denoted by uppercase letters. If \(M \in [0, 1]\), then it can be represented as \(M = [M_L, M_U]\), where \(M_L\) and \(M_U\) are the lower and upper limits of \(M\). An interval valued fuzzy set, \(A\) in \(X\), is given by
\[
A = \{(x, M_A(x))|x \in X\},
\]
where \(M_A : X \rightarrow [0, 1]\), \(M_A(x)\) denote the degree of membership of the element \(x\) to the set \(A\) and \(0 \leq M_A \leq M_A U \leq 1\).

**Definition 6** (Hatzimichailidou, Papakostas, & Kaburlasos, 2016). For any two interval valued fuzzy sets \(A = \{(x, M_A(x))|x \in X\}\) and \(B = \{(x, M_B(x))|x \in X\}\) of the universe of discourse \(X = \{x_1, x_2, ..., x_n\}\), where \(M_A(x) = (M_{AL}(x), M_{AU}(x))\) and \(M_B(x) = (M_{BL}(x), M_{BU}(x))\) respectively, we have

- **Hamming Distance:**
  \[
d_{H}(A, B) = \frac{1}{2} \sum_{i=1}^{n} \left| (M_{AL}(x_i) - M_{BL}(x_i)) \right| + \left| (M_{AU}(x_i) - M_{BU}(x_i)) \right|
\]

- **Normalized Hamming Distance:**
  \[
d_{H-n}(A, B) = \frac{1}{2n} \sum_{i=1}^{n} \left| (M_{AL}(x_i) - M_{BL}(x_i)) \right| + \left| (M_{AU}(x_i) - M_{BU}(x_i)) \right|
\]

- **Euclidean Distance:**
  \[
d_{E}(A, B) = \sqrt{\frac{1}{2} \sum_{i=1}^{n} \left( (M_{AL}(x_i) - M_{BL}(x_i))^2 + (M_{AU}(x_i) - M_{BU}(x_i))^2 \right)}
\]

- **Normalized Euclidean Distance:**
  \[
d_{E-n}(A, B) = \sqrt{\frac{1}{2n} \sum_{i=1}^{n} \left( (M_{AL}(x_i) - M_{BL}(x_i))^2 + (M_{AU}(x_i) - M_{BU}(x_i))^2 \right)}
\]

2. **Proposed algorithm**

In this section, we present an IVFWDA for performance evaluation using IVFSM. The expected skills of the employee such as punctuality, work achievement, communication, managerial flexibility, care, risk management and safety are recorded via IVFSM. The proposed method is different from the existing TOPSIS method and convenient. It takes into account only the expected criteria for each grades instead of entire criteria set. The proposed method involves three stages: (1) Finding distances between the expected interval and the observed interval of employee’s criteria given by decision makers. (2) Finding the score values by applying weights to each criterion. (3) Ranks are assigned to the employees on the basis of their score values.

2.1. **Method**

The study is adopted a qualitative approach, by collecting the qualitative data from the healthcare workers in hospitals, utilizing decision makers observations and self-administered questionnaire. Decision makers express their opinion in terms of linguistic scales. Further, it is converted into interval valued fuzzy numbers with the help of membership functions. Collected data is analyzed with the help of IVFWDA.

2.2. **Methodology and algorithm**

Suppose \(E\) is a set of employee, \(S\) is a set of performance skills and \(D\) is a set of promotion grade. The proposed algorithm involves the following steps.

Step 1. We construct IVFSM relation matrix \(P\), called employee-skills matrix, using IVFSS \((F, S)\) over \(P\), where \(F\) is a mapping given by \(F : S \rightarrow F(P)\).

Step 2. Construct another FSS \(G\) over \(D\), where \(G\) is a mapping \(G : S \rightarrow F(D)\). This FSS gives a relation matrix \(Q\) (the matrix \(Q\) can be either an expert matrix or any set of required relation matrix) which contains the expected skill to have employees. During the selection process, corresponding to the grade \(D_i\), the HR priority may be on few skills like \(S_1, S_2, S_3, S_4\) whereas the other skills in the set \(S\) may not be in focus. Similarly, the priority for grade \(D_2\) is \(S_1, S_2, S_3, S_4, S_5\) and the priority for grade \(D_3\) is \(S_1, S_2, S_3, S_4, S_5, S_7\).

Step 3. Compute the distance relation matrix \(C = [c_{ik}]_{m \times p}\), where
\[
c_{ik} = \begin{cases}
PL_{ij} - QL_{ij} & \text{if } PL_{ij} \leq QL_{ij} \\
PU_{ij} - QU_{ij} & \text{if } PL_{ij} \leq PU_{ij} \text{ & } QU_{ij} \leq PU_{ij} \\
0 & \text{otherwise}
\end{cases}
\]

Step 4. We use the weighted relation matrix \(W = [z_k]_{m \times p}\), where
A for each positive and negative deviations of the per-

2.3. Note

Using the proposed algorithm Step-4, we can map all the distances in real line with decimal weights that will help to identify the corresponding distances for each positive and negative deviations of the performances. For example: Let us assume that the positive distances for candidates A and B are 0, 0.2, 0.1, 0.1, 0.2, 0, 0 and 0, 0.2, 0.3, 0.1, 0, 0, 0 respectively. The sum of distance in each case is 0.6, but the candidate B qualified only three criteria while A used for candidates A and B to get the performance distances as

\[
0 + 11000 + 10000 + 10000 + 11000 + 0 + 0 + 0 = 42000,
0 + 11000 + 11100 + 10000 + 0 + 0 + 0 = 32100.
\]

Here, we can clearly identify that the performance of A is better than B.

3. Illustration for the proposed algorithm

In this section, we present an example as a case study to illustrate the proposed algorithm with minimum number of employees to be selected for evaluating process as presented in Sect. 2.

3.1. Case study (illustrate example)

Let \( \{E_1, E_2, E_3, E_4, E_5, E_6\} \) be the set of six employees. Suppose, the employee-skills set for analysis consists: Punctuality (S_1), Discipline (S_2), Communication (S_3), Managerial (S_4), Flexibility (S_5), Care (S_6), Risk Management (S_7) and Safety (S_8). Let the promotion grades related to the skills be denoted by \( D = \{D_1, D_2, D_3\} \), where \( D_1, D_2 \) and \( D_3 \) are the promotion grades for leaders in admission, nursing and emergency section respectively. The objective is to promote the employees based on the expectations of HRM. We construct the IVFSS, which represents a relation matrix \( P \), called qualitative employee-skills matrix relation, and again construct another soft set \( G \) over \( D \), where \( G \) is a mapping \( G : S \rightarrow F(D) \). These relation matrices are shown in following matrices \( P \) and \( Q \).

- Observed ratings of six employees under each criterion in terms of IVFSS determined by decision makers (employee-skills relation matrix) is given by

\[
P = \begin{pmatrix}
S_1 & S_2 & S_3 & S_4 & S_5 & S_6 & S_7 & S_8 \\
0.50 & 0.60 & 0.60 & 0.70 & 0.50 & 0.80 & 0.30 & 0.50 \\
0.20 & 0.40 & 0.40 & 0.30 & 0.40 & 0.50 & 0.20 & 0.50 \\
0.50 & 0.60 & 0.50 & 0.70 & 0.40 & 0.50 & 0.60 & 0.70 \\
0.40 & 0.60 & 0.50 & 0.50 & 0.60 & 0.60 & 0.80 & 0.80 \\
0.30 & 0.50 & 0.40 & 0.60 & 0.60 & 0.70 & 0.60 & 0.70 \\
0.60 & 0.80 & 0.60 & 0.70 & 0.70 & 0.80 & 0.60 & 0.40 \\
E_1 & E_2 & E_3 & E_4 & E_5 & E_6
\end{pmatrix}
\]

- Expected ratings of six employees under each criterion in terms of IVFSS given by decision makers (employee-promotion grade relation matrix) is
Table 1. For  i = 1, i.e., for grade D₁,

| Employee | Value of Dᵢ.Rᵢ | Value of Dᵢ.Rᵢ⁺ | Ranking position of PDᵢ.Rᵢ⁺ | Ranking position of PDᵢ.Rᵢ⁻ | Dᵢ.R = PDᵢ.Rᵢ⁺ + PDᵢ.Rᵢ⁻ |
|----------|-----------------|----------------|-------------------------------|-------------------------------|-----------------------------|
| E₁       | 11,000          | 1–0.21100 = 0.7900 | 3                             | 2                             | 5                           |
| E₂       | 0               | 0–1.54310 = 0.4569 | 6                             | 6                             | 12                          |
| E₃       | 21,000          | 1–0.21100 = 0.7890 | 2                             | 3                             | 5                           |
| E₄       | 11,000          | 1–0.32100 = 0.6790 | 3                             | 4                             | 7                           |
| E₅       | 10,000          | 1–0.41000 = 0.5900 | 4                             | 5                             | 9                           |
| E₆       | 42,000          | 1–0.11000 = 0.8900 | 1                             | 1                             | 2                           |

- Finally, the ranking preference order is

\[
T = \begin{pmatrix}
D₁ & D₂ & D₃ \\
E₁ & 5 & 10 & 7 \\
E₂ & 12 & 10 & E₃ \\
E₄ & 7 & 4 & 5 \\
E₅ & 9 & 7 & 8 \\
E₆ & 2 & 5 & 6
\end{pmatrix}
\]

From Table 1, we have least value at Dᵢ.R = PDᵢ.Rᵢ⁺ + PDᵢ.Rᵢ⁻ = 2, which is for E₆. Therefore, it is clear that the employee E₆ gets the promotion grade D₁. Similarly, we can find the rank for other grades

\[
D₁ = \begin{pmatrix}
(0,0,2,0,0,2,0,0,0) & (0,0,3,0,0,2,0,0,0) & (0,0,3,0,0,2,0,0,0) \\
(0,0,2,0,0,2,0,0,0) & (0,0,3,0,0,2,0,0,0) & (0,0,3,0,0,2,0,0,0) \\
(0,0,2,0,0,2,0,0,0) & (0,0,3,0,0,2,0,0,0) & (0,0,3,0,0,2,0,0,0)
\end{pmatrix}
\]

\[
C = \begin{pmatrix}
(0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0) \\
(0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0) \\
(0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0) \\
(0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0) & (0.0,11000,0.0,11000,0.0,11000,0.0)
\end{pmatrix}
\]

- Now, the score matrix (using algorithm Step-5) is obtained as

\[
C = \begin{pmatrix}
D₁ & D₂ & D₃ \\
11000.21000 & 11100.32100 & 11000.43100 & E₁ \\
0.54310 & 0.44100 & 0.53321 & E₂ \\
21000.21100 & 31100 & 21000.1000 & E₃ \\
11000.32100 & 32100.1000 & 10000.1100 & E₄ \\
10000.41000 & 20000.21000 & 0.42100 & E₅ \\
42000.11000 & 33000.21100 & 10000.33100 & E₆
\end{pmatrix}
\]

- Assessment values and rankings for selecting alternatives (the ranking order for grades Dᵢ). When  i = 1, For Grade-D₁ using algorithm Step-6) are given Table 1. Similarly, D₂ and D₃ can be calculated.

3.2. Maple implementation

In this section, we provide sample computations using the Maple implementation. We have data type
Decision_Support_Hospital(PL, PU, QL, QU), where PL and PU are the lower and upper IVFSM relation matrix $P$ (called employee-skills matrix); and QL, QU are the lower and upper IVFSM relation matrix $Q$ (called Performance-promotion grade matrix). Full Maple code of the proposed algorithm is available in Appendix.

### 3.3. Sample computations

```maple
> PL := Matrix([[.5,.6,.5,.3,.4, .4,.4], [.2,.4,.3,.3,.2,.5,.3,.2], [.5,.7,.5,.4,.6,.7,.6,.7], [.4,.5,.3,.6,.6,.8,.7,.7], [.3,.4,.5,.6,.6,.7,.6,.7], [.6,.6,.7,.5,.6,.4,.4,.4]]):
> PU := Matrix([[.6,.8,.7,.8,.5,.5,.5,.6], [.4,.5,.4,.5,.5,.6,.6,.4], [.6,.8,.7,.5,.7,.8,.7,.8], [.6,.6,.5,.6,.8,.7,.9,.8], [.5,.6,.6,.8,.7,.6,.7,.7], [.8,.7,.8,.7,.8,.5,.6,.6]]):
> QL := Matrix([[.5,.4,.6], [.5,.4,.5], [.6,0,0], [.7,0,0], [.4,.5,0], [.0,.7,6], [.0,.5,.6], [.0,0,.7]]):
> QU := Matrix([[.6,.6,.7], [.6,.5,.6], [.7,0,0], [.8,0,0], [.6,.6,0], [.0,.8,7], [.0,.6,.8], [.0,0,.8]]):
> S := Decision_Support_Hospital(PL, PU, QL, QU):
```

### 4. Discussions and conclusions

#### 4.1. Discussions

The expected interval and the actual interval of the significant factors like work achievement, management skill, punctuality, personal quality, care, safety and risk management features of employees are extracted in terms of IVFSM and which is effectively done using the proposed algorithm. An illustrative example (case study) is presented to illustrate the proposed algorithm. Implementation of the proposed algorithm in Maple is discussed with sample computations. The paper develops an algorithm and applies a customized version of balanced score card based on a new set of performance measures. All in all, our findings suggest that it can be considered an effective framework for measuring the research hospital performance.

### 4.2. Conclusion

In this paper, we have presented a multi-criteria decision making algorithm. The decision is based on the maximum number of required factors/criteria while the methods in literature are based on maximum scores. The proposed algorithm is incorporated the weights for the distance between the expected and actual intervals. It reduces the repetition of grades by ranking the employee performance levels. To enhance the job satisfaction, HRM should take the measures to improve the work conditions, pay more attention to the professional development and raise work reward of the employees. For example, strengthening the standard functions such as the human resources information system, improve the management training or develop an approach to performance appraisal, rewards and incentives, staff motivation. This study can be extended to the cases in which the data of the problem has extensions of neutrosophic fuzzy sets, fuzzy multi-sets and bipolar fuzzy sets.

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### Author’s contributions

P. Shanmugasundaram is involved in creating the proposed algorithm. S. Thota is participated in modifications, corrections, writing of the manuscript and implementation of the algorithm in Maple. B. Derebew is involved in modifications and corrections. T. Asfetsami is involved in modifications and corrections. All authors read and approved the final manuscript.

### Availability of data and materials

The datasets generated and analyzed during the current study are provided in the manuscript.

### Disclosure statement

The authors declare that they have no competing interests.

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