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Dealing with heterogeneous information in engineering evaluation processes

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Abstract

Before selecting a design for a large engineering system several design proposals are evaluated studying different key aspects. In such a design assessment process, different criteria need to be evaluated, which can be of both of a quantitative and qualitative nature, and the knowledge provided by experts may be vague and/or incomplete. Consequently, the assessment problems may include different types of information (numerical, linguistic, interval-valued). Experts are usually forced to provide knowledge in the same domain and scale, resulting in higher levels of uncertainty. In this paper, we propose a flexible framework that can be used to model the assessment problems in different domains and scales. A fuzzy evaluation process in the proposed framework is investigated to deal with uncertainty and manage heterogeneous information in engineering evaluation processes.

Keywords: Engineering; Evaluation processes; Heterogeneous information; Fuzzy sets; 2-Tuple fuzzy linguistic model; Decision making

1. Introduction

The minimization of cost in selecting a design option is traditionally the main objective in the design of engineering systems. Nowadays design selection has become much more complicated due to the necessity of reaching a required level of safety whilst also keeping cost low. Multi-criteria decision making (MCDM) techniques [18] can be used to help choose the best design among different design options for an engineering system.

The evaluation of different design options often involves experts from different areas with distinct knowledge and multiple criteria need to be taken into account. These criteria may have different kinds of nature, either quantitative or qualitative, and assessment information provided by the experts can be vague or

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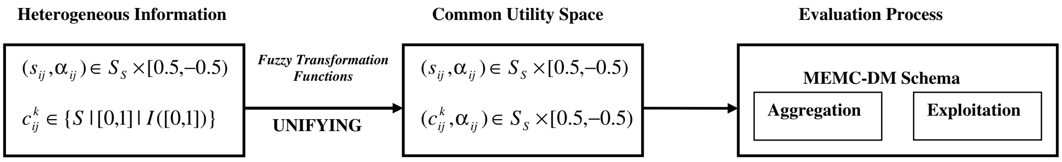

Fig. 1. Fuzzy evaluation schema for dealing with heterogeneous information.

uncertain. Many aspects of uncertainties in this type of problems have non-probabilistic characteristics since they are related to imprecision and vagueness in meanings. Therefore, linguistic descriptors, such as *likely* and *impossible,* are used by engineers and safety analysts to describe an event. In such cases, the fuzzy linguistic approach [21–24] provides a systematic way to represent linguistic variables in a natural decision-making procedure. It does not require an expert to provide a precise point at which a risk factor exists. So it can be used as a complementary tool to classical methods to deal with uncertainty, and especially linguistic information is suitable for representing risk factors in risk analysis [4,14–16].

As mentioned above, it is not uncommon that evaluation frameworks for modeling these problems could be heterogeneous. The assessments provided by experts may be measured in different formats such as real numbers and intervals for quantitative criteria and linguistic terms for qualitative ones according to expert's knowledge areas and the nature of evaluated criteria.

This paper aims to develop a fuzzy evaluation schema based on a decision model (see Fig. 1), which can be used to deal with heterogeneous information, and also to evaluate different engineering design options in light of *safety* and *cost* criteria that will be assessed using different formats.

First of all, we define an evaluation framework used in this schema.

- Safety will be assessed based on fuzzy logic and the evidential reasoning approach, referred to as a *belief rule-based evidential reasoning* (BRBER) approach [10,19]. The synthesis of the safety assessments for each option is expressed and implemented using a linguistic 2-tuple scheme [7].
- The cost assessments will be supplied directly by experts and measured according to the nature and the uncertainty of experts' knowledge (numerical, interval-valued and linguistic labels).
- All these assessments defined in a heterogeneous context will be used as the inputs for a multi-expert multi-criteria decision making (MEMC-DM) problem used to evaluate and rank the different design options.

Once the framework has been defined we then propose a two-step resolution scheme [13] for solving the MEMC-DM problem to evaluate the different engineering design options:

- *Step 1, Aggregation*: It computes a collective value that represents as a whole the input assessments provided by all experts regarding each design option.
- *Step 2, Exploitation*: The options are ranked to choose the most suitable one.

The main difficulty to solve the above problem comes with the aggregation process for assessments conducted in different formats. We propose different fuzzy transformation functions to manage this type of information and thus solve the problem.

This paper is structured as follows. In Section 2, we review some linguistic foundations used in the fuzzy evaluation process to deal with heterogeneous information. In Section 3 we present our evaluation framework for this problem. In Section 4 we define different fuzzy transformation functions to deal with heterogeneous information. In Section 5 we outline the evaluation process to rank the design options for an engineering system. The paper is concluded in Section 6.

2. Linguistic background

This section revises some concepts about the fuzzy linguistic approach and the linguistic 2-tuple model that we shall use to deal with heterogeneous information.

2.1. Fuzzy linguistic approach

Information in a quantitative setting is usually expressed by means of numerical values. However, many aspects 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 such a case, a better approach may be the use of linguistic assessments instead of numerical ones. The fuzzy linguistic approach represents qualitative aspects as linguistic values by means of linguistic variables [21–24]. This approach has been successfully applied to many different areas [2,3,6,17,20].

The use of the fuzzy linguistic approach implies to choose the appropriate linguistic descriptors for the term set and their semantics. The universe of the discourse over which the term set is defined is problem specific and linguistic term sets are usually defined in the interval $[0,1]$.

One possibility of generating the linguistic term set is to directly supply the term set by considering all terms distributed on a scale on which a total order is defined [6], e.g., a set of five terms S, could be given as:

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

In these cases, it is usually required that there exist:

- A negation operator $\mathrm{Neg}(s_i) = s_j$ such that $j = g - i$ ($g + 1$ is the cardinality).
- A *min* and a *max* operator in the linguistic term set: $s_i \leqslant s_j \iff i \leqslant j$.

The semantics of the terms are given by fuzzy numbers defined in the interval of $[0,1]$, which are described by membership functions. One way to characterize a fuzzy number is to use a representation based on the parameters of its membership function [3]. This parametric representation is achieved by the 4-tuple $(\mathbf{a},\mathbf{b},\mathbf{d},\mathbf{c})$, where $\mathbf{b}$ and $\mathbf{d}$ indicate the interval in which the membership value is 1, with $\mathbf{a}$ and $\mathbf{c}$ indicating the left and right limits of the definition domain of the trapezoidal membership function [3]. For example, we may assign the following semantics to the set of five terms, see Fig. 2.

2.2. The 2-tuple fuzzy linguistic representation model

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. This model has initially overcome the drawback of the loss of information [7,8] presented by the classical linguistic computational models [5,6] and has additionally shown its abilities in managing heterogeneous information.

Definition 1. The symbolic translation of a linguistic term $s_i \in S = \{s_0, \ldots, s_g\}$ 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 $\{0, \ldots, g\}$ that indicates the index of the closest linguistic term in S (s_i), being $[0, g]$ the interval of granularity of S.

Following Definition 1, this model represents the linguistic information by means of 2-tuples (s_i, α_i), $s_i \in S$ and $\alpha_i \in [-0.5, 0.5)$. This model defines a set of functions between the linguistic 2-tuple and numerical values.

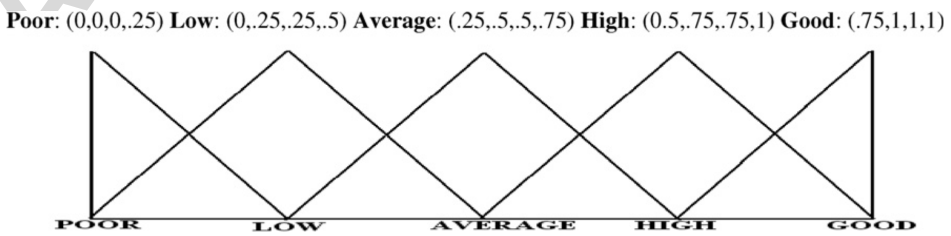

Fig. 2. A linguistic term set of five terms and its semantics.

Definition 2. Let $S = \{s_0, \ldots, s_g\}$ 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 using the following function:

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

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

where s_i has the closest index label to "β" and "α" is the symbolic translation.

Proposition 1 [7]. *Let $S = \{s_0, \ldots, s_g\}$ be a linguistic term set and (s_i, α_i) be a linguistic 2-tuple. There is always a function Δ^{-1} such that from a 2-tuple it returns its equivalent numerical value $\beta \in [0, g]$ in the interval of granularity of S.*

This model has a computational technique with aggregation, comparison and negation operators [7].

3. Evaluation framework

Every evaluation process is defined in an evaluation framework in which criteria are assessed. Assessment criteria are *safety* and *cost* in our case-study.

3.1. Safety evaluation

Safety is assessed using a framework based on fuzzy logic and the evidential reasoning approach, referred to as the BRBER approach [10,19]. In this framework safety evaluation is generated as a fuzzy variable described linguistically using the linguistic term set, S_S (see Fig. 2):

$$S_S = \{\text{Poor}, \text{Low}, \text{Average}, \text{High}, \text{Good}\}.$$

The BRBER approach uses a belief rule-base with belief structures to capture uncertainty and nonlinear causal relationships in safety assessments. The inference process of such a belief rule-based system was characterized by a rule expression matrix and implemented using the evidential reasoning approach. Hence, we shall obtain as a final result a belief distribution on a safety expression:

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

Being ϑ_i the belief degree to which the safety of a potential cause of technical failure, is believed to be assessed by an expert with the ith linguistic term, $s_i \in S_S$. This belief distribution will be transformed in a rational way into a linguistic 2-tuple in S_S [11], to express experts' safety assessments as, $(s_i, \alpha_i^s) \in S_S \times [-0.5, 0.5)$ (see Table 1). For a further description of this safety evaluation framework, we refer to [10,11,19].

3.2. Cost modeling

Cost and safety are two most important criteria in design of complex engineering systems, but they are usually in conflict because high safety normally leads to high costs. Cost incurred for safety improvement

Table 1
Expert assessments of design options on multiple criteria

Design options	Criteria			
Expert_j	Safety	Cost		
		f_1	$\cdots$	f_k
O_1	(s_{1j}, α_{1j}^s)	c_{1j}^1	$\cdots$	c_{1j}^k
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
O_m	(s_{mj}, α_{mj}^s)	c_{mj}^1	$\cdots$	c_{mj}^k

associated with a design option can be affected by many factors [16], for example, *cost for provision of redundancies of critical components, provision of protection systems, alarm systems, use of more reliable components and cost for system redesign*.

These factors can be different in each engineering system and may include various forms of uncertainty. Therefore, it is appropriate to model several aspects related to cost incurred in safety improvements associated with design options on a subjective basis. In the literature [15] cost was estimated and described using fuzzy sets defined over linguistic variables. Nevertheless, many aspects related to cost could be assessed using numerical assessments (numbers or interval-values).

3.3. An evaluation framework for engineering systems

We model our evaluation problem as a multi-expert multi-criteria decision making problem defined in a flexible framework where experts can provide their assessments on different criteria in different domains and scales. All assessments can be summarized as in Table 1.

Note that (s_{ij}, α^s_{ij}) is the safety assessment provided by expert j for the design option O_i, i.e., it is estimated by the BRBER approach and transformed into a linguistic 2-tuple format. While c^k_{ij} is the cost assessment for the factor k provided by expert j for the design option O_i, it can be assessed in different formats as linguistic terms, numerical values or intervals in $[0, 1]$:

$$(s_{ij}, \alpha_{ij}) \in S_{\mathrm{S}} \times [-.05, 0.5) \quad \text{and} \quad c^k_{ij} \in \{S|[0,1]|I([0,1])\}.$$

4. Fuzzy transformation functions for dealing with heterogeneous information

The evaluation framework presented in the previous section deals with input assessments conducted in different formats. Following the evaluation schema showed in Fig. 1 we have to aggregate them in a common format. The linguistic term set $\boldsymbol{S}_{\mathrm{S}}$ can be chosen as the common format to unify the heterogeneous information. This decision is made in order to improve the comprehension of the final results and to facilitate the unification and evaluation processes, because it implies a small number of transformation steps in the unification process.

This section presents the transformation functions which we use to unify linguistic, numerical and interval-valued information into the common format, S_{S}. The heterogeneous information will be unified into fuzzy sets in the linguistic term set S_{S} and they will be further transformed into linguistic 2-tuples.

4.1. Transforming numerical values into fuzzy sets in S_S

Let $s^N_{ij} \in [0, 1]$ be a numerical assessment provided by experts for cost. Then we will transform it into a fuzzy set in S_{S} computing its membership degree in each linguistic term of the term set S_{S}. To do so, we use the following transformation function:

$$\begin{aligned}
&\tau : [0,1] \to F(S_{\mathrm{S}}),\\
&\tau(s^N_{ij}) = \{(s_0, \gamma_0), \ldots, (s_g, \gamma_g)\},\ s_i \in S_{\mathrm{S}},\ \gamma_i \in [0,1],\\
&\gamma_i = \mu_{s_i}(s^N_{ij}) = \begin{cases} 0 \text{ if } s^N_{ij} \notin & \text{Support } \left(\mu_{s_i}\left(s^N_{ij}\right)\right),\\ \frac{s^N_{ij} - a_i}{b_i - c_i} & \text{if } a_i < s^N_{ij} < b_i,\\ 1 & \text{if } c_i < s^N_{ij} < d_i,\\ \frac{c_i - s^N_{ij}}{c_i - d_i} & \text{if } d_i < s^N_{ij} < c_i. \end{cases}
\end{aligned} \tag{1}$$

Remark 1. In (1) the membership function, $\mu_{s_i}\left(s^N_{ij}\right)$, is represented over the linguistic term set $s_i \in S_{\mathrm{S}}$ by a parametric function (a_i, b_i, c_i, d_i), see Fig. 2.

For example, $s_{ij}^N = 0.78$ can be transformed into a fuzzy set S_S as follows:

$$\tau(0.78) = \{(s_0, 0), (s_1, 0), (s_2, 0), (s_3, 0.88), (s_4, 0.12)\}.$$

4.2. Transforming linguistic labels in S into fuzzy sets in S_S

Let $s_{ij}^L \in S$ be a linguistic label provided by experts for cost. Then we can transform it into a fuzzy set in S_S as follows:

$$\begin{aligned} &\tau_{SS_S} : S \to F(S_S), \\ &\tau_{SS_S}\left(s_{ij}^L\right) = \{(s_0, \gamma_0), \ldots, (s_g, \gamma_g)\},\ s_i \in S_S,\ \gamma_i \in [0, 1], \\ &\gamma_i = \max_y \ \min\{\mu_{s_{ij}^L}(y), \mu_{s_k}(y)\}, \end{aligned} \tag{2}$$

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

Suppose a linguistic term set with seven labels $C = \{c_0, \ldots, c_6\}$ is triangle-shaped and symmetrically distributed. Let $s_{ij}^L = c_3$ be a linguistic term whose semantic is $(0.16, 0.33, 0.33, 0.5)$. Its transformation into a fuzzy set in S_S is given by:

$$\tau_{CS_S}(c_3) = \{(s_0, 0), (s_1, 0.32), (s_2, 1), (s_3, 0.32), (s_4, 0)\}.$$

4.3. Transforming interval-valued assessments into fuzzy sets in S_S

Let $s_{ij}^I = [\underline{i}, \overline{i}]$ be an interval value in $[0,1]$, before transforming the interval-value is assumed the representation based on the membership function of the fuzzy sets [9], as in (3).

$$\mu_I(\vartheta) = \begin{cases} 0 & \text{if } \vartheta < \underline{i} \\ 1 & \text{if } \underline{i} \leqslant \vartheta \leqslant \overline{i} \\ 0 & \text{if } \overline{i} < \vartheta \end{cases} \tag{3}$$

Therefore the transformation function we propose to transform the interval value into a fuzzy set in S_S is as follows:

$$\begin{aligned} &\tau_{IS_S} : I([0, 1]) \to F(S_T), \\ &\tau_{IS_S}\left(s_{ij}^L\right) = \{(c_k, \gamma_k)/k \in \{0, \ldots, g\}\}, \\ &\gamma_k^i = \max_y \ \min\{\mu_{s_{ij}^I}(y), \mu_{c_k}(y)\}, \end{aligned} \tag{4}$$

where $\mu_{s_{ij}^I}(y)$ is the membership function associated with the interval-valued s_{ij}^I. Suppose that $s_{ij}^I = [0.6, 0.78]$. Its transformation into a fuzzy set in S_S is given by:

$$\tau_{IS_S}([0.6, 0.78]) = \{(s_0, 0), (s_1, 0), (s_2, 0.6), (s_3, 1), (s_4, 0.2)\}.$$

4.4. Transforming fuzzy sets in S_S into linguistic 2-tuples in S_S

Now, the assessments provided by experts for cost are expressed in the same format as for safety but its modeling is still different from the safety modeling. The next function presents how to transform the fuzzy sets in S_S into the linguistic 2-tuples in S_S:

$$\begin{aligned} &\chi : F(S_S) \to S_S \times [-0.5, 0.5), \\ &\chi\left(\tau\left(s_{ij}^-\right)\right) = \chi(\{(s_j, \gamma_j),\ j = 0, \ldots, g\}) = \Delta\left(\sum_{j=0}^{g} j \cdot \gamma_j \Big/ \sum_{j=0}^{g} \gamma_j\right). \end{aligned} \tag{5}$$

Table 2
Unified assessments of design options on each criterion

Options	Criteria			
Expert$_j$	Safety	Cost		
		f_1	…	f_k
O_1	$\left(s_{1j}, \alpha^s_{1j}\right)$	$\left(c^1_{1j}, \alpha^{c1}_{1j}\right)$	…	$\left(c^k_{1j}, \alpha^{ck}_{1j}\right)$
⋮	⋮	⋮	⋮	⋮
O_m	$\left(s_{mj}, \alpha^s_{mj}\right)$	$\left(c^1_{mj}, \alpha^{c1}_{mj}\right)$	…	$\left(c^k_{mj}, \alpha^{ck}_{mj}\right)$

An example of such a transformation function could be as:

$$\chi(\tau_{IS_S}([0.6, 0.78])) = \chi(\{(s_0, 0), (s_1, 0), (s_2, 0.6), (s_3, 1), (s_4, 0.2)\}) = (s_3, -0.22).$$

Therefore, using the functions (1), (2), (4) and (5) we can unify the heterogeneous input information provided by experts on different criteria. In the next subsection we shall present the whole unification process.

4.5. Unifying the heterogeneous information in a common format

The unification process starts from the given values in Table 1. According to our evaluation framework the safety assessments are synthesized by means of the BRBER approach [10,19] and transformed to linguistic 2-tuples assessed in S_S [11], $(s_i, \alpha^S_i) \in S_S \times [-0.5, 0.5)$. These assessments are already expressed in the selected common format.

As cost assessments are assessed in different domains (numerical, interval-valued, or linguistic), we shall unify them into fuzzy sets and further transform into linguistic 2-tuples in S_S using the transformation functions (1), (2), (4) and (5):

- Numerical assessments:

  $$\tau\left(c^k_{ij}\right) = \{(s_0, \gamma_0), \ldots, (s_g, \gamma_g)\}, \; s_i \in S_S, \; \gamma_i \in [0, 1].$$

- Linguistic assessments:

  $$\tau_{SS_S}\left(c^k_{ij}\right) = \{(s_0, \gamma_0), \ldots, (s_g, \gamma_g)\}, \; s_i \in S_S, \; \gamma_i \in [0, 1].$$

- Interval valued assessments:

  $$\tau_{IS_S}\left(c^k_{ij}\right) = \{(s_0, \gamma_0), \ldots, (s_g, \gamma_g)\}, \; s_i \in S_S, \; \gamma_i \in [0, 1].$$

  So, all cost assessments are now expressed by means of fuzzy sets in S_S:

  $$\{(s_0, \gamma_0), \ldots, (s_g, \gamma_g)\}, \; s_i \in S_S, \; \gamma_i \in [0, 1].$$

- To transform the fuzzy sets in S_S into linguistic 2-tuples in S_S, we use the function $\chi\left(\tau_{-}\left(c^k_{ij}\right)\right)$. At this moment all assessments are expressed by means of 2-tuples in S_S (see Table 2).

In Table 2 $\left(s_{ij}, \alpha^s_{ij}\right)$ is the safety assessments synthesized from the opinions of expert j for the design option O_i and $\left(c^k_{ij}, \alpha^{ck}_{ij}\right)$ is the cost assessment for factor k provided by expert j for the design option O_i, both expressed as linguistic 2-tuples in the common format.

5. Evaluation process: ranking design options for an engineering system

The last task of the evaluation schema presented in Fig. 1 is the *evaluation process* in which different design options are ranked once the information has been unified. This evaluation process is based on two phases: (i) aggregation and (ii) exploitation.

5.1. Aggregation

Suppose there are 2 options that are assessed by 2 experts on 2 cost factors. From the unification process suppose that we have already obtained the assessments of Table 3.

The aggregation phase aims to obtain a collective utility value for each design option according to all experts' opinions. To do so, first of all, it computes an overall cost value for each design option using a 2-tuple aggregation operator for each expert. To simplify the computations for this example we shall use the extended arithmetic mean [7] assuming that all cost aspects are equally important:

$$\left(c_{1j},\alpha_{1j}^{c}\right)=\mathrm{AM}^{*}\left(\left(c_{1j}^{1},\alpha_{1j}^{c}\right),\ldots,\left(c_{1j}^{k},\alpha_{1j}^{c}\right)\right)=\frac{1}{k}\sum_{i=1}^{k}\Delta^{-1}\left(c_{1j}^{i},\alpha_{1j}^{c}\right).$$

Applying this operator to Table 3, we obtain the cost overall assessment of Table 4.

The objective is to obtain a collective value for each design option. Therefore, the overall utilities of each option on all criteria are aggregated to obtain an overall utility. Here we use the 2-tuple arithmetic mean for this computation. According to Section 3.2 we must keep in mind that not all criteria are monotonic (e.g., the higher the cost, the less the suitability). To obtain a valid overall utility value for each design option, the values to be aggregated must have the same interpretation. In our case we convert cost assessments into an increasing interpretation by computing their negation. Collective cost values are thus computed as follows:

$$(p_{ij},\alpha_{ij})=\mathrm{AM}^{*}\left(\left(s_{ij},\alpha_{ij}^{s}\right),\mathrm{Neg}(c_{ij},\alpha_{ij}^{c})\right),$$

where (p_{ij},α_{ij}) is the overall utility value for the option O_i according to expert j. In our example the overall utility obtained for each expert is showed in Table 5.

Table 3
Unified experts assessments

Options	Criteria					
	Expert$_1$			Expert$_2$		
	Safety	Cost		Safety	Cost	
		f_1	f_2		f_1	f_2
O_1	$(s_1,0.3)$	$(s_3,0.12)$	$(s_2,-0.23)$	$(s_2,-0.3)$	$(s_2,0.1)$	$(s_2,0.2)$
O_2	$(s_2,-0.1)$	$(s_1,0.45)$	$(s_2,-0.3)$	$(s_2,0.1)$	$(s_2,-0.3)$	$(s_2,0.45)$

Table 4
Overall assessments of design options on each criterion

Options	Criteria			
	Expert$_1$		Expert$_2$	
	Safety	Cost	Safety	Cost
O_1	$(s_1,0.3)$	$(s_2,0.44)$	$(s_2,-0.3)$	$(s_2,0.15)$
O_2	$(s_2,-0.1)$	$(s_2,-0.43)$	$(s_2,0.1)$	$(s_2,0.08)$

Table 5
Overall assessments of design options on all criteria

Design options	Criteria (collective assessment)	
	Expert$_1$	Expert$_2$
O_1	$(s_1,0.43)$	$(s_2,-0.22)$
O_2	$(s_2,0.23)$	$(s_2,0.01)$

Table 6
Collective assessments for each design option according to all the experts

Design options	Collective assessment
O_1	$(s_2, -0.4) \Rightarrow (\text{Average}, -0.4)$
O_2	$(s_2, 0.12) \Rightarrow (\text{Average}, 0.12)$

As the evaluation process is a multi-expert problem we have to aggregate the utility values obtained from experts to obtain a collective utility value for each design option. In our case again, we shall use the arithmetic mean, obtaining in our example the results showed in Table 6

$$(p_i, \alpha_i) = \mathrm{AM}^*((p_{ij}, \alpha_{ij})).$$

5.2. Exploitation

In the exploitation phase, the collective values obtained in the aggregation phase, (p_i, α_i) are used to support the selection of alternatives. Different choice functions have been proposed in the choice theory literature [1,12]. The choice functions rank alternatives according to different possibilities and from the ranking the best one/s are obtained. In our framework the information is expressed by means of the linguistic 2-tuple representation that already provides a complete ranking order.

In the example presented in this section the design option O_2 is more suitable than the option O_1 for the evaluated engineering system.

6. Conclusions

To deal with heterogeneous information measured in different formats is a central step in engineering decision processes. In this paper, we focus on the evaluation of design options on both safety and cost criteria. To do so, we defined an evaluation schema and developed an evaluation framework in which information can be assessed in different expression domains and scales, i.e., by means of heterogeneous information. To manage such information different fuzzy functions were proposed to transform heterogeneous information into a common format. Finally, we developed an evaluation process based on a MEMC-DM model to evaluate the suitability of different design options.

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