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## **FUZZY LOGIC BASED DRIVING PATTERNS RECOGNITION SYSTEM FOR VEHICLE CO<sub>2</sub> EMISSIONS AND FUEL CONTROL**

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**Abstract.** *Due to recent concerns about climate change as well as the rise in the mean global temperature, it was held in December 2015, in Paris, the 21st Conference of the Parties of the UNFCCC (United Nations Framework Convention on Climate Change) to set an agreement to reduce greenhouse gases emissions. Since the Automobile Industry is responsible for a large amount of CO<sub>2</sub> and NO<sub>x</sub> emissions, a small reduction would be significant to the overall emission levels. In this context, several works relates a major part of the vehicular emissions contributions are due to the driver's behavior or operational parameters that relates to the driver's intention and style. For that purpose, this work aims to recognize driving styles based on fuzzy logic to easily obtain relevant information and present it to the user, in order to obtain significant reduction in fuel consumption and gases emissions. This system, therefore, will allow drivers to keep on track of its vehicle performance as well as help to reduce the effects on climate change in a long run. Since most recent vehicles have onboard multimedia units, the system implementation would not imply cost addition to automobile industries.*

**Keywords:** *Fuzzy Logic, Vehicle Emissions, Fuel Consumption, Onboard Diagnosis*

### **1. INTRODUCTION**

Nowadays, much is being discussed about climate change and the increase in the mean temperature due to greenhouse gas emissions. With the growing concerns, the 21st Conference of the United Nations Framework Convention on Climate Change (UNFCCC) was held in Paris. Known as the Paris Agreement, the treaty aimed to establish measures to reduce CO<sub>2</sub>. Compared to 2005, Brazil has committed to reduce greenhouse gas emissions by 37% by 2025, and by 43% by 2030 (ITAMARATY).

According to the Ministry of Science, Technology and Innovation in 2012, the Energy sector (sector that uses fuel burning processes) accounted for 37% of CO<sub>2</sub> emissions, where 47.5% is a consequence of the use of motor vehicles, therefore one of the main sources of emissions in urban areas.

One way to assess the impact of vehicular emissions is by standard driving cycles. Thus, environmental protection agencies have defined test standards that simulate driving conditions (urban area, highways, aggressive driving, etc.), acting normatively to add a new vehicle to the market. The most important cycles are the Federal Procedure Test (FTP75), used in the United States, and the New European Driving Cycle (NEDC) in the European market. However, several studies have shown that these normative cycles are not representative, resulting in emissions and fuel consumption values that are not compatible with the dynamometer tests. According to Tzirakis and Zannikos, 2014, changes in the highway, expansion and fleet changes, differences in fuel, driver behavior, legislation, among others, have a great impact on the speed profiles of a vehicle, and it is necessary to adjust the standard driving cycles to each specific area.

Vehicle emissions, coupled with the growing pursuit of improved energy efficiency, are the main factors driving automotive industries, encouraging the development of new technologies. Most notable are the pursuit of reduced tire rolling friction, mass reduction and aerodynamic improvement, and changes in the motor part (motorization, hybridization, downsizing, etc.). Nevertheless, energy efficiency is still totally dependent on the driver's behavior and driving style. In a study conducted by Toyota, such behavior can affect up to 20% of total fuel consumption, disregarding other factors.

Table 1 shows results obtained in the work of Tzirakis, Zannikos and Stournas, 2006, where particulate emissions and fuel consumption were analyzed comparing the defensive and aggressive driving style. Increasing fuel consumption and emissions in an aggressive driving style, while obvious, does not seem to be common sense among

the population. Moreover, despite the direct economical perception, the effects on the environment are not visible in the short term, which leads the government and regulatory agencies to encourage strategies to lower vehicle emission levels. Even with new less polluting vehicles, due to technological advances in engine and fuel designs, an eco-friendly driving style should be encouraged, called Eco-driving.

Table 1. Driving styles differences, defensive and aggressive, in regards to vehicle emissions (g/km) and fuel consumption (km/l). Adapted from Tzirakis, Zannikos e Stournas, 2006

Vehicles	Defensive Driving Style					Aggressive Driving Style				
	FC	CO	CO2	HC	NO	FC	CO	CO2	HC	NO
Primera	9.1	9.7512	236.035	0.2696	0.6123	18.4	71.2202	384.29	4.4698	0.5626
307 XSI	9.4	0.2942	258.324	0.0514	0.0648	17	7.7983	445.51	0.2010	0.7515
Golf FSi	9.3	0.0030	240.201	0.0127	0.2110	19	7.2199	421.74	0.0608	0.1813
206	8.6	0.0010	231.343	0.0457	0.3169	17.8	0.3092	473.04	0.1300	3.0888
AR 145	9.4	7.2261	243.773	0.2912	0.0125	19	11.9576	473.90	1.1902	0.5903
Ibiza	9.3	0.0247	264.530	0.0149	0.0357	16.6	12.8374	414.34	0.1255	0.4149
M2	8.7	0.1384	250.507	0.0589	0.0276	17.1	20.6775	427.23	0.4119	0.1638
M3	8.8	0.1892	240.754	0.1376	0.0100	24.2	11.7173	461.18	0.3919	0.1339
M6	10.2	0.1902	319.972	0.0413	0.0088	23.9	44.2498	470.46	0.1365	0.0270

The aim of this paper is to study artificial intelligence strategies, more specifically fuzzy logic and cluster algorithms, to identify predetermined driving styles based on fuel consumption. Such identification, if satisfactorily informed to the drivers, can give them means to improve driving performance, contribute to reduce fuel usage and vehicle maintenance costs, as well as reducing greenhouse gas emissions.

## 2. LITERATURE REVIEW

In this section, it is discussed the recognition of driving patterns based on artificial intelligence algorithms. Some systems presented in the literature regarding fuzzy logic is presented, as well as works with identification of driving patterns via SVM and k-means. Finally, at the end of the project, an attempt to analyze data from an actual test by a trained professional is examined. Differences between systems is also discussed and further studies will be proposed as a continuation of the project.

### 2.1 Related Works

Driving style analysis plays a key role in smart vehicle design. But characterizing driving styles, understanding what each driver's action implies in vehicle variables, is not a simple task, and companies that develop Ecodrive systems often rely only on direct fuel consumption information. However, the lack of relevant information to users creates confusion when using such systems.

In this way, several studies have been performed to identify in real time parameters related to driver behavior that define the driving style as good or bad. Thus, artificial intelligence-based learning systems become powerful tools for understanding the effect of such actions on the vehicle's ultimate performance

In the work of Angkititrakul et al., 2012 and Wang et al., 2018, a non-parametric Bayesian approach based on a hidden semi-Markov model (HSMM) was introduced to extract the primitive driving patterns from conduction data from multidimensional time series without prior knowledge of these driving patterns. For each driver, several primitive driving patterns are preset semantically according to their physical and psychological perception thresholds. Individual driving styles are semantically analyzed based on the distribution over primitive driving patterns, and the similarity between drivers is then assessed. Experimental results demonstrate that using the primitive driving pattern provides a semantically interpretable way to analyze driver behavior and driving style.

Zhang et al. (2016) conducted a driver classification based on their driving profile. Experiments were performed with predefined routes, a car and different drivers, and another non-defined experiment that collected car data over a period of time from a group of participating drivers. As a profiling technique, a Supporting Vector Machine (SVM) was used to train a manually generated data set and set as default.

Coupled with the SVM technique, Wang and Xi, 2016, used the k-Means clustering technique to discriminate driver behaviors and reduce the number of SVM support vectors. The k-means clustering method is used to extract and gather both types of driving data and shorten the recognition time. Then, based on clustering results, an SVM approach is used to generate the hyperplane to judge and predict which types of driving the user is subject to. Finally, to verify the validity of the kMC-SVM method, a cross-validation experiment is designed and conducted. Research results show that kMC-SVM is an effective method for classifying driving styles over a short period of time compared to the SVM method.

The k-Means unsupervised learning technique, in fact, has proven to be quite powerful for determining driving patterns. Higgs and Abbas, 2013, for example, used k-Means as a technique for identifying driver actions. Based on a series of sensors installed in vehicles and specific segments of the route, the k-Means method was chosen because it can identify the instances closest to what it assigns as centroids. Their choice resulted in a good hit rate (up to 100%) for experiments that used static and dynamic aspects of car driving.

The abovementioned techniques proved to be effective in determining what was being studied. But many of them require multiple drivers and sensors, and use of variables other than the vehicle itself. Thus, another technique studied for determining driving profiles, simpler and using few readable variables, is fuzzy logic. As done by Wang, Xi and Li, 2016, and Aljaafreh, Alshabat and Al-Din, 2012, by only reading two vehicle variables (acceleration pedal position and speed) were able to build an understanding of driving patterns. In addition, the study by Wang, Xi and Li, 2016, compared fuzzy logic techniques with a Bayesian approach (kernel density estimation). Despite having worse results, fuzzy logic, even being a simple technique, is quite accurate.

In this way, the present work will focus its study on works using fuzzy logic to determine driving profiles, with variations between aggressive and non-aggressive. Finally, an attempt will be made to compare with the k-Means method to verify the effectiveness of the proposed method.

## 2.2 Fuzzy Logic

Fuzzy logic differs from Boolean logic in the way it treats the most complex regions of the system, intermediate regions where outcome evaluation cannot be considered to be totally true or false, where uncertainties must be investigated (Rignel, Chenci and Lucas, 2011). Because there are no defined limits, in this theory, the elements have a degree of pertinence determining the fuzzy set.

For each fuzzy set, besides having a region of pertinence, linguistic variables define the set and to which it refers. Its main function is to provide a systematic way of approaching complex or not well-defined phenomena (Gonçalves, 2007). The pertinence region represents the context where the fuzzy set is inserted, and can be represented by a membership function.

By this definition, several engineering problems can be solved based on fuzzy logic, which are possible to determine sets and functions of pertinence that characterize the system. In relation to vehicle mechanics, Araújo et. al., 2012, developed an online direction assistant where it provides the user with tips for driving improvement through real-time analysis of vehicle parameters. Each hint is evaluated separately by means of fuzzy sets, defining the likelihood for each hint. After this definition, a new fuzzy evaluation is defined to decide which tip will inform the driver (gear shift, excessive acceleration or deceleration, aggressive pedal, speed reduction, etc.).

## 3. METHODOLOGY

Taking into account the purpose of this work, the evaluation of the parameters for obtaining the driver's style was done as analyzed by Wang, Xi and Li, 2016, and by Aljaafreh, Alshabat and Al-Din, 2012. Both take into account the speed of the vehicle as the first parameter to be evaluated, but use different parameters to define the rules to be followed, the first being the accelerator pedal, and the second the acceleration itself. In contrast, the two distinct parameters characterize the driver's intention. If we consider a flat cycle, and disregard frictional losses, the pedal position and acceleration are correlated variables. For this study, therefore, only the position of the pedal is considered as characterization of the behavior of the driver.

For the first case, the linguistic variables attributed to both parameters were defined as Lower, Medium and High, and the membership functions were defined by experienced drivers. After the defuzzification, information about the driver's driving mode is obtained, which is defined by LN (low normal), N (normal), M (medium), A (aggressive) and HA (high aggressive). In the second case, considering the same input variables, the linguistic variables assigned to the velocity were VS (very slow), S (slow), M (medium), H (high) and VH (very high). The linguistic variables for the pedal position, as well as the membership function, were maintained as in the previous case. After the defuzzification, information is obtained regarding the driver's driving mode, which is defined by BN (below normal), N (normal), A (aggressive) and VA (very aggressive). Figure 1 shows the membership functions for both cases and Tab. 2 the assigned fuzzy rules.

With the fuzzy sets defined and the rules established, a surface defining the fuzzy system and process mapping can be obtained, which can be seen in Fig 2, for both cases.

Once having set the membership functions, fuzzy rules and the output map for the two cases presented in the literature, both rules was applied to a real test. Since the purpose of the work is to correctly identify normal or aggressive steering situations, the result should be compared to the fuel consumption (g / km) obtained during the test. The implementation of these algorithms for real-time use by conductors can represent a significant gain in terms of the reduction of particulate emissions in the atmosphere and thus contribute to the deceleration of climatic effects.

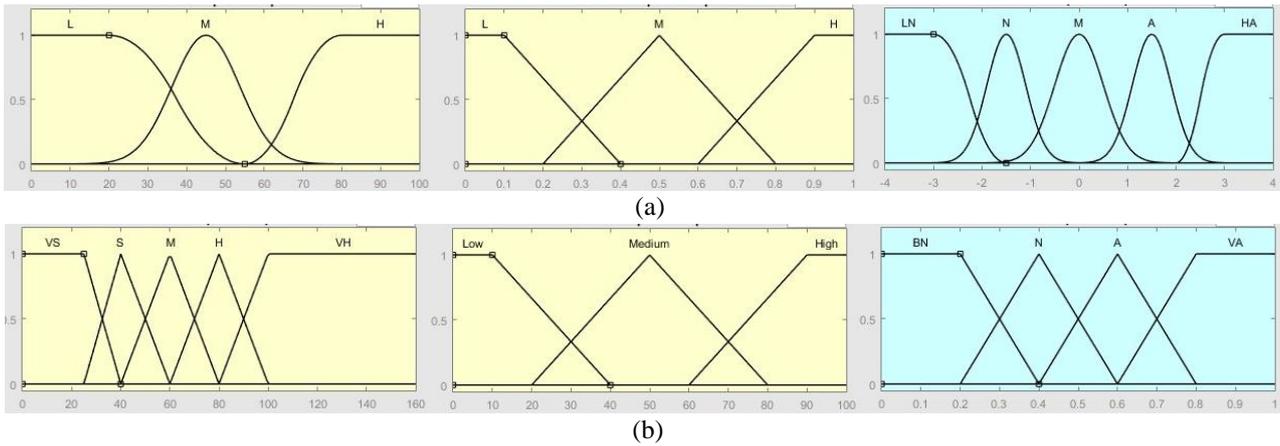


Figure 1. Membership Functions for Vehicle Speed, pedal position and the output for (a) Case 1 and (b) Case 2

Table 2. Fuzzy rules for setting driving styles, for both cases

CASE 1				CASE 2			
Speed	Operator	Throttle	Output	Speed	Operator	Throttle	Output
L	and	L	LN	VS	and	L	BN
L	and	M	M	VS	and	M	M
L	and	H	HA	VS	and	H	BN
M	and	L	N	S	and	L	BN
M	and	M	M	S	and	M	BN
M	and	H	A	S	and	H	N
H	and	L	HA	M	and	L	N
H	and	M	A	M	and	M	A
H	and	H	HA	M	and	H	A
---	---	---	---	H	and	L	A
---	---	---	---	H	and	M	A
---	---	---	---	H	and	H	VA
---	---	---	---	VH	and	L	A
---	---	---	---	VH	and	M	VA
---	---	---	---	VH	and	H	VA

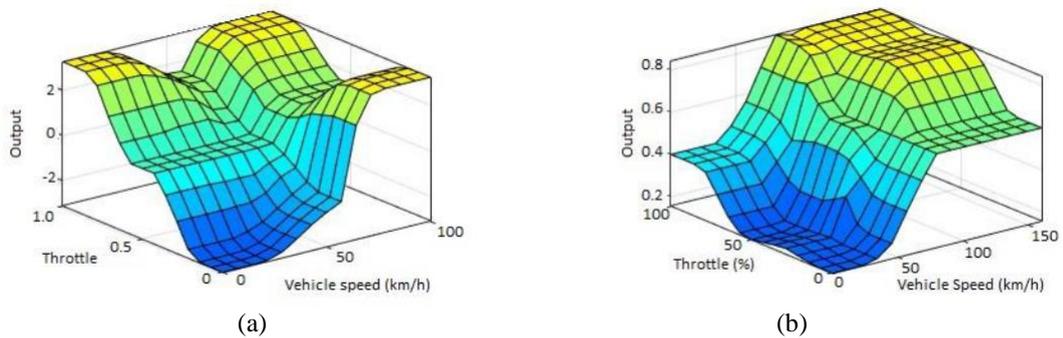


Figure 2. Fuzzy output map (a) Case 1, (b) Case 2

## 4. RESULTS

### 4.1 Fuzzy Logic Systems

In order to verify the fuzzy systems discussed, it was held a small vehicle test under real world conditions, with a proper acquisition system. For this reason, the dataset must enclose fuel consumption information, as well as the variables used to define the fuzzy logic (throttle position and vehicle speed). The vehicle used was a FIAT Argo, 1.0, 2016, and the dataset represents the driver's behavior and vehicle's response throughout the test. Figures 3 and 4 show the results after applying the fuzzy logic for both cases along with fuel consumption information for driving style analysis.

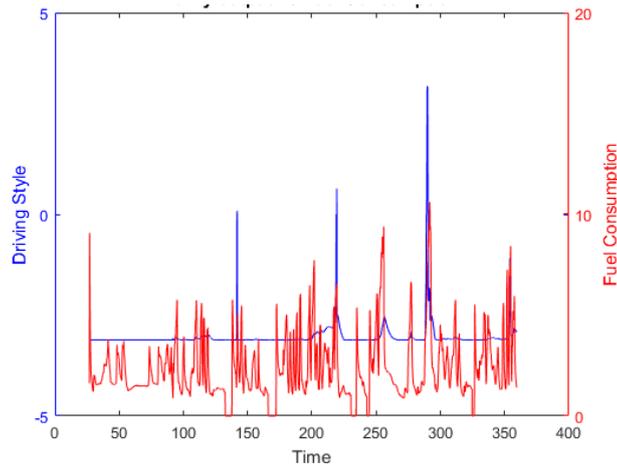


Figure 3. Output data (driving style) versus fuel consumption for case 1

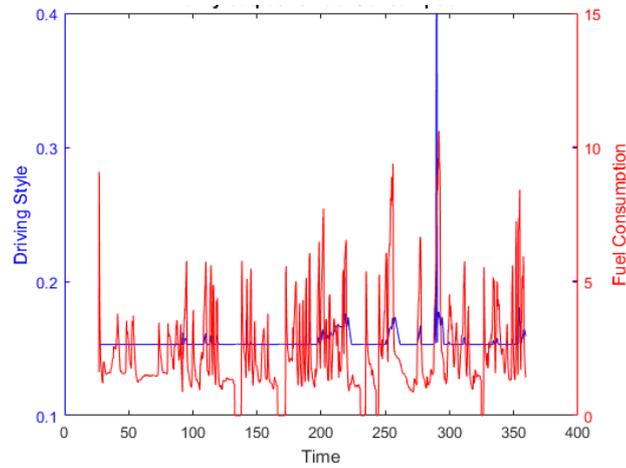


Figure 4. Output data (driving style) versus fuel consumption for case 2.

In both cases, most of the time, a normal, economical driving style have been identified, and a more aggressive driving moment around the test 300s. Hence, it can serve as a prediction of the driving style. However another analysis has to be taken into account to explain their differences. Figure 5 shows the ratio of gears to fuel consumption obtained in the standard road test.

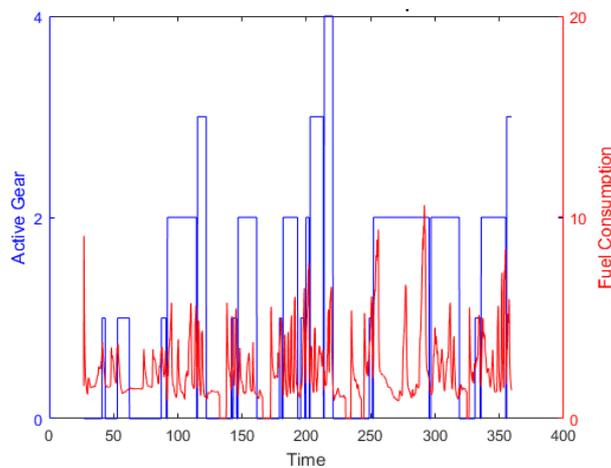


Figure 5: Active gear ratio throughout the test

By analyzing Fig. 3, 4 and 5, it can be seen, in the first case, the peaks that indicate a Medium and Aggressive driving style correspond exactly to gear shifting moments which most likely indicate a delay in their occurrence. The highest value (300s approximately), corresponding to the aggressive driving style in both cases, is followed by a zero gear, and a hasty activation of the same gear (2nd gear), which may indicate a hesitation of its change, occurring in a high fuel consumption at that time instant.

With this result, some observations can be taken. Although both cases could represent and identify more aggressive driving styles, other tests must be performed by extrapolating driving limits, that is, constantly varying more and less aggressive attitudes, and checking the behavior of the algorithms. Another consideration is the insertion of a membership function that defines each gear and then different rules for each gear ratio.

Given the transmission ratio used as a factor that can be attributed to the driving style, fuzzy logic can also be studied and made possible in order to obtain its optimization and, so, decrease in fuel consumption, as proposed by Casavola, Prodi and Rocca, 2010. In their work, and with standard driving test information, a two-layer fuzzy logic-based algorithm was developed in order to indicate up and down gearshifts in order to obtain an increase in energy efficiency.

After an evaluation of the parameters and identification of driving patterns, the next step is to integrate the fuzzy system with a real-time acquisition system by tracking vehicle parameters via the vehicle's On-Board Diagnostics (OBD-II) port. With the help of fuzzy logic, it can be reported to the driver information about its performance so that he can act to achieve energy efficiency improvements and emission reductions.

## 4.2 Clustering

For clustering evaluation using the k-Means method, another dataset was used, which includes 16 variables acquired through the OBD-II diagnostic port of a vehicle and a mobile device. The variables, as well as sensory data of the device used, were defined by availability, based on the SAE J1979 standard. However, not all variables presented in this standard are possible to be tracked by OBD-II without direct access to the vehicle's CAN network.

In this way, the variables chosen were: Time, Latitude, Longitude, Altitude, Barometric Pressure, Coolant Temperature, Fuel Level, Engine Load, Ambient Temperature, Engine Speed, Intake Manifold Pressure, Mass Air Flow, Intake Air Temperature, Vehicle Speed, Fuel Short Trim, and Acceleration Pedal Position. Since data were not labeled and therefore, to have a prior estimate of driving style, the fuzzy logic techniques discussed were used (Wang, Xi and Li, 2016; Aljaafreh, Alshabat and Al-Din, 2012).

Figures 6 and 7 show the data split into 2 and 3 clusters by the k-means method, presented by the mass air flow versus engine speed ratio (MAF vs RPM). In the first graph, Fig. 6, where two clusters were separated, it can be easily seen the data separation for different air flows characteristics. Thus, the data separated for higher air flows represents, in this case, more aggressive driving conditions, besides being present for higher engine revolutions. Similarly, data as present in lower MAF and RPM values are considered as non-aggressive driving styles.

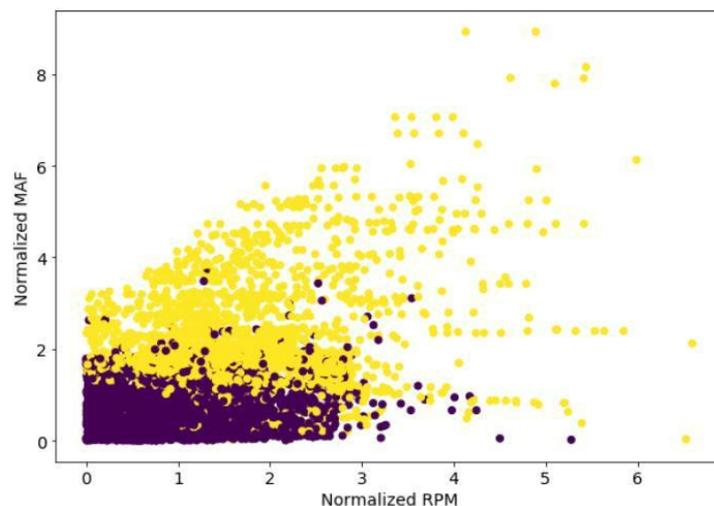


Figure 6. K-means algorithm for defining 2 clusters, aggressive and non-aggressive

After separating the data into two clusters, the accuracy of the method used with the previously used labels was verified, where fuzzy logic was applied for evaluation. However, approximately 51% of the data labeled by k-means had the same representation as that labeled by the Fuzzy. Because of the lack of accuracy, the two methods most likely definitions converged in regions with greater certainty of driving style, ie, where it represents higher and lower values of fuel consumption and engine speed. Thus, the intermediate region was probably not well defined by either method.

Since the presented graph of MAF vs RPM has some sense in the separation of the data, it can be said that fuzzy logic, as applied, did not characterize well the intermediate conditions of greater uncertainty.

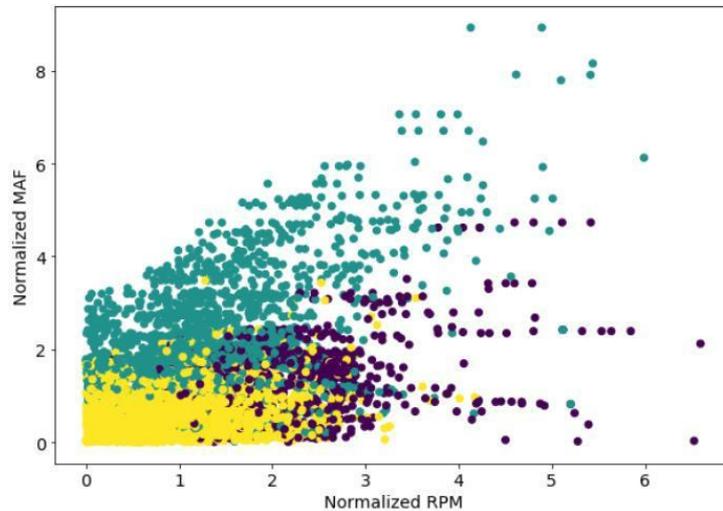


Figure 7. K-means algorithm for defining 3 clusters, aggressive, non-aggressive and normal driving style

In the second graph, Fig. 7, where 3 clusters were characterized, the same separation pattern was obtained, creating an intermediate classification for average consumption and engine speed values (in addition to lower consumption, but higher revs). ). Therefore, the separation between 3 clusters corroborates for the evaluation of the k-means model to have more meaning than the label initially used by fuzzy logic.

## 5. CONCLUSIONS

Several problems today can be described and studied based on fuzzy logic. The systems presented were able to provide information to predict driving styles, identifying aggressive and fuel-efficient maneuvers. By comparing the results with fuel consumption and active gears, both cases could be validated, requiring a better understanding of the membership functions used for the variables.

Nevertheless, further testing is required for correct identification of driving modes, and thorough evaluation is required. Since the gear ratio used, as well as gear shifts, was a major parameter for identifying an aggressive, fuel - efficient maneuver, another system can be evaluated considering membership functions and new fuzzy rules that relate exactly the active gears.

Comparing fuzzy logic with the k-means method, in the second part of the study, it was observed that the second method is quite assertive, having considerable differences with the data previously labeled by fuzzy logic. However, for the training of the k-means algorithm, several variable readings were required at the same time, whereas only two readings were used for fuzzy logic. Also, since the system varies greatly over time, the results obtained by fuzzy logic can be considered satisfactory, despite the need for further studies and to verify the validity of a future application.

The implementation of these algorithms for real-time use by drivers can represent a significant gain with respect to reduced fuel consumption and particulate emissions in the atmosphere and thus contribute to the deceleration of climate effects.

## 6. ACKNOWLEDGEMENTS

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