A MCDM MODEL FOR PERFORMANCE APPRAISAL

Rocío de Andrés[a] **José Luis García-Lapresta**[b] **Mariano Jiménez**[c]

[a] PRESAD Research Group, Departamento de Fundamentos del Análisis Económico e Historia e Instituciones Económicas, Universidad de Valladolid, Spain.
E-mail: rocioac@eco.uva.es.

[b] PRESAD Research Group, Departamento de Economía Aplicada, Universidad de Valladolid, Spain.
E-mail: lapresta@eco.uva.es.

[c] Departamento de Economía Aplicada I, Universidad del País Vasco, San Sebastián, Spain.
E-mail: mariano.jimenez@ehu.es.

Abstract

This paper proposes a linguistic performance appraisal from a competency management perspective, where there are different sets of reviewers taking part in the evaluation process that have a different knowledge about the evaluated employees. Reviewers can express their assessments in different linguistic domains according to their knowledge. The proposed method will conduct each linguistic label provided by reviewers as a fuzzy set in the common domain to compute collective assessments that will allow to the management team to make their decisions about employees.

Keywords: Performance appraisal; Multi-criteria decision making; Goal Programming; OWA operators.

1 Preliminaries

We introduce a scheme for an integral appraisal problem and afterwards we show a classical evaluation method for it. The aim of this problem is to evaluate 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: $C = \{c_1, \ldots, c_t\}$.

Employees will be evaluate attending to different criteria: $Y_1, \ldots, Y_p$. Assessments of $a_i \in A$, $b_i \in B$ and $c_i \in C$ on employee x_j according to the criterion Y_k will be denoted by a_j^{ik}, b_j^{ik} and c_j^{ik}, respectively.

In this contribution we consider a multi-granular linguistic framework. So, we assume that each member of the collectives can use different linguistic term sets 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 $j \in \{1, \ldots, n\}$.

We note that any appropriate linguistic term set S_{-}^k is characterized by its cardinality or *granularity*, $|S_{-}^k|$.

2 The procedure

Our proposal follows a classical decision scheme [6] and a multi-granular linguistic decision scheme [3].

2.1 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 [4], the *Basic Linguistic Term Set*, *BLTS*, $\overline{S} = \{\overline{s}_0, \overline{s}_1, \ldots, \overline{s}_g\}$ satisfying

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

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 functions $T_{S\overline{S}}$ [1] as in Table 1.

Table 1: Individual orders

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

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 [1] as in Table 2.

Table 2: Transformation functions into 2-tuple

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

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

2.2 Aggregation 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 [2] to accomplish the aggregation process. 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 results obtained are the following [1]:

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

     $$v_A^k(x_j) = F_A^k\big(a_j^{1k}, \ldots, a_j^{rk}\big) \in \langle\overline{S}\rangle,$$

     where $F_A^k : (S_A^k)^r \xrightarrow{\mathbf{H}_A^k} \langle\overline{S}\rangle^r \xrightarrow{G_{A,k}^{w}} \langle\overline{S}\rangle$ and $\mathbf{H}_A^k = (H_A^k, \overset{r}{\ldots}, H_A^k)$.

- *Collaborators.* Each employee has associated a 2-tuple over the BLTS, with respect to the collaborators and the criterion Y_k:
$$v_B^k(x_j) = F_B^k\big(b_j^{1k}, \dots, b_j^{sk}\big) \in \langle\overline{S}\rangle,$$
where $F_B^k : (S_B^k)^s \xrightarrow{\mathbf{H}_B^k} \langle\overline{S}\rangle^s \xrightarrow{G_{B,k}^w} \langle\overline{S}\rangle$ and $\mathbf{H}_B^k = (H_B^k, \overset{s}{\dots}, H_B^k)$.
- *Customers.* Each employee has associated a 2-tuple over the BLTS, with respect to the customers and the criterion Y_k:
$$v_C^k(x_j) = F_C^k\big(c_j^{1k}, \dots, c_j^{tk}\big) \in \langle\overline{S}\rangle,$$
where $F_C^k : (S_C^k)^t \xrightarrow{\mathbf{H}_C^k} \langle\overline{S}\rangle^t \xrightarrow{G_{C,k}^w} \langle\overline{S}\rangle$ and $\mathbf{H}_C^k = (H_C^k, \overset{t}{\dots}, H_C^k)$.

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

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.

3 Rating process

Our rating process is inspired on Goal Programming approach [5]. We assume that companies assign a linguistic target to each competency and minimize the non achievement of the targets in order to rank the employees.

Since companies show their targets with linguistic terms and the aggregated values are 2-tuples, we consider the injective mapping $\overline{S} \longrightarrow \langle\overline{S}\rangle$ that transforms each linguistic term $\overline{s}_i \in \overline{S}$ into the 2-tuple $(\overline{s}_i, 0) \in \langle\overline{S}\rangle$. On the other hand, we need to compare 2-tuples for ranking employees. For this purpose, we use the linear order $\succ$ on $\langle S\rangle$ defined by
$$(\overline{s}_k, \alpha_k) \succ (\overline{s}_l, \alpha_l) \Leftrightarrow \begin{cases} k > l, \\ \text{or} \\ k = l \ \text{ and } \ \alpha_k > \alpha_l. \end{cases}$$

We propose a process for selecting and ranking employees with four stages:

1. In the first stage of the process, companies carry out an initial selection process establishing a minimum linguistic threshold for each competency: $\underline{v}^1, \dots, \underline{v}^p \in \overline{S}$. By applying this initial selection process, companies have a new set of employees to be ranked:
$$\widehat{X} = \{x_j \in X \mid \forall k \in \{1, \dots, p\} \quad v^k(x_j) \geq (\underline{v}^k, 0)\}.$$
2. Once the first selection has been carried out, in the second stage of the rating process companies fix a linguistic target for each competency: $v^{1*}, \dots, v^{p*} \in \overline{S}$. Before to carry out the second stage of the rating process, it is necessary to transform both the linguistic targets and the linguistic global competency values into numerical values. In this way, the function that allows us to transform a linguistic 2-tuple in the BLTS into a numerical value [1] $\Delta_{\overline{S}}^{-1} : \langle\overline{S}\rangle \longrightarrow [0, g]$ is defined by $\Delta_{\overline{S}}^{-1}(\overline{s}_i, \alpha) = i + \alpha$. Therefore, the 2-tuples of $\langle\overline{S}\rangle$ can be identified with the numerical values in the interval $[0, g]$. Thus, every linguistic target $v^{k*} \in \overline{S}$ is transformed into a numerical target
$$\mathbf{v}^{k*} = \Delta_{\overline{S}}^{-1}(v^{k*}, 0) \in \{0, 1, \dots, g\} \subset [0, g],$$
and the linguistic global competency value $v^k(x_j) \in \langle\overline{S}\rangle$, for each competency Y_k and each employee x_j, is transformed into a numerical value
$$\mathbf{v}^k(x_j) = \Delta_{\overline{S}}^{-1}(v^k(x_j)) \in [0, g].$$

3. In order to rank employees, we consider that the target value for each competency Y_k is connected with the corresponding global competency value through negative and positive deviation variables η_{jk} and ρ_{jk}, respectively:
$$\mathbf{v}^k(x_j) + \eta_{jk} - \rho_{jk} = \mathbf{v}^{k*},\ \eta_{jk} \geq 0,\ \rho_{jk} \geq 0.$$
Notice that η_{jk} and ρ_{jk} measures, respectively, the lack and the excess of success of the employee x_j in the competency Y_k. In addition, for each employee x_j we work out the maximum lack of success, that is to say, the maximum negative deviation
$$D(x_j) = \max\{\eta_{j1}, \ldots, \eta_{jp}\}.$$

4. Finally we assign the following global score to each employee
$$M(x_j) = (1-\lambda)D(x_j) + \lambda\left(\sum_{k=1}^{p} \alpha_k\, \eta_{jk} + \beta_k\, \rho_{jk}\right),$$
where $\lambda \in [0,1]$ represents the balance between the minimization of the maximum lack of success and the minimization of a weighted sum of the deviation variables in relation to the target values. On the other hand, α_k and β_k are the preferential weights for the negative and positive deviation respectively for the competency Y_k. The lack of success should be always penalized, therefore $\alpha_k > 0$ for every $k \in \{1, \ldots, p\}$. But, depending on the context, the excess of success could be considered in a different way. So, $\beta_k = 0$ means that the excess of success in the competency Y_k is neutral, $\beta_k < 0$ means that it is rewarded, and $\beta_k > 0$ means that it is penalized. In any case, the weight of the lack of success should be greater than the weight of the excess of exit, so $|\beta_k| < |\alpha_k|$ for every $k \in \{1, \ldots, p\}$.

Taking into account the values of $M(x_j)$ obtained for each employee, the organization can decide about different aspects of its human resources' policy.

References

[1] R. de Andrés, J. L. García-Lapresta and L. Martínez, A multi-granular linguistic model for management decision-making in performance appraisal. Submitted.

[2] F. Herrera and L. Martínez, A 2-tuple fuzzy linguistic representation model for computing with words. *IEEE Transactions on Fuzzy Systems* 8 (2000), pp. 746-752.

[3] F. Herrera and L. Martínez, A model based on linguistic 2-tuples for dealing with multigranularity hierarchical linguistic contexts in multiexpert decision-making. *IEEE Transactions on Fuzzy Systems* 31 (2001), pp. 227-234.

[4] F. Herrera, L. Martínez and P. J. Sánchez, Managing non-homogeneous information in group decision making. *European Journal of Operational Research* 166 (2005), pp. 115-132.

[5] C. Romero, A general structure of achievement function for a goal programing model. *European Journal of Operational Research* 153 (2004), pp. 675-686.

[6] M. Roubens, Fuzzy sets and decision analysis. *Fuzzy Sets and Systems* 90 (1997), pp. 199-206.