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Monitoring and control of an efficient industrial performance improvement within a MAUT assessment framework

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Abstract

This paper begins by discussing the implementation of monitoring and control strategies to improve industrial performance. Industrial performance is presently defined in terms of multiple and multi-level criteria, which need to be synthesized for overall improvement purposes. The Multi-Attribute Utility Theory (MAUT) provides tools relevant to decision-making within this specific context. According to our approach, overall company performance is expressed as the aggregate value of each elementary performance relative to each criterion, with the aggregation operator being a Choquet integral. The paper then recalls previous studies regarding the design of efficient improvements within this same MAUT framework, before focusing on an analysis of overall performance gain in terms of elementary performance improvements. The contribution of an aggregate performance gain criterion plays a key role in this study. Two improvement strategies will moreover be examined and compared in light of this concept development. A case study has also been included to illustrate the proposals set forth in the paper.

Keywords: operations management, performance improvement, industrial performance, criterion contribution, efficiency, multi-criteria decision-making.

1. Problem statement

As a means of coping with the complexity of the current industrial context, new control strategies designed to introduce continuous improvements must include not only aspects of multi-criteria performance expression, but also pertinent relational modeling (Bititci, 1995; Berrah, 2000; Berrah *et al.*, 2001). Control strategies are in fact required to define, compare and select improvement actions with respect to the relationships existing between performance expressions (Bititci, 1995). Performance Measurement Systems (PMS), which are instruments that support decision-making (Bititci, 1995; Neely, 1999; Kueng *et al.*, 1999), fulfill such a purpose. From a global perspective, a PMS is a multi-criteria

instrument for informing decision-makers on a variety of matters, e.g. performance level, criteria necessitating improvement. A PMS is composed of a set of performance expressions that need to be consistently organized with respect to company objectives (Berrah *et al.*, 2001). In support of the decision, the set of performances must be processed in order to compare the various situations. By their very nature, PMS require the use of multi-criteria methods (Santos *et al.*, 2002). The primary quantitative frameworks found in the literature on PMS are intended to reduce dimensionality and hence a product of the MAUT (Multi-Attribute Utility Theory) aggregation model school (Diakoulaki *et al.*, 1992; Lee *et al.*, 1995; Rangone, 1996; Kim *et al.*, 1997; Suwignjo *et al.*, 2000), although a few studies have been based on outranking models (Mareschal *et al.*, 1991; Babic *et al.*, 1998).

MAUT models allow defining the overall performance of a company with respect to its various elementary objectives (Berrah *et al.*, 2004). Moreover, they serve to highlight priorities in the decision-maker's strategy (Clivillé *et al.*, 2007). The aggregate performance model is thus able to incorporate a portion of the company's policy. According to our approach, the aggregation model is applied with a Choquet integral, which enables handling both the relative weighting of criteria and their interactions (Berrah *et al.*, 2008a).

This paper is based on previous work presented in Berrah *et al.* (2008a) and Sahraoui *et al.* (2007a,2007b), which has proposed decision-support tools able to assist managers improve design performance as regards company strategy, so as to reach a goal while minimizing costs. Multi-criteria optimization techniques are suggested to attain this goal and, in so doing, characterize an efficient improvement (Berrah *et al.*, 2008b). The paper will focus here on a related issue: what exactly is the contribution of an elementary performance to overall performance gain? This concept of contribution plays a vital role in understanding the way improvements operate. The recommendations forwarded on elementary performance targeted for improvement still rely on this concept. Two different improvement

policies are semantically analyzed and justified through this point of view. The first is based on statistical considerations relative to the most likely profitable criteria contributions towards overall performance gain. The main idea herein is to determine those criteria on which the company should statistically improve, first in order to raise its overall performance as much as possible. The theoretical work behind this proposal was initially proposed in Labreuche (2004). The second improvement policy is related to the concept of efficient improvement (Sahraoui, 2007a,2007b), which states the principle of defining a step-by-step, locally-efficient improvement within a multi-criteria context until an anticipated comprehensive goal has been achieved. The corresponding iterative procedures are provided and then formalized into algorithms A_1 and A_2 . In both cases, the contribution of an individual criterion to overall performance improvement plays a key role. Consequently, a monitoring function of criteria contributions over time is provided for a quantitative and theoretical comparison of both types of improvement rationale.

This paper has been organized as follows. Section II briefly recalls the basic MAUT principles and discusses the characteristics of industrial performance expressions. The Choquet integral will be proposed as a solution for handling the interactive multi-criteria aspects of industrial performance. The aggregation framework motivates us to redefine concepts such as efficiency; performance improvement problems will be modeled as optimization problems. Section III then defines the contribution of elementary performance to overall performance gain. The algorithm used to compute this contribution will be provided. Section IV will introduce two different control policies derived from criteria contributions, in the aim of performing an efficient improvement. These policies will first be semantically compared before providing a more quantitative comparison, based on the previous theoretical analysis of elementary contributions to overall performance gain, by means of a case study (Section V).

2. The aggregative model of overall performance

2.1. MAUT: A model of preferences

Defining an improvement within the multi-criteria performance context poses a number of problems. First of all, it must be possible to compare any two of the situations described by their elementary performance expressions.

Decision support can thus consist of reducing dimensionality in order to facilitate analysis. It is generally recognized that humans lose their ability to make rational decisions once more than 3 to 5 criteria

are involved. MAUT (Multi-Attribute Utility Theory) (Fishburn, 1970,1982; Keeney and Raiffa, 1976) provides the necessary set of tools to resolve this problem.

Preference representation is a central topic in decision-making and measurement theory (Modave *et al.*, 1998) and usually entails finding a real-valued utility function U , such that for any pair of alternatives x, y in a set X of alternatives of interest, $x \succeq y$ (i.e. x is preferred to y) *iff* $U(x) \geq U(y)$. When alternatives are n -dimensional,

i.e. $X = \prod_{i=1}^n X_i$, one widespread model is the decomposable model developed by Krantz *et al.* (1971), where U assumes the form $U(x_1, \dots, x_n) = g(u_1(x_1), \dots, u_n(x_n))$ and where $u_i(\cdot)$ are real-valued functions. Assuming that \succeq is a weak order on X , it is known that a representation with g being strictly increasing can be derived *iff* \succeq satisfies independence and X is separable (Krantz *et al.*, 1971).

MAUT is based on utility theory, which offers a systematic approach to quantifying individual preferences. Utility theory consists of interpreting any measurement as a degree of satisfaction on $[0, 1]$, with 0 related to the worst alternative and 1 to the best. Measurements are thus made to be commensurable and interpretable. In this manner, a utility function $u_i(x_i)$ is associated with each measurement x_i , and MAUT is then intended to provide the synthesis utility U that yields a solution to the comparison problem of two situations described by their elementary utilities. Many MAUT studies have examined both the required properties of decision-maker preferences to be included in the analytical form g and the way in which g can be identified.

2.2. Overall performance in the MAUT framework

In practice, elementary performance is provided by so-called performance indicators; this assessment stems from the straightforward comparison of objectives (as obtained by breaking down the overall objective considered) with recorded measurements. The performance expressions can thus be formalized by means of the following mapping (Berrah, 2000):

$$P: O \times M \rightarrow E$$

$$(o, m) \rightarrow P(o, m) = P$$

O , M and E are respectively the universes of discourse for the set of objectives o , the set of measurements m and normalized performance

$P \in [0,1]$. A performance expression therefore corresponds to an elementary utility function.

Let's denote $\bar{P} = (P_1, P_2, \dots, P_n)$ as a performance profile and C the set of n criteria implied by PMS. An aggregation of performances can then be expressed as an operation that synthesizes the elementary performances into an overall expression:

$$g : [0,1]^n \rightarrow E \quad (1)$$

$$(P_1, P_2, \dots, P_n) \rightarrow P = g(P_1, P_2, \dots, P_n)$$

In light of MAUT, overall performance is thus viewed as a synthesized utility function.

2.3. The Choquet integral model

In this study, the aggregative model g is a Choquet integral, which enables accommodating both the relative importance of each criterion and the interactions taking place among them. This choice will not be discussed herein (see Berrah *et al.* (2008a) for further justification). Let's simply note at this point that the interactions considered in our preference model are not the physical ones (material constraints) dealt with in Felix (1994), where action plans may exert a combined impact on several performance indicators. In our preference model, an interaction occurs between any two criteria once they need to be satisfied simultaneously (i.e. positive synergy) or when their simultaneous satisfaction is seen as a redundancy (negative synergy) (see Montmain, 2009 for a more precise comparison).

P^k is the aggregate performance of the elementary performance profile $\bar{P}^k = (P_1^k, \dots, P_n^k)$

$$P^k = C_\mu(\bar{P}^k) = C_\mu(P_1^k, P_2^k, \dots, P_n^k) = \sum_{i=1}^n (P_{(i)}^k - P_{(i-1)}^k) \cdot \mu(A_{(i)}^k) \quad (2),$$

where $\mu : P(C) \rightarrow [0,1]$ is a fuzzy measure; (\cdot) indicates a permutation, such that the partial performances $P_{(i)}^k \in [0,1]$ are ranked

$0 \leq P_{(1)}^k \leq \dots \leq P_{(n)}^k \leq 1$ and $A_{(i)}^k = \{c_{(i)}, \dots, c_{(n)}\}$. This expression can then be rewritten as:

$$C_\mu(P_1^k, \dots, P_n^k) = \sum_{i=1}^n (P_{(i)}^k - P_{(i-1)}^k) \cdot \mu(A_{(i)}^k) = \sum_{i=1}^n \Delta \mu_{(i)}^k \cdot P_{(i)}^k \quad (3)$$

where $\mu_{(i)}^k = \mu(A_{(i)}^k)$, $\mu_{(n+1)}^k = 0$ and

$$\Delta \mu_{(i)}^k = \mu_{(i)}^k - \mu_{(i+1)}^k.$$

Note that a simplex $H_{(i)} = \{P \in [0,1]^n / 0 \leq P_{(1)} \leq \dots \leq P_{(n)} \leq 1\}$ is associated

with each profile \bar{P}^k : this corresponds to the ranking (\cdot) , where the Choquet integral assumes a linear expression. Such a remark proves critical to solving optimization problems that involve a Choquet integral, in terms of linear programming within simplex regions.

2.4. Overall performance improvement

Let \bar{P}^I be the initial performance profile of the company and \bar{P}^F its final one, i.e. $\bar{P}^I = (P_1^I, \dots, P_n^I)$ and $\bar{P}^F = (P_1^F, \dots, P_n^F)$. The evolution from \bar{P}^I to \bar{P}^F is considered as an improvement iff \bar{P}^F is preferred to \bar{P}^I . In the MAUT framework, this condition provides the following definition of improvement:

The three following propositions are equivalent:

(1) $\bar{P}^F \succeq \bar{P}^I$, i.e. \bar{P}^F is preferred to \bar{P}^I with respect to company development policy;

(2) $C_\mu(\bar{P}^F) \geq C_\mu(\bar{P}^I)$, where C_μ models company development policy;

(3) Substantial improvement has been achieved between the two observed states \bar{P}^I and \bar{P}^F .

2.5. Efficient improvement in the MAUT framework

The following step has been introduced to assist decision-makers in their analysis by considering how performance could be improved. Decision-makers generally know which actions need to be carried out in order to increase an elementary performance. Their problem then is to design an improvement that leads to the required overall performance with a minimal increase allocated to each elementary performance, i.e. a minimum additional cost relative to each individual elementary performance. This notion of optimal improvement is directly correlated with the concept of efficient improvement. The notion of efficiency actually implies both the target objective and the resource allocation (costs, efforts, means, risks, etc.) associated with the improvement: an improvement is thus efficient if any restrictive modification to its allocated resources necessarily entails a decrease in overall performance.

A performance improvement from \bar{P}^I to \bar{P}^F that induces a cost C and leads to an evolution, such that $\bar{P}^F \succeq \bar{P}^I \Leftrightarrow C_\mu(\bar{P}^F) \geq C_\mu(\bar{P}^I)$, can be characterized by its overall performance gain $C_\mu(\bar{P}^F) - C_\mu(\bar{P}^I)$ relative to its cost C . The higher the overall performance gain and the lower the cost, the more efficient the improvement becomes.

Let $\bar{P}^I = (P_1^I, P_2^I, \dots, P_n^I)$ be the initial performance profile and $P^I = g(\bar{P}^I)$ the associated aggregate performance. The problem to be solved then calls for identifying the most "efficient" way to improve overall performance, i.e. the least costly improvement in elementary performance that achieves an expected overall performance $P^* > P^I$. What then is the minimum investment in each criterion that enables attaining P^* ? The response consists of computing the improvement vector that

requires minimum investment. Let's denote $\bar{\delta}^* = (\delta_1^*, \delta_2^*, \dots, \delta_n^*)$ as the solution to this problem.

$\bar{\delta}^*$ is thus associated with the most efficient strategy for a given $C_\mu(\cdot)$ model along with a predefined set of cost functions related to each PMS criterion.

Let's also denote $c_i(P_i, \delta_i)$ as the cost related to a partial improvement from P_i to $P_i + \delta_i$. For the sake of simplicity, $c_i(P_i^l, \delta_i)$ is assumed to be a linear function with respect to δ_i , i.e.: $c_i(P_i^l, \delta_i) = cu_i \cdot \delta_i$, with cu_i being a unit cost. The cost function for an overall improvement from $C_\mu(\bar{P}^l) = P^l$ to $C_\mu(\bar{P} + \bar{\delta})$, with $\bar{P} = (P_1, \dots, P_n)$ and $\bar{\delta} = (\delta_1, \dots, \delta_n)$, can be written as (with the cost separability assumption):

$$c(\bar{P}, \bar{\delta}) = \sum_{i=1}^n c_i(P_i, \delta_i) \quad (4)$$

The search for an efficient improvement may then be formalized into the following optimization problem (**P₁**):

Objective function:

$$\min c(\bar{P}, \bar{\delta})$$

Constraints:

$$C_\mu(\bar{P} + \bar{\delta}) = P^* \text{ - (behavioral constraint)}$$

$$\forall i, \delta_i^d \leq \delta_i \leq 1 - \delta_i^s - P_i \text{ - (boundary constraints)}$$

where δ_i^s and δ_i^d are threshold parameters derived from the application (e.g. improvement with respect to criterion i cannot exceed 30%).

A second associated optimization problem (**P₂**) can now be considered for the efficiency characterization: it consists of computing the maximum expectable improvement for a given additional investment δB . (**P₂**) is defined as follows:

Objective function:

$$\max_{\bar{\delta}} C_\mu(\bar{P} + \bar{\delta})$$

Constraints:

$$c(\bar{P}, \bar{\delta}) = \delta B \text{ - (behavioral constraint)}$$

$$\forall i, \delta_i^s \leq \delta_i \leq 1 - \delta_i^d - P_i \text{ - (boundary constraints)}$$

The MAUT model thus enables incorporating managers' preferences into an analytical format that facilitates the introduction of concepts such as efficiency in the form of optimization problems.

The piecewise linearity of C_μ enables solving (**P₁**) as a linear programming problem. C_μ indeed behaves like a WAM on each simplex $H_{(i)} = \{\bar{P} \in [0, 1]^n / 0 \leq P_{(i)} \leq \dots \leq P_{(n)} \leq 1\}$. This remark serves to break down the initial problem into $n!$ linear programming sub-problems. Nonetheless, this

solution can only be considered for low n values (Berrah *et al.*, 2008a).

Another idea calls for considering the problem as a whole and then introducing complementary linear programming considerations (Sahraoui *et al.*, 2007a, 2007b). To this end, let's start with the following statement: Guaranteeing that a potential solution belongs to a given $H_{(i)}$ implies adding $(n-1)$ constraints to the problem definition: $\forall i, P_{(i)} + \delta_{(i)} \leq P_{(i+1)} + \delta_{(i+1)}$. Next, by noting that all realizable solutions related to a linear programming problem belong to a convex hull, the associated vertices \bar{x} exhibit a particular profile due to the three types of inequalities included in the problem model ($\forall i, \delta_i^s = \delta_i^d = 0$ for the sake of simplicity):

$$(a) \forall i, 0 \leq \delta_{(i)}$$

$$(b) \forall i, \delta_{(i)} \leq 1 - P_{(i)} \quad (5)$$

$$(c) \forall i, P_{(i)} + \delta_{(i)} \leq P_{(i+1)} + \delta_{(i+1)}$$

A vertex \bar{x} is thus defined by n equations: $(n-1)$ from the preceding constraints taken to equality conjointly with

$$C_\mu(\bar{P}^l + \bar{\delta}) = \sum_{i=1}^n \Delta\mu_{(i)} \cdot (\bar{P}^l + \bar{\delta})_{(i)} = P^*, \text{ where } \Delta\mu_{(i)} \text{ 's}$$

are coefficients of the linear expression for C_μ in simplex $H_{(i)}$, defined by type (c) inequalities. The set of constraints is generated for any simplex $H_{(i)}$ and all vertices are computed. The minimum distance between \bar{P}^l and a vertex yields the solution to the global problem.

Let's now remark that after rearrangement, a vertex \bar{x} is a vector with 3 distinct coordinate blocks:

- (a) unchanged coordinates with respect to the initial vector \bar{P} ($\delta_{(i)} = 0 \Rightarrow x_{(i)} = P_{(i)}$),

- (b) coordinates equal to 1 ($\delta_{(i)} = 1 - P_{(i)} \Rightarrow x_{(i)} = 1$),

- (c) a subset of coordinates with the same value β ($P_{(i)} + \delta_{(i)} = P_{(j)} + \delta_{(j)} = x_{(i)} = x_{(j)}$).

Linear programming results indicate that $\bar{P}^l + \bar{\delta}^*$ can only assume exceptional values as coordinates, which means that after rearrangement, $\bar{P} + \bar{\delta}^*$ can always be rewritten in the following form, denoted **F** (Sahraoui *et al.*, 2007a):

$$[1, \dots, 1, \beta, \dots, \beta, P_{(i)}, \dots, P_{(j)}]^T \quad (6)$$

This proves to be a relevant piece of information for decision-making and serves to generalize the obvious result obtained with a WAM, e.g. $[1, \dots, 1, \beta, P_{(i)}^l, \dots, P_{(j)}^l]^T$. Further details are provided in Sahraoui *et al.* (2007b).

3. Elementary performance contributions to overall performance gain

Let's proceed by considering the following question: what is the contribution of criterion i to the overall performance gain from \vec{P}^I to \vec{P}^* ? This contribution cannot be *a priori* computed with just the initial data of (\mathbf{P}_1) : $\vec{P}^I, C_\mu, \forall i, c\mu_i$ and P^* . Criteria contributions actually depend on the way in which overall performance evolves from \vec{P}^I to \vec{P}^* . Let's now consider the following illustration (see Fig. 1):

Three possible paths $\mathcal{E}_{j=1,2 \text{ et } 3}$ from \vec{P}^I to \vec{P}^* are depicted in Figure 1. The total cost C^* is provided by (\mathbf{P}_1) : it is identical for all paths \mathcal{E}_j from \vec{P}^I to \vec{P}^* , whereas the criteria contributions to $C_\mu(\vec{P}^*) - C_\mu(\vec{P}^I)$ depend on the individual path.

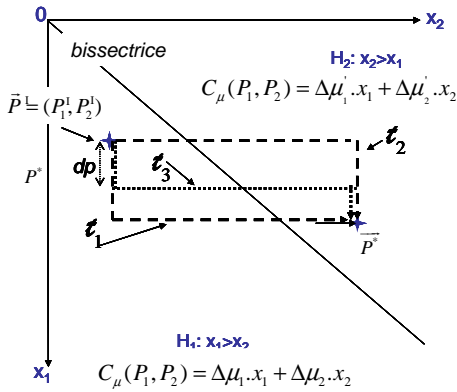


Fig. 1: Contributions and trajectories

The contributions of criterion 1, $C_1^{E_j}$, $j=1,2$ and 3 are: $C_1^{E_1} = \Delta\mu_1 \cdot (P_1^* - P_1^I)$, $C_1^{E_2} = \Delta\mu_1 \cdot (P_1^* - P_1^I)$ and $C_1^{E_3} = \Delta\mu_1 \cdot dp + \Delta\mu_1 \cdot (P_1^* - P_1^I - dp)$. Similarly, for criterion 2, $C_2^{E_j}$, $j=1,2$ et 3 are:

$$\begin{aligned} C_2^{E_1} &= \Delta\mu_2 \cdot (P_1^I - P_2^I) + \Delta\mu_2 \cdot (P_2^* - P_1^I), \\ C_2^{E_2} &= \Delta\mu_2 \cdot (P_1^I - P_2^I) + \Delta\mu_2 \cdot (P_2^* - P_1^I) \text{ and} \\ C_2^{E_3} &= \Delta\mu_2 \cdot (P_1^I + dp - P_2^I) + \Delta\mu_2 \cdot (P_2^* - P_1^I - dp). \end{aligned}$$

It can easily be verified that:

$$\forall j, C_\mu(\vec{P}^*) - C_\mu(\vec{P}^I) = C_1^{E_j} + C_2^{E_j}$$

with $\Delta\mu_1 + \Delta\mu_2 = \Delta\mu_1' + \Delta\mu_2' = 1$ (i.e. Choquet integral continuity).

Consequently, for a given path \mathcal{E}_j , the *a posteriori* contribution of criterion $C_i^{E_j}$ can easily be computed. On the other hand, the *a priori* contribution of a criterion to $C_\mu(\vec{P}^*) - C_\mu(\vec{P}^I)$ is not a precise quantity. In the following discussion, a method will be proposed to compute the lower and upper endpoints of the interval containing all possible values for the contribution of any criterion i . The aim

here is to provide both the minimum and maximum expected profitability. A criterion must necessarily contribute at least up to $C_i^N = \min_j C_i^{E_j}$, yet it is entirely possible for the contribution to reach $C_i^\Pi = \max_j C_i^{E_j}$. $[C_i^N, C_i^\Pi]$ characterizes the level of inaccuracy in the *a priori* contribution of criterion i to the overall gain $C_\mu(\vec{P}^*) - C_\mu(\vec{P}^I)$.

The principle used to compute $[C_i^N, C_i^\Pi]$ will now be given; it involves a three-step procedure.

Step 1: The non-oriented, complete graph Γ is built first; it ties all of the $n!$ simplexes $H_\sigma = \{\vec{P} \in [0,1]^n / 0 \leq P_{\sigma(i)} \leq \dots \leq P_{\sigma(n)} \leq 1\}$ together.

Let H_{σ_i} be the simplex where \vec{P}^I belongs and H_{σ_f} the simplex of \vec{P}^* . H_{σ_i} would thus be the source of Γ and H_{σ_f} the sink.

- For each H_σ , it is verified that at least one point $\vec{P}(\sigma)$ exists such that: $\forall i \in \{1; \dots; n\}, P_i^I \leq P_i(\sigma) \leq P_i^*$;
- If such a point does not exist, then H_σ is to be deleted along with all arcs whose H_σ is an endpoint;
- Lastly, once each node H_σ has been verified, a filtered graph Γ_F is obtained.

Step 2: For each node H_σ in Γ_F , the range of allowed values for $P_i(\sigma)$ is computed for each criterion i : $[B_i^{Inf}(\sigma); B_i^{Sup}(\sigma)]$. This computation is given by the following expression:

$$B_i^{Inf}(\sigma) = \max_{j \leq \sigma^{-1}(i)} P_{\sigma(j)}^I; B_i^{Sup}(\sigma) = \min_{j \geq \sigma^{-1}(i)} P_{\sigma(j)}^* \quad (7)$$

Step 3: Γ_F defines a set of paths $Path_k, k=1..m$, with

H_{σ_i} as the source and H_{σ_f} the sink without the presence of any cycles. For each node H_σ in $Path_k$, a determination can be made of $[B_i^{Inf}(\sigma); B_i^{Sup}(\sigma)]$ and $\Delta\mu_i(\sigma)$, in addition to the linear coefficient of C_μ for criterion i in simplex H_σ . Let $\mathcal{E}_i^{Path_k}$ be the series of disjoint intervals $I_i(\sigma)$ such that $I_i(\sigma) \subseteq [B_i^{Inf}(\sigma); B_i^{Sup}(\sigma)]$ and

$$\bigcup_{\sigma / H_\sigma \in \text{Nodes}(Path_k)} I_i(\sigma) = [P_i^I; P_i^*].$$

With $L(I)$ denoting the

length of interval I , the following can then be computed:

$$\begin{aligned} \min_{\mathcal{E}_i^{Path_k}} \sum_{\sigma / H_\sigma \in \text{Nodes}(Path_k)} \Delta\mu_i(\sigma) \cdot L(I_i(\sigma)) \text{ and} \\ \max_{\mathcal{E}_i^{Path_k}} \sum_{\sigma / H_\sigma \in \text{Nodes}(Path_k)} \Delta\mu_i(\sigma) \cdot L(I_i(\sigma)) \end{aligned}$$

Ultimately:

$$\begin{aligned}
C_i^N &= \min_{Path_k} \min_{\mathcal{E}^{Path_k}} \sum_{\sigma / H_\sigma \in Nodes(Path_k)} \Delta\mu_i(\sigma).L(I_i(\sigma)) \\
C_i^\Pi &= \max_{Path_k} \max_{\mathcal{E}^{Path_k}} \sum_{\sigma / H_\sigma \in Nodes(Path_k)} \Delta\mu_i(\sigma).L(I_i(\sigma)) \quad (8)
\end{aligned}$$

Let's note that C_i^N and C_i^Π can be indexed by time k for monitoring purposes. $[C_i^N(k), C_i^\Pi(k)]$ could in fact be computed at each intermediate point \bar{P}^k of the trajectory from \bar{P}^l to \bar{P}^* . We then obtain the following relation:

$[C_i^N(k), C_i^\Pi(k)] \supseteq [C_i^N(k+1), C_i^\Pi(k+1)]$. This implies that the level of inaccuracy related to the contribution of a criterion to overall improvement gain $C_\mu(\bar{P}^*) - C_\mu(\bar{P}^l)$ naturally decreases as \bar{P}^k approaches \bar{P}^* . Once \bar{P}^* has been reached at $k = k^*$,

$C_i^N(k^*) = C_i^\Pi(k^*)$, i.e.: $L([C_i^N(k^*); C_i^\Pi(k^*)]) = 0$. At this point, there is obviously no remaining inaccuracy relative to the *a posteriori* contribution. The manager thus knows at any point in time the full range of expected values for the contribution of each criterion. These computations enable quantitatively comparing any two control policies from \bar{P}^l to \bar{P}^* in terms of criteria contribution. This aspect has been illustrated in the following section.

Given the elementary increase vector $\bar{\delta} = (\delta_1, \dots, \delta_n)$, we can finally introduce w_i^N and w_i^Π such that:

$$\begin{aligned}
C_i^N &= w_i^N \cdot \delta_i \text{ and } C_i^\Pi = w_i^\Pi \cdot \delta_i, \text{ which leads to:} \\
w_i^N &\leq \tilde{w}_i \leq w_i^\Pi \quad (9)
\end{aligned}$$

where \tilde{w}_i is the expected average contribution of criterion i to overall performance gain $C_\mu(\bar{P}^*) - C_\mu(\bar{P}^l)$. w_i^N and w_i^Π are the lower and upper bounds of the expected weight, respectively.

4. The improvement control problem

The problem to be solved now consists of determining a step-by-step evolution over time for the performance profile \bar{P} , from \bar{P}^l to \bar{P}^* . \bar{P}^* is the set-point of this control problem, with \bar{P} being the controlled variable.

The basic idea herein is to define some exceptional points \bar{P}^k on the trajectory from \bar{P}^l to \bar{P}^* in order to plan an expected step-by-step evolution of \bar{P}^k . Providing the series of intermediate points \bar{P}^k , from \bar{P}^l to \bar{P}^* , enables defining the guidelines that managers *would like* the company improvement strategy to follow. This represents a purely managerial perspective. The contribution of a criterion to the overall performance gain introduced in Section 3 is key to this control perspective.

4.1. A statistical perspective: The worth index

This first perspective has been inspired by the work of Labreuche in (Labreuche, 2004); in this paper, the author proposes an importance index for determining the criteria based on which a candidate first needs to improve in order to raise his overall score within a MAUT framework to the greatest extent possible. These results have been transposed here in the case of industrial performance improvement. Let's note that no quantitative objective P^* is provided in Labreuche's paper, and the qualitative aim merely stipulates doing one's best.

Let's start by briefly recalling the notion of worth index, as developed in (Labreuche, 2004). This work was initiated in (Grabisch *et al.*, 2001) with no initial profile \bar{P}^l being specified. Labreuche's goal was to generate advice on the criteria for which company performance first needs to be improved from a statistical perspective. This identification step depends on the aggregation model H as well as on partial performances $\bar{P}^l = (P_1^l, P_2^l, \dots, P_n^l)$. To offer advice on the criteria slated for improvement, Labreuche has proposed introducing an index denoted by $\omega_A^C(H)(\bar{P}^l)$ for the aggregation function

H and initial profile \bar{P}^l . For any $A \subset C$, $\omega_A^C(H)(\bar{P}^l)$ will be the worth for profile \bar{P}^l , to be improved in the criteria set among A , subject to the evaluation function H . The author then constructed $\omega_A^C(H)(\bar{P}^l)$, which will be large if improving \bar{P}^l with respect to criteria A yields a strong improvement in the overall evaluation $H(\bar{P})$. The recommended set of criteria to be improved first is the overlap $A^* \subset C$ that maximizes $\omega_A^C(H)(\bar{P}^l)$. Put more precisely, improving the criteria in A^* maximizes the chances that overall performance reaches the highest level possible. Labreuche also proposed an axiomatic construction for the worth index $\omega_A^C(H)(\bar{P}^l)$. In the following discussion, only the case $H = C_\mu$ will be considered.

Let's now turn our attention to two profiles \bar{P}^l, \bar{P}^l and $A \subset C$. The following notations are introduced: $[P_A^l, P_{C \setminus A}^l]$ is the compound profile, whose partial performances are such that: $P_i^l > P_i^l$ if $i \in A$, else

P_i^l . For any subset of criteria $A \subset C$, P_A is the restriction of \bar{P} on A .

One possible formula for the worth index is:

$$\omega_A^C(C_\mu)(\bar{P}^l) = \frac{1}{\prod_{i \in A} (1 - P_i^l)} \int_{P_i^l \in [P_i^l, 1]} [C_\mu(P_A, P_{C \setminus A}^l) - C_\mu(\bar{P}^l)] dP_A \quad (10)$$

$\omega_A^C(C_\mu)(\bar{P}^l)$ is thus the mean value of gain relative to the aggregate performance calculated over all expected values the improvement could assume

$P_A^j \in [P_A^j, 1_A]$ within the upper hypercube (see Fig. 2). Let's also note that the upper bound of the integral equals 1_A (i.e. no quantitative objective P^* has been specified).

When cost functions with respect to partial improvements are introduced, a natural extension becomes:

$$\omega_A^j(C_\mu)(\bar{P}^j) = \frac{1}{\prod_{i \in A} (1 - P_i^j)} \int_{P_{i \in A}^j, 1_A} [C_\mu(P_A^j, P_{C_A}^j) - C_\mu(\bar{P}^j)] dP_A^j \quad (11)$$

The benefit $C_\mu(P_A^j, P_{C_A}^j) - C_\mu(\bar{P}^j)$ is replaced by the benefit-to-cost ratio: $\frac{C_\mu(P_A^j, P_{C_A}^j) - C_\mu(\bar{P}^j)}{c(P_A^j, P_A^j - P_A^j)}$.

In this framework, the alliance $A^* / \max_A \omega_A^j(C_\mu)(\bar{P}^j)$ stems from a statistical interpretation: $\omega_A^j(H)(\bar{P}^j)$ actually provides the criteria that maximize the expectancy of $C_\mu(P_A^j, P_{C_A}^j) - C_\mu(\bar{P}^j) / c(P_A^j, P_A^j - P_A^j)$ appearing as a variate. No accurate value can be provided for overall improvement with $\omega_A^j(H)(\bar{P}^j)$, which merely guarantees that criteria in A^* maximize the chance of reaching a high overall performance.

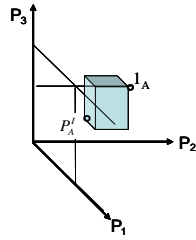


Fig. 2: The upper hypercube $P_A^j - 1_A$ lower bound P_A^j - upper bound 1_A

This statistics-based advice is expected for the theory games community, but proves to be somewhat disturbing for the field of industrial systems engineering. We will now see how Labreuche's model can be slightly modified and integrated into a step-by-step improvement procedure whenever a quantitative goal P^* has been assigned to the improvement.

We are thus authorizing an upper bound P_C^{sup} not necessarily equal to 1_C (as a consequence, the upper bounds in (10) and (11) will be P_A^{sup} and not 1_A). This has been denoted as follows:

$$\omega_A^j(C_\mu)(\bar{P}^j, P_C^{sup}) \text{ with } \omega_A^j(C_\mu)(\bar{P}^j, 1_C) = \omega_A^j(C_\mu)(\bar{P}^j) \quad (12)$$

Let's now return to the control problem of \bar{P} from \bar{P}^j to \bar{P}^* . $\omega_A^j(C_\mu)(\bar{P}^j, P_C^{sup})$ can be used for strategic control purposes. Let's also set $P_C^{sup} = \bar{P}^*$, where \bar{P}^* is a solution for (P_1) . The aim here is to plan an expected step-by-step evolution over time for \bar{P}^k from \bar{P}^j to \bar{P}^* .

The algorithm (A_1) then consists of the following:

```

Given  $\bar{P}^j, C_\mu, \forall i, cu_i$ 
 $k = 0, \bar{P}^0 := \bar{P}^j$ 
while  $C_\mu(\bar{P}^k) < C_\mu(\bar{P}^*)$ 
Compute:
 $A^* / \omega_A^j(C_\mu)(\bar{P}^k, \bar{P}^*) = \max_{A \subset C} \omega_A^j(C_\mu)(\bar{P}^k, \bar{P}^*)$ 
Improve partial performances with respect to the
criteria contained in  $A^*$ , until reaching time  $k+1$ .
Verify that all improved performance be kept in the
upper hypercube  $P_A^k - P_A^*$ .
Note  $\bar{P}^{k+1}$  as the new attained performance profile
at  $k+1$ .
Evaluate overall performance  $C_\mu(\bar{P}^{k+1})$ .
 $k = k+1$ 
End while
The series of points  $\bar{P}^k$  now defines the required
trajectory.

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Be aware that this step-by-step procedure is indeed feasible because \bar{P}^* remains a solution of (P_1) with any \bar{P}^k as the initial profile within the upper hypercube $\bar{P}^j - \bar{P}^*$ (for proof, consider that L_1 norm is used in (P_1) and no regression is authorized with respect to any criterion). (A_1) ensures that from any \bar{P}^k to \bar{P}^{k+1} , the improved criteria correspond to those that maximize the chance of reaching a high level of performance at time $k+1$. This constitutes an optimum in the statistical sense: on average, the criteria of A^* guarantee maximum expectancy for overall improvement at $k+1$, which does not necessarily mean that each intermediate \bar{P}^k corresponds to an efficient improvement. Constraining the improvement to be efficient at each intermediate \bar{P}^k corresponds to another perspective, which will now be explained.

4.2. The local efficiency perspective

Let's once again consider the control problem of \bar{P} from \bar{P}^j to \bar{P}^* . We are no longer interested here in maximizing the chances of reaching high performance at each step k , as suggested by the worth index method, and the decisive strategic factor is now to guarantee efficiency at any intermediate point \bar{P}^k .

The basic notion is to "locally" reuse (P_1) in order to define such a series of points \bar{P}^k . Intermediate points \bar{P}^k indeed prove necessary whenever P^* appears as an ambitious set-point requiring extensive time before being reached. Managers must define short terms and gradual improvements, for which it is simpler to plan adequate implementation. These intermediate points can be anticipated as a locally-efficient improvement. The guidelines consist of providing short-term objectives to be reached

efficiently and thus proceeding, step-by-step, until \bar{P}^* . Below is the \mathbf{A}_2 algorithm description:

Given $\bar{P}^l, C_\mu, \forall i, cu_i$
 Provide a real series of overall objectives P^k , such that $C_\mu(\bar{P}^l) \leq P^k \leq P^*$ (e.g. if \bar{P}^* is reached in p steps, we may choose $P^k = C_\mu(\bar{P}^l) + k \cdot \frac{P^* - C_\mu(\bar{P}^l)}{p}, k = 1, \dots, p$. This is a passing suggestion, with the idea being merely to ensure short-term and gradual improvements).
 $k = 0, \bar{P}^0 := \bar{P}^l$.
 while $C_\mu(\bar{P}^k) < C_\mu(\bar{P}^*)$
 Solve (\mathbf{P}_1) with \bar{P}^k as the initial point and P^{k+1} as the set-point, along with boundary constraints $\forall i, \delta_i^l = 0, \delta_i^r = 1 - P_i^*$, which is responsible for providing \bar{P}^{k+1} .
 $k = k + 1$
 End while
 The series of points \bar{P}^k serves to define this required trajectory.

This strategy guarantees a local efficient improvement once \bar{P}^k has been reached. The implementation is both locally and globally efficient when \bar{P}^* is ultimately reached. Local efficiency is another way of foreseeing the trajectory from \bar{P}^l to \bar{P}^* , which obeys a different decisive factor from that included in the worth index method. Each one corresponds to clearly distinct attitudes with respect to the potential risk for failure.

4.3 Semantic comparison

From a semantic perspective, this second alternative approximates control theory modeling, whereas the first alternative tends to be oriented in favor of games theory with a statistical semantic. Both can be easily legitimated: the first ensures that improved criteria correspond to the maximum expected overall gain at any point in time. On the other hand, the second relies on a decisional criterion based upon local and global efficiency. Both have their advantages - they are justifiable at any time - yet also feature a number of drawbacks. The worth index rationale will indeed provide the most statistically profitable criteria, although nothing can be determined regarding the expected resultant gain. For example, the maximum worth index can be associated with a criterion whose margin of improvement is highly reduced (the company's partial performance with respect to this criterion is already excellent and even if perfection is reached (i.e. a value of 1), the overall performance will not be significantly improved). Furthermore, at each \bar{P}^k , the worth index relies on statistical considerations; hence, the performance evaluation at time $k + 1$ can in practice be discouraging! On the

other hand, a (\mathbf{P}_1) -based logic guarantees efficiency at each \bar{P}^k if and only if \bar{P}^k is precisely reached. Moreover, this condition requires that managers define the series of real values P^k .

5. Case study

The case study concerns an SME producing kitchens and has been discussed in detail in (Clivillé *et al.*, 2007). The overall objective of the company is to continuously increase productivity. Let's start by supposing that a partial breakdown of the strategic objective, relative to productivity rate, into four basic criteria is to be processed: *Inventories, Equipment availability, Operator skill, and Quality*. Overall performance is defined as the aggregation of these four associated indicators with a Choquet integral C_μ . All numerical information presented hereafter has been obtained by interviewing management staff, in accordance with the Macbeth methodology (Clivillé *et al.*, 2007). Table 1 provides the current performances $\bar{P}^l = (P_1^l, \dots, P_n^l)$, the relative importance of each criterion to the SME activity, and the estimated cu_i costs for improving performance.

In this example, we have used a 2-additive C_μ (only the interactions between two criteria are considered in this model). In the present case, we obtain:

$\Delta\mu_{(i)} = v_{(i)} + \frac{1}{2} \sum_{j>i} I_{(i)(j)} - \frac{1}{2} \sum_{j<i} I_{(i)(j)}$, where $v_{(i)}$ are the Shapley indices and $I_{(i)(j)}$ the interaction coefficients between criteria i and j (Table 2).

Table 1: Weights, costs and initial performances

	Indicator	v_i	cu_i	\bar{P}^l
C_1	<i>Inventories</i>	0.30	1,000 k€	0.80
C_2	<i>Equipment availability</i>	0.25	3,000 k€	0.25
C_3	<i>Quality</i>	0.30	2,000 k€	0.75
C_4	<i>Operator skill</i>	0.15	3,000 k€	0.50

Table 2: Interaction coefficients

Interactions between:	Value
<i>Inventories - Equipment availability</i>	0.30
<i>Inventories - Quality</i>	0.25
<i>Operator skill - Quality</i>	0.30

Current aggregate performance equals $C_\mu(\bar{P}^l) = C_\mu(0.8, 0.25, 0.75, 0.5) = 0.483$. The expected overall performance stands at $P^* = 0.9$. Solving (\mathbf{P}_1) with \bar{P}^l as the initial point and $P^* = 0.9$ yields $\bar{P}^* = (1, 1, 1, 0.636)$, which corresponds to a global improvement cost $C^* = 3358k€$. This reflects the static perspective of efficient improvement. $P^* = 0.9$

now appears as an ambitious set-point, such that the manager decides to reach it within three years. The procedure adopted to achieve this goal must then be defined, and the manager opts to set intermediate targets each year. The two strategies described in this paper have been envisaged (see algorithms A_1 and A_2 , respectively).

- Local efficiency rationale: The manager chooses more pragmatic and short-term overall performance levels for each end-of-year, i.e. P^1 and P^2 . The optimization problem (P_1) is first solved with \bar{P}^1 as the initial profile and P^1 as the expected overall performance, which yields \bar{P}^1 at the end of the first year. Next, (P_1) is solved with \bar{P}^1 and P^2 : the result at the end of the second year is \bar{P}^2 . Lastly, the improvement from \bar{P}^2 to \bar{P}^* over the last year remains. The manager justifies his strategy as an efficient step-by-step improvement implementation. The computations have been summarized in Table 3 (left-hand part).

- Worth index rationale: The worth index is computed at the beginning of each year; it provides the criteria that need to be improved first. At the end of the year, the performance vector can be observed. The worth index is then recalculated using this new vector until reaching \bar{P}^* . These results are summarized in the right-hand part of Table 3. Thus, $A^* = \{c_2\}$ for the first year (with the maximum worth index being derived for $\omega_{A^*}^c(C_\mu)(\bar{P}^1, \bar{P}^*) = \omega_{\{c_2\}}^c(C_\mu)(\bar{P}^1, \bar{P}^*) = 0,01303$) and $\bar{P}^3 = (0,8, 0,65, 0,75, 0,5)$ is reached, then for the second year $A^* = \{c_1, c_2, c_3\}$ (with the maximum worth index obtained for $\omega_{A^*}^c(C_\mu)(\bar{P}^2, \bar{P}^*) = \omega_{\{c_1, c_2, c_3\}}^c(C_\mu)(\bar{P}^2, \bar{P}^*) = 0,01147$), and $\bar{P}^4 = (1, 0,9, 0,8, 0,5)$ is attained. For the last year, the improvement from \bar{P}^4 to \bar{P}^* remains. The manager justifies this strategy as the most statistically profitable, step-by-step implementation.

Table 3 - left part: Trajectory with local efficiency; right part: Trajectory with the worth index

	1 st year				1 st year			
	2 nd year		2 nd year		2 nd year		2 nd year	
	3 rd year				3 rd year			
\bar{P}	\bar{P}^1	\bar{P}^2	\bar{P}^3	\bar{P}^4	\bar{P}^5	\bar{P}^6	\bar{P}^7	\bar{P}^8
C_1	0.8	0.8	0.914	1	0.8	0.8	1	1
C_2	0.25	0.759	0.914	1	0.25	0.65	0.9	1
C_3	0.75	0.759	0.914	1	0.75	0.75	0.8	1
C_4	0.5	0.5	0.5	0.636	0.5	0.5	0.5	0.636
$C_\mu(\bar{P})$	0.483	0.69	0.8	0.9	0.483	0.643	0.768	0.9

Moreover, for a quantitative comparison of both control strategies, the interval $[C_i^N(k), C_i^II(k)]$ ($k = 3$ years) providing the lower and upper bounds of the criterion i contribution is computed with \bar{P}^1 as the initial point. Results are reported in Table 4. The "Improvement" column provides the coordinates of vector $\bar{\delta}^*$ from \bar{P}^1 to \bar{P}^* . The "Costs" column lists the costs corresponding to each criterion for optimal improvement. Columns $C_i^N(t)$ and $C_i^II(t)$ yield the minimum and maximum expected contributions for an efficient improvement from \bar{P}^1 to \bar{P}^* . Column 6 (resp. 7) indicates the corresponding minimum (resp. maximum) expected profitability (i.e. contribution/cost ratio) for each criterion. Columns 8 and 9 display the *a posteriori* contribution and profitability of each criterion towards $C_\mu(\bar{P}^*) - C_\mu(\bar{P}^1)$, respectively, when a locally-efficient strategy has been adopted. On the other hand, columns 10 and 11 offer the same data for the worth index rationale. Note that both of these strategies reveal opposite effects on the current example: the most profitable criterion for one is the least for the other. For the local efficiency control strategy, the most profitable criterion is indeed *Inventories* and the least profitable is *Quality*. In contrast, for the worth index control strategy, the most profitable criterion is *Quality* and the least is *Inventories*.

Conclusion

The MAUT provides an appropriate framework for analyzing industrial performance and designing relevant improvements. Multi-criteria optimization problems do in fact serve as basic useful tools in the design of an efficient improvement when overall company performance is being modeled as the aggregation of elementary performances. Yet, they merely introduce the expected performance profile to be reached in a case of efficiency. A deeper investigation would be required both to understand the role of each criterion in the improvement and to design the way performance should evolve over time in order to attain the expected profile. To resolve this issue, the concept of criterion contribution to overall performance gain has been applied, and it plays a key role in improvement analysis. Contribution criteria can actually be input to design monitoring functionalities that supervise the way in which an efficient improvement is performed; the computation of such functionalities allows grasping the role of any criterion in the improvement. They may also be used in control policies to establish the way performance should evolve from the initial performance profile to the expected end profile. This study has adopted a purely managerial perspective for the improvement process; it does not take into account the material and operational constraints inherent in any improvement

project. MAUT models are preference models, meaning they only capture what managers are expecting for their company's development (see Montmain, 2009 for further details concerning the transition from motivation to action).

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Table 4: Expected and observed contribution and profitability

Criterion	Improv ^t	Cost (k€)	$C_i^N(t)$	$C_i^{\Pi}(t)$	Minimum Expected Profitability (%)	Maximum Expected Profitability (%)	Observed Contribution Strategy 1: Local efficiency	Observed Profitability (%) Strategy 1	Observed Contribution Strategy 2: Worth index	Observed Profitability (%) Strategy 2
C ₁	0.2	200	0.0099	0.11	4.95 ^E -3	5.5 ^E -2	0.11	5.5 ^E -2	0.01	5 ^E -3
C ₂	0.75	2,250	0.24	0.3	1.067 ^E -2	1.33 ^E -2	0.24	1.067 ^E -2	0.3	1.33 ^E -2
C ₃	0.25	500	0.02875	0.06875	5.75 ^E -3	1.375 ^E -2	0.02875	5.75 ^E -3	0.06875	1.375 ^E -2
C ₄	0.136	408	0.0374	0.0374	9.17 ^E -3	9.17 ^E -3	0.0374	9.17 ^E -3	0.0374	9.17 ^E -3
Total		3,358					0.41615		0.41615	