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Diagnostics in Tire Retreading Based on Classification with Fuzzy Inference System

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Abstract: Currently, there are tire retreading companies whose evaluations are not wholly accurate; due to various factors, sometimes customers are forced to agree to what is decided, and this means that the customer can sometimes pay for services that do not necessarily guarantee the correct operation of the tire or, failing that, shorten its life. This work aims to develop a tire diagnostic system that allows for evaluating a tire's faults and can thus be more precise when determining if it needs retreading or a change process. The diagnostic system is focused on demonstrating that fuzzy logic can be applied in diagnosing the condition of tires. The methodology consisted of determining the variables to be considered in the evaluation of tires, such as blowing out, flange breakage, band failure, and patching, then applying fuzzy logic. Subsequently, the execution tests of the built diagnostic software were carried out for its validation in a case study of a tire retreading company. The result was a margin of error of 1.6% accuracy versus 5.6% from the operator experience. The conclusion was that fuzzy logic could be applied correctly in the field of tire retreading, providing substantial savings in time and resources for related companies, as well as giving customers confidence since, by using more accurate results, the diagnostic system will make the tire evaluation efficient.

Keywords: diagnosis; retreading; classification; tires; fuzzy logic; software

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1. Introduction

1.1. Background

Tire failure is a problem that occurs worldwide, and every driver knows that there are tire failures when driving a vehicle that can affect your safety, such as inflation pressure, overload, sudden braking, etc., which may be the cause of accidents. The primary source of tire failure is high shear due to plying anisotropy, modulus, rubber mismatch, and hydrostatic tensile stresses at the tread edge [1].

In addition, the number of "End-of-Life-Tires" (ELT) is increasing at a rapid rate around the world, which has a tremendous adverse impact on the environment, ecological systems, and human health [2]. One of the options to take advantage of your tire's lifetime is retreading.

This leads to regularly checking the tires that can determine if they can be retreaded or discarded; however, carrying out this process does not guarantee that the retreaded tire can extend its useful life [3] as it should, although pressure inflation and road hazards are the main causes of continuous wear of tires both newly and already retreaded.

Going into the retreading process, in addition to other factors such as the reliability with which a tire was retreaded, it was unreliable, as it was not guaranteed that the life of the tire could be extended as it should, or they only retreaded the tire to obtain a temporary solution for the driver or customer. In addition, there was a lack of confidence in retreading companies in general when making an incorrect diagnosis. Likewise, different tire retreading companies carried out diagnoses in an empirical way, and because of the results obtained due to the high demand for tire evaluations, it was possible to verify that there was a margin of error on the operator's decision when evaluating a tire.

On the other hand, Artificial Intelligence (A.I.) is widely accepted as a technology that offers an alternative way of tackling complex and ill-defined problems. They can learn from examples; they can handle noisy and incomplete data; and, once trained, they can make reasonable predictions and generalizations. One branch of A.I. is fuzzy logic, which is more efficient than traditional logic by using multiple binding inputs to a single output in a non-linear domain [4].

Consequently, due to this problem, the present work focuses on improving the possibility of delivering an accurate response regarding a tire's faults through fuzzy logic. The focus was primarily to contribute the solution to the hands-on human worker experience diagnosing tire failures using fuzzy logic in a web app to determine if a tire should be retreaded or scrapped.

1.2. Related Work

According to Yang et al. [5], driving safety is the most basic requirement of autonomous vehicles, but it is also the most challenging task at the same time. Innovative tires equipped with sensors to recognize the interaction conditions between the tire and the road have been proposed to realize continuous tire information measurement and decision making.

Tahami, Farhangi, and Kazemi [6] mention the support the system provides to the electric vehicle driver with trajectory correction, thus improving linear stability and providing safety when driving. Actual vehicle speed is estimated using a multi-sensor data fusion method. The neural network maps vehicle speed and steering angle to generate the reference required by the rotation sensor.

The detection and classification of tire defects are fundamental research topics for driving safety and performance improvement. The study by Zheng et al. [7] points out that automatic quality control has aroused great interest from academia and industry in recent decades. They built a new deep convolutional sparse coding network (DCScNet) for tire defect classification.

El Hajjaji, Ciocan, and Hamad [8] describe through specific analyzes the stability of the lateral movement of a vehicle, including forwarding variations of the steering angle, and introduce the representation of the non-linear vehicle model by the fuzzy model Takagi-Sugeno (T-S). This model gives sufficient conditions to generate the strength of the fuzzy Tagaki-Sugeno (T-S) model using the regeneration controllers. Fuzzy control is developed based on the fuzzy model to improve vehicle stability. Necessary tests determined that to demonstrate the effectiveness of the proposed fuzzy controller, simulation results are given showing the vehicle performance improvements in terms of strength and maneuverability in critical situations. Mainly, they focus on driver safety.

Çarman [4] defines the manageability of neural network systems, in this case using fuzzy logic, and since they are fault-tolerant, as we already know, they can be managed on incomplete data. They can deal with non-linear problems, but above all, once adequately trained or optimized, they can make predictions and generalize information at high speeds.

According to Buckholtz [9], using control based on fuzzy logic is described to determine and assign tire slips for each vehicle corner. The objective of the management is to track the overall dynamics of the desired vehicle, such as the desired tracking of a steering angle, by assigning an appropriate tire slip, as each of the slips on each tire is used as an input reference for control of the dynamics of the tire itself since the work is developed from the controller based on high-level logic.

In the opinion of researchers such as Garcia-Pozuelo et al. [10], innovative tires are one of the most promising research fields for automotive engineers. These tires are equipped with sensors that provide information about your activity. In the research work by Zhang et al. [11], they appreciate the operation of a fuzzy logic controller that has been designed by considering the qualitative relationships between the parameters of tire pressure, temperature, and speed. The intelligent tire system with a fuzzy logic controller has been modeled on the vehicle dynamics.

According to Cong et al. [12], a fuzzy observer-based control algorithm for a vehicle is proposed. The proposed scheme is based on a fuzzy rule on a slip angle (β). The vehicle dynamics are represented by Tagaki-Sugeno-type fuzzy models in the fuzzy model design strategy. Initially, equivalent vehicle models were built using the linear approximations of vehicle dynamics for low and high lateral acceleration, respectively, over operating regimes.

In this paper, the same bases that fuzzy logic has will be used since they are essentially multivalued logics extending classical logic when defining them. The latter imposes only true or false values on their statements. They have adapted to the general modeling of which human thought can perceive. However, they are not wholly deterministic. Measurements will be used not only for stability but also for other factors such as tire pressure and tail height to diagnose whether a tire could be replaced.

2. Materials and Methods

2.1. Methodology

Various artificial intelligence methodologies [13] have recently been used to estimate the performance parameters of work machines and off-road vehicles. Due to the non-linear and stochastic characteristics of the ground-wheel interactions, the knowledge of the Mamdani fuzzy expert system for estimating the contact area and the contact pressure is detailed in said article.

The Mamdani-type fuzzy logic model was used, as shown in Figure 1.

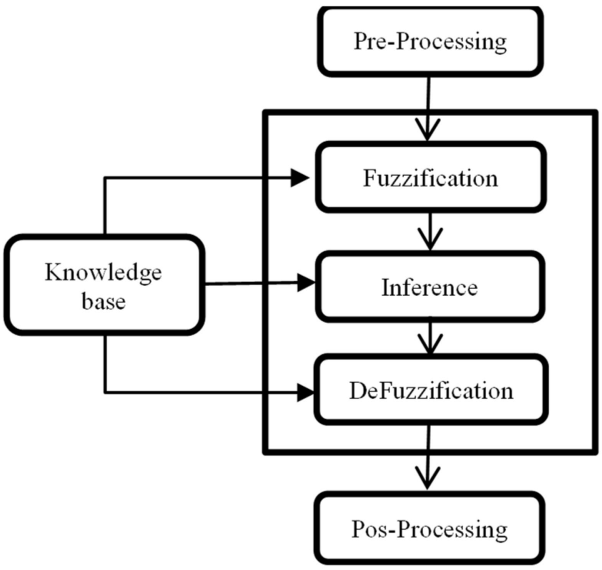

Figure 1. Fuzzy Logic Modeling.

- Pre-Processing: Input variables are those variables or data that will be entered into the control system to be first recognized and then interpreted by the fuzzy logic control in the next step.
- Fuzzification: Its objective is to convert the actual values into fuzzy values; in addition, degrees of membership are granted to the input values or variables associated with association with the previously interpreted fuzzy logic sets, using the membership functions associated with the collections of fuzzy logic. In this process, four input variables have been determined together with the human operator, such as Tire Blowout (cm), Tap Breakage (cm), Band Fault (cm), and Tire Patching (units), as shown below in Figure 2. The statistical summary of the input variables is minimum = 0 cm, maximum 9 cm, average = 4.5, and standard deviation of 4.81 cm.
- Inference: Joins the input and fuzzy output logic sets represented in the rules established in the control system or model. In this part, information from the knowledge base is used to develop these rules through conditionals, such as: if case 1 and case 2,

then action 1. Mainly what is determined in this part would be the set of the output of each rule; 45 fuzzy rules divided into the two conditionals AND and OR have been established. To support such an approach, reference to similar studies from other domains is provided [14].

Figure 2. Tire Input Variables.

- Defuzzification: Here, the procedure of converting numerical values into linguistic values through simple mathematical models, such as the centroid method, weighted average method, or maximum mean method, is performed. For the present work, the centroid method will be used to adapt to the type of modeling of the system and, above all, its effectiveness.
- Post-Processing: The output values are data that, after having executed the fuzzy logic model with the points mentioned above, are exposed to determine how the decision has been made. It is in this part where the result of the evaluation of each tire determines whether it goes for retreading or is rejected.

For the tire diagnostic software development, techniques, tools, and instruments were used for data collection, such as observation at the tire retreading company site and interviews with those in charge.

2.2. WEB System

We opted for developing a web system with the Java language that offers a set of frameworks specialized in backend development and the front-end of the web application with responsive design.

The frameworks used were Spring MVC [15], a Spring subproject aimed at facilitating and optimizing the process of creating web applications using the MVC pattern (Model-View-Controller). JSON Web Token is an open standard based on JSON [16] (RFC 7519) for creating access tokens that allow the propagation of identity and privileges. Hibernate is a programming tool that will enable us to abstract from the database and only interact with objects of our classes. Postgresql, an object-relational database management system, is the market's most powerful open-source database management system. Semantic U.I. [17] is a framework designed to create responsive interfaces using readable HTML/CSS; it comes integrated with other frameworks or libraries such as Angular, React, Ember, or Meteor. Chart Scatter. It is a web development tool for graphics in responsive environments using JavaScript libraries. iText is an open-source Java library that supports the development and conversion of PDF documents. Java Server Pages (JSP) is a Java technology that allows you to combine static HTML code with dynamically generated code in the same file. Netbeans (version 12.5, Sun Microsystems, Austin, TX, USA) is the development environment used because it is complete, adequate, and easy to use; it is ideal for working in Java (version 8.0, Sun Microsystems, Austin, TX, USA), making it a powerful application development tool.

2.3. Scrum Framework

For the development of the system, the Scrum framework [18] was used, making partial and regular deliveries of the final product, prioritized by the benefit they bring to the project recipient. For this reason, Scrum is especially suitable for business projects, where results need to be obtained as soon as possible, where the requirements are changing or poorly defined, and where innovation, competitiveness, flexibility, and productivity are essential.

Table 1 shows the distribution of use cases of the tire diagnostic system.

Table 1. Distribution of cases of use of the diagnostic system.

Id	Use Case
CU001	Validate Access
CU002	Manage Users
CU003	Manage Variables
CU004	Manage Fuzzy Sets
CU005	Manage Evaluations
CU006	Manage Tire Characteristics
CU007	Manage Tire Feature Options
CU008	Evaluate Tires
CU009	Make Reports

2.4. Software Architecture

The architecture used for the present work was the Model View Controller Spring MVC (version 5.3, SpringSource, Palo Alto, CA, USA). It is a software architectural design pattern that serves to classify the information, the logic of the system, and the interface presented to the user. In this type of architecture, there is a central system or controller that manages the inputs and outputs of the system, one or several models responsible for searching for the necessary data and information, and an interface that shows the results to the end-user.

The MVC model developed in the proposal is presented in Figure 3:

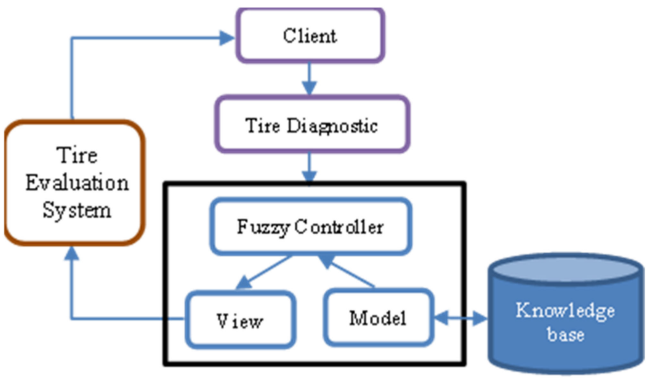

Figure 3. The architecture of the Fuzzy Controller View Model.

2.5. Fuzzy Logic

As a fundamental aspect of fuzzy logic-based prediction systems, a set of fuzzy if-then rules are used where they were used following the principles of fuzzy logic. Linguistic if-then rules are included to develop an intelligent predictive model based on the Centroid method in a defuzzification scenario.

The Fuzzy Inference System [19] of the tire diagnostic system elaborated in Matlab (version 2020a, MathWorks, Natick, MA, USA) [20] with the four input variables with their respective value ranges (min, max, unit) are as follows:

- Band Fault (0, 9, cm)
- Broken Tab (0, 9, cm)
- Tire Blowout [21] (0, 9, cm)
- Tire Patching (0, 9, units)

As well as the resulting output of retreading, which is shown in Figure 4.

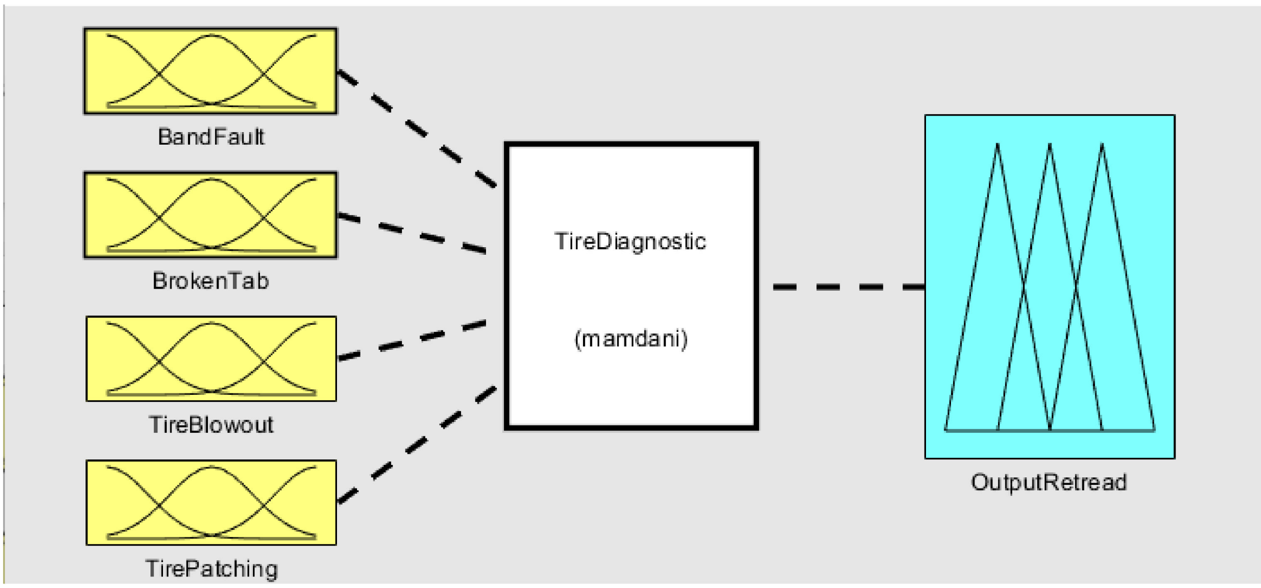

Figure 4. Tire Diagnostic Fuzzy Inference System.

For each variable, the trapezoidal membership function was used. Equation (1) describes the shape of the trapezoidal membership function [22]. Figure 5 shows the Trapezoidal Membership Functions of input variables.

$$f(x;a,b,c) = \max\left\{min\left(\frac{x-a}{b-a}, \frac{b-x}{b-c}\right), 0\right\} \quad (1)$$

a and d are located at the bottom of the trapezoid, and b and c are at the top. Membership values are computed for each input value in x.

2.5.1. Input Variables

The system is configured to work with average tires used on city streets, using the following input and output variables and fuzzy rules.

1. Band Fault [No Fault, Fault, Fair Fault, High fault]
2. Broken Tab [No Broken, Slightly Broken, Regular Broken, Broken, High Broken]
3. Tire Blowout [No Blowout, Blowout, Regular Blowout, High Blowout]
4. Tire Patching [No Patching, Little Patching, Regular Patching, Patching, High Patching, Over Patching]

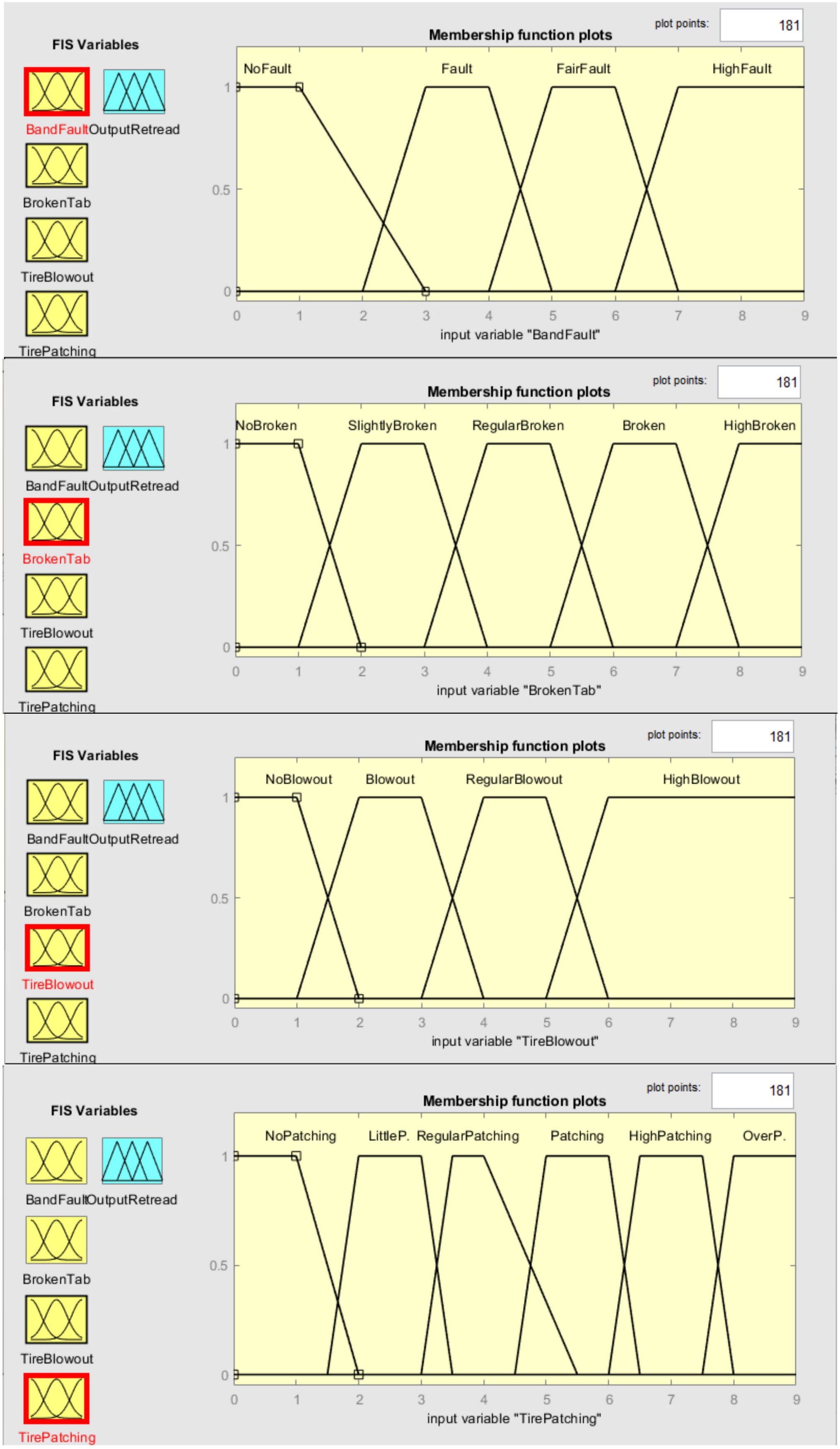

Figure 5. Trapezoidal Membership Functions of input variables.

2.5.2. Output Variable

There is an output variable called "result with a fuzzy set", and this provides a base for decision making.

1. Result (No Retread, Medium Retread, High Retread)

2.5.3. Fuzzy Rules

1. If the result is not within the pre-established rules, it will result in [Rejected]

Table 2 below shows the respective input and output variables defined in a matrix that has been prepared based on the data previously obtained by the tire retreading Company.

Table 2. Distribution of Fuzzy Rules as a Result of Rejected.

Id	Input Variables				Output Variable
	Band Fault	Tire Blowout	Tab Break	Tire Patching	Result
1	High fault	Blowout	Broken	Patching	No Retread
2	High fault	Blowout	Broken	High Patching	No Retread
3	High fault	Blowout	Broken	Over Patching	No Retread
4	High fault	Regular Blowout	Broken	Patching	No Retread
5	High fault	Regular Blowout	Broken	High Patching	No Retread
6	High fault	Regular Blowout	Broken	Over Patching	No Retread
7	High fault	High Blowout	Broken	Patching	No Retread
8	High fault	High Blowout	Broken	High Patching	No Retread
9	High fault	High Blowout	Broken	Over Patching	No Retread
10	High fault	Blowout	High Broken	Patching	No Retread
11	High fault	Blowout	High Broken	High Patching	No Retread
12	High fault	Blowout	High Broken	Over Patching	No Retread
13	High fault	Regular Blowout	High Broken	Patching	No Retread
14	High fault	Regular Blowout	High Broken	High Patching	No Retread
15	High fault	High Blowout	High Broken	Over Patching	No Retread
16	High fault	High Blowout	High Broken	Patching	No Retread
17	High fault	High Blowout	High Broken	High Patching	No Retread
18	High fault	High Blowout	High Broken	Over Patching	No Retread
19	High fault	Blowout	Regular Broken	Patching	No Retread
20	High fault	Blowout	Regular Broken	High Patching	No Retread
21	High fault	Blowout	Regular Broken	Over Patching	No Retread
22	High fault	Regular Blowout	Regular Broken	Patching	No Retread
23	High fault	Regular Blowout	Regular Broken	High Patching	No Retread
24	High fault	Regular Blowout	Regular Broken	Over Patching	No Retread
25	High fault	High Blowout	Regular Broken	Patching	No Retread
26	High fault	High Blowout	Regular Broken	High Patching	No Retread
27	High fault	High Blowout	Regular Broken	Over Patching	No Retread

Table 3 shows the input and output variables defined in a matrix based on the Medium or High Retread Result data.

Table 3. Distribution of Fuzzy Rules as a Result of Medium or High Retread.

Id	Input Variables				Output Variable
	Band Fault	**Tire Blowout**	**Tab Break**	**Tire Patching**	**Result**
28	No-Fault	No Blowout	No Broken	No Patching	High Retread
29	No-Fault	No Blowout	No Broken	Little Patching	High Retread
30	No-Fault	No Blowout	No Broken	Regular Patching	High Retread
31	No-Fault	No Blowout	Slightly Broken	No Patching	High Retread
32	No-Fault	No Blowout	Slightly Broken	Little Patching	High Retread
33	No-Fault	No Blowout	Slightly Broken	Regular Patching	High Retread
34	Fault	No Blowout	No Broken	No Patching	Medium Retread
35	Fault	No Blowout	No Broken	Little Patching	Medium Retread
36	Fault	No Blowout	No Broken	Regular Patching	Medium Retread
37	Fault	No Blowout	Slightly Broken	No Patching	Medium Retread
38	Fault	No Blowout	Slightly Broken	Little Patching	Medium Retread
39	Regular Fault	No Blowout	Slightly Broken	Regular Patching	Medium Retread
40	Regular Fault	No Blowout	No Broken	No Patching	Medium Retread
41	Regular Fault	No Blowout	No Broken	Little Patching	Medium Retread
42	Regular Fault	No Blowout	No Broken	Regular Patching	Medium Retread
43	Regular Fault	No Blowout	Slightly Broken	No Patching	Medium Retread
44	Regular Fault	No Blowout	Slightly Broken	Little Patching	Medium Retread
45	Regular Fault	No Blowout	Slightly Broken	Regular Patching	Medium Retread

3. Results

The results of the decision system for used tires are obtained by building a web application that allows validating the proposal.

The main screen of the developed software is distributed through a dashboard; the interface presents the different options that the diagnostic system has, as seen below in Figure 6.

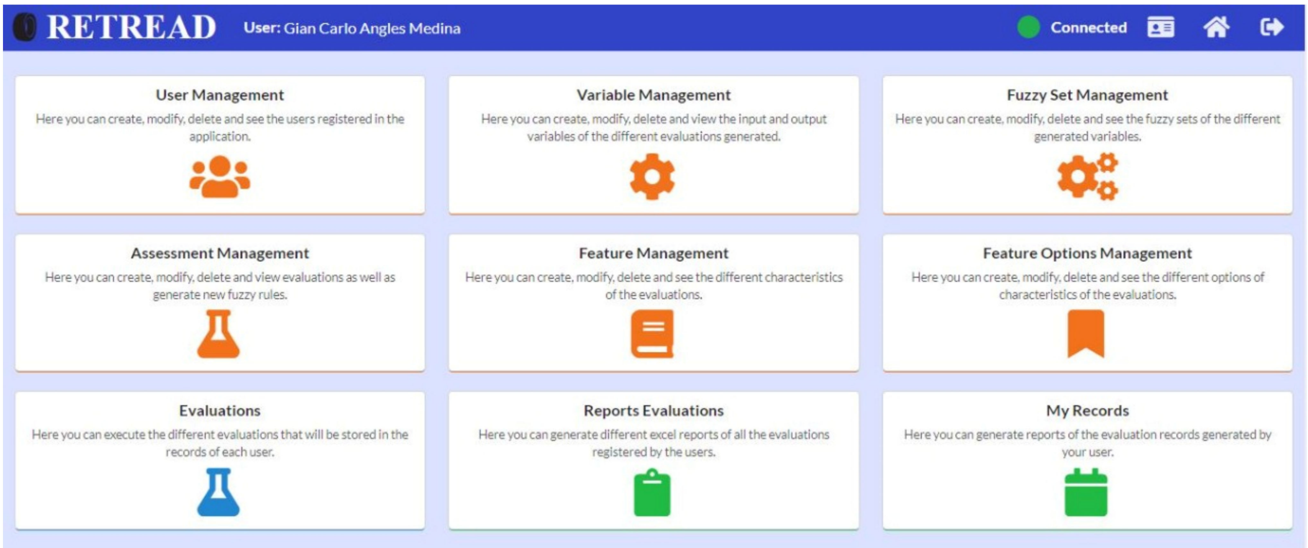

Figure 6. Main Screen of the Tire Diagnostic System.

3.1. Management of Fuzzy Sets

In this section, it is possible to search for a particular fuzzy set and to be able to carry out its respective modification or elimination; it must be considered that the determination of the values of the points A, B, C, and D must be managed under strict review. Figure 7 shows some values entered as the input variables.

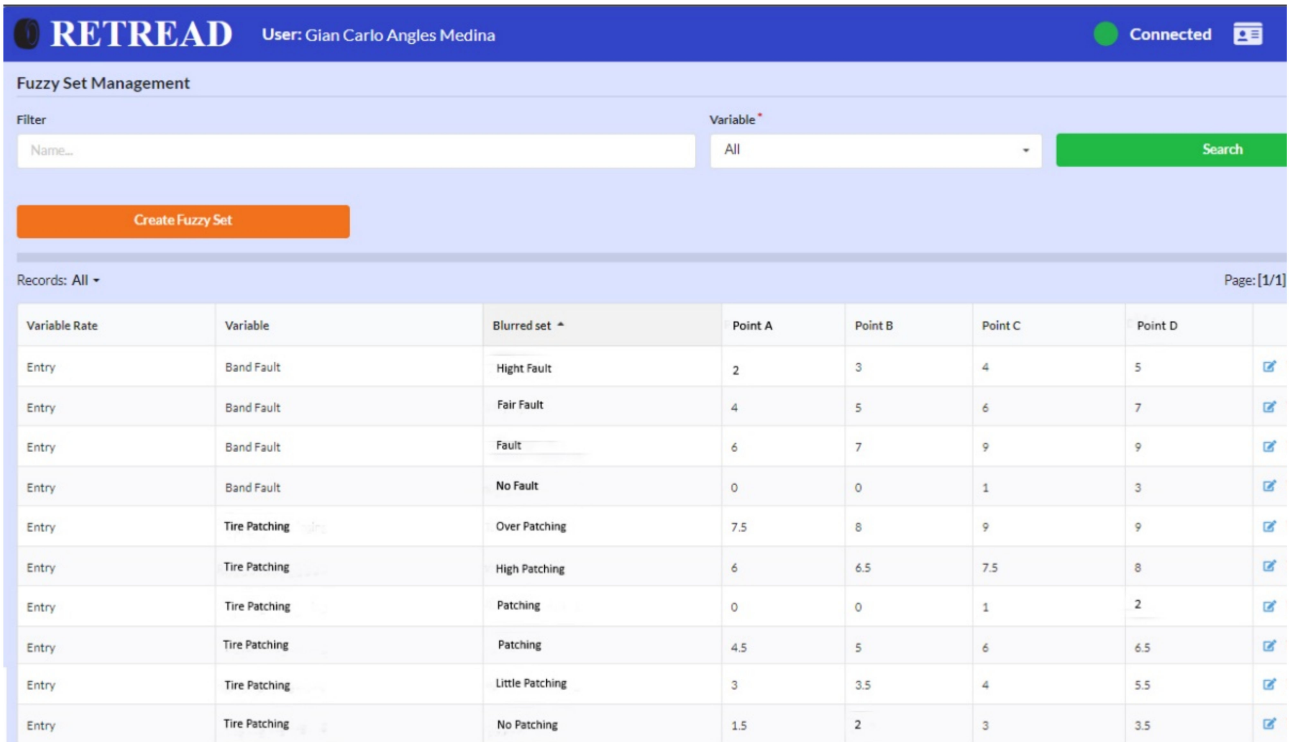

Figure 7. Fuzzy Set Management screen.

3.2. Management Evaluations

In this section, you can perform the respective search for the name of an evaluation you have registered to modify, edit fuzzy rules, and delete it. You can enter the new fuzzy rules within the same assessment; it should be considered that to build a set of fuzzy rules, you can use the AND/OR conjunction within the Activation drop-down list and enter the priority with which they are applied. Next, in Figure 8, you can see the screen where you can edit the fuzzy rules. You are going to add these rules; it should be considered that 45 fuzzy rules have been established between combinations of AND/OR conjunctions for the correct operation of the tire evaluation. Therfore, it is recommended to manage these fuzzy rules very carefully.

Figure 8. Edit the Fuzzy Rules screen.

3.3. Tire Evaluations

This section lists the names of the evaluations with their respective characteristics, which have been created previously in the management of evaluations. Just click inside the evaluation box to access any of them, as shown below in Figure 9. Table 4 shows an example of a test scenario for the fuzzy system.

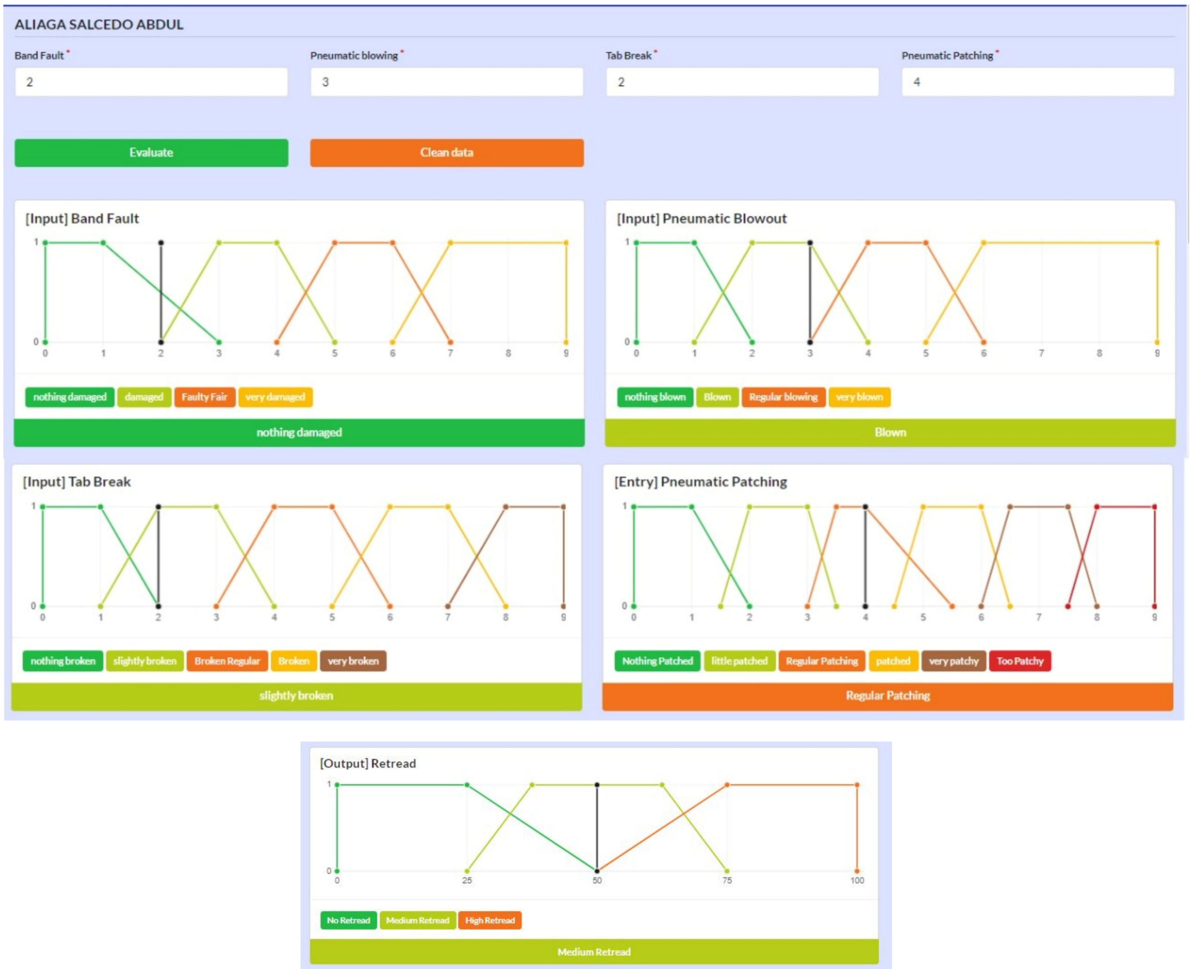

Figure 9. Tire Evaluation Screen.

Table 4. Example of a test scenario for the fuzzy system.

Id	Input Variables				Output Variable
	Band Fault	**Tire Blowout**	**Tab Broken**	**Tire Patching**	**Result**
1	5	6	9	4	No Retread
2	1	1	2	3	Medium Retread
3	1	0	1	0	High Retread
4	6	7	8	7	No Retread
5	2	1	3	0	High Retread
6	3	1	1	0	Medium Retread
7	1	2	2	1	No Retread
8	0	0	0	2	High Retread
9	2	1	4	3	No Retread
10	8	1	2	1	No Retread

3.4. Operator Evaluations of Tire Evaluations

The evaluations were carried out with the Tire Diagnosis system and at the same time as the evaluation of the operator on the tire evaluations; for this case, a sample of 150 tires was taken to evaluate the precision of both. The methodology used by the human operator must be considered since, due to his experience, he only uses the tire review through his vision; for this reason, it can fail on certain occasions generating a loss of resources, delay, and customer dissatisfaction. Next, Figure 10 shows the result of the assessments carried out by the operator of the company; therefore, the evaluations carried out with the Tire Diagnostic System shows the result of the evaluations approved by the tire company operator. Those observed by the retreading area identified them and had to go through the inspection area again to determine the final rejection.

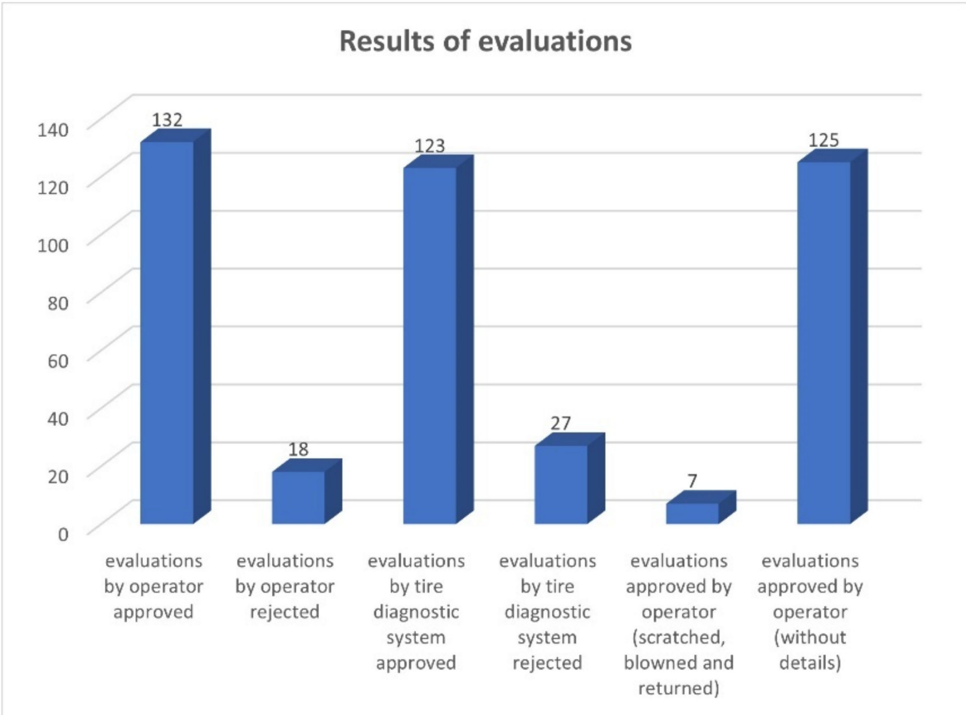

Figure 10. Results of evaluations.

The evaluations approved by the operator were 132 tires; then, seven were observed, and only 125 tires passed correctly to the retreading process, giving a margin of error of 5.6% accuracy.

The evaluations approved by the Tire Diagnostic System were 123 tires that passed correctly to the retreading process without any observation; based on the 125 previous tires that the operator correctly evaluated, then it was defined that the margin of error of the Diagnostic System is 1.6% precision compared to 5.6% of the operator of the company Relino S.A.C. (125th Sepulveda Av, Miraflores, Arequipa, Peru)

4. Discussion

The tire diagnosis allows for evaluating a tire's faults when determining if it goes for the retreading or change process. This procedure can be performed more accurately if fuzzy logic is used.

Our results show that tire diagnosis can be performed using fuzzy logic, which was validated with the construction of the Tire Diagnosis System software through quality metrics using software engineering tools, obtaining passing results in the functional tests and performance with a margin of error of 1.6% accuracy vs. 5.6% by operator experience.

Precisely, these results coincide with the use of fuzzy membership functions found by Shaout [23] when using the input variables of driving time, acceleration data, number of rotation messages received, and car speed. In contrast, the defined output variables are equipped and not equipped. Considering our work and the previous work, the values provide results associated with the tires and their respective maintenance; what makes the difference are the tools they provide for the input values, which are rotating sensors (acceleration data).

This is related to what was expressed by Zhang et al. [11], in which they describe input variables such as tire temperature, tire pressure, and tire speed; velocity compensation and pressure compensation are defined as output variables. The results obtained for this study show that the fuzzy logic controller can reduce the wear coefficient of the tire and increase the safety coefficient of the pressure; if we transfer this to a comparison with our research work, we will realize that the result is similar, since what they grant is mainly how much wear a tire has. Ours indicate that said wear depends on whether a tire is retreaded able or not.

In fact, by applying fuzzy logic, it is possible to obtain much more specific results and guarantee that the choice made by the system will be based on the data obtained from the tire company and thus be able to determine with greater precision if a tire can be retreaded able or disposable.

On the other hand, different studies also use fuzzy logic but focus on the suspension [24] or brake system [25], which complements how important it is for the comfort and safety [26] of a vehicle.

In essence, this study represents a significant contribution to the diagnosis of the condition of tires using fuzzy logic; however, a limitation found in the study was not having had sufficient resources to have achieved more excellent coverage of companies dedicated to this area, and although it was not the purpose of the study, it could have generated a baseline on the prediction in the diagnosis of tires using fuzzy logic.

From the results found and the built software tool, it can be applied to companies dedicated to tire diagnosis and retreading, as well as personnel interested in knowing the condition of their vehicle tires.

As for future work, it is necessary to advance new research that addresses the evaluation of other input and output variables to be considered with fuzzy logic for tire diagnosis. Regarding the software tool, it is possible to measure the impact on the specialization of personnel, as well as the improvement of practices in diagnosing tires using the proposed built software.

5. Conclusions

Implementing the diagnostic system for tire maintenance using fuzzy logic was possible. For the human expert, the choice of tires that goes through the retreading process is done through the visual and auditory technique, becoming fault intolerant.

The current state of the situation of the tires and the technologies present were determined; for this, the previous works were reviewed in order to have an amplitude on fuzzy logic and its use in technology, specifically in tires and their maintenance, having shown that fuzzy logic is mainly used for vehicle stabilization. For tires, innovative tires are developed that contain sensors that at the moment can only measure the pressure of a tire and no other factors that, as mentioned previously, can determine the need for the retreading of a tire or its complete disposal. Fuzzy logic allowed the detection of tire failures more precisely than the operator's experience.

The Tire Diagnostic System was validated through quality metrics using software engineering tools, and passing results were obtained in functional and performance tests.

Being able to correctly demonstrate that fuzzy logic can be applied in the field of tire retreading, it was determined that in the future, a much more sophisticated system could be implemented using state-of-the-art technology to be used in a company professionally.

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