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Modelling driver propensity for traffic accidents: a comparison of multiple regression analysis and fuzzy approach

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This research proposes an assessment and decision support model to use when a driver should be examined about their propensity for traffic accidents, based on an estimation of the driver's psychological traits. The proposed model was tested on a sample of 305 drivers. Each participant completed four psychological tests: the Barratt Impulsiveness Scale (BIS-11), the Aggressive Driving Behaviour Questionnaire (ADBQ), the Manchester Driver Attitude Questionnaire (DAQ), and the Questionnaire for Self-assessment of Driving Ability. In addition, participants completed an extensive demographic and driving survey. Various fuzzy inference systems were tested and each was defined using the well-known Wang-Mendel method for rule-base definition based on empirical data. For this purpose, a programming code was designed and utilised. Based on the obtained results, it was determined which combination of the considered psychological tests provides the best prediction of a driver's propensity for traffic accidents. The best of the considered fuzzy inference systems might be used as a decision support tool in various situations, such as in recruitment procedures for professional drivers. The validity of the proposed fuzzy approach was confirmed as its implementation provided better results than from statistics, in this case multiple regression analysis.

Keywords: traffic accidents; road safety; driving behaviour; fuzzy systems; fuzzy rules based on data; multiple regression

1. Introduction

The Global Status Report on Road Safety 2018 (World Health Organization, 2018) reveals that in 2016, approximately 3700 people died in traffic accidents per day, and tens of millions of people are injured or disabled every year. Traffic safety professionals have a complex task to determine the reasons for accident occurrence. This should enable policy-makers to make better decisions to improve safety.

Each accident is unique with many particular circumstances; however, some general causes relate to the driver, such as human factors, the vehicle and the road conditions (Evans, 2004). A notable study that considers the vehicle factor is by Vranjes, Vasiljevic, Jovanov, Radovanovic and Duric (2019) where a research was carried out to investigate how certain vehicle malfunctions affect the road safety. Based on data for the period from 1997 to 2014, they concluded that the technical malfunction of vehicles as a cause for accident occurrence has a share of just 0.72% in the total number of accidents.

When it comes to the road characteristics as a cause of accidents, it may also be stated that this factor rarely contributes to the occurrence of accidents. For example, Rudny and Sallmann (2016) critically analysed the actual physical evidence of accidents involving alleged road defects. However, the severity of road accident can be strongly correlated with hazardous weather conditions, such as fog, snow, heavy rainfall and storms (Lee, Chae, Yoon, and Yang, 2018). Certain conclusions about the road safety can be obtained by analysing the road characteristics and Shah and Ahmad (2019) proposed a methodology for identification of risky segments of a motorway considering the road infrastructure and traffic stream characteristics.

In the literature, it is generally accepted that human factors have the biggest and most frequent impact on the occurrence of traffic accidents. For example, based on European Union research (European Commission, 2019), 95% of all traffic accidents on Europe's roads involve human error. This factor may be analysed in various segments, such as fatigue, inattention, impairment from drugs or alcohol, risky manoeuvres, violation of traffic rules, etc. Duan, Xu, Ru, and Li (2019) classified and quantified driving fatigue according to the driving fatigue degree. Further, they came to the conclusion that drivers become fatigued within a significantly shorter time while driving in high-altitude area. Dehzangi, Sahu, Taherisadr, and Galster (2018) proposed a monitoring system to assess the level of driver distraction, which occurs as a results of different non-driving related activities such as communicating with passengers, phone use, eating and drinking. Li and Chang (2019) used the geographic information system to collect traffic accidents data and concluded that the most frequent cause of accidents were: illegal overtaking, road races, lane change, improper driving direction, drunk driving and not maintaining a safe distance.

Although previously mentioned depicts the complexity of identifying the cause of an accident, there are studies confirming that the driver's personality can affect their behaviour in traffic, and the likelihood of being involved in a traffic accident (Shinar, 2007). Accordingly, there is a need to investigate which psychological traits can indicate an accident-prone driver, and how to identify them in order to prevent or reduce the number of traffic accidents and their consequences.

In this research, we chose four psychological instruments to measure certain psychological characteristics of participants and to assess their driving behaviour. The aim was to determine which of these four instruments might be the best tool to use for the identification of characteristics that accident-prone drivers possess. This might be possible using just one instrument, or a combination of two or three, or all four instruments. In addition, the goal was to propose a decision support tool that could be used, for example, in recruitment procedures for professional drivers. For these purposes, fuzzy logic was used. Various fuzzy inference systems (FIS) were designed and tested on empirical data. The results from FIS tests that provide the minimum error in the description of data were compared with the implementation of multiple regression analysis, which was previously demonstrated in the paper by Cubranic-Dobrodolac, Lipovac, Cicevic, and Antic (2017).

The organisation of this paper is as follows. In the next section, a review of literature on fuzzy logic implementation in the field of transportation (particularly driver behaviour) is presented. The third section offers a detailed explanation of modelling process, including a description of the variables used and the procedure of fuzzy rules generation, based on empirical data. The calculations and results are given in Section 4. A detailed procedure for solving the FIS with two input variables (x_1 and x_2) is demonstrated, followed by the results of the complete modelling process, where 15 various FIS structures are tested. Finally, we conclude with a specification of possible benefits from the obtained results and proposals for further research.

2. Related work

Fuzzy logic is widely used in the field of road transportation. Ivanov (2015) offers a review of fuzzy methods in automotive engineering applications where the following domains are differentiated: vehicle dynamic control systems, driver and driving environment identification, ride comfort control, and energy management of electric vehicles. The field of interest for the current paper relates to modelling driver behaviour. This field is of particular relevance for fuzzy applications, because psychological and emotional parameters generally imply a certain level of imprecision and fuzziness.

By reviewing the literature, we segment the implementation of fuzzy logic to model driver behaviour in the following areas:

- Examination of interaction between the driver and road infrastructure;
- Examination of interaction between the driver and in-vehicle systems;
- Testing the psychophysical characteristics of drivers;
- Determining a driving style.

An example of modelling the interaction between the driver and road infrastructure using fuzzy logic can be found in the study by Lee and Donnell (2007), where a preference is determined for particular types of road markings most suitable during night-time driving. On the other hand, Sentouh, Nguyen, Rath, Floris, and Popieul (2019) analysed the interaction between the driver and the in-vehicle system, and proposed a steering controller for keeping in lane, based on the integrated driver-vehicle model using the Takagi-Sugeno control technique.

With regard to the psychophysical characteristics of drivers, Boyraz, Acar, and Kerr (2008) designed an FIS to predict the drowsiness level of the driver. The selected signals for analyses included the level of eye closure, gaze vector, head motion, steering wheel angle, vehicle speed, and force applied to the steering wheel by the driver. Similar research was carried out by Wu and Chen (2008), who analysed the facial images of drivers and proposed a fuzzy system to warn the driver of drowsiness.

Lin, Tsai, and Ko (2013) used fuzzy logic as a method for the early detection of motion sickness. These type of distractions while driving can endanger safety because of a decline in a person's ability to maintain self-control.

Fazio, Santamaria, De Rango, Tropea, and Serianni (2016) used fuzzy logic to identify a particular driving style and to model driving behaviour. However, their conclusions about driving style were based on the car velocity and acceleration measurement using on-board diagnostics in the vehicle. Similar research with the same input parameters and on-line collection of data was previously proposed by Dorr, Grabengiesser, and Gauterin (2014). Saleh, Aljaafreh, and Albdour (2013) proposed a fuzzy system to classify driving styles in terms of vehicle-human interactions. They used three input variables: acceleration, speed, and distance between the preceding and host car.

Aggressiveness in driving, although a psychological category may be assessed by explicit parameters of vehicle movement, for example by analysing driving performance. An example of this is demonstrated in the paper by Aljaafreh, Alshabatat, and Najim Al-Din (2012). The authors measured aggressiveness based on the Euclidean norm of lateral and longitudinal acceleration, as well as considering car velocity.

In the current study, we use four psychological instruments to assess driver behaviour. The aim is to propose a model that when implemented would quantify driver propensity for traffic accidents, based on scores obtained from the considered tests. For this purpose, we use fuzzy logic and compare the results with the implementation of multiple regression analysis. The proposed model is described further in the next section.

3. Model development

The result of the modelling process will be the proposal of a model that can provide information about driver propensity for traffic accidents, based on the scores obtained from four psychological instruments. The modelling process consists of testing various types of FIS to select the one that produces the minimum amount of error in the description of data. Finally, the selected FIS will be compared with the results of statistical analyses; in this case with multiple regression analysis.

All the variables that appear in the tested FIS structures are presented in Subsection 3.1 together with the sample description. An explanation of the modelling concept and method used for fuzzy rules generation based on data is presented in Subsection 3.2.

3.1 The sample and variables description

The sample included 305 drivers, comprising 103 drivers of privately owned vehicles, 100 bus drivers, and 102 truck drivers. A convenience sampling technique (a nonprobability technique), was implemented. To collect data on professional drivers, 12 transport companies (with some sort of previous cooperation with the authors) were contacted. This might explain why there was a very high response rate, because of this connection. The participating professional drivers completed paper-based questionnaires, while drivers of privately owned vehicles completed web-based questionnaires. The online response rate was 65.6%, which is well above the average of 34.2% determined by Poynton, DeFouw, and Morizio (2019).

The sample comprised 88% male and 12% female drivers. This relationship was expected due to the demanding nature of professional driving and the fact that generally a large majority of drivers are male. With regard to age structure, 18% of the sample were aged 18 to 30 years old, 56% between 31 and 45, 17% between 46 and 60, and 9% above 60 years old. Further descriptive statistics could be presented with more detail; however, this is not the focus of this paper.

For data collection, the modelling process required two methods of testing of the participants. The first methods utilised four psychological instruments for assessing driver behaviour and the second method involved a demographic and driving survey. Four psychological instruments considered in this research, which were the Aggressive Driving Behaviour Questionnaire (ADBQ), the Barratt Impulsiveness Scale (BIS-11), the Manchester Driver Attitude Questionnaire (DAQ), and the Questionnaire for Self-Assessment of Driving Ability. The demographic and driving survey completed by the respondents provides a range of information; however, for this study, the main purpose was to obtain information about the number of traffic accidents in which each respondents had been involved. Accordingly, the final database for the modelling process contained data on the score each participant obtained for each of the psychological instruments (which could be taken as input to the system or independent variables), and the number of accidents per participant, which may be considered as output or dependent variables.

The ADBQ was designed by Mouloua, Brill, and Shirkey (2007). The intention of the authors was to create an instrument with good predictive power considering aggressive situations that are typical in driving. These vary from gestures directed toward other drivers, to explicit aggressive outbursts, such as passing through a red light at an intersection. The instrument contains 20 questions. The respondents were asked to assess the likelihood of manifestation of aggressive driving using a 6-point Likert scale. Results were given in the range of 1 = never to 6 = almost always.

To define the variables of FIS, in the modelling process the score from the ADBQ was taken as variable x_1. This variable was named *Aggressiveness* in the programming code. The possible values that variable x_1 can take is from 20 to 120. However, when examining the values of ADBQ scores from our sample of 305 drivers, the minimum value was 26 and the maximum was 76. Therefore, the scores below 26 belong to the fuzzy set for very low aggressiveness (VLA) with the value of membership function equal to 1 ($\mu(x) = 1$). Conversely, scores above 76 are in the fuzzy set for very high aggressiveness (VHA), also with the value of membership function equal to 1. The average value of all ADBQ scores from the sample was close to 49. Therefore, this value was taken as the highest membership function value ($\mu(x) = 1$) in the fuzzy set for medium aggressiveness (MA). The remaining two fuzzy sets, low aggressiveness (LA) and high aggressiveness (HA) were defined between the limit values and medium value, as shown in Fig. 1. The same logic was used to define other input variables. The domains and descriptive statistics for the scores achieved by respondents are shown in Table 1.

Variable x_2 represents a score obtained from the BIS-11. This instrument is used for the assessment of impulsivity while driving; therefore, this variable was named *Impulsiveness* in the programming code. In this study, we used a version of BIS-11 constructed by Patton, Stanford, and Barratt (1995). The questionnaire consists of 30 questions, which cover a variety of situations and aspects characteristic of impulsive behaviour. The respondents were required to estimate, using a 4-point Likert scale, the extent to which they agree with the statements that describe the most representative impulsive habits and practices. The scaled responses correspond to the following statements: from 1 = never/rarely to 4 = always/almost always. For certain questions in the questionnaire, inverse response values were provided.

Variable x_2 is described by the following fuzzy sets: very low impulsiveness (VLI), low impulsiveness (LI), medium impulsiveness (MI), high impulsiveness (HI), and very high impulsiveness (VHI). The shape and disposition of membership functions for variable x_2 are shown in Fig. 2.

Variable x_3 relates to the score obtained on the Manchester DAQ. The DAQ is a questionnaire for the assessment of attitudes toward risk propensity while driving, devised by Parker, Lajunen, and Stradling (1998). The variable x_3 is named *Risk* in the programming code.

The questionnaire consists of 20 questions with a Likert scale of answers from 1 = strongly disagree to 5 = strongly agree. Most questions refer to the typical traffic situations that can be characterised as high-risk. The DAQ includes statements relating to speeding, drink-driving, close-following, and dangerous overtaking. We arranged the scores such that higher scores correspond to higher risk propensity while driving. Scores of subjects could range from 20 to 100 points.

Variable x_3 is described by the following fuzzy sets: very low risk (VLR), low risk (LR), medium risk (MR), high risk (HR), very high risk (VHR). The shape and disposition of membership functions for variable x_3 are shown in Fig. 3.

Variable x_4 is based on the score obtained from the Questionnaire for Self-assessment of Driving Ability. This questionnaire was developed by Tronsmoen (2008). It consists of a set of statements about how drivers react in certain traffic situations. Based on the responses, it is possible to obtain information about participants' self-perception as a driver. There are 22 questions and answers in the form of 4-point Likert scale. Answers ranged from 1 = never, to 4 = always/almost always. Higher score on the test corresponds to a better evaluation of one's own driving abilities.

Variable x_4 is described by the following fuzzy sets: very low self-assessment (VLS), low self-assessment (LS), medium self-assessment (MS), high self-assessment (HS), and very high self-assessment (VHS). The shape and disposition of membership functions for variable x_4 are shown in Fig. 4. The variable x_4 is named *Self-assessment* in the programming code.

The output variable y relates to the number of traffic accidents experienced by respondents. In the sample, respondents reported the number of accidents from 0 to 8 (Fig. 5). To describe the variable y, we used 7 membership functions unlike in the previous cases where 5 membership functions were used even though the domains of input variables cover 100, 90, 80 and 66 points, respectively. The domain of output variable y implies 9 points; however, the number of membership functions is increased in this case because the traffic accidents are relatively rare events and the intention of the authors was to describe each category of drivers as precise as possible. However, drivers who participated in 6, 7 or 8 accidents were extremely rare and consequently they were grouped under one membership function. Therefore, the output variable y was defined as shown in Fig. 6. The following fuzzy sets were introduced: very small number of accidents (VSNA), small number of accidents (SNA), moderately small number of accidents (MSNA), medium number of accidents (MNA), moderately high number of accidents (MHNA), high number of accidents (HNA), and very high number of accidents (VHNA). The variable y is named *Accidents* in the programming code.

3.2 The concept of modelling and fuzzy rules generation based on data

In the modelling process, the described variables x_1, x_2, x_3, x_4, and y were used to form various FIS structures to test which would make the minimum error in description of the data. Four types of FIS were considered, as follows: one input–one output system, two input–one output system, three input–one output system, and four input–one output system. The concrete FIS concepts to be tested are shown in Table 2. The results of the test should lead to a conclusion as to which psychological instrument, or which combination of two, three, or all four of them, provides the best prediction results regarding driver propensity for traffic accidents.

The basis for fuzzy rules is essential for the performance of FIS. In this paper, we used the well-known approach for defining fuzzy rules proposed by Wang and Mendel (1992). This method is widely used in the literature. Some examples could be found in the papers of Chang, Hieh, and Liao (2005), to solve a problem of due-date assignment in semiconductor manufacturing factory. D'Andrea and Lazzerini (2013) assessed the condition of solar photovoltaic energy installation, and Blagojevic, Selmic, Macura, and Sarac (2013) determined the number of postal units in the network. The Wang-Mendel method may be further combined with other optimisation algorithms to optimise the FIS structure. For example, Yanar and Akyurek (2011) used simulated annealing metaheuristic to tune a Mamdani-type fuzzy model. In the literature, there are several examples of improvements to the Wang-Mendel method (Gou, Fan, Wang, Luo & Chi, 2016; Gou, Hou, Chen, Wang & Luo, 2015; Lee & Shin, 2003; Wang, 2003; Yang, Yuan, Yuan & Mao, 2010). However, we use the original version of this method, because the purpose of our research was to determine the relationship between the considered instruments and how they explain driver propensity for traffic accidents, and not to carry out the optimisation of FIS structure.

The Wang-Mendel method consists of five steps. Step 1 divides the input and output spaces of the given numerical data into fuzzy regions. In the case of this research, the implementation of Step 1 is illustrated in Section 3.1. Although this study tested 15 FIS structures, and each of them use different input variables, all the used variables are described here. For each, the domain interval was determined, that is, the interval of the possible values of variables. Each domain interval was divided into 2N+1 regions. The length of these regions and fuzzy membership functions that describe them were determined based on the logic explained in Section 3.1.

Step 2 generates fuzzy rules from the collected data. First, our data set was structured as shown in Table 3, where letter *i* represents one of 305 respondents from the sample. Depending on the chosen FIS, the specific input–output pairs were considered, as shown in Table 4. At the beginning, one data pair was used for construction of one fuzzy rule. For example, if we consider FIS No. V, the degrees of a given pair $(x_1^{(i)}, x_2^{(i)}; y^{(i)})$ should be determined in different regions. Then, this data pair should be assigned to the regions with maximum degree. Thus, finally, one fuzzy rule from one pair of desired input-output data was obtained. The IF part was composed of the names of regions with maximum degree for input variables, and the THEN part from the name of region with maximum degree for output variables.

In Step 3, a problem of conflicting rules needed to be solved. These are the rules that have the same IF part, but a different THEN part. For this purpose, each of the formed rules should be assigned a degree, defined by Eq. (1) for the case when a rule is defined as following: “IF x_1 is A and x_2 is B, THEN y is C”.

$$D(Rule) = \mu_A(x_1) * \mu_B(x_2) * \mu_C(y) \tag{1}$$

D(Rule) is a degree of a rule, $\mu_A(x_1)$ is a value of membership function of the region A when input value is x_1, etc. In a conflict group, only the rule that has maximum degree should be accepted.

Step 4 makes a combined fuzzy rule base, which consists of rules obtained from empirical data and linguistic rules acquired from a human expert. Finally, Step 5 determines a mapping from input to output space using a defuzzification procedure. In this study, we compared the results of FIS testing in the case when all FIS structures use just rules from empirical data and the case when all considered FIS structures use a complete rule base. In defining a complete rule base, expert logic was based on the assumption of linear interdependence between input and output variables.

4. Calculation and results

This section consists of three parts. In the first part, a detailed procedure for solving an FIS based on empirical data is demonstrated. The second part presents the complete modelling process, in which 15 various FIS are tested. Here, the essence is in the results, not the procedure. Further, it is in the second part that the results of the FIS (that makes the minimum error in describing the data) is compared with multiple regression analysis. Finally, in the third part a sensitivity analysis of the FIS No. XV based on the sample decomposition is performed.

4.1 Demonstration of solving the FIS with two input variables x_1 and x_2

To illustrate the proposed methodology, we offer a detailed description of solving FIS No. V, with corresponding programming code applied in MATLAB.

FIS No. V uses two input variables (x_1 and x_2), which are in the programming code labelled as *Aggressiveness* and *Impulsiveness*, respectively. The output variable y is denoted as *Accidents*.

Because we used the Wang-Mendel method for the design of the FIS, the previously described five steps were solved in the following way. We divided the input and output spaces of the given numerical data into fuzzy regions (Step 1), as explained in Section 3.1. The variables *Aggressiveness*, *Impulsiveness*, and *Accidents* are shown in Figures 1, 2, and 6, respectively.

Algorithm 1 prepared the data for realisation of Steps 2 and 3. The main aim was for it to obtain the values in the matrix Membership Functions Product (*MFPROD*). In this case, this matrix has four columns. The first represents the product of values of membership functions of the regions with maximum degree, both for input and output variables. This value is a prerequisite for the implementation of Step 3, because it practically represents the value of *D(Rule)* from Eq. (1). The second, third, and fourth columns denote the region with maximum degree for *Aggressiveness*, *Impulsiveness*, and *Accidents*, respectively. This information is essential for the implementation of both Step 2, to generate all possible 305 fuzzy rules, and Step 3, to reduce these rules to the appropriate number.

After the creation of 305 fuzzy rules, there were many same rules in the base. To resolve this problem, Algorithm 2 was implemented. In the case of FIS No. 5, after excluding the same fuzzy rules, there were 53 remaining. By implementing the proposed programming code, the remaining rules could be found in the matrix *MFPRODfin*.

Among 53 rules, there were certain conflict rules with the same IF part and a different THEN part. According to the procedure described in Step 3 of the Wang-Mendel method, Algorithm 3 was proposed. The final fuzzy rule base was set in the matrix *Drules*, that is in the matrix *Dsort* where all the rules are sorted from lower to higher values of the first input variable, and afterwards of the second. In the case of FIS No. V, there were 18 fuzzy rules obtained from the collected data.

According to Step 4, the final rule base was formed and missing rules were added based on human expert opinion. In this procedure, we used the assumption that there was a linear interdependence between input and output variables; for example, if the aggressiveness is higher, the number of accidents experienced by a driver should be higher. Accordingly, the final fuzzy rule base of FIS No. V containing 25 rules is shown in Table 5. Note that the rules written in *Italic* are proposed by the authors and other 18 rules are obtained from the empirical data.

Finally, the defined FIS No. V required testing. This was performed based on Equation 2. Cumulative deviation (*CD*) is a measure that describes how well the FIS describes the empirical data. *CD* was calculated as an absolute value of difference between the actual number of accidents experienced by drivers in the sample, and corresponding results of FIS No. V. This calculation of absolute values of differences was completed for each respondent from the sample, meaning that in this case, *CD* is a sum of all 305 deviations. The result of FIS No. V for a respondent number *i* in Eq. (2) is marked as *Propensity(i)*. The same concept of calculating the performance of FIS structures can be found in other papers (see Cubranic-Dobrodolac, Molkova, and Svadlenka, 2019; Jovcic, Prusa, Dobrodolac, and Svadlenka, 2019).

$$CD = \sum_{i=1}^{305} \left| y^{(i)} - Propensity(i) \right| \tag{2}$$

The result of the final calculation is presented in Table 6. It is interesting to note that the results of FIS (where fuzzy rules are based only on empirical data) and FIS with complete fuzzy rules base are very similar, and vary in less than 1% in this case. A comparison of empirical data and results of FIS No. V is presented in Figure 7. With a visual comparison of these results and the results presented in the paper of Cubranic-Dobrodolac et al. (2019), a conclusion can be reached that the considered psychological traits explain the occurrence of traffic accidents significantly better compared to the assessment of dangerous places on the road and road characteristics. Further, it is interesting to compare the results of other FIS structures proposed in this paper, which appears in the next subsection.

4.2 Results of all 15 FIS tests and comparison with multiple regression analysis

To achieve the essential aim of this study—to conclude which psychological instruments provide the best assessment of driver propensity for traffic accidents—we needed to test all of the proposed 15 FIS structures. This was carried out by the same procedure as previously described in the case of FIS No. V. The proposed programming code was used in all cases; however, certain minor changes were made concerning the used variables and their number.

The results of testing are shown in Table 7. By comparing the second and third columns, it is evident how many fuzzy rules were obtained from the empirical data compared to the complete fuzzy rule base. Further, the results of testing various FIS structures in two cases where the FIS was designed only from fuzzy rules from the empirical data, and where there is a complete fuzzy rule base, are presented in the fourth and fifth columns, respectively. Even though the results in these columns are very similar, there are certain cases where the complete fuzzy rules base provides worse results. This means there is a space for optimisation of the fuzzy rule base; however, this is not a topic of interest in this paper. The general conclusion from this research is that driver propensity for traffic accidents can be modelled in the best way by using all four considered psychological instruments.

Finally, the FIS that shows the best performance should be compared with the results of statistical analyses, in this case with multiple regression analysis. The results from tests with the same data using multiple regression analysis are described in detail in the paper by Cubranic-Dobrodolac et al. (2017). However, the essential aspect of this paper, which important for the purpose of comparison, is as follows. A set of data may be described by Eq. (3), and in our case Eq. (4) is also valid.

$$y = b_0 + b_1x_1 + \ b_2x_2 + \cdots + \ b_nx_n \tag{3}$$

$$y = b_0 + b_1x_1 + \ b_2x_2 + \ b_3x_3 + b_4x_4 \tag{4}$$

where y and x_n are variables that mark the same as in the FIS structures, i.e. y is Accidents, x_1 is Aggressiveness, x_2 is Impulsiveness, x_3 is Risk, and x_4 is Self-assessment. b_1, b_2, b_3, and b_4 are the corresponding regression coefficients, and b_0 is the intercept.

After the necessary calculations, the results are as follows: b_0 = - 2.770, b_1 = 0.023, b_2 = 0.039, b_3 = 0.013, and b_4 = - 0.011. Based on the formed regression equation, and by testing this using Eq. (2), the CD value is 326.7150. The results of testing the FIS structures and multiple regression analysis are shown jointly in Figure 8. As is evident, FIS No. XV offers the minimum error in description of data, which makes it the best decision-making tool in assessing the driver propensity for traffic accidents.

4.3 Sensitivity analysis of the FIS No. XV based on the sample decomposition

Because the FIS No. XV was determined to be the best of the analysed FIS structures, we were interested to perform a sensitivity analysis considering particular groups from the sample. Accordingly, we tested FIS No. XV based on the individual categories considering gender and age. In this procedure, the calculation of cumulative deviation (CD) was slightly different, because the number of respondents differed from group to group. To be able to compare the CD values, the following Eq. (5) was used:

$$CD_g = \frac{n}{k} \times \sum_{i=1}^{k} \left| y^{(i)} - Propensity(i) \right| \tag{5}$$

where CD_g is a cumulative deviation of the considered group, n is the total number of respondents, and k is the number of respondents in the considered group.

The results of the test procedure are shown in Table 8. It can be noticed that FIS No. XV showed the best performance in three groups: male respondents, respondents aged 31–45, and those aged over 60. However, in the remaining three groups, the number of respondents was relatively small: 12% for the female group, 18% for those aged 18 to 31, and 17% for those aged 46 to 60. To validate the results for smaller groups, the research should be expanded to new respondents of respective groups. Additionally, the implementation of certain methods for FIS structure optimisation, such as metaheuristic algorithms, would be welcome.

5. Conclusions

The main aim of this paper was to determine which of the considered four psychological instruments should be used to assess driver propensity for traffic accidents successfully. The results indicate that the most suitable approach was to use a combination of all four instruments: the BIS-11, the ADBQ, the Manchester DAQ, and the Questionnaire for Self-assessment of Driving Ability.

Fuzzy logic was shown to be a convenient technique for obtaining these results, offering better results when compared to multiple regression analysis. Furthermore, the FIS that makes the minimum error in description of empirical data may be used as a useful tool in decision-making processes in various situations. Because the proposed FIS provides information about driver propensity for traffic accidents, the criteria used in the selection of professional drivers could be significantly improved. This would involve the use of proposed instruments for assessing personality traits along with the psychomotor tests.

The results may have their practical implications in the design of training and education processes for candidates applying for a driving license. Furthermore, programmes for the prevention of accidents and violations of laws, or for the rehabilitation of drivers who have been deprived of their driving license may be developed more effectively, according to the personality traits of the driver.

Further, the results of this research could be usefully applied for some categories of vulnerable drivers to raise awareness about the consequences of risky behaviour in traffic. For example, young drivers show a high rate of involvement in traffic accidents, especially at the beginning of their driving experience. According to the World Health Organization (2018), road traffic injuries are the leading killer of people aged 5–29 years.

Finally, we would conclude with possible directions for further research. It would be useful to perform further sensitivity analysis of the obtained results. This means that the parameters of considered FIS structures, such as the shape of membership functions, their positions, rules, and method of defuzzification, should be changed and tested regarding the consequences. This type of examination represents the optimisation of the FIS structure, which would be the final aim in defining the most appropriate decision-making tool for assessing driver propensity for traffic accidents.

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Algorithm 1. Determination of regions with maximum degree

```
MFPROD=zeros(length(Aggressiveness),4);
for j=1:length(Aggressiveness)
    a = Aggressiveness(j);
    i = Impulsiveness(j);
    n = Accidents(j);
    amax = [];
    imax = [];
    nmax = [];
    for c=1:length(Propensity.input(1).mf)
        amax = [amax
evalmf(a,Propensity.input(1).mf(c).params,Propensity.input(1).mf(c).type)];
    end
    for d=1:length(Propensity.input(2).mf)
        imax = [imax
evalmf(i,Propensity.input(2).mf(d).params,Propensity.input(2).mf(d).type)];
    end
    for f=1:length(Propensity.output.mf)
        nmax = [nmax
evalmf(n,Propensity.output.mf(f).params,Propensity.output.mf(f).type)];
    end
    [mfa,ida] = max(amax);
    [mfi,idi] = max(imax);
    [mfn,idn] = max(nmax);
    EVAL(j,1)=mfa;
    EVAL(j,2)=mfi;
    EVAL(j,3)=mfn;
    MFPROD(j,1)=EVAL(j,1)*EVAL(j,2)*EVAL(j,3)
    MFPROD(j,2)=ida
    MFPROD(j,3)=idi
    MFPROD(j,4)=idn
end
```

Algorithm 2. Reducing the same rules

```
MFPRODnew=MFPROD;
for k=1:size(MFPROD,1)
   H=zeros(length(Aggressiveness),1);
   for g=1:size(MFPROD,1)
     X(g,1)=MFPROD(k,2)==MFPROD(g,2) & MFPROD(k,3)== MFPROD(g,3) &
MFPROD(k,4)== MFPROD(g,4);
     H(g,1)=X(g,1)*g;
     VMF(g,1)=X(g,1)* MFPROD(g,1);
     MMAX=max(VMF);
   end
   S=nonzeros(H);
   MFPRODnew(S,1)=MMAX;
end
MFPRODfin=unique(MFPRODnew,'rows','stable')
```

Algorithm 3. Reducing the conflict rules

```
D=MFPRODfin;
for k=1:size(D,1)
H=zeros(size(D,1),1);
  for g=1:size(D,1)
     Y(g,1)=D(k,2)==D(g,2) & D(k,3)==D(g,3);
     H(g,1)=Y(g,1)*g;
     VVMF(g,1)=Y(g,1)*D(g,1);
     [MMAX,idMMAX]=max(VVMF);
   end
   H(idMMAX,1)=0;
   Hfin=nonzeros(H);
   D(Hfin,:)=0;
end
B=zeros(size(D,1),length(Propensity.input)+2);
Drules = setdiff(D,B,'rows','stable')
Dsort = sortrows(Drules,[2 3])
```

Table 1. Domain intervals for x_1, x_2, x_3, x_4 and y and descriptive statistics of the sample.

Variable	Domain	Descriptive statistics of the sample			
		Number of respondents	Minimum	Mean	Maximum
x_1	[20,120]	305	26	49.46	76
x_2	[30,120]	305	49	68.44	86
x_3	[20,100]	305	24	62.52	83
x_4	[22,88]	305	34	66.58	88
y	[0,8]	305	0	1.46	8

Table 2. Tested fuzzy interference systems

FIS No.	Used variables	Name of used variable in the programming code
I	x_1, y	Aggressiveness – Accidents
II	x_2, y	Impulsiveness – Accidents
III	x_3, y	Risk – Accidents
IV	x_4, y	Self-assessment – Accidents
V	x_1, x_2, y	Aggressiveness, Impulsiveness – Accidents
VI	x_1, x_3, y	Aggressiveness, Risk – Accidents
VII	x_1, x_4, y	Aggressiveness, Self-assessment – Accidents
VIII	x_2, x_3, y	Impulsiveness, Risk – Accidents
IX	x_2, x_4, y	Impulsiveness, Self-assessment – Accidents
X	x_3, x_4, y	Risk, Self-assessment - Accidents
XI	x_1, x_2, x_3, y	Aggressiveness, Impulsiveness, Risk – Accidents
XII	x_1, x_2, x_4, y	Aggressiveness, Impulsiveness, Self-assessment – Accidents
XIII	x_1, x_3, x_4, y	Aggressiveness, Risk, Self-assessment – Accidents
XIV	x_2, x_3, x_4, y	Impulsiveness, Risk, Self-assessment - Accidents
XV	x_1, x_2, x_3, x_4, y	Aggressiveness, Impulsiveness, Risk, Self-assessment – Accidents

Table 3. Data set of input and output values

Respondent	$x_1^{(i)}$	$x_2^{(i)}$	$x_3^{(i)}$	$x_4^{(i)}$	$y^{(i)}$
1	66	76	69	41	8
2	50	60	55	73	0
3	43	62	52	70	0
4	61	76	46	56	3
....	....	....	....	....	....
305	45	75	55	66	3

Table 4. The use of data in a particular fuzzy inference system

FIS No.	Used input-output data
I	$(x_1^{(1)}; y^{(1)}), (x_1^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}; y^{(305)})$
II	$(x_2^{(1)}; y^{(1)}), (x_2^{(2)}; y^{(2)}),\ldots, (x_2^{(305)}; y^{(305)})$
III	$(x_3^{(1)}; y^{(1)}), (x_3^{(2)}; y^{(2)}),\ldots, (x_3^{(305)}; y^{(305)})$
IV	$(x_4^{(1)}; y^{(1)}), (x_4^{(2)}; y^{(2)}),\ldots, (x_4^{(305)}; y^{(305)})$
V	$(x_1^{(1)}, x_2^{(1)}; y^{(1)}), (x_1^{(2)}, x_2^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}, x_2^{(305)}; y^{(305)})$
VI	$(x_1^{(1)}, x_3^{(1)}; y^{(1)}), (x_1^{(2)}, x_3^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}, x_3^{(305)}; y^{(305)})$
VII	$(x_1^{(1)}, x_4^{(1)}; y^{(1)}), (x_1^{(2)}, x_4^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}, x_4^{(305)}; y^{(305)})$
VIII	$(x_2^{(1)}, x_3^{(1)}; y^{(1)}), (x_2^{(2)}, x_3^{(2)}; y^{(2)}),\ldots, (x_2^{(305)}, x_3^{(305)}; y^{(305)})$
IX	$(x_2^{(1)}, x_4^{(1)}; y^{(1)}), (x_2^{(2)}, x_4^{(2)}; y^{(2)}),\ldots, (x_2^{(305)}, x_4^{(305)}; y^{(305)})$
X	$(x_3^{(1)}, x_4^{(1)}; y^{(1)}), (x_3^{(2)}, x_4^{(2)}; y^{(2)}),\ldots, (x_3^{(305)}, x_4^{(305)}; y^{(305)})$
XI	$(x_1^{(1)}, x_2^{(1)}, x_3^{(1)}; y^{(1)}), (x_1^{(2)}, x_2^{(2)}, x_3^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}, x_2^{(305)}, x_3^{(305)}; y^{(305)})$
XII	$(x_1^{(1)}, x_2^{(1)}, x_4^{(1)}; y^{(1)}), (x_1^{(2)}, x_2^{(2)}, x_4^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}, x_2^{(305)}, x_4^{(305)}; y^{(305)})$
XIII	$(x_1^{(1)}, x_3^{(1)}, x_4^{(1)}; y^{(1)}), (x_1^{(2)}, x_3^{(2)}, x_4^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}, x_3^{(305)}, x_4^{(305)}; y^{(305)})$
XIV	$(x_2^{(1)}, x_3^{(1)}, x_4^{(1)}; y^{(1)}), (x_2^{(2)}, x_3^{(2)}, x_4^{(2)}; y^{(2)}),\ldots, (x_2^{(305)}, x_3^{(305)}, x_4^{(305)}; y^{(305)})$
XV	$(x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, x_4^{(1)}; y^{(1)}), (x_1^{(2)}, x_2^{(2)}, x_3^{(2)}, x_4^{(2)}; y^{(2)}),\ldots, (x_1^{(305)}, x_2^{(305)}, x_3^{(305)}, x_4^{(305)}; y^{(305)})$

Table 5. Final fuzzy rule base of fuzzy inference system No. V

x_1	**VLA**	*VSNA*	VSNA	MSNA	*SNA*	*MSNA*
	LA	VSNA	VSNA	VSNA	MNA	SNA
	MA	VSNA	VSNA	MSNA	VHNA	VSNA
	HA	MSNA	VSNA	SNA	MHNA	*MNA*
	VHA	*SNA*	*MSNA*	MSNA	MHNA	*HNA*
		VLI	**LI**	**MI**	**HI**	**VHI**
		x_2				

Table 6. The result of testing fuzzy inference system No. V

	FIS No. V (18 fuzzy rules based on data)	FIS No. V (25 fuzzy rules – complete base)
CD	473.5682	473.0376

Table 7. Results of all 15 FIS structures testing

FIS No.	Number of rules obtained from empirical data	Number of rules in the complete fuzzy rule base	*CD* when FIS use just fuzzy rules from empirical data	*CD* when FIS use the complete fuzzy rule base
I	5	5	397.3646	397.3646
II	5	5	584.1899	584.1899
III	5	5	365.4782	365.4782
IV	5	5	402.1822	402.1822
V	18	25	473.5682	473.0376
VI	19	25	329.0113	327.1454
VII	21	25	350.2779	349.0564
VIII	17	25	323.3962	324.5296
IX	19	25	306.4532	306.8304
X	20	25	376.0972	378.7192
XI	45	125	344.9796	343.0711
XII	55	125	313.9698	318.7048
XIII	50	125	354.7903	359.2937
XIV	47	125	329.1417	329.7905
XV	101	625	299.7392	305.8853

Table 8. The results of sensitivity analysis of the FIS No. XV based on the sample decomposition

FIS No.	*CD* values					
	Gender		Age			
	Female	Male	18–30	31–45	46–60	over 60
I	448.4745	390.3084	365.0573	401.1536	396.7205	439.0159
II	677.1041	571.3622	521.6775	589.0191	568.4074	706.9715
III	511.7653	345.2819	307.2864	374.8513	331.8670	485.2964
IV	487.5104	390.4018	354.1721	402.9592	432.9751	434.5825
V	527.2683	465.5505	431.1230	477.5572	465.6013	541.7410
VI	465.0236	308.1100	294.2280	335.2239	300.9599	391.3869
VII	436.5012	336.9838	360.1556	341.3357	365.3794	343.8167
VIII	461.4502	305.6264	269.9744	321.1395	373.4631	361.3978
IX	332.9108	303.2297	281.4712	304.9135	319.1121	345.4724
X	527.9542	358.1160	357.2947	375.6479	381.4629	434.3549
XI	452.9036	327.9077	298.4880	335.4774	398.5793	373.6620
XII	366.0940	312.1624	281.0126	330.0676	313.9347	332.6145
XIII	482.5661	342.2748	327.6299	342.7775	415.5273	417.3337
XIV	414.9863	318.0284	328.6142	322.7749	355.0851	327.7203
XV	407.1964	291.8982	281.3575	291.1322	378.4428	308.8877

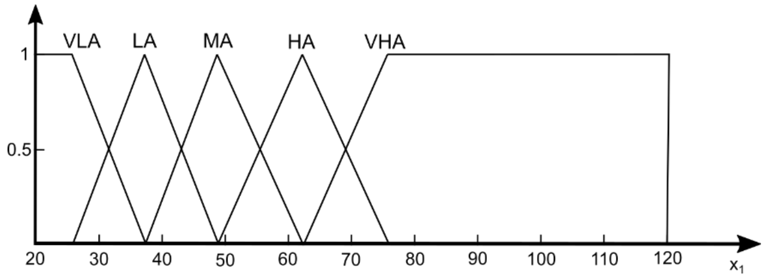

Figure 1. Input variable x_1 – Aggressiveness.

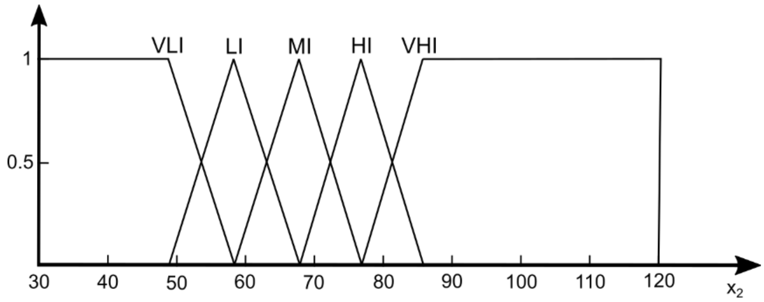

Figure 2. Input variable x_2 – Impulsiveness.

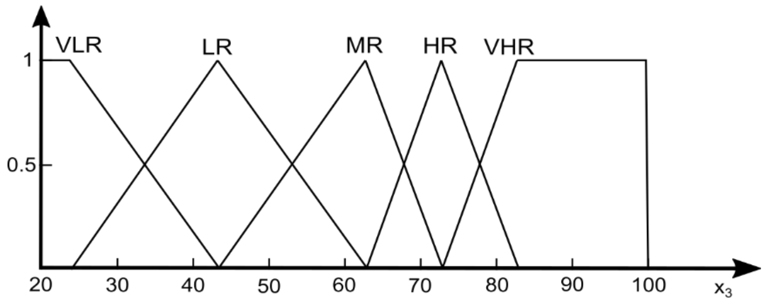

Figure 3. Input variable x_3 – Risk.

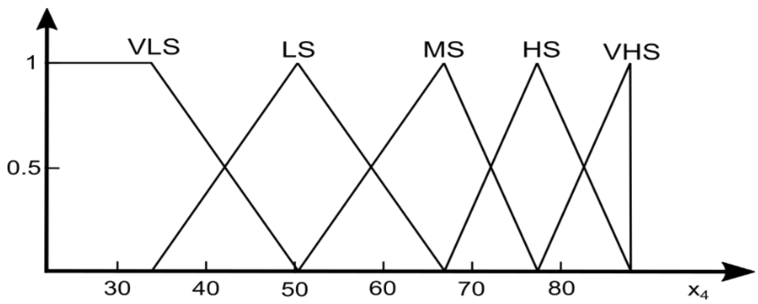

Figure 4. Input variable x_4 – Self-assessment.

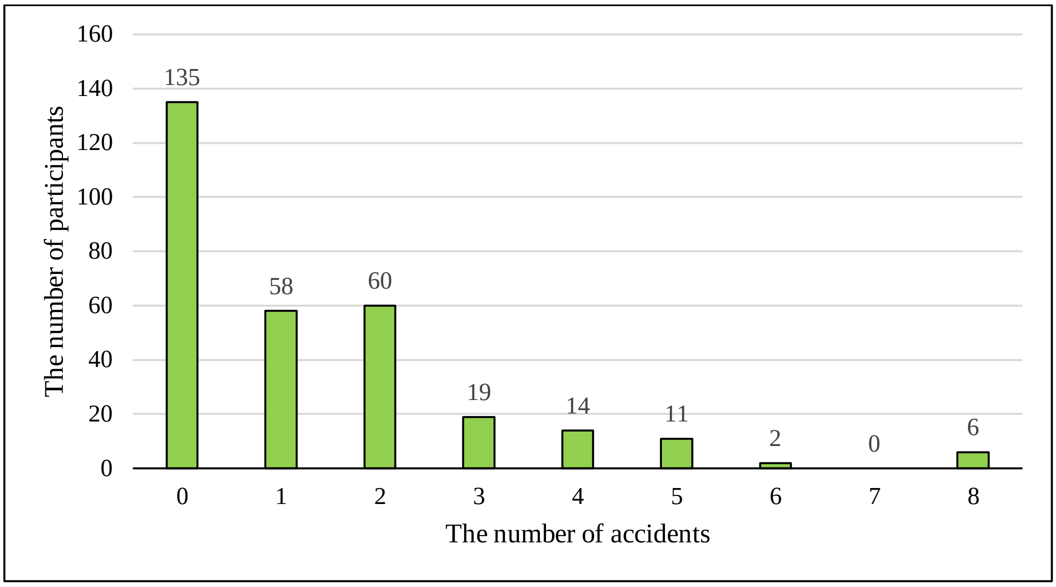

Figure 5. The number of traffic accidents in the sample

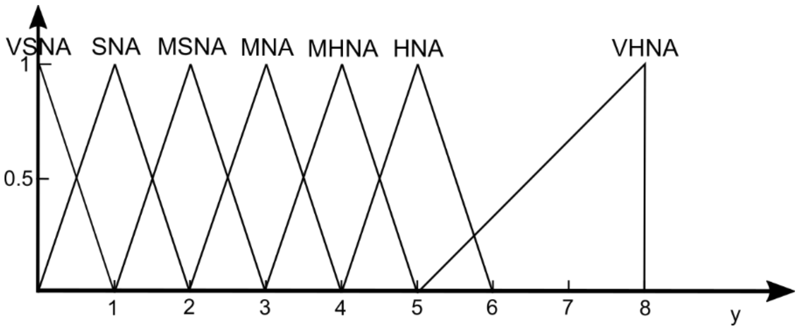

Figure 6. Output variable *y* – Accidents.

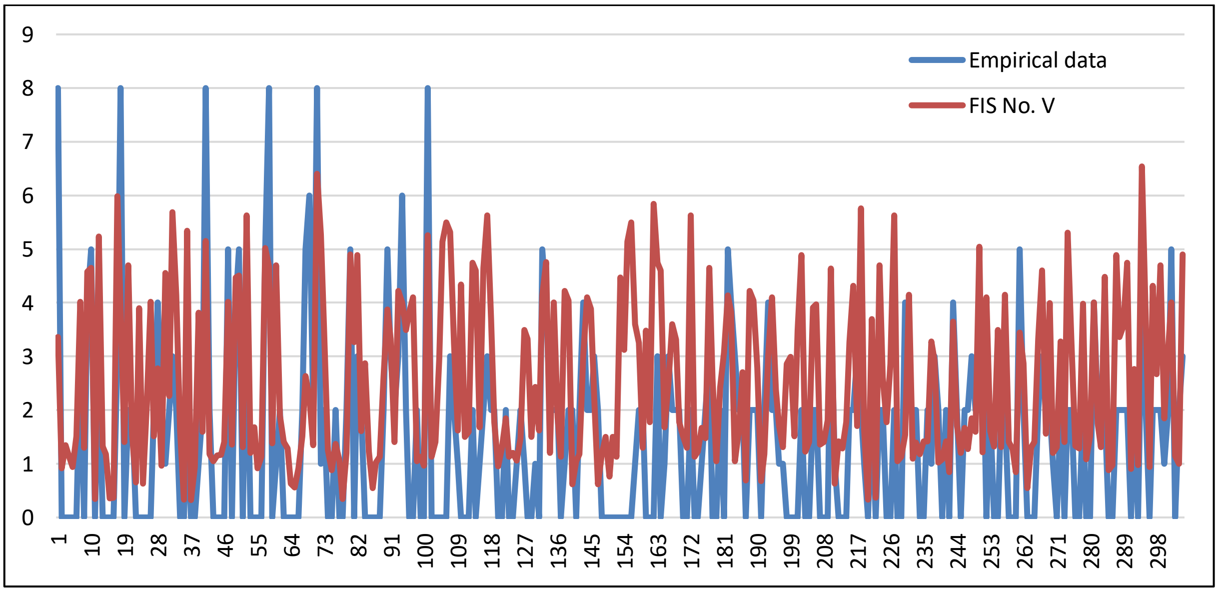

Figure 7. Comparison of empirical data and results of FIS No. V

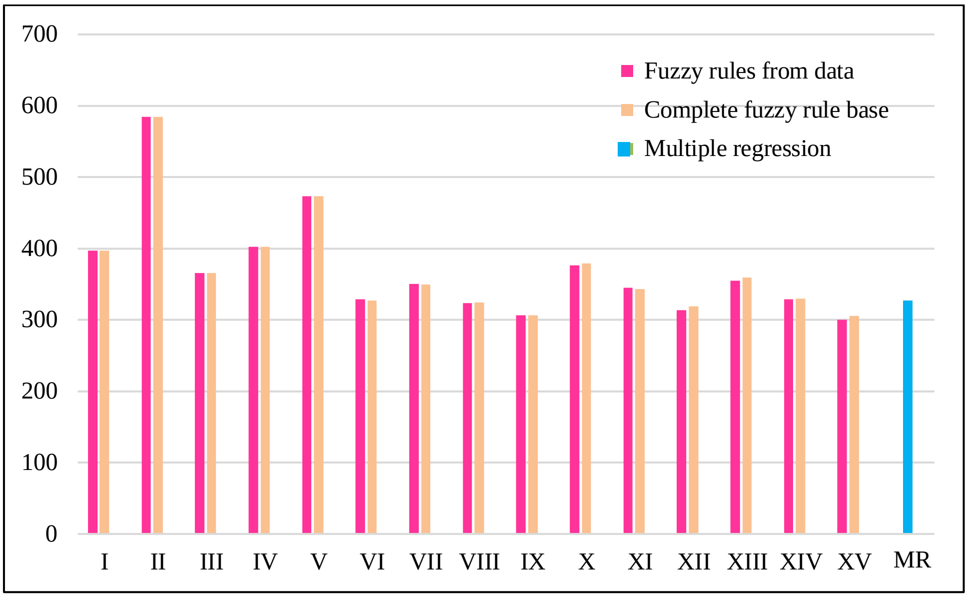

Figure 8. Comparison of results of the FIS structures and multiple regression analysis