Attitude-Driven Web Consensus Support System for Large-Scale GDM Problems Based on Fuzzy Linguistic Approach

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Abstract. In real-life Group Decision Making problems defined under uncertainty, it is usually necessary to carry out a consensus reaching process to achieve a solution that is accepted by all experts in the group. Additionally, when a high number of experts take part in such processes, it may sometimes occur that some subgroups of them with similar interests try to bias the collective opinion, which makes it more difficult to reach a collective agreement. The consensus reaching process could be optimized if the group's attitude towards consensus were integrated in it, and the complexity of dealing with large groups of experts could be reduced with the adequate automation of such a process. This paper presents a Web-based Consensus Support System for large-scale group decision making problems defined under uncertainty, that integrates the group's attitude towards consensus and allows experts to provide their preferences by means of linguistic information. The underlying consensus model of the proposed system carries out processes of Computing with Words to deal with linguistic preferences effectively.

Keywords: Linguistic Group Decision Making, Consensus Reaching, Consensus Support System, Attitude.

1 Introduction

Decision making is a usual mankind process in daily life. In a group decision making (GDM) problem, a group of decision makers or experts try to reach a common solution to a problem consisting of a set of possible alternatives [3]. Real GDM problems are often defined under an uncertain environment, so that experts may prefer in some occasions to provide information (preferences about alternatives) in a domain closer to human natural language, e.g. by means of linguistic information [1, 10].

An increasingly important aspect in many real GDM problems is the need for a common solution which is accepted by all experts in the group, which can be achieved if Consensus Reaching Processes (CRPs) are introduced as part of the

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GDM problems resolution process [7]. Nowadays computational advances make it possible the participation of larger groups of experts in CRPs. However, some challenges arise in CRPs during the resolution of large-scale GDM problems:

– The possible existence of subgroups of experts with an own-group interest, who try to deviate the solution of the GDM problem to a solution according to their aims forgetting about the CRP, so that it is much more difficult to achieve an agreed solution. In such cases, the integration of the group's attitude towards consensus, i.e. experts' capacity to modify their own preferences during the CRP, becomes an important aspect to optimize CRPs involving large groups [5].
– Despite CRPs are classically guided and supervised by a human moderator [7], the management of large groups not only turns his/her tasks more complex, but also complicates physical meetings. The design of a Consensus Support System (CSS) that automates the moderator's tasks and facilitates non-physical meetings becomes then necessary.

This paper presents a web-based CSS that supports consensus processes for large-scale GDM problems defined under uncertainty. The underlying consensus model of such a system integrates the group's attitude towards consensus in the CRP, and it allows experts the use of linguistic information to provide their preferences. In order to facilitate computations on linguistic information across the CRP, the methodology of Computing with Words (CW) [6,11] is considered, by utilizing the 2-tuple linguistic model [2] to carry out such computations.

This paper is structured as follows: Section 2 revises some basic concepts. Section 3 presents the proposed CSS and its underlying consensus model. Section 4 shows an example of the CSS performance, and Section 5 concludes the paper.

2 Basic Concepts

In this section, some preliminary concepts used in our proposal about linguistic GDM, the 2-tuple linguistic model and attitude integration in CRPs are reviewed.

2.1 Linguistic Group Decision Making

GDM problems are formally defined as decision situations in which a set $E = \{e_1, \ldots, e_m\}$, $(m \geq 2)$, of decision makers or *experts* must express their preferences over a finite set of *alternatives* $X = \{x_1, \ldots, x_n\}$, $(n \geq 2)$ by using a preference structure, for instance a *linguistic preference relation* P_i [1]:

$$P_i = \begin{pmatrix} - & \ldots & p_i^{1n} \\ \vdots & \ddots & \vdots \\ p_i^{n1} & \ldots & - \end{pmatrix}$$

where each assessment $p_i^{lk} = s_u \in S$ represents e_i's degree of preference of alternative x_l over x_k, $(l \neq k)$, expressed as a linguistic term s_u in a term set

$S = \{s_0, \ldots, s_g\}$ with granularity g. Without loss of generality, it is assumed in this paper that S is chosen by considering that linguistic terms s_u ($u = 0, \ldots, g$), are symmetrically distributed in an ordered scale, with odd cardinality, $|S| = g + 1$. It is also assumed here that the semantics of a term $s_u \in S$ will be represented by a triangular fuzzy number in the unit interval [4].

2.2 2-tuple Linguistic Computational Model for CW

Classical resolution schemes for linguistic GDM [1], showed the necessity of using models to operate with linguistic information accurately and obtain understandable results [6]. The methodology of CW was proposed by L. Zadeh in [11] to facilitate reasoning, computational and decision making processes on linguistic information. In the field of CW, there exist multiple linguistic computational models that define different operations on linguistic information, such as aggregation, comparison, etc. One of the most extended models of CW in linguistic decision making is the so-called 2-tuple linguistic model [2], which avoids the loss of information and guarantees accurate and understandable results.

The 2-tuple linguistic model represents the information by means of a pair (s, α), where $s \in S$ is a linguistic term and $\alpha \in [-0.5, 0.5)$ is a *symbolic translation* that supports the "difference of information" between a counting of information β assessed in the interval of granularity of S, $[0, g]$, and its closest value in {0,. . . ,g}, which indicates the index of the closest linguistic term in S. Some functions were defined to facilitate computational processes on 2-tuples by transforming them into numerical values. A bijective function $\Delta : [0, g] \to S \times [-0, 5, 0.5)$ is defined as follows [2]:

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} i = \text{round}(\beta), \\ \alpha = \beta - i, \end{cases} \tag{1}$$

where *round* assigns β its closest value $i \in \{0, \ldots, g\}$. An inverse function $\Delta^{-1} : S \times [-0, 5, 0.5) \to [0, g]$ which, given a linguistic 2-tuple, returns its equivalent numerical value β, is also defined as:

$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \tag{2}$$

The 2-tuple linguistic computational model defined different operations on 2-tuples [2]. The consensus approach proposed (see Sect. 3.1) considers the use of 2-tuple aggregation operators across the CRP [4, 6].

2.3 Attitude Integration in Consensus Reaching

The integration of the group's attitude towards consensus in situations in which several subgroups of experts with different interests take part in a large-scale GDM problem, might help optimizing CRPs according to their needs and the characteristics of each particular problem. A model that integrates such an attitude was recently proposed in [5], where the following two types of group's attitudes were presented:

- *Optimistic attitude*: Achieving an agreement is more important for experts than their own preferences. Therefore, more importance is given to positions in the group with higher agreement.
- *Pessimistic attitude*: Experts prefer to preserve their own preferences. Therefore, positions in the group with lower agreement are given more importance.

Here, we also introduce the possibility of adopting a neutral attitude:

- *Neutral attitude*: Experts consider that both achieving an agreement and preserving their own preferences are equally important. Therefore, positions in the group with an intermediate degree of agreement attain a greater importance.

In order to integrate the attitude of experts in CRPs, it is used an aggregation operator, so-called Attitude-OWA, which extends OWA aggregation operators [8] and is specially suitable for dealing with large groups of experts [5]. Attitude-OWA uses two *attitudinal parameters* provided by the decision group:

- $\vartheta \in [0,1]$ represents the group's attitude, which can be optimistic ($\vartheta > 0.5$), pessimistic ($\vartheta < 0.5$) or neutral ($\vartheta = 0.5$). It is equivalent to the *orness* measure that characterizes OWA operators [8].
- $\varphi \in [0,1]$ indicates the amount of agreement positions that are given non-null weight in the aggregation. The higher φ, the more values are considered.

Attitude-OWA operator is then defined as follows:

Definition 1. *[5] An* Attitude-OWA operator *on a set $A = \{a_1, \ldots, a_h\}$, based on attitudinal parameters ϑ, φ, is defined by:*

$$Attitude - OWA_W(A, \vartheta, \varphi) = \sum_{j=1}^{h} w_j b_j \tag{3}$$

being $W = [w_1 \ldots w_h]^\top$ a weighting vector, with $w_i \in [0,1], \sum_i w_i = 1$, and b_j the j-th largest of a_i values.

Weights w_i are computed based on ϑ and φ, so that they reflect the attitude adopted by experts. The following scheme was proposed to compute them [5]:

i) The values of ϑ, φ are determined, based on the interests of experts in the group and/or the nature of the GDM problem.
ii) A *Regular Increasing Monotone* quantifier with membership funcion $Q(r)$,

$$Q(r) = \begin{cases} 0 & \text{if } r \leq \gamma, \\ \frac{r-\gamma}{\delta-\gamma} & \text{if } \gamma < r \leq \delta, \\ 1 & \text{if } r > \delta. \end{cases} \tag{4}$$

is defined, being $r \in [0,1]$, $\gamma = 1 - \vartheta - \frac{\varphi}{2}$ and $\delta = \gamma + \varphi$.
iii) Yager's method is applied to compute weights w_i [9]:

$$w_i = Q\left(\frac{i}{h}\right) - Q\left(\frac{i-1}{h}\right), i = 1, \ldots, h \tag{5}$$

3 Consensus Support System

This section presents an attitude-based Web CSS aimed to solve large-scale linguistic GDM problems. Its main novelty is the consensus model implemented, which extends the one proposed in [5], by introducing the necessary steps to manage linguistic information based on the 2-tuple linguistic model, and improving the feedback mechanism applied during the CRP to avoid generating an excessive amount of advice for experts. The Web-based CSS architecture is also presented.

The CSS description is divided into two parts: (i) a detailed scheme of the consensus model; and (ii) an overview of the architecture and functionalities of the system.

3.1 Consensus Model

A scheme of the proposed consensus model is depicted in Fig. 1. Its phases are described in detail below:

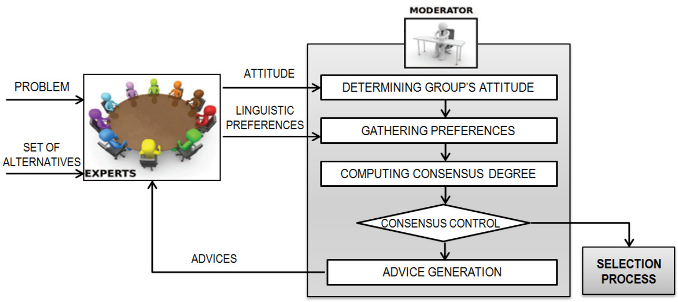

Fig. 1. Consensus model scheme

1. *Determining Group's Attitude*: The group's attitude towards consensus is determined by gathering attitudinal parameters ϑ, φ.
2. *Gathering Preferences*: Each e_i provides his/her preferences on X by means of a linguistic preference relation $P_i = (p_i^{lk})^{n \times n}$, $p_i^{lk} \in S$ (see Sect. 2.1).
3. *Computing Consensus Degree*: The degree of collective agrement is computed as a value in [0,1] (inspired by Kacprzyk's notion of "soft consensus" [3]). This paper introduces the use of the 2-tuple linguistic model in this phase to carry out processes of CW on linguistic information. Additionally, the group's attitude towards consensus is integrated during this phase:
   (a) For each linguistic assessment $p_i^{lk} = s_u$ $(u = 0, \ldots, g)$, its corresponding β value (which will be denoted as β_i^{lk}) is computed as follows:
$$\beta_i^{lk} = \Delta^{-1}\left((s_u, 0)_i^{lk}\right) = u \tag{6}$$
   being $(s_u, 0)_i^{lk}$ the 2-tuple associated to an assessment $p_i^{lk} = s_u \in S$ and Δ^{-1} the transformation function shown in Eq. (2) [2].

(b) For each pair e_i, e_t, $(i < t)$, a *similarity matrix* $SM_{it} = (sm_{it}^{lk})^{n \times n}$, $sm_{it}^{lk} \in [0,1]$, is computed:

$$sm_{it}^{lk} = 1 - \left| \frac{\beta_i^{lk} - \beta_t^{lk}}{g} \right| \quad (7)$$

(c) A *consensus matrix* $CM = (cm^{lk})_{n \times n}$ is obtained by aggregating similarity values, by means of Attitude-OWA operator, which integrates the group's attitude in the CRP (see Sect. 2.3) [5]. This aggregation step is the main novelty, with respect to other previous consensus models, for the management of large groups in CRPs:

$$cm^{lk} = Attitude - OWA_W(SIM^{lk}, \vartheta, \varphi) \quad (8)$$

where the set $SIM^{lk} = \{sm_{12}^{lk}, \ldots, sm_{1m}^{lk}, \ldots, sm_{(m-1)m}^{lk}\}$ represents all pairs of experts' similarities in their opinion on (x_l, x_k), and cm^{lk} is the degree of consensus achieved by the group in their opinion on (x_l, x_k).

(d) Consensus degrees ca^l on each alternative x_l, are computed as

$$ca^l = \frac{\sum_{k=1, k \neq l}^{n} cm^{lk}}{n-1} \quad (9)$$

(e) Finally, an overall consensus degree is computed:

$$cr = \frac{\sum_{l=1}^{n} ca^l}{n} \quad (10)$$

4. *Consensus Control*: Consensus degree *cr* is compared with a consensus threshold $\mu \in [0,1]$, established a priori by the group. If $cr \geq \mu$, the CRP ends and the group moves on the selection process; otherwise, the process requires further discussion. A parameter $Maxrounds \in \mathbb{N}$ can be also defined to limit the maximum number of discussion rounds.
5. *Advice Generation*: When $cr < \mu$, experts must modify their preferences to make them closer to each other and increase the consensus degree in the following CRP round. Despite a human moderator has been traditionally responsible for advising and guiding experts during CRPs [7], the proposed CSS automates his/her tasks, most of which are conducted in this phase of the CRP. Two novelties are introduced in this phase: the use of the 2-tuple linguistic model to carry out computations on linguistic assessments, and a threshold parameter that will improve the feedback generation mechanism.

(a) Compute a collective preference and proximity matrices: A 2-tuple-based collective preference $P_c = (p_c^{lk})^{n \times n}$, $p_c^{lk} \in S \times [-0.5, 0.5)$, is computed for each pair of alternatives by aggregating experts' preference relations:

$$p_c^{lk} = (s_u, \alpha)_c^{lk} = \nu((s_u, \alpha)_1^{lk}, \ldots, (s_u, \alpha)_m^{lk}) \quad (11)$$

where $s \in S$ and ν is a 2-tuple aggregation operator [2,4,6]. Afterwards, a proximity matrix PP_i between each e_i's preference relation and P_c

is obtained. Proximity values $pp_i^{lk} \in [0,1]$ are computed for each pair (x_l, x_k) as follows:

$$pp_i^{lk} = 1 - \left| \frac{\beta_i^{lk} - \beta_c^{lk}}{g} \right| \tag{12}$$

being $\beta_c^{lk} = \Delta^{-1}\left((s,\alpha)_c^{lk}\right)$.

(b) Identify preferences to be changed (CC): Assessments on pairs (x_l, x_k) whose consensus degrees ca^l and cp^{lk} are not enough, are identified:

$$CC = \{(x_l, x_k) | ca^l < cr \wedge cp^{lk} < cr\} \tag{13}$$

Based on CC, the model identifies those experts who should change their opinions on each of these pairs, i.e. those e_is whose assessment p_i^{lk} on $(x_l, x_k) \in CC$ is furthest to p_c^{lk}. To do so, an average proximity $\overline{pp}^{lk}$ is calculated, by using an aggregation operator λ:

$$\overline{pp}^{lk} = \lambda(pp_1^{lk}, \ldots, pp_m^{lk}) \tag{14}$$

Experts e_i whose $pp_i^{lk} < \overline{pp}^{lk}$ are advised to modify their assessments p_i^{lk} on (x_l, x_k).

(c) Establish change directions: Some direction rules are checked to suggest the direction of changes proposed to experts on their linguistic assessments. Here, we propose a novel mechanism that optimizes the performance of this step in large-scale GDM, by introducing an acceptability threshold $\varepsilon \geq 0$, to allow a margin of acceptability in the cases that β_i^{lk} and β_c^{lk} are close to each other. This approach prevents generating an excessive number of unnecessary advice for experts in such cases.

- DIR.1: If $(\beta_i^{lk} - \beta_c^{lk}) < -\varepsilon$, then e_i should *increase* his/her assessment p_i^{lk} on (x_l, x_k).
- DIR.2: If $(\beta_i^{lk} - \beta_c^{lk}) > \varepsilon$, then e_i should *decrease* his/her assessment p_i^{lk} on (x_l, x_k).
- DIR.3: If $-\varepsilon \leq (\beta_i^{lk} - \beta_c^{lk}) \leq \varepsilon$ then e_i should not modify his/her assessment p_i^{lk} on (x_l, x_k).

3.2 System Architecture

The CSS is based on a client/server architecture with a Web user interface, so that users do not have to install any specific software to use the CSS in their computer. Figure 2 depicts the architecture of the CSS and the communication between the client and server sides, which will be explained in further detail below.

The main advantage of the system is the automation of the human moderator, thus eliminating any biasness caused by his/her possible subjectivity, and it facilitates ubiquitous CRPs amongst large groups of experts. The CSS functions are divided into two categories: client and server functions.

Client. On the client side, the following four interfaces have been designed to communicate the CSS with experts participating in a GDM problem:

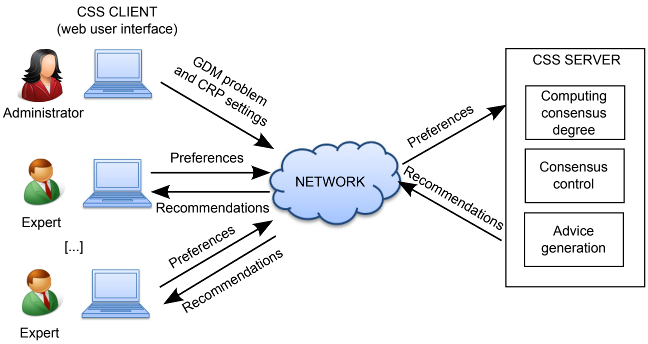

Fig. 2. CSS architecture and client-server communication

- *Authentication*: An expert introduces his/her username and password to authenticate in the CSS.
- *Problem selection*: The expert is shown information about the GDM problem/s to which he/she has been invited to take part.
- *Preferences elicitacion* (Fig. 3): Experts provide their preferences by means of a linguistic preference relation (Sect. 3.1, phase 2), whose assessments are linguistic terms in a term set defined a priori by the administrator of the CSS, as will be explained below.
- *Checking advice received during the CRP*: At the end of a discussion round (after phase 5 in Sect. 3.1), the application shows each expert the advice to modify his/her preferences.

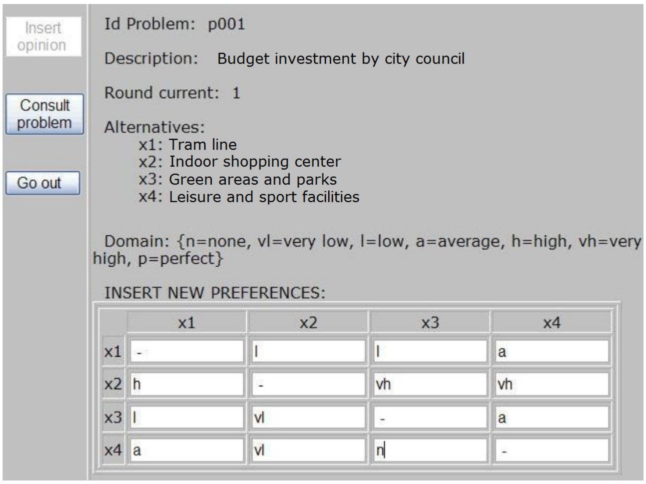

Fig. 3. Expressing preferences

Additionally, some users can log in the system under the role of administrator to define the initial GDM problem settings, including: the GDM problem description and alternatives, experts invited to take part in the problem, parameters of the CRP and the linguistic term set to be used by experts.

Server. The server communicates with the client interfaces to send/receive information to/from experts by means of the Internet. Some modules that correspond with different phases of the consensus model described in Sect. 3.1 are implemented here to automate the human moderator tasks during the CRP: (i) computing the consensus degree (Sect. 3.1, phase 3), (ii) consensus Control (Sect. 3.1, phase 4) and (iii) advice Generation (Sect. 3.1, phase 5).

4 System Performance

In this section, a large-scale GDM problem is introduced and solved by using the proposed CSS. The problem is formulated as follows: a group of 41 students from Computer Science M.Sc. Degree, $E = \{e_1, \ldots, e_{41}\}$, must make an agreed decision about choosing a place to celebrate their graduation dinner. The set of proposed restaurants is $X = \{x_1$: 'Santa Catalina' castle, x_2: 'Los Caballos' ranch, x_3: 'Pegalajar' caves, x_4: 'Juleca' complex$\}$.

The following linguistic term set is defined to allow students provide their preferences, $S = \{s_0 : None(n),\ s_1 : Very\ low(vl),\ s_2 : Low(l),\ s_3 : Average(a),\ s_4 : High(h),\ s_5 : Very\ high(vh),\ s_6 : Perfect(p)\}$.

The group stated that they preferred to achieve a collective agreement as fast as possible, rather than preserving their own individual preferences. The CRP was first applied without considering the group's attitude (the arithmetic mean operator was used instead of Attitude-OWA to compute cm^{lk} in Eq. (8)). Afterwards, the CRP was carried out again twice, by defining two different attitudes: an optimistic and a pessimistic attitude. Table 1 shows the parameters defined for the CRP, including the two attitudes considered.

Table 1. Parameters defined at the beginning of the CRP

Attitudinal param.	Optimistic $\vartheta = 0.65, \varphi = 0.6$ Pessimistic: $\vartheta = 0.35, \varphi = 0.6$
Consensus threshold	$\mu = 0.85$
Max. #rounds	$Maxrounds = 10$
Accept. threshold	$\varepsilon = 0.2$

Once all experts logged in the system, selected the GDM problem to take part in it and submitted their initial preferences by means of the Web user interface (see Fig. 3), the CRP began. Table 2 shows the convergence towards consensus, i.e. the consensus degree achieved at each round, for each case defined above. Students were most satisfied with the solution achieved when an optimistic attitude was adopted, because a fewer number of discussion rounds was required in this case to reach a consensus.

The proposed CSS facilitated the resolution of the large-scale GDM problem defined, taking into account the attitude of experts towards consensus and letting them provide their preferences by means of linguistic terms. The 2-tuple linguistic model made it possible to make the necessary computations of the CRP on linguistic information without any loss of information.

Table 2. Global consensus degree for each round

Consensus round:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Without attitude	0.695	0.743	0.772	0.805	0.823	**0.855**		
Pessimistic	0.512	0.587	0.656	0.707	0.749	0.801	0.839	**0.868**
Optimistic	0.793	0.828	**0.851**					

5 Concluding Remarks

In this paper, we have presented a Web-based Consensus Support System to deal with large-scale linguistic group decision making problems. The presented system, which incorporates a client-server architecture that automates the consensus reaching process to a high degree, is characterized by integrating the group's attitude towards consensus. The consensus model carries out processes of Computing with Words based on the 2-tuple linguistic model to deal with linguistic information provided by experts, thus preventing any loss of information.

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