A New Adaptive Consensus Reaching Process Based on the Experts' Importance

Ignacio J. Pérez[1], F.J. Cabrerizo[2], S. Alonso[3], and Enrique Herrera-Viedma[1]

[1] Dept. of Computer Science and Artificial Intelligence, University of Granada
{ijperez,viedma}@decsai.ugr.es

[2] Dept. of Software Engineering and Computer Systems, Distance Learning University of Spain, UNED
cabrerizo@issi.uned.es

[3] Dept. of Software Engineering, University of Granada
zerjioi@ugr.es

Abstract. Usually, in a group decision context, the importance level, confidence degree and amount of knowledge are very different among individuals. So, when all the individuals have to reach agreement, is quite important to model these kind of features in order to get more appropriate decisions. Last related works are focussed in the selection process to model the importance of the experts, but such approach, under some circumstances, can behave badly. In this contribution, we present a new adaptive consensus reaching model specifically designed to undertake group decision making situations in which the experts have different importance or confidence levels.

1 Introduction

Group decision making (GDM) consists of multiple individuals interacting to reach a decision. Each decision maker (expert) may have unique motivations or goals and may approach the decision process from a different angle, but have a common interest in reaching eventual agreement on selecting the "best" option(s) [3,16]. To do this, experts have to express their preferences by means of a set of evaluations over a set of alternatives.

There exist different representation formats that experts can use to express their preferences [1,2]. Fuzzy Preference Relations (FPRs) [1,2,3,6,8] have been widely used because they are a very expressive format and also they present good properties that allow to operate with them easily.

Two processes are necessary to solve GDM problems: a consensus process and a selection process. The consensus process is necessary to reach a final solution with a certain level of agreement among the experts. On the other hand, the selection process computes all individual preferences in order to obtain a collective solution. Clearly, it is preferable that the set of experts reach a high degree of consensus before applying the selection process. In order to measure the degree of consensus, different approaches have been proposed [7,9,10,17,18].

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To achieve a good 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.

There are some GDM situations defined in homogeneous decision contexts, i.e., all experts' opinions are considered with equal importance, and others in heterogeneous decision contexts, i.e., where the importance levels or confidence degrees experts are quite different. To model such situations, the most of authors suggest to assign weight values in order to compute a weighted aggregation of the preferences [4,5,9,11,19,20]. This approach tries to focus on the discussion on a weighted collective preference and, in such a way, the most considerable experts are the main leaders of the discussion. They try to focuss the negotiation to close the remaining preferences in order to reach agreement. On the other hand, in some situations with many low-important experts, this mechanism could miss the target resulting in the opposite effect to the desired. That is, the moderator could send several recommendations to the high-important experts, who have at their disposal a larger amount of knowledge, in order to change their preferences to narrow them to the remaining experts' opinions. Consequently, the less important experts become the leaders of the discussion.

In this paper we propose a new consensus approach to overcome such problem. We take into account the importance weights not only to aggregate the experts' preferences but also when advising experts to change their preferences. Firstly, the most important experts are advised in order to reach some agreement among them. Then, the remaining experts receive some advice to achieve a high global consensus level. Furthermore, this new approach computes the recommendations in a different way depending on experts' importance in such a way that the experts with lower level of knowledge will need more advice than those experts that previously have at their disposal much more information to make good decisions.

In order to do this, the paper is set out as follows. Some general considerations about GDM and consensus reaching process are presented in Section 2. Section 3 presents the new importance-based consensus reaching process. Finally, Section 4 draws our conclusions.

2 Related Works

2.1 Group Decision Making

A decision making process, consisting in deriving the best option from a feasible set, is present in just about every conceivable human task. It is obvious that the comparison of different actions according to their desirability in decision problems, in many cases, it cannot be done by using a single criterion or an unique person. Thus, we interpret the decision process in the framework of GDM.

In a classical GDM situation there is 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 this set of alternatives to achieve a common solution [12,14,15]. To do this, each expert has to express his preferences on the set of alternatives by means of a fuzzy preference relation, that is defined as $P^k \subset X\text{x}X$, with a membership function, $\mu_{P^k} : X\text{x}X \rightarrow [0,1]$, where $\mu_{P^k}(x_i, x_j) = p_{ij}^k$ denotes the preference degree of the alternative x_i over x_j for the expert e_k.

- $p_{ij}^k > 1/2$ indicates that x_i is preferred to x_j.
- $p_{ij}^k < 1/2$ indicates that x_j is preferred to x_i.
- $p_{ij}^k = 1/2$ indicates indifference between x_i and x_j.

When cardinality of X is small, the preference relation may be conveniently represented by the n x n matrix $P^k = (p_{ij}^k)$.

Usual resolution methods for GDM problems are composed by two different processes [3] (see Figure 1):

1. *Consensus process:* Clearly, in any decision process, it is preferable that the experts reach a high degree of consensus on the solution set of alternatives. Thus, this process refers to how to obtain the maximum degree of consensus or agreement among the experts on the solution alternatives.
2. *Selection process:* This process consists in how to obtain the solution set of alternatives from the opinions on the alternatives given by the experts.

2.2 Classical Consensus Reaching Process

A consensus reaching process in a GDM problem is an iterative process composed by several discussion rounds, in which experts are expected to modify their

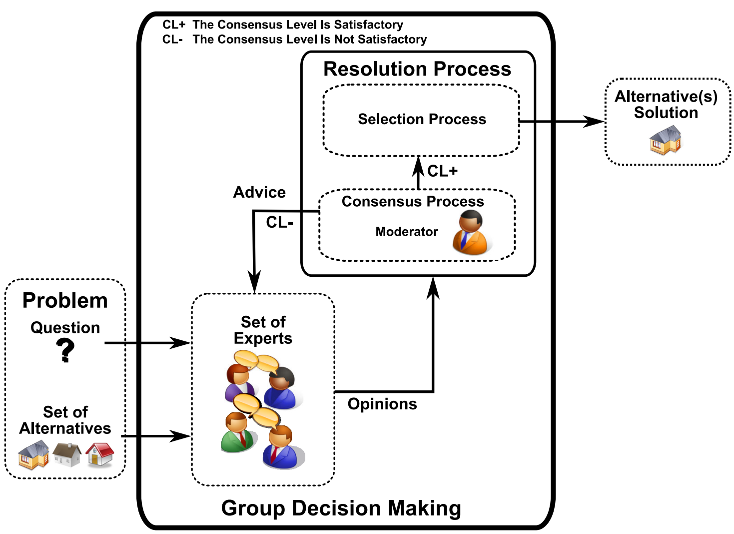

Fig. 1. Resolution process of a GDM

preferences according to the advice given by the moderator. The moderator plays a key role in this process. Normally, the moderator is a person who does not participate in the discussion but knows the preferences of each expert and the level of agreement during the consensus process. He is in charge of supervising and driving the consensus process toward success, i.e., to achieve the maximum possible agreement and reduce the number of experts outside of the consensus in each new consensus round.

Usually, 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. (See Figure 2)

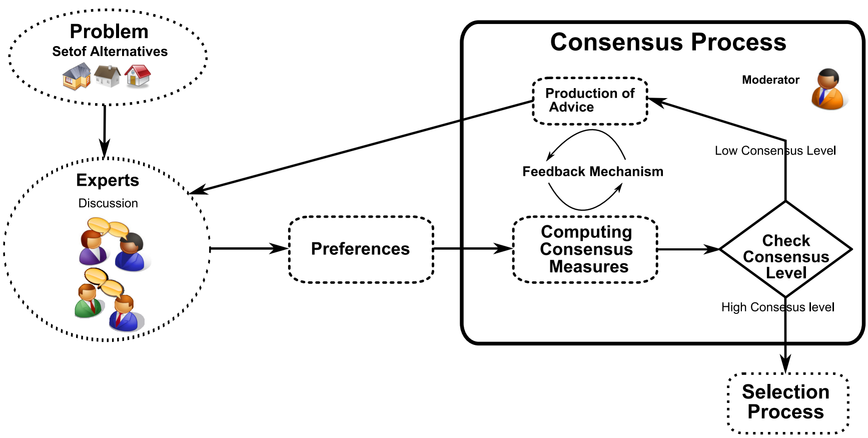

Fig. 2. Classical consensus reaching process

In order to evaluate the agreement, it is required to compute similarity measures among the experts [3,7,17,18]. Two types of measurements to guide the consensus reaching process were proposed in [3]:

1. *Consensus degrees* to evaluate the level of agreement among all the experts. They will be used to identify the preference values where the agreement is not sufficient.
2. *Proximity measures* to evaluate the distance among the experts individual preferences and the group or collective one. They will be used to identify the experts who should change their preferences in the next rounds.

These measurements are computed at the three different levels of representation of a preference relation: pairs of alternatives, alternatives, and relation.

3 Importance-Based Consensus Reaching Process

In heterogeneous GDM scenarios that include a large number of experts with different levels and kind of knowledge, could be necessary to take into account the importance degree of each expert in order to compute the global consensus degree in a more appropriate and realistic way. Usually, these situations have been modeled by some authors by including the weights in the computation of the global preferences [4,5,9,11,19,20]. In this contribution, we use the experts' importance on the discussion phase to generate importance based recommendations and present a new importance based feedback mechanism that sends different recommendations to the experts according to their own importance degrees.

When the agreement among all experts is low, we can notice one of the following two different reasons. The first one is that the opinions of a few important experts were far away from each other. The second possibility is that, being agreement among all the important experts, there exists many low-important experts in disagreement [11].

Anyway, it seems reasonable to change only those particular opinions that are hindering the agreement [11,13]. In such a case, in order to bring the preferences closer to each other, we propose to model that situation with a two-step feedback mechanism. The first step tries to reach consensus between the most important experts and then, if the global consensus is not high enough, the second step deal with all the low-important experts sending them some recommendations to change their preferences in order to reach agreement among all the opinions.

Besides to take into account the importance degree of each expert, we are taking another step further to compute more precise recommendations by considering only the preferences with low agreement degree (Adaptive Search for Preferences), this process can be studied with more detail in [13]. In summary, we try to adapt the search for preferences in disagreement to the current state of the consensus process. To do so, we distinguish two kind of states, "reaching high-important experts agreement" and "reaching low-important experts agreement". When we are dealing with hight-important experts, it is obvious that their opinions belong to a wider knowledge than the remaining ones. In such a case, only a few number of changes of opinions might lead to consensus. Similarly, when the experts have low-importance, a high number of changes of opinions might be necessary to achieve consensus. Thus, two different methods to identify the preferences that each expert should modify, in order to increase the consensus level in the next consensus round, are defined.

Then, we present an importance-based consensus reaching process in order to compute more suitable advice composed of three stages (see Figure 3).

1. *Computing Consensus Degrees and Control the Consensus Process.*
2. *Importance-Based Search for Preferences.*
3. *Production of advice.*

3.1 Computing Consensus Degree and Control the Consensus Process

Once the preferences have been given, we can compute the level of agreement achieved in the current round. To do so, we firstly define for each pair of experts (e^k, e^l) $(k < l)$ a similarity matrix $SM^{kl} = \left(sm_{ij}^{kl}\right)$ where

$$sm_{ij}^{kl} = \left(1 - \left|p_{ij}^k - p_{ij}^l\right|\right)$$

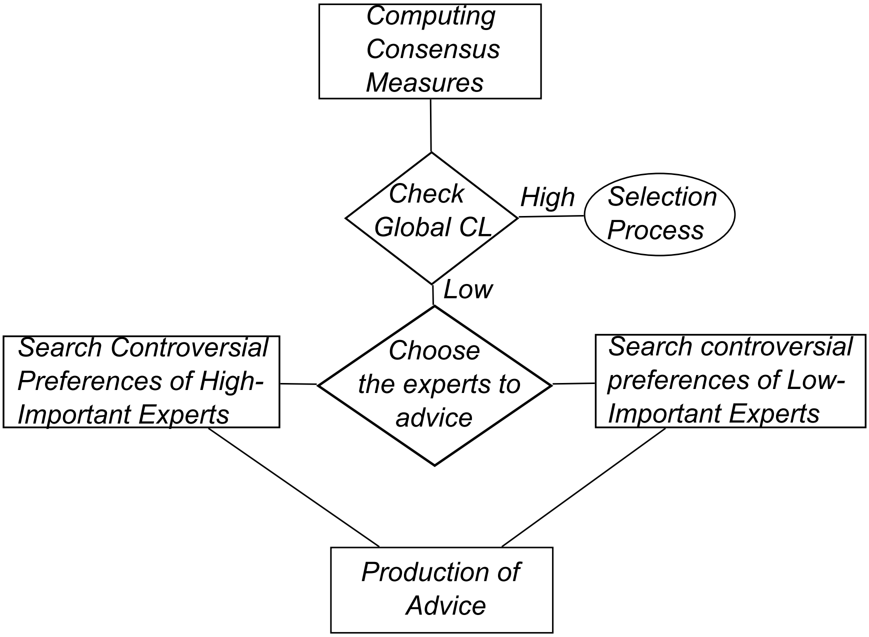

Fig. 3. Importance-based consensus reaching process

Then, a consensus matrix, CM, is calculated by aggregating all the similarity matrices using the arithmetic mean as the aggregation function ϕ:

$$cm_{ij} = \phi(sm_{ij}^{12}, sm_{ij}^{13}, \ldots, sm_{ij}^{1m}, sm_{ij}^{23}, \ldots, sm_{ij}^{(m-1)m}).$$

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:

1. *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:

$$cop_{ij} = cm_{ij}$$

2. *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:

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

3. *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:
$$CR = \frac{\sum_{i=1}^{n} ca_i}{n}$$

When the consensus measure CR has not reached the required consensus level CL and the number of rounds has not reached a maximum number of iterations (defined prior to the beginning of the decision process), the experts' opinions that are hindering the agreement must be modified.

The consensus indicators make it possible to point out the most controversial alternatives and/or experts isolated in their opinions. Thus, we propose a new importance-based search for preferences to obtain some advice that can narrow the experts' minds.

3.2 Importance-Based Search for Preferences

The importance-based search for preferences is developed with the aim of modeling those group decision making situations in which the experts' knowledge is quite different among each others.

In such a case, experts are assigned weights of importance (it means relevance, competence, confidence,...) modeled as a fuzzy subset I where the membership function $\mu_I(e_k) \in [0,1]$ denotes a degree of importance of the expert e_k.

The preferred method for some authors [4,5,9,19,20] is to use the weight values like an aggregation operator's parameter and, in this way, to obtain a weighted collective opinion. However, in this contribution, we are modeling the importance in a different way [11].

To do so, the experts are included by their own importance degree into two different subsets E_{High} and E_{Low} in the following way:

- if $\mu_I(e_k) > \lambda_1 \rightarrow e_k \in E_{High}$, and
- if $\mu_I(e_k) < \lambda_2 \rightarrow e_k \in E_{Low}$.

Where λ_1 and λ_2 are two threshold parameters whose values depend on the problem dealt with.

At first, the process is focused on reaching consensus between the experts in E_{High}. Then, the second step tries to narrow the opinions of the experts in E_{Low} to the global opinion. Consequently, if the consensus degree among experts in E_{High} is not high enough, we should identify the preferences of the high-important experts to be changed in order to reach agreement between them. Otherwise, if that agreement has been already reached, we should identify the preferences of the low-important experts to be changed in order to reach a global agreement.

1. **Identify High-Important Experts' Controversial Preferences**
   In this situation, we are only dealing with experts whose knowledge level is so high that does not need to be strongly modified in order to get a

good solution. Therefore, the agreement can be improved by suggesting a few changes, that is, we only need to change the mind of those experts who have proximity values on the pairs of alternatives identified in disagreement smaller than an specific proximity threshold at level of pairs of alternatives.

2. **Identify Low-Important Experts' Controversial Preferences**
   In the last consensus rounds, the system advises experts with low knowledge or confidence level. It seems reasonable that, a priori, these experts can make more mistakes. Thus, the agreement should be improved by suggesting more changes that in the previous case. To do this, the procedure tries to modify the preference values on all the pairs of alternatives where the agreement is not high enough.

It is worth noting that both searching methods have been previously used to solve a different adaptive reaching consensus model based on the current consensus level. It can be studied with more detail in [13].

3.3 Production of Advice

Once that the system has identified the preferences to be changed depending on the importance degree of the experts, the model shows the right direction of the changes in order to achieve the agreement. For each preference value to be changed, the model will suggest increasing or decreasing the current assessment.

In this contribution, we use a mechanism based on a set of direction rules to identify and suggest the changes [13]. These rules compare the central values of the individual and collective preference assessments $cv(p_{ij}^k)$ and $cv(p_{ij}^c)$. The central value represents the center of gravity of the information contained in the set [13].

As there are two different consensus levels to be reached, at first, in order to reach agreement between high-important experts, the collective preference refers the aggregated preferences from experts in E_{High} and is noted as $p_{ij}^{\sim c}$.

The direction rules in this case are as follows.

- if $(cv(p_{ij}^k) - cv(p_{ij}^{\sim c}) < 0)$, then the expert e_k should increase the assessments associated with the pair of alternatives (x_i, x_j).
- if $(cv(p_{ij}^k) - cv(p_{ij}^{\sim c}) > 0)$, then the expert e_k should decrease the assessments associated with the pair of alternatives (x_i, x_j).
- if $(cv(p_{ij}^k) - cv(p_{ij}^{\sim c}) = 0)$, then the expert e_k should not modify the assessments associated with the pair of alternatives (x_i, x_j).

Once the first objective has been achieved, the next one is to close the preferences of the remaining experts. So, the direction rules are similar, the only change is that the collective preference refers the aggregated preferences from all the experts instead of only the important ones.

- if $(cv(p_{ij}^k) - cv(p_{ij}^c) < 0)$, then the expert e_k should increase the assessments associated with the pair of alternatives (x_i, x_j).
- if $(cv(p_{ij}^k) - cv(p_{ij}^c) > 0)$, then the expert e_k should decrease the assessments associated with the pair of alternatives (x_i, x_j).

– if $(cv(p_{ij}^k) - cv(p_{ij}^c) = 0)$, then the expert e_k should not modify the assessments associated with the pair of alternatives (x_i, x_j).

Finally, it is worth noting that the changes suggested are only recommendations presented for consideration to the experts and they decide if and how to take them into account.

4 Concluding Remarks

In this contribution we have presented a novel consensus approach which has been specially designed to model heterogeneous decision contexts. Assuming fuzzy preference relations to express experts' preferences and different levels of importance in their preferences we present a consensus model in which the more important experts lead the discussion of the consensus reaching process. Moreover, the feedback mechanism computes different kind of recommendations according to the expert importance levels.

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