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Optimization of Seal Steam Turbine Pressure Control on CCPP Boiler System Using Fuzzy-PID Auto-Tuning Method

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Abstract – This study optimizes the High-Pressure to Turbine Seal Steam Pressure Control Valve system in a Combined Cycle Power Plant to address nonlinear characteristics and fluctuating load dynamics. Conventional fixed-gain controllers structurally fail to manage these conditions effectively. We propose a hybrid Relay Feedback with Fuzzy-PID strategy, employing a quantitative simulation design validated with industrial data from the Muara Tawar CCPP. Using a First Order Plus Dead Time model, the method integrates Relay Feedback for initial parameter identification and Fuzzy Logic for real-time PID adjustment. Evaluated via MATLAB/Simulink across various scenarios, the hybrid approach yielded superior transient performance, outperforming metaheuristic benchmarks (Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO)) in stabilizing the system. Crucially, validation against real operational data demonstrated that the proposed method eliminated oscillatory valve behavior, yielding a massive improvement in actuator energy efficiency and significantly reducing the Root Mean Square Error (RMSE). The novelty lies in integrating Relay Feedback autotuning with Fuzzy self-tuning PID, explicitly validated using real operational data. This practical approach provides robust control and extends actuator lifespan by mitigating mechanical wear.

Keywords: CCPP, Pressure Control Valve, Fuzzy-PID, Relay Feedback, Energy Efficiency.

I. INTRODUCTION

Combined Cycle Power Plants (CCPPs) represent the most efficient fossil-fuel generation technology in widespread deployment, converting gas turbine exhaust enthalpy into additional electrical output via a bottoming steam cycle [1], [2]. Within this architecture, the Heat Recovery Steam Generator (HRSG) is the critical thermal interface: it produces high-pressure steam whose temperature and pressure must remain tightly regulated to sustain turbine performance and longevity[3]. Among the controlled variables in the HRSG, the High-Pressure (HP) turbine seal steam pressure, governed by a dedicated Pressure Control Valve (PCV), occupies a position of particular operational significance. Insufficient seal steam pressure permits atmospheric air ingress into the turbine, accelerating seal wear and degrading thermodynamic efficiency, while excessive pressure may trigger safety-system trips. Both failure modes carry direct costs in unplanned maintenance, reduced plant availability, and increased specific CO_2 emissions per unit of output.

In current industrial practice, the PCV is regulated by a fixed-gain Proportional-Integral-Derivative (PID) controller. Operational records from the Muara Tawar CCPP Block 3 (the plant studied here) document a recurring pattern of high-amplitude oscillation around the 8.5 Bar setpoint, with RMSE reaching 3.9902, indicating that the deployed controller is unable to manage the nonlinear dynamics and transient load fluctuations characteristic of CCPP operation. This failure is not site-specific: comparative studies confirm that conventional tuning methods systematically produce aggressive overshoot and poor disturbance rejection under nonlinear operating conditions [4], [5]. Furthermore, advanced metaheuristic optimizations like Salp Swarm Algorithms and Ant Lion Optimization have proven effective in broader power flow applications [6], [7], but are often computationally heavy for real-time valve control. Recent implementations of adaptive PID control demonstrate its necessity in handling transport delays [8], while contemporary applications of Fuzzy Inference Systems provide highly effective nonlinear gain scheduling [9]. The core technical limitation is structural: a fixed-gain controller optimized at a single operating point cannot compensate for gain changes induced by valve nonlinearity, steam-side load variation, or shifting ambient conditions.

Two methodological streams in the literature address this structural deficiency. The first is model-free autotuning via Relay Feedback, in which a relay element is inserted into the control loop to induce a sustained limit cycle, enabling online identification of the ultimate gain (Ku) and ultimate period (Pu) without requiring plant shutdown or mathematical modelling [10], [11]. The Relay Feedback method provides a principled, industrially tractable starting point for PID parameterisation. Its limitation, however, is that parameters are fixed once identified: the resulting controller remains a fixed-gain PID and therefore retains the structural inability to adapt to operating-point variations following initial commissioning [11].

The second stream is intelligent gain scheduling via Fuzzy Logic Control (FLC). A Fuzzy Inference System (FIS) encodes heuristic expert knowledge as IF-THEN linguistic rules, enabling real-time, non-linear adjustment of PID gains without requiring an explicit plant model [12]. Hybrid Fuzzy-PID architectures have demonstrated clear advantages over fixed-gain PID in HRSG drum-level control [13], thermal power plant unit coordination [14], and magnetic levitation [15]. However, the dominant limitation of existing Fuzzy-PID studies in the CCPP domain is twofold: (a) they rely exclusively on simulation validation, without exposure to real plant data, and (b) they employ static fuzzy rule bases derived offline, which do not benefit from the systematic, plant-specific initialization that relay-based identification provides [16].

A synthesis of the two streams, specifically relay-based initialization followed by fuzzy self-tuning adaptation, is theoretically motivated but has not been reported for CCPP seal steam pressure control, nor has it been validated against large-scale real operational data in any CCPP application. This constitutes a specific, falsifiable research gap. The present study closes that gap by proposing, implementing, and validating a Relay Feedback-based Fuzzy Self-Tuning PID (RF-FSTPID) controller for the HP-to-Turbine Seal Steam PCV at the Muara Tawar CCPP Block 3.

The novel contributions of this work are explicitly as follows:

(C1) Methodological novelty: The RF-FSTPID architecture is the first to couple online relay-feedback identification with a Fuzzy Self-Tuning PID specifically for CCPP HP turbine seal steam pressure control. The relay stage furnishes plant-specific initial gains (Kp0, Ki0, Kd0) without a priori modelling; the fuzzy stage continuously refines these gains via a 7×7 heuristic rule base, operationalizing online non-linear gain scheduling that is structurally inaccessible to fixed-parameter or offline-optimized controllers.

(C2) Comparative benchmark: The RF-FSTPID is evaluated against five alternative controllers (Ziegler-Nichols PID, Cohen-Coon PID, Fuzzy Fixed, PSO-PID, ACO-PID) across six simulation scenarios, providing a multi-criterion, multi-disturbance performance map not previously reported for this application.

(C3) Industrial field-data validation: Performance is validated against 80,640 samples of 24-hour real operational data from the Muara Tawar CCPP Block 3, a validation standard absent from existing CCPP adaptive pressure control literature. This validation reveals a 575-fold improvement in actuator energy efficiency (ISK: $2.50\times10^{8} \rightarrow 4.34\times10^{5}$) relative to the currently deployed Baseline PID, with direct implications for valve service-life extension.

II. METHODS

Research Design

This study adopts a quantitative, simulation-based control system design combined with industrial data validation. The research is structured to evaluate the effectiveness of a hybrid Relay Feedback–based Fuzzy-PID controller for regulating High-Pressure (HP) turbine seal steam pressure in a Heat Recovery Steam Generator (HRSG) system of a Combined Cycle Power Plant (CCPP).

To ensure both theoretical rigor and practical relevance, the methodological framework is executed in four systematic stages:

- Stage 1: system modelling and problem formulation.
- Stage 2: Controller design and tuning.
- Stage 3: Performance evaluation through simulation.
- Stage 4: Simulation validation using actual operational plant data.

This design enables both theoretical performance assessment and practical relevance, which is essential for control-oriented energy system studies.

Subject and Research Location

The plant under study is the HP-to-Turbine Seal Steam Pressure Control Valve (PCV) system at the Muara Tawar CCPP Block 3, operated by PLN Nusantara Power, Bekasi, Indonesia. Operational data were acquired from the plant's Distributed Control System (DCS) historian at a sampling interval of 1 second over a continuous 24-hour period on 14 August 2025, yielding a total of 80,640 data samples. The steam pressure setpoint for the HP turbine seal system is 8.5 Bar. Figure 1 presents the schematic of the HRSG seal steam system.

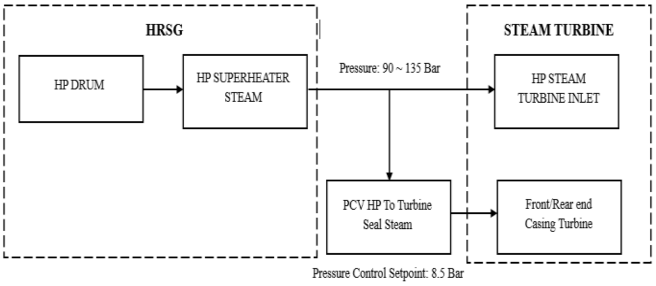


Figure 1. Schematic diagram of the Steam Seal System in HRSG PLTGU Muara Tawar

System Identification

The plant dynamics were approximated using a First Order Plus Dead Time (FOPDT) model based on historical open-loop data. This model was chosen because it offers the best compromise between computational simplicity and representativeness for industrial thermal processes [17]. Furthermore, as discussed by Maxim and De Keyser (2023) [18], FOPDT models remain robust even when estimated from noisy step response data typical of operational plants. The transfer function is defined as:

$$G(s) = \frac{Ke^{-\theta s}}{\tau s + 1} \quad (1)$$

Where K represents the process gain, τ is the time constant, and θ is the dead time (delay). The specific parameters (K, τ, θ) were identified using the Process Reaction Curve method applied to historical open-loop step response data. This approach effectively captures the system's transport delays and time constants without requiring complex analytical modeling [15].

Control Design: Relay Feedback with Fuzzy-PID

As illustrated in Figure 2, the proposed control architecture consists of two main stages: initial autotuning and continuous self-tuning. It is important to clarify the operational context of the Relay Feedback stage: the relay test depicted in Figure 2 was conducted in simulation, applied to the derived FOPDT transfer function model of the plant, not as an on-site autotuning routine on the actual Distributed Control System (DCS). The FOPDT parameters (K, τ, θ) were first identified from historical open-loop plant data; the relay feedback test was then performed on this validated simulation model to determine the critical parameters (Ku, Pu) used for initial PID gain calculation. The proposed control strategy consists of two stages:

1). Relay Feedback (Autotuning)

This stage employs a relay feedback test to trigger controlled limit cycle oscillations. This method allows for the online determination of the system's critical parameters (Ku, Pu) without disrupting plant operations, a technique widely supported for its efficiency [10], [19] To ensure accuracy in estimating the ultimate point, the Describing Function analysis is used [20]:

$$K_u = \frac{4h}{\pi a} \tag{2}$$

Where h is amplitude of the relay output signal, a the amplitude of the process output oscillation. The Ultimate Period (Pu) is determined directly from the time interval between consecutive peaks of the oscillation. These critical parameters (Ku, Pu) serve as the basis for calculating the initial PID parameters (Kp0, Ki0, Kd0) using the Ziegler-Nichols frequency response method.

2). Fuzzy-PID (Self-Tuning)

To handle system nonlinearities, a Fuzzy Logic Controller (FLC) tunes the PID gains in real-time. This self-tuning capability is crucial for thermal systems where operating points shift frequently [12], [21]. The Fuzzy Inference System uses Error (e) and Change of Error (Δe) to output correction factors (ΔKp, ΔKi, ΔKd), ensuring the controller adapts to disturbances dynamically. The standard PID control law in the time domain is defined as:

$$u(t) = K_p e(t) + k_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{3}$$

The gains are adapted dynamically according to the following mechanism:

$$K_p(t) = K_{P0} + \Delta K_p,\ K_i(t) = K_{i0} + \Delta K_i, \\ K_d(t) = K_{d0} + \Delta K_d \tag{4}$$

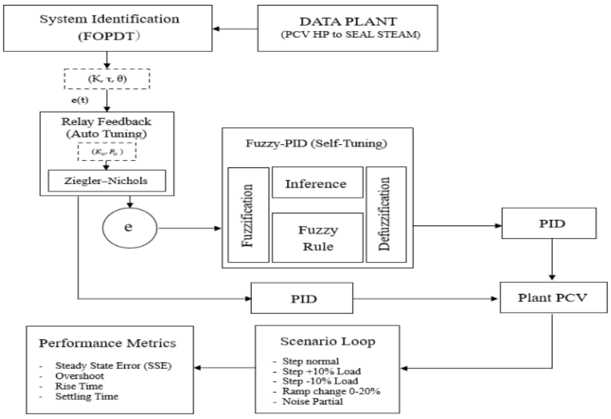


Figure 2. Proposed control architecture: Relay Feedback integration with Fuzzy Self-Tuning PID.

The Fuzzy Inference System (FIS) uses Error (e) and Change of Error (Δe) as inputs. We utilized triangular membership functions for the inputs, normalized to the range [-0.8, 0.8]. A 7 × 7 Rule Base was designed based on heuristic knowledge of steam pressure dynamics. For instance, if the error is large (Positive Big), the proportional gain is increased to accelerate rise time, while the derivative gain is adjusted to prevent overshoot. Defuzzification is performed using the Centroid method.

Table 1. Fuzzy Rule Base for Proportional Gain Correction (ΔKp)

E/dE	**NB**	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	PB	PM	PS	NS	PS	PM	PB
NM	PM	PS	ZE	NS	ZE	PS	PM
NS	PS	ZE	NS	NM	NS	ZE	PS
ZE	ZE	NS	NM	NB	NM	NS	ZE
PS	PS	ZE	NS	NM	NS	PM	PS
PM	PM	PS	ZE	NS	ZE	PS	PM
PB	PB	PM	PS	NS	PS	PM	PB

Test Scenarios and Performance Metrics

1). Simulation Scenarios

Simulations were conducted in MATLAB/Simulink to evaluate the robustness of the controller under six distinct scenarios: (1) Normal Step response, (2) +10% Load Step disturbance, (3) -10% Load Step disturbance, (4) Ramp Change from 0-20%, (5) Random Noise injection, and (6) Validation against real plant data.

2). Performance Evaluation Criteria

To quantify the controller performance, several time-domain characteristics and error indices were calculated.

a. Transient Response Metrics: To ensure a comprehensive evaluation, we utilized four distinct indices [12]]:

- Rise Time (tr): The time required for the system response to rise from 10% to 90% of its final value were calculated:

$$t_r = t_{90\%} - t_{10\%} \tag{5}$$

- Settling Time (ts): The time required for the response curve to reach and stay within a ±2% tolerance band of the final steady-state value, its formula:

$$|y(t) - y_{ss}| \leq \pm 0.02 y_{ss}, \text{ for all } t \geq t_s \tag{6}$$

- Maximum Overshoot (Mp): The maximum peak value of the response curve measured relative to the setpoint, expressed as a percentage:

$$M_p = \frac{y_{\max} - y_{ss}}{y_{ss}} \times 100\% \tag{7}$$

- Steady-State Error (SSE): The difference between the reference setpoint ® and the system output (y) as time approaches infinity:

$$\boldsymbol{e_{ss}} = \lim_{t\to\infty} [\boldsymbol{r(t)} - \boldsymbol{y(t)}] \tag{8}$$

b. Error Integral Criteria: To assess the tracking accuracy over the entire simulation period, Root Mean Square Error (RMSE) and Integral Square Error (ISE) were calculated

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - y_i)^2} \tag{9}$$

$$ISE = \int_0^T e^2(t)\, dt \tag{10}$$

c. Performance Metric: To evaluate the system response by accumulating absolute error over time without overweighting error amplitude (providing a balance between response speed and oscillation damping), the Integral of Absolute Error (IAE) was used:

$$IAE = \int_0^T |e(t)| dt \tag{11}$$

d. Energy Efficiency Metric: To evaluate the control effort and actuator energy consumption (Valve wear), the Integral Square of Control Signal (ISK) was used [14]:

$$ISK = \int_0^T (u(t))^2 dt \tag{12}$$

Where a lower ISK value indicates smoother valve movement and lower energy consumption.

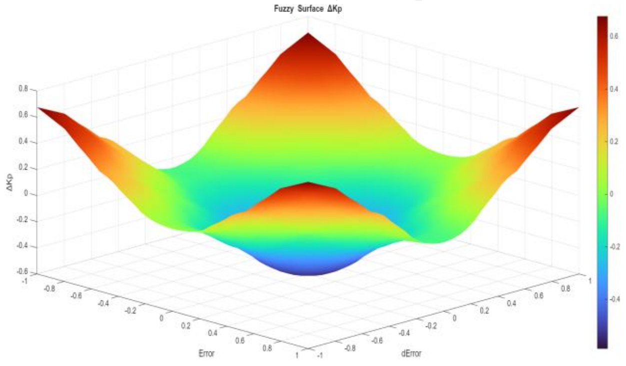
III. RESULT AND DISCUSSION

Tuning Parameters

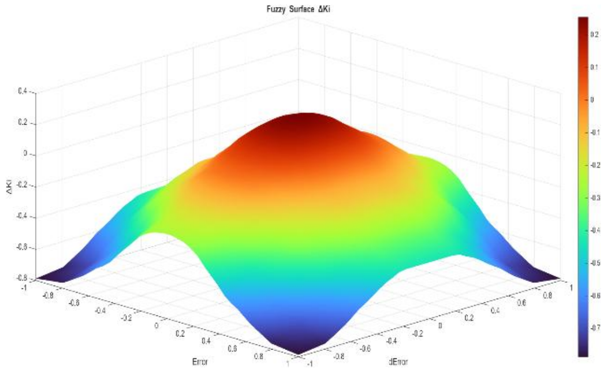
The performance evaluation begins with the definition of the plant dynamics and the determination of the initial controller parameters. Based on the open-loop data identification described in the methodology, the plant dynamics were characterized using the FOPDT model. The resulting parameters were identified as process gain K = 0.3685, time constant τ= 3.00s, and dead time θ= 1.00s. These values confirm the transport delay characteristics inherent in the thermal pressure system.

A critical observation arising from the identified FOPDT parameters concerns the dead-time-to-time-constant ratio (θ/τ = 1.00/3.00 ≈ 0.33). In process control theory, this ratio is a key indicator of the controllability challenge posed by a given plant. A ratio of 0.33 places the HP turbine seal steam pressure system in the category of difficult-to-control processes, where the dead time constitutes a substantial fraction of the dominant time constant. For fixed-gain PID controllers, such a ratio implies that any corrective control action is delayed by a significant proportion of the system's natural response time, making it structurally prone to high-amplitude oscillations when gains are tuned for adequate disturbance rejection. This is precisely the dynamic responsible for the chronic oscillatory behaviour observed in the Muara Tawar CCPP Baseline PID operation, with RMSE reaching 3.9902. As the dead time increases relative to the time constant, the phase lag introduced into the control loop grows, shrinking the achievable phase margin and forcing a trade-off between response speed and stability that no fixed set of PID gains can optimally resolve across varying operating conditions. This analysis therefore provides a quantitative and theoretically grounded explanation for why the Baseline PID is structurally inadequate for this plant, and reinforces the necessity of an adaptive mechanism—such as the proposed RF-FSTPID—capable of dynamically adjusting its gains to compensate for this inherent controllability limitation.

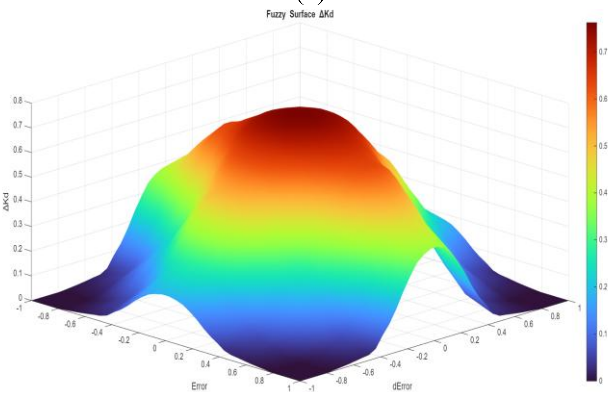
Subsequently, The Relay Feedback process yielded critical parameters Ku = 7.4778 and Pu = 6.0000 seconds. Following the Fuzzy self-tuning process under nominal conditions, the final PID parameters obtained were Kp = 1.8694, Ki = 0.9436, and Kd = 3.9595. The Fuzzy logic surface analysis, explicitly depicted in Figures 3(a), 3(b), and 3(c), shows that the controller aggressively increases gain during large errors and dampens the response as the error approaches zero, a characteristic unattainable by fixed-parameter PID.



(a)



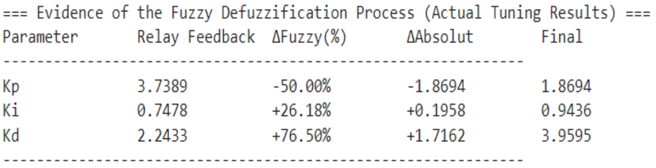
(b)



(c)

Figure 3. Fuzzy control surface for proportional, integral and derivative gain adjustment on (a) Delta surface ΔK_p, (b) Delta surface ΔK_i and (c) Delta surface ΔK_d).

The Fuzzy Self-Tuning Optimization To overcome the limitations of fixed parameters, the Fuzzy Logic controller adjusted these baseline values (from Relay Feedback) in real-time. Through the defuzzification process (using the Centroid method), the system calculated specific correction values (Δ) based on the error dynamics. The final PID parameters were obtained by summing the initial Relay Feedback values with the Fuzzy correction outputs, as detailed in Figure 4.



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=== Evidence of the Fuzzy Defuzzification Process (Actual Tuning Results) ===
Parameter       Relay Feedback  ΔFuzzy(%)       ΔAbsolut        Final
-------------------------------------------------------------

Kp              3.7389          -50.00%         -1.8694         1.8694
Ki              0.7478          +26.18%         +0.1958         0.9436
Kd              2.2433          +76.50%         +1.7162         3.9595
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Figure 4. Summary Table of Parameter Evolution (Relay Feedback + Fuzzy PID).

Transient Performance Comparison

The proposed method was compared against Ziegler-Nichols (ZN), Cohen-Coon, PSO-PID, ACO-PID, and Fuzzy Fixed. As shown in Table 2, although numerical optimization methods like PSO-PID showed competitive speeds, the Relay + Fuzzy-PID method provided the best overall performance balance, prioritizing tracking accuracy (lowest SSE) and stability.

Table 2. Average Performance Comparison of Various Methods

Methods	SEE	Over shoot (%)	Rise Time (s)	Settling Time (s)	Overall Assessment
Relay + Fuzzy-PID	300.39	11.28	28.0	55.33	Most Accurate & Stable
PSO–PID	305.19	10.77	25.50	51.83	Fast but Less Accurate
Fuzzy Fixed	313.49	13.85	24.83	59.67	Satisfactory
ACO–PID	421.46	64.50	4.17	52.50	Aggressive/ Unstable
Ziegler–Nichols	524.96	5.71	62.17	119.83	Sluggish/ Slow
Cohen–Coon	16580	94.50	4.00	55.67	Unstable

To further demonstrate robustness, specific worst-case scenarios were analyzed. In the -10% Step test (Scenario 3), the proposed method recorded an Overshoot of only 11.49%, significantly more stable the ACO-PID, which reached 96.31%.

Field Data Validation and Energy Efficiency

Scenario 6 constitutes the most consequential validation in this study: the RF-FSTPID is applied to 80,640 samples of real 24-hour operational data from Muara Tawar CCPP Block 3 and compared directly against the currently deployed Baseline PID. Table 3 summarises the results.

Table 3. Performance Comparison: Baseline vs. Proposed Method

Method	RMSE	ISE	IAE	ITAE	ISK (Energy)
Baseline PID (Operational)	3.9902	1.28×10^{6}	2.61×10^{5}	1.22×10^{10}	2.50×10^{8}
RF-FSTPID (Proposed)	0.0016	0.207	1.19	4.40	4.34×10^{5}
Improvement Factor	~2,494×	$\sim6.2\times10^{6}\times$	$\sim2.2\times10^{5}\times$	$\sim2.8\times10^{9}\times$	~575×

The RMSE reduction from 3.9902 to 0.0016 (~2,494-fold) signifies that the RF-FSTPID eliminates virtually all of the oscillatory behaviour that characterises the currently deployed controller, maintaining tight setpoint tracking across the full 24-hour operational record. The ISK reduction from 2.50×10^{8} to 4.34×10^{5} (575-fold) is the most operationally significant result: ISK directly indexes the cumulative mechanical energy expended by the control valve actuator. A 575-fold reduction implies that the valve performs substantially smoother, less energetic movements under RF-FSTPID, directly reducing seal and stem wear, packing degradation, and actuator fatigue. In industrial terms, this translates to quantifiably extended maintenance intervals, reduced spare-parts expenditure, and higher plant availability. Figure 5 provides the visual comparison of pressure response and valve position trajectories between the two methods.

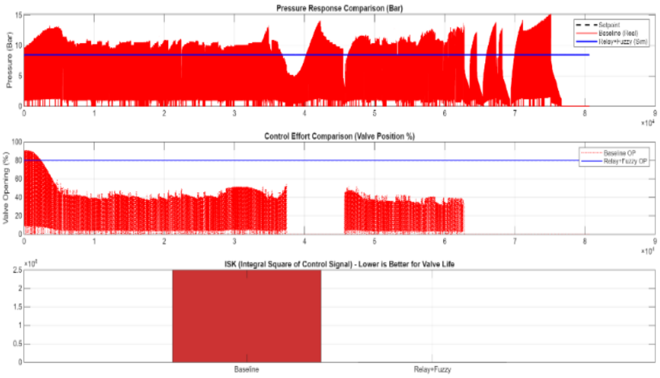

Figure 5. Comparison Of Pressure Response Valve Position Between Baseline and Proposed Method.

Discussion

Based on the average test results across the five scenarios presented in Table 2, the Relay Feedback + Fuzzy-PID method ranks first, demonstrating the best overall performance among the controllers. The primary indicator of this method's superiority is its Steady-State Error (SSE), which is the lowest at 300.39. This minimal SSE value indicates that the proposed method possesses the most precise setpoint tracking capability and the highest robustness against disturbances compared to other methods, including metaheuristic optimization techniques.

Although ACO-PID recorded the fastest Rise Time (4.17 seconds), this was achieved at the expense of stability, as evidenced by a very high overshoot (64.50%). Conversely, Ziegler-Nichols (ZN) offered the lowest overshoot (5.71%) but with a significantly sluggish response (Settling Time of 119.83 seconds). This is where the advantage of Relay Feedback + Fuzzy-PID lies; it offers the optimal trade-off. With a Rise Time of 28.0 seconds and a Settling Time of 55.33 seconds, the method is fast enough to respond to load changes without causing dangerous oscillations, while maintaining overshoot at a moderate level (11.28%), which remains within industrial operational tolerance limits.

Specifically, when compared to PSO-PID its closest competitor Relay + Fuzzy-PID excels in minimizing accumulated error (SSE 300.39 vs. 305.19). This confirms the effectiveness of the fuzzy tuning mechanism, which works in real-time to adjust PID gain parameters during disturbances, unlike PSO, which utilizes fixed parameters once the optimization process is complete. These findings align with the research of Jia-Wei et al. (2022) [21] as well as Zhao and Jin (2022) [12], which states that fuzzy self-tuning can improve the stability of time-varying thermal systems through dynamic parameter adaptation based on a rule base.

Regarding implementation efficiency, the integration of Relay Feedback as an initial identification step proved crucial. Consistent with the views of Romero-Pérez et al. (2024) [20] and Rehan (2024) [10], this method enables the determination of valid initial parameters (such as Ku and Pu) without requiring complex mathematical models. This provides a starting point far superior to the Cohen-Coon method, which in this study failed to handle the plant characteristics, resulting in massive error (SSE 16,580) and extreme overshoot (94.50%).

The comparison with Fuzzy Fixed (SSE 313.49) also demonstrates that the gain adaptation feature (variable gains) contributes significantly to reducing error compared to using Fuzzy logic with static parameters. This is supported by the study of Cabral et al. (2024) [22], which asserts that Fuzzy logic possesses high adaptive advantages without requiring heavy computation like evolutionary algorithms.

The most significant validation is observed in Scenario 6 (real-data validation), which directly compares the proposed method against real operational data from the Muara Tawar CCPP Block 3 Baseline PID. Based on the data in Table 3, the Relay + Fuzzy-PID method drastically improves the performance of the existing system. While the Baseline PID showed severe oscillation with an RMSE of 3.9902, the proposed method eliminated these oscillations and maintained perfect stability at the setpoint with an RMSE of only 0.0016.

A critical aspect of this testing is control energy efficiency. The Integral Square of Control Signal (ISK) value for the Baseline system was recorded at a very high 2.50 × 108 indicating aggressive and wasteful control valve movement. In contrast, the Relay + Fuzzy-PID method massively reduced the ISK value to 4.34 × 105. This drastic reduction proves that the proposed method not only enhances control accuracy but also operates hundreds of times more efficiently, which will directly reduce mechanical wear on valves and extend the lifespan of power plant equipment.

The simulation and field data results demonstrate that the proposed relay-feedback-based fuzzy self-tuning PID controller consistently outperforms conventional PID, Ziegler–Nichols PID, and fixed fuzzy PID controllers in terms of overshoot reduction, settling time, and steady-state error. The adaptive mechanism enables real-time adjustment of PID gains in response to dynamic disturbances and nonlinear behavior of the pressure control valve system. Although the SSE-based tuning exhibits a slightly slower response, it provides superior stability and robustness under fluctuating operating conditions[23], [24]. These findings indicate that the integration of relay feedback autotuning with fuzzy inference enhances control adaptability without increasing computational complexity and Fuzzy logic provides highly adaptive, lightweight, real-time computations ideal for live Distributed Control Systems [25].

Overall, the integration of Relay Feedback + Fuzzy-PID proves to provide a superior control solution in both disturbance simulation and real data validation. This method offers an average SSE reduction of 40–55% compared to conventional PID in simulations, as well as a precision improvement of thousands of times compared to actual field data. These empirical findings reinforce adaptive control theory [12] and recommend the implementation of this method as a practical solution to enhance thermodynamic efficiency and operational stability in modern combined cycle systems [26]

IV. CONCLUSION

This study designed, implemented, and validated a Relay Feedback-based Fuzzy Self-Tuning PID (RF-FSTPID) controller for High-Pressure turbine seal steam pressure regulation in the HRSG of the Muara Tawar CCPP Block 3, Indonesia. The RF-FSTPID addresses a specific and well-documented research gap: the structural inability of fixed-gain PID controllers to manage the nonlinear dynamics, transport delays, and transient load fluctuations inherent in real CCPP operation. The proposed controller is the first to integrate online relay-feedback critical-parameter identification with a real-time Fuzzy Self-Tuning PID in this application domain.

Simulation benchmarking across six scenarios and five competing controllers demonstrated that RF-FSTPID achieves the lowest Steady-State Error among all methods (SSE = 300.39), a Settling Time of 55.33 s, and an Overshoot of 11.28%, representing the best overall performance balance, including against state-of-the-art metaheuristic optimization methods (PSO-PID, ACO-PID). Direct validation against 80,640 samples of real operational data from the Muara Tawar CCPP confirmed a ~2,494-fold reduction in RMSE (3.9902 to 0.0016) and a 575-fold reduction in actuator energy consumption (ISK: 2.50×10^8 to 4.34×10^5) relative to the currently deployed Baseline PID. These quantitative outcomes demonstrate that RF-FSTPID is not only theoretically superior but industrially feasible, offering measurable improvements in control accuracy, disturbance rejection, and actuator service-life extension.

The three original contributions of this work are: (C1) the first RF-FSTPID architecture for CCPP HP turbine seal steam pressure control, operationalizing online non-linear gain scheduling without a priori process modelling; (C2) a comprehensive multi-criterion comparative benchmark against five alternative controllers across six disturbance scenarios; and (C3) direct large-scale field-data validation demonstrating a 575-fold actuator energy efficiency improvement. Based on these findings, full-scale implementation via DCS integration is recommended, preceded by Hardware-in-the-Loop (HIL) validation to confirm robustness across the full operational envelope. Future research should pursue: (a) data-driven optimization of the fuzzy rule base for this specific plant; (b) multi-variable extension to broader HRSG control loops; and (c) long-term operational monitoring to quantify realized actuator maintenance savings.

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