Contents

on Virtual Reality

ID:34 Pixel-by-pixel classification of edges with machine learning techniques

ID:35 New Rules for Combining Classifiers Using Fuzzy Majority and Plurality Voting

ID:37 A linguistic ELECTRE III method for heterogeneous multicriteria ranking problems

ID:38 Digital twin for energy optimization in the paper drying process based on genetic algorithm and CADSIM Plus

ID:39 A Coupled-Inductor-Network-Based High-step-up Converter for renewable energy\

ID:40 A High-Frequency Input CCM PFC Converter for Bypass Switch Cabinet

ID:41 Assessing Drivers' Hazard Prediction Ability: A Multiple Layer Dea Application

ID:42 BERT-RS: A Neural Personalized Recommender System with BERT

ID:43 HOUSEHOLD MICRO-GRID FRAMEWORK AND GOSSIP POWER OPTIMIZATION ALGORITHM

ID:44 A Semi-Supervised Learning Method with Attention Mechanism for Pancreas Segmentation

ID:46 A Named Entity Recognition Model Based on Context and Multi-Granularity Feature Fusion for Chinese Medical Text

ID:47 Latest Research Trends of Wearable Sensor based Data Modeling for Fall Risk Prediction in Community-dwelling Elderly

ID:48 ExpandDetector: A Novel Platform of Android Malware Intelligent Detection

ID:49 Formal Modeling of Mobile Agent Control System in Uncertain Environment

ID:50 Lightweight fusion channel attention convolutional neural network for helmet recognition

ID:51 Research on the coordination of logistics service supply chain with the participation of Non-car Operating Carrier

ID:53 Risk Evaluation of Differential Security Checks for Metro

ID:54 Evaluation of a financial technology project decision in the central bank of Oman by the multistage one-shot decision-making approach

ID:55 Scoped Literature Review of Artificial Intelligence Marketing Adoptions for Ad Optimization with Reinforcement Learning

ID:56 Exploring Consumers' Discernment Ability of Autogenerated Advertisements

ID:57 Bearing Fault Diagnosis Based on STFT-SPWVD and Improved Convolutional Neural Network

ID:58 Dynamic Document Clustering Method Based on Neighborhood System and Text Connotation

ID:59 A principle of clause elimination: multi-literal implication modulo resolution

ID:60 Collaborative Control Model of Automatic Intersection based on Vehicle Networking Environment

ID:62 Treelet-edge-weighted graph neural network for premise selection in first-order logic

ID:63 Enable Anomaly detection in Electroplating

ID:64 Examining QFD based Omnichannel Capacity of Service Industries with Interval Type-2 Hesitant DEMATEL-TOPSIS

ID:66 Detection of 0ocyte Nucleus Motion Based on Mean Drift Algorithm

ID:69 Component Preserving and Adaptive Laplacian Eigenmaps for Data Reconstruction and Dimensionality Reduction

ID:70 Rule Extraction Based on Fuzzy Linguistic Concept Knowledge

ID:71 Linguistic Truth-valued Fuzzy Negation Operator Based on Lattice Implication Algebra

ID:72 Intelligent assessment approach to garment fit degree for garment e-mass customization using probabilistic neural network

ID:74 TOPSIS decision making method based on linguistic formal context with fuzzy object

ID:75 The Best of Translation: RNN-based Machine Translation and Post-editing

ID:77 A transmission line tension prediction model based on auxiliary information

ID:78 Some discussions of Yager preference aggregation with uncertainty

ID:79 Differential Evolution Variants for finding D-optimal Designs

ID:80 Intelligent computational techniques for implementation of sustainable circular economy: review and perspectives

ID:81 Research on the Restoration of Costumes in the Paintings of Ladies in the Ming Dynasty

ID:82 Designing Wearables for Assistive Correction of Children's Sitting Posture

ID:83 Interactive Game-based Device for Sustainability Education Among Teenagers

ID:84 A Generalized Linguistic Variable and A Generalized Fuzzy Set GFScom

ID:85 Deep Learning-based Facial Expression Recognition

ID:86 Sustainability Driven Apparel Supplier Selection

ID:87 Research on the system of smart wearable design factors for aging in place in the sustainable perspective

ID:88 Ensemble Transfer Learning For Plant Leave Disease Identification

Author Indexes

M

N

O

P

Q

R

S

T

W

Asymmetric distance-based Comprehensive Minimum Cost Consensus Model

Wen He * and Rosa M. Rodríguez and Luis Martínez

Department of Computer Science, University of Jaén,
Jaén, 23071, Spain
**E-mail: whe@ujaen.es*

Consensus reaching processes (CRPs) try to reach an agreement among decision makers involved in a Group Decision Making (GDM) problem to obtain an accepted solution for all of them. In CRPs without feedback, Minimum Cost Consensus (MCC) models stand out among the consensus models because of their simplicity to achieve the consensus automatically with the minimum cost, that is, to change as less as possible the initial decision makers' preferences. However, these MCC models cannot guarantee to achieve the consensus threshold, because they do not consider reaching a minimum consensus level amongst decision makers. To overcome this limitation, the Comprehensive MCC (CMCC) models have been recently proposed including a new constraint to achieve the consensus threshold. These models apply the same unit cost when the decision makers' preferences are increased or decreased, and in some GDM situations, it should not be the same. Therefore, we propose to use asymmetric costs in the CMCC models by appliyng an asymmetric distance that considers the direction of the change. These models are called, asymmetric distance-based CMCC models and are developed to deal with fuzzy preference relations.

Keywords: comprehensive minimum cost consensus model; asymmetric distance; group decision making; fuzzy preference relations.

1. Introduction

In real world, due to the complexity of social and economic development, decisions are made by multiple decision makers giving rise to the Group Decision Making[1] (GDM) problems. Generally, GDM problems are modeled by preferences over a set of feasible alternatives provided by decision makers, aiming to achieve a common solution. However, this common solution could not satisfy all decision makers because some of them might feel that their opinions have been ignored. To overcome this drawback, it is necessary to require a Consensus Reaching Process (CRP)[2] to achieve agreed solutions before making a decision. A CRP is a dynamic iterative process supervised by a moderator, where decision makers modify their initial preferences in different rounds to increase the degree of agreement and reach a consensual solution acceptable to all. CRPs can be classified into two types: with feedback, in which decision makers change their opinions according to the suggestions provided by the moderator to increase the consensus degree in the next round; and without feedback, in which decision makers' opinions are modified automatically to increase the consensus degree. Within the latter ones, the outstanding and widely used model is the Minimum Cost Consensus (MCC)[3] model, which was introduced by Ben-Arieh and Easton to control the minimum cost of reaching consensus. Since then, it has become a hot research topic in CRPs[3–6]. Afterwards, Zhang et al.[6] studied how the use of different aggregation operators to obtain the collective opinion influences in the degree of agreement within the group. However, the unit cost used in all these models is the same, which does not always apply in all situations. Considering that the unit cost might be asymmetric cost, Cheng et al.[4] extended the MCC model to add a directional constraint by means of applying asymmetric costs according to the decision maker's preferences are increased or decreased. Subsequently, Labella et al.[5] pointed out that these MCC models ignore a minimum level of agreement between decision makers and proposed the Comprehensive MCC (CMCC) models including an additional minimum consensus level constraint to guarantee to achieve the consensus threshold. Therefore, considering such a situation in which the direction of the change can have different costs, we propose new Asymmetric Distance-based CMCC (AD-CMCC) models to deal with Fuzzy Preference Relations (FPRs), which utilizes asymmetric distances to identify the directions that will be applied in the asymmetric costs of adjusting decision makers' preferences.

The remainder of this paper is organized as follows. Section 2 reviews some concepts that help to come up with new models. Section 3 introduces the AD-CMCC models, which use asymmetric distances to model the objective and constraint functions. Section 4 briefly shows an illustrative example to prove the feasibility and performance of the proposed model. Finally, some conclusions and future works are pointed out in Section 5.

2. Preliminaries

This section briefly reviews some concepts such as asymmetric distance, CRP for GDM dealing with FPRs, and CMCC model. All of them are the basis for proposing new AD-CMCC models.

2.1. *Asymmetric distance*

Compared with the general distance, the asymmetric distance[7] does not satisfy the symmetry property because it implies direction.

Definition 2.1.[7] Let X be a non-empty set and $\mathbf{R}$ be the set of all real numbers. The function $d : X \times X \to \mathbf{R}$ is an asymmetric distance if d satisfies

- **Non-negativity:** $\forall x, y \in X,\ d(x,y) \geq 0$ and $d(x,x) = 0$;
- **Weak symmetry:** $\forall x, y \in X,\ d(x,y) = d(y,x) = 0$ implies $x = y$;
- **Triangle inequality:** $d(x,z) \leq d(x,y) + d(y,z)$ for all $x, y, z \in X$.

If the symmetry property, i.e., $\forall x, y \in X,\ d(x,y) = d(y,x)$, is added to the above definition, then it becomes to the general distance. The widely used asymmetric distance[7] in the existing literature is given as follows:

$$d(x,y) = \max\{y - x, 0\} = (y - x)^{+}. \tag{1}$$

2.2. *A GDM dealing with FPRs*

The classical solution process of a GDM problem is a selection process[1], which aims to select an appropriate alternative/s among a set of feasible alternatives. However, there may be cases where decision makers do not accept the solution because some of them may feel that their opinions have not been taken into account. To overcome this limitation, a CRP[2,5] needs to be added before the selection process to achieve an agreed solution within the group.

Usually, a GDM problem is constructed by the following elements[8]: (i) a problem to be solved; (ii) a set of feasible alternatives, i.e., $\mathcal{A} = \{\mathcal{A}_1, \mathcal{A}_2, \cdots, \mathcal{A}_n\} \quad (n \geq 2)$; and (iii) a group of multiple decision makers, i.e., $E = \{e_1, e_2, \cdots, e_m\} \quad (m \geq 2)$, to expressing their individual opinions over the alternatives set $\mathcal{A}$. The information is often represented by a reciprocal FPR[9] matrix $P = (p_{ij})_{n\times n}$ verifying $p_{ij}, p_{ji} \in [0,1]$ and $p_{ij} + p_{ji} = 1$, in which $p_{ij}\,(\forall i, j = 1, 2, \cdots, n)$ is interpreted as the preference degree of alternative $\mathcal{A}_i$ over $\mathcal{A}_j$: (i) $p_{ij} > 0.5$ indicates that $\mathcal{A}_i$ is preferred to $\mathcal{A}_j$; (ii) $p_{ij} = 1$ indicates that $\mathcal{A}_i$ is absolutely preferred to $\mathcal{A}_j$; and (iii) $p_{ij} = 0.5$ indicates indifference between $\mathcal{A}_i$ and $\mathcal{A}_j$.

2.3. *CMCC model*

Consensus models can be classified into two categories: (i) with feedback, when decision makers are asked to change their preferences following the guidance provided by the moderator and (ii) without feedback, when the preferences are changed automatically. Among the consensus models with non-feedback, the MCC models stand out as linear programming models that find an optimal solution to achieve the consensus with the minimum cost. However, Labella et al.[5] pointed out that this is not enough to guarantee to achieve the consensus threshold, and thus, they proposed CMCC models which include an additional constraint to achieve a minimum consensus level amongst decision makers. The CMCC model dealing with FPRs is defined as follows:

$$(\mathbf{M-1}) \quad \min \quad \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\sum_{k=1}^{m} c_k |p_{ij}^{'k} - p_{ij}^{k}|$$

$$\text{s.t.} \quad \begin{cases} p_{ij}^{c} = \sum\limits_{k=1}^{m} \omega_k p_{ij}^{'k}; \\ & k = 1, 2, \cdots, m, \\ |p_{ij}^{c} - p_{ij}^{'k}| \leq \varepsilon, & i = 1, 2, \cdots, n-1, \\ & j = i+1, \cdots, n; \\ \mathbf{C}\left(P_1^{'}, P_2^{'}, \cdots, P_m^{'}\right) \geq \alpha. \end{cases}$$

where $P_k = \left(p_{ij}^{k}\right)_{n\times n}$, $P_k^{'} = \left(p_{ij}^{'k}\right)_{n\times n}$ and $P_c = \left(p_{ij}^{c}\right)_{n\times n}$ represent the initial opinions, the adjusted consensus opinions, and the collective opinions, respectively. And ω_k is the k^{th} decision maker's weight satisfying $\omega_k \in [0,1]$ and $\sum\limits_{k=1}^{m} \omega_k = 1$. $\mathbf{C}(\cdot)$ represents the consensus level achieved, the parameter α is a predefined consensus threshold, ε is the maximum acceptable distance between decision makers' opinion and the collective opinion.

It should be pointed out that $\mathbf{C}(\cdot)$ can be calculated by the distance between decision makers' opinions or the distance between each decision maker's opinion and the collective opinion (see[5] for more details).

3. Novel AD-CMCC model dealing with FPRs

Distance plays a key role in the CMCC model, where the involved distances are computed by symmetric distances as $|p_{ij}^{'k} - p_{ij}^{k}|$ and $|p_{ij}^{c} - p_{ij}^{'k}|$, respectively. However, Cheng et al.[4] pointed out that the cost of increasing or decreasing the preferences should be different in some GDM problems, which implies using asymmetric costs. Therefore, we propose new AD-CMCC models that extends the CMCC models to consider the asymmetric costs and asymmetric distance.

For sake of clarity and simplicity, let c_i^U and c_i^D represent unit costs in the increasing and decreasing directions identified by asymmetric distances $d(x,y)=(y-x)^+$, then the AD-CMCC model dealing with FPRs is defined as follows:

$$(\mathbf{M-2})\quad \min \sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[c_k^U\left(p_{ij}^{\prime k}-p_{ij}^{k}\right)^+ + c_k^D\left(p_{ij}^{k}-p_{ij}^{\prime k}\right)^+\right]$$

$$\text{s.t.}\begin{cases} p_{ij}^{\prime k}-\left(p_{ij}^{\prime k}-p_{ij}^{k}\right)^+ + \left(p_{ij}^{k}-p_{ij}^{\prime k}\right)^+ = p_{ij}^{k}, & k=1,2,\cdots,m,\ i=1,2,\cdots,n,\ j=1,2,\cdots,n;\\ p_{ij}^{c}=\sum_{k=1}^{m}\omega_k p_{ij}^{\prime k}; & \\ 0\le \left(p_{ij}^{c}-p_{ij}^{\prime k}\right)^+, \left(p_{ij}^{\prime k}-p_{ij}^{c}\right)^+ \le \varepsilon, & k=1,2,\cdots,m,\ i=1,2,\cdots,n,\ j=1,2,\cdots,n;\\ \mathbf{C}\left(P_1^{\prime},P_2^{\prime},\cdots,P_m^{\prime}\right)\ge \alpha. & \end{cases}$$

where $\mathbf{C}(\cdot)$ represents the achieved consensus level based on the asymmetric distance, the parameters α and ε are the same as $\mathbf{Model-1}$.

Therefore, due to the different extensions of the consensus measures $\mathbf{C}(\cdot)$ introduced by Labella[5], the following AD-CMCC models dealing with FPRs can be proposed:

(i) $\mathbf{C}(\cdot)$ is computed based on the asymmetric distance[10] between each decision maker's opinion and the collective opinion:

$$(\mathbf{M-2_1})\quad \min \sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[c_k^U\left(p_{ij}^{\prime k}-p_{ij}^{k}\right)^+ + c_k^D\left(p_{ij}^{k}-p_{ij}^{\prime k}\right)^+\right]$$

$$\text{s.t.}\begin{cases} p_{ij}^{\prime k}-\left(p_{ij}^{\prime k}-p_{ij}^{k}\right)^+ + \left(p_{ij}^{k}-p_{ij}^{\prime k}\right)^+ = p_{ij}^{k}, & k=1,2,\cdots,m,\ i=1,2,\cdots,n,\ j=1,2,\cdots,n;\\ p_{ij}^{c}=\sum_{k=1}^{m}\omega_k p_{ij}^{\prime k}; & \\ 0\le \left(p_{ij}^{c}-p_{ij}^{\prime k}\right)^+, \left(p_{ij}^{\prime k}-p_{ij}^{c}\right)^+ \le \varepsilon, & k=1,2,\cdots,m,\ i=1,2,\cdots,n,\ j=1,2,\cdots,n;\\ 1-\frac{2}{n(n-1)}\sqrt[\lambda]{\sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_k\left(\left(p_{ij}^{c}-p_{ij}^{\prime k}\right)^+\right)^{\lambda}}\ge\alpha, & \lambda\ge 1. \end{cases}$$

Noticing that in the last constraint $\mathbf{C}(\cdot)$ can also use $\left(p_{ij}^{\prime k}-p_{ij}^{c}\right)^+$

instead of $\left(p_{ij}^{c} - p_{ij}^{\prime k}\right)^{+}$ without changing the result.

(ii) $\mathbf{C}(\cdot)$ is computed based on the asymmetric distance[10] between decision makers' opinions:

$$(\mathbf{M-2_2}) \quad \min \sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[c_k^U\left(p_{ij}^{\prime k}-p_{ij}^{k}\right)^{+}+c_k^D\left(p_{ij}^{k}-p_{ij}^{\prime k}\right)^{+}\right]$$

$$\text{s.t.} \begin{cases} p_{ij}^{\prime k}-\left(p_{ij}^{\prime k}-p_{ij}^{k}\right)^{+}+\left(p_{ij}^{k}-p_{ij}^{\prime k}\right)^{+}=p_{ij}^{k}, & k=1,2,\cdots,m,\ i=1,2,\cdots,n,\ j=1,2,\cdots,n; \\ p_{ij}^{c}=\sum\limits_{k=1}^{m}\omega_k p_{ij}^{\prime k}; & \\ 0\le\left(p_{ij}^{c}-p_{ij}^{\prime k}\right)^{+},\left(p_{ij}^{\prime k}-p_{ij}^{c}\right)^{+}\le\varepsilon, & k=1,2,\cdots,m,\ i=1,2,\cdots,n,\ j=1,2,\cdots,n; \\ 1-\frac{2}{n(n-1)}\sqrt[\lambda]{\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n}\sum\limits_{k=1}^{m}\sum\limits_{l=1}^{m}\frac{\omega_l+\omega_k}{m-1}\left(\left(p_{ij}^{\prime l}-p_{ij}^{\prime k}\right)^{+}\right)^{\lambda}}\ge\alpha, & \lambda\ge1. \end{cases}$$

Similarly, in the last constraint $\mathbf{C}(\cdot)$ can also use $\left(p_{ij}^{\prime l} - p_{ij}^{\prime k}\right)^{+}$ to replace $\left(p_{ij}^{\prime k} - p_{ij}^{\prime l}\right)^{+}$ for computation.

4. Illustrative example

Due to the limited space, we will only apply the model $\mathbf{M-2_1}$ with $\lambda = 1$ to show the applicability and effectiveness of the proposed AD-CMCC models dealing with FPRs. In this problem, there are three decision makers e_1, e_2, e_3 associated with the same weights $(\omega_1, \omega_2, \omega_3)^T = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)^T$, and with respectively unit costs $\left(c_1^U, c_2^U, c_3^U\right)^T = (2,4,3)^T$ and $\left(c_1^D, c_2^D, c_3^D\right)^T = (5,4,2)^T$. The initial assessments over the four alternatives $\mathcal{A} = \{\mathcal{A}_1, \mathcal{A}_2, \mathcal{A}_3, \mathcal{A}_4\}$ using reciprocal FPRs, $P_k = \left(p_{ij}^k\right)_{4\times4}$ $(k = 1,2,3)$, are shown as follows:

$$P_1 = \begin{pmatrix} \mathbf{0.5} & 0.6 & 0.3 & 0.3 \\ 0.4 & \mathbf{0.5} & 0.2 & 0.9 \\ 0.7 & 0.8 & \mathbf{0.5} & 1 \\ 0.7 & 0.1 & 0 & \mathbf{0.5} \end{pmatrix}; \quad P_2 = \begin{pmatrix} \mathbf{0.5} & 0.7 & 0.5 & 0.9 \\ 0.3 & \mathbf{0.5} & 0.5 & 0.6 \\ 0.5 & 0.5 & \mathbf{0.5} & 0.1 \\ 0.1 & 0.4 & 0.9 & \mathbf{0.5} \end{pmatrix}; \quad P_3 = \begin{pmatrix} \mathbf{0.5} & 0.7 & 0.4 & 0.5 \\ 0.3 & \mathbf{0.5} & 0.9 & 0.1 \\ 0.6 & 0.1 & \mathbf{0.5} & 0.7 \\ 0.5 & 0.9 & 0.3 & \mathbf{0.5} \end{pmatrix}.$$

The results are shown in Table 1. Obviously, $\mathbf{C}(\cdot)$ is highly dependent on the value of ε, therefore, we can conclude that:

Table 1. The minimum cost according to different values of ε and α of $\mathbf{M}-\mathbf{2_1}$.

cost	$\alpha = 0.65$	$\alpha = 0.7$	$\alpha = 0.75$	$\alpha = 0.8$	$\alpha = 0.85$	$\alpha = 0.9$	$\alpha = 0.95$
$\varepsilon = 0.05$	9.299	9.299	9.299	9.299	9.549	9.950	10.450
$\varepsilon = 0.1$	7.725	8.000	8.350	8.800	9.250	9.799	10.425
$\varepsilon = 0.15$	7.199	7.649	8.100	8.550	9.150	9.750	10.425
$\varepsilon = 0.2$	6.949	7.400	7.900	8.500	9.100	9.750	10.425
$\varepsilon = 0.25$	6.699	7.250	7.850	8.450	9.075	9.750	10.425
$\varepsilon = 0.3$	6.599	7.190	7.800	8.400	9.075	9.750	10.425

(i) Obviously, for a fixed α, the minimum cost decreases as the value of ε increases; For a given ε, the minimum cost increases as the value of α increases.

(ii) There are some special cases. For instance, for $\varepsilon = 0.05$, if $\alpha \leq 0.8$, the minimum cost is a constant 9.299; Similarly, $\alpha = 0.95$, the minimum cost is a constant 10.425 when $\varepsilon \geq 0.1$.

5. Conclusions and Future work

Consensual solutions are becoming increasingly important in GDM problems, driving to include CRPs in the solving process. There are CRPs with feedback and without feedback. In the latter case, it stands out the MCC models, which aims to achieve consensus with minimal cost. Recently, a CMCC model has been proposed to guarantee the consensus between decision makers. However, the cost of increasing or decreasing the decision makers' preferences are usually equal and sometimes they might be different. Thus, in this contribution, AD-CMCC models that deal with FPRs using an asymmetric distance have been presented, where the asymmetric distance provides the direction to apply the asymmetric costs when decision makers' preferences are increased or decreased.

In future research, we will study the application of the proposed model to linguistic information.

Acknowledgements

This work is partially supported by the Spanish Ministry of Economy and Competitiveness through the Spanish National Project PGC2018-099402-B-I00, and the Postdoctoral fellow Ramón y Cajal (RYC-2017-21978), the FEDER-UJA project 1380637 and ERDF.

References

1. M. Roubens, Fuzzy sets and decision analysis, *Fuzzy sets and systems* **90**, 199 (1997).
2. C. L. Butler and A. Rothstein, *On conflict and consensus: A handbook on formal consensus decisionmaking* (Citeseer, 2007).
3. D. Ben-Arieh and T. Easton, Multi-criteria group consensus under linear cost opinion elasticity, *Decision support systems* **43**, 713 (2007).
4. D. Cheng, Z. Zhou, F. Cheng, Y. Zhou and Y. Xie, Modeling the minimum cost consensus problem in an asymmetric costs context, *European Journal of Operational Research* **270**, 1122 (2018).
5. Á. Labella, H. Liu, R. M. Rodríguez and L. Martinez, A cost consensus metric for consensus reaching processes based on a comprehensive minimum cost model, *European Journal of Operational Research* **281**, 316 (2020).
6. G. Zhang, Y. Dong, Y. Xu and H. Li, Minimum-cost consensus models under aggregation operators, *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* **41**, 1253 (2011).
7. F. Plastria, Asymmetric distances, semidirected networks and majority in fermat–weber problems, *Annals of Operations Research* **167**, 121 (2009).
8. J. Kacprzyk, Group decision making with a fuzzy linguistic majority, *Fuzzy sets and systems* **18**, 105 (1986).
9. K. Nakamura, Preference relations on a set of fuzzy utilities as a basis for decision making, *Fuzzy sets and systems* **20**, 147 (1986).
10. X. Blasco, G. Reynoso-Meza, E. A. Sánchez Pérez and J. V. Sánchez Pérez, Asymmetric distances to improve n-dimensional pareto fronts graphical analysis, *Information Sciences* **340-341**, 228 (2016).