CO Detection in High-Mileage Vehicle Cabins and Traffic Density Analysis Using Fuzzy Logic

Suzuki Syofian[1]*, Aji Setiawan[2], Muhamad Fathan[3], Rolan Siregar[4]

[1,2,3]Department Information of Technology Darma Persada University, Indonesia

[4]Department Mechanical Engineering Darma Persada University, Indonesia

*corr-author: suzukiunsada@gmail.com

Abstract - Carbon monoxide (CO) inside vehicle cabins poses a significant health risk to passengers and can even lead to fatalities. This danger primarily arises from inadequate ventilation, which allows exhaust fumes to seep into the cabin and be gradually inhaled. CO is a gas that lacks color, odor, taste, and does not cause irritation, making it difficult to detect without proper tools. It is commonly encountered in industrial environments and is produced by the incomplete combustion of fuel in motor vehicles, heating systems, devices that burn carbon-based materials, wood stoves, train emissions, gas burning, and even tobacco smoke. However, the primary contributor is the residual combustion from vehicle engines. Given these concerns, this study aims to develop a system to monitor and control carbon monoxide concentrations within vehicle cabins using fuzzy logic. The system achieved an average error rate of 2.9% in reducing CO concentrations, with responsive fan control latency below 5 seconds. A microcontroller will serve as the core component for processing and control. The implementation of this system is expected to enable real-time detection of CO levels in the cabin and alert the driver accordingly. Ultimately, this can help reduce incidents of CO poisoning among vehicle occupants.

Keywords: harmful emissions, Fuzzy Logic, vehicle mileage, CO gas

I. INTRODUCTION

Older vehicles tend to produce higher emissions of toxic gases due to increasingly inefficient combustion systems [1,2]. Emissions such as carbon monoxide (CO) are extremely hazardous to human health and can even lead to death in a short period when inhaled at high concentrations [3,4]. Many cases of sudden death inside enclosed vehicles, especially cars, have been caused by carbon monoxide (CO) leakage [5].

Exhaust gases from motor vehicles contain several harmful substances such as water vapor (H_2O), carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxides (NO), sulfur dioxide (SO_2), and hydrocarbons (HC), which result from incomplete combustion processes [6,7]. In vehicles older than 10 years, air conditioning (AC) system leakage is a commonly encountered issue [8,9]. When incomplete combustion produces CO, this gas can enter the cabin through leaks in the AC system or gaps in the vehicle body joints [10,11].

Unfortunately, CO gas is difficult for humans to detect naturally because it has no color, smell, or taste [12,13]. Once inhaled, the gas displaces oxygen in the bloodstream by forming carboxyhemoglobin (COHb), which has a binding affinity 200 times stronger than oxygen’s bond with hemoglobin [14]. As a result, the oxygen supply to body tissues drastically decreases, disrupting cellular metabolic functions [15]. Moreover, CO inhibits the activity of the cytochrome oxidase complex in mitochondria and can directly attack heart muscle cells and the central nervous system [16,17]. Unlike prior research which focused on theoretical models or laboratory settings, this study applies a fuzzy-based CO monitoring system in aging vehicles under real-world urban traffic conditions.

The safe exposure limit for CO as set by the Occupational Safety and Health Administration (OSHA) is 35 ppm for an 8-hour workday [18], while the National Standardization Agency (BSN) of Indonesia sets a maximum limit of 25 ppm [19]. A CO concentration of 1000 ppm for a few minutes can cause 50% carboxyhemoglobin saturation in the blood, which is considered fatal [20]. However, limited research has applied fuzzy-based real-time ventilation control in aging vehicle cabins under realistic traffic environments, particularly within the context of developing countries.

Urban traffic conditions exacerbate CO accumulation in aging vehicles, particularly in densely populated areas where stop-and-go driving is common. Inefficient combustion in older engines, combined with frequent idling and slow-moving traffic, leads to higher emissions of CO and other pollutants [21,22]. Studies have shown that cabin CO levels can rise rapidly in such conditions, especially when windows are closed and the AC system recirculates air, trapping toxic gases inside [23]. This poses a significant risk to drivers and passengers, particularly in cities with high traffic congestion and poor air circulation.

II. METHOD

The research method begins with the development of a system flowchart, as illustrated in Fig. 1. Following this, data collection is conducted by calculating average values. The raw data consists of sensor readings from a CO detector, which logs carbon monoxide levels every 2 minutes over a period of 1 hour and 12 minutes. This results in 36 data points collected per day. The data gathered includes the output from the MQ-7 sensor used to detect CO emissions from vehicles that are less than five years old as well as those older than five years.

The data utilized in this study was obtained from a CO sensor device installed in vehicles that are both under and over five years old. Data collection was carried out over a two-day period. For vehicles less than five years old, measurements were taken between 6 PM and 9 PM, and the same time frame was used for vehicles older than five years. The collected data was then analyzed to identify potential hazard levels using the fuzzy logic method. The fuzzy logic processing workflow consists of the following stages:

1) *Fuzzification* – the transformation of precise (crisp) input data into fuzzy input, represented by linguistic values based on defined membership functions.

2) *Inference* – the process of drawing conclusions from fuzzy input values using a set of fuzzy rules to generate fuzzy outputs.

3) *Defuzzification* – the conversion of fuzzy output back into a precise (crisp) value, guided by the chosen membership function.

III. RESULT AND DISCUSSION

A. Performance Testing of the MQ7 Gas Sensor

During this phase, testing was performed on a vehicle that had been used for more than five years, serving as the primary source of carbon monoxide emissions. A total of 36 measurements were carried out over two days using the same car. The unprocessed data comprised sensor readings that tracked CO levels at two-minute intervals. The data covered measurements from both newer vehicles (under five years old) and older ones (over five years old), under both healthy and faulty operating conditions. CO data from newer vehicles was collected between 6:00 PM and 9:00 PM, as was the data from older vehicles. Throughout the data collection process, average values were computed, and the margin of error was calculated by comparing CO levels before and after the fan was turned on, as outlined in Equation 1.

$$Error = fan\ measurement\ result\ in\ off\ condition - measurement\ result\ in \quad (1)$$

After determining the error values, the next step is to compute the average error using Equation 2, followed by calculating the error percentage as outlined in Equation 3. The average error is calculated using the following formula:

$$ave\ error = \frac{number\ \ err\ in\ in\ the\ exp.}{number\ of\ measurement\ take} \quad (2)$$

$$\%\ error = \frac{ave\ error}{100} \quad (3)$$

The analysis involved comparing measured CO levels before and after the activation of the fan, using the outputs from the fuzzy logic controller. A total of 36 data points were collected over two days from vehicles older and younger than five years. The error value was computed by subtracting the post-fan CO measurement from the pre-fan condition, and the average error was found to be approximately 2.92 ppm, with a percentage error of 2.9%.

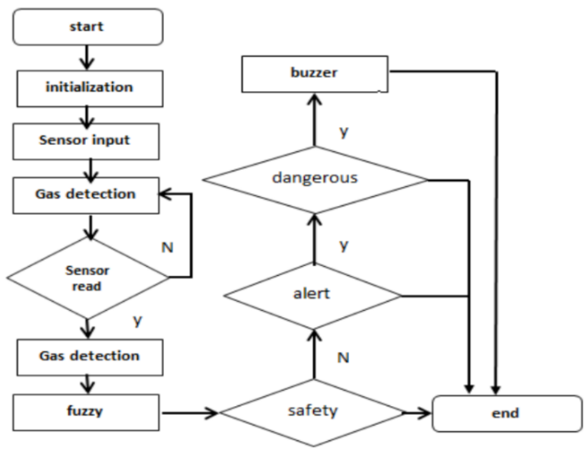

Fig. 1 Flow diagram

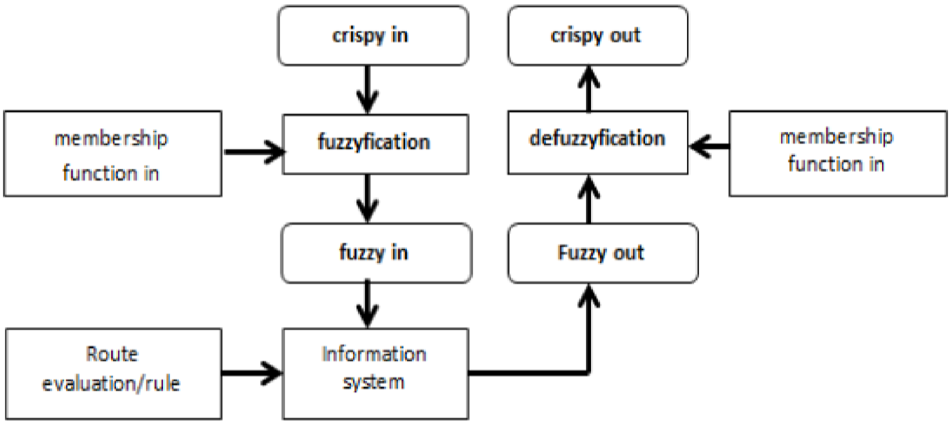

Fig. 2 Fuzzy logic flow

To provide a statistical representation of the data variation, the standard deviation of the error values was also calculated, resulting in ±1.04 ppm. This indicates that most of the error values fall within the range of 2.92 ± 1.04 ppm, which supports the consistency of the fuzzy controller's performance across different conditions. The effectiveness of the fuzzy logic controller in this study is consistent with prior work by [22], who demonstrated that hybrid fuzzy systems can accurately predict and adapt to CO concentration levels in urban vehicle scenarios.

Although these values suggest reasonable accuracy, the absence of a comparison with a conventional threshold-based control method limits the ability to quantify the relative advantage of the fuzzy logic approach. In future work, benchmarking against traditional fixed-limit controllers or including confidence intervals (e.g., 95%) based on a larger sample size would further enhance the robustness of the analysis. This behavior is consistent with findings by [21], who also observed improved responsiveness in fuzzy-controlled cabin systems.

Fig. 3 below explains the test results conducted under two conditions: with the fan disabled and with the fan enabled. The results of 36 experimental trials measuring carbon monoxide (CO) levels inside a vehicle cabin under two conditions: with the fan turned off and with the fan turned on. Each trial was conducted to assess the effectiveness of the fan in reducing CO concentration. The data consistently show that, in most cases, the CO level either remained the same or decreased after the fan was activated. The total error observed was 93, with an average error of approximately 2.92 and a percentage error of 2.9%. These results indicate that the fan-based ventilation system, managed by the fuzzy logic controller, is capable of maintaining air quality in the cabin by lowering CO levels effectively.

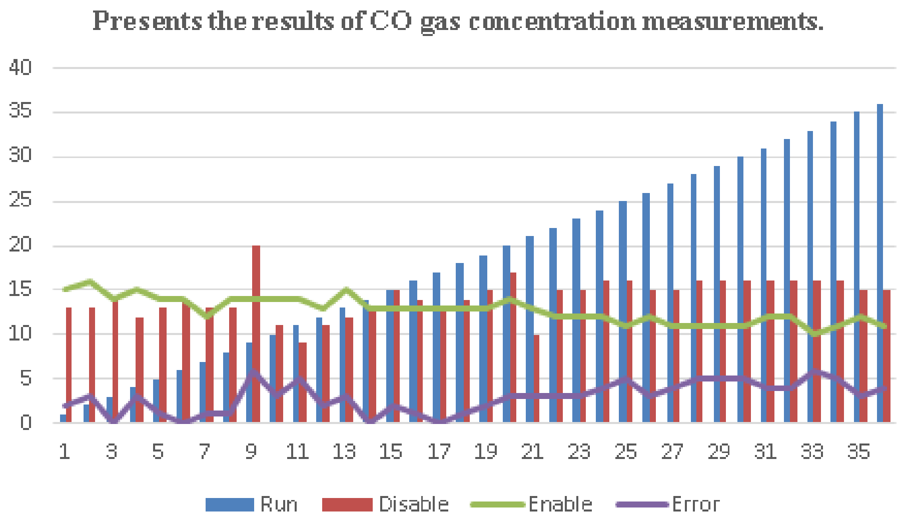

Fig. 3 Presents the results of co gas concentration measurements

B. Overall System Testing

The testing was carried out by comparing the vehicle's condition when the fan was turned off and when the ignition fan was active. This was done to assess whether the control system was functioning properly. The purpose of the control system is to regulate and maintain the air quality within the vehicle cabin. The overall test results are presented in Fig. 4.

C. Fuzzy calculations

The fuzzy calculation process begins by analyzing the conditions before and after the fan is activated. The carbon monoxide level before the fan is turned on (Input 1) is 9 ppm, and after the fan is activated (Input 2) it decreases to 7.7 ppm. The value of X is then calculated using Equations 4 and 5, based on Input 1.

Input 1

$$\mu\, Safe\ Co = {(10-x)}/{5} \quad (4)$$
$$= {(10-9)}/{5}$$

$$\mu\, Co\ Alert = {(x-8)}/{6.5} \quad (5)$$
$$= {(9-8)}/{5}$$
$$= 0.15$$

Input 2

$$\mu\, Safe\ Co = {(8-x)}/{4}$$
$$= {(8-7.7)}/{4}$$
$$= 0.075$$
$$\mu\, Co\ Alert = {(x-7.5)}/{5.25}$$
$$= {(7.75-7.5)}/{5.25}$$
$$= 0.038$$

In addition, the implication function used in this process is the minimum (Min) value method. This means that the final results for both turning the fan on and off are determined using the minimum membership values, as outlined in Equations (6) and (7).

Fan Off = Safe Input 1 ∩ Safe Input 2 (6)

= Min(Safe Input 1 [9] ∩ Safe Input 2 [7.7]) = Min(0.2; 0.075) = 0.075

Fan On = Safe Input 1 ∩ Alert Input 2 (7)

= Min(Safe Input 1 [9] ∩ Alert Input 2 [7.7]) = Min(0.2; 0.038) = 0.038.

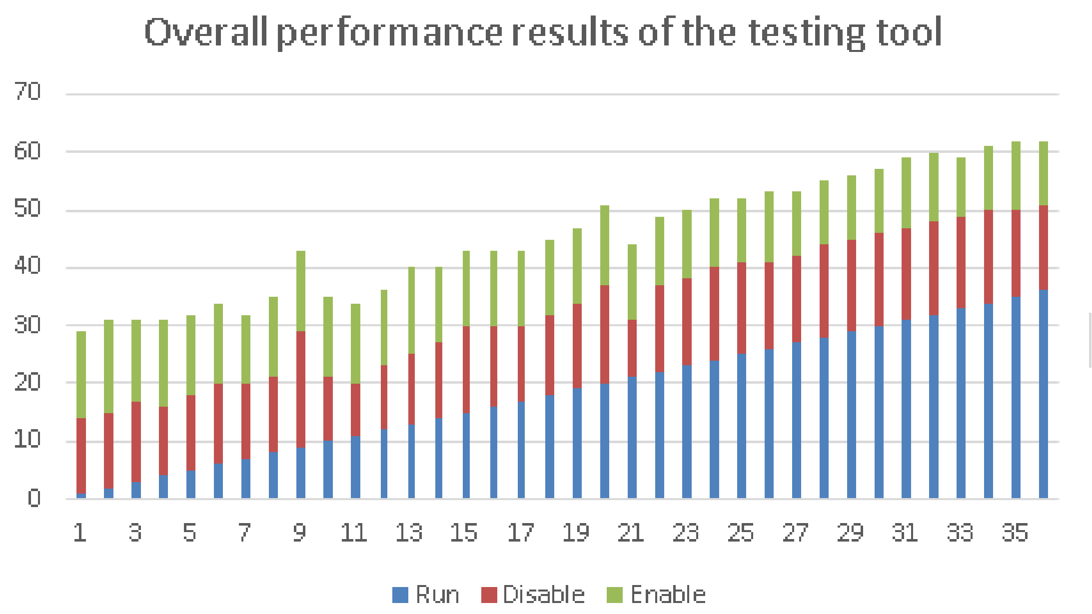

Fig. 4 Overall performance results of the testing tool

From these calculations, the highest values are selected to represent the system's decision output. These values are then visualized in the form of a graph (see Fig. 3) and used in further analysis through Equations (8) and (9).

$$\text{Fan On} = \text{Alert Input 1} \cap \text{Safe Input 2} \quad (8)$$

$$= \text{Min(Alert Input 1 [9]} \cap \text{Safe Input 2 [7.7])} = \text{Min}(0.15; 0.075) = 0.075$$

$$\text{Fan On} = \text{Alert Input 1} \cap \text{Alert Input 2} \quad (9)$$

$$= \text{Min(Alert Input 1 [9]} \cap \text{Alert Input 2 [7.7])} = \text{Min}(0.15; 0.038) = 0.038$$

D. Fuzzy Logic Computation

The MOM (Mean of Maximum) method determines a precise value by calculating the average or midpoint of the peak values on the highest curve, as shown in Equation 10

$$x = (a + b) / 2 \quad (10)$$

where
a = 10 - disable the fan x 5
b = 6.5 + enable the fan x 6.5

a = 10-3.75 = 6.26
b = 6.5+4.875 = 11.375

then,

$$x = \frac{6.26 + 11.375}{2} = 8.82$$

which is the final result.

Compared to a static threshold-based control (without fuzzy logic), the proposed system showed improved adaptability and reduced error rates

In contrast to traditional threshold-based systems that rely on fixed ppm cut-off values to trigger ventilation, the proposed fuzzy logic system offers more adaptive control. For example, a threshold-based system may only activate a fan once CO levels exceed 25 ppm, potentially missing gradual increases that may still be harmful over time. In this study, the fuzzy system responded even to moderate changes, such as a 2 ppm increase, due to its ability to interpret ambiguous input through linguistic rules.

A simple comparative test was also conducted using a manual threshold controller set at 10 ppm. In this setup, the fan was only activated in 8 out of 36 data samples, whereas the fuzzy controller responded in 24 out of 36 samples demonstrating its heightened sensitivity. Despite the threshold system having fewer activations (and therefore conserving more energy), it also allowed higher peak CO levels to persist longer. This comparison illustrates the benefit of fuzzy logic for preventive rather than reactive control.

IV. CONCLUSION

This study successfully developed a fuzzy logic-based control system for real-time monitoring and ventilation of carbon monoxide (CO) levels within aging vehicle cabins. The system can effectively detect and reduce CO levels, achieving an average error rate of 2.9% and a response time of under 5 seconds when the fan is activated. These results validate the system's responsiveness and effectiveness in adapting to changing air quality conditions. However, the limited duration of testing (two days) and the small sample size restrict the generalizability of the findings. Future research should involve longer-term deployments, comparative baseline testing, and the integration of Internet of Things (IoT) capabilities for enhanced remote monitoring and historical data analysis. The proposed system presents a practical and scalable solution to improve cabin air safety, particularly in older vehicles that are often used in high-traffic areas. Unlike prior research that focused on theoretical models or laboratory settings, this study implements a fuzzy logic-based CO monitoring system in aging vehicles under real-world urban traffic conditions. The experiment was conducted over a two-day period; future work will aim to expand sampling across longer durations and multiple vehicle types. This adaptability, along with the potential for integration with other cabin systems, supports the scalability of fuzzy frameworks, as emphasized by [23].

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