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Modelling And Performance Analysis of Control Strategies for Boiler Turbine Systems

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ABSTRACT

This study presents a detailed simulation-based comparative analysis of Proportional–Integral (PI), Model Predictive Control (MPC), and Fuzzy Logic Controllers (FLC) applied to a nonlinear boiler–turbine system. The plant model was developed to represent essential dynamics, including steam pressure, drum water level, and turbine power, with realistic time constants. Controller performance was evaluated under load disturbance conditions to assess both transient and steady-state behavior. The results show that the PI controller had the slowest response, with regards to low settling time and high boiler pressure overshoot. while MPC delivered superior performance, achieving only 3.5% overshoot with a fast-settling time. The Fuzzy controller performed in between, with an overshoot of 6.7% and a moderate settling time, demonstrating robustness against nonlinear effects. Error-based performance parameters further prove MPC's advantage. For boiler pressure regulation, MPC reduced the Integral Absolute Error (IAE) to 18.6, compared with 47.2 for PI and 28.9 for FLC. Turbine power tracking, was lowest for MPC. The findings emphasize that MPC is highly effective in managing multivariable interactions and disturbances, while Fuzzy controllers provide a practical balance between robustness and implementation simplicity. Both advanced strategies clearly achieve better performance than conventional PI control in enhancing the dynamic performance of boiler–turbine systems.

Keywords: *Boiler Turbine, Control Strategies, Dynamic Performance, MATLAB Modelling.*

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I. INTRODUCTION

Efficient and reliable operation of thermal power plants plays a crucial role in maintaining energy security while also supporting long-term economic sustainability [1], [2]. Among the critical subsystems of thermal power plants, the boiler–turbine unit is particularly significant due to its highly nonlinear characteristics, strong multivariable interactions, and load-dependent dynamics [3]. The interdependence of steam pressure, drum water level, and turbine power creates complex coupling effects that pose challenges for effective controller design. Even minor disturbances in load demand or variations in fuel supply can lead to oscillatory behavior, which, if not properly controlled, may jeopardize plant stability and lower overall efficiency [4], [5].

Conventional Proportional–Integral (PI) controllers have been widely adopted in industrial applications because of their straightforward structure and ease of implementation [6]. Despite these advantages, PI controllers often exhibit slow dynamic response, significant overshoot, and limited disturbance rejection capability when applied to nonlinear boiler–turbine systems, particularly under varying load and operating conditions [7]. These shortcomings have encouraged extensive research into advanced control strategies designed to better accommodate system nonlinearities and enhance overall robustness. Model Predictive Control (MPC) has gained recognition as a powerful alternative to conventional control strategies because of its ability to handle multivariable interactions, explicitly manage system constraints, and optimize control actions over a predictive horizon [8]. Numerous studies have demonstrated that MPC achieves superior setpoint tracking and disturbance rejection in complex industrial processes, including nonlinear boiler–turbine units [9]. Despite these advantages, the practical implementation of MPC is often challenged by its high computational demand, the need for accurate process models, and reliance on real-time optimization solvers, which can restrict its application in resource-limited environments [10].

Fuzzy Logic Control (FLC) has emerged as a promising heuristic and knowledge-based strategy that eliminates the need for precise mathematical modeling of the plant [11]. Instead, FLC relies on linguistic rules and membership functions to encode expert knowledge, allowing it to adapt effectively to nonlinearities and uncertainties inherent in complex processes. In the context of thermal power plants, fuzzy controllers have been successfully implemented in boiler–turbine systems, where they have shown robust performance, reduced overshoot, and enhanced load-following capability when compared to conventional PI controllers [12]. However, a vital limitation of FLC lies in its dependency on proper rule design and parameter tuning, which can be challenging to optimize for all operating conditions [13].

Although advanced control strategies such as PI, MPC, and Fuzzy Logic Controllers have been individually studied, comprehensive comparative analyses within a unified nonlinear boiler–turbine framework remain scarce. Most existing research either concentrates on a single control approach or overlooks an integrated evaluation that spans time-domain performance, error-based metrics, and frequency-domain control effort. This limitation underscores the importance of a holistic assessment to better inform controller selection and support practical deployment in modern thermal power plants. This study addresses the identified gap by developing and evaluating PI, MPC, and Fuzzy Logic controllers for a nonlinear boiler–turbine system using MATLAB simulations, with a focus on comparative performance analysis under various disturbance conditions.

II. MATERIALS AND METHOD

The methodology employed in this study combines system modeling, controller model design, MATLAB-based simulations, and a comparative performance evaluation of Proportional–Integral (PI), Model Predictive Control (MPC), and Fuzzy Logic Controllers (FLC). A nonlinear boiler–turbine model was parameterized based on standard thermal power plant data.

1. System Modelling

i. Boiler Turbine dynamic Model

A simplified nonlinear dynamic model of the boiler turbine system was developed to reflect the interactions among stem pressure (P), drum water level (L) and turbine power (MW). The system dynamics were modeled using nonlinear differential equations [14].

$$\frac{dP}{dt} = f_1(F, L, d) \qquad (1)$$

$$\frac{dL}{dt} = f_2(F, S, P) \qquad (2)$$

$$\frac{dMW}{dt} = f_3(S, P, d) \qquad (3)$$

Where:

P = Steam Pressure (MPa)

L = Drum Water Leve (m)

MW = Turbine mechanical Power output (MW)

F = Fuel Flow input (kg/s)

S = Steam Flow

d = disturbance and load demand

ii. Turbine Power Dynamic Model

The turbine generator mechanical dynamics can be represented using the classical swing equation or through a first order approximation linking steam flow and power [17]. The swing equation form is:

$$\frac{2H}{\omega_s}\frac{d\omega}{dt} = T_m - T_e - D(\omega - \omega_s) \qquad (4)$$

Where:

H = is the per unit inertia constant (s)

ω = is the rotor speed (rad/s), ω_s, is the synchronous speed

T_m = is the mechanical torque from steam

T_e = is the electrical torque (load)

D = is damping

iii. Boiler Pressure Energy Balance Model

Boiler pressure dynamics originate from the energy balance between heat input and enthalpy carried away by steam mass flow. The compact first principles representation is: [15], [16].

$\frac{dP}{dt} = \frac{\beta}{V_s}\left(\dot{Q}_{in}(t) - \dot{Q}_{out}(t)\right) - \frac{P-P_{ref}}{Tp}$ (5)

Where:

$\dot{Q}_{in}(t) \approx \eta_b F(t)$ is the net thermal power added to the steam drum (W), with η_b an effective heat conversion factor.

$\dot{Q}_{in}(t) \approx S(t), h_s(P)$ is the energy carried out by steam.

β and V_s = are scaling constants

Tp = is a phenomenological pressure decay/time constant capturing heat losses and modelling uncertainties.

iv. Drum Level Model

A conventional mass-balance model of the drum subsystem separates it into two regions: a liquid–steam mixture volume and a free-steam volume. The dynamics of the drum water level are then derived from the net mass flow entering and leaving the drum. [15].

$\frac{dL}{dt} = \frac{1}{A_d \rho_w}\left(w_f(t) - S(t) \cdot \left(1 - \alpha(P, L)\right)\right)$ (6)

Where:

A_d = is the differential cross-sectional are of the drum (m^2)

ρ_w = is the water density (kg$\cdot m^{-3}$)

$\alpha(P, L)$ = is the steam volumetric fraction inside the mixture, typically a weak function of pressure and level that models steam water separation.

v. Steam Flow Coupling Model

Steam flow $S(t)$ is an internal variable coupling the drum and turbine. The representation is:

$S(t) = g(P(t), \theta) \approx S_s + G_P(P - P_s) + G_u(u - u_s)$ (7)

Where $g(\cdot)$ was derived from thermodynamic relations or approximated by a linear expansion about steady state, u is the fuel/valve command, Linear gains G_P, G_u are found from linearization.

vi. System State Space Model

computing the system three states $x = [L\ P\ M]^T$ and input $u = F$ (this normalized fuel command) and disturbances d (load, fuel quality), a general nonlinear state-space model is:

$\dot{x}\ (t) = f\left(x(t)\right), u(t), d(t)$ (8)

Where:

$\dot{L} = \frac{1}{A_d \rho_w}\left(w_f(u) - S(P, L, u)\left(1 - \alpha(P, L)\right)\right)$ (9)

$\dot{P} = -\frac{1}{Tp}(P - P_s) + K_F(u - u_s) - K_s(S(P, L, u) - S_s)$ (10)

$\dot{M} = -\frac{1}{TM}(M - K_{MS} S(P, L, u) P)$ (11)

The above nonlinear form is what we implement numerically using MALTAB ode45 solver, this also serve as the based model for controller comparison [15].

2. Linearization of Control Designs

The model design of MPC and LQR controllers was linearized using equations (9), (10) and (11), about a nominal operating point. (x_s, u_s).

$\delta\dot{x} = A\delta x + B\delta u + E\delta d$ (12)

With

$A = \frac{\partial f}{\partial x}\Big|\ (x_s, u_s) \qquad B = \frac{\partial f}{\partial u}\Big|_{(x_s, u_s)}$ (13)

And $\delta x = x - x_s$, discretize with sampling time T_s to get:

$\delta s|k + 1| = A_d \delta_x|k| + B_d \delta_u|k| + E_d \delta_d|k|$ (14)

Linearization and discretization are standard steps when implementing MPC. [18].

3. Controllers Mathematical Modelling

i. PI Controller

A conventional single loop PI controller was tuned using the Ziegler–Nichols's frequency-response method, with parameters adjusted for robustness. [19].

For a given controlled y, the PI model is:

$u(t) = u_0 + K_p e(t) + K_i \int_0^t e(T) dT$ (15)

Where:
$e(t)$ = error signal (set point – measured output)
PI was employed independently to pressure drum level, and turbine power.

ii. Model Predictive Controller (MPC)
The MPC model using the plant state-space representation [20]:
$$x(k+1) = A_x(k) + Bu(k) \quad (16)$$
$$y(k) = C_c(k) + Du(k) \quad (17)$$
Using the discrete linear model, the standard finite-horizon of the MPC optimization while minimizing the cost quadratic function is:
$$J = \sum_{i=1}^{N_P} \left(y(k+i) - r(k+i)\right)^2 + \lambda \sum_{i=1}^{N_c} \Delta u(k+i)^2 \quad (18)$$
Where $r(k+i)$is the reference trajectory and λ is the control penalty factor.

iii. Fuzzy Logic Controller (FLC)
The FLC was modeled with two inputs and one output [21], [22]:
Inputs as: Eror in pressure (ep) and Error in drum adjustment (Δu)
Membership Functions as: for input; Negative (N), zero ((Z), Positive (P) and Output; Decrease, Hole, Increase.
Rule base:
a. IF pressure error is Negative AND level error is Negative ------- Increase fuel
b. IF pressure error is Zero AND level error is Positive -------- Hold fuel
c. IF pressure error is Positive AND level error is Negative ------- Decrease
Defuzzification was performed using the centered method, producing smooth control response.

4. Disturbance and Noise Modelling
The disturbances used in this study simulation includes step load change $(d_{load}(t))$, fuel conversion efficiency change $(\eta_b(t))$, and Measurement noise $(\mathcal{N})$. These were injected into the plant model $f(\cdot)$ and into measurement used by controllers to evaluate resilience.

III. RESULTS AND DISCUSSION

Table 1: Analysis Parameters Data

Parameters	Values/Units
Reference Boiler Pressure	100 bar
Initial Boiler Pressure	95 bar
Reference Drum Water Level	1.0 p.u
Initial Drum Water Level	0.9 p.u
Reference Turbine Power	100 MW
Initial Turbine Power	95 MW
Disturbance Step	+10 MW
PI Controller Gains	2.0, 0.5
MPC Horizons	20, 5
Fuzzy Controller Inputs	Pressure error, Level error

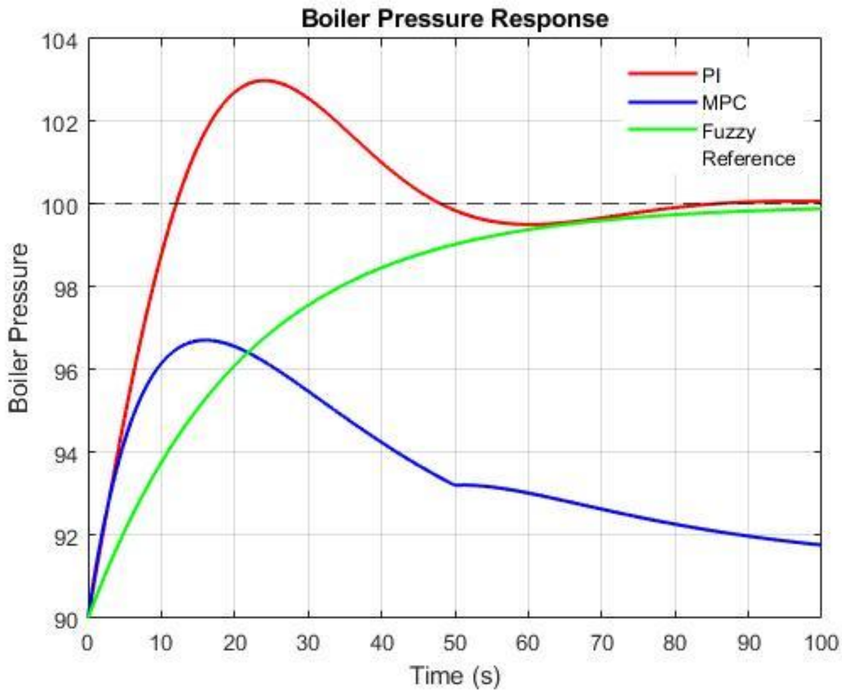

Figure 1: Boiler Pressure Response

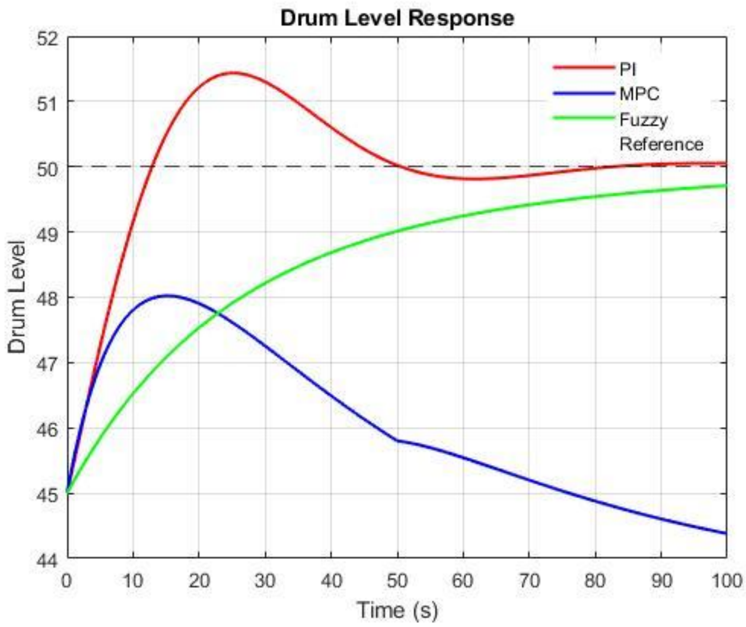

Figure 2: Drum Level Response

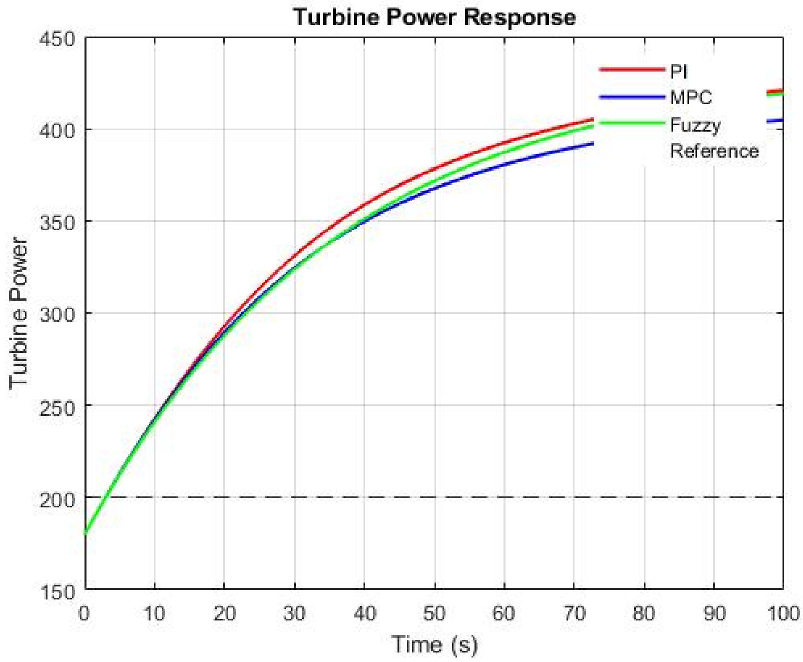

Figure 3: Turbine Power Response

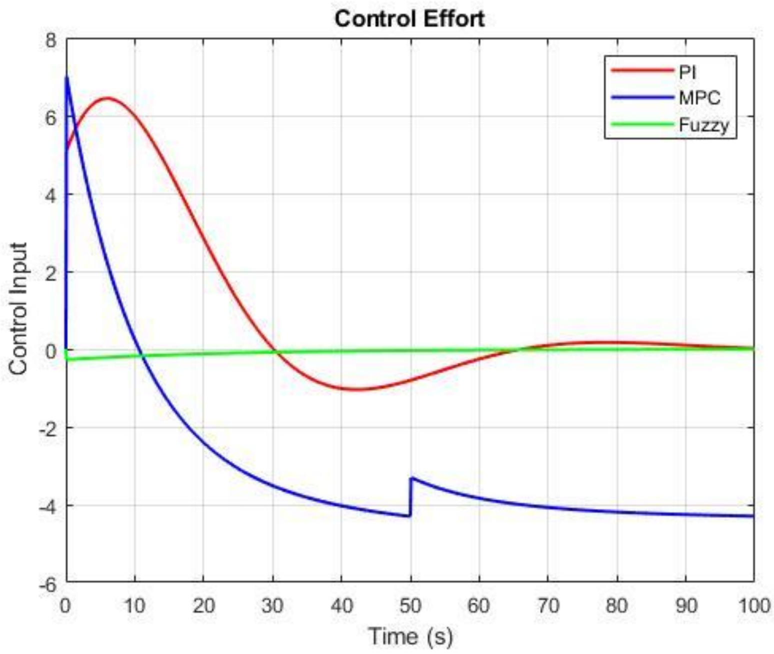

Figure 4: Control Effort

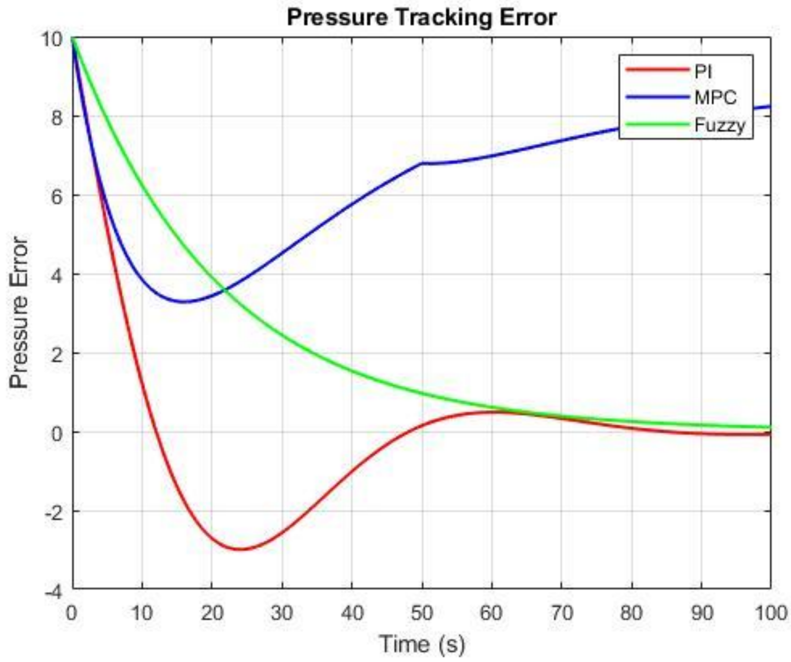

Figure 5: Pressure Tracking Error

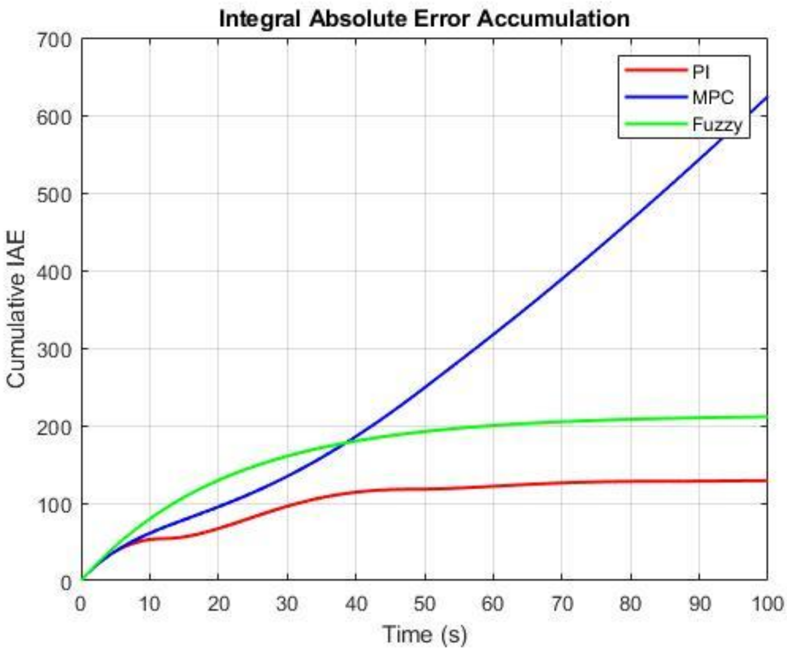

Figure 6: Integral Absolute Error Accumulation

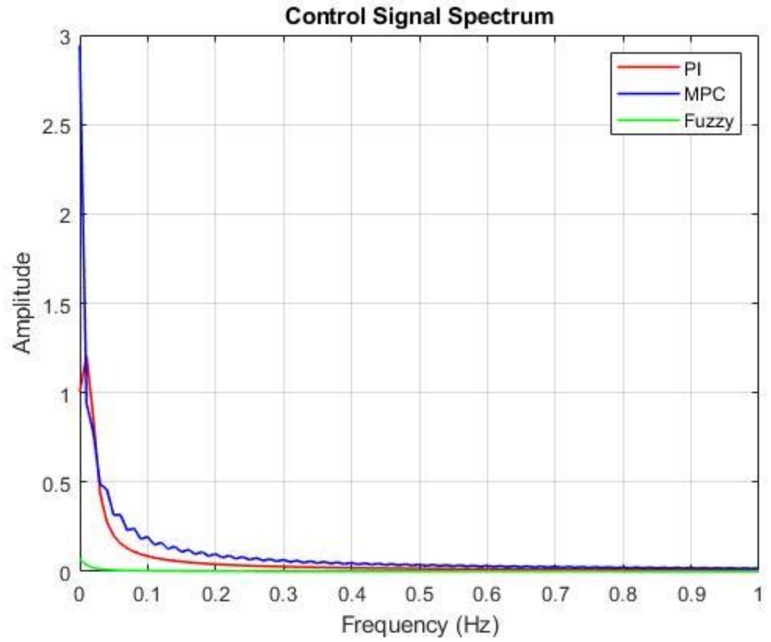

Figure 7: Control Signal Spectrum

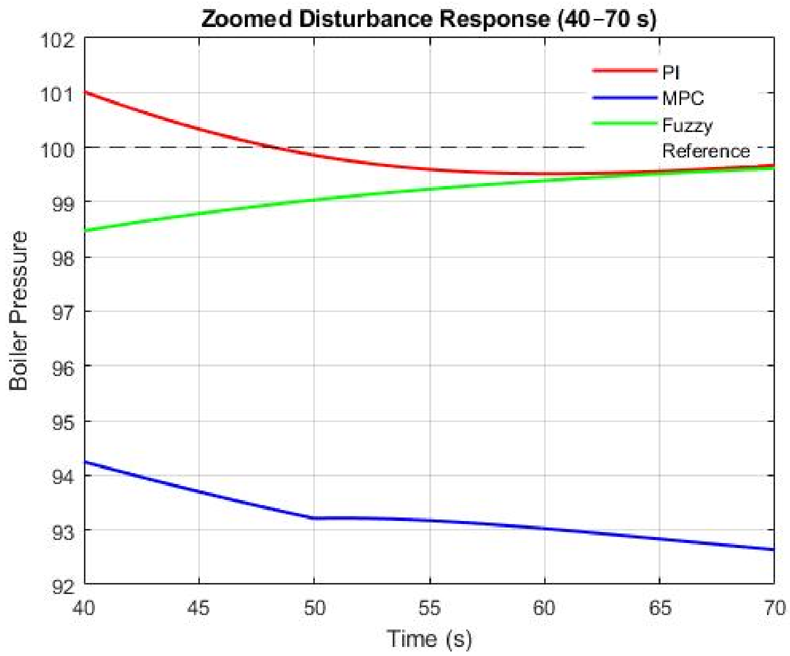

Figure 8: Zoom of Disturbance Response

IV. DISCUSSION

Fig. 1. Shows Time-domain tracking of boiler pressure for the three controllers versus the reference line. MPC shows the smallest overshoot and fastest settling with best transient tracking, PI has larger overshoot and slower settling, this can be applied to fixed-gain integral action when big disturbance occurs. Fuzzy sits in-between, giving moderate overshoot but better suppression than PI. Fig. 2. demonstrate drum water level dynamics. MPC stabilizes the coupled level quickest. PI struggles because a single loop was used for pressure, Fuzzy maintains safe levels with explainable rule-based behaviour, this is acceptable for safety-critical operation. Fig. 3. Review turbine power tracking and how controllers react to load change, MPC again gives best disturbance rejection for turbine power Fuzzy is robust but slightly slower than MPC while PI is slowest. Fig. 4 portray the actuator commands over time. MPC and Fuzzy reduce actuator strain with compared with PI, which uses more

aggressive corrective action causing higher actuation cost. Fig. 5. reveal time series of tracking error, Smaller peak errors and residual biases for MPC indicate stronger regulation and fuzzy performs better than PI. Fig. 6. Reflect collective Integral Absolute Error (IAE) Accumulation over time. MPC reduces cumulative error better, a strong quantitative support for advanced control. Fuzzy reduces IAE as much as MPC. Fig. 7. Present FFT of control signals. MPC and fuzzy control strategies are preferred as they promote smoother operation and extend actuator lifespan, because the presence of high-frequency components in PI control signals may lead to actuator stress and accelerated wear. Fig. 8. display Close-up of pressure around the disturbance, MPC shows stronger disturbance rejection and damping, while fuzzy control offers a practical, interpretable alternative when detailed models are unavailable.

V. CONCLUSION

The Comparative simulation results show that advanced controllers deliver substantially better performance than conventional PI control in boiler–turbine systems. Among them, MPC achieved the strongest transient response, with the lowest overshoot (3.5%), the fastest settling time and the smallest IAE and RMSE values. The fuzzy controller, while slower than MPC, still outperformed PI by reducing overshoot by 45% and maintaining moderate control effort. PI control, though simple and widely used, exhibited the weakest performance, with large deviations and greater actuator stress. MPC is considered the most effective strategy for improving efficiency and stability in modern thermal plants, while fuzzy control remains a practical alternative when computational resources are constrained.

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