Prediction of Fine in Accidents using Fuzzy Rule Based Model

Jaya Pal[1], Vandana Bhattacherjee[2]
[1,2]Department of Computer Science & Engg.,
Birla Institute of Technology, Ranchi, India
[1]jayapal@bitmesra.ac.in
[2]vbhattacharya@bitmesra.ac.in

Abstract

Any society needs some disciplinary measures to curb the violations which its members tend to make as a result of growth of income, status, living styles and reducing family sizes resulting in less monitoring from within the family. Rash driving among youngsters as well as their seniors is one of the major threats to healthy and safe life. Traffic problems aren't something to take lightly anymore, not when we have been proclaimed as the nation with the most traffic accidents. In this paper we have proposed to build a model developed using collected statistics of accidents (age of the driver, cost of repair and fine charged) to enable the law imposers to make the calculations of fine impersonally. This is an attempt to develop a system which could be used uniformly to calculate the fine imposed on a driver. Fuzzy rule based system has been used as the tool.
Keywords: *Fuzzy logic, fuzzy inference system, Fine prediction, fuzzy rule base.*

1. Introduction

In order to give effective rights to the person injured or expired in an accident, Fatal Accidents Act, 1885 was enacted in India. The assessment of compensation, however, be made good but cannot be said to be foolproof. In every such assessment certain assumptions are to be made and there is all possibility of variance from Judge to Judge in applying the various principles enunciated by the Courts from time to time. Supreme Court, in one case has stated that there is no exact uniform rule for measuring the value of human life and measure of damages cannot be arrived at by a mathematical calculation. The law of accident claims is fast growing and the amendments to suit the requirement of the object are necessitated. The evaluation of accident costs crucially depends on the availability of an estimate for the economic value of statistical life [1]. They propose a model based on systems dynamics approach. They developed the model using different income growth rates. In this paper we have proposed to build a model developed using collected statistics of accidents (age of the driver, cost of repair and fine charged) to enable the law imposers to make the calculations impersonally. This is an attempt to develop a system which could be used uniformly to calculate the fine imposed on a driver. Fuzzy rule based system has been used as the tool. An automobile insurance company is interested in revising its insurance policy towards drivers who are involved in accident and are arrested for drunk driving. The company has requested the State Development of Transportation to provide it with the records of all such motor vehicles accidents as invested by the police. The Department has maintained a separate file for such accidents in which a drunk driver is involved. The information about the driver of the car and the locality of the accident and some other relevant information are recorded. Certain variables are used in preparing the record file for each such accident and used in this paper to develop the model. The data is adapted from [2]. Fuzzy logic based systems have already been used to model traffic signal control by [3]. A neuro-fuzzy approach has been presented by [4] to predict vehicle collision.

2. Fuzzy Rule Base Model

A Fuzzy rule based model using fuzzy inference system is represented by Fig.1 It consists of four main components:

1. Fuzzification: that contains predefined set of linguistic values. It converts non-fuzzy (Deterministic) inputs of fuzzy system into fuzzy inputs for inferencing mechanism.

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2) Kknowledge base: that consists of two parts: database that defines linguistic variables Fuzzy sets, and rule base that represents the mapping of fuzzy input set into a fuzzy output set. Rules are fuzzy conditional statements (implications).

3) Decision logic: that simulates human decision making based on fuzzy concepts. Conclusion of certain condition is derived by decision making logic.

Fig.1: Schematic representation of Fuzzy Rule based Model

4) Defuzzification: that converts rule base fuzzy outputs into non-fuzzy (numerical) values.

Central mechanism of knowledge base and decision making logic considers the fuzzy extension of conventional rule inferencing concept to **fuzzy rules inferencing**. Premises and conclusions of rules now contain fuzzy values. These facts by definition describe practically continual input set of characteristics. In this manner, one rule can replace more conventional rules. **Fuzzy inferencing rules** generally connect **m** conditional variables $X1,..., Xm$ to **n** consequent variables $Y1,..., Yn$ in form of:

IF (**X1** is A1 and ………..Xm is Am) **THEN** (**Y1** is B1 and ... Yn is Bn).
Where $A1,..., Am$ and $B1,..., Bn$ are linguistic terms of linguistic variables $X1,...,Xm$ and $Y1,..., Yn$, respectively.

The **IF** part is called the "antecedent" and the **THEN** part is called the "consequent". To make a decision based on a set of rules, a rules-based system follows these steps:

1. All the rules that apply are invoked, using the membership functions and truth values obtained from the inputs (by a process called **fuzzification**)**,** to determine the result of the antecedent.

2. This result in turn will be mapped into a membership function and truth value controlling the output variable. This process is known as **implication**. Two of the more common implication functions are: clipping (the fuzzy set is clipped to a value given by the level of activation of the input variables) and scaling (the fuzzy set is multiplied by a value given by the level of activation of the input variables).

3. These results are combined by a process called aggregation. One common approach for the aggregation involves using the "maximum" of the implicated sets.

4. Finally, a process known as defuzzification is used to compute a single value that is representative of the aggregated fuzzy set.
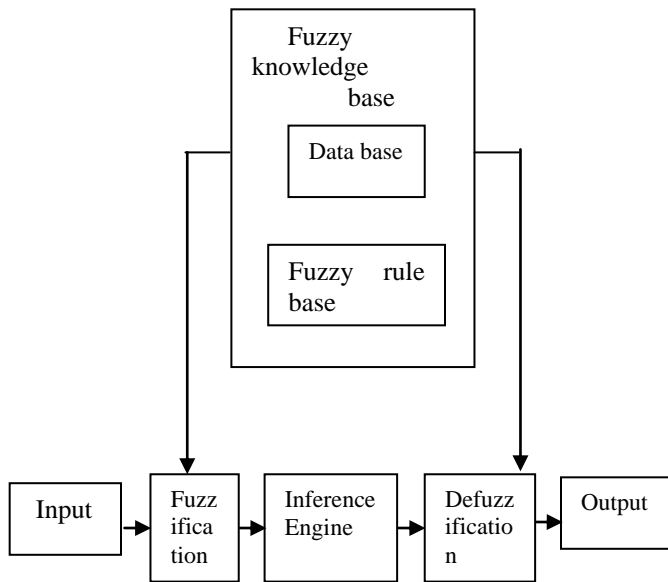
3. Fuzzy Rule Base Model for Fine Prediction

The system consists of two fuzzy inputs, namely *age* (of driver) and *cost of repair* and one fuzzy output *amount of fine* as shown in Figure 2.
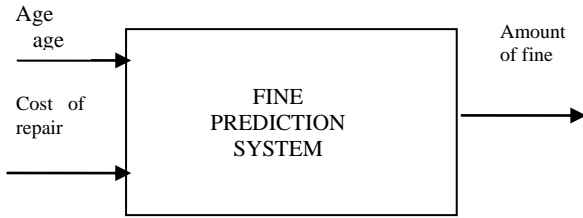
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Fig. 2: Fine Prediction System

Table 1: Fuzzy sets for different variables

Age	Cost of repair	Amount of fine
EY - Extremely young	EL - Extremely less	ES – Extremely small
VY- Very young	VL - Very less	VS – Very small
Y - Young	L - Less	S - Small
M - Middle	AV- Average	Mean
S - Senior	H - High	L - Large
VS- Very senior	VH- Very high	VL – Very large
VS- Very senior	EH- Extremely high	EL – Extremely large

3.1 Fuzzy Rule Base

A sample fuzzy rule base R governing the system is as follows:

Rule   1:   If (age) is M and (cost_of_repair) is VL then amount_of_fine is VS.
Rule   2:   If (age) is S and (cost_of_repair) is L then amount_of_fine is ES.
Rule   3:   If (age) is M and (cost_of_repair) is L then amount_of_fine is VL.
Rule   4:   If (age) is Y and (cost_of_repair) is L then amount_of_fine is VS.
Rule   5:   If (age) is S and (cost_of_repair) is H then amount_of_fine is S.
Rule   6 :   If (age) is VS and (cost_of_repair) is H then amount_of_fine is Mean.
Rule   7:   If (age) is EY and (cost_of_repair) is EL then amount_of_fine is ES.
Rule   8 :   If (age) is ES and (cost_of_repair) is L then amount_of_fine is S.
Rule   9 : If (age) is S and (cost_of_repair) is VL then amount_of_fine is ES.
Rule 10 :   If (age) is VY and (cost_of_repair) is L then amount_of_fine is VS.
Rule 11: If (age) is VY and (cost_of_repair) is EL then amount_of_fine is ES.
Rule 12: If (age) is VS and (cost_of_repair) is VL then amount_of_fine is VS.
Rule 13: If (age) is ES and (cost_of_repair) is EH then amount_of_fine is Mean.

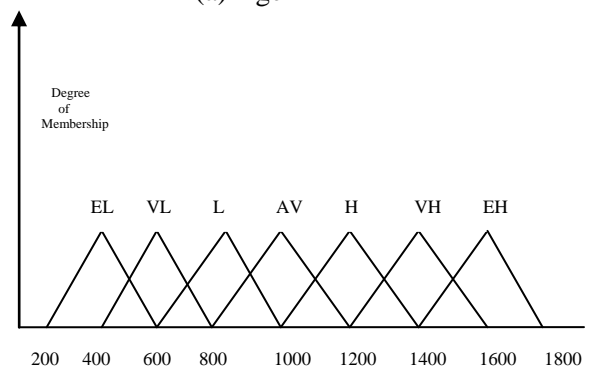Fuzzy sets for age, cost of repair and amount of fine are given in Table 1.

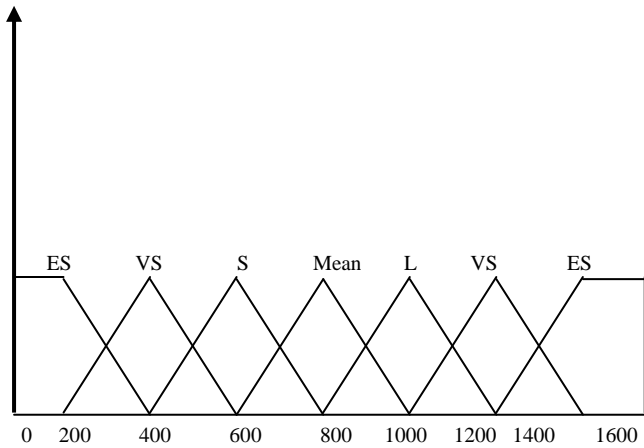The membership functions for the fuzzy sets which characterize the inputs and output are as given in Fig. 3.

(a) Age

(b) Cost of repair

$$\text{Degree of membership} = \min \begin{cases} \text{dis1 * slope1} \\ \text{dis2 * slope2} \\ \text{Max} = 1 \end{cases}$$

4. Illustration

Let the measured age be 21 and the cost of repair be 250.

The computations of fuzzy membership values for the given inputs are shown in Figure 5 and Figure 6.
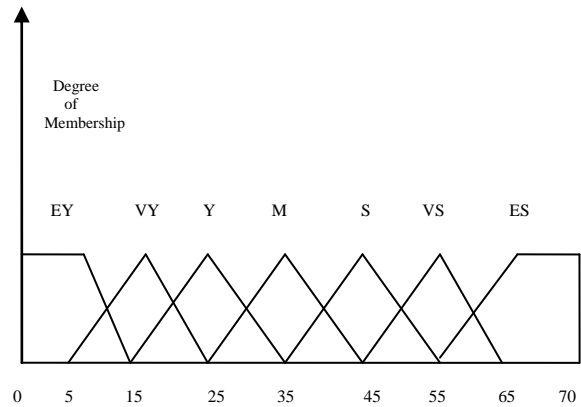
(c) Amount of fine

Fig.3: Membership functions characterizing fuzzy sets

3.2 Fuzzification of inputs

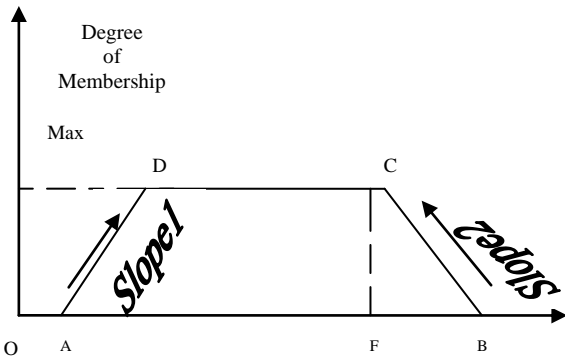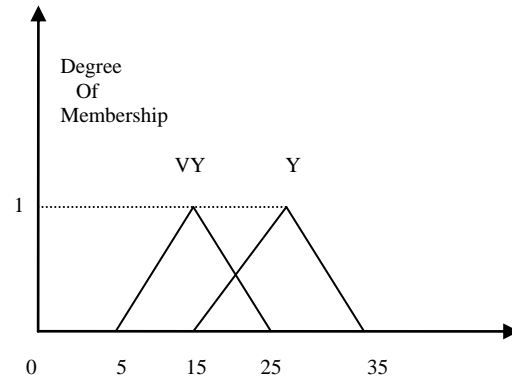To compute membership for the antecedents, the formula is as follows:

Fig.4: Computation of fuzzy membership value

To calculate the degree of membership of any point F,

Compute *dis1* = OF - OA
Compute *dis2* = OB - OF

If (*dis1*<=0) or (*dis2*<=0) then degree of membership = 0

Else

Figure 5: Fuzzification of age=21

For age(x=21) the qualifying fuzzy sets are shown in Fig 4.

The member function of x = 21 for VY is
$$\mu_{VY}^{(X)} = 0.4$$
and for Y is
$$\mu_{Y}^{(X)} = 0.6$$

The membership function of x with remaining fuzzy sets EY, M, S, VS and ES is zero. Similarly for the cost of repair (x=250) the qualifying fuzzy sets are as shown in fig. 5.
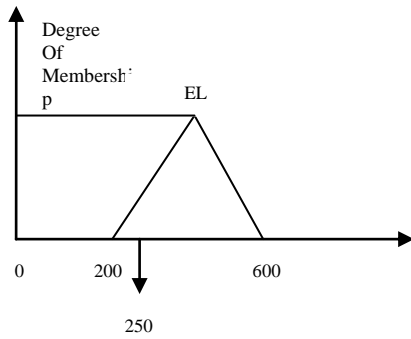
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Fig.6: Fuzzification of cost of repair

The membership function of x=250 for EL is

$\mu_{EL}(X) = 0.25$

Rule strength of computation

The rule strengths are obtained by computing the minimum of the membership functions of the antecedents. For sample rule base R given in the Table 1 the rule strengths using the above fuzzy membership values are:

Rule 1:   min(0,0) = 0
Rule 2:   min(0,0) = 0
Rule 3:   min(0,0) = 0
Rule 4:   min(0,0) = 0
Rule 5:   min(0,0) = 0
Rule 6:   min(0,0) = 0
Rule 7:   min(0,0.25) = 0
Rule 8:   min(0,0) = 0
Rule 9:   min(0,0) = 0
Rule 10:   min(0.4,0) = 0
Rule 11:   min(0.4,0.25) = 0.25
Rule 12:   min(0,0) = 0
Rule 13:   min(0,0) = 0

Fuzzy Output

The fuzzy output of the system is 'fuzzy OR 'of all fuzzy outputs of the rules with non zero strengths. In the given Rule base R, the competing fuzzy output is the rule 11 with the strength 0.25.

Defuzzification

The centre of gravity (CG) method is applied to defuzzify the output. The Figure 7 illustrates the computation of CG for the competing output of rule 11 with the strength 0.25.
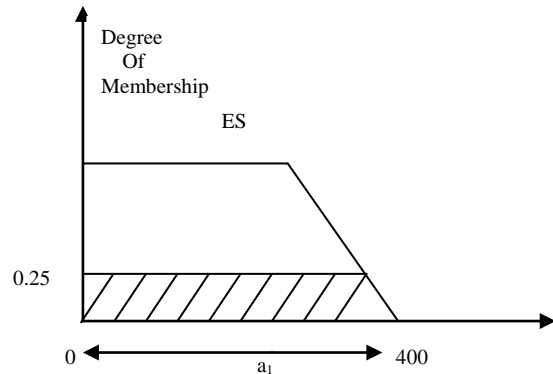

Figure 7: Computation of CG

For the fuzzy set ES

Weighted average, $CG = \Sigma Ax' / \Sigma A$

where, centroid x' = 197.5
Area $A = \frac{1}{2} h (a_1+b_1) = \frac{1}{2} * 0.25 * (400+390)$
           = 98.75
Weighted average, CG = 19503.125/ 98.75
                            =197.5
In crisp terms, amount of fine is to be set as 197.5.

Results

The proposed fuzzy rule based system was validated upon the data set obtained as mentioned earlier. The prediction error analysis for the same is given in Table 2.

Table 2: Prediction Error Analysis

	Testing Data	Training Data
Mean MRE	0.04177	0.02402
Min. MRE	00	00
Pred (0.10)	100%	100%
Pred (0.066)	75%	88%

5. Conclusion

In this paper a fuzzy rule based model has been developed using collected statistics of accidents (age of the driver, cost of repair and fine charged) to enable the law imposers to make the calculations of fine impersonally. This is an attempt to develop a

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system which could be used uniformly to calculate the fine imposed on a driver. Fuzzy rule based system has been used as the tool. To the best of our knowledge we could not get any existing soft computing model to compare our results with, however our own attempts at building a statistical regression model for the same set of data had given much higher error values (approximately 30% for test data and slightly better for train data). These would not be acceptable for any prediction model. Our fuzzy logic based model however gives much better results. 100% data are predicted within 10% error, and 75% test data while 88% train data are within 6.6% error. Our ongoing work is collection of data from varied sources and validation of the proposed model.

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First Author:

Ms. Jaya Pal received the degree of Master in Computer Science Application from Birla Institute of Technology, Mesra, Ranchi, India in 2003. She is a research student of Dr. Vandana Bhattacherjee, Birla Institute of Technology, Mesra, Ranchi, India.Currently, she is an Assistant Professor, Department of Computer Science & Engineering, Birla Institute of Technology, Ranchi, India. Her interests are in Data Mining and Soft Computing.

Second Author:

Dr. Vandana Bhattacherjee received the B.E. (CSE) degree from Birla Institute of Technology, Mesra, Ranchi, India in 1989 and M. Tech degree from JNU, New Delhi India in 1991. She received the Ph.D. degree in Computer Science from JNU, New Delhi, in 1995.Currently, she is a professor at Birla Institute of Technology, Ranchi, India. Her research interests include Software Process Models, Software cost estimation, Data Mining and Software Metrics and Soft Computing.