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Linguistic Consensus Models Based on a Fuzzy Ontology

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Abstract

The main purpose of a Group Decision Making model is to reach a consensual solution as quickly as possible by decreasing the gap between the perceptions of different decision makers. The perception of the decision makers depends on the various relations between alternatives and attributes. As a real life example, one can mention the present problem of the euro crisis: before finding a solution for the situation, the different perceptions of each country have to be attuned to have a common ground for negotiations. We have to cope with two different issues when modeling a Group Decision Making problem: (1) the relations describing alternatives and attributes are known only partially in most of the cases and (2) these relations change dynamically. Fuzzy ontologies can provide a solution to handle both issues in an efficient way: we can model incomplete and uncertain information using the well-established theory of fuzzy logic and we can dynamically model the changes in the structure by employing ontologies. Therefore, we propose a new linguistic extension of a consensus model to deal with the psychology of negotiation by using the power of a fuzzy ontology as weapon of influence in order to improve group decision scenarios making them more precise and realistic.

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1. Introduction

Decision Making, that is, selecting the the optimal solution from a feasible set, is a very common task present in almost every human activity. Thus, it provokes a great interest in the study of decision making situations and mechanisms that allow to solve decision making problems, not only in Decision Theory, but also in other disciplines as Artificial Intelligence, Economy, Sociology, Engineering and so on.

It is obvious that the comparison of different actions according to their desirability in decision problems, in many cases, cannot be done by using a single criterion or by a single decision maker. Consequently, we interpret the decision process in the framework of Group Decision Making (GDM) [1]. In these situations, problems can be solved in different ways involving a group of experts to achieve a common solution. There have been several efforts in the specialized literature to create different models to properly address and solve GDM situations. Some of these proposals have provided interesting results with the help of fuzzy set theory [2], as it is an efficient tool to model and deal with vague or imprecise options, alternatives and opinions of several decision makers [3, 4, 1]. However, there are decision situations in which the experts' preferences cannot be assessed precisely in a quantitative form but may be in a qualitative one, and thus, the use of a *linguistic approach* is necessary [5]. The *linguistic approach* is an approximate technique which represents qualitative aspects as linguistic values by

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means of *linguistic variables*, that is, variables whose values are not numbers but words or sentences in a natural or artificial language [6].

In a GDM problem we have a finite set of alternatives that have to be ranked from the best to the worst, using the information given by a set of experts. But sometimes the identification of the elements of a GDM problem (experts and alternatives) is not an immediate task [7]. In other situations, when the feasible set of alternatives is very large, the experts are not able to venture an opinion about each possible solution. In such a way, the set of alternatives can be described and outlined with the use of a fuzzy ontology [8]. An ontology is a collection of statements which define the relations between concepts and specify logical rules for reasoning about them. Typically, this is done with a taxonomy and a set of inference rules. Therefore, when the experts have to express their opinions, we can easily find a small and practical discussion subset of the alternatives according to the ontology and some preliminary information given by the decision makers. This subset should cover a bit more: a common set of concepts, a joint understanding of the alternatives and the relations and restrictions connected with them.

In an ideal world, GDM problems would be solved only regarding the experts self-interest, that is, the desire to maximize benefits and minimize costs. But in real world GDM problems, experts are suffering continuous attempts by their partners to influence their opinions [9]. In such a way, the interaction between experts usually involves a person trying to change another person's opinions and behavior, that is, a discussion or negotiation process. The process of negotiation is a pervasive activity in human society ranging from negotiations between nations to individual negotiations in everyday life. In order for a negotiation to be successful, there must be a common ground between parties for the process to bring together their respective positions [10].

The aim of this contribution is to extend the new consensus model proposed in [11] to overcome these issues by using a fuzzy linguistic approach. To do so, this contribution combines the power of a fuzzy ontology and fuzzy linguistic aggregation operators. The negotiation process is also addressed in our extension as part of the linguistic consensus model by using the fuzzy ontology knowledge in order to drive the decision behavior of the involved parties.

The rest of the contribution is set out as follows. Some general considerations about consensual processes, fuzzy linguistic approach and fuzzy ontologies are discussed in Section 2. The proposed new consensus model is described in Section 3. Finally, our conclusions will be pointed out in Section 4.

2. Preliminaries

In this section we show the main elements and features of GDM problems, consensus reaching processes and the use of fuzzy ontologies in decision making.

2.1. Group decision making and consensual processes

A classical GDM situation consists of a problem to solve, a solution set of possible alternatives, $X = \{x_1, x_2, \ldots, x_n\}$, $(n \geq 2)$, and a group of two or more experts, $E = \{e_1, e_2, \ldots, e_m\}$, $(m \geq 2)$, characterized by their own ideas, attitudes, motivations and knowledge, who express their opinions about the set of alternatives to achieve a common solution.

One of the problems in this field is to find the best way to represent the information. There are situations in which the information cannot be assessed precisely in a quantitative form but may be in a qualitative one. For example, when attempting to qualify phenomena related to human perception, we are often led to use words in natural language instead of numerical values, e.g. when evaluating quality of a football player, terms like *good*, *medium* or *bad* can be used.

The ordinal fuzzy linguistic approach [5] is a tool based on the concept of linguistic variable [12] to deal with qualitative assessments. It is a very useful kind of fuzzy linguistic approach because its use simplifies the processes of computing with words as well as linguistic representation aspects of problems. It has proven its usefulness in many problems, e.g., in decision making, web quality evaluation, information retrieval, recommender systems, political analysis, etc.

It is defined by considering a finite and totally ordered label set $S = \{s_i\}, i \in \{0, ..., g\}$ in the usual sense, i.e., $s_i \geq s_j$ if $i \geq j$, and with odd cardinality (usually 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 label set is established from the ordered structure of the label set by considering that each label for the pair (s_i, s_{g-i}) is equally informative [6]. For example, we can use the following set of seven labels to represent linguistic information: $S = \{s_0 = N, s_1 = VL, s_2 = L, s_3 = M, s_4 = H, s_5 = VH, s_6 = P\}$, where N=*Null*, VL=*Very Low*, L=*Low*, M=*Medium*, H=*Hight*, VH=*Very Hight* and P=*Perfect*.

Using this approach, it is possible to define automatic and symbolic aggregation operators of linguistic information, as for example the LOWA operator [13].

In GDM, there are several methods that can be applied. These methods can be classified along a spectrum, from directive to participatory decision making. The methods that are closer to the directive range, imply that the decision is made by a limited, small number of decision makers in the group. On the other hand, the methods that are lower on the spectrum, towards the participatory range, mean that the decision is made by all the parties involved.

In this contribution, we propose to use a decision model composed by two different processes [14]:

1. *Consensus process:* This process refers to how to obtain the maximum degree of agreement among the experts on the solution alternatives. It is very important because, in any decision process, it is preferable that the experts reach a high degree of consensus on the solution set of alternatives before obtaining the final solution.
2. *Selection process:* This process describes how to obtain the solution set of alternatives from the opinions on the alternatives given by the experts. It consists of two phases: aggregation and exploitation. The aggregation phase defines a collective opinion according to the preferences provided by the experts. The exploitation phase transforms the global information about the alternatives into a global ranking.

In such a way, we assume that the experts give their preferences by using Fuzzy Linguistic Preference Relations.

A Fuzzy linguistic Preference Relation (FLPR) P^h given by an expert e_h is a fuzzy set defined on the product set $X \times X$, that is characterized by a linguistic membership function

$$\mu_{P^h} : X \times X \longrightarrow S$$

where the value $\mu_{P^h}(x_i, x_k) = p^h_{ik}$ is interpreted as the linguistic preference degree of the alternative x_i over x_k for the expert e_h.

Moreover, we assume that consensus is a measurable parameter with the highest value corresponding to unanimity and the lowest one to complete disagreement [15]. We can use specific consensus degrees to measure the current level of consensus in the decision process. Assuming FLPRs as representations of the experts' preferences, we could compute the consensus degrees at three different levels [5]: pairs of alternatives, alternatives and relations. The computation of the consensus degrees is carried out as follows:

1. For each pair of experts, e_k, e_l $(k < l)$, a similarity matrix, $SM^{kl} = (sm^{kl}_{ij})$, is defined where
$$sm^{kl}_{ij} = 1 - \frac{|I(p^k_{ij}) - I(p^l_{ij})|}{g}.$$
being $I : S \rightarrow \{0, \ldots, g\} \mid I(s_p) = p \; \forall s_p \in S$.
2. Then, a consensus matrix, CM, is calculated by aggregating all the similarity matrices using the arithmetic mean as the aggregation function ϕ:
$$cm_{ij} = \phi(sm^{12}_{ij}, sm^{13}_{ij}, \ldots, sm^{1m}_{ij}, sm^{23}_{ij}, \ldots, sm^{(m-1)m}_{ij}).$$
3. Once the similarity and consensus matrices are computed we proceed to obtain the consensus degrees at the three different levels to obtain a global consensus degree, called consensus on the relation:
   (a) *Consensus degree on pairs of alternatives*. The consensus degree on a pair of alternatives (x_i, x_j), denoted cop_{ij}, is defined to measure the consensus degree amongst all the experts on that pair of alternatives:
   $$cop_{ij} = cm_{ij}.$$

(b) *Consensus degree on alternatives*. The consensus degree on alternative x_i, denoted ca_i, is defined to measure the consensus degree amongst all the experts on that alternative:

$$ca_i = \frac{\sum_{j=1; j \neq i}^{n} (cop_{ij} + cop_{ji})}{2(n-1)}.$$

(c) *Consensus degree on the relation*. The consensus degree on the relation, denoted CR, is defined to measure the global consensus degree amongst all the experts' opinions:

$$CR = \frac{\sum_{i=1}^{n} ca_i}{n}.$$

Initially, in this consensus model we consider that in any nontrivial GDM problem the experts disagree in their opinions so that decision making has to be viewed as an iterative process composed by several discussion rounds, in which experts are expected to modify their preferences according to the advice given by the moderator. This means that agreement is obtained only after some rounds of consultation. In each round, we calculate the consensus measures and check the current agreement existing among experts using CR.

Normally, to achieve consensus among the experts, it is necessary to provide the whole group of experts with some advice (feedback information) on how far the group is from consensus, what are the most controversial issues (alternatives), whose preferences are in the highest disagreement with the rest of the group, how their change would influence the consensus degree, and so on.

In such a way, the moderator carries out three main tasks: (i) to compute the consensus measures, (ii) to check the level of agreement and (iii) to produce some advice for those experts that should change their minds.

2.2. Decision making with a fuzzy ontology

Since the introduction of fuzzy logic in the context of decision making [16], fuzzy sets and possibility theory became a widely used alternative to model uncertainty. When facing incomplete information, decision support systems based on fuzzy modeling can provide a useful tool to aid decision makers. In many applications, the information that can be used in the decision making process is available in the form of an ontology. However, classical (crisp) ontologies are not appropriate to represent imprecise and vague knowledge. To handle this problem, the concept of fuzzy ontology was introduced into different domains and proved to be useful for example in information retrieval, e-learning, medical applications or weather forecasting. In recent years, decision making has been identified as one of the potential application areas of fuzzy ontology/fuzzy description logic [17, 8].

An ontology can be defined as a systematic description of relationships and entity dependencies: a hierarchical representation of concepts with associated properties. The concept of fuzzy ontology as an extension of classical ontology emerged in the 2000's to deal with imprecise and vague concepts. Contrary to classical ontology, there exists no unique definition of fuzzy ontology: it is usually anchored to the specific domain or application area. In general, a fuzzy ontology is simply an ontology which uses fuzzy logic to provide a natural representation of imprecise and vague knowledge and eases reasoning over it [18].

Throughout the contribution, we will define the fuzzy ontology as a set of fuzzy relations [8]:

$$R_i : A_i \times B_i \to [0, 1]. \tag{1}$$

R_i can represent different types of relationships or dependencies:

$$\{a_i \in A_i\} \, \texttt{is\_part\_of} \, \{b_i \in B_i\},$$

$$\{a_i \in A_i\} \, \texttt{has\_property} \, \{b_i \in B_i\},$$

with $R_i(a_i, b_i)$ describing the degree of the strength of the relation. The values of the relation are usually determined by experts or estimated using different sources of information. After the fuzzy ontology is created, the reasoning can be performed using different classes of fuzzy description logic ($fuzzyDL$).

In the context of decision making, the fuzzy relation R_i can be seen as the evaluation of a set of different alternatives (A_i) with respect to a set of given criteria (B_i).

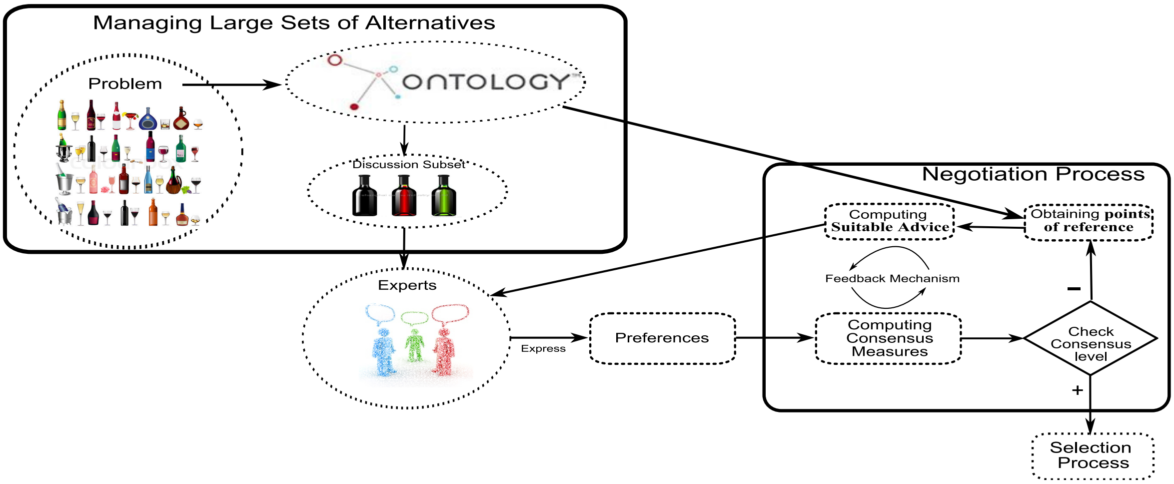

Fig. 1. New consensus reaching process based on a fuzzy ontology

3. Modeling Consensual Processes with a Fuzzy Ontology

In this section we propose a new consensus model with two different phases. Firstly, as we are considering decision contexts with a large number of alternatives, we show the use of a fuzzy ontology to deal with large sets of alternatives. Then, a new negotiation process to influence group decision behavior based on two different points of reference (consensual and social) is formally illustrated. Therefore, this consensus model uses two kinds of criteria to guide the negotiation process among experts (see Figure 1).

3.1. The use of a fuzzy ontology to manage large sets of alternatives in GDM problems

As we have previously mentioned, making the correct decisions, in an effective way, is today a relevant problem in many areas. The data about different issues is becoming more detailed. This, and the fact that also the number of different alternatives is increasing, makes it necessary to find new solutions for finding the optimal alternatives. Nowadays, as the datasets are increasing in size, it implies that experts that should make decisions based on this information are faced with an increasing amount of alternatives. However, by using a fuzzy ontology, it is possible to obtain a smaller set of alternatives which are more "appropriate" in a given context than the others.

In such a way, experts can specify a hierarchy of criteria or contexts (a logical combination of different criteria) which they consider to be the most relevant in a given situation. Using the reasoning system of the fuzzy ontology, we can identify the alternatives which satisfy this set of criteria to the highest degree.

One important question is the aggregation of different attributes. OWA operators can be included in ontologies to increase the precision and effectiveness of the reasoning. By using OWA operators for the purpose to combine concepts, one can create new ones which are combinations of previously defined concepts [8].

3.2. Negotiation process

Once we obtain a suitable discussion subset, each expert e_k has to express his/her preferences on the selected alternatives by means of a FLPR P^k. Then, the system can compute the current level of agreement achieved among the experts (CR) as has been described in Section 2.1.

If the consensus measure CR is not high enough and if the number of rounds has not reached a maximum number of iterations, some experts' opinions should be modified. Thus, a negotiation phase has to be initiated. In such a case, it is necessary to find some tactics or weapons of influence to convince some of the experts to change their minds in order to coordinate the preferences and reach a consensual solution.

To guide the change of the experts' opinions, current approaches try to simulate a group negotiation session in which a feedback mechanism is applied [14]. This mechanism can substitute the moderator's actions in the consensus reaching process. However, the main problem for the feedback mechanism is to find the way of convincing experts to make their individual positions converge and, therefore, to support them in obtaining and agreeing on a particular feasible solution [7].

To do that, we propose a three steps negotiation process. Firstly, it is necessary to fix some points of reference in order to drive the negotiation to an optimal and consensual solution narrowing the gaps between the positions of experts. Secondly, additional consensus measures, called proximity measures, are computed [5]. Finally, these measures and points of reference allow us to build a new feedback mechanism as a kind of recommender system so that experts receive some advice and, if they take the recommendations into account, they will change their preferences to quickly obtain a high consensus level [19].

3.2.1. Obtaining fuzzy linguistic preference relations as points of reference

Current approaches use a collective FLPR to represent the group opinion. This FLPR, $P^c = \left(p^c_{ij}\right)$, is obtained by means of the aggregation of all individual preference relations $\left\{P^1, P^2, \ldots, P^m\right\}$. It indicates the global preference between every pair of alternatives according to the majority of experts' opinions. The aggregation is carried out by means of the LOWA operator ϕ_Q guided by a fuzzy linguistic non-decreasing quantifier Q [20]:

$$p^c_{ij} = \phi_Q(p^1_{ij}, \ldots, p^m_{ij}).$$

In such a way, P^c is taken as point of reference P^r to drive the negotiation process. The main advantage of this election appears when experts are willing to obey the recommendations, because the experts that are hindering the agreement are identified and quickly guided to the consensual solution. But sometimes, to convince an expert to modify his/her preferences based only on the quicker way to reach consensus can be insufficient to change the experts' mind. Therefore, according to Cialdini [9], we propose the use of the *Social Proof* as a powerful weapon to influence people. The principle of *Social Proof* states that one important mean that people use to decide what to do in a situation is to look at what others are doing or have done there. This principle can be used to stimulate a person's compliance with a request by informing the person that many other individuals have been complying with it [9].

We employ fuzzy ontology once again, but this time, the query is refined in order to obtain the virtual optimal solution according to the knowledge stored and modeled by the fuzzy ontology. In such a way, we can use the taxonomy and inference rules, which have been gathered from the society's habits and wisdom, as weapon of influence to persuade some experts. At the same time, as the solution is considered optimal by the fuzzy ontology, we can help experts to reach better decisions.

Usually fuzzy ontologies are able to give us some fuzzy utility values for each alternative of the discussion subset. As we are dealing with FLPRs, we can use a transformation function [21] in order to obtain the optimal fuzzy preference relation, from the ontology and finally, we are able to compute the optimal FLPR, P^o, by using the labels' membership functions.

Therefore, we can propose this optimal FLPR P^o as a new point of reference P^r to compute suitable advice for the experts. In such a way, those experts whose opinions are far away from the optimal solution given by the ontology, will be also asked to change their preferences with the appeal that it is the best solution according to the whole society. Thus, the negotiation is lead both ways (optimal and consensual) at the same time. It manages to persuade experts and reduces the probability for process stagnation.

3.2.2. Computing proximity measures

Proximity measures evaluate the agreement between the individual experts' opinions and a feasible solution. To compute them for each expert, we use both points of reference P^r, previously proposed, in order to establish the direction of the negotiation. Thus, the proximity measures are computed as follows:

1. For each expert, e_k, two proximity matrices, $PM^{kr} = (pm^{kr}_{ij})$, are obtained where

$$pm^{kr}_{ij} = 1 - \frac{|I(p^k_{ij}) - I(p^r_{ij})|}{g}.$$

2. Computation of proximity measures at three different levels:

(a) *Proximity measures on pairs of alternatives,* pp_{ij}^{kr}. They measure the proximity between the preferences on each pair of alternatives of the expert e_k and each point of reference P^r:

$$pp_{ij}^{kr} = pm_{ij}^{kr}.$$

(b) *Proximity measure on alternatives,* pa_i^{kr}. They measure the proximity between the preferences on each alternative x_i of the expert e_k and each point of reference P^r:

$$pa_i^{kr} = \frac{\sum_{z=1;z\neq i}^{n} pp_{iz}^{kr}}{2(n-1)}.$$

(c) *Proximity measure on the relation,* pr^{kr}. They measure the global proximity between the preferences of each expert e_k and each point of reference P^r:

$$pr^{kr} = \frac{\sum_{z=1}^{n} pa_z^{kr}}{n}.$$

3.2.3. Advising experts: feedback mechanism

Once we have computed the proximity measures from each expert to both points of reference (the collective solution P^c and the optimal solution P^o), we need to identify those experts who should change their preferences and to compute some easy rules to drive the negotiation process. To do so, the production of advice to influence the experts in order to achieve a good and consensual solution, trying to avoid the stagnation, is carried out in two phases: *Identification phase* and *Recommendation phase*.

- *Identification phase:*
  We must identify the experts, alternatives and pairs of alternatives that contribute less to reach a high degree of consensus and those that are far away from the optimal solution.
  1. *Identification of experts.* We identify the set of experts, $EXPCH$, that should receive advice on how to change some of their preference values:

     $$EXPCH_c = \{k \mid pr^{kc} < \gamma_1\}\ ;\ EXPCH_o = \{k \mid pr^{ko} < \gamma_2\}$$

     where γ is the minimum proximity level required for the expert to be noted to change.
  2. *Identification of alternatives.* We identify the alternatives whose associated assessments should be taken into account by the above experts in the change process of their preferences:

     $$ALT_{kc} = \{x_i \in X \mid pa_i^{kc} < \gamma_1 \ \wedge k \in EXPCH_c\}\ ;\ ALT_{ko} = \{x_i \in X \mid pa_i^{ko} < \gamma_2 \ \wedge k \in EXPCH_o\}$$

  3. *Identification of pairs of alternatives.* In this step we identify the particular pairs of alternatives (x_i, x_j) whose respective assessments p_{ij}^k the expert e_k should change.

     $$PALT_{kc} = \{(x_i, x_j) \mid pp_{ij}^{kc} < \gamma \wedge x_i \in ALT_{kc} \wedge k \in EXPCH_c\}$$

     $$PALT_{ko} = \{(x_i, x_j) \mid pp_{ij}^{ko} < \gamma \wedge x_i \in ALT_{ko} \wedge k \in EXPCH_o\}$$

- *Recommendation phase:*
  In this phase we recommend changes to the experts of their preferences according to two kinds of rules:
  1. *Rules to increase the consensus level.* We must find out the direction of change to be applied to the preference assessment of each expert $e_k \in EXPCH_c$, p_{ij}^k, with $(x_i, x_j) \in PALT_{kc}$. To do this, we define some direction rules by comparing p_{ij}^k and p_{ij}^c :
  2. *Rules to improve the quality of the solution.* We must find out the direction of change to be applied to the preference assessment of each expert $e_k \in EXPCH_o$, p_{ij}^k, with $(x_i, x_j) \in PALT_{ko}$. To do this, we define some direction rules by comparing p_{ij}^k and p_{ij}^o :

4. Concluding Remarks

In this contribution, we have proposed a novel consensus reaching process, using a fuzzy linguistic approach and fuzzy ontology as a support for GDM methods. OWA and LOWA operators were employed as a basis to aggregate preferences and also to combine different criteria to create contextual variables which can describe complex contexts.

In such a way, the experts only need to specify a general set of criteria, the reasoner connected to the fuzzy ontology then automatically produces a set of good alternatives. The experts are then only required to negotiate and reach consensus regarding this smaller set of alternatives and both reference points.

Although the consensus reaching process does not seem to be as direct as it is in previous approaches, in practice it is more effective. The main advantage of our proposal lies in the persuasive power of the society. At each consensus stage, not only those experts whose minds are far away from the consensual solution receive recommendations, but also those that are far away from the optimal solution of the fuzzy ontology. It reduces the opinion changing aversion of the experts decreasing the stagnation, modeling with more accuracy real world GDM scenarios and reaching better consensual solutions.

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