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Two examples of decision support in the law[1]

ISTVÁN BORGULYA
Janus Pannonius University Faculty of Business and Economics H-7621, Pécs Rákóczi út 80
E-mail:Borgulya@ktk.jpte.hu

Abstract. There are several systems which provide computer support to legal decisions. Perhaps the most significant ones, besides various computerised systems for administration, are information retrieval systems that locate statutes and documents. Other research projects, however, deal with legislation and adjudication, making it possible to use information techniques in making legal decisions. I wish to describe two decision-support programs and to link them to some theoretical findings of my former researches. What connects those programs is that they give some new information for decisions on the basis of previous similar legal cases; both describe cases with the help of criteria and use diverse artificial intelligence methods for different types or criteria. The first of the two programs aims to support decisions of insurance specialists by assessing the measure of the compensation for immaterial damage. The result is given by the combination of a neural network, based upon previous judicial cases, and an expert system. The neural network gives the first assessment for the sum of compensation while the expert system refines the network's output. The other program can be used by judges and lawyers in the course of preparing a decision. Studying cases of road accidents, we find that fuzzy logic methods can help to approximate decisions actually given by judges. In this way, the process of decision making by courts and lawyers receives an additional piece of information, obtained by comparing the seriousness of the actual case with that of previous cases.

Key words: decision support, expert system, fuzzy logic, fuzzy ranking method, insurance, neural network, traffic cases

1. Introduction

I am going to describe two examples of decision support systems that use AI methods. The first one assesses the measure of compensation in the field of insurance using a neural network (NN) and an XPS at the same time. The second one models judicial decisions in traffic law by means of fuzzy logic. Both examples concern support to decision-making and demonstrate how different methods should be applied to model different decision-criteria. In particular, in the first example, a NN considers alternative (case) models, where the criteria have numerical values, and an XPS applies general rules. In the second example, fuzzy logic is used for handling criteria describable by fuzzy sets.

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2. Insurance

2.1. THE PROBLEM AND APPROACH

There are several court decisions concerning immaterial damage compensation (in German: “Schmerzensgeld”). Most of those cases concern road accidents, and the damaged persons frequently start legal proceedings because they find the compensation offered to them (by insurance companies) too low. If insurance companies would calculate the compensation sum more or less according to the same principles used by judges, the two sums will be close to each other. In the long run, this would reduce the litigation.

In this area of the law the prediction of future court decisions can be grounded on many available cases. For more than twenty years, statistics and graphs have been used in this assessment. The increasingly popular methods of AI offer new possibilities. My example is going to be an assessment using XPSs and NNs simultaneously. (Though the cases used are from the 80s, the method works just as well with the more recent data.)

I have already studied many cases of immaterial damage compensation by security companies (Borgulya 1994, 1997a). These cases concerned the damages of the injured parties or of their relatives. I have considered abstracts of approximately 500 cases to find a method for calculating compensation.

The method I propose takes two steps to arrive at an assessment of the sum to be paid by the insurance. The first step is to evaluate cases which are “typical”, meaning that they concerns regular, common situations. In “special cases”, the sum due in the corresponding typical cases may have to be modified (e.g., it has to be reduced if the injured is an alcoholic) or an allowance (instead of a lump sum) may have to be granted. The system determines the measure of these alterations according to rules.

The most difficult parts of the development of this system were the elaboration, uniform description and codification of the cases. First, I established 17 criteria gathering all the factors by which the cases were described and the sentences were justified. Next I reduced the factors to 5 main groups and then divided the first main group into 13 sub-groups. As the cases dealt with accidents and injuries, the sub-groups contained the typical factors concerning each injured part of the body. I then gave relative scores to the gravity of each factor in every group, in order to determine the total sum of compensation. (I estimated the relative point values with the help of a medical doctor).

The description of a case was done with these 17 groups of criteria, and each group had to be given a relative score. If there was a factor in the case that was not listed in the corresponding group, the relative score had to be assessed. The following is a list of the five main groups:

1. Permanent physical health impairment
2. Permanent mental health impairment
3. Change in capability for work

4. Job, profession, social activities
5. Sports, leisure time, family

The following is a breakdown of the 13 sub-groups:

1.1. Upper limbs, 1.2. Lower limbs, 1.3. Hips, spine, 1.4. Eyes, 1.5. Ears, 1.6. Brain, sense of smell, sense of taste, talking, internal organs, 1.7. Any other functional disorder.

Aesthetic injuries 1.8. Aesthetic injuries on the head, 1.9. Various degrees of burn, 1.10. Aesthetic injuries on the trunk or limbs.

Limitation of motion without amputation or paralysis:

1.11. Lower limb, 1.12. Upper limb, hips, spine, head, 1.13. Walking and motion in general.

Each item in those sub-groups is further developed into list of more specific descriptions. For example, in sub-group 1.10, the following situations are listed along with the corresponding relative scores:

1.10. Aesthetic injuries on the trunk or limbs

– shortening of leg, distorting scar on knees, smaller scars on thighs	5
– distortion of an ankle, scars on breasts, skin of legs altered	10
– protuberant scar on thighs, the size of a palm	15
– distortion of legs, smaller chest deformity, distorting scars on legs	25
– loss of nipples (in the case of a woman)	30
– visible surgical scars at several places	40
– striking asymmetry on the trunk	50
– distorting scars at several parts of the body	80
– striking, aesthetically disturbing injuries on several parts of the body	140

Thus, we determined the case by a series of relative scores taken from a of 17 elements (marked M1, M2, . . . , M17), where Mi is the relative score corresponding the i-criterion. The value of relative scores in the examined cases oscillated in the [0,300] interval and the sums of award all in the [6,650] interval. (In the actual sentences, the sums were a thousand times the numbers given above.)

2.2. THE ASSESSMENT PROGRAM

The following aspects played a decisive role in the selection of methods adopted in the program:

1. Each past case is described by the numerical values of the above described factors.
2. There are many typical cases. As we describe past cases with numeric values, it is simpler to estimate the related damages by referring to past cases, than by

using several hundred of IF ... THEN ... rules. Therefore, I have chosen to use a NN to estimate the damages in typical cases.

3. Few special cases occur and they can be generalised from court decision. For example, due to lower marginal productivity, an alcoholic's health deterioration carries less influence than if he was not an alcoholic. In this light, only a given percentage of the customary damage is awarded by the court. On the basis of my examinations, the damages to be given a special case can be computed from those given in the corresponding general case; and the general calculation method can be described by IF ... THEN ... rules and applied by an XPS.

I estimated the damages on this basis using the following steps and methods:

- Step one: I treat each case as typical (if it is not typical, I disregard the values which make it special, e.g., alcoholism), and estimate the damage using the NN.
- Step two: If the case is special, an XPS modifies the damage estimated by the NN (For the sake of a simpler technical realisation of the program, I also applied an Excel program to connect the NN and XPS).

The program assessing compensation is made up of two parts. The parts and their tasks are the following:

1. A NN that assesses the award (using the Neuroshell 2 program) for typical cases
2. An XPS that modifies the sum assessed in by the NN, to keep into account special features of the cases (using the Level 5 Object shell), and that also guarantees the connection with the user (data input)

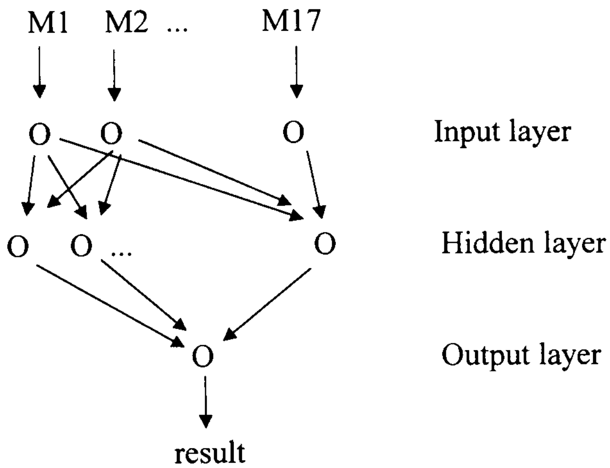
2.2.1. *Assessment with a NN*

With the adoption of a NN, I expected to get a more precise assessment of the awards and so decided to study those 210 samples of cases that I had already examined with statistical methods. Thus, the description of the case by means of a series of scores could be used as a learning pattern for the NN.

I then made an assessment for the sum in two different ways. In one variation I started off from a function approximation; in the other I chose a classification on the basis of the compensation awarded in the decisions. As we know both methods of approaching the problem belong to the field of hetero-associative networks. We can find several approaches to function approximation, among which, in particular, the *backpropagation model*, is suitable. Several methods are available also for the classification of similar cases. The most well-known methods classify the cases independently, by considering the typical correspondences alone. I, however, chose to define the classes beforehand (with the help of the backpropagation model), by creating a NN that recognises the classes.

NN model for an approximate value-definition

In the case of function approximation, the model structure of backpropagation is the following:



I looked for the most suitable NN with the help of different NN shells by applying a 190-factor learning pattern and a 20-factor test for control. In a further phase of the work, I used IBM Neural Network Utility, then Neuroshell 2 (Ward System Group Inc.). This shell automatically generated a NN structure with 23 hidden neurones and made it possible to choose randomly test cases (I chose 10% of the cases for testing). I tested the net various times: I looked for the best result in regard to test and at the training set, according to the average error.

The comprehensive chart of the results:

Average error		NN results (%)				
Training set	Test set	Precision:				
		1%	1–2%	2–3%	>3%	
0.00020	0.0011	35	23	15	27	(best test set)
0.00004	0.00047	79	15	4	2	(best training set)
0.00004		74	20	1	5	(best training set without test set)

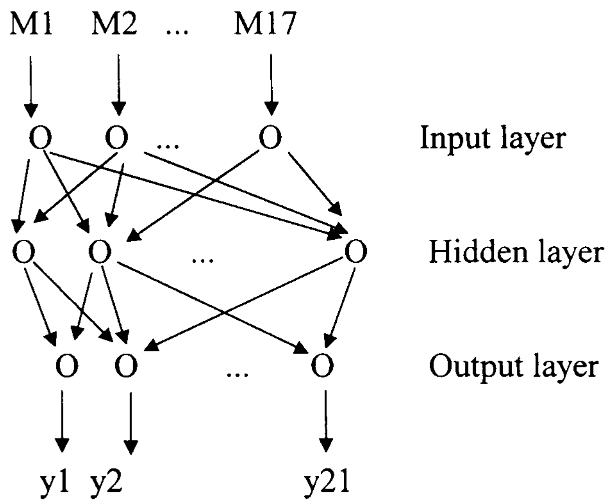
A NN for the classification of cases

The other way of approaching the problem is to classify the sentences with the help of a NN. Here I did not create the classes on the basis of the NN algorithm, but defined the classes beforehand and established a correspondence between the appropriate class and each of the learning pattern factors. This grouping was made according to the severity of sentences, i.e., the amount of the award (taking a great number of cases, we may assume that the award reflects the seriousness of the case).

As courts award usually round sums, fairly few classes had to be determined. The cases of the sample with only a few exceptions can be grouped into 21 classes which denote the subsets of the [20,405] interval, e.g.:

1. Class	Total: 20–25
2. Class	Total: 26–35
....	
21. Class	Total: 396–405

I created the NN, just like in the previous example, according to the backpropagation model. The structure of the network, however, differed from that of the previous networks because I connected a separate neuron to each class in the output layer. The structure of the network now is this:



The y1, y2, . . . y21 output series give the classes. Their value can be 0 or 1, so the result has to be understood in the following way: 1. class if we get (1, 0, 0, . . . , 0); 2. class if we get (0, 1, 0, . . . , 0); . . . 21. class if we get (0, 0, 0, . . . , 1). Since a NN rarely gives a result consisting merely of zeroes and ones, the class will be marked by the 'winner' neurone, i.e., the max. (y1, y2, . . . , y21) serial number.

Searching for the appropriate NN for this case, I finally also tried the program Neuroshell 2, which generated a NN structure with 33 hidden neurones. As before, I chose 10% of the cases for testing. I tried to study more versions: I looked for the best result in the test and the training set on the basis of average error and accuracy of class estimation.

Comprehensive chart of the results:

Average error		NN results (%)				
Training set	Test set	Deviation from the class of the learning pattern				
		0	±1	±2	More	
0.29	0.79	29	3	9	59	(best test set)
0.05	1.17	91	2	0	7	(best training set)
0.036		99	1	0	0	(best training set without test set)

Comparing the results
We may compare the results of the two approaches, that of function approximation and the assessment of the class serial number. For the sake of comparison, we have to take into account the following correlation's:

– an error rate of 1% can be regarded a precise result;
– a mistake of ±1 class numbers is equivalent to a ±1–2% error,
– a mistake of ±2 class numbers is equivalent to a ±2–3% error.

For comparison, let us use a test series of 28 elements differing from the earlier cases. The result of comparison:

Method	NN results (%) Precision:				
	0–1%	1–2%	2–3%	More	
Classifying NN	18	0	21	61	(best test set)
	18	7	7	68	(best training set)
	50	7	7	36	(best training set without test set)
Function approximation with the NN	15	15	24	46	(best test set)
	15	15	24	46	(best training set)
	57	15	10	18	(best training set without test set)

Taking into account the percentages, it can be concluded that with regard to this problem NN produced the best result without test-set training. From the point of view of practice, it is advisable to use the function approximation method. The 210 cases give sufficient information for the interpolation of functions, but it is still insufficient for the interpolation of classes. About 1–2000 cases would be needed

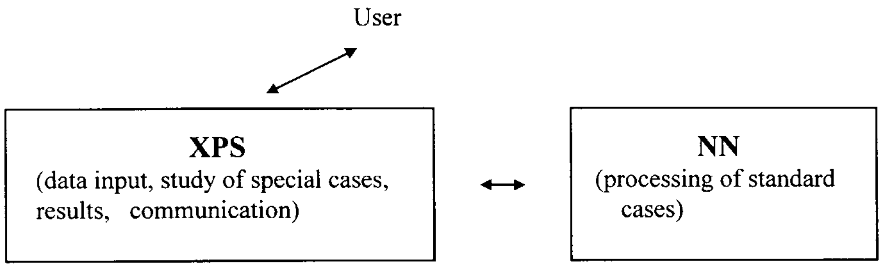


Figure 1. The structure of the assessment program.

to ensure that the classification based on a NN could be applied in practice with great precision, too.

2.2.2. *The Expert System*

The task of the XPS is to elaborate on the assessment given by the NN in special cases. According to judicial practice, the XPS:

- reduces the assessed sum or does not recommend compensation (if, for example, an improvement can be expected in the health of the injured or the damages cease after a while)
- decides whether the compensation should be paid in one sum or in the form of an allowance.

The XPS also checks the input data, which gives us an opportunity to provide the menus and the data groups necessary for the description of the cases and for inserting the corresponding scores.

Another important question is the relationship between the NN and the XPS. As suggested by the manuals, I established the communication between the NN and the XPS in the form of an Excel spreadsheet. (The complete structure of the whole program can be seen in Figure 1.)

2.3. THE APPLICATION OF THE PROGRAM

The assessment program is capable of supporting the decisions of insurance experts. In the cases of immaterial damage compensation, it gives this assessment on the basis of previous judicial cases. Regarding first the case as a standard one, it estimates the sum with the NN. If the case is a special one, the XPS processes the estimation of the NN. In the end, the program determines the probable sum of compensation with a 0–2% error rate in 70% of the cases.

The catalogue of standard cases helps to describe the cases, as it lists the possible damages grouped by the criteria. If a situation is not listed in the catalogue, the user has to decide about the value of the relative score.

3. Traffic Cases

The previous example evaluated alternatives (legal cases) characterised by multiple criteria having numeric values, and determined the value connected to the alternatives by proximity function. However, there are numerous types of cases which are characterised by criteria treated as sets (i.e., fuzzy sets) rather than as points. In these cases, the evaluation of the alternatives requires fuzzy logic methods, and their arrangement requires fuzzy ranking methods. In the following cases, I will present a model which arranges alternatives (legal cases) characterised by fuzzy criteria.

3.1. CASES PROVIDED FOR BY COURT DECISIONS

A few years ago, using a sample of 35 cases, I tried to established an order over cases according to their seriousness. I studied court files (just like in the previous cases in the field of insurance) to find ways of grouping the decisions and to select the most typical decision-criteria. I characterised the possible values of those criteria with relative scores, and a judge estimated their weight in judicial decision-making. For the ordering of the cases, the comparative method of COMBINEX[1] was used. I obtained the same sequence of order as with the COMBINEX method (Borgulya 1985).

It is difficult, however, to use this method in the study of cases. Scoring the values of the criteria requires great consideration, and defining the scores themselves is completely different from judicial practice. A more natural approach to this problem is made possible by fuzzy logic.

Several articles have already addressed the possibility of applying fuzzy logic in the field of law. For example, Philipps (1995) recommended Yager's method for ordering cases by fuzzy logic methods. Following this idea, I will show that traffic offences can be settled also with the help of the methods of fuzzy logic. Besides, I would recommend the definition of criteria with marks instead of scores, which seems to provide a more natural and practical description of cases. Such an approach to cases can have some practical advantages. The consistency of a decision of a court or a lawyer can be strengthened by grouping the actual case among the already adjudicated cases according to its seriousness.

3.2. DESCRIBING CASES BY FUZZY CRITERIA

In traffic cases, most of the criteria express notions that cannot be described precisely (e.g., the cause of the violation of law, the seriousness of the injuries, etc.). A definition of such notions is possible with fuzzy sets, and we can handle them as

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[1] Fallon's Method: 1. Define the criteria. 2. Estimate the weights of the criteria. 3. Measure the criteria values on a 1–100 point scale. 4. Arrange the alternatives by the sum of the weighted criteria values.

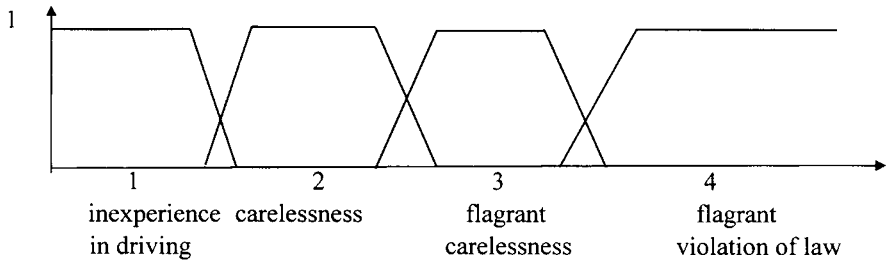

Figure 2. The linguistic variable 'the cause of the violation of law'.

'linguistic variables' – to use the terminology of fuzzy logic. Let us see for example two criteria in detail:

The criteria of age are the following:

– child
– juvenile
– middle-aged adult
– aged.

If we take age as a linguistic variable, each of its values has to be written down with a separate fuzzy set, and the total of these sets is going to be the set we are looking for. (Given the set, we can use the number of years and sort the values into intervals according to this.)

The criteria of the 'cause of violation of law' are:

– inexperience in driving
– carelessness
– flagrant carelessness
– flagrant violation of law.

Those criteria may be considered as the specification of a linguistic variable, so that we do not need to have numbers which describing the criteria's values as fuzzy sets. In this case, we may choose successive number intervals, assuming that the listed values (inexperience in driving, carelessness, flagrant carelessness, flagrant violation of law) mean sequenced grades and marks. A possible fuzzy set description is shown in Figure 2.

The trapezoid membership functions above the interval give the grade of connection to the set. Apparently, the borderlines tend to fade, i.e., it is difficult to distinguish between 'carelessness' and 'flagrant carelessness' for the value of 2.

Should we choose any one of the criteria, it can be described similarly as a linguistic variable. What is going to differ, of course, are merely the intervals, the shape of the membership functions and the name of the values.

From the point of view of practical study, it is useful to characterise the criteria by marks. Let's choose the marking system used in education and designate the value of each criterion with a mark. The grades of the marking scale are arbitrary. We chose the 5-grade system with marks 1, 2, 3, 4 and 5 allowing fractional marks (e.g., 2.2) to be given as well.

The marks have to be defined with fuzzy sets having membership functions expressing the range of the fractional marks belonging to the mark set. Moreover, they have to express the fractional marks and values of their near environment (for example 1.5, 2.5, 3.5, ...) belonging to two neighboured mark sets. The support of a mark can be given for example, by the interval [mark − 1, mark + 1]. The membership function of the fuzzy set of the mark is a symmetric function, which takes the value of 1 in the middle of the interval and decreases monotonically in both directions from the midpoint. We may define the fuzzy sets of marks by symmetric triangles, or Gaussian curves.

Ordering the marks according to the values of a certain criteria is unambiguous if the values denote sequenced grades. With the criteria of "age", at least with road accidents, marks do not necessarily increase with the number of years, so the linguistic variable shown above should be replaced by a fuzzy set structured in another way:

The marks of "age" in cases of road accidents:

– child	1
– juvenile	3
– middle aged adult	5
– aged	3.

It is much more difficult to connect the mark to the set when the criterion is of a hardly distinguishable grade or contains mitigating and aggravating circumstances as well. Let us see two further criteria of these:

The marks of "the damages of the accused":

– a close relative dies	0
– a close relative is injured or he himself is injured fatally	1
– seriously injured	2
– has a severe material loss	3
– he himself is lightly injured	4
– he has no or insignificant damages	5.

The marks of "the technical conditions of the vehicle and other circumstances":

– street-lighting or road deficiency, or the disruptive behaviour of the passengers	1
– technical fault on a journey	2
– normal conditions	3
– driving a technically defective car	5.

In the cases studied before, the description of the accused and of the case was based, in the decisions, on such criteria. I chose the 25 most frequent occurrences of the criteria, and a judge estimated their weight-numbers. I gave the highest weight-number the No. 1. Then I found the criteria significant in 14 cases (the weight-number $\geq$0.1). Following are the criteria and corresponding weight-numbers:

Criteria	Weight-number
1. Traffic offence	1
2. Age	0.7
3. The damages of the offender	0.5
4. More damages than the aggravated case of injuries	0.31
5. Past traffic record	0.3
6. The type of driving licence	0.26
7. Circumstances after the accident concerning the injured	0.25
8. Family, alimony obligation	0.24
9. The cause of the offence	0.21
10. The vehicle used	0.2
11. The technical condition of the car, other extrinsic circumstances	0.16
12. The offender’s traffic morals	0.15
13. The exact time of the accident	0.14
14. The frequency of similar cases	0.1

If we study the words of the statute (BTK [Hungarian Criminal Code] Art. 187), we can define further aggravating cases, and select criteria that rank them into various groups (delicts, crimes). Without these aggravating criteria the previous 14 criteria can only properly describe the cases within one group. For our purpose of examination, this will be enough. At least as a first approach, we are going to rank the cases separately within the groups.

Criterion serial number	Case													
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
1	1	3	3	3	5	4	5	1	3	5	3	3	5	5
2	5	1	1	5	5	5	5	5	1	5	5	5	5	5
3	5	5	5	3	5	5	5	3	0	2	5	5	5	5
4	3	4	3	2	3	4	4	4	2	3	0	0	0	0
5	0	0	0	0	2	2	1	0	4	0	0	0	5	5
6	5	5	5	5	5	5	5	5	5	5	5	1	5	5
7	0	0	0	0	0	0	0	0	0	1	0	0	0	0
8	2	3	4	0	3	4	0	3	5	5	1	0	1	1
9	3	2	2	2	1	4	5	1	1	5	4	4	5	3
10	3	3	3	3	3	3	3	3	3	3	3	5	3	3
11	3	3	3	3	3	3	3	1	3	3	3	5	3	3
12	0	1	0	0	0	0	3	0	0	3	0	0	3	3
13	3	3	3	3	1	3	3	3	3	3	3	3	3	3
14	0	5	5	5	0	0	5	1	1	5	1	0	1	5

Figure 3. Description of legal cases with marks.

3.3. RANKING OF TRAFFIC OFFENCE CASES

As observed in the description of cases, the criteria of traffic offence cases can be separated into two groups:

- those that rank the cases into various categories according to law (aggravating criteria), and
- standard criteria that can be typical in any of the categories.

I chose examples of ranking from two different categories: the cases of grievous bodily injury and the cases of fatal injury. Figure 3. shows the description of the examples on the basis of standard criteria marks.

I first used the recommended Yager method for ranking. This method assigns a number to each of the cases for the purpose of ranking them. I created a provisional method to solve the problem. This “mark based method” treats the criteria values as “marks”. On the basis on the marks, it assigns a further mark to each case: and with this aid, the cases can be ranked.

The results of the ranking with the two different ranking methods can be seen in Figure 4. Studying the results, we can say that:

- The numbers we obtained by applying the Yager method show correctly the gravity of the penalty. In some cases, this method gave similar values to different sentences that, however, followed each other in the sequence. It did not differentiate, for example, between cases F2 and F3 (penalty equal to 50 and

Case	sentence	Yager's method	mark based method
F1	30 days fine	1	2.53
F2	50 days fine	1.5	2.73
F3	70 days fine	1.5	2.79
F4	7 months imprisonment suspended	3	3.49
F5	7 months imprisonment	3.45	3.84
F6	8 months corrective training	3.5	4.18
F7	7 months imprisonment	3.5	4.42
F8	1 year imprisonment s.	1	2.31
F9	1 year imprisonment	1.5	2.54
F10	1 year 2 month imprisonm.	2.5	4.06
F11	1 year 2 month imprisonm.	3	3.68
F12	1 year 2 month imprisonm.	3	3.68
F13	1 year 6 month imprisonm.	3.45	4.25
F14	1 year 8 month imprisonm.	3.45	4.71

Figure 4. The ranking results.

70 days fine.) But we also found examples to the contrary: in cases F10, F11, F12, the sentences were the same, while the method distinguished the cases.

– The mark giving method assigns another mark to almost every case, and the marks correspond to the order of the sequence. It is just in the cases F10, F11 and F12 that the order differs from that of the Yager method. In these cases, the "mark based method" gives a better result - for if we check supplementary punishments, too (driver’s license revoked), the correct order of cases is F11, F12, F10, that corresponds to the order of the marking method.

Summary: Both methods rank the legal cases correctly.

3.4. RANKING METHODS

The ranking methods for a multicriteria basis offer a choice among 10 fuzzy set methods. Their common feature is that they:

– assume that the criteria can only be measured on a sequence scale; so arithmetic operations cannot be done with the criteria values
– assign a value to each of the alternatives to be ranked and order these values on the basis of these alternatives. The value is one of the values of the membership functions of the criteria given to the alternative.

From among the ranking methods, I chose the Yager method and the "mark based method". Without studying the other possible ranking methods, let us sketch these two.

The Yager method. Originally, Yager developed his method for economic problems to determine the most appropriate one of several alternatives (e.g., the one with the highest economic effect) (Yager 1978). The method assumes that

– $a_1, a_2, \ldots, a_n$ alternatives are given by criteria measurable on a sequence scale with $k_1, k_2, \ldots, k_m$,
– the criteria are fuzzy sets interpreted by the [0, 1] interval,
– the membership functions of the fuzzy sets show how appropriate the alternative ai is from the point of view of criterion j.

Taking into account the p_j 'potential value' of criteria, the method assigns a y_i number to every alternative.

$$y_i = \max \min(p_j, \mu_{kj}(a_i)) \text{ for every } k_j (1 \leq j \leq m).$$

Moreover, the Yager method regards the alternative belonging to the maximum value of y_i as the best solution. The y_i values at the same time give a monotonous ranking of the alternatives.

In the presented ranking course, the potential value of the criteria ai was chosen as equal to the weight-number of the criteria (the maximum weight-number being (1); and according to the marks, I performed the calculation by transposing the values into the interval [0, 5], instead that into the interval [0, 1].

The mark based method. The problem with ranking is the following: The alternatives to be ranked are characterised by aggravated multicriteria where the criteria values are also fuzzy sets.

I approached this problem from two directions:

– I assumed as a special case that the values of criteria are given by marks used in education or can be transformed into them.
– In general cases, I regarded the criteria values themselves as marks, though they do not have the characteristics marks used in education.

In both cases, just one number, an 'extra mark' was given to every alternative by the method, and the alternatives could be ranked on this basis (Borgulya, 1995, 1997b).

The special case. The thought behind the method is the following: The criteria at the $a_1, a_2, \ldots, a_n$ alternatives to be ranked are given unified marks, although not necessarily of same-grade fuzzy sets. We may define the fuzzy sets of marks by symmetric triangles, or Gaussian curves. The method produces an ‘extra mark’ set for each of the alternatives according to the marks. The ‘extra mark’ sets are created as the subsets of a common ‘result set’ that makes their comparison possible. (The ’result set’ is also made up of the fuzzy sets of the possible marks.) The order of the alternatives is going to be determined by the y_i center of gravity of the ‘extra mark’ set.

For any alternative given by the marks of criteria, the y_i value is determined by the following rules:

– Each mark has to be mapped onto the identically named subset of the result set,
– Each mark has to affect the range of its criterion weight-number (g_i). Let us decide, however, that first the higher criteria weight-numbers should affect the result. To realise this aim, multiply the height of the fuzzy sets of the marks by the square of their weights.
– If more criteria get the same mark, we have to render different subsets to different multiplied marks in the corresponding mark set of the ‘result set’.
– By aggregating the subsets (obtained by mapping the marks in the result set), the ‘extra mark’ set is created. The centre of gravity of the ‘extra mark’ set and its projection on the X-axis give the y_i value.

The general case. Keeping to the concept of mark giving, let us rule out the transformation of criterion values into marks. We can then disregard the p-step scale marks given by fuzzy sets, which represent the criterion values, as marks, instead. As any value of any criterion may be a fuzzy set, even the “marks” can take different forms and amounts of fuzzy sets with regard to different criteria. Let us allow the criteria to take scalar values, too, but these values have to be transformed into fuzzy sets as well.

The concept of the “mark based method” generalised this way differs from the special case at three points:

– The fuzzy values of the criteria do not have to be transformed into unified marks, but the criterion values themselves are regarded as marks.
– The vivid concept of fractional marks and average extra marks appear and cannot be interpreted in general.
– As the marks do not possess the characteristics of those in education any more, the result set is created from the union of criteria.

The program of the system. In the “general case”, we create a fuzzy system for the obtainment of “extra mark” sets by rules that uses Kosko’s FAM system (FAM: fuzzy associative memories) – (Kosko, 1992). When the fuzzy sets are defined, we can describe the criterion value with the following rules:

$$
\begin{array}{lllll}
(w_1) & \textbf{IF} & k_1 = S11 & \textbf{THEN} & E = S11 \\
(w_1) & \textbf{IF} & k_1 = S12 & \textbf{THEN} & E = S12 \\
\multicolumn{5}{l}{\dotfill} \\
(w_1) & \textbf{IF} & k_1 = S1p1 & \textbf{THEN} & E = S1p1 \\
(w_2) & \textbf{IF} & k_2 = S21 & \textbf{THEN} & E = S21 \\
(w_2) & \textbf{IF} & k_2 = S22 & \textbf{THEN} & E = S22 \\
\multicolumn{5}{l}{\dotfill} \\
(w_2) & \textbf{IF} & k_2 = S2p2 & \textbf{THEN} & E = S2p2 \\
\multicolumn{5}{l}{\dotfill} \\
(w_m) & \textbf{IF} & k_m = Sm1 & \textbf{THEN} & E = Sm1 \\
(w_m) & \textbf{IF} & k_m = Sm2 & \textbf{THEN} & E = Sm2 \\
\multicolumn{5}{l}{\dotfill} \\
(w_m) & \textbf{IF} & k_m = Smp_m & \textbf{THEN} & E = Smp_m
\end{array}
$$

where $w_i = g_i^2$, $(i \leq i \leq m)$ are the weight-numbers of the FAM rules. The criterion values of k_j are given by the variables $Sj1, Sj2, \ldots, Sjp_j$.

The created fuzzy system shown here determines the y_i centre of gravity of the 'extra mark' set to each ai alternative on the basis of the input mark series; and on the basis of y_i values obtained, the alternatives are rankable.

Note: In the "special case", when the result set is defined as the union of criteria, the possibility of fusion of marks is lost; however, the result of the ranking remains invariant.

3.5. CASE RANKING MODEL

The possibility of ranking the traffic offences into different groups (categories) leads to the idea of a unified model that could rank all traffic accidents , taking into account the aggravating criteria at the description of a certain model.

With the help of a judge, I obtained the general and the aggravating criteria weight-numbers as well. These were 2–3 times greater values than those of the standard criteria studied so far. If we add these aggravating criteria to the 14 criteria we have studied already and determine the maximum weight-number again as 1, the standard criteria will get very small weight-numbers (0.3, 0.2, 0.15, 0.07, ...), the squares of which won't influence the final mark. Thus, the aggravating circumstances should rather be taken separately: First, we group them on the basis of aggravating criteria and then rank the cases by the methods discussed above inside the groups.

Studying the article "causing a traffic accident" (BTK Art.187), and disregarding defection and driving while intoxicated, the law distinguishes the following groups:

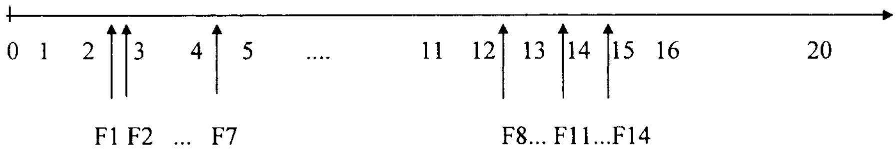

Figure 5. The “set of sentences”.

c1: severe deterioration of health

c2: lasting deterioration of health or a mass accident caused by the offender

c3: fatal accident with one or two deaths

c4: more than two deaths or a fatal mass accident.

To distinguish these groups, we only need another criterion (k_0)

With the previously studied rankings, we obtained the final result in one result set, at least with the mark based method it was so. Let us render now a result set to each group and delineate the 4 result sets one by one. We name the new set “set of sentences”. The cases studied before are going to change groups: the cases F1, F2, ..., F7 will belong to c1; the F8, F9, ..., F14 cases to group c3. Though c1 and c3 group result sets could have a common section according to the sentences, we would rather regard them as independent sets for the sake of a more simple administration. (To define the common sections precisely, we need to study further cases.)

The ranking fuzzy-model will then work in this way:

1. Each legal case is defined with the criteria $k_0, k_1, k2, \ldots, k_m$.
2. In a certain case the model decides according to the k_0 aggravating criterion which group the case belongs to; it also gives the final mark in the result set of the group with the mark giving method.
3. A marked point (the weight point of the “extra mark”) is rendered to each studied case in the “set of sentences”.

The points of the “set of sentences” do not show the gravity of the sentences themselves, but they do make it possible to set up the relative order. This relative order can compare the gravity of the new case to the previous ones if we have already rendered some adjudged cases to certain points. If, for example, we begin with the cases F1, F2, ..., F14 (Figure 5), we can measure the gravity (i.e., the sentence) of a new case on the basis of earlier cases.

The model is very practical from a technical point of view. It can easily be programmed. Whether we apply a fuzzy-logic program or a fuzzy expert system, it can be run and transformed into a complete software without difficulty. The user has to give the data of the new case only, then read the result and compares it to previous cases.

4. Conclusion

The fuzzy decision model presented (ranking the chosen cases according to the gravity of the sentence) shows that legal cases can be processed and ranked by fuzzy-logic methods. Moreover, a vivid and easily understandable ranking is possible if we choose the most general characteristics of criteria based on the marking system.

With a properly chosen field of law and with the help of selected cases, this ranking model can be used for decision support. (Such efforts can be found at several places; e.g., Schild, 1995.) It can be a very useful piece of information for legal decisions to know what place the presented case takes compared to previous cases already decided.

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