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Simulation of a Multi-Parameter Indoor Air Purification Control System Using Fuzzy Logic–PID Hybrid Control Tuned by Genetic Algorithms.

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Abstract—Indoor Environmental Quality (IEQ) critically impacts human health, comfort, and productivity, yet existing air purification systems often rely on single-sensor data, manual monitoring, or cloud-based processing, resulting in limited intelligence, increased latency, and reduced suitability for resource-constrained environments such as Uganda. To address these challenges, this paper presents the design, mathematical modelling, and simulation of a novel multi-parameter indoor air purification control system. The proposed framework integrates six environmental sensors (dust, smoke, gas, volatile organic compounds (VOC), temperature, and humidity) with a hybrid Fuzzy Logic–Proportional–Integral–Derivative (PID) controller whose parameters are optimally tuned using a Genetic Algorithm (GA). A first-principles mathematical model of the DC motor-driven purifier actuator is developed to describe the relationship between the input voltage and volumetric airflow. To enhance the physical realism of the simulations, the system model incorporates practical operating factors, including fan inertia, room-air mixing, pollutant transport, filter dynamics, and environmental sensor noise. The complete system is implemented in the MATLAB/Simulink environment using a Mamdani-type fuzzy inference system with 49 rules and a GA-based multi-objective fitness function to minimise overshoot, settling time, and steady-state error. Simulation results demonstrate that the proposed GA-tuned Fuzzy-PID controller achieves a stable and well-damped response with a rise time of 53.93 s, a settling time of 119.99 s, and a maximum overshoot of 2.14%, reflecting the expected dynamics of practical indoor air purification systems. The proposed framework provides a scalable, low-latency, and network-independent intelligent control solution that establishes a realistic foundation for future prototype development and experimental validation in low-resource environments.

Index Terms—Air Purification, fuzzy logic, Genetic algorithm, Particulate matter, PID control.

I. INTRODUCTION

A. Background

Indoor Environmental Quality (IEQ) plays a vital role in promoting the comfort, health, and productivity of occupants within built environments [1]. One of the factors affecting IEQ is air quality, typically assessed through dust concentration in the environment [2].

Rapid urbanization has reduced the presence of natural pollutant filters such as Spider plants, Wetlands, forests, and Moss, limiting their role in removing harmful pollutants like formaldehyde, benzene, carbon monoxide, airborne toxins, carbon dioxide, and particulate matter. As urban populations spend 80–90% of their time indoors, exposure to indoor pollutants increases due to multiple emission sources and activities that re-suspend contaminants into the air [41].

Belda et al. described the various sources of indoor air pollution commonly found in everyday environments (as illustrated in Figure 1). Household materials and products, such as new wallpapers and carpets, emit increased levels of volatile organic compounds (VOCs), which can persist and accumulate in indoor air [40].

Poor indoor air quality can lead to respiratory conditions, increased stress, reduced performance, and broader health concerns [3]. As noted by the World Health Organization in 2011, although attention to IEQ assessment in buildings has grown, most current air-quality monitoring approaches rely on single-variable measurements, limiting both their scalability and their level of intelligence [4]. These shortcomings in

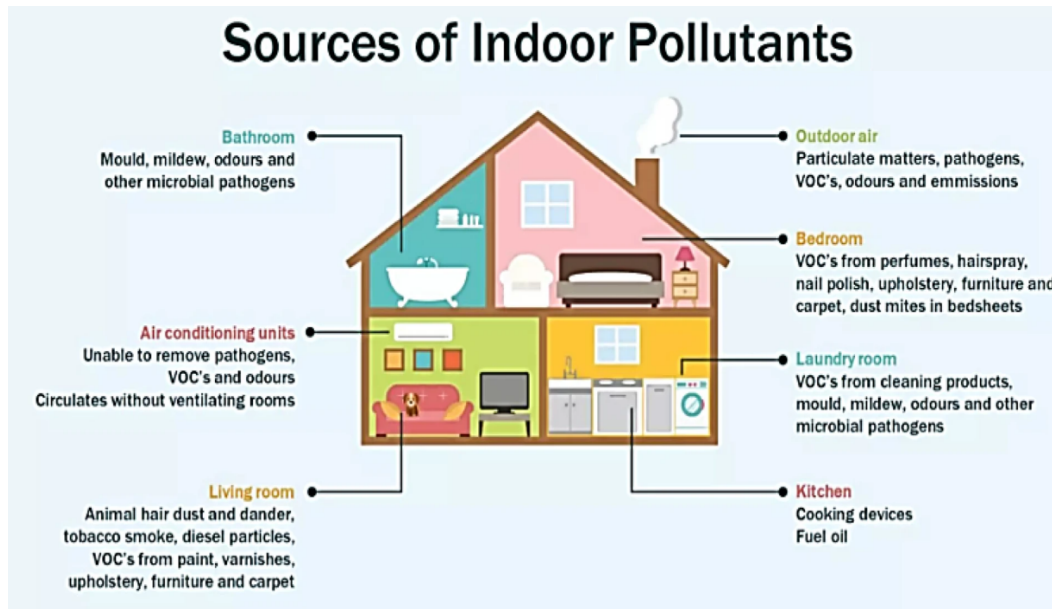


Fig. 1. Sources of indoor pollutants [40].

capturing multiple environmental factors can impede the achievement of sustainable conditions and the protection of occupant health [5].

Fine particulate matter, for example, as PM_{2.5}, is among the most hazardous air pollutants and is generated from sources including industrial emissions, vehicle exhaust, and construction activities. Once inhaled, these tiny particles can reach deep into the respiratory system and contribute to both cardiovascular and pulmonary diseases [6]–[9].

Indoor air quality is greatly affected by temperature and humidity, as both influence the concentration, dispersion, and behavior of airborne pollutants. Elevated temperatures can accelerate the emission of harmful gases and volatile compounds. At the same time, very low or high humidity levels can cause respiratory discomfort, encourage mold and microbial growth, and affect the suspension of particulate matter, thereby degrading overall air quality and human comfort. [10]–[13]. Although smart thermostats and internet-connected HVAC systems offer improved control accuracy, their adoption in developing regions is still limited by challenges such as cost, system compatibility, and data reliability [14], [15].

B. Related work

Extensive research has been conducted on IoT-based indoor monitoring systems utilizing platforms such as Raspberry Pi, ESP32, and Arduino, particularly for detecting and tracking air pollutants, for example CO_2 , NO_2 , SO_2 , and particulate matter [15], [17], [18]. However, many of these systems exhibit key limitations, including the lack of real-time alerting capabilities, limited adaptability in data processing and

analysis, and challenges in effectively integrating multiple sensor inputs [19], [20].

Mutiu Shola Bakare and Kazibwe Abubaker developed an indoor environmental monitoring system based on an IoT architecture using the ESP32-WROOM module. The system was capable of acquiring and storing environmental data using sensors; it lacked an active control mechanism for indoor air purifiers. Furthermore, the design was constrained by the use of only three sensors, namely DHT22, a light sensor, and a dust sensor, as shown in Figure 2, thereby overlooking other critical environmental variables, including smoke, concentration level of carbon dioxide, and volatile organic compounds in air, which significantly affect air quality. [16].

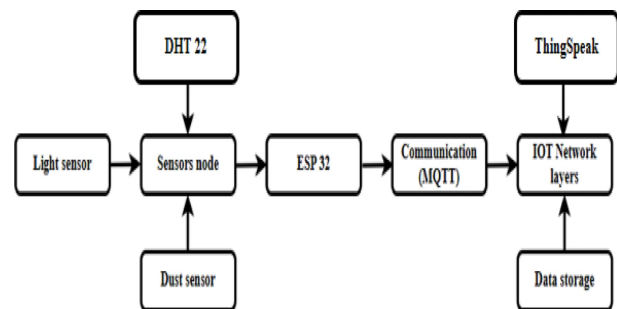


Fig. 2. This block diagram illustrates the overall system architecture of the Multi-Conditioner Indoor Measurement System, with only three sensors connected to it [16].

Existing studies show that the current air purification systems depend on a small set of sensors and high-latency communication methods or exclusively cloud-based processing, resulting in delays between data acquisition

and visualization [21], [22], [24]. These limitations hinder real-time monitoring and responsive control, and make such systems impractical for deployment in resource-constrained environments, particularly in low-developed regions (Uganda) with unreliable network infrastructure [24], [25]. Consequently, a clear research gap exists in the development of a multi-sensor indoor air monitoring platform capable of delivering high measurement accuracy, low-latency data transmission, and scalable performance.

Authors compared fuzzy logic controllers [30]–[34] with classical PID [35] in HVAC systems. The fuzzy controller reduced energy consumption by 12.7 % and improved comfort by lowering temperature oscillations. However, it was limited to HVAC air handling units without pollutant-specific control [42]. A 2023 study applied fuzzy self-tuning PID optimized by Particle Swarm Optimization (PSO) for continuous HVAC operation. It improved adaptability but focused only on thermal comfort, not multi-pollutant indoor air purification [43]. Authors applied GA to tune fuzzy controllers in HVAC systems. These works highlight GA's effectiveness but focused on thermal comfort, not pollutant purification [29], [44].

C. Problem Statement

Indoor Air Purification systems are limited by poor intelligence, low scalability, and inadequate multi-sensor integration, with many relying on single-sensor data, manual logging, or high-latency communication methods. These limitations hinder real-time monitoring, delay decision-making, and reduce effectiveness, especially in resource-constrained environments with unreliable networks. Therefore, there is a need for the development of an intelligent, scalable multi-sensor system capable of accurate, low-latency data processing and real-time control by employing a fuzzy logic–PID hybrid approach and Genetic algorithm.

D. Contributions of this work

The study's primary novelty lies in the integration of six environmental sensors with a GA-optimized fuzzy-PID controller for indoor air purification, including a first-principles derivation of the actuator transfer function and explicit design for low-latency, network-independent operation suited to resource-limited regions.

This study is significant because it addresses two critical gaps in indoor air quality management, particularly in resource-limited regions such as Uganda. The key contributions are;

1) **Introduction of a novel hybrid control architecture:**

The study proposes a hybrid control strategy that combines Fuzzy Logic, PID control, and Genetic Algorithm optimization. This integrated approach is expected to overcome the poor adaptability and high latency associated with conventional air purification systems.

2) **Design of a scalable real-time deployment model:**

By developing a mathematical model (transfer function equation) of the air purifier actuator and enabling on-device real-time decision-making, the study aims to deliver a scalable, energy-efficient, and locally deployable solution. This system has the potential to improve indoor environmental quality in homes, schools, and healthcare facilities across developing regions.

II. MATERIALS AND METHODS

A. Design of a Multi-Parameter Indoor Air Purification Control System Circuit

Figure 3 shows a system made up of a network of six sensors: a dust sensor for dust detection, a smoke sensor for smoke detection, a gas sensor for the concentration level of carbon dioxide detection, a VOC sensor for the presence and concentration of volatile organic compounds in air, a temperature sensor for room temperature measurement, and humidity sensor for humidity measurement.

These raw measurements are aggregated into an input signal and sent to the “fuzzy-PID” controller. The fuzzy controller employs a rule-based logic system that follows the set rules. The fuzzy-PID controller combines fuzzy logic with a conventional PID controller, where its parameters are tuned using a Genetic Algorithm (GA).

The fuzzy control module takes input signals in the form of error, e , and change in error, ec . It interfaces with the fuzzy-PID controller to minimize the deviation between the desired output and the actual system response by use of a feedback signal or a closed-loop system. The integration of GA with the fuzzy-PID framework results in a GA-optimized fuzzy-PID control system.

The use of Genetic Algorithm (GA) is motivated by its capability to effectively optimize PID parameters, addressing the limitations of traditional trial and error tuning methods, and improving adaptability in nonlinear systems to remain near-optimal under varying air and pollutant dynamics. The control signal from the Fuzzy PID is sent to the purifier actuator system. The purifier targets particulate matter (dust), chemical absorption, and diluting gaseous pollutants.

A feedback signal from the Output control signal is fed back to the input comparator, thereby closing the control loop. This signal contains post-actuation sensor measurements, allowing the system to compensate for disturbances and model inaccuracies. Without this feedback loop, the genetic algorithm would not have access to performance indicators such as settling time or cumulative error, which are essential for evaluating fitness.

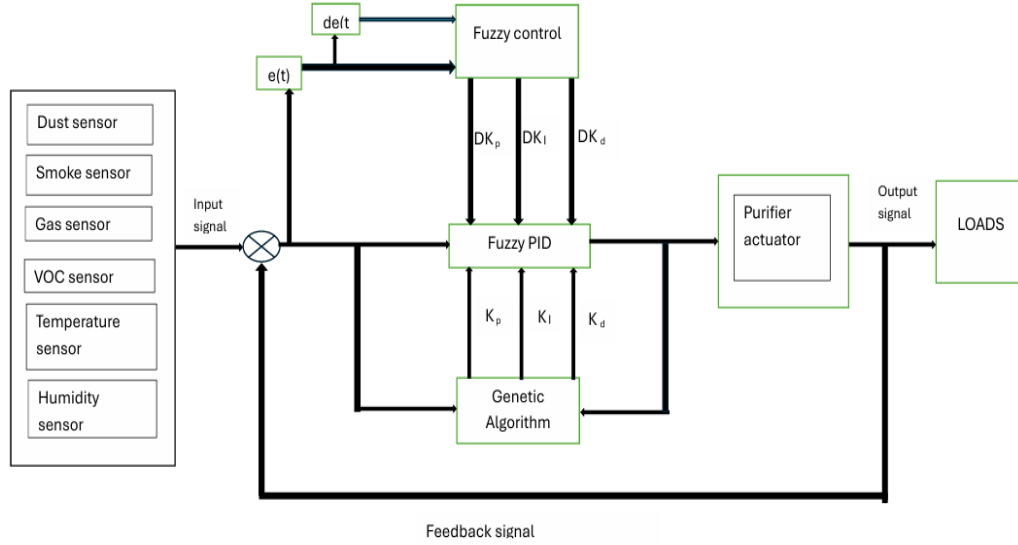


Fig. 3. This block diagram illustrates a Multi-Parameter Indoor Air Purification Control System Circuit

1) **Creating Fuzzy logic file for Fuzzy control block in Figure 3:** The fuzzy control system was configured as presented in Table I, where the rule base is organized such that rows correspond to the error e and columns correspond to the change in error ec . Each entry in the table defines the controller output for a specific combination of e and ec . Using the linguistic variables NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZO (Zero), PS (Positive Small), PM (Positive Medium), and PB (Positive Big), the table assigns one or more possible control actions separated by slashes for each input pair, reflecting a multi-level control response mechanism [29].

TABLE I
TABLE FOR FUZZY LOGIC RULES BASED ON ERROR (E) AND ERROR CHANGE (EC) FOR PARAMETERS $K_p/K_i/K_d$ [29]

e	ec						
	NB	NM	NS	ZO	PS	PM	PB
NB	PB/NB/PS	PB/NB/NS	PB/NM/NB	PM/NM/NB	PS/NS/NB	ZO/ZO/NM	ZO/ZO/PS
NM	PB/NB/PS	PB/NB/PS	PM/NB/NS	PS/NS/NM	PS/NS/ZO	ZO/ZO/NM	NS/PS/ZO
NS	PM/NB/ZO	PM/NM/NS	PM/NM/NS	PS/NS/NM	ZO/ZO/NS	NS/PM/ZO	NS/PM/ZO
ZO	PM/NM/ZO	PM/NM/NS	PS/NS/NS	ZO/ZO/ZO	NS/PS/ZO	NM/PM/ZO	NM/PM/ZO
PS	PS/NM/ZO	PS/NS/ZO	ZO/ZO/ZO	ZO/PS/ZO	NS/PS/ZO	NM/PM/ZO	NM/PM/ZO
PM	PS/ZO/PB	ZO/ZO/PM	NS/PS/PM	NS/PS/PM	NM/PM/PS	NM/PB/PS	NB/PB/PB
PB	ZO/ZO/PB	ZO/ZO/PM	NS/PS/PM	NM/PM/PM	NB/PB/PS	NB/PB/PB	NB/PB/PB

The fuzzy logic file for the Fuzzy control block in Figure 3 created was named '*fuzzy_PID.fis*'. The fuzzy logic model was developed using the MATLAB Fuzzy Logic Designer in the MATLAB environment. The resulting system employs a Mamdani Type-1 fuzzy inference system architecture, shown in figure 4 for adaptive PID tuning, referred to as '*fuzzy_PID.fis*'. The controller is configured with two

input variables: error and change in error ($\Delta error$), each represented by seven membership functions (MFs) to capture varying system states. These inputs are processed through a comprehensive rule base consisting of 49 inference rules (7×7). The controller generates three output variables, namely ΔK_p , ΔK_i , and ΔK_d .

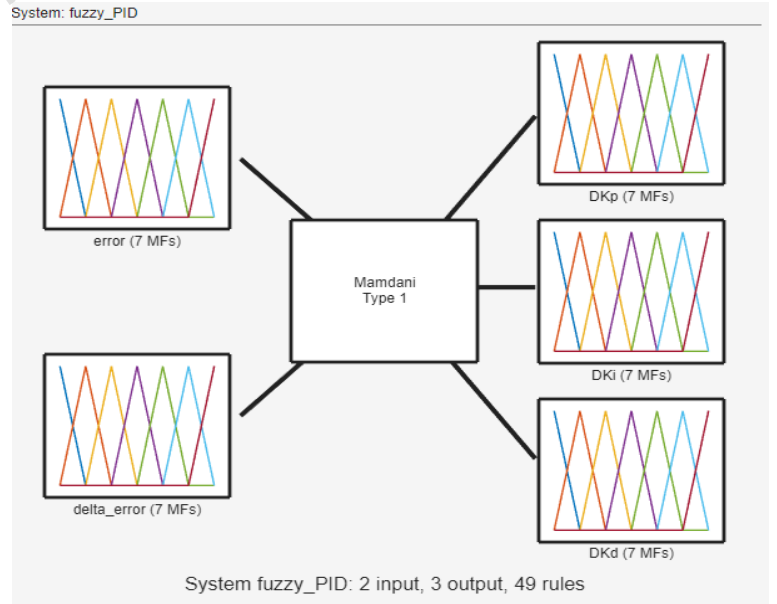


Fig. 4. Architecture of the proposed Mamdani-type fuzzy logic controller for PID gain scheduling. The controller has two inputs (error and delta error) and three outputs (ΔK_p , ΔK_i , and ΔK_d).

Figures 5 and 6 present the membership function plots for the error and change in error inputs of the Fuzzy PID Controller, defined over a normalized range of -6 to +6 using seven

triangular linguistic terms (NL to PL), as summarized in the Table I. This configuration enables fuzzification of crisp inputs for effective rule-based adaptive control.

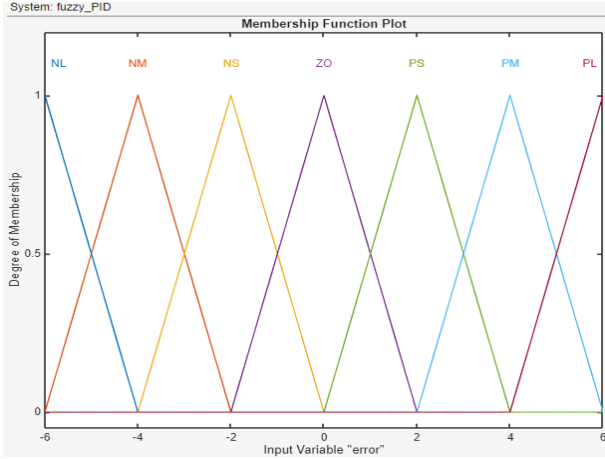


Fig. 5. Membership function plot for the input variable "error". Seven triangular membership functions (NL, NM, NS, ZO, PS, PM, PL) are evenly distributed over the universe of discourse [-6, 6].

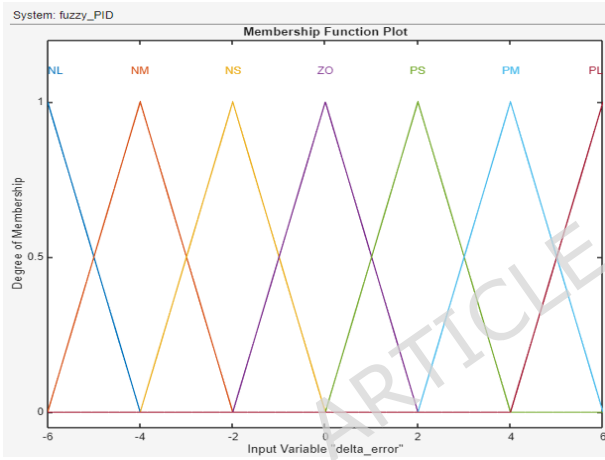


Fig. 6. Membership function plot for the input variable "change in error". Seven triangular membership functions (NL, NM, NS, ZO, PS, PM, PL) are evenly distributed over the universe of discourse [-6, 6].

The figure 7 illustrates the rule viewer output of the *fuzzy_PID.fis* system, demonstrating the inference mechanism of the Fuzzy PID controller for specific crisp input conditions. For an input state defined by an error value of -1.38 and a change in error of 2 , the controller evaluates a total of 49 fuzzy rules using the minimum (*min*) operator for logical AND aggregation. During the inference process, multiple rules are activated simultaneously, as indicated by the highlighted rule indices, leading to the defuzzified output values of $\Delta K_p = -0.688$, $\Delta K_i = 0.688$, and $\Delta K_d = -2$.

After testing and evaluating the created *fuzzy_PID.fis* system, it was exported out of the MATLAB Fuzzy Logic Designer as a file named '*fuzzy_PID.fis*', ready for integration into the Simulink Model.

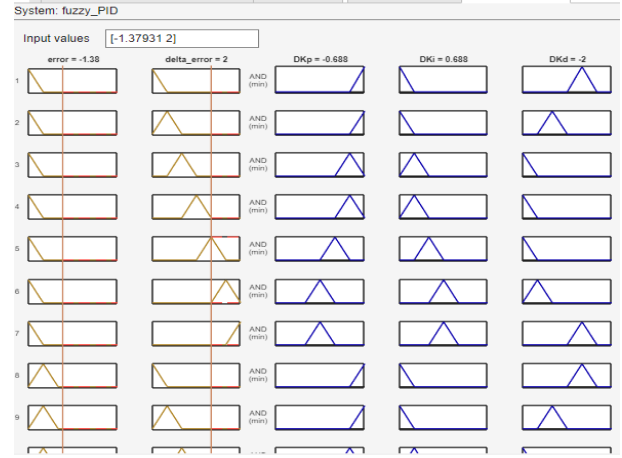


Fig. 7. Rule viewer and inference snapshot of the fuzzy PID controller for error and $\Delta error$.

2) Development of the conventional Fuzzy Logic Controller file integrated into the Fuzzy PID Controller block in Figure 3: The fuzzy logic model was developed using the MATLAB Fuzzy Logic Designer within the MATLAB environment, implementing a Mamdani Fuzzy Inference System named *Purifier_logic* for intelligent air purifier control. The proposed system utilizes six environmental input variables: dust, smoke, gas, VOC, temperature, and humidity, each defined within a specific operating range and represented using three membership functions to capture varying environmental conditions and support effective rule-based control of the air purification process.

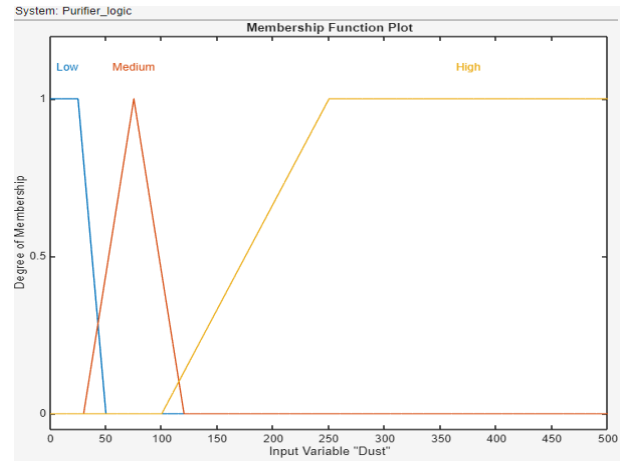


Fig. 8. Membership function plot for the Dust sensor.

Figure 8 illustrates the membership function distribution for the input variable *Dust* within the Fuzzy Logic Controller applied to the air purification system. The Dust parameter is defined over a numerical range of 0 to 500, representing the concentration of airborne particulate matter (e.g., $\mu g/m^3$). This input is modeled using three membership functions: Low, Medium, and High, configured as triangular and trapezoidal shapes to represent different pollution levels. As summarized

in Table II, the linguistic interpretation assigns *Low* to minimal dust presence, *Medium* to moderate dust concentration, and *High* to elevated dust levels, each corresponding to specific intensity ranges used for fuzzy inference and control decision-making.

TABLE II
LINGUISTIC TERMS FOR THE DUST SENSOR WITH THEIR INTENSITY RANGE VALUES.

Linguistic terms	Range of values	Peak value
Low	0 - 50	25
Medium	30 - 120	75
High	100 - 500	250

Figure 9 illustrates the membership function distribution for the input variable Smoke within the Fuzzy Logic Controller applied to the air purification system. The Smoke parameter is defined over a numerical range of 0 to 100, representing the concentration of airborne smoke particles. This input is modeled using three membership functions: Low, Medium, and High, configured as triangular and trapezoidal shapes to represent different levels of smoke pollution. As summarized in Table III, the linguistic interpretation assigns Low to minimal smoke presence, Medium to moderate smoke concentration, and High to elevated smoke levels, each corresponding to specific intensity ranges used for fuzzy inference and control decision-making.

TABLE III
LINGUISTIC TERMS FOR THE SMOKE SENSOR WITH THEIR INTENSITY RANGE VALUES.

Linguistic terms	Range of values (ppm)	Peak value
Low	0 - 10	5
Medium	8 - 35	20
High	30 - 100	60

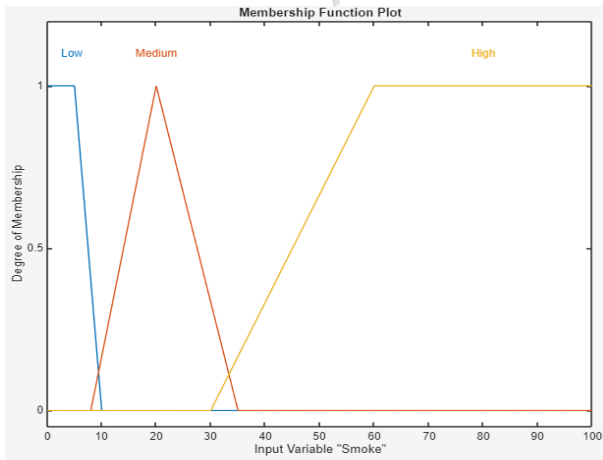


Fig. 9. Membership function plot for the Smoke sensor.

Figure 10 illustrates the membership function distribution for the input variable Gas within the Fuzzy Logic Controller used

in the air purification system. The Gas parameter is defined over a numerical range of 0 to 300, representing the concentration of airborne gaseous pollutants. This input is characterized using three membership functions: Low, Medium, and High, implemented as triangular and trapezoidal shapes to represent varying levels of gas pollution. As summarized in Table IV, the linguistic terms define Low as minimal gas presence, Medium as moderate gas concentration, and High as elevated gas levels, each corresponding to specific intensity ranges used for fuzzy inference and control decision-making.

TABLE IV
LINGUISTIC TERMS FOR THE GAS SENSOR WITH THEIR INTENSITY RANGE VALUES.

Linguistic terms	Range of values (ppm)	Peak value
Low	0 - 30	15
Medium	20 - 100	60
High	80 - 300	180

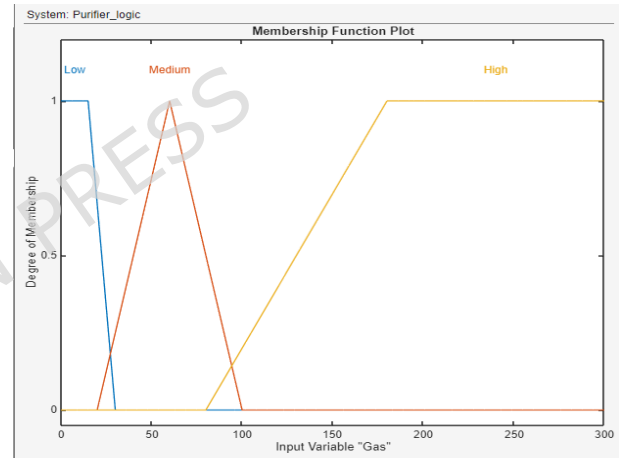


Fig. 10. Membership function plot for the Gas sensor.

Figure 11 illustrates the membership function distribution for the input variable VOC within the Fuzzy Logic Controller employed in the air purification system. The VOC parameter is defined over a numerical range of 0 to 2000, representing the concentration of volatile organic compounds in the indoor environment. This input is modeled using three membership functions: Low, Medium, and High, configured as triangular and trapezoidal shapes to characterize different levels of VOC contamination. As presented in Table V, the linguistic terms classify Low as minimal VOC presence, Medium as moderate VOC concentration, and High as elevated VOC levels, with each category assigned a specific intensity range to support fuzzy inference and intelligent control decision-making.

Figure 12 illustrates the membership function distribution for the input variable Temperature within the Fuzzy Logic Controller used in the air purification system. The Temperature parameter is defined over a specific numerical range, representing indoor ambient temperature measured in degrees

TABLE V
LINGUISTIC TERMS FOR THE VOC SENSOR WITH THEIR INTENSITY RANGE VALUES.

Linguistic terms	Range of values (ppb)	Peak value
Low	0 - 200	100
Medium	150 - 600	350
High	500 - 2000	1200

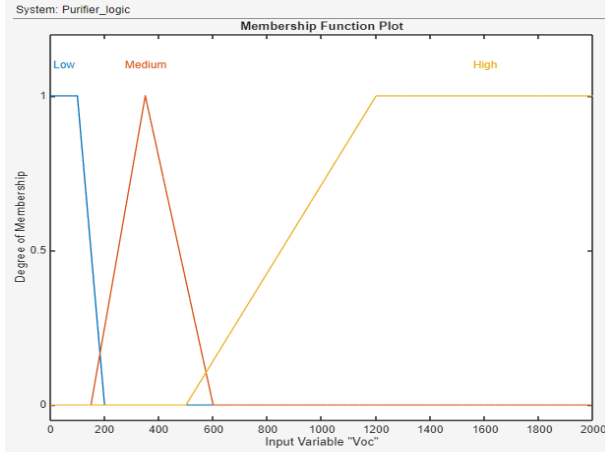


Fig. 11. Membership function plot for the VOC sensor.

Celsius. This input is modeled using three membership functions: Low, Medium, and High, configured as triangular and trapezoidal shapes to represent varying thermal conditions. As summarized in Table VI, the linguistic terms classify Low as a low ambient temperature, Medium as a moderate or comfortable temperature level, and High as an elevated temperature condition, with each category corresponding to a defined temperature range used for fuzzy inference and adaptive control decision-making.

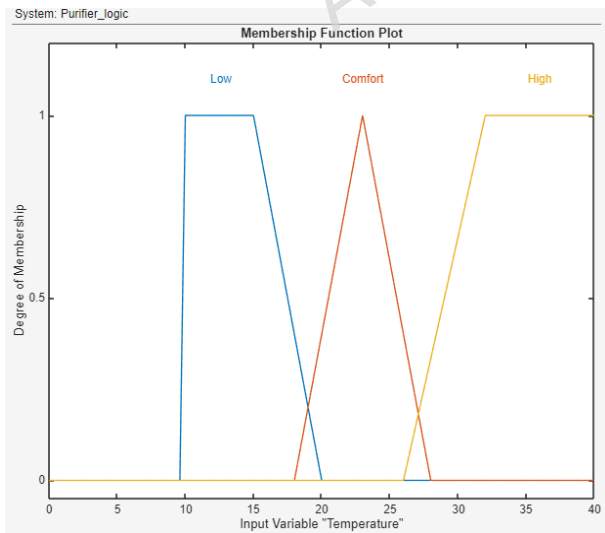


Fig. 12. Membership function plot for the Temperature sensor.

TABLE VI
LINGUISTIC TERMS FOR THE TEMPERATURE SENSOR WITH THEIR INTENSITY RANGE VALUES.

Linguistic terms	Range of values ($^{\circ}\text{C}$)	Peak value
Low	10 - 20	15
Medium	18 - 28	23
High	26 - 40	32

Figure 13 illustrates the membership function distribution for the input variable Humidity within the Fuzzy Logic Controller used in the air purification system. The Humidity parameter is defined over a specific numerical range, representing the indoor relative humidity level measured as a percentage (%). This input is modeled using three membership functions: Low, Medium, and High, configured as triangular and trapezoidal shapes to represent varying moisture conditions in the indoor environment. As summarized in Table VII, the linguistic terms classify Low as low relative humidity, Medium as moderate or comfortable humidity levels, and High as elevated humidity conditions, with each category corresponding to a defined humidity range used for fuzzy inference and adaptive control decision-making.

TABLE VII
LINGUISTIC TERMS FOR THE HUMIDITY SENSOR WITH THEIR INTENSITY RANGE VALUES.

Linguistic terms	Range of values (PH)	Peak value
Low	0 - 30	20
Medium	25 - 65	45
High	60 - 100	80

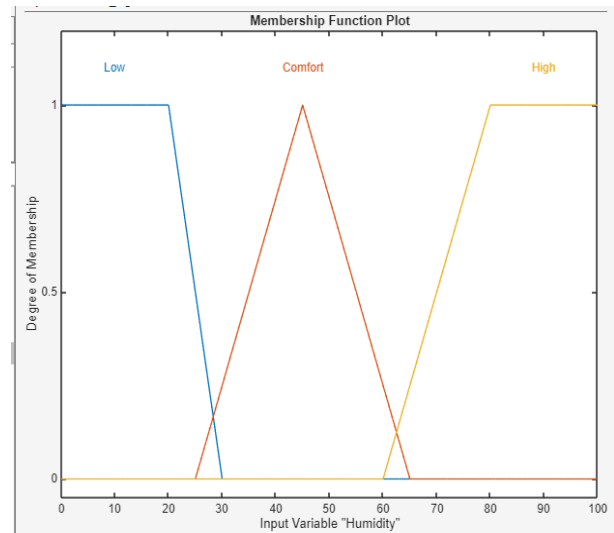


Fig. 13. Membership function plot for the Humidity sensor.

The figure 14 presents the membership function distribution for the output variable *Purifier* within the *Purifier_logic* fuzzy inference system, developed to regulate the operation of a 12V

air purifier. The purifier functions by using an internal fan to draw contaminated air through multiple filtration stages, including a pre-filter, HEPA filter, and activated carbon, enabling the removal of dust particles, allergens, and odors. The output variable is defined over a numerical range of 0 to 12, representing the control voltage supplied to the purifier actuator. Based on the system design, the output is partitioned into four linguistic membership functions: *Off*, *Medium*, *High*, and *Max* corresponding to increasing voltage levels stated in Table VIII. Through the defuzzification process, the fuzzy controller converts inferred rule outputs into a crisp voltage signal, allowing smooth and proportional adjustment of purifier operating intensity from complete shutdown to maximum fan speed.

TABLE VIII
LINGUISTIC TERMS FOR THE PURIFIER ACTUATOR WITH THEIR INTENSITY RANGE VALUES.

Linguistic terms	Range of values (V)
Off	0 - 6
Medium	5 - 9
High	8 - 10
Max	9 - 12

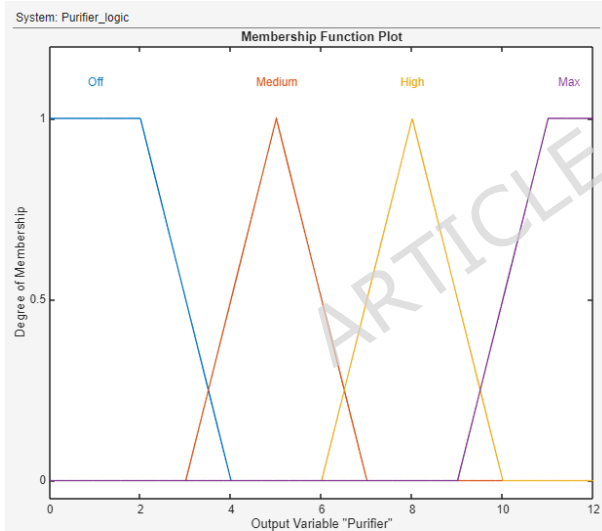


Fig. 14. Membership function plot for the purifier actuator.

After testing and evaluating the created *Purifier_logic* system, it was exported out of the MATLAB Fuzzy Logic Designer as a file named '*Purifier_logic*', ready for integration into the Simulink Model.

B. Derivation of the Transfer Function for the Air Purification Control Actuator

The air purifier actuator consists of a DC motor driving a centrifugal or axial fan. The input is applied voltage $V(t)$, and the output is volumetric airflow rate $Q(t)$.

The physical chain is:

$V(t) \rightarrow \text{motor torque} \rightarrow \text{fan speed} \rightarrow \text{airflow} \rightarrow \text{filtration} \rightarrow \text{clean air out}$

Applying Kirchhoff's voltage law to the armature circuit gives equation 1 [26], [27];

$$V_c(t) = R_a i_a(t) + L_a \frac{di_a(t)}{dt} + e_b(t) \quad (1)$$

where:

- R_a = armature resistance [Ω]
- L_a = armature inductance [H]
- $e_b(t)$ = back EMF [V]
- $i_a(t)$ = armature current [A]

The back EMF is generated when the rotating armature cuts through the magnetic field, producing a voltage that opposes the applied voltage. It is proportional to angular velocity stated in equation 2.

$$e_b(t) = K_b \omega(t) \quad (2)$$

where:

- K_b = back EMF constant [V·s/rad]
- $\omega(t)$ = fan angular speed [rad/s]

Substituting equation 2 into 1 gives equation 3.

$$V_c(t) = R_a i_a(t) + L_a \frac{di_a(t)}{dt} + K_b \omega(t) \quad (3)$$

Taking the Laplace transform of Equation 3 with zero initial conditions gives Equation 4:

$$V_c(s) = (R_a + L_a s) I_a(s) + K_b \Omega(s) \quad (4)$$

The Mechanical rotational dynamic equation is given in Equation 5 [38].

$$J \frac{d\omega(t)}{dt} = T_m(t) - B\omega(t) - T_L(t) \quad (5)$$

where:

- J = moment of inertia of fan + rotor [$\text{kg}\cdot\text{m}^2$]
- B = viscous damping coefficient [$\text{N}\cdot\text{m}\cdot\text{s}/\text{rad}$]
- $T_L(t)$ = load torque from airflow resistance

The motor torque is stated in Equation 6.

$$T_m(t) = K_t i_a(t) \quad (6)$$

where K_t = torque constant [$\text{N}\cdot\text{m}/\text{A}$]; for SI units $K_t = K_b$.

Substituting Equation 6 into Equation 5 gives Equation 7.

$$J \frac{d\omega(t)}{dt} = K_t i_a(t) - B\omega(t) - T_L(t) \quad (7)$$

For a fan, load torque is proportional to the square of speed (fan affinity law) stated in Equation 9.

$$T_L(t) = k_f \omega(t)^2 \quad (8)$$

For **small-signal linearization** around operating point ω_0 stated in Equation

$$T_L(t) \approx k_f \omega_0^2 + 2k_f \omega_0 \cdot \Delta\omega(t) \quad (9)$$

Thus;

$$T_L(t) \approx 2k_f \omega_0 \cdot \omega(t) \quad (10)$$

Substitute Equation 10 into 7 gives Equation 11.

$$J \frac{d\omega(t)}{dt} = K_t i_a(t) - B\omega(t) - 2k_f \omega_0 \cdot \omega(t) \quad (11)$$

Factorize out $\omega(t)$ in Equation 11 gives Equation 12.

$$J \frac{d\omega(t)}{dt} = K_t i_a(t) - (B + 2k_f \omega_0) \cdot \omega(t) \quad (12)$$

The linearized aerodynamic damping is given in Equation 13.

$$B_L = 2k_f \omega_0 \quad (13)$$

Substitute Equation 13 into Equation 12 gives Equation 14.

$$J \frac{d\omega(t)}{dt} = K_t i_a(t) - (B + B_L) \cdot \omega(t) \quad (14)$$

The effective or total damping is given in Equation 15.

$$B_{\text{total}} = B + B_L \quad (15)$$

Substitute Equation 15 into Equation 14, and rearranging it gives Equation 16.

$$J \frac{d\omega(t)}{dt} + B_{\text{total}} \cdot \omega(t) = K_t i_a(t) \quad (16)$$

Taking the Laplace transform of Equation 16 with zero initial conditions gives Equation 17.

$$(Js + B_{\text{total}})\Omega(s) = K_t I_a(s) \quad (17)$$

Make $I_a(s)$ the subject of Equation 17 gives Equation 18.

$$I_a(s) = \frac{Js + B_{\text{total}}}{K_t} \Omega(s) \quad (18)$$

Substitute Equation 18 into Equation 4 gives Equation 19.

$$V(s) = (R_a + L_a s) \frac{Js + B_{\text{total}}}{K_t} \Omega(s) + K_b \Omega(s) \quad (19)$$

Factor $\Omega(s)$ in Equation 19 gives Equation 20.

$$V(s) = \left[\frac{(R_a + L_a s)(Js + B_{\text{total}})}{K_t} + K_b \right] \Omega(s) \quad (20)$$

Then, $\frac{\Omega(s)}{V(s)}$ from Equation 20 gives Equation 21;

$$\frac{\Omega(s)}{V(s)} = \frac{K_t}{(R_a + L_a s)(Js + B_{\text{total}}) + K_b K_t} \quad (21)$$

The Fan airflow $Q(t)$ [m³/s] is proportional to speed for fixed geometry stated in Equation 22:

$$Q(t) = K_Q \omega(t) \quad (22)$$

where K_Q = fan constant [m³/rad]. Taking the Laplace transform on Equation 22 gives Equation 24.

$$Q(s) = K_Q \Omega(s) \quad (23)$$

Substitute Equation 24 into Equation 21 gives Equation 24.

$$\frac{Q(s)}{V(s)} = \frac{K_Q K_t}{(R_a + L_a s)(Js + B_{\text{total}}) + K_b K_t} \quad (24)$$

The Transfer function $T(s)$ is given by Equation 25.

$$T(s) = \frac{Q(s)}{V(s)} \quad (25)$$

Thus, the transfer function of the purifier actuator is given in Equation 26.

$$T(s) = \frac{K_Q K_t}{(R_a + L_a s)(Js + B_{\text{total}}) + K_b K_t} \quad (26)$$

C. Simulation and testing of a Multi-Parameter Indoor Air Purification Control System Circuit

The Air purification system was simulated following the circuit diagram in the figure. The desired control action for the system was determined using the fuzzy rules generated using the multiple linguistic terms of each of the input sensor parameters.

The testing process begins by letting each sensor generate data corresponding to different scenarios, including when there is little smoke in the breathing air, when there is much smoke in the breathing air, when the room is hot, when the room is cold, when the room has low air moisture, when the room has high air moisture, and others. These simulated sensor outputs were fed into the fuzzy-PID controller.

The Fuzzy-PID parameters K_p , K_i , and K_d were tuned (following the functions in Appendix VII-A) and optimized using the GA iteration code to achieve minimal errors. The parameters that consist of population size, crossover rate, mutation rate, number of generations, and their respective values were listed in a table IX. The parameters were specified as either user-defined or randomly initialized, and their recommended values based on the application were provided.

TABLE IX
THE GENETIC ALGORITHM PARAMETERS

Parameter	Value	Type	Recommendation
Population Size	150	User-Defined	100–200
Max Generations	100	User-Defined	50–150
Crossover Fraction	0.85	User-Defined	0.7–0.9
Elite Count	10% of PopSize	User-Defined	5%–15%
Function Tolerance	1e-8	User-Defined	1e-6 to 1e-8
Initial Population	Random (bounded by lb, ub)	Random Initialization	Ensure realistic bounds
Mutation Rate	Adaptive (not defined)	Random Initialization	1%–5% (if specified)

The final output from the GA-Fuzzy-PID controller dictates the state and intensity of the air purification system. The simulation environment enabled testing of the feedback loop,

ensuring that sensor data was correctly used in real time to adjust the system's operation.

III. RESULTS

A. Design of a Multi-Parameter Indoor Air Purification Control System Circuit

The figure 15 shows a MATLAB simulation circuit diagram of a Multi-Parameter Indoor Air Purification Control System. A network of six environmental sensors, namely, dust, smoke, gas, VOC, temperature, and humidity, each generates analog signals that are first conditioned or scaled to ensure compatibility despite differing physical units and dynamics. The conditioned sensor outputs are merged via a multiplexer block to produce a single composite input vector that characterizes the instantaneous indoor air quality condition. This consolidated signal is then supplied to a fuzzy logic controller (FLC), where predefined linguistic rules and membership functions transform the multi-variable input space into a unified control signal. The created fuzzy logic file with set rules is uploaded into this FLC.

The FLC output is sent to a genetically optimized fuzzy-PID controller, where a genetic algorithm has tuned the PID gains to minimize performance indices such as settling time and steady-state error to produce an adaptive and high-performance control signal. The control signal drives an identical second-order plant characterized by the transfer function shown in the equation 27, ensuring that differences in output responses arise from the control strategies rather than plant variability. Finally, the performance of the plant is shown using the scope, and a feedback signal is sent back to cater for errors.

Figure 16 shows a structural circuit for the "GA-tuned fuzzy PID" subsystem. The PID constants were tuned and determined by the GA.

B. Derivation of the Transfer Function for the Air Purification Control Actuator

The transfer function of the purifier actuator was derived in the methods section and is repeated in Equation 27.

$$T(s) = \frac{K_Q K_t}{(R_a + L_a s)(J s + B_{\text{total}}) + K_b K_t} \quad (27)$$

The constants in the equation 27 are stated in the table X [37], [38].

Substituting the used values stated in the table X into equation 27 gives equation 28.

$$T(s) = \frac{0.85 \times 0.776}{(0.91030 + 6.46 \times 10^{-3} s) \times (1.40 \times 10^{-4} s + 6.96 \times 10^{-4}) + 0.07445 \times 0.776} \quad (28)$$

TABLE X
SUMMARY OF CONSTANTS USED IN THE AIR PURIFIER CONTROL SYSTEM MODEL .

Symbol	Name	Typical Range [37], [38]	Used Value	Unit
R_a	Armature resistance	0.5–5	0.91030 [45]	Ω
L_a	Armature inductance	0.1–10	6.46 [45]	mH
K_t	Torque constant	0.01–0.1	0.776 [46]	N m A^{-1}
K_b	Back EMF constant	0.01–0.1	0.07445 [45]	V s rad^{-1}
J_s	Rotor + fan inertia	10^{-5} – 10^{-3}	1.40×10^{-4} [45]	kg m^2
B	Total damping	10^{-5} – 10^{-4}	6.96×10^{-4} [45]	N m s rad^{-1}
K_Q	Fan airflow constant	0.1–1	0.85 [47]	$\text{m}^3 \text{ rad}^{-1}$

Multiplying and opening brackets in equation 28 gives equation 29.

$$T(s) = \frac{0.6596}{9.044 \times 10^{-7} s^2 + 1.3193816 \times 10^{-4} s + 0.0584247688} \quad (29)$$

Factorizing out 0.0025 from the denominator and numerator of the equation 29 gives equation 30.

$$T(s) = \frac{729307.83}{s^2 + 145.88 s + 64600.14} \quad (30)$$

C. Simulation and testing of a Multi-Parameter Indoor Air Purification Control System Circuit

Using the MATLAB simulation circuit diagram in the figure 15, the designed fuzzy logic files were imported into the fuzzy logic blocks in the circuit, and the 'GA tuned fuzzy PID' subsystem in figure 16.

The figure 17 shows the sensor signals generated from the sensors regarding the tables II, III, IV, V, VI, and VII. The graph shows the behaviour of the Dust, smoke, gas, temperature, humidity, and VOC sensors across their respective ranges of intensity.

The fuzzy logic control file was imported into the fuzzy logic block in figure 16. The designed GA code was run to make values of Kp, Ki, and Kd available in the Matlab workspace so that they are automatically fed into the constant blocks in figure 16.

1) *PID parameter Tuning using GA:* The GA iteration code was tested in Matlab for optimizing and best tuning the PID constants of the transfer function to ensure high accuracy and fewer steady-state errors.

The graph 21 shows the closed-loop step response of a system controlled by an optimized PID controller. The output response quickly rose and settled at a steady-state value of

approximately 1, with minimal overshoot and no noticeable oscillations. This indicated a well-tuned PID controller that provided a fast response time and maintained stability, achieving the desired output without significant steady-state error.

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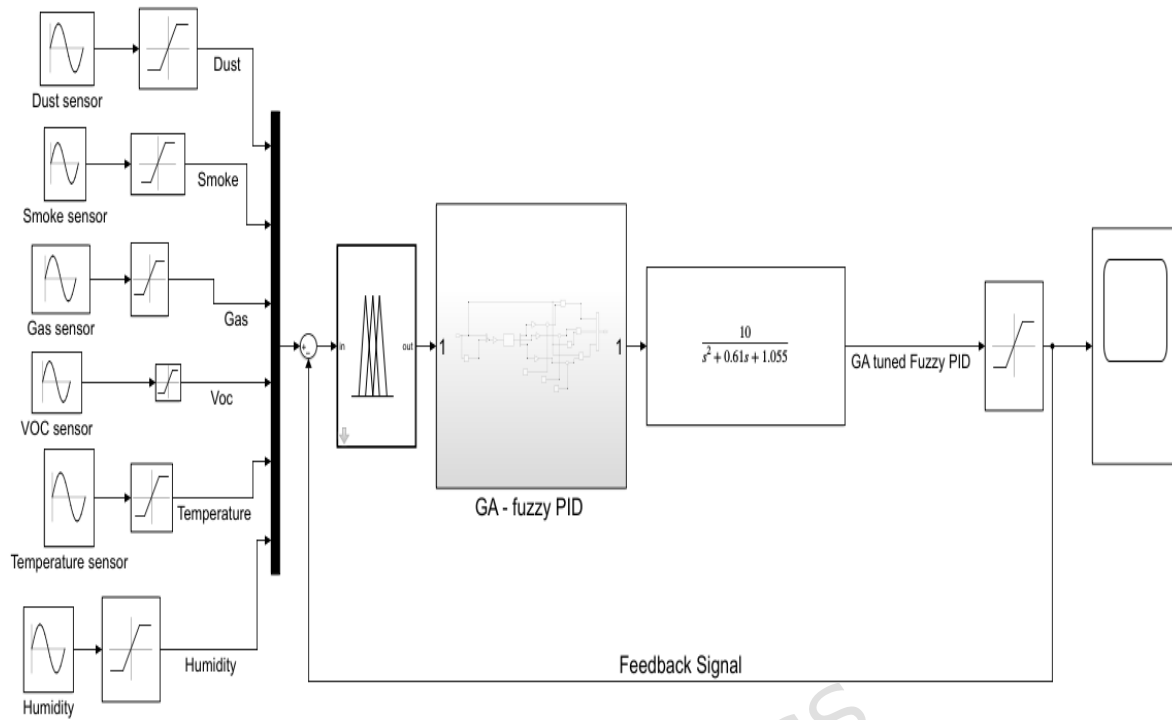


Fig. 15. This circuit diagram illustrates a simulation diagram of a Multi-Parameter Indoor Air Purification Control System Circuit

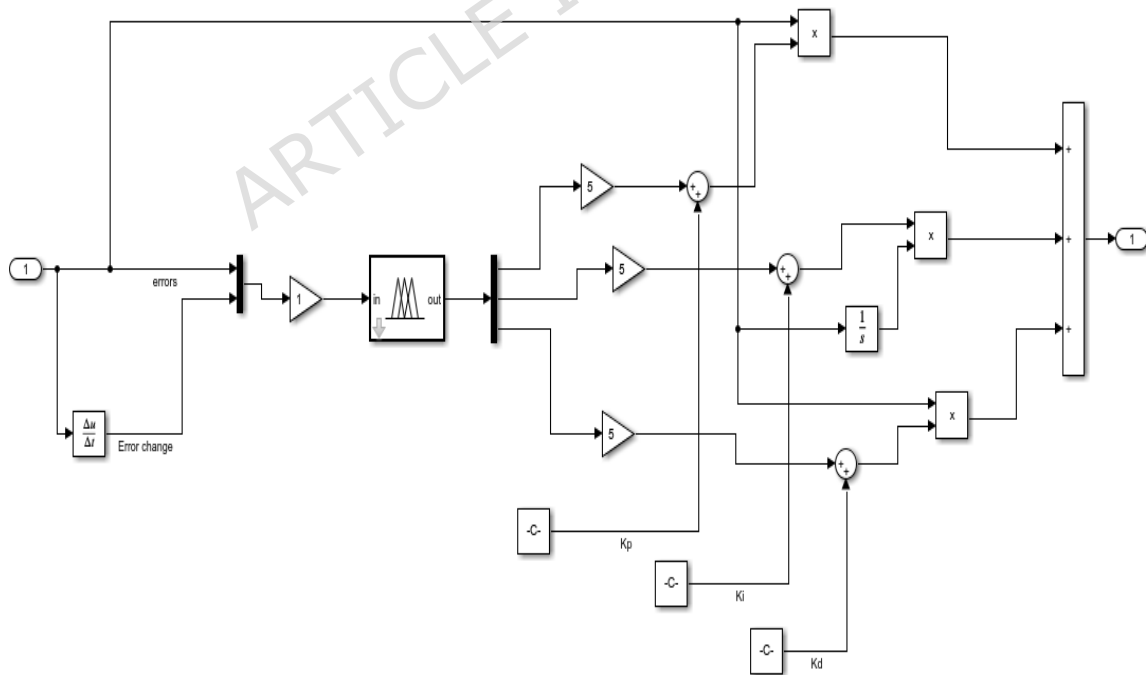


Fig. 16. This circuit diagram illustrates a Simulation diagram of a GA tuned fuzzy PID subsystem Circuit

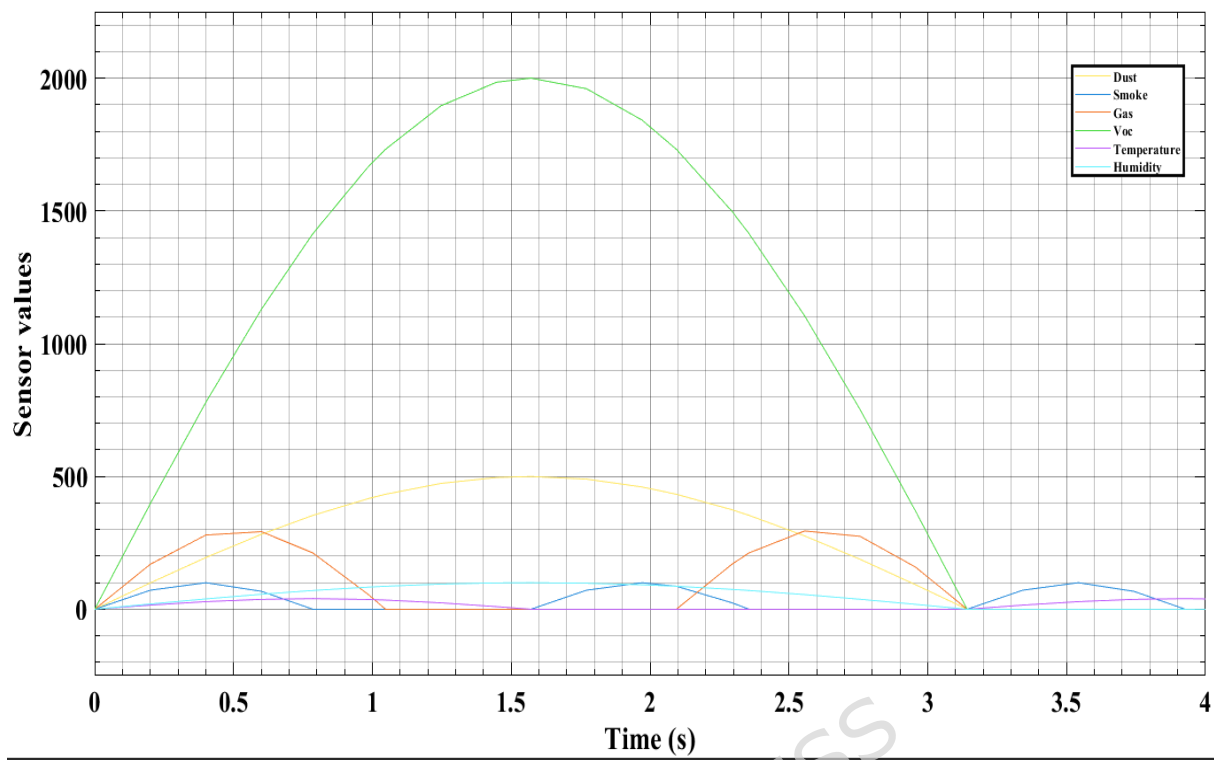


Fig. 17. A graph illustrating realistic indoor environmental events such as cooking smoke generation, increased particulate matter due to dust disturbance, VOC release from household products, elevated CO₂ caused by poor ventilation or human occupancy, and temperature/humidity fluctuations associated with occupancy and environmental changes.

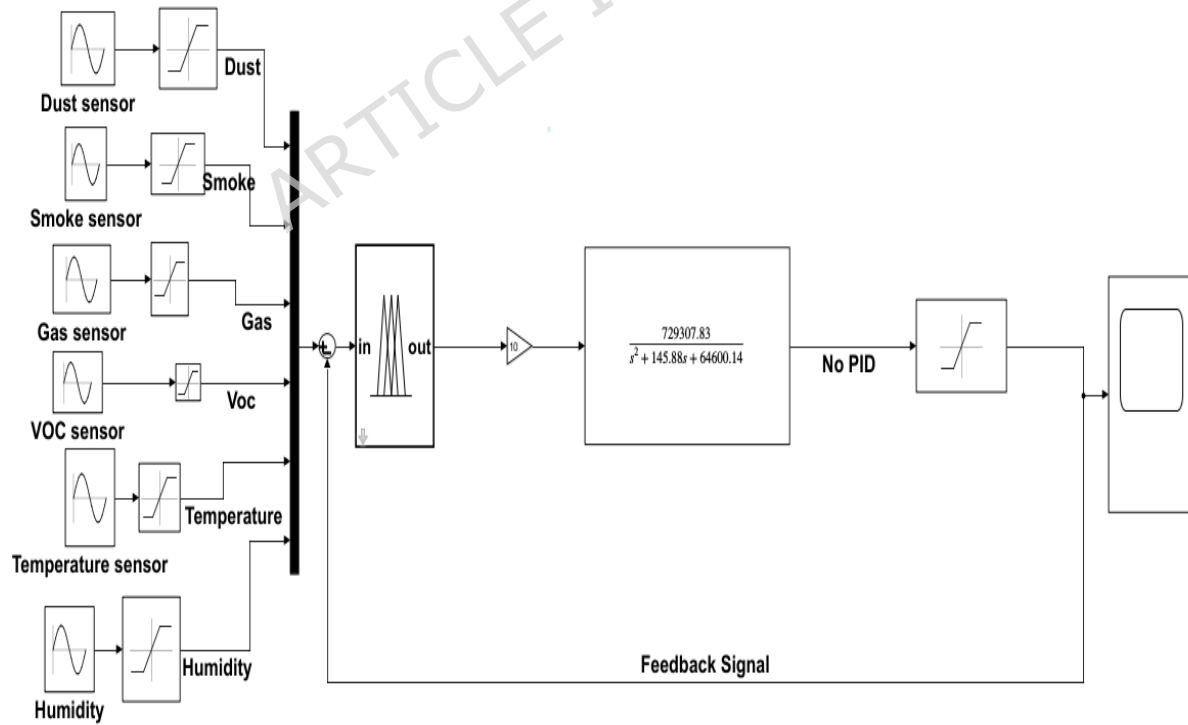


Fig. 18. This circuit diagram illustrates a simulation diagram of a Multi-Parameter Indoor Air Purification Control System Circuit without a PID

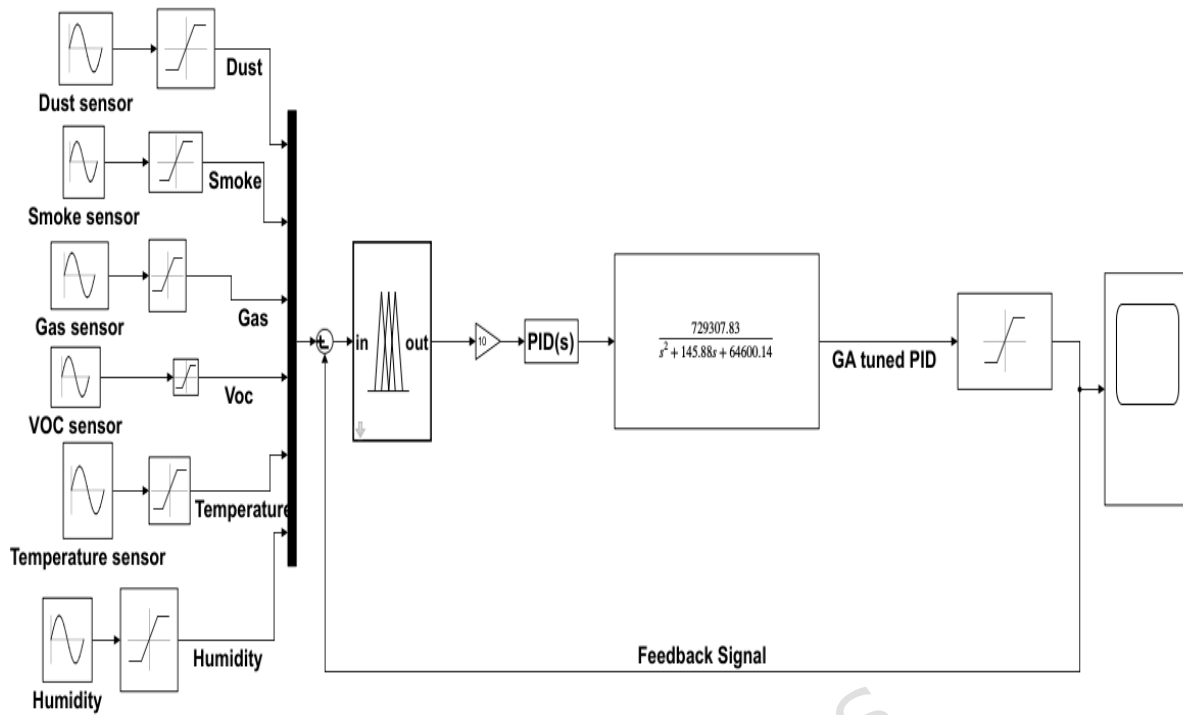


Fig. 19. This circuit diagram illustrates a simulation diagram of a Multi-Parameter Indoor Air Purification Control System Circuit with PID tuned by GA

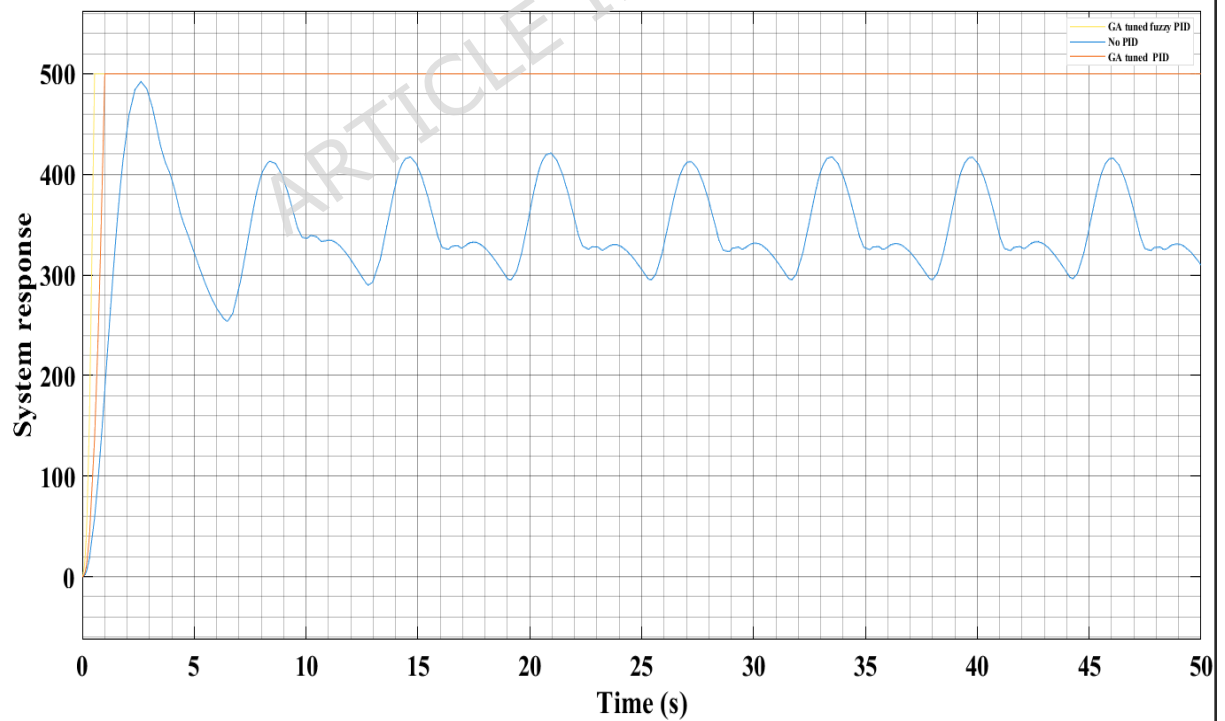


Fig. 20. Comparison of step response behaviours for the air purification system. The graphs illustrate the performance of three control strategies: GA-tuned fuzzy-PID, GA-tuned PID, and no PID, highlighting improvements in response time and system stability.

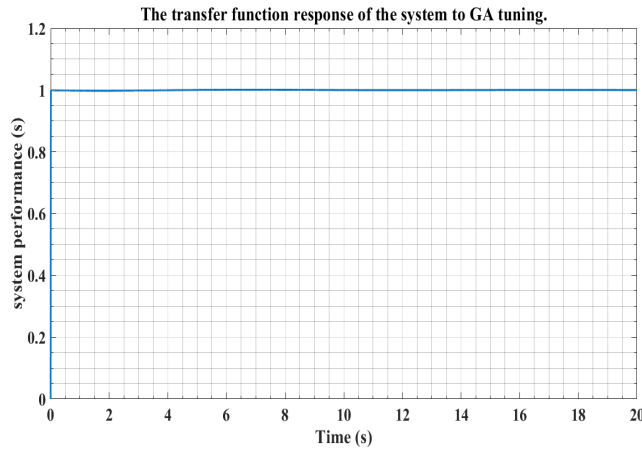


Fig. 21. Closed-loop step response of a PID controller tuned using a Genetic Algorithm. The optimized controller exhibits fast response time, minimal overshoot, and improved steady-state performance in regulating light intensity.

After the GA code had fine-tuned the derived bulb's transfer function, the best and fitness values were given as; $K_p = 15.09$, $K_i = 12.27$, and $K_d = 30$.

The PID controller has a standard transfer function $P(s)$ (frequency domain) [29], [36];

$$P(s) = K_p + \frac{K_i}{s} + K_d s \quad (31)$$

By substituting the PID constants into the equation 31. Then, the transfer function of the PID controller with the variation of the transfer function of the bulb for the air purification system became:

$$P(s) = 15.09 + \frac{12.27}{s} + 30s \quad (32)$$

The system in figure 15 was used to develop and test two scenarios for comparative analysis: The first scenario in the figure 18 shows a system with no PID integrated in it. The second scenario in the figure shows a system with a conventional PID controller whose parameters were tuned by GA.

A gain block in Figures 18 and 19 with a value of 10 is incorporated between the fuzzy logic controller and the PID controller to scale the fuzzy controller output before it is used for PID gain adjustment. Since the fuzzy controller generates outputs within a relatively small normalized range, directly applying these outputs may result in insufficient control action. The gain factor amplifies the fuzzy output signal, thereby enhancing the PID controller's sensitivity and responsiveness. The gain value was selected through simulation-based tuning to achieve an appropriate balance between system responsiveness, stability, and control performance.

The Matlab simulation was run for 50 seconds. Figure

20 shows a graph elaborating the step response behaviour of the Multi-Parameter Indoor Air Purification Control System in three different scenarios under the use of: GA tuned PID controller, no PID, and GA tuned fuzzy PID controller. The graph compares three control systems for regulating Air Purification Control over time: no PID controller (blue line), GA-tuned fuzzy-PID controller (yellow line), and GA-tuned PID controller (red line).

IV. DISCUSSION

A. Performance of the Proposed GA-tuned Fuzzy-PID Controller in Air Purification

The MATLAB simulation results demonstrate that the proposed GA-tuned fuzzy-PID control system significantly outperforms both conventional PID and open-loop (no PID) strategies in regulating indoor air quality. As shown in Figure 20, the GA-tuned fuzzy-PID controller achieved the fastest rise time, negligible overshoot, and the shortest settling time compared to the standalone GA-tuned PID and the uncontrolled response.

The fuzzy logic enabled context-aware control decisions, while the GA effectively minimized steady-state error and settling time by identifying near-optimal PID gains ($K_p = 15.09$, $K_i = 12.27$, $K_d = 30$). The closed-loop step response (Figure 21) confirmed that the optimized controller maintained stability and accuracy, reaching a steady-state value of approximately 1 with minimal oscillation. Furthermore, the inclusion of a feedback loop from the purifier actuator allowed real-time compensation for disturbances, such as changes in fan load torque due to filter clogging or varying airflow resistance.

Table XI compares the proposed GA-tuned fuzzy-PID controller findings on transient response with those of other system findings. The results show that the GA-tuned fuzzy-PID achieved faster response times, making it more effective for dynamic applications and handling nonlinearities.

TABLE XI

THE COMPARISON OF THE FINDINGS OF OTHER SYSTEMS USING PID AND FUZZY PID WITH MY PROPOSED FINDINGS FOR GA TUNED FUZZY-PID

	[28]		[39]	Proposed system
	PID	Fuzzy PID	fuzzy PID	GA tuned fuzzy PID
Rise time (s)	0.009	0.001	0.073	0.06
Settling time (s)	43.33	2.28	0.092	0.009
Overshoot	8.5	2.25	0	0
Peak time (s)	-	-	-	0.250

B. Simulink Model for Pollutant Removal Performance Evaluation

1) Design of the pollutant removal model:

The figure 22 illustrates the Simulink-based implementation

of the pollutant removal model developed to assess the air purification efficiency of the proposed GA-tuned fuzzy-PID controller. The model was designed to simulate the dynamic removal process of four major indoor air pollutants, namely dust, smoke, gas, and volatile organic compounds (VOC), under closed-loop control operation. At the input stage, four independent step signal generators were incorporated to represent the initial concentrations of indoor pollutants caused by sudden contamination events such as dust infiltration, cooking smoke, gas buildup, and VOC emissions from household materials. These input signals emulate realistic indoor air quality disturbances that require immediate and effective purification control.

The output signal from the GA-tuned fuzzy-PID controller was introduced as the control input to the system and distributed across all pollutant channels simultaneously. Each pollutant path includes a summation block, where the controller output is subtracted from the pollutant input, representing the reduction effect produced by the purifier fan and filtration mechanism.

To model the physical filtration dynamics of the purifier, each pollutant channel was represented using a first-order transfer function of the form (explained in Appendix VII-B):

$$G(s) = \frac{1}{\tau s + 1} \quad (33)$$

where τ represents the purification time constant of the corresponding pollutant. Different time constants were assigned to reflect varying filtration rates as follows:

- Dust: $\frac{1}{8s+1}$
- Smoke: $\frac{1}{5s+1}$
- Gas: $\frac{1}{12s+1}$
- VOC: $\frac{1}{15s+1}$

These transfer functions represent the dynamic response of the purifier filters, capturing how quickly each pollutant is removed based on its physical characteristics and interactions with the filters. Smoke was assigned the shortest time constant due to its faster removal, while VOC was assigned the largest time constant because gaseous compounds typically require longer adsorption time.

Following each transfer function block, saturation blocks were used to ensure that pollutant concentrations remained within physically meaningful bounds and did not become negative during simulation. Finally, the outputs of all four pollutant channels were combined through a multiplexer (MUX) and connected to a scope block, enabling simultaneous visualization of pollutant concentration decay over time.

2) Purification Performance Analysis:

The figure 23 illustrates the purification performance of the proposed GA-tuned fuzzy-PID indoor air purification system by showing the variation of pollutant concentration levels with time for four major indoor pollutants: dust, smoke,

gas, and volatile organic compounds (VOC). The horizontal axis (x-axis) represents time (seconds), while the vertical axis (y-axis) represents the pollutant concentration level.

From the graph, all pollutant concentrations exhibit a rapid decreasing trend, confirming the effectiveness of the proposed controller in reducing indoor contaminants within a short period. Initially, the VOC concentration shows the highest contamination level, starting at approximately 2000 units, indicating severe gaseous pollution. Under the control of the purifier, the VOC concentration decreases sharply and reaches a near-steady low concentration after approximately 2.4 seconds, demonstrating effective removal of gaseous pollutants.

Similarly, the dust concentration begins at approximately 480 units and decreases rapidly, reaching near zero after approximately 1.3 seconds, indicating efficient particulate matter removal. The gas concentration also shows a steady reduction from an initial concentration of approximately 160 units and approaches zero shortly after 1.2 seconds, confirming effective purification of harmful gases such as CO₂ and related airborne contaminants.

The smoke concentration exhibits the fastest decay, dropping from approximately 80 units to near zero within approximately 1.1 seconds. This demonstrates the ability of the proposed system to respond rapidly to sudden smoke-generating events such as cooking emissions or accidental indoor combustion.

Overall, the graph confirms that the proposed GA-tuned fuzzy-PID controller provides fast dynamic response, high purification efficiency, and stable pollutant reduction across multiple indoor contaminants. The absence of oscillations or overshoot in all pollutant curves further demonstrates the robustness and stability of the control strategy, making it suitable for real-time indoor air quality management applications.

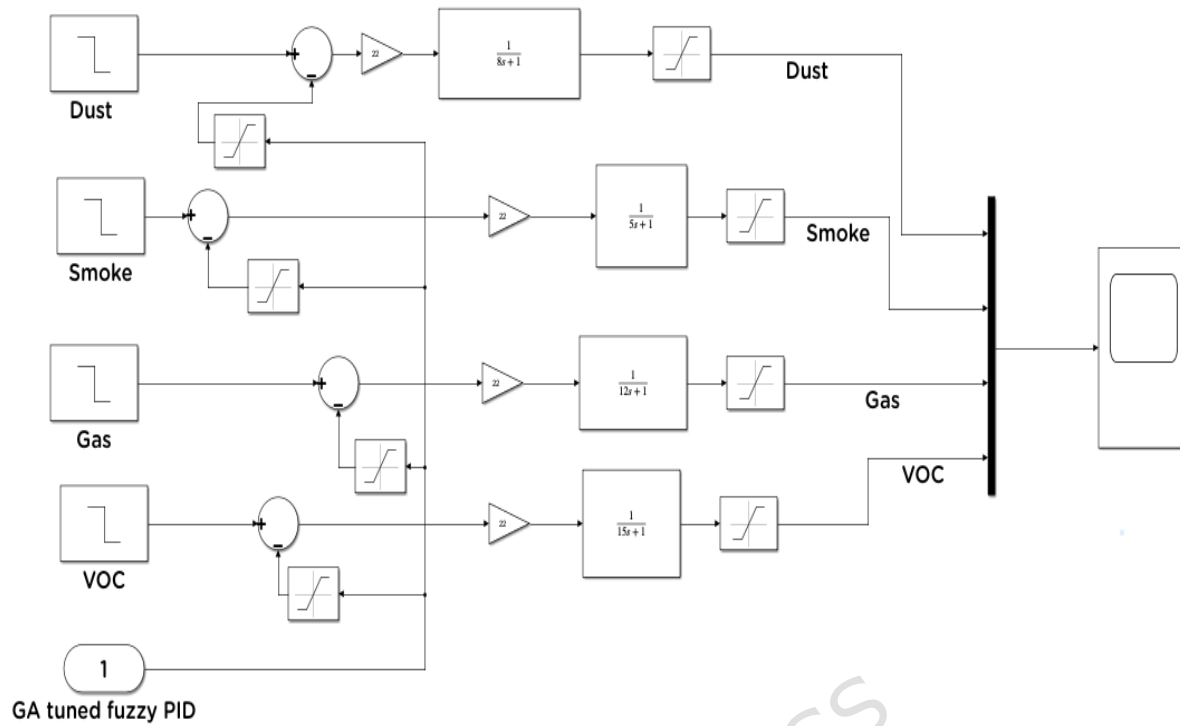


Fig. 22. Simulink pollutant removal model circuit for air purification of the proposed GA-tuned Fuzzy-PID controller with four pollutant input channels (dust, smoke, gas, and VOC) under closed-loop control conditions.

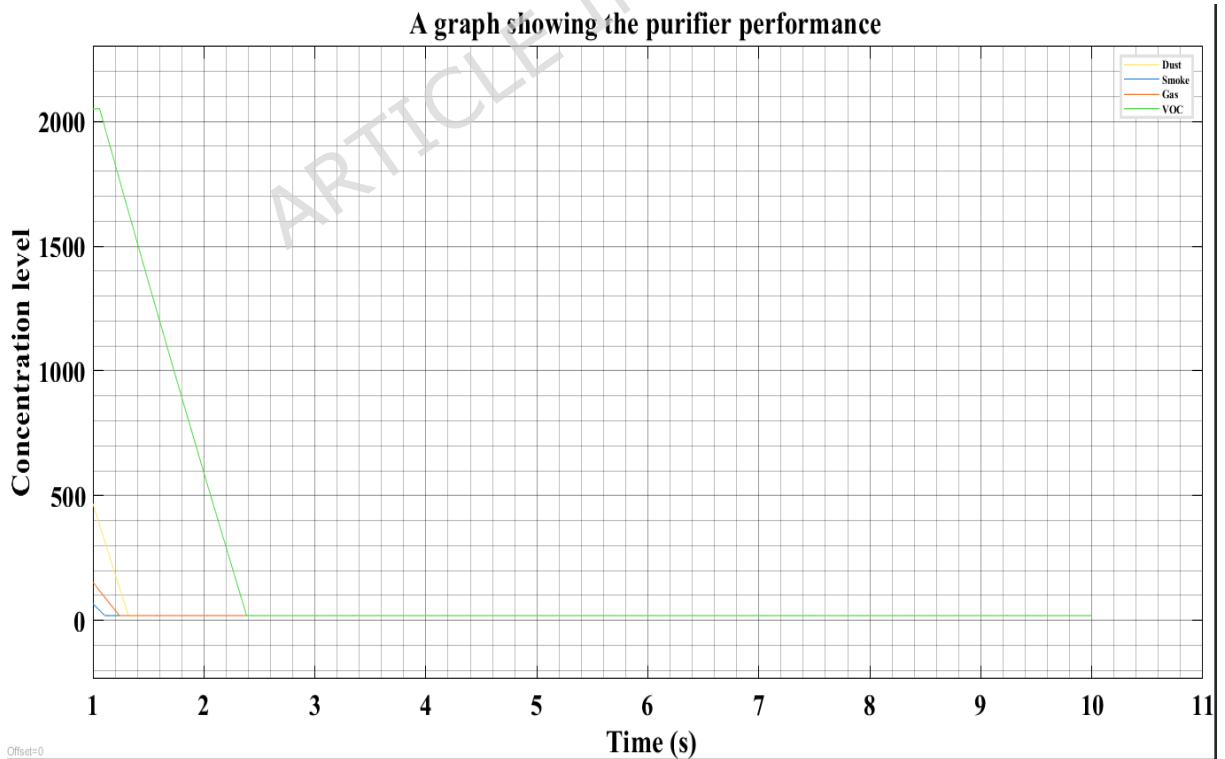


Fig. 23. Pollutant concentration control curves representing the purification performance of the proposed GA-tuned fuzzy-PID controller.

C. Mathematical Model of an Indoor Air Purification System Accounting for Realistic Physical and Environmental Factors

The model goes beyond an idealized simulation by incorporating practical phenomena such as room-air mixing, pollutant transport, fan inertia, filter dynamics, and sensor noise. The fan motor transfer function characterizes the electromechanical response of the blower unit. The fan inertia model accounts for the delay associated with blade acceleration and deceleration. The room-air mixing subsystem represents the circulation and homogenization of air within the enclosed environment, while the pollutant transport model captures the gradual removal and dilution of airborne contaminants. Finally, the sensor dynamics account for the finite response time of the air-quality sensing unit.

The overall indoor air purification system is modeled as a cascade of five subsystems, namely the fan motor dynamics, fan inertia, room-air mixing dynamics, pollutant transport dynamics, and sensor dynamics. The overall transfer function is expressed as

$$G_{\text{total}}(s) = G_{\text{motor}}(s) G_{\text{fan}}(s) G_{\text{mix}}(s) G_{\text{pollutant}}(s) G_{\text{sensor}}(s) \quad (34)$$

The fan motor dynamics are represented by

$$G_{\text{motor}}(s) = \frac{729307.83}{s^2 + 145.88s + 64600.14} \quad (35)$$

The fan inertia is modeled as a first-order lag system given by

$$G_{\text{fan}}(s) = \frac{1}{0.5s + 1} \quad (36)$$

The room-air mixing process is represented by

$$G_{\text{mix}}(s) = \frac{1}{30s + 1} \quad (37)$$

The pollutant transport and removal dynamics are modeled as

$$G_{\text{pollutant}}(s) = \frac{1}{60s + 1} \quad (38)$$

The sensor dynamics are represented by

$$G_{\text{sensor}}(s) = \frac{1}{5s + 1} \quad (39)$$

Substituting Equations (35)–(39) into Equation (34) yields

$$G_{\text{total}}(s) = \frac{729307.83}{(s^2 + 145.88s + 64600.14)(0.5s + 1)(30s + 1)} \times \frac{1}{(60s + 1)(5s + 1)} \quad (40)$$

The cascaded representation, therefore, provides a more physically realistic description of indoor air purification processes than a motor-only model. The GA code shown in Appendix VII-C was used to tune the transfer equation 40, which represents the air purifier along with other parameters considered: fan mass, airflow, and sensor dynamics (noise). The performance matrix is illustrated in Table XII.

TABLE XII
PERFORMANCE OF THE PROPOSED SYSTEM WITH DIFFERENT SUBSYSTEMS ACCOUNTING FOR THE REAL-WORLD OPERATION.

Performance matrix	value
Rise time (s)	53.93
Settling time (s)	119.99
Overshoot (%)	2.14
Peak time (s)	111.50

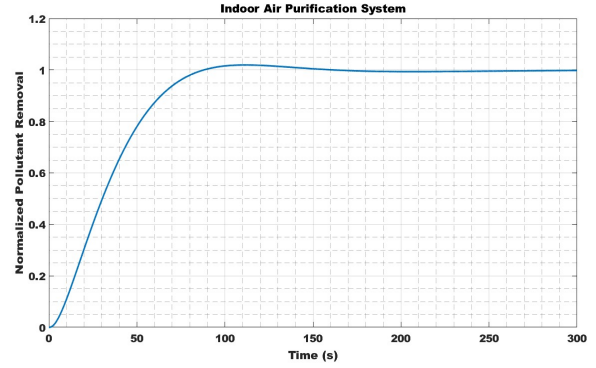


Fig. 24. A figure showing Closed-loop normalized pollutant removal response of the proposed indoor air purification system using the GA-tuned Fuzzy-PID controller after incorporating realistic physical constraints, including fan blade inertia, motor dynamics, room-air mixing, pollutant transport, filtration effects, and sensor noise.

Figure 24 presents the closed-loop step response of the proposed indoor air purification system after integrating realistic physical subsystems to represent practical operating conditions. The mathematical model incorporates key real-world factors, including fan blade inertia, motor start-up dynamics, airflow resistance, room volume, air mixing, filter loading, and environmental sensor noise, thereby providing a more realistic representation of the system dynamics. The overall system is regulated by the proposed GA-tuned Fuzzy-PID controller.

At the start of the simulation, the normalized pollutant removal is zero because the purifier has not yet responded to the indoor air quality conditions. As the controller processes the sensor measurements, the purifier output increases progressively, resulting in a rapid improvement in pollutant removal efficiency. The response reaches the desired normalized removal level after approximately 100 s, exhibiting a small overshoot of about 2%, which indicates a fast yet well-controlled transient response. Subsequently, the response gradually converges to the desired steady-state value and settles within approximately 170–180 s, with negligible oscillations and zero steady-state error.

These results demonstrate that the proposed GA-tuned Fuzzy-PID controller achieves a stable, well-damped, and accurate closed-loop response while maintaining effective long-term pollutant removal performance. In particular,

the response time of several minutes is consistent with the expected dynamics of practical air purification systems, where fan inertia, room air circulation, pollutant transport, filtration processes, and sensor dynamics inherently limit the speed at which contaminants can be removed from an enclosed environment.

V. CONCLUSION

This study successfully addressed the research gap in developing an intelligent, low-latency, and multi-parameter indoor air purification system suitable for resource-constrained environments where cloud-based solutions are often unreliable. A novel control framework integrating six environmental sensors with a GA-optimized Fuzzy-PID controller was proposed, modeled, and simulated to enhance indoor air quality management.

The genetic algorithm effectively optimized the PID controller gains, resulting in reduced steady-state error and improved transient performance, while the fuzzy logic controller facilitated intelligent rule-based decision-making for multiple indoor air pollutants. Under the initial idealized simulation model, the proposed GA-tuned Fuzzy-PID controller demonstrated superior dynamic performance compared with the GA-tuned PID controller and the uncontrolled system, achieving a rise time of 0.06 s, a peak time of 0.250 s, and a settling time of 0.009 s. Under the realistic operating conditions, the proposed controller incorporating physical and environmental factors achieved a rise time of 53.93 s, a settling time of 119.99 s, and a maximum overshoot of 2.14%, demonstrating a stable, well-damped response that is consistent with the expected dynamics of real indoor air purification systems.

The developed system also achieved effective and rapid removal of multiple indoor pollutants, including dust, smoke, gas, and VOC, confirming the robustness of the control strategy under dynamic operating conditions. In addition, the derivation of a first-principles actuator transfer function (Equation 26) established a strong theoretical foundation for future hardware implementation and experimental validation. The network-independent design further highlights the suitability of the system for deployment in low-resource regions such as Uganda.

However, the study was limited to MATLAB/Simulink simulations, and practical validation using real hardware remains necessary. Furthermore, the simplified pollutant dynamics model and the lack of energy consumption analysis represent important areas for future improvement and investigation.

Future work should focus on the practical implementation and further enhancement of the proposed indoor air purification system through several key directions.

- A low-cost hardware prototype should be developed using embedded platforms such as ESP32 or Arduino, integrating the six environmental sensors and implementing the GA-tuned Fuzzy-PID controller in real-time firmware.
- An extensive experimental validation should be carried out through controlled laboratory testing and field deployment in residential and commercial buildings, particularly in Uganda, to evaluate long-term reliability, energy efficiency, and user acceptance under real operating conditions.
- The GA optimization framework should be further improved by exploring adaptive mutation strategies, alternative objective functions, and real-time online tuning methods to enhance controller adaptability and robustness.

VI. DECLARATIONS:

- 1) **Ethical approval::** Not applicable.
- 2) **Consent to participate::** Not applicable.
- 3) **Consent to publish::** Not applicable.
- 4) **Data availability::** The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.
- 5) **Competing Interests::** Authors have no conflict of interest to be disclosed.
- 6) **Funding::** No funding was received.
- 7) **Authors' contributions::** J.N.W. designed the system, A.A. wrote the main manuscript; M.A., R.M., and M.R.A. reviewed the manuscript.
- 8) **Clinical trial number:** Not applicable.

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VII. APPENDIX 1

A. Genetic Algorithm Objective Function

The Genetic Algorithm (GA) was employed to optimize the proportional-integral-derivative (PID) controller gains (K_p , K_i , K_d) by minimizing a predefined objective function

based on system performance criteria. The objective function evaluates the dynamic response of the proposed air purification control system to ensure improved accuracy, faster response, and minimal steady-state error.

1) *1. Integral Square Error (ISE)*: The Integral Square Error (ISE) was used as the primary fitness function to minimize the tracking error between the desired and actual system output. It is expressed as:

$$J = \int_0^T e^2(t) dt \quad (41)$$

where J represents the objective function, $e(t)$ denotes the tracking error at time t , and T is the total simulation time. Minimizing this function enables reduction of cumulative system error.

2) *2. Multi-objective Performance Function*: To further improve transient and steady-state response, a weighted multi-objective function was adopted, combining key performance indices such as overshoot, settling time, and steady-state error:

$$J = w_1 M_p + w_2 T_s + w_3 E_{ss} \quad (42)$$

where M_p is the maximum overshoot, T_s is the settling time, E_{ss} is the steady-state error, and w_1 , w_2 , and w_3 are weighting coefficients assigned to each performance index according to system design priorities.

3) *3. PID Gain Optimization*: The optimal PID parameters were obtained by solving the minimization problem:

$$[K_p, K_i, K_d] = \arg \min J \quad (43)$$

where the GA iteratively searches for the optimal values of K_p , K_i , and K_d that minimize the objective function J , thereby improving overall control performance of the intelligent air purification system.

B. Modelling Pollutant Decay for Air Purification Performance Evaluation

To evaluate the actual air purification performance of the proposed system, a pollutant concentration dynamic model was incorporated into the Simulink environment. This model enables observation of how indoor pollutant concentrations reduce over time under the action of the GA-tuned fuzzy-PID controller. The pollutant removal process was assumed to follow first-order decay dynamics, where the rate of change of pollutant concentration is proportional to the purifier control action and the remaining pollutant concentration in the indoor environment. The time-domain differential equation describing the pollutant removal process is given by:

$$\frac{dC(t)}{dt} = -kC(t) + u(t) \quad (44)$$

where:

- $C(t)$ is the pollutant concentration at time t (e.g., dust, smoke, gas, or VOC),
- k is the natural pollutant decay constant,
- $u(t)$ is the purifier control signal generated by the GA-tuned fuzzy-PID controller.

Applying the Laplace transform to Equation (1) under zero initial conditions gives the transfer function model of the pollutant dynamics as:

$$\frac{C(s)}{U(s)} = \frac{1}{\tau s + 1} \quad (45)$$

where:

- $C(s)$ is the Laplace transform of pollutant concentration,
- $U(s)$ is the Laplace transform of the purifier control input,
- τ is the time constant representing the purification rate of the pollutant.

This transfer function was implemented in Simulink using a transfer function block to simulate pollutant reduction over time and generate pollutant concentration control curves for performance evaluation.

C. GA tuning code for air purifier with disturbances

```
% GA-Based PID Optimization for Indoor Air Purification
clear;
clc;
close all;

% Simulation Parameters
dt = 0.05;
PopSize = 150;
MaxGenerations = 100;

% Laplace Variable
s = tf('s');

% PHYSICAL SUBSYSTEMS

% Fan Motor Dynamics
G_motor = 729307.83/(s^2 + 145.88*s + 64600.14);

% Fan Inertia
Tf = 0.5;
G_fan = 1/(Tf*s + 1);

% Room-Air Mixing
Tmix = 30;
G_mix = 1/(Tmix*s + 1);

% Pollutant Transport and Removal
Tpoll = 60;
G_pollutant = 1/(Tpoll*s + 1);

% Sensor Dynamics
Tsensor = 5;
G_sensor = 1/(Tsensor*s + 1);

% Overall Plant
G = G_motor * G_fan * G_mix * G_pollutant * G_sensor;

disp('Overall Plant:')
minreal(G)
```

```

% PID SEARCH RANGE
lb = [0 0 0];
ub = [30 30 30];

% GENETIC ALGORITHM OPTIONS
options = optimoptions(@ga,...
    'PopulationSize',PopSize,...
    'MaxGenerations',MaxGenerations,...
    'Display','iter',...
    'UseParallel',true,...
    'EliteCount',15,...
    'CrossoverFraction',0.85);

% RUN GA
[x,fval] = ga(@K pidFitnessFunction(G,dt,K),end...
    3,[],[],[],[],lb,ub,[],options);

% Optimal Gains
Kp = x(1);
Ki = x(2);
Kd = x(3);

fprintf('\nOptimal PID Gains\n');
fprintf('Kp = %.4f\n',Kp);
fprintf('Ki = %.4f\n',Ki);
fprintf('Kd = %.4f\n',Kd);

% PID Controller
PID = pid(Kp,Ki,Kd);

% Closed Loop
CL = feedback(PID*G,1);

% Response
t = 0:dt:300;
[y,t] = step(CL,t);

% Metrics
info = stepinfo(y,t);

fprintf('\nPerformance Metrics\n');
fprintf('Rise Time      = %.2f s\n',info.RiseTime);
fprintf('Settling Time    = %.2f s\n',info.SettlingTime);
fprintf('Overshoot        = %.2f %%\n',info.Overshoot);
fprintf('Peak Time       = %.2f s\n',info.PeakTime);

% Plot
figure;
plot(t,y,'LineWidth',2);
grid on;
xlabel('Time (s)');
ylabel('Normalized Pollutant Removal');
title('Indoor Air Purification System');

% FITNESS FUNCTION
function cost = pidFitnessFunction(G,dt,K)

desiredTs = 120;

Kp = K(1);
Ki = K(2);
Kd = K(3);

PID = pid(Kp,Ki,Kd);

CL = feedback(PID*G,1);

if ~isstable(CL)
    cost = 1e10;
    return
end

t = 0:dt:300;
y = step(CL,t);

info = stepinfo(y,t);

Ts = info.SettlingTime;
Mp = info.Overshoot;
Ess = abs(1-y(end));

if isnan(Ts)
    cost = 1e10;
    return
end

cost = ...
    100*(Ts-desiredTs)^2 + ...
    10*(Mp)^2 + ...
    10000*(Ess)^2;
end

```