FINDING KERNEL IN GROUP DECISION-MAKING

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ABSTRACT

A methodological combination of the DRV Processes and the ELECTRE I method is proposed to obtain a kernel solution and consensus-building. DRV processes include three phases: stabilization, aggregation, and ordering. The first phase concerns problem structuring, preferences evaluating so that the forms of ignorance of information are controlled and the consensus is favored. Aggregation phase was originally carried out with linear weighting, a strategy that allows us to obtain an ordering or the selection of the best alternative. Solutions to problems that seek to discriminate a kernel set are not formalized. A methodological combination is formalised to find kernel solutions in group decision making and we show an application case in which we obtained the set of good alternatives. The results show that the bias of underestimating good points with low importance is reduced using outranking methods in the aggregation and ordering phases.

KEYWORDS: Group decision making - ELECTRE I - DRV Processes - Kernel.

1. INTRODUCTION

The study of Multi-Criteria Group Decision-Making (MGDM) is formalized with the seminal paper of Hwang and Lin (Hwang and Lin, 1987)) and since then it has increased. In the last decade, this growth has been emphasized considerably with applications in various fields (Ervural et al., 2016). However, there are still unresolved problems, such as the lack of consideration of the level of consensus reached and the reconciliation of the priorities of decision-makers whose experiences and knowledges are dissimilar (Kabak and Ervural, 2017; Koksalmis and Kabak, 2019).

For the reconciliation of the priorities, the combination of problem structuring methods (PSM) with MGDM has proven to be effective since it allows to exchange opinions and experiences (Belton and Stewart, 2010; Marttunen et al., 2017). However, the form of exchange is not trivial and can affect the result. Among the things that affect the exchange is the call path dependence which refers to a process where the used mechanism in problem modeling (or interaction forms of actors, methods, and context to constitute the praxis) can accumulate various biases and impact the result (Hämäläinen and Lahtinen, 2016).

Accordingly, the consensus verification is crucial to mitigate the effects of the dependent path due to social dynamics that influence the modeling process (Kotlar et al., 2018). Nevertheless, the percentage of MGDM that are concerned about the subject is reduced (Kabak and Ervural, 2017). Furthermore, there are forms of ignorance on the available information (uncertainty or cases where information only induces some way of partial knowledge, imprecisions related to measuring errors and unavailability of some data) (Smets, 1991; Jiao et al., 2016) that can affect the relationship between the context, actors and methods and influence the praxis.

Among the approaches proposed to deal with the forms of ignorance are the theory of evidence (Fu and Yang, 2012), the fuzzy sets (Galo et al., 2018; Merigó and Gil-Lafuente, 2011), and the Theory of Multi-Attribute Utility (MAUT) (Autran Monteiro Gomes et al., 2004; Velasquez and Hester, 2013). In general, MGDM considers consensus with measurements obtained through fuzzy sets (Kabak and Ervural, 2017). From MAUT, three possible approaches emerged which refer to the omission of the forms of ignorance, modeling of forms of ignorance without reducing them, and reduction of forms of ignorance after modeling.

Similarly, the MGDM can pursue various objectives, among which are: the selection of the best alternative, the ordering of alternatives or the choice of a set of good alternatives (kernel) with the rejection of bad ones (Roy, 1985). In general, MGDM is oriented to the first two problems, so there are unoccupied niches for selecting a kernel set of good alternatives (Ervural et al., 2016).

In this situation, we propose a methodological combination that integrates Decision Processes with Variability Reduction (DRV processes) and ELimination and Choice Expressing the REality in its version 1 (ELECTRE I, for its acronym in French). We use that particular mix to take advantage of the strengths of each method. In this way, the DRV Processes method, which is characterized by evaluating and controlling the forms of ignorance and the level of consensus through MAUT and statistical resources, is combined with the ELECTRE I method, which seeks to establish a maximum possible kernel of good alternatives.

The use of the DRV Processes is based on the possibility of a sequential application with another method that incorporates the advantages aforementioned. Then, with the basic data obtained with the DRV Processes, it is possible to identify the kernel by way of ELECTRE I. In this way, we guarantee that there are no epistemological paradigm clashes because each method is applied sequentially (Munda, 1993, 2004). There are similar experiences documented about this (Figueira et al., 2005; Tervonen et al., 2008; Corrente et al., 2014; Roy et al., 2014). For the choice of the outranking method, we considered the intervention moment of the p and q thresholds in different methods (Tzeng and Huang, 2011). We opted for ELECTRE I because their thresholds intervene in the evaluation of the outranking relation, and consequently, they make viable its application with data obtained using another method.

PROMETHEE, on the contrary, uses the thresholds in the preparatory phase hence it can make difficult the combination.

This paper is structured as follows. First, we present the materials and methods (both in its original version and in the formalization of the proposed combination). Then, we discuss the obtained results. Finally, we present our conclusions and specify future research areas.

2. MATERIALS AND METHODS

2.1. DRV PROCESSES

This method has been presented in Zanazzi (2016). It can be applied in MGDM where group members share objectives (Zanazzi et al., 2014; Castellini et al., 2017). The method is developed through a three-phase process: Stabilization, Aggregation, and Ordering.

Stabilization phase

The general problem is divided into sub-problems: one concerns the criteria analysis and the following ones refer to the comparison of the alternatives for each criterion. At the beginning of the stabilization phase of a sub-problem, the perceptions of the members are varied, because each person has his or her own distinctive experiences and previous knowledge (Velez-Castiblanco et al., 2016). Therefore, the group should work to build consensus on each subproblem and reduce variability in opinions. Thus, the activity begins in a focus group, with exercises that favor the collaborative knowledge building (Wenger-Trayner et al., 2014), including the adoption of a shared language and the elaboration of joint definitions of the criteria and the elements compared. At some point, the analysis task allows us to suppose that basic agreements have been established.

Then, group members assign utilities to the compared elements of the subproblem, which are analyzed statistically. The method assumes that when the group's priorities and preferences are extremely dispersed, utilities can be considered as extracted from a Uniform Distribution. Instead, group work should contribute to reducing the differences and the observed dispersion should maintain a sustained tendency to decrease. For this reason, when members reconcile their positions, subjective utilities should tend to be similar. Thus, it is assumed that under consensus conditions, the assigned utilities to each compared element must be assimilated to a Normal Distribution as demonstrated in the Ph.D. dissertation of Zanazzi (2016).

This consensus is verified in two different ways. The first is verified with an indicator called the Remaining Variability Index (IVR, for its acronym in Spanish) for which the expected values under consensus conditions have been approximated. The IVR can be obtained through the quotient between the sum of squares within the group's elements and the sum of squares of the uniform distribution - see equation (1) -.

$$IVR = \frac{\sum_{k=1}^{K} \sum_{n=1}^{N} (u_{kn}^{*} - \overline{u_k^{*}})^2}{\frac{N-1}{3k}} .100 \qquad (1)$$

Where N is the total number of group participants and K is the total number of evaluated elements. Henceforth, sub-index n (with 1 ≤ n ≤ N) identifies each participant, and sub-index k (with 1 ≤ k ≤ K) is used to identify each generic element in a sub-problem. Thus, u*kn represents the utility assigned when evaluating the generic element k by participant n, and uk* is the average utility of the generic element k obtained when considering the assignments of N participants. The second way is verified with the normality assumption of the utilities, with statistical tools, including the Shapiro Wilks test of normality, or its version modified by Raman and Govindarajulu (Rahman and Govindarajulu, 1997).

Once a subproblem can be considered stable and under consensus, it is passed to the next subproblem and so on, until the analysis is complete.

Aggregation and Ordering Phase

The aggregation phase is done by Linear Weighting. To represent it in terms of the standard notation, the utility obtained by analyzing the criteria analysis subproblem is assimilated to Wj and the utilities of the alternatives comparison subproblems in relation to each criterion are Uij. The global values of a generic alternative Vi are obtained as indicated in (2).

$$V_i = \sum_{i=1}^{J} W_j * U_{ij} \tag{2}$$

where sub-index i (with 1 ≤ i ≤ I) identifies the alternatives and sub-index j (with 1 ≤ j ≤ J) identifies the criteria.

The comparison of the average values of the valuations Vi allows the establishment of a first ranking from the most to the least preferable. However, since the observed values can be affected by the sampling errors, it is possible for this option to lead to the identification of preference relations that are not real. In order to identify these situations, the method applies repeated comparison tests for dependent variables and controls the tendency to Type I errors, using the false discovery rate proposed by Benjamini and Yekutieli (2001).

2.2. ELECTRE I

This methodology uses outranking relationships to determine a restricted kernel or subset of good alternatives through the study of a concordance matrix and a discordance matrix (Figueira et al., 2005, 2010). The preferences are modeled by using binary outranking relations, which evaluates if a generic alternative at least as good as any other (Govindan and Jepsen, 2016). Utilities that assessment an alternative in the criterion j are used to identify the criteria set where alternative 1 is equal to or preferred to alternative 2 for each criterion j and the criteria set where alternative 1 is worse than alternative 2.

Two indices are constructed which synthesize the information from the pairwise comparisons (Figueira et al., 2010). The first is called the concordance index and expresses a measure of the intensity in which alternative 1 is equal to or preferred to alternative 2 and is calculated in the following way:

$$C_{(1,2)} = \frac{\sum_{j:U_{1j} \geq U_{2j}} W_j}{\sum_{j=1}^{J} W_j} \qquad (3)$$

Where Uij denotes the valuation of a generic alternative i in criterion j and Wj represents the weight of criterion j. This index takes values between 0 and 1, where 0 represents the minimum possible intensity and 1 the maximum intensity.

The discordance index is calculated by considering those performances of the alternative1 that are worse than those of 2. Last index is defined as:

$$D_{(1,2)} = \frac{1}{d} \max_{j:U_{1j}<U_{2j}} [U_{2j} - U_{1j}] \qquad (4)$$

Where d is the maximum possible intra-criterion difference and it is calculated as: $d = max_j \; max_{(1,2) \in A} [U_{2j} - U_{1j}] \; \forall j = 1, 2, ..., J$ with a set of alternatives denoted A. The discordance index takes values between 0 and 1, where the values closest to one represent a situation where alternative 1 is strongly worse than 2 and values closer to zero represent the opposite.

To construct global outranking relations, it is convenient to normalize the concordance and discordance indexes and define thresholds or degrees of tolerances. Thus, the concordance threshold is denoted by p* and reflects the minimum required so that proposition 1 exceeds or is equal to 2 is not rejected. For its part, the discordance threshold is symbolized with q* and denotes the maximum difference allowed so that proposition 1 does not exceed 2 is not rejected.

An outranking matrix is constructed where the possible values are 0 and 1. The hits assume a value of one and simultaneously fulfill two conditions: the concordance index of the generic alternative i about another given is equal to or exceeds the threshold p* and the discordance index of the generic alternative i about another given is less or equal to the threshold q*. The breach with any of the two conditions is represented by zero. Finally, the interpretation of the outranking matrix allows the identification of the kernel.

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2.3. METHODOLOGICAL COMBINATION PROPOSED

The methodological proposal of this work modifies the aggregation and ordering phases of the DRV processes method. The sequence of operations is:

Phase I: Stabilization

(1) Problem Structuring: The collection of information is based on PSM methods to define the criteria to be used.

(2) Subproblem study: the subproblems were run, one by one.

(3) Subproblem group analysis: exercises are carried out to define the elements to be compared in the subproblem and to exchange knowledge. The joint analysis contributes to the reduction of posture differences.

(4) Allocation of Utilities: the participants assigning subjective utilities to the compared elements in independent form when compared in pairs the adjacent elements in the chosen preorder, answering the question: How many times is an element preferred compared to the adjacent one?
(5) Analysis of the utilities: the IVR Indicator and data normality obtained were analyzed.
(6) Consensus verification: when all the utilities could be represented with a Normal Distribution and IVR indicator is less or equal to 25%, it was possible to assume consensus and move on to a new subproblem (return step 2).

Phase II and III: Aggregation And Ordering.

As a result of the stabilization phase, the analysis of each subproblem obtained samples of size N of the normalized utilities in scale [0,1]. To summarize these sample values in a representative measure of the set, the average was used, since it is a good estimator under normal conditions. Arithmetic means were calculated according to (5) and it is a measure of the utility that the group recognizes in its join.

$$\overline{U_{ij}} = \frac{u_{ijn}}{N} \qquad (5)$$

where sub-index i (with $1 \leq i \leq I$) identifies the alternatives, sub-index j(with $1 \leq j \leq J$) identifies the criteria, and sub-index n (with $1 \leq n \leq N$) identifies the participants.

It is pertinent to specify that the assigned utilities represent a desirable value and, therefore, the criteria to be considered under study contain a sense of maximization. The concordance index can be calculated as:

$$C_{(2,1)} = \frac{\sum_{j:\overline{U_{2j}} \geq \overline{U_{1j}}} \overline{W_j}}{\sum_{j=1}^{J} \overline{W_j}} \qquad (6)$$

The discordance index can be calculated as:

$$D_{(2,1)} = \frac{1}{d} \max_{j:\overline{U_{2j}} < \overline{U_{1j}}} \left|\overline{U_{1j}} - \overline{U_{2j}}\right| \qquad (7)$$

Where d is the maximum possible intra-criterion difference and is calculated as: $d = max_j \; max_{(2,1)\in A} \left|\underline{U_{1j}} - \underline{U_{2j}}\right| \; \forall j = 1, 2, ..., J$ with alternatives set denoted by A.

Some differences in the average values can only be apparent due to the sampling error. Consequently, we proposed to use hypothesis tests to verify these apparent differences. We used Paired-Samples t-Tests for each criterion j with its lower-tailed alternative hypothesis H_1: $\mu_2 - \mu_1 < 0$ and its null hypothesis H_0: $\mu_2 - \mu_1 \geq 0$.

Then, in the t-test on criterion j, if the observed p-value is greater than α, the null hypothesis is not rejected which implies that $\mu_2 \geq \mu_1$. Thus, the alternative 1 is not strictly preferred to the alternative 2 and the alternative 2 is preferred or equal to the alternative 1 in the criterion j. For the calculated discordance index $D_{(2,1)}$, the criterion j obtained a zero that competes for the maximum. For the calculated concordance index $C_{(2,1)}$ the corresponding average weight ($\bar{W}_j$) in the numerator of the expression (5) is summed. If the observed p-value is less than α, then the null hypothesis is rejected and $\mu_2 < \mu_1$ and the opposite considerations are valid.

The concordance and discordance thresholds were determined. The outranking matrix was constructed by considering the alternatives that simultaneously respect both thresholds.

3. METHOD APPLICATION CASE

The everyday activities of a public university generate tons of pathogenic waste that must be collected and treated. Given the necessity to select a new provider to be in charge of the final disposal of pathogenic waste, bidding was carried out in which three offerers participated (Hereafter O1, O2, and O3).
A team of six expert members was formed for the evaluation and final decision. During the structuring of the problem, seven evaluation criteria were adopted, which include: operational modality (MO), cost (CO), provider experience (EXP), vehicle fleet (FL), improvement of service (MS), hygiene and safety conditions (HS), and treatment and final disposal (TR).
The stabilization phase required various exercises. The sub-problem of criteria evaluation needed two iterations. A summary of this evolution is presented in TABLE 1. The sum of the squares in TABLE 1 indicates the levels of uncertainty and imprecision affecting the decision process. In this case, the forms of ignorance dropped to below 15%, which means that the apparent consensus situation is overcome. In the second iteration, all normality tests had acceptable results.

Iteration	Sum of squares	IVR
Reference element	0.2381	100.00%
First iteration	0.1044	43.85%
Second iteration	0.0345	14.49%

TABLE 1: Sub-problem analysis alternatives for MO criterion

The stabilization process continued towards the comparison of offerers, regarding the different criteria considered. The FIGURE 1 summarize the sub-problems that require new iteration before being considered stable. The subproblems of alternatives analysis for each criterion referred to MO (j0), CO (j1), and EXP (j2) needed a new iteration to achieve the reduction of the forms of ignorance.

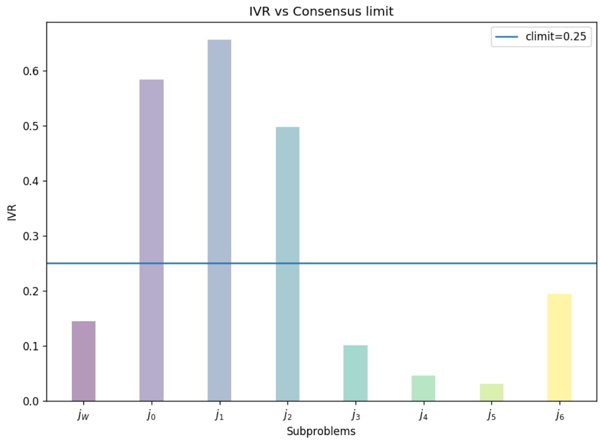

FIGURE 1: IVR Analysis of remaining sub-problems after stabilization of criteria analysis sub-problem. The blue line represents the acceptable limit of variability to verify consensus (consensus limit) and the bars represent the value of IVR indicator in the iteration for each criterion

FIGURE 2 shows the samples of size 6 of the normalized utilities in scale [0,1] after stabilizing the subproblems. FIGURE 2 also shows that O1 and O2 perform well in almost all criteria except for the last one. If aggregation is obtained with a compensatory method, the compensation of the loss on a given criterion by a profit on another one will be presented. We used non-compensatory methods that accumulate several small differences to analyze if they become significant. In particular, the ELECTRE family is framed in the non-compensatory group.

From the normalized utilities, we construct the concordance and discordance indexes for each paired comparison of the alternatives. TABLE 2 presents an illustration of the construction of the indices that emerged from the comparison between alternatives 2 and 1.

The level of significance α determines the acceptance or rejection of the overcoming of one alternative with respect to another. Thus, with α equal to 0,10 the concordance index C(2,1) is 0.419 while α equal to 0.05 C(2,1) it is 0.710. In this case, Type I errors arise when we reject the overcoming between a given alternative and another when this is true. In a complementary way, type II errors appear with the non-rejection of a false null hypothesis. We adopt α equal to 0.10 for coverage of the Type II errors.

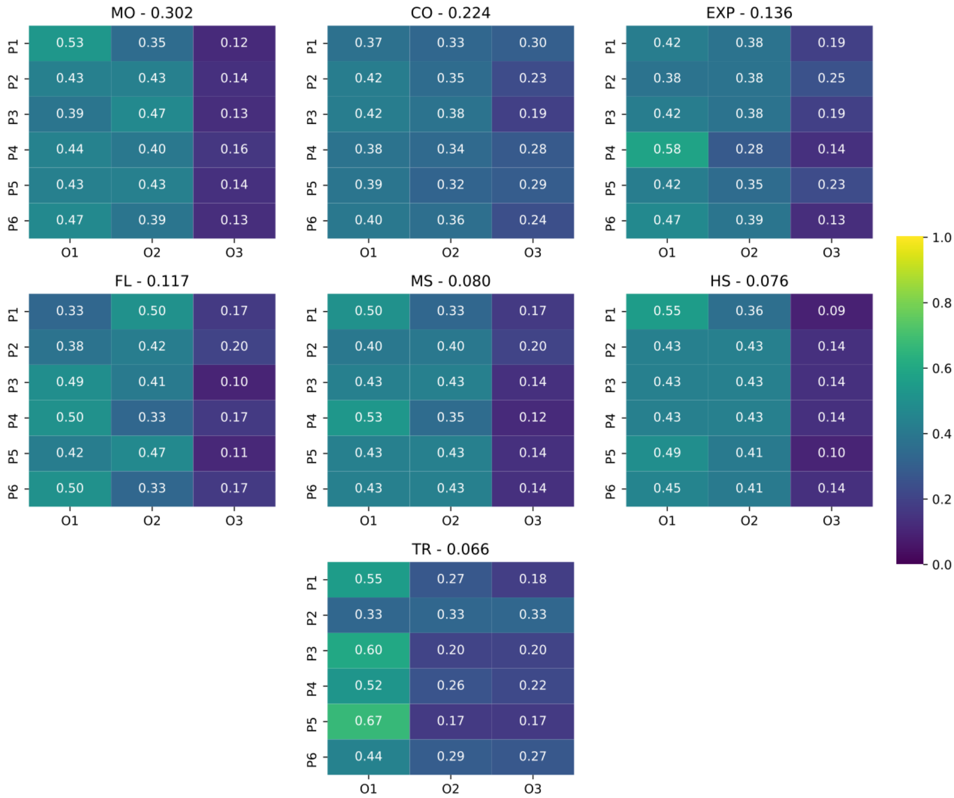

FIGURE 2: Heat map of the utilities normalized of the I alternatives for each criterion and for each participant (with tags P1, P2, P3, P4, P5, and P6).

By repeating the procedure in all possible binary comparisons of an alternative with another, we obtained the concordance and discordance matrices. Based on the p * and q * thresholds of 0.65 and 0.35 respectively, we constructed the outranking matrix. The summary information can be analyzed in TABLE 3.

Regarding the interpretation of the outranking matrix: in reading by rows, the numbers one are interpreted as the dominance of the row alternative about the alternatives of the columns. In this case, the row of alternative O1 shows that alternative O1 dominates over O2 and O3. In contrast, if the numbers one of the outranking matrix are analyzed by columns, they represent that the alternative of the column is dominated by the alternative of the row. If it is positioned in the second column of the third matrix (column O2), we observe that the alternative O2 is dominated by O1. With the logic exposed, it can be seen that O1 is not dominated by any other alternative and integrates the kernel.

With α equal to 0.10	**MO**	**CO**	**EXP**	**FL**	**MS**	**HS**	**TR**
Sample mean of the differences	-0.04	-0.05	-0.09	-0.03	-0.06	-0.05	-0.26
Sample standard deviation of the differences	0.09	0.02	0.11	0.13	0.09	0.07	0.18
t-statistic	-1.02	-6.83	-1.97	-0.49	-1.58	-1.73	-3.63
P-value	0.18	0.00	0.05	0.32	0.09	0.07	0.01
Does O2 exceed or equal to O1? (Not reject H0)	Yes	No	No	Yes	No	No	No
Weight to add in C(2,1)	0.302	0.000	0.000	0.117	0.000	0.000	0.000
Concordance Index	C(2,1) = (0.302+0+0+0.117+0+0+0)/1 = 0.419						
Does O2 is worse to O1? (Reject H0)	No	Yes	No	No	No	No	Yes
$\frac{1}{d}\lvert \underline{U_{1j}} - \underline{U_{2j}} \rvert$	0.000	0.137	0.264	0.000	0.170	0.151	0.784
Discordance Index	D(2,1) = 0.784						

TABLE 2: Obtention of concordance and discordance index of O2 in relation to O1

Concordance matrix			
	O1	O2	O3
O1	--	1	1
O2	0.419	--	1
O3	0	0	--

Discordance matrix			
	O1	O2	O3
O1	--	0	0
O2	0.784	--	0
O3	0.849	1	--

Outranking matrix.			
	O1	O2	O3
O1	--	1	1
O2	0	--	1
O3	0	0	--

TABLE 3: Concordance, discordance and outranking matrix.

Reflections when comparing with linear weighting

In this case, the aggregation with linear weighting shows global utilities of 0.44, 0.38, and 0.18 for O1, O2, and O3. With the application of the Benjamini and Yejutieli's algorithm, it is obtained contrast p-values/p-values observed of 0.009/0.006, 0.018/0.000 and 0.0273/0.000 in the comparison of O1 with O2, O1 with O3, and O2 with O3 respectively. When the contrast p-value is higher than the p-value observed, the difference is significant. In this case, we find a strict preference for alternative O1 over the others. In TABLE 4 we analyzed global contribution of a generic alternative in the criterion MO. In other words, we indicate how much the criterion MO contributes to the global utilities of 0.44, 0.38, and 0.18 for O1, O2, and O3 mentioned before.

	O1 for criterion MO $W_{nj}*U_{nij}$	O2 for criterion MO $W_{nj}*U_{nij}$	O3 for criterion MO $W_{nj}*U_{nij}$
P1	0.296*0.53 = 0.1569	0.296*0.35 = 0.1046	0.296*0.12 = 0.0349
P2	0.267*0.43 = 0.1143	0.267*0.43 = 0.1143	0.267*0.14 = 0.0381
P3	0.250*0.39 = 0.0987	0.250*0.47 = 0.1184	0.250*0.13 = 0.0329
P4	0.361*0.44 = 0.1588	0.361*0.40 = 0.1443	0.361*0.16 = 0.0577
P5	0.319*0.43 = 0.1365	0.319*0.43 = 0.1365	0.319*0.14 = 0.0455
P6	0.322*0.47 = 0.1525	0.322*0.39 = 0.1271	0.322*0.13 =0.0424
PP	0.1363	0.1242	0.0419

TABLE 4: Global Contribution of a generic alternative in the criterion MO

If the participant one (P1) changes his judgments to 0.35 for O1 and 0.53 for O2 (and the other participants keep their subjective utilities), the normality tests are still verified and the IVR is below 25%. However, the global contribution of this criterion change to 0.1274 and 0.1329 for O1 and O2 respectively (see row PP). Note that the majority of participants continue their preference for O1, and the social choice axioms indicate that preference group pattern must be taken into account by all the members and are arrived at considering all participant preferences. In this way, we emphasize that the effects of compensation occur. That is, in the extreme position, a good performance in the criterion with greater weight can compensate for a poor performance in all the other criteria given.

4. CONCLUSIONS

In this work, we found a solution kernel in MGDM through the methodological combination that takes advantage of the strong points of the DRV processes and the ELECTRE I method. We exemplify this with a real case that helps in proposal understanding and implementation. In particular, the combination makes possible to use the problems structuring methods as part of the DRV processes, facilitates the construction of collaborative knowledge, and allows to fill the existing deficiencies in the incorporation of preferences of multiple experts under consensus. The non-compensation characteristic included in the aggregation and ordering phases reduced the bias of underestimating good points with low importance.

Working with the combined methodology supported by Paired-Samples t-Tests implies that the decision-maker must be chosen with a significance level to work (), which is added to their decisions on the thresholds to consider. In the future, a sensitivity analysis will be carried out assessing what happens with a different choice of the level.

Since the method does not allow to obtain a score, the research line is open to work with other methodologies of the ELECTRE family that allow the ordering and the incorporation of the advantages of non-compensation. In the future, it is possible to extend this investigation towards the comparison of results by considering these new alternatives in the aggregation phase of the DRV processes method.

The data used to support the findings of this study have been deposited in the Github repository in https://github.com/nluczywo/Finding_Kernel_GDM

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