DIGITAL TWIN-DRIVEN ADAPTIVE MULTI-POINT HEAT VARIATION TRACKING AND PREDICTIVE CONTROL SYSTEM USING EDGE AI

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ABSTRACT

Accurate thermal regulation in industrial systems is often challenged by limited sensing coverage and dynamic operating conditions. This study proposes a Digital Twin-driven Adaptive Multi-Point Heat Variation Tracking and Predictive Control System using Edge AI. The framework integrates distributed temperature sensing, thermal-state reconstruction, predictive analytics, and reinforcement learning (RL)-based control for real-time thermal management. A digital twin continuously synchronizes with the physical process to estimate the complete thermal field, while an RL controller optimizes control actions without manual tuning. Simulation results demonstrate superior performance compared with a conventional PID controller, achieving energy efficiency improvements from 78.2% to 89.5% under low-load conditions and from 68.9% to 85.4% under dynamic operating conditions, representing gains of 14.5–23.9%. The Thermal Uniformity Index also improved from 0.82 to 0.93 under low-load conditions and from 0.70 to 0.87 under dynamic conditions, corresponding to improvements of 13.4–24.3%. In addition, the developed system achieved lower temperature tracking errors, improved disturbance rejection, and enhanced thermal stability. These results demonstrate the effectiveness of combining digital twins, Edge AI, and reinforcement learning to achieve intelligent, scalable, and energy-efficient industrial thermal management.

Keywords: Digital Twin, Edge AI, Reinforcement Learning, Multi-Point Sensing, Predictive Control, Thermal Management.

1.0 INTRODUCTION

Efficient temperature regulation is essential in industrial systems because it directly influences product quality, operational safety, energy consumption, equipment reliability, and overall productivity. Industrial sectors such as food processing, pharmaceuticals, metallurgy, chemical production, and power generation rely on precise thermal management to maintain stable and efficient operations. However, many existing control systems are still based on conventional controllers and limited number of sensors, which restrict their ability to fully capture complex and spatially varying thermal behavior. As a result, temperature variations caused by process disturbances and uneven heat distribution may remain undetected, leading to reduced efficiency and higher operational costs. To address these limitations, Industry 4.0 has introduced advanced intelligent technologies for improved process monitoring and control. Digital Twin technology is one of the most significant developments, providing a continuously updated virtual representation of physical systems. This enables real-time monitoring, performance assessment, predictive analysis, and enhanced decision-making (Su *et al*., 2025). In parallel, Artificial Intelligence (AI) and Edge AI improve industrial automation by enabling fast, localized data processing, reducing latency, and supporting real-time control actions (Zhang *et al*., 2024a).

Another key challenge in thermal systems is the inability of single-point sensing to represent spatial temperature variations accurately. Multi-point sensing improves this by capturing temperature data from different locations, enabling a more complete understanding of heat distribution and improving detection of abnormal thermal conditions. When combined with digital twin models, this approach enhances thermal-state estimation and predictive capability. Furthermore, reinforcement learning has emerged as an adaptive control approach that learns optimal policies through interaction with the environment, reducing reliance on manual tuning. Its integration with digital twin systems has shown potential for improving process optimization, energy efficiency, and autonomous control in industrial applications (Khdoudi *et al.,* 2024). Despite these advancements, there is still limited research integrating digital twins, multi-point sensing, Edge AI, predictive analytics, and reinforcement learning into a unified thermal management framework. This study therefore presents a Digital Twin-Driven Adaptive Multi-Point Heat Variation Tracking and Predictive Control System using Edge Artificial Intelligence. The system combines distributed sensing, real-time digital twin modeling, predictive analytics, and adaptive control to enhance thermal regulation, improve stability, and support energy-efficient industrial operation.

2.0 REVIEW OF RELATED WORKS

The development of industrial thermal regulation systems has progressively shifted toward the integration of cyber-physical systems, artificial intelligence, and data-centric control approaches. Although PID controllers remain widely applied in industrial settings due to their simplicity and dependable performance under linear operating conditions, their effectiveness reduces significantly when applied to complex thermal processes. Such processes are typically characterized by nonlinear behavior, strong coupling between variables, spatial temperature variation, and frequent disturbances. These constraints have been widely reported in literature and have motivated research into more adaptive and intelligent control strategies (Okeke *et al*, 2020; Åström & Hägglund, 2006; Ogunnaike & Ray, 1994).

To improve monitoring capability in thermal systems, researchers have proposed multi-point and distributed sensing approaches. Compared to single-sensor configurations, these methods provide spatially distributed temperature measurements that allow better reconstruction of thermal fields and improved detection of localized faults or anomalies. Recent studies show that distributed sensing improves both estimation accuracy and diagnostic performance in industrial thermal applications (Garcia *et al*., 2025; Wang *et al*., 2025a). However, challenges such as sensor calibration instability, increased data transmission requirements, and difficulties in real-time data fusion continue to limit their widespread industrial adoption. Digital Twin (DT) technology has become an important framework in modern intelligent manufacturing systems. A digital twin creates a continuously updated virtual representation of a physical process by integrating real-time data with computational models. This enables continuous monitoring, system simulation, fault detection, and predictive analytics within a unified environment. Existing research indicates that digital twin systems improve operational visibility, enhance decision-making, and increase overall system efficiency in industrial applications (Su *et al*., 2025; Meng *et al*., 2026; Kritzinger *et al*., 2018). Furthermore, combining digital twins with data-driven intelligence techniques has been shown to improve predictive capability and system adaptability under uncertain and dynamic operating conditions (Raihan, 2026a; Bibri & Huang, 2025; Imo *et al*, 2025).

Artificial Intelligence (AI), especially machine learning techniques, has become a key component in modern industrial control systems. Deep learning models are widely used for nonlinear system modeling, process prediction, fault detection, and optimization tasks, particularly in cases where physics-based models are insufficient. Studies show that AI-based methods significantly enhance forecasting accuracy and improve fault detection performance in thermal systems (Venkatasubramanian, 2019; Goodfellow *et al*., 2016). In addition, Edge AI has emerged as a distributed computing paradigm that performs data processing near the source of data generation. This reduces latency, minimizes communication overhead, and enables faster decision-making in real-time industrial thermal applications (Zhang *et al*., 2024b; Liu *et al*., 2025a). Reinforcement learning (RL) has also emerged as an effective data-driven control strategy for complex and uncertain industrial systems. Unlike conventional control methods that rely on predefined models or manually tuned parameters, RL-based methods learn optimal control actions through continuous interaction with the environment. This allows improved adaptability in nonlinear and time-varying conditions. Recent research confirms that reinforcement learning improves robustness, energy efficiency, and control performance in industrial applications (Agu *et al*, 2019; Sutton & Barto, 2018; Kiumarsi *et al*., 2017). Furthermore, combining reinforcement learning with digital twin environments has been shown to enhance autonomous decision-making, predictive capability, and closed-loop optimization in industrial systems (Tsai *et al*., 2025a; Khan *et al*., 2025; Ali *et al*., 2025).

Despite these technological advances, most existing studies still address sensing, modeling, prediction, and control as separate modules rather than a unified system. This separation limits overall system efficiency and reduces coordination in complex thermal environments. As a result, recent literature emphasizes the need for integrated cyber-physical frameworks that combine digital twins, artificial intelligence, edge computing, and adaptive control into a single architecture. This study contributes to this direction by presenting a unified Digital Twin–Edge AI–Reinforcement Learning framework for multi-point thermal monitoring and predictive control.

3.0 MATERIALS AND METHOD

3.1 Research Framework

This work developed a Digital Twin–Edge AI framework for intelligent thermal regulation in industrial systems. The framework integrates distributed temperature sensing, thermal-state estimation, predictive modeling, and reinforcement learning-based control to support real-time monitoring and adaptive decision-making. Temperature measurements are continuously acquired, processed at the edge layer, synchronized with a digital twin model, and utilized for prediction and control optimization (Su *et al*., 2025; Raihan, 2026b).

3.2 System Architecture

The system architecture comprises five interconnected modules:

- Multi-point temperature sensing
- Edge data processing
- Digital twin modelling
- Predictive temperature forecasting
- Reinforcement learning control

Sensor data are processed locally and used to update a virtual representation of the thermal process. The digital twin provides real-time state awareness, while predictive and control modules generate corrective actions to maintain thermal stability (Nele *et al*., 2024; Tsai *et al*., 2025b).

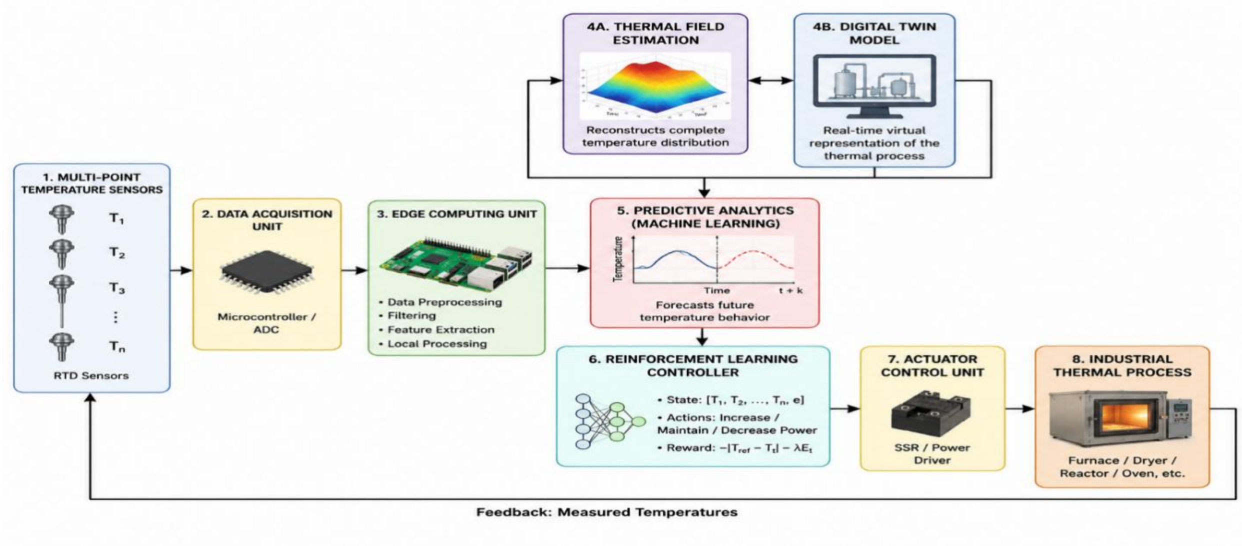

Figure 3.1: The Digital Twin–Driven Adaptive Multi-Point Heat Variation Tracking and Predictive Control System Using Edge AI

Figure 3.1 shows the Digital Twin–Edge AI–Reinforcement Learning architecture for adaptive multi-point heat variation tracking and predictive thermal control. The framework integrates distributed sensing, thermal-state estimation, predictive analytics, and intelligent control within a closed-loop industrial thermal management system.

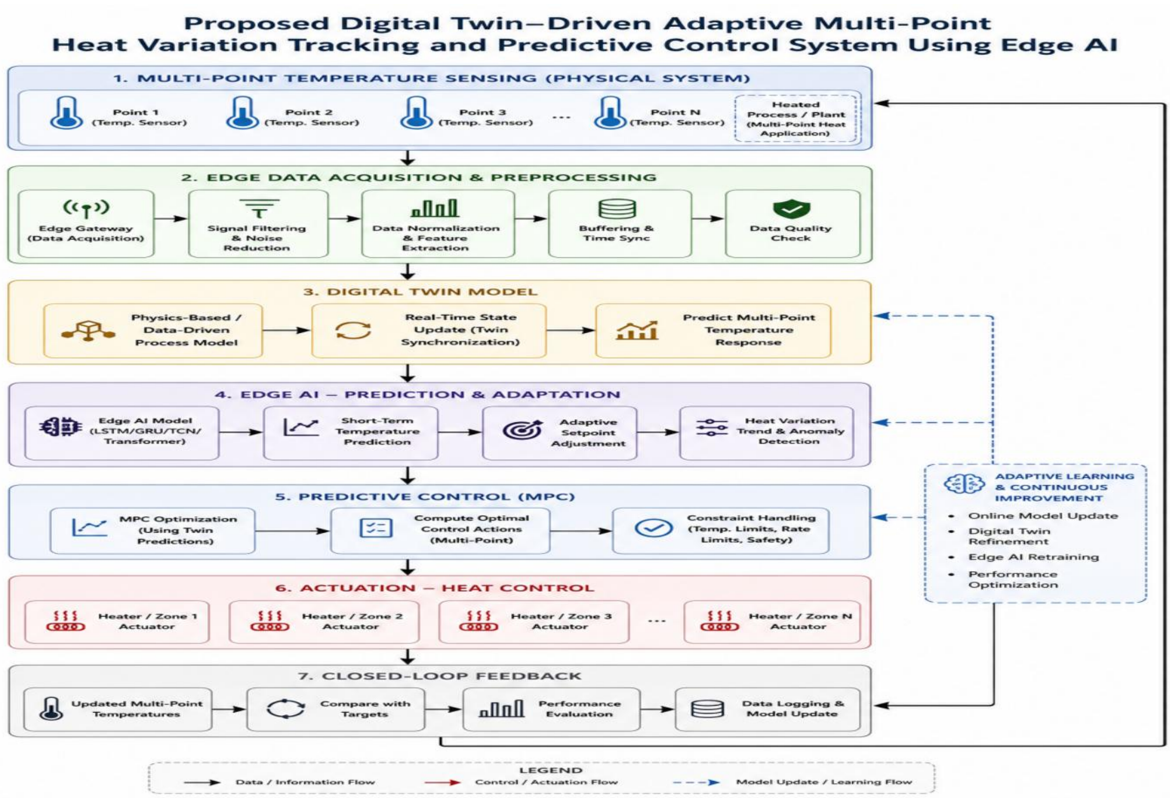

Figure 3.2: The Digital Twin-Driven Multi-Point Heat Tracking System Flow Chat

The system presents a Digital Twin–driven adaptive multi-point thermal regulation framework enhanced with Edge AI for real-time industrial heat management. Distributed temperature sensors capture spatial thermal variations across multiple zones, and the acquired data is transmitted to an edge layer for preprocessing, including noise filtering, normalization, feature extraction, and validation. The processed data updates a real-time digital twin that integrates physics-based and data-driven models to estimate full-field temperature distribution. An Edge AI module performs short-term thermal forecasting, anomaly detection, and adaptive setpoint optimization. These outputs are fed into a model predictive control (MPC) unit that computes optimal multi-zone control actions under operational constraints. The resulting commands are executed via distributed actuators to regulate heating processes. A closed-loop feedback mechanism continuously refines sensor measurements, digital twin states, and AI models, enabling adaptive, accurate, and robust thermal control in real time.

3.3 Materials

Hardware Components

The experimental setup consists of RTD temperature sensors, a microcontroller-based acquisition unit, a Raspberry Pi edge-computing platform, solid-state relays, electrical heating elements, and wireless communication modules for data transmission and control (Garcia *et al*., 2025; Wang *et al.,* 2025b).

Software Components

Python, TensorFlow/PyTorch, MATLAB/Simulink, Node-RED, and a database management system were employed for model development, simulation, visualization, and data management. These tools support machine learning implementation, thermal process simulation, and digital twin deployment (Goodfellow *et al*., 2016; Bibri & Huang, 2025).

3.4 Multi-Point Temperature Sensing

Temperature data are acquired from multiple spatial locations to improve observability of the thermal process. Compared to single-point measurement, distributed sensing provides richer spatial information and enhances thermal-state awareness (Garcia *et al*., 2025; Wang *et al*., 2025b).

The temperature state vector is defined as:

$$T(t)=[T1(t),T2(t),\ldots,Tn(t)]T \quad (1)$$

where Ti(t) is the temperature measured by the ith sensor.

3.5 Thermal-State Reconstruction

The full thermal field is estimated from sparse sensor data to capture spatial gradients and anomalies (Wang *et al*., 2025; Meng *et al*., 2026).

$$T\hat{}(x,y,t)=F(T1,T2,\ldots,Tn) \quad (2)$$

where F(·) represents the reconstruction model.

3.6 Digital Twin Modeling

A digital twin replicates the thermal dynamics of the physical system for real-time monitoring and prediction (Su *et al*., 2025; Meng *et al*., 2026).

$$dT/dt=\beta Q-\alpha(T-T_a) \quad (3)$$

where Q is heat input, Ta is ambient temperature, and α,β are thermal coefficients.

3.7 Predictive Analytics

Future temperatures are forecast using historical data to enable proactive control (Nele *et al*., 2024; Bibri & Huang, 2025).

$$T_{t+k}=G(T_t,T_{t-1},\ldots,T_{t-m}) \quad (4)$$

where G(·) is the prediction model.

3.8 Reinforcement Learning Control

Reinforcement learning optimizes thermal regulation through interaction with the environment (Khdoudi *et al*., 2024; Tsai *et al*., 2025).

State space:
$$S=[T_1,T_2,\ldots,T_{n-e}] \quad (5)$$

Action space:
A={Increase Power, Maintain, Decrease Power}

Reward function:
$$R_t=-|T_{ref}-T_t|-\lambda E_t \quad (6)$$

3.9 Edge Intelligence

All prediction and control tasks are executed at the edge to reduce latency, improve responsiveness, and minimize cloud dependency (Zhang *et al*., 2024; Liu *et al*., 2025).

3.10 Performance Evaluation

System performance is evaluated using standard metrics (Garcia *et al*., 2025; Wang *et al*., 2025):
$$MAE=1/N\sum_{i=1}^{N}|T_{ref}-T_i|$$

$$RMSE=1N\sum_{i=1}^{N}(T_{ref}-T_i)$$

$$\eta=Q_{useful}/Q_{input}\times 100\%$$

$$TUI=1-\sigma_T/U \quad (7)$$

3.11 Operational Procedure

The system operates through sequential stages: multi-point sensing, edge preprocessing, digital twin synchronization, thermal reconstruction, prediction, RL-based control, actuator execution, and continuous performance evaluation.

4.0 RESULTS AND DISCUSSION

4.1 Temperature Tracking Performance

The control strategy maintains the process temperature closer to the reference set-point across different operating conditions. Compared to the PID controller, it exhibits lower deviation, improved damping behavior, and faster stabilization during disturbances.

4.2 Prediction Performance

The forecasting module accurately estimates future thermal states using historical trends. This predictive capability enables early corrective actions, reducing the likelihood of significant temperature deviation and enhancing overall system stability.

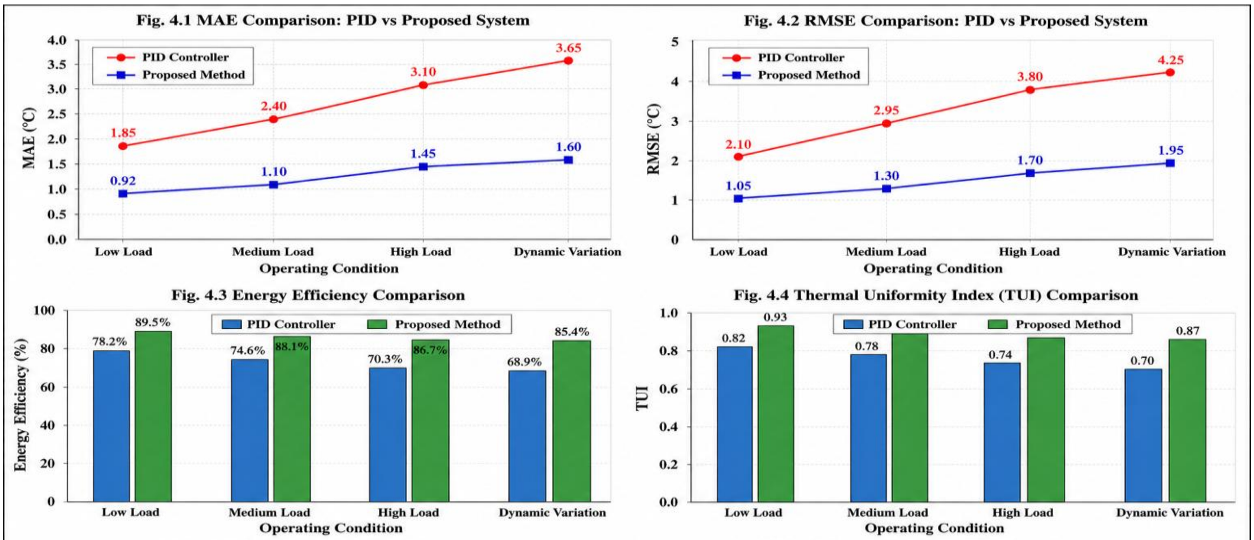

Table 4.1 Performance Error Comparison

Operating Condition	MAE (°C)			RMSE (°C)		
	PID	Proposed	Improvement (%)	PID	Proposed	Improvement (%)
Low Load	1.85	0.92	50.3	2.10	1.05	50.0
Medium Load	2.40	1.10	54.2	2.95	1.30	55.9
High Load	3.10	1.45	53.2	3.80	1.70	55.3
Dynamic Variation	3.65	1.60	56.2	4.25	1.95	54.1

Table 4.2 Energy Efficiency and TUI Comparison

Operating Condition	Energy Efficiency (%)			TUI		
	PID	Proposed	Improvement (%)	PID	Proposed	Improvement (%)
Low Load	78.2	89.5	14.5	0.82	0.93	13.4
Medium Load	74.6	88.1	18.1	0.78	0.91	16.7
High Load	70.3	86.7	23.3	0.74	0.89	20.3
Dynamic Variation	68.9	85.4	23.9	0.70	0.87	24.3

Figure 4.1 – 4.4: Performance Evaluation of the System

4.3 Reinforcement Learning Control Performance

The reinforcement learning controller continuously adapts to process variations by updating its control policy through interaction with the thermal environment. Unlike the fixed-gain PID approach, the proposed method dynamically balances tracking accuracy and energy consumption.

4.4 Temperature Tracking Error (MAE Comparison)

The figures 4.1 – 4.4 shows that the developed approach consistently yields lower MAE values than the PID controller. The improvement becomes more evident under high and dynamic operating conditions, indicating stronger robustness.

4.5 Energy Efficiency Analysis

Table 4.1: Energy Efficiency Analysis

Operating Condition	PID (%)	Proposed (%)	Improvement (%)
Low Load	78.2	89.5	14.5
Medium Load	74.6	88.1	18.1
High Load	70.3	86.7	23.3
Dynamic Variation	68.9	85.4	23.9

The developed system demonstrates improved energy utilization across all operating conditions. This is attributed to the reinforcement learning agent’s ability to optimize control actions based on system feedback.

4.6 Thermal Uniformity Analysis

Table 4.2: Thermal Uniformity Analysis

Operating Condition	PID	Proposed	Improvement (%)
Low Load	0.82	0.93	13.4
Medium Load	0.78	0.91	16.7
High Load	0.74	0.89	20.3
Dynamic Variation	0.70	0.87	24.3

The results indicate that the proposed system achieves more uniform spatial temperature distribution. This improvement is supported by multi-point sensing and digital twin-based reconstruction.

4.7 RMSE Performance Comparison

The RMSE results further confirm that the proposed system maintains lower prediction and tracking error magnitude compared to the PID controller, particularly under dynamic conditions.

4.8 Discussion of Results

The overall results demonstrate that the proposed framework consistently outperforms the conventional PID controller in all evaluated metrics. The reduction in MAE and RMSE indicates improved tracking precision and system stability. Higher energy efficiency values confirm that the reinforcement learning mechanism effectively reduces unnecessary energy consumption while maintaining performance. Additionally, the improved thermal uniformity highlights the effectiveness of multi-point sensing and digital twin reconstruction in stabilizing spatial temperature distribution. The combined integration of predictive analytics, edge computing, and reinforcement learning contributes significantly to system adaptability under nonlinear and time-varying thermal conditions.

5.0 CONCLUSION

This study developed a Digital Twin–based multi-point thermal control system integrated with Edge AI for real-time industrial temperature regulation. The framework addresses limitations of conventional single-sensor and PID-based approaches through distributed sensing, edge processing, digital twin modeling, and predictive intelligence. By combining real-time thermal state estimation, machine learning prediction, and model predictive control (MPC), the system enables coordinated multi-zone regulation with improved stability, accuracy, and responsiveness under operational constraints. Results show enhanced temperature tracking, reduced fluctuations, improved energy efficiency, and better thermal uniformity compared to traditional methods. The closed-loop structure also supports continuous adaptation to changing thermal conditions. Overall, the proposed framework offers a scalable and efficient solution for intelligent industrial thermal management with improved precision and operational performance.

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