



HAL
open science

An Approach Based on MCDA and Fuzzy Logic to Select Joint Actions.

Abdelhak Imoussaten

► **To cite this version:**

Abdelhak Imoussaten. An Approach Based on MCDA and Fuzzy Logic to Select Joint Actions.. Scalable Uncertainty Management, 2018, Lecture Notes in Artificial Intelligence (LNAI) series., 10.1007/978-3-030-00461-3_10 . hal-01945317

HAL Id: hal-01945317

<https://hal.science/hal-01945317v1>

Submitted on 31 May 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

An Approach Based on MCDA and Fuzzy Logic to Select Joint Actions

Abdelhak Imoussaten

LGI2P, IMT Mines Ales, Univ Montpellier, Ales, France
abdelhak.imoussaten@mines-ales.fr

Abstract. To satisfy a fluctuating demand and achieve a high level of quality and service, companies must take into account several features when designing new products in order to become or remain market leaders. When a single company is unable to meet this objective alone, it is appropriate for it to join its actions with other companies. The product design consists of the complex task to select from various potential actions that allowing the fulfilment of several requirements: functional, technical, environmental, economic, security, etc. Furthermore, the task is even more difficult when actions are related to distinct services or companies that do not necessarily know the capacities of each others which makes complex the coordination of joint actions. Interactions between services may be affected by antagonist personal interests.

Based on a multiple criteria decision analysis (MCDA) framework and a fuzzy model that links actions to the satisfaction of objectives, this paper proposes to treat two extreme views related to the collective selection of the necessary actions to design a product: 1) The first point of view corresponds to an ideal situation where each service reveals its capacities and the unique objective is to succeed in the realization of the common goal ; 2) the second point of view corresponds to a more realistic situation where only necessary information for the progress of collective action are shared and where collective and personal goals coexist and are to be taken into account. The first situation corresponds to a classical case where a single decision maker (DM) has to express his preferences then a classical optimization problem under constraints has to be solved in order to efficiently select actions. In the second situation the services do not share the same preferences and each service wants to maximize its gain, in this case we propose to build a negotiated solution between services.

Keywords:

MCDA · Fuzzy logic · Constraint programming · Debate modeling.

1 Introduction

When company designers/operators choose a new product or system, they have to check whether the new system satisfy company's strategic goals, customers needs and technical specifications. Furthermore, these issues are obviously not devoid of budgetary constraints.

MCDA is an interesting setting to evaluate and compare all alternatives for the new system based on their satisfaction of the previous multiple requirements. The MCDA setting provides approaches for rigorous multidimensional evaluation. Indeed a set of non correlated attributes are carefully defined to measure the characteristics of the candidate solutions. Then the measures are mixed up with the subjectivity of the decision maker (DM) to deduce the degree of satisfaction provided by each candidate solution. In MCDA we distinguish several methods depending on the number of candidate solutions, number of attributes, compensation hypothesis, etc (see [3] for more details). In this paper we focus on Multi objective Optimisations methods. Let denote by: $S = \{s_1, s_2, \dots\}$ a set of finite or infinite candidate solutions for the new system, $\{X_1, X_2, \dots, X_n\}$ a finite set of attributes where X_i is the space of values taken by the i^{th} characteristic, $N = \{1, \dots, n\}$ and $X = \prod_{i \in N} X_i$. Each element of S can be represented by its results obtained on the set of attributes, then $s_k \in S$ can be represented by the vector (x_1^k, \dots, x_n^k) where $\forall i \in N, x_i^k$ is the result of s_k on the i^{th} characteristic. Thus, the satisfaction provided by the solution s_k can be represented by a real $v(s_k)$ where v is a bounded function ($v : X \rightarrow [0, 1]$). Finally, the problem of choosing the new system can be setted as follows:

$$\begin{aligned} & \max v(s) \\ & \text{s.t:} \\ & \begin{cases} s \in S \\ c(s) \leq c_0 \end{cases} \end{aligned} \tag{1}$$

where $c : S \rightarrow]0, +\infty[$ is the function associating to each candidate solution its cost and $c_0 > 0$ is the maximal cost allocated to the new system. When functions c and v are known we are faced to a classical optimization problem under constraints.

Usually in MCDA, a single DM holds the preferential information that allows to build the function v . Particularly, in Multi Attribute Value Theory (MAVT [6] [1]) the existence of a such value function is guaranteed when DM preference relation over S denoted \succeq , $s_k \succeq s_{k'}$ means s_k is at least as good as $s_{k'}$, is a weak order. In this case, v represents the DM preferences over S and we have :

$$\forall s_k, s_{k'} \in S, \quad s_k \succeq s_{k'} \Leftrightarrow v(s_k) \geq v(s_{k'}). \tag{2}$$

The easiest way to find v is to build it from the DM preference relation on each attribute $i \in N$ denoted \succeq_i and represented by a value function $v_i : X_i \rightarrow [0, 1]$. In [7] the conditions of a such construction are given. Furthermore, a single DM who has a perfect knowledge about implementation actions of a solution can estimate their costs. Thus, in this case of a single DM, c and v can be identified.

Unfortunately, this hypothesis of the existence of a single decision maker who knows the costs of actions and with whom we can build the utility function, is not adapted to all companies configurations. Indeed, in many cases, these actions are generally spread/distributed onto several services which are then in charge of their own actions.

Classically in MCDA, the behavioural relationship between actions related to a candidate solution and the results obtained on the system characteristics are not considered. As mentioned previously, in this case, a candidate solution is represented only by its results obtained on the set of attributes. In the case of several services, the reference to the actions composing the candidate solution is required. Indeed, it would be difficult to establish with certainty the consequences of a set of actions on the attributes since actions are related to several services and applied jointly. This is because no services has complete information about all actions.

In this situation two models are envisaged, based on distinct hypothesis. Either, services collaborate fully then they share their knowledge between each others such that all services will have complete information. The problem to resolve here is to select the subset of actions guaranteeing the "best" satisfaction of common goals at minimal cost (see [8] for more details). Or, services act as autonomous agents but are cooperating: they make their possible to reach collective objectives although they have also personal interests in the project. The more actions are carried out in a service, the greater his budget. It is a thorny problem because each service has only a partial information and don't necessarily know the capacities of other services. The problem to resolve here is to build a solution by selecting a subset of actions from all services guaranteeing the satisfaction of all services and respecting budget constraints.

The aim of this paper is to propose two different models for these two situations. In the first situation the decision process is stated in the form of an multi objective optimisation problem under constraints and in the second situation, the decision process is modelled as a debate.

The paper is structured as follows. First, section 2 establishes the model of relationships between actions and objectives satisfaction. Sections 3 and 4 presents the formalization of the problem of defining joint actions composing the solution satisfying all services and respecting cost constraints respectively on the collaborative and cooperative situations.

2 Fuzzy Relationship Between Actions and the Satisfaction of Objectives

We consider a group of services denoted $\mathcal{D} = \{d_1, \dots, d_l\}$ that are in charge of building a common solution for the design of a new product or system. Each service d is in charge of a set of actions \mathcal{A}_d . For instance, an action consists in a person performing a task, a mechanical or software component, etc. Each service proposes his actions to compose a candidate solution with other services. Thus the set of candidate solutions $\mathcal{S} = \{s_1, s_2, \dots\}$ is composed of all admissible joint actions. These actions must guarantee a good performance of the new system. We assume here that the performance of the new system induced by a set of joint actions $s \in \mathcal{S}$ is measured by $v(s)$ where the value function v is defined in formula 2. The function v represents the overall satisfaction of the objectives set for the new system. Here, v will be built on the basis of what the services

will provide as information about the effects of their actions on the satisfaction of the objectives of the system. Moreover, we consider that the value function v may be obtained through the partial value functions v_i , $i \in N$ representing the satisfaction on each single objective using an appropriate aggregation operator.

The transformation that links actions in \mathcal{A}_d and the i^{th} objective, $i \in N$, is composed of two transformations: 1) The transformations T_i ($i \in N$) that represents the behavioral relation between inputs (actions) and each of its outputs (characteristics); 2) the value functions v_i expressing the satisfaction of the service related to the achievement of the i^{th} objective.

Most of the time, the transformation $T = (T_1, \dots, T_n)$ cannot be precisely known in a complex system. In some cases, the acquisition of T requires complex simulations or experiments, which are costly and time consuming (example of military architecture, [?]). Hence transformation T generally needs to be approximated. We will use a fuzzy behavioral model. Indeed, as the gathered information originates from the experts or managers perception rather than being factually measured, it is intrinsically imprecise [8].

Furthermore, each action considered must allow the satisfaction of at least one objective but it is not excluded that this action may have a negative impact on other objectives. Thus, the scale used for the evaluation of each objective must be bivariate allowing positive and negative evaluation [2]. For instance, in the automotive industry, the action of "using modular platform" reduce the weight of cars and then has a positive impact on the objective "reducing the shock with a pedestrian, animal or cyclist" but this action could impact the stability of the vehicles then it has a negative impact on the objective "safety of the driver". In our setting, we propose to use two linguistic variables to represents the impact of actions on each objective: *satisfaction* and *dissatisfaction* variables.

In [4] [5] [8] a degree in $]0, 1]$ called the "degree of belief" for positive or negative impact of an action on an objective is introduced. The semantic of this degree is unclear and then not easy to provide by experts. In addition, the imprecision inherent to expert knowledge is not taken into account. In this paper we propose to represent the impact of actions on objectives within the setting of fuzzy logic. Thus several linguistic terms can be associated to each of the two previous linguistic variables. For example, terms *low*, *medium* and *strong* can be used.

Definition 1. Consider the i^{th} objective, denoted Obj_i where $i \in N$, and an action $a \in \mathcal{A}$. Either, action a induce a satisfaction on Obj_i in a such case S_i^a denote the associated linguistic term describing the degree of a such satisfaction. Or, action a induce a dissatisfaction on Obj_i in a such case D_i^a denote the associated linguistic term describing the degree of a such dissatisfaction.

The bivariate fuzzy model described in Definition 1 can be represented through a digraph between \mathcal{A} and N , denoted $Dig(\mathcal{A}, N)$, such that (Fig. 1 shows an example): the arc between a and Obj_i defined

$$\text{Arc}(a, Obj_i) = \begin{cases} +S_i^a & \text{in case of satisfaction} \\ -D_i^a & \text{in case of dissatisfaction} \end{cases} \quad (3)$$

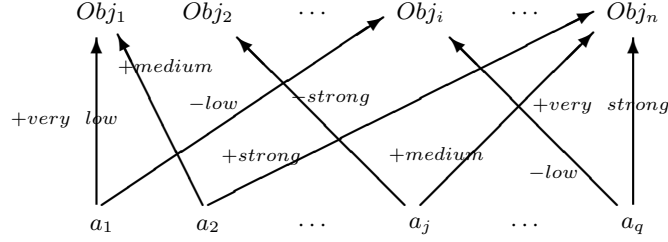


Fig. 1. Digraph of actions-objectives relationships

As we can remark in the example given above of automotive industry, a single action can not satisfy all the objectives. Thus several actions are required. Let consider a subset of actions ap and an objective Obj_i . Several actions in ap may induce satisfaction on Obj_i and several other actions in ap may induce dissatisfaction on Obj_i . We denote by $A_i^S(ap)$ (resp. $A_i^D(ap)$) the crisp subset of actions in ap that induce satisfaction (resp. dissatisfaction) on Obj_i .

To obtain the overall satisfaction and dissatisfaction of the joint implementation of actions in ap , it is important to consider all the interactions and results emerging from the joint implementation of some actions. The simplest solution is to evaluate the impact of all possible combinations of actions. However, when the set of actions is very large, this solution seems unrealistic. To simplify, we consider again a soft model based on mathematical operator applied to fuzzy subsets. In order to reduce the number of actions that do the same thing, we consider that the satisfaction and dissatisfaction caused by the joint actions can not be additive. Thus, based on cautious behaviour, we keep all the maximum possibility degrees of satisfaction and dissatisfaction in the aggregated result by using a conjunctive operator. Finally, we propose to synthesize the satisfaction and dissatisfaction of ap on Obj_i as follows:

$$\mu_{S_i^{ap}} = \bigvee_{a \in A_i^S(ap)} \mu_{S_i^a}; \quad (4)$$

$$\mu_{D_i^{ap}} = \bigvee_{a \in A_i^D(ap)} \mu_{D_i^a}. \quad (5)$$

where $\mu_{S_i^a}$ (resp. $\mu_{D_i^a}$) is the fuzzy subset associated to linguistic term S_i^a (resp. D_i^a).

The next step is to verify if service is satisfied by the impact of actions in ap on Obj_i . This is done here by comparing the center of area of the resulting two fuzzy subsets $\mu_{S_i^{ap}}$ and $\mu_{D_i^{ap}}$ to two thresholds $\alpha_i, \beta_i \in]0, 1]$ fixing the limits of satisfaction and dissatisfaction degrees.

Definition 2. Let consider an action plan ap , an objective Obj_i and two thresholds $\alpha_i, \beta_i \in]0, 1]$. We consider that ap satisfies Obj_i if:

$$1. \frac{\int y \times \mu_{S_i^{ap}}(y) dy}{\int \mu_{S_i^{ap}}(y) dy} \geq \alpha_i \text{ and}$$

$$2. \frac{\int y \times \mu_{D_i^{ap}}(y) dy}{\int \mu_{D_i^{ap}}(y) dy} \leq \beta_i.$$

Equations (4), (5) and definition 2 concerns a single objective but can be extended to any subset of objectives.

The principle extension of Zadeh allows aggregating satisfactions and dissatisfactions as follows:

$$\mu_{S_N^{ap}}(y) = \bigvee_{\substack{(y_1, \dots, y_n) \\ \phi_S(y_1, \dots, y_n) = y}} \bigwedge_{i \in N} \mu_{S_i^{ap}}(y_i). \quad (6)$$

where ϕ_S is an aggregation operator representing the DM trade-off on the satisfaction of objectives.

$$\mu_{D_N^{ap}}(y) = \bigvee_{\substack{(y_1, \dots, y_n) \\ \phi_D(y_1, \dots, y_n) = y}} \bigwedge_{i \in N} \mu_{D_i^{ap}}(y_i). \quad (7)$$

where ϕ_D is an aggregation operator representing the DM trade-off on the dissatisfaction of objectives.

Note that ϕ_S and ϕ_D are two operators applied to a vector of real values from $[0, 1]^n$ to $[0, 1]$. They can be a classical operators like *min*, *max* or *weighted average* operator or more sophisticated operators like Choquet integral or Sugeno integral.

We can also define the satisfaction and dissatisfactions of *ap* on a subset of objectives $I \subset N$ by fixing the results of *ap* on the remaining objectives, *i.e.*, $N \setminus I$, at given values:

$$\mu_{S_I^{ap}}(y) = \bigvee_{\substack{y_I \\ \phi_S(y_I, y_{N \setminus I}^0) = y}} \bigwedge_{i \in I} \mu_{S_i^{ap}}(y_i). \quad (8)$$

$$\mu_{D_I^{ap}}(y) = \bigvee_{\substack{y_I \\ \phi_D(y_I, z_{N \setminus I}^0) = y}} \bigwedge_{i \in I} \mu_{D_i^{ap}}(y_i). \quad (9)$$

where the notation y_I represents the components of the vector (y_1, \dots, y_n) for the indices in I and the notation $(y_I, y_{N \setminus I}^0)$ represents the vector z where $z_i = y_i$ if $i \in I$ and $z_i = y_i^0$ if $i \in N \setminus I$.

In the similar way as in definition 2, we verify if *ap* satisfy the subset of objectives I .

Definition 3. Let consider an action plan *ap*, a subset of objectives $I \subseteq N$ and two thresholds $\alpha_I, \beta_I \in [0, 1]$. We consider that *ap* satisfies objectives in I if:

1. $s_I(ap) = \frac{\int y \times \mu_{S_I^{ap}}(y) dy}{\int \mu_{S_I^{ap}}(y) dy} \geq \alpha_I$ and
2. $d_I(ap) = \frac{\int y \times \mu_{D_I^{ap}}(y) dy}{\int \mu_{D_I^{ap}}(y) dy} \leq \beta_I$.

If the two previous conditions are satisfied, $s_I(ap)$ is considered as the degree of satisfaction of objectives on I by *ap*, otherwise $s_I(ap) = 0$.

Note that the dissatisfaction degree will be less mentioned than the satisfaction degree in the following. Indeed, the satisfaction the degree is the aggregated $s_I(ap)$ result of ap , including dissatisfaction degree, and if $s_I(ap) = 0$ it means that $d_I(ap) \leq \beta_I$.

3 Selecting Joint Actions from Collaborative Services

An operational cost $c(ap)$ is associated with each action plan ap . We assume for any action a , $c(\{a\}) > 0$ and: $c(ap) = \sum_{a \in ap} c(\{a\})$.

In most instances, a cost constraint is applicable to the new system such that the cost of an action plan cannot exceed a predetermined budget denoted $b_0 \in]0, \infty]$. In addition, the new system may require a degree of satisfaction higher than a predetermined threshold $\alpha_0 \in]0, 1]$. Nevertheless, services of course prefer the solution with the highest satisfaction degree when the cost is the same; inversely, they prefer the cheapest solutions when the satisfaction degree is the same.

Let us define the Pareto order \prec_{Pareto} over action plans:

$$\begin{aligned} (s_N(ap), -c(ap)) &\prec_{\text{Pareto}} (s_N(ap'), -c(ap')) & (10) \\ \Leftrightarrow & [(s_N(ap) < s_N(ap')) \text{ and } (c(ap) \geq c(ap'))] \\ & \text{or } [(s_N(ap) \leq s_N(ap')) \text{ and } (c(ap) > c(ap'))] \end{aligned}$$

Action plan ap is dominated by action plan ap' if $(s_N(ap), -c(ap)) \prec_{\text{Pareto}} (s_N(ap'), -c(ap'))$.

In collaborative approach where service share all their knowledge of the system before collective action, the complete digraph $Dig(\mathcal{A}, N)$ is known and the multi-objective optimization problem of formula (1) is adapted for our fuzzy model as follows:

$$\begin{aligned} &\max (s_N(ap), -c(ap)) \\ &\text{s.t:} \\ &\left\{ \begin{array}{l} ap \subseteq \mathcal{A} = \bigcup_{d \in \mathcal{D}} \mathcal{A}_d \\ s_N(ap) \geq \alpha_0 \\ c(ap) \leq b_0 \end{array} \right. & (11) \end{aligned}$$

When the number of actions is very large the resolution of this optimization problem clearly raises a combinatorial problem.

The hypothesis of collaboration leading to the optimisation problem of formula (11) means that the services involved in the process of designing the new system share their partial knowledge on the fuzzy model of relationship between action and objectives so that all services have full knowledge of the model before committing collective action. This assumption is not always valid; service heads are not always willing to share knowledge of their own design service. However, they are willing to cooperate to build a common solution. Thus collaborative

approach is not often feasible in practice. It seems more natural to consider that the teams will cooperate more than collaborate. In the following section, we address the problem of selecting joint actions from cooperative services.

4 Selecting Joint Actions from Cooperative Services to Achieve Common Goals

In the case of cooperating services, the model is constructed gradually: each service contributes when it is required, there is no a priori planning. The collective choice of action plan is thus modelled as a debate. Services exchange knowledge and negotiate the way actions will be distributed. The more actions are carried out in a service the greater his budget.

We consider that no service is able to possess the action plan satisfying all the objectives. Thus, each service needs actions from others to build joint action plan.

4.1 General Principle for Debate Structure

Let consider a service $d \in \mathcal{D}$. Actions in \mathcal{A}_d induce impacts only on a subset $I_d = \{i_1^d, \dots, i_{|I_d|}^d\} \subseteq N$. The partial digraph $Dig(\mathcal{A}_d, I_d)$ of service d is presented in figure 2.

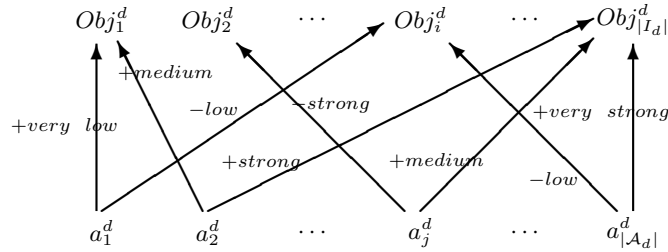


Fig. 2. Partial digraph of actions-objectives relationships

For simplification purpose and to limit the information required from the experts, we consider that the thresholds of satisfaction and dissatisfaction for subsets of objectives can be deduced from those of single objective as follows: $\forall I \subseteq N, \alpha_I = \min_{i \in I} \alpha_i$, and $\beta_I = \max_{i \in I} \beta_i$. It comes $\alpha_0 = \min_{i \in N} \alpha_i$. This is an optimistic way of considering aggregated satisfaction and dissatisfaction thresholds.

Services would propose their actions in order to increase their budget, then we need to manage the turn of propositions. This is done by selecting the service having the best offer for the common objective at the current stage. Then services have to learn from the previous propositions in order to make adequate next proposition.

Indeed, at the beginning, the services do not know the impacts induced by the actions of others services. At this stage, the information shared between the services are: the set of objectives to be satisfied N , the constraints $\alpha_i, \beta_i, \forall i \in N$ and the constraint concerning the cost of the proposed actions that should not exceed the budget b_0 . However, each service d start with a fictive complete digraph by introducing fictive actions that are supposed to be owned by other services and satisfying objectives that are not satisfied by d .

When a proposal is made, the service reveals required information on the proposed actions. Each service has to take advantage from this information and complete his partial digraph to make successful propositions.

Let us introduce time variable t explicitly in the notations. Let ap_t be the common action plan build at time t and I_t the subset of objectives satisfied, *i.e.*, $s_{I_t}(ap_t) \geq \alpha_0$, by ap_t . The debate organization is broken down into the following steps:

- At $t = 0$, $ap_0 = \emptyset$ and $I_0 = \emptyset$.
- At $t \geq 1$, the current action plan is ap_{t-1} and the satisfied objectives are in I_{t-1} .
 1. Each service propose an action plan to complete ap_{t-1} . The new proposal should satisfy new objectives in $N \setminus I_{t-1}$ and should guarantee $s_{I(t)} > 0$. He adopts a suitable strategy to make a proposal that maximizes his earnings (see subsection (4.2)). The algorithm solving the optimisation problem (11) is used locally by the service to select actions forming his proposal;
 2. A selection is made for the next action plan to add to ap_{t-1} (see subsection 4.3);
 3. Action plan ap_t satisfying I_t is built by adding new actions to ap_{t-1} ;
 4. Each service updates his information about the proposed actions (see subsection 4.4). Thus the partial digraph of a service is time depending, denoted $Dig(\mathcal{A}_d(t), I_d(t))$.
- When at $t \geq 1$ no proposal can be made by services because of cost constraint, the debate starts from the beginning, *i.e.* the resulting common action plan is emptied, and services update their information.
- The debate ends when $I_{t+1} = N$ and cost constraint is respected.

Note that when a joint action plan satisfying all the objectives is found all other remaining actions are no longer receivable.

4.2 Individual Action Plan Choice Strategies

At each step t , all the services with available actions must adopt an appropriate strategy to propose the most relevant actions. The stake is twofold: 1) the actions proposed by a service must be chosen at time t and, 2) the common action plan must be successful.

Let $AP_d(t)$ the Pareto front of solutions for the optimisation problem (11) for the digraph $Dig(\mathcal{A}_d(t), I_d(t))$. The following criteria may be introduced to select a solution $sap_d(t)$ from $AP_d(t)$ depending on the debate stage:

- $sap_d(t)$ may maximize the number of satisfied objectives, *i.e.*, there is no cost conflict;
- $sap_d(t)$ may maximize the satisfaction degree;
- $sap_d(t)$ has minimal cost.

4.3 Fair Resources Sharing

Let denote $props(t)$ the set containing the next propositions of the services (each service propose a single sub action plan).

Let consider the following notations:

- $G_d^{max} = \sum_{a \in \mathcal{A}_d} c(a)$ the maximal expected gain for service d ,
- $G_d(ap_t) = \sum_{a \in ap_t \cap \mathcal{A}_d} c(a)$ the individual gain of service d from the common action plan ap_t .

To quantify the loss of earnings for service d with respect to ap_t we can use the following formula: $G_d^{max} - G_d(ap_t)$. However, for homogeneity reasons, the formula (12) is preferred.

$$\rho(d, ap_t) = (G_d^{max} - G_d(ap_t)) / G_d^{max}. \quad (12)$$

We assume that each service have at least an action with strictly positive cost.

We consider in our approach that the group tries to avoid an unfair sharing of the allocated budget by minimizing the loss of earnings of the worst paid service. The worst paid service with respect to to common action plan ap_t is defined as follow:

$$d(ap_t) = arg \max_{d \in \mathcal{D}} [\rho(d, ap_t)]. \quad (13)$$

It comes that the new proposition $sap(t)$ should verify:

$$sap(t) = arg \min_{sap \in props(t)} \max_{d \in \mathcal{D}} [\rho(d, sap \cup ap_{t-1})]. \quad (14)$$

The new common action is $ap_t = sap(t) \cup ap_{t-1}$.

4.4 Digraphs Updating

Let $d(t)$ the service owner of the proposal $sap(t) \subseteq \mathcal{A}_{d(t)}$. Service $d \in \mathcal{D} \setminus \{d(t)\}$ a priori don't know satisfactions and dissatisfactions induced by actions in $sap(t)$. The service $d(t)$ must give the necessary information about his actions so that the other services can complete their digraph and make the next proposals. $d(t)$ should reveal the following information:

- the new satisfied objectives $I_{d(t)}^s$;
- the new dissatisfied objectives $I_{d(t)}^d$;
- the maximum dissatisfaction degree induced on $I_{d(t)}^d$;

- the cost of actions in $sap(t)$;
- the new satisfaction degree.

From those information and from the fact that new actions should guarantee $s_{I(t)} > 0$, services in $\mathcal{D} \setminus \{d(t)\}$ have a quantity of helpful information to continue the construction of their complete digraph.

5 Conclusion

This article offers an aid to the evaluation of the degree of satisfaction of a new product or system to a set of expected objectives when various candidate solution are possible and several teams are involved in the project. The evaluation focuses on the actions leading to the implementation of new product or system. We have shown the link between this problem and a classical decision-making process based on MCDA approach and we have distinguished two configurations of services in a company: collaborative services and cooperative services. In the first configuration a multi-objective optimisation problem is stated to resolve the problem of selecting the optimal set of actions with regard to cost and satisfaction degree constraints. In the second configuration, the problem is stated as a debate between services where the objective is to build a common action plan satisfying a set of objectives under the same previous constraints. The debate modelling is better suited to practical situations where each service controls his own know-how, and only shares the part of his knowledge which is required achieving the global objective, defending his own interests and not necessarily revealing his weaknesses. The debate model can be also seen as a decision-support system used by a service (or a group of services) during the real debate to optimize his own interest. In the two cases fuzzy logic and MCDA tools are used to represent the relationship between actions and objectives satisfaction.

This is a preliminary work. In order to complete our debate modelling, several points in our approach deserve to be deepened in the future works. For instance, we are currently working on refining and finalizing the knowledge updating phase. In addition, we are working to provide an illustrative example of the approach. Furthermore, we will work to establish links between this work and existing approach dealing with debate modelling as the fields of game theory and theory of argumentation.

References

1. Dyer, J.S.: Multiattribute utility theory (maut). In: Multiple Criteria Decision Analysis, pp. 285–314. Springer (2016)
2. Grabisch, M., Greco, S., Pirlot, M.: Bipolar and bivariate models in multicriteria decision analysis: Descriptive and constructive approaches. *International Journal of Intelligent Systems* **23**(9), 930–969 (2008)
3. Greco, S., Figueira, J., Ehrgott, M.: Multiple criteria decision analysis. Springer's International series (2005)

4. Imoussaten, A., Montmain, J., Trouset, F., Labreuche, C.: Multi-criteria improvement of options. In: European Society for Fuzzy Logic and Technology. p. 1 (2011)
5. Imoussaten, A., Trouset, F., Montmain, J.: Improving performances in a company when collective strategy comes up against individual interests. In: EUSFLAT Conf. pp. 904–911 (2011)
6. Keeney, R.L., Raiffa, H.: Decision with multiple objectives (1976)
7. Krantz, D.H., Luce, R.D., Suppes, P., Tversky, A.: Foundations of measurement (additive and polynomial representations), vol. 1 (1971)
8. Montmain, J., Labreuche, C., Imoussaten, A., Trouset, F.: Multi-criteria improvement of complex systems. *Information Sciences* **291**, 61–84 (2015)