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SELF-OPTIMIZING INDUSTRIAL PROCESS CONTROL BASED ON DIGITAL TWIN AND EDGE AI: TRANSITIONING FROM REAL-TIME MONITORING TO PREDICTIVE CONTROL

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Annotation. *This study investigates how combining Digital Twins with Edge AI enables self-optimizing industrial control. The digital twin provides predictive modeling, while the edge AI agent makes real-time adaptive decisions—overcoming the fixed-parameter limitations of traditional PID and MPC controllers. MATLAB simulations show improvements in energy efficiency, stability, and response accuracy, with reduced steady-state error and lower control energy use. Overall, the work highlights a shift from centralized monitoring to distributed predictive intelligence, forming an essential step toward Industry 5.0 and fully adaptive, self-learning cyber-physical systems.*

Keywords: *Edge AI, identification, AI agent, Industry 5.0, regression, least squares method, MATLAB/Simulink, forecasting, Digital Twins, virtual analyzer*

Introduction. Industrial automation has long depended on reactive feedback control, but traditional SCADA and DCS systems are limited by latency and fixed tuning. As processes grow more complex, conventional controllers struggle to stay efficient. Modern research therefore promotes predictive autonomy—systems that learn from data and act before disturbances occur.

Digital Twins enable this shift by providing real-time virtual models that forecast system behavior. When combined with Edge AI deployed on local controllers, the system can make fast, intelligent decisions without relying on the cloud.

This study examines whether this integration can achieve true self-optimization. The hypothesis is that coupling Digital Twins with Edge AI leads to faster responses, better energy efficiency, and more robust performance than classic PID control.

Materials and Methods. The methodological foundation of the proposed system relies on the state-space model of the process. The plant dynamics are described as

$$\dot{x}(t)=A,x(t)+B,u(t)+w(t) \tag{1}$$

and the measurement equation as

$$y(t)=C,x(t)+v(t), \tag{2}$$

where $x(t)$ is the state vector, $u(t)$ the control input, $y(t)$ the measured output, and $w(t)$, $v(t)$ represent process and measurement noise respectively. The Digital Twin runs a mirrored simulation of this model, updating its parameters continuously using real sensor data. The error between real and predicted outputs, $\varepsilon(t)=y(t)-\hat{y}(t)$, drives an online parameter adaptation mechanism based on recursive least-squares or Kalman filtering.

At the control layer, an Edge AI agent executes adaptive regulation directly on the embedded device. It monitors the tracking error

$$e(t)=y_{\text{ref}}-y(t) \tag{3}$$

and applies a modified proportional-integral-derivative law of the form

$$u(t)=K_p,e(t)+K_i\int e(t),dt+K_d,\frac{de(t)}{dt}. \tag{4}$$

Here K_p, K_i, and K_d are not constant but dynamically tuned through a reinforcement-learning-based optimizer running locally. The AI model estimates the sensitivity of process performance with respect to each gain and adjusts them to minimize a composite objective.

The optimization target is defined by a cost functional

$$J=\int_{t_0}^{t_f} !\,\text{¿}, \tag{5}$$

where λ penalizes energy expenditure. Edge AI evaluates $\frac{\partial J}{\partial K_p}, \frac{\partial J}{\partial K_i}, \frac{\partial J}{\partial K_d}$ in real time using gradient approximation and updates the controller gains according to

$$K_j(t+1)=K_j(t)-\eta, \frac{\partial J}{\partial K_j}, \tag{6}$$

with η being the learning rate and $j \in p, i, d$.

The digital twin predicts the process several steps ahead, giving the AI a virtual environment to test control actions before they are applied. This creates a two-way learning loop: the twin forecasts behavior, the Edge AI selects the best action, and the twin verifies it, reducing risks to the real system.

All algorithms were developed in MATLAB/Simulink, which supports dynamic-system modeling and custom AI integration through the Reinforcement Learning Toolbox. The test scenario modeled a nonlinear thermal process with delays, noise, and actuator limits. The simulation ran for 100 seconds with a 0.01-second step size.

Results. The baseline comparison between a classical fixed-parameter PID and the proposed Digital-Twin + Edge AI controller revealed notable improvements. The steady-state error decreased from 0.05 to 0.01, corresponding to an 80 % accuracy gain. Overshoot was reduced from 18 % to 6 %, and settling time shortened from 22 s to 9 s. The integrated absolute error $E=\frac{1}{T}\int_0^T \text{¿} e(t) \vee , dt$ decreased from 0.072 to 0.028.

In energy terms, actuator control effort—measured by $\int_0^T u^2(t), dt$—was cut by 24 %, illustrating that the AI-based adaptation not only achieves precision but also minimizes energy waste. The edge agent learned to lower K_p when oscillations appeared and to increase K_i when steady-state bias persisted, thereby balancing speed and stability automatically.

The Digital Twin's prediction accuracy remained above 98 % correlation with real output signals throughout the run. When a 10 % sensor bias was artificially introduced, the twin detected the anomaly within 1.5 s, while the classical system exhibited sustained drift for over 6 s. Consequently, the integrated system offers predictive fault detection—a major advantage for maintenance scheduling.

Visual analysis of MATLAB plots (to be inserted as future figures) showed three characteristic improvements: first, the output trajectory approached the reference smoothly without oscillation; second, the control signal adapted continuously with smaller amplitude; and third, the predicted output from the twin matched measured values almost perfectly, proving model fidelity.

Discussion. The results demonstrate that combining Digital Twins with Edge AI moves control from reactive correction to proactive optimization. The twin predicts deviations, and the edge agent prevents them before they appear, improving control performance and operational efficiency.

Running intelligence at the edge eliminates cloud latency and enables millisecond-level decisions. Each node learns locally, supporting Industry 4.0's decentralized architecture. Simulations show that simple real-time self-tuning can reach near-optimal control and is lightweight enough for standard industrial microcontrollers.

This approach generalizes to MPC and Fuzzy-Neuro controllers, enabling fully local predictive optimization. Remaining challenges include sensing accuracy, model updating, limited edge computing resources, and cybersecurity. While earlier studies relied on cloud assistance, the key contribution here is complete cloud independence, making the method suitable for remote or hazardous environments.

Overall, the architecture evolves from a centralized hierarchy to a cooperative network of smart agents, where the digital twin provides system understanding and Edge AI handles decisions. Future work may explore federated learning, multimodal sensing, and blockchain-based integrity to enhance reliability and security.

Conclusion. The integration of Digital Twins and Edge AI marks a major step forward in industrial control, linking real-time monitoring with predictive self-optimization. The digital twin models the process continuously, while the edge AI adapts control decisions directly on the device, forming a cognitive loop that learns and optimizes autonomously.

MATLAB simulations show clear benefits: an 80% reduction in steady-state error, 2.5× faster settling time, and 25% lower control energy. These improvements translate into lower costs, longer equipment life, and fewer shutdowns, shifting control from reactive to intelligent and self-aware operation.

As embedded hardware and on-device AI accelerators advance, this architecture will become increasingly practical. It aligns with the goals of Industry 5.0, promoting resilient, sustainable, and human-centric automation while contributing to the development of autonomous, learning-based control systems.

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