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Fuzzy Logic and Neural Network-Based Self-Tuning PID for Vacuum Pressure Stabilization

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ABSTRACT

The conventional PID controller is widely used for vacuum pressure control; however, it has limitations when faced with nonlinear system characteristics and external disturbances, leading to a decline in performance. Several previous studies have proposed the integration of PID with intelligent methods, such as neural networks or fuzzy logic separately. Nevertheless, these singular approaches still encounter limitations in terms of adaptability and robustness. This study aims to develop a self-tuning PID method based on the combination of Neural Networks (NN) and Fuzzy Inference Systems (FIS) to enhance the stability and accuracy of vacuum pressure control. A nonlinear vacuum system plant model is constructed within the Simulink environment to generate a dataset used for training the NN with the Levenberg-Marquardt algorithm. The NN is employed to predict changes in PID parameters adaptively, while the FIS provides fine corrections to strengthen system stability. Simulation results demonstrate that the proposed approach effectively reduces overshoot from 36.47% to 31.51%, decreases steady-state error from 0.069 to 0.052, and lowers the RMSE value from 0.125 to 0.108 compared to conventional PID. Thus, the integration of NN and FIS within the self-tuning mechanism proves to be more effective in addressing nonlinear dynamics and external disturbances, resulting in a more stable and accurate system response.

I. INTRODUCTION

Various modern control approaches have utilized PID algorithms to enhance the performance of dynamic systems. Proportional-Integral-Derivative (PID) controllers are the most widely used control methods across various industrial applications due to their simple design, ease of implementation, and reliable performance in controlling linear systems. However, the limitations of conventional PID in addressing nonlinear systems and varying dynamics have prompted the development of adaptive and intelligent approaches. Research [1] indicates that traditional PID struggles to maintain optimal performance in the face of load changes or model uncertainties, leading to the development of neural network-based PID methods that adaptively adjust parameters based on system identification using multi-layer perceptron (MLP) neural networks. These approaches include integration with wavelet-based neural networks in liquid-level systems [2], a combination of fuzzy self-tuning gain with radial basis function (RBF) neural networks in composite controllers[3], and the development of PID controllers that are automatically tuned using backpropagation neural networks (BP neural networks) in industrial applications [4].

Research[5] highlights that integrating PID with fuzzy logic and bio-inspired learning structures can enhance the stability and responsiveness of control systems in industrial applications. The combination of PID with intelligent methods such as fuzzy logic and artificial neural networks has proven effective in addressing the challenges of adaptive control in complex and nonlinear environments. Fuzzy logic has been widely utilized to tackle nonlinearity and uncertainty in adaptive control systems. For instance, researchers[6] have demonstrated that the combination of fuzzy-PID with BP-PID can improve temperature control performance in water-cooled PEMFC systems compared to conventional PID.

Research[7] applies fuzzy self-tuning PID to active suspension systems to enhance dynamic stability, while[8] integrates fuzzy logic with Active Disturbance Rejection Control (ADRC) to effectively mitigate external disturbances. Additionally, metaheuristic algorithms such as Genetic Algorithm (GA) and Social Spider Algorithm (SSA) have strengthened the optimization of fuzzy parameters in various industrial applications.

The concept of "self-tuning" or automatic adjustment is crucial for enhancing the adaptability and performance of control systems, particularly in complex machinery and electrical power systems. Research[9] emphasizes the significance of "self-adaptive" fuzzy neural networks in optimizing the operation of UHV power transmission systems to address uncertainty and nonlinearity. Meanwhile, [10] discusses the application of hybrid techniques that combine neural networks and fuzzy logic for "self-tuning" in controlling three-phase induction motors to improve performance and stability. Research [11] demonstrates that the use of artificial neural networks in tokamak plasma control systems can perform automatic "self-tuning" to accurately reconstruct plasma states and support the stability and operational efficiency of future nuclear reactors.

Neural networks (NN) have been extensively utilized in intelligent control systems due to their ability to model nonlinear relationships and adaptively adjust parameters. In the pressure control system of a PWR reactor pressurizer, the combination of fuzzy-NN enhances the real-time tuning performance of PID controllers [12]. Researchers[13] employed self-tuning IPID based on two neural networks and the IAJS algorithm for the heading control of wave glider vehicles, addressing complex marine dynamics. Furthermore, in thermal applications, adaptive NN is used to adjust controllers in response to changes in load and time [14]. In robotic applications, NN-based trajectory tracking controllers, along with backstepping and sliding mode control methods, improve resilience to external disturbances [15].

Self-tuning methods based on artificial intelligence have developed rapidly over the past decade, enhancing the accuracy and efficiency of complex nonlinear control systems. Research [16] demonstrates that the use of artificial neural networks (ANN) with a bidirectional coupling mechanism can dynamically predict the daily performance of PV/T systems, reducing reliance on traditional rigid physical models in response to system dynamics. Research [17] emphasizes that ANFIS can serve as a data-driven self-tuning regulator in high-precision nonlinear mechanical systems. An adaptive chaotic fuzzy neural network has been developed to mitigate seismic vibrations in real-time using multi-layer perceptron (MLP) and extended Kalman filter (EKF) techniques [18]. The integration of deep neural networks within a feedback-error-learning framework alongside fuzzy PID has been applied to inverted pendulum systems[19]. Meanwhile, [20] utilizes the Dragonfly algorithm to train feedforward neural networks, addressing the limitations of gradient methods in neural network training. Research[21] combines backpropagation neural networks (BP-NN) with Genetic Algorithms (GA) to construct an offline database that ensures an even data distribution and avoids unstable gain combinations, resulting in 86% of the tests meeting dynamic response specifications in DC motor speed control.

Research[22] utilizes a Radial Basis Function Neural Network (RBFNN) with Lyapunov-based adaptation laws to approximate unknown dynamics and maintain stability in the presence of external disturbances. Approach [23] combines Fuzzy Logic and Neural Networks in the form of an Adaptive Fuzzy Neural Network Controller (AFNNC), which adjusts the membership function parameters and network weights online, enabling the system to respond quickly and with high precision to parameter changes. Meanwhile,[24] focuses on compensating for time delays in Networked Control Systems by integrating Cuckoo Search-optimized Backpropagation Neural Networks (CS-BP) with Implicit Generalized Predictive Control (IGPC), effectively predicting and correcting delays to sustain real-time signal tracking performance. Research [25] develops an artificial neural network (ANN) model to predict the performance of a pneumatic seed-metering device by considering both seed physical parameters and operational parameters. This model estimates seed placement quality without the need for field tests, yielding high prediction accuracy that is beneficial for design optimization and machine adjustments. Meanwhile, [26] employs an ANN with the Levenberg–Marquardt algorithm to predict the optimal vacuum pressure in a water-suction seed-metering device based on seed physical characteristics, achieving an R^2 of 0.9949. This result indicates a high level of predictive accuracy, supporting the calibration of precision planting machines for various seed types.

This research specifically aims to develop a self-tuning PID control method based on the integration of Neural Networks (NN) and Fuzzy Inference Systems (FIS) for nonlinear vacuum systems. This approach is expected to address the limitations of conventional PID in dealing with nonlinear dynamics, external disturbances, and variations in system parameters. The novelty of this research lies in the combination of NN-based learning adaptation with fuzzy rules, which provides a more flexible and robust tuning capability for PID parameters compared to previous methods that utilized NN or fuzzy logic separately. Consequently, the primary contribution of this study is the development of an intelligent control model that reduces overshoot, accelerates settling time, and minimizes steady-state error and RMSE compared to conventional PID. The structure of this paper is organized as follows: Section II explains the proposed methodology and algorithm, Section III presents the simulation results and performance analysis of the control system, and Section IV concludes the research findings and offers directions for future development.

The primary contribution of this research is the proposal of a self-tuning PID mechanism based on the integration of a Neural Network (NN) and a Fuzzy Inference System (FIS) for vacuum pressure control. The NN plays a role in predicting adaptive adjustments of the PID parameters (ΔKp, ΔKi, ΔKd), while the FIS provides fine-tuning corrections to enhance system stability. This integration represents a novel approach that is more effective than previous methods that utilized NN or FIS separately.

II. METHOD

The proposed method aims to maintain pressure stability in the vacuum system chamber using an automatically tuned PID controller combined with Fuzzy Logic and a Backpropagation-based Neural Network (NN). The NN is employed to predict changes in the PID parameters (ΔKp, ΔKi, ΔKd) adaptively based on the current error conditions and their rates of change, while Fuzzy Logic is utilized to provide fine-tuning adjustments to these parameters. The architecture of this method is illustrated in Figure 1, which consists of four main components:

1. Vacuum System Plant Model.
2. PID Controller
3. Neural Network Adjustment Module
4. Fuzzy Logic Adjustment Module

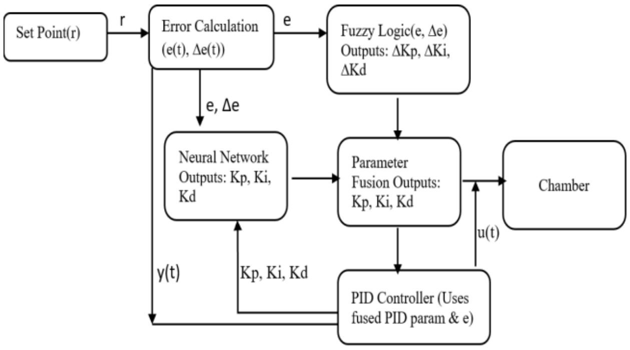

Figure 1. Architecture of the Adaptive Self-Tuning PID Control System

Figure 1. Architecture of the proposed adaptive self-tuning PID control system, consisting of four main components: (1) Vacuum System Plant Model, (2) PID Controller, (3) Neural Network Adjustment Module, and (4) Fuzzy Logic Module. The error signal is obtained from the difference between the setpoint and the system output, and is then processed through two pathways: (a) the NN pathway to predict changes in the PID parameters (ΔKp, ΔKi, ΔKd) adaptively, and (b) the Fuzzy Logic pathway to fine-tune the NN's predictions, thereby enhancing system stability and responsiveness. The adjusted PID parameters are utilized by the controller to generate the control signal u(t) directed towards the plant. The actual pressure output from the plant is fed back into the error calculation, forming a closed-loop system capable of adapting to changes in system conditions as well as external disturbances.

A. *Vacuum System Plant Model*

The vacuum system plant model is constructed to represent the pressure dynamics within the vacuum chamber. This model serves as both the control object and a reference for evaluating the performance of the controller. The dynamics of the plant are implemented in a Simulink environment, facilitating direct integration with the PID control module and the parameter adjustment algorithms.

B. *Dataset and Data Partitioning*

The data used in this research was generated from the vacuum plant, utilizing scenarios of error (e) and delta error (Δe) as the primary inputs. The dataset is structured in a two-dimensional matrix format, where input_train contains pairs of values [e, Δe], and target_train consists of three output variables: ΔKp, ΔKi, and ΔKd. A total of 4000 simulation samples were obtained, which were then divided into three subsets: 70% for training, 15% for validation, and 15% for testing. Data normalization was performed using the mapminmax method to ensure that each feature falls within the range of [-1,1], thereby accelerating convergence during the training of the artificial neural network. With this division and normalization, the model is expected to achieve good generalization and avoid overfitting.

C. *Acquisition and Processing of Neural Network Training Data*

This stage aims to collect data that will be used for training the neural network. The data is obtained from simulation results or measurements of real systems, encompassing error, error changes, and adjustment values of control parameters. The data is then processed, including normalization and cleaning to eliminate NaN or Inf values before being utilized for training. This process ensures that the neural network is capable of optimally learning the pattern of relationships between the inputs (e, Δe) and the outputs (ΔKp, ΔKi, ΔKd). The training dataset for the neural network consists of input-output pairs :

Input:

$e(t)=r(t)-y(t)$

$\Delta e(t)=e(t)-e(t-1)$

where r(t) is the pressure set point and y(t) is the actual pressure.

Output:

ΔKp,ΔKi,ΔKd : The desired changes in the PID parameters are stored in the initial dataset referred to as data_training. To prevent instability during training, data cleaning is performed to remove columns containing NaN or ∞ values.

D. *Training of the Neural Network*

The neural network (NN) is designed to predict changes in PID parameters (ΔKp, ΔKi, ΔKd) based on input error and delta error. Training is conducted using the Levenberg–Marquardt algorithm, with the data divided into training, validation, and testing subsets. The results of the training are measured using Mean Squared Error (MSE) to evaluate prediction accuracy. The training phase of the neural network (NN) is the core of the PID parameter adaptation process within this system. The goal of the training is to develop an

NN model capable of accurately predicting control parameter changes (ΔKp, ΔKi, ΔKd) based on input error and Δe. This process utilizes the dataset acquired earlier, which is divided into training, validation, and testing data. The selection of network architecture, the number of hidden neurons, training algorithms, and training parameters such as epochs and goal error are adjusted to achieve a balance between convergence speed and prediction accuracy. The NN training is performed using MATLAB, employing a Feedforward Neural Network architecture with the Levenberg–Marquardt algorithm.

Neural Network Specifications:

1. Number of neurons in the hidden layer: [128 40]. Activation function: tansig in the hidden layer, purelin in the output layer
2. Normalization function: mapminmax for inputs and outputs
3. Data division ratio: 70% training, 15% validation, 15% testing
4. Stopping criterion: early stopping if there is no improvement in validation for 12 epochs
5. Target MSE: $1{\times}10^{-6}$

The training process of the artificial neural network is conducted using the Levenberg–Marquardt (LM) algorithm. The selection of LM is based on its advantages in combining gradient descent and Gauss–Newton approaches, thereby achieving faster and more stable convergence for nonlinear problems. With a relatively moderate amount of training data (approximately 4000 samples), LM is an optimal choice as it is known to be more efficient and accurate compared to other algorithms such as stochastic gradient descent or conjugate gradient, which generally require more iterations. Furthermore, LM has been shown to produce lower prediction errors in feedforward networks with multiparameter targets (ΔKp, ΔKi, ΔKd), thereby supporting the requirements of the PID control system to significantly reduce overshoot, steady-state error, and RMSE. Therefore, LM is considered most suitable to ensure that the NN model can provide rapid, accurate, and robust predictions of PID parameters in relation to the nonlinear characteristics of the vacuum system.

E. *Neural Network Training Algorithm*

```
Neural Network Training for ΔKp, ΔKi, ΔKd
Input: Training dataset D = {(e, de) → (ΔKp, ΔKi, ΔKd)}, learning rate η
Output: Trained neural network model Net
1. Initialize weights W and biases b randomly
2. For each epoch = 1 to MaxEpoch do
3.    For each training sample (e, de) do
4.       Forward pass:
5.          h = f(W_in * [e; de] + b_in)      # hidden layer activation
6.    ŷ = W_out * h + b_out    # predicted ΔKp, ΔKi, ΔKd
7.       Compute error:
8.          E = (ŷ - y_true)²              # MSE loss
9.       Backpropagation:
10.         δ_out = (ŷ - y_true)
11.         δ_h  = f'(h) * (W_out^T * δ_out)
12.      Update weights:
13.         W_out ← W_out - η * δ_out * h^T
14.         W_in  ← W_in  - η * δ_h * [e; de]^T
15.   End For
16.   If stopping criterion met (MSE < ε) then break
17. End For
18. Return Net(W,b)
```

To clarify the proposed process, the self-tuning PID control algorithm is formulated mathematically as follows:

Given a dataset: :

$X = \{\left(e^{(i)}, de^{(i)}\right)\}_{i=1}^{N}, Y = \{\left(\Delta K_p^{(i)}, \Delta K_i^{(i)}, \Delta K_d^{(i)}\right)\}_{i=1}^{N}$

1. Forward pass:

$h^{(i)} = f\left(w_{in}.x^{(i)} + b_{in}\right)$

$\hat{y}^{(i)} = W_{out}.h^{(i)} + b_{out}$

2. Loss function (MSE):

$E = \frac{1}{N}\sum_{i=1}^{N}\left\|\hat{y}^{(i)} - y^{(i)}\right\|^2$

3. Backpropagation:

$\delta_{out} = \hat{y}^{(i)} - y^{(i)}$

$\delta_h = f'\left(h^{(i)}\right).\left(W_{out}^T\delta_{out}\right)$

4. Update rule:

$W_{out} \leftarrow W_{out} - \eta.\delta_{out}.\left(h^{(i)}\right)^T$

$W_{in} \leftarrow W_{in} - \eta.\delta_h.(x^{(i)})^T$

F. *Fuzzy Logic Module*

The fuzzy logic module is utilized to provide additional control parameter adjustments heuristically based on predefined rules. A Fuzzy Inference System (FIS) is constructed with membership functions and a rule base designed to anticipate nonlinear conditions and system uncertainties. The principle is to leverage fuzzy rules formulated based on experience or domain knowledge, allowing for fine-tuning of the PID parameter changes produced by the neural network (NN). This module takes inputs from the error value and Δe, then generates a more refined correction signal, particularly during transient conditions or when the system approaches the setpoint. The integration of the NN and Fuzzy Logic enables the control system to exhibit rapid adaptation while maintaining stability in the face of load variations and disturbances. The Fuzzy Inference System is designed using the Mamdani method and Gaussian membership functions.

1. Input Fuzzy: error (ee) and delta error (Δe)
2. Output Fuzzy: Additional Correction to ΔKp,ΔKi,ΔKd
3. Number of Rules: 9 IF-THEN Rules Based on Expert Knowledge
4. Defuzzification: centroid method.

G. *Integration of Neural Networks and Fuzzy Logic in PID Control.*

The prediction results from the neural network (NN) and the output from the fuzzy logic module are combined to adaptively adjust the PID parameters. This integration aims to leverage the predictive capabilities of the NN and the flexibility of fuzzy logic in managing load variations and disturbances in the vacuum system. The NN plays a role in dynamically predicting the values of parameter changes (ΔKp, ΔKi, ΔKd), while fuzzy logic provides additional corrections based on linguistic rules. The final output of this integration is applied directly to the PID controller, enabling the controller to respond to system dynamics in real-time, adjusting control characteristics to accommodate changes in load conditions and external disturbances without requiring manual intervention..

H. *Self-Tuning PID Deployment Algorithm*

NN+FIS Self-Tuning PID Control
Input: Set point sp, plant output y, trained Net, FIS
Output: Control signal u
1. Initialize Kp, Ki, Kd
2. For each sampling instant k do
3. Compute error: e(k) = sp - y(k-1)
4. Compute delta error: de(k) = e(k) - e(k-1)
5. Predict ΔK from NN: [dKp_nn, dKi_nn, dKd_nn] = Net([e(k); de(k)])
6. Predict ΔK from FIS: [dKp_fis, dKi_fis, dKd_fis] = evalFIS([e(k), de(k)])
7. Combine corrections:
8. dKp = dKp_nn + α * dKp_fis
9. dKi = dKi_nn + α * dKi_fis
10. dKd = dKd_nn + α * dKd_fis
11. Update gains:
12. Kp ← clamp(Kp + dKp)
13. Ki ← clamp(Ki + dKi)
14. Kd ← clamp(Kd + dKd)
15. Compute control signal:
16. u(k) = u(k-1) + Kp*(e(k)-e(k-1)) + Ki*e(k) + Kd*(e(k)-2e(k-1)+e(k-2))
17. Apply saturation: u(k) ← clamp(u(k), [umin, umax])
18. Update plant: y(k) = f(u(k))
19. End For

The following equations present the mathematical formulation of the proposed self-tuning PID algorithm, which integrates Neural Network (NN) backpropagation with fuzzy logic adaptation.

1. Error and delta error:

$e(k) = r(k) - y(k), \Delta e(k) = e(k) - e(k-1)$

2. Gain correction prediction by NN:

$[\Delta K_p^{NN}, \Delta K_i^{NN}, \Delta K_d^{NN}] = Net([e(k), \Delta e(k)])$

3. Gain correction prediction by FIS:

$[\Delta K_p^{FIS}, \Delta K_i^{FIS}, \Delta K_d^{FIS}] = FIS([e(k), \Delta e(k)])$

4. Combination:

$\Delta K_p = \Delta K_p^{NN} + \alpha \cdot \Delta K_p^{FIS}$
$\Delta K_i = \Delta K_i^{NN} + \alpha \cdot \Delta K_i^{FIS}$
$\Delta K_d = \Delta K_d^{NN} + \alpha \cdot \Delta K_d^{FIS}$

5. Update PID parameters:

$K_p(k) = K_p(k-1) + \Delta K_p,$
$K_i(k) = K_i(k-1) + \Delta K_i,$
$K_d(k) = K_d(k-1) + \Delta K_d$

6. Incremental control signal:

$$u(k) = u(k-1) + K_p(k)(e(k) - e(k-1)) + K_i(k)e(k) + K_d(k)(e(k) - 2e(k-1) + e(k-2))$$

7. Nonlinear plant:

$$y(k) = y(k-1) + 0.1 \cdot u(k) \cdot sin(u(k)) - 0.01y(k-1)^2 + \epsilon(k)$$

I. *Simulation and Performance Evaluation.*

The simulation of the system is conducted in MATLAB/Simulink under various load and disturbance scenarios. Performance evaluation includes measurements of overshoot, settling time, rise time, and steady-state error. A comparison is made between conventional PID control and NN and fuzzy logic-based self-tuning PID to assess the improvement in system performance. The simulation environment is constructed in MATLAB, incorporating the vacuum system plant model, the adaptive PID controller based on NN and Fuzzy Logic, and various testing scenarios. Evaluation is based on performance parameters such as rise time, settling time, overshoot, and steady-state error. Additionally, the stability of the system is tested under load variations and random disturbances to ensure the reliability of the method. The results of this evaluation serve as a reference for the feasibility of implementing the method in physical systems. Simulations are conducted in MATLAB/Simulink with parameters.

1. Duration of simulation: 200 iterations
2. Pressure set point: 1.0 (relative units)
3. Noise model for the plant: Band-Limited White Noise to represent environmental disturbances.

Control performance is evaluated based on:

1. Rise Time : the time taken to reach 90% of the set point
2. Settling Time: the time spent within ±5% of the set point
3. RMSE of Pressure: Root Mean Square Error
4. Response to disturbances.

III. RESULTS AND DISCUSSION

This section presents the simulation results and performance analysis of the self-tuning PID control based on Neural Networks (NN) and Fuzzy Logic in a vacuum system. The evaluation focuses on key performance parameters such as rise time, settling time, response to setpoint, system error, and comparisons between linear and nonlinear models.

A. Quantitative Simulation Results

The simulation results demonstrate the performance of the conventional PID compared to the NN+FIS Self-Tuning PID method. The evaluation is conducted based on five key metrics: Rise Time, Settling Time, Overshoot, Steady-State Error (SS Error), and Root Mean Square Error (RMSE). Table 1 presents a quantitative comparison of the test results:

TABLE 1.
PERFORMANCE COMPARISON BETWEEN CONVENTIONAL PID AND NN+FIS SELF-TUNING PID.

Metrics	Fixed PID	NN+FIS Self-Tuning
Rise Time (s)	3.60	3.40
Settling Time (s)	399.95	399.95
Overshoot (%)	36.47	31.51
SS Error (abs)	0.0691	0.0518
RMSE	0.1254	0.1079

Based on Table 1, the comparison of performance between the conventional PID (Fixed PID) and the NN+FIS Self-Tuning PID demonstrates a significant improvement in several key metrics. In terms of rise time, the NN+FIS method accelerates the system response from 3.60 seconds to 3.40 seconds, although this difference is relatively small. This indicates that the adaptive parameter adjustment mechanism helps the system reach the setpoint more quickly without compromising stability. For settling time, both methods yield the same value of approximately 399.95 seconds. This condition suggests that the NN+FIS approach does not adversely affect the long-term stability of the system, even though there is no significant improvement in stabilization time.

B. System Response using NN+FIS Self-Tuning PID Controller

Figure 1 illustrates the system response using the NN+FIS Self-Tuning PID controller. The simulation results demonstrate that the system is capable of reaching the set point value with a relatively quick rise time while remaining stable around the reference value. The fluctuations observed around the set point are a consequence of the nonlinear characteristics of the plant and the presence of noise in the system; however, their amplitudes are relatively small, and the system does not experience significant long-term deviations. In comparison to the fixed PID controller, the performance of the NN+FIS Self-Tuning controller shows significant improvement. Overshoot is reduced, steady-state error is minimized, and the Root Mean Square Error (RMSE) value is lower. This evidence indicates that the integration of Neural Networks (NN) and Fuzzy Inference Systems (FIS) can adaptively adjust PID parameters according to the dynamic conditions of the plant, resulting in a smoother, more robust, and accurate response to changes and uncertainties in the system. Thus, the NN+FIS Self-Tuning PID controller proves to be superior in maintaining pressure stability compared to the conventional PID, particularly in systems with nonlinear characteristics.

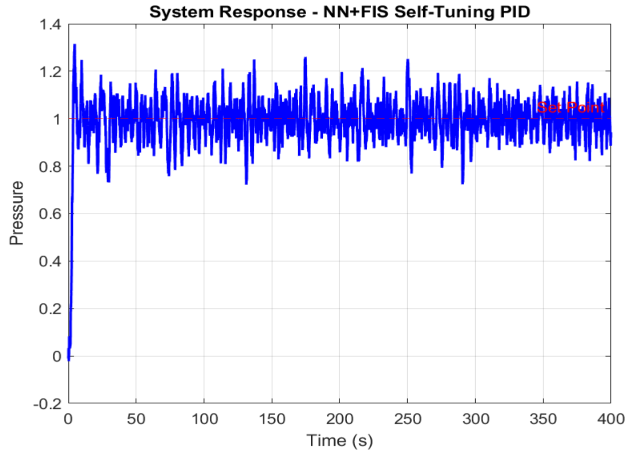

Figure 2. System Response using NN+FIS Self-Tuning PID Controller

C. System Response Comparison between Fixed PID and NN+FIS Self-Tuning

Figure 3 illustrates the comparison of system responses between the conventional PID and the NN+FIS Self-Tuning controller. It is evident that the conventional PID still produces significant oscillations with a relatively large steady-state deviation from the set point. In contrast, the NN+FIS Self-Tuning controller is capable of adaptively adjusting the control parameters, resulting in a more stable system response, reduced overshoot, and decreased steady-state error. This indicates that the integration of artificial neural networks with a fuzzy inference system provides better adaptability to the nonlinear dynamics of the system compared to fixed PID control.

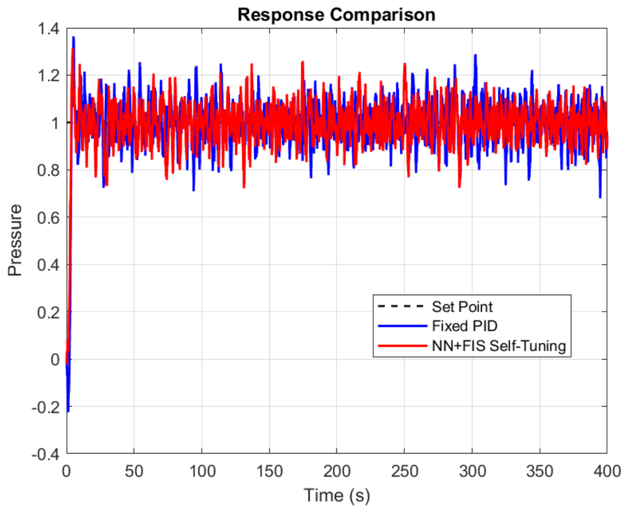

Figure 3. System Response Comparison between Fixed PID and NN+FIS Self-Tuning

D. Error Response Comparison (Fixed PID vs NN+FIS Self-Tuning)

Figure 4 illustrates the comparison of error to the set point between the fixed PID controller and the NN+FIS Self-Tuning controller. In the initial phase, the error is significant

(~1.0) due to the difference between the initial conditions and the set point. Over time, the NN+FIS Self-Tuning controller is able to reduce the error more rapidly than the fixed PID, with error values fluctuating around zero and not accumulating. In contrast, the fixed PID controller exhibits relatively larger errors due to the limitations of static parameters that cannot adapt to the system's dynamics. These results emphasize that the NN+FIS-based self-tuning mechanism provides more stable and accurate performance in maintaining error relative to the set point.

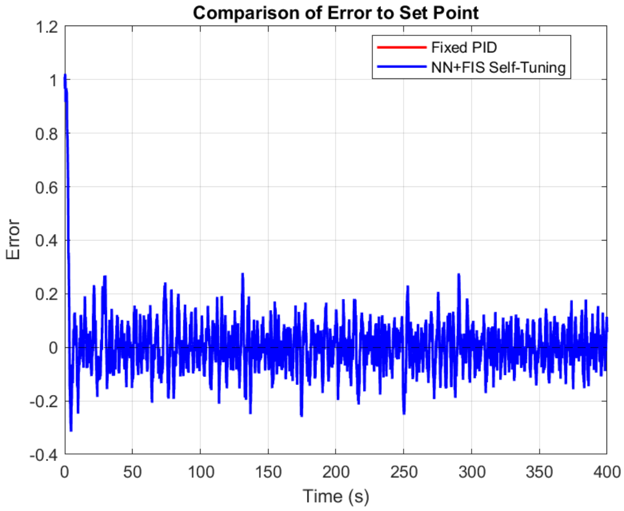

Figure 4. Error Response Comparison (Fixed PID vs NN+FIS Self-Tuning)

E. Comparison of Linear vs. Nonlinear Models

Figure 5 presents a comparison of the responses of linear and nonlinear models to system pressure.

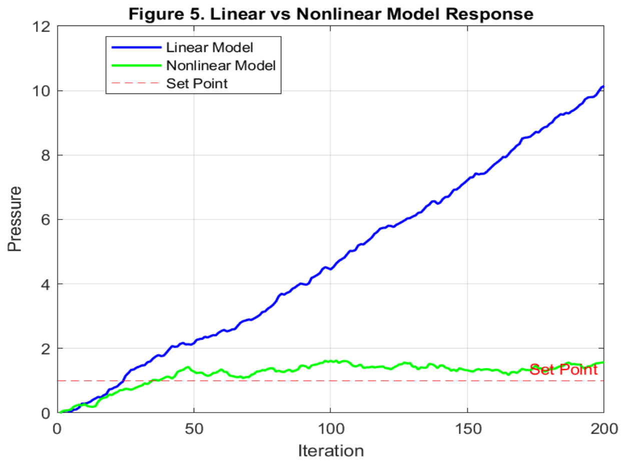

Figure 5. Comparison of Linear vs. Nonlinear Models

The response of the linear model continues to increase cumulatively and significantly exceeds the set point, rendering it unsuitable as a representation of the actual system. In contrast, the nonlinear model exhibits a more controlled response, with fluctuations remaining around the set point. This emphasizes that the nonlinear model is more representative of the plant dynamics, as it can capture the effects of saturation and nonlinearities that are not addressed by the linear model. Therefore, the use of a nonlinear model provides better validity in simulations and controller testing.

F. Comparison of Control Signals between Fixed PID and NN+FIS Self-Tuning PID

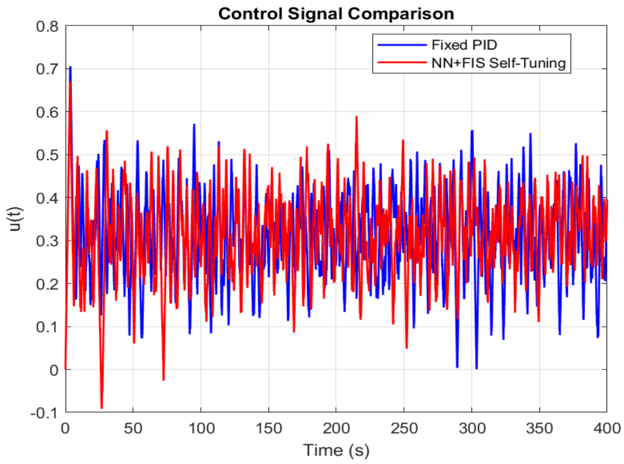

Figure 6. Comparison of Control Signals between Fixed PID and NN+FIS Self-Tuning PID

Figure 6 presents a comparison of the control signal u(t)$u(t)$ between the Fixed PID controller and the NN+FIS Self-Tuning PID controller. It is evident that the Fixed PID generates a control signal with higher fluctuations and frequent extreme changes. This condition indicates that the conventional controller is less adaptive to the dynamics of nonlinear systems, which demands heavier actuator performance and potentially increases energy consumption.

In contrast, the NN+FIS Self-Tuning PID produces a more adaptive control signal with relatively moderate amplitudes. This is attributed to the capability of the artificial neural network (NN) to dynamically adjust PID parameters, along with the support of the fuzzy inference system (FIS) in providing additional corrections. Thus, the control produced is more efficient, reducing the load on the actuator and enhancing the overall stability of the system.

These findings reinforce previous results, indicating that the NN+FIS-based self-tuning approach not only improves system response in terms of rise time, overshoot, and steady-state error but also delivers a more optimal and controlled control signal compared to conventional PID methods.

G. Analysis of Performance Comparison Based on Time and Accuracy Metrics.

Based on the visualization results in Figures 7-a and 7-b, it is evident that the NN+FIS Self-Tuning PID method outperforms the conventional PID. In terms of accuracy/error metrics (Figure 7-a), the adaptive controller successfully reduces overshoot from 36.47% to 31.51%, decreases steady-state error from 0.069 to 0.052, and lowers RMSE from 0.125 to 0.108.

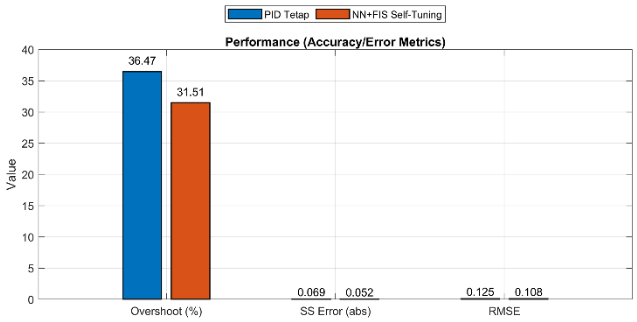

Figure 7-a Accuracy and Error Metrics Comparison between Fixed PID and NN+FIS Self-Tuning

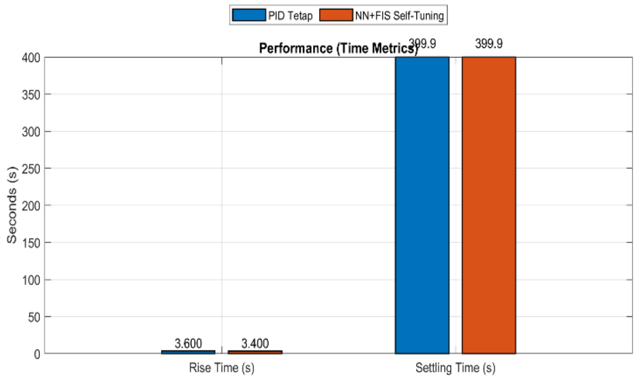

Figure 7-b. Time Metrics Comparison (Rise Time and Settling Time) between Fixed PID and NN+FIS Self-Tuning

This indicates that the system with NN+FIS is more precise, stable, and capable of maintaining the output closer to the setpoint value. Meanwhile, in the time metrics (Figure 7-b), it is observed that the rise time decreased from 3.60 seconds to 3.40 seconds, indicating an acceleration in the initial response toward the setpoint. However, the settling time does not experience significant change, remaining at approximately 399.9 seconds for both the Fixed PID and NN+FIS methods. This condition suggests that although the NN+FIS method excels in terms of accuracy and error reduction, the long-term stability of the system is relatively comparable to that of the conventional PID. Overall, both graphs reinforce the notion that the NN+FIS Self-Tuning PID is superior in reducing oscillations, minimizing errors, and accelerating the initial response, although it does not provide significant improvement in settling time. These results are consistent with the concept that the integration of Neural Networks and Fuzzy Logic can offer better adaptive capabilities than PID with fixed parameters.

H. Discussion

The research findings indicate that the integration of Backpropagation Neural Networks (BNN) with a Fuzzy Logic module as a self-tuning PID controller significantly enhances the stability of the vacuum system. Simulation results show a reduction in overshoot from 36.47% to 31.51%, a decrease in steady-state error from 0.069 to 0.052, and a lower RMSE from 0.125 to 0.108 compared to conventional PID. These improvements demonstrate the ability of the proposed method to produce a faster and more precise system response. The findings are in line with research[27], which developed a hybrid actor–critic neural network-based self-tuning PID for quadcopter systems and reported significant improvements in stability and adaptive response to dynamic disturbances. Similarly, research [28] combined BNN with the metaheuristic Enhanced Dung Beetle Optimization for PID tuning in DC motors, achieving an overshoot of only 0.5% and a settling time of 0.02 seconds, underscoring the benefit of intelligent and adaptive tuning mechanisms.

Beyond numerical improvements, the superiority of the proposed hybrid method lies in the complementary roles of BNN and Fuzzy Logic. The neural network adaptively predicts parameter changes (ΔKp, ΔKi, ΔKd) based on error and delta error, enabling the controller to adjust in real-time to nonlinear dynamics and load variations. Meanwhile, the fuzzy logic module performs fine-tuning of the NN outputs, preventing oscillations and ensuring system stability. This synergy allows the self-tuning PID to be both adaptive and robust, outperforming methods that rely solely on NN or Fuzzy Logic. This synergy allows the self-tuning PID to be both adaptive and robust, outperforming methods that rely solely on NN or Fuzzy Logic. This observation is consistent with studies [29] and [30], which highlight that real-time adaptive tuning is critical to maintaining optimal performance in nonlinear and MIMO systems.

Despite the performance advantages, several trade-offs accompany the proposed approach. First, the computational cost is higher due to the NN training process and the combined execution of NN and fuzzy modules during operation. This may challenge real-time deployment in systems with limited computational resources. Second, the design complexity increases because constructing both NN architectures and fuzzy rule bases requires additional effort compared to conventional PID tuning. Third, the approach heavily depends on the quality and representativeness of the training dataset; insufficient data variation could limit generalization to extreme or unseen conditions. Future work should therefore consider sensitivity analysis under broader operating scenarios, as well as comparisons with alternative NN training algorithms to further evaluate robustness.

From an industrial perspective, the proposed NN–FIS self-tuning PID has strong potential for real-time applications in vacuum-based systems. In semiconductor manufacturing, stable vacuum pressure is critical for wafer fabrication quality; in cryogenics, robust control ensures safe operation of ultra-low temperature systems; in pharmaceutical freeze-drying, adaptive tuning can shorten drying cycles without compromising product integrity; and in thin-film deposition, improved stability leads to more uniform coatings. Technically, the model can be implemented in real-time by training the neural network offline, exporting the trained weights, and embedding the NN–FIS modules into industrial controllers such as PLCs, DSPs, or FPGAs. Modern simulation tools like MATLAB/Simulink also support automatic code generation for such hardware, ensuring low-latency operation. Thus, while computational optimization is needed, the method is feasible for direct industrial deployment, providing both theoretical and practical contributions.

IV. CONCLUSION

Based on the results of the simulations and analyses conducted, the self-tuning PID method based on a combination of Neural Networks (NN) and Fuzzy Logic demonstrates effective performance in adaptively regulating pressure in vacuum systems. The system is capable of achieving a rapid rise time and a relatively short settling time, with low steady-state error.

The integration of the NN allows for dynamic prediction of changes in PID parameters (ΔKp, ΔKi, ΔKd), while the Fuzzy Logic module provides fine-tuning to enhance stability and reduce oscillations. Test results indicate that this combined control pathway yields a more stable system response compared to conventional PID settings, particularly under complex nonlinear model conditions.

Furthermore, comparisons between linear and nonlinear models underscore that the proposed method is more adaptive in nonlinear systems, with the ability to maintain pressure close to the setpoint despite disturbances. Overall, this method has the potential for application in various industrial control systems that require high accuracy and adaptability to changes in process characteristics.

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