MYRIAD: a tool for Preference Modeling Application to Multi-Objective Optimization

Christophe Labreuche[1] **& Fabien Le Huédé**[1]

THALES Research and Technology France,
Route Départementale 128, 91767 Palaiseau cedex - France
{fabien.lehuede;christophe.labreuche}@thalesgroup.com

Abstract. We present a software called Myriad for MCDA, based on a two-additive Choquet integral in the context of multi-criteria preference handling in optimization problems. The parameters of the model are determined from the preferential information provided by the decision maker. The model can be used in the Eclair CP solver to solve multi-criteria combinatorial problems. A solution can then be assessed by the model in Myriad, the software helps the decision maker in understanding the flaws and assets of the solution.
Keywords: Multi-Criteria Combinatorial Optimization, Choquet integral.

1 Introduction

Handling complex preferences is still difficult in combinatorial optimization problems. When preferences between solutions can be taken from an expert according to the solutions values on a set of attributes, Multi-Criteria Decision Aiding (MCDA) proposes several approaches for expertise modeling. Recently, we integrated one of these models in CP in order enhance multi-criteria combinatorial optimization [9, 11]. In this paper, we focus essentially on the tools that are developed in Thales to enable both constructing and using a preference model.

Multi-Criteria Decision Aiding (MCDA) aims at helping a decision maker (DM) in making up his mind about the assessment of an option or the selection of the best option among several alternative options, on the basis of several decision criteria. This difficult task requires the use of a preference model and a process. The model represents the way the options are assessed and compared. It formalizes the expertise constructed from the interview of a DM. The process formalizes the interaction between the DM and the preference model. On the one hand, the DM provides some preferential information from which the optimal values of the parameters of the preference model are deduced. This is the *disaggregation* phase. On the other hand, the preference model is run on prototypical or real options, and the results are presented to the decision makers. This is the *aggregation* phase. These two phases need to be instrumented by a software.

Within the Thales group, we deal with many MCDA applications:

- Evaluation problems such as trainee's evaluation in which one shall give an assessment of each option together with a synthesis of its main assets and flaws,

- Acquisition problems (products' design) in which one shall assess the quality of a product on the basis of some criteria and provide some recommendations about the *most efficient* way to improve the product,
- Classification problems such as threat or risk assessment, or classification from information coming from several sources, in which each option shall be assigned to a category,
- Optimization problems in which the cost function depends on multiple criteria and the set of options is so wide that it is described by combinatoric techniques.

Since these applications concern mainly experts know-how, the underlying model must be versatile and elaborate enough to encompass most commonly encountered decisional behaviors. Conversely, the model shall not be too complicated so that the DM is able to understand the model and the recommendations made from it. This leaded us to construct an approach based on Multi-Attribute Utility Theory (MAUT) [2] where an overall utility is computed for each option, and the use of the two-additive Choquet integral as an aggregation function. The 2-additive Choquet integral is a good compromise between versatility and ease to understand. In addition, as the MAUT model establishes a score for a solution, it offers good integration properties for multi-criteria optimization techniques. We present here a tool named MYRIAD developed at Thales for MCDA applications based on a two-additive Choquet integral.

Section 2 describes the model used. The disaggregation phase is dealt with in Section 3 whereas the aggregation one is considered in Section 4. The principles of the integration of the Choquet integral in CP are introduced in Section 5. The last section shows how these tools can be applied on a multi-criteria trip planning problem.

2 General framework

For the sake of simplicity, we assume in this part that the set $N = \{1, \dots, n\}$ of criteria is organized in a single level of aggregation. The set of attributes is denoted by $X_1, \dots, X_n$. All the attributes are made commensurate thanks to the introduction of partial utility functions $u_i : X_i \to [0, 1]$. The $[0, 1]$ scale depicts the satisfaction of the DM regarding the values of the attributes. An option x is identified to an element of $X = X_1 \times \cdots \times X_n$, with $x = (x_1, \dots, x_n)$. Then the overall assessment of x is given by

$$U(x) = H(u_1(x_1), \dots, u_n(x_n)) \tag{1}$$

where $H : [0, 1]^n \to [0, 1]$ is the aggregation function. The overall preference relation $\succeq$ over X is then

$$x \succeq y \iff U(x) \geq U(y) \ .$$

The two-additive Choquet integral is defined for $(z_1, \ldots, z_n) \in [0,1]^n$ by [5]

$$H(z_1, \ldots, z_n) = \sum_i \left(v_i - \frac{1}{2} \sum_{j \neq i} |I_{i,j}| \right) z_i + \sum_{I_{i,j}>0} I_{i,j}\, z_i \wedge z_j + \sum_{I_{i,j}<0} |I_{i,j}|\, z_i \vee z_j \tag{2}$$

where v_i is the relative importance of criterion i and $I_{i,j}$ is the interaction between criteria i and j, $\wedge$ and $\vee$ denote the min and max functions respectively. Assume that $z_i < z_j$. A positive interaction between criteria i and j depicts complementarity between these criteria (positive synergy) [5]. Hence, the lower score of z on criterion i conceals the positive effect of the better score on criterion j to a larger extent on the overall evaluation than the impact of the relative importance of the criteria taken independently of the other ones. In other words, the score of z on criterion j is *penalized* by the lower score on criterion i. Conversely, a negative interaction between criteria i and j depicts substitutability between these criteria (negative synergy) [5]. The score of z on criterion i is then *saved* by a better score on criterion j.

Figure 1 shows two representations of the Choquet integral on two criteria. The first curve represents a case where the interaction between the two criteria is positive (they are said to be *complementary*). It models a preference relation where a solution has to be good on both criteria to be considered good. On the contrary, the right hand curve models *substitutive* criteria (i.e., negative interaction). In this case, a solution is considered good by the expert as soon as it is good on one criterion.

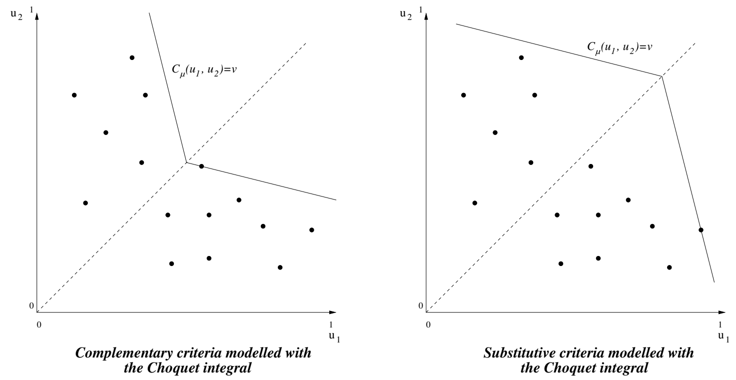

Fig. 1. Level curves of the Choquet integral for the aggregation of two criteria

3 The disaggregation phase

As said earlier, the aim of the disaggregation phase is to construct a preference model such as (1) combined with (2) from interviews of the DM. Three stages are needed.

The first stage is the structuring phase. It consists in determining the stakes that are involved and identifying the potential viewpoints. Cognitive maps can be used to help in making the right criteria emerge in a bottom-up approach. We obtain a hierarchy structure of the criteria where the root corresponds to the overall aggregation (highest level of aggregation) and the leaves are the attributes. This hierarchy is entered in Myriad.

The second stage aims at constructing the partial utility functions u_i. When aggregation function H is a weighted sum, the independence of the criteria makes it possible to *separate* the criteria and focus on a criterion i for the construction of its associated utility function u_i, *forgetting* the other criteria and the multi-criteria nature of the problem during this phase. The MACBETH approach [1] is a method that is consistent in a measurement standpoint for the construction of the interval scale u_i. Due to the use of an aggregation function allowing interaction between criteria, isolating the criteria cannot be carried out so that one cannot ask to the DM, information regarding directly u_i. It has been showed in [8] that the utility functions u_i can be constructed from information relating on the overall preference relation $\succeq$, generalizing the MACBETH approach (see Figure 2).

Let us give a little bit more details on that. An interval scale is given up to a dilation and a shift. In order to fix the two degrees of freedom in each utility function u_i, the idea is to identify two elements of X_i that are *perfectly satisfactory* for the DM (denoted by $\mathbf{1}_i$) and *unacceptable* for the DM (denoted by $\mathbf{0}_i$), and to fix $u_i(\mathbf{1}_i) = 1$, $u_i(\mathbf{0}_i) = 0$. We have shown in [8] that asking questions about the difference of satisfaction between the two acts $(x_i, \mathbf{0}_{N\setminus i})$ and $(y_i, \mathbf{0}_{N\setminus i})$, for all $x_i, y_i \in X_i$ enables us to construct u_i whatever the interaction between criteria may be. In the Macbeth methodology, the decision maker is asked to give an assessment of the difference of satisfaction between any two acts $(x_i, \mathbf{0}_{N\setminus i})$ and $(y_i, \mathbf{0}_{N\setminus i})$ (for all $x_i, y_i \in X_i$) in the ordinal scale composed of 6 elements: $\{$*very small, small, mean, large, very large, extreme*$\}$ [1].

The last stage concerns the determination of the parameters of the aggregation model, that is the importance and interaction indices of the two-additive Choquet integral. The DM enters in MYRIAD preferential information about each aggregation level composed of a mix of the following three types of data.

- the DM prefers an option to another one;
- the DM gives an overall assessment to an option;
- the DM gives some information directly the importance or the interaction indices, for instance a criterion is more important than another one, a criterion is important (i.e. $v_i > 1/n$), or the interaction between two criteria is positive.

An algorithm then finds the optimal parameters associated with previous information. The algorithm implemented in MYRIAD is close to the method developed by J.L. Marichal [5]. The information provided by the DM may be inconsistent in the sense that there might be no value of the parameters satisfying the information provided by the DM. In this case, the preferential information that is at the origin of the inconsistency are extracted and showed to the DM.

Once the model is thoroughly specified, an interpretation of this model can be displayed to the DM, in terms of the most/less important criteria, and the pairs of criteria for which the interaction is positive/negative. The DM has then a better insight on the preference model obtained. He can turn back to stage 2 or 3 if he desires to change the model.

4 The aggregation phase

The aggregation step is essential for Evaluation or Acquisition problems. It consists in applying the preference model obtained previously on one or several options. This step is not restricted to the computation of the utilities of each option on all elementary criteria and aggregation functions. In order that the assessments and comparisons carried out during the aggregation phase help the DM in validating or rejecting some preference information, the results must be explained. The DM wants to understand precisely the results of the computations by the model. The major point concerns the aggregation part.

A graphical representation of the aggregation by the two-additive Choquet integral is presented in MYRIAD. Let us look at expression (2). From the monotonicity properties on the importance and interaction indices, one has

$$\forall i \in N \ , \quad v_i - \frac{1}{2}\sum_{j\neq i} |I_{i,j}| \geq 0 \ ,$$

$$\sum_{I_{i,j}>0} I_{i,j} + \sum_{I_{i,j}<0} |I_{i,j}| + \sum_i \left(v_i - \frac{1}{2}\sum_{j\neq i} |I_{i,j}| \right) = 1$$

Hence all coefficients appearing in (2) are non-negative and they sum-up to one. Expression (2) is thus a convex sum $H(z) = \sum_k \alpha_k h_k(z)$, where only three types of decisional behaviors are present: $z_i \wedge z_j$ (intolerant behavior characterizing a positive synergy between i and j), $z_i \vee z_j$ (tolerant behavior characterizing a negative synergy between i and j), and z_i (linear term corresponding to criterion i taken alone).

One can "plot" the result of H in a pie-chart in which each segment represents an elementary behavior h_k (see Figure 6). The aperture of the segment related to h_k is $2\pi\alpha_k$, and this segment is covered at rate $h_k(z)$. Hence, the surface covered by this segment is $\alpha_k h_k(z)$ so that the overall covering of the disk is precisely $H(z)$. This graphical representation makes it easy to understand why result $H(z)$ is rather high (the disk is pretty filled up) or low (the disk is almost empty). This graphical representation is displayed in MYRIAD.

A semantic explanation is also determined. This argumentation aims at presenting to the elementary decision behaviors that are really at the origin of the evaluation made [7]. These arguments are returned in one or more sentences in MYRIAD (see Figure 6).

In some circumstances, the options are not fixed and can be modified and improved in some ways. We can think of trainees that can improve themselves, or of an industrial product that we want to be as close as possible to the customers' needs. In this case, the DM is not only interested in an assessment of the options. This appears essential in the acquisition cycle. Some recommendations shall provide the most promising improvement ways. We develop an approach based on a sensitivity analysis performed on each coalition of criteria [4,6]. The determination of the criteria on which it is the most rewarding to improve an option is far more complicated than just itemizing the criteria on which the option has bad marks. Actually, it depends on the aggregation function H. If the aggregation is the minimum operator (the DM is very intolerant), it is clear that the only criterion on which an act shall be improved is the criterion that has the smallest score. If the aggregation function is the maximum (the DM is very tolerant), the option shall be improved first on the criterion that has the largest score. Finally, if the aggregation function is a weighted sum, acts shall be improved first on the most important criterion. In [6], we have defined an indicator $\omega_A(H,x)$ which measures *the worth to improve option x w.r.t. H on some criteria A* as follows

$$\omega_A(H,x)=\int_0^1 \frac{H\big((1-\tau)x_A+\tau, x_{N\setminus A}\big)-H(x)}{E_A(\tau,x)}\,d\tau$$

where $E_A(\tau,x)$ is the effort to go from the profile x to the profile $((1-\tau)x_A + \tau, x_{N\setminus A})$. Function $\omega_A(H,x)$ depicts the average improvement of H when the criteria of coalition A range from x_A to 1_A divided by the average effort needed for this improvement. We assume generally that E_A is of order 1, that is $E_A(\tau,x) = \tau\sum_{i\in A}(1-x_i)$. The expression of $\omega_A(H,x)$ when H is a Choquet integral is given in [6]. We recommend the DM to improve of coalition A for which $\omega_A(H,x)$ is maximum (see Figure 7).

5 Optimization phase

For combinatorial optimization problems, the integration of the general Choquet integral in Constraint Programming has been introduced in [9]. The same principles can be used to integrate any multi-criteria aggregation function [12]. Integrating this model reduces the multi-criteria optimization problem into a mono-objective maximization problem.

In summary, we consider n utility variables $u_1,\dots,u_n\in[0,1]$ that are connected with the attributes of the problem by the utility functions (modeled with piecewise linear constraints in our case). The global evaluation that will be optimized is modeled by the variable $y\in[0,1]$. We aim to establish and propagate the equality between the y variable and the aggregation of $u_1,\dots,u_n$ with a function $\mathcal{H}$. Mathematically, we want to enforce:

$$y=\mathcal{H}(u_1,\dots,u_n)$$

Let us denote *Aggregation*$(\mathcal{H}, y, \{u_1,\dots,u_n\})$ a global constraint that aims at enforcing this relation. The propagation of *Aggregation* can be achieved by maintaining the arc-B-consistency on this constraint. Let us denote $[\underline{x},\overline{x}]$ the domain of a variable x.

Definition 1. *(Arc-B-consistency) [10]*
Given a constraint c over q variables $x_1, \ldots, x_q$, and a domain $d_i = [\underline{x_i}, \overline{x_i}]$ for each variable x_i, c is said to be "arc-B-consistent" if and only if for any variable x_i and each of the bound values $v_i = \underline{x_i}$ and $v_i = \overline{x_i}$, there exist values $v_1, \ldots, v_{i-1}, v_{i+1}, \ldots, v_q$ in $d_1, \ldots, d_{i-1}, d_{i+1}, \ldots, d_q$ such that $c(v_1, \ldots, v_q)$ holds.

Arc-B-consistency is weaker than the *arc-consistency* property. This is verified when, for each value in the domain of each variable, there is a set of values in the domain of the other variables that verifies the constraint.

If we suppose the monotonicity and the continuity of the function $\mathcal{H}$, we can verify that an *Aggregation* constraint is arc-B-consistent by checking two conditions per variable:

Proposition 1. *(Arc-B-consistency with respect to the Aggregation constraint) Let $\mathcal{H}$ be an increasing continuous aggregation function and C =Aggregation($\mathcal{H}, y, \{u_1, \ldots, u_n\}$) be an Aggregation constraint. C is Arc-B-consistent if and only if the following four conditions hold:*

(A) $\underline{y} \geq \mathcal{H}(\underline{u_1}, \ldots, \underline{u_n})$
(B) $\overline{y} \leq \mathcal{H}(\overline{u_1}, \ldots, \overline{u_n})$
(C) $\forall k \in \{1, \ldots, n\} \ : \ \mathcal{H}(\overline{u_1}, \ldots, \overline{u_{k-1}}, \underline{u_k}, \overline{u_{k+1}}, \ldots, \overline{u_n}) \geq \underline{y}$
(D) $\forall k \in \{1, \ldots, n\} \ : \ \mathcal{H}(\underline{u_1}, \ldots, \underline{u_{k-1}}, \overline{u_k}, \underline{u_{k+1}}, \ldots, \underline{u_n}) \leq \overline{y}$

Note that for such a continuous function on numeric variables then checking arc-B-consistency also ensures that the constraint is arc-consistent [10].

Nevertheless, integrating a multi-criteria aggregation function in a CP solver raises the problem of defining search heuristics to quickly find good solutions. Since criteria are often contradictory, it is difficult to find a single search strategy that is good for all of them. In [11], we proposed a search framework that alternates various search strategies (one per criterion) to build more efficient and robust algorithms in multi-criteria optimization.

6 Application to the trip planning problem

We present an application of the softwares on a trip planning problem. This problem consists in constructing a tour in a country during a given number of days. A tour is composed of cities (one city per day in the tour), activities in the cities (two per day) and hostels. It has to verify maximum distance constraints between consecutive cities as well as an overall maximum distance constraint for the tour. Each activity is classified in one category among {*Sightseeing, Museum, Sport, Entertainment*}. The objective here is to find a tour that offers various kind of activities, as much comfort as possible in the hostels and minimizes the accommodation costs.

The quality of a tour is given by a two level multi-criteria model. First of all, a tour is assessed with respect to the diversity of its activities. Then the overall evaluation aggregates the activities aspects with the cost and comfort considerations.

6.1 The disaggregation phase

The criteria hierarchy is given in Figure 2. Letters u, c and a denote universes (i.e. attributes), criteria and aggregation functions respectively.

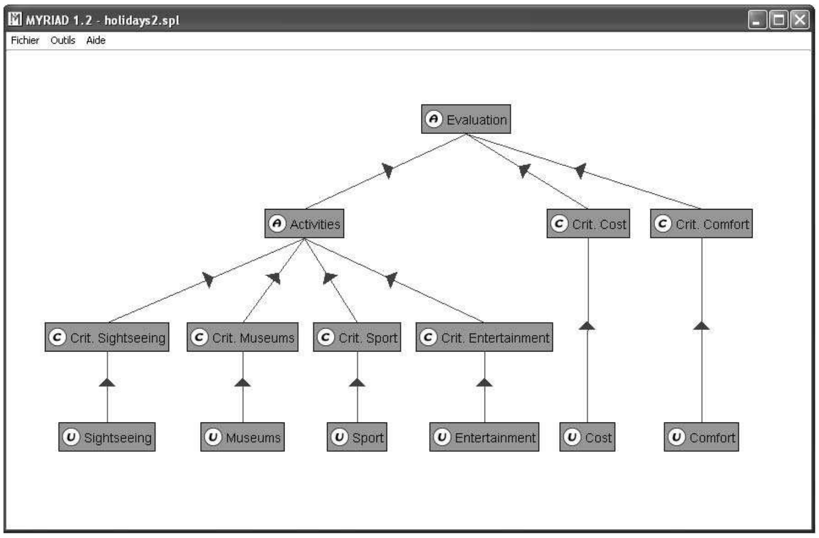

Fig. 2. Criteria hierarchy.

Utility functions The evaluation on an activity criterion relies on the average number of time this class of activity is planned per day. The same utility function is given for each class. For a given class of activity, the $\mathbf{0}$ element corresponds to no occurrence in the planning and the $\mathbf{1}$ element corresponds to one occurrence per day in average. For a class of activity i, the DM feels that the difference between $(\mathbf{0}_i, \mathbf{0}_{-i})$ and $(0.25, \mathbf{0}_{-i})$ and the difference between $(0.5, \mathbf{0}_{-i})$ and $(\mathbf{1}_i, \mathbf{0}_{-i})$ are small. On the contrary, the difference between $(0.25, \mathbf{0}_{-i})$ and $(0.5, \mathbf{0}_{-i})$ is considered large. Hence, considering for instance criterion "Sightseeing", we obtain the following values : $u_1(0) = 0$, $u_1(0.25) = 0.2$, $u_1(0.5) = 0.8$ and $u_1(1) = 1$ (see Figure 3). We obtain similar utility functions on the other activity criteria.

Regarding the other criteria, the cost criterion relies on the average room price per day. For the comfort point of view, only the minimum of all hostels category in the tour is considered. According to these attributes, the second stage of the disaggregation phase results in the utility functions of Figure 4.

Aggregation "Activities" Considering the aggregation of the vector of activity criteria (*Sightseeing, Museum, Sport, Entertainment*):

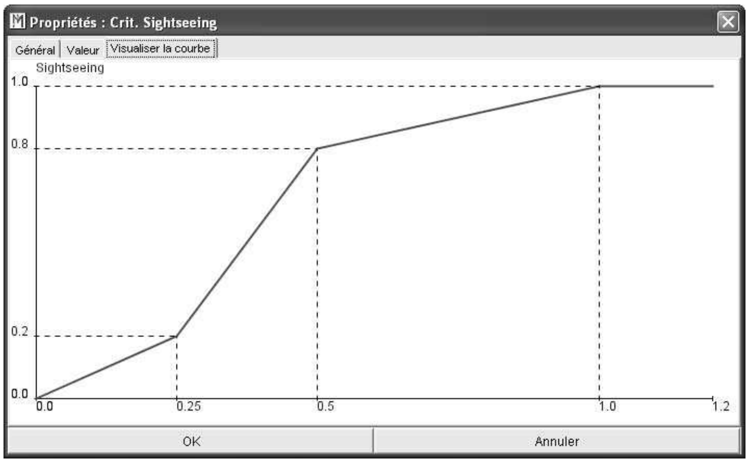

Fig. 3. The utility function on criterion "Sightseeing".

- The DM first expresses a **complementarity between all criteria**, giving four examples of comparisons between virtual alternatives:

$$\forall i \in \{1, \ldots, 4\}, U((1_i, 0_{-i})) < U((0.25, 0.25, 0.25, 0.25)$$

- Then, the DM gives the following examples:

$$U(1, 0, 1, 1) > U(0.5, 0.5, 1, 1)$$

$$U(0, 1, 1, 1) > U(0.5, 0.5, 1, 1)$$

  to express **redundancy between Sightseeing and Museum**. Two other similar comparisons are given to express **redundancy between Sport and Entertainment**.

This gives the preferential information used to compute the parameters of the 2-additive capacity (Figure 5).

The following tables give respectively the Shapley index v_i (relative importance of criterion i) and the interaction index $I_{i,j}$ obtained.

criterion	v_i
Sight.	0.25
Mus.	0.25
Sport	0.25
Ent.	0.25

$I_{i,j}$	Sight.	Mus.	Sport	Ent.
Sight.	0	-0.15	0.175	0.175
Mus.		0	0.175	0.175
Sport			0	-0.15
Ent.				0

From these results we can conclude that all criteria are equally important. Considering the interaction indices:

- As required, the pairs of criteria (Sightseeing, Museum) and (Sport,Entertainment) are redundant. This means that the Activities criterion will be well satisfied if in the above pairs, one of the criteria is satisfied.

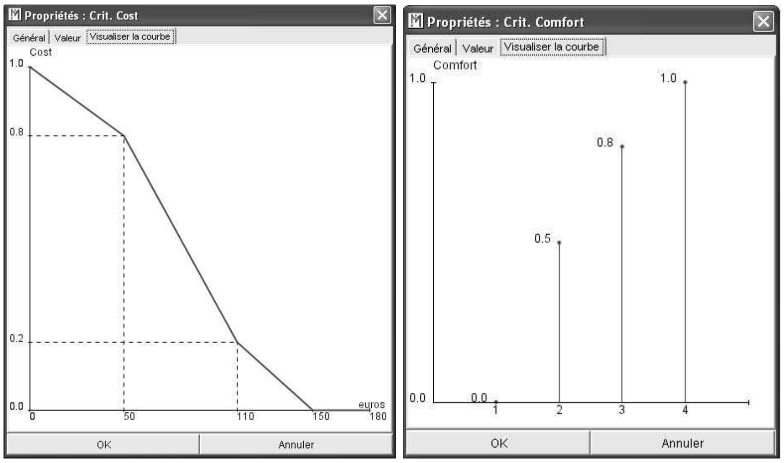

Fig. 4. Utility functions on criteria "Cost" and "Comfort".

- Four pairs of criteria have a positive interaction, which means that for each pair, both criteria need to be *simultaneously* satisfied in order to get a good evaluation for Activities.
- There is no veto nor favor among the set of criteria. This means that one cannot make a quick analysis to see whether the richness is either good or bad, looking only at one or two criteria.

Aggregation Evaluation Evaluation aggregates the Activities, Cost and Comfort criteria.

- First of all, the DM stipulates that **Activities is a veto**:

$$U(0, 1, 1) = 0$$

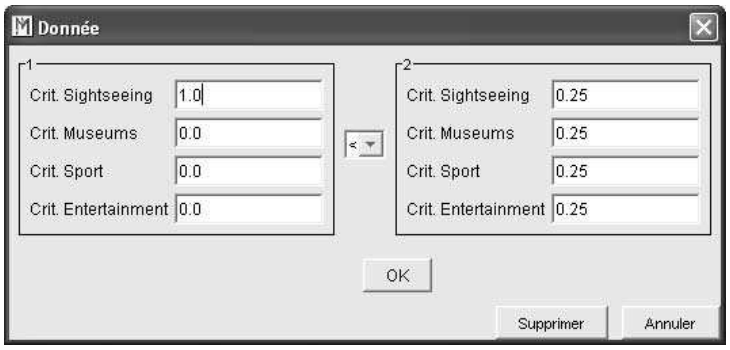

Fig. 5. Example of preferential information.

In other words, a trip that does not propose any activity is not interesting, whatever may be the scores on the other criteria.

- This information also brings:

$$U(0.3, 0.6, 0.6) < U(0.6, 0.3, 0.3)$$

but, reducing the performance of criteria Cost and Comfort in the right alternative causes the left one to be preferred:

$$U(0.3, 0.6, 0.6) > U(0.6, 0, 0)$$

- Then, the DM indicates the following **relative importance** for the criteria:

$$\textit{Importance(Activities)} > \textit{Importance(Cost)} > \textit{Importance(Comfort)}$$

- Finally, he specifies the **tradeoff between Cost and Comfort** with the following comparison on the attribute space:

$$(1, 1, 1, 1, 50, 2) \equiv (1, 1, 1, 1, 90, 4)$$

The parameters calculated for these examples are given in the following tables:

criterion	v_i
Act.	0.64
Cost	0.2
Comf.	0.16

$I_{i,j}$	Act.	Cost	Comf.
Act.	0	0.4	0.32
Cost		0	0
Comf.			0

As for the previous aggregation, Myriad provides an Analysis of these parameters. Concerning the importance of criteria, it is clear that the most important criterion is Activities. The less important one is Comfort. The most complementary pairs of criteria are (Act.,Cost) and (Act.,Comf.). Activities is a strict veto and there are also lighter veto effects on Cost and Comfort. This mean that as soon as one criterion is not well satisfied (especially if it is Activities), the solution cannot be good.

This analysis helps in knowing what are a priori the most important criteria and ways to combine criteria in order to find good solutions or design new products.

6.2 Optimization phase

The above preference model is then implemented in the Eclair solver. The implemented constraint model is quite simple and mainly based on the *element* constraint. These models are run on an instance composed of 11 cities and 2 to 6 activities and hostels per city to find a 6 day trip planning. An optimal solution is found for this evaluation in 40 s. with the following characteristics:

Attribute	Value
Nb. Sightseeing activities	3
Nb. Museums	3
Nb. Sport activities	3
Nb. Entertainment activities	3
Accommodation cost	410
Minimum comfort	3

Criterion	Value
Sightseeing	0.8
Museums	0.8
Sport	0.8
Entertainment	0.8
Activities	0.8
Cost	0.62
Comfort	0.8
Evaluation	0.73

The DM can then simply take the solution if it is considered satisfactory, or he can operate an aggregation phase in Myriad to investigate further on this solution.

6.3 The aggregation phase

As said before, the aggregation phase is mainly used on Evaluation or acquisition problems to compare solutions.

In optimization, the DM can go a little deeper in the solution. Figure 6 shows an explanation of the overall assessment of the solution found with the same technique as described in [7], together with the pie chart we told about in Section 4. The pie chart clearly shows the segment on which the solution behaves well or not. The DM can react on that. If he disagrees on some points, he can go back to the disaggregation phase and change or enrich the preferential information. This is an interesting tool to make the DM react about the model.

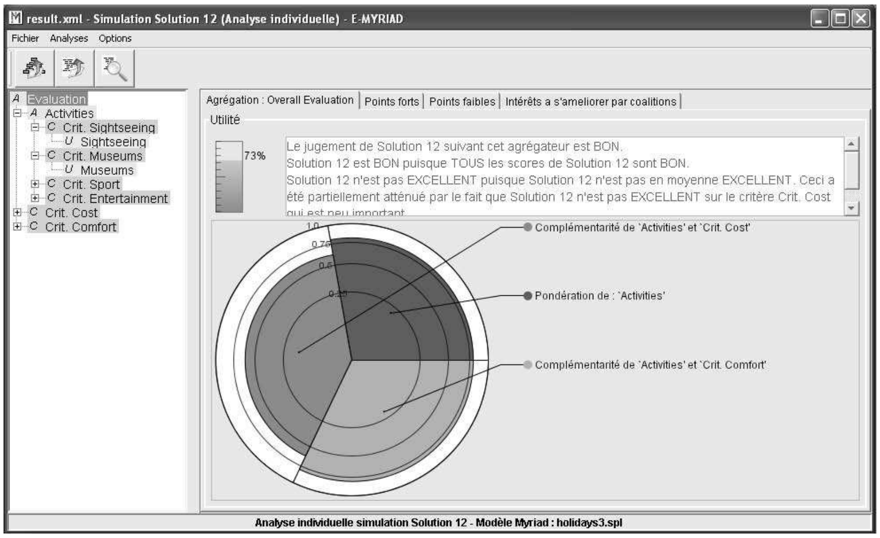

Fig. 6. Assessment of the optimization result.

When the DM validates the evaluation made, he may be interested in the sensibility analysis so that to help him in enriching his data to allow better solutions to be constructed. He wants to know on which criteria it is the most rewarding to improve the solution in order to improve as much as possible its evaluation. To this end, we present the values of the worth indicator ω described in Section 4.

Coalitions	worth
Cost	0.65
Sightseeing & Museums & Sport & Entertainment & Comfort	0.37

The recommendation is that the solution should be improved first on "Cost". This may not always be the criterion on which the solution has the worst score. It has a strong positive synergy with Activities and has a smaller score than this criterion so this recommendation makes sense. All the other criteria have the same satisfaction level and are implied in many complementarity phenomena. Hence, improving only one will not improve the conjunctive decision terms between them. It is more rewarding to improve them simultaneously than only one, even for a higher value.

Thus, the DM has greater interest in looking for new 3* hostels with better prices than for new activities.

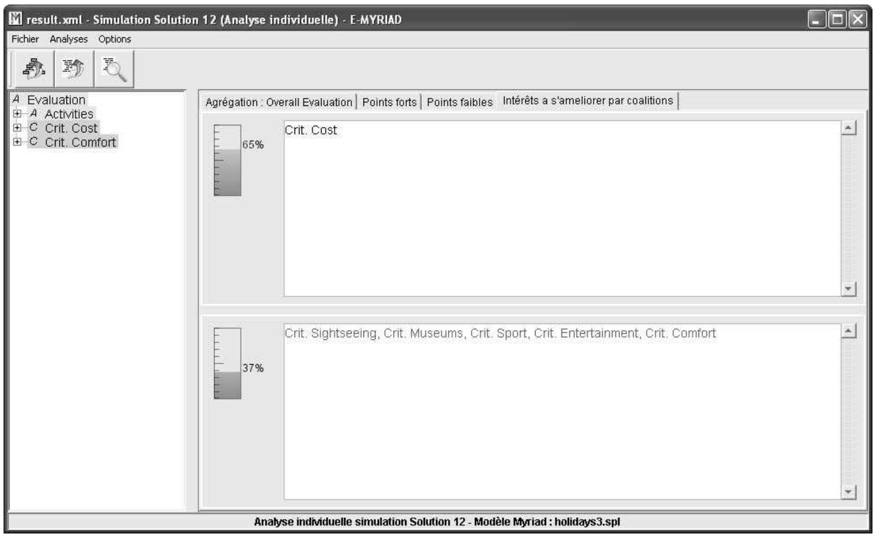

Fig. 7. Promising improvement recommendations for the solution

7 Conclusion

In this paper we tried to introduce the modeling and solving of a multi-criteria optimization problems as it is performed in Thales. Although the followed multi-criteria methodology is not new in MCDM, we tried to illustrate it on a detailed case study in order to give a good view of its principles to the CP community. We also recalled that this model integrates quite naturally in CP as it uses a single objective function that aggregates the problem criteria.

References

1. C.A. Bana e Costa, and J.C. Vansnick. Applications of the MACBETH approach in the framework of an additive aggregation model. J. of Multi-Criteria Decision

Analysis 6 (1997) 107-114.
2. R.L. Keeney and H. Raiffa. *Decision with Multiple Objectives.* Wiley, New York, 1976.
3. M. Grabisch and C. Labreuche. Fuzzy measures and integrals in MCDA. J. Figuera, S. Greco, M. Erghott (Eds.), Multiple Criteria Decision Analysis: state of the art surveys, Sringer, 2005.
4. C. Labreuche, and M. Grabisch. How to improve acts: an alternative representation of he importance of criteria in MCDA. Intern. J. of Uncertainty and Knowledge Based Systems, 9(2):145-157, 2001.
5. M. Grabisch, T. Murofushi and M. Sugeno, Fuzzy measures and integrals, Physica-Verlag, Heidelberg, New York, 2000.
6. C. Labreuche. Determination of the criteria to be improved first in order to improve as much as possible the overall evaluation. Conf. IPMU 2004, pp. 609-616, Perugia, Italy.
7. C. Labreuche. Argumentation of the results of a multicriteria evaluation model in individual or group decision making. Conf. EUSFLAT 2005, submitted.
8. C. Labreuche, and M. Grabisch. The Choquet integral for the aggregation of interval scales in multi-criteria decision making, Fuzzy Sets & Systems, 137:11-26, 2003.
9. Le Huédé, F., Gérard, P., Grabisch, M., Labreuche, C., Savéant, P.: Integration of a Multicriteria Decision Model in Constraint Programming. In Brabble, B., Koehler, J., Refanidis, I., eds.: Proceedings of the AIPS'02 Workshop on Planning and Scheduling with Multiple Criteria, Toulouse, France (2002) 15–20
10. Lhomme, O.: Consistency techniques for numerical CSPs. In: Proceedings of IJCAI 1993, Chambery, France (1993) 232–238
11. Le Huédé, F., Grabisch, M., Labreuche, C., Savéant, P.: MCS - a new algorithm for Multicriteria Optimisation in Constraint Programming. Special issue on Multiobjective Discrete and Combinatorial Optimization, Annals of OR (2005) *(submitted)*
12. Le Huédé, F.: Intégration d'un modèle d'Aide à la Décision Multicritère en Programmation Par Contraintes. PhD thesis, Universitée Paris 6 (2003)