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A qualitative method for evaluation in conceptual design

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Abstract: In systems engineering, evaluation is required each time design choices must be made or justified. Generally, design choices take place according to multiple criteria: some of them may be contradictory. Moreover, since knowledge is still missing at the conceptual stage, it is often difficult to anticipate the consequences of design decisions on the ultimate effectiveness of the final product. An original qualitative evaluation method, taking into account the decision makers' optimistic or pessimistic attitude, and combining a preferences model on the criteria is proposed for the purpose of highlighting the most promising alternative system design solutions. An example in the mechatronics field serves to illustrate our proposals.

Keywords: Systems engineering, Qualitative evaluation, Multicriteria analysis, Mechatronics

1. INTRODUCTION

In the competitive marketplace, both time and finances are often lacking to finalizing several product concepts and then retaining only the most satisfactory one. Engineers therefore require support in reviewing possible system design solutions (called more shortly 'alternatives' hereafter) and in making and defending the best design choices from the earliest product design stages (Hehenberger et al., 2010). The design evaluation process however faces a number of challenges, including:

- 1) Though the initial choices are definitely critical to ensuring a successful design, rating the merit factors of each alternative during the conceptual design stage is generally subject to uncertainty and imprecision due to the lack of knowledge about the system/product behaviour;
- 2) When designing complex products such as mechatronics ones, assessing the consequences of choices among several alternatives is a critical issue that has still not been resolved effectively to this day (Torry-Smith et al., 2011);
- 3) Design choices can benefit to some criteria and can damage some others. The challenge then is to identify satisfactory alternatives that achieve an acceptable balance between the technical requirements.

Our proposal seeks to address above issues by extending some qualitative reasoning to determine the level of satisfaction of considered alternatives (Imoussaten et al., 2011) (Couturier et al., 2014). After defining in section 2 the role of evaluation within the Systems Engineering (SE) framework, section 3 presents our qualitative approach for evaluation. Based on the relationships between a behaviour model of the system being designed and a decision-making model, a qualitative evaluation taking into account the decision makers' pessimistic or optimistic attitude is developed. Then a satisfaction score is associated to each alternative taking into account a preferences model on the criteria. MAUT

multicriteria analysis method (Keeney et al., 1987) has been chosen since we are interested to evaluate the satisfaction score of each alternative on each criteria (regardless other alternatives) and since we limit the expression of the preferences model to the relative importance of criteria, considered as independent. The method improves goals model reasoning (Giorgini et al., 2002) since conflicts resulting from contradictory qualitative influences on goals can be solved. Moreover, it is proved, in section 3, that the proposed evaluation operators are consistent with the optimistic or pessimistic attitude of the decision makers. Section 4 illustrates our proposals through the design of an autonomous mobile robot.

2. EVALUATION IN SYSTEMS ENGINEERING

Systems Engineering (SE) is an interdisciplinary and collaborative approach based on the standards ISO/IEC 15288 (ISO/IRC, 2008), ANSI/EIA 632 and IEEE 1220, as well as on conceptual guidelines, e.g. SEBoK (BKCASE, 2012) and best practice guidelines, e.g. INCOSE handbook (INCOSE, 2011) or Nasa handbook (Nasa, 2007). SE promotes vocabulary, concepts and a comprehensive approach that facilitates communication within a design team, regardless of the underlying technological field, and moreover relies on a set of standardized processes and activities that have become widely and successfully applied across various industrial fields (SE Guide book, 2007).

Among the aforementioned SE components, five technical processes run in an iterative manner when engineering a system. These iterative and recursive processes are (SEBoK, 2012): Mission analysis, Stakeholders' needs definition, System requirements specification, Logical architecture design, and Physical architecture design. They are supported by three services, namely: System verification, System validation, and System analysis.

According to standards EIA 632, IEEE 1220, SEBok 2012, technical performance assessment and trade-offs studies are necessary activities of System analysis.

Thus this paper addresses the set of evaluation issues 1) to 3) (see section 1) and focuses on evaluating the effectiveness of technical product under design. The proposed evaluation method could also be applied in other SE application domains, including the development or the amelioration of socio technical systems such as manufacturing systems. The limitation of the method is the availability of reliable expertise in the application field.

The next section will present the generic activities associated with the evaluation process in SE.

2.1 Evaluation process

In SE, an evaluation is required each time engineering choices must be made or justified, e.g. choices of major operations and solution concepts, research and resolution of inconsistencies between requirements, choice of logical vs. physical architecture.

This evaluation process includes generic activities, as summarized in Fig. 1. Without going into the details (see (Couturier et al., 2014) for more explanation), the main activities composing the evaluation process consist of: defining the evaluation objectives ("why" and "what"), preparing the job ("how"), producing and analysing the robustness of the results ("do" and "check"), and finally delivering outcomes ("conclude"). If the evaluation objectives are not met or if results lack adequate differentiation or show excessive dependence on the evaluation methods, then the evaluation process should return to one of its previous steps.

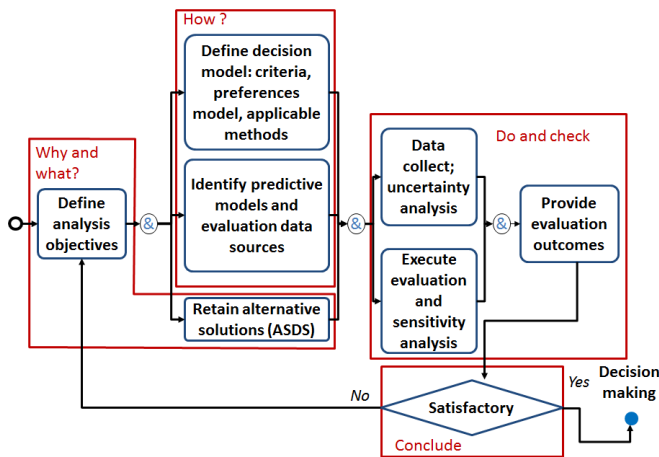


Fig. 1: Evaluation process

Since the evaluation process constitutes the backbone of the decision-making process, the decision-making model must be specified in the 'How activities'. Such a model takes into account core elements, e.g. evaluation criteria, decision-makers' preferences, scoring functions used to assign satisfaction levels to system attributes, and aggregation methods chosen to provide a global satisfaction score of alternatives.

2.2 Multicriteria analysis in evaluation

Alternatives should be assessed or ranked according to most suitable multicriteria analysis methods. Regarding the evaluation of product effectiveness, three main families of multi-criteria decision-making methods can be distinguished (Fülop, 2005): total aggregation methods (Multi-Attribute utility Theory MAUT (Keeney et al., 1987) (Fishburn,1982), paired comparison methods (Analytic Hierarchy Process AHP (Saaty et al., 2007), and outranking approaches (French methods PROMETHEE, GAIA, ELECTRE I, II, III (Roy, 1991).

Each of these methods varieties has advantages and disadvantages and is best suited depending on application cases. Comparing these methods is not an objective of this paper. However, the MAUT framework seems to us best suited for our case. Indeed, we are interested to evaluate the behaviour of each alternative on each characteristics of the system (regardless other alternatives) and we are also potentially interested to assess the evolution of alternatives evaluations when new components are added to it. Thus aggregation operators are needed.

We consider that performance indicators are used to assess an alternative on a criterion. For instance, when designing an autonomous robot, performance indicators such as the 'maximum robot speed reached by the robot on a straight way' or the 'capacity of the robot to turn on itself' can be used to assess a 'mobility' type criterion. The goal to reach by a performance indicator is specified by the performance requirements: For instance, a maximum speed between 0.5m/s and 1.5m/s; a turn capacity between -180° and +180°.

The values taken by an indicator depend on the design choices made by the designers all along the SE process: for instance the number of driving wheels, the type of motors etc. So, the values of the performance indicators generally change until the final product is built. To help designers make the most satisfactory choices all along the SE process, the performance indicators values have to be predicted using some models of the product.

With such models and from the design parameters choices (the inputs of the models) can be predicted the performance indicator values (the outputs of the models). For instance, when designing an autonomous robot, a predictive model could be used to estimate the value of the 'maximum speed of the robot' (output variable) from the number of driving wheels, the type of engine etc. (input variables). In the following section, no distinction is made between performance indicators and 'output variables' nor between design parameters and 'input variables'.

Because of the lack of knowledge before the system is built, predictive models tend to be coarse at the conceptual design stage, whereas at the detailed design stage, more specialized and precise models are taken into consideration in order to derive product feature data.

Let's precise now how predictive models are linked to decision-making models in order to evaluate alternatives.

3. QUALITATIVE EVALUATION

3.1 Predictive and decision-making models

Let's start by considering a situation with m input variables. Each input variable takes its values in the set denoted X_j with $j = 1, \dots, m$. Let's denote $X = X_1 \times X_2 \times \dots \times X_m$ the set of all m -tuples $x = (x_1, x_2, \dots, x_m)$ where $x_j \in X_j$ is the value of the j^{th} input variable of x . X_j may be a set of nominal, discrete or continuous values. Each admissible element of X stands for an alternative.

Let's also consider that the system may be described by n output variables relative to the decision-making criteria. Each output variable takes its values in the set denoted Y_i with $i = 1, \dots, n$. Let's denote $Y = Y_1 \times Y_2 \times \dots \times Y_n$ the set of all n -tuples $y = (y_1, y_2, \dots, y_n)$, where $y_i \in Y_i$ is the value assigned to the i^{th} output variable of y . Y_i may be a set of nominal, discrete or continuous values.

To each input in X corresponds an output in Y representing the characteristics of interest for the decision makers/designers. Let's indicate this correspondence by the transformation $T = (T_1, \dots, T_n)$ where $T_i: X \rightarrow Y_i, i = 1, \dots, n$ (Fig.2).

T may be a formal transformation deduced either from physical laws or from available and validated knowledge in the field.

The values taken by the output variables must then be interpreted in terms of satisfaction with respect to the decision makers'/designers' goals. The Multi-Attribute Utility Theory allows expressing the degree of satisfaction of an output variable by a real-valued utility function in $[0,1]$. Let denote $u_i: Y_i \rightarrow [0,1]$ the utility function for the i^{th} output variable. Thus $u_i(y_i)$ represents the extent to which the goal associated with the i^{th} output variable is satisfied by the value y_i .

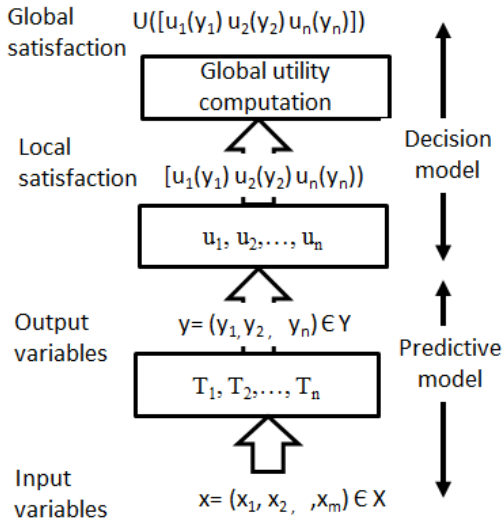


Fig. 2: Decision model and predictive model

Then the global satisfaction level of an alternative should be computed using some aggregation operator U (Fig. 2). For example, U can represent the weighted average operator.

However, as mentioned above, the predictive models that provide transformation T are typically unknown or incomplete during the conceptual design phase. The scenario is then often played out where experts or senior engineers are asked to advice on alternatives and judge the qualitative effects of

design choices on decision makers'/designers' satisfaction. To deal with this kind of uncertainty context, we have relied on the research work presented in (Montmain et al., 2014) regarding qualitative analyses.

3.2 Qualitative evaluation

The notion behind the qualitative model in (Montmain et al., 2014) is that an expert can express the fact that an input variable value will improve (positive effect) or deteriorate (negative effect) the performance of the system under design with regard to a criterion. Moreover, experts are also able to associate a degree of confidence to this fact. Authors state: " j^{th} input variable value may improve (resp. deteriorate) i^{th} output variable with a confidence degree δ_{ij}^+ (resp. δ_{ij}^-)" (see Fig.3). We use the same semantic in this paper and consider that δ_{ij}^+ and δ_{ij}^- take their values in an ordinal scale QS containing a zero, top and intermediate values. It can be for example a scale of four values $QS = \{zero = null, low, medium, top = strong\}$.

We intend to compare the alternatives taking into account both the improvement and the deterioration effects of alternatives on each output variable (Giorgini et al., 2002).

At this aim, we define the impact of an alternative on an output variable as the pair: (confidence degree in amelioration, confidence degree in deterioration).

To assign such impact degrees we introduce two aggregation operators along with two propagation constraints as in (Montmain et al., 2014).

Each combination of an aggregation operator with a propagation constraint yields a decision-maker's attitude. The following pessimistic or optimistic attitude of the decision-maker can serve as a guide.

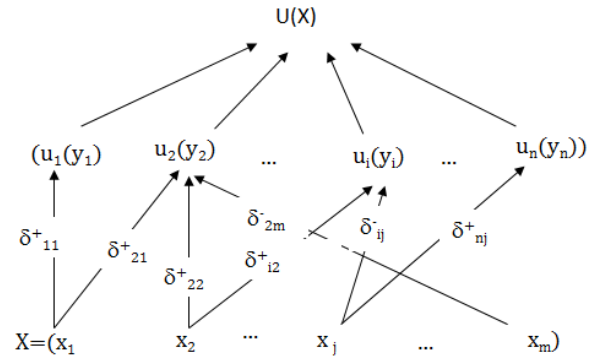


Fig. 3: Negative and positive effects on output variables

Indeed, the estimation of an alternative impact on the output variable naturally depends on the design choices, as well as on the decision maker's decisional behavior: a pessimistic attitude (whereby a risk aversion position will lead to retaining the most highly negative impact degree) vs. an optimistic attitude (whereby risk acceptance will retain the most highly positive impact degree).

Let's denote $at \in \{1,2\}$ the decision-maker's attitude ("1" encodes the pessimistic attitude and "2" the optimistic attitude). For each at and $x \in X$, let's also denote $\delta_{i,x}^{at}$ the impact of alternative x on the i^{th} output variable. As proposed above $\delta_{i,x}^{at} \in QS \times QS$ can be represented by the pair of ordinal

values $(\delta_{i,x}^{+,at}, \delta_{i,x}^{-,at})$, where $\delta_{i,x}^{+,at}$ (resp. $\delta_{i,x}^{-,at}$) corresponds to an aggregation of the degrees of confidence in positive (resp. negative) effects.

The pessimistic attitude is modeled by assigning the least positive impact degree as the aggregation of improvement cases (less favorable cases) and the worst negative impact degree as the aggregation of deterioration cases (less favorable cases again). The propagation constraint consists of comparing the least positive impact degree to the worst negative impact degree on the i^{th} output variable, resulting in:

$$\delta_{i,x}^{+,1} = \begin{cases} \min_j \delta_{ij}^{+,1} & \text{if } \min_j \delta_{ij}^{+,1} > \max_j \delta_{ij}^{-,1} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{i,x}^{-,1} = \begin{cases} 0 & \text{if } \min_j \delta_{ij}^{+,1} > \max_j \delta_{ij}^{-,1} \\ \max_j \delta_{ij}^{-,1} & \text{otherwise} \end{cases} \quad (1)$$

The optimistic attitude is modeled by assigning the highest positive impact degree as the aggregation of improvement cases and the worst negative impact degree as the aggregation of deterioration cases. The propagation constraint consists of comparing the highest positive impact degree to the worst negative impact degree on the i^{th} output variable hence:

$$\delta_{i,x}^{+,2} = \begin{cases} \max_j \delta_{ij}^{+,2} & \text{if } \max_j \delta_{ij}^{+,2} > \max_j \delta_{ij}^{-,2} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{i,x}^{-,2} = \begin{cases} 0 & \text{if } \max_j \delta_{ij}^{+,2} > \max_j \delta_{ij}^{-,2} \\ \max_j \delta_{ij}^{-,2} & \text{otherwise} \end{cases} \quad (2)$$

It is clear that for a same output variable, both the positive impact degree and the negative impact degree can't be different from 0 at the same time, that is: $\forall i, \min(\delta_{i,x}^{+,at}, \delta_{i,x}^{-,at}) = 0$

It can be verified that the positive impact on any criterion according to an optimistic attitude is greater or equal to the positive impact according to a pessimistic attitude:

$$\forall i \quad \delta_{i,x}^{+,2} \geq \delta_{i,x}^{+,1} \quad (3)$$

Verification of expression (3):

Whether $\min_j(\delta_{ij}^+) > \max_j(\delta_{ij}^-)$ then $\delta_{i,x}^{+,2} = \max(\delta_{ij}^+) \geq$

$$\min_j(\delta_{ij}^+) = \delta_{i,x}^{+,1}$$

or $\min_j(\delta_{ij}^+) \leq \max_j(\delta_{ij}^-)$ then $\delta_{i,x}^{+,1} = 0$ and $\delta_{i,x}^{+,2} =$

$$\max_j(\delta_{ij}^+) \geq \delta_{i,x}^{+,1}$$

In the same way, it can be easily verified that the deterioration impact on any criterion according to a pessimistic attitude is superior or equal to the deterioration impact according to an optimistic attitude:

$$\forall i \quad \delta_{i,x}^{-,1} \geq \delta_{i,x}^{-,2} \quad (4)$$

Let's denote $\delta_x^{at} = (\delta_x^{+,at} = F_1(\delta_{i,x}^{+,at}), \delta_x^{-,at} = F_2(\delta_{i,x}^{-,at}))$ the 'global impact' of the alternative x on the global satisfaction level. Operators F_1 and F_2 are chosen not only to avoid risky choices but also to facilitate the ranking of alternatives. For instance, the global impact can be computed by taking F_1 as "min" operator and F_2 as "max" operator.

$$\delta_x^{at} = (\min_i(\delta_{i,x}^{+,at}), \max_i(\delta_{i,x}^{-,at})) \quad (5)$$

In section 3.3 we show how importance of criteria can be taken into account so as to smooth veto and dictator effects of some poor but uncertain score through min or max operators.

3.3 Introducing a preferences model in the qualitative evaluation

In this first work we limit the expression of preferences model to the consideration of the relative importance of criteria.

Let's assume that decision-makers/designers can express the importance of criteria in estimating the global impact of the alternatives. In order to keep the global impact interpretable, criteria importance take values in the scale QS .

Let denote for $\omega \in QS$, $-\omega$ the value corresponding to the reversed scale of ω (i.e., $-null = strong$, $-low = medium$, ...). It is the counter part of $1 - \omega$ on the $[0,1]$ interval scale.

Let's denote $\omega_i \in QS$ the weight of the i^{th} criterion and $\omega = (\omega_1, \omega_2, \dots, \omega_n)$ the weights vector.

The importance of criteria are taken into account in changing the aggregation operator of expression (5) δ_x^{at} into $\delta_{x,\omega}^{at}$:

$$\delta_{x,\omega}^{at} = (\delta_{x,\omega}^{+,at}, \delta_{x,\omega}^{-,at}) = (\min_i(\delta_{i,x,\omega_i}^{+,at}), \max_i(\delta_{i,x,\omega_i}^{-,at})) \quad (6)$$

with $\delta_{i,x,\omega_i}^{+,at} = \max(-\omega_i, \delta_{i,x}^{+,at})$; $\delta_{i,x,\omega_i}^{-,at} = \min(\omega_i, \delta_{i,x}^{-,at})$

Aggregation operator (6) limits the veto given to each criterion through the "min" and "max" operators of expression (5).

Indeed, low weights reduce the penalizing effect of a low improvement impact degree in the $\min(\max(\omega_i, \delta_{i,x}^{+,at}))$

expression. Similarly, low weights mitigate the penalizing effect of strong deterioration impact degree in the $\max(\min(-\omega_i, \delta_{i,x}^{-,at}))$ expression. It comes:

$$\delta_{x,strong}^{at} = \delta_x^{at} \text{ and } \delta_{x,null}^{at} = (strong, null)$$

Let us verify, hereafter, that the proposed evaluation operators are consistent with the optimistic or pessimistic attitude of the decision makers.

It can be verified that for any weight (extending the case without any weight), the positive impact on any criterion according to optimistic attitude is equal or greater than the aggregated positive impact according to the pessimistic attitude:

$$\forall i \quad (\delta_{i,x,\omega_i}^{+,2} \geq \delta_{i,x,\omega_i}^{+,1}) \quad (7)$$

Verification for expression (7):

Whether $\delta_{i,x,\omega_i}^{+,2} = -\omega_i$ then from (3) it comes $(-\omega_i \geq$

$$\delta_{i,x}^{+,2} \geq \delta_{i,x}^{+,1}) \text{ and } \delta_{i,x,\omega_i}^{+,1} = -\omega_i = \delta_{i,x,\omega_i}^{+,2}$$

or $\delta_{i,x,\omega_i}^{+,2} = \delta_{i,x}^{+,2} \geq -\omega_i$ and from (3) it comes $\delta_{i,x,\omega_i}^{+,2} \geq \max(-\omega_i, \delta_{i,x}^{+,1}) = \delta_{i,x,\omega_i}^{+,1}$

In the same way, it can be verified that for any weight, the negative impact on any criterion according to the pessimistic attitude is equal or greater than the aggregated negative impact according to the optimistic attitude:

$$\forall i \quad (\delta_{i,x,\omega_i}^{-,1} \geq \delta_{i,x,\omega_i}^{-,2}) \quad (8)$$

It comes, using F_1 and F_2 operators that the global positive impact (respectively the global negative impact) according to the optimistic attitude (respectively to the pessimistic attitude) is equal or greater than the global positive impact (respectively

global negative impact) according to the optimistic attitude (respectively to the pessimistic attitude):

$$(\delta_{x,\omega}^{+,2} \geq \delta_{x,\omega}^{+,1}) \text{ and } (\delta_{x,\omega}^{-,1} \geq \delta_{x,\omega}^{-,2}) \quad (9)$$

In section 5 we illustrate the proposed qualitative evaluation in the case of the design of an autonomous mobile robot.

4. QUALITATIVE EVALUATION: AN ILLUSTRATION

4.1 Context

To illustrate our qualitative evaluation approach we consider the design of a small autonomous mobile robot. It concerns an educational robotic challenge RobAFIS 2013 (Robafis,2013), promoted by AFIS, the French association of Systems Engineering. The purpose of RobAFIS is to better understand and develop the use of systems engineering best practices, as recommended and formalized by AFIS.

In RobAFIS 2013, the autonomous robot had to be built using some provided and imposed materials. It was limited to a 0,3m square cube and it had to achieve the following mission as quickly as possible: to grasp and transport some various coloured spheres between several stock devices spread over a plan playground. Some dark lines were drawn on the ground to guide the robot between stock devices.

The robot was broken down into four sub-systems: a gripper device, sensors equipment, a rolling base, a control device. The physical alternatives (the possible robot configurations) depend on the design option of the other sub-systems than the control device that was imposed to the competitors.

The solution principles are resumed in Table 1. There are three principles for designing the gripper device, three for the rolling base and two for the sensors equipment. Thus, there are 18 alternatives to compare, corresponding to the 3x3x2 admissible configurations.

Table 1. Solution principles

Gripper device	Rolling base	Sensors equipment
G1: Fork (taking the sphere from below)	R1: Four wheels rolling base	S1: two colour sensors for following the dark lines, one light sensor for recognizing the sphere colour
G2: Lateral gripper (pinching laterally the sphere)	R2: Two wheel drive and one free wheel rolling base	S2: one colour sensor for following the dark line, one colour sensor for recognizing the sphere colour
G3: Grapnel (taking over the sphere)	R3: rolling base with tracks	

Three independent criteria are retained: the sparsity of used components (Cr1), the robot speed capability (Cr2), the number of successful missions (Cr3).

Let consider for this case study the ordinal scale $QS = \{Null(0), Low (L), Medium (M), High (H)\}$. Table 2 presents, for each of the three criteria, the positive impact (denoted by "+") or negative impact (denoted by "-") of each

input variable value with their confidence degrees as provided by the experts.

Table 2. Qualitative evaluation

	pieces nbr	mobility speed	success nbr
	Cr1	Cr2	Cr3
G1: fork	+M	-M	-L
G2: gripper	+M	-L	+L
G3: graspel	-M	+L	+M
R1: 4 wheel	+M	-L	+L
R2: 3 wheel	-L	+M	+M
R3: trackers	-M	-L	+L
S1: 2+1	-L	+M	+M
S2: 1+1	+M	-L	+L

To illustrate the use of operators introduced in sections 3.2 and 3.3, Let's consider the alternative $x = [G2, R3, S1]$, (grey cases in Table 2) and a pessimistic attitude ($\alpha=1$), then according to (5),(6) the global impact of alternatives can be computed considering a preferences model or not.

4.2 Case of same importance of criteria

For the Cr_1 criterion "pieces nbr" we have $\min_j \delta_{Cr_1j}^{+,1} = M$

$\max_j \delta_{Cr_1j}^{-,1} = M$ so according to expression (1) $\delta_{Cr_1x}^{+,1} = 0$

and $\delta_{Cr_1x}^{-,1} = M$ and the impact of alternative x on Cr_1 is $\delta_{Cr_1x}^1 = (\delta_{Cr_1x'}^{+,1}, \delta_{Cr_1x}^{-,1}) = (0, M)$. In the same way we obtain : $\delta_{Cr_2x}^1 = (M, 0)$, and $\delta_{Cr_3x}^1 = (L, 0)$.

So according to (5) the global impact of alternative x is:

$$\delta_x^1 = (\delta_x^{+,1}, \delta_x^{-,1}) = (\min(0, M, L), \max(M, 0, 0)) = (0, M)$$

In the same way for an other alternative $x' = [G1, R2, S1]$, we can compute the global impact:

$$\delta_{x'}^1 = (\delta_{x'}^{+,1}, \delta_{x'}^{-,1}) = (0, M) = (\min(M, 0, M), \max(0, M, 0))$$

The eighteen alternatives are then ordered according to the decreasing values of global positive impacts and for ex aequo according to the increasing values of global negative impacts. The most promising alternatives have then been found to be $[G2, R1, S1], [G2, R2, S1], [G2, R2, S2]$ with for each of them a global impact of $(L, 0)$.

According to an optimistic attitude, the most promising alternatives have been found to be the same as above but with a global impact $(M, 0)$.

There is no promising robot with a degree $-M$ on any criterion (cases where experts think with a good confidence that the robot will deteriorate at least one criterion). Robots with R1 and S2 options are not found to be promising configurations too.

4.3 Case of preferences model on criteria

Let's consider now that the relative importance of criteria Cr_1, Cr_2, Cr_3 are taken into account and let $\omega = (H, L, H)$ the weights vector (i.e. the time spent to achieve the mission is not so important). According to expression (6), the new global

score for $x' = [G1, R2, S1]$ becomes: $\delta_{x',\omega}^1 = (\delta_{x',\omega}^{+,1}, \delta_{x',\omega}^{-,1}) = (M, L) = (\min(\max(0, M), \max(M, 0), \max(0, M)), \max(\min(H, 0), \min(L, M), \min(H, 0)))$

and it appears now that x' is a more promising alternative than x . Indeed:

$$\delta_{x,\omega}^1 = (\delta_{x,\omega}^{+,1}, \delta_{x,\omega}^{-,1}) = (L, M) = (\min(\max(M, 0), \max(M, M), \max(0, L)), \max(\min(H, M), \min(L, 0), \min(H, 0)))$$

This can be explained by the fact that the poor score of G1 on Cr2 is now considered not so important in the estimation of the global impact of alternative x' .

So it has been shown how veto and dictator effects of poor qualitative scores on less important criteria can be smoothed by using a weights vector describing the preferences model of the decision-makers'/designers'.

5. CONCLUSION

The role of the evaluation process in Systems Engineering is to support designers each time engineering choices need to be made or justified. However it is often difficult to anticipate, during the conceptual design phase, given that the data are quite uncertain or imprecise. The proposed evaluation method aims at achieving this objective by adopting an original qualitative analysis in order to detect the most promising alternative design solutions while taking into account the risk aversion of decision-makers (pessimistic attitude verso optimistic attitude) but also a model of their preferences on criteria. Our proposals have been illustrated through the design of an autonomous mobile robot. This work will be completed in proposing intermediate attitude (between pure optimistic and pessimistic ones) and in introducing levels on degradation and amelioration opinions. The formalism should be also extended to deal with the fusion of experts' opinions in the case where the members of a design group do not necessarily agree.

More generally, our research consists in incorporating most of the recent progresses in multicriteria decision aid in the aim of increasing the level of confidence designers can show in the choices they make during the Systems Engineering processes.

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