Decision Support Systems 84 (2016) 1–15

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

# Integrating experts' weights generated dynamically into the consensus reaching process and its applications in managing non-cooperative behaviors

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ARTICLE INFO

*Article history:*
Received 12 August 2015
Received in revised form 15 December 2015
Accepted 5 January 2016
Available online 14 January 2016

*Keywords:*
Group decision making
Consensus reaching process
Self-management mechanism
Non-cooperative behaviors

ABSTRACT

The consensus reaching process (CRP) is a dynamic and iterative process for improving the consensus level among experts in group decision making. A large number of non-cooperative behaviors exist in the CRP. For example, some experts will express their opinions dishonestly or refuse to change their opinions to further their own interests. In this study, we propose a novel consensus framework for managing non-cooperative behaviors. In the proposed framework, a self-management mechanism to generate experts' weights dynamically is presented and then integrated into the CRP. This self-management mechanism is based on multi-attribute mutual evaluation matrices (MMEMs). During the CRP, the experts can provide and update their MMEMs regarding the experts' performances (e.g., professional skill, cooperation, and fairness), and the experts' weights are dynamically derived from the MMEMs. Detailed simulation experiments and comparison analysis are presented to justify the validity of the proposed consensus framework in managing the non-cooperative behaviors.


## 1. Introduction

Group decision making (GDM) [29,63] can be viewed as a task to find a collective solution to a decision problem in situations in which experts express their opinions regarding multiple alternatives. Usually, at the beginning of the GDM problem, the experts' opinions may differ substantially. The consensus reaching process (CRP) is often a necessity to achieve a general consensus regarding the selected alternatives in GDM [21,24]. Classically, consensus is defined as the full and unanimous agreement of all experts regarding all possible alternatives. However, this definition is inconvenient and complete agreement is not always necessary in real life. This belief has led to the use of a “soft” consensus level (i.e., consensus measure) [7,8,26,30,31,39,56]. Based on a “soft” consensus level, different types of CRPs have been proposed: (i) CRPs under different preference representation formats [10,13,15,17,28,35,55]; (ii) CRPs with minimum adjustments or cost [5,6,12,16,22,23,66,68,69]; (iii) CRPs based on consistency and consensus measures [18,20,25,54,67]; (iv) CRPs that consider the attitudes of experts [38,45]; (v) CRPs under dynamic/Web contexts [1,2,32,43,65]; (vi) CRPs based on trust or experts' weights [4,42,53].

In GDM problems, a large number of non-cooperative behaviors exist. For example, some experts will express their opinions dishonestly or refuse to change their opinions to obtain their own interests. Hence, it is necessary to address non-cooperative behaviors to ensure the quality of the GDM results. In the extant literature, Pelta and Yager [41] and Yager [59,60] investigated the non-cooperative behaviors that are called strategic manipulation behaviors and occur in the aggregation function that is used in the selection process of GDM problems. Recently, Palomares et al. [40] proposed a consensus model for addressing non-cooperative behaviors in the CRP of GDM problems, in which the weights of the experts who have the non-cooperative behaviors are compulsively penalized by a moderator. Although these approaches are very useful, they still need to be further improved to cope with non-cooperative behaviors in real-world GDM problems because (1) in the works of Pelta and Yager [41] and Yager [59,60], the non-cooperative behaviors are considered solely in the selection process of GDM problems and are not considered in the CRP and (2) in the work of Palomares et al. [40], the management of the non-cooperative behaviors is heavily dependent on a moderator and is occasionally excessively demanding for the moderator.

Therefore, the objective of this study is to propose a novel consensus framework based on a self-management mechanism to manage non-cooperative behaviors in the CRP. In this novel consensus framework, the experts provide not only preference information about alternatives but also mutual evaluation information for experts. The mutual evaluation information is given by means of multi-attribute mutual evaluation matrices (MMEMs). We propose an optimization-based approach to obtain the experts' weights from the MMEMs. Furthermore, the obtained experts' weights are integrated into the CRP. During the CRP, the experts not only modify their preference information about alternatives to

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http://dx.doi.org/10.1016/j.dss.2016.01.002
0167-9236/

achieve a consensus but also modify their MMEMs regarding experts' performances (e.g., professional skill, cooperation, and fairness). We propose detailed simulation experiments and a comparison analysis to justify the validity of the proposed consensus framework in managing non-cooperative behaviors.

The proposal with the self-management mechanism can be applied to address non-cooperative behaviors in the CRPs of practical GDM problems. When an academic conference committee wants to select a best paper or a science foundation committee hopes to find outstanding projects to support, some committee members may adopt non-cooperative behaviors to obtain their own interests; thus, the committees are confronted with the need to manage non-cooperative behaviors. The proposal provides a self-management mechanism to help the committees cope with the non-cooperative behaviors by using the means that the committee members provide and update their MMEMs in the multiple rounds of discussion.

The remainder of this study is arranged as follows. Section 2 introduces preliminaries. Then, Section 3 describes the consensus-based GDM with non-cooperative behaviors and proposes the resolution framework. Next, we apply the proposed consensus framework to manage non-cooperative behaviors in Section 4. Following this, in Section 5, an illustrative example is provided. Finally, concluding remarks are included in Section 6.

## 2. Preliminaries

This section introduces the basic knowledge regarding the ordered weighted average (OWA) operator, the additive preference relations (also called fuzzy preference relations), and the selection process to obtain the ranking of alternatives, which provide a basis for this study.

For a GDM problem, let $X=\{x_1,x_2,...,x_n\}$ $(n\geq 2)$ be a finite set of alternatives and $E=\{e_1,e_2,...,e_m\}$ $(m\geq 2)$ be a set of experts. When experts express their opinions about alternatives, the preference representation formats are popular techniques. There are several different preference representation formats, including utility functions [51], preference orderings [47], multiplicative preference relations [46,48], additive preference relations [27,36,51], and linguistic preference relations [14,44,50]. Herrera-Viedma et al. [28] discussed the transformation functions among different preference representation formats. In this study, we assume that experts provide their opinions about alternatives by means of additive preference relations.

(1) OWA operator

Let $\{c_1,c_2,...,c_N\}$ be a set of values to aggregate. The OWA operator [57] is defined as

$$OWA(c_1,c_2,\ ...,c_N)=\sum_{k=1}^{N}\pi_k b_k. \tag{1}$$

where $b_k$ is the $k$th largest value in $\{c_1,c_2,...,c_N\}$, and $\pi=(\pi_1,\pi_2,...,\pi_N)^T$ is an associated weight vector such that $\pi_k\in[0,1]$ and $\sum_{k=1}^{N}\pi_k=1$.

In [58], Yager suggested an effective method to compute $\pi=(\pi_1,\pi_2,...,\pi_N)^T$ using linguistic quantifiers, which, in the case of a non-decreasing proportional quantifier $Q$ [64], is given by the following expression:

$$\pi_i=Q\left(\frac{i}{N}\right)-Q\left(\frac{i-1}{N}\right),\ \ i=1,2,...,l\ , \tag{2}$$

where $Q(c)$ can be represented as

$$Q(c)=\begin{cases}0, & c<a\\ \dfrac{c-a}{b-a}, & a\leq c\leq b\\ 1, & c>b\end{cases} \tag{3}$$

with $a,b,c\in[0,1]$.

There are several common linguistic quantifiers, such as *all*, *most*, *at least half*, and *as many as possible*, where the parameters $(a,b)$ are (0,1), (0.3,0.8), (0,0.5), and (0.5,1), respectively. When a linguistic quantifier $Q$ is used to compute the weights of the OWA operator, it is symbolized by $OWA_Q$.

(2) Additive preference relations

**Definition 1.** *Additive preference relations* [36,51]. An additive preference relation on a set of alternatives $X=\{x_1,x_2,...,x_n\}$ is represented by a matrix $P=(p_{ij})_{n\times n}$, where $p_{ij}\in[0,1]$ denotes the preference degree of the alternative $x_i$ over $x_j$. An additive preference relation is usually assumed to be additive reciprocal, i.e., $p_{ij}+p_{ji}=1,\ \forall i,j$.

For simplicity, we call the additive preference relations the preference relations in this study. Let $\Pr=(pr_1,pr_2,...,pr_n)^T$ be the preference vector over alternatives $X$ derived from the preference relation $P=(p_{ij})_{n\times n}$, where $pr_i\geq 0$ is the preference value of the alternative $x_i$. In this study, the quantifier-guided dominance degree $QGDD_i$ is used to quantify the preference value of the alternative $x_i$ as follows [28]:

$$pr_i=QGDD_i=OWA_Q(p_{i1},p_{i2},\ldots,p_{in}). \tag{4}$$

(3) Selection process in GDM

The selection process which is used to obtain the ranking of alternatives from a group of preference relations consists of two phases [28]: aggregation and exploitation.

1) Aggregation phase

Let $P^{(c)}=(p_{ij}^{(c)})_{n\times n}$ be a collective preference relation obtained by means of the aggregation of the individual preference relations $P^{(k)}=(p_{ij}^{(k)})_{n\times n}$ $(k=1,2,...,m)$. The weighted average (WA) operator and OWA operators are most widely used in GDM problems. This study integrates the experts' weights into the CRP; thus, we use the WA operator to implement the aggregation operation as follows:

$$p_{ij}^{(c)}=WA\left(p_{ij}^{(1)},p_{ij}^{(2)},...,p_{ij}^{(m)}\right)=\sum_{k=1}^{m}\lambda_k p_{ij}^{(k)} \tag{5}$$

where $\lambda_k\in[0,1]$ is weight of the expert $e_k\in E$ and $\sum_{k=1}^{m}\lambda_k=1$.

2) Exploitation phase

Let $Pr^{(c)}=(pr_1^{(c)},pr_2^{(c)},...,pr_n^{(c)})^T$ be the collective preference vector over alternatives $X$ derived from the collective preference relation $P^{(c)}=(p_{ij}^{(c)})_{n\times n}$, where $pr_i^{(c)}\geq 0$ is the collective preference value of the alternative $x_i$. Based on Eq. (4), we can obtain $pr_i^{(c)}$, i.e.,

$$pr_i^{(c)}=QGDD_i^{(c)}=OWA_Q\left(p_{i1}^{(c)},p_{i2}^{(c)},\ldots,p_{in}^{(c)}\right). \tag{6}$$

Based on $Pr^{(c)}$, the collective ranking of the alternatives $X$ can be obtained.

## 3. Consensus-based GDM with non-cooperative behaviors

This section describes the consensus-based GDM problem with non-cooperative behaviors, and then proposes its resolution framework.

### 3.1. Decision problem and proposed framework

(1) **Decision problem**

As noted in Section 1, a large number of non-cooperative behaviors exist in the CRP. Here, we propose the consensus-based GDM problem with non-cooperative behaviors as follows:

Let $E=\{e_1,e_2,...,e_m\}$ $(m\geq 2)$ be a set of experts, $X=\{x_1,x_2,...,x_n\}$ $(n\geq 2)$ be a set of alternatives, and $P^{(k)}=(p_{ij}^{(k)})_{n\times n}$ $(k=1,2,...,m)$ be a preference relation provided by the expert $e_k$.