FUZZY MODELS TO DEAL WITH HETEROGENEOUS INFORMATION IN DECISION MAKING PROBLEMS IN ENGINEERING PROCESSES*

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Before implementing an engineering system in the design process are studied different proposals to evaluate and rank them. In this evaluation process several experts assess different aspects and criteria according to their knowledge and preference on them. These criteria may have different nature (quantitative, qualitative) and the experts could belong to different areas and have different knowledge on each criterium, so the assessments used to express the value on each criterium could be assessed with different types of information (numerical, linguistic, interval-valued). In such a case, to select the best proposal we must deal with this *heterogeneous information* to evaluate and rank the different proposals. In this contribution we show different fuzzy approaches for dealing with heterogeneous information.

1. Introduction

In the design of traditional engineering systems the main objective for selecting a design option is to minimize *cost*. In recent years, however, the design selection has increased its complexity due to the need of taking into account aspects or criteria such as safety, cost and technical performance

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simultaneously. In the future all solicitations involving source selection should be structured using safety, cost and technical performance considerations [9]. Also, the decision of implementing a design in an engineering system will depend on if the design can satisfy technical and economical constraints.

Therefore, Multi-Criteria Decision Making (MCDM) techniques [2,10] could be applied for ranking the different design options. In these MEMC-DM problems the preferences provided by the experts for the different criteria may be expressed with different types of information depending on the knowledge of the experts and on the nature of the criteria (quantitative and qualitative). When the experts do not have a precise knowledge about the criteria the probability theory could be useful to deal with vague information, but it is not too difficult to find many aspects of uncertainties that do not have a probabilistic character since they are related to imprecision and vagueness of meanings. In addition qualitative aspects are difficult to assess by means of precise numbers.

To rank engineering designs using MEMC-DM problems we deal with criteria as safety, cost and technical performance. In these problems, intrinsically vague information appear and could be assessed by means of numerical information (probabilistic), interval values and in those cases such that the nature of the criterium is qualitative the use of linguistic information [12] is common and suitable. Therefore, it is not a seldom situation to deal with numerical, interval valued and linguistic information in the evaluation process of engineering designs [8,11]. We shall call this type of information as *heterogeneous information*. The decision model to rank the different designs assessed by means of heterogeneous information taking into account the criteria of safety, cost and technical performance will use a framework as the following one [8,11]:

- Safety assessments will be synthesized for each design.
- Cost and technical assessments will be provided by the experts.
- These assessments will be the input information for a MEMC-DM that we shall solve to rank the different designs.

In this MEMC-DM problem the assessments for the criteria will be combined to obtain a degree of suitability of each design option. The main difficulty to solve this problem is that the values used to assess the criteria are expressed in different utility spaces (heterogeneous information) and we shall need to unify the different utility spaces to combine the input information in order to obtain the degree of suitability of each design option.

In this contribution we shall show an approach to unify this heterogeneous information dealing with fuzzy sets [1] and after how this approach could be improve using the linguistic 2-tuple model [4].

This contribution is structured as follows. In section 2 we show how to unify heterogeneous information dealing with fuzzy sets. In section 3 we review the linguistic 2-tuple model and its application to deal with heterogeneous information. Finally some conclusions are pointed out.

2. Using fuzzy sets to deal with Heterogeneous Information

We must keep in mind we are dealing with heterogeneous contexts composed by numerical, interval valued and linguistic information. Our aim is to rank the different proposals characterized with this type of information. So, we need to unify the heterogeneous information into a common utility space to operate on it easily.

Here, we show how to unify numerical, interval valued and linguistic information into a common utility space that is fuzzy sets on a linguistic term set, S_T. The common utility space S_T may be chosen depending on the specific problem, according to the conditions shown in [6]. Afterwards, each numerical, interval-valued and linguistic evaluation, is transformed into a fuzzy set in S_T, $F(S_T)$, using the following transformation functions:

(1) Transforming numerical values, $s_{ij}^N \in [0,1]$, into $F(S_T)$:

$$\tau : [0,1] \rightarrow F(S_T)$$
$$\tau(s_{ij}^N) = \{(s_0, \gamma_0), \ldots, (s_g, \gamma_g)\}, s_i \in S_T \; and \; \gamma_i \in [0,1]$$
$$\gamma_i = \mu_{s_i}(s_{ij}^N) = \begin{cases} 0, & if \; s_{ij}^N \notin Support(\mu_{s_i}(x)) \\ \frac{s_{ij}^N - a_i}{b_i - a_i}, & if \; a_i \le s_{ij}^N \le b_i \\ 1, & if \; b_i \le s_{ij}^N \le d_i \\ \frac{c_i - s_{ij}^N}{c_i - d_i}, & if \; d_i \le s_{ij}^N \le c_i \end{cases}$$

Remark: We consider membership functions, $\mu_{s_i}(\cdot)$, for linguistic labels, $s_i \in S_T$, are represented by a parametric function (a_i, b_i, d_i, c_i). And being γ_i the degree of membership of the number into the linguistic terms of S_T.

(2) Transforming linguistic terms, $s_{ij}^L \in S$, into $F(S_T)$:

$$\tau_{SS_T} : S \rightarrow F(S_T)$$
$$\tau_{SS_T}(s_{ij}^L) = \{(c_k, \gamma_k^l) \, / \, k \in \{0, \ldots, g\}\}, \forall s_{ij}^L \in S$$
$$\gamma_k^l = \max_y \min\{\mu_{s_{ij}^L}(y), \mu_{c_k}(y)\}$$

where $\mu_{s_{ij}^L}(\cdot)$ and $\mu_{c_k}(\cdot)$ are the membership functions of the fuzzy sets associated with the terms s_{ij}^L and c_k, respectively.

(3) Transforming interval-valued, s_{ij}^l in $[0,1]$ into $F(S_T)$. Let $I = [\underline{i}, \bar{i}]$ be an interval in $[0,1]$. We assume that the interval-valued has a representation, inspired in the membership function of fuzzy sets [7]:

$$\mu_I(\vartheta) = \begin{cases} 0, \; if \; \vartheta < \underline{i} \\ 1, \; if \; \underline{i} \leq \vartheta \leq \bar{i} \\ 0, \; if \; \bar{i} < \vartheta \end{cases}$$

The transformation function is:

$$\tau_{IS_T} : I \rightarrow F(S_T)$$

$$\tau_{IS_T}(s_{ij}^l) = \{(c_k, \gamma_k^i) \,/\, k \in \{0, ..., g\}\},$$

$$\gamma_k^i = \max_y \min\{\mu_{s_{ij}^l}(y), \mu_{c_k}(y)\}$$

where $\mu_{s_{ij}^l}(\cdot)$ is the membership function associated with the interval-valued s_{ij}^l.

At this moment all the input information (heterogeneous information) is expressed in a common utility space and we can operate with this information easily to obtain a ranking of the alternatives. This method has been applied successfully in the process of safety synthesis in [8,11]

3. Using 2-tuples to deal with heterogeneous information

The use of fuzzy sets allow us to unify the heterogeneous information, but the results to rank the different proposals will be fuzzy sets that are not straight to order and not easy to understand for all the experts. However, the use of the linguistic 2-tuple model will allow to order straightly the different proposals [5] and the results will be easily understandable by all the experts.

Now, we review briefly the linguistic 2-tuple model and show how to convert the fuzzy sets obtained in the section 2 into linguistic 2-tuples.

3.1. *The 2-Tuple Fuzzy Linguistic Representation Model*

The 2-tuple fuzzy linguistic representation model, presented in [4], will be used in this contribution to unify the heterogenous information. This model is based on symbolic methods and takes as the base of its representation the concept of Symbolic Translation.

Definition 1. *The Symbolic Translation of a linguistic term $s_i \in S = \{s_0, ..., s_g\}$ is a numerical value assessed in $[-.5, .5)$ that support the "difference of information" between an amount of information $\beta \in [0, g]$ and the closest value in $\{0, ..., g\}$ that indicates the index of the closest linguistic term $s_i \in S$, being $[0, g]$ the interval of granularity of S.*

From this concept the linguistic information is represented by means of 2-tuples (r_i, α_i), $r_i \in S$ and $\alpha_i \in [-.5, .5)$.

This model defines a set of functions between linguistic 2-tuples and numerical values.

Definition 2. *Let $S = \{s_0, ..., s_g\}$ be a linguistic term set and $\beta \in [0, g]$ a value supporting the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following function:*

$$\Delta : [0, g] \longrightarrow S \times [-0.5, 0.5)$$

$$\Delta(\beta) = (s_i, \alpha), \ with \begin{cases} s_i & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-.5, .5) \end{cases}$$

where $round(\cdot)$ is the usual round *operation, s_i has the closest index label to "β" and "α" is the value of the symbolic translation.*

Proposition 1. *Let $S = \{s_0, ..., s_g\}$ be a linguistic term set and (s_i, α) be a linguistic 2-tuple. There is always a Δ^{-1} function, such that, from a 2-tuple it returns its equivalent numerical value $\beta \in [0, g]$ in the interval of granularity of S.*

Proof. It is trivial, we consider the function:

$$\Delta^{-1} : S \times [-.5, .5) \longrightarrow [0, g]$$
$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$$

A linguistic computational model for 2-tuples was introduced in [4].

3.2. *Transforming fuzzy sets in S_T into linguistic 2-tuples*

In section 2 the heterogeneous information was unified by means of fuzzy sets in the common utility space, S_T, now we shall transform them into linguistic 2-tuples in S_T. This transformation is carried out using the function χ and the Δ function (Def. 2):

$$\chi : F(S_T) \rightarrow [0, g]$$

$$\chi(\tau(\vartheta)) = \chi(\{(s_j, \gamma_j), j = 0, ..., g\}) = \frac{\sum_{j=0}^{g} j\gamma_j}{\sum_{j=0}^{g} \gamma_j} = \beta$$

β is a numerical value in the granularity interval of S_T, i.e., $S_T = \{s_0, ..., s_g\}$, $\beta \in [0, g]$. Then, to obtain the linguistic 2-tuple from we shall use the Δ function presented in the *Definition 2*: $\mathbf{\Delta}(\beta) = (s_i, \alpha)$

Now all the input information are expressed in a common utility space, S_T, by means of linguistic 2-tuples. So we can use all the linguistic 2-tuple operators [4] to obtain the results we are looking for.

This model has been used to deal with heterogeneous processes in evaluation and decision processes in [3,6].

4. Conclusions

In engineering we can face problems involving decision processes dealing with information assessed in different utility spaces. In this contribution we have showed two fuzzy approaches to deal easily with heterogeneous information composed by numerical, interval valued and linguistic values.

In the future we shall apply these approaches to the whole decision process in the engineering problem.

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