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On multi-granular fuzzy linguistic modeling in group decision making problems: A systematic review and future trends

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ABSTRACT

The multi-granular fuzzy linguistic modeling allows the use of several linguistic term sets in fuzzy linguistic modeling. This is quite useful when the problem involves several people with different knowledge levels since they could describe each item with different precision and they could need more than one linguistic term set. Multi-granular fuzzy linguistic modeling has been frequently used in group decision making field due to its capability of allowing each expert to express his/her preferences using his/her own linguistic term set. The aim of this research is to provide insights about the evolution of multi-granular fuzzy linguistic modeling approaches during the last years and discuss their drawbacks and advantages. A systematic literature review is proposed to achieve this goal. Additionally, some possible approaches that could improve the current multi-granular linguistic methodologies are presented.
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1. Introduction

Decision making is a process that all humans carry out many times in their daily activities and it consists in choosing, among several possible actions, the one that is considered to give better profit. An important part of the decision making process is the way that experts express their preferences about a set of possible alternatives. The chosen method for the recollection and storage of the expert's information is vital because, if it is not intuitive for them, they will not be able to express themselves correctly. In such a case, the decision making process would be hindered. Linguistic modeling and multi-granular FLM methods can be used in order to solve this problem.

The fuzzy linguistic approach proposed by Zadeh in 1975 [60–62] has been used satisfactorily to represent linguistic information during the last 40 years. In the current literature, it is possible to find two kinds of fuzzy linguistic approaches in order to represent linguistic information [15,16]: traditional fuzzy linguistic approach and ordinal fuzzy linguistic approach. The former is more classical and is based on the membership functions associated to each label [60–62], while the latter is based on the symbolic ordinal representation of the labels [2,19,28,45]. The symbolic approximation approach has awakened high interest among the scientific community because of its simplicity and application possibilities [14,36,40,44,46].

In some environments, using a unique Linguistic Term Set (LTS) is not enough to give a clear representation of the information. It is very important to use an adequate number of labels to represent each concept because, if the granularity is too low, then loss of precision is produced. On the other hand, if granularity is too high, then too much information is kept in each LTS and to choose the precise label that best resembles the item that is being described could become a tiresome task. In such cases, the use of several LTSs with different granularities and shapes, becomes essential. Thus, a multi-granular linguistic context should be used, i.e., several LTS should be used in order to represent the linguistic information [17]. The multi-granular fuzzy linguistic modeling (FLM) is appropriate in cases where several information providers need different criteria to express their preferences. For example, this could happen when they have different knowledge levels and need different expression linguistic domains with a different granularity and/or semantics. Multi-granular FLM has been applied successfully in areas such as information retrieval [20,21], recommender systems [27,43], consensus [5,31], web quality [22,23] and decision making [17,25].

The aim of this paper is to show a comprehensive presentation of the state of the art of all known multi-granular FLM approaches, with an in-depth analysis of the respective problems and solutions as well as more relevant applications. Furthermore, in order to give

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Table 11
Comparative about techniques used for dealing with multi-granular information.

Technique	Refs.	Loss of data	Repr. type	Complexity	Set restrictions	Results in input sets
MFLM based on fuzzy membership functions	[25,64]	No	Semantic	Medium	Medium	No
FLM based on a Basic LTS	[9,17,56]	No	Semantic	Medium	Medium	No
MFLM based on 2-tuple	[13,19,63]	No	Symbolic	Low	High	Yes
MFLM based on hierarchical trees	[24]	Yes	Symbolic	Low	Low	Yes
MFLM based on description spaces	[42]	No	Symbolic	High	Low	Yes
MFLM based on discrete fuzzy numbers	[30]	No	Symbolic	Low	Low	Yes

some advice of how the described methods could be improved, new trends and challenges of multi-granular FLM are going to be discussed. From this viewpoint, this paper reports the results of a systematic literature review of researches published in international journals since 2000, taking into account their importance and impact in nowadays published methods. Methods selected after carrying out the systematic review process have been classified into six different categories:

- **Traditional multi-granular FLM based on fuzzy membership functions:** Methods classified in this category use the semantics associated to each label to carry out the operations among elements of different LTSs [25,64].
- **Ordinal multi-granular FLM based on a basic Linguistic Term Set (LTS)**: All the labels belonging to different LTSs are uniformed by expressing them using a unique LTS called Basic Linguistic Term Set (BLTS) and working on this special linguistic term set the required operations are carried out [9,17,56].
- **Ordinal multi-granular FLM based on 2-tuple FLM**: In this category, methods use the 2-tuple FLM and its properties [18] to manage the multi-granular linguistic information [13,19,63].
- **Ordinal multi-granular FLM based on hierarchical trees:** The multi-granular linguistic information is managed using the concept of hierarchical trees [24].
- **Multi-granular FLM based on qualitative description spaces**: This method uses the concept of generalized description space to model and manage the multi-granular linguistic information [42].
- **Ordinal multi-granular FLM based on discrete fuzzy numbers:** Discrete fuzzy numbers mathematical environment [49] is used to deal with the multi-granular linguistic information [30].

This paper is organized as follows. Section 2 presents the Preliminaries, i.e., the basis of multi-granular FLM and the strategy followed to develop the systematic review. In Section 3, different multi-granular fuzzy linguistic approaches are described. In Section 4, a comparison among those multi-granular fuzzy linguistic approaches is presented and future research lines are discussed. Finally, some conclusions are pointed out.

2. Preliminaries

This section presents some basic information about multi-granular FLM and Group Decision Making (GDM) problems. Moreover, the chosen strategy to develop a systematic (organized, efficient and accurate) literature review is described.

2.1. Basis of multi-granular FLM and GDM problems

Multi-granular FLM was first introduced in the seminal paper by Herrera et al. [17]. They designed a GDM method where each expert can use a different ordinal LTS in order to provide his/her preferences. In such a way, they defined a new fuzzy linguistic framework to make decisions that allowed experts to express their preferences using the concept of linguistic variable introduced by Zadeh [60–62], but in a more flexible way, i.e., using different LTS to express the different assessments of the linguistic variable. This multi-granular fuzzy linguistic approach was introduced assuming that the qualitative information in the GDM problem was modeled using an ordinal fuzzy linguistic approach [2,19,22].

The ordinal fuzzy linguistic approach is defined by considering a finite and totally ordered label set $S = \{s_i\},\ i \in \{0,\dots,\mathcal{T}\}$ in the usual sense, i.e., $s_i \geqslant s_j$ if $i \geqslant j$, and with odd cardinality (typically 7 or 9 labels). The mid term represents an assessment of *approximately 0.5*, and the rest of the terms are placed symmetrically around it. The semantics of the linguistic term set is established from the ordered structure of the term set by considering that each linguistic term in the pair $(s_i, s_{\mathcal{T}-i})$ is equally informative. For example, we can use the following set of seven labels to provide the expert preferences: *S* = {*N* = *None*, *VL* = *Very_Low*, *L* = *Low*, *M* = *Medium*, *H* = *High*, *VH* = *Very_High*, *T* = *Total*}. An important issue to analyze is the "granularity of uncertainty", i.e, the cardinality of the linguistic term set. The granularity of *S* should be small enough so as not to impose useless precision levels on the users but large enough to allow a discrimination of the assessments in a limited number of degrees. Additionally, the following property is assumed:

1. There is a negation operator: $Neg(s_i) = s_j$ such that $j = \mathcal{T} - i$.

Sometimes, the semantics of *S* can be completed by associating to the labels any fuzzy numbers defined on the unit interval $[0,1]$. One way to characterize a fuzzy number is by using a representation based on parameters of its membership function. For example, the following semantics can be assigned to a set of seven terms via triangular fuzzy numbers:

$$N = None = (0, 0, 0.17)$$
$$VL = Very\_Low = (0, 0.17, 0.33)$$
$$L = Low = (0.17, 0.33, 0.5)$$
$$M = Medium = (0.33, 0.5, 0.67)$$
$$H = High = (0.5, 0.67, 0.83)$$
$$VH = Very\_High = (0.67, 0.83, 1)$$
$$T = Total = (0.83, 1, 1)$$

A GDM problem is classically defined as a decision situation where a set of experts, $E = \{e_1, e_2, \dots, e_m\}$ $(m \geqslant 2)$, express their preferences about a set of feasible alternatives, $X = \{x_1, x_2, \dots, x_n\}$ $(n \geqslant 2)$, and they work to achieve a consensus solution. In many decision situations it is assumed that each expert e_i provides his/her preferences by means of a fuzzy preference relation, $P_{e_i} = [p_i^{lk}],\ l,k \in \{1,\dots,n\}$ with $p_i^{lk} = \mu_{P_{e_i}}(x_l, x_k)$ assessed in the unit interval $[0,1]$ and being interpreted as the preference degree of the alternative x_l over x_k according to the expert e_i [1,10,38,39]. Another possibility is that experts use linguistic preference relations to represent their preferences, i.e., with $p_i^{lk} = \mu_{P_{e_i}}(x_l, x_k)$ assessed in a LTS *S*. The ideal situation for GDM problems defined in linguistic contexts would be that all the experts use the same linguistic term set *S* to express their

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