Multi-granular linguistic performance appraisal model

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Abstract

Performance appraisal is a process used for some firms in order to evaluate the efficiency and productivity of their employees for planning their promotion policy. Initially this process was carried out just by the executive staff, but recently it has evolved to an evaluation process based on the opinion of different appraisers, supervisors, collaborators, customers and the employees themselves. In such a evaluation process the appraisers evaluate some indicators related to the employee performance. These indicators are usually subjective and qualitative in nature that implies vagueness and uncertainty in their knowledge. However, most of performance appraisal models force appraisers to provide their assessments about the indicators in an unique precise quantitative domain. We consider this obligation drives to a lack of precision in the final results. Therefore in this contribution we propose a linguistic evaluation framework to model qualitative information and manage its uncertainty. Additionally due to the fact that there are different sets of appraisers taking part in the evaluation process that have different degrees of knowledge about the employee, it seems suitable to offer a flexible framework in which the appraisers can express their assessments in different linguistic domains according to their knowledge. The final aim is to compute a global evaluation for each employee, easy to interpret and understand by the management team to make decisions regarding their personnel policy.

1. Introduction

One of the main challenges of companies and organizations is the improvement of productivity and efficiency. Performance appraisal is essential for the effective management and evaluation of corporations. Recently more and more companies are trying to increase their productivity through the human performance measurement. Performance appraisal is used for the evaluation of employees estimating their contribution to the goals of the organization, behavior and results.

In classical performance appraisal methods just supervisors evaluated employees. However, corporations are adopting new methods that use information from different people (appraisers) connected with each evaluated worker. In fact, *360^0 appraisal* or *integral evaluation* is a methodology for evaluating worker's performance that includes the opinions of supervisors, collaborators, customers and employees themselves (see [5] and [11]). Then, each appraiser from the different collectives (supervisors, collaborators, customers, employee) evaluates indicators used for measuring the performance of the evaluated worker. Usually these indicators are qualitative in nature and involve uncertainty. However most of evaluation process force the appraisers to provide their assessments in a unique quantitative precise scale (see [2]). Finally the method generates a global evaluation value according to all the indicators and all the appraisers aggregating their assessments.

The use of a precise scale to assess qualitative information can produce a lack of precision in the assessments provided by the appraisers due to the difficulty of expressing uncertain knowledge in a precise way. In the literature the use of the Fuzzy Linguistic Approach [13] to model and manage the qualitative and uncertain information has provided successful results [1, 4].

Taking into account the above problems we propose in this contribution a model for performance appraisal in a multi-granular linguistic framework to model and manage appraisers' assessments such that they can express their valuations about the workers in different linguistic scales according to their degree of knowledge. To deal with linguistic information conducted in different linguistic term sets, the model will unify it in an unique linguistic domain by means of linguistic 2-tuples in order to obtain a global valuation for the worker that supports the management team to develop companies' personnel policies. Thus, the problem falls, in a natural way, into the collective decision making context.

The paper is organized as follows. Section 2 is devoted to introduce the terminology and functions of the arisen problem. In Section 3 we introduce a multi-granular linguistic 360° performance appraisal model. Finally, some concluding remarks are included in Section 4.

2. Preliminaries

Before we introduce the performance appraisal model proposed in the above section some concepts and processes used in it are revised to facilitate its comprehension.

2.1. Fuzzy linguistic approach

Information in a quantitative setting is usually expressed by means of numerical values. However, there are situations dealing with uncertainty or vague information in which a better approach to qualify aspects of many activities 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]. This approach is adequate when attempting to qualify phenomena related to human perception as in the problem we focus in.

We have to choose the appropriate linguistic descriptors for the term set and their semantics also an important parameter to be determined is the "granularity of uncertainty", i.e., the cardinality of the linguistic term set used to express the information.One possibility of generating the linguistic term set consists in 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:

$$\begin{aligned} S \;=\; \{ & s_0\text{: N},\ s_1\text{: VL},\ s_2\text{: L},\ s_3\text{: M}, \\ & s_4\text{: H},\ s_5\text{: VH},\ s_6\text{: P}\} \end{aligned}$$

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 [3].

2.2. Dealing with multi-granular linguistic information

Due to the fact that we consider multi-granular linguistic framework for our evaluation model, we will have to accomplish computations with this type of information. There does not exist any computational model to operate directly with it. Therefore, here we review in short a process presented in [10] to deal with such a type of information that consists in the following steps:

1. To choose a linguistic domain called Basic Linguistic Term Set (BLTS) to unify the linguistic information

2. To conduct the linguistic information into the BLTS by means of fuzzy sets.

3. To transform fuzzy sets in the BLTS into linguistic 2-tuples.

2.2.1. Chosing the BLTS

To deal with multi-granular linguistic information, first it will be conducted in an unique expression domain. This domain will be a linguistic term set called BLTS that is selected with the aim of keeping as much knowledge as possible. Therefore this term set should have the maximum granularity of the multi-granular linguistic context.

2.2.2. Conducting information into fuzzy sets

Once the BLTS has been chosen in order to accomplish processes of computing with words with the multi-granular information. We will conduct it in the BLTS by means of fuzzy sets. To do so, we will use the transformation function presented in [10]:

Definition 1 Let $S = \{s_0, s_1, \ldots, s_h\}$ and $\overline{S} = \{\overline{s}_0, \overline{s}_1, \ldots, \overline{s}_g\}$ be two linguistic term sets, with $h \leq g$. The *linguistic transformation function* $T_{S\overline{S}} : S \longrightarrow \mathcal{F}(\overline{S})$ is defined by:

$$T_{S\overline{S}}(s_j) = \{(\overline{s}_0, \gamma_0), (\overline{s}_1, \gamma_1), \ldots, (\overline{s}_g, \gamma_g)\}$$

with

$$\gamma_i = \max_y \min \{\mu_{s_j}(y),\, \mu_{\overline{s}_i}(y)\},\ i = 0, 1, \ldots, g$$

where $\mathcal{F}(\overline{S})$ is the set of fuzzy sets on $\overline{S}$, and μ_{s_j} and $\mu_{\overline{s}_i}$ are the membership functions of the linguistic labels $s_j \in S$ and $\overline{s}_i \in \overline{S}$, respectively.

The function $T_{S\overline{S}}$ is used for transforming individual assessments over S into fuzzy sets in the BLTS, $\overline{S}$.

At this moment the information is conducted in one expression domain, but with view to the management team, if we operate with the fuzzy sets and the appraisal results are expressed by means of fuzzy sets those results are difficult to interpret and use. Then we will transform these fuzzy sets into a linguistic 2-tuple representation that is easier to use and understand by the management team.

2.2.3. Unification into linguistic 2-tuples

Before introducing the transformation process of the above fuzzy sets into linguistic 2-tuples. We review in short the fuzzy linguistic 2-tuple representation model.

The 2-tuple fuzzy linguistic representation model is based on the concept of *symbolic translation* [7]. This model represents the linguistic information through a 2-tuple (s, α), where s is a linguistic term and α is a numerical value representation of the symbolic translation [7]. So, being $\beta \in [0, g]$ the value which represents the result of a symbolic aggregation operation, then we can assign a 2-tuple (s, α) that expresses the equivalent information of that given by β.

Definition 2 Let $S = \{s_0, \ldots, s_g\}$ be a set of linguistic terms. The *2-tuple set associated with* S is defined as $\langle S\rangle = S \times [-0{,}5, 0{,}5)$. We define the function $\Delta_S : [0, g] \longrightarrow \langle S\rangle$ given by,

$$\Delta_S(\beta) = (s_i, \alpha), \quad \text{with} \quad \begin{cases} i = \ \text{round}\,(\beta), \\ \alpha = \beta - i, \end{cases}$$

where *round* assigns to β the integer number $i \in \{0, 1, \ldots, g\}$ closest to β.

We note that Δ_S is bijective [8, 9] and $\Delta_S^{-1} : \langle S\rangle \longrightarrow [0, g]$ is defined by $\Delta_S^{-1}(s_i, \alpha) = i + \alpha$. In this way, the 2-tuples of $\langle S\rangle$ will be identified with the numerical values in the interval $[0, g]$.

Remark 1 We can consider the injective mapping $S \longrightarrow \langle S\rangle$ that allows us to transform a linguistic term s_i into a 2-tuple: $(s_i, 0)$. On the other hand, $\Delta_S(i) = (s_i, 0)$ and $\Delta_S^{-1}(s_i, 0) = i$, for every $i \in \{0, 1, \ldots, g\}$.

The 2-tuple fuzzy linguistic representation model has a linguistic computational associated model in which different aggregation operators were presented in [7]. This computational model demonstrated that the operations with symmetrical and triangular-shaped labels are conformed without loss of information. Also this computational model for 2-tuples defined a lexicographic order over linguistic 2-tuples.

Definition 3 Let $S = \{s_0, \ldots, s_g\}$ be a set of linguistic terms. We define $\succ$ the binary relation on $\langle S \rangle$ as

$$(s_k, \alpha_k) \succ (s_l, \alpha_l) \Leftrightarrow \begin{cases} k > l, \\ \text{or} \\ k = l \ \text{ and } \ \alpha_k > \alpha_l. \end{cases}$$

Notice that $\succ$ ranks the linguistic 2-tuples of $\langle S \rangle$.

Once we have reviewed the 2-tuple representation model, we present a function that will allow us to transform the fuzzy sets obtained in the above unification process.

Definition 4 Given the linguistic term set $\overline{S} = \{\overline{s}_0, \overline{s}_1, \ldots, \overline{s}_g\}$, the function $\chi : \mathcal{F}(\overline{S}) \longrightarrow [0, g]$ is defined by

$$\chi\left(\{(\overline{s}_0, \gamma_0), (\overline{s}_1, \gamma_1), \ldots, (s_g, \gamma_g)\}\right) = \frac{\displaystyle\sum_{j=0}^{g} j\, \gamma_j}{\displaystyle\sum_{j=0}^{g} \gamma_j}.$$

So, given $\{(\overline{s}_0, \gamma_0), (\overline{s}_1, \gamma_1), \ldots, (\overline{s}_g, \gamma_g)\}$, a fuzzy set over $\overline{S} = \{\overline{s}_0, \overline{s}_1, \ldots, \overline{s}_g\}$, we have that

$$\beta = \chi\left(\{(\overline{s}_0, \gamma_0), (\overline{s}_1, \gamma_1), \ldots, (s_g, \gamma_g)\}\right)$$

is a numerical value that represents linguistic information from $\mathcal{F}(\overline{S})$. This numerical value can be transformed into a linguistic 2-tuple through the function $\Delta_{\overline{S}}$.

3. A multi-granular linguistic 360^{o} performance appraisal model

Here we introduce our proposal for solving a 360^0 performance appraisal problem defined in a multi-granular linguistic framework. Our model has the following phases:

1. Definition of the multi-granular linguistic evaluation framework
2. Unification of the information
3. Rating workers

3.1. Evaluation Framework

The aim of this problem is to evaluate the employees taking into account the opinions of different collectives related to them. We now present the main features and terminology we consider for the arisen problem.

It is supposed there is a set of employees $X = \{x_1, \ldots, x_n\}$ to be evaluated by the following collectives:

- A set of supervisors (executive staff):
$$A = \{a_1, \ldots, a_r\}.$$
- A set of collaborators (fellows):
$$B = \{b_1, \ldots, b_s\}.$$
- A set of customers:
$$C = \{c_1, \ldots, c_t\}.$$
- X (the opinion of each employee about himself can be taken into account).

The employees will be evaluate attending to different criteria: $Y_1, \ldots, Y_p$.

The assessments of $a_i \in A$, $b_i \in B$ and $c_i \in C$ on the employee x_j according to the criterion Y_k will be denoted by a_j^{ik}, b_j^{ik} and c_j^{ik}, respectively. Moreover, x_j^{jk} is the assessment of x_j on himself with respect to Y_k. Therefore, there are $(r + s + t + 1)\, p$ assessments for each employee provided by the different collectives.

In this contribution we consider multi-granular linguistic framework. So, we assume that each member of the collectives can use different linguistic term sets [7, 8] to assess each criterion Y^k, $k = 1, \ldots, p$:

- $a_j^{ik} \in S_A^k$ for each $i \in \{1, \ldots, r\}$ and each $j \in \{1, \ldots, n\}$.
- $b_j^{ik} \in S_B^k$ for each $i \in \{1, \ldots, s\}$ and each $j \in \{1, \ldots, n\}$.
- $c_j^{ik} \in S_C^k$ for each $i \in \{1, \ldots, t\}$ and each $j \in \{1, \ldots, n\}$.
- $x_j^{jk} \in S_X^k$ for each $j \in \{1, \ldots, n\}$.

We note that any appropriate linguistic term set S_{-}^{k} is characterized by its cardinality or *granularity*, $|S_{-}^{k}|$. Since there are p criteria and 4 collectives, we have at most $4p$ different sets of linguistic labels. Although usually it is much less than $4p$.

3.2. Unification information phase

To operate with linguistic terms assessed in different linguistic term sets, first of all we have to conduct the multi-granular linguistic information provided by the different collectives into a unique expression domain, BLTS, $\overline{S} = \{\overline{s}_0, \overline{s}_1, \ldots, \overline{s}_g\}$, that is selected as:

$$g \geq \text{máx}\{|S_A^1|, \ldots, |S_A^p|, |S_B^1|, \ldots, |S_B^p|, \\ |S_C^1|, \ldots, |S_C^p|, |S_X^1|, \ldots, |S_X^p|\}.$$

Once the BLTS has been chosen, the multi-granular linguistic information must be conducted to it. To do so, we transform this information into fuzzy sets in $\overline{S}$ by means of the function $T_{S\overline{S}}$ presented in Definition 1.

- Supervisors:

$$T_{S_A^k \overline{S}} : S_A^k \longrightarrow \mathcal{F}(\overline{S}).$$

- Collaborators:

$$T_{S_B^k \overline{S}} : S_B^k \longrightarrow \mathcal{F}(\overline{S}).$$

- Customers:

$$T_{S_C^k \overline{S}} : S_C^k \longrightarrow \mathcal{F}(\overline{S}).$$

- Employee:

$$T_{S_X^k \overline{S}} : S_X^k \longrightarrow \mathcal{F}(\overline{S}).$$

In this way, the information obtained in the evaluated process will be expressed into an unique linguistic term set, through fuzzy sets in $\overline{S}$.

In order to facilitate the aggregation process and the understandability of the results, we transform the fuzzy sets in $\overline{S}$ into linguistic 2-tuples using the functions χ and Δ presented in Definitions 2 and 4:

- Supervisors:

$$H_A^k : S_A^k \xrightarrow{T_{S_A^k \overline{S}}} \mathcal{F}(\overline{S}) \xrightarrow{\chi} [0, g] \xrightarrow{\Delta_{\overline{S}}} \langle \overline{S} \rangle.$$

- Collaborators:

$$H_B^k : S_B^k \xrightarrow{T_{S_B^k \overline{S}}} \mathcal{F}(\overline{S}) \xrightarrow{\chi} [0, g] \xrightarrow{\Delta_{\overline{S}}} \langle \overline{S} \rangle.$$

- Customers:

$$H_C^k : S_C^k \xrightarrow{T_{S_C^k \overline{S}}} \mathcal{F}(\overline{S}) \xrightarrow{\chi} [0, g] \xrightarrow{\Delta_{\overline{S}}} \langle \overline{S} \rangle.$$

- Employee:

$$H_X^k : S_X^k \xrightarrow{T_{S_X^k \overline{S}}} \mathcal{F}(\overline{S}) \xrightarrow{\chi} [0, g] \xrightarrow{\Delta_{\overline{S}}} \langle \overline{S} \rangle.$$

We can note that all the information provided by the different collectives (supervisors, collaborators, customers and employee) has already unified into 2-tuples in the BLTS.

3.3. Rating phase

The aim of this phase is to obtain a value that assess the performance of the evaluated worker according to the different collectives that have evaluated her. To do so, the assessments provided by the members of the different collectives will be aggregated. Due to the fact that the information has been unified by means of linguistic 2-tuples we will use 2-tuple OWA operators to accomplish the aggregation process.

Definition 5 [12] Let $\mathbf{w} = (w_1, ..., w_m) \in [0,1]^m$ be a weighting vector such that $\sum_{i=1}^m w_i$. The *ordered weighted averaging* (OWA) operator associated with $\boldsymbol{w}$ is the function $F^{\boldsymbol{w}} : \mathbb{R}^m \longrightarrow \mathbb{R}$ defined by

$$F^{\boldsymbol{w}}(a_1, \ldots, a_m) = \sum_{i=1}^m w_i \, b_i,$$

where b_i is the i-th largest element in the collection $\{a_1, \ldots, a_m\}$.

Remark 2 OWA operators satisfy some interesting properties as *compensativeness*, *idempotency*, *symmetry* and *monotonicity*. Moreover, $F^{\boldsymbol{w}}$ is self-dual if and only if $w_{m+1-i} = w_i$ for every $i \in \{1, \ldots, [\frac{m}{2}]\}$ (see [6, Prop. 5]).

Definition 6 Let $((l_1, \alpha_1), \ldots, (l_m, \alpha_m)) \in \langle\overline{S}\rangle^m$ be a vector of linguistic 2-tuples and $\boldsymbol{w} = (w_1, \ldots, w_m) \in [0,1]^m$ be a weighting vector such that $\sum_{i=1}^m w_i = 1$. The *2-tuple OWA operator associated with* $\boldsymbol{w}$ is the function $G^{\boldsymbol{w}} : \langle\overline{S}\rangle^m \longrightarrow \langle\overline{S}\rangle$ defined by

$$G^{\boldsymbol{w}}\Big((l_1, \alpha_1), \ldots, (l_m, \alpha_m)\Big) = \Delta_{\overline{S}}\left(\sum_{i=1}^m w_i\, \beta_i^*\right),$$

where β_i^* is the i-th largest element of $\Big\{\Delta_{\overline{S}}^{-1}(l_1, \alpha_1), \ldots, \Delta_{\overline{S}}^{-1}(l_m, \alpha_m)\Big\}$.

The aggregation procedure consists in the following steps:

1. *Computing appraisers' collective criteria values*, $v_{\_}^k(x_j)$: For each appraisers' collective, their assessments about a given criterion Y_k are aggregated by means of a 2-tuple OWA operator, $G_{\_}^{\boldsymbol{w}}$, that can be different for each appraisers' collective.

   For each collective and for every $k \in \{1, \ldots, p\}$, the process is conducted in the following manner.

   - *Supervisors*. Taking into account the function $\mathbf{H}_A^k : (S_A^k)^r \longrightarrow \langle\overline{S}\rangle^r$ defined by

     $$\mathbf{H}_A^k(a_j^{1k}, \ldots, a_j^{rk}) = (H_A^k(a_j^{1k}), \ldots, H_A^k(a_j^{rk})),$$

     we introduce the function

     $$F_A^k : (S_A^k)^r \xrightarrow{\mathbf{H}_A^k} \langle\overline{S}\rangle^r \xrightarrow{G_{A,k}^{\boldsymbol{w}}} \langle\overline{S}\rangle$$

     which assigns a 2-tuple over the BLTS to each vector of individual assessments.

     Thus, each employee has associated a 2-tuple over the BLTS, with respect to the supervisors and the criterion Y_k:

     $$v_A^k(x_j) = F_A^k\Big(a_j^{1k}, \ldots, a_j^{rk}\Big).$$

   - *Collaborators*. Taking into account the function $\mathbf{H}_B^k : (S_B^k)^s \longrightarrow \langle\overline{S}\rangle^s$ defined by

     $$\mathbf{H}_B^k(b_j^{1k}, \ldots, b_j^{sk}) = (H_B^k(b_j^{1k}), \ldots, H_B^k(b_j^{sk})),$$

     we introduce the function

     $$F_B^k : (S_B^k)^s \xrightarrow{\mathbf{H}_B^k} \langle\overline{S}\rangle^s \xrightarrow{G_{B,k}^{\boldsymbol{w}}} \langle\overline{S}\rangle$$

     which assigns a 2-tuple over the BLTS to each vector of individual assessments.

     Thus, each employee has associated a 2-tuple over the BLTS, with respect to the collaborators and the criterion Y_k:

     $$v_B^k(x_j) = F_B^k\Big(b_j^{1k}, \ldots, b_j^{sk}\Big).$$

   - *Customers*. Taking into account the function $\mathbf{H}_C^k : (S_C^k)^t \longrightarrow \langle\overline{S}\rangle^t$ defined by

     $$\mathbf{H}_C^k(c_j^{1k}, \ldots, c_j^{tk}) = (H_C^k(c_j^{1k}), \ldots, H_C^k(c_j^{tk})),$$

     we introduce the function

     $$F_C^k : (S_C^k)^t \xrightarrow{\mathbf{H}_C^k} \langle\overline{S}\rangle^t \xrightarrow{G_{C,k}^{\boldsymbol{w}}} \langle\overline{S}\rangle$$

     which assigns a 2-tuple over the BLTS to each vector of individual assessments.

     Thus, each employee has associated a 2-tuple over the BLTS, with respect to the customers and the criterion Y_k:

     $$v_C^k(x_j) = F_C^k\Big(c_j^{1k}, \ldots, c_j^{tk}\Big).$$

   - *Employee*. Each employee has associated a 2-tuple over the BLTS, with respect to the criterion Y_k:

     $$v_X^k(x_j) = H_X^k(x_j^{jk}) \in \langle\overline{S}\rangle.$$

Although the opinion that each employee has about himself, x_j^{jk} (and the associated 2-tuple $v_X^k(x_j)$), can be useful for the organization, we do not take into account this information in the aggregation process. The reason is that 2-tuple OWA operators do not distinguish the origin of the assessments (they are anonymous). Consequently, to include the self-evaluation of employees could disturb the aggregation phase, because the corresponding outcomes could be biased by that self-evaluations.

2. *Computing global criteria values*, $v^k(x_j)$: The previous collective assessments $v_A^k(x_j)$, $v_B^k(x_j)$ and $v_C^k(x_j)$ are aggregated by means of a 2-tuple OWA operator

$$G_k^{\boldsymbol{w}} : \langle \overline{S} \rangle^3 \longrightarrow \langle \overline{S} \rangle$$

obtaining a 2-tuple over the BLTS for each criterion Y_k:

$$v^k(x_j) = G_k^{\boldsymbol{w}}\Big(v_A^k(x_j), v_B^k(x_j), v_C^k(x_j)\Big) \in \langle \overline{S} \rangle.$$

3. *Computing a final value*, $v(x_j)$: It is obtained by aggregating the global criteria values related to the employee x_j, by means of a 2-tuple OWA operator

$$G^{\boldsymbol{w}} : \langle \overline{S} \rangle^p \longrightarrow \langle \overline{S} \rangle$$

obtaining a 2-tuple over the BLTS:

$$v(x_j) = G^{\boldsymbol{w}}\Big(v^1(x_j), \ldots, v^p(x_j)\Big) \in \langle \overline{S} \rangle.$$

The final outcomes obtained in each step of the aggregation process, $v_A^k(x_j)$, $v_B^k(x_j)$, $v_C^k(x_j)$, $v^k(x_j)$ and $v(x_j)$, are used either for sorting and ranking the employees or to establish the companies' policy in the exploitation phase.

The weighting vectors appearing in each stage of the aggregation procedure can be determined in different ways, being one of the most usual that given by linguistic quantifiers.

After aggregation process companies must rank their employees. In this way, employees will be sorted and ranked according to the corresponding 2-tuples over the BLTS obtained in each stage of the aggregation phase. The process of pairwise comparison among linguistic 2-tuples is carried out according to an ordinary lexicographic order given in Definition 3 (see [7]). According to this lexicographic order, in each stage we can initially sort employees by the linguistic term of the corresponding 2-tuples over the BLTS. Secondly, we can rank employees sorted in the same linguistic category by considering the corresponding values α_i of the symbolic translations.

We now show the outputs we have to sort and rank. They have been obtained in different stages of the aggregation process.

1. *Appraisers' collective criteria values, for collectives*:
   - *Supervisors.*
   - *Collaborators.*
   - *Customers.*
2. *Global criteria values.*
3. *Final value*.

Moreover, the organization can rank the aggregated information obtained for each employee, joint with the self-evaluation, in each criterion Y_k. Thus, the organization can compare the collective opinions and the self-evaluation for each employee in each criterion.

Obviously, other comparisons are possible. Taking into account all the information obtained in the aggregation process, the organization can decide about different aspects of its human resources' policy.

4. Concluding remarks

Performance appraisal is a process that allow companies and organizations to determine efficiency and effectiveness of their employees . In this contribution we have presented a 360° performance appraisal model,taking into account that appraisers can present different degrees of knowledge about evaluated employees.

Thus, appraisers could express their assessments in different linguistic domains according to their knowledge, defining a multi-granular linguistic evaluation framework. Consequently, this model offers an increment of flexibility and an improvement in the treatment of information with uncertainty in performance appraisal model.

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