Journal of Applied Science, Technology & Humanities
Volume 3, Issue 3, June, 2026, Pages 1085-1105

ISSN 3032-5765
DOI: https://doi.org/10.62535/3wta8665

Implementation of Mamdani Fuzzy Logic in Fire Early Warning Based on Gas Leaks

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Abstract

Gas leaks represent one of the most critical triggers of residential and industrial fire accidents, particularly in environments reliant on Liquefied Petroleum Gas (LPG). Conventional threshold-based detection systems exhibit fundamental limitations in interpreting the gradual and simultaneous dynamics of multiple hazardous parameters, rendering them prone to delayed responses or false alarms. This study proposes an intelligent early warning system for fire detection based on gas leakage, employing the Mamdani Fuzzy Inference System (FIS) implemented on an Arduino Uno microcontroller. The system integrates three environmental input variables Gas Concentration (MQ-2 sensor), Flame Distance (IR flame sensor), and Ambient Temperature (DHT22 sensor) to determine the proportional speed output of a DC exhaust fan via Pulse Width Modulation (PWM) control. A rule base of 27 IF-THEN rules governs the inference process. The system was validated through MATLAB Fuzzy Logic Toolbox simulation and direct hardware implementation, yielding an average error rate of 0.22% between simulated, hardware computation, and actual outputs. The results demonstrate that the proposed multi-parameter Mamdani fuzzy system provides a significantly more adaptive and precise hazard assessment compared to conventional single-threshold approaches, offering a robust foundation for smart safety system deployment.

Keywords: Fuzzy Logic, Mamdani Method, Gas Leak Detection, Arduino Uno, Internet of Things (IoT).

INTRODUCTION

The widespread utilization of Liquefied Petroleum Gas (LPG) as a primary energy source in both household and industrial sectors provides efficient and relatively clean combustion solution, its inherently flammable nature poses significant safety risks (Susanto et al., 2025). Gas leakage from worn seals, improper storage, or accidental physical damage to distribution infrastructure is recognized as one of the leading catalysts of catastrophic fire accidents and explosions in enclosed residential and industrial spaces (Landi et al., 2025). Because of the time between leak occurrence, critical gas accumulation beyond the Lower Explosive Limit (LEL), and a fatal ignition event is exceptionally narrow, the critical urgency of developing autonomous, highly responsive, and computationally intelligent early warning systems (Azizah et al., 2025).

Despite advances in LPG monitoring technologies, many existing gas leak detection systems still rely on single- or dual- parameter threshold mechanisms, where alarms are triggered only when gas concentration exceeds a predefined value (Fahreza et al., 2024). These binary approaches fail to represent gradual hazard levels and often ignore other environmental parameters that significantly influence fire risks such as ambient temperature and the presence of ignition sources. Consequently, these systems may produce false notifications or delayed responses under complex condition (Oktavianto et al., 2022; Rolis et al., 2022; Chanpal et al., 2025; Sampurna et al., 2023). To overcome these limitations, this study introduces a novel multi-parameter LPG Leak detection system based on the Mamdani Fuzzy Logic algorithm on an Arduino Uno microcontroller. The system processes three simultaneous input parameters which are gas concentration, flame distance, and ambient temperature, evaluates composite environmental fuzziness and generates a proportionally controlled actuator response (Mutiara Susilo & Rakhmawati, 2025; Shaputra et al., 2023). The fuzzy output is utilized to dynamically modulate the Pulse Width Modulation (PWM) signal of a DC exhaust fan, enabling graduated ventilation responses proportional to the calculated hazard level. Concurrently, real-time parameter values including gas concentration, flame distance, and ambient temperature are monitored directly through the Arduino IDE Serial Monitor, enabling continuous situational awareness during system testing and validation (Azzahra & Yudono, 2025; Wicaksana & Hirzan, 2024).

Several studies have attempted to overcome these limitations. Waluyo et al. (2024) and Sesanti & Rahmanto (2025) developed an LPG leak monitoring system integrating an MQ-2 gas sensor with microcontroller, transmitting hazard alerts via a Telegram bot to enhance user awareness. Nurhapsari et al. (2025) further proposed an IoT-based gas leak detection system with rapid sensor response, while Irfanianingrum et al. (2023), Nurazizah et al. (2026) and Fitriadi et al. (2022) applied Fuzzy Logic and Mamdani inference for early forest fire, gas detection in smart home environments and building fire detections systems.

Based on the identified research gaps and the proposed novelty, the primary objective of this study is to design, implement, and rigorously evaluate the performance of an intelligent early warning system for gas leak-induced fire detection based on the Mamdani Fuzzy Logic method. Specifically, this research aims to construct a multi-parameter fuzzy inference system capable of interpreting composite environmental hazard levels, to validate the analytical accuracy of the fuzzy algorithm through comparative evaluation between MATLAB simulation and physical hardware implementation, and to demonstrate how multi-parameter fuzzy decision-making eliminates false alarms while providing proportional, automated mitigation responses to prevent fire outbreaks in LPG-dependent environments (Lianda et al., 2025; Tian & Lv, 2024).

METHODS

This research was conducted through a systematic series of stages encompassing problem identification, system requirements analysis, hardware and software design, Mamdani Fuzzy Logic implementation, and performance validation through comparative testing. The overall research methodology follows an experimental engineering design approach, wherein the system is first analytically modeled using MATLAB Fuzzy Logic Toolbox, subsequently implemented on physical hardware, and finally validated through quantitative error analysis between simulated and empirical outputs (Fahreza et al., 2024; Susanto et al., 2025).

1. System Requirement Analysis

The system requirements analysis stage was undertaken to identify the functional and non-functional requirements of the proposed early warning system in accordance with the defined operational objectives (Azizah et al., 2025). Functionally, the system must detect gas concentration levels, identify the proximity of open flame, and monitor ambient temperature continuously in real time. Non-functionally, the system must respond to hazardous conditions within an acceptable latency, minimize false alarm rates, and provide both local actuator control and remote monitoring capability. The block diagram of the proposed system architecture is illustrated in Figure 1, which divides the system into three structural components: the Input section comprising the sensor ensemble, the Process section encompassing the microcontroller and fuzzy inference engine, and the Output section consisting of the actuator and monitoring interface.

The Input section integrates three primary sensors. The MQ-2 gas sensor detects combustible gases including LPG, methane, and propane by generating an analog voltage signal proportional to the ambient gas concentration in parts per million (ppm), which is subsequently converted via the Arduino Uno Analog-to-Digital Converter (ADC) prior to fuzzy processing (Mahitala et al., 2025; Tian & Lv, 2024). The IR flame sensor detects infrared radiation emitted by combustion sources and provides a digital output representing the detection distance in centimeters, serving as a critical supplementary parameter to reinforce detection reliability and suppress false positives (Falih Diny Nurfikri, 2024; Sampurna et al., 2023). The DHT22 temperature and humidity sensor measures ambient temperature in degrees Celsius to identify abnormal thermal accumulation conditions, contributing to improved hazard classification accuracy and reduced false alarm rates when incorporated into the fuzzy rule base (Agape et al., 2022). The Process section employs an Arduino Uno microcontroller to perform data acquisition from the sensor ensemble, execute fuzzy computation through the embedded Mamdani inference algorithm, and generate proportional actuator control signals. The Output section comprises a DC exhaust fan driven through an L298N motor driver module via PWM signals, enabling graduated ventilation proportional to the defuzzified hazard level, and a real-time monitoring interface implemented through the Arduino IDE Serial Monitor for data logging and output verification during system testing (Mutiara Susilo & Rakhmawati, 2025; Waluyo et al., 2024).

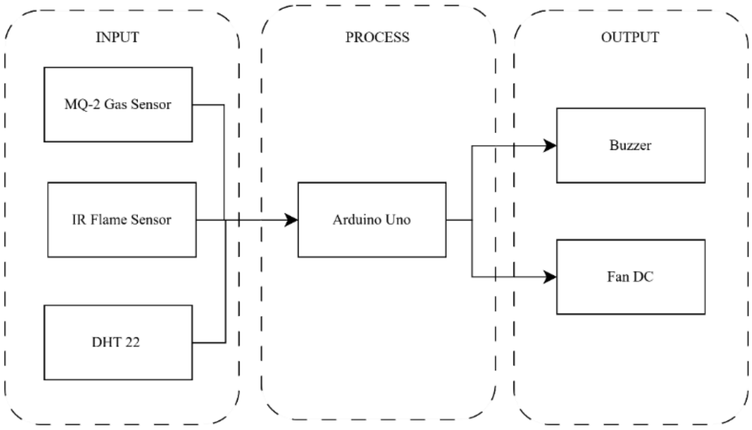

Figure 1. Block Diagram of the Gas Leak Fire Early Warning System

2. System Design

The hardware design of the proposed system integrates three input sensors, one processing unit, and two output mechanisms into a cohesive circuit architecture. The wiring configuration connects the MQ-2 gas sensor's analog output (AOUT) to analog pin A0 of the Arduino Uno for continuous concentration measurement. The IR flame sensor's digital output (DOUT) is interfaced with digital pin D2, providing binary flame proximity detection at configurable distance thresholds. The DHT22 temperature sensor's data pin is connected to digital pin D3, and all sensor modules share a common 5V power supply and ground reference from the Arduino. The DC exhaust fan actuator is driven through an L298N motor driver module, with pin D3 (PWM-capable) connected to the ENA pin to enable proportional speed control, pins D5 and D6 interfaced with IN1 and IN2 respectively for directional control, and the L298N supplied by an external 12V power source through its terminal, with fan output connected to the OUT1 and OUT2 terminals of the driver module (Lazuardi et al., 2025; Nurhapsari et al., 2025). The complete hardware assembly, including connectivity for remote monitoring of gas concentration, temperature, and fan PWM values, is illustrated in Figure 2.

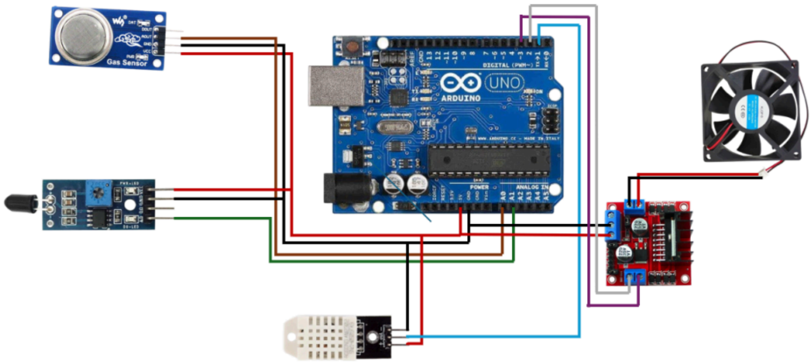

Figure 2. Wiring Diagram of the Fire Early Warning System

3. Fuzzy Logic

The intelligent decision-making core of the proposed system is built upon the Mamdani Fuzzy Inference System (FIS), which is recognized as one of the most intuitive and widely adopted methods for fuzzy rule-based control in safety-critical applications (Chanpal et al., 2025; Hariyadi et al., 2025). The Mamdani FIS processes three crisp sensor inputs through a four-stage pipeline: fuzzification, rule evaluation, aggregation, and defuzzification, ultimately yielding a crisp output in the form of a PWM signal to control fan speed proportionally to the identified hazard level (Fitriadi et al., 2022; Lianda et al., 2025; Sachrrial & Iskandar, 2023).

The FIS diagram, as presented in Figure 3, illustrates the structural configuration of the inference system with three input variables Gas, Flame, and Temperature converging into a single Mamdani processing block to produce the Fan DC output variable. This multi-input single-output (MISO) architecture ensures that no single sensor parameter independently triggers an actuator response; instead, all three environmental signals are evaluated simultaneously, thereby significantly reducing the false alarm probability inherent in single-threshold detection paradigms (Azzahra & Yudono, 2025; Oktavianto et al., 2022; Rolis et al., 2022).

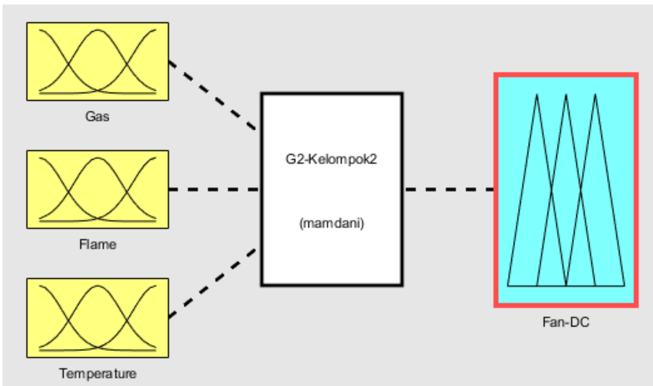

Figure 3. Fuzzy Inference System (FIS) Diagram

3.1. **Fuzzification**

Fuzzification is the process of transforming crisp numerical sensor values into degrees of membership within predefined linguistic fuzzy sets, enabling the system to reason under uncertainty in a manner analogous to human cognitive evaluation (al afgani et al., 2024; Wicaksana & Hirzan, 2024). Each input variable is defined across a specific Universe of Discourse and partitioned into three linguistic sets, while the output variable encompasses three membership sets, as summarized in Table 1.

The membership functions employ two geometric forms to model the linguistic variables. Triangular membership functions are utilized for intermediate sets Medium (Gas), Medium detect (Flame), Warm (Temperature), and Medium speed (Fan DC) as they represent gradual transitions centered on a single peak value. Trapezoidal membership functions are applied to boundary (shoulder) sets Low and High (Gas), Large detect and Small detect (Flame), Normal and Hot (Temperature), and Low speed and High speed (Fan DC) as the trapezoidal form maintains a stable plateau over a range of values at the extremities of each variable's domain, effectively modelling stable operational boundaries (Agape et al., 2022; Arif & Astutik, 2024). The mathematical formulation of the trapezoidal membership function, parameterized by [a, b, c, d], is expressed as:

$$\mu(x) = \left\{ 0, \; if\ x \leq a\ atau\ x \geq d\ \frac{x-a}{b-a}, \quad if\ a < x \leq b\ 1, \quad if\ b < x \leq c\ \frac{d-x}{d-c}, \quad if\ c < x \leq d \right\}$$

Correspondingly, the triangular membership function, parameterized by [a, b, c], is defined as:

$$\mu(x) = \left\{ 0, \; if\ x \leq a\ atau\ x \geq d\ \frac{x-a}{b-a}, \quad if\ a < x \leq b\ \frac{c-x}{c-b}, \quad if\ b < x \leq c \right\}$$

Table 1. Input and Output Membership Function Parameters

Variable	Parameter	a	b	c	d	Type	Min	Max	Unit
	Low	0	0	150	225	Trapezoidal			
Gas (Input)	Medium	150	225	300	–	Triangular	0	500	ppm
	High	225	300	500	500	Trapezoidal			
	Small detect	0	0	30	40	Trapezoidal			
Flame (Input)	Medium detect	30	50	70	–	Triangular	0	100	cm
	Large detect	60	70	100	100	Trapezoidal			
	Normal	0	0	30	35	Trapezoidal			
Temperature (Input)	Warm	30	37.5	45	–	Triangular	0	100	°C
	Hot	40	45	100	100	Trapezoidal			
	Low speed	0	0	70	85	Trapezoidal			
Fan DC (Output)	Medium speed	60	85	110	–	Triangular	0	255	PWM
	High speed	85	150	255	255	Trapezoidal			

The Gas concentration (0–500 ppm) is divided into three fuzzy sets: Low [0, 0, 150, 225], Medium [150, 225, 300], and High [225, 300, 500, 500]. Low and High use trapezoidal functions for stability at extreme values, while Medium uses a triangular function to model the transitional hazard zone (Fahreza et al., 2024).

The Flame distance (0–100 cm) is classified as Large detect [0, 0, 30, 40], Medium detect [30, 50, 70], and Small detect [60, 70, 100, 100]. This inverse-distance formulation treats closer flames as higher risk, reflecting the increased ignition potential at short range (Falih Diny Nurfikri, 2024; Sampurna et al., 2023).

The Temperature (0–100°C) consists of Normal [0, 0, 30, 35], Warm [30, 37.5, 45], and Hot [40, 45, 100, 100]. Elevated temperature is included as a risk factor because it accelerates gas vaporization and lowers ignition thresholds (Azzahra & Yudono, 2025; Falih Diny Nurfikri, 2024; Irfanianingrum et al., 2023).

The Fan DC output (PWM 0–255) is defined as Low speed [0, 0, 70, 85], Medium speed [60, 85, 110], and High speed [85, 150, 255, 255]. This graded output enables proportional ventilation control, improving upon conventional binary threshold systems (Lestari et al., 2025; Mahitala et al., 2025).

3.2. **Rule Base**

The inference system relies on an expert knowledge base comprising 27 IF-THEN rules derived from all possible permutations of the three input linguistic variables (3 × 3 × 3 = 27 rules). The rule base is constructed based on domain expertise in gas leak and fire hazard scenarios, drawing on validated rule structures established in prior fuzzy-based safety systems (Arif & Astutik, 2024; Azizah et al., 2025).

The rule structure reflects the combined nature of fire hazards. High fan speed is assigned mainly when gas concentration is High (Rules 19–27) as it represents the dominant risk factor. When gas concentration is Low, fan speed remains lower unless accompanied by High temperature or close flame distance (Rules 3, 6, 9). This hierarchical hazard weighting aligns with established multi-parameter risk assessment models (Lianda et al., 2025; Tian & Lv, 2024; Wafeeq & Hendrawati, 2023).

3.3. **Inference**

The inference stage evaluates all 27 rules in the knowledge base using the Mamdani MIN-MAX method. For each rule, The AND operator is resolved with the MIN function, selecting the smallest membership degree (α-predicate) among antecedents (Hariyadi et al., 2025). This α-predicate represents the firing strength of each rule and is formally expressed as:

$$\alpha_i = MIN(\mu_1(x),\ \mu_2(x),\ \mu_3(x))$$

The implication process applies the firing strength to truncate the corresponding output membership function, ensuring each active rule contributes to the output proportionally to its activation level. The truncated output functions from all active rules are subsequently combined using the MAX aggregation operator, which takes the maximum membership value at each point across all activated rule consequents to form a unified composite membership function representing the total fuzzy solution region (Chanpal et al., 2025; Sachrrial & Iskandar, 2023). This MAX aggregation is formally expressed as:

$$\mu_{agg}(x) = MAX(\mu'_1(x), \mu'_2(x), \mu'_3(x), \ldots)$$

3.4. **Defuzzification**

Defuzzification converts the aggregated fuzzy output into a single crisp numerical value that can be directly executed by the hardware actuator as a PWM signal. This study employs the Centroid (Center of Gravity) defuzzification method, which computes the weighted centroid of the composite membership function area. The Centroid method was selected due to its demonstrated consistency and precision in proportional control systems, its ability to produce smooth output transitions that prevent abrupt actuator behavior, and its widespread validation in analogous IoT-based fuzzy control applications (Fitriadi et al., 2022; Hariyadi et al., 2025; Oktavianto et al., 2022). The Centroid defuzzification formula is expressed as:

$$Z^* = \frac{\int x\, \mu_{agg}(x)\, dx}{\int \mu_{agg}(x)\, dx}$$

The resulting Z* value is directly mapped to the PWM duty cycle driving the L298N motor driver and DC exhaust fan, enabling continuous and proportional ventilation modulation as a function of the real-time composite hazard assessment.

3.5. **System Validation**

System performance was validated using a two-tier comparative approach. First, the Mamdani FIS was simulated in the MATLAB Fuzzy Logic Toolbox to obtain theoretical output baselines. Second, the same inputs were applied to the hardware system, and PWM outputs were recorded via the Arduino IDE Serial Monitor. Percentage error between simulation and hardware results was used as the main validation metric, with values below 1% considered acceptable (Fahreza et al., 2024). Real-time gas concentration, temperature, and PWM outputs were monitored throughout testing (Lazuardi et al., 2025; Susanto et al., 2025).

RESULTS AND DISCUSSION

The implemented gas leak early detection system uses three input sensors, namely the MQ-2 gas sensor, an infrared (IR) flame sensor, and a DHT22 temperature sensor, along with an actuator in the form of a DC exhaust fan. The Mamdani fuzzy logic method is applied to assess the risk level and control the actuator response in real-time. The MQ-2 sensor measures gas concentration in parts per million (ppm) which is then classified into three linguistic variables, namely Low, Medium, and High. The IR flame sensor detects the presence of fire based on detection distance (cm) which is grouped into Small detect, Medium detect, and Large detect, while the DHT22 sensor measures ambient temperature in degrees Celsius which is used as an additional indicator of hazardous conditions. These three parameters are processed by the Mamdani fuzzy inference system to produce an output in the form of a Pulse Width Modulation (PWM) signal that regulates the fan speed according to the identified risk level.

1. Fuzzification

In the fuzzification stage, each crisp input value obtained from the sensors is transformed into linguistic variables using predefined membership functions. This process enables the system to reason under uncertainty in a manner analogous to human cognitive evaluation (al afgani et al., 2024; Wicaksana & Hirzan, 2024).

The gas concentration input range (0-500 ppm) is divided into three fuzzy sets: Low with parameters [0, 0, 150, 225] ppm, Medium with parameters [150, 225, 300] ppm, and High with parameters [225, 300, 500, 500] ppm. The Low and High sets are modeled using trapezoidal (trapmf) membership functions to provide stability at extreme values, while the Medium set uses a triangular (trimf) membership function to represent gradual transition. For a representative test input value of x = 254 ppm, the membership degrees are evaluated as follows.

The Low category is represented using a trapezoidal membership function with parameters [0 0 150 225].

$$\mu_{Low}(x) = \left\{ 0,\ if\ x \le 0\ atau\ x \ge 225\ \ \frac{225-x}{225-150}, \qquad if\ 150 < x < 225\ 1, \qquad if\ 0 < x \le 225 \right\}$$

$$\mu_{Low}(254) = 0$$

The Medium category is represented using a triangular membership function with parameters [150 225 300].

$$\mu_{Medium}(x) = \left\{0, \ \ if\ x \le 150\ atau\ x \ge 300\ \frac{x-150}{225-150}, \quad if 150 < x \le 225\ \frac{300-x}{300-225}, \quad if\ 225 < x \le 300 \right\}$$

$$\mu_{Medium}(254) = \frac{300-254}{300-225} = \frac{46}{75} = 0.61$$

The High category is represented using a trapezoidal membership function with parameters [225 300 500 500].

$$\mu_{High}(x) = \left\{0, \ \ if\ x \le 0\ atau\ x \ge 225\ \frac{x-225}{300-225}, \quad if\ 225 < x \le 300\ \ 1, \quad if\ 300 < x \le 500 \right\}$$

$$\mu_{High}(254) = \frac{254-225}{300-225} = \frac{29}{75} = 0.38$$

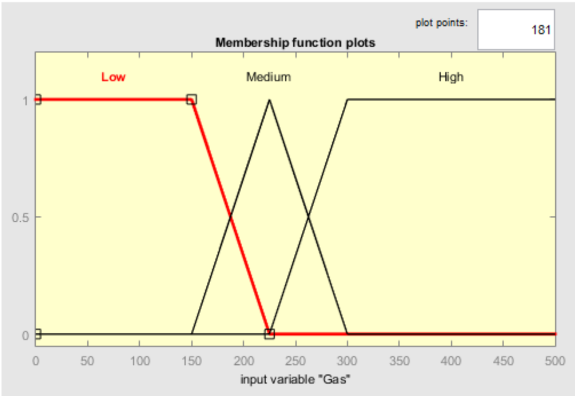

Figure 4. Membership Function Variable Input Gas

The flame distance input range (0-100 cm) is divided into three fuzzy sets: Large detect with parameters [0, 0, 30, 40] cm, Medium detect with parameters [30, 50, 70] cm, and Small detect with parameters [60, 70, 100, 100] cm. The Large detect and Small detect sets use trapezoidal functions, while the Medium detect set uses a triangular function. For a test input value of x = 63 cm, the membership degrees are calculated as follows.

The Large category is represented using a trapezoidal membership function with parameters [0 0 30 40].

$$\mu_{Large}(x) = \left\{0, \ \ if\ x \le 0\ atau\ x \ge 40\ \frac{40-x}{40-30}, \quad if\ 30 < x \le 40\ \ 1, \quad if\ 0 < x \le 40 \right\}$$

$$\mu_{Large}(63) = 0$$

The Medium category is represented using a triangular membership function with parameters [30 50 70].

$$\mu_{Medium}(x) = \left\{0, \ \ if\ x \le 30\ atau\ x \ge 70\ \frac{x-30}{50-30}, \quad if\ 30 < x \le 50\ \frac{70-x}{70-50}, \quad if\ 50 < x \le 70 \right\}$$

$$\mu_{Medium}(63) = \frac{70-63}{70-50} = \frac{7}{20} = 0.35$$

The Small category is represented using a trapezoidal membership function with parameters [60 70 100 100].

$$\mu_{Small}(x) = \left\{0, \ \ if\ x \le 60\ atau\ x \ge 100\ \frac{x-60}{70-60}, \quad if\ 60 < x \le 100\ 1, \quad if\ 70 < x \le 100 \right\}$$

$$\mu_{Small}(63) = \frac{63-60}{70-60} = \frac{3}{10} = 0.3$$

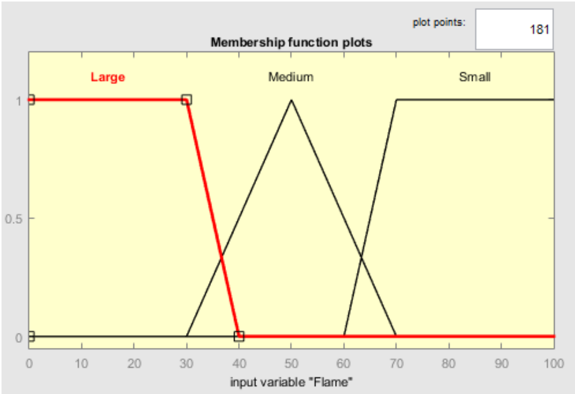

Figure 5. Membership Function Variable Input Flame

The temperature input range (0-100 °C) is divided into three fuzzy sets: Normal with parameters [0, 0, 30, 35] °C, Warm with parameters [30, 37.5, 45] °C, and Hot with parameters [40, 45, 100, 100] °C. The Normal and Hot sets use trapezoidal functions, while the Warm set uses a triangular function. For a test input value of x = 31°C, the membership degrees are evaluated as follows.

The Normal category is represented using a trapezoidal membership function with parameters [0 0 30 35].

$$\mu_{Normal}(x) = \left\{0,\ \ if\ x \leq 0\ atau\ x \geq 35\ \frac{35-x}{35-30},\qquad if\ 30 < x < 35\ 1,\qquad if\ 0 < x \leq 35\ \right\}$$

$$\mu_{Normal}(31) = \frac{35-31}{35-30} = \frac{4}{5} = 0.8$$

The Warm category is represented using a triangular membership function with parameters [30 37.5 45].

$$\mu_{Warm}(x) = \left\{0,\ \ if\ x \leq 30\ atau\ x \geq 45\ \frac{x-30}{37.5-30},\qquad if\ 30 < x \leq 37.5\ \frac{45-x}{45-37.5},\qquad if\ 37.5 < x \leq 45\right\}$$

$$\mu_{Warm}(31) = \frac{31-30}{37.5-30} = \frac{1}{7.5} = 0.13$$

The Hot category is represented using a trapezoidal membership function with parameters [40 45 100 100].

$$\mu_{Hot}(x) = \left\{0,\ \ if\ x \leq 40\ atau\ x \geq 100\ \frac{x-40}{45-40},\qquad if\ 40 < x \leq 45\ \ 1,\qquad if\ 45 < x \leq 100\right\}$$

$$\mu_{Hot}(31) = 0$$

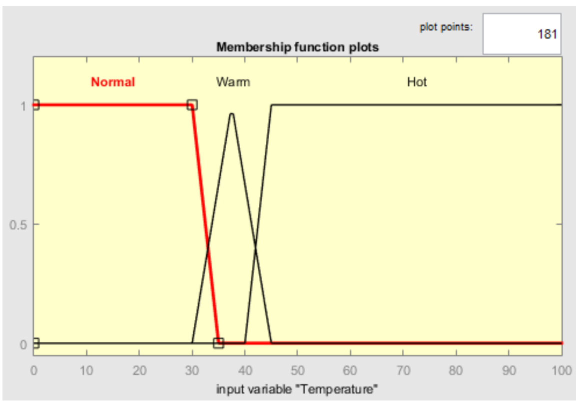

Figure 6. Membership Function Variable Input Temperature

The Fan DC output range (0-255 PWM) is divided into three fuzzy sets: Low speed with parameters [0, 0, 70, 85], Medium speed with parameters [60, 85, 110], and High speed with parameters [85, 150, 255, 255]. The Low speed and High speed sets are modeled using trapezoidal functions, while the Medium speed set uses a triangular function to represent a gradual transition zone.

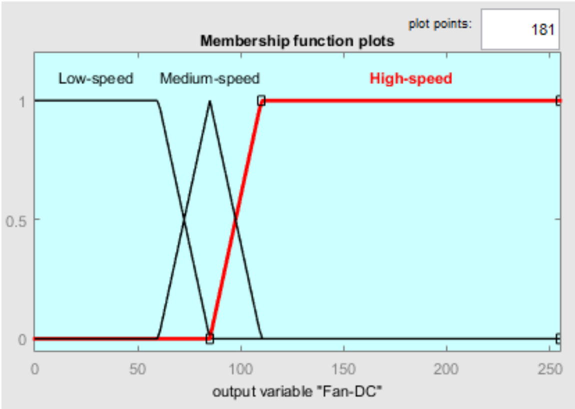

Figure 7. Membership Function Variable Output Fan DC

2. Rule Base Evaluation

The fuzzy rule base is determined using three input variables in Gas, Flame, and Temperature, and one output variable represented by the DC fan speed (Low, Medium, High). The rule base is structured into 27 IF-THEN rules derived from all possible input condition combinations (3 × 3 × 3). So, the following IF-THEN fuzzy rule base can be formed based on all possible combinations of the three input variables (Gas, Flame, and Temperature) and the output variable (Fan Speed):

Table 3. Rule Base Table

No.	Rule Base
1	IF Gas Low AND Flame Small AND Temperature Normal THEN Fan Low speed
2	IF Gas Low AND Flame Small AND Temperature Warm THEN Fan Low speed
3	IF Gas Low AND Flame Small AND Temperature Hot THEN Fan Medium speed
4	IF Gas Low AND Flame Medium AND Temperature Normal THEN Fan Medium speed
5	IF Gas Low AND Flame Medium AND Temperature Warm THEN Fan Low speed
6	IF Gas Low AND Flame Medium AND Temperature Hot THEN Fan High speed
7	IF Gas Low AND Flame Large AND Temperature Normal THEN Fan Low speed
8	IF Gas Low AND Flame Large AND Temperature Warm THEN Fan Low speed
9	IF Gas Low AND Flame Large AND Temperature Hot THEN Fan Medium speed
10	IF Gas Medium AND Flame Small AND Temperature Normal THEN Fan High speed
11	IF Gas Medium AND Flame Small AND Temperature Warm THEN Fan High speed
12	IF Gas Medium AND Flame Small AND Temperature Hot THEN Fan High speed
13	IF Gas Medium AND Flame Medium AND Temperature Normal THEN Fan Low speed
14	IF Gas Medium AND Flame Medium AND Temperature Warm THEN Fan Medium speed
15	IF Gas Medium AND Flame Medium AND Temperature Hot THEN Fan High speed
16	IF Gas Medium AND Flame Large AND Temperature Normal THEN Fan Low speed

No.	Rule Base
17	IF Gas Medium AND Flame Large AND Temperature Warm THEN Fan Low speed
18	IF Gas Medium AND Flame Large AND Temperature Hot THEN Fan Medium speed
19	IF Gas High AND Flame Small AND Temperature Normal THEN Fan High speed
20	IF Gas High AND Flame Small AND Temperature Warm THEN Fan High speed
21	IF Gas High AND Flame Small AND Temperature Hot THEN Fan High speed
22	IF Gas High AND Flame Medium AND Temperature Normal THEN Fan High speed
23	IF Gas High AND Flame Medium AND Temperature Warm THEN Fan High speed
24	IF Gas High AND Flame Medium AND Temperature Hot THEN Fan High speed
25	IF Gas High AND Flame Large AND Temperature Normal THEN Fan High speed
26	IF Gas High AND Flame Large AND Temperature Warm THEN Fan High speed
27	IF Gas High AND Flame Large AND Temperature Hot THEN Fan High speed

3. Implication Function

Before the implication stage, an inference process must be carried out to calculate the predicate value (α) for each rule. Based on the previously defined rule base, the AND operator is used, which refers to the MIN function to determine the activation level of each rule through the following equation:

$$\alpha_i = MIN(\mu_{Gas}(x),\ \mu_{Flame}(x),\ \mu_{Temperature}(x))$$

Table 4. Firing Strength in Rule

No.	Rule Base	Firing Strength	Status
1	IF Gas Low AND Flame Small AND Temperature Normal THEN Fan Low speed	MIN(0, 0, 0.80) = 0	No Implication
2	IF Gas Low AND Flame Small AND Temperature Warm THEN Fan Low speed	MIN(0, 0, 0.13) = 0	No Implication
3	IF Gas Low AND Flame Small AND Temperature Hot THEN Fan Medium speed	MIN(0, 0, 0) = 0	No Implication
4	IF Gas Low AND Flame Medium AND Temperature Normal THEN Fan Medium speed	MIN(0, 0.35, 0.80) = 0	No Implication
5	IF Gas Low AND Flame Medium AND Temperature Warm THEN Fan Low speed	MIN(0, 0.35, 0.13) = 0	No Implication
6	IF Gas Low AND Flame Medium AND Temperature Hot THEN Fan High speed	MIN(0, 0.35, 0) = 0	No Implication
7	IF Gas Low AND Flame Large AND Temperature Normal THEN Fan Low speed	MIN(0, 0.30, 0.80) = 0	No Implication
8	IF Gas Low AND Flame Large AND Temperature Warm THEN Fan Low speed	MIN(0, 0.30, 0.13) = 0	No Implication

No.	Rule Base	Firing Strength	Status
9	IF Gas Low AND Flame Large AND Temperature Hot THEN Fan Medium speed	MIN(0, 0.30, 0) = 0	No Implication
10	IF Gas Medium AND Flame Small AND Temperature Normal THEN Fan High speed	MIN(0.61, 0, 0.80) = 0	No Implication
11	IF Gas Medium AND Flame Small AND Temperature Warm THEN Fan High speed	MIN(0.61, 0, 0.13) = 0	No Implication
12	IF Gas Medium AND Flame Small AND Temperature Hot THEN Fan High speed	MIN(0.61, 0, 0) = 0	No Implication
13	IF Gas Medium AND Flame Medium AND Temperature Normal THEN Fan Low speed	MIN(0.61, 0.35, 0.80) = 0.35	Implication
14	IF Gas Medium AND Flame Medium AND Temperature Warm THEN Fan Medium speed	MIN(0.61, 0.35, 0.13) = 0.13	Implication
15	IF Gas Medium AND Flame Medium AND Temperature Hot THEN Fan High speed	MIN(0.61, 0.35, 0) = 0	No Implication
16	IF Gas Medium AND Flame Large AND Temperature Normal THEN Fan Low speed	MIN(0.61, 0.30, 0.80) = 0.30	Implication
17	IF Gas Medium AND Flame Large AND Temperature Warm THEN Fan Low speed	MIN(0.61, 0.30, 0.13) = 0.13	Implication
18	IF Gas Medium AND Flame Large AND Temperature Hot THEN Fan Medium speed	MIN(0.61, 0.30, 0) = 0	No Implication
19	IF Gas High AND Flame Small AND Temperature Normal THEN Fan High speed	MIN(0.38, 0, 0.80) = 0	No Implication
20	IF Gas High AND Flame Small AND Temperature Warm THEN Fan High speed	MIN(0.38, 0, 0.13) = 0	No Implication
21	IF Gas High AND Flame Small AND Temperature Hot THEN Fan High speed	MIN(0.38, 0, 0) = 0	No Implication
22	IF Gas High AND Flame Medium AND Temperature Normal THEN Fan High speed	MIN(0.38, 0.35, 0.80) = 0.35	Implication
23	IF Gas High AND Flame Medium AND Temperature Warm THEN Fan High speed	MIN(0.38, 0.35, 0.13) = 0.13	Implication
24	IF Gas High AND Flame Medium AND Temperature Hot THEN Fan High speed	MIN(0.38, 0.35, 0) = 0	No Implication
25	IF Gas High AND Flame Large AND Temperature Normal THEN Fan High speed	MIN(0.38, 0.30, 0.80) = 0.30	Implication
26	IF Gas High AND Flame Large AND Temperature Warm THEN Fan High speed	MIN(0.38, 0.30, 0.13) = 0.13	Implication
27	IF Gas High AND Flame Large AND Temperature Hot THEN Fan High speed	MIN(0.38, 0.30, 0) = 0	No Implication

The implication process is carried out by applying the firing strength obtained from the active rules to modify the corresponding output membership function. This is achieved by truncating the output membership function at the firing strength value (α) of each active rule, as expressed by the following equation:

$$\mu'_{Output}(x) = MIN(\alpha_i, \mu_{Output}(x))$$

This ensures that each active rule contributes to the output according to its firing strength. The truncated membership functions are then ready to be aggregated for further processing. The following section presents the computation for all active rules, showing how their truncated membership functions are combined to determine the overall output fuzzy set.

For $\alpha_{Low} = 0.35$, the trapezoidal membership function (0, 0, 70, 85).

Left Side:

$$\alpha_{Low} = \frac{x-a}{b-a}$$
$$0.35 = \frac{x-0}{0-0}$$
$$0 = x_1$$

Right Side:

$$\alpha_{Low} = \frac{d-x}{d-c}$$
$$0.35 = \frac{85-x}{85-70}$$
$$79.75 = x_2$$

For $\alpha_{Medium} = 0.3$, the triangular membership function (60, 85, 110).

Left Side:

$$\alpha_{Medium} = \frac{x-a}{b-a}$$
$$0.3 = \frac{x-60}{85-60}$$
$$67.5 = x_1$$

Right Side:

$$\alpha_{Medium} = \frac{d-x}{d-c}$$
$$0.3 = \frac{110-x}{110-85}$$
$$102.5 = x_2$$

For $\alpha_{High} = 0.13$, the trapezoidal membership function (85, 150, 255, 255).

Left side:

$$\alpha_{High} = \frac{x-a}{b-a}$$
$$93.45 = x_1$$

Right side:

$$\alpha_{High} = \frac{d-x}{d-c}$$
$$255 = x_2$$

4. **Aggregation**

After generating the implications of each rule, the next step is aggregation. Aggregation combines all truncated output membership functions into a single fuzzy set using the MAX operator. This operator takes the maximum membership value at each point in the output of all activated rules, as expressed by the following equation:

$$\mu_{agg}(x) = MAX(\mu'_{Low}(x), \mu'_{Medium}(x), \mu'_{High}(x), \ldots)$$

Based on the rule implication stage, several rules are activated with different trigger strength values. Each activated rule produces an output membership function truncated according to its trigger strength. This trigger strength value represents the degree of influence each rule has on the system response.

$$\mu_{agg}(x) = \{\frac{x}{70},\ 0 \le x \le 67.5\ 0.35, \quad 67.5 \le x \le 79.75\ \frac{x-85}{65},\ 79.75 \le x \le 93.45\ \ 0.3, \quad 93.45 \le x \le 102.5\ \frac{11}{11}$$

5. **Defuzzification**

In this study, the output domain is defined within the range of 0–255 PWM. Since the aggregated membership function consists of multiple linear and constant segments obtained from the MAX aggregation process, the centroid integral must be computed piecewise over each interval. The moment calculation is as follows:

$$M1 = \int_{0}^{67.5} x\frac{x}{70}\, dx = \frac{1}{70}\int_{0}^{67.5} x^{2}\, dx = \frac{1}{70}\left[\frac{x^{3}}{3}\right]_{0}^{67.5} = 531.45$$

$$M2 = \int_{67.5}^{79.75} 0.35x\, dx = 0.35\left[\frac{x^{2}}{2}\right]_{67.5}^{79.75} = 315.85$$

$$M3 = \int_{79.75}^{93.45} x\frac{85-x}{15}\, dx = \frac{1}{15}\int_{79.75}^{93.45} (85x - x^{2})\, dx = \frac{1}{15}\left[\frac{85x^{2}}{2} - \frac{x^{3}}{3}\right]_{79.75}^{93.45} = 249.41$$

$$M4 = \int_{93.45}^{102.5} 0.3x\, dx = 0.3\left[\frac{x^{2}}{2}\right]_{93.45}^{102.5} = 266.46$$

$$M5 = \int_{102.5}^{110} x\frac{110-x}{25}\, dx = \frac{1}{25}\int_{102.5}^{110} (110x - x^{2})\, dx = \frac{1}{25}\left[\frac{110x^{2}}{2} - \frac{x^{3}}{3}\right]_{102.5}^{110} = 119.53$$

$$M6 = \int_{110}^{255} 0.13x\, dx = 0.13\left[\frac{x^{2}}{2}\right]_{110}^{255} = 3903.8$$

The result area calculation is as follows:

$$A1 = \int_{0}^{67.5} \frac{x}{70}\, dx = \frac{1}{70}\int_{0}^{67.5} x\, dx = \frac{1}{70}\left[\frac{x^{2}}{2}\right]_{0}^{67.5} = 11.81$$

$$A2 = \int_{67.5}^{79.75} 0.35\, dx = 0.35[x]_{67.5}^{79.75} = 0.35\,(79.45 - 67.5) = 4.29$$

$$A3 = \int_{79.75}^{93.45} \frac{85-x}{15}\, dx = \frac{1}{15}\int_{79.75}^{93.45} (85 - x)\, dx = \frac{1}{15}\left[85x - \frac{x^{2}}{2}\right]_{79.75}^{93.45} = 2.88$$

$$A4 = \int_{93.45}^{102.5} 0.3\, dx = 0.3[x]_{93.45}^{102.5} = 2.72$$

$$A5 = \int_{102.5}^{110} \frac{110-x}{25}\, dx = \frac{1}{25}\int_{102.5}^{110} (110 - x)\, dx = \frac{1}{25}\left[110x - \frac{x^{2}}{3}\right]_{102.5}^{110} = 1.125$$

$$A6 = \int_{110}^{255} 0.13\, dx = 0.13[x]_{110}^{255} = 18.85$$

Based on the results of the Moment and Area Calculations, the results are as follows:

$$Z^{*} = \frac{\Sigma(M1+M2+M3+M4+M5+M6)}{\Sigma(A1+A2+A3+A4+A5+A6)}$$

$$Z^{*} = \frac{(531.45 + 315.85 + 266.46 + 119.53 + 3903.8)}{(11.81 + 4.29 + 2.88 + 2.72 + 1.125 + 18.85)} = \frac{5386.5}{41.68} = 129.2$$

6. Visualization Crisp Output

Based on the MATLAB Fuzzy Logic Toolbox simulation executed under the defined test conditions (Gas = 254 ppm, Flame = 63 cm, Temperature = 31°C), the system produced a defuzzification output of Fan DC = 129 PWM. The Rule Viewer visualization confirming this result is presented below.

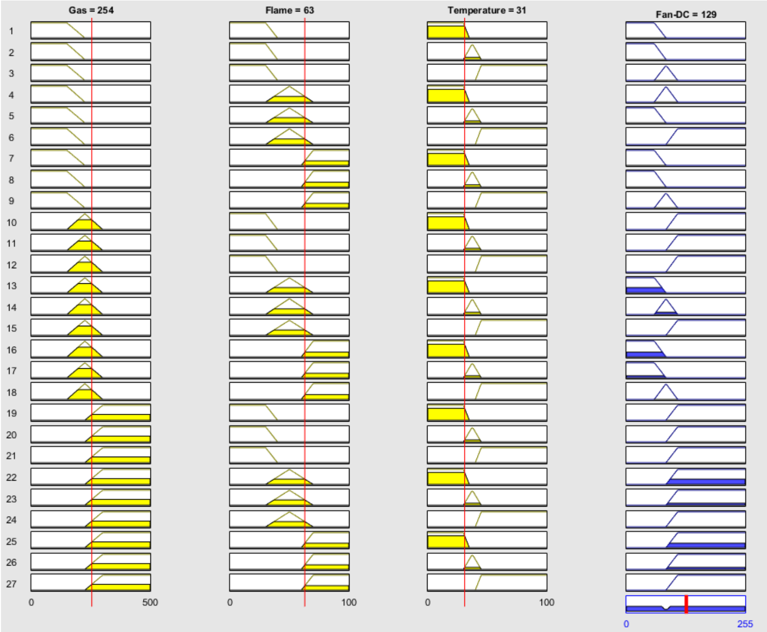

Figure 8. Rule Viewer MATLAB

The three-dimensional surface plots further illustrate the adaptive response behavior of the system across varying input combinations. Figure 9. presents the relationship between Gas Concentration and Flame Distance against the Fan DC output.

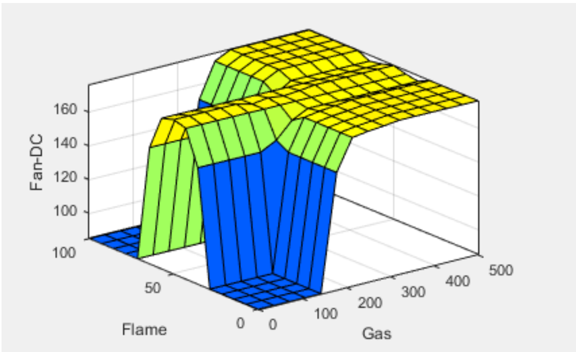

Figure 9. Surface Plot Gas and Flame

Figure 10. presents the relationship between Gas Concentration and Ambient Temperature against the Fan DC output, and

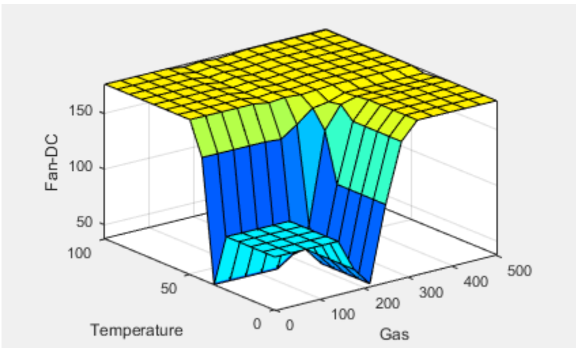

Figure 10. Surface Plot Gas and Temperature

Figure 11. presents the relationship between Ambient Temperature and Flame Distance against the Fan DC output.

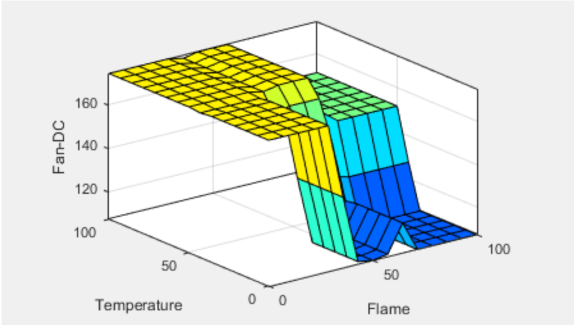

Figure 11. Surface Plot Temperature and Flame

These surface visualizations show that the Fan DC output forms a stepped surface rather than a linear response, confirming smooth and proportional ventilation across varying environmental conditions. This output is physically meaningful with a gas concentration of 254 ppm sitting at the boundary between Medium and High hazard, a flame detected at 63 cm in the Medium detect range, and an ambient temperature of 31°C reflecting a primarily Normal condition with slight Warm overlap, the system correctly identifies this as a moderate-to-elevated hazard scenario. The resulting 129 PWM response drives the DC exhaust fan at a substantial but non-maximum speed, providing effective ventilation without excessive response.

This graduated behavior demonstrates the advantages of multi-parameter Mamdani fuzzy inference over conventional binary threshold systems. A single-threshold system may fail to respond when gas levels are below the set limit or, conversely, trigger a maximum alarm regardless of favorable flame distance and near-normal temperature conditions. In contrast, the proposed system evaluates gas concentration, flame distance, and temperature simultaneously, producing a proportional 129 PWM output that more accurately reflects the actual composite level. This approach aligns with the research objective of minimizing false alarms while providing adaptive mitigation responses.

7. System Validation

System performance was validated through a comparative evaluation between MATLAB Fuzzy Logic Toolbox simulation, high-resolution centroid calculation, and hardware-equivalent computation. A single representative test scenario was selected to demonstrate the system's behavior under specific conditions, with inputs set as Gas = 254 ppm, Flame = 63 cm, and Temperature = 31 °C. The corresponding hardware-computed output for this scenario is illustrated in Figure 12.

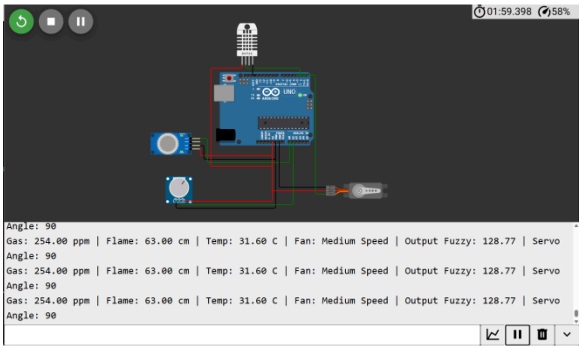

Figure 12. Hardware Simulation

The fuzzy output was hardware-equivalent computation resulted in 128.77 in Figure 12. The complete validation results are presented in Table 5.

Table 5. Resulting Comparison

No.	Gas (ppm)	Flame (cm)	Temp (°C)	Output MATLAB	Output Calculation	Output Hardware	Status
1	254	63	31	129	129.2	128.77	Medium Speed

As demonstrated in Table 5., the system performance shows a high level of consistency across software simulation, high-resolution calculation, and hardware-equivalent computation for the representative medium-hazard scenario. For the scenario with inputs Gas = 254 ppm, Flame = 63 cm, and Temperature = 31 °C, the MATLAB simulation produced an output of 129, the high-resolution centroid calculation yielded 129.2, and the hardware-equivalent computation resulted in 128.77. The corresponding percentage errors were 0.18 % between MATLAB and hardware, 0.33 % between the high-resolution calculation and hardware, and 0.16 % between MATLAB and the high-resolution calculation. The average error across these three comparisons is approximately 0.22 %.

This low-error behavior reflects the stable medium-hazard operating region of the system, where all three environmental inputs map into a coherent fuzzy response region, producing a proportional output categorized as Medium Speed. The minor differences in percentage errors are attributable to discretization resolution variations between the methods, rather than system deficiencies. Importantly, these results demonstrate that the Mamdani fuzzy inference framework maintains near-perfect consistency across MATLAB simulation, high-resolution calculation, and hardware-equivalent implementation, supporting reliable actuator response in practical operating conditions.

CONCLUSION

This study successfully designed and implemented an intelligent early warning system for gas leak-induced fire detection based on the Mamdani Fuzzy Inference System, implemented on an Arduino Uno microcontroller and validated through MATLAB Fuzzy Logic Toolbox simulation. The system integrates three environmental input parameters gas concentration (MQ-2 sensor), flame detection distance (IR flame sensor), and ambient temperature (DHT22 sensor) processed through a 27-rule Mamdani fuzzy rule base to generate a proportional PWM output signal controlling a DC exhaust fan via an L298N motor driver. The implementation of the Mamdani MIN-MAX inference method with Centroid defuzzification demonstrated that the system is capable of producing graduated, context-sensitive actuator responses calibrated to the composite hazard level across all three environmental dimensions simultaneously. In the representative medium-hazard scenario (Gas = 254 ppm, Flame = 63 cm, Temperature = 31 °C), the MATLAB simulation produced a defuzzified Fan DC output of 129 PWM, the high-resolution centroid calculation yielded 129.2 PWM, and the hardware-equivalent computation resulted in 128.77 PWM. The corresponding percentage errors were 0.18 % (MATLAB vs Hardware), 0.33 % (Calculation vs Hardware), and 0.16 % (MATLAB vs Calculation). The average error is approximately 0.22 %, which remains well below the 1 % threshold typically considered acceptable for embedded fuzzy logic implementations, confirming strong agreement among the three evaluation approaches.

These results demonstrate that the Mamdani fuzzy logic algorithm provides accurate and proportional actuator responses even in a single representative scenario. The low-error behavior highlights the advantage of multi-parameter fuzzy inference over conventional single-threshold systems, which may either fail to respond or trigger false alarms under isolated parameter exceedances. By evaluating all three environmental inputs simultaneously, the system produces graduated outputs that accurately reflect the composite hazard level, ensuring adaptive mitigation responses in LPG-dependent environments. Future work may explore extending the input parameter set to include humidity and smoke density, integrating deep learning-based anomaly detection to complement the fuzzy inference layer, and deploying the system across distributed IoT sensor networks for larger-scale industrial fire prevention applications.

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