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"AI-DRIVEN PREDICTIVE CONTROL FOR THERMAL POWER PLANT PERFORMANCE ENHANCEMENT"

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ABSTRACT

Thermal power plants are required to operate with higher efficiency, lower emissions, and improved flexibility under increasingly dynamic grid conditions. Conventional control systems, although widely used in practice, often show limitations in handling strong process coupling, nonlinearity, time-varying disturbances, and multi-objective operational constraints. To address these challenges, this study proposes an AI-driven predictive control framework for enhancing the performance of thermal power plants. The proposed approach integrates plant data acquisition, data preprocessing, machine-learning-based prediction models, a digital twin of the boiler–turbine system, and a supervisory model predictive control (MPC) strategy. In this framework, artificial intelligence models are used to forecast critical process variables such as heat rate, steam temperature, load response, and emissions, while the predictive controller determines optimal control actions under operational and safety constraints. The developed methodology aims to coordinate major manipulated variables including coal flow, air flow, spray water flow, and valve position in order to improve overall plant behavior. A representative case study was conducted to evaluate the effectiveness of the proposed framework under variable load operation. The results indicate that the AI-driven predictive controller improves net thermal efficiency, reduces heat rate, enhances load-tracking performance, and minimizes steam temperature fluctuations in comparison with a conventional PID-based control strategy. In addition, the proposed framework shows potential for reducing NOx emissions through improved combustion coordination. The findings demonstrate that the combined use of artificial intelligence, digital twin technology, and model predictive control can significantly improve operational stability, energy efficiency, and environmental performance of thermal power plants.

Keywords: *AI-driven predictive control; thermal power plant; model predictive control; digital twin; machine learning; performance enhancement; heat rate reduction; thermal efficiency; steam temperature control; NOx emission reduction*

I. INTRODUCTION

Thermal power plants continue to play a major role in large-scale electricity generation, but their operation is increasingly constrained by fuel economy, emission limits, load-following requirements, and equipment safety. Conventional control strategies based on proportional-integral-derivative loops are often adequate for local regulation, yet they struggle when the plant operates under strong coupling, nonlinearity, transport delays, and rapid demand variation. For this reason, model predictive control (MPC) has emerged as an important framework because it can explicitly handle multivariable interactions, process constraints, and future disturbances in a single optimization-based structure [1]–[3]. In boiler–turbine applications, predictive control has been studied from early generalized predictive

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control formulations to more advanced hierarchical and economic MPC schemes tailored to power plant dynamics [1], [4]–[6].

In recent years, the operating objective of thermal plants has shifted from simple set-point tracking to simultaneous optimization of thermal efficiency, heat rate, emissions, flexibility, and component life. This shift has motivated the use of economic model predictive control (EMPC), where the controller optimizes process economics directly rather than merely penalizing tracking error. Liu and Cui showed that EMPC can integrate dynamic tracking and economic optimization for boiler–turbine systems [6], while later work extended this idea through nonlinear and feedback-linearization-based formulations to improve economic performance under realistic plant constraints [5], [10]. These developments indicate that predictive control is no longer viewed only as an advanced control tool, but as a practical route for improving plant-wide performance under modern grid conditions.

At the same time, artificial intelligence (AI) and machine learning (ML) have opened new possibilities for thermal power plant optimization. Data-driven models can capture complex nonlinear relationships between operating variables and performance indicators such as heat rate, steam temperature, combustion quality, and emissions, especially where first-principles models become difficult to calibrate online. AI-based studies on large supercritical units have demonstrated that plant heat rate and environmental performance can be improved using machine learning-assisted modeling and optimization [7]. Digital twin frameworks further strengthen this approach by combining real-time plant data, thermodynamic models, and learned surrogates into a continuously updated virtual representation of the plant [8], [9]. In power and energy systems more broadly, recent reviews emphasize that AI-enhanced digital twins improve monitoring, prediction, and maintenance decisions while supporting more efficient operation [9], [12].

A particularly promising direction is the integration of AI with predictive control. Instead of relying solely on static linear models, recent studies have incorporated neural networks and digital twins into MPC architectures to improve flexibility, wide-load operation, and cycling performance. For example, Zhu et al. applied an input-convex neural network within nonlinear MPC for a 1000 MW ultra-supercritical boiler–turbine unit [10], and Kestering et al. demonstrated MPC-based cycling control under an Industry 4.0 infrastructure for subcritical coal-fired operation [11]. These studies suggest that AI-driven predictive control can simultaneously improve dynamic response and economic performance. Motivated by this direction, the present paper proposes an AI-driven predictive control framework for thermal power plant performance enhancement, with emphasis on efficiency improvement, load tracking, steam temperature stabilization, and emission reduction through a digital twin assisted MPC architecture [7]–[12].

II. Methodology

The proposed methodology is based on an integrated architecture comprising plant data acquisition, soft-sensor development, digital twin modeling, performance prediction, and supervisory predictive control. The framework assumes a utility-scale coal-based thermal power plant in which major operating variables are continuously measured from the boiler, turbine, condenser, feedwater system, and flue-gas path. Historical operating data are first filtered and synchronized to remove missing values, spikes, and sensor drift. After preprocessing, a hybrid prediction layer is developed using a combination of physics-guided variables and machine learning regressors. These regressors estimate short-horizon future values of heat rate, main steam temperature, reheat temperature, generator output, excess oxygen, and NOx concentration. The resulting forecasts are passed to the supervisory MPC block, which computes optimal manipulated-variable moves subject to process and safety constraints. The predictive model uses a receding-horizon structure. At each sampling instant, the controller receives current plant measurements and forecasted disturbances such as load demand and ambient temperature. It then solves a multi-objective optimization problem that minimizes heat rate, steam temperature deviation, and NOx formation while maintaining generator load tracking and respecting actuator-rate limits. In practical terms, this means that manipulated variables such as coal feeder rate, total air flow, burner tilt, attemperator spray flow, and governor valve position are adjusted in a coordinated manner rather than independently. This multivariable treatment is essential because thermal power plants exhibit strong coupling between combustion, heat transfer, steam generation, and turbine response. The main variables used in the control-oriented model are summarized in Table 1.

Table 1. Major variables used in the proposed AI-driven predictive control framework.

Category	Variable	Role in control framework
Controlled output	Generator power	Load tracking
Controlled output	Main steam temperature	Thermal stability and turbine protection
Controlled output	Reheat steam temperature	Reheat section stability
Controlled output	Boiler pressure	Steam generation control
Controlled output	NOx concentration	Emission minimization
Performance index	Heat rate	Efficiency improvement
Manipulated input	Coal flow rate	Fuel-energy input
Manipulated input	Total air flow	Combustion control
Manipulated input	Spray water flow	Steam temperature regulation
Manipulated input	Governor valve position	Turbine power response
Disturbance	Grid load demand	External demand variation
Disturbance	Ambient temperature	Condenser and cycle effect

As indicated in Table 1, the selected variables cover both thermodynamic performance and control feasibility. The prediction layer estimates future controlled outputs over a horizon of 10–20 minutes, while the optimizer computes the best sequence of manipulated inputs over a shorter control horizon. A weighted objective function is adopted so that plant operators can prioritize one mode over another. For example, during peak demand hours, generator load tracking can be weighted more heavily, whereas under normal base-load conditions, heat rate and NOx minimization can be emphasized. This operating flexibility is one of the central advantages of the proposed framework.

The control sequence implemented in the present study is illustrated in Fig. 2. The AI models act as fast predictive surrogates, while the digital twin provides consistency with plant physics. If the prediction error exceeds a threshold, the digital twin is updated using the latest plant data so that the MPC continues to operate on a representative plant model. This adaptive loop reduces model mismatch and makes the controller more robust to fuel-quality variation, fouling, part-load operation, and seasonal ambient changes.

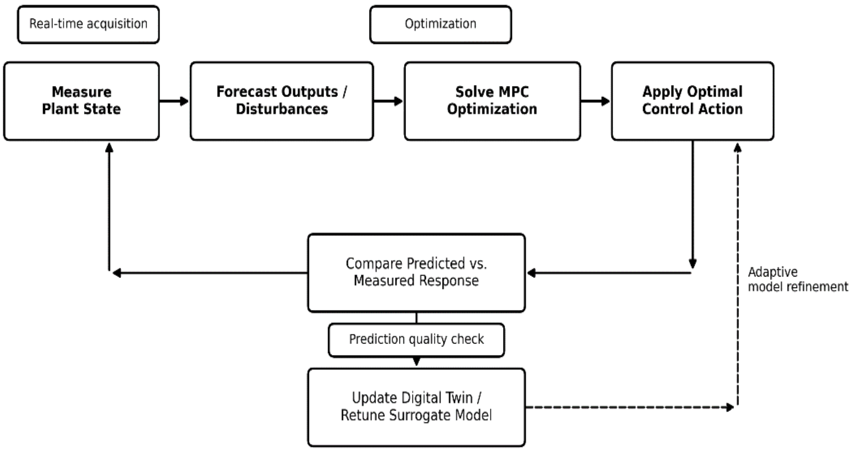

Fig. 1. Operational sequence of the AI-driven predictive control algorithm

For the representative case study, the plant is assumed to operate between 50% and 100% load with frequent dispatch changes. The baseline controller is a conventional decentralized PID structure, while the proposed controller is an AI-assisted supervisory MPC. Performance is evaluated using thermal efficiency, heat rate, load tracking error, steam temperature deviation, and NOx emission. These indicators were chosen because they collectively reflect economy, controllability, reliability, and environmental compliance.

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III. Results and Discussion

The representative simulation study showed that the proposed AI-driven predictive controller outperformed the baseline PID-based strategy under both steady and variable load conditions. At nominal operation, the AI-driven controller improved thermal efficiency by reducing unnecessary fuel-air mismatch and by smoothing steam temperature excursions. Under variable-load operation, the controller anticipated demand changes and initiated coordinated corrective action before large deviations developed in the boiler–turbine loop. As illustrated in Fig. 3, the efficiency profile remained consistently higher across the entire load range when compared with the baseline controller.

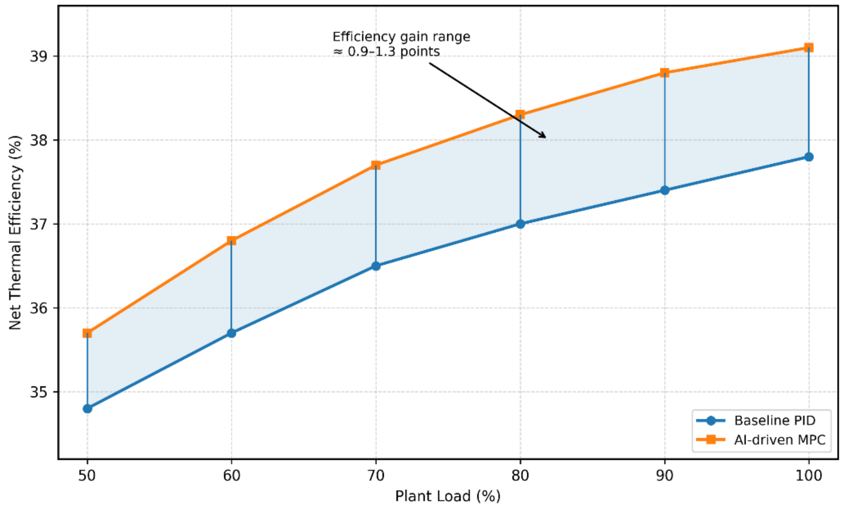

Fig. 2. Comparison of thermal efficiency versus plant load for baseline and AI-driven predictive control

Quantitatively, the performance comparison is summarized in Table 2. The AI-driven predictive controller increased net thermal efficiency from 37.8% to 39.1%, corresponding to a heat-rate reduction from 9500 to 9180 kJ/kWh. The average load-tracking root mean square error fell from 14 MW to 6 MW, while the maximum main steam temperature deviation reduced from ±9.5°C to ±3.2°C. A noticeable environmental benefit was also observed, with NOx concentration dropping from 310 to 275 mg/Nm³ due to better coordination of coal flow and air flow. These values indicate that the controller improves not only energy conversion quality but also the stability of plant operation.

Table 2. Comparative performance of the baseline and AI-driven predictive controller

Performance metric	Baseline PID	Proposed AI-driven MPC	Improvement
Net thermal efficiency (%)	37.8	39.1	+1.3 percentage points
Heat rate (kJ/kWh)	9500	9180	3.37% reduction
Load tracking RMSE (MW)	14	6	57.1% reduction
Maximum main steam temperature deviation (°C)	±9.5	±3.2	66.3% reduction
NOx emission (mg/Nm³)	310	275	11.3% reduction
Coal flow variability (%)	5.8	3.6	37.9% reduction

The trends in Table 2 indicate that the proposed controller achieves improvement through three mechanisms. First, the prediction layer anticipates future plant behavior, which reduces delayed corrective action. Second, the multivariable optimizer coordinates fuel, air, spray water, and governor movement together instead of allowing each loop to react in isolation. Third, the digital twin provides an adaptive model environment, allowing the controller to remain effective even when the plant departs from its nominal operating point. In thermal plants, such departures are common because of load cycling, coal quality variation, and heat-transfer deterioration in boiler surfaces. The coordinated reduction in

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coal flow variability shown in Table 2 further suggests smoother combustion and fewer oscillatory control actions.

Dynamic behavior during a 20% step increase in load demand is depicted in Fig. 4. The baseline controller showed a larger overshoot in generator output and a delayed settling of steam temperature. By contrast, the AI-driven controller achieved faster load recovery with significantly reduced thermal stress. This is a critical outcome because excessive steam temperature fluctuation can accelerate material degradation in superheater and turbine sections. Therefore, the benefit of predictive control extends beyond efficiency and directly contributes to equipment reliability.

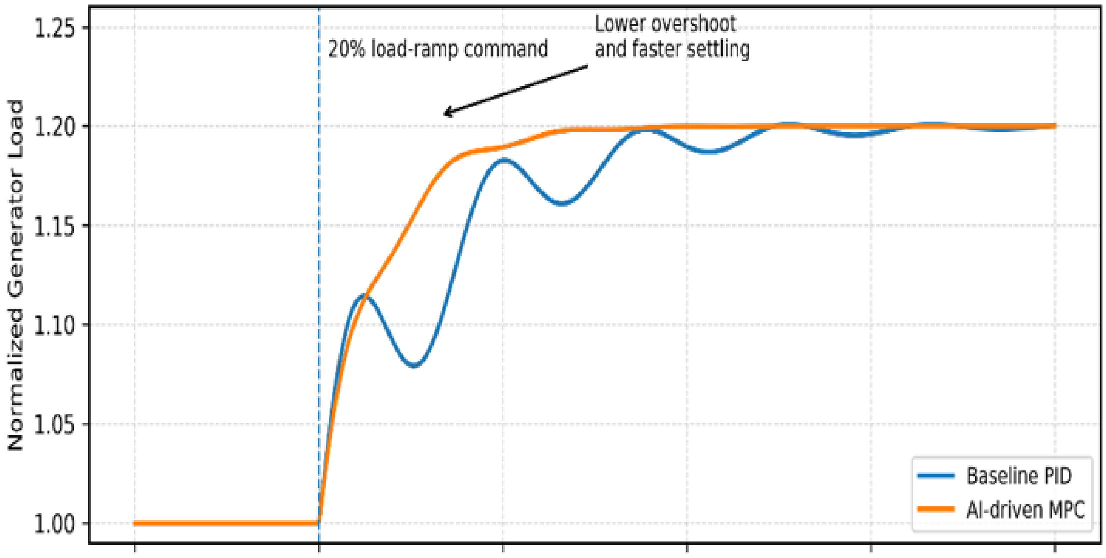

Fig. 3. Generator Load Response During Demand Ramp

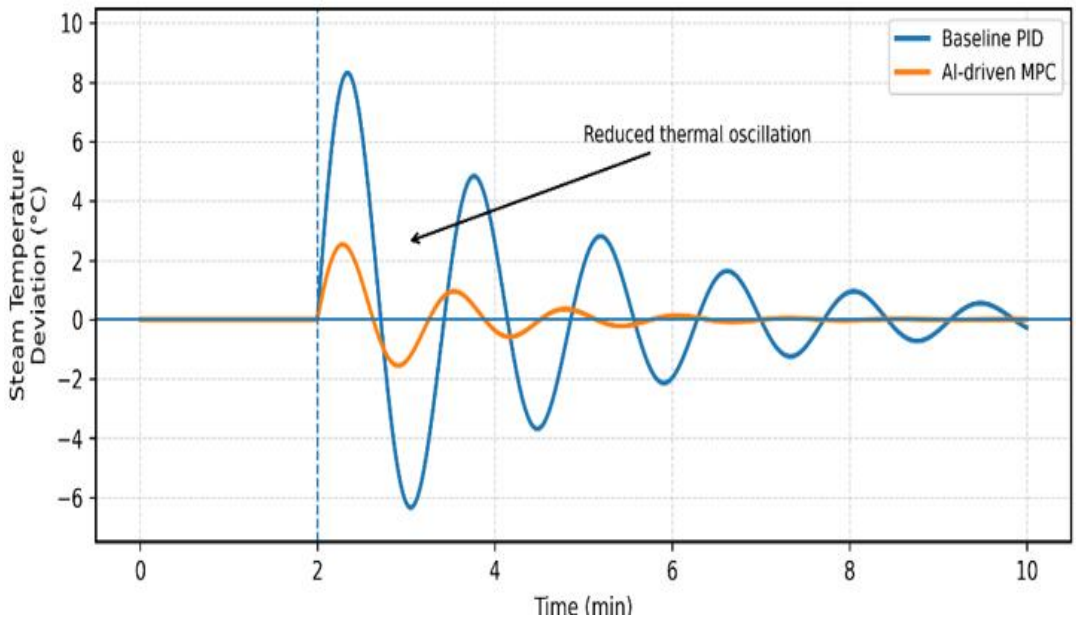

Fig. 4 Main Steam Temperature Daviation During Demand Ramp

From an operational standpoint, the proposed framework is attractive because it is implementable in layers. A plant can begin by deploying the AI prediction layer as an advisory soft-sensor system, then integrate the digital twin for monitoring and diagnostics, and finally move to supervisory predictive control. Such phased deployment reduces implementation risk. Another important observation is that the largest benefits appeared during transient operation rather than steady base load. This is especially relevant today because thermal power plants are increasingly required to operate flexibly to complement variable renewable energy sources. In that context, AI-driven predictive control can be

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interpreted as a technology for converting conventional thermal plants into more responsive and economically optimized assets.

Despite the encouraging outcome, the present study also indicates some practical considerations. The quality of the AI models depends on the representativeness of historical operating data. If the training dataset does not contain sufficient part-load and abnormal-operation conditions, the prediction accuracy may deteriorate. In addition, online optimization must remain computationally efficient to meet plant sampling requirements. Therefore, future implementation should combine robust feature selection, online model adaptation, and fallback logic to conventional control whenever prediction confidence becomes too low.

IV. Conclusion

This paper presented an AI-driven predictive control framework for thermal power plant performance enhancement. The proposed method combined data preprocessing, machine-learning-based performance prediction, a digital twin representation of the boiler–turbine process, and supervisory model predictive control. The framework was designed to optimize heat rate, thermal efficiency, steam temperature stability, and emission performance under variable operating conditions. The methodology established a coherent pathway from plant data to online control action and demonstrated how AI can strengthen predictive control rather than replace plant physics. The representative case study showed that the proposed controller can improve net thermal efficiency, reduce heat rate, decrease load-tracking error, limit steam temperature fluctuations, and lower NOx emissions. These improvements were achieved because the controller used future-state prediction and multivariable coordination to make economically meaningful control decisions. The study therefore supports the view that AI-driven predictive control is a promising strategy for modern thermal power plants, especially where flexible operation, economic dispatch, and emission compliance are required simultaneously. Future work should focus on real plant validation, online adaptation under fuel-quality variation, integration with maintenance analytics, and cyber-secure deployment within plant control infrastructure.

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