Multi-agent-Based Semi-supervised Consensus Support System for Large-Scale Group Decision Making

Iván Palomares, Francisco J. Quesada and Luis Martínez

Abstract Consensus reaching processes (CRPs) in group decision-making (GDM) problems seek a high level of collective agreement before making a decision. The presence of large groups of experts in such problems is increasingly frequent; therefore, it is necessary to propose new consensus models and approaches that reduce the high cost of the discussion process in these cases and to develop consensus support systems based on scalable architectures that facilitate the management of large groups computationally. This contribution presents a consensus support system for large-scale GDM problems, based on a multi-agent architecture that incorporates an agent-based semi-supervised autonomy approach aimed to minimize the cost invested in the CRP.

1 Introduction

In a group decision-making (GDM) problem, two or more experts try to find a common solution to a problem composed by several alternatives or possible solutions to such a problem [4, 6]. Classically, GDM problems have been solved by applying an alternative selection process solely, irrespective of the degree of agreement among experts' opinions, which implies that the solution achieved might not be accepted by some of them [1]. In order to obtain a high level of

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agreement in the group before making a decision, it is convenient to carry out a consensus reaching process (CRP), in which experts discuss and modify their preferences to make them closer to each other, guided by a moderator [13].

CRPs have become a prominent research topic in GDM. As a result, a large number of consensus models have been proposed in the literature in the last decades [10, 13, 15]. Some of these models have been utilized in the development of consensus support systems (CSS), aimed to give further assistance to groups during CRPs [9, 16]. Some of these CSSs replace the human figure of the moderator, thus automating the tasks usually carried out by him/her.

Despite the achievements made with the proposed consensus models and CSS, new requirements that have not been considered yet in CRPs have arisen, such as the need for managing large groups, whose presence in GDM problems is increasingly frequent due to the rise of novel paradigms and means to make large-scale group decisions, e.g., social networks [14] and e-democracy [5]. Therefore, the so-called large-scale GDM problems are attaining importance in these contexts [8]. In these problems, the existence of experts or subgroups with very different opinions is especially frequent. Due to this fact, experts might need to dedicate a higher amount of time to revise and modify their preferences during the CRP. For this reason, it would be convenient to provide current models and CSS with mechanisms that minimize the necessity of human supervision of preferences, automating such supervision in those cases that it does not imply an important change on the preferences of experts. On the other hand, it is necessary to develop a CSS based on a highly scalable and distributed architecture, which is suitable to support computationally CRPs in large-scale GDM problems, in which it is difficult to organize physical meetings which all experts can attend. Examples of such architectures are the ones based on the multi-agent system paradigm [11].

In this paper, a CSS based on a multi-agent architecture for the resolution of large-scale GDM problems is presented. The system incorporates a semi-supervised autonomy approach that lets human experts delegate on software agents during the supervision of their preferences across the CRP, thus reducing the cost invested in it. Its underlying multi-agent architecture incorporates a web user interface that facilitates the communications with experts physically separated asynchronously.

The remaining of this paper is structured as follows: in Sect. 2, some preliminary concepts are introduced. Section 3 presents the CSS, showing in detail its architecture and the semi-supervised autonomy approach it implements, followed by an example of its use. Finally, some concluding remarks are given in Sect. 4.

2 Preliminaries

In this section, we review some basic concepts about GDM problems and CRPs, which are necessary to understand the main features of our proposal.

2.1 Group Decision-Making Problems

GDM problems are characterized by the existence of multiple experts with different points of view, who must find a common solution to a decision-making problem [6]. Formally, a GDM problem consists of the following elements [1, 4]:

〉 A set $X = \{x_1, \ldots, x_n\}$ $(n \geq 2)$ of *alternatives* or possible solutions to the problem.
〉 A set $E = \{e_1, \ldots, e_m\} (m \geq 2)$ of individuals or *experts*, who express their opinions on alternatives in X by means of a preference structure.

One of the most utilized preference structures in GDM problems under uncertainty is the so-called *fuzzy preference relation* [7]. A fuzzy preference relation P_i associated to an expert e_i is characterized by a membership function $\mu_{P_i} : X \times X \to [0, 1]$ and, given X finite, it can be represented as a matrix of dimension $n \times n$ as:

$$P_i = \begin{pmatrix} p_i^{11} & \cdots & p_i^{1n} \\ \vdots & \ddots & \vdots \\ p_i^{n1} & \cdots & p_i^{nn} \end{pmatrix}$$

being each assessment $p_i^{lk} = \mu_{P_i}(x_l, x_k) \in [0, 1]$ the degree of preference of alternative x_l over x_k, according to e_i, so that $p_i^{lk} > 0.5$ indicates preference of x_l over x_k, $p_i^{lk} < 0.5$ indicates preference of x_k over x_l, and $p_i^{lk} = 0.5$ indicates indifference between both alternatives.

Classical selection processes for the resolution of GDM problems [3] consist of an *aggregation phase*, in which the preferences of experts are combined, and an *exploitation phase*, where an alternative or subset of alternatives is obtained as the solution to the problem [12].

2.2 Consensus Reaching Processes

In the resolution of GDM problems, it may occur that some experts do not agree with the decision made because they think that their own opinions have not been taken into account sufficiently. CRPs, in which experts discuss and modify their preferences progressively, to make them closer to each other and reach a high level of collective agreement before making a decision, were proposed to overcome this limitation [13].

Among the different approaches of consensus proposed in the literature, the notion of *soft consensus* proposed by Kacprzyk [4] has been one of the most utilized. This approach considers different degrees of partial agreement in groups (usually measured as values in the unit interval), and it is based on the concept of fuzzy majority, according to which there exists consensus when "most experts taking part in the problem agree with their opinions on the most relevant alternatives."

The CRP is a dynamic and iterative process, which is usually coordinated by a human figure known as *moderator*, responsible for supervising and guiding experts across such a process [13]. Figure 1 shows a general CRP scheme based on the use of fuzzy preference relations to express preferences [9]:

1. *Gathering Information*: Each e_i provides to the moderator a fuzzy preference relation P_i on X.
2. *Computing Consensus Degree*: The moderator computes the current level of agreement in the group, $cr \in [0, 1]$, by means of consensus measures that are normally based on the use of similarity measures and aggregation operators.
3. *Consensus Control*: cr is compared with a minimum consensus threshold fixed a priori by the group, $\mu \in [0, 1]$. If consensus is enough, the group moves on to the selection process; otherwise, it is necessary to carry out another discussion round. In order to prevent an excessive number of rounds, a parameter $\text{Maxround} \in \mathbb{N}$ indicating the maximum number of rounds allowed can be defined.
4. *Advice Generation*: The moderator identifies the assessments p_i^{lk} of experts e_i who are farthest from consensus in the current round and advises them to modify (either increase or decrease) such assessments, in order to increase the consensus degree in the next round.

3 Consensus Support System for Large-Scale GDM

In this section, a CSS based on a multi-agent architecture, aimed at the resolution of large-scale GDM problems, is presented. Such a system extends the one presented in [9], and it introduces two novelties to facilitate the management of large groups in CRPs:

〉 A *semi-supervised autonomy model* that allows experts to delegate partially the supervision of their preferences to software agents, which carry out such supervisions autonomously, thus minimizing the amount of human intervention required during the CRP.

〉 A *web user interface* to facilitate the participation of experts physically separated in a CRP. Such an interface allows experts to send and revises their preferences, and also to choose a behavioral profile, which is implemented by a software agent responsible for modifying the assessments of each expert, as will be shown in Sect. 3.1.

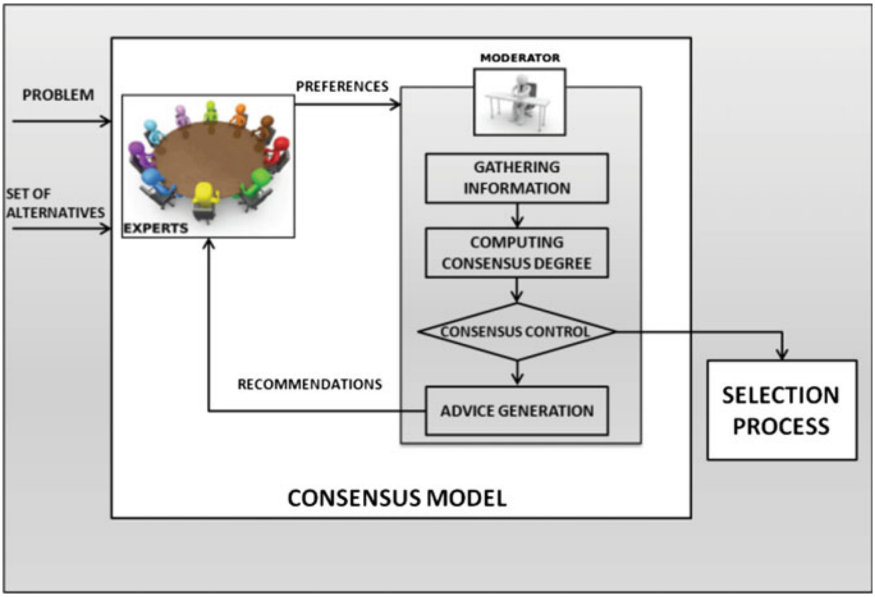

Fig. 1 General CRP scheme

The CSS description is divided into three parts: (1) the semi-supervised autonomy model proposed, (2) the architecture and main functionalities of the system, and (3) an example of its operation.

3.1 Agent-based Semi-supervised Autonomy Approach

The constant supervision of preferences by experts, based on the advice received (see *Advice Generation* phase, Sect. 2.2), might cause some problems, such as a high amount of time invested in revising preferences and the possible loss of motivation and interest in the CRP by some experts. In order to prevent these problems, we propose a semi-supervised autonomy model based on a set of *change profiles* and *supervision rules* implemented by a group of *expert agents* [9], which are responsible for carrying out human experts' tasks partially, by emulating their behavior and modifying their preferences semi-autonomously throughout the CRP. It is remarkable that despite some consensus models propose a full automation of the tasks carried out by experts [15], our interest focuses on letting the human expert supervise his/her preferences in certain cases that the advice suggested implies an important change in his/her opinions, thus preserving experts' sovereignty to some degree.

In the following, the main components of the proposed semi-supervised autonomy model are described: change profiles and supervision rules.

3.1.1 Change Profiles

The purpose of change profiles is to establish the strategy adopted by the expert to modify his/her assessments autonomously, when human supervision is not necessary. In the underlying consensus model of the proposed CSS [9], experts express their preferences by means of fuzzy preference relations, and each single piece of advice consists in a triplet $(e_i, (x_l, x_k)$, direction), which indicates that expert $e_i \in E$ must modify his/her assessment p_i^{lk} in the direction given by direction $\in \{\text{Increase, Decrease}\}$.

In CRPs, experts usually adopt different strategies to modify preferences. In order to emulate such strategies, we propose the definition of the following three types of change profiles:

1. *Sure profile*: It represents experts who are sure about their initial opinions. They apply minor changes at the beginning of the CRP, although such changes become greater as the number of discussion rounds increases.
2. *Unsure profile*: It represents experts who are rather unsure about their initial opinions. They apply major changes at the beginning of the CRP, but these changes become smaller as the process goes on.
3. *Neutral profile*: It represents experts who are moderately sure about their initial opinions and prefer to apply uniform changes on them during the CRP.

Each expert chooses the profile that better reflects his/her behavior. The profile is adopted by an expert agent that assumes the supervision of such an expert's preferences. To do so, change profiles are modeled by *change functions* (whose definition is based on agent negotiation functions such as *Kasbah* [2]) that determine the degree of increase/decrease $\Delta(r)$ on an assessment p_i^{lk}, according to the current consensus round $r \in \mathbb{N}$. A sure, unsure or neutral profile can be modeled by an increasing, decreasing or constant change function, respectively, as shown in Fig. 2.

3.1.2 Supervision Rules

Although change profiles may eliminate the need for human expert supervision completely, there are some situations in which significant changes are proposed on assessments; therefore, it would be desirable that the expert supervises such changes and decides whether he/she accepts them or not. We propose a rule-based mechanism to detect these situations. Based on the evaluation of some rules, an agent decides whether it applies changes suggested by the consensus model autonomously, or it requests supervision to its corresponding human expert.

The proposed CSS is flexible enough to facilitate modifying or extending the supervision rules considered. Here, we consider the following supervision rules:

〉 R.1: IF $p_{i(r+1)}^{lk} > 0.5$ AND $p_{i1}^{lk} \leq 0.5$ THEN request e_i's supervision on assessment p_{ir}^{lk}.

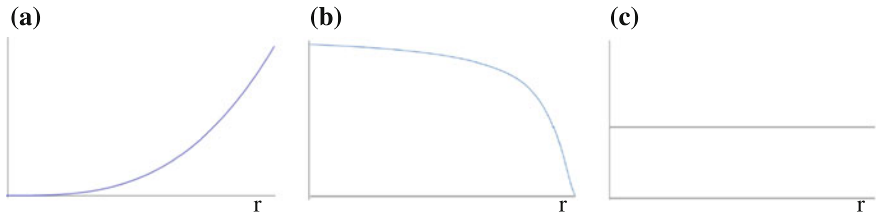

Fig. 2 Change function for **a** sure, **b** unsure and **c** neutral profile

〉 R.2: IF $p^{lk}_{i(r+1)} < 0.5$ AND $p^{lk}_{i1} \geq 0.5$ THEN request e_i's supervision on assessment p^{lk}_{ir}.

where p^{lk}_{ir} represents e_i's current assessment on the pair of alternatives (x_l, x_k) at round r, p^{lk}_{i1} is his/her initial assessment, and $p^{lk}_{i(r+1)} = p^{lk}_{ir} \pm \varDelta(r)$ represents the new value it would take after accepting the advice, according to the change profile chosen by e_i. In other words, the system requests human supervision when the acceptance of an advice suggested implies a change on the alternative preferred in an assessment, with respect to the initial opinion.

3.2 System Architecture

The CSS we present is based on a multi-agent architecture and a client/server architecture with a web user interface. Figure 3 shows a simplified scheme of the system architecture, focused on the communication flow with users.

The multi-agent system has been implemented with the aid of the JADE[1] agent development platform. Agents in the CSS automate completely the human moderator tasks [9], thus facilitating CRPs in large-scale GDM problems. The web interface, whose implementation is based on Servlets and JSP, allows an asynchronous communication between users and agents.

The system distinguishes two types of users: expert user and administrator user. The functionalities offered by the system to each of them are detailed below:

3.2.1 Expert Users

The main functions that expert users can perform are the following ones:

〉 *Introduce preferences*: Each expert user introduces his/her initial assessments on the alternatives of the GDM problem considered and sends them to the system

[1] http://jade.tilab.com

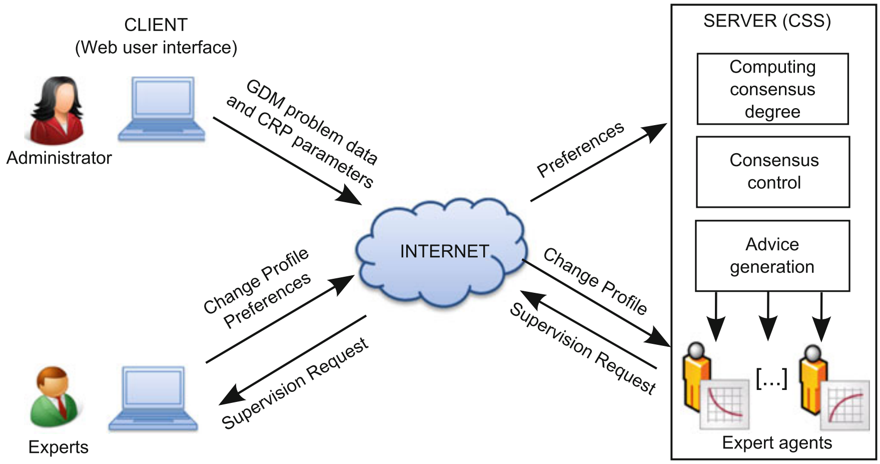

Fig. 3 System architecture

(Fig. 4). Moreover, before beginning the CRP, the expert can choose the change profile desired for such a problem.

〉 *Supervise change recommendations*: The system sends each expert one or more requests to supervise those change recommendations that imply an important change in his/her assessment, thus letting him/her accept or ignore each advice.

〉 *Modify user profile*: Each expert has a modifiable user profile in the system, with information about personal data and the default change profile adopted.

〉 *Consult information about the problem*: During the CRP, an expert user can consult information about the current GDM problem status, as well as the current discussion round and the consensus degree achieved.

3.2.2 Administrator User

This user is responsible for carrying out the following actions:

〉 *Create problem*: It consists in defining a new GDM problem and its main parameters, including: set of alternatives, experts invited to take part in the problem and parameters for the CRP.

〉 *Manage experts*: The administrator can create, modify or delete the existing expert users in the system.

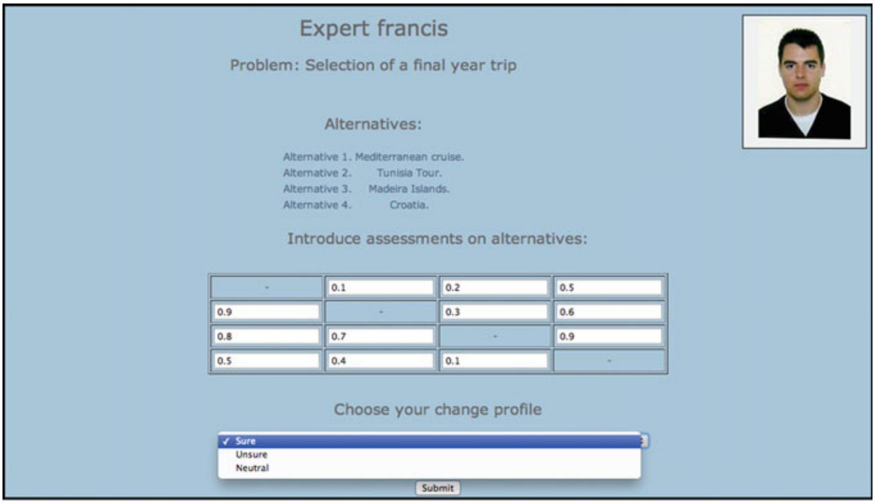

Fig. 4 Introducing initial preferences and change profile

3.3 Application Example

Here, it is shown an example of the CSS application to solve a GDM problem under consensus, with the aim of illustrating the advantages of the proposed semi-supervised autonomy model.

The GDM problem formulation is as follows: a group of 23 Business Management Degree students, $E = \{e_1, \ldots, e_{23}\}$, tries to achieve an agreement to decide the destination of their final year trip. The possible destinations are: $X = \{x_1$: Mediterranean cruise, x_2: Tunisia Tour, x_3: Madeira Island and x_4: Croatia$\}$. The degree of agreement desired by the group is $\mu = 0.85$, and the maximum number of discussion rounds is Maxround $= 10$. Students choose the following change profiles: 4 sure, 9 unsure and 10 neutral. Table 1 shows the change functions $\Delta(r)$ associated with such profiles.

For the problem resolution, students attended a laboratory session at the faculty; they accessed the system and introduced their initial opinions (see Fig. 4).

After a consensus round, each student receives a request to carry out the necessary supervisions (if any) on his/her assessments. Expert agents generate such request if any of the rules defined in the semi-supervised approach accomplishes (see Sect. 3.1), otherwise changes proposed are applied automatically.

Results obtained at each consensus round, r, are summarized in Table 2, and they include the consensus degree achieved, the total number of change recommendations generated for single assessments, the number of supervisions necessary and the number of experts who had to perform any supervision in such a round (denoted as *#Experts sup*). Results show that the number of required supervisions is much lower than the total number of recommendations generated at

Table 1 Change functions considered

Change profile	Change function $\Delta(r)$
Sure	$0.2\left(\frac{r}{10}\right)^3$
Unsure	$0.2\left(1-\left(\frac{r}{10}\right)^3\right)$
Neutral	0.1

Table 2 CRP results

r	Consensus degree	#Recommendations	#Supervisions	#Experts sup
1	0.6484	108	**0**/108	**0**/23
2	0.7317	82	**5**/82	**4**/23
3	0.7811	65	**25**/65	**6**/23
4	0.8100	55	**14**/55	**6**/23
5	0.8351	13	**3**/13	**2**/23
6	**0.8502**			

each round; therefore, most of them do not mean an important change in assessments' values. Additionally, only a minor proportion of experts must supervise their preferences across the CRP. It is concluded that the CSS presented contributes to reduce the temporal cost invested in conducting CRPs for the resolution of large-scale GDM problems.

4 Concluding Remarks

In this contribution, we have presented a consensus support system based on a multi-agent architecture, to facilitate the resolution of (CRPs) in large-scale GDM problems. Such a system incorporates a web user interface suitable to conduct non-physical meetings, and it is characterized by implementing a semi-supervised autonomy model that eliminates the problem of constant supervision of preferences by experts.

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