

Adaptive PLC Scan-Time Optimization in a Unified PLC–SCADA Architecture

Yuda Bakti Zainal

Department of Electrical Engineering, Universitas Jenderal Achmad Yani, Cimahi 40531, Indonesia

ARTICLE INFO

Article history:

Received : 08/07/2026

Revised : 22/07/2026

Accepted : 31/07/2026

Keywords:

Digital Twin; Industrial Internet of Things (IIoT); PLC; Predictive Maintenance; SCADA

ABSTRACT

Industrial automation systems require integrated intelligence to support Industry 4.0 manufacturing. However, PLC, IoT, predictive maintenance, and digital twin technologies are typically implemented independently, limiting system performance. This study proposes a unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IoT monitoring, machine learning-based predictive maintenance, and digital twin synchronization within a cyber–physical framework. The proposed system was validated through a 14-day laboratory experiment using 40,320 time-stamped observations. Performance was evaluated in terms of energy consumption, PLC scan time, communication latency, and predictive maintenance accuracy. Compared with a conventional PLC architecture, the proposed framework reduced energy consumption by 25%, PLC scan time by 60.4%, and communication latency by 20.1%, while achieving 95.0% predictive maintenance accuracy. These results demonstrate the effectiveness of the proposed architecture for energy-efficient, intelligent, and data-driven industrial automation.



This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/)

Corresponding Author:

Yuda Bakti Zainal

Department of Electrical Engineering, Universitas Jenderal Achmad Yani, Cimahi 40531, Indonesia

Email: yuda.bakti@lecture.unjani.ac.id

1. INTRODUCTION

Industrial automation has become a key enabler of Industry 4.0 by integrating cyber–physical systems (CPS), the Industrial Internet of Things (IIoT), artificial intelligence, and data-driven decision-making to improve manufacturing productivity, reliability, and operational efficiency [1,6], [10], [12]. Programmable Logic Controllers (PLCs) remain the core real-time control platform because of their deterministic execution and high reliability. However, conventional PLCs generally employ fixed scan cycles that may increase computational overhead and energy consumption while limiting responsiveness under dynamic operating conditions [13, 15].

Recent studies have introduced IIoT monitoring, predictive maintenance, and digital twin technologies to enhance industrial intelligence [5, 9], [16], [17], [18, 22]. Nevertheless, these technologies are typically implemented as separate subsystems. Existing PLC–SCADA solutions mainly focus on supervisory monitoring, while predictive maintenance and digital twin applications are commonly deployed independently, resulting in limited closed-loop optimization and adaptive control capabilities. Consequently, adaptive PLC scan-time optimization integrated with predictive intelligence and digital twin synchronization remains insufficiently investigated.

Table 1 summarizes representative studies and demonstrates that most existing approaches do not simultaneously integrate adaptive PLC scan-time optimization, predictive maintenance, digital twin synchronization, and energy-aware closed-loop control.

To address this research gap, this study proposes a unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IIoT monitoring, machine learning-based predictive maintenance, and digital twin synchronization within a cyber–physical framework. The proposed architecture enables continuous closed-loop optimization to improve energy efficiency, communication performance, controller responsiveness, and operational reliability. The proposed framework was validated through laboratory-scale experiments, demonstrating its feasibility as an integrated intelligent automation solution for Industry 4.0.

Table 1. Methodological comparison of previous studies and the proposed framework

Reference	Methodological Approach	Main Limitation	IM	PM	DT	APST	EO	Scientific Contribution
Lu and Cecil [18]	IIoT-enabled PLC monitoring	Fixed PLC scan cycle; no adaptive control or digital twin integration	✓	✓	✗	✗	✗	Real-time industrial monitoring
Lu et al. [5]	Digital Twin-based industrial monitoring	Digital twin used mainly for visualization; no adaptive PLC optimization	✓	✓	✓	✗	✗	Digital twin-assisted monitoring
Doke et al. [8]	Machine learning-based predictive maintenance	No PLC–SCADA integration and no closed-loop optimization	✓	✓	✗	✗	✗	Intelligent fault prediction
Proposed Method	Unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IIoT monitoring, predictive maintenance, and digital twin feedback	Laboratory-scale validation (future large-scale industrial deployment required)	✓	✓	✓	✓	✓	Closed-loop adaptive industrial automation with energy-aware PLC optimization

Where:

IM = IoT Monitoring; PM = Predictive Maintenance; DT = Digital Twin; APST = Adaptive PLC Scan-Time; EO =Energy Optimization.

2. RESEARCH METHOD

2.1. System Architecture

Figure 1 presents the proposed unified adaptive PLC–SCADA architecture integrating adaptive PLC scan-time optimization, IIoT monitoring, predictive maintenance, digital twin synchronization, and closed-loop energy optimization. The architecture continuously adapts PLC operation using real-time process feedback to improve energy efficiency, controller responsiveness, and operational reliability for Industry 4.0 manufacturing environments [1], [3], [9], [22]. It consists of eight functional layers forming a closed-loop industrial automation ecosystem.

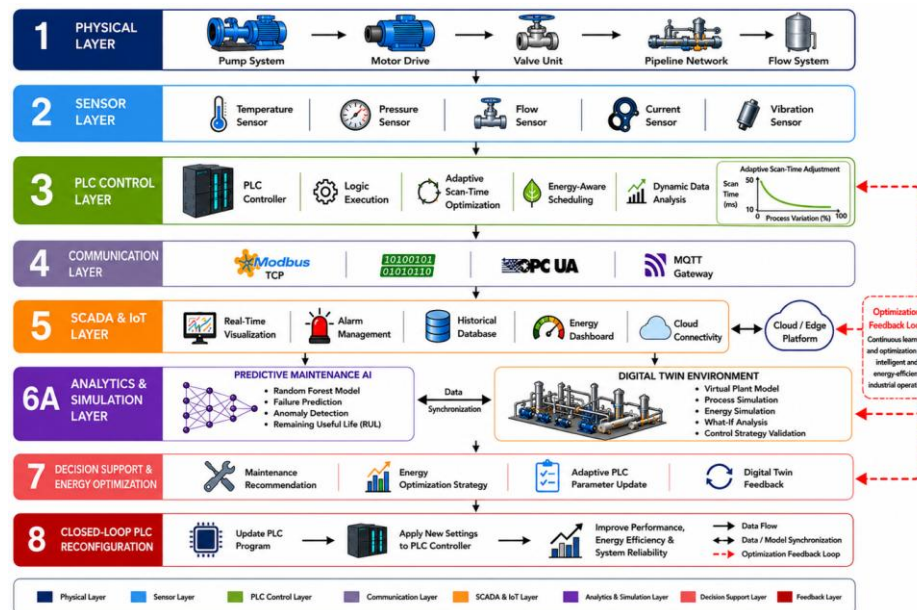


Figure 1. Proposed adaptive PLC–SCADA architecture for intelligent industrial automation

1. **Physical Industrial Process Layer**
The Physical Industrial Process Layer represents the industrial plant, including pumps, electric motors, valves, pipelines, and flow systems. Operational data acquired from these assets provide the foundation for adaptive PLC control, predictive maintenance, and digital twin synchronization within the proposed cyber–physical architecture [1], [3], [16].
2. **Sensor Acquisition Layer**
The Sensor Acquisition Layer continuously acquires real-time process variables, including temperature, pressure, flow rate, electrical current, and vibration. These measurements provide input for adaptive PLC control, predictive maintenance, digital twin synchronization, and scan-time optimization, enabling real-time monitoring in IIoT-based industrial automation [3], [14], [15].
3. **Adaptive PLC Control Layer**
The Adaptive PLC Control Layer serves as the real-time control unit of the proposed framework. Unlike conventional PLCs with fixed scan cycles, it dynamically adjusts the scan interval according to normalized process variability (Δx). The process-variability threshold was set to $\delta = 0.02$, corresponding to a 2% change on the Min–Max normalized scale, while the adjustment step was $\Delta T = \pm 5$ ms. These values were selected through preliminary experiments to balance controller responsiveness and computational efficiency [15], [17], [22].
4. **Industrial Communication Network Layer**
The Industrial Communication Network Layer provides reliable, low-latency communication between field devices, the PLC, SCADA, and cloud services using standard industrial protocols, including Modbus TCP, PROFINET, OPC UA, and MQTT. This layer enables interoperable real-time data exchange for the proposed adaptive PLC–SCADA architecture [3], [11].
5. **SCADA and IoT Platform Layer**
The SCADA and IoT Platform Layer provides real-time supervisory monitoring, alarm management, historical data storage, and cloud connectivity for remote monitoring and edge-to-cloud synchronization. It supports real-time data visualization and operational monitoring within the proposed adaptive PLC–SCADA architecture [3], [7], [11].
6. **Analytics and Simulation Layer**
The Analytics and Simulation Layer comprises two intelligent subsystems: (1) a Random Forest-based predictive maintenance module that analyzes real-time sensor data for anomaly detection, failure prediction, and Remaining Useful Life (RUL) estimation, and (2) a Digital Twin module

that synchronizes with the physical process to support process validation, control evaluation, and energy analysis. Together, these subsystems enable data-driven optimization within the proposed adaptive PLC–SCADA architecture [6], [8]–[10], [22].

7. Decision Support and Energy Optimization Layer

The Decision Support and Energy Optimization Layer integrates predictive maintenance and digital twin outputs to generate adaptive PLC settings, energy optimization strategies, and maintenance recommendations. These outputs enable data-driven operational optimization within the proposed adaptive PLC–SCADA architecture [6], [9], [22].

8. Closed-Loop PLC Reconfiguration Layer

The Closed-Loop PLC Reconfiguration Layer automatically updates PLC control parameters using optimization results from the Decision Support Layer, enabling continuous adaptive control under varying operating conditions [1], [6], [22].

Together, the eight functional layers establish a unified adaptive PLC–SCADA architecture that integrates real-time monitoring, industrial communication, predictive maintenance, digital twin synchronization, adaptive control, and energy optimization within a closed-loop cyber–physical framework for data-driven industrial automation [1], [3], [6], [22].

2.2. Mathematical Modeling

To quantitatively evaluate the proposed adaptive PLC–SCADA architecture, a mathematical model is developed to describe the relationships among energy consumption, PLC scan time, process variability, predictive maintenance, and digital twin simulation. The formulation is based on the following assumptions:

- (1) the industrial process operates under continuous monitoring;
- (2) the electrical power remains positive during operation;
- (3) the PLC executes cyclic scan operations;
- (4) sensor measurements are sampled at constant intervals; and
- (5) communication delays are assumed to be sufficiently stable during each PLC execution cycle and therefore do not affect the adaptive scan-time decision.

$$E = \int_0^T P(t)dt \quad (1)$$

Equation (1) represents the cumulative electrical energy consumed by the industrial system during the operating interval. Since electrical power varies continuously according to the operating condition of pumps, PLC execution, communication modules, and auxiliary devices, the total energy is obtained by integrating the instantaneous power over the entire operating period.

where :

E (kWh) = total energy consumption; $P(t)$ (kW) = instantaneous electrical power at time t ; T (h) = total operating duration.

$$T_{scan} = T_{input} + T_{logic} + T_{output} \quad (2)$$

The PLC scan cycle consists of three sequential execution stages: input acquisition, program execution, and output updating [17]. Therefore, the total scan time can be expressed as the summation of these three execution intervals, as shown in Equation (2). Reducing any of these components contributes directly to improving controller responsiveness and computational efficiency.

Where:

T_{scan} = total PLC scan time; T_{input} = input acquisition time; T_{logic} = ladder logic execution time; T_{output} = output update time.

Adaptive PLC scan-time adjustment is driven by the magnitude of process-variable variation between two consecutive sampling instants. The absolute difference is selected because it provides a simple yet effective indicator of process dynamics regardless of the direction of change.

$$\Delta x = |x(t) - x(t - 1)| \quad (3)$$

A small value of Δx indicates steady-state operation, allowing the PLC to increase its scan interval and reduce computational load. Conversely, a large Δx indicates rapid process dynamics requiring a shorter scan interval to improve control responsiveness.

where:

Δx represents the variation of the process variable between two consecutive sampling times; $x(t)$ denotes the current value of the process variable at time t ; $x(t-1)$ denotes the previous value of the process variable at time $t-1$; $|\cdot|$ represents the absolute value operator, which ensures that the magnitude of the variation is always non-negative.

If the variation is below a predefined threshold, the scan interval is increased to reduce computational overhead. Otherwise, the scan interval is decreased to improve responsiveness.

$$T_{scan}(k+1) = \begin{cases} T_{scan}(k) + \Delta T, & \Delta x < \delta \\ T_{scan}(k) - \Delta T, & \Delta x \geq \delta \end{cases} \quad (4)$$

with limits:

$$20 \text{ ms} \leq T_{scan} \leq 100 \text{ ms}$$

where:

$\delta = 0.02$ is the dimensionless process-variation threshold on the Min–Max normalized scale; $\Delta T = 5 \text{ ms}$ is the scan-adjustment step; $T_{scan}(k)$ is the current scan interval; and $T_{scan}(k+1)$ is the updated scan interval.

Equation (4) constitutes the core mathematical formulation of the proposed algorithm. The scan interval is increased during steady-state operation to reduce computational workload and energy consumption, whereas it is decreased during dynamic operating conditions to improve controller responsiveness. The scan interval is constrained between 20 ms and 100 ms to ensure deterministic PLC execution.

2.3. Adaptive PLC Scan-Time Optimization Algorithm

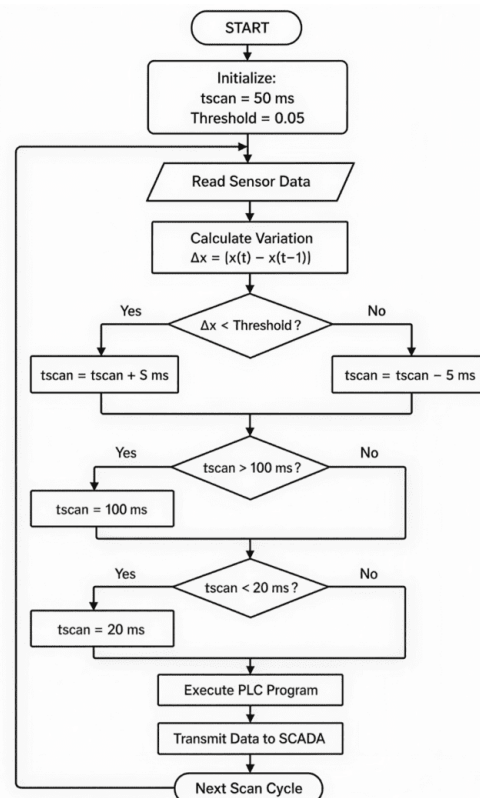


Figure 2. Adaptive PLC scan-time optimization algorithm

Figure 2 illustrates the proposed adaptive PLC scan-time optimization. The PLC adjusts the scan interval according to normalized process variability (Δx). When $\Delta x < \delta = 0.02$, the scan interval is increased to reduce computational load; otherwise, it is decreased to improve control responsiveness. The scan interval is constrained to 20–100 ms, with a 5 ms adjustment step, to maintain stable PLC operation. Compared with a fixed-cycle PLC, this strategy provides energy-aware control based on real-time process feedback [1], [15], [17].

2.4. Predictive Maintenance Model

Predictive maintenance was implemented using five operational features collected from the industrial pumping system:

$$X = \{\text{temperature, pressure, flow rate, vibration, current}\} \quad (5)$$

These features characterize the mechanical and electrical operating conditions [8], [9]. The dataset comprised 40,320 time-stamped observations collected at 30 s intervals over 14 days. After missing-value removal and Min–Max normalization, the data were divided into 80% training and 20% independent testing subsets. Binary labels comprised 34,272 normal observations (85%) and 6,048 fault observations (15%). A fault was assigned when at least one measured variable met the following criterion: temperature ≥ 60 °C, pressure outside 1.8–2.2 bar, flow rate < 18 L/min, vibration ≥ 4.5 mm/s RMS, or current ≥ 5.5 A. The thresholds were established from pump specifications and preliminary experiments.

A Random Forest classifier was selected because it can model nonlinear interactions, is comparatively robust to noisy measurements, and provides feature-importance estimates that support interpretation of multivariable industrial data [8], [9], [21]. The probability of equipment failure is expressed as:

$$P_{\text{failure}} = f(X) \quad (6)$$

Where $f(\cdot)$ denotes the trained Random Forest classifier. The model was implemented using 100 decision trees, a maximum tree depth of 10, and the Gini impurity criterion. Performance was evaluated using five-fold cross-validation and an independent testing dataset, with accuracy, precision, recall, and F1-score as evaluation metrics.

The five input features were selected based on their relevance to equipment health and their widespread use in industrial predictive maintenance.

2.5. Digital Twin Simulation

To further validate the proposed architecture, a Digital Twin was developed to estimate electrical power consumption (kW) and reproduce the behavior of the physical pumping system under real-time operating conditions.

$$Q = K \sqrt{\frac{P_{\text{in}} - P_{\text{out}}}{\rho}} \quad (7)$$

Motor power consumption is estimated using:

$$P = VI_{\cos\theta} \quad (8)$$

The Digital Twin continuously synchronizes its estimated electrical power consumption with physical-system measurements. Normalization was used only for Random Forest model inputs; Digital Twin outputs were evaluated in their original kW scale.

2.6. Experimental Setup

A laboratory-scale pumping platform comprising an Omron CP1E PLC, ESP32 IoT gateway, centrifugal pump, current, vibration, and temperature sensors, and Node-RED SCADA was used for validation (Figure 3 and Table 2). Data were sampled every 30 s for 14 days, producing 40,320 time-stamped observations. Three configurations were evaluated under the same pump load, supply voltage, environmental conditions, and experimental duration: (1) conventional PLC, (2) PLC with IoT monitoring, and (3) the proposed adaptive PLC with predictive maintenance and Digital Twin integration. Fault labels followed the operating thresholds defined in Section 2.4.

Table 2. Experimental hardware specifications

Component	Specifications
PLC	Omron CP1E
IoT Gateway	ESP32
Current Sensor	SCT013
Vibration Sensor	MPU6050
Temperature Sensor	DS18B20
SCADA	Node-RED
Communication	MQTT / Modbus TCP
Pump	Centrifugal Pump



Figure 3. Experimental setup of the proposed adaptive PLC-SCADA system

2.7. Statistical Analysis

Statistical inference was performed using 14 daily mean observations for each control configuration. Aggregation at the daily level reduced short-term temporal autocorrelation and avoided treating the 30 s samples as independent replicates. Although the configurations were evaluated under equivalent pump-load, supply-voltage, and environmental conditions, each configuration constituted a separately operated dataset; therefore, an independent two-sample t-test was used to compare configuration means at $\alpha = 0.05$ (95% confidence level). Means and standard deviations were also reported for each performance metric.

3. RESULTS AND DISCUSSION

The proposed architecture was evaluated experimentally using the laboratory-scale platform described in Section 2.6. Performance was assessed in terms of energy consumption, PLC scan time, predictive maintenance accuracy, communication latency, and Digital Twin validation.

3.1. Energy Consumption Analysis

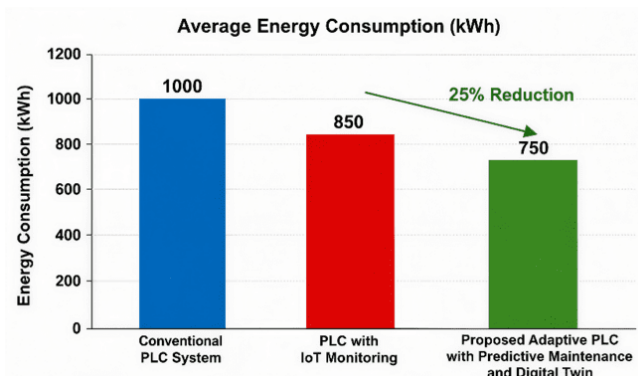


Figure 4. Energy consumption analysis

Figure 4 compares the energy consumption of three control configurations under identical operating conditions. The proposed adaptive PLC architecture reduced energy consumption from 1000 kWh (conventional PLC) to 750 kWh, corresponding to a 25% reduction (Table 3). This improvement is achieved by adaptive scan-time optimization, which increases the PLC scan interval during steady-state operation to reduce processor utilization and communication activity, while shortening the interval only when significant process variations are detected. Statistical analysis confirmed that the reduction was significant ($p = 0.003$), supporting the effectiveness of the proposed energy-aware control strategy. Similar energy-saving trends have been reported in adaptive industrial automation studies [15], [17], [22].

All three control configurations were evaluated under identical operating conditions, load profiles, and experimental duration to ensure a fair comparison.

Table 3. Statistical analysis of energy consumption

System configuration	MEC (kWh)	SD (kWh)	ER (%)	p-value
Conventional PLC	1000	42.6	-	-
PLC + IoT Monitoring	850	35.2	15	0.021
Proposed Adaptive PLC	750	28.4	25	0.003

where:

MEC = Mean Energy Consumption (kWh); SD = Standard Deviation (kWh); ER = Energy Reduction (%).

3.2. PLC Scan Time Performance

Figure 5 compares the PLC scan-time performance of the three control architectures. The proposed adaptive PLC reduced the average scan time from 75.2 ms (conventional PLC) to 29.8 ms, corresponding to a 60.4% reduction.

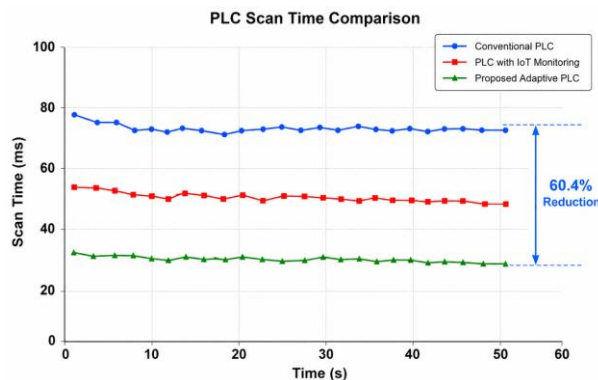


Figure 5. PLC scan time performance

This improvement results from adaptive scan-time optimization, which dynamically adjusts the PLC execution cycle according to real-time process variability, reducing computational load while maintaining rapid controller response [15], [17]. Statistical analysis (Table 4) confirmed a significant reduction in scan time ($p < 0.05$), demonstrating improved controller responsiveness with lower computational overhead.

Table 4. Statistical analysis of PLC scan time

System configuration	MST (ms)	SD (ms)	I (%)	p-value
Conventional PLC	75.2	4.8	-	-
PLC + IoT Monitoring	50.7	3.2	32.6	0.009
Proposed Adaptive PLC	29.8	2.1	60.4	0.001

where:

MST = Mean Scan Time (ms); I = Improvement (%).

The statistical analysis confirms that the proposed adaptive PLC significantly reduced scan time ($p < 0.05$), demonstrating improved controller responsiveness with lower computational overhead.

3.3. Predictive Maintenance Accuracy

The predictive maintenance subsystem used temperature, pressure, flow rate, vibration, and current measurements. The dataset contained two classes: 34,272 normal observations (85%) and 6,048 fault observations (15%), and was divided into 80% training and 20% independent testing data. The Random Forest achieved 95.0% accuracy, 94.8% precision, 95.2% recall, and a 95.0% F1-score on the independent test set, indicating reliable binary fault classification [8], [9], [21].

3.4. Network Communication Efficiency

Figure 6 compares the communication latency of the conventional architecture and the proposed IoT gateway. The proposed method reduced the average latency from 100.3 ms to 80.1 ms (20.1%, $p = 0.007$) through local data aggregation and optimized ESP32-based routing. The results demonstrate improved Industrial IoT communication efficiency and are consistent with previous studies [3], [11].

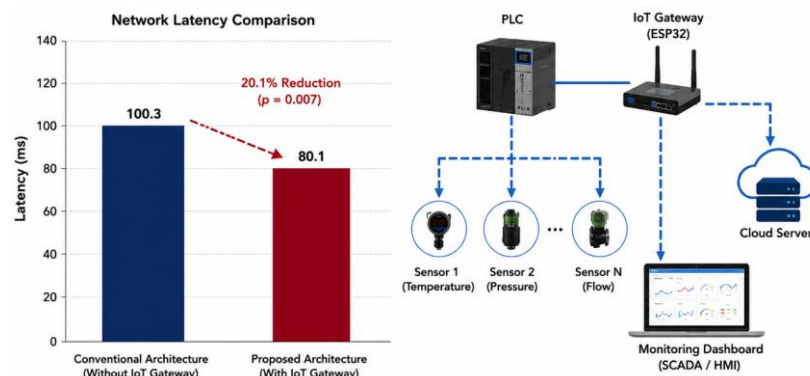


Figure 6. Network communication efficiency

3.5. Digital Twin Validation

The Digital Twin was validated by comparing estimated electrical power consumption with synchronized physical-system measurements in the original kW scale. It achieved RMSE = 0.82 kW, MAE = 0.64 kW, and $R^2 = 0.97$, indicating close agreement within the laboratory operating range. Unlike primarily visualization- or simulation-based studies [5], [9], [22], the framework links Digital Twin feedback with adaptive PLC scan-time optimization and predictive maintenance; however, industrial-scale validation is still required.

4. CONCLUSION

This study experimentally validated a unified PLC–SCADA framework integrating adaptive scan-time optimization, IoT monitoring, Random Forest-based predictive maintenance, and Digital Twin feedback. The architecture improved energy efficiency, scan time, communication latency, and fault-classification performance relative to the conventional PLC configuration. Its principal contribution is closed-loop integration of adaptive control, predictive intelligence, and Digital Twin synchronization. Because validation was limited to a laboratory pumping platform, future work should examine industrial deployment, multi-PLC coordination, cybersecurity, and AI-based optimization.

REFERENCES

- [1] J. Lee, B. Bagheri, and H.-A. Kao, "A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems," *Manufacturing Letters*, vol. 3, pp. 18–23, Jan. 2015, doi: 10.1016/j.mfglet.2014.12.001.
- [2] J. Wan, J. Yang, Z. Wang, and Q. Hua, "Artificial Intelligence for Cloud-Assisted Smart Factory," *IEEE Access*, vol. 6, pp. 55419–55430, 2018, doi: 10.1109/ACCESS.2018.2871724.

- [3] Y. Lu, "Industry 4.0: A Survey on Technologies, Applications and Open Research Issues," *Journal of Industrial Information Integration*, vol. 6, pp. 1–10, 2017, doi: 10.1016/j.jii.2017.04.005.
- [4] A. Kusiak, "Smart Manufacturing," *International Journal of Production Research*, vol. 56, no. 1–2, pp. 508–517, 2018, doi: 10.1080/00207543.2017.1351644.
- [5] Y. Lu, C. Liu, I.-K. Wang, H. Huang, and X. Xu, "Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues," *Robotics and Computer-Integrated Manufacturing*, vol. 61, Art. no. 101837, Feb. 2020, doi: 10.1016/j.rcim.2019.101837.
- [6] J. Lee et al., "2026 Roadmap on Artificial Intelligence and Machine Learning for Smart Manufacturing," *Machine Learning: Engineering*, 2026, doi: 10.1088/3049-4761/ae5967.
- [7] S. F. Chevtchenko, E. S. Rocha, M. C. M. dos Santos, R. L. Mota, D. M. Vieira, E. C. de Andrade, and D. R. B. de Araújo, "Anomaly Detection in Industrial Machinery Using IoT Devices and Machine Learning: A Systematic Mapping," *arXiv:2307.15807*, 2023.
- [8] D. Doke, T. Nagaraju, P. K. H., R. R., and S. Kumar, "Machine Learning for Predictive Maintenance Applications in Industrial Equipment and Manufacturing Processes," *ITM Web of Conferences*, vol. 76, 01008, 2025, doi: 10.1051/itmconf/20257601008.
- [9] C. Chen, H. Fu, Y. Zheng, F. Tao, and Y. Liu, "The Advance of Digital Twin for Predictive Maintenance: The Role and Function of Machine Learning," *Journal of Manufacturing Systems*, vol. 71, pp. 581–594, 2023, doi: 10.1016/j.jmsy.2023.10.010.
- [10] H. Kagermann and W. Wahlster, "Ten Years of Industrie 4.0," *Sci*, vol. 4, no. 3, Art. no. 26, 2022, doi: 10.3390/sci4030026.
- [11] S. Wang, J. Wan, D. Li, and C. Zhang, "Implementing Smart Factory of Industrie 4.0: An Outlook," *International Journal of Distributed Sensor Networks*, vol. 12, no. 1, 2016, doi: 10.1155/2016/3159805.
- [12] A. W. Colombo, S. Karnouskos, O. Kaynak, Y. Shi, and S. Yin, "Industrial Cyberphysical Systems: A Backbone of the Fourth Industrial Revolution," *IEEE Industrial Electronics Magazine*, vol. 11, no. 1, pp. 6–16, Mar. 2017, doi: 10.1109/MIE.2017.2648577.
- [13] M. Brettel, N. Friederichsen, M. Keller, and M. Rosenberg, "How Virtualization, Decentralization and Network Building Change the Manufacturing Landscape: An Industry 4.0 Perspective," *World Academy of Science, Engineering and Technology, International Journal of Information and Communication Engineering*, vol. 8, no. 1, pp. 37–44, 2014.
- [14] A. Gilchrist, *Industry 4.0: The Industrial Internet of Things*. Berkeley, CA, USA: Apress, 2016, doi: 10.1007/978-1-4842-2047-4.
- [15] J. Lee, *Industrial AI: Applications with Sustainable Performance*. Singapore: Springer, 2020, doi: 10.1007/978-981-15-2144-7.
- [16] D. Sinha and R. Roy, "Reviewing Cyber-Physical System as a Part of Smart Factory in Industry 4.0," *IEEE Engineering Management Review*, vol. 48, no. 2, pp. 103–117, Jun. 2020, doi: 10.1109/EMR.2020.2992606.
- [17] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-Driven Smart Manufacturing," *Journal of Manufacturing Systems*, vol. 48, pp. 157–169, Jul. 2018, doi: 10.1016/j.jmsy.2018.01.006.
- [18] Y. Lu and J. Cecil, "An Internet of Things (IoT)-Based Collaborative Framework for Advanced Manufacturing," *International Journal of Advanced Manufacturing Technology*, vol. 84, nos. 5–8, pp. 1141–1152, 2016, doi: 10.1007/s00170-015-7772-0.
- [19] D. Mourtzis, E. Vlachou, and N. Milas, "Industrial Big Data as a Result of IoT Adoption in Manufacturing," *Procedia CIRP*, vol. 55, pp. 290–295, 2016, doi: 10.1016/j.procir.2016.07.038.

-
- [20] J. Manyika, M. Chui, P. Bisson, J. Woetzel, R. Dobbs, J. Bughin, and D. Aharon, The Internet of Things: Mapping the Value Beyond the Hype. McKinsey Global Institute, Jun. 2015.
- [21] A. Puthanveetil Madathil, X. Luo, Q. Liu, C. Walker, R. Madarkar, and Y. Qin, "A Review of Explainable Artificial Intelligence in Smart Manufacturing," International Journal of Production Research, 2025, doi: 10.1080/00207543.2025.2513574.
- [22] L. Lattanzi, R. Raffaeli, M. Peruzzini, and M. Pellicciari, "Digital Twin for Smart Manufacturing: A Review of Concepts Towards a Practical Industrial Implementation," International Journal of Computer Integrated Manufacturing, vol. 34, no. 6, pp. 567–597, 2021, doi: 10.1080/0951192X.2021.1911003.