A Heterogeneous Evaluation Model for Engineering Systems

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Abstract To choose a design for a large engineering system it is necessary to evaluate different key criteria before its implementation. We have noticed that these criteria can have different nature (quantitative or qualitative) and the experts involved in such a evaluation process could belong to different areas and their knowledge about these criteria may be vague and/or incomplete. So, the assessments provided by the experts could be assessed with different types of information (numerical, linguistic, interval-valued). In this contribution, we propose an evaluation model based on a decision process that is able to deal with the uncertainty and manage the heterogeneous information in an evaluation framework defined for this type of problems.

Keywords: Engineering systems, decision making, heterogeneous information, evaluation models, 2-tuple fuzzy linguistic model

1 Introduction

The decision of implementing a design in a large engineering system depends on that the design satisfies technical and economical constraints. Multi-Criteria Decision Making (MCDM) techniques could be applied to obtain a ranking order of different design options.

These problems involve criteria that may have different nature, quantitative or qualitative. Usually the information provided by the experts to assess the criteria for evaluating the design options is vague or uncertain. Many aspects of uncertainties clearly have a non-probabilistic character since they are related to imprecision and vagueness of meanings. Therefore, linguistic descriptors may be used to describe an event due to the fact that they are often used by engineers and safety analysts. The Fuzzy Linguistic Approach [11] provides a systematic way to represent linguistic variables in a natural decision-making procedure.

We have observed that it is not a seldom situation that the definition context of these problems could be non homogeneous [6], i.e., the information provided by the experts may be assessed in different utility spaces, according to the nature of the evaluated criteria such that could be numerical and interval-valued assessments for quantitative criteria and linguistic terms for qualitative ones.

The aim of this contribution is to define an evaluation framework for these problems that will take into account the criteria of *Safety*, *Cost* and *Technical* *perfomance*. Afterwards we shall develop an evaluation model based on a decision process that allows us to deal with heterogeneous contexts that evaluates the different design options for an engineering system. To do so, first we shall define a framework used for expressing the assessments for the safety, cost and technical performance criteria:

- Safety will be assessed based on fuzzy logic and the evidential reasoning approach, referred to as a *FUzzy Rule-Based Evidential Reasoning* (FURBER) approach [5], which is based on the RIMER approach proposed recently in [10]. The synthesis of the safety assessments for each option is expressed using a linguistic 2-tuple scheme [1].
- The cost and technical performance assessments of each design option are directly supplied by the experts and they will be assessed according to their nature and the expert's knowledge (numerical, interval-valued and linguistic labels).
- All these assessments define an heterogeneous context and will be the input values for a Multi-Expert Multi-Criteria Decision Making (MEMC-DM) problem that we shall solve to evaluate and rank the different design options.

To solve these MEMC-DM problems is used a two-step resolution scheme [7]:

- *Aggregation step*: it combines the input assessments to obtain a collective degree for each criterion according to all the experts.
- *Exploitation step*: it ranks the options using a choice degree to choose the most suitable one.

The main difficulty to use this scheme in our problem is the aggregation of the input information because the assessments are conducted in different utility spaces. Therefore, in this paper we shall develop an evaluation model based on a decision process that allows us to manage heterogeneous information composed by three steps, where the first one will be an unification method to express the input information in one expression domain. We shall select as unification domain the linguistic one expressing the unified information by means of linguistic 2-tuples.

In order to do so, this contribution is structured as follows: in Section 2 we review some linguistic foundations we shall use to deal with heterogeneous information. In Section 3 we present the framework that we shall use in our model. In Section 4 we outline the model to evaluate and choose the best design option for an engineering system in a heterogeneous evaluation framework. The paper is concluded in Section 5.

2 Linguistic Background

Here we review briefly some core concepts about the fuzzy linguistic approach and also the linguistic 2-tuple representation model we shall use in our proposal to deal with heterogeneous contexts.

2.1 Fuzzy Linguistic Approach

Usually, we work in a quantitative setting, where the information is expressed by numerical values. However, many aspects of different activities in the real world cannot be assessed in a quantitative form, but rather in a qualitative one, i.e., with vague or imprecise knowledge. In that case a better approach may be to use linguistic values instead of numerical ones. The fuzzy linguistic approach represents qualitative aspects as linguistic values by means of linguistic variables [11].

We have to choose the appropriate linguistic descriptors for the term set and their semantics. In the literature, several possibilities can be found [3]. One possibility of generating the linguistic term set consists of directly supplying the term set by considering all terms distributed on a scale on which a total order is defined. For example, a set of seven terms S, could be:

S ={s_0:Poor; s_1:Low; s_2:Average; s_3:High; s_4:Good}

In these cases, it is required that there exist:

- A negation operator Neg(s_i) = s_j such that $j = g-i$ (g+1 is the cardinality).
- A minimization and a maximization operator in the linguistic term set: $s_i <= s_j$ ⇔ $i<=j$.

The semantics of the terms are given by fuzzy numbers defined in the [0,1] interval, which are described by membership functions. A way to characterize a fuzzy number is to use a representation based on parameters of its membership function (Fig. 1). Since the linguistic assessments given by the users are just approximate ones, some authors consider that linear trapezoidal membership functions are good enough to capture the vagueness of those linguistic assessments, since it may be impossible and unnecessary to obtain more accurate values [3].

2.2 The 2-tuple Linguistic Model

This model was presented in [1], for overcoming the drawback of the loss of information presented by the classical linguistic computational models [2]: (i) The semantic model , (ii) and the symbolic one. The 2-tuple fuzzy linguistic representation model is based on the symbolic method 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 [-0.5,0.5) that supports 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 in S (s_i), being [0,g] the interval of granularity of S.

From this concept a linguistic representation model was developed, which represents the linguistic information by means of 2-tuples $(s_i, \alpha_i), s_i \in S$ and $\alpha_i \in [-0.5, 0.5)$.

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:

$$\Delta : [0, g] \rightarrow S \times (-0.5,.0.5)$$

$$\Delta(\beta) = (s_i, \alpha), with \quad \begin{cases} s_i & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-0.5, 0,5) \end{cases}$$

where 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_i) be a linguistic 2-tuple. There is always a Δ^{-1} function, such that, from a 2-tuple it returns its equivalent numerical value $\beta \in [0, g]$.

Proof. It is trivial, we consider the function:

$$\Delta^{-1} : S \times [-0,5,0.5) \rightarrow [0, g]$$
$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$$

Remark 1. *From definitions 1 and 2 and proposition 1, it is obvious that the conversion of a linguistic term into a linguistic 2-tuple consist of:*

$$s_i \in S \Rightarrow (s_i, 0)$$

The computational technique based on the 2-tuples was presented in [1]:

1. **Aggregation of 2-tuples:** it consists of obtaining a value that summarizes a set of values, therefore, the result of the aggregation of a set of 2-tuples must be a linguistic 2-tuple. In [1] we can find several 2-tuple aggregation operators.
2. **Comparison of 2-tuples:** it is carried out according to an ordinary lexico-graphic order (more details [1]).
3. **Negation Operator of a 2-tuple:** defined as,

   $$Neg(s_i, \alpha) = \Delta\ (g - \Delta^{-1}(s_i, \alpha))$$

   where g+1 is the cardinality of S, $s_i \in S = \{s_0, ..., s_g\}$.

3 Evaluation Framework for Engineering Systems

In this section we show briefly how are sinthesised the safety assessments by means of the FURBER approach [5, 10] and how are the cost and technical performance assessments provided by the experts.

3.1 Safety Evaluation

The safety criterion will be assessed using a framework based on fuzzy logic and the evidential reasoning approach, referred to as a fuzzy rule-based evidential reasoning FURBER approach [5]. And the safety synthesis will be based on the ordinal fuzzy linguistic approaches.

This framework will obtain as safety evaluation a fuzzy variable described linguistically using the following linguistic term set, denoted as $\boldsymbol{S}_S$ in this paper, whose semantics are shown in the Fig. 1:

S_S ={ "*Poor*", "*Low*", "*Average*", "*High*", "*Good*"}

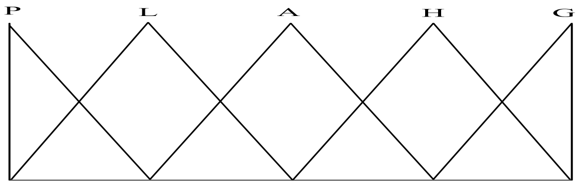


Fig. 1: $\boldsymbol{S}_S$ set of five terms and their semantics

To obtain this safety evaluation, we use a fuzzy rule base with believe structures and the FURBER approach. Hence, we shall obtain as final result a belief distribution on a safety expression:

$$\{(Poor,\vartheta_1),(Low,\vartheta_2),(Average,\vartheta_3,),(High,\vartheta_4,),(Good,\vartheta_5)\}$$

Therefore to express this result as a linguistic value belongs to S_S, this framework uses the linguistic 2-tuple representation model to express the safety assessments as:

$$(s_i,\alpha), s_i \in S_S$$

The linguistic 2-tuples expressing the safety evaluation will be used as the input assessment in our MEMC-DM problem. For a further and detailed description of this safety evaluation framework see [5,10].

3.2 Cost Modelling

Cost and safety are two important criteria in design of complex engineering systems, but they are usually in conflict because higher safety normally leads to higher costs. The cost incurred for safety improvement associated with a design option is usually affected by different factors [9]:

- Cost for provision of redundancies of critical components
- Provision of protection systems
- Alarm systems
- Use of more reliable components
- Cost for redesign of the system.
- Etc.

These factors can be different in each system and often include uncertainties. Therefore, it is more appropriated to model several aspects related to the cost incurred in safety improvement associated with the design options on a subjective basis. In [9] cost was estimated and described using fuzzy sets over the linguistic variables. Nevertheless, other aspects related to cost could be assessed by means of numerical assessments (numbers or interval-values).

Therefore the experts provide the cost assessments (see Table 1) on each factor, f_k, for all the design options O_i, where c_{ij}^k is the cost of the factor k for a design option i provided by the expert j, where the assessments of each factor c_{ij}^k could be a linguistic, numerical or interval-valued value.

Remark 2. *Cost assessments have a different interpretation of suitability for a design option regarding other criteria assessments. Therefore, to calculate a value for the suitability of a design option we shall take into account this feature.*

3.3 Technical Performance Modelling

Performance measurement is an area that has become increasingly important, sophisticated and more demanding. Hence technical performance is taken into account as an evaluation criterion to rank the different design options for engineering systems [8]. The technical performance is different in each engineering system and usually includes uncertainties. Due to this fact, it is difficult to fix a type of assessment for measuring technical performance suitable for any engineering system. In this paper, we propose that the expert can provide different types of assessments according to the system and the performance evaluated (numerical, interval-valued and linguistic).

The experts provide performance assessments (see Table 1) on each element, b_l, for all the design options O_i, where t_{ij}^l is the technical performance assessment of the element l for a design option i provided by expert the j ,where these assessments of each subsystem t_{ij}^l could be assessed as a linguistic, numerical or interval-valued values.

3.4 Evaluation Framework

We shall model our evaluation problem as a Multi-Expert Multi-Criteria Decision Making problem where each expert provides assessments for different cost and technical factors and his/her opinions for the parameters used to synthesise the safety assessments. All the assessments are summarised in the Table 1.

Table 1:Experts Assessments for each criteria of all the design options

Design Options	*Criteria*						
Expert$_j$	**Safety**	**Cost**			**Tech. Perf.**		
		f_1	…	f_k	b_1	…	b_l
O_1	(s_{1j}, α)	c_{1j}^1	…	c_{1j}^k	t_{1j}^1	…	t_{1j}^l
:	:	:	:	:	:	:	:
O_n	(s_{nj}, α)	c_{nj}^1	…	c_{nj}^k	t_{nj}^1	…	t_{nj}^l

Where (s_{ij}, α) is the safety assessments synthesized from the opinions of the expert e_j for the design option O_i, i.e., estimated based on the fuzzy rule-based system produced at lower levels, and then synthesised to obtain the safety assessment of the system by means of linguistic 2-tuples in the linguistic term set, S_S. While c_{ij}^k are the cost factors assessments provided by the experts e_j that could be assessed in different utility spaces (linguistic labels, numbers, interval values). And t_{ij}^l are the technical performance assessments provided by the experts, and as well could be assessed in different utility spaces. So:

$$(s_{ij}, \alpha) \in S_s \quad and \quad c_{ij}^k, t_{ij}^l \in \{\ S \mid [0,1] \mid I([0,1])\ \}$$

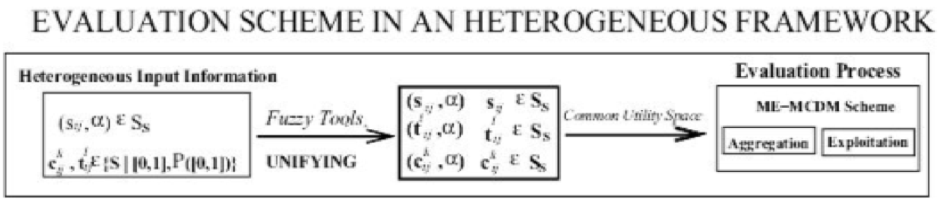
We can observe that the input values we obtain from our evaluation framework are assessed in different utility spaces. In the next section we shall present an evaluation model based on a decision process dealing with different fuzzy tools to manage this heterogeneous information.

4 Evaluation Model

We shall solve our evaluation problem by means of a MEMC-DM process whose resolution scheme consists of a two step process in which the information is aggregated and afterwards exploited in order to obtain a solution. However we cannot apply this scheme straighly to our problem due to the fact that the input information is non homogeneous and we cannot directly aggregate it. So we propose the following resolution scheme for our problem (graphically see Fig. 2):

1. Unification phase: it unifies the input information into a common utility space.
2. Aggregation phase: it combines the unified information.
3. Exploitation phase: it looks for a solution.

Fig. 2: Evaluation Scheme dealing with heterogeneous information



4.1 Unification phase

We are dealing with heterogenous information. To manage it the model unifies it in a common utility space. In our case we have chosen the linguistic term set S_S. The unification process is based on different fuzzy tools presented in [4] that transform the numerical, interval valued and linguistic information into fuzzy sets in S_S:

- Numerical Information. $\tau : [0,1] \to F(S_S)$
- Linguistic Information. $\tau_{SS_S} : S \to F(S_S)$
- Interval valued information. $\tau_{IS_S} : I([0,1]) \to F(S_S)$

and afterwards the fuzzy sets in S_S are transformed into linguistic 2-tuples by means of the function χ presented in [4]:

- $\chi : F(S_S) \to S_S \times [-0.5, 0.5)$

So all the input information is conducted in a common utility space, S_S, by means of linguistic 2-tuples such as can be seen in the Table 2. Where (s_{ij}, α) is the safety assessments synthesized from the opinions of the expert e_j for the design option O_i. While (c_{ij}^k ,α) are the cost assessment for factor k provided by the expert e_j for the design option O_i, and (t_{ij}^l ,α) are the technical performance assessments for element l provided by the expert e_j for the design option O_i, both are expressed as linguistic 2-tuples in S_S.

Table 2: Unified Experts Assessments for each criteria of all the design options

Design Options	*Criteria*						
Expert$_j$	**Safety**	**Cost**			**Tech. Perf.**		
		f_1	...	f_k	b_1	...	b_l
O_1	(s_{1j}, α)	(c_{1j}^1, α)	...	(c_{1j}^k, α)	(t_{1j}^1, α)	...	(t_{1j}^l, α)
:	:	:	:	:	:	:	:
O_n	(s_{nj}, α)	(c_{nj}^1, α)	...	(c_{nj}^k, α)	(t_{nj}^1, α)	...	(t_{nj}^l, α)

A further description about the transformation functions used to unify the heterogeneous information can be seen in [4].

4.2 Aggregation phase

The aim of this phase is to obtain a collective utility value for each option design according to all the experts' opinions.

To do so, first of all, this phase computes an overall value for the cost and the technical performance for each design option using an aggregation operator for each expert. We have to keep in mind, that the individual utilities for cost and technical performance are currently expressed by means of linguistic 2-tuples so we shall use an aggregation operator for 2-tuples [1]. And, we obtain the cost and technical performance individual utilities provided by the experts (see Table 3).

Table 3: Expert *j* Individual Utilities

Design Options	*Criteria*		
Expert$_j$	**Safety**	**Cost**	**Tech. Perf.**
O_1	(s_{1j}, α)	(c_{1j}, α)	(t_{1j}, α)
:	:	:	:
O_n	(s_{nj}, α)	(c_{nj}, α)	(t_{nj}, α)

Secondly, for each design option we shall aggregate its utilities for each criteria in order to obtain an expert overall utility for that option (see Table 4).

Table 4: Expert *j* Collective Utilities for each option

Design Options	
Expert$_j$	**Collective Assessment**
O_1	(p_{1j}, α)
:	:
O_n	(p_{nj}, α)

And finally we obtain a collective utility value for each design option aggregating the utility values obtained from each expert taking into account the Remark 2 (see Table 5).

Table 5: Collective Assessments for each option

Design Options	
I	**Collective Assessment**
O_1	(p_1, α)
:	:
O_n	(p_n, α)

4.3 Exploitation phase

Over the collective values obtained in the aggregation phase, (p_i, α), the exploitation phase, applies a choice degree to obtain a selection set of alternatives. In our problem the information is expressed by means of the linguistic 2-tuple representation model that has defined a total order over itself. Then in our problem one choice could be rank the results using this order.

5 Conclusions

In engineering we can face problems involving decision processes dealing with information assessed in different utility spaces due to its nature and uncertainty. We have focused on the evaluation of engineering designs for an engineering system according to different criteria as safety, cost and technical performance whose evalutions are assessed with heterogeneous information in order to offer the experts a more flexible and accurate framework. We have presented an evaluation model that manages this type of framework by means of fuzzy tools and have been obtained promising results in the evaluation process.

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References

[1] F. Herrera, L. Martínez. A 2-tuple fuzzy linguistic representation model for computing with words**.** *IEEE Transactions on Fuzzy Systems* **8:6** pp.746-752, (2000).

[2] F. Herrera, L. Martínez, An approach for combining numerical and linguistic information based on the 2-tuple fuzzy linguistic representation model in Decision Making. *International Journal of Unceraintу., Fuzziness and Knowledge–Based Systems.* **8:5** pp. 539-562 (2000).

[3] F. Herrera and E. Herrera-Viedma, Linguistic Decision Analysis:Steps for Solving Decision Problems under Linguistic Information, *Fuzzy Sets and Systems* **115** (2000) pp. 67-82.

[4] F. Herrera, L. Martínez. P.J. Sánchez. Managing non-homogeneous information in GDM. *European Journal of Operational Research* 166:1(2005) pp. 115-132

[5] J. Liu, J. B. Yang, J. Wang, H. S. Sii and Y. M. Wang, Fuzzy rule-based evidential reasoning approach for safety analysis, *Int. Journal of General Systems* Vol. 33, No.2-3, pp.183-204, 2004

[6] L. Martínez J. Liu, J.B. Yang,L.G. Pérez, A Multi-Granular Linguistic Model for Design Evaluation Based on Multiple Criteria Analysis**.** *Technical Report TR-4-2004*, Univ. of Jaén, 2004.

[7] M. Roubens. Fuzzy sets and decision analysis. *Fuzzy Sets & Syst*, **90**, pp.199-206, (1997).

[8] H.S. Sii and J. Wang, A subjective design for safety framework for offshore engineering products, Workshops on reliability and Risk Based Inspection Planning and ESRA Technical Committee on Offshore Safety, Switzerland (2000).

[9] J. Wang, J.B. Yang, P. Sen, Safety analysis and synthesis using fuzzy sets and evidential reasoning. *Reliab. Engineeting System Safety* **41** pp. 103-118 (1995).

[**10**] J.B. Yang, J. Liu, J. Wang and H.S. Sii, A generic rule-base inference methodology using the evidential reasoning approach – RIMER, *IEEE Transactions on Systems, Man, and Cybernetics.* To appear.

[11] L.A. Zadeh, The Concept of a Linguistic Variable and Its Applications to Approximate Reasoning. Part I, *Information Sciences* **8** 199-249, Part II, *Inormation. Sciences* **8** 301-357, Part III, *Information Sciences.* **9** 43-80, (1975).