
FUZZY-INTELLIGENT PID CONTROL FOR ANODE PRESSURE REGULATION IN PEMFC SYSTEMS: A HARDWARE-IN-THE-LOOP VALIDATION STUDY

**Abubakar Unguwanrimi Yakubu^{1,*}, Jiahao Zhao², Xuanhong Ye², Fahim Ullah²,
Shusheng Xiong²**

¹College of Energy Engineering, Zhejiang University, China

²College of Energy Engineering, Zhejiang University, Hangzhou, 310027, China

Email: yakabu3002@gmail.com*, DC_zjh@outlook.com, 12327023@zju.edu.cn, fahimullah@zju.edu.cn,
xiongss@zju.edu.cn

*Corresponding author: Abubakar Unguwanrimi Yakubu

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ABSTRACT

Proton Exchange Membrane Fuel Cells (PEMFCs) require precise anode pressure regulation to ensure optimal performance, prevent fuel starvation, and extend stack durability. However, conventional PID controllers have inherent limitations in handling rapid load changes, purge-valve disturbances, and system nonlinearities. This paper presents a novel Fuzzy-Intelligent PID (Fuzzy-iPID) controller, integrated with an Extended State Observer (ESO), for adaptive disturbance rejection in PEMFC hydrogen supply systems. We developed a comprehensive control-oriented dynamic model that incorporates electrochemical, thermodynamic, and fluid-dynamic behaviors. We validated this model against experimental data, achieving voltage prediction errors below 3% and pressure prediction errors below 5%. We evaluated the proposed controller through both simulation and Hardware-in-the-Loop (HIL) testing under transient load variations and periodic purge operations. In the HIL validation, the Fuzzy-iPID controller achieved a 94% reduction in mean pressure overshoot, decreasing it from 103.5 Pa with the conventional PID controller to 6.25 Pa. The HIL response time also decreased by about 80%, from 0.46 s to 0.09 s. These HIL results confirmed the proposed controller's superior dynamic performance and lower variability. Furthermore, the controller effectively minimized voltage fluctuations and enhanced electrochemical stability, thereby mitigating degradation mechanisms such as membrane stress, flooding, and nitrogen accumulation. This validated control architecture bridges the gap between theoretical control design and practical PEMFC implementation, establishing a foundation for real-time digital twin integration and predictive maintenance.

Keywords: PEMFC; anode pressure control; fuzzy logic; intelligent PID; extended state observer; hardware-in-the-loop

1. INTRODUCTION

Proton Exchange Membrane Fuel Cells (PEMFCs) have become a promising clean energy technology for a variety of applications, including automotive, stationary, and portable power sources. This is due to their high efficiency, low operating temperature, and quick start-up capabilities (Jiangyun et al., 2023). Maintaining stable anode inlet pressure is essential to achieve optimal fuel utilization, prevent fuel starvation, and ensure the long-term durability of the fuel cell stack (Schmittinger, 2008). However, the nonlinear, time-varying characteristics of PEMFC systems pose significant challenges for pressure regulation, particularly during rapid load changes and periodic purge valve operation (He et al., 2025).

Conventional Proportional-Integral-Derivative (PID) controllers are widely used in industrial PEMFC applications because of their simplicity and ease of implementation (Zhongwei, 2025). However, these controllers have inherent limitations in handling disturbances, parameter uncertainties, and nonlinear system dynamics. This often leads to unacceptable overshoot, slow response times, and voltage instability (Alnefaie., 2025)

To address these challenges, researchers have proposed several advanced control strategies, including Model Predictive Control (MPC) (Feng-Fei Jin et al., 20120), Active Disturbance Rejection Control (ADRC) (Chen et al., 2017), sliding mode control (Qu et al., 2020), and adaptive control approaches (Tang et al., 2024). Despite their potential advantages, many of these methods rely on precise mathematical models, complex design procedures, or extensive computational resources, which can limit their practical application in real-world scenarios.

Fuzzy logic control offers an attractive alternative by incorporating human expert knowledge into the control framework, enabling effective handling of nonlinearities and uncertainties without requiring exact system models (Lei et al., 2018). Recent advances in intelligent PID (i-PID) control, which integrate online estimation and adaptation mechanisms into conventional PID structures, have demonstrated improved performance across various applications (Lihua et al., 2025). The Extended State Observer (ESO) provides a powerful approach for real-time estimation and compensation of internal and external disturbances (Shengquan et al., 2025).

This study addresses critical research gaps by: i. developing a validated, control-oriented dynamic model of the PEMFC hydrogen supply system; ii. Designing a novel Fuzzy-iPID controller integrated with an ESO for adaptive disturbance rejection; iii. implementing a comprehensive (HIL) testing framework; and iv. Conducting a rigorous performance comparison with conventional PID controllers.

The proposed Fuzzy-iPID control architecture contributes not only to improved PEMFC performance but also to broader sustainability objectives by enabling more reliable and efficient hydrogen-energy systems. This advancement supports the global transition toward cleaner energy technologies and provides a potential foundation for future clean-energy applications in developing economies, including Nigeria.

2. SYSTEM MODELING AND VALIDATION

2.1 Hydrogen Supply System Configuration

The parameter values defining the hydrogen supply configuration were collected from validated references and manufacturers' specifications, as shown in previous HIL simulation experiments (Xueying et al, 2023; Francesco et al, 2025; Nikolas, 2025). These parameter values were set as nominal values for developing the hydrogen-supply PEMFC control-oriented model.

1. High-Pressure Hydrogen Storage Tank: The tank operates at a nominal pressure of 70 MPa and has a hydrogen-storage capacity of 5.6 kg (Xueying et al, 2023; Francesco et al, 2025; Nikolas, 2025).

2. Pressure-Reducing Valve: The valve was represented using a discharge coefficient of 0.85 and a throat area of $1.8 \times 10^{-61.8} / \text{times } 10^{-6} \text{ m}^2$. (Xueying et al., 2023, Francesco et al., 2025, Nikolas, 2025).

3. Supply Manifold: The supply manifold has an internal volume of $1.2 \times 10^{-31.2} / \text{times } 10^{-3} \text{ m}^3$ and was modeled using a flow-resistance coefficient of $\lambda=0.45$. (Xueying et al., 2023, Francesco et al., 2025, Nikolas, 2025).

4. Hydrogen Circulation Pump: The pump has a maximum flow rate of $3000 \text{ L} \cdot \text{min}^{-1}$, a motor torque constant of $0.0649 \text{ N} \cdot \text{m} \cdot \text{A}^{-1}$, and a back-EMF constant of $0.059 \text{ V} \cdot \text{s} \cdot \text{rad}^{-1}$ (Xueying et al, 2023; Francesco et al, 2025; Nikolas, 2025).

5. Return Manifold: The return manifold has an internal volume of $8.0 \times 10^{-48.0} / \text{times } 10^{-4} \text{ m}^3$ and a flow-resistance coefficient of $\lambda=0.52$. (Xueying et al., 2023; Francesco et al., 2025; Nikolas, 2025).

6. Periodic Purge Valve: The purge valve has an orifice area of $2.5 \times 10^{-62.5} / \text{times } 10^{-6} \text{ m}^2$ and a discharge coefficient of 0.72. (Xueying, et al., 2023, Francesco, et al., 2025, Nikolas, 2025).

The PEMFC stack is rated at 80 kW and comprises 316 cells connected in series, with an active membrane area of 0.1 m^2 .

2.2 Dynamic Modeling Approach

The following assumptions were adopted in developing the control-oriented model:

- (1) All gases are assumed to obey the ideal-gas law.
- (2) The gas within the supply manifold, return manifold, and PEMFC anode control volume is assumed to behave isothermally over the pressure-control time scale; therefore, temperature variations are neglected because the thermal dynamics are considerably slower than the pressure dynamics considered in the model.
- (3) For the rapid gas-flow process through the pressure-reducing valve, heat exchange with the surroundings is neglected over the short flow time scale. This assumption is restricted to the valve-flow process and does not apply to the manifold or anode control volumes specified as isothermal in assumption (2).
- (4) Flow within the manifolds is assumed to be laminar
- (5) Hydrogen permeation and liquid-water migration are neglected.
- (6) Lumped-parameter representations are used for the valve and manifold dynamics.

A first-order differential equation can represent anode-pressure dynamics.

$$\dot{\chi} = -\frac{1}{\tau} \chi + \frac{K}{\tau} \mu \quad (1)$$

Where χ represents the state variable (anode pressure deviation), τ is the system time constant, and μ is the control input (hydrogen flow rate)

The output voltage of a single fuel cell is calculated by subtracting polarization losses from the open-circuit voltage.

$$V_{ac} = E - V_{ohm} - V_{act} - V_{con} \quad (2)$$

Where E_{Nernst} is the Nernst open-circuit voltage, which can be expressed as:

$$E_{Nernst} = 1.229 - 8.5 \times 10^{-4} (T_{yc} - 298.15) + 4.308 \times 10^{-5} \times T_{at} \quad (3)$$

$$\left[\ln(\rho_{H_2}) + 0.5 \ln(\rho_{O_2}) \right]$$

The variable T_{yc} represents the working temperature of the stack, ρ_{H_2} denotes the adequate partial pressure of hydrogen at the anode, and ρ_{O_2} indicates the adequate oxygen partial pressure at the cathode.

Ohmic loss voltage refers to the voltage lost during the flow of electrons and protons due to the resistance encountered by the proton exchange membrane, as well as the cathode and anode electrodes. This loss can be expressed as:

$$V_{ohm} = iR_{ohm} \quad (4)$$

Where i is the current density of the fuel cell stack, and the internal ohmic resistance, denoted as, R_{ohm} is influenced by the temperature and humidity surrounding the fuel cell.

2.3 Model Validation

The Model parameters were identified using a systematic five-step approach that utilized experimental polarization and pressure-current data. The model demonstrates excellent agreement with the experimental results, achieving voltage prediction errors of less than 3% and pressure prediction errors of less than 5% (see Fig. 1). An uncertainty analysis reveals that a $\pm 5\%$ variation in critical

pressure parameters results in a $\pm 6.2\%$ variation in anode inlet pressure predictions, indicating that the model is sufficiently efficient.

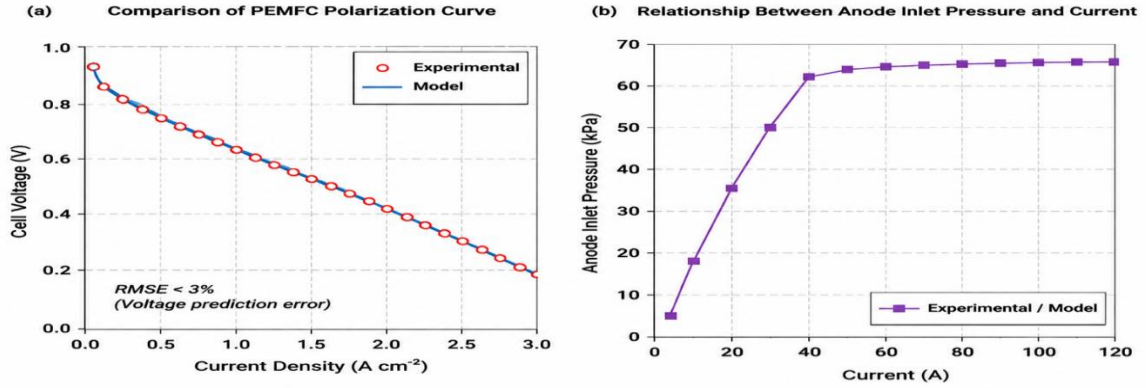


Fig. 1. (a) Comparison of the PEMFC polarization curve; (b) Relationship between anode inlet pressure and current.

3. CONTROL SYSTEM DESIGN

3.1 Intelligent PID Controller Architecture

Following the model-free control framework introduced by Fliess and Join, a general nonlinear single-input single-output system can be represented locally by the ultra-local model (Join, 2009)

$$y^{(a)} = F + \bar{\alpha} \cdot u_i \quad (5)$$

Where $n \geq 1$ denotes the derivative order of the output, y, u_i is the control signal u_i , and $\bar{\alpha}$ is the input gain. F represents the lumped unknown dynamic disturbance if $n = 1$ the first-order system can be chosen to define the dynamics of the controlled system.

If F and $\bar{\alpha}$ are well-known items, then the intelligent PID controller can be proposed as:

$$u_i = \frac{1}{\bar{\alpha}} \left(-\hat{F} + \dot{y}^* + K_p (e_i) + K_i \int (e_i) dt + K_d \frac{d(e_i)}{dt} \right) \quad (6)$$

where $\hat{F}$ represents the lumped unknown dynamic disturbance estimated by the Extended State Observer (ESO), y^* denotes the desired reference output, e_i represents the control error, and $K_p, K_i, \text{ and } K_d$ are the proportional, integral, and derivative gains, respectively.

These values can be determined by minimizing the objective function using the PSO algorithm. The objective of the formulation in Eq. (6) is to prove the superiority of the iPID controller compared to classical approaches of the PID controller. The PSO algorithm optimizes the adjustable parameters of the iPID controller.

This article estimates the disturbance using an ESO approach (Shangquan et al., 2025, & Shihua et al., 2010). The advantage of the ESO in the control system is that it estimates internal and external disturbances and uncertainties in real time (Pawar et al., 2021). Hence, a reasonable estimation of the disturbance or uncertainty is achieved by employing ESO, followed by compensation utilizing the feedback technique to cancel the total disturbance in the input, as displayed in Fig. 2.

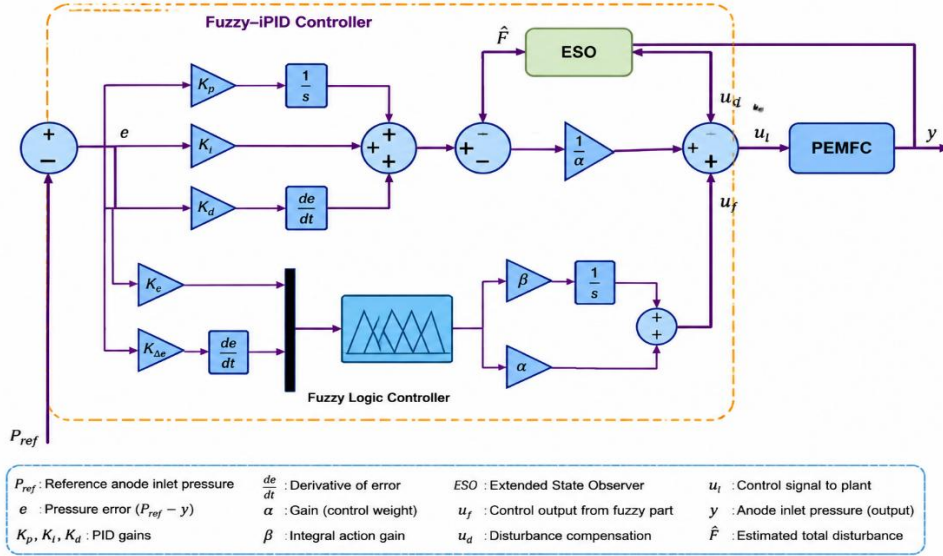


Figure 2: Fuzzy-iPID control structure.

The ESO approach can be represented as:

$$\begin{cases} \bar{e}_1 = z_1 - y \\ \dot{z}_1 = z_2 - \beta_1 \bar{e}_1 + \alpha \cdot u_1 \\ \dot{z}_2 = -\beta_2 |\bar{e}_1|^{0.5} \text{sign}(\bar{e}_1) \\ \hat{F} = z_2 \end{cases} \quad (7)$$

Where β_1 and β_2 are constants, $\bar{e}_1$ is the estimated error of the ESO, z_1 and z_2 are the intermediate states, u_1 is the control signal, and y is the plant output. In the ESO framework, z_2 represents the ESO estimate. So, in this case, we have $z_2 = \hat{F}$.

3.2 Fuzzy-iPID Controller Design

In this section, we enhanced the controller's performance by introducing an additional input to the system that compensates for the estimation error. The structure of the hybrid fuzzy-logic intelligent proportional-integral-derivative (Fuzzy-iPID) controller is shown in Fig. 3.

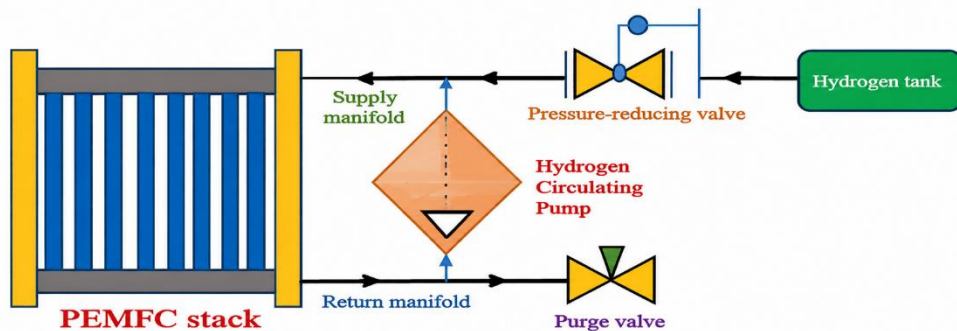


Figure 3: Structure of the hydrogen supply system

u_{Fuzzy} indicates the extra input to the system. Therefore, the final expression of the fuzzy-iPID controller can be stated as:

$$u_{Fuzzy-iPID} = u_{PID} + u_{Fuzzy} \quad (8)$$

The framework of the fuzzy-iPID controller, as described in Fig. 3, has been built from two inputs and one rule base. The Fuzzy Logic Controller (FLC) uses two input variables: the anode-pressure control error ee and the rate of change of the control error e' . The FLC output provides the supplementary control signal u_{FLC} , which compensates for the estimation error. Denote the area control error and the derivative of the area control error of area ii , which is the extra control signal, and can be modeled as (Pawar et al., 2021):

$$u_{FLC} = f(e, e') \quad (9)$$

Where u_{FLC} denotes the FLC output, and α and β are the scaling factors applied to the direct fuzzy-control output and its integral component, respectively. It has been referred to in (Vonglao, 2007) that the relation between the input and output variables for the product-sum crisp pattern of the fuzzy controller can be modeled as: (Pawar et al., 2021)

$$u_{FLC} = \alpha e + \beta \int e dt \quad (10)$$

Therefore, the signal u_{Fuzzy} can be obtained by substituting Eq. (7) into Eq. (2) as follows:

$$u_{Fuzzy} = u_{FLC} + u_{ESO} \quad (11)$$

The result showed that the FLC acts like a time-varying PID controller. Hence, the equivalent control synthesis of the fuzzy-iPID type controller results in a proportional gain K_p , integral gain K_i , and derivative gain K_d . The PSO algorithm optimizes the fuzzy-iPID controller's adjustable parameters.

The result showed that the FLC acts like a time-varying PID controller. Hence, the equivalent control synthesis of the fuzzy-iPID type controller results in a proportional gain $\alpha K_1 P + \beta K_2 D$, integral gain, and derivative gain $\alpha K_2 D$. The PSO algorithm optimizes the adjustable parameters of the fuzzy-iPID controller. In this article, the FLC system is constructed by fuzzifying. It comprises three membership functions, two input signals, and one output signal. Each membership function consists of two trapezoidal membership functions and three triangular membership functions, as displayed in Fig. 4.

Table 1 defines the linguistic labels NB, N, Z, P, and PB and presents the resulting 25-rule fuzzy rule base. For example, the rule at the intersection of the third row and fifth column indicates that when the first input is Z and the second input is PB, the corresponding fuzzy output is P, as shown in Table 1.

Remarks: NB denotes Negative Big, N denotes Negative, Z denotes Zero, P denotes Positive, and PB denotes Positive Big. These five linguistic labels form an ordered and symmetric negative-to-positive scale, $NB \rightarrow N \rightarrow Z \rightarrow P \rightarrow PB$, used for the fuzzy-controller input and output variables, as outlined in Table 1.

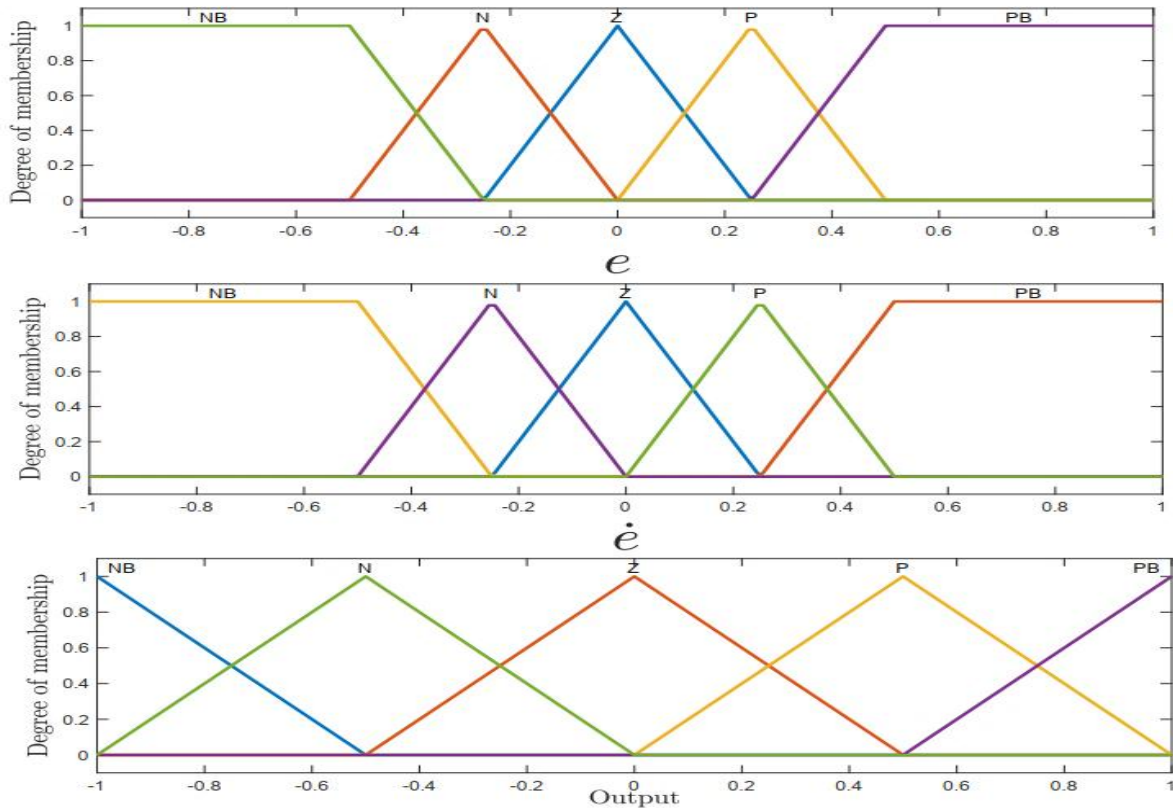


Fig. 4 The membership function of the fuzzy system.

Table 1: Fuzzy linguistic rule base for the Fuzzy-iPID controller

e	$\dot{e}$				
	NB	N	Z	P	PB
NB	NB	NB	N	N	Z
N	NB	N	N	Z	P
Z	N	N	Z	P	P
P	N	Z	P	P	PB
PB	Z	P	P	PB	PB

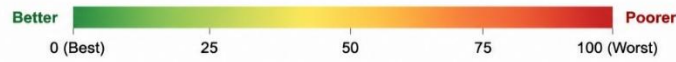
4. SIMULATION AND HARDWARE-IN-THE-LOOP VALIDATION

4.1 Simulation Results

Simulation studies were conducted under two disturbance scenarios: step changes in load current (80 A to 290 A) and periodic purge-valve operation (10-second cycle with a 0.4-second opening time). Table 2 provides a detailed comparison of controller performance under different current step conditions.

Table 2: Controller Performance Comparison Under Current Disturbances

Current Step (A)	Fuzzy-iPID Response Time (s)	Fuzzy-iPID Overshoot (Pa)	PID Response Time (s)	PID Overshoot (Pa)
80 → 140	0.10	9	0.25	195
80 → 180	0.07	5	0.35	63
80 → 290	0.07	3.8	0.33	82
80 → 240	0.07	4.8	0.40	53
80 → 260	0.075	4.5	0.40	36
Mean	0.078	5.4	0.346	85.8



Under the simulation test conditions, the Fuzzy-iPID controller consistently outperformed the conventional PID controller. Across the simulated current-step disturbances, the average pressure overshoot decreased from 85.8 Pa for the PID controller to 5.4 Pa for the Fuzzy-iPID controller, corresponding to an approximately 94% reduction. The mean simulated response time decreased from 0.346 s to 0.078 s, representing an approximately 77% reduction. These values represent simulation results and are therefore reported separately from the HIL validation results presented in Section 4.3

4.2 Hardware-in-the-Loop Testing Framework

To bridge the gap between simulation and practical implementation, we developed a comprehensive Hardware-in-the-Loop (HIL) testing platform. This HIL system integrates a real Fuel Cell Unit (FCU) controller with a virtual Proton Exchange Membrane Fuel Cell (PEMFC) model running on a real-time simulation platform. The key components of this system include:

HIL Central Control Computer: This manages and coordinates all hardware and software signals.

Real-Time Simulation Platform: A high-performance controller that runs the PEMFC system model.

Signal Conditioning System: This ensures electrical compatibility among different system components.

Tested Controller: The actual FCU hardware that incorporates control software.

In this setup, the control algorithm was implemented in the FCU controller. The pressure-reducing valve is controlled via a duty-cycle signal communicated over the Controller Area Network (CAN). Additionally, the hydrogen circulation pump operates at 4.8 volts and 3000 revolutions per minute (rpm), while a state-flow state machine manages the purge valve. The following HIL results form a separate validation dataset from the numerical simulation results reported in Section 4.1; therefore, differences in absolute overshoot and response-time values between the two test phases are expected.

4.3 HIL Test Results

HIL testing provided quantitative evidence that the Fuzzy-iPID controller performed better than the conventional PID controller under real-time implementation conditions. Unlike the simulation results reported in Section 4.1, this section presents all quantitative values from the HIL validation experiments. The Fuzzy-iPID controller achieved a mean pressure overshoot of 6.25 Pa compared with 103.5 Pa for the conventional PID controller, corresponding to an approximately 94% reduction. Similarly, the mean response time decreased from 0.46 s with the conventional PID controller to 0.09 s

with the Fuzzy-iPID controller, representing an approximately 80% reduction. Fig. 5 summarizes the quantitative HIL performance comparison between the Fuzzy-iPID and conventional PID controllers, while Fig. 6 presents the corresponding transient pressure responses under current-step and purge-valve disturbances.



Figure 5: HIL performance comparison of the Fuzzy-iPID and conventional PID controllers under current and purge disturbances.

The standard deviation analysis was calculated from the response metrics obtained across the evaluated HIL disturbance conditions, including the five current-step load variations and the periodic purge-valve disturbance scenario. The Fuzzy-iPID controller exhibited substantially lower performance variability than the conventional PID controller. The standard deviation of pressure overshoot was 5.12 Pa compared with 130.2 Pa for the conventional PID controller, while the corresponding response-time standard deviations were 0.012 s and 0.244 s, respectively. These results indicate that the Fuzzy-iPID controller provided more consistent dynamic responses across the tested HIL operating conditions.

For statistical evaluation, the performance indices (overshoot and response time) were extracted from each disturbance test condition, and the standard deviation was calculated across the complete set of evaluated HIL experiments to quantify controller-response variability.

The transient responses in Fig. 6 further illustrate the differences between the two controllers. Under the evaluated HIL conditions, the Fuzzy-iPID controller showed smaller pressure excursions and converged more rapidly to the target pressure than the conventional PID controller during both current-step and purge-valve disturbances.

(a)

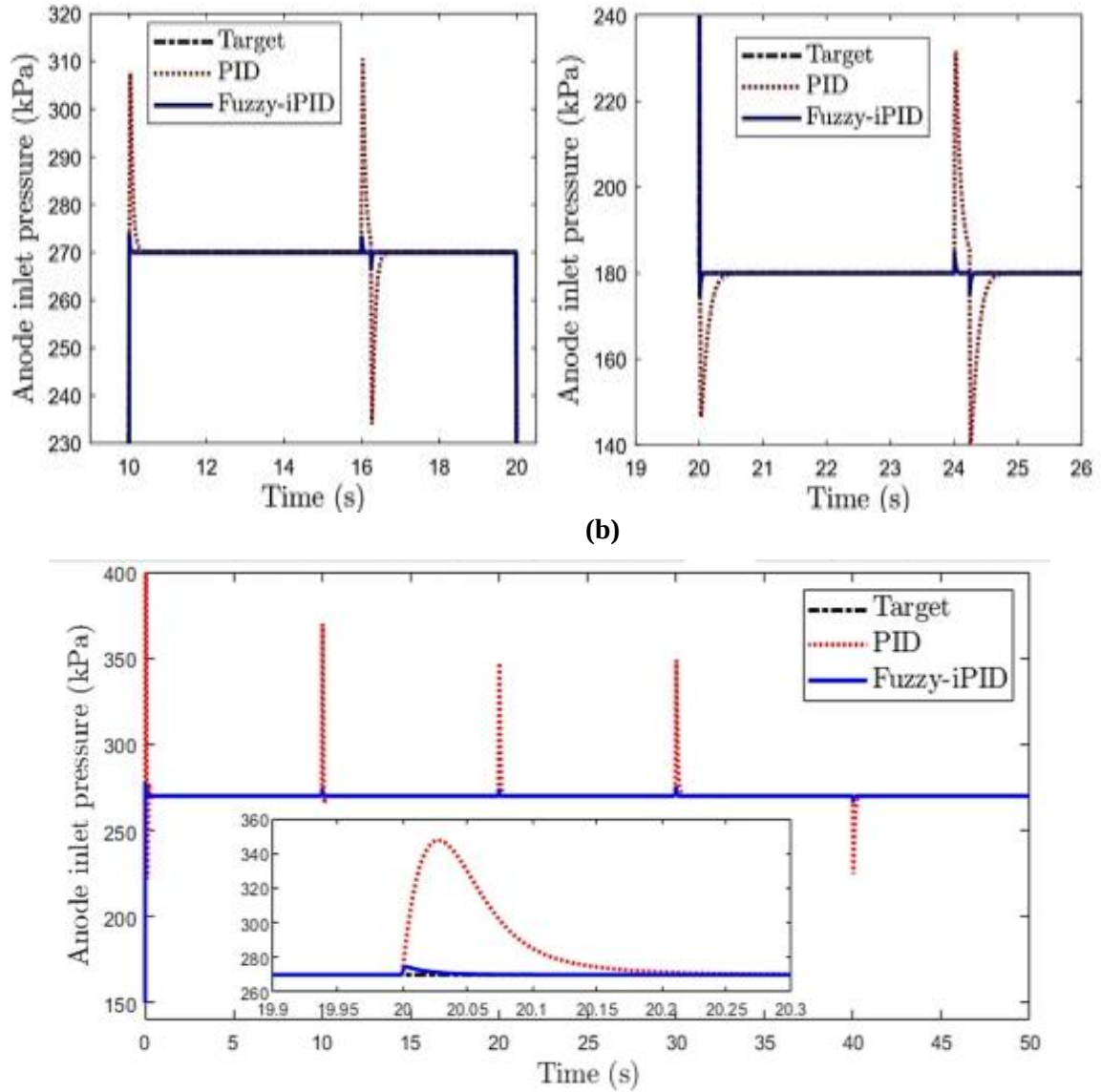


Figure 6: HIL pressure responses of the Fuzzy-iPID and conventional PID controllers: (a) response to current-step disturbances and (b) response to the purge-valve disturbance.

5. DISCUSSION

5.1 Control Performance and Efficiency

The Fuzzy-iPID controller's superior performance stems from its adaptive capabilities and disturbance rejection. By integrating fuzzy logic with intelligent PID control, this system can adjust its control gains in real time to account for varying operating conditions. Additionally, the Extended State Observer effectively estimates and compensates for system disturbances and uncertainties.

This combination effectively addresses the inherent limitations of conventional PID control, especially in handling nonlinear disturbances, rapid load changes, and parameter uncertainties. The substantial reduction in performance variability is particularly important for real-world applications, where operating conditions are constantly changing. The controller's consistent performance across different current levels and disturbance scenarios showcases its adaptability and efficiency.

5.2 Electrochemical and Thermal Implications

The Fuzzy-iPID controller's improved pressure regulation significantly affects electrochemical performance and stack durability. By maintaining stable anode pressure, the system ensures uniform reactant distribution, preventing local fuel starvation and associated degradation mechanisms. Reducing pressure fluctuations minimizes membrane stress and mechanical fatigue, thereby extending the stack's lifetime. Additionally, improved voltage stability indicates better electrochemical stability, reducing activation losses and ohmic heating.

Moreover, anode pressure dynamics are intrinsically linked to thermal management. Variations in hydrogen pressure influence reactant mass flow rates, gas velocity profiles, and Reynolds numbers, which, in turn, affect convection heat transfer coefficients and cooling efficiency. The Fuzzy-iPID controller's capability to maintain stable pressure regulation contributes to more uniform heat distribution within the stack.

5.3 Implications for Digital Twin and AI Integration

The validated control-oriented model and the Hardware-in-the-Loop (HIL) testing framework provide a scalable digital foundation for future integration with digital twin architectures. This integration facilitates:

Predictive Maintenance: Forecasting system behavior and identifying potential degradation mechanisms.

Real-time Optimization: Implementing Model Predictive Control (MPC) and optimization algorithms.

AI-enhanced Supervisory Control: Integrating machine learning algorithms for adaptive parameter tuning and fault diagnosis.

Virtual Sensor Development: Generating synthetic sensor data for fault detection.

6. CONCLUSION

In this research, we proposed an intelligent control approach for effective anode pressure control in a PEMFC hydrogen system. The proposed intelligent control approach involved designing a dynamical model using electrochemical, thermodynamic, and fluid-dynamics properties, which showed significant agreement with experimental results, with prediction errors of less than 3% for voltage and less than 5% for pressure. Based on the proposed dynamic model, a Fuzzy-iPID controller with ESO was designed for disturbance rejection and pressure control.

Simulation analysis and Hardware-in-the-Loop (HIL) testing demonstrated the suggested controller's better performance compared with classical PID control. With HIL test analysis, the Fuzzy-iPID controller reduced the mean pressure overshoot to 6.25 Pa from 103.5 Pa and the mean response time to 0.09 seconds from 0.46 seconds. Lower pressure fluctuations improved voltage stability and reduced degradation-related protection issues.

The presented structure offers a practical way to implement adaptive control in PEMFC applications in real time. The combination of prediction, disturbance, and fuzzy adaptation improves hydrogen management compared to traditional fixed-gain control. It paves the way for future implementation of digital twins, predictive maintenance, and artificial intelligence-based energy management systems.

Further work will compare the proposed approach with other control strategies such as Model Predictive Control (MPC), Active Disturbance Rejection Control (ADRC), and reinforcement learning-based methods. Moreover, further investigations will focus on implementing automatic controller tuning and integrating the degradation models.

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