Hospital rankings: a new challenge for MCDA and preference learning?

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Abstract. The aim of this paper is to convince the MultiCriteria Decision Aid (MCDA) and Preference Learning communities to investigate and to contribute in the development of methodologies dedicated to hospital ranking. To do so, we present the French hospital ranking and show how these rankings can be built properly through two existing methods: decision tree and ELECTRE Tri.

Key words: MCDA; Machine Learning; Hospital rankings; Decision tree; ELECTRE TRI

1 Introduction

MultiCriteria Decision Aid (MCDA) aims at representing the preferences of a Decision-Maker (DM), or a group of Decision-Makers, over a finite set of alternatives evaluated on several criteria often conflicting. Many softwares implementing MCDA methods have been developed and most of them have proved their efficiency in real applications, e.g. MACBETH [1], MYRIAD [10]. One of the problem statement treated by MCDA is the elaboration of rankings.

Since many years, there exist some hospital rankings published by newspapers. In France, three newspapers publish every year their hospital rankings. In reality they do not evaluate the global hospital, but only its surgery specialties. In our knowledge, two other countries publish regularly hospital rankings:

- *United Stated of America*: these rankings are published each year by a news paper called Usnews[2]. The methodology used is based on the weighted sum and developed by the Research Triangle Institute (RTI international), a scientific organism. The report of 129 pages about this methodology is free available[3].
- *United Kingdom*: the rankings are elaborated by the National Health Service (NHS)[4].

From the view of MCDA, we were interested in the methodologies used in French hospital rankings. We studied them in details, but we were disappointed because all the French methodologies are just presented in few lines (not more than a half page) compared to the Usnews methodology which is presented in more than 100 pages. Furthermore there is no relevant information concerning MCDA aspects. The main reason is that, behind these rankings, there are only journalists (François Malye and Jérôme Vincent for "Le point") and some very small consulting companies (Le Guide santé for "Le Figaro Magazine" and Santé Value "Le Nouvel Observateur") without knowledge about good best practices of MCDA. In general, to improve their reputation, the hospitals need and wish to know each year their rank in the published hospital rankings. Most of these hospitals choose to advertise this rank, when they are good, in their website. Health governments agencies also can use these rankings to identify which are the "weak" hospitals.

The challenge we propose here is to use all the scientific background of MCDA to properly structure these real and concrete applications. We propose to identify relevant indicators (criteria) with machine learning methods such as decision tree. The opportunity to test also preference learning algorithms should be investigate. Let us recall that preference learning is a subfield in machine learning in which the goal is to learn a predictive preference model from observed preference information [8]. Because the databases of indicators filled by the French hospitals are public and available under some minor conditions, we can solve this actual problem by giving a valid methodology where algorithms and methods of the two communities are applied.

The paper is organized as follows: we present in Section 2 the three French hospital rankings, especially in weight loss surgery and we give our propositions in Section 3.

2 About French hospital rankings

In France, hospital rankings are published each year by three newspapers: "Le Nouvel observateur"[5], "Le Point"[6] and "Le Figaro Magazine"[7]. To establish these rankings, they manipulate data coming from some official databases like HOSPIDIAG[8]. This latter, a tool developed by the national performance support agency (Agence Nationale d'Appui à la Performance : ANAP), sheds light on a given facility, bringing together data from different databases (PMSI, annual institutional statistics, etc.) in a single tool [2]. The databases contain around eighty indicators which are likely to be filled each year by all the hospitals. In French health system, there are approximately 1600 hospitals classified as public, nonprofit private and commercial private.

All the three newspapers propose a ranking per surgery specialty, for instance a ranking of weight loss surgery. Our analysis in this paper is focused on weight loss surgery. The remarks and comments developed here are valid for all the specialties.

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[2] http://health.usnews.com/best-hospitals
[3] http://www.usnews.com/pubfiles/BH_2014_Methodology_Report_Final_Jul14.pdf
[4] http://www.nhs.uk
[5] http://classement-hopitaux.nouvelobs.com/
[6] http://hopitaux.lepoint.fr/
[7] http://sante.lefigaro.fr
[8] http://hospidiag.atih.sante.fr

2.1 Weight loss surgery

Bariatric surgery[9] (weight loss surgery) includes a variety of procedures performed on people who are obese. Weight loss is achieved by reducing the size of the stomach with a gastric band or through removal of a portion of the stomach (sleeve gastrectomy or biliopancreatic diversion with duodenal switch) or by resecting and re-routing the small intestines to a small stomach pouch (gastric bypass surgery).

To identify the "best" hospitals in weight loss surgery, the newspapers combine a part of the following indicators:

1. (CR_1) *Volume of activity:* it is the number of stays of all patients with respect to the value of care and some homogeneous price.
2. (CR_2) *Activity*: number of procedures performed during one year. "Le Point" supposes that if an hospital has a good score on activity then its teams are more trained and often have good results. This opinion is not totally shared by some other experts who estimate that a good score on the activity of an hospital does not imply necessarily that its teams are best. In this case, one should also investigate if this hospital does not focus on getting grants of the government because in France some grants depend on the activity.
3. (CR_3) *Average Length Of Stay (ALOS)*: a mean calculated by dividing the sum of inpatient days by the number of patients admissions with the same diagnosis-related group classification. A variation in the calculation of ALOS can be to consider only the length of stay during the period under analysis. If an hospital is more organized in terms of resources then its ALOS score should be low.
4. (CR_4) *Notoriety*: Its corresponds to the reputation and attractiveness of the hospital.
   For "the Nouvel Observateur", the attractiveness of the hospital depends on the distance between the hospital and the patient's home. This distance is considered significant if it is more than fifty kms. Its reputation reflects the gradual isolation of patients: the more they come from far away, the more the reputation of the institution is important.
   The notoriety indicator of "Le Point" is a percentage of patients treated in the hospital but living in another French administrative department. More the percentage increases, more the hospital is attractive.
5. (CR_5) *Heaviness*: it is a percentage measuring the level of resources consumed (equipment, staff, ...) in the hospital.
6. (CR_6) *Quality score of French National Authority for Health (HAS)* [10]: It is the score (between • and • • • • •) obtained by the hospital after the accreditation and quality visit made by the experts of HAS.
7. (CR_7) *% of By-Pass*: It is the percentage of surgical procedures using gastric bypass system.
8. (CR_8) *Technicality*: this particular indicator measures the ratio of procedures performed with an efficient technology compared to the same procedures performed with obsolete technology. The higher the percentage is, the more the team is trained in advanced technologies or complex surgeries.

[9] http://en.wikipedia.org/wiki/Bariatric_surgery
[10] French National Authority for Health (HAS) aims to improve quality and safety of healthcare. The objectives are to accredit health care organizations and health professionals, to produce guidelines for health professionals (practices, public health, patient safety), to develop disease management for chronic conditions, to advise decision makers on health technologies (drugs, devices, procedures), and to inform professionals, patients, and the public.

Remark 1. *"Le Nouvel Observateur" use the term activity as a composite indicator of ALOS (CR_3) and volume of activity (CR_1).*

2.2 The 2013 results

The rankings given by "Le Nouvel observateur" [12] take into account, in the same tables, both public and private hospitals. They argue that this logic is in spirit of their readers. In terms of MCDA, this justification of the choice of this set of alternatives appears weak and seems to be only a "marketing argument". Table 1 presents the ranking of only 20 public hospitals (among the first hundred hospitals evaluated) in weight loss surgery published by "Le Nouvel observateur" in 2013. These hospitals are evaluated on five indicators: Volume of activity (CR_1), ALOS (CR_3), % of By-Pass (CR_7), Heaviness (CR_5) and Notoriety (CR_4). In their methodology, they mention that they chose indicators which are most significant in terms of medical innovation, but nothing is said about the concrete selection of such indicators. The last column, F_O, concerns the aggregation function used. Again, nothing is said about this function and how they calculated the score of each hospital. We imagine that it could be a simple weighted sum.

Hospitals	CR_1	CR_3	CR_7	CR_5	CR_4	F_O
Georges-Pompidou	406	5.2	55	77	95	**19.3**
Bichat	203	7.8	75	83	94	**18.9**
Ambroise-Paré	193	6.6	90	83	94	**18.7**
Strasbourg	330	6.2	84	79	45	**18.2**
Nice	351	6.5	94	79	20	**18.1**
Nancy	230	6.9	87	81	76	**17.9**
Louis-Mourier	154	5.0	81	81	27	**17.9**
Pitié-Salpetrière	127	6.0	75	79	92	**17.8**
Laon	299	1.8	0	54	58	**17.7**
Lille	233	6.2	68	83	30	**17.4**
Colmar	192	3.5	97	77	19	**17.4**
Conception	287	3.1	28	63	22	**17.3**
Caen	152	6.7	89	79	63	**17.1**
Toulouse	173	4.3	63	77	87	**17.0**
Antibes	181	5.6	96	77	23	**16.9**
Edouard-Herriot	89	4.9	52	81	38	**16.9**
Havre	115	2.7	78	74	9	**16.5**
Jean-Verdier	116	6.7	44	79	32	**16.4**
Timone adultes	69	5.0	32	81	36	**16.3**
Orleans	131	6.1	69	81	41	**16.4**

Table 1. The best 20 hospitals in Weight loss surgery (2013). Source: "Le Nouvel Observateur" [12]

"Le Point" [13] have analyzed 952 hospitals in their rankings. Just 50, 40, 30, 25 or 20 best hospitals per specialty were published. In Table 2, the ranking published in 2013 concerns the 20 best hospitals in weight loss surgery evaluated on Activity (CR_2), (Notoriety) (CR_4) ; ALOS (CR_3) and Technicality: (CR_8). The last column of the table refers to the scores obtained by using an aggregation function F_P. Like the previous newspaper, nothing is said about this function and nothing about the elaboration of criteria. They only indicate that it is a weighted sum.

Among 1308 hospitals analyzed by the last newspaper, "Le Figaro Magazine" [11], only 830 have been evaluated. The rankings published concern the 10 best hospitals per specialty and per French region. We show in Table 3 some best hospitals in eight regions. The criteria used are: Activity (CR_2) and Quality score of French National Authority for Health (HAS) (CR_6). The ranking is based on

Hospitals	$CR_{\mathbf{2}}$	$CR_{\mathbf{4}}$	$CR_{\mathbf{3}}$	$CR_{\mathbf{8}}$	F_P
Bichat	372	80	7.8	94	**17.84**
Nice	253	19	8.2	95	**17.59**
Nancy	208	60	8	90	**17.37**
Ambroise-Paré	140	85	6.5	96	**17.23**
Colmar	165	14	3.8	99	**17.20**
Caen	167	47	6.7	96	**17.14**
Strasbourg	289	25	6.3	82	**17.13**
Georges-Pompidou	394	80	5.5	56	**17.06**
Lille	247	18	4.8	63	**17.02**
Antibes	156	13	5.5	96	**16.75**
Orleans	167	35	6.7	86	**16.66**
Rouen	237	29	5.1	48	**16.55**
Jean-Verdier	174	40	9.7	82	**16.45**
Conception	332	19	3.8	24	**16.44**
Louis-Mourier	166	51	5.3	86	**16.36**
Poissy/St Germain	192	34	4.1	60	**16.30**
Montpellier	297	25	5.6	33	**16.24**
Toulouse	181	73	4.6	50	**15.94**
Amiens	170	28	3.8	10	**15.63**
Laon	242	23	1.4	0	**15.54**

Table 2. The best 20 hospitals in Weight loss surgery (2013). Source: "Le Point" [13]

Hospitals	$CR_{\mathbf{2}}$	$CR_{\mathbf{6}}$
Georges-Pompidou	878	● ● ● ● ●
Bichat	384	● ● ●●
Saint-Louis	285	● ● ●●
Rouen	300	● ● ●●
Laon	277	●●
Lille	271	● ● ●●
Caen	179	●●
Nantes	175	●●
Limoges	103	● ● ●
Rennes	89	●●
Montpellier	353	●●
Nice	263	●●
Orleans	206	● ● ●●
Tours	122	● ● ●
Jean-Mermoz Lyon	312	●●
Sens	140	● ● ●
Nancy	305	●●
Colmar	169	●●
Toulouse	352	● ● ●●
Bordeaux	133	●●

Table 3. The best 20 hospitals in Weight loss surgery (2013). Source: "Le Figaro Magazine" [11]

a lexicographic order ($CR_{\mathbf{6}} \ll CR_{\mathbf{2}}$), but nothing about how these rankings were elaborated.

We are not really surprised if the interesting information for researchers about methodologies used by these three newspaper are poor and not available. Indeed, in France, the sales of newspapers devoted to hospital ranking are often the best of the year. So there exist a real competition between the three organisms. Therefore, each of them has to keep secret its methodology.

3 Our propositions

We think that, the *elaboration of hospital ranking* is a practical application where algorithms of MCDA and Machine Learning can be applied. Compared to the newspapers, the academic background of researchers of these two domains can help to better understand this kind of real problem and to propose some valid methodologies. Furthermore, there exists available real data to test these methods and algorithms or to elaborate some benchmarks. Of course, to have a good interpretation of results and indicators, there is a need to work with experts from health systems. Let us give below some suggestions indicating how to proceed.

3.1 Machine learning aspects

In hospital rankings problems, machine learning algorithms can help to determine relevant indicators to use, i.e. to determine which relevant criteria, in each specialty, are needed in the MCDA methodologies. In this case, we can use predictive algorithms like decision tree algorithms.

Decision tree learning [9, 15] is one of the most successful techniques for supervised classification learning. It builds classification or regression models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes. So the goal is to create a model that predicts the value of a target variable based on several input variables. It is closely related to the fundamental computer science notion of "divide and conquer". A decision node has two or more branches. Leaf node represents a classification or decision. The topmost decision node in a tree which corresponds to the best predictor called root node. Decision trees can handle both categorical and numerical data.

To illustrate our suggestion, let us apply the J48 algorithm of the suite of machine learning software *Weka*[11] to data of hospital rankings given in Tables 1 and 2. J48 is an implementation of the C4.5 algorithm developed by Ross Quinlan [14] to generate a decision tree.

By considering column F_P in Table 2, we can compute two classes from the "Le Point" ranking of weight loss surgery like this: the class VeryGood for hospitals with a score between 16.5 and 18, and the class Good for those having a score between 15 and 16.49. The idea here is to predict these two classes by applying a decision tree algorithm. The Figure 1 shows the results of this example by applying the

[11] Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes. Weka is open source software issued under the GNU General Public License. `http://www.cs.waikato.ac.nz/ml/weka/`.

algorithm J48 of Weka. Only 12 hospitals among 20 have been correctly classified. The decision tree obtained is given by Figure 2. In this classification problem, ALOS seems the only relevant indicator.

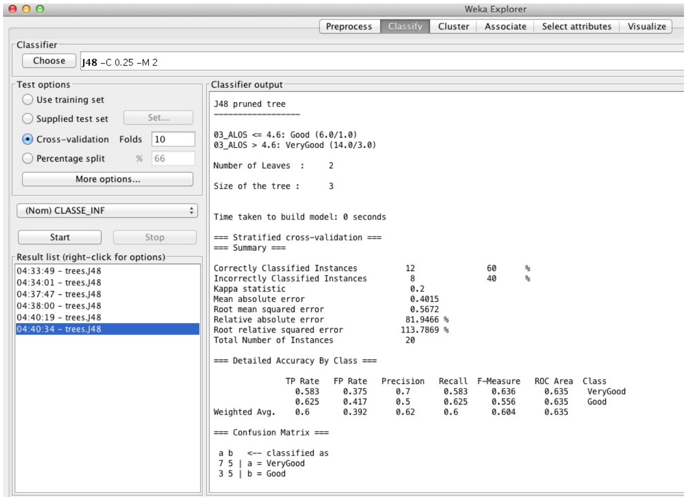

Figure 1. Applying J48 in Weka from "Le Point" ranking

Figure 2. Decision tree from "Le Point" ranking

From the "Le Nouvel Observateur" ranking in weight loss surgery (see Table 1), lets us define two classes as follows: the class VeryGood for hospitals with a score belonging to the interval [19.5;17.5], and the class Good for those having a score between 15.5 and 16.49. By applying the algorithm J48 of Weka, Figure 3 shows that only 11 hospitals among 20 have been correctly classified. In the decision tree produced and represented in Figure 4, ALOS seems to be an irrelevant indicator.

3.2 MultiCriteria Decision Aid aspects

As indicated in [3], we have to start with a a number of crucial questions when trying to build an evaluation (ranking) model in MCDA [5, 6]. These questions, known as good practices, are:

1. What is the definition of objects to be evaluated?
2. What is the purpose of the model? Who will use it?
3. How to structure objectives?
4. How to achieve a "consistent family of criteria"?
5. How to take uncertainty, imprecision, and inaccurate definition into account? All the French hospital ranking fail this last point.

After answering these questions, the choice of the suitable MCDA method will be another problem. Some methodologies are based on the weighted sum (e.g. methodologies of "Le Point" and "Le Nouvel Observateur"), because this function is simple and understandable by many persons who are not experts in MCDA.

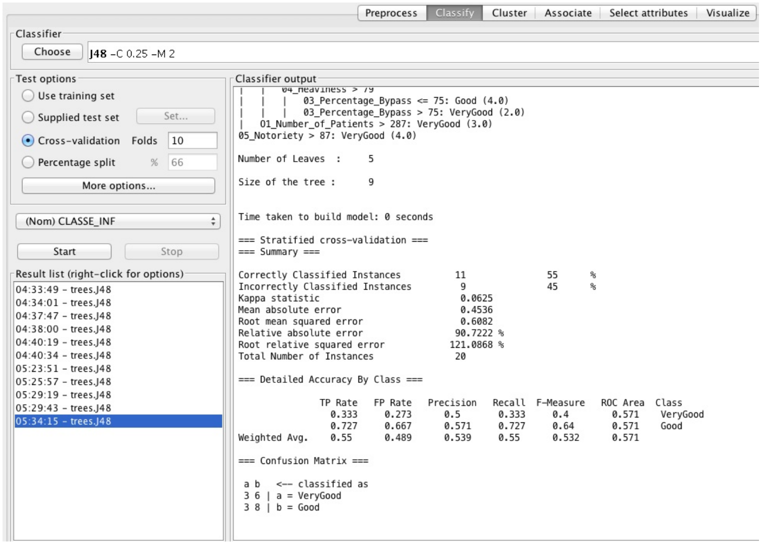

Figure 3. Applying J48 in Weka from "Le Nouvel Observateur" ranking

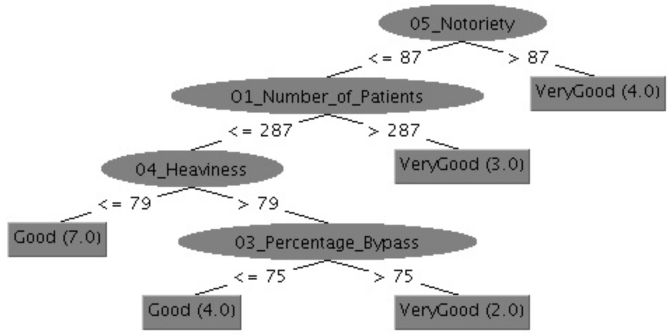

Figure 4. Decision tree from "Le Nouvel Observateur" ranking

If we consider the following four hospitals evaluated on three criteria: Notoriety, ALOS and Technicality:

	Notoriety	ALOS	Technicality
Hospital 1	35	80	90
Hospital 2	37	80	89
Hospital 3	35	40	90
Hospital 4	37	40	89

It seems reasonable to give these preferences: hospital 1 is strictly prefer to the hospital 2 (if ALOS is "weak", it is preferable to have an hospital with good evaluation in Technicality) and hospital 4 is strictly prefer to hospital 3 (If ALOS is "good", we prefers in this case an hospital with good evaluation in Notoriety). But it is well known that these aggregation function cannot be model by a weighted sum because they contain some interactions between criteria [4]. Therefore it will be useful to study the dependence between criteria in hospital rankings and then introduce other aggregation functions instead of weighted sum.

We end this section by showing that it is possible to apply an outranking method in this type of application. Because our aim is not to show that the rankings obtained by applying these methods are better than those presented above, we just chose ELECTRE TRI method as an example. ELECTRE TRI [7] is a MCDA method which deals with the sorting problematic. We present hereafter a simple version of ELECTRE TRI, without any preference thresholds and veto, which is sufficient in our context.

Let us denote by $A = \{a_1; a_2; \ldots; a_m\}$ a set of m alternatives or options, $N = \{1; 2; \ldots; n\}$ a set of n criteria or points of view, $C = \{C_1; C_2; \ldots; C_t\}$ a set of ordered categories (C_1 is the worst one and C_t is the best one) and $B = \{b_1; \ldots; b_{t-1}\}$ a set of profiles (reference alternatives which can be fictitious) that separate consecutive categories. Each category C_i, except C_1 and C_t, is limited by two profiles: b_i is the upper limit and b_{i-1} is the lower limit.

The MCDA ELECTRE TRI method assigns alternatives to categories by using the concept of outranking relation $\mathcal{S}$ on $A \times B$. An alternative $a_i \in A$ outranks a profile $b_h \in B$ (denoted $a_i \; \mathcal{S} \; b_h$) if it can be considered at least as good as the latter (i.e., a_i is not worse than b_h), given the values (performances) of a_i and b_h at the n criteria. If a_i is not worse than b_h in every criterion, then it is obvious that $a_i \; \mathcal{S} \; b_h$. However, if there are some criteria where a_i is worse than b_h, then a_i may outrank b_h or not, depending on the relative importance of those criteria and the differences in the evaluations (small differences might be ignored). Roughly speaking,

$$a_i \text{ outranks } b_h \; (a_i \; \mathcal{S} \; b_h) \Leftrightarrow \sum_{1}^{n} k_j \; c_j(a_i, b_h) \geq \lambda.$$

Where

- $c_j(a_i, b_h) = \begin{cases} 1 \text{ if } a_i \;\succsim_j\; b_h \\ 0 \text{ otherwise} \end{cases}$.

  The relation $a_i \;\succsim_j\; b_h$ means that the value of a_i on the criterion j is at least as good as the value of b_h on the same criterion j.
- k_j is the importance (weight) of criterion j such that $\sum_{1}^{n} k_j = 1$.
- λ is the cutting level i.e. a threshold that indicates whether the credibility is significant or not. This parameter is often taken between 0.5 and 1.

Hence ELECTRE TRI assigns the alternative a_i to the highest category C_h such that a_i outranks b_{h-1} i.e.
for $h = 2, \ldots, t-1$,

$$\begin{cases} a_i \text{ belongs to } C_1 \Leftrightarrow \; \text{not}(a_i \; \mathcal{S} \; b_1) \\ a_i \text{ belongs to } C_h \Leftrightarrow a_i \; \mathcal{S} \; b_{h-1} \text{ and not}(a_i \; \mathcal{S} \; b_h), \\ a_i \text{ belongs to } C_t \Leftrightarrow a_i \; \mathcal{S} \; b_{t-1} \end{cases}$$

We applied ELECTRE TRI on the data given in Tables 1 and 2 by using the software IRIS[12]. This dataset is translated in the performance tables given in Figures 5 and 6.

For each problem, we consider two categories C_1 and C_2. The profile between these two categories are presented in Figures 7 and 8. For instance, the profile considered in "Le Point" ranking in weight loss surgery is $b_1 = (150; 60; 5; 80)$. Note that, $g(b_1)$ in Figure 8 corresponds to the values of b_1.

The assignments proposed by ELECTRE TRI is given in Figure 10 and 9 with the values of weights of criteria (denoted by k1, K2,

[12] IRIS is a software implementing the ELECTRE TRI method. It is free available at http://www.lamsade.dauphine.fr/spip.php?rubrique64

Actions | Fixed Par. | Bounds | Constraints

Action	ELow	EHigh	CR1	CR3	CR7	CR5	CR4
Georges-F	2	2	406	5.2	55	77	95
Bichat	2	2	203	7.8	75	83	94
Ambroise	2	2	193	6.6	90	83	94
Strasbour	1	2	330	6.2	84	79	45
Nice	1	2	351	6.5	94	79	20
Nancy	1	2	230	6.9	87	81	76
Louis-Mo	1	2	154	5.0	81	81	27
Pitié-Salp	1	2	127	6.0	75	79	92
Laon	1	2	299	1.8	0	54	58
Lille	1	2	233	6.2	68	83	30
Colmar	1	2	192	3.5	97	77	19
Conceptic	1	1	287	3.1	28	63	22
Caen	1	2	152	6.7	89	79	63
Toulouse	1	2	173	4.3	63	77	87
Antibes	1	1	181	5.6	96	77	23
Edouard-I	1	2	89	4.9	52	81	38
Havre	1	1	115	2.7	78	74	9
Jean-verd	1	1	116	6.7	44	79	32
Timone A	1	1	69	5.0	32	81	36
Orleans	1	1	131	6.1	69	81	41

Figure 5. Performance table of "Le Nouvel Observateur" in weight loss surgery

Actions | Fixed Par. | Bounds | Constraints

Action	ELow	EHigh	CR2	CR4	CR3	CR8
Bichat	2	2	372	80	7.8	94
Nice	2	2	253	19	8.2	95
Nancy	1	2	208	60	8	90
Ambroise-	2	2	140	85	6.5	96
Colmar	1	2	165	14	3.8	99
Caen	1	2	167	47	6.7	96
Strasbour	1	2	289	25	6.3	82
Georges-I	1	2	394	80	5.5	56
Lille	1	2	247	18	4.8	63
Antibes	1	2	156	13	5.5	96
Orleans	1	2	167	35	6.7	86
Rouen	1	2	237	29	5.1	48
Jean-Verc	1	2	174	40	9.7	82
Conceptic	1	2	332	19	3.8	24
Louis-Mo	1	2	166	51	5.3	86
Poissy	1	2	192	34	4.1	60
Montpellie	1	2	297	25	5.6	33
Toulouse	1	1	181	73	4.6	50
Amiens	1	2	170	28	3.8	10
Laon	1	2	242	23	1.4	0

Figure 6. Performance table of "Le Point" in weight loss surgery

	CR1	CR3	CR7	CR5	CR4
g(b1)	250	5.5	60	70	80
q1	0	0	0	0	0
p1	0	0	0	0	0
v1					
MAX/min	1	1	1	1	1

Figure 7. Profile of "Le Nouvel Observateur" in weight loss surgery

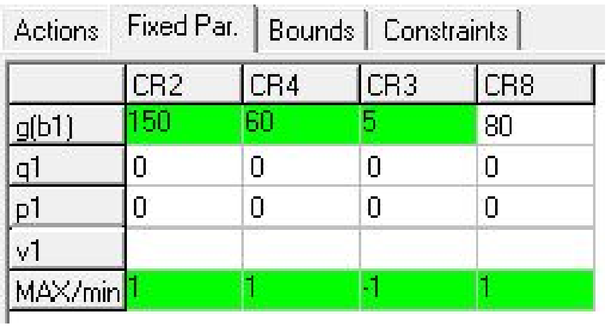

Figure 8. Profile of “Le Point” in weight loss surgery

...) and the value of the threshold λ (denoted by lamda). For instance, ELECTRE tri assigns in the same category the five last hospitals whenever you take one of the two rankings given in Tables 2 and 1.

Figure 9. Assignments of hospitals in “Le Point” ranking related to weight loss surgery

4 Conclusion

We analyzed French hospital rankings, especially in weight loss surgery, made by three newspapers. There is very little official information about how these rankings are made, and the process is not transparent. We showed that this problem is a practical problem where tools of preference learning and MCDA communities (e.g. decision tree and ELECTRE TRI method) can be used in a complementary way.

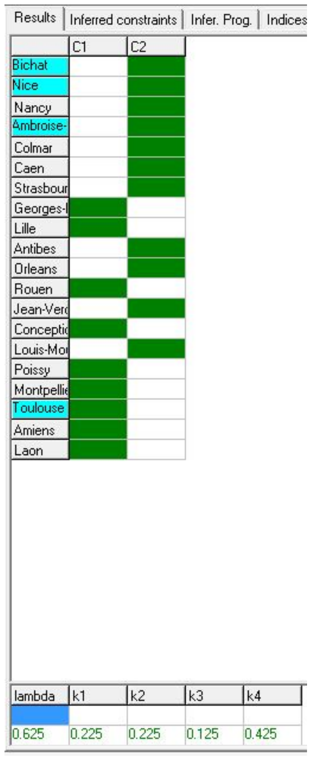

Figure 10. Assignments of hospitals in “Le Nouvel Observateur” ranking related to weight loss surgery

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