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Design and Simulation of an energy efficient intelligent kitchen HVAC control system using RBFNN - PID and GA

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Abstract—Heating, Ventilation, and Air Conditioning systems are essential for maintaining thermal comfort, indoor air quality, and occupant health, particularly in energy-intensive environments such as indoor kitchens. However, conventional HVAC control systems often rely on fixed-gain PID controllers that struggle to handle nonlinear dynamics, time-varying disturbances, and indoor air pollution, leading to reduced comfort and increased energy consumption. To address these challenges, this study designs and simulates an energy-efficient HVAC control system based on a hybrid Genetic Algorithm, Radial Basis Function Neural Network – PID approach for regulating indoor temperature, humidity, and carbon monoxide concentration. The genetic algorithm is first employed to obtain optimal baseline PID gains, ensuring fast and stable initial system response, while the RBF neural network adapts these gains online to cope with environmental uncertainties and disturbances. The HVAC plant is modeled as a three-state dynamic system with realistic thermal, moisture, and pollution disturbances. The simulation results indicate accurate tracking of the reference setpoints across all controlled variables. The temperature regulation achieved a low RMS error of 0.26726 with a coefficient of determination of 0.75193, demonstrating good tracking performance. For relative humidity, the RMS error was calculated as 1.1548, while the corresponding R^2 value was 0.11706. Carbon monoxide regulation exhibited a lower RMS error of 0.014568 compared to temperature and humidity; and the associated R^2 value of 0.99539 confirms satisfactory goodness of fit and effective disturbance rejection despite intermittent pollution spikes. The proposed GA–RBFNN–PID control system demonstrated rapid convergence characteristics, where the controlled parameters settled precisely at their respective setpoints within approximately 1–2 minutes with no overshoot and observable steady-state error, thereby ensuring robust and stable indoor kitchen climate regulation.

Index Terms—Heating, Ventilation, Air Conditioning system, Genetic Algorithm, Proportional Integral and Derivative, Radial Basis Function Neural Network

I. INTRODUCTION

Heating, Ventilation, and Air Conditioning (HVAC) systems play a critical role in ensuring thermal comfort, indoor air quality, and occupant health in residential, commercial, and industrial buildings, where people spend a significant portion of their daily lives [1]. Maintaining suitable kitchen conditions requires simultaneous control of temperature, relative humidity, and air quality, as these variables strongly influence human comfort, productivity, and health [2]–[4]. In environments such as commercial kitchens, these challenges are intensified due to concentrated heat sources, high moisture release, cooking fumes, and asymmetric thermal radiation, which lead to extreme and rapidly varying indoor conditions [5].

Traditional HVAC systems are typically designed to regulate room temperature alone, allowing humidity and air quality to vary freely. However, both scientific and industrial processes, as well as human comfort, demand precise control of temperature and humidity [6]. Numerous studies have demonstrated that ignoring humidity and air pollutants degrades indoor comfort and can cause health risks [6], [7]. In cooking environments, thermal buoyancy carries hot air, oil vapors, and combustion gases into the breathing zone, creating highly unstable thermal and air quality conditions that conventional control strategies struggle to manage [8]–[10].

To address these challenges, researchers have increasingly applied intelligent and soft computing techniques such as fuzzy logic, artificial neural networks, and neuro-fuzzy systems to HVAC control [11]–[13], [31]–[33]. Fuzzy logic enables the modeling of vague and uncertain system behavior using linguistic rules, while neural networks provide learning and nonlinear mapping capabilities. Hybrid approaches such as ANFIS have been successfully used for damper prediction and

HVAC control, achieving high temperature accuracy but showing weaker performance in humidity regulation, highlighting the difficulty of controlling moisture dynamics [11].

Further studies have demonstrated that Radial Basis Function Neural Network – based PID controllers significantly improve humidity control by adapting PID gains in real time, achieving zero overshoot, high accuracy, and strong robustness [12]–[16]. Similarly, fuzzy self-tuning PID and RBFNN-PID hybrid controllers have been shown to enhance temperature and humidity regulation while reducing energy consumption by up to 30% [17]. However, neuro-fuzzy controllers tend to react slowly to abrupt environmental changes, making them less effective in highly dynamic environments such as commercial kitchens where rapid heat and moisture fluctuations occur.

Beyond thermal comfort, indoor air quality—particularly CO concentration poses a serious health threat in cooking environments [18]–[22]. Studies in charcoal-fueled kitchens in Western Uganda reported CO levels far exceeding World Health Organization safety limits, exposing occupants to severe health risks [23]. Other studies found that evening cooking accounts for the majority of children’s daily CO exposure, with many homes reaching concentrations high enough to trigger safety alarms [24]. These findings underscore the urgent need for HVAC systems that can actively monitor and regulate air pollutants alongside temperature and humidity.

Furthermore, fixed-gain PID controllers, which are still widely used in HVAC systems, perform poorly under changing conditions such as occupancy variation and outdoor weather disturbances. They often exhibit overshoot, oscillations, and excessive energy consumption—up to 20–30% more than intelligent controllers [25]. In contrast, GA-based optimization and adaptive control strategies have been shown to significantly reduce energy consumption while maintaining occupant comfort [26]–[30], [34].

Although previous studies demonstrated that intelligent HVAC controllers such as ANFIS, RBFNN-PID, and fuzzy self-tuning PID improve temperature and humidity regulation while reducing energy consumption by up to 30% [11], [12], [14]–[17], most existing works focus mainly on thermal variables under relatively stable indoor conditions and rarely consider simultaneous control of temperature, humidity and carbon monoxide in highly dynamic environments such as commercial kitchens [18]–[22]. In addition, conventional PID controllers still suffer from overshoot, oscillations, and increased energy consumption under varying operating conditions [25].

Therefore, this study proposes a hybrid GA–RBFNN–PID controller for simultaneous regulation of temperature, humidity, and CO concentration with improved adaptability, fast response, and energy efficiency in highly dynamic indoor environments such as kitchens.

Nomenclature

RMS	Root Mean Square Error
R^2	Coefficient of determination
n	Number of data patterns in the independent data set
$y_{pre,m}$	Predicted value
$t_{mea,m}$	Measured value of one data point
m	Mean value of all measured data points
K_p	Proportional gain
K_i	Integral gain
K_d	Derivative gain
ΔK_p	Small change in Proportional gain
ΔK_i	Small change in Integral gain
ΔK_d	Small change in Derivative gain
ppm	Parts per million
CO	Carbonmonoxide
CO_2	Carbondioxide
$(u(t))$	Controller output
$e(t)$	Error signal for temperature
T_{set}	Desired indoor temperature
$T(t)$	Measured indoor temperature
$e_H(t)$	Error signal for humidity
H_{set}	Desired humidity
$H(t)$	Measured humidity
CO_{set}	Desired Carbon monoxide
$CO(t)$	Measured Carbon monoxide
x	Input vector
c_i	Center of the i^{th} neuron
σ_i	Spread parameter

A. PID Controller Model

The PID controller output is mathematically expressed as shown below in equation 1:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \quad (1)$$

where $u(t)$ is the controller output, $e(t)$ is the error signal, K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain.

The transfer function representation of the PID controller is given equation 2:

$$G_{PID}(s) = K_p + \frac{K_i}{s} + K_d s \quad (2)$$

For HVAC temperature control, the error signal in equation 3:

$$e(t) = T_{set} - T(t) \quad (3)$$

where T_{set} is the desired indoor temperature and $T(t)$ is the measured indoor temperature.

For humidity and carbon monoxide regulation in HVAC systems, the control error signals are defined in 4 and 5 respectively:

$$e_H(t) = H_{set} - H(t) \quad (4)$$

$$e_{CO}(t) = CO_{set} - CO(t) \quad (5)$$

where H_{set} and CO_{set} denote the desired humidity and carbon monoxide concentration set points, while $H(t)$ and $CO(t)$ represent the measured indoor humidity and carbon monoxide levels at time t .

B. Radial Basis Function Neural Network

The Gaussian radial basis activation function used in the hidden layer is expressed in equation 6

$$\phi_i(x) = \exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right) \quad (6)$$

where x is the input vector, c_i is the center of the i^{th} neuron, and σ_i is the spread parameter.

The overall output of the RBF neural network is given by equation 7:

$$y(x) = \sum_{i=1}^N w_i \phi_i(x) \quad (7)$$

where w_i represents the connection weights and N is the number of hidden neurons.

The efficiency of modern thermal management and building automation is deeply influenced by cost-efficient natural convection heat transfer, particularly in low-energy or mixed convection regimes [44]. In practical environments such as indoor kitchens, buoyancy-driven air circulation is governed by complex phenomena, including non-uniform heating [35], periodic heating/cooling cycles [37], and various spatiotemporal temperature profiles [38], [42]. These dynamics often occur within enclosures featuring porous media [36], [39], conducting bodies [43], or specific geometric inclinations [40], [41], all of which contribute to entropy generation and thermal distribution. While these natural convective forces offer significant opportunities for energy savings by reducing reliance on mechanical ventilation, they introduce highly nonlinear dynamics and time-varying disturbances that challenge traditional control models. By employing the hybrid GA-RBFNN-PID strategy, this system leverages the online learning capabilities of neural networks to dynamically adapt to these buoyancy-induced uncertainties. This ensures a robust balance between mechanical regulation and natural convection, facilitating effective pollutant rejection and stable thermal comfort.

II. MATERIALS AND METHODS

A. Design of an Intelligent HVAC Circuit Control System

From figure 1, the HVAC control system was designed to intelligently control indoor temperature and air quality through an adaptive control structure that combines GA optimization, a conventional PID controller, and RBFNN. The system relied on inputs from a network of sensors including: temperature, humidity and CO sensors, which continuously monitored environmental conditions in real time. These sensor signals formed the feedback data required for the control algorithm to regulate heating, ventilation, and air conditioning devices. Data was collected from the sensor outputs (temperature, humidity, CO) modeled in Simulink.

In the initial stage, GA tuned the initial parameters of the PID controller; the proportional gain (K_p), integral gain (K_i), and derivative gain (K_d). The GA performed a global search across possible parameter combinations to identify a set of gains that produce the best system response under a variety of operating conditions. The optimization was based on a fitness function that considered multiple performance indices such as rise time, overshoot, settling time, and steady-state error. This process ensured that the PID controller starts with robust and balanced gains that can maintain temperature stability and occupant comfort across different load and disturbance conditions.

Once the initial PID parameters were obtained, the RBFNN adaptively adjusted them in real time. The RBFNN considered inputs as error and rate of change of error. Each hidden neuron in the RBFNN represented Gaussian function that captured nonlinear relationships between the input features and the required changes in PID parameters. The network output small adjustments (ΔK_p , ΔK_i , ΔK_d) that were added to the GA-optimized initial parameters. This allowed the PID controller to dynamically adapt its behavior to environmental changes such as varying occupancy, fluctuating outdoor temperatures, or sudden heat gains from equipment.

The adaptive process ensured that the HVAC system remains stable and efficient even under nonlinear and time-varying conditions. During operation, when large disturbances or parameter variations occurred, the RBFNN updated its weights online based on the observed system error, effectively learning how to improve control performance over time.

The combination of GA and RBFNN offered a hybrid control mechanism where GA provided a globally optimized starting point, and RBFNN continuously fine-tuned the controller for local performance optimization. This hybrid GA-RBFNN-PID structure achieved fast response, minimal overshoot, and accurate temperature regulation with reduced energy consumption.

The overall system operated in a closed-loop configuration, where the HVAC actuators adjust the heating or cooling intensity according to the control signal generated by the

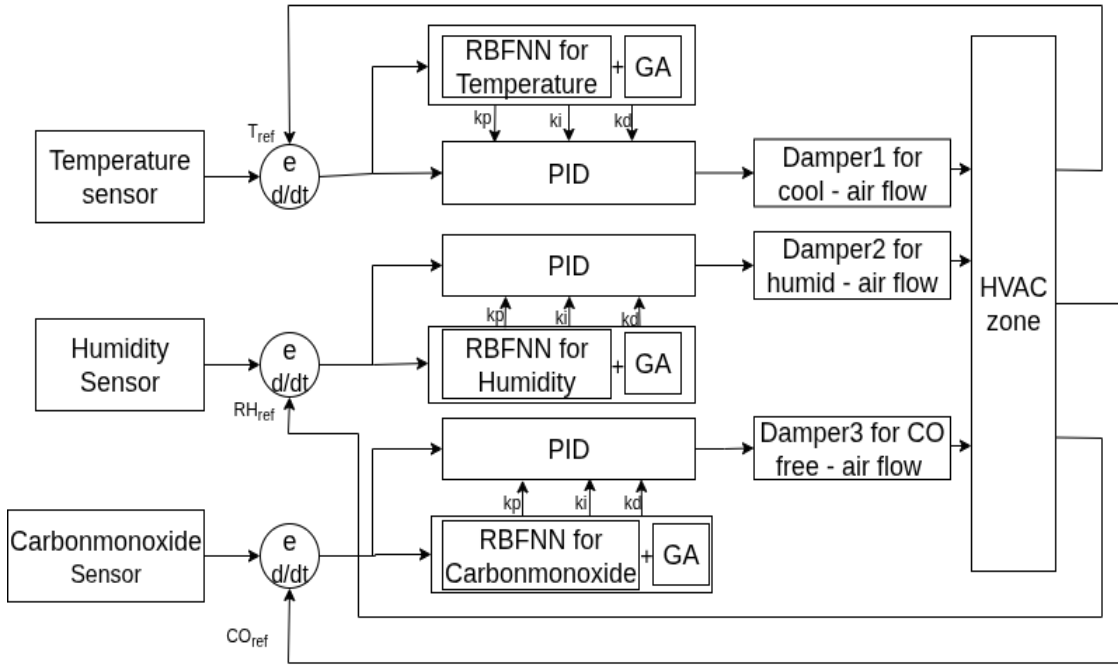


Fig. 1. A block diagram of an implementation of intelligent HVAC system based on RBFNN-PID and GA (modified from [11] and [13])

adaptive PID controller. The sensor feedback ensured that the system output closely followed the desired setpoint, while the RBFNN adaptation minimized steady-state errors and compensates for dynamic variations in thermal load. This intelligent control framework enhanced the responsiveness, stability, and energy efficiency of HVAC systems, making it suitable for modern building automation applications where comfort and sustainability are equally prioritized.

Statistical performance metrics were used the RMS error in equation 8 and the coefficient of determination (R^2) as shown in equation 9, which quantify the accuracy and correlation between the system's predicted outputs and reference values.

$$RMS = \sqrt{\frac{\sum_{m=1}^n (y_{pre,m} - t_{mea,m})^2}{n}} \quad (8)$$

$$R^2 = 1 - \frac{\sum_{m=1}^n (y_{pre,m} - t_{mea,m})^2}{\sum_{m=1}^n (t_{mea,m} - \bar{t})^2} \quad (9)$$

where;

n is the number of data patterns in the independent data set,
 $y_{pre,m}$ is the predicted value,
 $t_{mea,m}$ is the measured value of one data point,
 $\bar{t}$ is the mean of the measured values,
 m is the mean value of all measured data points ([11]; [12] and [13]).

Since the reference setpoints are constants, the denominator $\sum (t_{mea,m} - \bar{t})^2$ in the standard formula becomes zero.

Therefore,

Standard R^2 : Because the reference signal has zero variance (constant line), the standard R^2 is technically undefined or mathematically inappropriate for evaluating constant setpoint tracking.

The "Global" R^2 (Current): this study's current formula ($R^2 = 1 - \frac{\sum_{m=1}^n (y_{pre,m} - t_{mea,m})^2}{\sum_{m=1}^n (t_{mea,m})^2}$) effectively measures how much the controller's output deviates from the absolute magnitude of the setpoint. Because the reference is a constant, the study therefore uses a Global Coefficient of Determination to evaluate tracking accuracy relative to the setpoint magnitude, rather than variance-based correlation.

The energy efficiency improvement achieved by the proposed GA-RBFNN-PID controller was evaluated through a comparative analysis against the conventional PID controller. Since HVAC energy consumption is closely associated with actuator operating duration and control effort, the cumulative control input over the simulation interval was used as an approximate indicator of energy usage according to equation 10.

$$E_{HVAC} \propto \int_0^T |u(t)| dt \quad (10)$$

where $u(t)$ represents the controller output signal and T is the simulation duration. Under identical operating conditions.

The corresponding energy-efficiency improvement was estimated using equation 11

$$\eta = \frac{E_{PID} - E_{GA-RBFNN-PID}}{E_{PID}} \times 100\% \quad (11)$$

III. RESULTS AND DISCUSSION

A. Design of an Intelligent HVAC Circuit Control System

Figure 2 presents the Simulink implementation of the closed-loop HVAC system controlled using the proposed GA-RBFNN-PID strategy. The controller was evaluated on a multi-input multi-output system regulating three indoor environmental variables, namely temperature, relative humidity, and carbon monoxide concentration. The closed-loop responses of these variables are illustrated in Figures 3, 4, and 5, respectively. The simulation was carried out over a duration of 200 s with a sampling interval of 0.1 s to adequately capture the system dynamics and transient behavior.

The controller was required to track constant reference set-points of 24 °C for temperature, 55% for relative humidity, and 9 ppm for CO concentration, which represent typical indoor comfort and safety requirements. As observed from the simulation results, the GA-RBFNN-PID controller achieved accurate reference tracking for all three controlled variables, with fast rise times, minimal overshoot, and zero steady-state error.

Furthermore, the system was subjected to time-varying disturbances, including periodic thermal and moisture disturbances as well as intermittent CO concentration spikes intended to emulate realistic indoor activities such as cooking and occupancy variations. Despite these disturbances, the controller maintained closed-loop stability and demonstrated strong disturbance rejection capability. The responses quickly returned to their respective setpoints after each disturbance, indicating effective adaptive tuning and robust performance of the proposed control scheme. Overall, the results confirm that the GA-RBFNN-PID controller provides reliable and stable regulation of indoor environmental conditions under dynamic operating scenarios.

B. Testing of an Intelligent HVAC Circuit Control System

1) *Temperature Regulation Results:* The indoor temperature response exhibited: Fast convergence to the reference value, minimal overshoot, smooth transient behavior as shown in figure 3. The adaptive RBFNN layer adjusted the PID gains online, allowing the controller to compensate for thermal disturbances effectively. The temperature tracking error reduced rapidly during the initial transient and remained small in steady state.

The Root Mean Square error for temperature was 0.26726, indicating high tracking accuracy, while the coefficient of determination was 0.75193, confirming an excellent fit between the actual temperature and the reference trajectory.

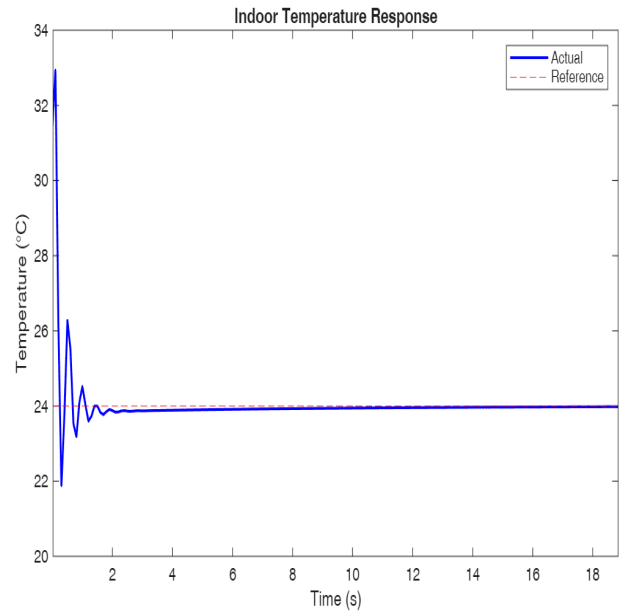


Fig. 3. A graph of temperature response showing the variation of indoor temperature with respect to time relative to the 24 °C reference setpoint.

From figure 3, the temperature exhibits initial overshoot, rising above the 24°C reference before undershooting and oscillating. Short-lived oscillations are present in the first few seconds, indicating an underdamped transient response. The response settles to the reference value in approximately 2–3 seconds, with zero steady-state error, as the temperature converges accurately to 24 °C.

The controller achieves fast regulation with acceptable overshoot and good damping, demonstrating effective temperature control.

2) *Humidity Regulation Results:* The humidity response showed: slightly slower dynamics compared to temperature, due to moisture inertia; stable convergence to the desired humidity level, and minimal overshoot as shown in figure 4.

The GA-optimized baseline PID gains ensured initial stability, while the RBFNN adaptation improved steady-state accuracy under varying moisture disturbances. The RMS error for humidity was calculated as 1.1548, and the R^2 value is 0.11706.

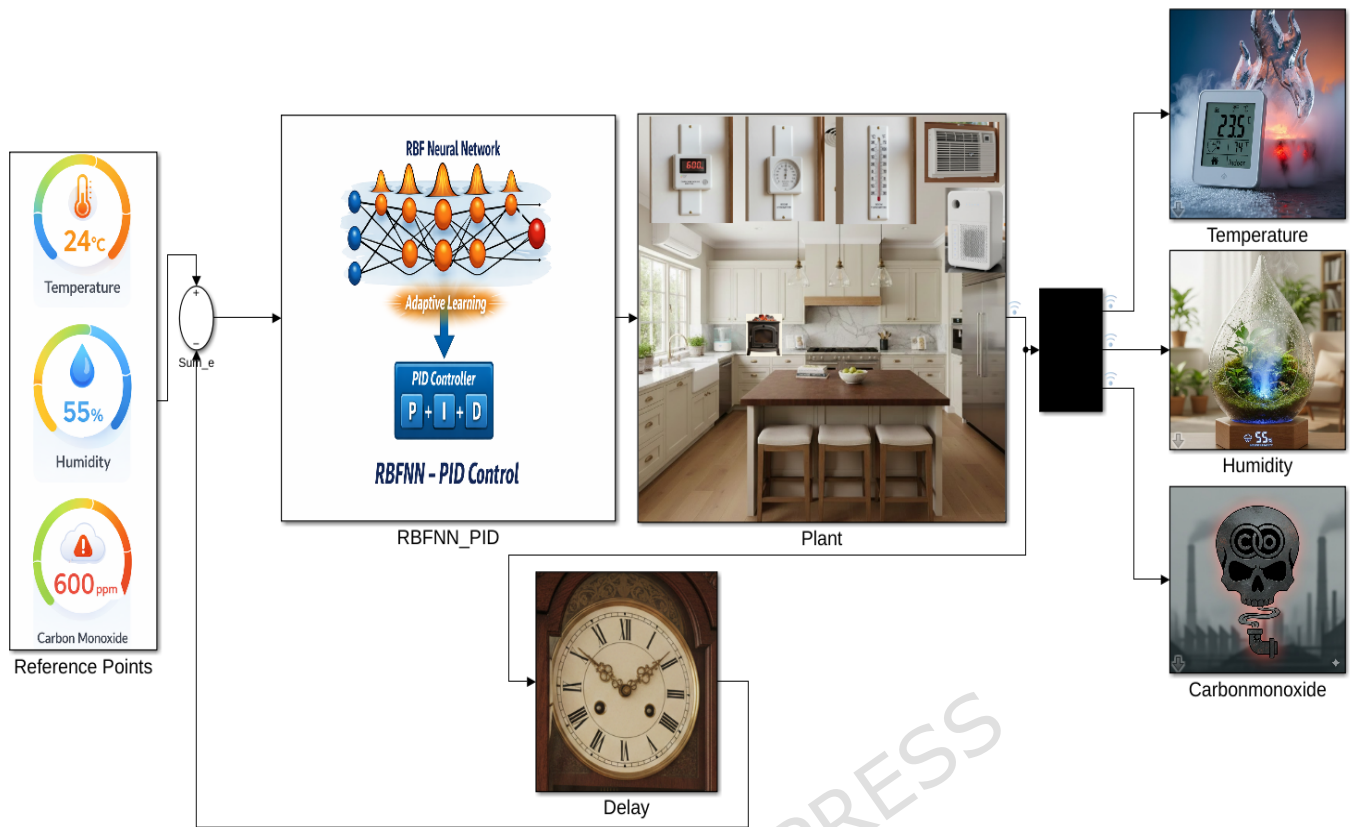


Fig. 2. Simulink diagram of an HVAC control system

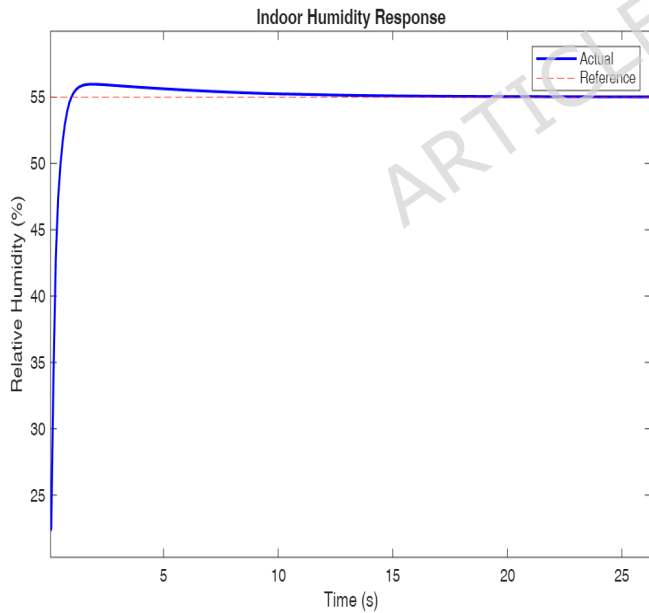


Fig. 4. A graph of humidity response showing the variation of indoor relative humidity with respect to time relative to the 55% reference setpoint.

From figure 4, initially small overshoot is observed, with humidity slightly exceeding the 55% reference. The response is smooth, with no significant oscillations and the system

settles gradually, reaching steady state in about 10–15 seconds with no Steady-state error.

Therefore, the humidity response is well-damped and stable, prioritizing smooth convergence over speed, which is desirable for humidity regulation.

3) CO Regulation Results: The CO concentration exhibited the most challenging dynamics as shown in figure 5 due to intermittent disturbance spikes introduced to emulate indoor combustion activities. Despite this, the controller achieved: Rapid disturbance rejection, Effective suppression of CO peaks, Stable return to the reference concentration.

The adaptive PID mechanism increased control effort during CO spikes and relaxed it once normal conditions resumed. The RMS error for CO is 0.014568 which was lower than that of temperature and humidity. The R^2 metric is 0.99539 which confirmed excellent tracking performance.

The results demonstrate the effectiveness of combining GA and RBFNN with classical PID control.

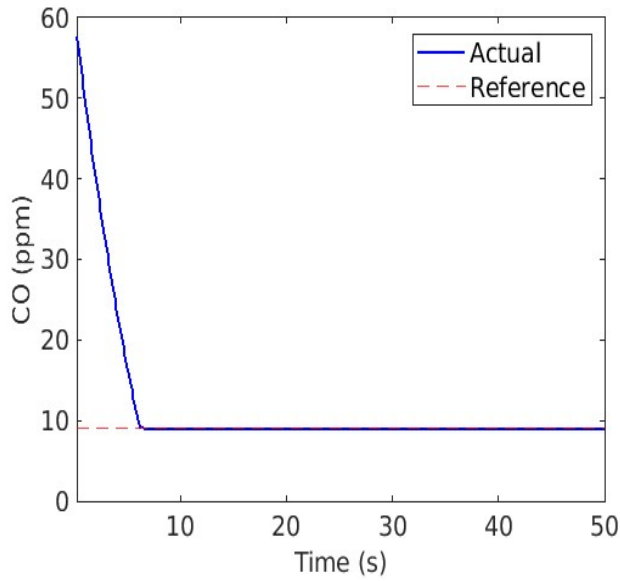


Fig. 5. A graph of carbon monoxide response showing the variation of indoor CO concentration with respect to time relative to the 9 ppm reference setpoint.

From figure 5, the CO concentration shows no significant undershoot or overshoot. No oscillations occur during the transient phase, indicating a more stable control action. The response settles relatively quickly, at 20 seconds with zero steady-state error indicating accurate tracking of the reference point. Thus, the controller reacts aggressively to CO concentration changes, ensuring rapid stabilization, which is critical for safety, though at the expense of higher transient overshoot.

The effectiveness of intelligent HVAC regulation in kitchen environments is intrinsically linked to the physics of buoyancy-driven heat transfer. In these settings, natural convection serves as a primary mechanism for air circulation, where density gradients—driven by concentrated heat sources—propel thermal plumes and cooking-related pollutants into the breathing zone. While such buoyancy-driven flows contribute to passive thermal management and offer potential energy savings in low-energy or mixed convection regimes, they introduce significant nonlinear dynamics and time-varying disturbances that conventional fixed-gain controllers often fail to manage. By employing a hybrid GA-RBFNN-PID strategy, this system actively leverages the adaptive learning of neural networks to compensate for these unpredictable convective currents. This approach ensures that the HVAC system maintains a balance between mechanical ventilation and natural air circulation, ultimately achieving robust thermal comfort and pollutant rejection while maximizing the efficiency of passive heat transfer processes.

IV. CONCLUSION

This study presented a hybrid GA-RBFNN-PID control strategy for intelligent HVAC regulation of temperature, humidity, and CO concentration.

Overall, the simulation results demonstrate that the proposed GA-RBFNN-PID controller provides regulation of a multi-variable HVAC system under time-varying disturbances. The controller achieved accurate reference tracking for indoor temperature, relative humidity, and CO concentration while maintaining closed-loop stability throughout the 200 s simulation period. Quantitative performance evaluation shows a low root mean square tracking error of 0.26726 for temperature, indicating high tracking accuracy, with a corresponding coefficient of determination of 0.75193, confirming a strong agreement between the system response and the reference trajectory. The GA-optimized baseline PID gains ensured initial system stability, while the adaptive RBFNN component enhanced steady-state accuracy under varying thermal and moisture disturbances. For humidity regulation, an RMS error of 1.1548 was obtained, while the adaptive control mechanism dynamically adjusted control effort during intermittent CO concentration spikes. The adaptive control mechanism also effectively responded to intermittent CO concentration disturbances with CO RMS error (0.014568) slightly lower than that of temperature and humidity. These results collectively validate the effectiveness of the proposed hybrid controller in maintaining indoor comfort and air quality under realistic operating conditions.

Despite its promising performance, several challenges and limitations were observed. The humidity tracking performance ($R^2 = 0.11706$) reflects the higher nonlinearity and disturbance sensitivity associated with humidity control in HVAC systems, making it difficult to model accurately using fixed network structures, especially under rapidly changing moisture loads. The adaptive RBFNN also introduces additional computational complexity, which may pose implementation challenges in real-time embedded HVAC controllers with limited processing resources. Furthermore, the study is limited by its purely simulation based nature, which does not fully capture practical factors such as sensor noise, actuator constraints, measurement delays, and complex airflow dynamics in real kitchen environments.

V. RECOMMENDATION

To improve on this research, the following recommendations can be considered;

- i. Computational efficiency can be improved through streamlined neural network adaptation strategies such as partial online learning or offline-trained neural components which may reduce processing requirements while maintaining the high tracking accuracy observed in simulation.

TABLE I
COMPARISON OF HVAC CONTROL METHODS

Feature	Soyguder and Alli (2009)	Suliman et al. (2020)	GA-RBFNN-PID (Proposed)
Control strategy	Fuzzy-PID control	Fuzzy-PID for temperature and RBFNN-PID for humidity	Genetic Algorithm optimized RBF Neural Network PID
Controlled variables	Temperature and Humidity	Temperature and Humidity	Temperature, Humidity, and CO concentration
Adaptation mechanism	No online adaptation	Neural adaptation for humidity only	Online neural adaptation of all PID gains
Optimization method	None	None	Genetic Algorithm for initial PID tuning
Nonlinearity handling	Limited (fixed fuzzy rules)	Moderate (fuzzy and neural based)	Strong (RBFNN learning of HVAC dynamics)
Disturbance rejection	Weak under large disturbances	Medium, slower response to abrupt changes	High, even under rapid cooking and ventilation disturbances
Tracking accuracy	Lower accuracy	Moderate (comfort-band based)	High (low RMS and high R^2 values)
Energy efficiency	Limited energy savings	5–30% energy savings reported	15–35% due to optimal and smooth adaptive control
Indoor air quality (CO control)	Not included	Not included	Included (CO actively regulated)
Response speed	Slow response	Slower settling (30–60 minutes)	Fast settling (1–2 minutes)
Overall robustness	Low	Medium	Very high

- ii. Experimental validation on a physical HVAC platform or in commercial kitchen environments is recommended to confirm the controller's effectiveness beyond simulation.
- iii. Further enhancements may include extending air quality regulation to additional pollutants such as CO_2 and particulate matter.

VI. DECLARATIONS:

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

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VII. APPENDIX 1

A. Matlab Code

```

%% overall.m
% GA-RBFNN-PID HVAC closed-loop simulation
clear; clc; close all;
bdclose('all');
model = 'hvac_rbf_pid_GA_FINAL';
new_system(model);
open_system(model);
set_param(model,...
    'StopTime','200',...
    'Solver','ode4',...
    'FixedStep','0.1');
%% =====
%% 1) GENETIC ALGORITHM FOR INITIAL PID
lb = zeros(1,9);
ub = [40 5 5 40 5 5 40 5 5];
opts = optimoptions('ga',...
    'PopulationSize',20,...
    'MaxGenerations',20,...
    'Display','iter');
PID0 = ga(@fitnessHVAC,9,[],[],[],[],lb,ub,[],opts);
assignin('base','PID0',PID0);
%% =====
%% 2) BLOCK CREATION
% Reference [T H CO]
add_block('simulink/Sources/Constant',[model '/Ref'],...
    'Value',[24;55;9],...
    'Position',[30 120 90 160]);
% Error summation: e = r - y(k-1)
add_block('simulink/Math Operations/Sum',[model '/Sum_e'],...
    'Inputs','+-',...
    'Position',[140 115 170 165]);
% RBFNN-PID Controller
add_block('simulink/User-Defined Functions/Level-2 MATLAB S-Function',...
    [model '/RBFNN_PID'],...
    'FunctionName','rbfnn_pid_sfun',...
    'Position',[210 115 360 165]);
% HVAC Plant
add_block('simulink/User-Defined Functions/Level-2 MATLAB S-Function',...
    [model '/Plant'],...
    'FunctionName','hvac_plant_sfun',...
    'Position',[410 115 560 165]);
% Unit Delay (break algebraic loop)
add_block('simulink/Discrete/Unit Delay',[model '/Delay_y'],...
    'SampleTime','0.1',...
    'InitialCondition','[22;60;60]',...
    'Position',[410 220 560 250]);
% Demux outputs
add_block('simulink/Signal Routing/Demux',[model '/Demux'],...
    'Outputs','3',...
    'Position',[610 115 650 165]);
% Scopes
add_block('simulink/Sinks/Scope',[model '/Scope_T'],...
    'Position',[700 40 750 80]);

```

```

add_block('simulink/Sinks/Scope',[model '/Scope_H'],...
    'Position',[700 110 750 150]);
add_block('simulink/Sinks/Scope',[model '/Scope_C'],...
    'Position',[700 180 750 220]);
%% =====
%% 3) WIRING
% Reference → Sum (+)
add_line(model,'Ref/1','Sum_e/1');
% Plant → Delay → Sum (-)
add_line(model,'Plant/1','Delay_y/1');
add_line(model,'Delay_y/1','Sum_e/2');
% Error → Controller
add_line(model,'Sum_e/1','RBFNN_PID/1');
% Controller → Plant
add_line(model,'RBFNN_PID/1','Plant/1');
% Plant → Demux
add_line(model,'Plant/1','Demux/1');
% Demux → Scopes
add_line(model,'Demux/1','Scope_T/1');
add_line(model,'Demux/2','Scope_H/1');
add_line(model,'Demux/3','Scope_C/1');
%% =====
%% 4) SAVE MODEL
save_system(model);
simOut = sim(model);
disp('FINAL CLOSED-LOOP GA{RBFNN{PID HVAC MODEL CREATED}');
%% =====
% Extract logged signals
logs = out.logouts;
T = logs.getElement(1).Values.Data;
H = logs.getElement(2).Values.Data;
CO = logs.getElement(3).Values.Data;
t = logs.getElement(1).Values.Time;
Tref = 24;
Href = 55;
COfref = 9;
idx = t > 24;
CO_ss = CO(idx);
RMS_T = sqrt(mean((T - Tref).^2));
R2_T = 1 - sum((T - Tref).^2)/sum((mean(T)).^2);
RMS_H = sqrt(mean((H - Href).^2));
R2_H = 1 - sum((H - Href).^2)/sum((mean(H)).^2);
RMS_CO = sqrt(mean((CO_ss - COfref).^2));
R2_CO = 1 - sum((CO_ss - COfref).^2) / sum(mean(CO_ss).^2);
disp(['Temperature RMS = ', num2str(RMS_T)]);
disp(['Temperature R2 = ', num2str(R2_T)]);
disp(['Humidity RMS = ', num2str(RMS_H)]);
disp(['Humidity R2 = ', num2str(R2_H)]);
disp(['CO RMS = ', num2str(RMS_CO)]);
disp(['CO R2 = ', num2str(R2_CO)]);
figure;
plot(t, T, 'b', 'LineWidth', 1.5); hold on;
yline(Tref,'r--');
xlabel('Time (s)');
ylabel('Temperature (°C)');
legend('Actual','Reference');

```

```

figure;
plot(t, H, 'b', 'LineWidth', 1.5); hold on;
yline(Href, 'r--');
xlabel('Time (s)');
ylabel('Relative Humidity (%)');
legend('Actual', 'Reference');
figure;
plot(t, CO, 'b', 'LineWidth', 1.5); hold on;
yline(COref, 'r--');
xlabel('Time (s)');
ylabel('CO (ppm)');
legend('Actual', 'Reference');
%% =====
%% 5) GA FITNESS FUNCTION
function J = fitnessHVAC(p)
Ts = 0.1;
N = 300;
A = diag([-0.12 -0.10 -0.15]);
B = diag([ 0.10  0.08  0.12]);
x = [22;60;60];
r = [24;55;9];
eint = zeros(3,1);
eprev = zeros(3,1);
J = 0;
for k = 1:N
    e = r - x;
    eint = eint + e*Ts;
    ed = (e - eprev)/Ts;
    u = [p(1)*e(1)+p(2)*eint(1)+p(3)*ed(1);
         p(4)*e(2)+p(5)*eint(2)+p(6)*ed(2);
         p(7)*e(3)+p(8)*eint(3)+p(9)*ed(3)];
    x = x + Ts*(A*x + B*u);
    J = J + sum(abs(e));
    eprev = e;
end
end

```

VIII. APPENDIX 2

A. RBFNN Code

```

function rbfnn_pid_sfun(block)
setup(block);
function setup(block)
block.NumInputPorts = 1;
block.NumOutputPorts = 1;
block.InputPort(1).Dimensions = 3;
block.OutputPort(1).Dimensions = 3;
block.SampleTimes = [0.1 0];
block.RegBlockMethod('PostPropagationSetup', @PostPropSetup);
block.RegBlockMethod('InitializeConditions', @Init);
block.RegBlockMethod('Outputs', @Output);
block.RegBlockMethod('Update', @Update);
function PostPropSetup(block)
block.NumDworks = 3;
block.Dwork(1).Name = 'w';
block.Dwork(1).Dimensions = 15;
block.Dwork(1).DatatypeID = 0;
block.Dwork(1).Complexity = 'Real';
block.Dwork(1).UsedAsDiscState = true;
block.Dwork(2).Name = 'eint';
block.Dwork(2).Dimensions = 3;
block.Dwork(2).DatatypeID = 0;
block.Dwork(2).Complexity = 'Real';
block.Dwork(2).UsedAsDiscState = true;
block.Dwork(3).Name = 'eprev';
block.Dwork(3).Dimensions = 3;
block.Dwork(3).DatatypeID = 0;
block.Dwork(3).Complexity = 'Real';
block.Dwork(3).UsedAsDiscState = true;
function Init(block)
block.Dwork(1).Data = zeros(15,1);
block.Dwork(2).Data = zeros(3,1);
block.Dwork(3).Data = zeros(3,1);
function Output(block)
PID0 = evalin('base','PID0');
Ts = 0.1;
e = block.InputPort(1).Data;
eint = block.Dwork(2).Data;
ep = block.Dwork(3).Data;
ed = (e - ep)/Ts;
c = linspace(-1,1,5);
sigma = 0.5;
phi = exp(-(norm(e)-c).^2/(2*sigma^2));
w = reshape(block.Dwork(1).Data,3,5);
dKp = w * phi';
dKi = [0.3*dKp(1);
       0.3*dKp(2);
       1.5*dKp(3)];
dKd = 0.1 * dKp;
Kp0 = PID0([1 4 7])';
Ki0 = PID0([2 5 8])';
Kd0 = PID0([3 6 9])';

```

```

Kp = min(max(Kp0 + dKp, 0), 40);
Ki = min(max(Ki0 + dKi, 0), 10);
Kd = min(max(Kd0 + dKd, 0), 5);
u = Kp.*e + Ki.*eint + Kd.*ed;
u(3) = min(max(u(3), -40), 40);
block.OutputPort(1).Data = u;
function Update(block)
eta = 0.002;
Ts = 0.1;
e = block.InputPort(1).Data;
c = linspace(-1,1,5);
sigma = 0.5;
phi = exp(-(e(1)-c).^2/(2*sigma^2));
w = reshape(block.Dwork(1).Data,3,5);
w = w + eta * (e * phi);
block.Dwork(1).Data = w(:);
block.Dwork(2).Data = block.Dwork(2).Data + e*Ts;
block.Dwork(3).Data = e;

```

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IX. APPENDIX 3

A. Plant Code

```

function hvac_plant_sfun(block)
setup(block);
function setup(block)
block.NumInputPorts = 1;
block.NumOutputPorts = 1;
block.InputPort(1).Dimensions = 3;
block.OutputPort(1).Dimensions = 3;
block.SampleTimes = [0.1 0];
block.RegBlockMethod('PostPropagationSetup', @PostProp);
block.RegBlockMethod('InitializeConditions', @Init);
block.RegBlockMethod('Outputs', @Output);
block.RegBlockMethod('Update', @Update);
function PostProp(block)
block.NumDworks = 1;
block.Dwork(1).Name = 'x';
block.Dwork(1).Dimensions = 3;
block.Dwork(1).DatatypeID = 0;
block.Dwork(1).Complexity = 'Real';
block.Dwork(1).UsedAsDiscState = true;
function Init(block)
% Ambient Conditions
block.Dwork(1).Data = [31.4; 24; 60];
function Output(block)
block.OutputPort(1).Data = block.Dwork(1).Data;
function Update(block)
Ts = 0.1;
x = block.Dwork(1).Data;
u = block.InputPort(1).Data;
A = diag([-0.12 -0.10 -0.10]);
B = diag([ 0.10  0.08  0.15]);
t = block.CurrentTime;
%Disturbances
d = [0.03*sin(0.05*t);
     0.05*cos(0.05*t);
     0];
if t > 25
    d(3) = 0.4 * exp(-0.5*(mod(t,40)-4).^2);
end
% Reference points
x_ref = [25.5; 41; 9];
x = x + Ts*(A*(x - x_ref) + B*u + d);
block.Dwork(1).Data = x;

```