

## Research

# Simulation of a scalable corridor waning radiance system using fuzzy PID and genetic algorithm

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## Abstract

Modern lighting systems do not adapt to real-time environmental and occupancy changes using binary and continuous electrical signals. The traditional switch-based systems are inefficient, leading to excessive energy consumption due to poor adaptability. Previous studies use remote control of appliances, but only use binary switches to control the appliances. To address these issues, this research proposes a scalable corridor-waning radiance system using a GA-optimized Fuzzy-PID controller, which integrates both binary and continuous sensors to dynamically adjust lighting based on factors like proximity, ambient light, sound, and human presence. Fuzzy logic manages uncertainties, while GA optimizes PID parameters for better response time, reduced steady-state errors, and improved efficiency. MATLAB/Simulink simulations confirm the system's superior performance achieving faster rise time of 0.90 s, a settling time of 1.57 s, and a peak time of 2.47 s with minimal error as compared to recent studies. The proposed system can now accommodate the binary and continuous switches and the end-user can scale-up the system inputs by adding more switches with the OR-logic capability.

**Keywords** Genetic algorithm · Fuzzy logic · Fuzzy PID controller · Neural network · Logic gates · Sensors · Matlab/ Simulink

## 1 Introduction

### 1.1 Background

#### 1.1.1 Switch

Electrical energy is a necessity supporting our daily activities and lives [1–5]. It is generated at power plants and transported to substations via transmission lines [6]. The distribution lines carry the electricity from substations to different consumer locations, thus reaching the Consumer Control Unit (CCU) [7–9]. The main switch turns the distribution lines ON or OFF, and each light or appliance is controlled by its corresponding lighting or socket switch [10, 11].

In 1884, John Henry Holmes introduced the inaugural light switch incorporating “quick-break technology” [12]. A switch interrupts the flow of electric charges in a circuit, enabling current flow via two terminals, thus facilitating interaction between electrical components [13]. Approximately 40 percent of the global energy consumption is attributed to buildings including; hospitals, shopping malls, and university campuses. These campuses comprise numerous buildings

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and facilities that host a substantial population engaged in various activities and thus contribute 30 percent of greenhouse gas emissions [14].

The conventional corridor light system relies on mechanical switches as its primary control mechanism [10]. The essential components include; mechanical switches, wiring, light fixtures, and a power source. Mechanical switches are of various types like single pole single throw (SPST), single pole double throw (SPDT), and multi-way switches [15, 16]. SPST switches have the simplest method for turning on or off lights from a single location, while SPDT switches enable light control in a two-way circuit from two different places. However, the challenges in these systems include; electrical hazards like electric shock due to poor wire insulation, plus energy wastage due to lights being left on when not in use [11, 17, 18].

The dependence on one-way or two-way light switches in corridors contributes to the excessive use of electricity where lights remain ON and people often forget to turn off even when not needed. This situation led to the development of a smart automatic lighting system. Such systems enhance energy efficiency by ensuring that lights are only used when required [19].

### 1.1.2 Related work

Pratibha et al. designed a smart corridor lighting control system that employs PIR motion sensors. Sensors were placed between bulbs and activated the adjacent bulb whenever a motion was detected. However, this setup had difficulty in distinguishing between humans and objects. Additionally, the system's inefficiency resulted from the lack of a microcontroller and the employment of a single PIR motion sensor, which only detected moving radiation, failing to identify constant radiation [20].

Zhang and Ma improved the system suggested by Pratibha et al., by employing various occupancy sensors and advanced microcontrollers. This system used a loop-conditioned program on the microcontroller to control sound, human infrared, and photosensitive sensors. However, it faces several significant limitations; The system only accommodates limited input devices; There was a delay in response between sensor motion detection and activation of the lights caused by optimisation of the loop checking intervals; They fall short in optimising performance over time [21] because they have fixed conditions with no learning making it difficult to adapt to real-time environmental changes [22]. These shortcomings result in limited intelligence.

Wanzala and Atim developed and simulated a multi-input Exclusive-Or master switch system for remotely controlling lighting and socket systems using wireless switching. It comprised of a Global System for Mobile Communication (GSM) control system [23–25], Bluetooth control system [26] and Wireless Fidelity (Wi-Fi) control system [27, 28] using mobile phones [29–31]. However, the design was limited to processing binary input signals, excluding inputs that generate continuous signals. As a result, the system could not integrate analog-based sensors or adapt to changing environmental conditions [32]. Consequently, it is essential to develop a scalable corridor-waning radiance system that considers both binary and continuous signals from sensors.

Previous research have improved on the intelligence of the electrical appliances. Starting with mechanical switches, then remote switching, but the control of the binary and continuous signals are not single-controlled and the switches can not be scaled-up by the end-users. This research therefore involves designing and simulating a scalable corridor lighting system using a Fuzzy-PID controller optimized by a Genetic Algorithm (GA) for adaptive lighting control. The system integrates binary (PIR motion, switches) and continuous (ultrasonic, light, sound) sensors to adjust lighting based on real-time conditions.

## 1.2 Research problem

Conventional automated light control systems accommodate limited input sensors, making it difficult to consider various parameters while adjusting to the changing environmental conditions and user behaviors. Therefore, there is a need to develop a multi-input sensor corridor-waning radiance system using fuzzy PID and genetic algorithm.

### 1.3 Significance of this study

The importance of this work includes:

- 1) A framework for combining binary and continuous sensors to handle different switching systems. Previous authors only look at binary switches such as mechanical switches, without continuous signals such as human presence.

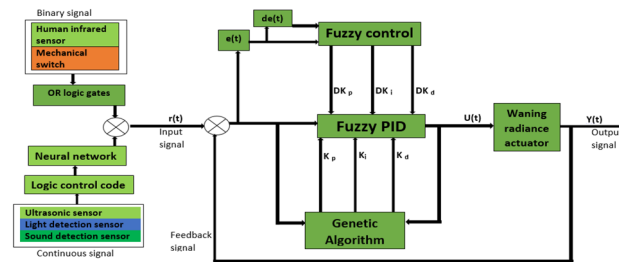


**Fig. 1** This block diagram illustrates the integration of binary (PIR motion, mechanical switch) and continuous (ultrasonic, light, and sound) sensors in a scalable corridor lighting system. The system processes sensor signals through: OR-logic gates; a logic control module, before normalizing continuous data via a neural network; and the processed signals are then fed into a fuzzy-PID controller optimized by GA

**Table 1** Table for fuzzy logic rules based on error (e) and error change (ec) for parameters  $K_p/K_i/K_d$

| 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 |

2) A scalable and modular design enabling future sensor expansion for both binary and continuous signals.

## 2 Materials and methods

### 2.1 Design of a scalable corridor waning radiance system circuit

Figure 1 shows the assimilation diagram for the design of a scalable corridor waning radiance system circuit. The system consists of inputs from a network of sensors that capture analog data (binary signal): human infrared sensor to detect human heat radiation and a mechanical switch; and digital data (continuous signal): ultrasonic sensor to measure the object distance, light detection sensor to gauge light levels, and the sound detection sensor to detect sound.

A network of sensors that produce “binary signals” is connected through OR-logic gates and a network of sensors that produce “continuous signals” is connected to the “logic code control” to choose the best signals, and then to “neural network” to normalize the continuous signals into a binary form [33–38]. The outputs from the binary and continuous signal network of sensors are sent to the “fuzzy-PID” controller. The fuzzy controller employs a rule-based logic system following rules shown in Appendix VI-A.

The “fuzzy-PID” controller integrates fuzzy logic with a traditional PID controller, whose parameters are optimized by GA. The “Fuzzy control” receives the “input signal” in the form of errors and changes in errors, and connects to the “fuzzy-PID” controller to reduce errors between the desired and actual output. Combining GA and “fuzzy-PID” controller forms a GA Fuzzy-PID controller.

The necessity of GA arises from its ability to efficiently tune the PID parameters, overcoming the trial-and-error limitations of conventional tuning methods and enhancing adaptability in nonlinear environments. By integrating fuzzy logic, the system ensures smooth transitions between lighting states based on sensor inputs, while GA optimizes the controller to achieve faster response times and minimal steady-state errors [39–41]

The “fuzzy control” was set up as shown in Table 1 that represents fuzzy rules where the rows represent the “error” (e) and the columns represent the “error change” (ec). Each cell in the table specifies the controller’s output based on the current values of e and ec. Thus, using linguistic terms: NB (Negative Big), NM (Negative Medium), NS (Negative Small),

**Table 2** Linguistic terms for ultrasonic sensor with their intensity range values

| Linguistic terms | Range of values (cm) | Normalized values |
|------------------|----------------------|-------------------|
| Near             | 0–300                | 0–0.33            |
| Far              | 300–600              | 0.33–0.67         |
| No detection     | 600–900              | 0.67–1            |

**Table 3** Linguistic terms for light detection sensor with their intensity range values

| Linguistic terms | Range of values (lux) | Normalized values |
|------------------|-----------------------|-------------------|
| Dark             | 0–1                   | 0–0.01            |
| Dim              | 1–70                  | 0.01–0.7          |
| Bright           | 70–100                | 0.7–1             |

**Table 4** Linguistic terms for sound detection sensor with their intensity range values

| Linguistic terms | Range of values (dB) | Normalized values |
|------------------|----------------------|-------------------|
| Quiet            | 0–20                 | 0–0.25            |
| Some sound       | 20–30                | 0.25–0.375        |
| Loud sound       | 30–80                | 0.375–1           |

**Table 5** Linguistic terms for human infrared sensor with their intensity values

| Linguistic terms   | Value |
|--------------------|-------|
| No human detection | 0     |
| Human detection    | 1     |

**Table 6** Linguistic terms for mechanical switch with their intensity values

| Linguistic terms | Value |
|------------------|-------|
| OFF              | 0     |
| ON               | 1     |

ZO (Zero), PS (Positive Small), PM (Positive Medium), and PB (Positive Big), multiple possible control actions are specified for each pair of  $e$  and  $ec$  (separated by slashes), indicating a multi-level response strategy.

Table 2 describes the linguistic terms for sensors that produce continuous signals. The ultrasonic sensor with “Near” meaning too close to the sensor, “Far” meaning far from the sensor, and “No detection” meaning out of detection range, with their intensity range values of “0–300 cm”, “300–600 cm” and “600–900 cm” respectively. The intensity range values were normalised into “0–1” to match the binary intensity range values using the formula in Eq. 1.

$$\text{Normalized Value} = \frac{\text{Signal} - \text{Min}}{\text{Max} - \text{Min}} \quad (1)$$

Table 3 describes the linguistic terms: “Dark”, “Dim” and “Bright” for light detection sensors with the respective range of values and normalized values. Table 4 describes the linguistic terms: “Quiet”, “Some sound” and “loud sound” for sound detection sensors with the respective range of values and normalized values.

Table 5 represents the linguistic terms for sensors that produce binary signals. The Human infrared sensor has “No human detection” and “Human detection” with their respective intensity values of; “0” and “1”. Table 6 represents the linguistic terms for the mechanical switch with “OFF” and “ON” and having intensity values of “0” and “1” respectively.

For having a common signal fed into fuzzy-PID, the name for the parameters was changed as shown in Table 7. For scalability of the system, all future additions of binary sensors through OR-Logic gates will be categorized by a new group name of “binary”. The OR-Logic gates allow the addition of infinite ( $n^{\text{th}}$ ) binary sensors to the circuit as shown in Fig. 2.

**Fig. 2** Illustration of an OR-logic gate implementation that allows the system to accommodate an unlimited number of binary sensors (human infrared sensors and mechanical switches)

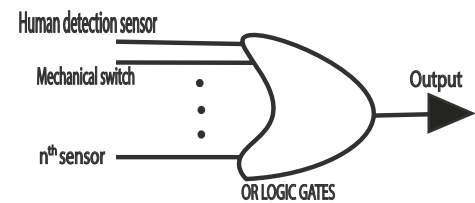


**Table 7** The names of parameters

| Old name                                    | Proposed name |
|---------------------------------------------|---------------|
| Human infrared sensor and Mechanical switch | Binary        |
| Light detection sensor                      | Continuous 1  |
| Ultrasonic sensor                           | Continuous 2  |
| Sound detection sensor                      | Continuous 3  |

The future additions of continuous sensors depending on their intensity range values will be categorized by new group names of “continuous 1”, “continuous 2” and “continuous 3”. The fuzzy-PID employs fuzzy logic rules VI-A based on the proposed names to make lighting commands.

The linguistic terms for the five parameters considered when generating the multiple fuzzy rules are shown in Appendix VI-A. The generated rules were then used to control the system's output, in the form of lighting, with the duration varying from longest to shortest period for most and least critical conditions. The most and least critical conditions include: when a human passes in the presence of natural light, when the dog passes in the absence of light, and when a human passes in the absence of natural light.

The final “output signal” from the GA Fuzzy-PID controller is fed into the waning radiance system that controls the load and its intensity. The system operates in a closed-loop configuration while continuously adjusting based on the sensor “feedback signal” in real-time, thus ensuring adaptive and efficient control that remains stable in dynamic environments.

The lighting control being a linear process, the fuzzy logic was employed to adjust the light intensity based on linguistic rules, uncertainties, and nonlinear sensor data (data from the combination of continuous and binary sensors) that linear controllers cannot efficiently manage.

## 2.2 Derivation of the transfer function for the scalable corridor waning radiance system

The transfer function of a bulb is described by the relationship between its electrical input (voltage/current) and its output (light intensity) as shown in Eq. 2.

$$G(t) = \frac{I(t)}{V(t)} \quad (2)$$

Where  $V(t)$  is the input voltage and  $I(t)$  is the current.

Consider the bulb behaves as a purely resistive element with resistance  $R$  varying with the bulb's temperature. Assume  $x(t)$  represents the bulb's temperature,  $u(t)$  represents the input voltage to the bulb, and  $y(t)$  represents the bulb's brightness. Due to energy balance, the rate of change of the thermal energy equals the change in the power in the bulb as shown in Eq. 3 [42].

$$C \frac{dx(t)}{dt} = P_{in} - P_{out} \quad (3)$$

where  $C$  is bulb's capacitance,  $P_{in}$  is power in and  $P_{out}$  is power lost.

But power is defined as  $P_{in} = \frac{V^2}{R}$  [42].

But voltage  $V = u(t)$ , therefore:

$$P_{in} = \frac{(u(t))^2}{R} \quad (4)$$

From Newton's law of cooling, the power lost is proportional to the ratio of the bulb's temperature to thermal time constant as shown in Eq. 5 [43].

$$P_{out} = \frac{x(t)}{T} \quad (5)$$

where  $T$  is defined as the bulb's thermal time constant.

Equations 4 and 5 were then substituted into Eq. 3.

$$C \frac{dx(t)}{dt} = \frac{(u(t))^2}{R} - \frac{x(t)}{T} \quad (6)$$

Using thermal model [43].

$$\Delta u(t) = u(t) - V_{nom} \quad (7)$$

$$\Delta x(t) = x(t) - T_{nom} \quad (8)$$

$$\Delta y(t) = y(t) - B_{nom} \quad (9)$$

where  $V_{nom}$  is nominal input voltage,  $T_{nom}$  is nominal temperature and  $B_{nom}$  is nominal brightness.

The expansion of Eq. 7;

$$u(t)^2 = (V_{nom})^2 + 2V_{nom}\Delta u(t) + (\Delta u(t))^2$$

But  $\Delta u(t)^2$  is very small and approximated to zero.

$$u(t)^2 = (V_{nom})^2 + 2V_{nom}\Delta u(t) \quad (10)$$

Equation 10 fed into Eq. 6.

$$C \frac{d(\Delta x(t) + T_{nom})}{dt} = \frac{(V_{nom})^2 + 2V_{nom}\Delta u(t)}{R} - \frac{\Delta x(t) + T_{nom}}{T} \quad (11)$$

since  $T_{nom}$  is independent of  $t$ , then  $C \frac{d(\Delta x(t) + T_{nom})}{dt} = C \frac{d(\Delta x(t))}{dt}$

Equation 11 becomes;

$$C \frac{d(\Delta x(t))}{dt} = \frac{(V_{nom})^2}{R} + \frac{2V_{nom}\Delta u(t)}{R} - \frac{\Delta x(t)}{T} - \frac{T_{nom}}{T} \quad (12)$$

At  $t = 0$  s. Equation . 12 becomes;

$$0 = \frac{(V_{nom})^2}{R} - \frac{T_{nom}}{T} \quad (13)$$

$$\frac{T_{nom}}{T} = \frac{(V_{nom})^2}{R} \quad (14)$$

substituting Eqs. 14 into 12. Equation 12 becomes;

$$C \frac{d(\Delta x(t))}{dt} = \frac{2V_{nom}\Delta u(t)}{R} - \frac{\Delta x(t)}{T} \quad (15)$$

By making  $\frac{2V_{nom}\Delta u(t)}{R}$  the subject, Eq. 15 becomes;

$$C \frac{d(\Delta x(t))}{dt} + \frac{\Delta x(t)}{T} = \frac{2V_{nom}\Delta u(t)}{R} \quad (16)$$

Application of Laplace transform on Eq. 16,

$$Cs(\Delta X(s)) + \frac{\Delta X(s)}{T} = \frac{2V_{nom}\Delta U(s)}{R} \quad (17)$$

Factorizing  $\Delta X(s)$  in Eq. 17;

$$\Delta X(s)(Cs + \frac{1}{T}) = \Delta U(s) \frac{2V_{nom}}{R} \quad (18)$$

Making  $\Delta X(s)$  the subject of Eq. 18;

$$\Delta X(s) = \frac{2V_{nom}}{R(Cs + \frac{1}{T})} \Delta U(s) \quad (19)$$

From the brightness definition [42],

$$\Delta y(t) = K \Delta x(t) \quad (20)$$

where K is the brightness constant.

Using Laplace transform.

$$\Delta Y(s) = K \Delta X(s) \quad (21)$$

Equation 19 fed into Eq. 21.

$$\Delta Y(s) = \frac{2KV_{nom}}{R(Cs + \frac{1}{T})} \Delta U(s) \quad (22)$$

The transfer function of the bulb  $G(s)$  as stated in Eq. 2 becomes;

$$\begin{aligned} G(s) &= \frac{\Delta Y(s)}{\Delta U(s)} \\ &= \frac{2KV_{nom}}{CR(s + \frac{1}{CT})} \end{aligned} \quad (23)$$

Taking;  $W = \frac{2KV_{nom}}{CR}$ ;  $a = \frac{1}{CT}$   
Then Eq. 23 becomes;

$$G(s) = \frac{W}{s + a} \quad (24)$$

Equation 24 is the transfer function of the bulb.

### 2.3 Simulation and testing of the scalable corridor waning radiance system

The corridor waning radiance system was simulated following the circuit diagram in Figure 3.1. The desired control action for the corridor waning radiance system was determined using the fuzzy rules VI-A generated using the multiple linguistic terms of each of the parameters.

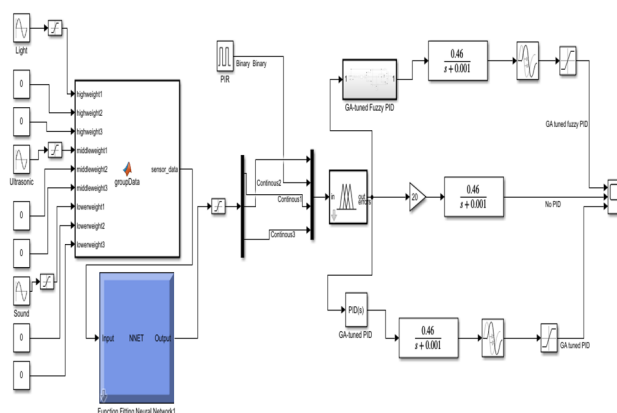
The testing process begins by letting each sensor generate data corresponding to different scenarios including; when there is much natural light in the room, when there is little natural light in the room, when there is motion of a person, when there is motion of an object, when the switch is turned on, when the switch is turned off and others. These simulated sensor outputs were fed into the fuzzy-PID controller.

The computational complexity of the proposed GA-tuned Fuzzy-PID controller primarily depends on the Genetic Algorithm's iterative nature and the fuzzy inference process. The time complexity of GA is approximately  $O(g \times p \times c)$ , where  $g$  is the number of generations,  $p$  is the population size, and  $c$  is the cost function evaluation time. The spatial complexity is  $O(p \times d)$ , where  $d$  is the number of parameters to be optimized. Compared to other optimization methods like Particle Swarm Optimization (PSO) or Differential Evolution (DE), GA has a slightly higher computational cost due

**Table 8** 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)     |

**Fig. 3** The Matlab circuit diagram shows sensor data processing through a logic control block, followed by normalization via a neural network fitting model, and final control through a fuzzy-PID controller. The GA-based tuning optimizes the PID parameters



to its crossover and mutation operations, but it provides a more diverse search space exploration. While traditional PID tuning methods have lower complexity, they lack adaptability to nonlinear systems [44, 45].

The Fuzzy-PID parameters  $K_p$ ,  $K_i$  and  $K_d$  were tuned and optimized using the GA iteration code to achieve minimal errors that consists: population size, crossover rate, mutation rate, number of generations, and their respective values were listed in Table 8. The parameters were specified between being user-defined or randomly initialized and their recommended values based on the application were provided.

The final output from the GA-Fuzzy-PID controller dictates the state and intensity of the corridor-waning radiance system. The simulation environment allowed the testing of the feedback loop to ensure that the sensor data was correctly used in real-time to adjust the system's operation.

### 3 Results and discussion

#### 3.1 Design of a scalable corridor waning radiance system circuit

Figure 3 shows a Matlab simulation circuit diagram for the design of a scalable corridor waning radiance system. A network of nine sensors was categorized into three types; high-weight (light sensor and two free slots), middle-weight (ultrasonic sensor and two free slots), and lower-weight (sound sensor and two free slots) were connected to the Matlab function block (termed as "groupData"). This is because the designed logic control code VI-C allows the connection of three sensors to each weight type. The high-weight takes in sensors with a maximum value ranging from 300 to 900, the middle-weight takes in sensors with a maximum value ranging from 100 to 299, and the lower-weight takes in sensors with a maximum value ranging from 0 to 99.

The Matlab function block was connected to the neural network fitting block (termed as "Function Fitting Neural Network"), then to the demux block connected to the PIR block. The "PIR" block represents a network of human infrared sensor and mechanical switch through the OR logic gates (allows the connection of infinite binary sensors) forming one binary signal (True "1" or False "0").

The combined data was categorized as: 'binary', 'continuous 1', 'continuous 2', 'continuous 3' and 'continuous 4' fed into the fuzzy logic controller. The fuzzy logic controller is then connected to; a subsystem termed as "GA-tuned fuzzy PID",

connected to the transfer function block and then to the scope block; PID block, then connected to the transfer function block and then to the scope block.

Figure 4 shows a structural circuit for “GA-tuned fuzzy PID” subsystem. The PID constants were tuned and determined by the GA.

Sect. 3.1.1 describes the design of the “logic control code” uploaded in the “groupData” block and section 3.1.2 describes the design of the neural network training process that forms a “Function Fitting Neural Network” block.

### 3.1.1 Logic control code

The logic control code VI-C was loaded in the Matlab function block (labelled groupData in Fig. 3). This code provided nine slots for connecting different sensors categorized into three types; high weight, middle weight, and lower weight. The code iterated through the different loop-set or logic if statement conditions, and selected one group of data of a specific sensor according to the set logic rules of the if statements. Selected data from each sensor was combined to form sensor data fed into the neural network block. The logic control code was made of four parts namely: the input function for sensor data; arrays for each weight group; logic code for the selection of one group data from each weight group; and the output of the selected sensor data.

### 3.1.2 Neural network training

The neural network fitting model block was constructed in Matlab using the neural network toolbox accessed by the command “nnstart” in the command window. The training began with the generation of different sensor data that mimic the environmental behaviour in the virtual world by use of the sensor data generation code.

By use of sensor data generation code VI-B, different sensor data were generated which included; ultrasonic or proximity data ranging from 0 to 900 cm; light intensity data ranging from 0 to 100 lux; and sound data ranging from 0 to 80 decibels. The generated data was categorized into three types namely: sensor input, target data, and test input. The sensor input and target data were imported and used as predictors and responses respectively during the neural network training. The following graphs were obtained that elaborated the different parameters such as gradient, errors, and regression, that occurred during the training process of the neural network fitting model.

Figure 5 shows a graph of the error histogram during the neural network training process. This error histogram shows the distribution of neural network prediction errors with most values clustered close to zero, indicating high accuracy. Training (blue), validation (green), and test (red) errors were represented with infrequent larger errors in validation and test sets, suggesting good generalization.

Figure 6 shows a graph of gradient and validation variation during the neural network training process. This graph shows the training of a neural network over 65 epochs, with the gradient decreasing to a low value, indicating effective error minimization. The learning rate parameter ( $\mu$ ) stabilized at  $1 \times 10^{-7}$ , reflecting controlled convergence. Validation checks increased near the end, suggesting possible overfitting and the end of training at epoch 65.

Figure 7 shows a graph of train validation performance during the neural network training process. This graph shows the mean squared error (MSE) over 65 epochs with training, validation, and test errors. Training errors decreased steadily

**Fig. 4** Structural representation of the GA-tuned fuzzy-PID subsystem, highlighting how the PID parameters ( $K_p$ ,  $K_i$ ,  $K_d$ ) are optimized through Genetic Algorithm tuning

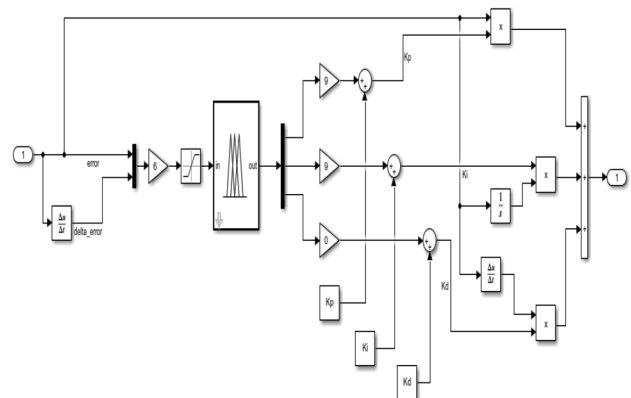


**Fig. 5** Error histogram showing the distribution of neural network prediction errors across training, validation, and test datasets

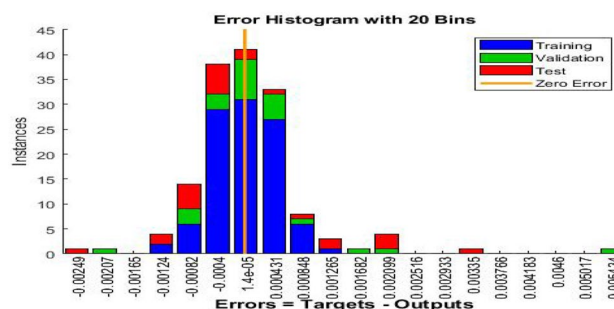


**Fig. 6** Graph showing the gradient and validation variation during neural network training. The gradient decreases significantly over 65 epochs, reflecting effective error minimization, while validation checks increase towards the end, suggesting potential overfitting

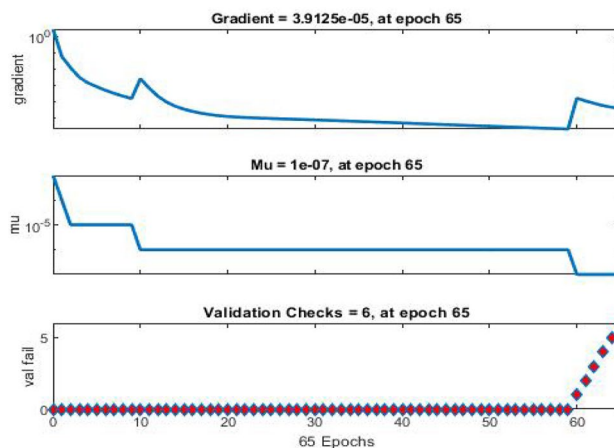
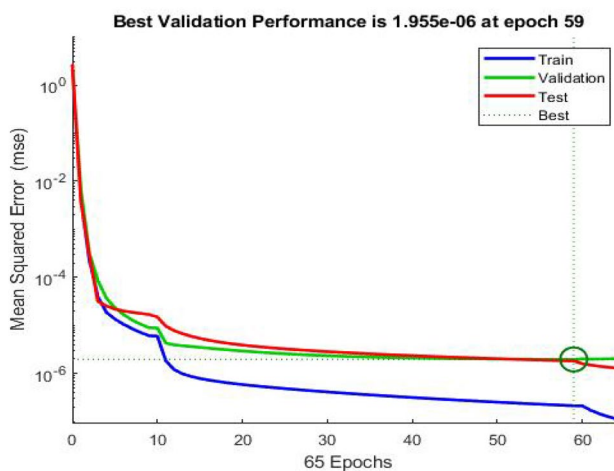


**Fig. 7** Graph depicting the mean squared error (MSE) of training, validation, and test sets during neural network training. The model achieves optimal validation performance at epoch 59 with a minimal MSE, indicating effective generalization



while validation and test errors decreased initially and then plateaued at a low MSE, indicating good generalization. The best validation performance ( $\text{MSE} = 1.955 \times 10^{-6}$ ) occurred at epoch 59, as highlighted by the green circle.

Figure 8 shows a graph of train regression performance during the neural network training process. This set of graphs shows the relationship between the model's output and target values for training, validation, testing, and overall datasets with a line indicating the ideal fit ( $Y = T$ ). Each graph included a correlation coefficient ( $R$ ) that reflected how well the model's predictions aligned with the target values. High correlation values close to one (Training:  $R = 1$ , Validation:  $R = 0.99999$ , Test:  $R = 0.99999$ , All:  $R = 1$ ) indicated an excellent fit across all datasets, meaning the model is highly accurate in predicting outputs that closely match the targets.

The test input and target data were imported and used to test the performance of the trained neural network model. Figure 9 shows a graph of the tested data regression of the neural network fitting model. This graph shows the correlation between the model's output and target values on an additional test set, with a line representing the ideal fit ( $Y = T$ ).

**Fig. 8** Regression analysis of the neural network training process, illustrating the correlation between predicted and actual values. High correlation coefficients ( $R = 1$ ) across training, validation, and test datasets confirm the model's accuracy and predictive reliability

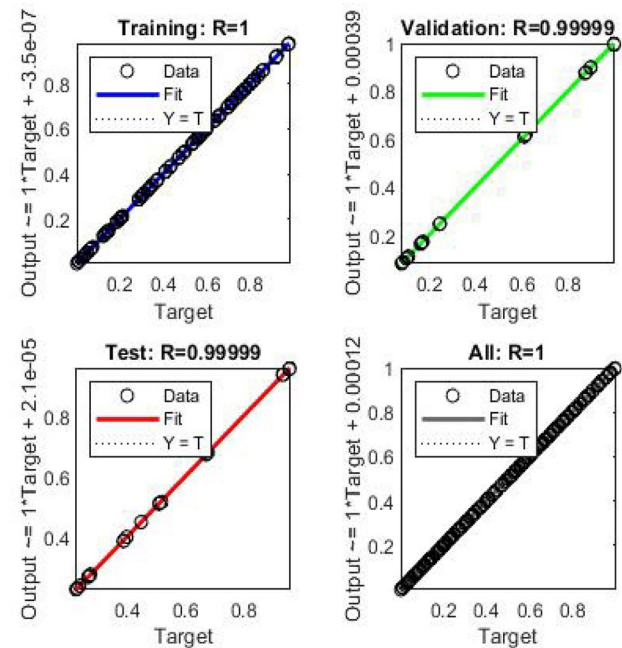
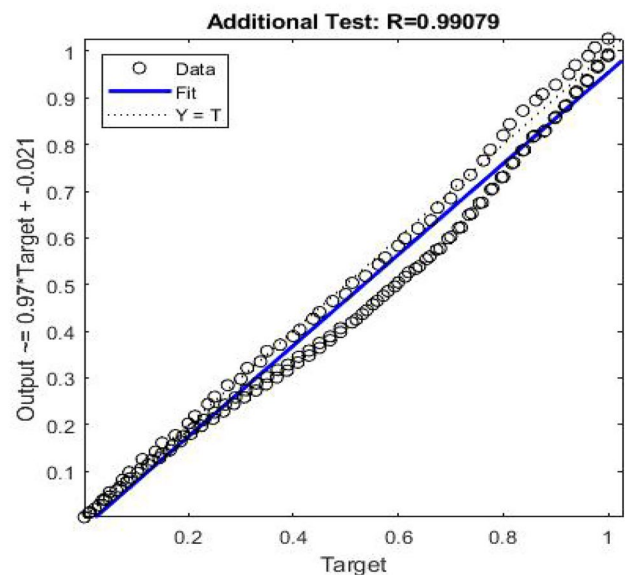


**Fig. 9** Tested data regression graph comparing predicted and target values of the trained neural network model. The correlation coefficient ( $R = 0.99079$ ) indicates strong predictive accuracy



The correlation coefficient ( $R=0.99079$ ) is close to 1, indicating a strong linear relationship and high predictive accuracy. The fitted line equation,  $\text{Output} = 0.97 * \text{Target} - 0.0021$ , shows a slight deviation from the ideal slope of 1, meaning the model slightly underpredicts as values increase. Overall, the model performed well with a minor bias in the additional test set and exported into the circuit diagram in Fig. 3.

After the Neural network training and the testing process, a "Function Fitting Neural Network" was exported from the training model and imported into the designed Matlab circuit system shown in Fig. 3.

### 3.2 Derivation of the transfer function for the scalable corridor waning radiance system

[46] stated that the households in Africa receive a standard voltage that ranges between 220 V to 240 V, thus taking  $V_{nom} = 220$  V. Considering 100-watt powered bulb [47, 48], the standard value for incandescent bulb's thermal capacitance  $C = 100$  J/°C and the standard value for the brightness constant  $K = 10$  lux.

Taking  $V_{nom} = 220$  V. The bulb's resistance is given by;

$$R = \frac{V^2}{P} = \frac{220^2}{100} = 484 \quad \Omega \quad (25)$$

The thermal time constant is given by:

$$T = \frac{R}{C} = \frac{484}{100} = 4.84 \quad s. \quad (26)$$

Then;

$$W = \frac{2KV_{nom}}{CR} = \frac{2 * 10 * 220}{100 * 484} = \frac{4400}{48400} = 0.09 \quad (27)$$

$$a = \frac{1}{CT} = \frac{1}{100 * 4.84} = 0.002 \quad (28)$$

Substituting Eqs. 27 and 28 into Eq. 24;

$$G(s)_{220} = \frac{W}{s + a} = \frac{0.09}{s + 0.002} \quad (29)$$

Taking  $V_{nom} = 230$  V. The bulb's resistance is given by;

$$R = \frac{V^2}{P} = \frac{230^2}{100} = 529 \quad \Omega \quad (30)$$

The thermal time constant is given by:

$$T = \frac{R}{C} = \frac{529}{100} = 5.29 \quad s. \quad (31)$$

Then;

$$W = \frac{2KV_{nom}}{CR} = \frac{2 * 10 * 230}{100 * 529} = 0.087 \quad (32)$$

$$a = \frac{1}{CT} = \frac{1}{100 * 5.29} = 0.00189 \quad (33)$$

Substituting eqs. 32 and 33 into Eq. 24;

$$G(s)_{230} = \frac{W}{s + a} = \frac{0.087}{s + 0.00189} \quad (34)$$

Taking  $V_{nom} = 240$  V. The bulb's resistance is given by;

$$R = \frac{V^2}{P} = \frac{240^2}{100} = 576 \quad \Omega \quad (35)$$

The thermal time constant is given by:

$$T = \frac{R}{C} = \frac{576}{100} = 5.76 \quad s. \quad (36)$$

Then;

$$W = \frac{2KV_{nom}}{CR} = \frac{2 * 10 * 240}{100 * 576} = 0.083 \quad (37)$$

**Fig. 10** Graph depicting data signals from continuous-type sensors (ultrasonic, light, and sound detection) over their respective intensity ranges. These signals are normalized before being processed by the fuzzy logic controller

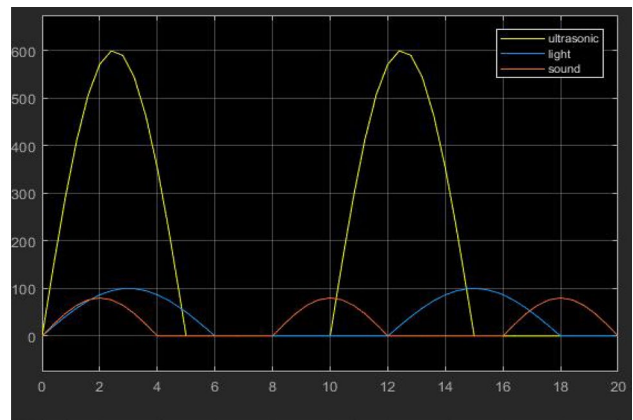
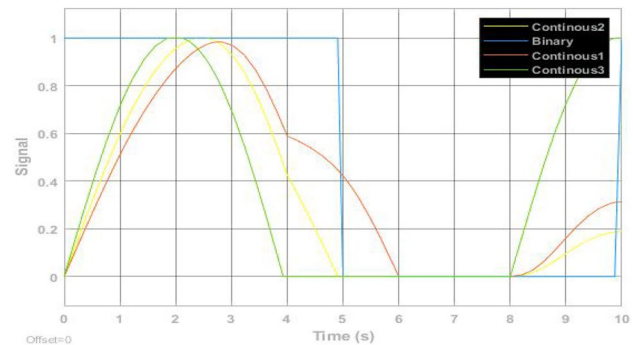


**Fig. 11** Graph showing combined data signals from binary and continuous sensors after normalization



$$a = \frac{1}{CT} = \frac{1}{100 * 5.76} = 0.001736 \quad (38)$$

Substituting eqs. 37 and 38 into Eq. 24;

$$G(s)_{240} = \frac{W}{s + a} = \frac{0.083}{s + 0.001736} \quad (39)$$

### 3.3 Simulation and testing of the scalable corridor waning radiance system

Using the Matlab simulation circuit diagram in Fig. 3; the logic control code VI-C was imported into the Matlab function block; the designed fuzzy logic file was imported into the fuzzy logic block; the designed neural network fitting model was imported into the circuit diagram as shown in Fig. 3.

Figure 10 shows the sensor signals generated from the continuous type of sensors in regards to Tables 2, 3, and 4. The graph shows the behaviour of ultrasonic, light, and sound detection sensors to their range of intensities.

Figure 11 shows the combined data signals generated from both continuous sensors after being normalised by the "Function fitting Neural Network" block and the binary sensors in regards to Table 7. These data signals were fed into the fuzzy logic block in circuit diagram 3.

The fuzzy logic control file was imported into the fuzzy logic block in Fig. 4. The designed GA code was run to make values of  $K_p$ ,  $K_i$  and  $K_d$  be availed in the Matlab workspace so that they are automatically fed into the constant blocks in Fig. 4.

#### 3.3.1 PID parameter tuning using GA

The GA iteration code was tested in Matlab for the optimization and best tuning of the PID constants about the transfer function to ensure high accuracy and fewer steady-state errors.

**Fig. 12** Graph depicting the GA optimization process for tuning PID parameters over multiple generations

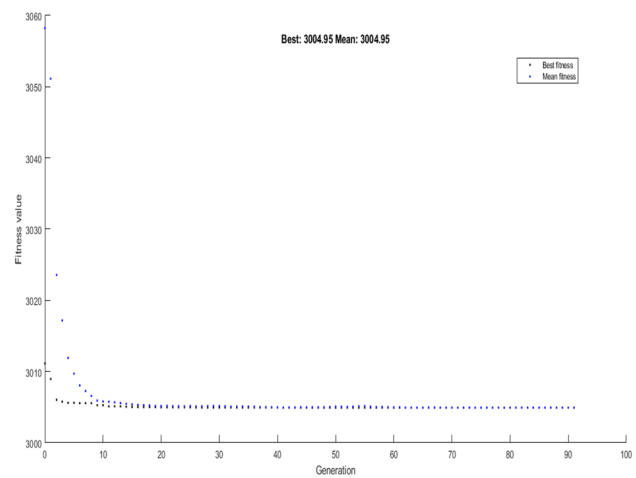
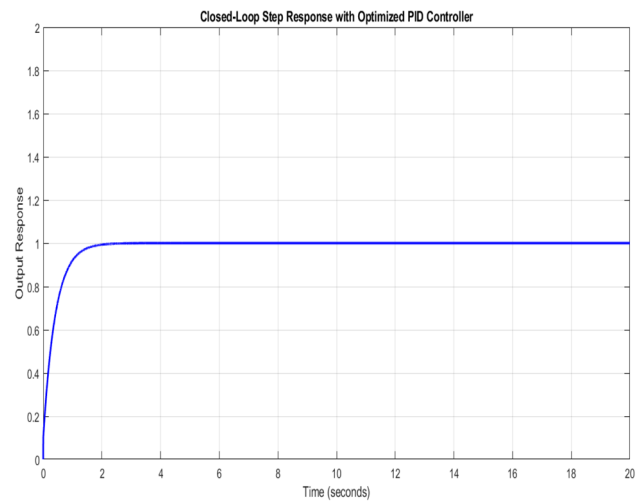


**Fig. 13** Closed-loop step response of a PID controller tuned using a Genetic Algorithm. The optimized controller exhibits fast response time, minimal overshoot, and improved steady-state performance in regulating light intensity



The graph 12 shows the convergence of GA optimizing the fitness value over generations. The vertical axis represents the fitness value, while the horizontal axis represents the generation count. Initially, the fitness values were high, but they rapidly decreased and converged around 1001.57, with the best and mean fitness values stabilizing close to this minimum value. This indicated that the GA effectively optimized the solution within the first few generations, reaching a stable optimum with minimal variation in later generations.

The graph 13 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.

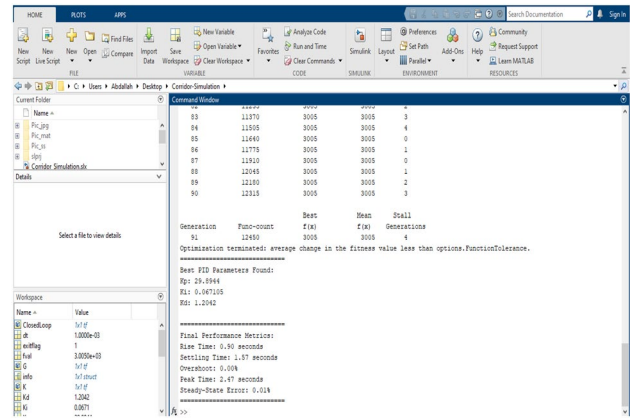
After the GA code had fine-tuned the derived bulb's transfer function, the best and fitness values were given as;  $K_p = 29.8944$ ,  $K_i = 0.06105$  and  $K_d = 1.2042$ . The GA code output is given in Fig. 14.

The PID controller has a standard transfer function  $P(s)$  (frequency domain) [49];

$$P(s) = K_p + \frac{K_i}{s} + K_d s \quad (40)$$

By substituting the PID constants into the Eq. 40. Then for  $V_{nom} = 220$  V, the transfer function of the PID controller with the variation of the transfer function of the bulb for the corridor waning radiance system became:

**Fig. 14** A figure showing PID constant controller response with genetic algorithm tuning



$$P(s)_{220} = 29.8944 + \frac{0.06105}{s} + 1.2042s \quad (41)$$

The GA code was run for transfer functions corresponding to  $V_{nom} = 230$  V and  $V_{nom} = 240$  V. The following transfer functions for the PID controller were obtained respectively.

$$P(s)_{230} = 29.7204 + \frac{0.056167}{s} + 1.2027s \quad (42)$$

$$P(s)_{240} = 30 + \frac{0.052899}{s} + 1.2629s \quad (43)$$

The Matlab simulation was run for 1000 s. Figures 15, 16 and 17 show a graph elaborating the step response behaviour of the corridor waning radiance system in two different scenarios under the use of: GA tuned PID controller, no PID, and GA tuned fuzzy PID controller. The graph compared three control systems for regulating light intensity over time: no PID controller (blue line), GA-tuned fuzzy-PID controller (yellow line), and GA-tuned PID controller (red line).

### 3.4 Discussion

The MATLAB simulation confirmed that the system could process sensor data efficiently, normalizing continuous signals into a range of 0 to 1 while integrating them with binary signals for fuzzy-PID control. The derivation of the

**Fig. 15** Comparison of step response behaviors for the corridor lighting system under different voltage conditions (220 V). 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

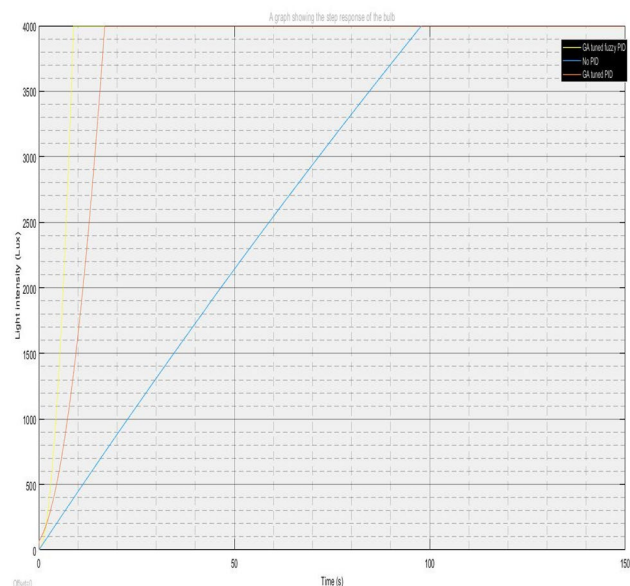


**Fig. 16** Comparison of step response behaviors for the corridor lighting system under different voltage conditions (230 V). The graphs illustrate the performance of three control strategies: GA-tuned fuzzy-PID, GA-tuned PID, and no PID, highlighting improvements in response time and system stability

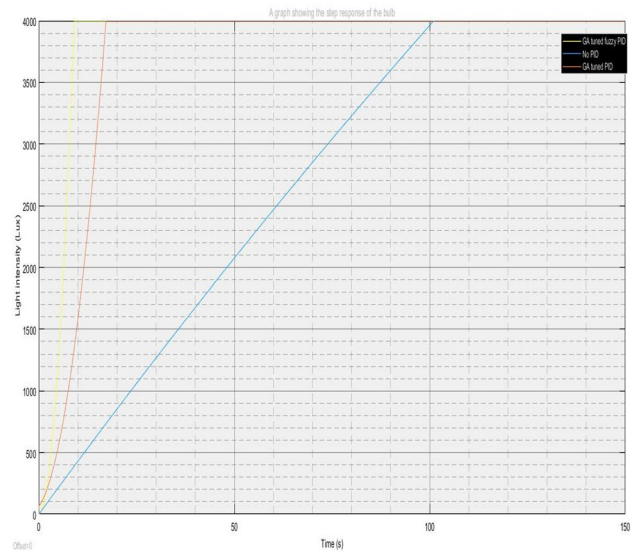
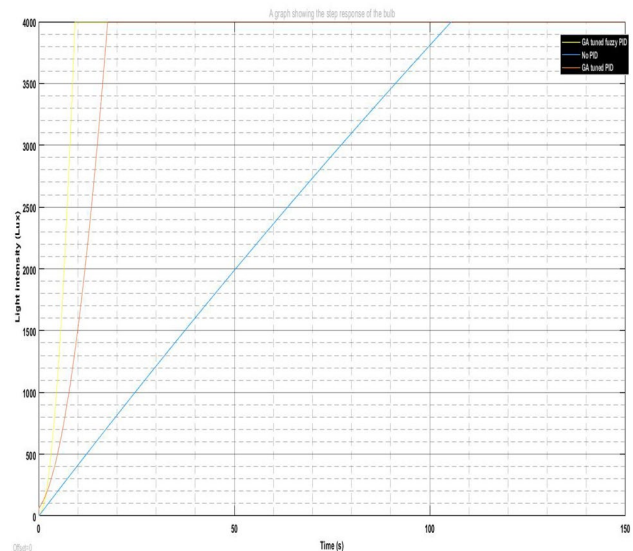


**Fig. 17** Comparison of step response behaviors for the corridor lighting system under different voltage conditions (240 V). The graphs illustrate the performance of three control strategies: GA-tuned fuzzy-PID, GA-tuned PID, and no PID, highlighting improvements in response time and system stability



transfer function provided a mathematical model for the lighting system's response, accounting for the electrical and thermal properties of a 100 watt incandescent bulb under different nominal voltages of: 220 V, 230 V, 240 V, and the derived transfer function was  $G(s)_{220} = \frac{0.09}{s+0.002}$ ,  $G(s)_{230} = \frac{0.087}{s+0.00189}$  and  $G(s)_{240} = \frac{0.083}{s+0.001736}$  respectively allowing for precise control tuning and stability analysis.

Finally, the system's effectiveness was validated through simulation and testing, where the GA-tuned fuzzy-PID controller significantly improved performance metrics. The results indicated a remarkable rise time of 0.90 s, a settling time of 1.57 s, and a peak time of 2.47 s outperforming conventional control methods.

cite37 developed an intelligent remote control system for home automation, optimizing a 100 watt bulb's dimming levels using a PID controller to regulate light intensity and room humidity. They compared the performance of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for tuning the PID controller.

Table 9 presents [49] findings on transient response, comparing PID, GA-PID, and PSO-PID controllers to the proposed GA-tuned fuzzy-PID controller. The results show that the GA-tuned fuzzy-PID achieved faster response times, making it more effective for dynamic applications and handling nonlinearities.

**Table 9** The comparison of the findings of Rajesh Singh et al. paper for performance matrix using PID, GA-PID, and PSO-PID with my proposed findings for GA Fuzzy-PID

|                   | [49]    |        |       | Proposed system           |                           |                           |
|-------------------|---------|--------|-------|---------------------------|---------------------------|---------------------------|
|                   | PSO-PID | GA-PID | PID   | $V_{nom} = 220 \text{ V}$ | $V_{nom} = 230 \text{ V}$ | $V_{nom} = 240 \text{ V}$ |
| Rise time (s)     | 0.906   | 2.017  | 2.553 | 0.90                      | 0.94                      | 0.97                      |
| Settling time (s) | 4.696   | 6.522  | 7.651 | 1.57                      | 1.63                      | 1.69                      |
| Overshoot         | 0       | 0      | 0     | 0.1                       | 0                         | 0                         |
| Peak time (s)     | 10.561  | 19.222 | 15.89 | 2.47                      | 2.57                      | 2.67                      |

## 4 Conclusion

This study presents a scalable corridor-waning radiance system utilizing a GA-optimized fuzzy-PID controller. The system integrates multiple sensors for adaptive lighting control, including ultrasonic, human infrared, light detection, and sound sensors. Its modular design allows for seamless expansion, supporting unlimited binary sensors and up to nine continuous sensors without modifying the control logic. Combining binary and continuous sensors enhances adaptability to real-world conditions, ensuring accurate and efficient lighting regulation.

The study derives the transfer function of a 100 watt incandescent bulb by analyzing its thermal and electrical properties at 220 V, 230 V, and 240 V. Key parameters, including resistance, thermal capacitance, and brightness constants, define the lighting system's dynamic behaviour. This derivation provides a foundational model for optimizing control strategies using a GA-tuned fuzzy-PID controller, ensuring efficient light regulation while maintaining system stability.

The system demonstrated superior performance by integrating fuzzy logic with PID control, optimized by Genetic Algorithms, demonstrating significant improvements in response time, and adaptability. MATLAB/Simulink simulations confirm the system's ability to achieve a rise time of 0.90 s, a settling time of 1.57 s, and a peak time of 2.47 s outperforming traditional switches, conventional PID and GA-PID controllers in both performance and scalability.

This study presents a system that works in Uganda after testing its step response performance under 220 V, 230 V and 240 V as recommended by ref. [46]. However, this study acknowledges the limited number of continuous sensors (nine) that can be added.

### 4.1 Recommendations

To improve this system, the following recommendations may be considered:

- 1) *Enhancing continuous sensor scalability* Future researchers can further investigate how to implement a modular framework in the control system to integrate with building management systems (BMS) for larger, more complex facilities. This will help the system control different appliances in the buildings.
- 2) *Multi-objective approaches* Future work can explore multi-objective approaches in optimization systems in comparison with the single-objective approaches.

**Author contributions** Authors contributed equally.

**Funding** No funding was received.

**Data availability** Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

## Declarations

**Ethics approval and Consent to participate** Not applicable.

**Consent for publication** All authors agreed to publish.

**Competing interests** The authors declare no competing interests.

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## Appendix 1

### Fuzzy rules for fuzzy-PID

1. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Quiet) then (wanning radiance control is Dim lights)
2. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Some sound) then (wanning radiance control is Dim lights)
3. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Loud sound) then (wanning radiance control is Bright lights)
4. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Dim) and (continuous3 is Quiet) then (wanning radiance control is Off lights)
5. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Dim) and (continuous3 is Some sound) then (wanning radiance control is Off lights)
6. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Dim) and (continuous3 is Loud sound) then (wanning radiance control is Dim lights)
7. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Bright) and (continuous3 is Quiet) then (wanning radiance control is Off lights)
8. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Bright) and (continuous3 is Some sound) then (wanning radiance control is Off lights)
9. If (continuous2 is No detection) and (binary is Human detection) and (continuous1 is Bright) and (continuous3 is Loud sound) then (wanning radiance control is Off lights)
10. If (continuous2 is Far) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Quiet) then (wanning radiance control is Dim lights)
11. If (continuous2 is Far) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Some sound) then (wanning radiance control is Dim lights)
12. If (continuous2 is Far) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Loud sound) then (wanning radiance control is Dim lights)
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14. If (continuous2 is Far) and (binary is Human detection) and (continuous1 is Dim) and (continuous3 is Some sound) then (wanning radiance control is Dim lights)
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19. If (continuous2 is Near) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Quiet) then (wanning radiance control is Bright lights)
20. If (continuous2 is Near) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Some sound) then (wanning radiance control is Bright lights)

21. If (continuous2 is Near) and (binary is Human detection) and (continuous1 is Dark) and (continuous3 is Loud sound) then (wanning radiance control is Bright lights)
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41. If (continuous2 is Far) and (binary is No human detection) and (continuous1 is Dim) and (continuous3 is Some sound) then (wanning radiance control is Off lights)
42. If (continuous2 is Far) and (binary is No human detection) and (continuous1 is Dim) and (continuous3 is Loud sound) then (wanning radiance control is Off lights)
43. If (continuous2 is Far) and (binary is No human detection) and (continuous1 is Bright) and (continuous3 is Quiet) then (wanning radiance control is Off lights)
44. If (continuous2 is Far) and (binary is No human detection) and (continuous1 is Bright) and (continuous3 is Some sound) then (wanning radiance control is Off lights)
45. If (continuous2 is Far) and (binary is No human detection) and (continuous1 is Bright) and (continuous3 is Loud sound) then (wanning radiance control is Off lights)
46. If (continuous2 is Near) and (binary is No human detection) and (continuous1 is Dark) and (continuous3 is Quiet) then (wanning radiance control is Off lights)

47. If (continuous2 is Near) and (binary is No human detection) and (continuous1 is Dark) and (continuous3 is Some sound) then (wanning radiance control is Off lights)
48. If (continuous2 is Near) and (binary is No human detection) and (continuous1 is Dark) and (continuous3 is Loud sound) then (wanning radiance control is Off lights)
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53. If (continuous2 is Near) and (binary is No human detection) and (continuous1 is Bright) and (continuous3 is Some sound) then (wanning radiance control is Off lights)
54. If (continuous2 is Near) and (binary is No human detection) and (continuous1 is Bright) and (continuous3 is Loud sound) then (wanning radiance control is Off lights)

### Sensor data generation code

```
%Generating the sensor data.
ultrasonic= round(linspace(1, 600, 50));
light = round(linspace(1, 100, 50));
sound = round(linspace(1,80,50));
sensor_input = [light;ultrasonic;sound];

%Creating the target-data by normalising the different data.
ultrasonic_norm = ultrasonic/600;
light_norm = light/100;
sound_norm = sound/80;
target_data = [ light_norm;ultrasonic_norm;sound_norm];

%Generating the testing data for this simulation.
ultrasonic_test= round(linspace(1, 500, 50));
light_test = round(linspace(1, 95, 50));
sound_test = round(linspace(1,75,50));
test_input = [light_test;ultrasonic_test;sound_test];
```

## Logic control code

```
function sensor_data = groupData(highweight1, highweight2, highweight3, ...
                                middleweight1, middleweight2, middleweight3, ...
                                lowerweight1, lowerweight2, lowerweight3)

% Create arrays for each weight group
highWeights = [highweight1, highweight2, highweight3];
mediumWeights = [middleweight1, middleweight2, middleweight3];
lowWeights = [lowerweight1, lowerweight2, lowerweight3];

% Logic code for selecting one group data from the highweight type.
if (highweight1>=0.1)&&(highweight2<=0)&&(highweight3<=0)
    highOutput = highWeights(1);
elseif (highweight1<=0)&&(highweight2>=0.1)&&(highweight3<=0)
    highOutput = highWeights(2);
elseif (highweight1<=0)&&(highweight2<=0)&&(highweight3>=0.1)
    highOutput = highWeights(3);
elseif (highweight1>=0.1)&&(highweight2>=0.1)&&(highweight3>=0.1)
    highOutput = highWeights(1);
else
    highOutput = highWeights(1);
end
% Logic code for selecting one group data from the mediumweight type.
if (middleweight1>=0.1)&&(middleweight2<=0)&&(middleweight3<=0)
    mediumOutput = mediumWeights(1);
elseif (middleweight1<=0)&&(middleweight2>=0.1)&&(middleweight3<=0)
    mediumOutput = mediumWeights(2);
elseif (middleweight1<=0)&&(middleweight2<=0)&&(middleweight3>=0.1)
    mediumOutput = mediumWeights(3);
elseif (middleweight1>=0.1)&&(middleweight2>=0.1)&&(middleweight3>=0.1)
    mediumOutput = mediumWeights(1);
else
    mediumOutput = mediumWeights(1);
end
% Logic code for selecting one group data from the lowweight type.
if (lowerweight1>=0.1)&&(lowerweight2<=0)&&(lowerweight3<=0)
    lowOutput = lowWeights(1);
elseif (lowerweight1<=0)&&(lowerweight2>=0.1)&&(lowerweight3<=0)
    lowOutput = lowWeights(2);
elseif (lowerweight1<=0)&&(lowerweight2<=0)&&(lowerweight3>=0.1)
    lowOutput = lowWeights(3);
elseif (lowerweight1>=0.1)&&(lowerweight2>=0.1)&&(lowerweight3>=0.1)
    lowOutput = lowWeights(1);
else
    lowOutput = lowWeights(1);
end
% Return the selected sensor data as a 3-element array for plotting
sensor_data = [highOutput, mediumOutput, lowOutput]; % 1x3 array for plotting
end
```

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