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Fuzzy expert system for road type identification and risk assessment of conventional two-lane roads

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Abstract

This paper first presents a fuzzy expert system to identify and classify conventional two-lane roads based on geometric characteristics. Both fuzzy and neuro-fuzzy techniques have been used. Fuzzy logic has proved suitable to address this problem, since in this case, there is a variability of input information, and classical rules are not suitable to be used due to the uncertainty introduced by some combinations of the variables. Each road's geometric features were measured by sensors in an equipped vehicle, and are subsequently used to classify the roads according to their real condition. The conventional two-lane roads used for this research are located in the Madrid Region, in Spain. This intelligent system may be used to update the road database regarding the assigned type to each conventional road, according to their present features and state. Also, a risk identification system has been developed to assess whether a vehicle is driving on a two-lane road with an inappropriate speed, combining variables such as the former identification model, vehicle type, road longitudinal gradient, the angle covered by each horizontal curve, and the existence or not of an additional traffic lane. A fuzzy risk index is proposed for this approach. This fuzzy model may be useful to detect road sections where safety must be enhanced by revising the speed limit, since less safe situations may arise from travelling at unappropriated speeds.

KEYWORDS
expert system, fuzzy logic, identification, risk assessment, safety, two-lane road

1 | INTRODUCTION

User experience in roads, regarding both comfort and driving safety, depends largely on road conditions. Both pavement and road infrastructure beneath and around it may deteriorate due to multiple causes: vegetative wear and tear, rain, ice, heavy vehicle (HV) traffic, and so forth (Martín et al., 2016; Shah & Ahmad, 2019). Moreover, road geometry also has a significant impact on making the driving predictable and safe, and in how safe a road section is.

The set of geometric characteristics of a road is used to define different road types, according to which the appropriate applicable traffic regulations will be set. These geometric criteria are, among others, the number of lanes, shoulder width, camber, gradient, curve radius, and so forth.

The speed limit is usually set in the road design phase, according to the assigned class and local section terrain class and other features. But, over time, road conditions may change, either because it was never built as originally thought or due to wear and tear, weather, degradation, erosion, aging, encroachment of vegetation, new roadside buildings and developments, and so forth. This may cause the initial road categorization to become incorrect, and in such case, the current road section must be reclassified. Sometimes, these variations apply only to a portion of the road, and that part would require a reclassification, as it should no longer be held in the original assigned type. Therefore, it is important to keep a correct updated assignment of the road type, since the recommended safe speed or legal speed limit will depend on it, as well as some other guidelines and regulations on what may be on and around the road.

In this paper, some Soft Computing techniques were applied, particularly fuzzy and neuro-fuzzy systems, in order to classify two-lane road sections based on their current geometric characteristics, and the expected vehicle performance considering passenger cars, trucks, and buses (Barreno et al., 2020). As far as we know, the identification problem of two-lane roads using fuzzy logic has not been proposed before and, therefore, the fuzzy perception of the classification of highways is novel. These techniques have been proved useful when facing similar tasks (Lattarulo et al., 2020; Santos, 2011; Sierra & Santos, 2018). Results on conventional two-lane roads of the Madrid Region, Spain, are encouraging. This intelligent system may be used to maintain and update the road databases regarding the assigned type to each conventional road, according to their present characteristics.

In addition, a risk identification system to assess whether a vehicle is driving on a two-lane road with an inappropriate speed is presented, making use of the identification model and other variables such as the vehicle type, the road longitudinal gradient, the angle covered by each horizontal curve, and the existence or not of an additional lane of traffic. A fuzzy risk index (FRI) is proposed following this approach. This fuzzy risk assessment system may be used to verify relatively unsafe road sections, where more accidents are prone to happen.

This paper is structured as follows. Section 2 summarizes related works. Section 3 describes two-lane road classes and their geometric characteristics, which constitute the basis for the fuzzy identification system. In Section 4, the risk assessment expert system is developed, that includes a fuzzy identification of the actual road classes. Results are presented and discussed in Section 5. Conclusions and future work end the paper.

2 | RELATED WORKS

Regarding the available literature on the identification of type of road, in Amini et al. (2002), authors use fuzzy logic to identify roads using Ikonos satellite images. In Tuncer (2007), a road detection algorithm based on fuzzy techniques is described, using satellite images from a GIS. In Yan et al. (2013), the road geometry is analysed to establish an adaptive cruise control. To provide a vehicle with that functionality, geometric characteristics (radius and slope) and GPS information about speed limit are used in Schwickart et al. (2014). A flexible logic-based approach is applied in Burrieza et al. (2019), where the qualitative reasoning is applied to maintain the allowed speed as a function of some geometric factors such as the road slope.

These works support the interest of this paper, as there are some initiatives using the geometric characteristics of two-lane roads to adjust the travelling speed. However, unlike the one presented here, they do not use fuzzy geometric variables, and are mainly focused on vehicle cruise control, and many of them not do not deal with other road features or are not focused on safety-related issues except speed.

But when it comes to analyse the risk of driving in conventional roads due to present road characteristics, the literature is scarcer and mainly focused on historical data. To mention some of them. In Chen et al. (2016) logistic regression and statistical method are combined to analyse accident data in order to find the relationship between highway geometric factors and accident rate. The results provide references to identify unsafe locations. The study by Lin et al. (2020) presents a complete machine-learning pipeline to find the patterns of crashes involving teen drivers on rural roads. According to these authors, road class, speed limit and the first harmful event are the top three factors affecting crash severity.

Deficiencies in the geometric design of existing roads could lead to an accident, such as those occurring on sharp curves and slippery pavement surface (Wedajo et al., 2017). The research study focused on the analysis of traffic accidents related to the geometric design parameters of the existing asphalt paved road. It was revealed that the main cause of traffic accidents in the study area was due to geometric deficiencies in traffic accident-prone areas. In Rengarasu et al. (2009) the authors determined the effects of road geometry and road cross-section variables on the number of accidents. Two negative binomial models were developed with homogeneous road segments and one with 1 km road segments. The homogeneous road segments were divided according to the horizontal alignment of the road. The combination of variables showed a significant effect on the number of accidents.

In Karlaftis and Golias (2002) the question of the relationship between the geometric characteristics of rural roads, accident rates, and their prediction was addressed using a tree-based hierarchical regression. The results show that, although the importance of single variables differs between two-lane and multi-lane, geometric design, and pavement condition variables are the two most important factors affecting accident rates. In Guerrero-Barbosa et al. (2015) the influence of factors associated with road geometry and environment, vehicle volumes, and speeds on the frequency of accidents on the urban road network is determined using field variables, accident data, and their subsequent evaluation, with a model based on Poisson and negative binomial regressions. The analysis of the results showed that variables such as carriageway width, number of intersections, pavement type, vehicle volumes, and average traffic speed are related to accident rates.

In Afandizadeh and Hassanpour (2020) the effect of road and roadside development factors on the accident frequency rate was evaluated using ANalysis Of VAriance and χ^2 tests on a rural road. The results indicated that operating speed and differences between speed limits and operating speed are the most influential factors on accident frequency rate. Single-vehicle hit-and-run collisions in urban areas are a growing problem that deserves more attention from authorities and researchers (Álvarez et al., 2020). That study aims to detect risk factors in road geometric design that characterize the locations where crashes could occur in urban areas. In Othman et al. (2009) the aim of road safety research was to find the critical road parameters that affect the accident rate. The study was based on crash and maintenance data from roads in Sweden. Statistical analysis showed variations in the accident rate when road elements changed, confirming that road characteristics affect the accident rate. The results indicated that large radius turning bends are more dangerous during lane change manoeuvres. In Vayalamkuzhi and Amirthalingam (2016) the authors focus on the analysis of the influence of geometric design features on traffic safety, using bi-directional data on a divided highway operated under heterogeneous traffic conditions in India. The study provided a better understanding of the factors related to road geometry that influence the frequency of crashes. The study also found that traffic speed is a significant contributor to the total number of crashes.

Road factors, including road and shoulder design elements, play an important role in determining the risk of road accidents (Ahmed, 2013). These factors include those where a road defect directly triggers an accident, where some road element misleads the road user and thus leads to human error. In Dadashova et al. (2016) the effect of road geometry and other accident-causing conditions is studied. Data mining techniques were applied to the processing and combination of two databases of factors associated with road accident severity and geometry standards, respectively. The effect of influencing factors on the severity of road accidents was estimated using a non-parametric statistical methodology, the random forest. Road geometry design standards were found to have a significant effect on road accident severity.

In Stanković et al. (2020) a new fuzzy multi-criteria decision-making model for traffic risk assessment based is proposed. It applies the fuzzy pairwise pivot relative criteria importance assessment to determine the weights of the criteria. In Mitrović Simić et al. (2020) a new multiphase model is proposed, using fuzzy logic, to determine the level of traffic safety on road sections under the conditions of uncertainty.

On the other hand, the identification of higher-risk road sections is of great interest to road authorities and safety specialists. Research into which road parameters most influence accidents has been extensive. In Mohamedhah et al. (1993) a model for the determination of the accident involvement rate of trucks per kilometre per year was formulated, as a function of the average daily intensity of trucks and other vehicles. In Garber and Ehrhart (2000), the influence of average speed, standard deviation of speed, flow per lane, lane width, and the existence of a hard shoulder on accident rates was determined using multivariate analysis, robust regression, and linear regression. In Bauer and Harwood (2000) the influence of traffic at intersections and in acceleration lanes was evaluated, concluding that a low percentage of accidents are related to geometry, with traffic volume being the most influential factor. In Karlaftis and Golias (2002) average daily traffic volume was identified as the variable that best explains accidents on multi-lane roads, as well as improved safety in the presence of medians and access control. In Hiselius (2004) the high influence of HV traffic on accident rates compared to the influence of total traffic was assessed.

The influence of horizontal and vertical layout elements such as curve radius or slopes has been analysed by authors such as Vogt and Bared (1998), Persaud et al. (2000), and Chang and Chen (2005). That work also provides an innovative criterion for locating higher-risk short sections, which are likely to be the location of a higher accident rate, taking into account how the lane, and shoulder width can affect road safety, as well as other geometric road factors such as the angle covered by each horizontal curve, the gradient, and the type of vehicle being driven.

3 | ROAD CLASSES AND GEOMETRIC CHARACTERISTICS

3.1 | Two-lane road classes

Roads are usually considerably long in most countries, and their designation is controlled by the start and finish points, which are most usually towns and cities, and sometimes other roads. Since they are long, and may cross-different areas, with different degrees of development and environmental protection, they can and should be divided into sections that have similar characteristics. For example, a road section may have road barriers, or a median, or a climbing or passing lane, and these features does not hold along its total length. Even more, these sections may not correspond to the original type assigned to the road. This may be quite relevant as traffic regulations, regulations, and control differ depending on the assigned road type.

Conventionally, the road classes in Spain are named with a letter followed by a number. The 'A' letter stands for highways (or freeways, in the United States) and 'C' for conventional two-lane roads. These letters are followed by a number that indicates the design speed, *Vp* (km/h), without considering the maximum speed allowed by the regulation (Order FOM/273/2016: Ministerio de Fomento (FOM) (Spanish Ministry of Development), 2016).

The design speed of a section (*Vp*) that depends on the geometric characteristics of that cross-section, is calculated as:

$$Vp^2 = 127R\left(f_t + \frac{\rho}{100}\right), \tag{1}$$

where *Vp* is the design speed (km/h), *R* is the radius (m), f_t the tire-pavement friction coefficient, and ρ is the inclination of the cross slope in %.

TABLE 1 Road types and correspondence with conventional sections

Road type	Two-lane road	Class (HCM, 2018)
Intercity	C-90	I
Suburban	C-80, C-70, C-60	III
Accessibility	C-50, C-40	II
Urban	C-50, C-40	IV

Table 1 shows the classification of two-lane roads according to their design speed and class (use and location), according to the official regulation (Order FOM/273/2016). These conventional roads may belong to more than one type. For example, the C-50 road is included in two classes, II and IV.

3.2 | Geometric characteristics of the road

The geometric characteristics of a road section include both the cross-section and the horizontal and vertical geometries. These features are mainly the slope, the camber, horizontal radius and carriageway dimensions (Barreno et al., 2020).

From the construction point of view, the travelled section of a road is composed of lanes and shoulders. The lane is part of the road intended for vehicular traffic, and a road consists of a certain number of lanes. The adjacent strip of the road is called shoulder if it may be used by vehicles to make eventual short stops (or sidewalk, if the road is in an urban environment). The shoulders do not belong to the road proper, and vehicles cannot travel on them in normal conditions. On roads with divided carriageway, the median separates the vehicles by direction. The platform width is the total of the right and left shoulders and the lane widths.

The rolling resistance coefficient, R_p, depends on the nature of the road surface, the tyre characteristics, and the load on the wheels. Its value also increases slightly with speed. On the other hand, overcoming the tendency of the weight to fall downhill is quantified as the proportion of the weight that corresponds to the slope in percent per one, a formula that is applicable to low slopes, such as those used in roads:

$$R_p = \frac{\frac{W}{P}}{C_r + \frac{i}{100}} \frac{i}{100}, \tag{2}$$

where i is the slope in % (positive on ramp and negative on slope), W is the power, C_r is the friction coefficient, and P is weight (N).

The speed that a passenger car or a HV can develop on a ramp, and, by extension, on a slope, taking into account all, or only some of the driving resistances: rolling resistance, slope gradient, and aerodynamic drag, can be expressed as:

$$E = \frac{W}{V} = \left(C_r + \frac{i}{100}\right) \cdot P + \left(\frac{\rho}{2} C_D A_f\right) \cdot V^2, \tag{3}$$

where E is the tractive force, V is the speed (km/h), C_d is the aerodynamic coefficient, A_f is vehicle frontal area (m^2), ρ is air density (1.29 kg/m^3 under normal conditions).

This solution can be representative of the vehicle fleet as a whole, if appropriate vehicle types are chosen. If aerodynamic drag is neglected, the final speed V_f to which the vehicle tends on a sufficiently long ramp, irrespective of the initial velocity, is:

$$V = \frac{\frac{W}{P}}{C_r + \frac{i}{100}}, \tag{4}$$

where W/P is power-to-weight ratio, C_r is the coefficient of friction, and i is the slope.

It is easy to see that the vehicle speed tends to stabilize at the final speed independently of the initial speed. When the ramp is sufficiently long, the vehicle will reach this final speed which is the maximum speed at which the vehicle can negotiate the ramp.

The road curvature is visually perceived by the driver. To estimate the sinuosity of the road, the angle between the tangent lines of two consecutive transition curves at their inflection points is used. The specific angle of each element of the road is calculated from the actual bending curvature radius data. Curve perception has been evaluated with the Spanish national criteria, that is, a curve is considered perceptible for the driver when it simultaneously fulfils (FOM/273/2016):

1. The variation in azimuth between the ends of the colthood is ≥1/18 rad.
2. The setback of the circular curve is ≥50 cm.

According to this, the angle Ω (gon) is determined as:

$$\Omega = {}^{L \cdot 500}\!/_{R \cdot \pi} \quad \text{if } R \geq 972\,m \; L = {}^{R}\!/_{9}, \tag{5}$$

$$\Omega = {}^{L \cdot 500}\!/_{R \cdot \pi} \quad \textit{if } R < 972\,m \; L = 2\sqrt{3R}, \tag{6}$$

where R is the radius of curvature (m) and L minimum length of segment (m). In addition, the variation in azimuth between the ends of the colthood is greater than or equal to one fifth of the total angle (Ω) between consecutive straight alignments into which the colthood is inserted.

4 | RISK ASSESSMENT INTELLIGENT SYSTEM FOR TWO-LANE ROADS

The perception of a safe speed is different for each driver (Zhang et al., 2020). Moreover, the same driver is not expected to make necessarily the same decision on different trips, as external factors may produce different results. The system proposed here takes into account some of these driver subjective perceptions. This intelligent driving risk assessment system considers factors of different nature, in particular the geometry of the road and vehicle type driving.

The chosen solution is an intelligent multiple-inputs single output (MISO) system, designed and developed to assess the unsafe speed risk for a vehicle circulating on a conventional road. It is composed of five interrelated subsystems (Figure 1). The following modules: road identification, speed variation, road risk from geometry, and offtracking estimation receive external outputs. The risk estimation subsystem is fed with the output of the fuzzy road class identification system with the road type officially assigned by the Civil Administration. The outputs of other fuzzy

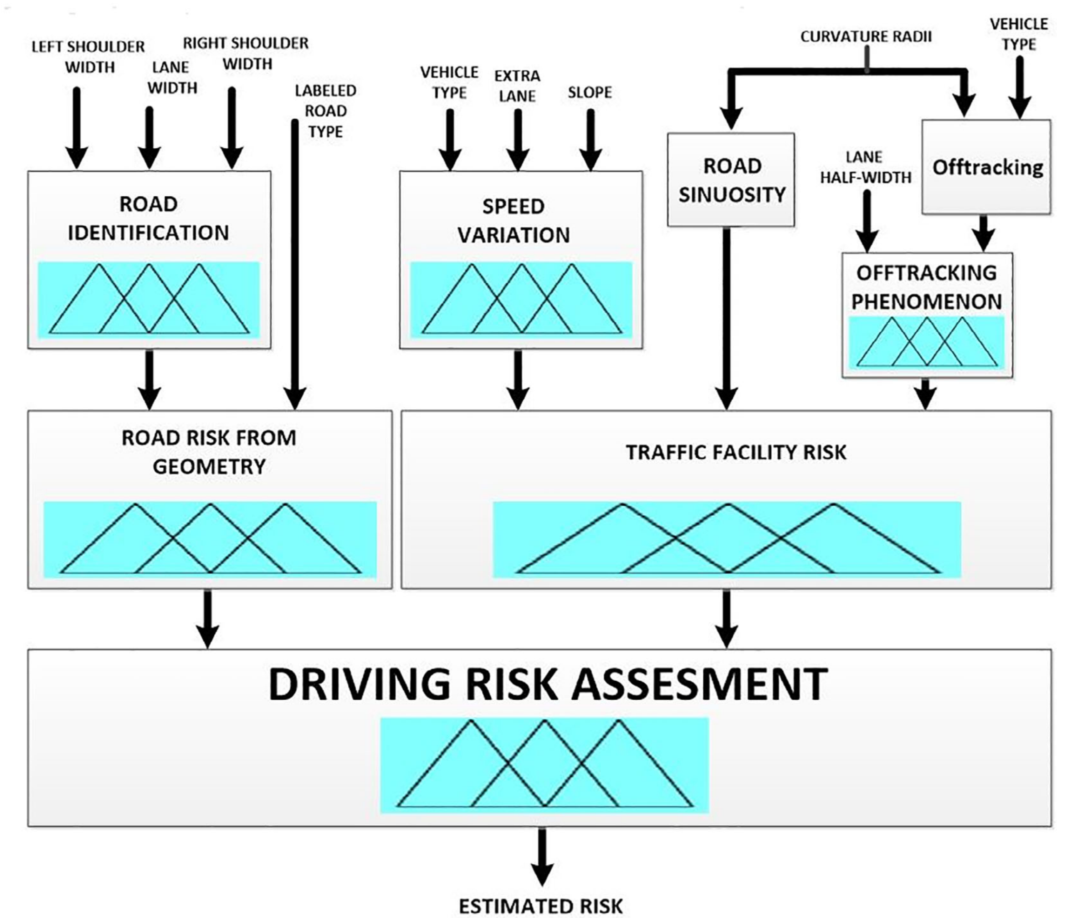

FIGURE 1 Driving risk assessment system

modules go to the traffic analysis subsystem, together with the road sinuosity. Finally, a fuzzy subsystem estimates the risk of each road section. Each fuzzy subsystem of Figure 1 will be described in the next subsections.

All fuzzy systems will have fuzzy sets defined by trapezoidal or triangular membership functions. Expert knowledge is represented by fuzzy rules of the type *if-then*. The t-norm operator has been chosen as the AND operator. The centroid defuzzification method has been used to determine the output.

4.1 | Fuzzy identification of two-lane roads actual type

The identification system is applied to some roads of the region of Madrid, Spain, namely: M-607, M-519, M-852, M-618, M-305, M-509, and M-601. Roads are associated with a particular class though they are composed of road sections that can be of different types along the same road. This is shown in Table 2. Roads M-607, M-519, and M-509 are assigned to Class I, while roads M-305 and M-601 to Class III. Road M-618 is made up of road sections of at least two classes, I and III, and M-852 of Classes II and III. These classes were assigned by experts.

4.1.1 | Identification using a Mamdani fuzzy system

First, a fuzzy Mamdani system is proposed (Barreno et al., 2020). The input variables of this fuzzy identification system that represent the road geometry are the width of the right and left shoulders, and the lane width. Some other geometric variables are not considered (radius of curvature, cross slope, and longitudinal slope), since they are not necessarily indicative of a certain road class, but only of the geometric design characteristics used in a road section.

The linguistic terms of these variables are represented by trapezoidal membership functions. Three fuzzy sets are assigned to each input variable, left shoulder width, lane width, and right shoulder width, that are: N, narrow; M, medium; and W, wide. The variable lane width is within the range [0–165 dm] (semi-lane width, in fact, as the vehicle measures distance from driver to the right side), and the shoulders width is in the range [0–65 dm].

The output is the class of road, which can be I (intercity), II (accessibility), and III (suburban). The value obtained after the defuzzification process may not be an integer. In that case, the closest class is assigned according to the membership degree.

The rules combine road dimensions such as: if at least one of the shoulders and lane are medium or wide, output is Class I; if the lane and shoulders are narrow, output is Class II; if the lane is medium and the shoulders are narrow, output is Class III.

The results are given in terms of the value of μ, defined as the ratio between the samples of road correctly classified over the total number of samples (accuracy) (7):

$$\mu=\left(\frac{\text{correctly identified samples}}{\sum \text{total samples}}\right)\bullet 100. \tag{7}$$

Table 3 shows the results of the identification with the Mamdani-type fuzzy classifier. The best values are bolded. When the percentage is greater than 80% it is considered that the type of road has been well identified, as it is the case with M-607, M-618, M-305, M-509, and M-601 roads. The system gave the right class in five out of the seven cases studied. Nevertheless, regarding M-519 and M-852 roads, there are road sections misclassified or, alternatively, they may have sections of different classes.

TABLE 2 Assigned classes to roads under study

Two-lane road	Road type	Class
M-607	Intercity[a]	I
M-519	Intercity[a]	I
M-852	Accessibility, suburban	II, III
M-618	Intercity, suburban	I, III
M-305	Suburban	III
M-509	Intercity[a]	I
M-601	Suburban	III

[a]In Intercity roads, relatively high speeds are expected.

TABLE 3 Fuzzy identification system results

	μ (% sections of each class identified)		
Road section	Class I	Class II	Class III
M-607	**95.58**	4.19	0.23
M-519	28.30	2.78	**68.92**
M-852	6.21	**77.40**	16.39
M-618	6.86	5.50	**87.64**
M-305	**91.19**	0	8.81
M-509	**82.83**	6.64	10.53
M-601	12.69	2.94	**84.37**

TABLE 4 Classification performance per section with the fuzzy system and confusion matrix

			Predicted class		
Road section	% trues	% fails	Class I	Class II	Class III
Class I	73.62	26.38	**378**	14	116
Class II	86.09	13.91	5	**99**	11
Class III	37.32	62.68	79	10	**53**

Note: Bold values highlight the best performance results.

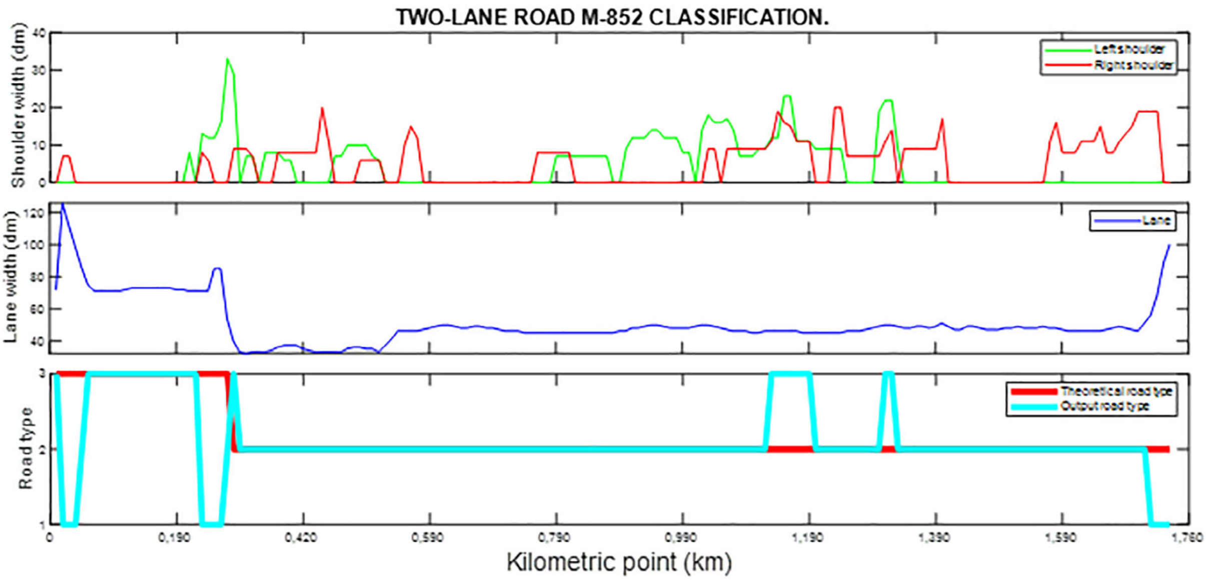

FIGURE 2 Results for the classification of different sections of M-852 road

Comparing Tables 2 and 3, M-607, M-601, M-509, and M-852 roads are rightly identified, but M-519, M-618, and M-305 roads are wrongly classified. In some cases, a specific road is only partially misclassified, as happens with M-618 road that has sections that belong to Classes I and III. As the percentage of sections classified as Class I is so small, it is assigned to Class III.

Table 4 shows the classification performance and confusion matrix per section. The road sections of each class on all roads analysed are considered, and repeated samples are eliminated in order to carry out this performance assessment. The good performance is confirmed for Classes I and II and is shown to be somewhat worse for Class III.

The fuzzy road class identification rule-based system achieved better results than the neuro-fuzzy system so it is the one that is applied. Figure 2 shows the road types found along the road M-852. In all roads the width is expressed in decimetres. This road has sections that belong to Classes II and III. Most of the road has a narrow lane and shoulders that the fuzzy system identifies as Class II (77.40%). There are also some road sections that have a medium lane with narrow shoulders, identified as Class III (16.39%).

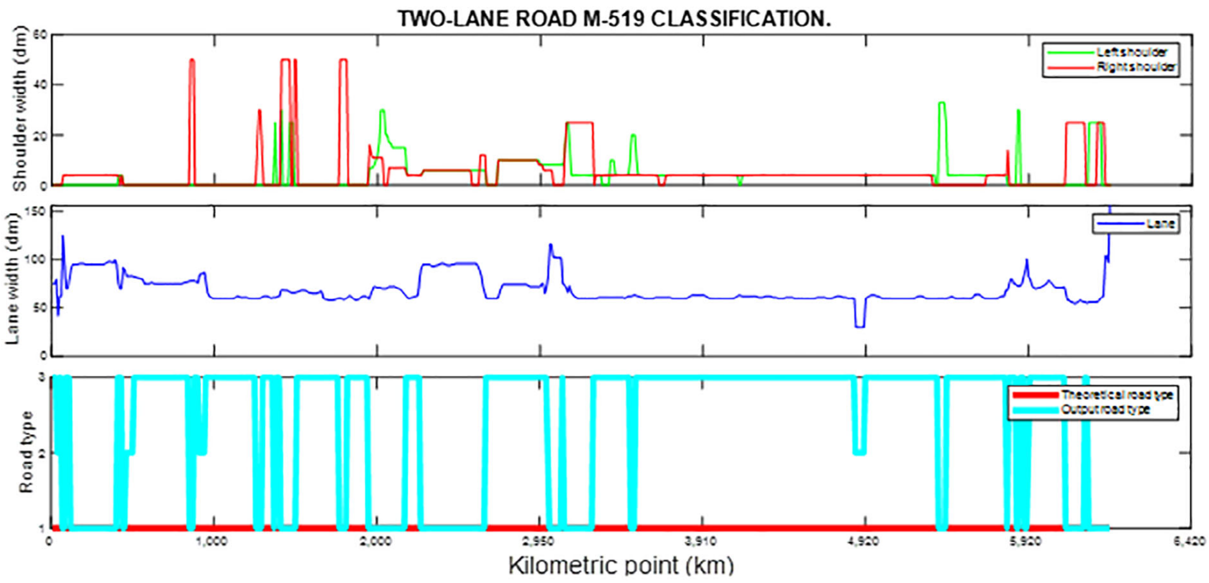

FIGURE 3 Results for the classification of different sections of M-519 road

TABLE 5 Neuro-fuzzy system identification results (% correct)

Road section	μ (% sections of each class correctly identified)		
	Class I	Class II	Class III
M-607	**94.31**	5.69	0
M-519	38.66	**63.16**	0.18
M-852	9.72	**88.70**	1.58
M-618	**80.31**	19.69	0
M-305	**85.38**	14.09	0.53
M-509	**90.79**	9.17	0.04
M-601	6.24	**85.12**	8.64

Note: Bold values highlight the best performance results.

Similarly (Figure 3), M-519 road is officially considered Class I, but it has a section classified as Class III (suburban). Most of the road has a medium or wide lane with narrow shoulders, thus the fuzzy system identifies it as Class III. It is questionable whether M-519 is only Class I, since its geometry is not similar to other Class I roads such as M-607 road that has wider shoulders. Therefore, M-519 should be considered as a medium speed road (Class III).

4.1.2 | Identification of two-lane road actual type by a neuro-fuzzy system

An adaptive network-based fuzzy inference system (ANFIS) neuro-fuzzy identification system is proposed (Santos et al., 2006; Santos & Dexter, 2001). This strategy has been applied in four phases. The first phase removes the repeated samples from the input set, since the redundant information generates an additional computational cost. This way neural network over-fitting is prevented. In the second phase, the input set is randomly split into two, training set (60%) and validation set (40%). The third phase generates the ANFIS model. Finally, the validation is carried out with a k-fold cross validation scheme, with $k = 5$.

The inputs of the model are the width of the lane, right and left shoulders. The outputs for each data sample are labelled as a value {1, 2, 3}, corresponding to Classes I, II, and III, respectively. It the results are not an integer, a threshold is applied to determine the closest class according to the membership degree, as in the previous identification system. The results of applying the neuro-fuzzy classifier are shown in Table 5.

The neuro-fuzzy system correctly identified sections of M-607 and M-509 roads and sections of roads M-852. Nevertheless, it fails for any road section of Class III. Thus, the neuro-fuzzy system gives worse results than the Mamdani fuzzy one.

TABLE 6 Neuro-fuzzy results per section and confusion matrix

			Predicted class		
Road section	% hits	% fails	Class I	Class II	Class III
Class I	83.46	16.54	**413**	93	2
Class II	93.04	6.96	5	**108**	2
Class III	28.16	71.84	32	67	**43**

Note: Bold values highlight the best performance results.

Table 6 shows the classification performance and confusion matrix per section. The road sections of each class on all roads are considered, and repeated samples are eliminated in order to carry out this performance assessment. The good performance is confirmed for Classes I and II (M-607, M-509, and M-852), while samples for Class III are misclassified in most cases. In addition, this model was not able to identify correctly different sectors in the same road, that is, a road composed by sections of two classes, as M-852 and M-618.

4.2 | Road risk from geometry subsystem

The fuzzy "road risk from geometry" subsystem represents the driver's perception of the road layout in terms of its geometric characteristics. This has a direct influence on the chosen speed, since the user will feel safer when travelling on a wider road, for example, and therefore a driver will be able to increase the operating speed within the allowed limits (Godley et al., 2004).

This fuzzy system has as inputs the type of road obtained by the identification module and the road type assigned by the Administration (Class I, II, or III), according to the design geometric characteristics that may be not updated. When these characteristics are deteriorated, the posted speed that is usually higher may be less safe. Three fuzzy sets have been assigned to the road type inputs (I, II, and III). The output is the safety degree of the recommended speed, with two fuzzy sets: Not_Ok, that is centred at -1 and means unsafe speed, and Ok, centred at 1, i.e., safe).

The fuzzy rules state that on road sections where actual features are worse than the ones that correspond to the official class, vehicles may travel with less safe speed if the follow the posted speed recommendation.

4.3 | Offtracking estimation fuzzy subsystem

Since most vehicles change direction by changing the orientation of the wheels of an angle, usually the front axle, the rear axle or axles, where wheels do not change direction, follows a different trajectory. This means that the covered surface does not always have a constant width. Offtracking is the name applied to this fact. Two types of offtracking exist: low speed and high speed.

Low-speed offtracking occurs when vehicles travelling at very low speeds make a turn. When a vehicle turns at low speed, the front wheels turn as set by the driving wheel, but the rear axle or axles follow a trajectory with a different radius, moving towards the inside of the curve. This feature is negligible for bicycles and cars. However, in the case of HVs, and particularly in articulated vehicles, it can be considerable, and it is an important factor in the design of low radius curves, intersections, ramps, and other road elements. Offtracking gradually increases as the length of the turning manoeuvre increases (Christensen & Blythe, 2000).

High-speed offtracking happens due to dynamic effects, and becomes more pronounced as vehicle speed increases (Christensen & Blythe, 2000). When a vehicle is travelling through a curve at higher speeds, there is a tendency for the rear axles of the vehicle to move outwards. This effect may compensate the low-speed offtracking as it acts in the opposite direction.

Therefore, at low speeds trucks and buses experience offtracking towards the inside of the curve, at a certain speed both effects cancel out, and at higher speeds the net result is that the rear of the vehicle tends to moves outside of the front.

Offtracking will depend on the vehicle inter-axle distance. The offtracking of a vehicle with two axles can be calculated using the Pythagorean theorem (Christensen & Blythe, 2000):

$$OT = -R + \sqrt{R^2 - l^2}, \tag{8}$$

where R is the radius of curvature (m) and l is distance between two axles (m). Negative values means that the rear of the vehicle moves inwards, towards the centre of the curve. In this work, the vehicle lengths considered are 4 m for cars, 10 m for buses and 15 m for large trucks. Offtracking contributes to increase the risk when HVs negotiate small radius curves, since they approach or invade the opposite lane.

Offtracking is considerable for radii up to 125 m, when its value is less than 0.5. Normalized offtracking has been fuzzified by using two classes, low and high offtracking. If offtracking (OT) is very small, close to zero, the difference between the sweep of both axes is minimal; thus, the offtracking is low. OT has been compared with the lane half width between vehicle and taper in dm. The lane half width has been fuzzified into three fuzzy sets (Narrow, Medium, and Wide).

The behaviour of this system states that a combination of high offtracking (a small curvature radius) and a narrow lane will produce a higher risk introduced by the offtracking phenomenon, since the vehicle may drift out of the lane, or decrease the distance between crossing vehicles, which may be less safe for higher relative speeds, due to aerodynamic phenomena that introduce considerable sudden changes in lateral pressures.

4.4 | Speed variation subsystem

The fuzzy speed variation system estimates the speed changes of a vehicle type (truck, bus, and car) in relation to the slope of the road and whether or not there is an additional lane. The vehicle type is defined using power-to-weight ratio for trucks (8 CV/t), bus (10 CV/t), and cars (30 CV/t) that corresponds to the fuzzy sets: T (truck), B (bus), and C (car). Additional lane has been fuzzified in two fuzzy singletons, not lane and extra lane. The slope, defined between -400 and 400 (‰), has been fuzzified as negative and positive (ramp). Finally, the speed variation output can be slow and fast.

The driver's perceptions used as expert knowledge for the fuzzy rules are the following. If a truck vehicle travels on a road at a slow speed on a ramp, vehicles arriving from behind would have to brake, and therefore there will be a rapid speed variation (deceleration). If there is an additional lane, the speed would not change as much. While negotiating a road section, sudden changes in speed imply a higher risk than a regular speed.

4.5 | Traffic facility risk

The fuzzy traffic facility risk system takes into account the speed changes of the vehicle, the road sinuosity and the offtracking phenomenon. This module characterizes the driving process in a specific road section.

The angle between two consecutive transition curves (entry and exit curve) has been fuzzified into three fuzzy sets: small, medium, and large. The output is the driving pattern that has three fuzzy sets, smooth, medium, aggressive.

Expert knowledge for the fuzzy rules can be stated as follows. A slow speed variation, combined with low offtracking phenomenon with a medium turned angle, will result in a smooth driving pattern through the curve. If the speed variation is high and the curve is tight, the driving pattern will be aggressive.

4.6 | Driving risk assessment

Driving risk assessment takes into account the road risk obtained from the geometry fuzzy subsystem and the traffic analysis. The estimated risk, that is the output, is fuzzified into four fuzzy sets: not_risk, low, medium, and high.

The knowledge implemented in the rules is the following. If the speed is inadequate (the output of the road risk from geometry is Not_Ok) for the actual road class, that is, the actual road class is different from the posted speed, the risk may vary depending on the driving pattern. For instance, with an aggressive driving the risk will be medium or even high although the speed is appropriate. On the contrary, the risk may be low even for a high sinuosity and fast speed if the driving is smooth.

The risk assessment is made by checking if drivers are induced to choose an inadequate speed for the actual road class. Should this be the case, this implies a higher risk.

5 | SIMULATION AND DISCUSSION OF FUZZY RISK ASSESSMENT SYSTEM RESULTS

The data used in this study belong to the road inventory records from Coordination and Information Center, Madrid Region, Spain (n.d.). The registers have the following information: road name, mileage post, number of lanes, additional lanes, width of the lane and shoulders, radius of curvature, camber, and slope. Each data is collected every 10 m (Table 7).

TABLE 7 Sample of the data for M-509 road

Kilometre point	Mileage post (m)	No. of lanes	Carriage width (dm)	Left shoulder width (dm)	Lane width two lanes (dm)	Right shoulder width (dm)	Curvature radius (m)	Cross slope (‰)	Slope (‰)
32	130	2	95	8	75	12	1110	51	15
32	140	2	86	8	66	12	1540	53	14

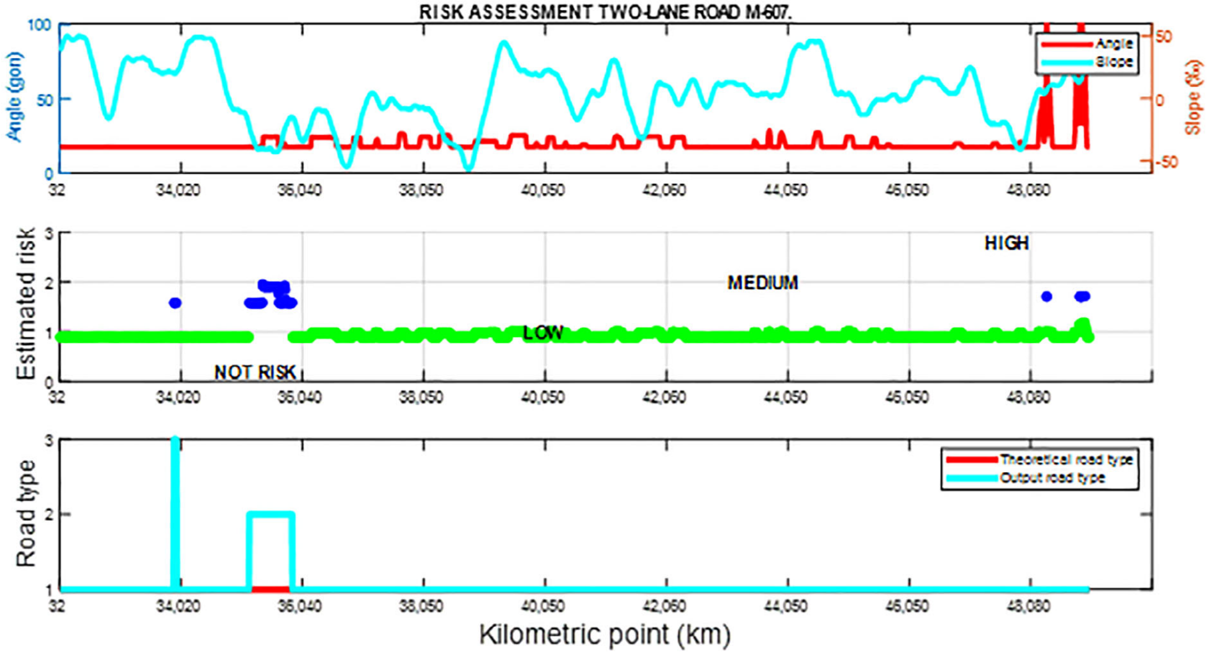

FIGURE 4 Road M-607 assessment considering with a truck

For each road the driving risk assessment system has been applied. This takes into account the actual geometric conditions, which do not always coincide with those officially assigned to the road. There may be sections where some features have changed and, therefore, a different speed, usually lower, should be applied for safe driving.

The results of the application of the risk assessment fuzzy system are shown in this section. In the following figures, the upper graph shows the sinuosity (red line) given by the angle in gons, and slope (cyan) in ‰. The middle graph shows the estimated relative risk, that is: no risk (black), low risk (green), medium risk (blue), and high risk (red). The bottom graph represents the identified road type (cyan) and theoretical road type (red). Figure 4 shows the results obtained by the system with a truck vehicle in the M-607 road.

It can be observed in this Figure 4 that the road type identified with the expert system is mostly the same along the section although the system identifies Class III instead of Class I at km 34 and Class II instead of Class I in a short subsection, around km 35–36. Therefore, the posted speed is higher than it should be at these points, and the vehicle may travel at an unsuitable, less safe speed. On the other hand, there are few variations in road sinuosity, according to turning angles (upper graph). Hence, the system estimates that few kilometre points are medium risk in this road section, where the road class changes between the one identified and the one labelled by the administration, and the rest has low risk.

Figure 5 shows the results obtained for trucks in the M-852 road. The identification system detects mainly class II but there are some short sections misclassified. On the other hand, there are quite a few variations in the angle that determines the sinuosity of the road. Thus, the system estimates that some stretches have medium risk in this road.

Figure 6 shows the results obtained by the system for a car in the M-519 road. First, it can be seen that the identified type for this road section (III) is different than the class initially assigned by the administration (I) throughout most of the section analysed (third graph). Therefore, the posted speed is not adequate, and it should be lower in order to reduce the risk. In this case a Class III road is identified, on which the posted speed is lower than on a Class I road. Besides, there are many variations in road sinuosity and therefore the risk is medium at some points or even high.

Table 8 shows the estimated fuzzy risk for a number of stretches for the two-lane roads analysed in this work. For each km, the system estimates the risk according to vehicle type, car, bus, or truck.

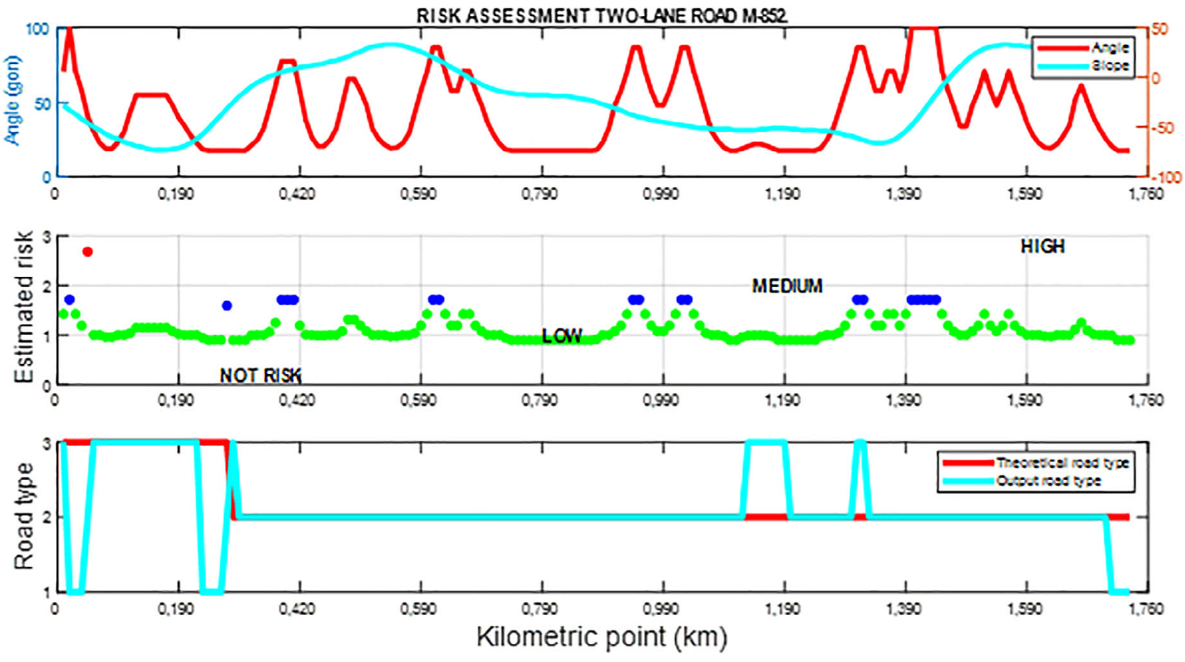

FIGURE 5 Road M-852 assessment with a truck vehicle

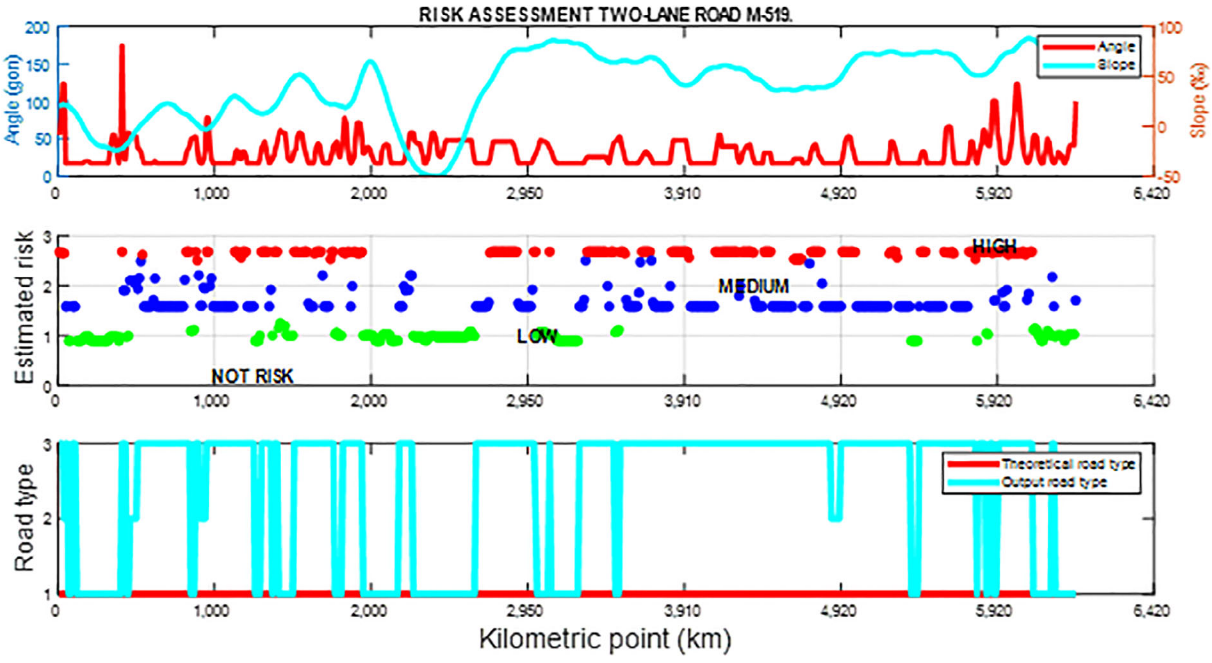

FIGURE 6 Road M-519 assessment with a car vehicle

A risk index is defined based on driver's subjective assessment of the potential road safety risks for in-service roadways. The objective of this safety risk index is to support road safety analysis. We propose a road FRI, presented in (9).

$$\mathrm{FRI} = \frac{1}{3}\left(\frac{\sum_{i=1}^{n} x_i}{n}\right), \tag{9}$$

TABLE 8 Estimated fuzzy risk kilometric points for two-lane road sections

Risk degree		Safe	Low risk	Medium risk	High risk
M-852	*Truck*	0	158	18	1
	Bus	0	158	18	1
	Car	0	170	7	0
M-607	*Truck*	0	1613	59	25
	Bus	0	1614	58	25
	Car	0	1614	83	0
M-601	*Truck*	0	797	21	1
	Bus	0	806	13	0
	Car	0	806	13	0
M-618	*Truck*	0	77	330	192
	Bus	0	77	330	192
	Car	0	77	462	60
M-305	*Truck*	0	193	0	0
	Bus	0	193	0	0
	Car	0	193	0	0
M-509	*Truck*	0	699	126	48
	Bus	0	721	113	39
	Car	0	722	139	12
M-519	*Truck*	0	181	239	230
	Bus	0	181	239	230
	Car	0	181	256	213

TABLE 9 Fuzzy risk index for two-lanes road sections

	M-852	M-601	M-607	M-618	M-305	M-509	M-519
Truck	0.3799	0.3370	0.3224	0.6306	0.2978	0.3807	0.6073
Bus	0.3799	0.3321	0.3218	0.6306	0.2978	0.3714	0.6073
Car	0.3435	0.3321	0.3173	0.5780	0.2978	0.3613	0.5994

where x_i is the estimated risk vector composed of all risk evaluations made along the road section, estimated by the fuzzy risk assessment system, and n is the number of samples (km points) of each road section analysed. The summation term in the formula gives a real number between 0 and 3 according to four labels of the risk module output. FRI results in a number between 0 and 1, where 0 is safe and 1 is high risk.

As it is possible to see in Table 9, fuzzy risk indices are identical or very similar for trucks and buses, as they have similar power-to-weight ratios, 8 and 10 Cv/t, respectively. Nevertheless, for passenger cars this FRI is lower, as the power to weight ratio is much higher (30 Cv/t or more), and the changes in road speed are not as abrupt.

However, a moderately high traffic risk can be considered when the FRI is higher than 0.5. This may happen either because the actual class of the road is different from the one initially assigned by the administration, and this causes a vehicle to drive at a potentially unsuitable speed, or because there are sharp turning angles in the road layout, unsuitable for certain speeds. In these sections, the probability of a passenger car having to brake when a truck or bus is found is significantly higher.

6 | CONCLUSIONS AND FUTURE WORK

In this paper, first a fuzzy system has been designed and applied to classify conventional two-lane roads according to their geometric characteristics. These features are readily available in existing inventories, and, if not, are easy to obtain using equipped vehicles that are able to measure them in real time. The classifier based on fuzzy rules uses the current lane and shoulders width as inputs.

The results are interesting and useful. Clearly, the system correctly identifies road classes for two-lane roads. In some cases, there are road stretches where the actual geometric characteristics imply that the road class should be changed. This has also been detected. This is important because driving speed is related to safety, and therefore the speed limit should be changed depending on the road class. In addition, winter management and maintenance programs are developed and assigned based on road class. Therefore, a more updated and realistic classification allows increasing consistency, road safety, and comfort for travellers and drivers.

Additionally, a road FRI is presented. This risk index allows to know which is the relative driving risk based on lane and shoulder widths, slope, road sinuosity and offtracking phenomenon through curvature radius and vehicle type. Those estimations have been obtained by different fuzzy subsystems. The combination of all of them gives the risk assessment.

As future work, designing a driving risk assessment tool according to the actual class of road section and other road variables is proposed. This risk determination system could be applied to identify potentially less safe sections to generate maps for preventing accidents, and correlate these results with accident databases over extended time periods.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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