HR management through linguistic fuzzy rule bases - a versatile and safe tool?

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Abstract. In this paper we advocate the use of linguistic fuzzy rule-based classifiers in HR management, we discuss their possible benefits and shortcomings both from practical and from the mathematical point of view. We show that many decision tasks in HR management can be formulated in the language of classification and represented by fuzzy rule-based models. We illustrate the versatility of these models on several examples of decision making and evaluation problems. A major advantage of the linguistic rule base representation of the decision making process is its clarity and easy understandability for all people involved in the HR management process including the staff. Expert knowledge and experience can be reflected, modifications of the models are possible in real time and can be done by the practitioners. We discuss several examples of the use of linguistic fuzzy modeling in HR management in the context of interpretability and comprehensibility of the results provided by the mathematical models and possible risks and misinterpretations. The analysis was performed from the behavioral operations research point of view.

Keywords: fuzzy rule base, linguistic scale, classification, HR management, decision support, evaluation.

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AMS classification: 90C15

1 Introduction

Human resource (HR) management involves a great deal of decision making and evaluation. Available inputs are usually numerous, their character however ranges widely from crisp numerical values to linguistic (narrative) pieces of information. As human beings are involved and the well being of the organisation in question has to be considered, context of the decision making plays an important role as well. Decision support tools able to provide quick summaries and to preprocess the vast data available can improve the HR management processes significantly. This claim can be supported by the vast literature on decision support systems (DSS) for management including HR management that have been developed recently. It is important to stress that in the area of HR management, as well as in other fields of human science, the outputs provided by the DSS and other mathematical tools need to be easy to understand and interpret. The more complex or abstract the outputs are, the more misunderstanding and misuse of these results we can expect from practitioners.

Providing preprocessed information in an easy to understand form while still retaining all the uncertainty stemming from the inputs (as in human systems there usually is uncertainty) is necessary. Mainly to enable the HR managers to concentrate on the interpretation of the preprocessed data and incorporating context and relevant soft variables into the decision process. From this perspective fuzzy rule based classification or decision support is not intended to replace the human factor in HR management. On the contrary - its proper use may enhance the potential of effective HR management by allowing the HR professionals to concentrate on issues that really require their skill, expertise and above all that

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are directly linked with their responsibility. In our opinion any mathematical model used in the HR management context should only provide support for the decision making, not the final decisions.

All the decisions regarding people (and the well being of the company/institution) should be made by people (we need to admit that mathematical models still can not reflect the whole context of the situation adequately) and the responsibility for the consequences of their decisions should never be taken from the managers by the use of mathematical models. To achieve this, the mathematical models used to "ease the decision making process" need to provide the results carefully, with proper explanations and with a clear information on their actual (un)certainty attached. The role of the decision maker and his/her goals (as well as the goals of the organisation he/she represents) should not be neglected as well. The ethical aspects of decision support, responsibility for the decisions, comprehensibility of models for practitioners, the soundness of assumptions concerning the models - all these issues deserve appropriate attention of researchers in the field of operations research. In accordance with the ideas of the newly forming branch of OR - behavioral operations research (see [2]), we would like to address these issues here, and also discuss the advantages, as well as possible shortcomings of using advanced mathematical decision support tools such as linguistic fuzzy modeling in HR management.

2 Preliminaries

We will briefly summarize here the key concepts of fuzzy set theory and linguistic fuzzy modelling as introduced in [8] and [7] (see e.g. [1]). A (type-1) *fuzzy set* A on a universal set U can be defined by the mapping $A : U \to [0, 1]$. The symbol $\mathcal{F}(U)$ denotes the *family of all fuzzy sets* on U. $\mathrm{Ker}(A) = \{x \in U \mid A(x) = 1\}$ denotes a *kernel* of A. For any $\alpha \in [0, 1]$, $A_\alpha = \{x \in U \mid A(x) \geq \alpha\}$ denotes an *α-cut* of A. A *support of* A is defined as $\mathrm{Supp}(A) = \{x \in U \mid A(x) > 0\}$. The symbol $\mathrm{hgt}(A)$ denotes a *height of a fuzzy set* A, $\mathrm{hgt}(A) = \sup \{A(x) \mid x \in U\}$. If the *support of* A is a finite set, $\mathrm{Supp}(A) = \{x_1, \ldots, x_k\}$, then the fuzzy set A will be denoted as $A = \{^{A(x_1)}/_{x_1}, \ldots, {}^{A(x_k)}/_{x_k}\}$. A *union* of fuzzy sets A and B on U is a fuzzy set $A \cup B$ on U with the membership function for all $x \in U$ given by $(A \cup B)(x) = \max\{A(x), B(x)\}$. An *intersection* of fuzzy sets A and B on U is a fuzzy set $A \cap B$ on U with the membership function for all $x \in U$ given by $(A \cap B)(x) = \min\{A(x), B(x)\}$. Let A be a fuzzy set on U and B be a fuzzy set on V. Then the *Cartesian product* of A and B is the fuzzy set $A \times B$ on $U \times V$ with the membership function defined for all $(x, y) \in U \times V$ by $(A \times B)(x, y) = \min\{A(x), B(y)\}$.

A *fuzzy number* is a fuzzy set C on the set of all real numbers $\Re$ which satisfies the following conditions: a) $\mathrm{Ker}(C) \neq \varnothing$, b) C_α are closed intervals for all $\alpha \in (0, 1]$ and c) $\mathrm{Supp}(C)$ is bounded. If $\mathrm{Supp}(C) \subseteq [a, b]$ we call C a *fuzzy number on* $[a, b]$. A fuzzy set $C = \{1/_{x_1}\}$ is called a *fuzzy singleton* and represents the crisp value $x_1 \in \Re$ as a fuzzy number. A *fuzzy scale on* $[a, b]$ is defined as a set of fuzzy numbers $T_1, T_2, ..., T_s$ on $[a, b]$ that form a Ruspini fuzzy partition (see [4]) of the interval, i.e. for all $x \in [a, b]$ it holds that $\sum_{i=1}^{s} T_i(x) = 1$, and the T's are indexed according to their ordering ($T_1 < T_2 < \cdots < T_s$).

A *linguistic variable* (see [7]) is defined as a quintuple $(\mathcal{X}, \mathcal{T}(\mathcal{X}), U, G, M)$, where $\mathcal{X}$ is the name of the variable, $\mathcal{T}(\mathcal{X}) = \{\mathcal{T}_1, \mathcal{T}_2, ..., \mathcal{T}_s,\}$ is a set of its linguistic values (linguistic terms), U is a universal set on which the meanings of the linguistic terms are modeled, G is a syntactic rule for generating linguistic terms from $\mathcal{T}(\mathcal{X})$, and M is a semantic rule which to every linguistic term $\mathcal{A} \in \mathcal{T}(\mathcal{X})$ assigns its representation, $A = M(\mathcal{A})$, which is a fuzzy set on U. For better clarity, from now on we will distinguish a linguistic term $\mathcal{A}$ from its mathematical meaning A, which is a fuzzy set, by a different font. In real-life applications, the universe U is usually a closed interval of real numbers, i.e. $U = [a, b]$, and the meanings of the linguistic terms are fuzzy numbers on U. A *linguistic scale* is a special case of a linguistic variable, the fuzzy numbers $T_1, T_2, ..., T_s$, representing meanings of its linguistic values, form a fuzzy scale on $[a, b]$. Let us now consider m linguistic scales $(\mathcal{E}_j, \mathcal{T}(\mathcal{E}_j), [p_j, q_j], M_j, G_j)$, $j = 1, \ldots, m$. Let $\mathcal{A}_{i,j} \in \mathcal{T}(\mathcal{E}_j)$ be linguistic values, and $A_{ij} = M_j(\mathcal{A}_{i,j})$ fuzzy numbers on $[p_j, q_j]$ representing the meanings of the respective linguistic variable's values. We can now define the relationship between the values of the linguistic variables $\mathcal{E}_j$ and an output linguistic variable $(\mathcal{H}, \mathcal{T}(\mathcal{H}), U_\mathcal{H}, M_\mathcal{H}, G_\mathcal{H})$ with values $\mathcal{D}_i \in \mathcal{T}(\mathcal{H})$ by a *fuzzy rule base* in the following form:

$$\begin{array}{l}
\text{If } \mathcal{E}_1 \text{ is } \mathcal{A}_{1,1} \text{ and } \ldots \text{ and } \mathcal{E}_m \text{ is } \mathcal{A}_{1,m}, \text{then } \mathcal{H} \text{ is } \mathcal{D}_1 \\
\text{If } \mathcal{E}_1 \text{ is } \mathcal{A}_{2,1} \text{ and } \ldots \text{ and } \mathcal{E}_m \text{ is } \mathcal{A}_{2,m}, \text{then } \mathcal{H} \text{ is } \mathcal{D}_2 \\
\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
\text{If } \mathcal{E}_1 \text{ is } \mathcal{A}_{n,1} \text{ and } \ldots \text{ and } \mathcal{E}_m \text{ is } \mathcal{A}_{n,m}, \text{then } \mathcal{H} \text{ is } \mathcal{D}_n.
\end{array}$$

The input linguistic variables are frequently linguistic scales. The output linguistic variable can also be a linguistic scale or a more complex structure based on a linguistic scale; the meanings of its linguistic terms can alternatively be modelled by fuzzy singletons defined on a subset of integers (these fuzzy singletons can represent the indices of linguistic terms of $\mathcal{H}$; there might exist a natural ordering of the linguistic terms, but the set of linguistic terms can be unordered as well). In HR management decision support a linguistic scale as an output variable in the fuzzy rule base corresponds with an evaluation on a cardinal scale. The case of ordered linguistic terms represented by fuzzy singletons corresponds with an evaluation on an ordinal scale and unordered linguistic terms represented by fuzzy singletons correspond with a nominal evaluation scale. Examples of such applications are provided in this paper. There are many approaches how to construct the mathematical model of each rule, the whole rule base and also how to compute and output D for an input vector $(A_1, \dots, A_n) \in \mathcal{F}([p_1, q_1] \times \cdots \times [p_m, q_m])$. Based on the purpose and the required character of the evaluation scale a proper inference mechanism has to be chosen to compute outputs for given inputs from the fuzzy rule base. In this particular paper we aim to deal with more general issues and hence we refer the reader to the numerous books and papers on fuzzy rule bases for more details.

3 Practical applications

We stress the linguistic approach here in the context of HR management, as it provides tools for easy information transfer and for building interfaces that are easy to understand for people with no (or just a basic) mathematical background. We need to understand that decision support systems in these fields have to provide self explanatory and unambiguous results, that are not fuzzier (more uncertain) nor more precise than can be actually inferred based on the quality of the inputs (and other variables influencing the decision process, including the precision of the goals set and so on). Among the HR management tasks that can really benefit from linguistic fuzzy decision support tools, we can identify several categories, that will be briefly discussed in the following sections.

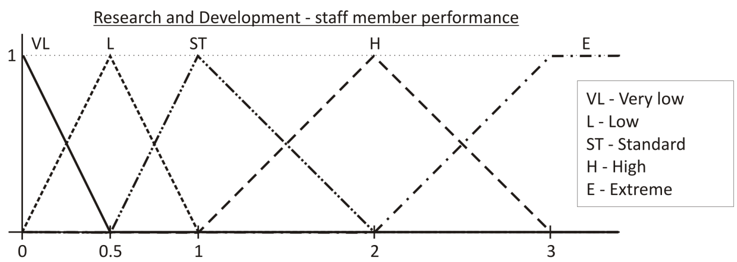

Figure 1 Meanings of the values of a linguistic scale describing performance of a worker in the area of Research and Development. Units on the x-axis are multiples of a standard performance score.

3.1 Data preprocessing

Applications of linguistic fuzzy modeling here can include transforming available data into a more manageable format and identifying relevant or key features in the data. This points to linguistic granulation, use of linguistic variables as well as to the identification of important patterns (or indicators) in data using linguistic fuzzy rules (e.g. answers to "do we need to consider promotion of this employee?", "how much are the data complete/consistent?"). Fuzzy classification can also be used in this context to point to the linguistic granule (e.g. a value of a linguistic variable describing a given aspect e.g. "very consistent") that best suits the data. Important features characterizing a given person in linguistic terms can thus be made available to the HR specialist. Linguistic granulation can also help to describe the evaluation and management process to the employees. Linguistic level of modeling provides a good communication platform between HR managers and the models, but also between HR managers and the people that are being managed. Figure 1 provides an example of a linguistic granulation of "staff member's performance in research and development". We can see that only 5 levels of performance are distinguished. Although it might be possible to compute precise numbers of the "multiples of standard score", it would be impractical to use these when providing descriptions of e.g. an evaluation procedure. By identifying 5 levels of performance, we can assign each of them a future intervention (e.g. a warning, or some bonus).

Obviously the meanings of the linguistic terms are not defined as crisp and overlap partially. This reflects the uncertainty of linguistic description (of the meaning of words). However when using linguistic labels, we need to make sure that the meanings of these labels are at least known to (and ideally also accepted and understood by) all the people using them. If the meanings of the linguistic terms are defined in a way that contradicts their common use or intuition, the changes made to a model on a linguistic level may result in an unexpected behavior of the mathematical level of the model.

3.2 Categorization

Based on the predefined (and granulated) characteristics, a classification task can be easily formulated by specifying linguistic (fuzzy) rules. Staff promotion, choosing new employees, selecting members for a new team - all these can be formulated as classification tasks (see e.g. [9] for an application from HR management in a software company). Software tools capable of implementing such rules already exist (see e.g. [3, 6]) or can be easily custom made. The use of linguistic fuzzy rule bases provides not only a high level of comprehensibility due to the linguistic level of description, but also easy adjustability of the model. Hence the tools can be easily adapted to emerging situations and to meet new requirements, goals of the organisation etc. The two tables in Figure 2 provide an example of how easy it might be to alter our model by simply changing the linguistic rules (two linguistic rule bases and two corresponding evaluation functions). The case here is to determine, to which performance class a current staff member belongs - 5 linguistically labeled classes are distinguished (from *unsatisfactory* to *excellent performance*). Using such linguistic fuzzy rule bases, a staff member can belong to more than one class (even in a different degree of membership). Also here we need to be careful and always provide meanings of the linguistic terms that are being used (see e.g. Figure 1 for the meanings of R&D performance linguistic values). We need to be aware that meanings are context dependent (the meaning of a linguistic term in a scale can even change, if we add more values to the scale and apply it to the same problem - consider a term set {young, old} and a term set {young, middle_aged, old} for the description of age; will the meanings of "young" and "old" be the same using these two term sets?). Using a developed model in a new context therefore always requires revision and analysis of its appropriateness. This requires an "informed" user or an expert to supervise changes in such models. Although linguistic representation is appealing, it is too easy to forget about context dependency of meanings. Experts designing such models should therefore be able to explain the possibilities (and restrictions) for adaptation and possible risks connected with changes of the model to the model users. Otherwise the responsibility for any mistakes is at least shared by the expert who designed the initial model. We can not provide people with tools they do not sufficiently understand and act as if the misuse of these methods is their problem and responsibility. If changes to the model might result in problematic functionality of the model, the changes should not be allowed. Let us consider Figure 2 to describe two variants of an evaluation situation (see also the next subsection), and let the outputs be computed in the following way (see [5] for more details):

$$eval(pa, rd) = \frac{\sum_{i=1}^{n} A_{i1}(pa) \cdot A_{i2}(rd) \cdot ev_i}{\sum_{i=1}^{n} A_{i1}(pa) \cdot A_{i2}(rd)} = \sum_{i=1}^{n} A_{i1}(pa) \cdot A_{i2}(rd) \cdot ev_i, \tag{1}$$

where $eval(pa, rd)$ is the output value (specifically here a real number from $[0, 2]$; pa is a multiple of standard score in the first area, rd in second), $A_{i,1}$ are the meanings of linguistic values *very low* to *extreme* describing performance in the first area of interest ($A_{i,2}$ analogically for another area of interest - see Figure 1) and the corresponding fuzzy scale and ev_i describes an output of i-th rule (crisp numbers are considered in Figure 2 as the meanings of the values of the output variable). Figure 2 then allows us to see what changes are made to the evaluation function by changing the linguistic rules. If these changes reflect well the intentions of the evaluator, everything is fine. The question is - Since we are not aware of the shape of our evaluation function when constructing the rules - does it really reflect our intentions well? And is a practitioner inexperienced with interpretation of graphs capable of assessing this? In our opinion after proper explanation the answer is yes - yet the explanation must take place and has to be done so that the model is well understood by those using it. "Black boxes" might lead to unpredictable results if modifications by the user are allowed.

3.3 Evaluation

If the linguistic values on the consequent parts of the rules allow us to asses the fulfillment of a given goal, the fuzzy rule base represents an evaluation function (see e.g. [5]). Using e.g. a Ruspini fuzzy partition to model the meanings of the linguistic terms of the output variable (see the meanings of *very low* to *extreme* in Figure 1), we obtain an evaluation scale. The linguistic terms and their meanings are ordered. Each value from the universe (described in terms of multiples of standard performance scores) can be interpreted using either single, or two neighboring linguistic terms. In fact each value is sufficiently described by its membership degrees to all the meanings of linguistic terms. A performance of a person can thus be described as e.g. 25% *standard* and 75% *high* (in fact this can also be interpreted that the performance is somewhere between *standard* and *high* and its compatibility with the label *high* is larger). This provides an easy to understand, yet uncertain, linguistic output - a valuable information for the evaluation. Alternatively as in (1) the meanings of the linguistic terms of the output variable can be represented by fuzzy singletons (with kernels ev_i) forming a uniform evaluation scale to obtain outputs of this kind.

Linguistic level - variant a)

Overall performance of a current academic staff member in PA and RD		Research and Development performance				
		Very low	Low	Standard	High	Extreme
Pedagogical Activities performance	Very low	Unsatisfactory	Unsatisfactory	Substandard	Standard	Very good
	Low	Unsatisfactory	Unsatisfactory	Substandard	Very good	Excellent
	Standard	Substandard	Substandard	Standard	Very good	Excellent
	High	Standard	Very good	Very good	Excellent	Excellent
	Extreme	Very good	Excellent	Excellent	Excellent	Excellent

Linguistic level - variant b)

Overall performance of a current academic staff member in PA and RD		Research and Development performance				
		Very low	Low	Standard	High	Extreme
Pedagogical Activities performance	Very low	Unsatisfactory	Unsatisfactory	Substandard	Substandard	Standard
	Low	Unsatisfactory	Unsatisfactory	Substandard	Standard	Very good
	Standard	Substandard	Substandard	Standard	Very good	Excellent
	High	Substandard	Standard	Very good	Excellent	Excellent
	Extreme	Standard	Very good	Excellent	Excellent	Excellent

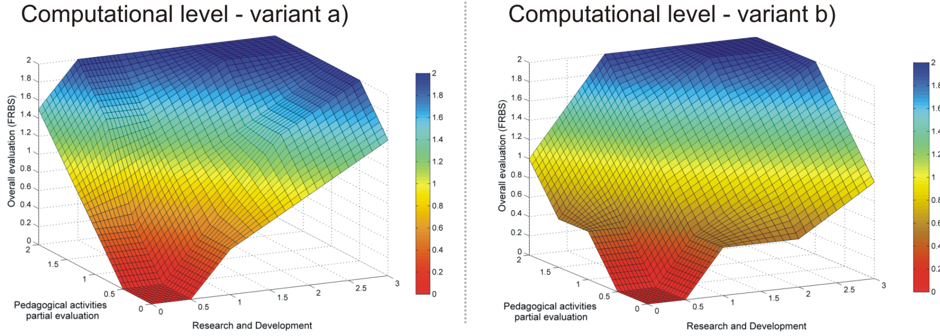

Figure 2 Example of two fuzzy rule bases differing only in the output (consequent) parts of the rules. The change of the mathematical model - the evaluation function - caused by changes in linguistic rules is obvious. Note that a complex evaluation function is described in both cases by 25 easy to understand linguistic rules and the transition from variant a) to variant b) requires no mathematical knowledge from the practitioner (user of the model). See [5] for details concerning the computation or the linguistic scales used to derive the outputs, the scale for Research and Development is depicted in Figure 1.

3.4 Data interpretation

The above mentioned outputs open a way to graphical representation of evaluation results (see e.g. [5]). In many cases we do not need precise results and more importantly precise numerical results are in fact determined based on imprecise inputs and rules. As such these should not be used or interpreted as precise. New ways of presenting outputs of fuzzy (linguistic) models might be useful to help people understand the uncertainty of the outputs, the need to interpret them in context of additional data and so on. Graphical representation using colors seems to be a promising first step.

In general using linguistic rules to describe the desired procedure, we can obtain results that are fuzzy sets with known linguistic labels assigned to them (these can be interpreted easily supposed that the labels and their meanings were defined in cooperation with the user of the model). More frequently we get fuzzy sets that partially overlap with one or more terms of our scale. In this case some procedure of assigning a linguistic label to them is necessary. Many methods were proposed in the literature, involving concentrations and dilatations of the meanings of the linguistic terms (= use of linguistic hedges such as *very* or *somewhat)*, the use of intermediate values, finding the label whose meaning is closest to the obtained fuzzy set and so on. We need to realize that these methods result in an approximate result. Also here we need to be able to find a reasonable tradeoff between approximation and precision (although e.g. "*very [between (more or less standard) and very high*]" is a linguistic description, we need to be sure that the user is able to use it and derive information from it). Finding methods of presenting interpretable outputs without unnecessary loss of information is an important objective to be addressed now.

4 Conclusions

To answer the question posed in the title of this paper, we have presented several examples of possible uses of fuzzy rule based models in HR management setting. The usefulness and versatility of these models in HR management setting is, as we hope, apparent. The question whether these models are safe to use by laymen is, however, not so easy to answer. At least basic knowledge of the concepts of linguistic fuzzy modeling is required to be able to find problems or discrepancies between the model and reality. Fortunately the basic concepts of linguistic fuzzy modeling can be explained to laymen in reasonable time. Not doing so can, however, lead to misuses of our models and misinterpretations of their results. It is even more important when providing outputs of these models in the form of fuzzy sets. Although fuzzy outputs can carry all the information (e.g. concerning the uncertainty of the output), these are not always elementary to interpret. The price for providing easy to understand outputs is apartial loss of information (precision loss during linguistic approximation, apparent precision increase during defuzzification and so on). Graphical and linguistic outputs can be seen as a compromise between the loss of information and easy interpretability of the outputs. The tradeoff should, however, be studied more in the future and the implications of context dependency and "(the lack of) mathematical skills" of model users carefully investigated. Good explanation skills are also required when making models for practitioners, and as such should be encouraged and developed during the education of young model designers.

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