



Full Length Research Article

DIAGNOSIS OF FAILURES IN A SPARK IGNITION ENGINE USING FUZZY LOGIC

***Néstor Rivera, Jairo Castillo, Steven Ronquillo, Yasmani Aguilar**

Research Group Transport Engineering, Universidad Politécnica Salesiana, Calle Vieja 1230,
Cuenca Ecuador

ARTICLE INFO

Article History:

Received 22nd March, 2016
Received in revised form
29th April, 2016
Accepted 01st May, 2016
Published online 30th June, 2016

Key Words:

Fuzzy logic,
Poorly combusted hydrocarbons,
Carbon dioxide,
Engine speed,
Manifold Absolute Pressure Sensor.

ABSTRACT

This document presents the development of a system for detecting faults through fuzzy logic, using different parameters such as poorly combusted hydrocarbons (HC), Carbon Dioxide (CO₂), engine speed (RPM), and Manifold Absolute Pressure Sensor (MAP) to predict the faults that may occur in the engine. In order to determine the behavior of the inputs, there were generated different faults in a sonata 2.0 gasoline engine, such as poorly calibrated spark plugs, improper fuel pressure, air filter and catalytic converter clogging. The input and output variables are analyzed by fuzzy logic. Rules are generated for these variables, which will give logical knowledge to the system; these proposed rules are verified through the system programming that is presented by simulink. Each input variable establishes a diverse output parameter. Through this system, it can be determined the level of the response parameters, which will give reliable values for detecting the faults when performing corrective maintenance; consequently, it will save time and money.

Copyright©2016, Néstor Rivera, et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

INTRODUCTION

The gases from the combustion are a reflection of the internal combustion engine status. There is a need to reduce pollution caused by internal combustion engines, as well as to use artificial intelligence for performing a corrective maintenance, avoiding the engine disassembly. The current investigation, within the context of science, is based on the main use of one of the branches of artificial intelligence, which is fuzzy logic. Several mathematical software such as Matlab allow the implementation of this technology in internal combustion engines; thus, this could prevent and correct failures that may occur on these machines. Within the context of our society, considering the analyzed parameters, this research work allow people who have vehicles to determine engine faults, and subsequently, it will allow to perform a precise corrective maintenance. There are several research works conducted using fuzzy logic with satisfactory results. In (Valencia et al., 2015), it is presented a model that shows the development of a fuzzy system for detection and diagnosis of failures in the steam generation by using fuzzy logic and MATLAB SIMULINK.

In (Vargas, 2014), the fuel injection is successfully controlled through fuzzy logic and use of HHO as a complementary fuel. In (Al-Jarrah, 2011), it is established the method for developing an advanced thermal control in vehicles through using fuzzy logic. In (Guarnizo Lemus, 2011; García-Sucerquia and Palacio-Gómez, 2011 and Rojas López, 2015), it is determined the control by fuzzy logic in applications that include the fuel switching and the use of different input variables such as EGR and MAP; in addition, it is observed the difference between using PI and PID controllers. In (Otero Quijano, 2011), the failures in ball bearings are detected through fuzzy logic, using vibration signals; the results were satisfactory and they were reflected in the construction of a test bench.

All these investigations are based on the use of logic fuzzy as the nucleus of development. Fuzzification, analysis, determination of rules for the intelligent system, and finally defuzzification are carried out in each one of these investigations. The models are elaborated in Matlab Simulink. The aim of the present study is to develop an artificial intelligence system by using fuzzy logic, with the purpose of obtaining the gasses emissions from combustion (input variables) and failures (output variables) that produce modifications in the analyzed gasses.

***Corresponding author: Néstor Rivera**

Research Group Transport Engineering, Universidad Politécnica Salesiana, Calle Vieja 1230, Cuenca Ecuador

MATERIALS AND METHODS

Sampling equipment

Engine

This experimental research was carried out in a SONATA 2.0 gasoline engine. It can be observed in Figure 1, and its features are shown in Table 1.



Figure 1. Test Model

Table 1. General engine specifications.

Denomination	Value
Number of cylinders	4
Engine capacity	1991 cm ³
Bore	8.3 cm
Stroke	9.2 cm
C _r	17.7 : 1
Torque / rpm	421 N.m / 1800
Maximum power	110.45 KW

Gas Analyzer

The QGA 6000 gas analyzer was used to obtain the exhaust gases; its technical specifications are detailed in Table 2.

Table 2. Technical analyzer specifications.

Specification	Description
Target subject	CO ₂ , CO, HC, O ₂ , Lambda
Repetition time	Lower than ± 2 % FS
Response time	Within 10 seconds (90 % of the time)
Preheat time	Approx. 2-8 minutes
Sample requirement	4-6 l / min
Voltage supply	AC110v o AC220v +/- 10 %, 50/60 Hz
Power consumption	Approx. 50 W
Weight	6.9kg

Experimental Design

A designed experiment is a test or series of tests where deliberate changes are induced in the input variables of a process or system; therefore, it is possible to observe and

identify the causes of changes in the output responses (Montgomery, 2002).

Output Variables

The values of the output variables are expressed in levels, which cause the engine failure and define the behavior of each one of the gases at different values of the inputs. The values of the output variables can be observed in Table 3.

Table 3. Output variables

Physical variable	Unit	Minimum	Medium	Maximum
Fuel	MPa	0.125	0.3	0.475
Pressure	mm	0.8	1	1.2
Poorly calibrated spark plugs	cm ²	7.54	14.8	22.06
Catalytic converter clogging	%	25	62.5	100
Air filter clogging				

Input Variables

The analysis of the behavior of gases was conducted with a sample of n=160, using Minitab. The variables that have greater interaction are shown below: Figure 2 for CO₂, Figure 3 for HC, and Figure 4 for MAP. The figures are response surfaces that represent the reaction of the output variables against the behavior of each one of the input variables with the purpose of identifying which output variable reacts in a better way and represents the satisfactory model that is going to be used.

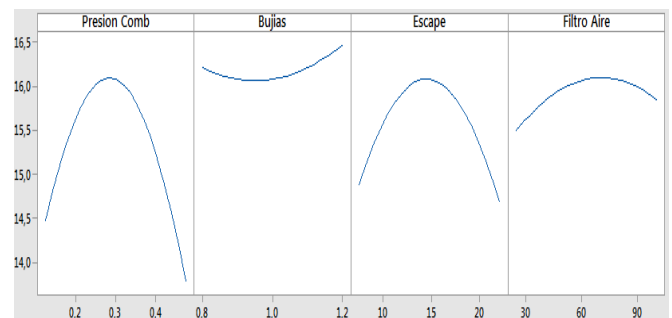


Figure 2. CO₂ behavior

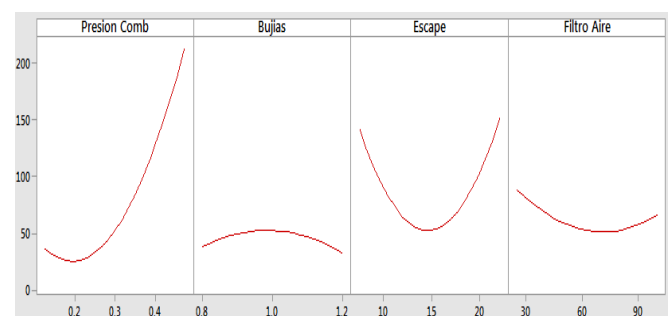


Figure 3. HC behavior

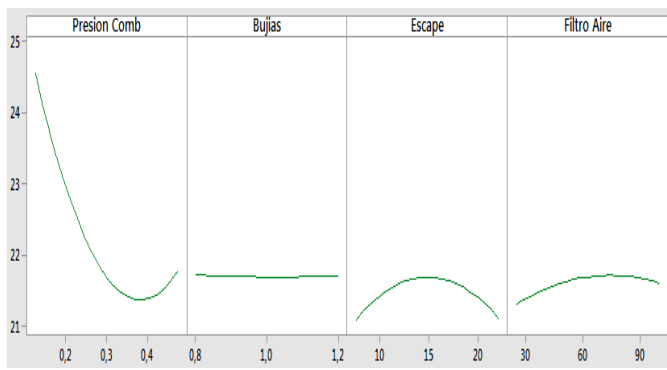


Figure 4. MAP behavior

Fuzzification

Input Variables

Membership degrees are assigned to each one of the input variables pursuant to established norms¹; thereby, the memberships of these variables are obtained, which can be observed in Figure 5, and their specified values are shown in Table 4.

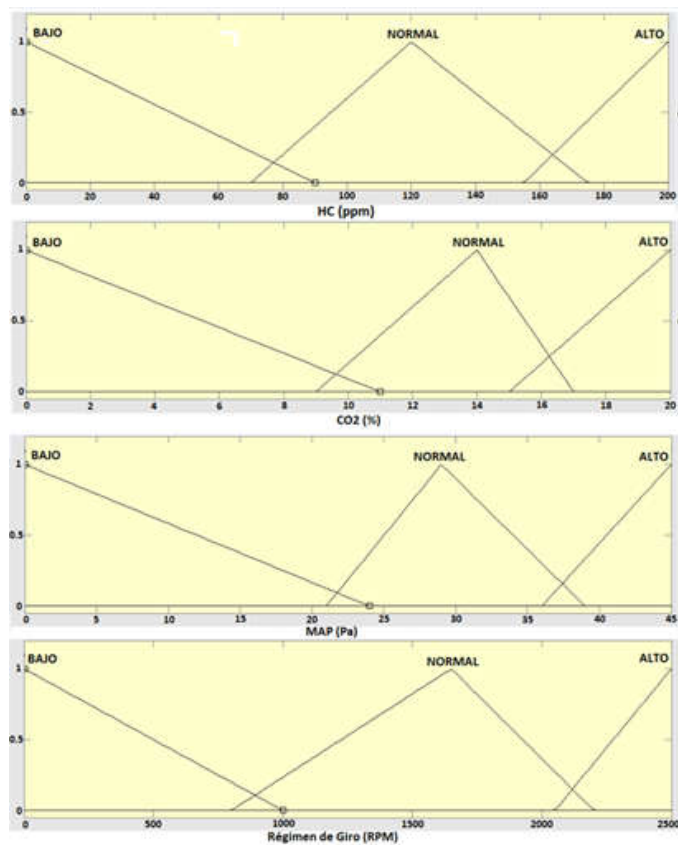


Figure 5. Membership for input variables

Table 4. Input variables fuzzification

	HC (ppm)	CO2	MAP (Pa)	RPM
Low	0-50	0-11.3	0-20	0-800
Normal	50-140	11.3-15	20-29	800-1650
High	140-200	15-16.5	29-45	1650-2500

Output Variables

The values of the memberships for output variables are detailed in Table 5 and can be observed graphically in Figure 6.

Table 5. Output variables fuzzification.

	Fuel pressure (MPa)	Spark plugs calibration (mm)	Catalytic converter clogging (cm ²)	Air filter clogging (%)
Low	0-0.125	0-0.8	0-7.54	0-25
Normal	0.125-0.4	0.8-1.2	7.54-20	25-65
High	0.4-0.6	1.2-1.4	20-30	65-100

Fuzzy inference

Inference is obtained from the knowledge acquired in the experimental design, with the purpose of observing the system performance at different parameters; thus, rules can be established to satisfy the system. These rules are cited in Table 6. The relationship between input and output variables can be observed in Figure 7.

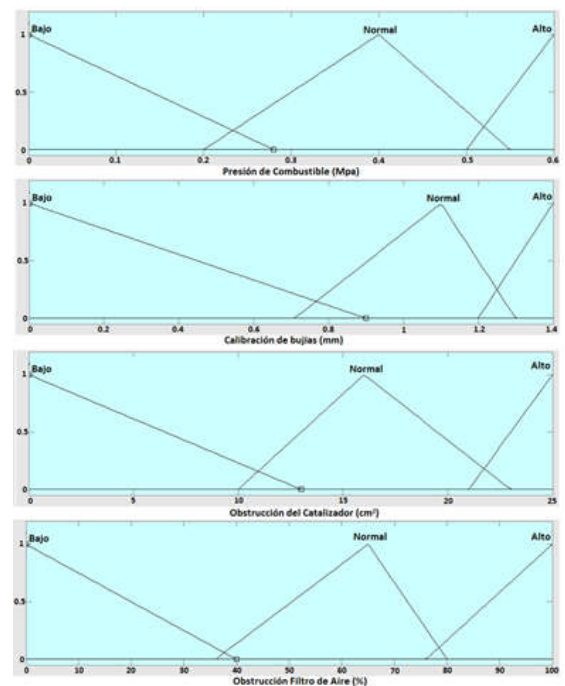


Figure 6. Membership for output variables

Table 6. Basis of rules.

HC	CO2	MAP	RPM	Fuel pressure	Spark plugs calibration	Catalytic converter clogging	Air filter clogging
Low	Low	Low	High	Low	Low	Normal	Low
Low	High	Normal	Low	Normal	Normal	Normal	Low
Normal	Normal	Normal	High	Low	High	Normal	Normal
Normal	High	High	Normal	High	Low	High	Normal
High	High	Normal	Normal	Normal	High	Normal	Normal

The proposed model contains 4 input variables and 4 output variables that are related according to the engine performance and the mentioned failures; this relation is gathered by the rules of the fuzzy system. These rules are shown in Figure 8.

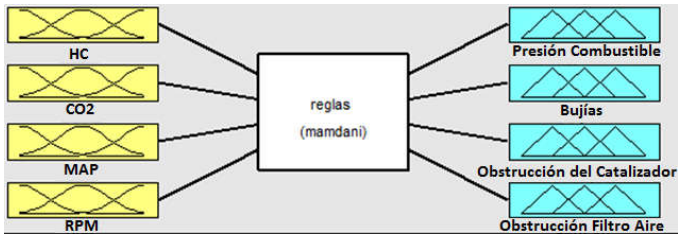


Figure 7. Fuzzy inference

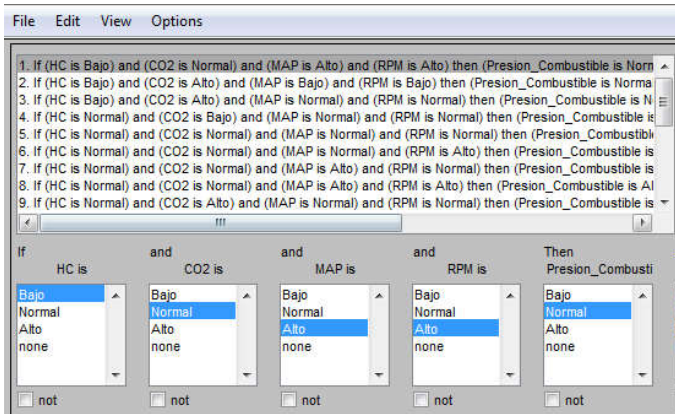


Figure 8. Established rules for fuzzy system

Defuzzification

The obtained response surfaces are the result of the proposed rules in the system. In Figure 9, it is observed that the behavior of Fuel Pressure is normal when the value of the HC is in the normal range and CO2 goes over the whole range from low to high.

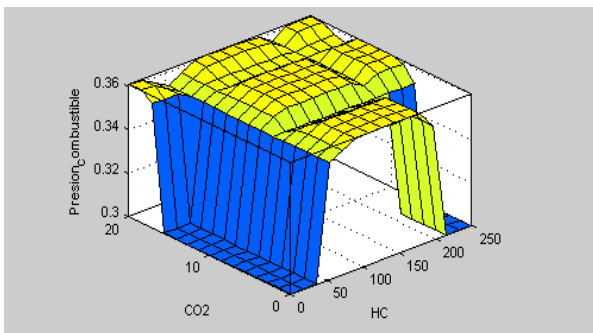


Figure 9. Fuel Pressure Surface

The spark plug gap is high when the value of the HC is in the normal range and CO2 goes over the whole range from low to high, as shown in Figure 10. As can be seen in Figure 11, the catalytic converter clogging is high when the value of the HC is in the normal range and CO2 goes over the whole range from low to normal. The air filter clogging is high when the value of the HC is high and CO2 goes over the whole range from low to normal. This behavior is shown in Figure 12.

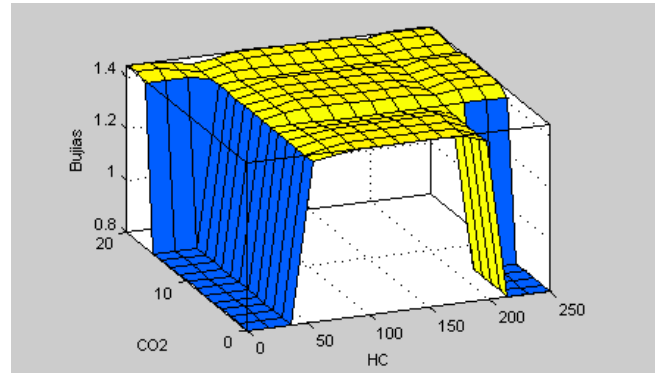


Figure 10. Spark plugs surface

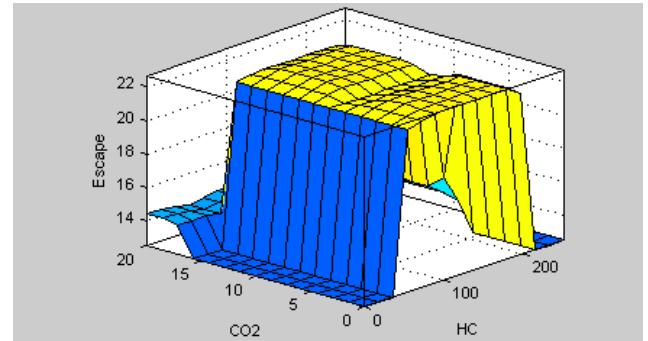


Figure 11. Catalytic Converter Clogging Surface

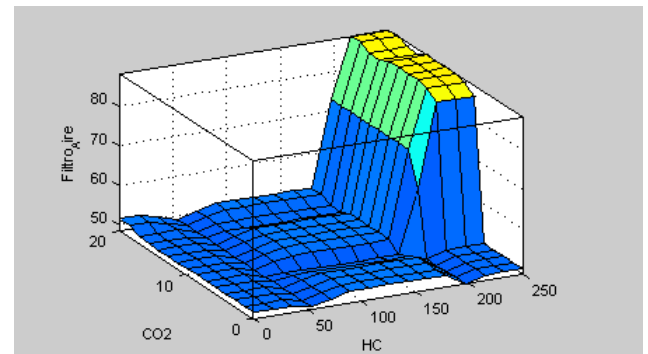


Figure 12. Air Filter Clogging Surface

RESULTS AND DISCUSSION

Once the rules for the correct functioning of the fuzzy system and each one of the memberships of the input and output variables have been obtained, tests are executed, varying each of the input parameters such as: HC, CO2, MAP, and RPM; thus, through these variations, the fuzzy system operation can be verified. In order to verify the veracity of the rules, the simulation in the Simulink platform is carried out. This platform has facilities for the development of the programming, providing rapid and reliable responses, as illustrated in Figure 13. Table 7 presents the results of 5 samples taken from the engine while simulating failures, which were obtained when performing several modifications in the input variables; thus, it could be observed the behavior of the output variables. The study results are shown in Table 8. These results were generated in the simulation performed in the Simulink platform. In order to obtain these values and verify them with the ones obtained from the Sonata 2.0

engine, there were used the samples taken from the engine (output variables) and subsequently, the verification of each of the input variables was performed.

The output variables were defined according to the relevance of the failures that are commonly detected in vehicles. It was possible to verify the feasibility of implementing a fuzzy

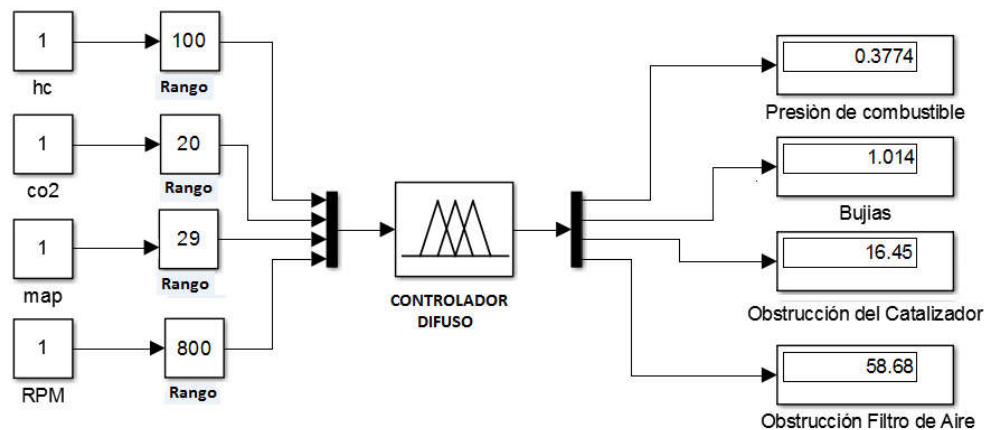


Figure 13. Algorithm of the fuzzy control system, designed in Simulink

Table 7. Samples taken from the engine.

HC	CO2	MAP	RPM	Fuel pressure	Spark plugs calibration	Catalytic converter clogging	Air filter clogging
28.9	13.7	34.06	800	0.125	1.01	16.45	17.82
178.54	18.93	22.47	1500	0.3499	1.315	16.44	58.83
67.8	12.08	44.98	2400	0.7	0.7	12.5	50
157.07	8.56	22.3	1614.7	0.1262	0.8839	14.74	58.61
184	18	41.98	2288.47	0.5632	1.027	23.53	91.06

Table 8. Results obtained in Simulink.

HC	CO2	MAP	RPM	Fuel pressure	Spark plugs calibration	Catalytic converter clogging	Air filter clogging
30	14	32	800	0.125	1.01	16.45	17.82
175	19	23	1500	0.3499	1.315	16.44	58.83
65	14	44	2400	0.7	0.7	12.5	50
154.37	9	23.11	1614.7	0.1262	0.8839	14.74	58.61
186.17	18.68	42.46	2288.47	0.5632	1.027	23.53	91.06

Table 9. Percentage error

HC	CO2	MAP
3.66 %	2.18 %	6.04 %
1.98 %	0.36 %	2.35 %
3.06 %	0.66 %	2.17 %
1.71 %	5.14 %	3.63 %
1.17 %	3.77 %	1.14 %

In sample 1, it is observed a low pressure fuel, a normal spark plugs calibration, a normal catalytic converter clogging, and a low air filter clogging. These conditions lead to a low HC, a normal CO₂, a normal MAP and low RPM, which demonstrate reliability of the system. The percentage error between the data taken from the internal combustion engine and the data obtained from the fuzzy system simulation carried out in the Simulink platform is shown in Table 9. The simulation results prove the stability and correct functioning of the engine applying the proposed fuzzy control system; thus, it has a maximum percentage error of 6%.

Conclusion

CO₂, HC and MAP were selected as input variables since they have greater inference over the corresponding output variables, as shown in Figures 2, 3 and 4.

system in the area of artificial intelligence through the study and research of the fuzzy logic theory and using the functionality of the FUZZY DESIGNER software; therefore, it could be performed a corrective maintenance in an internal combustion engine, rapidly and safely. Each response surface of the input variables enables to identify the behavior of the output variables, verifying the condition they are for performing the corrective maintenance, if necessary. The maximum percentage error of 6% ensures that the designed fuzzy control system works with high reliability.

REFERENCES

- Al-Jarrah, A. M., Salah, M. H., and Al-Tamimi, A. A. 2011. "Fuzzy logic control design for advanced vehicle thermal management systems," in *Proceedings of the 13th IASTED International Conference on Control and Applications*, pp. 200–204.
- García-Sucerquia, J. and Palacio-Gómez, C. 2011. "Control de temperatura utilizando lógica difusa", *Revista Colombiana de Física*, vol. 42, no. 3, p. 378.
- Guarnizo Lemus, C. 2011. "Metodología para la implementación de controlador difuso tipo takagi-sugeno en plc s7-300", *Tecnura*, vol. 15, no. 30, pp. 44–51.

- Montgomery, D. C., 2002. "Diseño y análisis de experimentos. México, Limusa", 2002.
- Otero Quijano, F. J., Pardo González, J. J., and Quiroga Méndez, J. E. 2011. "Vibration based fuzzy classifier for bearing monitoring", *Revista de Ingeniería*, no. 35, pp. 20–26.
- Rojas López, M. D., Sánchez Uribe, J. D. and L. M. Londoño Vásquez, 2015. "Una estrategia de innovación en fertilizantes orgánicos mediante lógica difusa", *Revista Facultad Nacional de Agronomía-Medellín*, vol. 68, no. 1.
- Valencia, F. A. and J. A. Estupiñan, 2015. "Sistema difuso para la detección y diagnóstico de falla en la generación a vapor", *Scientia et Technica*, vol. 20, no. 1, pp. 4–9.
- Vargas, E. G. C. 2014. "Diseño e implementación de un controlador difuso que interviene la inyección electrónica de combustible en un vehículo para la utilización de hho como combustible complementario".
