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Comprehensive Minimum Cost Consensus for Analyzing Different Agreed Solutions

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Consensus Reaching Processes (CRPs) aim at guaranteeing that the decision-makers (DMs) involved in a Group Decision-Making (GDM) problem achieve an agreed solution for the decision situation. Among other proposals to obtain such agreed solutions, the Minimum Cost Consensus (MCC) models stand out because of their reformulation of the GDM problem in terms of mathematical optimization models. Originally, MCC models were limited to compute agreed solutions from a simple distance measure that cannot guarantee to achieve a certain consensus threshold. This drawback was lately fixed by the Comprehensive MCC (CMCC) models, which include consensus measures in the classic MCC approach. However, some real-world problems require analyzing the feasibility of the DMs to choose a certain alternative regarding the others, namely, the cost of achieving an agreed solution on a certain alternative. For this reason, this contribution introduces new CMCC models that drive DMs to an agreed solution on a given alternative and, in such a way, it provides a method to analyze the cost and appropriateness of guiding such group to a specific solution.

Keywords: Comprehensive Minimum Cost Consensus; Persuading model; Group Decision-Making

1. Introduction

The participation of multiple DMs in the resolution of a decision problem provides a heterogeneous view about such a problem, but also gives place to a significant phenomenon: the possibility of disagreements among the DMs. When discrepancies in GDM are neglected, it is possible that the reached solution does not satisfy some DMs, and they may even call into question the decision process[1]. The CRPs were proposed to avoid this situation. A CRP was initially proposed as a discussion process, usually coordinated by a moderator, which aims at smoothing such disagreements and obtaining a consensual solution to the decision problem that satisfies all members of the group. In order to model these consensus processes, the classic literature essentially considers two kinds of approaches[2] depending on if they use a feedback process, in which DMs are asked about if they want to accept the suggestions provided by the moderator, or without feedback, in which the participation of the DMs is omitted, and the changes are applied automatically without asking to achieve an optimal solution. Among the latter models, the well-known MCC models[3,4] stand out because of their simplicity and unique interpretation of the notion of consensus. Such MCC models are mathematical optimization problems that try to find a feasible agreed solution for a GDM problem according to a maximal allowed distance among the DMs' preferences and the collective opinion by preserving as much as possible the initial DMs' opinions. Over the years, these models have been studied in greater depth. Labella et al.[5] argued that the maximal distances between the DMs' preferences and collective opinion do not guarantee to reach a desired consensus threshold, and thus, it was necessary to include consensus measures in the optimization models, giving place to the CMCC models[5].

Even though, classic GDM and its MCC models aim at providing collective solutions to decision problems, traditional literature usually neglects the study of the cost of guiding/persuading the group towards a predetermined solution, in spite of achieving a given alternative under agreement could be necessary in certain real-world problems[6]. Hence, it would be interesting to analyze how to include mechanisms to guide the CMCC model to obtain an agreement from DMs' opinions on choosing a certain alternative in the decision process.

For instance, we can think about a financial institution which desires to establish a certain policy P which needs the approval of the regional managers. For such a policy P, there are several alternatives $p_1, p_2, ..., p_n$ with different characteristics: some of them could be more beneficial to the DMs, namely, the regional managers, but others could be more profitable for the interests of the institution. In this context, the institution would be interested in analyzing how feasible it is to convince these managers about the election of a predetermined alternative p_k by analyzing the cost of guiding the involved DMs to choose such an alternative p_k.

Therefore, this contribution proposes CMCC models for GDM which aim at driving the involved DMs to agree their opinions for choosing a predetermined alternative in order to analyze the cost of agreement on different alternatives in a GDM problem. To do so, our proposal extends the CMCC model to include a *persuading constraint*, such that the Persuasive-CMCC (P-CMCC) output provides an agreed solution which minimizes the cost of modifying DMs' opinions and guarantees an agreed solution on a predefined alternative. Our proposal deals with Fuzzy Preference Relations (FPRs)[5] to model DMs' preferences, because they are the most widely used preference structures in the GDM and CRP specialized literature.

The remainder of this contribution is summarized below: Section 2 reviews some basic concepts related to the proposal. Section 3 introduces the P-CMCC models and their performance is shown in Section 4. Finally, Section 5 draws some conclusions and future works.

2. Preliminaries

A GDM problem is a situation in which a group of DMs has to reach a common solution for a certain decision problem[2]. Formally, such problems are modelled by a finite set of alternatives $A = \{A_1, A_2, ..., A_n\}$ of possible solutions for the considered problem and the DMs set $E = \{E_1, E_2, ..., E_m\}$ who rate the alternatives in A.

Butler and Rothstein[7] proposed several rules like the majority rule or the Borda Count to model these decision situations. However, when using such algorithms, some DMs involved in the decision problem could feel that their opinions were not sufficiently considered during the process because they fully disagree with the solution. To overcome such limitations, CRPs were developed, which support discussion processes and aim for DMs to modify their preferences to obtain a collective group opinion which satisfies all DMs up to a certain degree, the so-called consensus threshold μ[2].

In the literature, several types of preference structures have been introduced to model the DMs' opinions. This contribution focuses on the well-known FPRs[5] because of their simplicity and easy construction. Formally, an FPR is a fuzzy set $P : A \times A \to [0, 1]$ defined on the alternative set A whose membership function satisfies $P(A_i, A_j) + P(A_j, A_i) = 1$ for all $i, j \in \{1, 2, ..., n\}$, where $P(A_i, A_j)$ represents the degree of preference of the alternative A_i over A_j according to a certain DM.

In the literature about consensus models, MCC models[3,4] highlight as models without feedback mechanism because they allow to translate the discussion process into a mathematical programming problem in which the objective function is the cost of modifying the original preferences of the corresponding DMs. In addition, these models ensure that the absolute deviation between the modified opinions and the group collective opinion is lower than a certain parameter ε. Formally, if the original DMs' preferences are modeled by the numerical vector $(o_1, o_2, ..., o_m) \in \mathbb{R}^m$ and a vector

$(c_1, c_2, ..., c_m) \in \mathbb{R}^m_+$ is used to represent the cost of moving the opinion of each DM, the resulting consensus model would be given as[3]:

$$\begin{aligned} &\min \sum_{k=1}^{m} c_k |x_k - o_k| \\ &s.t.\ |x_k - \overline{x}| \leq \varepsilon, k = 1, 2, \ldots, m. \end{aligned} \tag{MCC}$$

where $(x_1, \ldots, x_m)$ are the adjusted opinions of the DMs, $\overline{x}$ represents the collective opinion computed by using an arithmetic mean operator and ε is the maximum allowed absolute deviation between the modified opinions and the collective one.

Traditionally, the consensus computation has been established from two different kinds of consensus measures: those which compute the distance between DMs and group opinion and those based on the distances between DMs[2]. Nevertheless, classical MCC models use the distance between modified opinions and the collective one, i.e., $\max\limits_{i=1,\ldots,m} |x_i - \overline{x}|$ to obtain agreed solutions which cannot guarantee to reach a predefined consensus threshold, but a maximal distance between the DMs' preferences and the collective opinion. For this reason, Labella et al.[5] generalized the former proposal by introducing CMCC models which include the above consensus measures:

$$\begin{aligned} &\min \sum_{i=1}^{m} c_i |x_i - o_i| \\ &s.t. \begin{cases} \overline{x} = F(x_1, \ldots, x_m) \\ |x_i - \overline{x}| \leq \varepsilon, i = 1, 2, \ldots, m \\ consensus(x_1, \ldots, x_n) \geq \mu. \end{cases} \end{aligned} \tag{CMCC}$$

where $consensus(\cdot)$ represents the desired consensus measure and $\mu \in [0, 1[$ is the consensus threshold, which is fixed a priori.

3. CMCC persuasion model for analyzing the cost of agreeing on alternatives

This section is devoted to introducing P-CMCC models, which are able to guide DMs towards an agreement on selecting a certain alternative by modifying their preferences as little as possible. To do so, the CMCC models[5] are extended by including a linear constraint, which guarantees that the desired alternative will be chosen by the group. Since such models consider two types of consensus measures, depending on the distance between DMs and collective opinion and the distance between DMs, we propose two different nonlinear optimization P-CMCC models with nonlinear constraints.

Let $O_1, O_2, ..., O_m$ be the initial FPRs given by the DMs in $E = \{E_1, E_2, ..., E_m\}$, which contain their opinions about the alternatives $A =$

$\{A_1, A_2, ..., A_n\}$. The cost of moving one unit the DM E_k's rating of the alternative A_i over A_j is modeled by using the values $c_{ij}^k \in [0,1]$, which satisfies $\sum_{k=1}^{m} \sum_{i<j} c_{ij}^k = 1$. In order to guarantee that the chosen alternative is A_{i_0}, the corresponding consensus model is as follows:

- *Consensus model based on distance between DMs and collective opinion*

$$\min_{X_1,X_2,\ldots,X_m \in \mathcal{M}_{n\times n}([0,1])} \sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} c_{ij}^k |x_{ij}^k - o_{ij}^k|$$
$$s.t. \begin{cases} \overline{x}_{ij} = \frac{1}{m}\sum_{k=1}^{m} x_{ij}^k & 1 \le i < j \le n, \\ |x_{ij}^k - \overline{x}_{ij}| \le \varepsilon, & 1 \le i < j \le n, k = 1,2,\ldots,m, \\ 1 - \frac{2}{mn(n-1)}\sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} |x_{ij}^k - \overline{x}_{ij}| \ge \mu. & \\ x_{ij}^k + x_{ji}^k = 1 & 1 \le i < j \le n, k = 1,2,\ldots,m, \\ \sum_{j=1}^{n} \overline{x}_{i_0,j} \ge \sum_{j=1}^{n} \overline{x}_{i,j} & i \ne i_0. \end{cases} \tag{P-CMCC:1}$$

- *Consensus model based on distance between DMs*

$$\min_{X_1,X_2,\ldots,X_m \in \mathcal{M}_{n\times n}([0,1])} \sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} c_{ij}^k |x_{ij}^k - o_{ij}^k|$$
$$s.t. \begin{cases} \overline{x}_{ij} = \frac{1}{m}\sum_{k=1}^{m} x_{ij}^k & 1 \le i < j \le n, \\ |x_{ij}^k - \overline{x}_{ij}| \le \varepsilon, & 1 \le i < j \le n, k = 1,2,\ldots,m, \\ 1 - \frac{4}{m(m-1)n(n-1)}\sum_{k=1}^{m-1}\sum_{l=k+1}^{m}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} |x_{ij}^k - x_{ij}^l| \ge \mu. & \\ x_{ij}^k + x_{ji}^k = 1 & 1 \le i < j \le n, k = 1,2,\ldots,m, \\ \sum_{j=1}^{n} \overline{x}_{i_0,j} \ge \sum_{j=1}^{n} \overline{x}_{i,j} & i \ne i_0. \end{cases} \tag{P-CMCC:2}$$

where $X_1, X_2, ..., X_m$ are the FPRs which contain DMs' modified preferences, i.e., $X_k = (x_{ij}^k) \in \mathcal{M}_{n\times n}([0,1])$, where $x_{ij}^k + x_{ji}^k = 1 \quad \forall\, i,j = 1,2,...,n, \quad \forall\, k = 1,2,...,m$, $\overline{X}$ is the group collective opinion, the parameter $\varepsilon \in]0,1]$ represents the maximum distance between DMs and collective opinion and $\mu \in [0,1[$ is the consensus threshold. The GDM significance of the constraints in these models is as follows:

- The first one guarantees that the collective opinion is computed by the arithmetic mean.
- The second and the third constraints ensure that the desired consensus between the experts in the group is achieved.
- The purpose of the fourth one is to guarantee that the FPR structure is preserved during the optimization process.
- The last inequality guarantees that the overall preference of the alternative A_{io} over the others is greater than the same overall

preference of any other alternative and, consequently, that the alternative A_{i_0} will be chosen by the group.

4. Case study

Let us assume that is required to analyze the costs of guiding DMs to achieve an agreement on selecting a certain alternative regarding the costs obtained by the CMCC approach to analyze the feasibility of choosing such alternative.

Our example is based on a GDM problem that involves the financial company JaenBank, whose executive committee intends to implement a novel policy with the aim of reducing costs. Several possible measures $\{A_1, A_2, A_3, A_4\}$ are put to the financial directors of the different branches of the company $\{E_1, E_2, E_3, E_4\}$, who have to reach an agreement among themselves to implement the most convenient one according to their view. However, the top executives are interested in implementing the measure A_2, which could represent a better solution for the medium-long term. Since the financial directors are more interesting on the short-term feasibility of the policy, the top executives want to know a priori how much effort would be involved in convincing all directors to choose the A_2 policy according to their initial preferences. The financial directors have provided their opinions by means of FPRs as follows:

$$E_1 = \begin{pmatrix} - & 0.5 & 0.4 & 0.8 \\ 0.5 & - & 0.4 & 0.8 \\ 0.6 & 0.6 & - & 0.85 \\ 0.2 & 0.2 & 0.15 & - \end{pmatrix} E_2 = \begin{pmatrix} - & 0.95 & 1.0 & 1.0 \\ 0.05 & - & 0.92 & 0.94 \\ 0.0 & 0.08 & - & 0.58 \\ 0.0 & 0.06 & 0.42 & - \end{pmatrix}$$

$$E_3 = \begin{pmatrix} - & 0.6 & 0.33 & 1.0 \\ 0.4 & - & 0.25 & 1.0 \\ 0.67 & 0.75 & - & 1.0 \\ 0.0 & 0.0 & 0.0 & - \end{pmatrix} E_4 = \begin{pmatrix} - & 0.57 & 0.72 & 0.58 \\ 0.43 & - & 0.67 & 0.51 \\ 0.28 & 0.33 & - & 0.34 \\ 0.42 & 0.49 & 0.66 & - \end{pmatrix}$$

From these preferences, several consensus models are applied. Firstly, the previous GDM problem is solved by using the classical CMCC model, in which the consensus measure is based on the distance between the DMs' preferences and collective opinion. To do so, the consensus threshold is set as $\mu = 0.8$, the maximum allowed distance between DMs and collective opinion is $\varepsilon = 0.2$ and the cost of moving E_k's rating for the alternative A_i over A_j is assumed to be $c_k = \frac{2}{mn(n-1)}$ for the sake of simplicity. Afterwards, by solving the same GDM problem with the P-CMCC:1 model, it is analyzed the cost of agreeing on each alternative to evaluate the feasibility of guiding the DMs to choose each one and provide valuable information to the executives.

Table 1. Comparative results between P-CMCC and CMCC.

Consensus model	**Consensus parameters**	**Desired alternative**	**Cost**	**Ranking of alternatives**
CMCC	$\mu = 0.8, \varepsilon = 0.2$	-	0.048	$A_1 \succ A_2 \succ A_3 \succ A_4$
P-CMCC:1	$\mu = 0.8, \varepsilon = 0.2$	A_1	0.048	$A_1 \succ A_2 \succ A_3 \succ A_4$
		A_2	0.072	$A_2 = A_1 \succ A_3 \succ A_4$
		A_3	0.081	$A_3 = A_1 \succ A_2 \succ A_4$
		A_4	0.173	$A_4 = A_1 = A_2 \succ A_3$

Remark 1. Note that the minimum cost solutions to the P-CMCC:1 model are ranked the same as the minimum cost solution to the CMCC model. From the decision-making point of view, this means that the easier way to drive the DMs to choose a predefined alternative is to convince them that such alternative is as good as the one that they initially prefer.

The results of the CMCC model (see Table 1) show that the best policy according to the financial directors' point of view (short-term and possibly selfish) is the first alternative, whose cost in a $0-1$ scale is equal to 0.048 and thus, the most feasible to agree their opinions. However, by analyzing the results of the persuading models, the cost of choosing the alternative A_2, the preferred one by the top executives (long-term view), is 0.072, which is a 50% extra relative cost regarding the DMs' most preferred alternative A_1. Therefore, the executive should decide if such an extra cost is worthy to adopt the desired policy. Regarding the rest of the alternatives, their selection implies not only a greater extra cost, but also more changes than the optimal solution. Particularly, the most unfeasible alternative is A_4 because its cost is the highest one and thus its selection requires the greatest change in the DMs' preferences.

5. Conclusions

This contribution has extended CMCC models to propose two automatic consensus models, namely P-CMCC:1 and P-CMCC:2, which allow analyzing the cost of driving the DMs involved in a decision process to reach a predetermined agreed solution. To do so, these models provide a measure of the cost of convincing DMs of choosing a certain alternative over the others. By comparing the cost obtained in either P-CMCC:1 or P-CMCC:2 with the solution obtained in CMCC, it is possible to determine if it would be worthy in practice to convince the DMs of adopting a concrete alternative instead of the one preferred by the group. In addition, the practical applications of these persuasion models have been shown in an illustrative example.

Future research may be addressed by using the concept of persuasive consensus models. It would be interesting to study such an approach in classical CRPs that use feedback mechanisms and take into account the DMs' attitude. Regarding formal issues, a linearized version of the model could be proposed to deal with GDM problems with many DMs.

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