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Decision Support Method in the Assessment of Nuclear Knowledge Management using Fuzzy Logic

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1. Introduction

The knowledge of workers constitute as valuable resources, as they enable organizations to perform their functions successfully. However, there are conditions that favor the loss of this knowledge in organizations, as for example, the natural aging of workers and consequently the retirement and staff turnover. Then, it becomes important for organization to seek the preservation these knowledge. For a successful implementation of Knowledge Management (KM), it is important to identify the barriers or critical factors that affect the success of the KM process.

From the perspective of the nuclear organizations, no systematic framework exists on characterizing a set of critical success factors (CSFs) for implementing KM. Furthermore, the CSFs assessment deals with uncertainty and imprecision of human judgments. In this context, this paper presents a set of CSFs and a fuzzy model to establish a standard of importance of these CSFs based on experts opinion for the implementation of KM in nuclear organizations. Fuzzy theory is essentially used in mapping quantitative models for decision making and representation methods in imprecise and uncertain environments.

2. Methodology

The method developed in this paper was structured according to the following steps:

1) Selection of CSFs;
2) Determination of an ideal nuclear knowledge management (NKM);
3) Assessment of the NKM.

The list of CSFs was developed in seven themes, based on the literature[1][2][3][4][5][6]: top-level commitment, organizational culture, organizational structures, human resources management practices and policies, measuring and results, information technology and learning culture.

The second step of this decision support method is to obtain from experts on KM the degree of importance of each CSF, so that the implementation of KM in organization can be considered good. The relative importance of the expert will be calculated on the basis of subjective attributes (experience, knowledge of KM). We will use a questionnaire (Q) to identify the profile. Each questionnaire will contain information of a single expert. The relative importance of expert (RIEx) Ex_i (i = 1, 2, 3,.., k) will be a subset μ_i (k) Є [0,1] defined by Eq.1. According to the Eq.2, *tsQi*, will be the total score of expert *i*.

$$RIEx_i = \frac{tsQ_i}{\sum_{i=1}^{n} tsQ_i} \tag{1}$$

Each CSF can be seen as a linguistic variable, related to a linguistic terms set associated with membership functions. These linguistic terms will be represented by triangular fuzzy numbers to represent the importance degree of each CSF (Fig. 1). The linguistic terms will be: U (Unimportant), LI (Little

Important), I (Important) and VI (Very Important) to evaluate the importance of each CSF.

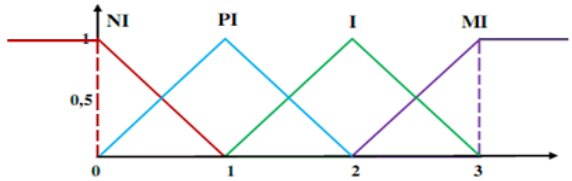

Figure 1: Membership functions for second step

The similarity aggregation method [7] will be used to combine the experts' opinions which are represented by triangular fuzzy numbers. The agreement degree (A) between expert Ex_i and expert Ex_j will be determined by the proportion of intersection area to total area of the membership functions. The agreement degree (A) is defined by Eq.2.

$$A = \frac{\int_x \left(\min\{\mu_{\tilde{N}i}(x), \mu_{\tilde{N}j}(x)\}\right) dx}{\int_x \left(\max\{\mu_{\tilde{N}i}(x), \mu_{\tilde{N}j}(x)\}\right) dx} \tag{2}$$

If two experts have the same estimates, the agreement degree between them will be one. If two experts have completely different estimates, the agreement degree will be zero. The higher the percentage of overlap, the higher the agreement degree. After all the agreement degrees between the experts calculated, we will construct an agreement matrix (AMX), which will give us insight into the agreement between the experts.

$$AMX = \begin{bmatrix} 1 & A_{12} & \cdots & A_{1j} & \cdots & A_{1n} \\ \vdots & \vdots & & \vdots & \vdots & \\ A_{i1} & A_{i2} & \cdots & A_{ij} & \cdots & A_{in} \\ \vdots & \vdots & & \vdots & \vdots & \\ A_{n1} & A_{n2} & \cdots & A_{nj} & \cdots & 1 \end{bmatrix}$$

The relative agreement of expert (RAEx) Ex_i (i = 1, 2, 3, …, k) will be given by Eq.3.

$$RAEx_i = \sqrt{\frac{1}{n-1} \cdot \sum_{j=1}^{n} (A_{ij})^2} \tag{3}$$

The calculate of the relative agreement degree of expert (RADEx) Ex_i (i = 1, 2, 3, …, k) by Eq.4 and the consensus coefficient of expert (CCEx) Ex_i (i = 1, 2, 3, …, k) will be given by Eq.5.

$$RADEx_i = \frac{RAEx_i}{\sum_{i=1}^{n} RAEx_i} \tag{4}$$

$$CCEx_i = \frac{RADEx_i \cdot RIEx_i}{\sum_{i=1}^{n} \left(RADEx_i \cdot RIEx_i\right)} \tag{5}$$

Let *W* be a fuzzy number for combining expert's opinions. *W* is the fuzzy value of each CSF which is also triangular fuzzy number. By definition of the consensus coefficient of expert (CCEx) Ex_i (i = 1, 2, 3,…, n), *W* can be defined by Eq.7. According to the Eq..6, w_i, is the triangular fuzzy number relating to the linguistic terms, U (Unimportant), LI (Little Important), I (Important) and VI (Very Important).

$$W = \sum_{i=1}^{n} \left(CCEx_i \cdot w_i\right) \tag{6}$$

Determination of an ideal NKM is established by calculating the normalized importance degree (NID) of each CSF that make up each property relevant to NKM. The normalized importance degree (NID) of each CSF will be given by deffuzification of its triangular fuzzy number W (a_i, b_i, c_i), where b_i represents the importance degree. Then, NID will be defined by Eq.7.

$$NID_i = \frac{NID_i}{\text{the largest numerical value of bi}} \quad (7)$$

The third step of the method is to obtain the actual level of NKM as perceived by each worker and compared it to the ideal NKM. It is suggested that the workers employ the linguistic terms SD (Strongly Disagree), PD (Partially Disagree), NAND (Neither Agree Nor Disagree), PA (Partially Agree), and SA (Strongly Agree). In Figure 2 we show the graphic presentations of membership functions for the linguistic terms SD (Strongly Disagree), PD (Partially Disagree), NAND (Neither Agree Nor Disagree), PA (Partially Agree) and SA (Strongly Agree).

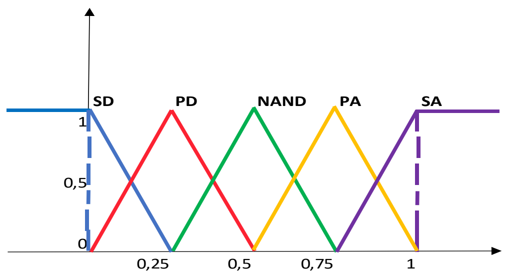

Figure 2: Membership functions for third step

3. Results and Discussion

The decision support method in was applied at the Laboratory of Human-Systems Interfaces of the Nuclear Engineering Institute. We selected the team of experts for determination of the degree of importance of each CSF, so that the implementation of KM in Laboratory of Human-Systems Interfaces can be considered good. The team of experts is comprised seventeen researchers with experience and, knowledge of KM. Afterwards, the relative importance score assigned to each expert will be determined by a questionnaire with ten questions, whose items were associated with a score. The ideal pattern for NKM was based on the opinion of theses seventeen experts in KM. The assessment of NKM in Laboratory of Human-Systems Interfaces was performed by five workers. The average assessment of the NKM was computed and is shown in Figure 3. We consider as satisfactory a compliance degree greater than 0.8, because this value represents agreement with the KNM pattern. The result of the average assessment showed that the Laboratory of Human-Systems Interfaces was satisfactory for all the themes.

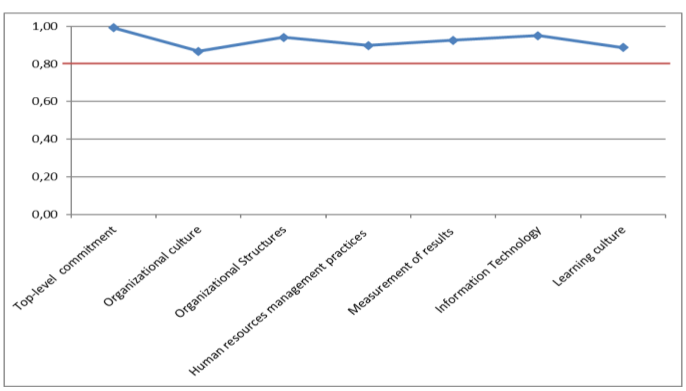

Figure 3: Assessment of NKM in Laboratory of Human-Systems Interfaces

4. Conclusions

In this paper we described a research study in which a decision support method for assessment of a nuclear knowledge management was proposed and used. The method uses CSF and the concepts and properties of Fuzzy Sets Theory. This study in the Laboratory of Human-Systems Interfaces showed that the method offers interesting perspectives for the implementation of KM process. This method can be applied in any safe-critical organization (e.g., nuclear industry, aviation, pharmaceutical) with adjustments in terms of the CSFs and their metrics according to the characteristics of these organizations. As suggestions for future research, we highlight: (1) the development of a computational system in order to automate the use of the method to assess an organization's KM online; (2) the periodic application of the method to estimate how new corrective actions change KM levels; (3) the use of the method in other safe-critical organizations in order to test its applicability.

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References

[1] IAEA, Nuclear Energy Series NG-T-6.11: Knowledge Loss Risk Management in Nuclear Organizations, Intenational Atomic Energy Agency, Viena (2007).

[2]Wong, K. Y.: "Critical Success Factors for Iimplementing Knowledge Management in Small and Medium Enterprises". Industrial Management & Data Systems 3, v.105,261-279, (2005).

[3]Takeuchi, H., Nonaka, I.: *Gestão do Conhecimento*, 1. Ed., Porto Alegre, Brasil (2008).

[4] Terra, J. A.*: Gestão do Conhecimento: O Grande Desafio Empresarial*, 5. Ed., Rio de Janeiro, Brasil (2005).

[5]Wang, J., Peters, H. P., Guan, J.: "Factors Influencing Knowledge Productivity in German Research Groups: lessons for developing countries". *Journal of Knowledge Management 4*, v.10, 113-126 (2006)

[6] Figueiredo, S.: *Gestão do Conhecimento – Estratégia Competitiva para a Criação e Mobilização do Conhecimento na Empresa*, 4. Ed, São Paulo, Brasil (2005).

[7] Hsu, H. M., Chen, C. T.: "Aggregation of Fuzzy Opinions under Group Decision Making. Fuzzy Sets and Systems", v. 79, pp. 279-285 (1996).