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A Multi-granular Linguistic Model to Evaluate the Suitability of Installing an ERP System

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Abstract

The use of Enterprise Resource Planning (ERP) has shown clearly useful and economically profitable in most very large organizations which manage a great deal of data in their information systems. Nevertheless, the decision of installing an ERP system is not easy and it depends on the size, future profits and other features of the companies. The assessments of the parameters (features, aspects) used to evaluate the suitability of the ERP may be vague and imprecise because they are usually perceptions of the experts. We propose the use of linguistic information to assess these parameters due to the fact that it is very suitable to model and manage human perceptions. In addition, it may be that each expert has a different knowledge about each parameter and prefers to express his/her preferences in his/her own linguistic term set. Therefore, to manage the evaluation problem of installing an ERP, in this contribution we present a multi-granular linguistic evaluation model that covers these necessities.

1 Introduction

The Enterprise Resource Planning (ERP) system [16, 18] is one of the information technology systems that has produced more changes in the current companies improving their productivity. The ERP systems affect several parts of the companies: they may help to make better decisions in the companies and have produced an optimization of the companies internal value chain and therefore important advantages and profits. However, the installation of an ERP system is always very complex, expensive and has a massive impact in the entire company. Before installing an ERP system, its impact and cost should be studied in order to avoid unsuccessful results in its implementation [16, 18].

In this paper, we shall use decision analysis techniques to evaluate the suitability of installing an ERP system because of the good results obtained by these techniques in other evaluation processes [4, 7, 12].

Most of the evaluation models force the experts involved in the evaluation to use the same fixed numerical evaluation scale to assess the parameters [1, 13, 19]. Nevertheless, we think it would be more suitable and so it should produce better results if the experts work in contexts closer to the experts' knowledge. The knowledge about the parameters evaluated in this process is related to own perceptions of the experts. These perceptions are usually vague and imprecise and are better expressed using words than numbers [22]. Besides, we must take into account that the knowledge of each expert has about the problem could be different from each other and hence, we should let each expert use the linguistic term set most suitable according to his/her knowledge for each parameter. So, we note that is not a seldom situation that the evaluation framework is composed by linguistic labels that belong to different linguistic term sets, i.e., the evaluation framework defines a multi-granular linguistic context.

In this paper, we shall propose an evaluation model defined in a multi-granular linguistic framework to study the suitability of installing an ERP system such as it is modelled as a decision process following a classical decision resolution scheme [17]:

1. *Aggregation phase:* the aim of this step is to obtain a collective value for each parameter according to the knowledge provided by all experts.
2. *Exploitation phase:* this phase will compute a suitability degree from the collective values of each parameter obtained in the before phase. This suitability degree will be used to make a decision regarding the installation of the ERP system.

The main problem of this approach is that there is not any operator to aggregate directly linguistic terms if they belong to different linguistic term sets. However, some works [8, 9, 11] have defined some representation models as the linguistic 2-tuple and operators that let us manage this type of information. We use them in order to develop the proposed evaluation model.

This paper is structured as follows: in section 2 we shall make a brief introduction to Enterprise Resource Planning systems and we shall present the evaluation scheme for our problem; in section 3 we shall make a brief review about core concepts of the Fuzzy Linguistic approach and the 2-tuple representation model. In section 4 we shall present the fuzzy evaluation model for studying the suitability of installing an ERP system and in section 5 we shall present an application of the fuzzy model. Eventually, some concluding remarks are pointed out.

2 Studying the suitability of an ERP system

In this section, we review the importance of an ERP system for a company and we present the evaluation scheme based on an Multi-Expert Decision Making (MEDM) problem that we shall use to evaluate the suitability of an ERP system in a company.

2.1 Enterprise Resource Planning

The goal of an ERP system is to optimize a company's internal value chain, changing, codifying and standardizing an enterprise business process and data. When transactional data, such as a sale, become available, is transformed into useful information and is collated in order to be analyse. This way, all the collected transactional data become information that companies can use to support their business decisions. Some of the benefits that an ERP system can yield are:

- Reduce cycle time.
- Enable faster information transactions.
- Facilitate better financial management.
- Lay groundwork for e-commerce.
- Better production scheduling and make tacit knowledge explicit.

The installation of an ERP system implies a lot of changes and costs in a company. On the one hand, it requires major changes in the organizational, cultural and business process. The organization is one of the most affected part of the company, because of the changes of individual roles that do not contribute in the profits into others more useful to the company. On the other hand, the implementation of an ERP system is always very expensive and time consuming, furthermore the productivity and profits of the company may not increase dramatically in some cases, such as it could be expected. None company can afford a great investment for installing an ERP without being so much worried about the short and long term profits, and so they need a way to know if the installation of the ERP will be profitable.

There is not a easy way to evaluate the suitability of an ERP system, and when companies decide to study the suitability of the ERP, it is very difficult that experts involve in this process agree and provide the same opinion. In this contribution, we present an evaluation model that helps the experts of a company to decide how suitable is the installation of an ERP.

2.2 Studying the Suitability of an ERP system: Evaluation Scheme

Our proposal for evaluating the suitability of an ERP system will model the evaluation process as a multiexpert decision scheme. Our problem consists of evaluating the assessments provided by a group of experts $E = \{e_1, \ldots, e_n\}$, that assess m parameters $X = \{x_1, \ldots, x_m\}$ by means of utility vectors:

$$e_i \rightarrow \{p_{i1}, \ldots, p_{im}\}$$

Let p_{ij} (i $\in\{1,\ldots,n\}$, j $\in\{1,\ldots,m\}$) being the preference assigned to the evaluated parameter x_j by expert e_i. Each expert provides an utility vector with his/her preferences.

One of the main novelties we propose in this paper is that, each expert, e_i, can assess each criterion, x_j, using his/her own linguistic term set related to his/her knowledge about the aspect or feature he/she is evaluating . Therefore, $p_{ij} \in S^i_j$

where S_j^i is the linguistic term set that has been chosen by the expert e_i to evaluate the criterion x_j. This consideration implies that the evaluation framework defined for this problem will be a multigranular linguistic context where the experts can provided their preferences in different linguistic term sets.

In this way, we will have n utility vectors with the experts' preferences:

$$\begin{array}{ccc} e_1 & \rightarrow & \{p_{11}, \ldots, p_{1j}, \ldots, p_{1m}\} \\ \vdots & \vdots & \vdots \\ e_i & \rightarrow & \{p_{i1}, \ldots, p_{ij}, \ldots, p_{im}\} \\ \vdots & \vdots & \vdots \\ e_n & \rightarrow & \{p_{n1}, \ldots, p_{nj}, \ldots, p_{nm}\} \end{array}$$

where $p_{ij} \in S_j^i$.

3 Linguistic Background

We have aforementioned the best way to represent the experts' opinions related to human perceptions is using linguistic terms instead of numbers according to [22]. In this section, we shall review the Fuzzy Linguistic Approach [21], that has shown itself a successful approach for managing phenomena related to human perceptions, and the 2-tuple Representation Model [9] that is an useful representation model to deal with multi-granular information [8, 10]

3.1 Fuzzy Linguistic Approach

Usually, we work in a quantitative setting, where the information is expressed by means of 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 variables which participate in these problems are assessed by means of linguistic terms [21]. This approach is adequate in some situations, for example, when attempting to qualify phenomena related to human perception, we are often led to use words in natural language. This may arise for different reasons. There are some situations where the information may be unquantifiable due to its nature, and thus, it may be stated only in linguistic terms (e.g., when evaluating the "comfort" or "design" of a car, terms like "bad", "poor", "tolerable", "average", "good" can be used [14]). In other cases, precise quantitative information may not be stated because either it is not available or the cost of its computation is too high, then an "approximate value" may be tolerated (e.g., when evaluating the speed of a car, linguistic terms like "fast", "very fast", "slow" are used instead of numerical values). The linguistic approach is less precise than the numerical one, however some advantages may be found using it:

1. The linguistic description is easily understood by human beings even when the concepts are abstract or the context is changing.

2. Furthermore, it diminished the effects of noise since, as it is known the more refined assessment scale is, then more sensitive to noise and consequently the more error facedown it becomes.

In short, the linguistic approach is appropriated for many problems, since it allows a more direct and adequate representation when we are unable to express it with precision. Hence, the burden of qualifying a qualitative concept is eliminated.

The fuzzy linguistic approach represents qualitative aspects as linguistic values by means of linguistic variables.

Usually, depending on the problem domain, an appropriate linguistic term set is chosen and used to describe the vague or imprecise knowledge. The number of elements in the term set will determine the granularity of the uncertainty, that is, the level of distinction among different counting of uncertainty. In our problem different experts can have different knowledge about different parameters that is the reason of the multi-granularity linguistic framework. In [2] the use of term sets with an odd cardinal was studied, representing the mid term by an assessment of "approximately 0.5", with the rest of the terms being placed symmetrically around it and the limit of granularity being 11 or no more than 13.

One possibility of generating the linguistic term set consists of directly supplying the term set by considering all terms distributed on scale on which total order is defined [20]. For example, a set of seven terms S, could be given as follows:

$$S = \{s_0 : none, s_1 : verylow, s_2 : low, s_3 : medium, s_4 : high, s_5 : veryhigh, s_6 : perfect\}$$

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. A max operator: $\max(s_i, s_j) = s_i \ if \ s_i \geq s_j$.
3. A min operator: $\min(s_i, s_j) = s_i \ if \ s_i \leq s_j$

The semantics of the terms is given by fuzzy numbers. A computationally efficient way to characterize a fuzzy number is to use a representation based on parameters of its membership function [2]. 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. The parametric representation is achieved by the 4-tuple (a, b, d, c), where b and d indicate the interval in which the membership value is 1, with a and c indicating the left and right limits of the definition domain of the trapezoidal membership function [2]. A particular case of this type of representation are the linguistic assessments whose membership functions are triangular, i.e., $b = d$, then we represent this type of membership functions by a 3-tuple (a, b, c). And example may be the following:

$$\begin{array}{ll}
P = Perfect = (.83, 1, 1) & VH = Very_High = (.67, .83, 1) \\
H = High = (.5, .67, .83) & M = Medium = (.33, .5, .67) \\
L = Low = (.17, .33, .5) & VL = Very_Low = (0, .17, .33) \\
N = None = (0, 0, .17), &
\end{array}$$

which is graphically shown in Figure 1.

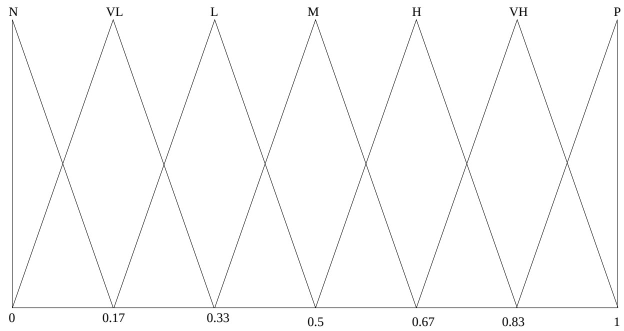

Figure 1: A Set of Seven Terms with its Semantic

Other authors use a non-parametric representation, e.g., Gaussian functions [3].

The use of linguistic variables implies processes of computing with words such as their fusion, aggregation, comparison, etc. To perform these computations there are different models in the literature:

- *The linguistic computational model based on the Extension Principle*, which allow us to aggregate and compare linguistic terms through computations on the associated membership functions [5].
- *The symbolic method* [6]. This symbolic model makes direct computations on labels, using the ordinal structure of the linguistic term sets.
- *The 2-tuple fuzzy linguistic computational model* [9]. It uses the 2-tuple fuzzy linguistic representation model and its characteristics to make linguistic computations, obtaining as results linguistic 2-tuples. A linguistic 2-tuple is defined by a pair of values, where the first one is a linguistic label and the second one is a real number that represents the value of the symbolic translation.

In the following subsection we shall review the 2-tuple model due to the fact, that it will be the representation model we shall use in our evaluation process to deal with multi-granular linguistic information.

3.2 The 2-tuple Representation Model

This model has been presented in [9] and has shown itself as useful to deal with heterogeneous information [10, 11], such as the multi-granular linguistic information that we shall use in this paper.

This linguistic model takes as a basis the symbolic aggregation model [6] and in addition defines the concept of Symbolic Translation.

Definition 1 [9] : *The Symbolic Translation of a linguistic term is a numerical value assessed in [-0.5,0.5) that supports the "difference of information" between an amount of information [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. Graphically, it is represented in Figure 2.*

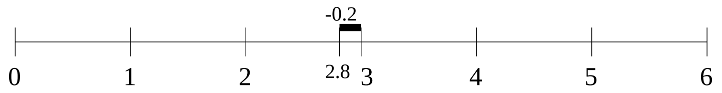

Figure 2: Example of a Symbolic Translation

From this concept in [9] was developed a linguistic representation model which represents the linguistic information by means of 2-tuples (s_i, α_i), $s_i \in S$ and $\alpha_i \in [-.5, .5)$.

This model defines a set of transformation functions between linguistic terms and 2-tuples, and between numeric values and 2-tuples.

Definition 2.[9] *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:*

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

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

where round 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.[9] *Let $S = \{s_0, ..., s_g\}$ be a linguistic term set and (s_i, α) be a 2-tuple. There is a Δ^{-1} function, such that, from a 2-tuple it returns its equivalent numerical value $\beta \in [0, g] \subset \mathcal{R}$.*

Proof.

It is trivial, we consider the following function:

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

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

Remark 1: From definitions 1 and 2 and from proposition 1, it is obvious that the conversion of a linguistic term into a linguistic 2-tuple consist of adding a value 0 as symbolic translation:

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

This representation model has associated a computational model that was presented in [9]:

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 [9] we can find several 2-tuple aggregation operators based on classical ones.

2. **Comparison of 2-tuples:** The comparison of information represented by 2-tuples is carried out according to an ordinary lexico-graphic order.

   - if $k < l$ then (s_k, α_1) is smaller than (s_l, α_2)
   - if $k = l$ then
     (a) if $\alpha_1 = \alpha_2$ then (s_k, α_1), (s_l, α_2) represents the same information
     (b) if $\alpha_1 < \alpha_2$ then (s_k, α_1) is smaller than (s_l, α_2)
     (c) if $\alpha_1 > \alpha_2$ then (s_k, α_1) is bigger than (s_l, α_2)

3. **Negation Operator of a 2-tuple:** The negation operator over 2-tuples is defined as:
$$Neg\,(s_i, \alpha) = \Delta\left(g - \Delta^{-1}\,(s_i, \alpha)\right)$$
   where $g + 1$ is the cardinality of S, $s_i \in S = \{s_0, \ldots, s_g\}$.

4 Evaluating the suitability of an ERP system

Our aim is to know the suitability of an ERP system for a company according to the information provided by the experts regarding the different criteria evaluated. Each expert will provide an utility vector with his/her opinions about different criteria and each criterion will be assessed in the linguistic term set chosen by the expert. The main problem we face in this process is that there is not any operator to aggregate directly multi-granular linguistic information. In the literature we can find multi-expert decision making models that manage this kind of information [8, 11] successfully. Our evaluation model is based on the models aforementioned and is carried out according to the following phases:

1. *Aggregation phase:* The aim of this step is to obtain a collective value for each parameter according to the knowledge provided by all experts.
   (a) *Making the information uniform:* The multigranular linguistic input information is unified into a unique domain by means of fuzzy sets in a basic linguistic term set (BLTS) in order to manage this information.
   (b) *Aggregation process:* Once all the information is expressed by fuzzy sets, this process obtains a collective value for each parameter using an aggregation operator. These collective values will be expressed by means of linguistic 2-tuples [9] in order to improve the comprehensibility of the results.
2. *Exploitation phase:* This phase will compute a suitability degree regarding the suitability of the installation of the ERP from the collective values obtained in the before phase.

In the next subsections, we present in detail the working of both phases.

4.1 Aggregation phase

In this phase the individual evaluation utility vectors provided by the experts are combined to obtain a collective utility vector. As the evaluation framework is a multi-granular linguistic context, to accomplish this phase are needed two stages:

1. *Making the information uniform:* The aim of this stage is to express the information in a unique domain that we note as the basic linguistic term set (BLTS) [9] in order to be able to aggregate the information. To do so, on the one hand, we need to know how to choose the most suitable BLTS for our problem and, on the other hand, a function that transforms the input information into the BLTS.

   Therefore, the first step is to choose the BLTS note as, S_T:

   $$S_T = s_0, \cdots, s_l, \cdots, s_g$$

   Where $g+1$ is the cardinality of the BLTS and s_l is linguistic term l of the BLTS. To choose the BLTS, S_T, we follow the restrictions set defined in [8].

   The next step is to define a transformation function that transforms the input information in the BLTS. We shall define a transformation function that will unify the multi-granular linguistic input information by means of fuzzy sets in the BLTS:

   Definition 3 [8] *Let $S = \{l_0, \ldots, l_p\}$ and $S_T = \{s_0, \ldots, s_g\}$ be two linguistic term sets. Then, a linguistic transformation function, τ_{SS_T}, is defined as:*

   $$\tau_{SS_T} : S \rightarrow F(S_T)$$
   $$\tau_{SS_T}(l_i) = \{(s_k, \gamma_k^i) \,/\, k \in \{0, ..., g\}\}, \forall l_i \in S$$
   $$\gamma_k^i = \max_y \min\{\mu_{l_i}(y), \mu_{s_k}(y)\}$$

   where $F(S_T)$ is the set of fuzzy sets defined in S_T, and $\mu_{l_i}(\cdot)$ and $\mu_{s_k}(\cdot)$ are the membership functions of the fuzzy sets associated with the terms l_i and s_k, respectively.

   The result of τ_{SS_T} for any linguistic value of S is a fuzzy set defined in the BLTS, S_T. Therefore, after unifying the input information with this transformation function the opinions provided by the experts are expressed by means of fuzzy sets in the BLTS.

   Example. Let $A = \{l_0, l_1, \ldots, l_4\}$ and $S_T = \{c_0, c_1, \ldots, c_6\}$ be two term sets, with 5 and 7 labels, respectively, and with the following semantics associated.

l_0	$(0, 0, .25)$	c_0	$(0, 0, .16)$
l_1	$(0, .25, .5)$	c_1	$(0, .16, .34)$
l_2	$(.25, .5, .75)$	c_2	$(.16, .34, .5)$
l_3	$(.5, .75, .1)$	c_3	$(.34, .5, .66)$
l_4	$(.75, 1, 1)$	c_4	$(.5, .66, .84)$
		c_5	$(.66, .84, 1)$
		c_6	$(.84, 1, 1)$

The fuzzy sets obtained after applying τ_{AS_T} for linguistic values l_0 and l_1 are:

$$\tau_{AS_T}(l_0) = \{(c_0, 1), (c_1, .58), (c_2, .18), (c_3, 0), (c_4, 0), (c_5, 0), (c_6, 0)\}$$

$$\tau_{AS_T}(l_1) = \{(c_0, .39), (c_1, .85), (c_2, .85), (c_3, .39), (c_4, 0), (c_5, 0), (c_6, 0)\}.$$

Remark 2 *In the case that the linguistic term set, S, of the multigranular contexts let be chosen as BLTS, then the fuzzy set that represents a linguistic term will be all* **0** *except the value correspondent to the ordinal of the linguistic label that will be* **1**.

Once we have applied this function to the input information we will obtain:

$$\begin{array}{ccc} e_1 & \rightarrow & \left\{p_{11}^{S_T}, \ldots, p_{1j}^{S_T}, \ldots, p_{1m}^{S_T}\right\} \\ \vdots & \vdots & \vdots \\ e_i & \rightarrow & \left\{p_{i1}^{S_T}, \ldots, p_{ij}^{S_T}, \ldots, p_{im}^{S_T}\right\} \\ \vdots & \vdots & \vdots \\ e_n & \rightarrow & \left\{p_{n1}^{S_T}, \ldots, p_{nj}^{S_T}, \ldots, p_{nm}^{S_T}\right\} \end{array}$$

Where $p_{ij}^{S_T} \in F(S_T)$ is a fuzzy set that expresses the preference assigned to the evaluated parameter x_j by the expert e_i and obtained as:

$$p_{ij}^{S_T} = \tau_{SS_T}(p_{ij}) = \left\{\left(s_0, \gamma_0^{ij}\right), \ldots, \left(s_k, \gamma_k^{ij}\right), \ldots, \left(s_g, \gamma_g^{ij}\right)\right\} s_k \in S_T,\ \gamma_k^{ij} \in [0, 1]$$

2. *Aggregating the individual utility vectors:* In this phase, once the information has been unified, we will obtain a collective value, p_j, for each parameter, x_j. To do so, the unified information (fuzzy sets) will be aggregated. The collective utility vector obtained is:

$$\{p_1, \cdots, p_j, \cdots, p_m\}$$

Where p_j is the collective value for the factor x_j and is expressed by means of a fuzzy set in the BLTS:

$$p_j = \{(s_0, \gamma_0^{c1}), \cdots, (s_l, \gamma_l^{cj}), \cdots, (s_g, \gamma_g^{cj})\}$$

and where $s_j \in S_T$ and γ_l^{cj} is compute by means of:

$$\gamma_l^{cj} = \mu(\gamma_l^{ij}),\ i \in \{1, ..., n\}$$

Where μ is an "aggregation operator" and n is the number of experts.

Therefore, these collective values will be expressed by means of fuzzy sets. These fuzzy sets are difficult to manage and hard to understand by the experts. So, in order to simplify the computations and improve the comprehensibility of the results obtained in this phase, we shall transform the collective values expressed by means of fuzzy sets on the BLTS into linguistic 2-tuples in the BLTS. We define the function, χ, to transform directly a fuzzy set in $F(S_T)$ into a linguistic 2-tuple:

$$\chi : F\left(S_T\right) \rightarrow S_T \times [-0.5, 0.5)$$

$$\chi\left(F\left(S_T\right)\right) = \chi\left(\left\{\left(s_j, \gamma_j\right), j = 0, \ldots, g\right\}\right) = \Delta\left(\frac{\sum_{j=0}^{g} j\gamma_j}{\sum_{j=0}^{g}\gamma_j}\right) = \Delta\left(\beta\right) = (s, \alpha)$$

After applying χ to the fuzzy sets in the BLTS, we shall obtain a collective preference vector whose values are expressed by means of linguistic 2-tuples:

$$\left\{p_1' = \left(s_1, \alpha_1\right), \ldots, p_j' = \left(s_j, \alpha_j\right), \ldots, p_m' = \left(s_m, \alpha_m\right)\right\}$$

Where $p_j' = \chi\left(p_j\right)$ and is the collective value for the parameter x_j expressed by means of linguistic 2-tuples.

4.2 Exploitation phase

Once we have obtained the collective preference vector, we want to obtain an overall value expressed by means of a linguistic 2-tuple. This overall value expresses a measurement of the degree of suitability for the installation of the ERP software in the company. To compute this overall measurement we need to aggregate the collective value for each parameter (different aggregation operators can be used depending on the importance of the parameters).

Example: Let suppose that we have m parameters, each parameter has the same importance and the collective preference vector we have obtained in the before step is: $\left\{p_1' = \left(s_1, \alpha_1\right), \ldots, p_j' = \left(s_j, \alpha_j\right), \ldots, p_m' = \left(s_m, \alpha_m\right)\right\}$. So, to compute the degree of suitability for the installation of the ERP software in the company, we use the 2-tuple arithmetic mean presented in [9]:

$$AM^*\left(p_1', \cdots, p_j', \cdots, p_m'\right) = \Delta\left(\sum_{j=1}^{n} \frac{1}{n}\Delta^{-1}\left(p_j'\right)\right) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n}\beta_i\right)$$

However, for the companies obtain a suitable degree is not enough, they need a recommendation or a piece of advice, about if an ERP system should be installed or not. To achieve this goal, we evaluate this suitable degree within a table, such that, according to its value it points out the suitability or unsuitability of installing the ERP system (see Table 1). The values of this table depends on the company, the cost of the ERP, profits per year ,... and must be built after an ad-hoc research.

Where $h_i \in 0, \cdots, g$ and $s_{h_i} \in S_T$ and $S_T = \{s_0, \cdots, s_g\}$

Degree of suitability	**Recommendation**
$\leq s_{h_1}$	Not install
$> s_{h_1}$ and $\leq s_{h_2}$	The installation is not suitable
$> s_{h_2}$ and $\leq s_{h_3}$	The installation is feasible
$> s_{h_3}$ and $\leq s_{h_4}$	The installation is suitable
$> s_{h_4}$	The installation is very suitable

Table 1: Example of table of suitability

5 Example: Evaluating the suitable of installing an ERP.

In this example, we shall evaluate the suitability of installing an ERP in a given company. In this case, we take into account nine basic parameters of the company in order to simplify the computation of the example:

1. x_1 Investment in Information Technologies for employee.
2. x_2 Price of the implementation.
3. x_3 Urgency in the implementation.
4. x_4 Standard degree.
5. x_5 Interrelation with other subsystems.
6. x_6 Capacity of the user to specify.
7. x_7 Request of change by the user.
8. x_8 Availability of staff.
9. x_9 Capacity of influence of the client in the provider.

But in a real case, it could take into account more parameters that will depend on the evaluated company.

Four experts, $E = \{e_1, e_2, e_3, e_4\}$, evaluate the suitability of the ERP. As we have aforementioned, each expert may have a different knowledge about the criteria that he or she is evaluating, and because of this reason we let every expert chooses for each parameter the most suitable linguistic term set in order to express his/her opinion according to his/her knowledge.

In this example the experts can choose among the linguistic term sets showed in the Figure 3 whose semantics can be seen at Table 2. The linguistic term sets that have been chosen by the experts are in Table 3.

The experts will provide their preferences by means of the utility vector showed in Table 4.

At this moment, we shall apply the evaluation process presented in section 4 to the preferences provided by the experts in order to evaluated the suitability of installing the ERP.

Ling. term set A	Ling. term set B	Ling. term set C	Ling. term set D
$a_0 = (0, 0, 0.5)$	$b_0 = (0, 0, 0.25)$	$c_0 = (0, 0, 0.16)$	$d_0 = (0, 0, 0.12)$
$a_1 = (0, 0.5, 1)$	$b_1 = (0, 0.25, 0.5)$	$c_1 = (0, 0.16, 0.34)$	$d_1 = (0, 0.12, 0.25)$
$a_2 = (0.5, 1, 1)$	$b_2 = (0.25, 0.5, 0.75)$	$c_2 = (0.16, 0.34, 0.5)$	$d_2 = (0.12, 0.25, 0.37)$
	$b_3 = (0.5, 0.75, 1)$	$c_3 = (0.34, 0.5, 0.66)$	$d_3 = (0.25, 0.37, 0.5)$
	$b_4 = (0.75, 1, 1)$	$c_4 = (0.5, 0.66, 0.84)$	$d_4 = (0.37, 0.5, 0.62)$
		$c_5 = (0.66, 0.84, 1)$	$d_5 = (0.5, 0.62, 0.75)$
		$c_6 = (0.84, 1, 1)$	$d_6 = (0.62, 0.75, 0.87)$
			$d_7 = (0.75, 0.87, 1)$
			$d_8 = (0.87, 1, 1)$

Table 2: Semantics of the linguistic term sets A, B, C and D

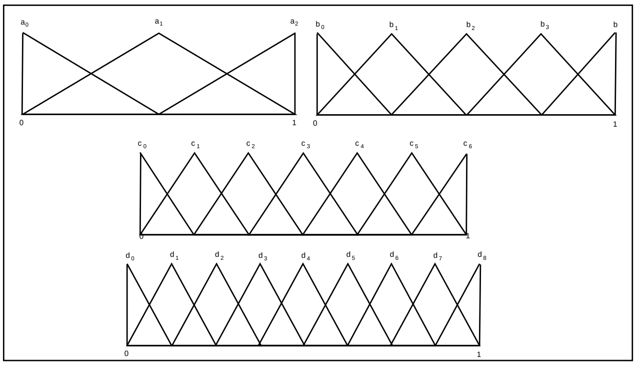

Figure 3: Semantics of the lingustic term sets A,B,C, and D graphically

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
e_1	A	C	D	C	B	D	A	C	D
e_2	A	C	A	C	B	D	A	C	A
e_3	B	C	B	C	B	D	A	C	B
e_4	A	C	C	C	B	D	A	C	C

Table 3: Linguistic term sets that have been chosen by the experts.

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
e_1	a_0	c_3	d_8	c_2	b_2	d_2	a_1	c_0	d_7
e_2	a_1	c_6	a_0	c_3	b_2	d_5	a_2	c_1	a_1
e_3	b_2	c_5	b_1	c_4	b_2	d_6	a_0	c_0	b_0
e_4	a_1	c_1	c_2	c_3	b_2	d_5	a_0	c_2	c_6

Table 4: Utility vectors

1. Aggregation phase:

   (a) Making the information uniform: The BLTS that we have chosen in this example is the linguistic term set D according to the rules presented in [11]. So, $S_T = D = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8\}$. Applying the transformation function,τ_{SS_T}, we obtain the tables 5 and 6:

	e_1	e_2
x_1	$(1, 0.80, 0.60, 0.40, 0.20, 0, 0, 0, 0)$	$(0.2, 0.4, 0.6, 0.8, 1, 0.8, 0.6, 0.4, 0.2)$
x_2	$(0, 0, 0.14, 0.57, 1, 0.57, 0.14, 0, 0)$	$(0, 0, 0, 0, 0, 0, 0.14, 0.57, 1)$
x_3	$(0, 0, 0, 0, 0, 0, 0, 0, 1)$	$(1, 0.80, 0.60, 0.40, 0.20, 0, 0, 0, 0)$
x_4	$(0, 0.29, 0.71, 0.86, 0.43, 0, 0, 0, 0)$	$(0, 0, 0.14, 0.57, 1, 0.57, 0.14, 0, 0)$
x_5	$(0, 0, 0.33, 0.67, 1, 0.67, 0.33, 0, 0)$	$(0, 0, 0.33, 0.67, 1, 0.67, 0.33, 0, 0)$
x_6	$(0, 0, 1.0, 0, 0, 0, 0, 0, 0)$	$(0, 0, 0, 0, 0, 1, 0, 0, 0)$
x_7	$(0.2, 0.4, 0.6, 0.8, 1, 0.8, 0.6, 0.4, 0.2)$	$(0, 0, 0, 0, 0.20, 0.40, 0.60, 0.80, 1)$
x_8	$(1, 0.57, 0.14, 0, 0, 0, 0, 0, 0)$	$(0.43, 0.86, 0.71, 0.29, 0, 0, 0, 0, 0)$
x_9	$(0, 0, 0, 0, 0, 0, 0, 1, 0)$	$(0.2, 0.4, 0.6, 0.8, 1, 0.8, 0.6, 0.4, .2)$

Table 5: Unified utility vectors for experts 1 and 2

	e_3	e_4
x_1	$(0, 0, 0.33, 0.67, 1, 0.67, 0.33, 0, 0)$	$(0.2, 0.4, 0.6, 0.8, 1, 0.8, 0.6, 0.4, 0.2)$
x_2	$(0, 0, 0, 0, 0, 0.29, 0.71, 0.86, 0.43)$	$(0.43, 0.86, 0.71, 0.29, 0, 0, 0, 0, 0)$
x_3	$(0.33, 0.67, 1, 0.67, 0.33, 0, 0, 0, 0)$	$(0, 0.29, 0.71, 0.86, 0.43, 0, 0, 0, 0)$
x_4	$(0, 0, 0, 0, 0.43, 0.86, 0.71, 0.29, 0)$	$(0, 0, 0.14, 0.57, 1, 0.57, 0.14, 0, 0)$
x_5	$(0, 0, 0.33, 0.67, 1, 0.67, 0.33, 0, 0)$	$(0, 0, 0.33, 0.67, 1, 0.67, 0.33, 0, 0)$
x_6	$(0, 0, 0, 0, 0, 0, 1, 0, 0)$	$(0, 0, 0, 0, 0, 1, 0, 0, 0)$
x_7	$(1, 0.8, 0.6, 0.4, 0.2, 0, 0, 0, 0)$	$(1, 0.8, 0.6, 0.4, 0.2, 0, 0, 0, 0)$
x_8	$(1, 0.57, 0.14, 0, 0, 0, 0, 0, 0)$	$(0, 0.29, 0.71, 0.86, 0.43, 0, 0, 0, 0)$
x_9	$(1, 0.67, 0.33, 0, 0, 0, 0, 0, 0)$	$(0, 0, 0, 0, 0, 0, 0.14, 0.57, 1)$

Table 6: Unified utility vectors for experts 3 and 4

   For example, the preference of the expert e_1 and parameter x_1 is computed as:

$$\tau_{AS_T}(a_0) = \{(s_0, 1), (s_1, 0.80), (s_2, 0.60), (s_3, 0.40), (s_4, 0.20),$$

$$, (s_5, 0), (s_6, 0), (s_7, 0), (s_8, 0)\}$$

   (b) Computing collective values: To obtain the collective value of each parameter. We shall apply as aggregation operator the arithmetic mean. Maybe that each expert would have a different importance, in this case, we could use a weighted aggregation operator. However, we are going to use the arithmetic mean to simplify this example. The collective utility vector obtained and expressed by means of linguistic 2-tuples is (see Tables 7 and 8):

x_1	x_2	x_3	x_4	x_5
$(s_4, -0.5)$	$(s_5, -0.31)$	$(s_3, -0.42)$	$(s_4, 0)$	$(s_4, 0)$

Table 7: Collective utility vector expressed by means of linguistic 2-tuple

x_6	x_7	x_8	x_9
$(s_4, 0.50)$	$(s_3, 0.43)$	$(s_1, 0.36)$	$(s_4, 0.24)$

Table 8: Collective utility vector expressed by means of linguistic 2-tuple

For example, the value x_1 is obtained according to the expression:

$$x_1 = ((1, 0.80, 0.60, 0.40, 0.20, 0, 0, 0, 0) + (0.2, 0.4, 0.6, 0.8, 1, 0.8, 0.6, 0.4, 0.2) +$$

$$+ (0, 0, 0.33, 0.67, 1, 0.67, 0.33, 0, 0) + (0.2, 0.4, 0.6, 0.8, 1, 0.8, 0.6, 0.4, 0.2))/4 \Rrightarrow$$

$$\Rrightarrow \chi\left((1.4, 1.6, 2.13, 2.67, 3.2, 2.27, 0.93, 0.8, 0.4)/4\right) = (s_4, -0.5)$$

2. Exploitation phase: In this phase we obtain an overall suitability value for the installation of the ERP that will be evaluated according to the recommendation table (Table 9). This table has been defined according to the features of the problem we are solving.

Degree of suitability	Recommendation
$\leq s_2$	Not install
$> s_2$ *and* $\leq s_3$	The installation is not suitable
$> s_3$ *and* $\leq s_4$	The installation is feasible
$> s_4$ *and* $\leq s_6$	The installation is suitable
$> s_6$	The installation is very suitable

Table 9: Example of table of suitability

We use the 2-tuple arithmetic mean operator [9] to obtain the degree of suitability for the installation of the ERP:

$$AM^*((s_4, -0.5), (s_5, -0.31), (s_3, -0.42), (s_4, 0), (s_4, 0),$$

$$, (s_4, 0.50), (s_3, 0.43), (s_1, 0.36), (s_4, 0.24)) = (s_4, -0.41)$$

Therefore the installation of the ERP is **feasible**.

6 Concluding remarks

In this contribution, we have presented a multi-granular linguistic model to evaluate the suitability of installing an ERP system. This model is based on multi-expert decision-making model able to deal with multi-multigranular linguistic information.

The process evaluates several parameters, of the current conditions of the company, according to the opinions of the experts. Each expert can assess his preference regarding each parameter using the most suitable linguistic term set according to his knowledge about the problem and about the aspect or feature (parameter) he is evaluating. Once all the experts have evaluted the parameters the model combines the information in order to obtain an overall measurement of the suitability for the installation of the ERP.

This evaluation process provides a greater flexibility and better results than other ones because the experts are able to express their opinios in their own linguistic sets instead of using an unique expresion domain [15].

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