A Multi-Granular Linguistic Evaluation model for Engineering Systems

Luis Martínez, L.G. Pérez
Dpto. de Informática Universidad de Jaén
Jaén, Spain
martin,lgonzaga@ujaen.es

Jun Liu, Jian-Bo Yang
Manchester School of Management,
UMIST, Manchester, UK
j.liu, Jian-bo.yang @umist.ac.uk

ABSTRACT

Before of implementing a design for an Engineering System different design proposals should be evaluated to choose the most suitable one. This evaluation process is carried out according to different criteria, the main problem is that the knowledge about these criteria is usually vague and incomplete. In this contribution, we use the fuzzy linguistic approach and the Dempster-Shafer theory of evidence to deal with it. We shall propose an evaluation model of different designs based on the *Safety, Cost* and *Technical performance* criteria. To develop this evaluation model we shall define a multi-granular linguistic evaluation framework and after propose a evaluation model based on a decision process.

KEYWORDS: Engineering systems, decision making, multi-granular linguistic information

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. Particularly in the feasibility and concept selection stages of an engineering system. Subjective assessments about safety, cost and technical performance can be studied together to determine the best risk reduction action and to choose the best design/operation option. Multiple analysts can provide their subjective judgments for each design option on these criteria.

Typical safety assessment approaches may be difficult to use in situations where there is a lack of information, past experience, or ill-defined situation in risk analysis [11]. Therefore, linguistic descriptors, such as, *"Likely", "Impossible",* are used to describe an event due to the fact they are used commonly by engineers and safety analysts. Hence, the use of the fuzzy linguistic approach [13] is a good model to analyse the safety of engineering systems with incomplete information. Also the estimation of the cost and technical performance are ill-defined situations, therefore the use of the linguistic approach is adequated too. Although they may be conducted in different utility spaces, i.e., multi-granular linguistic information.

The aim of this paper is to develop a multi-granular linguistic decision model that evaluates the different design options for an engineering system according to multiple criteria assessed linguistically in different utility spaces. First we define the linguistic framework used for expressing the linguistic assessments for each 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 [6], which is based on the RIMER approach [12]. The synthesis of the safety assessments for each option is expressed and implemented using a linguistic 2-tuple scheme [2].
- The cost and technical performance assessments of each design option are supplied directly by the experts in terms of linguistic labels.
- All these linguistic assessments defined in a multi-granular linguistic context 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.

In this contribution we shall propose a multi-granular linguistic evaluation model based on two different proposals presented in [3, 5], to evaluate the different design options.

In order to do so, this contribution is structured as follows: in Section 2 we make a brief review of linguistic tools. In Section 3 we describe the evaluation framework for modelling of large engineering systems. In Section 4 it will be presented the application of the linguistic decision model to evaluate the design options. And finally, some conclusions are pointed out.

2. LINGUISTIC BACKGROUND

Here we review briefly some core concepts about linguistic information as the *Fuzzy Linguistic Approach* and *2-tuple Linguistic model.*

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 assessments instead of numerical values. The fuzzy linguistic approach represents qualitative aspects as linguistic values by means of linguistic variables [13].

We have to choose the appropriate linguistic descriptors for the term set and their semantics. To do so, a very important concept is the *granularity of uncertainty*, i.e., the level of discrimination among different degrees of uncertainty, typical values of cardinality used in the linguistic models are odd ones, such as 7 or 9, where the mid term represents an assessment of "approximately 0.5", and the rest of the terms being placed symmetrically around it [1]. In the literature, several possibilities can be found [4]. 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 = *None;* s_1 = *Very Low;* s_2 = *Low;* s_3 = *Medium;* s_4 = *High;* s_5 = *Very High;* s_6 = *Perfect*}

Usually, in these cases, it is required that in the linguistic term set there exist:

1. A negation operator: $Neg(s_i) = s_j$ such that j = g-i (g+1 is the cardinality).
2. An order: $s_i \leq s_j \Leftrightarrow i \leq j$.

Therefore, there exists a minimization and a maximization operator.

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. 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 [4].

2.2 The 2-tuple linguistic model

This model was presented in [2]. 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 $s_i \in S = \{s_0,\dots,s_g\}$ 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 is 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 $S = \{s_0,\dots,s_g\}$ 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 $S = \{s_0,\dots,s_g\}$ 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 following function:

$$\Delta^{-1} : S \times [-0,5,0.5) \rightarrow [0, g]$$

$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$$

This model has a computational technique based on the 2-tuples were presented in [2]:

1. **Aggregation of 2-tuples**
   The aggregation of linguistic 2-tuples consist 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 [2] we can find several 2-tuple aggregation operators.
2. **Comparison of 2-tuples**
   The comparison of information represented by 2-tuples is carried out according to an ordinary lexico-graphic order (more details [2]).
3. **Negation Operator of a 2-tuple**
   The negation operator over 2-tuples is defined as:
   $$Neg(s_i, \alpha) = \Delta\ (g - \Delta^{-1}(s_i, \alpha))$$
   where g+1 is the cardinality of S, $s_i \in S = \{s_0,\dots,s_g\}$.

3 EVALUATION FRAMEWORK FOR ENGINEERING SYSTEMS

In this section we show briefly how are the assessments for safety using the FURBER approach [6, 12] and how are the other criteria provided by the experts assessed.

3.1 Safety evaluation framework

A generic framework for modelling system safety estimate using FURBER approach and for safety synthesis is outlined, more details see [6, 12].

Step #1: Identification of causes/factors: it can be done by a panel of experts during a brainstorming session at the early concept design stages.

Step #2: Identify and definite fuzzy input and fuzzy output variables (i.e., safety estimates)

The three fundamental parameters used to assess the safety level of an engineering system on a subjective basis are the failure rate (**FR**), consequence severity (**CS**) and failure consequence probability (**FCP**). Subjective assessments are more appropriate for analysis using these three parameters as they are always associated with great uncertainty.

Safety estimates is the only output fuzzy variable used to produce safety evaluation for a particular cause to technical failure. This variable is described linguistically, which is described and determined by the above parameters. In safety it is common to express a safety assessments assessed in the following linguistic term set [9], that we note as, $\mathbf{S_S}$, in this paper:

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

that are referred to as safety expressions.

Step #3: Construct a fuzzy rule-base

Fuzzy logic systems are knowledge-based or rule-based ones constructed from human knowledge in the form of fuzzy IF-THEN rules.

Let us suppose a linguistic term set with seven labels may be used for ***failure rate*** (i.e., J_1=7); five labels for ***consequence severity*** (i.e., J_2=7), seven labels for ***failure consequence probability*** (i.e., J_3=7)**,** described before.

Being *L* the total number of rules, in this case will be used a sample of 245 rules [6].

Step #4: Fuzzy rule-base inference mechanism

Suppose a fuzzy rule-base with the belief structure is given by *R*= {R_1,…, R_L}. The k^{th} rule in (1) can be represented as follows:

R_k: IF *U* is A^k

THEN ***safety estimate*** is *D* with belief degree γ_k ,

where *U* represents the antecedent attribute vector (**FR**, **CS**, **FCP**), A^k the packet antecedents { A_1^k , A_2^k , A_3^k }, *D* the consequent vector (D_1,…, D_N), γ_k the vector of the belief degrees (γ_{1k} ,,…,γ_{Nk}) and $k\in\{1,\ldots, L\}$.

Once a rule-base is built up, the knowledge contained in it can be used to perform the inference procedure.

In order to reach a safety assessment the fuzzy reasoning system expresses the ***safety estimates*** $S(e_i(a_l))$ as follows for the assessment done by the i^{th} expert e_i on the l^{th} potential cause a_l to a technical failure:

$$S\left(e_i\left(a_l\right)\right)=\left\{\begin{matrix}\left(Poor\,;\vartheta_{1i}^l\right),\left(Low;\vartheta_{2i}^l\right),\left(Average\,;\vartheta_{3i}^l,\right)\\ ;\left(High\,;\vartheta_{4i}^l,\right),\left(Good\,;\vartheta_{5i}^l\right)\end{matrix}\right\}$$

where e_i represents the i^{th} expert (i=1,…, p) and a_l represents the l^{th} (l=1,…, q) potential cause to a technical failure. ϑ_{ti}^l represents the belief degree to which the safety of a_l is believed to be assessed to D_t by the expert e_i. The inference procedure is based on fuzzy rule-base and evidential reasoning approach, referred to as a *fuzzy rule-based evidential reasoning approach* – FURBER approach [6]. The final result is still a belief distribution on safety expression, which gives a panoramic view about the safety level for a given input.

In this phase for the synthesis purpose, we transform the safety estimate into a linguistic 2-tuple, i.e., transform the distribution assessment $S(e_i(a_l))$ on the S_S into linguistic 2-tuples over the S_S.

Definition 3. *Let* χ_i^l *a function that transforms a distribution assessment in a linguistic term set* S_S *into a numerical value in the interval of granularity of* S_S*, [0, g-1], where g is the cardinality of* S_S*:*

$$\chi_i^l : S(e_i(a_l)) \rightarrow [0, g-1]$$

$$\chi_i^l(\{(s_t;\vartheta_{ti}^l), t=0,\ldots,g-1\}) = \frac{\sum_{t=0}^{g} t\,\vartheta_{ti}^l}{\sum_{t=0}^{g}\vartheta_{ti}^l} = \beta_i^l$$

Therefore, applying the Δ function (Definition 2) to β_i^l (i=1,…, p; l=1,…, q) we shall obtain a safety estimate whose values are linguistic 2-tuples (by the i^{th} expert on the l^{th} potential cause to a technical failure), e.g., if β_i^l = 1.2, then its equivalent linguistic 2-tuple representation is:

$$\Delta(1.2) = (Low, 0.2)$$

3.2 Cost modelling

Cost and safety are two important criteria in the 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 [10].

These factors can be different in each engineering system and often include uncertainties. Therefore, it may be more appropriate to model cost incurred in safety improvement associated with design options on a subjective basis.

In the literature [9, 10] cost was estimated and described using fuzzy sets over the linguistic variables belonging to the linguistic term set, $\mathbf{S_C}$, with seven labels. In our case we shall use linguistic labels belong to a linguistic term set whose linguistic terms have a semantic triangular shaped and symmetrically distributed:

S_C *={Very Low, Low, Moderately Low, Average, Moderately High, High, Very High}*

Remark 1. *Cost assessments have a different interpretation of suitability for the design option regarding of safety assessments, i.e., high cost assessments indicate low suitability of the design option.*

3.3 Technical performance modelling

Performance measurement is an area that has become increasingly important, sophisticated and more demanding. So technical performance is taken into account as evaluation criterion to rank the different design options for engineering systems [8]. The technical performance is different in each engineering system and usually include uncertainties. Due to this fact, it is difficult to fix a linguistic term set for measuring technical performance suitable to any engineering system. In this contribution we propose the use of a linguistic term set with nine terms, denoted as S_P, to assess the technical performance, but it could be possible to use different linguistic term sets depending on the engineering system on the performance we are dealing with.

In our case the experts provide their preferences about the technical performance using the linguistic term set S_P, simmetrically disrituted whose syntax are:

S_P ={None, Very Unsuitable, Unsuitable, A Little Unsuitable, Suitable, More than Suitable, Very Suitable, Almost Totally Suitable, Perfect}

Now cost, safety and technical performance assessments are expressed by means of linguistic values but in different linguistic utility spaces. In section 4 we propose an evaluation model based on a decision process able to deal with this multi-granular linguistic context.

4 EVALUATION MODEL: RANKING OPTIONS

Our aim is to choose the most suitable design option for an engineering system taking into account the features of safety, cost and technical performance. So far, the assessments of safety are assessed in S_S while the assessments of the cost are assessed in S_C and for technical performance in S_P. Therefore, to rank the options we shall apply a multi-granular linguistic decision model in order to solve our problem. This model is based on the models presented in [3, 5] to deal with multi-granular linguistic information in decision analysis that consist of two phases:

- *Aggregation phase*: it combines the assessments of safety and cost of the different experts into an overall suitability assessment for each design option. This phase has two steps:
  1. Normalization process: it makes the multi-granular linguistic information uniform over a linguistic term set called Basic Linguistic Term Set (BLTS).
  2. Aggregation process: it combines the information unified to obtain an overall value of suitability for each design option.
- *Exploitation phase*: it ranks the different design options according to assessments obtained in the aggregation phase by means of a choice degree.

We shall describe in further detail the steps of the decision model used to solve our multi-granular linguistic decision making problem.

Our problem is modelled as a MEMC-DM problem where each expert *i*, provides assessments for the cost and technical performance and according to his/her opinions the safety assessments are synthesised using the FURBER approach:

Design Options	*Criteria*		
Expert i	**Safety**	**Cost**	**Tech. Per.**
o_1	**(s_{i1}, α)**	**$(c_{i1}, 0)$**	**$(p_{i1}, 0)$**
:	**:**	**:**	**:**
o_n	**(s_{in}, α)**	**$(c_{in}, 0)$**	**$(p_{in}, 0)$**

Table 1. Expert's assessments

where (s_{ij}, α) are the safety assessments synthesized from the opinions of the expert e_i for the design option o_j, 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 S_S. While (c_{ij}, α) and (p_{ij}, α) are the assessments for cost and technical performance provided by the expert e_i for each design option o_j, assessed by linguistic values in the linguistic sets S_C and S_P.

4.1 Aggregation phase

In this phase the individual information of each expert is combined to obtain collective preference values for each design option. But as the criteria are assessed in a multi-granular linguistic context this phase combines the information in two steps.

A) Normalization Process

We are dealing with multi-granular linguistic information, to manage it the model unifies it in a common utility space, the BLTS. In the literature related to engineering systems evaluation [12,6] the utility space used to express the suitability of an engineering system is the following linguistic term set

S_T={*Slightly Preferred, Moderately Preferred, Average, Preferred, Greatly Preferred*}

So we propose it as BLTS.

Remark 2: *during the aggregation process we shall not use this syntax because it might be lead to misunderstandings due to the cost assessments have a decreasing interpretation and this syntax do not reflect it. Hence during the aggregation computations we shall use the notation, s_i^5, to refer to the aggregated values and when we obtain the overall utility values then they will be expressed by means of the syntax of BLTS.*

Once we have chosen the common utility space to express the suitability of the design options we shall transform all the input assessments into linguistic 2-tuples assessed in the BLTS. To do so firstly, we should notice:

a) Safety assessments are expressed in S_S that is similar to S_T except in the syntax. So the transformation of the safety assessments will consist of using the syntax of the BLTS without any other change.

b) Regarding the cost and technical performance assessments, they are assessed in S_C and S_P linguistic term sets with different granularity, syntax and semantics to the BLTS. So to convert these assessments into linguistic 2-tuples in the BLTS, we shall use the following process based on two different decision models presented in [3, 5]:

a. *Transforming linguistic values into fuzzy sets in the BLTS*: We use a transformation function which convert any linguistic value assessed S_C or S_P into a fuzzy set in S_T.

Definition 4. *Let* $S=\{s_0,...,s_p\}$ *and* $S_T=\{c_0,...,c_g\}$ *be two linguistic term sets, such that, p+1 and g+1 are the granularity of S and* S_T *respectively. Then, a multi-granularity transformation function,* τ_{SS_T} *is defined as:*

$$\tau_{SS_T}: S \rightarrow F(S_T)$$

$$\tau_{SS_T}(s_{ij}^L)=\{(c_k,\gamma_k)/k\in\{0,...,g\}\},\forall s_{ij}^L\in S$$

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

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

Using τ_{SS_T} such that *S* will be S_C and S_P we have converted the assessments provided by the experts for cost and technical performance into fuzzy sets in the BLTS. Therefore, at this moment the safety assessments are expressed by linguistic 2-tuples in S_T and cost and technical performance by means of fuzzy sets in S_T. So to unify all the information into linguistic 2-tuples in the BLTS we should transform the fuzzy sets we have just obtained using τ_{SS_T} into linguistic 2-tuples.

b. *Transforming fuzzy sets in* S_T *into linguistic 2-tuples in* S_T: The cost and technical performance assessments expressed by means of fuzzy sets in the BLTS are transformed into linguistic 2-tuples in the BLTS. This transformation is carried out using the χ function (Def. 3) and the Δ function (Def. 2). Now all the input assessments (safety, cost and technical performance) are expressed in an uniform way by means of linguistic 2-tuples in the BLTS.

Let us suppose that the expert ***i*** provide the assessments for cost and technical performance and the synthesised values for safety are (see Table 2):

	Expert i		
Options	**Safety**	**Cost**	**Tech. Per.**
$\mathbf{o_1}$	**(Poor,0.27)**	**(Moderated High,0)**	**(Suitable,0)**
:	**…**	**…**	**…**
$\mathbf{o_n}$	**(Low,-0.46)**	**(High,0)**	**(Very Suitable,0)**

Table 2. Input assessments provided by Expert *i*

After the normalization process we shall obtain as input assessments (see Table 3):

Options	*Expert i*		
	Safety	**Cost**	**Tech. Per.**
$\mathbf{o_1}$	**(s_0^5,0.27)**	**(s_3^5,-0.26)**	**(s_2^5,0.01)**
:			
$\mathbf{o_n}$	**(s_1^5,-0.46)**	**(s_3^5,0.25)**	**(s_3^5,-0.06)**

Table 3. Input assessments from expert *i* expressed by means of linguistic 2-tuples in the BLTS

This transformation is applied to all the expert opinions.

B) Aggregation Process

This process combines the assessments that express the values for the different criteria to obtain a global value for each design option. We want to obtain an evaluation value for each design option according to its values for cost, technical performance and safety expressed by means of linguistic 2-tuples in the BLTS. This global value will be expressed with the syntax of S_T. In this case we propose the use of the 2-tuple weighted aggregation operator [2]. We have a set of pairs of assessments $\{(s_i,\alpha),(c_i,\alpha),(t_i,\alpha)\}\in S_T$ for each design option. Taking into account Remark 1, since the cost assessments have a decreasing interpretation for the suitability, the aggregated value for each design option is obtained using the following expression:

$$W\_AM^*((s_i,\alpha),(c_i,\alpha),(t_i,\alpha)) =$$
$$\Delta\left(\Delta^{-1}(s_i,\alpha)\cdot\omega_s + \Delta^{-1}(Neg(c_i,\alpha))\cdot\omega_c + \Delta^{-1}(t_i,\alpha)\cdot\omega_p\right)$$

where $Neg\,(c_i,\alpha)$ is the assessment for the cost of design option *i* taking into account its decreasing interpretation and (s_i,α), (t_i,α) are the assessments for the safety and technical performance of the option *i* respectively. And $\omega_s,\omega_c,\omega_p$ such that $\omega_s+\omega_c+\omega_p=1$ being the importance for each criterion safety, cost and technical performance respectively. Suppose a value of $\omega_s=0.6$. $\omega_c=0.2$ and $\omega_p=0.2$. From Table 3 we obtain a global value for each option for each expert **i** (see Table 4):

Design Options	
Options *j*	**Utility**
$\mathbf{o_1}$	**(Moderated Preferred, 0.01)**
: :	: :
$\mathbf{o_n}$	**(Moderated Preferred, 0.24)**

Table 4. Design Options Utility Assessments

At this moment we have a suitability value of each design option expressed by means of a linguistic 2-tuple in S_T for each expert. To obtain a global suitability assessment for each design option we shall apply another aggregation operator to the global assessments of all experts. Now, we could consider that all the experts are equally important (arithmetic mean) or we could assign different weights to each expert (weighted average).

4.2 Exploitation phase

Finally the decision process applies a choice degree to obtain a selection set of alternatives. Different choice functions have been proposed in the choice theory literature [7]. The choice functions rank the alternatives according to different possibilities and from the ranking the best one/s are obtained.

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 we shall order the results using this order. If there is an only expert as in the Table 4 we could infer that the best design option is $\mathbf{o_n}$.

5 CONCLUSIONS

In this contribution we have presented an evaluation approach for design assessment of complex engineering systems based on a linguistic decision model. The use of a linguistic model is due to the fact that it is difficult to deal with vagueness and uncertainty using traditional probabilistic models and tools. The linguistic assessment approach provides a useful and natural way to support the solution of such complex decision problems. Our proposal is based on the evaluation of cost, technical performance and safety and can deal with multi-granular linguistic information. In the safety assessment, a fuzzy rule-base with the belief structures is used to capture uncertainty and nonlinear causal relationships in safety assessments. The evaluation is implemented by means of a multi-granular linguistic MEMC decision model.

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