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Abstract. A growing interest is expressed by organizations for the development of approaches enabling to take advantage of past experiences to improve their decision processes; they may be referred to as Lessons Learned (LL) processes. Within the LL processes implementation framework, the development of semi-automatic approaches able to distinguish criteria having major influence on the evaluation of experiences is crucial for identifying relevant recommendations and performing efficient prescriptive analysis. In this paper, we propose to contribute to LL study by focusing on the definition of an approach enabling, in a specific setting, to identify the criteria most influencing the decision process regarding the overall performance evaluation of a reduced set of experiences. The proposed approach is framed on Multi-Criteria Decision Analysis, and specifically is based on the Electre tri method. In this paper, an illustration of the proposed approach is provided studying the evaluation of logistical response strategies in humanitarian emergency situations.

Keywords: Multi-Criteria Decision Analysis (MCDA), Lessons Learned, Electre tri, Influencing Criteria Identification, Humanitarian domain.

1 Introduction

Lessons Learned process (LL)[1] refers to a general Knowledge Management approach aiming at ensuring and improving proper functioning of organizations by collecting, analysing, disseminating and reusing tacit experiential knowledge. One of the main focuses of LL is therefore to study how to improve techniques enabling to discover and further take advantage of expert knowledge that is not explicitly formalized into organizations' Information Systems. In this context, LL is particularly interested in taking advantage of knowledge that is most often difficult if not impossible to formalize nowadays - in particular because of the technical difficulties to systematically and efficiently formalize such knowledge considering every-day practices used in organizations, e.g. domain experts often

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[1] Sometimes referred to as Experience feedback.

take decisions based on complex bodies of professional histories. Importance of LL is thus critical to fight against sensitive losses of expertise in organizations, and to achieve well-supported and understood decision-making processes. LL can indeed help improving both the performance and the quality of organizations by analysing past experiences and by using problem-solving methods – narrow links with well-established related domains such as Case Based Reasoning, Multiple-Criteria Decision Analysis and Knowledge Management/Representation exist; some of them will further be discussed.

In this paper, we contribute to LL study by focusing on the definition of an approach enabling, in a specific setting, to identify the criteria most influencing the decision process regarding the overall performance evaluation of a reduced set of experiences. Identifying the criteria most impacting performance is indeed of major importance for numerous applications related to LL; it can also be central for the global implementation of the LL process, e.g. it indeed helps a lot to identify relevant recommendations and to perform efficient prescriptive analyses. Identifying such criteria in real-world problems can however be challenging. We indeed here consider - as it is most often the case in numerous complex decision processes - that no explicit and formal definition of performance based on criteria analysis can be provided by domain experts. Experts can indeed evaluate performance but are not able to explicitly define the way it is evaluated, i.e. to define the model on which the evaluation is based, if any. We also consider the following common constraints: only a reduced set of observations is available[2] and only limited interactions with domain experts can be expected. Additionally, we consider that it is most often unthinkable to perform automatic deep analyses of all pieces of information that could be related to each criterion to further distinguish relevant teachings. Therefore, based on the analysis of a reduced set of evaluated past experiences characterized by their performance on criteria, we propose a general approach framed on Multiple-Criteria Decision Analysis (MCDA) in order to distinguish the minimal set of criteria most impacting performance. The proposed approach is built upon Electre tri, a MCDA method enabling classifying a set of alternatives into predefined categories.

An application of the proposed approach to the humanitarian field is presented; it is used for analysing logistical response strategies in emergency situations. Our case study rests upon a corpus of past missions carried out by a Non-Governmental Organization (NGO); the core mission of the NGO is to deliver emergency aid to people affected by disasters (earthquake, tsunami, conflict, famine, epidemic...). Our general goal is therefore to exploit knowledge that can be extracted from prior missions in order to formulate relevant recommendations that could be used for better defining future logistical response strategies. To this aim, this paper focuses on identifying the set of criteria most impacting performance evaluation of logistical response strategies. The paper is structured as follows: Section 2 briefly introduces state of the art related to LL and motivates the use of MCDA for extracting knowledge from past experiences. Section 3 presents our contribution for identifying the criteria most impacting

[2] This *de facto* prevents the use of traditional Machine Learning approaches.

performance evaluation; an introduction to Electre tri, the MCDA method used in our work, is also given in that section. Section 4 illustrates the use of the proposed approach for studying the logistical response in humanitarian emergency situations. Section 5 concludes this paper and highlights future work.

2 Related Works and Positioning

Whatever the field of application, learning from experience is a growing concern for numerous organizations. In this context, several approaches have emerged to fulfil the different LL needs expressed by organizations; they differ both in (i) the nature and the heterogeneity of information to collect, as well as in (ii) the expected purpose: exploitation, reuse, capitalization, and dissemination of knowledge. Various types of LL approaches can therefore be identified in the literature. Some of them rely on databases composed of past experiences and take advantage of domain-specific querying strategies, e.g. REX method [1]. Other approaches take advantage of knowledge models - using techniques related to Knowledge Management and Knowledge Representation (KM/KR) such as CommonKads [2], or MKSM (Methodology for Knowledge System Management) [3]. Another category of LL approaches also considers the use of problem-solving methods. These methods, in particular Case-Based Reasoning (CBR) [4], rely on the use of knowledge extracted from previously experienced cases to solve similar new cases. A significant number of cases is however generally required to distinguish analogies using these methods.

In our study, we are considering LL towards an application to the logistical emergency response carried out by humanitarian organizations. In this domain, data collection is even more difficult, e.g. oral testimony often prevails, analyses most often rest upon reduced corpora of past missions. With this in mind, another challenge arises: to exploit and reason on a small number of complex past experiences. These experiences are composed of successions of decisions being influenced by different factors such as: the intuition, the context-dependent nature of the missions - instable environment, unpredictable events affecting the system - the multiple, and sometimes conflicting objectives. Nevertheless, despite decision-making complexity, according to the collaborating NGO, the logistical strategy of several missions could be, to a certain extent, generalized and reproduced. In that context, the NGO has established a procedure to learn lessons from past experiences, particularly from choices made in missions. It aims at providing an *a posteriori* evaluation of singular cases entailing a noteworthy success or a significant failure. To do so, a board of multidisciplinary experts conducts an analysis of the case based on related data and complementary interviews; then a conclusive report is provided. However, according to the NGO stakeholders, provided outcomes often face major weaknesses - e.g. hardly exploitable, lack of sharpness - the time-consuming nature of the process is also pointed out.

An open challenge is thus offered to LL automation for knowledge extraction from past experiences in NGOs. Recall however that in the humanitarian domain, relevant and accurate data is difficult to obtain, and cannot easily be automatically analysed - data access and analysis often require costly staff and experts involvement. A further constraint is therefore, while maintaining interactions with domain experts and decision-makers (DMs), to minimize information requests in order to lessen their involvement (both in terms of time and cognitive effort). All these constraints underline the need for a prior identification of relevant criteria in order to reduce the scope of analysis for applying deeper data analyses. In practice, DMs always - at least implicitly - consider a set of objectives that the mission has to reach in order to meet success. In addition, a set of relevant criteria can be considered to measure, for a specific mission, the degree of success of each objective, *i.e.*, performance. Such a performance evaluation can however be a complex process. Indeed, to be successful, for DMs (i) a mission does not necessarily require maximal performance with respect to each criterion, and (ii) the criteria may not have the same importance. We therefore propose to take advantage of MCDA techniques to identify the subset of criteria most impacting the overall performance assessment of a specific mission.

The best known MCDA approaches are those derived from Multi-Attribute Value/Utility Theory (MAVT/MAUT) [5] and outranking methods [6]. Since every MCDA method differently combines performance and criteria importance to define the overall performance of a mission, the identification of the subset of criteria of interest will necessarily depend on the selected MCDA method. In this work, we have chosen to use Electre tri, a method from the well-known ELECTRE family methods [7]. It has been selected according to three main criteria related to NGOs context: it is simple to reuse; non-compensatory, and techniques exist to reduce the amount of information asked to DMs while determining model parameters - agreement among DMs is considered here. The non-compensatory condition means that an excellent performance on specific criteria (e.g. cost) cannot compensate for a bad performance on other prevailing criteria (e.g. degree of achievement of the medical objectives). In order to reduce the amount of information that has to be provided, Electre tri relies on indirect identification of the parameters. In addition, Electre tri is an outranking method: instead of scoring alternatives, outranking methods are based on pair comparisons. Indeed, it is more natural for DMs to compare the strength and the weakness of two alternatives rather than assigning an arbitrary value to each alternative, and comparing them subsequently. Interestingly, outranking methods are based on relatively weak mathematical assumptions [8]. Nevertheless, obtaining the model parameters is a very difficult issue because of the non-linearity due to the thresholds induced in the model. However some recent works have proposed simplified assumptions and a procedure to determine the parameters of the Electre tri method has been proposed [9].

3 Determining Criteria Contribution within Electre tri

The following section first introduces the Electre tri method and is then dedicated to the presentation of our approach: the identification of the subset criteria having the major contribution on the overall performance of a mission.

3.1 General approach

The approach proposed in this paper aims to determine the criteria on which LL process should focus when a mission is analysed. To facilitate DMs' involvement, the information requirement is minimized and the cognitive effort reduced as much as possible. For instance, the parameters of the MCDA model used for the analysis will be transparent for DMs. They will only be asked to assign examples of fictive missions to the predefined categories. These examples of missions are defined by their performance on each evaluation criterion, such that DMs are able to easily classify them. The general approach can be decomposed as follows:

1. Determine the set of criteria on which missions will be evaluated;
2. Automatic identification of Electre tri parameters using a training set of fictive examples of missions;
3. Classify/Assign the mission to one of the predefined categories using this Electre tri model;
4. Determine the criteria strongly contributing to that classification.

3.2 Classifying alternatives using Electre tri

We introduce the technical details related to Electre Tri, the specific MCDA method used in our work.

Let $A = \{a_1, \ldots, a_m\}$ a set of alternatives, and $\mathcal{F}$ a set of criteria satisfying consistency conditions, i.e. completeness (all relevant criteria are considered), monotonicity (the better the evaluation of an alternative on considered criteria, the more it is preferable to another), and non–redundancy (no superfluous criteria are considered) [6]. According to traditional MCDA outranking methods notations, we denote $g_j(a)$ the score of alternative $a \in A$ on the criterion $j \in \mathcal{F}$. For some pairs of alternatives $a, b \in A$, Electre tri builds an outranking relation aSb meaning that 'a is at least as good as b'. To this aim, the method uses concordance, comprehensive concordance, discordance and credibility indices [7]. The concordance index is defined using the indifference $q_j(g_j(a))$ and preference $p_j(g_j(a))$ thresholds; these thresholds allow to take the imprecision of the evaluations $g_j(a)$ into account.[3]

Let's define three subsets $\mathcal{F}_1^c(a,b)$, $\mathcal{F}_2^c(a,b)$ and $\mathcal{F}_3^c(a,b)$ that divide criteria of $\mathcal{F}$ with regard to the comparison of a and b performances:

– $\mathcal{F}_1^c(a,b) = \{j \in \mathcal{F} : g_j(a) \leq g_j(b) - p_j(g_j(b))\}$,
– $\mathcal{F}_2^c(a,b) = \{j \in \mathcal{F} : g_j(b) - p_j(g_j(b)) < g_j(a) < g_j(b) - q_j(g_j(b))\}$,
– $\mathcal{F}_3^c(a,b) = \{j \in \mathcal{F} : g_j(b) - q_j(g_j(b)) \leq g_j(a)\}$.

[3] Note that Electre tri non-compensatory behaviour is defined by the fact that whenever $g_j(a) - g_j(b)$ is greater than $p_j(g_j(a))$ no distinction is made computing the concordance index; a big difference thus cannot compensate any negative difference on another criterion j with $j \neq i$.

The partial concordance index on criterion j is defined using the previous subsets as follows:

$$\forall a, b \in A, \quad c_j(a,b) = \begin{cases} 0 & \text{if } j \in \mathcal{F}_1^c(a,b), \\ \alpha_j(a,b) & \text{if } j \in \mathcal{F}_2^c(a,b), \\ 1 & \text{if } j \in \mathcal{F}_3^c(a,b). \end{cases} \tag{1}$$

where $\alpha_j(a,b) = \frac{g_j(a)-g_j(b)+p_j(g_j(b))}{p_j(g_j(b))-q_j(g_j(b))}$. Criteria in $\mathcal{F}_3^c(a,b)$ vote without reservation for alternative a; in $\mathcal{F}_2^c(a,b)$ only the proportion $w_j \cdot c_j$ is considered voting for alternative a.

The comprehensive concordance index is then defined using the relative importance w_j of each criterion $j \in \mathcal{F}$:

$$\forall a, b \in A, \quad c(a,b) = \sum_{j \in \mathcal{F}} w_j \cdot c_j(a,b) = \sum_{j \in \mathcal{F}_3^c(a,b)} w_j + \sum_{j \in \mathcal{F}_2^c(a,b)} w_j \cdot \alpha_j(a,b) \tag{2}$$

The discordance index is defined by introducing a veto threshold $v_j(g_j(b))$:

$$\forall a, b \in A, \quad d_j(a,b) = \begin{cases} 1 & \text{if } j \in \mathcal{F}_1^d(a,b), \\ \frac{g_j(a)-g_j(b)+p_j(g_j(b))}{p_j(g_j(b))-v_j(g_j(b))} & \text{if } j \in \mathcal{F}_2^d(a,b), \\ 0 & \text{if } j \in \mathcal{F}_3^d(a,b). \end{cases} \tag{3}$$

where:

- $\mathcal{F}_1^d(a,b) = \{j \in \mathcal{F} : g_j(a) \leq g_j(b) - v_j(g_j(b))\}$,
- $\mathcal{F}_2^d(a,b) = \{j \in \mathcal{F} : g_j(b) - v_j(g_j(b)) < g_j(a) < g_j(b) - p_j(g_j(b))\}$,
- $\mathcal{F}_3^d(a,b) = \{j \in \mathcal{F} : g_j(b) - p_j(g_j(b)) \leq g_j(a)\}$.

The credibility index is further defined as follows:

$$\rho_S(a,b) = c(a,b) \cdot \prod_{j \in \mathcal{F}^d(a,b)} \frac{1 - d_j(a,b)}{1 - c(a,b)} \tag{4}$$

where $\mathcal{F}^d(a,b) = \{j \in \mathcal{F} : d_j(a,b) > c(a,b)\}$. Finally, the outranking relation aSb is considered when $\rho_S(a,b) \geq \lambda$, $\lambda \in [0.5, 1]$ [9].

In Electre tri, the credibility index is used to assign alternatives to predefined categories. Suppose that alternatives should be assigned to p categories $\{C_1, ...C_p\}$ defined by $p-1$ profiles $\{b_1, ...b_{p-1}\}$. Each profile b_h, $h \in \{1, \ldots, p-1\}$, is the upper limit of C_h and the lower limit of C_{h+1}. Let a be an alternative to assign to a category C_h, $h \in \{1, \ldots, p\}$. Two assignment procedures are possible:

- Pessimistic procedure: a is compared first to profiles defining best categories until meeting the first b_h such that aSb_h, then a is assigned to C_{h+1}.
- Optimistic procedure: a is compared first to profiles defining worst categories until meeting the first b_h such that b_hSa, then a is assigned to C_h.

Note that Electre tri requires determining the following parameters:

– the profiles of the categories, defined by their evaluations $g_j(b_h)$, $\forall j \in \mathcal{F}$, $\forall h \in \{1, \ldots, p\}$,
– the weight coefficients, $w_j, \forall j \in \mathcal{F}$,
– indifference, preference and veto thresholds, $q_j(g_j(b_h))$,$p_j(g_j(b_h))$, $v_j(g_j(b_h))$, $\forall j \in \mathcal{F}$, $\forall h \in \{1, \ldots, p\}$,
– the cutting level λ.

These parameters define the preference model of the DMs. The direct elicitation of these parameters values, i.e. asking directly the DMs to provide them, remains difficult since they do not correspond to the usual language or indicators that DMs use to express their opinion and expertise. To overcome this issue, procedures have been proposed to infer the parameters of Electre tri model. Indeed, in [9] this inference is based on the assignment of a set of examples of alternatives A^* for which DMs have a clear preference. This is done by resolving a non-linear programming problem, given in equation (5), where Electre tri parameters are the variables. The slack variables x_k and y_k are introduced to transform the inequality constraints $\rho(a_k, b_{h_k-1}) \geq \lambda$ and $\rho(a_k, b_{h_k}) \leq \lambda$ into equality constraints. Further details about variables and constants involved in equation (5) are given in [9].

$$\left(\alpha + \epsilon \sum_{a_k \in A^*} (x_k + y_k)\right) \rightarrow max, \quad \text{such that:} \tag{5}$$

$$\begin{aligned}
&\alpha \leq x_k \quad \text{and} \quad \alpha \leq y_k, \quad \forall a_k \in A^* \\
&\frac{\sum_{j=1}^m w_j c_j(a_k, b_{h_k-1})}{\sum_{j=1}^m w_j} - x_k = \lambda, \quad \forall a_k \in A^* \\
&\frac{\sum_{j=1}^m w_j c_j(a_k, b_{h_k})}{\sum_{j=1}^m w_j} + y_k = \lambda, \quad \forall a_k \in A^* \\
&\lambda \in [0.5, 1] \\
&g_j(b_{h+1}) \geq g_j(b_h) + p_j(b_h) + p_j(b_{h+1}), \quad \forall j \in \mathcal{F}, \quad \forall h \in B \\
&p_j(b_j) \geq q_j(b_h), \quad \forall j \in \mathcal{F}, \quad \forall h \in B \\
&w_j \geq 0, \quad w_j \leq \frac{1}{2} \sum_{j=1}^m w_j, \quad q_j(b_h) \geq 0, \quad \forall j \in \mathcal{F}, \quad \forall h \in B
\end{aligned}$$

3.3 Determining Criteria of interest

Let consider a the alternative defined by the performance of the currently evaluated mission on all evaluation criteria. The alternative a is classified as "good", "medium" or "bad" by DMs. The aim of this section is to propose a method to determine which subset of criteria strongly contributes to the overall result of a. In our setting, this alternative is assigned to one of the categories using Electre tri; this problem is therefore equivalent to identifying the subset of criteria strongly contributing to the credibility index of a when it is compared to the profiles determining the category finally assigned to a.

As explained above, when an outranking method is used, the contribution of criteria to the overall score is the portion of their weights considered in the comprehensive concordance index. This contribution depends on the belonging of criteria to one of the three subsets $\mathcal{F}_1^c$, $\mathcal{F}_2^c$ and $\mathcal{F}_3^c$. Naturally, when comparing a to a profile b, we define the contribution of a subset of criteria $I \subseteq \mathcal{F}$ to the comprehensive concordance index, as the quantity $c_I(a,b)$:

$$c_I(a,b) = \sum_{j \in I} w_j \cdot c_j(a,b) = \sum_{j \in \mathcal{F}_3^c(a,b) \cap I} w_j + \sum_{j \in \mathcal{F}_2^c(a,b) \cap I} w_j \cdot \alpha_j(a,b) \qquad (6)$$

By convention $c_{\mathcal{F}}(a,b)$ is $c(a,b)$.

Let define two indices $r, s \in \{1, ..., p\}$ obtained by the two procedures of Electre tri classification:

1. Pessimistic procedure: $\forall h \in \{r, ..., p\}$, $not(aSb_h)$ and aSb_r: a is classified in category C_r;
2. Optimistic procedure: $\forall h \in \{1, ..., s-1\}$, aSb_h and b_sSa and $not(aSb_s)$: a is classified in category C_s.

Two cases have to be distinguished according to the quality of C_s:

1. The category C_s is considered as a "good" category. Then we have to determine criteria strongly contributing to the strength of a;
2. The category C_s is considered as a "bad" category. Then we have to determine criteria strongly contributing to the weakness of a.

Knowing that the criteria contributing strongly to the weakness of a are those strongly contributing to the strength of b_s, we only present the first case.

When a is assigned to a "good" category, we have aSb_r. Then for the cutting level $\lambda \in [0.5, 1]$ defined by the DMs, $\rho_S(a, b_r) > \lambda$ means:

$$c(a,b_r) \cdot \prod_{j \in \mathcal{F}^d(a,b_r)} \frac{1 - d_j(a,b_r)}{1 - c(a,b_r)} > \lambda \qquad (7)$$

Let denote $\lambda(a,b) = \frac{\lambda}{\prod\limits_{j \in \mathcal{F}^d(a,b)} \frac{1-d_j(a,b)}{1-c(a,b)}}$. The most contributing subset of criteria $I \subseteq \mathcal{F}$ is the one guaranteeing $c_I(a,b_r) > \beta\lambda(a,b_r)$, $\beta \in]0,1]$. The criteria of I are those having a large voting weight, i.e. $c_{\{j\}}(a,b_r)$, and the larger β is, the stronger the contribution of I is. Moreover the individual contribution of each criterion of I should exceed a minimal value $\gamma \in]0,1]$. This threshold prevents the selection of criteria that could contribute to state $c_I(a,b_r) > \beta\lambda(a,b_r)$ but in an insignificant proportion. Since the aim is to minimize the subset of criteria to analyse, we have to focus on the smallest subsets $I \subseteq \mathcal{F}$ such that the previous conditions are verified. Finally, we can set:

$$I^* = arg \min_{I \subseteq \mathcal{F}} \{|I| : c_I(a,b_r) > \beta^* \lambda(a,b_r) \;\; and \;\; \forall j \in I, c_{\{j\}}(a,b_r) > \gamma\} \qquad (8)$$

where β^* is the biggest $\beta \in]0,1]$ such that $\{I \subseteq \mathcal{F} : c_I(a,b_r) > \beta^* \lambda(a,b_r)\} \neq \emptyset$ and γ is chosen by the DMs. In case of existence of several subsets I^*, the choice of I^* is made considering performance of a on the criteria of I^*.

4 Case study

This section illustrates the use of the proposed approach in a practical case aiming at studying the logistical response in humanitarian emergency situations.

We consider the context of LL in a humanitarian organisation case (see Section 2), it aims at determining, *a posteriori*, if choices were good or bad w.r.t objectives of an analysed mission, and to explain why. We deal with this problem by (i) analysing a real mission using Electre tri method which assigns the mission to a predefined category characterizing its overall success, (ii) identifying the criteria contributing to the mission success and those most impacting its performance assessment. In this case study, among the diversity of missions carried out by the collaborating NGO, we are focusing on distribution missions - distribution of medicines, food and shelters - which clearly entail similar logistics. For this illustrative example, we consider a mission a, corresponding to a mission largely inspired – but slightly simplified for the example – from a real food distribution mission carried out by the NGO. We define three categories:

- C_1 includes failed missions for which objectives have not been reached,
- C_2 covers missions with met objectives but moderate success,
- C_3 covers successful missions: those exceeding the objectives.

The performance of a mission is evaluated according to a set of eight criteria, *i.e.* $\mathcal{F} = \{1, 2, ..., 8\}$, listed in Table 1. Criterion g_1 assesses deadline compliance, criterion g_3 assesses the portion of the logistical costs w.r.t the total costs and criterion g_4 the number of enlisted human resources. The preference decreases on these criteria. Criterion g_2 assesses the percentage of achievement of the targeted population: preference increase on it. Criteria g_5, g_6, g_7 and g_8 are assessed in a qualitative way using an ordinal scale with four levels: the scale is $\{Small, Medium, High, Very\ High\}$ for g_5 and g_6, and $\{Bad, Moderate, Good, Very\ Good\}$ for g_7 and g_8. We use the scale $\{1, 2, 3, 4\}$ to encode these two scales. Preferences on the criteria will further be characterized by the definition of pseudo-criteria using thresholds q_j, p_j and v_j.

Table 1. Evaluation criteria.

	Criterion	Preference
g_1	Deadline	$\searrow$
g_2	Achievement %	$\nearrow$
g_3	Portion of the logistics costs	$\searrow$
g_4	Human resources	$\searrow$
g_5	Added value for the organization	$\nearrow$
g_6	Added value for the beneficiary country	$\nearrow$
g_7	Environmental impact	$\nearrow$
g_8	Security level	$\nearrow$

4.1 Determination of Parameters

As a starting point, several parameters have to be fixed to determine the Electre tri model that best fits DMs' preferences. As mentioned in Section 3.2, an approach can be used to determine those parameters by solving a non-linear optimisation problem [9]. Similarly to the work proposed in that paper [9], to facilitate the optimisation problem setting and resolution, veto thresholds are not inferred, we assume that they are directly given by DMs (see Table 3). Therefore, the variables are: $g_j(b_h)$, w_j, $q_j(g_j(b_h))$, $p_j(g_j(b_h))$, $\forall j \in \{1, \ldots, 8\}$, $\forall h \in \{1, 2\}$, λ. The problem constraints are defined from parameters definition and the assignment of a training set:

- $p_j(g_j(b_h)) \geq q_j(g_j(b_h)) \geq 0$, $\lambda \in [0.5, 1]$,
- a_k assigned to C_h means that $a_k S b_{h-1}$ and not$(a_k S b_h)$.

Regarding the profiles of the categories, a training set of ten alternatives has been used (see Table 2); each alternative a_k is assigned to one of the three categories by the DMs. These fictive missions a_k, used as a training set to infer model parameters are distinct from the alternative a, a real mission that we aim at analysing here. Then in this context, we have to consider 58 variables and 90 constraints. Table 3 gives the values of parameters obtained from the resolution of the non-linear optimisation problem resulting from the training set analysis.

Table 2. Training set.

	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	Category
a_1	5	90	38	30	3	4	3	3	C_3
a_2	10	97	30	37	3	3	3	4	C_3
a_3	12	90	40	50	4	2	4	4	C_3
a_4	23	85	40	60	2	2	3	2	C_2
a_5	10	74	48	55	3	3	2	3	C_2
a_6	20	60	50	65	3	2	3	2	C_2
a_7	16	80	55	80	2	2	2	3	C_2
a_8	23	55	70	120	1	2	2	1	C_1
a_9	60	55	60	125	2	1	1	2	C_1
a_{10}	27	40	50	100	2	3	2	1	C_1

Table 3. Parameters values obtained from the optimisation problem resolution and given veto thresholds.

	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8
$g_j(b_1)$	26	62	53	80	2	1	2	2
$g_j(b_2)$	6.5	97	40	48	4	3	3	4
$q_j(g_j(b_1))$	3	3.5	2	7	0	0	0	0
$q_j(g_j(b_2))$	4.6	8	4	3	0	0	0	0
$p_j(g_j(b_1))$	10	5	6	14	1	0	1	1
$p_j(g_j(b_2))$	9.5	9	7	5	1	0	1	1
w_j	2.4	37.5	14	18.3	3.3	0.5	3.7	2.3
v_j	80	40	70	200	3	3	2	3
λ	0.93							

4.2 Criteria contribution

Let denote the analysed mission by a. DMs assess the performance of a on the criteria of $\mathcal{F}$ as shown in Table 4. We apply the pessimistic procedure of Electre tri using the identified model parameters (Table 3), and we consider the credibility indices $\rho(a, b_1) = 0.995$ and $\rho(a, b_2) = 0.2$. Then the mission a is assigned to category C_2, since not(aSb_2), and aSb_1 with b_1 the lower profile of C_2. Knowing that aSb_1, we are looking for the subset of criteria $I \subseteq \mathcal{F}$ that most contributes to the establishment of this outranking relation, both because of the importance of the criteria, and the performance of a on these criteria. Table 4 shows the individual contribution $c_{\{j\}}(a, b_1)$ of each criterion g_j to the global performance of a when it is compared to b_1.

Table 4. Individual criteria contribution.

	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8
$g_j(a)$	22	88	52	30	2	4	2	3
$c_{\{j\}}(a, b_1)$	0.03	0.46	0.17	0.22	0.038	0.006	0.04	0.03

Then in our Electre tri model, the cutting level is $\lambda = 0.93$ and the threshold $\gamma = \frac{c(a,b_1)}{2^n} = 0.004$ is considered, $n = |\mathcal{F}|$. Thus, solving the equation proposed in (8), the subset of criteria $I^* = \{2, 3, 4\}$ is identified, with a maximal $\beta^* = 0.914$. This identified subset has the contribution $c_I(a, b_1) = 0.85$, stating that I^* contributes to 91.4% of the global performance of a when it is compared to the reference profile b_1. In the example, the subset of identified criteria I^* corresponds to the subset of all criteria having a large weight ($w_2 = 37.5, w_3 = 14, w4 = 18.3$) w.r.t the others criteria having weights lower than 4. Thus, a outranks b_1 on all of the criteria of I^*. Conversely, the performance of a compared to b_2 on the important criteria gives $I^* \subset \mathcal{F}_2^c(a, b_2)$ with $\alpha_2(a, b_2) = 0.06$, $\alpha_3(a, b_2) = 6.10^{-6}$ and $\alpha_4(a, b_2) = 0.99$: the bad performance of a compared to b_2 is then explained.

In the presented solution, the selection of criteria in I^* is not affected by the defined threshold γ. Indeed, the coalition of criteria $\{2, 3, 4\}$ having significant contributions is enough to exceed λ. In order to highlight the role of γ, lets consider $\beta = 0.92$, such that $c_I(a, b_1)$ has to exceed 0.86. It means that at least one criterion with a weak contribution (≥ 0.01) has to be selected in I^*, e.g. $c_{\{1,2,3,4\}}(a, b_1) = c_{\{2,3,4,8\}}(a, b_1) = 0.88$ or $c_{\{2,3,4,5\}}(a, b_1) = c_{\{2,3,4,7\}}(a, b_1) = 0.89$. If a small threshold $\gamma_{small} = \frac{c(a,b_1)}{2^n} = 0.004$ is considered, it does not prevent the selection of any criterion with an insignificant contribution. Conversely, a large $\gamma_{large} = \frac{c(a,b_1)}{n} = 0.124$, refuses the selection of criteria $\{1, 5, 6, 7, 8\}$, then the subset I^* cannot be built. The higher the value of γ is, the more restrictive it is on the final identified subset of criteria.

It is important to mention here that we have applied the approach according to one selected combination of values for the parameters – local solution. Indeed, the programming problem solved to determine the parameters of the model has infinity of solutions, and thus the determined subset I^* could change. This solution also depends on the initial values provided to the program. In addition, for illustration purpose a small training set has been built. Consequently, a throughout robustness analysis should be carried out in our future works.

This application aimed at analysing, *a posteriori*, the performance of a food distribution mission. The proposed approach allowed to identify three criteria: "Percentage of population reached w.r.t the targeted one", "Number of human resources enlisted", "Invested logistical costs". It means that, in similar contexts, a good performance on these three criteria could guaranty a successful mission. It is then relevant to focus on these elements for learning lessons. Furthermore, identifying this subset of criteria is of major interest to restrain the search space to perform deeper analyses. Indeed, in a further step our work aims at identifying, between similar distribution missions, the shared features explaining the success or failure of the mission to then infer general lessons. Thus, knowing the criteria mainly responsible for the achievement of a *good* or *bad* overall performance, allows to focus searching on properties influencing these outlined criteria. In more comprehensive approaches that we are targeting, dealing with up to twenty criteria, the use of such a procedure will be required.

5 Conclusion

Organizations today express a growing interest for semi-automatic approaches enabling to take advantage of past experiences to improve their decision processes. In this paper, based on Electre tri - a well-known and established MCDA method -, we have presented an approach for identifying the criteria most influencing the decision process regarding the overall performance evaluation of a reduce set of experiences. A case study applying the approach to the humanitarian sector has also been proposed. Such an approach will further be used to enable searching for recommendations in large and highly dimensional search spaces. Future works are envisaged. First, as mentioned above a robustness analysis should be made. Furthermore, we plan to present an extended application, and to sophisticate the proposed model on several aspects: (i) to include veto thresholds into the procedure used to infer model parameters from assignment examples; (ii) to take into consideration the possible interactions/dependences between criteria; (iii) to consider potential disagreements of DMs. Finally, we are also interested by improving the procedure for minimizing the DM's cognitive load (i.e. information requirement), and to both manage and reduce experts' subjectivity.

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