Performance evaluation of employees with multi-granular linguistic information

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Abstract

Performance appraisal is a process used for some companies in order to evaluate the efficiency and productivity of their employees. 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 reviewers, including supervisors, collaborators, customers and employees themselves. This 360-degree method uses information from many people who can truly respond to how an employee performs on the job. In this contribution we propose an evaluation framework in which different groups of reviewers can evaluate employees with linguistic labels. In this way, we allow reviewers to use several sets of labels with different granularity according to their knowledge on employees and the criteria to be evaluated. Once defined the framework, we introduce a fuzzy model of performance appraisal based on classic processes of decision-making.

Keywords: decision-making, performance appraisal, fuzzy sets
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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], [11] and Figure 1 as well).

Then, each appraiser from the different collectives (supervisors, collaborators, customers, employee) evaluates indicators used for measuring the performance of the

$$\begin{array}{ccccc} & & \boxed{\text{Supervisors}} & & \\ & & \downarrow & & \\ \boxed{\text{Colleagues}} & \rightarrow & \boxed{\text{Employee}} & \leftarrow & \boxed{\text{Collaborators}} \\ & & \uparrow & & \\ & & \boxed{\text{Customers}} & & \end{array}$$

Figure 1: 360-degrees appraisal

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 [14] 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^o performance appraisal model. Finally, some concluding remarks are included in Section 4.

2 Preliminaries

In order to develop the performance appraisal method introduced in the above section it is necessary some terminology and basic notions about linguistic modeling. In this section we review in short the fuzzy linguistic approach.

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 [14]. This approach is adequate when attempting to qualify phenomena related to human perception as in the problem we focus in.

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 an specific problem, and linguistic term sets are usually defined in the interval [0,1]. 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 a linguistic term set, $S = \{s_0, ..., s_g\}$, consists in directly supplying the term set by considering all the terms distributed on a scale where a total order is defined [13]. For example, a set of seven terms S could be:

$$\begin{aligned} S \;=\; & \{s_0\text{: N (None)}, s_1\text{: VL (Very-Low)}, s_2\text{: L (Low)}, s_3\text{: M (Medium)}, \\ & s_4\text{: H (High)}, s_5\text{: VH (Very-High)}, s_6\text{: P (Perfect)}\} \end{aligned}$$

The semantics of terms is given by fuzzy numbers defined in the [0,1] interval, which are usually described by membership functions. For example, we may assign the following semantics to the above set of seven terms via triangular fuzzy numbers.

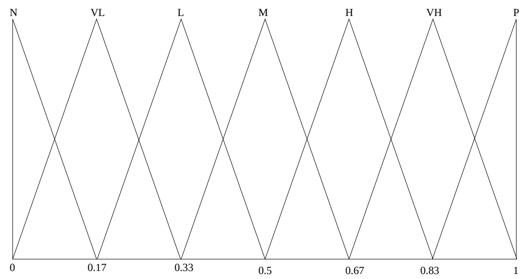

Figure 2: A set of seven terms with its semantics

2.2 Dealing with multi-granular linguistic information

Since we have considered multi-granular linguistic frameworks for our proposal of performance appraisal and due to the fact that the use of linguistic values implies processes of computing with words, it will be necessary to compute with linguistic assessments of different granularity. These computations cannot be directly carried out on the input labels. 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.

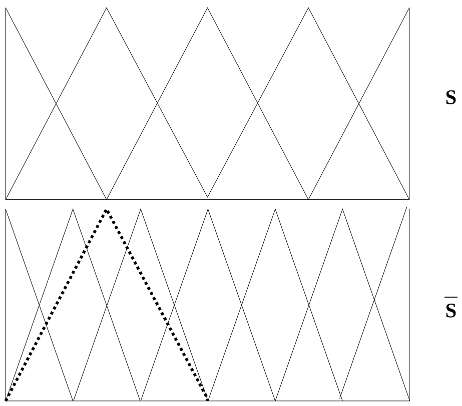

Figure 3: Transforming $s_1 \in S$ into a fuzzy set in $\overline{S}$

So far, we have conducted the multi-granular linguistic information in an unique linguistic domain, $\overline{S}$, by means of fuzzy sets.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 [7], from this one has been demonstrated that the operations with symmetrical and triangular-shaped labels are carried out without loss of information.

Now, we present the function that we allow to transform a fuzzy set over $\overline{S}$ into linguistic 2-tuples in the BLTS.

Definition 3 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

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

where β is a numerical value in the interval of granularity of $\overline{S}$. This numerical value can be transformed into a linguistic 2-tuple through the function $\Delta_{\overline{S}}$ (see Definition 2).

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

In this section we present a model to deal with 360^o performance appraisal problems defined in multi-granular linguistic frameworks. 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

We now present the scheme with the main features and terminology of this type of problems that evaluate the employees taking into account the opinions of different collectives related to them including the evaluated employee.

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: $Y = \{Y_1, \ldots, Y_p\}$.

The assessments provided by the members of the collectives $a_i \in A$, $b_i \in B$ and $c_i \in C$ on the employee x_j according to the criterion Y_k are 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 can have at most $4p$ different sets of linguistic labels, although usually the number will be much smaller.

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 an unique expression domain, BLTS, $\overline{S} = \{\overline{s}_0, \overline{s}_1, \ldots, \overline{s}_g\}$, with

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

Once the BLTS has been chosen, the multi-granular linguistic information is initially unified by means of fuzzy sets in $\overline{S}$ using the function $T_{S\overline{S}}$ presented in the 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 3:

- 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) is 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 4 [12] Let $\mathbf{w} = (w_1, \ldots, w_m) \in [0,1]^m$ be a weighting vector such that $\sum_{i=1}^m w_i = 1$. 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]).

But we have to keep in mind that the information is expressed by means of linguistic 2-tuples. So to aggregate them we will use 2-tuple OWA operator.

Definition 5 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 $\Big\{\Delta_{\overline{S}}^{-1}(l_1, \alpha_1), \ldots, \Delta_{\overline{S}}^{-1}(l_m, \alpha_m)\Big\}$.

Then the aggregation procedure has the following steps.

1. *Computing reviewers' collective criteria values*, $v_{\_}^{k}(x_j)$: For each reviewers' 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 reviewers' 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
   $$F_A^k : (S_A^k)^r \xrightarrow{\mathbf{H}_A^k} \langle \overline{S} \rangle^r \xrightarrow{G_{A,k}^{\boldsymbol{w}}} \langle \overline{S} \rangle$$

$$(a_j^{1k},\dots,a_j^{rk}) \mapsto G^{\boldsymbol{w}}_{A,k}(H^k_A(a_j^{1k}),\dots,H^k_A(a_j^{rk})) \in \langle\overline{S}\rangle$$

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:

$$v^k_A(x_j) = F^k_A\Big(a_j^{1k},\dots,a_j^{rk}\Big).$$

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

$$\mathbf{H}^k_B(b_j^{1k},\dots,b_j^{sk}) = (H^k_B(b_j^{1k}),\dots,H^k_B(b_j^{sk}))$$

we introduce the function

$$F^k_B : (S^k_B)^s \xrightarrow{\mathbf{H}^k_B} \langle\overline{S}\rangle^s \xrightarrow{G^{\boldsymbol{w}}_{B,k}} \langle\overline{S}\rangle$$

$$(b_j^{1k},\dots,b_j^{sk}) \mapsto (G^{\boldsymbol{w}}_{B,k}(H^k_B(b_j^{1k}),\dots,H^k_B(b_j^{sk})) \in \langle\overline{S}\rangle$$

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:

$$v^k_B(x_j) = F^k_B\Big(b_j^{1k},\dots,b_j^{sk}\Big).$$

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

$$\mathbf{H}^k_C(c_j^{1k},\dots,c_j^{tk}) = (H^k_C(c_j^{1k}),\dots,H^k_C(c_j^{tk}))$$

we introduce the function

$$F^k_C : (S^k_C)^t \xrightarrow{\mathbf{H}^k_C} \langle\overline{S}\rangle^t \xrightarrow{G^{\boldsymbol{w}}_{C,k}} \langle\overline{S}\rangle$$

$$(c_j^{1k},\dots,c_j^{tk}) \mapsto G^{\boldsymbol{w}}_{C,k}(H^k_C(c_j^{1k}),\dots,H^k_C(c_j^{tk})) \in \langle\overline{S}\rangle$$

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:

$$v^k_C(x_j) = F^k_C\Big(c_j^{1k},\dots,c_j^{tk}\Big).$$

- *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 each employee has on herself, 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:

$$v(x_j) = G^{\boldsymbol{w}}\Big(v^1(x_j), v^2(x_j), \ldots, v^p(x_j)\Big) \in \langle \overline{S} \rangle.$$

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 for sorting and ranking the employees either to establish the companies' policy in the exploitation phase.

Remark 3 The weighting vectors appearing in each stage of the aggregation procedure can be determined in different ways, being one of the most usual is the use of linguistic quantifiers.

The aim of the rating phase is to sort and rank the employees 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 the following ordinary lexicographic order presented in [7].

Definition 6 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 order the linguistic 2-tuples of $\langle S \rangle$. 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: $\overline{s}_0$, $\overline{s}_1$, $\ldots$, $\overline{s}_g$. 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^o 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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