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An Integrated Fuzzy-Rule and Case-Based Reasoning System for Enhanced Automobile Maintenance and Repair

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

Automated systems have become essential in assisting motorists with vehicle maintenance and repair, yet many still require technician intervention for output validation. This study introduces a novel framework for integrating fuzzy logic with case-based reasoning (CBR) to enhance the reliability of such systems, especially in handling ambiguous cases. The system efficiently retrieves similar cases from a comprehensive case base, applying proven solutions to new problems. In scenarios where no exact match is found, fuzzy logic approximates a viable solution. We tested this framework on 134 real-world cases from Akwa Ibom Transport Company, demonstrating its effectiveness in resolving vehicle issues by leveraging and approximating solutions. This research significantly advances the accuracy and reliability of automated vehicle maintenance systems, offering a more autonomous approach to diagnostics.

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Keywords: CBR; fuzzy logic; expert system; nearest neighbour; repair; maintenance; automobile; confidence; mechanic.

1. INTRODUCTION

Knowledge can be acquired through learning from a successful (desirable results) or an unsuccessful (unwanted results) experience. Most times automobile technicians (mechanics) apply heuristics techniques on a malfunctioned vehicle to make it work after many trials. These experiences acquired in repairing an automobile either successfully or unsuccessfully are called a “case” in this study. The accumulated cases could be termed a case base or a case library. The case base is used in reasoning to solve a new problem. To a large extent, similar problems have similar solutions, so a problem that is similar to the one in the case base has a similar solution.

In some cases, problems that are not similar to any case in the case base occur in varying degrees due to circumstances including the terminology used in describing a case. This could be from the antecedent clause employed in the rules. If a new problem has a wide difference between its closest cases in the case library, it becomes difficult to solve such a problem in the traditional case-based base reasoning except to revise the problem. Revision of a problem is a difficult task in case-based reasoning methodology. This is because of the ambiguous nature of cases and the quest to have an exactness between the problem and solution of the new case and some cases in the case base.

Fuzzy logic technology presents the features to resolve such ambiguities and uncertainties through its ability to handle fuzziness through collaborations, propagation, approximations and aggregations using the cases in the case library. Fuzzy logic is a superset of the conventional Boolean logic that helps to reason more like humans by approximation. It applies the principle of partial truth and falsity in its reasoning. It is not either true (1) or false (0) but a value between the two states [0,1]. This value represents the degree of confidence in the true state of the variable concerned.

Cases in the case base are problems where the true value of their solution has been established since they are tested and trusted to have worked successfully. Those whose falsity has also been established are so marked in the case base. In most situations, such cases (failure) are not recalled for use in solving a problem but rather to avoid using it. The tested and trusted solutions and their accompanied problems represent the true state of such a case. Fuzzy logic technology can be used to measure the degree of similarity of the case at hand and a case similar to it in the case base. The results obtained represent the confidence level of the solution proffered concerning the case that it is like.

This study therefore seeks to embed fuzzy logic in a case-based base reasoning methodology to diagnose faults in malfunctioning automobiles. The case-based base reasoning methodology uses the retrieve, reuse, revise and retain phases in its processing. A solution to a case in the library that is most similar or identical to the problem case is reused as a solution to the new case. Where there is a wide variation, then a revision is done. In either case, fuzzy logic is used to establish the degree of confidence between the new case and a case in the library whose solution is used as a solution to the new case at hand.

According to Goker et al. [1], diagnosis is the identification of the root cause of abnormal or defective behaviour in a system through means of exposed symptoms, the system’s state, general specification and the operating environment. Diagnosis involves performing fault detection and identification (FDI) generally performed using hardware redundancy or analytical redundancy methods [2].

When humans diagnose or troubleshoot a system, the experience of the expert such as the knowledge they use in solving a similar problem in the past is brought to bear in trying to solve the new problem. The expert will not reinvent the wheel but rather try to recall and reuse the method and solution obtained before and adapt it as the solution to the new problem provided the new problem is identical to the old one. This is also true when maintenance of an automobile is done, the experience of the past is brought in to provide either precautionary or predictive maintenance. [3] lists key components of Artificial Intelligence (AI) based predictive maintenance as consisting of sensors, data preprocessing, algorithms, decision-making models, communication and integration and user interface and reporting.

The objectives of the study are to; (i) gather cases of problems and solutions of automobile vehicles from some automobile mechanics in one of the popular road transport companies in Nigeria. (ii) develop a case base library of the cases (iii) use the nearest neighbour algorithm to perform the retrieval of the cases that are most similar to a new problem case received by the mechanic (iv) develop a fuzzy logic comprising fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification modules. (v) Test the functionality of the developed system.

The rest of the study is organized thus; in Section 2, related literature is reviewed and presented while the design methodology is presented in Section 3. In Section 4, the results of the implementation procedures are presented with a discussion of the results, while in Section 5, the conclusion drawn, and recommendations made are presented.

2. RELATED LITERATURE

The application of case-based reasoning (CBR) in solving problems cuts across all spheres of human endeavours including engineering, medical diagnosis, management, planning, repairs of equipment and gadgets etc. Humans can barely manage the large volume of information they process daily especially if they need to recall after a long period. Roadside mechanics process large volumes of information and store them in their very limited memory without caring to document such information for use in the future. Recalling information that was processed many years in the past has been one of the challenges of technicians in the course of carrying out their tasks of maintenance and repair. In most cases, they are found to start the routine they had done long ago from scratch since there was no documentation of such a routine.

CBR methodology is developed to acquire the experiential knowledge of experts, represent the knowledge and generate the processing (diagnosis) by comparing the case at hand with the existing cases in the case base (case library). Reuse of the solution of the case in the case library is done if the problem is identical or very similar to the case at hand. Otherwise, (if it is not identical or very similar), the solution to the new case is revised according to the degree of similarity to the most similar case in the case library. After the revision, the solution proffered is retained in the case base.

Several problems have been solved using CBR. In [4], cases of hepatitis diagnoses were gathered and a neuro-case-rule-base system was developed to help in diagnosing new cases of hepatitis. Results obtained show a 100% correct diagnosis and a 40% false diagnosis. [5] used artificial neural networks (ANN) and support vector machine (SVM) to develop a fault diagnosis of ball bearings. The vibration response was obtained and analyzed for the various defects of ball bearings from where specific defects were identified and a comparative experimental study of the effectiveness of ANN and SVM was carried out. Results reveal that a severe vibration occurs under bearings with rough inner race surfaces and balls with corrosion pitting. [6] implemented a CBR into an expert system for deciding a solution to mechanical failure in a car. The four CBR phases of retrieve, reuse, revise and retain were conducted on the system. However, cases were not generated by human experts but by a rule-based expert system. The system utilized fuzzy logic technology to test the similarity of past cases and new cases and found a positive correlation coefficient. The defect identification method based on CBR is explored in [7] where the focus is on automobile brake system defects. Only the reuse and retain phases of CBR were used in building the system. The results of implementing the system are encouraging.

Sandoval-Pillajo et al. [8] built an expert system for electronic vehicles to help common users identify automatic failures and the severity of damage caused by such failures. To achieve these objectives, data collection about the failures was conducted and this helped in generating production rules. The inference engine and the user interface were later developed for the system and results obtained show 71.43% effectiveness. [9-11] also developed similar expert systems with good and encouraging results. [12] applied the K-nearest neighbor algorithm to find similar cases between the case at hand and the cases in the case base to detect equipment damage to a power plant. A 97.98% accuracy and 95% precision were recorded when the confusion matrix was used to evaluate the developed system.

According to Page [13] the power of expert systems technology can be delivered in the form of interactive video which enables persons with limited reading skills to effectively utilize the knowledge of the expert. He integrated multimedia technology with an expert system driven by rule base and fuzzy logic to provide an easy-to-use platform that allows unskilled maintenance workers to perform at a level close to that performed by experienced technicians in the apparel industry.

Fuzzy logic, a multi-valued logic that considers between false (0) and completely true (1) states is applied in building many reliable systems including the repair and maintenance of automobiles. Automated Guided Vehicles developed in [14] utilize fuzzy logic technology in the design of the brake and steer behaviours of a mobile robot. The system is meant to give a Robot the ability to follow the track and avoid obstacles. Another component of the study is the fuzzy controller that generates crisp commands that carry information from the braking behaviour and the steering behaviours.

Bukowski et al. [15], used a fuzzy logic-based assessment method for the organization's maintenance support capability level. Experts' opinions were fuzzified based on the triangular membership function ranked, aggregated and quantified using the Mamdani fuzzy inference model. Kizito, et al. [16] employed the Mamdani fuzzy inference algorithm to detect faults identified in airbags, radiators, gearboxes and tyres. The symptoms that lead to the faults were identified and fuzzified then fuzzy rules were generated based on these. The rules were later used to quantify the fuzzy values after they were aggregated. The results were de-fuzzified into crisp values and the evaluation carried out showed 100% accuracy and precision, a recall rate of 61% and an F1-score of 75.8%.

The ability of fuzzy logic to handle imprecise and uncertain information is demonstrated in [17] in the design of an intelligent fuzzy logic system for automobile fault diagnosis. Inputs including the symptoms and signs of faults were fuzzified, rules were generated based on the inputs and fuzzified values through collaboration and aggregation results were obtained and de-fuzzified to get crisp outputs which show an accuracy of 73.14%, with a precision of 100% and F1-score of 75.72%. Fuzzy logic is also applied in automotive engineering diagnosis as seen in [18] where a fuzzy diagnostic model that contains fast fuzzy rule generation algorithms and a priority rule-based inference engine for the end-of-line test at automobile assembly plants was developed. The system performance was tested and found to be very reliable. To improve the quality of products that will lead to enhancing the comfort of drivers, fuzzy logic is used in [19]. A variety of automotive applications that use fuzzy logic technology including Anti-clock braking systems (ABS), Anti-slip regulation (ASR), Traction Control systems (TCS), active front systems (AFS), Traction Control systems (TCS) and others was considered. The effectiveness of ABS and ASR as important safety control features is improved with fuzzy logic controllers.

Rojek, et al.[20] used fuzzy logic to reduce the ambiguity of making decisions regarding the selection for machining. They demonstrated this with 553 cases of tool selection of input data such as type of machine, type of machine surface, type of workplace etc. which were fuzzified, aggregated and later subjected to fuzzy inferencing. Prentzasa et al. [21] reviewed the integration of CBR with other computational techniques such as fuzzy logic where the study of Liu et al. [22] that combined fuzzy rule base reasoning (RBR) with CBR to assess environmental impact was undertaken. They also reviewed [23] which combined CBR with fuzzy logic belief networks to assess threats associated with battlegrounds in the military. Voskoglou et al. [24] demonstrated the combination of fuzzy logic and CBR in the diagnosis of medical ailments based on symptoms to retrieve past cases whose symptoms are similar to those of new cases and suggest diagnoses based on matching pairs. Fuzzy logic was used based on the number of cases in the case base that match the problem case and ranked as intermediate success, high success and complete success which correspond to the revise, reuse and retain phases of the CBR respectively. Obot et al.[25] applied Fuzzy Cognitive Map (FCM) to differentiate tropical febrile diseases from a large dataset gathered from 16 hospitals in Nigeria. Results obtained from the study show that malaria disease had a very high degree of accuracy with the results diagnosed by the medical doctors.

3. MATERIALS AND METHODS

The system comprises the CBR and Fuzzy logic driven by fuzzy rules as shown in Fig. 1

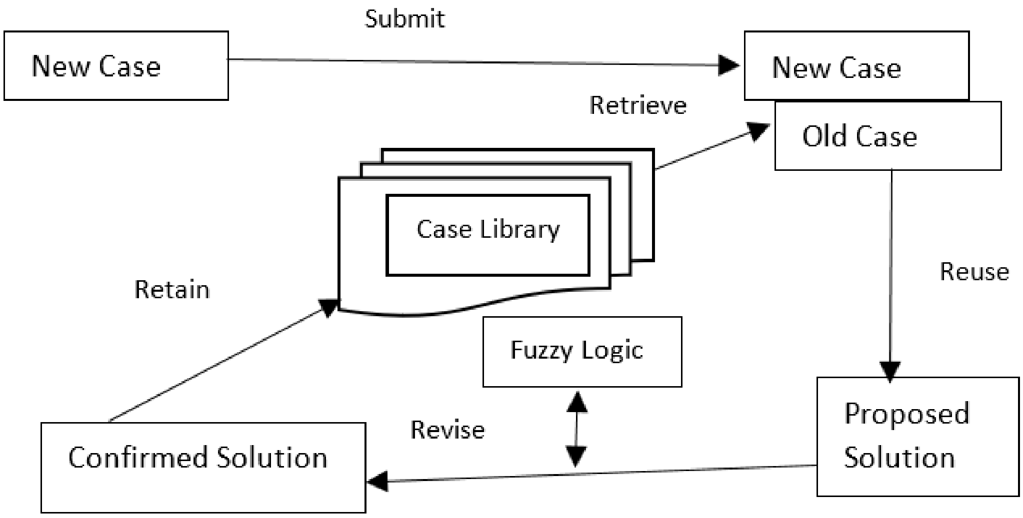

Fig. 1. A fuzzyrulecase based reasoning system flow diagram

3.1 Algorithm

Step 1. Gather cases from the automobile mechanics; these form a case base (a case is a problem and a solution to the problem)

Step 2. Retrieve a case similar to the problem at hand from the case base, if such is found in the case base.

Step 3. If the problem and solution between the case in the case base and the problem at hand are identical, then the solution of the similar case becomes the solution to the problem at hand.

Step 4. If the difference between the case in the case base and the problem at hand is not identical then apply fuzzy logic to resolve the problem through collaboration, aggregation, approximation and propagation. This will establish a degree of confidence or belief in the solution proffered.

3.2 Case Base Reasoning

CBR comprises cases of mechanical and electrical faults of vehicles obtained from more than 20 mechanics and technicians working in Akwa Ibom Transport Company (AKTC) in Nigeria. The cases include mostly the problems and successful solutions done and delivered in the last 2 years where they were instructed to document their performance under the strict supervision of one of the researchers of the study. CBR operates on four phases of Retrieve, Reuse, Revise and Retain. Retrieval is easy if there are few cases in the case base as a simple sequential search could be applied, in a situation where there are many cases the nearest neighbour algorithm is applied to find the closest case to a new (problem) case. The nearest neighbour ranks the cases according to their degree of nearness to the problem case. Fuzzy logic with its fuzzy rules is used to aggregate the cases in the case base through collaboration and approximation. Table 1 shows some of the cases in the case base.

3.3 Fuzzy Logic

The fuzzy logic module takes inputs (fuzzy rules and new problems to be reused or revised), fuzzifies the problem and carry out inference and composition based on the rules and ranking on the cases in the case base done by the nearest neighbor algorithm. This gives fuzzy outputs which are further de-fuzzified into a crisp output.

3.3.1 Membership function design

These membership functions define how the input 'difference' and the output 'confidence' are fuzzified and interpreted by the fuzzy logic system.

Input Variable: difference

Low Membership Function ('low'):

he Low MF is defined as a triangular fuzzy set with parameters:

Points: (0,0), (0,0.25), (0.25,0), (0, 0), (0, 0.25), (0.25, 0), (0,0), (0,0.25), (0.25,0)

This is defined in Equation 1 as follows:

$$\mu_{low}(x) = \begin{cases} 0 & if\ x \leq 0 \\ \frac{x}{0.25} & if\ 0 < x \leq 0.25 \\ \frac{0.25-x}{0.25} & if\ 0.25 < x \leq 0.5 \\ 0 & if\ x > 0.5 \end{cases} \quad (1)$$

Table 1. Some of the cases in the case library

Role	Problem	Solution
Auto Mechanic	Engine overheating	Replaced the thermostat and flushed the cooling system"
Auto Mechanic	Car not starting	Replaced the battery and checked the alternator
Auto Mechanic	Brakes squeaking	Replaced the brake pads and resurfaced the rotors
Auto Electrician	Headlights not working	Replaced the headlight bulbs and checked the wiring
Auto Electrician	Power windows malfunctioning	Replaced the window motor and checked the fuse
Auto Electrician	The Car stereo not turning on	Replaced the stereo unit and checked the connections
Panel Beater	Dent on the driver's door	Repaired the dent using paintless dent repair techniques
Panel Beater	Rear bumper damaged	Replaced the bumper and matched the paint
Panel Beater	Scratches on the hood	Sanded and repainted the hood
Gearbox Technician	Gear slipping	Replaced the front fender and matched the paint
Gearbox Technician	Difficulty shifting gears	Rebuilt the transmission and replaced the clutch
Gearbox Technician	Transmission fluid leak	solution": "Replaced the gearbox oil and adjusted the linkage
Alignment Technician	Car pulling to one side	Performed a wheel alignment and balanced the tyres
Alignment Technician	Uneven tyres wear	Adjusted the camber and toe angles and rotated the tyres
Alignment Technician	The steering wheel is not centered	Realigned the steering wheel and checked the alignment
Upholstery	Sagging headliner	Replaced the headliner fabric and tightened the supports
Upholstery	Faded dashboard	Re-dyed the dashboard and applied a UV protectant
Upholstery	Stains on the carpet	Deep-cleaned the carpet and applied a stain-repellent
AC Technician	AC making noise	Repaired or replaced noisy components
AC Technician	AC foul smell	Cleaned or replaced cabin air filter and checked for mould/mildew
AC Technician	AC fluid leak	Identified and repaired the refrigerant leak, then recharged the refrigerant

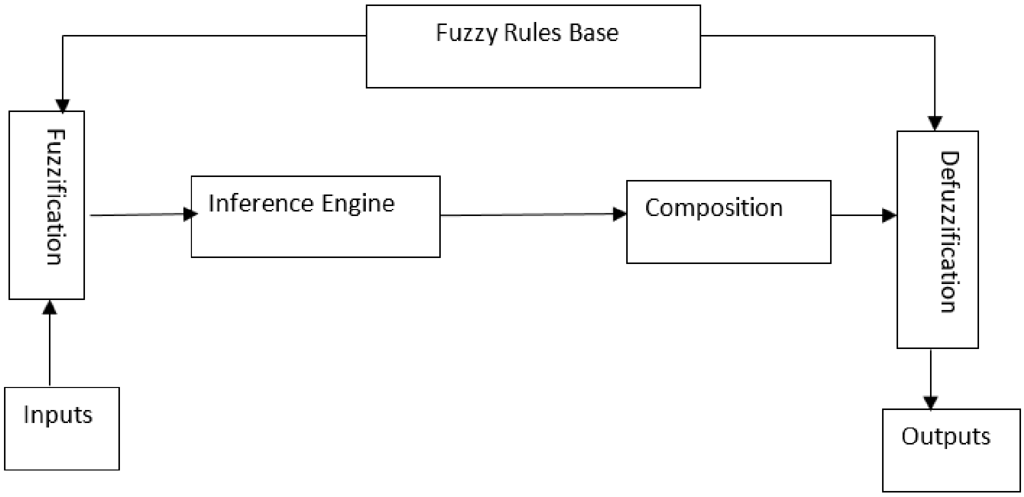

Fig. 2. Fuzzy logic model for the system

Table 2. Fuzzy logic rules

Rule	Antecedent (Input 'difference')	Consequent (Output 'confidence')
1	'low' (0 to 0.25)	'high' (0.75 to 1)
2	'medium' (0.25 to 0.75)	'medium' (0.25 to 0.75)
3	'high' (0.75 to 1)	'low' (0 to 0.25)

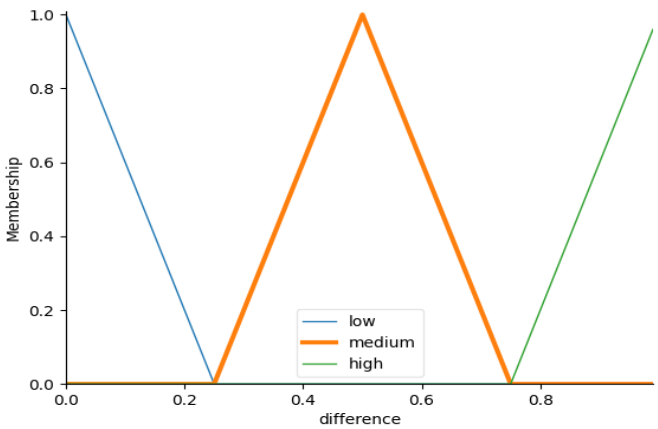

Fig. 3. Graph of low membership function

Medium Membership Function ('medium'):

The Medium MF is defined as a triangular fuzzy set with parameters:

Points: (0.25,0), (0.5,1), (0.75,0), (0.25, 0), (0.5, 1), (0.75, 0), (0.25,0), (0.5,1), (0.75,0)
This is shown in Equation 2 as follows:

$$\mu_{medium}(x) = \begin{cases} 0 & if\ x \leq 0 \\ \frac{x-0.25}{0.25} & if\ 0.25 < x \leq 0.5 \\ \frac{0.75-x}{0.25} & if\ 0.5 < x \leq 0.75 \\ 0 & if\ x > 0.75 \end{cases} \quad (2)$$

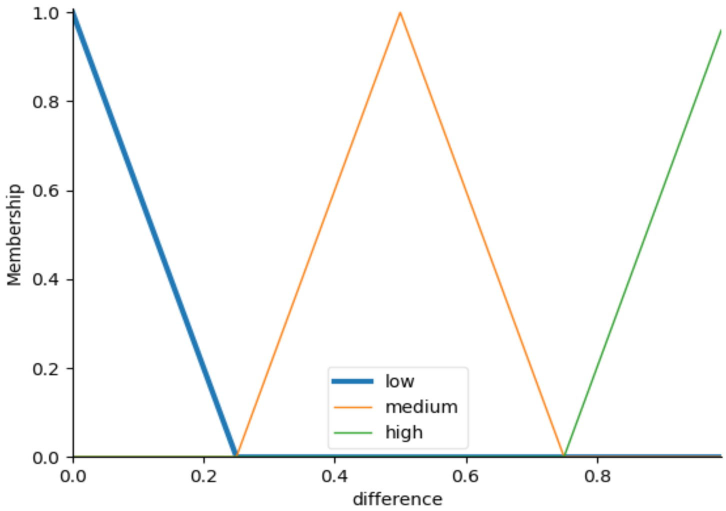

Fig. 4. Graph of the medium membership function

The graph of the membership function is depicted in Fig. 4.

High Membership Function ('high'):

The High MF is defined as a triangular fuzzy set with parameters:

Points: (0.75,0), (1,1), (1,0), (0.75, 0), (1, 1), (1, 0), (0.75,0), (1,1), (1,0)

This is shown in Equation 3 and the corresponding graph is depicted in Fig. 5:

$$\mu_{high}(x) = \begin{cases} 0 & if\ x \leq 0.75 \\ \frac{x-0.75}{0.25} & if\ 0.75 < x \leq 1 \\ 1 & if\ x > 1 \end{cases} \tag{3}$$

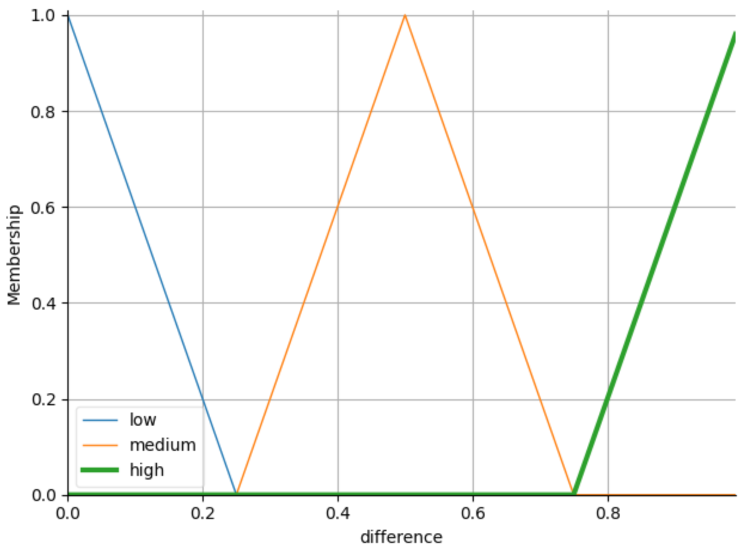

Fig. 5. Graph of high membership function

Output Variable: confidence

Low Membership Function ('low'):

The Low MF is defined as a triangular fuzzy set with parameters:

Points: (0,0), (0,0.25), (0.25,0), (0, 0), (0, 0.25), (0.25, 0), (0,0), (0,0.25), (0.25,0)
Equation 4 depicts this.

$$\mu_{low}(y) = \begin{cases} 0 & if\ y \leq 0 \\ \frac{y}{0.25} & if\ 0 < y \leq 0.25 \\ \frac{0.25-y}{0.25} & if\ 0.25 < y \leq 0.5 \\ 0 & if\ y > 0.5 \end{cases} \tag{4}$$

Medium Membership Function ('medium'):

The Medium MF is defined as a triangular fuzzy set with parameters:

Points: (0.25,0), (0.5,1), (0.75,0), (0.25, 0), (0.5, 1), (0.75, 0), (0.25,0), (0.5,1), (0.75,0)

This is depicted in Equation 5

$$\mu_{medium}(y) = \begin{cases} 0 & if\ y \leq 0.25 \\ \frac{y-0.25}{0.25} & if\ 0.25 < y \leq 0.5 \\ \frac{0.75-y}{0.25} & if\ 0.5 < y \leq 0.75 \\ 0 & if\ y > 0.75 \end{cases} \tag{5}$$

High Membership Function ('high'):

The High MF is defined as a triangular fuzzy set with parameters:

Points: (0.75,0), (1,1), (1,0), (0.75, 0), (1, 1), (1, 0), (0.75,0), (1,1), (1,0)

This is shown in Equation 6

$$\mu_{high}(y) = \begin{cases} 0 & if\ y \leq 0.75 \\ \frac{y-0.75}{0.25} & if\ 0.75 < y \leq 1 \\ 1 & if\ y > 1 \end{cases} \tag{6}$$

3.3.2 De-fuzzification

De-fuzzification is a crucial step in fuzzy logic systems where fuzzy outputs are translated into crisp values. This process involves converting the aggregated fuzzy set into a precise numerical value that can be used for decision-making or further processing. In our system, we employed Centroid, Mean of Maxima, Bisector and Smallest of Maxima defuzzification methods to determine the most effective approach. The Centroid method empirically is the most effective approach for converting fuzzy outputs into a definitive confidence score.

3.3.3 Centroid method

The Centroid method calculates the Centre of gravity (or centroid) of the aggregated fuzzy set. It provides the balance point where the fuzzy set's area is evenly distributed. It can be represented mathematically as;

$$Centroid = \frac{\int_a^c x\ .\ \mu(x)dx}{\int_a^b \mu(x)dx} \tag{7}$$

where:

$\int_a^c x\,.\,\mu(x)dx$ is computed for the rising part of the output triangular membership function.

$\int_a^b \mu(x)dx$ is computed for the falling part of the output triangular membership function.

A computational case is, for the rising part (0≤x<0.25) is calculated as

$$\int_0^{0.25} x.\frac{\text{x-0}}{\text{0.25-0}}dx = \int_0^{0.25} \frac{x^2}{0.25}dx = \frac{1}{0.25}.\frac{x^3}{3}\Big|_0^{0.25} = \frac{1}{0.25}.\frac{0.25^3}{3}=0.002083333$$

A computational case is, for the falling part (0.25≤x≤1) is calculated as

$$\int_{0.25}^{1} x.\frac{\text{1-x}}{\text{1- 0.25}}dx = \frac{1}{0.75}\int_{0.25}^{1}(x-x^2)dx = \frac{1}{0.75}\left[\frac{x^2}{2}-\frac{x^3}{3}\right]\Big|_{0.25}^{1} = 0.080833333$$

Total area under the curve is arearising + areafalling = 0.002083333 + $0.080833333 = 0.082916666$

The centroid resolves to

$$Centroid = \frac{\int_a^c x\,.\,\mu(x)dx}{\int_a^b \mu(x)dx} = \frac{0.002083333 + 0.080833333}{0.082916666} \approx 0.0832$$

In the experiment, we employed the np. trapz method from the NumPy Python library to compute the centroid for defuzzification. This method utilizes the trapezoidal rule to approximate the integrals needed to determine the centroid, or centre of gravity, of the fuzzy set. Specifically, np. trapz was used to calculate both the weighted sum of the membership function values and the total area under the curve, facilitating an accurate determination of the centroid value.

4. RESULTS AND DISCUSSION

Fig. 6 illustrates the similarity and confidence levels between each new fault and its closest matching case in the database. When examining Fig. 6, it becomes evident that:

i) Cases with a similarity score of 1 exhibit a confidence level greater than 0.8, indicating a high degree of similarity and certainty in the recommended solution.
ii) For cases where the similarity score is less than 1, Type 1 Fuzzy Logic (Type 1 FL) is utilized to determine the confidence level of the solution derived from the most similar case.

This approach ensures that in cases with varying degrees of similarity, the confidence in

Table 3. List of various cases

Example Case	Similar Case	Similarity	Confidence	Modified Solution based on a similar case
engine overheating	Engine overheating	1	0.88	Replaced the thermostat and flushed the cooling system
noisy brakes	Oil leak	0.5	0.4965	Replaced the oil pan gasket and cleaned the area
car not starting	Car not starting	1	0.88	Replaced the battery and checked the alternator
gear 5 refuses to drive	Gear refuses to drive due to damaged gears	0.625	0.4961	Found worn-out gear teeth; replaced the damaged gears and ensured proper alignment.
consumes more fuel	AC blower motor issue	0.5128	0.4967	Repaired or replaced malfunctioning blower motor
cannot reverse	AC making noise	0.5946	0.4963	Repaired or noisy components

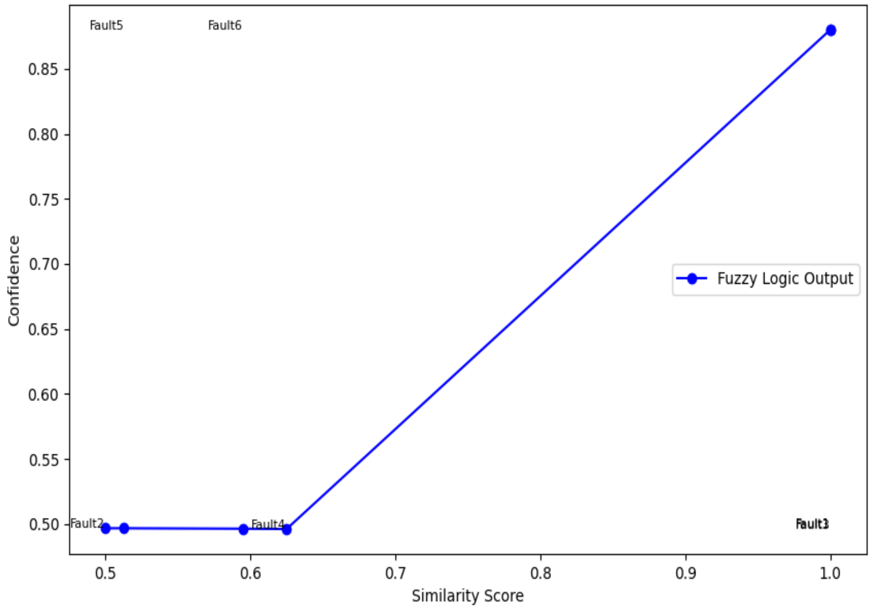

Fig. 6. Similarity and confidence analysis

the recommended solution for the repair or maintenance is appropriately communicated.

5. CONCLUSION

One of the key characteristics of intelligence is the ability to reason logically. CBR presents an approach of reasoning based on previous problems and their corresponding solutions. Reusing a case that is identical to the current case is a straightforward task but where there are differences, then revising the case to solve the problem at hand becomes complex depending on the extent of the differences. When faced with such a task, approximation and aggregation of the cases that are close to the case at hand become another means of tackling the problem. Fuzzy logic, a many-valued logic is known to solve the problem of approximation. This approach is employed in this study to handle the revision of cases in the case base.

Some cases treated by 20 mechanics in the AKTC were documented and used for this study. The implementation of the study was tested with a total of 134 cases in the case base, and 20 problem cases were used in matching with the case base. Results show that 15 cases were very similar, returning >= 0.80 degrees of confidence. After revision of the cases that were not very similar, varied degrees of confidence were recorded. With this, the mechanic can decide on the next line of action in such cases.

PRACTICAL IMPLICATION

Practically, the system will not only serve as a diagnostic tool for mechanics /technicians and motorists. It will also serve as a learning tool for all those who have not known the process and are desirous of learning vehicle maintenance and repairs. The comfort of getting a problem fixed without bothering to call a mechanic at the least notice of a simple fault could be very cheering to a motorist. This saves time and cost of maintenance in addition to curtailing over-reliance on the technician/mechanics.

FUTURE SCOPE

Implementing the framework in real-time within a vehicle behavioural model could give technicians instant feedback and solutions, enhancing their efficiency instead of waiting to experiment with the solution in a physical car. Additionally, creating a collaborative platform where technicians can contribute to a shared case database would enrich the system with diverse insights. Looking ahead, integrating further artificial intelligence techniques, like machine learning and deep learning could significantly improve the system's diagnostic accuracy and solution precision.

We also hope to increase the number of cases in the case base as the mechanics keep on improving on the documentation. With more cases, the results obtained in this study will surely improve. To further enhance the process of automobile repairs and maintenance, we are proposing a work on an authoring system where the multimedia technology would be integrated with the CBR-Fuzzy logic technology as a single coherent system.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

The Authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during the writing or editing of the manuscripts.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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