PERIODICA POLYTECHNICA SER. HUM. and SOC. SCI. VOL. 2, NO. 1, PP. 5-18 (1994)

COMBINATION OF CASE-BASED REASONING AND MULTI-ATTRIBUTE UTILITY THEORY IN LEGAL EXPERT SYSTEMS

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Received: Sept. 1, 1993

Abstract

Case-Based Reasoning (CBR) has become a relevant alternative to the classical rule-based approach in expert systems because it gives valuable information about the current problem by comparing it to previously analysed problems. CBR, however, does not make superfluous the analysis of problems in themselves. This paper presents a novel framework, called Case-Based Decision Making (CBDM), which is a special combination of CBR and Multi-Attribute Utility Theory (MAUT). The framework is applied to simulate judges' legal decision making by modelling case law and the 'doctrine of precedent'. First, the current decision problem is transformed into a decision matrix with two columns which is compared to matrices generated from previous problems, and we measure the distances between them. Finding a suitable distance measure is crucial. Decision, however, is not only based on nearness, but we also consider preference relations on alternatives and cases. Finally, global similarity between cases is defined from distance and preference. The technique can be used for any decision problem in which the number of alternatives can be reduced to two. The existence of a 'case-base' filled with previously evaluated problems is essential. The model has been implemented in a spreadsheet-based computer program, DEBORAH, that operates as a decision support tool allowing the user to set optional measures and functions for experimentation.

Keywords: case-based reasoning, multi-attribute utility theory, similarity measure, distance measure, legal expert system.

1. Introduction

Case-based reasoning (CBR) seems natural to be used in many applications areas, e.g. in law as a model of case law. The effectiveness of CBR, however, can be improved if it is combined with other, mathematically more established theories. The most typical combinations are with rule-based reasoning (GOLDING and ROSENBLOOM, 1991; RISSLAND and SKALAK, 1989). In our novel architecture Multi-Attribute Utility Theory (MAUT) was chosen to be amalgamated with CBR.

Our task is to develop an expert system model for judges' legal decision making process concerning civil law cases. On the legal side, we have to consider not only the system of case law and the 'doctrine of precedent', but also the elements of judges' subjective judgments. In legal decision making based on the doctrine of precedent, there are two steps in rough: 1. selecting precedents 2. drawing a decision using the most similar precedent. These steps will be modelled in this paper.

In case law, the more similar cases are, the more chance for them to have the same outcome. First, we determine the distances between the current case and other previous cases. Suppose that there is a decision space where cases are represented. The usual method in CBR approach is that the distance value is one-dimensional and the nearest case is selected, i.e. the one which has the smallest distance value from the current one. Thus, the outcome of the nearest case would also be the outcome of the current case. There are some problems with this model:

1. It is too rough to map the difference of many-dimensional objects into a single numeric value and draw a decision from that.

2. Since law is not an area which could be represented in a topological space, the classical measures (e.g. Euclidean) cannot be used in themselves to map the real similarity of cases. We shall distinguish nearness and similarity. Thus, we have to define a specific similarity function and then tune it to obtain the most appropriate results.

3. The most similar case may be a borderline one and therefore cannot be declared anything certain even about a very similar case to it.

In our approach, to tackle these problems (except the third one) we also apply a classical normative decision method, MAUT. When we consider a legal problem according to the classical decision analysis, we choose one alternative of two. In order to do that, one has to define a preference relation on the set of alternatives and decide which of them is preferred. MAUT gives some techniques how this preference relation should be determined. In a lot of cases, however, preference cannot be found, but there is indifference between the alternatives. How can we decide even so? CBR can assist. Section 6 below presents experimental evidence that in fact the combination of MAUT and CBR provides improved and more reliable decisions than any of these methods in itself.

Let us summarize the steps of the CBDM model (see *Fig. 1*). First, we transform legal cases into $q \times 2$ dimensional matrices of numerical values using MAUT. The next step is the application of CBR. We map thec subtraction of matrices of the current case and one of the previous cases into a *distance value*. Distance between decision matrices reflects the nearness of two cases, but not the real similarity of them. Afterwards, a MAUT step comes again, we also define a *deviation value* using utility functions.

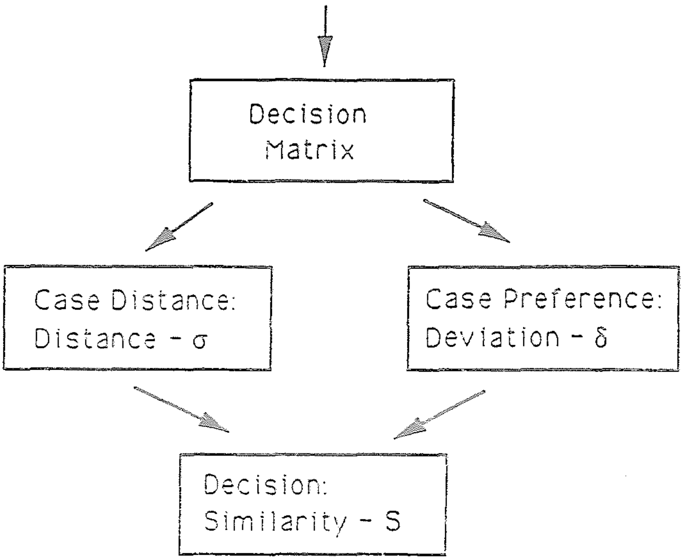

Fig. 1. The process of Case-Based Decision Making

Deviation means the difference in judgments of the alternatives of a case. Finally, in the decision step, *similarity* is defined and we select one of the parties as the winner of the case using the outcome of the most similar precedent.

Concerning the user, our *aim* is decision support and not the substitution of judges' decisions (VÁMOS, 1991). CBDM is a framework which the user can customize. The user can experiment with parameters to tune them. Thus, the user can consider which are the parameter values of borderline cases, i.e. the values of an indifferent judgment, and how parameters can be modified to get preference to one of the alternatives. Subjective elements in legal decision making can also be simulated by tuning the parameters. Our approach is also feasible to check consistency of decisions which were made in the past.

For what kind of *decision problems* can our method be used? There is only restriction concerning the number of alternatives. We can manage only two of them. This means one has to reduce the set of alternatives into a set of two by applying some filtering methods. Of course, this limitation does not mean constraint in legal cases.

The model has been implemented in a spreadsheet-based computer program, DEBORAH, that operates as a decision support tool allowing the user to set optional measures and functions for experimentation in a particular area. The potential *application area* of this system can be any decision problem where there is a memory of previously analysed cases. Legal and medical applications seem natural, since there can be found large databases of precedent legal cases, and the medical records of previous visits, respectively. But of course, there are other application areas as well, e.g. intelligent data retrieval where matches are not perfect, but the system should find similar occurrances. The record of major changes in stock exchange share prices with underlying reasons can also be considered a case-base.

2. Formalism

Suppose that we confront with a general decision problem over *two* alternatives. The following concepts and notation will be used throughout the paper. We consider q *attributes* to describe the features of problems. The *alternatives* of a problem will be denoted by their vectors: $\mathbf{x}^T = (x_1, x_2, \ldots, x_q)$, and $\mathbf{y}^T = (y_1, y_2, \ldots, y_q)$, respectively, where $x_i, y_i \in R$ are the utility values of the alternatives with respect to (w.r.t.) the ith attribute. Semantically we differentiate between them as $\mathbf{x}$ is the first alternative and $\mathbf{y}$ is the second one. The alternatives of the current problem are denoted by $\mathbf{a}$ and $\mathbf{b}$.

Let $\mathbf{w}^T = (w_1, w_2, \ldots, w_q)$ a weight vector, where $w_i \in [0 \ldots 1]$ is the importance weight of the ith attribute.

DEFINITION 1. By a *case* we shall mean the $q \times 2$ decision matrix (decision table) of a problem. The two columns will be distinguished and we will refer to them as the *first column* and the *second column*. Thus, the current case will be denoted by $C = [\mathbf{a}, \mathbf{b}]$.

DEFINITION 2. Let $\{P_1,\ P_2,\ \ldots,\ P_n\}$ be called *case-base*, the set of decision matrices of previously decided cases. The case-base, in our application, contains cases of a particular legal domain, that is matrices of the same form and interpretation.

The cases in the case-base belong to one or several of the following categories:

a) Every case in the case-base will be called *previous case* since they were decided previously and have unambiguous outcome.
b) *Precedent cases* are previous cases which are near enough to the current case. Distance will be precisely defined in Section 4.
c) *Relevant precedent* is the most similar precedent case to the current one and its outcome will determine the outcome of the current case. Similarity will be defined in Section 6.

DEFINITION 3. Let $\Omega_{()}$ be called *outcome function*, which gives the outcome of a previously decided case:

$$\Omega : R^q \times R^q \rightarrow \{1, 2\}.$$

An outcome '1' means in law that the plaintiff won and '2' means the defendant, respectively. The outcome of every previous case in the memory is explicitly stored, thus this function is in fact a retrieving operator.

It is important to emphasize that cases with equal matrices must have the same outcomes in our model. (This is not certainly true in law, because the meaning of concepts and attributes may change from time to time, and judgments of judges may also vary.)

DEFINITION 4. Let $\mathbf{d}$ be an *'intra-case' distance vector* between the columns of a case:

$$\mathbf{d} : R^q \times R^q \rightarrow \{1, 2\}.$$

$$\mathbf{d} = \mathbf{x}\text{-}\mathbf{y} = (x_1 - y_1,\ x_2 - y_2,\ \ldots,\ x_q - y_q)^T.$$

Let us go into details concerning the steps of the CBDM process.

3. Decision Matrix of a Case

The first step of the CBDM process is converting the legal case under investigation into a decision matrix using MAUT. In this paper, this step will not be described in details because there exist well-known methods in MAUT which can be used. (FRENCH, 1988; WINTERFELDT and EDWARDS, 1986). Of course, the process of conversion is not trivial and there are several difficulties in knowledge elicitation, but our focus is not on this.

A legal case can be considered as a decision problem with two alternatives, i.e. the plaintiff and the defendant. Both should be evaluated w.r.t. several attributes. Thus, the main task here is to determine the attributes which express the relevant features of a particular legal domain and by which the judgment of alternatives is influenced. Suppose that a list of attributes is determined and there is no hierarchy among the attributes. The value of the jth alternative w.r.t. the ith attribute is v_{ij}. Since the values of different attributes are of different kinds, there is a need to transform them into the same range. In MAUT, utility functions can be used to make the attribute values comparable. Thus, $u_i(v_{ij})$ is the value of the decision matrix referring to the ith attribute and jth alternative. If $j = 1$ then the ith value will be denoted by x_i, if $j = 2$ then by y_i. By this notation, a decision matrix can be written as $[\mathbf{x}, \mathbf{y}]$. In addition, we have to determine the weights of the attributes. Since there are also well known methods (HWANG and YOON, 1981), we do not go into detail.

When a case-base of a particular legal domain is defined, we take into account that the decision matrices of cases must be comparable, i.e. the matrices must stem from the same list of attributes with the same weights.

4. Distance of Cases

We present an approach for how the distance between matrices with two columns can be measured. General measure functions do not exist, but we have to fix a particular function for each application. Of course, we do not consider the function below as the sole possible measure even for the legal domain.

The task is to determine the degree of nearness between the current case and the previous ones from their differences, and find the *nearest* ones. Instead of defining nearness, a distance measure will be given. The smaller the distance between two cases, the nearer they are.

Initially, the matrix of the current problem, which is denoted by C, and the matrices of previous problems (i.e. cases of the case-base) are given.

DEFINITION 5. Let $\sigma()$ be an *'inter-case' distance function* between $q \times 2$-dimensional cases:

$$\sigma : (R^q \times R^q) \times (R^q \times R^q) \to R.$$

The σ function can be defined in many ways. A possible approach is that one-dimensional values are ordered to cases and the distance between them is the subtraction of these values. We consider another approach more appropriate. Let $C = [\,a,b]$ be the matrix of the current case and $P = [s,t]$ the matrix of an arbitrary previous case. Let $D = C - P = \{d_{ij}\}$ be the *subtraction matrix* of them, i.e. their difference. After thorough experimentation in our particular legal domain, we defined the distance measure as follows:

$$\sigma(P, C) = 10 \log_{10}(1 + z),$$

where $z = \sum_i w_i[d_{i1}^2 + d_{i2}^2]$ and $d_{i1} = a_i - s_i$,

$$d_{i2} = b_i - t_i.$$

What are the criteria for the goodness of this measure? The distance value was defined such that it should meet the following requirement. We determined pairs of hypothetical cases, e.g. a pair is $\{A, B\}$, in which cases are about the same distance from the current case in legal sense. Thus, $\sigma(A, C)$ and $\sigma(B, C)$ must be equal or nearly equal.

The inverse of distance value expresses the degree of nearness between two cases. However, this does not always mean the similarity of cases. Giving a legal example, suppose that in the current case alternatives are totally equal, i.e. $\mathbf{a} = \mathbf{b}$, and there is a previous case P_i in which the two alternatives slightly differ only in one value. Although here $\sigma(C, P_i)$ is very little, P_i is quite different in quality because there is no doubt which of the alternatives should be chosen. Thus, we have to consider additional factors to express legal similarity. Preference over cases will be defined in the next section for this reason.

Our distance measure is not a *metric*, because it does not satisfy the triangle inequality. This comes from the nature of similarity. If A and B are two cases with a subtraction matrix [0 1] and distance $\sigma(A, B) = 3.01$, and B and C are cases with a subtraction matrix [0 1] and distance $\sigma(B, C) = 3.01$, then the subtraction matrix [0 2] of A and C determine larger $\sigma(A, C) = 6.99$ distance than the sum of $\sigma(A, B)$ and $\sigma(B, C)$. This is in accordance with the fact that $\sigma(A, B)$ and $\sigma(B, C)$ mean slight differences, $\sigma(A, C)$, however, means more noticeable difference between A and C.

Those previous cases, which have big distance from the current one, are not in our scope of further investigation. In other words, we determine a limit σ_{max} such that only those cases will be considered *precedents* for which $\sigma(P, C) < \sigma_{max}$. There is no definition for σ_{max} but its value comes from experiments with the actual problem.

5. Preference of Cases

We use now MAUT to define a *preference relation* on the set of decision matrices, which is based on the concept of preference relation on alternatives.

DEFINITION 6. By *preference over two cases* we mean informally that the chance of deciding for the first alternative in the first case is greater than the chance of deciding for the first alternative in the second case.

In legal terms, a case is preferred if the chance of the plaintiff for winning is greater in that particular case than in the other one.

We start our investigation with the decision matrix of the current case. It is important to mention that the decision matrix here is not necessarily the same as the matrix for the evaluation of distance between cases. For the sake of simplicity we regard now the same matrices.

If any of the alternatives has dominance over the other, the decision is unambiguous and we do not have to proceed further.

DEFINITION 7. By *dominance* we shall mean a binary relation between q-dimensional vectors, $\mathbf{x}$ and $\mathbf{y}$, such that $\mathbf{x}$ dominates $\mathbf{y}$ iff $x_i >= y_i$ for all $i = 1, \ldots, q$, and there exists at least one index j for which $x_j > y_j$.

Let us assume that not any of the alternatives dominates the other in the current case. We represent preference between cases by means of a numerical function, called *deviation*. Deviation value, denoted by δ, gives evaluation of the difference vectors of cases and ranks them. The greater the absolute value of δ is, the greater the difference in the global judgment of alternatives.

We experimented with two kinds of functions using a global utility function on vectors, U, to determine δ:

1. $\delta = U(\mathbf{x}) - U(\mathbf{y})$
2. $\delta = U(\mathbf{x}-\mathbf{y}) = U(\mathbf{d})$

As a result of experiments we concluded that the latter formula is more useful for our purposes. We sought the precise deviation function in a form as follows:

$$U(\mathbf{d}) = k \sum_i (w_i \, d_i^p).$$

In our particular legal domain

$$k = 10, \text{ and } p = 1.6$$

values turned out to be the most appropriate.

DEFINITION 8. Let $\delta_{()}$ be a *deviation function* on $q \times 2$-dimensional cases, defined in our model as

$$\delta = 10 \sum_i w_i d_i |d_i|^{0.6}.$$

Thus, preference can be defined by means of δ:

DEFINITION 6a. By *preference over two cases* we mean the following relation:

$$\text{Pref}\,(A, B) \text{ iff } \delta(A) > \delta(B),$$

where A and B are $q \times 2$-dimensional cases.

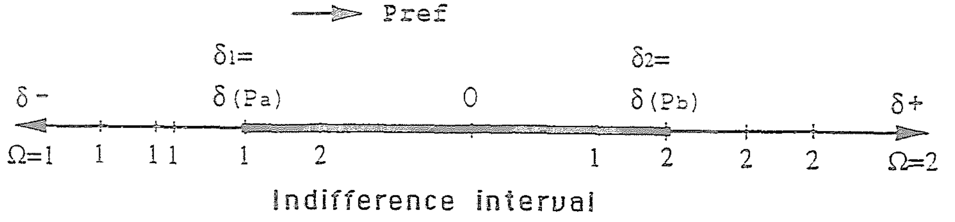

Fig. 2. The scale of deviation values and the indifference interval

When we order deviation values to all the previous cases in the case-base, cases are mapped to the deviation scale (see *Fig. 2*). Note that previous cases with outcome '1' are clustering at the left hand side of the scale, and cases with outcome '2' at the right hand side. In the middle of the scale around 0, however, outcomes of cases are mixed.

DEFINITION 9. By *indifference interval* we mean a segment on the deviation scale. The δ_1 and δ_2 endpoints of the interval are defined as follows (see *Fig. 2*):

$$\delta_1 = \delta(P_a) = \max \delta(P_k),$$

where P_k is any precedent case which satisfies

$$\Omega(P_k) = 1, \text{ and for any } P_i, \text{ Pref}(P_k, P_i) : \Omega(P_i) = 1.$$

$$\delta_2 = \delta(P_b) = \min \delta(P_l),$$

where P_l is any precedent case which satisfies

$$\Omega(P_l) = 2, \text{ and for any } P_i, \text{ Pref}(P_k, P_l) : \Omega(P_i) = 2.$$

From the definition it is trivial that if $\delta(C)$ does not fall into the indifference interval then decision relies on the preference of alternatives. *Fig. 2* shows that

$$\text{if Pref}(P_a, C), \text{ then } \Omega(C) = 1,$$

and

$$\text{if Pref}(C, P_b), \text{ then } \Omega(C) = 2.$$

In these situations decisions are made without using CBR. However, if $\delta(C)$ falls into the indifference interval, preference relation does not help anything in the decision because there are cases with both outcomes to both directions from $\delta(C)$ on the scale.

What are the criteria for the goodness of the deviation function? First, we defined hypothetical cases in which alternatives were not identical but judged about the same. Then, deviation value had to be 0 or slightly around it. On the other hand, the exponent was defined 1.6 and not 2. The reason was that e.g. $[0\ 1\ 1\ 1]^T$ and $[2\ 0\ 0\ 0]^T$ columns should be indifferent.

6. Decision

Having determined the distance values and the deviation value of the current case, we have all information that is needed to the decision. In the following, we discuss the decision process of CBDM.

1. Check of dominance. First, we check whether any of the two alternatives dominates the other in the current case C. If there is dominance, decision is unambiguous.

2. Calculation of distance values. We calculate the distance of the current case from each previous case and determine the minimum requirement for similarity, i.e. σ_{max}. Previous cases for which $\sigma(C, P_i) < \sigma_{max}$ will be considered precedents and will be tested concerning their deviation values.

3. Calculation of the deviation value of the current case, $\delta(C)$, and representing it on the deviation scale.

4. If $\delta(C)$ falls not into the indifference interval then decision is unambiguous.

5. Suppose now that the current case falls into the indifference interval. *Similarity* will be defined to determine the precedent case which is most similar in legal sense to the current case. The closest precedent is a relevant precedent and its outcome will be proposed for the current case. Let us represent every precedent case in a 2-dimensional *similarity space* where the abscissa is the deviation value and the ordinate is the distance value from the current case (see *Fig. 3*). The distance measure of this space is nearly Euclidean, but the square of the distance value is multiplied by m. m is a ratio factor for giving the relative importance of deviation and distance in determining the legal similarity.

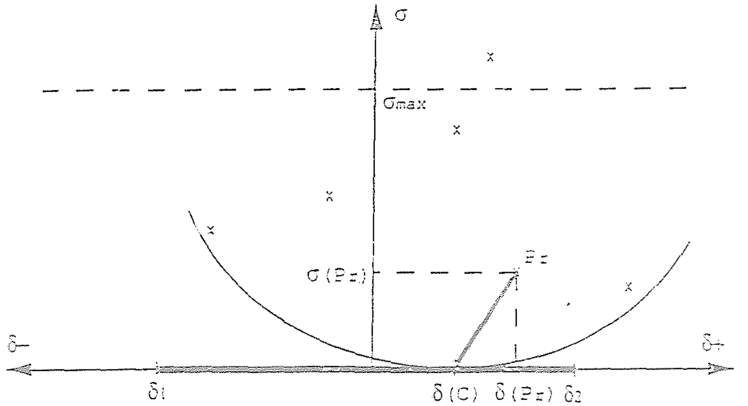

Fig. 3. Similarity space. Previous cases can only appear above the curve.

DEFINITION 10. By *similarity* of two cases, denoted by S, we shall mean

$$S(P_a, P_b) = 1\{[\delta(P_a) - \delta(P_b)]^2 + m[\sigma(P_a, P_b)]^2\}.$$

Thus, P_r is a relevant precedent if

$$S(C, P_r) = \max S(C, P_i) = \max 1\{[\delta(C) - \delta(P_i)]^2 + ms^2(C, P_i)\}.$$

Then $\Omega(C) = \Omega(P_r)$ is the proposed decision.

It is not trivial to determine m. The legal similarity value must reflect the legal expert's similarity judgment. The following test was made. A set of real legal cases were shown to a legal expert and she classified the pairs of cases into four groups: *very similar, similar, slightly similar* and *not similar*. On the other hand, the matrices of cases were compared and the similarities were calculated. As a result we could define intervals on the similarity scale which properly reflected the similarity degrees determined by the expert. However, when the legal expert felt a pair of cases more similar than another pair, our distance measure sometimes gave bigger distance for the first pair. We concluded that the defined similarity measure can properly classify previous cases in relation to the current one.

Concerning the outcome of the current case, it is only advised and not considered as the substitution of the judge's decision. The outcome is uncertain if the relevant precedent is a borderline case, and any change in it may alter its outcome.

7. Implementation

DEBORAH is a spreadsheet-based program for implementing the CBDM process. On the one hand, it contains the case-base, the set of matrices of previously decided problems. On the other hand, DEBORAH is an inference machine which performs the steps of the decision process starting from the matrix of the current case. It calculates distance values, deviation values and similarity values. Finally, the proposed decision is the output of the program.

It was emphasized throughout the paper that CBDM is a framework which allows the user to experiment with the tunable parameters of the system. Which are these options? First, the utility values of matrices can be modified, secondly, the weights of attributes. Moreover, m can be tuned in the similarity function. Of course, all of the functions can also be modified, but their alteration needs mathematical knowledge. We concluded that the system can be a useful decision support tool for law students who can experiment with real and hypothetical cases to analyse the nature of legal similarity.

8. A Legal Example

Suppose that we face a decision problem of *modification of a child custody order* (DANYI, 1989). These cases belong to Family Law. The judge must decide whether the custodial or the noncustodial parent is more appropriate to give sole custody for the mutual child in the future, or joint custody is desirable. We have the knowledge of this particular legal domain, that is a list of the most characteristic attributes was determined and a case-base is available in which dozens of similar cases are stored. ('Similar' here means that all of the previous cases were examined with respect to the same set of attributes as the current case.) The attributes we used are as follows:

1. Child's primary interests (medical, educational considerations) in relation to the parent.
2. Conduct of the parent in relation to the child.
3. Child's (expected) development in the custody of the parent.
4. Wishes of the child (if old enough to express them).
5. Impact of the parent's environment on the child.
6. Improvement in the parent's global impact on the child.
7. Material advantage of living with the parent.
8. Additional factors of indirect impact on the child (e.g. parent's respect for the law, etc.).

An additional attribute is the age of the child, but this was taken into account in another way. The judgment of attributes is different for ages 0–6, 6–12 and 12–18. We consider now only the 6–12-year old children. The weights of attributes here were determined by simply distributing 100 points so that the points reflected the relative importance.

In the first phase of the CBDM process, we have to fill in the decision table, that is determine the values of alternatives w.r.t. all attributes. Then, values are replaced by utility values from the [0..10] range in our example. Suppose that MAUT methodology can be used and the decision matrix of utilities can be determined. We do not go any deeper into this step here. The meaning of attributes will be neglected henceforth and we shall operate only with matrices as mathematical objects.

Children of age 6–12

		Current		Case 1		Case 2		Case 1	
Attr.	Wts	cp	ncp	cp	ncp	cp	ncp	cp	ncp
1	0.25	5	5	5	5	5	6	5	6
2	0.21	4	5	5	5	6	5	5	5
3	0.16	7	7	6	7	6	7	7	7
4	0.11	9	6	9	6	9	8	9	7
5	0.075	7	6	7	7	8	7	8	8
6	0.075	6	8	6	7	6	7	6	7
7	0.06	4	6	5	6	5	6	4	4
8	0.06	7	6	7	7	7	8	7	7
Distance					0.33		1.06		0.66
Deviation			0.19		0.43		−0.26		0.01
Similarity					5.96		0.75		2.12
Outcome		Custodial		Custodial		Noncust.		Joint cust.	

Fig. 4 Decision process in the child custody example.

The second phase starts with the input of the decision matrix (see *Fig. 4*).[1] Since not any of the alternatives dominates the other in the current case, we make investigations into two directions. On the one hand, we apply the distance function to find the precedents and, on the other hand, the deviation function is applied to determine $\delta(C)$. Suppose that $\delta(C)$ falls in the indifference interval. In our example three previous cases were investigated. The second case is too far from the current case because we determined $\sigma_{max} = 1.0$ and therefore it is not a precedent. Concerning the deviation values only, the third case is the nearest to the current one. However, similarity gives the final results (setting $m = 1$) and Case 1 was proved the most similar. Thus, the custodial parent is proposed for outcome of the current case.

9. Conclusion

A general model was presented for improving the performance of case-based reasoning through multi-attribute utility theory. Consideration of preference assists CBR through deeper case analysis. Conversely, precedents assist utility-based decisions through comparing the current problem to previously decided problems. We showed that the decision system could not have achieved this level of accuracy with CBR or MAUT alone. Knowledge elicitation for determining attributes was not detailed in the presentation, but we are aware of its great significance. In the legal example attributes were fixed after long experimentation and several consultations. The model was implemented for the full-scale problem of child custody cases with the assistance of a legal specialist. Results indicate that the system performs as an effective decision support tool for law students. Future research will investigate how the different types of human decision makers can be modelled in this framework by changing the distance, deviation and similarity functions. Moreover, efforts will be made to refine the process of fixing the attributes when a decision matrix is determined. We also intend to extend the approach to decision problems with more than two alternatives.

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[1] Notations: *Attr.*: Attributes; *Wts.*: Weights; *cp*: custodial parent; *ncp*: noncustodial parent.

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