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An Automatic Linguistic Consensus Model for Sustainability

1st Álvaro Labella
Dept. of Computer Science
University of Jaén
Jaén, Spain
alabella@ujaen.es

2nd Diego García-Zamora
Dept. of Computer Science
University of Jaén
Jaén, Spain
dgzamora@ujaen.es

3rd Rosa M. Rodríguez
Dept. of Computer Science
University of Jaén
Jaén, Spain
rmrodrig@ujaen.es

4st Luis Martínez
Dept. of Computer Science
University of Jaén
Jaén, Spain
martin@ujaen.es

***Abstract*—Minimum Cost Consensus (MCC) models were designed to seek an agreed collective solution that minimizes the cost associated with modifying the preferences of the experts involved in resolving Group Decision-Making (GDM) problems. Initially, these approaches were tailored for handling a vector with numerical evaluations, neglecting the utilization of linguistic data or multi-criteria decision problems. Therefore, this paper proposes a multi-criteria group decision-making approach based on the concept of MCC that can manage linguistic information. To do so, we will generalize MCC models to handle Extended Comparative Linguistic Expressions with Symbolic Translation (ELICIT). ELICIT offers a versatile continuous linguistic representation and enables precise linguistic calculations without sacrificing interpretability or losing information. As a result, we obtain a multi-criteria decision framework that takes the comparative linguistic expressions provided by experts as inputs and returns the consensual collective opinion that is closest to the individual opinions given by the experts. The methodology is applied to a case study at the University of Jaén, Spain, showcasing its applicability in resolving sustainability problems.**

***Index Terms*—Decision-making, minimum cost consensus, ELICIT information, sustainability**

I. Introduction

The Agenda 2030 adopted by all United Nations member States in 2015 [1], stands for a transformative and comprehensive blueprint for sustainable development. Its core is the 17 Sustainable Development Goals (SDG), interconnected objectives for addressing most of the world's pressing challenges by 2030, including poverty eradication, gender equality, and clean energy, among others.

Universities must keep continuous feedback with society, and play a key role in the achievement of the objectives included in the 17 SDGs [2]–[4]. For this reason, universities around the world define strategic plans that allow them to undertake the commitments and objectives set in line with the SDGs. The UI GreenMetric World University ranking [5] is the main international reference to measure such achievements, considering aspects related to infrastructure, energy and water, waste recycling, green transportation, and education and research.

However, universities' resources are limited, and all the objectives cannot be addressed at the same time. The actions carried out must be deeply thought through by decision-makers (DMs) who evaluate such actions based on aspects that are by no means superfluous, such as financial effort, impact on campus life, employability, etc. This contribution aims at proposing a methodology to support this decision.

To do so, we will face this problem from a multi-criteria group decision-making (MCGDM) perspective [6]. Generally speaking, in an MCGDM problem, several DMs evaluate a concrete set of alternatives on multiple criteria. In our particular case, DMs must decide what action to take to meet a series of objectives related to the SDGs and that must be evaluated considering the particular context of the universities. To deal with this MCGDM problem, it is necessary to consider two main aspects:

- A1 DMs' preferences elicitation: DMs must be able to express their opinions over the alternatives appropriately to obtain a reliable solution based on expert knowledge [7].
- A2 Disagreements among DMs: The participation of several DMs in the decision process may lead to the emergence of disagreements among them, which must be dealt appropriately to avoid obtaining a biased solution [8].

On one side, the DMs may provide their opinions in different ways, for instance, by using numerical assessments. However, such assessments require a high level of precision or may involve converting qualitative preferences into precise numerical values, which may not accurately capture the nuances of opinions. On the contrary, using linguistic information offers a more intuitive and flexible approach, effectively capturing uncertainty in opinions. This contribution makes use of the extended comparative linguistic expressions with symbolic translation (ELICIT) to model linguistic preferences, since they allow modeling DMs' assessments with richer linguistic expressions that represent DMs' hesitancy and performing precise linguistic computations [9], [10].

In addition, the participation of multiple DMs in a decision process may involve the emergence of conflicts among them. Smoothing out such disagreements is key to obtaining a solution that satisfies all the members of the group. To do so, we use the minimum cost consensus (MCC) concept [11]. MCC optimization models seek to find a collective agreement or compromise among multiple DMs with conflicting preferences. The objective is to identify the most agreeable solution

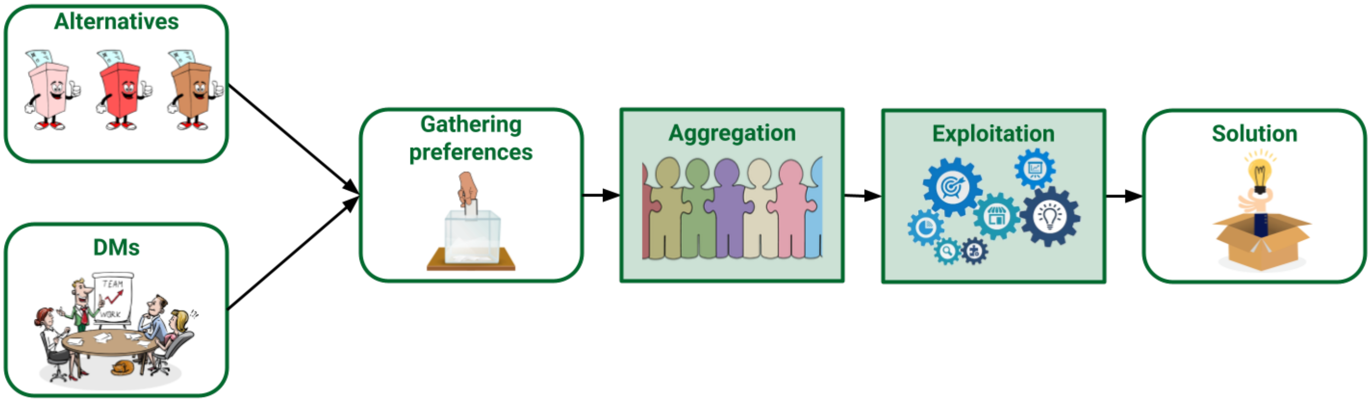

Fig. 1. MCGDM general scheme.

that minimizes the overall cost, considering the discrepancies in individual preferences. In this context, "cost" represents the extent of deviation from each DM's initial opinion and the modified one. Several MCC models have been proposed in the literature [10], [11] but, to the best of our knowledge, no one is capable of dealing with MCGDM problems and linguistic information simultaneously.

Therefore, the main features of our methodology are:

1) Linguistic preferences modeling based on ELICIT information. The DMs can provide their assessments by using rich linguistic expressions closer to their way of thinking.
2) MCC model for MCGDM problems. An MCC model capable of dealing with decision problems with multiple DMs and criteria.

Furthermore, the proposed methodology is applied to a real case study at the University of Jaén (UJA), Spain, in which five DMs are asked to evaluate actions for promoting the implementation of measures aimed at reducing pollutant emissions that produce negative effects on health at the university.

The remainder contribution is organized as follows: Section II reviews preliminary concepts. Section III introduces the methodology based on MCC that is applied in the real case study in Section IV. Finally, Section V draws conclusions and future works.

II. Preliminaries

This section revises some concepts such as MCGDM, consensus reaching processes, 2-tuple linguistic model, ELICIT information, and MCC to better understand the proposal.

A. Multi-criteria group decision-making

In a MCGDM problem, a group of DMs, denoted as $E = \{e_1, e_2, \ldots, e_K\}$, provides their individual opinions on a set of alternatives $A = \{a_1, a_2, \ldots, a_m\}$ evaluated across multiple criteria $C = \{c_1, c_2, \ldots, c_n\}$. The main objective is to obtain a ranking of the alternatives and select the most suitable one(s) based on the aggregated preferences of the DMs. The MCGDM problem-solving process can be divided into two distinct phases [12] (see Fig. 1):

- Aggregation: This phase comprises two steps. Firstly, the opinions provided by the DMs are aggregated to derive an overall opinion for each criterion. Subsequently, the criteria are fused to obtain a collective opinion for each alternative.
- Exploitation: Building upon the collective opinion acquired in the previous phase, the alternatives are ranked, and the best one is selected based on the established criteria.

Let us introduce some considerations about the previous solving scheme. Firstly, the DMs may provide their assessments in multiple formats. However, the lack of information about the problem and its complexity may lead to the emergence of uncertainty that cannot be modeled properly with single numeric values. Under this context, the use of linguistic information is a more intuitive and flexible approach for modeling preferences, since it is closer to the way human beings communicate with each other. Secondly, the conventional resolution scheme lacks the assurance of achieving unanimous agreement among DMs, often resulting in conflicts that may arise. Such conflicts can lead certain DMs to perceive their opinions as undervalued, potentially causing resistance to accepting the proposed solution and questioning the overall decision process. To mitigate this challenge, the inclusion of a consensus-reaching process (CRP) becomes imperative in the decision-making framework, aiming to establish a collective agreement before finalizing the selection of the optimal alternative [8].

B. ELICIT linguistic model

The ELICIT information, which is based on the 2-tuple linguistic model [13], allows representing DMs' assessments by rich linguistic expressions capable of modeling DMs' hesitancy and performing precise computing with words (CW) computations [14].

The 2-tuple linguistic model [13] was introduced to guarantee precise computations using linguistic terms. A 2-tuple linguistic value is denoted as $(s_i, \alpha) \in \overline{S} \subset S \times [-0.5, 0.5]$. Here, s_i represents a linguistic term belonging to a specific set of linguistic terms, denoted as $S = \{s_0, s_1, \ldots s_g\}$, where

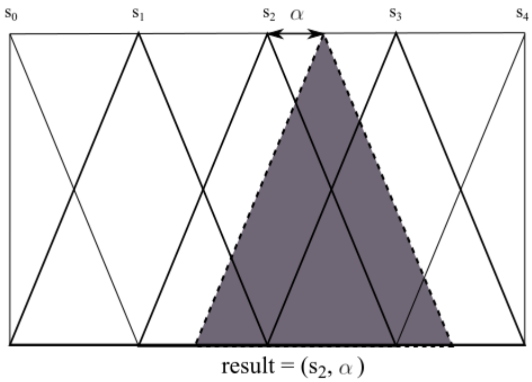

Fig. 2. Symbolic translation

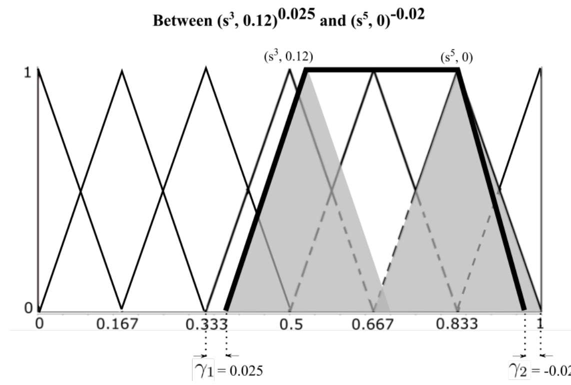

Fig. 3. Example of ELICIT linguistic expressions.

$g \in \mathbb{N}$ is a fixed even number. The parameter α is referred to the symbolic translation, signifying a numerical value that indicates the shift in the fuzzy membership function of s_i (as depicted in Fig. 2). For a given linguistic 2-tuple value $(s_i, \alpha) \in \overline{S}$, the allowable range of values for the symbolic translation α is as follows:

$$\alpha \in \begin{cases} [-0.5, 0.5) & if\ s_i \in \{s_1, s_2, \dots, s_{g-1}\} \\ [0, 0.5) & if\ s_i = s_0 \\ [-0.5, 0] & if\ s_i = s_g \end{cases}$$

The primary advantage of 2-tuple linguistic expressions lies in their ability to be translated into a numerical value $x \in [0, g]$. As a result, this approach yields accurate linguistic results following a CW scheme [15].

Proposition 1: [13] Given a linguistic term set $S = \{s_0, \dots s_g\}$, the function $\Delta_S^{-1} : \overline{S} \to [0, g]$ defined by

$$\Delta_S^{-1}(s_i, \alpha) = i + \alpha,\ \forall\ (s_i, \alpha) \in \overline{S}$$

is a bijection whose inverse $\Delta_S : [0, g] \to \overline{S}$ is defined as

$$\Delta_S(x) = (s_{round(x)}, x - round(x))\ \forall\ x \in [0, g],$$

where $round(\cdot)$ is the function that assigns the closest integer number $i \in \{0, \dots, g\}$.

Despite the advantages of the linguistic 2-tuple values, they cannot adequately model DMs' hesitancy when choosing between multiple linguistic terms. To address this limitation, Labella et al. [9] proposed a solution using ELICIT information. This linguistic approach preserves the accuracy and interpretability of the 2-tuple linguistic model while enhancing its expressiveness by integrating elements of hesitant fuzzy linguistic terms set (HFLTS) [16], thus offering a more comprehensive and robust representation of DMs' preferences.

An ELICIT value is an object $[\overline{s}_i, \overline{s}_j]_{\gamma_1, \gamma_2}$, where $\overline{s}_i, \overline{s}_j \in \overline{S}, i \leq j$ are two 2-tuple linguistic values and the parameters γ_1, γ_2 ensure preserving the uncertain information during the computational processes. The set of Trapezoidal Fuzzy Numbers (TrFN) [17] is bijective to the set of ELICIT values (see Fig. 3). We recall here that a TrFN is a function $T \equiv T(a, b, c, d) : [0, 1] \to [0, 1]$ of the form

$$T(x) = \begin{cases} 0 & \text{if } 0 \leq x \leq a \\ \frac{x-a}{b-a} & \text{if } a < x < b \\ 1 & \text{if } b \leq x \leq c \\ \frac{d-x}{d-c} & \text{if } c < x < d \\ 0 & \text{if } d \leq x \leq 1 \end{cases} \quad \forall\ x \in [0, 1]$$

for certain $0 \leq a \leq b \leq c \leq d \leq 1$. For the sake of clarity, the set of all TrFNs on the interval $[0, 1]$ will be denoted by

$$\mathcal{T} = \{T : [0, 1] \to [0, 1]\ :\ T \text{ is a TrFN}\}.$$

Proposition 2 ([10]): Let $\overline{\overline{S}}$ be the set of all possible ELICIT values. Then the mapping ζ given by:

$$\zeta : \mathcal{T} \to \overline{\overline{S}}$$
$$T(a, b, c, d) \to [\overline{s}_1, \overline{s}_2]_{\gamma_1, \gamma_2}$$

where

$$\overline{s}_1 = \Delta_S(gb) \quad \gamma_1 = a - \max\left\{b - \frac{1}{g}, 0\right\}$$
$$\overline{s}_2 = \Delta_S(gc) \quad \gamma_2 = d - \min\left\{c + \frac{1}{g}, 1\right\}$$

is a bijection whose inverse ζ^{-1} is defined by:

$$\zeta^{-1} : \overline{\overline{S}} \to \mathcal{T}$$
$$[\overline{s}_1, \overline{s}_2]_{\gamma_1, \gamma_2} \to T(a, b, c, d)$$

and allows computing the fuzzy representation of an ELICIT expression as follows:

$$a = \gamma_1 + \max\left\{\frac{\Delta_S^{-1}(\overline{s}_1) - 1}{g}, 0\right\}, b = \frac{\Delta_S^{-1}(\overline{s}_1)}{g},$$
$$c = \frac{\Delta_S^{-1}(\overline{s}_2)}{g}, d = \gamma_2 + \min\left\{\frac{\Delta_S^{-1}(\overline{s}_2) + 1}{g}, 1\right\}.$$

The ELICIT computational model follows the CW scheme to calculate fuzzy representations of linguistic expressions. These fuzzy representations are then later translated back into ELICIT information. From a theoretical perspective, ELICIT expressions are generated using a context-free grammar, and

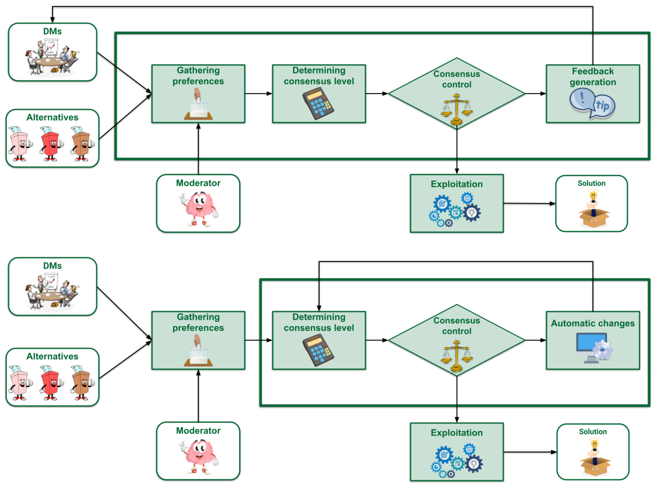

Fig. 4. CRP general scheme.

model comparative linguistic structures found in natural languages. Examples of such ELICIT expressions include phrases like *at least* $(\text{good}, 0.2)^{0.2}$, *at most* $(\text{bad}, 0.1)^{0.1}$, or *between* $(\textit{very good}, 0)^{-0.11}$ *and* $(\textit{excellent}, 0.32)^{0}$.

When addressing MCGDM problems, usually, DMs usually provide their opinions using a decision matrix in which the alternatives (rows) are evaluated according to their performance in different criteria (columns). Therefore, let us define the set of matrices whose items are TrFN:

$$\mathcal{M}_{m\times n}(\mathcal{T}) := \left\{(T^{ij})_{m\times n}\ :\ T^{ij}\in\mathcal{T}\ \forall\ 1\leq i\leq m, 1\leq j\leq n\right\}.$$

C. Consensus Reaching Processes

A CRP is an iterative process in which DMs change their preferences to bring them closer to the collective opinion. A CRP is usually guided by a moderator (a human person) who identifies the DMs who are far away from the collective opinion and suggests them to change their opinions to make them closer and achieve a consensus [18], [19]. However, other approaches replace the role of the moderator with an automatic process that changes the DMs' opinions to increase the consensus level and reach the consensus [20]. In any case, a CRP finishes when the consensus level reaches a threshold that is set a priori ($\mu_0\in[0,1]$), or when the number of discussion rounds carried out has accomplished the maximum allowed (see Fig. 4).

In this contribution, we will use an automatic CRP based on MCC models, which were introduced by Ben-Arieh and Easton [11] and allows translating the consensus problem into a mathematical programming model in which the cost of modifying DMs' opinions is minimized according to a consensus constraint. Let $(O_1,\ldots,O_K)$ be the opinions provided by the DMs $E=\{e_1,\ldots,e_K\}$ over an alternative, and c_k be the cost of changing DM e_k's opinion 1 unit. Then, the MCC model based on a linear cost function is as follows

$$\begin{array}{l}(\mathbf{M-1})\\ \min\sum\limits_{k=1}^{K} c_k|T_k-O_k|\\ s.t.\ |T_k-\overline{T}|\leq\varepsilon, k=\{1,\ldots,K\}\end{array}$$

where $(T_1,\ldots,T_K)$ are the modified DMs' opinions, $\overline{T}$ is the collective opinion and ε is the maximum acceptable distance of each DM to the collective opinion.

III. Methodology

MCC models have traditionally focused on precise assessments, but there is a growing interest in incorporating linguistic information into GDM these days [10]. Consequently, it is essential to propose MCC models for MCGDM that can handle this type of linguistic information to enhance research in this field. This section is dedicated to introducing MCC models that accommodate linguistic preferences represented by ELICIT information.

Let $O_1, O_2, ..., O_K \in \mathcal{M}_{m\times n}(\mathcal{T})$ be the decision matrices of TrFNs corresponding to the translation via the mapping ζ^{-1} of DMs' original preferences, and let $T_1, T_2, ..., T_K\in\mathcal{M}_{m\times n}(\mathcal{T})$ be the corresponding modified DMs' opinions. The cost function and the consensus measures for these values are modeled by using the geometric distance [21] $\delta:\mathcal{T}\times\mathcal{T}\to[0,1]$ defined by

$$\delta(T_1,T_2)=\frac{1}{4}(|a_1-a_2|+|b_1-b_2|+|c_1-c_2|+|d_1-d_2|)$$

where $T_1\equiv(a_1,b_1,c_1,d_1)$, and $T_2\equiv(a_2,b_2,c_2,d_2)$. Additionally, to compute the collective opinion, we use the fuzzy weighted average operator $A:\mathcal{T}^K\to\mathcal{T}$, which is defined by

$$A(T_1,T_2,...,T_K)=\\ (\sum_{k=1}^{K}w_kT_k^a,\sum_{k=1}^{K}w_kT_k^b,\sum_{k=1}^{K}w_kT_k^c,\sum_{k=1}^{K}w_kT_k^d),$$

where T_k^t denotes the t-th $t\in\{a,b,c,d\}$ coordinate of the TrFN $T_k, k=1,2,...,K$ and $w_1,w_2,...,w_K\geq 0$, $\sum_{k=1}^K w_k=1$ are the weights for the DMs.

Consequently, the ELICIT-MCC model can be defined as follows

$$\begin{array}{l}\min\limits_{T_1^{i,j},\ldots,T_m^{i,j}\in\mathcal{T}}\sum\limits_{k=1}^{K}\sum\limits_{i=1}^{m}\sum\limits_{j=1}^{n}c_k^{ij}\delta(T_k^{i,j},O_k^{i,j})\\ s.t.\left\{\begin{array}{l}\overline{T}^{i,j}=A(T_1^{i,j},T_2^{i,j},\ldots,T_K^{i,j}), i=1,...,m, j=1,...,n\\ 1-\frac{1}{m}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n}\omega_j w_k\delta(T_k^{i,j},\overline{T}^{i,j})\geq\mu_0,\end{array}\right.\end{array}\tag{ELICIT-MCC}$$

where $\mu_0\in[0,1]$ is the consensus threshold, $c_k^{ij}\in[0,1]$ model the cost of moving the DM e_k's preference of the alternative a_i over the criterion c_j, $w_1,w_2,...,w_K\in[0,1]$ ($\sum_{k=1}^K w_k=1$) are DMs' weights and $\omega_1,\omega_2,...,\omega_n\in[0,1]$ ($\sum_{k=1}^n\omega_j=1$) are the weights for the criteria. In order to accelerate the computational resolution of the ELICIT-MCC model, we provide below a linearized version, which provides exactly the same result in a shorter computational time.

Theorem 1 (Linear ELICIT-MCC): Let $O_k^{ij}[t]$ be the t-th coordinate ($t=1,2,3,4$) of the TrFN O_k^{ij} which represents the initial rating for the i-th alternative and j-th criterion provided by the DM e_k. In the same way, $T_k^{ij}[t]$ $t=1,2,3,4$ denotes the corresponding modified opinions. Then, the model ELICIT-MCC is linearized as follows:

$$\begin{array}{l}\min\limits_{T_k^{i,j}[t]\in[0,1]}\frac{1}{4}\sum\limits_{k=1}^{K}\sum\limits_{i=1}^{m}\sum\limits_{j=1}^{n}c_k^{ij}\sum\limits_{t=1}^{4}v_k^{ij}[t]\\ s.t.\left\{\begin{array}{l}u_k^{ij}[t]=T_k^{ij}[t]-O_k^{ij}[t], k\in\mathcal{I}_1^K, i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n, t\in\mathcal{I}_1^4\\ v_k^{ij}[t]\geq u_k^{ij}[t], k\in\mathcal{I}_1^K, i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n, t\in\mathcal{I}_1^4\\ v_k^{ij}[t]\geq -u_k^{ij}[t], k\in\mathcal{I}_1^K, i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n, t\in\mathcal{I}_1^4\\ \overline{T}^{ij}[t]=\sum_{k=1}^{K}w_kT_k^{ij}[t], i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n, t\in\mathcal{I}_1^4\\ y_k^{ij}[t]=T_k^{ij}[t]-\overline{T}_k^{ij}[t], k\in\mathcal{I}_1^K, i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n, t\in\mathcal{I}_1^4\\ z_k^{ij}[t]\geq y_k^{ij}[t], k\in\mathcal{I}_1^K, i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n, t\in\mathcal{I}_1^4\\ z_k^{ij}[t]\geq -y_k^{ij}[t], k\in\mathcal{I}_1^K, i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n, t\in\mathcal{I}_1^4\\ 0\leq T_k^{ij}[1]\leq T_k^{ij}[2]\leq T_k^{ij}[3]\leq T_k^{ij}[4]\leq 1, k\in\mathcal{I}_1^K, i\in\mathcal{I}_1^m, j\in\mathcal{I}_1^n\\ 1-\frac{1}{4m}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n}w_k\omega_j\sum_{t=1}^{4}z_k^{ij}[t]\geq\mu_0\end{array}\right.\end{array}\tag{L-ELICIT-MCC}$$

where $\mu_0\in[0,1]$ is the consensus threshold, $c_k^{ij}\in[0,1]$ model the cost of moving the DM e_k's preference of the alternative a_i over the criterion c_j, $w_1, w_2, ..., w_K \in [0,1]$ $(\sum_{k=1}^{K} w_k = 1)$ are DMs' weights and $\omega_1, \omega_2, ..., \omega_n \in [0,1]$ $(\sum_{k=1}^{n} \omega_j = 1)$ are the weights for the criteria.

The resolution of these optimization models provides the individual adjusted opinions that minimize the cost under consensual assumptions and the corresponding collective opinions. From such a collective opinion, it is possible to derive the collectively agreed solution to the multi-criteria GDM problem. To rank ELICIT expressions, after obtaining the global values for the alternatives as ELICIT expressions, their magnitudes [22] are computed as follows:

$$Mag([s_i, s_j]_{\gamma_1,\gamma_2}) = Mag(T(a,b,c,d)) = \frac{a + 5b + 5c + d}{12}.$$

IV. Case study

This section shows the feasibility of the proposed methodology in a case study that is assumed to be carried out at the UJA. The UJA is a young Spanish university, born in 1993, with 1000 professors and lecturers and more than 16000 students. Despite its youth, the UJA has achieved important recognition. It is top 200 in the Times Higher Education Young University Ranking[1]. Furthermore, the UJA has achieved important sustainable achievements, which has led it to be ranked 379th in the UI GreenMetric World University ranking[2].

To further develop policies that maintain progress toward a healthy and sustainable institution, UJA has developed a Strategic Plan that constitutes a series of guidelines for implementing the SDGs at all levels of the university activity. For the sake of space, this contribution focuses on one of these objectives, *"Promote the implementation of measures aimed at reducing polluting emissions that produce negative effects on health (noise, light, air quality, discharges...)"*. To reach this objective, the UJA has considered several actions:

- a_1 Install air quality analyzers on UJA campuses.
- a_2 Progressively replace UJA vehicles with combustion engines for vehicles with zero or eco-environmental badges.
- a_3 Improve the management and prevention of fluorinated refrigerant gas leaks.
- a_4 Improve wastewater management to reduce pollution.
- a_5 Drawing up strategic noise maps for the campuses.
- a_6 Progressively replace luminaires with more efficient and environmentally friendly ones.

However, the institution cannot apply all the actions at the same time without compromising its financial viability. For this reason, we use our methodology to select the most suitable action for the UJA. Firstly, we ask DMs with expert knowledge in the topic about the performance of each action over different criteria. These criteria have also been defined for the DMs to guarantee a correct evaluation of the actions. These criteria are:

- c_1 Investment: financial resources allocated to the initiative.
- c_2 Proliferation of rankings and certification systems: impact of the initiative for achieving top position in rankings and get official certificates related to sustainability issues.
- c_3 Affecting campus life: potential impact of the action on the daily lives and experiences of the university community, including students, faculty, staff, and other stakeholders.
- c_4 Education and awareness: extent to which the action contributes to increasing knowledge, understanding, and consciousness regarding the sustainable development of university community.

The selected DMs evaluate the actions according to the previous criteria by using ELICIT information and the linguistic terms set

$$S = \{s_0 : very\ bad, s_1 : bad, s_2 : fair, s_3 : good, s_4 : very\ good\}$$

[1]https://www.timeshighereducation.com/world-university-rankings/2022/young-university-rankings

[2]https://greenmetric.ui.ac.id/

Their assessments are shown below in Table I. In addition, the graphical representation of the DMs' opinions is pictured in Fig. 5. This representation has been made by using the Multidimensional Scaling (MDS) technique [23], representing the collective opinion in the center of the plot (yellow square) and the DMs' opinions around it (circles). The greater the disagreement, the greater the distance represented between the DMs' opinions and the collective one. The axes X and Y represent the relative distance between the preferences.

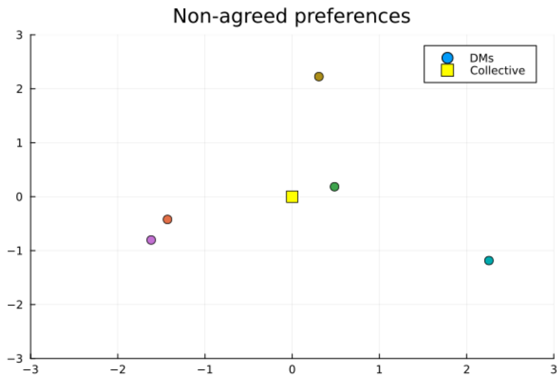

Fig. 5. MDS visualization for non-agreed preferences.

Fig. 5 shows clearly that there are disagreements in DMs' preferences. Therefore, it is key to smooth out such conflicts before making the decision. To do so, we apply the L-ELICIT-MCC model considering the parameter $\mu_0 = 0.85$.

After applying the MCC model, the resulting collective opinion of TrFNs is represented in Table II and its ELICIT representation in Table III. Also, Fig. 6 provides a graphical representation of the agreed DMs' preferences. Notice, the DMs' preferences are now closer, since the level of agreement in the group has increased.

To obtain the overall assessment for each alternative, we aggregate the collective value of each criterion for each alternative by using the fuzzy weighted average operator. Table IV shows the overall assessment for the alternatives, represented by TrFNs (see Fig. 7) and ELICIT information. In addition, we have included the magnitude value of each one to obtain the ranking. The most preferred action, according to the DMs' opinions, is a_5, drawing up strategic noise maps for the campuses. In this case, the least recommended action is a_4, improve wastewater management to reduce pollution. The general ranking is: $a_5 \succ a_1 = a_3 \succ a_2 \succ a_6 \succ a_4$

V. Conclusions

In conclusion, this research paper has successfully introduced and demonstrated the efficacy of a novel MCC model for handling ELICIT information and addressing MCGDM problems. The proposed model provides a powerful and intuitive approach to resolving sustainability problems, particularly in the context of ranking various sustainable actions aimed at achieving SDGs.

By leveraging the MCC model, the decision-making process was enhanced by considering diverse perspectives and preferences from multiple DMs. The model's ability to accommodate ELICIT information allowed for a more comprehensive and accurate representation of DMs' opinions, reducing subjectivity and enhancing the credibility of the final decision.

The application of the MCC model to the specific case study of the University of Jaén yielded valuable insights and actionable recommendations for sustainable development initiatives. The model facilitated the identification of optimal sustainable actions, considering both economic and social criteria, while ensuring a collective agreement among DMs.

TABLE I

DMs' assessments.

E	A	c_1	c_2	c_3	c_4
e_1	a_1	$[(s_4,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$
	a_2	$[(s_1,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$
	a_3	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_4	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$
	a_5	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_4,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_6	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$
e_2	a_1	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$
	a_2	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$
	a_3	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_4,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$
	a_4	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_5	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$
	a_6	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$
e_3	a_1	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_2	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$
	a_3	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$
	a_4	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$
	a_5	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_4,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_3,0.0)]_{0.0,0.0}$
	a_6	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$
e_4	a_1	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_2	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$
	a_3	$[(s_1,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$
	a_4	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$
	a_5	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$
	a_6	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_4,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$
e_5	a_1	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$
	a_2	$[(s_1,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_3	$[(s_2,0.0),(s_3,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_1,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_4	$[(s_0,0.0),(s_1,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_5	$[(s_0,0.0),(s_2,0.0)]_{0.0,0.0}$	$[(s_3,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_0,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$
	a_6	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_2,0.0),(s_4,0.0)]_{0.0,0.0}$	$[(s_0,0.0),(s_3,0.0)]_{0.0,0.0}$

TABLE II

TrFN agreed collective opinion.

$\overline{T}$	c_1	c_2	c_3	c_4
a_1	$T(0.29,0.4,0.94,1.0)$	$T(0.19,0.27,0.41,0.63)$	$T(0.18,0.29,0.87,1.0)$	$T(0.0,0.06,0.56,0.75)$
a_2	$T(0.02,0.31,0.81,0.81)$	$T(0.0,0.19,0.69,0.79)$	$T(0.1,0.35,0.7,0.9)$	$T(0.02,0.02,0.54,0.74)$
a_3	$T(0.15,0.4,0.85,1.0)$	$T(0.24,0.33,0.75,0.98)$	$T(0.06,0.25,0.51,0.82)$	$T(0.0,0.05,0.64,0.82)$
a_4	$T(0.0,0.0,0.08,0.45)$	$T(0.0,0.06,0.61,0.7)$	$T(0.0,0.1,0.8,0.95)$	$T(0.13,0.31,0.74,0.86)$
a_5	$T(0.0,0.06,0.5,0.71)$	$T(0.41,0.51,0.78,1.0)$	$T(0.25,0.43,0.86,0.92)$	$T(0.06,0.22,0.78,0.94)$
a_6	$T(0.05,0.15,0.7,0.94)$	$T(0.08,0.42,0.75,0.85)$	$T(0.19,0.35,0.56,0.71)$	$T(0.0,0.0,0.61,0.8)$

TABLE III

ELICIT agreed collective opinion.

	c_1	c_2	c_3	c_4
a_1	$[(s_2,-0.41),(s_4,-0.25)]_{0.15,0.0}$	$[(s_2,-0.91),(s_2,-0.35)]_{0.16,-0.04}$	$[(s_2,-0.84),(s_4,-0.53)]_{0.14,0.0}$	$[(s_1,-0.75),(s_3,-0.75)]_{0.0,-0.06}$
a_2	$[(s_2,-0.75),(s_4,-0.76)]_{-0.05,-0.19}$	$[(s_1,-0.25),(s_3,-0.25)]_{0.0,-0.15}$	$[(s_2,-0.6),(s_3,-0.2)]_{0.0,-0.05}$	$[(s_1,-0.92),(s_3,-0.85)]_{0.02,-0.05}$
a_3	$[(s_2,-0.4),(s_4,-0.6)]_{0.0,0.0}$	$[(s_2,-0.67),(s_3,-0.01)]_{0.16,-0.02}$	$[(s_1,0.0),(s_3,-0.96)]_{0.06,0.06}$	$[(s_1,-0.8),(s_3,-0.46)]_{0.0,-0.07}$
a_4	$[(s_0,0.0),(s_1,-0.7)]_{0.0,0.12}$	$[(s_1,-0.75),(s_3,-0.56)]_{0.0,-0.16}$	$[(s_1,-0.6),(s_4,-0.8)]_{0.0,-0.05}$	$[(s_2,-0.75),(s_3,-0.04)]_{0.07,-0.13}$
a_5	$[(s_1,-0.75),(s_2,0.0)]_{0.0,-0.04}$	$[(s_3,-0.95),(s_4,-0.88)]_{0.15,0.0}$	$[(s_2,-0.3),(s_4,-0.57)]_{0.07,-0.08}$	$[(s_1,-0.13),(s_4,-0.87)]_{0.06,-0.06}$
a_6	$[(s_1,-0.4),(s_3,-0.2)]_{0.05,-0.01}$	$[(s_2,-0.33),(s_3,0.0)]_{-0.08,-0.15}$	$[(s_2,-0.6),(s_3,-0.77)]_{0.09,-0.1}$	$[(s_0,0.0),(s_3,-0.55)]_{0.0,-0.06}$

As future works, we will study the use of the L-ELICIT-MCC model to large-scale scenarios, taking advantage of its linear definition. In addition, we will integrate ELICIT information to other MCGDM methods such as ARAS or AHP to support the decision with different approaches.

Acknowledgment

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References

[1] O. Cf, "Transforming our world: the 2030 agenda for sustainable development," *United Nations: New York, NY, USA*, 2015.

[2] A. Cuesta-Claros, S. Malekpour, R. Raven, and T. Kestin, "Understanding the roles of universities for sustainable development transformations: A framing analysis of university models," *Sustainable Development*, vol. 30, no. 4, pp. 525–538, 2022.

[3] B. Karatzoglou, "An in-depth literature review of the evolving roles and contributions of universities to education for sustainable development," *Journal of Cleaner Production*, vol. 49, pp. 44–53, 2013.

TABLE IV
ALTERNATIVES OVERALL ASSESSMENT.

$\overline{T}$	$TrFN$	$ELICIT$	Magnitude
a_1	$T(0.16, 0.26, 0.69, 0.84)$	$[(s_2, -0.98), (s_3, -0.22)]_{0.16,-0.1}$	0.48
a_2	$T(0.03, 0.22, 0.68, 0.81)$	$[(s_1, -0.13), (s_3, -0.26)]_{0.03,-0.12}$	0.45
a_3	$T(0.11, 0.26, 0.69, 0.9)$	$[(s_2, -0.97), (s_3, -0.26)]_{0.11,-0.03}$	0.48
a_4	$T(0.03, 0.12, 0.56, 0.74)$	$[(s_1, -0.52), (s_3, -0.78)]_{0.03,-0.06}$	0.35
a_5	$T(0.18, 0.3, 0.73, 0.89)$	$[(s_2, -0.78), (s_3, -0.08)]_{0.13,-0.09}$	0.52
a_6	$T(0.08, 0.23, 0.66, 0.82)$	$[(s_1, -0.08), (s_3, -0.38)]_{0.08,-0.08}$	0.44

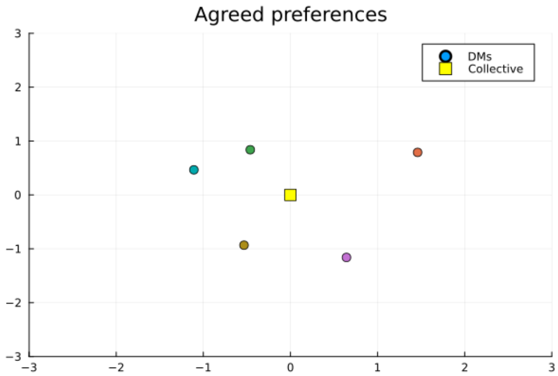

Fig. 6. MDS visualization for agreed preferences.

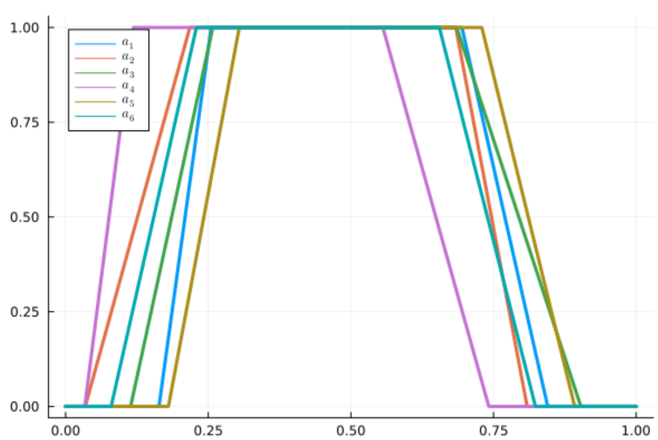

Fig. 7. Fuzzy representation of the alternatives

[4] W. L. Filho, "About the role of universities and their contribution to sustainable development," *Higher Education Policy*, vol. 24, pp. 427–438, 2011.

[5] K. B. Atici, G. Yasayacak, Y. Yildiz, and A. Ulucan, "Green university and academic performance: An empirical study on ui greenmetric and world university rankings," *Journal of Cleaner Production*, vol. 291, p. 125289, 2021.

[6] A. Ishizaka and P. Nemery, *Multi-criteria decision analysis: methods and software*. John Wiley & Sons, 2013.

[7] D. García-Zamora, Á. Labella, W. Ding, R. M. Rodríguez, and L. Martínez, "Large-scale group decision making: a systematic review and a critical analysis," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 6, p. 949–966, 2022.

[8] C. Butler and A. Rothstein, *On Conflict and Consensus: a Handbook on Formal Consensus Decision Making.* Portland: Food Not Bombs Publishing, 1987.

[9] Á. Labella, R. M. Rodríguez, and L. Martínez, "Computing with comparative linguistic expressions and symbolic translation for decision making: ELICIT information," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 10, pp. 2510–2522, 2019.

[10] D. García-Zamora, Á. Labella, R. M. Rodríguez, and L. Martínez, "A linguistic metric for consensus reaching processes based on ELICIT comprehensive minimum cost consensus models," *IEEE Transactions on Fuzzy Systems.*, vol. 31, pp. 1676 – 1688, 2023.

[11] D. Ben-Arieh and T. Easton, "Multi-criteria group consensus under linear cost opinion elasticity," *Decision Support Systems*, vol. 43, no. 3, pp. 713–721, 2007, integrated Decision Support.

[12] M. Roubens, "Fuzzy sets and decision analysis," *Fuzzy Sets and Systems*, vol. 90, no. 2, 1997, fuzzy Sets: Where Do We Stand? Where Do We Go?

[13] L. Martínez, R. M. Rodríguez, and F. Herrera, *The 2-tuple Linguistic Model*. Springer International Publishing, 2015.

[14] L. Zadeh, "Fuzzy logic = computing with words," *IEEE Transactions on Fuzzy Systems*, vol. 4, no. 2, pp. 103–111, 1996.

[15] R. R. Yager, "On the retranslation process in Zadeh's paradigm of computing with words," *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)*, vol. 34, no. 2, pp. 1184–1195, 2004.

[16] R. M. Rodriguez, L. Martinez, and F. Herrera, "Hesitant fuzzy linguistic term sets for decision making," *IEEE Transactions on fuzzy systems*, vol. 20, no. 1, pp. 109–119, 2011.

[17] L. A. Zadeh, "Fuzzy sets," in *Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by Lotfi A Zadeh*. World Scientific, 1996, pp. 394–432.

[18] W. Liang, Á. Labella, Y.-M. Wang, and R. M. Rodríguez, "Consensus reaching process under interval-valued hesitant fuzzy environment," *Computers & Industrial Engineering*, vol. 176, p. 108971, 2023.

[19] Y.-M. Wang, S.-F. He, D. G. Zamora, X.-H. Pan, and L. Martínez, "A large scale group three-way decision-based consensus model for site selection of new energy vehicle charging stations," *Expert Systems with Applications*, vol. 214, p. 119107, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S095741742202125X

[20] Á. Labella, Y. Liu, R. Rodríguez, and L. Martínez, "Analyzing the performance of classical consensus models in large scale group decision making: A comparative study," *Applied Soft Computing*, vol. 67, pp. 677–690, 2018.

[21] S. Heilpern, "Representation and application of fuzzy numbers," *Fuzzy sets and Systems*, vol. 91, no. 2, pp. 259–268, 1997.

[22] S. Abbasbandy and T. Hajjari, "A new approach for ranking of trapezoidal fuzzy numbers," *Computers & Mathematics with Applications*, vol. 57, no. 3, pp. 413–419, 2009.

[23] I. Borg and P. J. Groenen, *Modern multidimensional scaling: Theory and applications*. Springer Science & Business Media, 2005.

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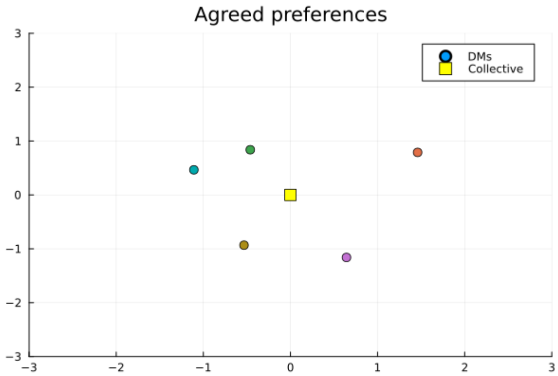

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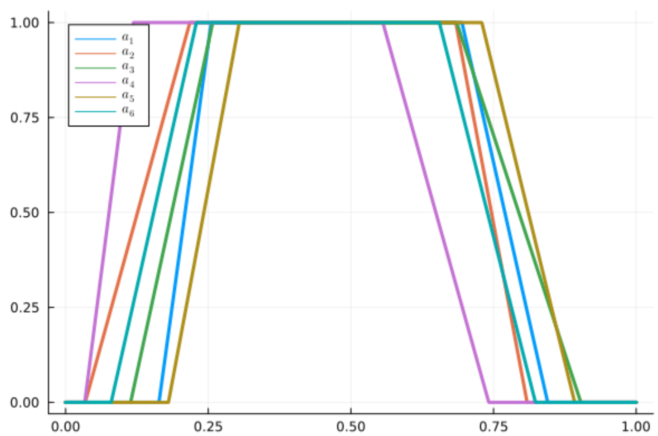

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[6] A. Ishizaka and P. Nemery, *Multi-criteria decision analysis: methods and software*. John Wiley & Sons, 2013.

[7] D. García-Zamora, Á. Labella, W. Ding, R. M. Rodríguez, and L. Martínez, "Large-scale group decision making: a systematic review and a critical analysis," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 6, p. 949–966, 2022.

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[9] Á. Labella, R. M. Rodríguez, and L. Martínez, "Computing with comparative linguistic expressions and symbolic translation for decision making: ELICIT information," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 10, pp. 2510–2522, 2019.

[10] D. García-Zamora, Á. Labella, R. M. Rodríguez, and L. Martínez, "A linguistic metric for consensus reaching processes based on ELICIT comprehensive minimum cost consensus models," *IEEE Transactions on Fuzzy Systems.*, vol. 31, pp. 1676 – 1688, 2023.

[11] D. Ben-Arieh and T. Easton, "Multi-criteria group consensus under linear cost opinion elasticity," *Decision Support Systems*, vol. 43, no. 3, pp. 713–721, 2007, integrated Decision Support.

[12] M. Roubens, "Fuzzy sets and decision analysis," *Fuzzy Sets and Systems*, vol. 90, no. 2, 1997, fuzzy Sets: Where Do We Stand? Where Do We Go?

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[14] L. Zadeh, "Fuzzy logic = computing with words," *IEEE Transactions on Fuzzy Systems*, vol. 4, no. 2, pp. 103–111, 1996.

[15] R. R. Yager, "On the retranslation process in Zadeh's paradigm of computing with words," *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)*, vol. 34, no. 2, pp. 1184–1195, 2004.

[16] R. M. Rodriguez, L. Martinez, and F. Herrera, "Hesitant fuzzy linguistic term sets for decision making," *IEEE Transactions on fuzzy systems*, vol. 20, no. 1, pp. 109–119, 2011.

[17] L. A. Zadeh, "Fuzzy sets," in *Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by Lotfi A Zadeh*. World Scientific, 1996, pp. 394–432.

[18] W. Liang, Á. Labella, Y.-M. Wang, and R. M. Rodríguez, "Consensus reaching process under interval-valued hesitant fuzzy environment," *Computers & Industrial Engineering*, vol. 176, p. 108971, 2023.

[19] Y.-M. Wang, S.-F. He, D. G. Zamora, X.-H. Pan, and L. Martínez, "A large scale group three-way decision-based consensus model for site selection of new energy vehicle charging stations," *Expert Systems with Applications*, vol. 214, p. 119107, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S095741742202125X

[20] Á. Labella, Y. Liu, R. Rodríguez, and L. Martínez, "Analyzing the performance of classical consensus models in large scale group decision making: A comparative study," *Applied Soft Computing*, vol. 67, pp. 677–690, 2018.

[21] S. Heilpern, "Representation and application of fuzzy numbers," *Fuzzy sets and Systems*, vol. 91, no. 2, pp. 259–268, 1997.

[22] S. Abbasbandy and T. Hajjari, "A new approach for ranking of trapezoidal fuzzy numbers," *Computers & Mathematics with Applications*, vol. 57, no. 3, pp. 413–419, 2009.

[23] I. Borg and P. J. Groenen, *Modern multidimensional scaling: Theory and applications*. Springer Science & Business Media, 2005.