A CONSENSUS MODEL FOR GROUP DECISION MAKING IN HETEROGENEOUS CONTEXTS

LUIS MARTINEZ,FRANCISCO MATA

Dept. of Computer Science
University of Jaén
23071 - Jaén, Spain
Email:martin,fmata@ujaen.es

ENRIQUE HERRERA-VIEDMA

Dept. of Computer Science and A.I.
University of Granada
18071 - Granada, Spain
Email:vieda@decsai.ugr.es

The consensus process in Group Decision Making (GDM) problems helps to achieve solutions that are shared by the different experts involved in such problems. Due to the fact that in GDM problems different experts take part in the decision process is common that they need to express their information in different domains [5,2]. In this contribution we focus on GDM problems defined in heterogeneous contexts with numerical, linguistic and interval valued information. And our aim is to define a consensus model that includes an *Advice Generator* to assist the experts in the consensus reaching process of GDM problems with heterogeneous preference relations. This model will provide two important improvements: (i) Firstly, its ability to cope with group decision-making problems with heterogeneous preference relations, and, (ii) secondly, the figure of the moderator, traditionally presents in the consensus reaching process, is replaced by an advice generator, and in such a way, the whole group decision-making process can be easily automated.

1. Introduction

In GDM problems are carried out two processes before obtaining a final solution [3,4,6,8]: *the Consensus Process* and *the Selection Process* (see Fig. 1). The first one refers to how to obtain the maximum agreement between the set of experts on the solution set of alternatives. Normally this process is guided by a human figure called moderator [4,8]. The second one obtains the solution set of alternatives.

In the literature has shown that in GDM problems could be necessary

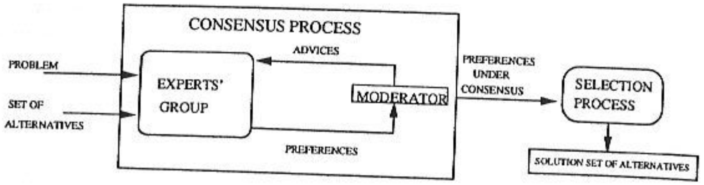

Figure 1: Resolution process of a group decision-making problem

or suitable that the experts can express their knowledge in different expression domains such as numeric, linguistic and/or interval ones and different *Selection Processes* [2,5] have been proposed to solve them, but there are not defined specific consensus processes for this type of problems.

Consequently, in this contribution we focus on the *Consensus Process* on heterogenous GDM problems. The consensus is defined as a state of mutual agreement among members of a group where all opinions have been heard and addressed to the satisfaction of the group [10]. The consensus reaching process is defined as a dynamic and iterative process composed of several rounds, where the experts express and discuss about their opinions. Traditionally this process is coordinated by a human moderator, who computes the agreement among experts in each round using different consensus measures [9,7]. If the agreement is not acceptable then the moderator recommends to the experts to change their furthest opinions from the group opinion in an effort to make their preferences closer in the next consensus round [1,11].

The moderator is usually a controversial figure because the experts complaints about his lack of objectivity and additionally in heterogeneous contexts it is difficult for him to understand all the different domains and scales in a proper way. Therefore, the aim of this contribution is to present a consensus model for GDM problems such that:

- The experts can express their preferences by means of linguistic, numerical or interval-valued preference relations.
- The moderator tasks are carried out by means of an automatic advice generator.

The rest of the paper is set out as follows. The scheme of an heterogenous GDM problem is described in Section 2. The intelligent consensus model is presented in Section 3. Finally, in Section 4 we draw our conclusions.

2. A Heterogeneous GDM Problem

A group decision-making (GDM) problem may be defined as a decision situation where there are $X = \{x_1, x_2, \ldots, x_n\}$ $(n \geq 2)$, a finite set of alternatives, and a group of experts, $E = \{e_1, e_2, \ldots, e_m\}$ $(m \geq 2)$; each expert e_i provides his/her preferences on X by means of a linguistic preference relation, $\mu_{P_{e_i}} : X \times X \rightarrow D$, where D is the expression domain used by the expert e_i to provide their preferences.

The ideal situation in a GDM problem is that all the experts have a precise knowledge about the alternatives and provide their opinions in a numerical precise scale. However, in some cases, experts may belong to distinct research areas and have different levels of knowledge about the alternatives. A consequence of this is that preferences can be expressed by means of numbers, interval values or linguistic terms, so $D \in \{N|I|L\}$.

In this contribution, we deal with heterogeneous GDM problems, i.e., GDM problems where each expert e_i may express his/her opinions on the set of alternatives using different expression domains $D_i \in \{N|I|L\}$, by means of a preference relation $\mathbf{P}_{\mathbf{e}_i} = (p_i^{jk})$, where $p_i^{jk} \in D_i$ represents the preference of alternative x_j over alternative x_k for that expert.

$$\mathbf{P}_{\mathbf{e}_i} = \begin{pmatrix} p_i^{11} & \cdots & p_i^{1n} \\ \vdots & \ddots & \vdots \\ p_i^{n1} & \cdots & p_i^{nn} \end{pmatrix}$$

This type of context implies the necessity of adequate tools to manage and model heterogeneous information [5].

3. A Consensus Model for Heterogeneous GDM problems

In this section are presented a consensus model for GDM problems defined in heterogeneous contexts that automates the moderator's functions (see Fig. 2) that is developed in four phases :

(1) *Making the information uniform*: it unifies all the different preferences into a single domain.
(2) *Computing consensus degrees*: these values measure the agreement amongst all the experts.
(3) *Checking the agreement*: these values are used to learn how close the collective and individual expert's preferences are.
(4) *Generating Advices*: an automatic advice generator guides the experts in order to improve the consensus recommending which opinions should change.

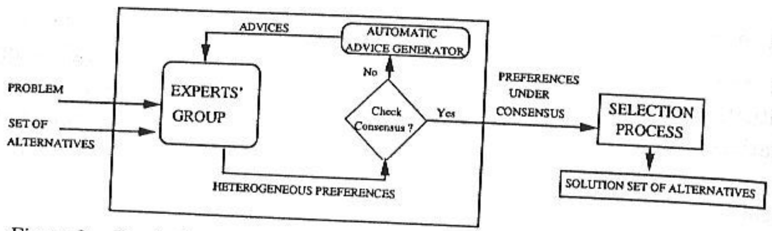

Figure 2. Resolution process of a heterogeneous group decision-making problem

The above model will be described in detail in the following subsections.

3.1. *Making the information Uniform*

We must keep in mind we are dealing with heterogeneous contexts composed by numerical, interval valued and linguistic information. So, we need to unify the heterogeneous information into a common utility space to operate on it easily. To do so we propose the use of the process proposed in [5] that transforms the heterogeneous input values into fuzzy sets on a linguistic term set, $S_T = \{s_0, ..., s_g\}$. So, each numerical, interval-valued and linguistic evaluation, is transformed into a fuzzy set in S_T, $F(S_T)$:

$$\tau_D : D \rightarrow F(S_T)$$
$$\tau_{DS_T}(p_i^{ij} = \{(c_h, \alpha_{ih}^{jk}) \;/\; h = 0, \ldots, g\} \text{ where at least } \exists \alpha_{ih}^{jk} \geq 0$$

After this unification process and assuming that each fuzzy set will be represented by means of its membership degrees $(\alpha_{i0}^{jk}, \ldots, \alpha_{ig}^{jk})$, the preference relation of each expert, P_{e_i}, whose elements are fuzzy sets:

$$P_{e_i} = \begin{pmatrix} p_i^{11} = (\alpha_{i0}^{11}, \ldots, \alpha_{ig}^{11}) & \cdots & p_i^{1n} = (\alpha_{i0}^{1n}, \ldots, \alpha_{ig}^{1n}) \\ \vdots & \cdots & \vdots \\ p_i^{n1} = (\alpha_{i0}^{n1}, \ldots, \alpha_{ig}^{n1}) & \cdots & p_i^{nn} = (\alpha_{i0}^{nn}, \ldots, \alpha_{ig}^{nn}) \end{pmatrix}$$

3.2. *Computation of Consensus Degrees*

The consensus degree measures the agreement among all the experts. To compute these degrees it is necessary to compute a consensus matrix obtained aggregating the distance among the experts preferences, comparing one with each other. The distance between two experts, e_i, e_j, is computed using distance matrices, $DM_{ij} = (d_{ij}^{lk})$. The values d_{ij}^{lk} express the distance between two preferences p_i^{lk}, p_j^{lk} and are calculated as:

$$d_{ij}^{lk} = d(p_i^{lk}, p_j^{lk}) = 1 - \left| \frac{cv_i^{lk} - cv_j^{lk}}{g} \right| \quad (1)$$

where cv_i^{lk} is the central value of the fuzzy set that represents the preference, p_i^{lk} that is calculated as:

$$cv_i^{lk} = \frac{\sum_{j=0}^{g} index(s_j^i) \cdot \alpha_{ij}^{lk}}{\sum_{j=0}^{g} \alpha_{ij}^{lk}}, \text{ being } index(s_j^i) = j. \quad (2)$$

The computation of the consensus degrees is carried out as follows:

(1) To compute the *central values* for each p_i^{ij}:
$$cv_i^{lk};\ \forall\, i = 1, \ldots, m;\ \ l, k = 1, \ldots, n \ \wedge\ l \neq k. \quad (3)$$

(2) To compute *distance matrix* $DM_{ij} = (d_{ij}^{lk})$ for each pair of experts:
$$d_{ij}^{lk} = d(p_i^{lk}, p_j^{lk}). \quad (4)$$

(3) A *consensus matrix*, $CM = (cm^{lk})$, is obtained by aggregating all the distance matrices at the level of pairs of alternatives:
$$cm^{lk} = \phi(d_{ij}^{lk});\ i, j = 1, \ldots, m \ \wedge \forall\, l, k = 1, \ldots, n \ \wedge\ i < j.$$
Where ϕ is an aggregation operator. This matrix CM is used to compute the consensus degrees.

(4) Computation of consensus degrees: This computation are carried out at three levels:

(a) *Consensus on pairs of alternatives, cp^{lk}:* it measures the agreement on the pair of alternatives (x_l, x_k) amongst all the experts:
$$cp^{lk} = cm^{lk},\ \ \forall l, k = 1, \ldots, n \ \wedge\ l \neq k.$$
The closer cp^{lk} to 1, the greater the agreement.

(b) *Consensus on alternatives, ca^l:* it measures the agreement on an alternative x_l amongst all the experts:
$$ca^l = \frac{\sum_{k=1}^{n} cm^{lk}}{n}. \quad (5)$$

(c) *Consensus on the relation, cr:* it measures the global consensus degree amongst the experts' opinions:
$$cr = \frac{\sum_{l=1}^{n} ca^l}{n}. \quad (6)$$

3.3. *Checking the Agreement*

The consensus model controls the agreement in each discussion round. Before starting the model, a consensus threshold, $\gamma \in [0,1]$, is fixed, which will depend on the particular problem we are dealing with. When the consensus measure cr reaches γ the consensus process is ended and the selection process will be applied to obtain the solution. Additionally a parameter, $Maxcycles$, controls the maximum number of discussion rounds.

3.4. *Generating Advices*

When the agreement is not good enough, $cr < \gamma$, the experts should modify their preferences to increase the agreement. To do so, this model computes which are the experts furthest from the collective opinion (proximity measures) and will generate advices for them recommending which and how do they change their preferences. Both processes are presented in detail.

3.4.1. *Computation of Proximity Measures*

Proximity measures evaluate the agreement between the individual experts' opinions and the group opinion. Thus, firstly a collective preference relation, $\mathbf{P}_{\mathbf{e}_c} = (p_c^{lk})$is calculated aggregating the individual preference relations $\{\mathbf{P}_{\mathbf{e}_i} = (p_i^{lk}); i = 1, \ldots, m\}$:

$$p_c^{lk} = \psi(p_1^{lk}, \ldots, p_m^{lk}) \text{ with } \psi \text{ an "aggregation operator"}$$

We use the equation (1) to measure the agreement between each individual expert's preferences, $\mathbf{P}_{\mathbf{e}_i}$, and the collective preferences, $\mathbf{P}_{\mathbf{e}_c}$. Therefore, the measurement of proximity is carried out in two steps:

(1) A *proximity matrix*, $PM_i = (pm_i^{lk})$, for each expert e_i, is obtained with $pm_i^{lk} = d(p_i^{lk}, p_c^{lk})$. These matrixes will be used to compute the proximity measures.

(2) Computation of proximity measures at different levels:

(a) *Proximity on pairs of alternatives* pp_i^{lk}: it measures the proximity between the preferences, on each pair of alternatives, of the expert, e_i, and the group:

$$pp_i^{lk} = pm_i^{lk}, \quad \forall l, k = 1, \ldots, n \;\; \wedge \;\; l \neq k$$

(b) *Proximity on alternatives*, pa^l: it measures the proximity between the preferences, on each alternative, x_l, of the expert, e_i, and the group:

$$pa_i^l = \frac{\sum_{k=1}^{n} pp_i^{lk}}{n} \tag{7}$$

(c) *Experts's proximity*, pe_i: it measures the global proximity between the preferences of each expert, e_i, and the group:

$$pe_i = \frac{\sum_{l=1}^{n} pa_i^l}{n} \tag{8}$$

If the above values are close to 1 then they have a positive contribution for the consensus to be high, while if they are close to 0 then they have a negative contribution to consensus.

3.5. *Advice Generator*

Finally, the consensus model will generate advices automatically in order to increase the agreement indicating who and how should change his/her opinions. This generation is carried out as:

- To identify the experts furthest from the agreement: *percentage*.
- To identify which alternatives must be changed, those alternatives whose consensus degree $ca^l < \gamma$.
- To identify the pairs of alternatives that must be changed. Once has been identified the expert e_i and the alternatives x_l to change, all the pairs p_i^{lk} $(k = 1, ..., n)$ such that $pp^{lk} < \beta$ must be changed. The parameter β is a proximity threshold that helps to choose which are the furthest alternatives from the collective opinion.
- Changing Direction Rules (CDR): finally the advice generator computes if the values of the pair of alternatives to change should increase or decrease. Taking account that p_i^{lk} are fuzzy sets the advice generator defines two direction parameters *ml* or main and *sl* or secondary. These parameters are used so to experts (eml, esl) as for the collective opinion (cml,csl). Each parameter are the value and position of the two highest membership values of the expert's preference $(eml_{pos}, eml_{val}, esl_{pos}, esl_{val})$ and the collective preference $(cml_{pos}, cml_{val}, csl_{pos}, csl_{val})$. This parameters are used by the following direction rules:

DR.1. IF $eml_{pos} > cml_{pos}$ THEN e_i should decrease the value of p_i^{lk}.
DR.2. If $eml_{pos} < cml_{pos}$ THEN e_i should increase the value of p_i^{lk}.
DR.3. If $eml_{pos} = cml_{pos}$ THEN DR.1 and DR.2 but with eml_{val} and cml_{val}.

DR.4. IF ($eml_{pos} = cml_{pos}$ AND $eml_{val} = cml_{val}$), THEN DR.1 and DR.2 but with sl.

4. Concluding Remarks

A consensus model to manage the consensus process of heterogeneous GDM problems has been presented. There are two main features of this model: (i) it is able to manage consensus processes in problems where experts may have different levels of background or knowledge to solve the problem, and (ii) it is able to generate advices on the necessary changes in the experts' opinions in order to reach consensus, which makes the figure of the moderator, traditionally present in the consensus reaching process, unnecessary.

References

1. N. Bryson. Group decision making and the analytic hierarchy process: Exploring the consensus-relevant information content. *Computers and Operational Research*, 23:27–35, 1996.
2. M. Delgado, F. Herrera, E. Herrera-Viedma, and L. Martínez. Combinig numerical and linguistic information in group decision making. *Information Sciences*, 107:177–194, 1998.
3. J. Fodor and M. Roubens. *Fuzzy preference modelling and multicriteria decision support*. Kluwer Academic Publishers, Dordrecht, 1994.
4. F. Herrera, E. Herrera-Viedma, and J.L. Verdegay. A model of consensus in group decision making under linguistic assessments. *Fuzzy Sets and Systems*, 79:73–87, 1996.
5. F. Herrera, L. Martínez, and P.J. Sánchez. Managing non-homogeneous information in group decision making. *European Journal of Operational Research*, 166(1):115–132, 2005.
6. E. Herrera-Viedma, F. Herrera, and F. Chiclana. A consensus model for multiperson decision making with different preference structures. *IEEE Transactions on Systems, Man and Cybernetics-Part A*, 32:394–402, 2002.
7. E. Herrera-Viedma, F. Mata, L. Martinez, F. Chiclana, and L.G. Perez. Measurements of consensus in multi-granular linguistic group decision making. *Lecture Notes in Artificial Intelligence, Vol. 3131*, 3131:194–204, 2004.
8. J. Kacprzyk, H. Nurmi, and M. Fedrizzi. *Consensus under Fuzziness*. Kluwer Academic Publishers, 1997.
9. L.I.Kuncheva. Five measures of consensus in gdm using fuzzy sets. In *Proc. IFSA 91*, pages 141–144, 1991.
10. S. Saint and J.R. Lawson. *Rules for Reaching Consensus. A Modern Approach to Decision Making*. Jossey-Bass, San Francisco, 1994.
11. S.Zadrozny. *Consensus under Fuzziness*, chapter An Approach to the Consensus Reaching Support in Fuzzy Environment, pages 83–109. Kluwer Academic Publishers, 1997.

Multi-Attribute Comparison of Ergonomics Mobile Phone Design based on Information Axiom 351
G. Yucel and E. Aktas

Facility Location Selection Using a Fuzzy Outranking Method 359
I. Kaya and D. Cinar

Evaluation of the Suppliers' Environmental Management Performances by a Fuzzy Compromise Ranking Technique 367
G. Büyüközkan and O. Feyzioğlu

A Fuzzy Multiattribute Decision Making Model to Evaluate Knowledge based Human Resource Flexibility Problem 375
M.E. Genevois and Y.E. Albayrak

Fuzzy Evaluation of on the Job Training Alternatives in Industrial Companies 383
G. Kayakutlu, G. Büyüközkan, B.C. Metin, and S. Ercan

A Study of Fuzzy Analytic Hierarchy Process: An Application in Media Sector 389
M. Özyol and Y.E. Albayrak

Prioritization of Relational Capital Measurement Indicators Using Fuzzy AHP 395
A. Beskese and F.T. Bozbura

Multicriteria Map Overlay in Geospatial Information System via Intuitionistic Fuzzy AHP Method 401
T. Silavi, M.R. Malek, and M.R. Delavar

A Consensus Model for Group Decision Making in Heterogeneous Contexts 409
L. Martínez, F. Mata, and E. Herrera-Viedma

A Linguistic 360-Degree Performance Appraisal Evaluation Model 417
R. de Andrés, J.L. García-Lapresta, and L. Martínez

An Interactive Support System to Aid Experts to Express Consistent Preferences 425
S. Alonso, E. Herrera-Viedma, F. Herrera, F.J. Cabrerizo, and F.Chiclana

A Model of Decision-Making with Linguistic Information based on Lattice-Valued Logic 433
J. Ma, S. Chen, and Y. Xu

Information Integration based Team Situation Assessment in an Uncertain Environment 441
J. Lu and G. Zhang

Scheduling a Flowshop Problem with Fuzzy Processing Times Using Ant Colony Optimization 449
S. Kiliç and C. Kahraman

Time Dependent Vehicle Routing Problem with Fuzzy Traveling Times under Different Traffic Conditions 457
T. Demirel and N.C. Demirel

A Programming Model for Vehicle Schedule Problem with Accident 465
C. Zeng, Y. Xu, and W. Xie

A Web Data Extraction Model based on XML and its Improvement 471
W. Xie and C. Zeng

Evaluation of E-Service Providers Using a Fuzzy Multi-Attribute Group Decision-Making Method 477
C. Kahraman and G. Büyüközkan

A Case based Research on the Directive Function of Website Intelligence to Human Flow 485
Z. Lu, Z. Deng, and Y. Wang

Genetic Algorithm for Interval Optimization and its Application in the Web Advertising Income Control 493
Q. Liao and X. Li

Applied Artificial Intelligence

Proceedings of the 7th International FLINS Conference

Edited by

Da Ruan
Pierre D'hondt
Paolo F. Fantoni
Martine De Cock
Mike Nachtegael
Etienne E. Kerre