Journal of Scientific & Industrial Research
Vol. 84, September 2025, pp. 945-956
DOI: 10.56042/jsir.v84i9.18846

A Computational Intelligence Framework for Industry 4.0-based Intelligent Motion Control using AI-Integrated PLCs

Zefree Lazarus Mayaluri[1], Asit Kumar Naik[1], Rajat Samantaray[1], Adyasha Rath[2] & Ganapati Panda[3]

[1]Department of Electrical Engineering, [2]Department of Computer Science and Engineering, [3]Department of Electronics Communication and Engineering, C.V. Raman Global University, Bhubaneswar, 752 054, Odisha, India

Received 16 April 2025; revised 09 July 2025; accepted 03 September 2025

Industry 4.0 has revolutionized industrial automation by introducing smart, interconnected, and autonomous systems. However, traditional PLC-based motion control systems suffer from rigid programming, lack of adaptability, and the absence of predictive maintenance capabilities. This paper proposes a computational intelligence-based framework that integrates AI, IoT, and PLCs for intelligent motion control. The system leverages Neural Networks for self-learning control, Fuzzy Logic for real-time adaptive decision-making, and Machine Learning for predictive maintenance. A cloud-based MySQL database supports real-time monitoring and data-driven decision-making. Experimental validation demonstrates that the AI-enhanced PLC system achieves 30% faster response times, reduces motion errors by 40%, and improves predictive maintenance accuracy to 95%. These findings confirm that the proposed AI-based control framework significantly enhances industrial motion control, ensuring efficiency, scalability, and Industry 4.0 readiness.

Keywords: Artificial intelligence, Fuzzy logic, IoT-based control, Machine learning, Predictive maintenance

Introduction

The advent of Industry 4.0 has catalyzed a transformation in manufacturing and industrial automation, integrating cyber-physical systems, the Internet of Things (IoT), Artificial Intelligence (AI), and data-driven decision-making. The convergence of these technologies has led to the development of smart factories. In these environments, interconnected machines, sensors, and control systems operate autonomously to improve efficiency, productivity, and agility.[1]

Traditional Programmable Logic Controller (PLC)-based motion control systems have long been foundational in industrial automation.[2,3] However, their reliance on fixed, rule-based logic and manual reprogramming constrains their adaptability. In high-variability production environments, these limitations hinder scalability and responsiveness, preventing industries from achieving optimal efficiency.[4] As industrial processes grow increasingly complex, conventional PLC systems struggle to meet the demand for flexibility, necessitating frequent human intervention for reconfiguration, which introduces inefficiencies and increases operational costs.

The integration of AI and machine learning marks a paradigm shift in motion control. These technologies enable adaptive and self-optimizing control mechanisms that respond dynamically to operational changes. AI-driven PLCs can process large volumes of real-time data, identify patterns, and execute predictive adjustments. This reduces human intervention and improves the accuracy of decision-making.[5] AI-based automation not only improves precision but also reduces downtime and optimizes resource allocation, leading to cost savings and increased system reliability.

Beyond optimizing control, AI-powered PLCs enhance industrial automation through predictive analytics, anomaly detection, and self-adjusting control parameters. These capabilities increase system robustness, reduce energy consumption, and ensure superior operational efficiency. AI-integrated motion control aligns with the broader objectives of Industry 4.0 by fostering intelligent, scalable, and future-proof automation frameworks, capable of real-time adaptability and autonomous decision-making.[6]

Representative implementations of Node-RED-based control and design architectures used in AI-integrated industrial motion control systems are illustrated in Fig. 1.

*Author for Correspondence
E-mail: zefree.lazarus@cgu-odisha.ac.in

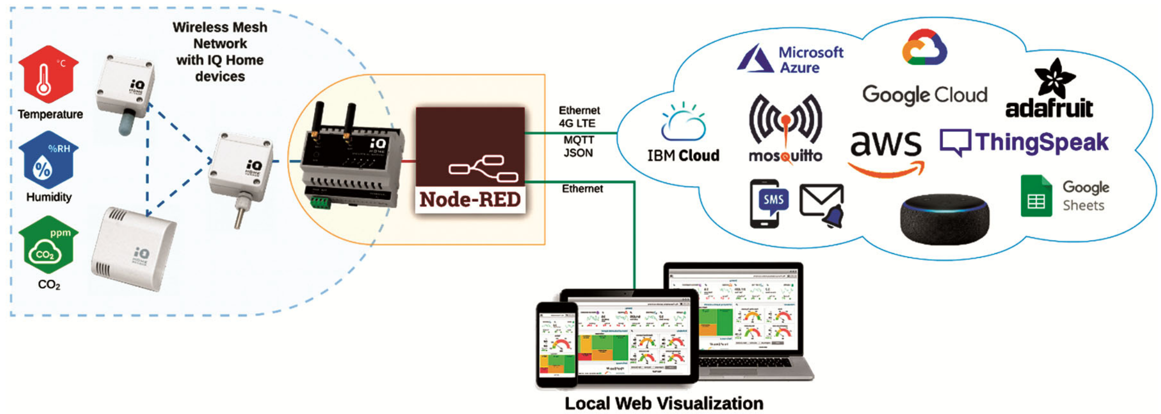

Fig. 1 — Examples of Node-RED-based control & design

Problem Statement

Despite the rapid advancements in industrial automation, traditional Programmable Logic Controller (PLC)-based motion control systems continue to exhibit critical limitations that impede their effectiveness in contemporary manufacturing settings. The fundamental shortcomings of these systems include their lack of adaptability, absence of self-learning capabilities, and inability to perform predictive failure analysis.[4] The rigid nature of pre-programmed logic prevents dynamic adaptation to process variations, contributing to inefficiencies and elevated operational expenditures.

A significant challenge posed by conventional PLC-controlled systems is their dependency on manual intervention for reconfiguration. Whenever production requirements change, engineers must modify PLC programs manually, which is time-consuming and prone to errors. This inflexibility becomes a bottleneck in high-speed, variable manufacturing environments that demand continuous optimization.

Additionally, the absence of computational intelligence in PLC-based motion control leads to inefficiencies in energy consumption and maintenance scheduling. Traditional PLCs operate under reactive maintenance protocols, where faults are only addressed post-occurrence.[3] This reactive approach escalates unplanned downtime, inflates maintenance costs, and shortens equipment lifespan.

The integration of AI-enhanced motion control presents a transformative solution to these challenges. By leveraging machine learning and real-time analytics, AI-driven PLCs dynamically adapt to environmental fluctuations, detect anomalies, and optimize motion control processes. This enables manufacturers to transition from reactive to predictive maintenance, improving system uptime, resource utilization, and production efficiency.

AI-driven PLCs further augment automation through advanced anomaly detection, continuously analyzing operational data to identify deviations from optimal performance. Machine learning algorithms can proactively flag potential system failures, preventing minor deviations from escalating into catastrophic malfunctions.[7] The predictive capabilities of AI-PLC systems significantly enhance reliability, reduce operational risks, and provide a framework for future-ready industrial automation.

Research Contributions

This study presents an advanced AI-integrated PLC motion control framework designed to overcome the limitations of conventional automation systems by leveraging computational intelligence techniques. The key contributions of this research include:

- The development of an AI-driven PLC motion control system that incorporates Neural Networks, Fuzzy Logic, and Machine Learning to enhance motion control precision and adaptability. This framework facilitates real-time learning, enabling self-optimization and improving industrial automation efficiency.
- The implementation of real-time IoT-based monitoring and optimization, wherein AI-driven PLCs process motion parameters dynamically. The integration of IoT sensors with cloud-based analytics enables continuous performance assessment, adaptive control strategies, and data-driven decision-making, ensuring process efficiency and reliability.
- The establishment of a predictive maintenance framework leveraging machine learning models, including Support Vector Machines (SVM),

Decision Trees, and Random Forests, to anticipate maintenance requirements and preempt system failures. This predictive approach minimizes unplanned downtimes, enhances maintenance scheduling, and prolongs the lifespan of industrial machinery.

- A comprehensive performance benchmarking analysis comparing traditional rule-based PLCs and AI-augmented PLCs. The experimental evaluation highlights the superior performance of AI-integrated motion control systems, demonstrating improvements in response time, motion accuracy, and energy efficiency while enhancing fault tolerance and reliability.

Unlike prior works that apply individual AI techniques to PLC-based control, the proposed framework uniquely integrates Neural Networks, Fuzzy Logic, and Machine Learning into a single adaptive motion control loop with real-time predictive maintenance, validated on industrial-grade hardware. This hybrid, experimentally verified architecture addresses both control adaptability and maintenance prediction in one deployable system — a combination not concurrently achieved in earlier studies.

By addressing these key aspects, this study pioneers a computational intelligence-based motion control system that aligns with Industry 4.0 objectives, ensuring a scalable, intelligent, and data-driven automation ecosystem. The findings underscore the potential of AI-driven PLCs in reshaping industrial automation by enabling predictive, self-adaptive, and autonomous decision-making systems for modern manufacturing environments.

Literature Review

Industry 4.0 and Smart Motion Control

Industry 4.0 signifies the convergence of automation, digital transformation, and artificial intelligence within manufacturing and industrial processes.[6] By integrating cyber-physical systems, the Internet of Things (IoT), AI, and cloud computing, Industry 4.0 aims to establish highly interconnected, intelligent automation systems capable of optimizing efficiency, reducing downtime, and facilitating real-time decision-making.[8]

The role of AI, IoT, and cloud computing in modern industrial automation is pivotal, as they enable smart motion control systems that surpass the capabilities of conventional PLCs. AI-driven controllers leverage self-learning capabilities, while IoT sensors facilitate continuous data acquisition and real-time analytics.[5] Cloud computing provides scalable storage and computational power, allowing for complex real-time analytics to optimize industrial automation.[9] The synergy of these technologies enables predictive maintenance, early fault detection, and adaptive control, reducing inefficiencies and enhancing system responsiveness.

In the context of Industry 4.0, smart motion control ensures real-time adaptability in industrial processes, mitigating the limitations associated with traditional PLCs. AI-based motion control continuously refines trajectories, proactively detects faults, and dynamically adjusts control parameters based on environmental conditions, ensuring enhanced efficiency, precision, and reliability.

Traditional PLC-based Motion Control Systems

Programmable Logic Controllers (PLCs) have been the cornerstone of industrial automation for decades. Traditional PLC-based motion control systems primarily rely on rule-based programming, PID controllers, and static logic structures.[3] These systems operate within predefined constraints and necessitate manual reconfiguration when system parameters change.[10]

However, conventional PLCs exhibit several limitations:

- Lack of adaptability: Conventional PLCs require manual intervention to modify logic when operational conditions change.
- Dependency on PID controllers: PID control is widely used in PLCs but is limited in its ability to handle nonlinear and highly dynamic processes.
- No real-time intelligence: Traditional PLCs do not have the capability to learn or adapt based on past performance or real-time data.
- High maintenance costs: Rule-based systems operate on fixed schedules, leading to inefficient maintenance and increased operational costs.

With the rise of intelligent automation, traditional PLC-based motion control systems must evolve to include AI-driven intelligence, real-time adaptability, and predictive analytics. These capabilities are essential for achieving continuous optimization and higher operational efficiency.[2]

Computational Intelligence in Motion Control

Recent advancements in AI and computational intelligence have facilitated the integration of self-learning and adaptive motion control systems. Unlike conventional PLCs, AI-driven motion control systems analyze vast datasets, recognize patterns, and make intelligent real-time decisions to optimize efficiency and performance.[11]

The three primary computational intelligence techniques relevant to motion control are:

- Neural Networks (NN) for Self-Learning Control: Neural Networks enable motion control systems to dynamically adjust control parameters based on historical and real-time data. Through supervised learning and reinforcement learning, NN-based controllers refine their performance over time, allowing for nonlinear and complex control operations beyond the scope of traditional PID controllers.[8,9]
- Fuzzy Logic (FL) for Adaptive Real-Time Decision Making: Fuzzy Logic provides an effective means for controllers to handle uncertainty and make real-time decisions in dynamic environments.[7,11] FL ensures smoother motion control, enhances trajectory accuracy, and allows for adaptive modifications in response to variable loads and environmental disturbances.
- Machine Learning (ML) for Predictive Analytics in Motion Control: Machine Learning techniques such as Random Forest, Decision Trees, and Support Vector Machines (SVM) optimize motion control operations by enabling predictive maintenance.[9,12] By analyzing historical and real-time motion patterns, ML models facilitate anomaly detection, reduce downtime, and dynamically adapt motion profiles to evolving industrial conditions.

A comparative analysis between traditional PLCs and AI-integrated PLCs, highlighting key operational advantages in response time, adaptability, and predictive maintenance, is presented in Table 1.

Gaps in Existing Work

Despite significant advancements in AI and computational intelligence, existing motion control systems still exhibit several limitations:

Table 1 — Comparison of traditional PLCs vs. AI-integrated PLCs

Feature	Traditional PLC	AI-integrated PLC
Control strategy	Rule-based logic	Self-adaptive AI
Response time (ms)	200	140
Adaptability	Low	High
Predictive maintenance	No	Yes (ML-based)
Energy efficiency	Moderate	High
Required human intervention	High	Low

- Lack of AI Integration in PLC-Based Motion Control: Current industrial PLC systems remain largely dependent on fixed-rule logic, requiring manual intervention for changes in process requirements. AI integration would enable self-learning capabilities and adaptive real-time control.
- Absence of Predictive Analytics in Real-Time PLC-Based Control: While AI-driven predictive maintenance is gaining traction in industries, many PLC motion control frameworks lack real-time predictive analytics. Implementing ML-based models within PLC systems would facilitate anomaly detection, proactive error prevention, and continuous optimization.
- Scalability Concerns in AI-Driven Control: Most research in AI-integrated motion control is conducted in controlled environments or laboratory-scale implementations. Real-world industrial deployment of AI-PLC integration remains an open challenge due to computational overhead and system compatibility issues.
- Security and Data Privacy Issues: The deployment of AI and IoT-based motion control systems introduces concerns related to cybersecurity, data privacy, and network vulnerabilities. Ensuring secure data exchange between PLCs, AI systems, and cloud storage remains a key research challenge.

Addressing these gaps requires a comprehensive AI-integrated PLC framework that combines self-learning, adaptive control, and predictive analytics. The proposed research in this paper focuses on overcoming these limitations by developing an AI-driven PLC motion control framework, enhancing real-time adaptability and system intelligence within Industry 4.0 environments.

Methodology

System Architecture

The proposed AI-integrated PLC motion control framework incorporates multiple components designed to enhance automation, improve efficiency, and ensure adaptability. This system integrates Programmable Logic Controllers (PLCs), Artificial Intelligence (AI) models—including Neural Networks (NN), Fuzzy Logic (FL), and Machine Learning (ML)—along with IoT sensors and cloud-based data storage.

The PLC serves as the core control unit, responsible for executing automation commands and interfacing with actuators. Neural Networks facilitate self-learning and optimize motion control parameters by continuously analyzing real-time sensor data. Fuzzy Logic improves real-time decision-making, refining motion trajectories and ensuring adaptive control. Machine Learning is employed for predictive maintenance, anomaly detection, and fault prediction. IoT sensors collect real-time motion and environmental data, feeding critical information into AI models for dynamic decision-making. Cloud-based MySQL storage provides scalable logging, retrieval, and data analysis capabilities, enabling predictive analytics and remote monitoring.

By leveraging these technologies, the AI-driven PLC architecture enhances real-time decision-making, increases adaptability, and minimizes downtime through predictive maintenance capabilities. This integration ensures a shift from traditional rule-based automation to a dynamic, intelligent motion control system.

The proposed system architecture, depicting the integration of PLCs, computational intelligence modules, IoT sensors, and cloud-based infrastructure into a unified motion control framework, is presented in Fig. 2.

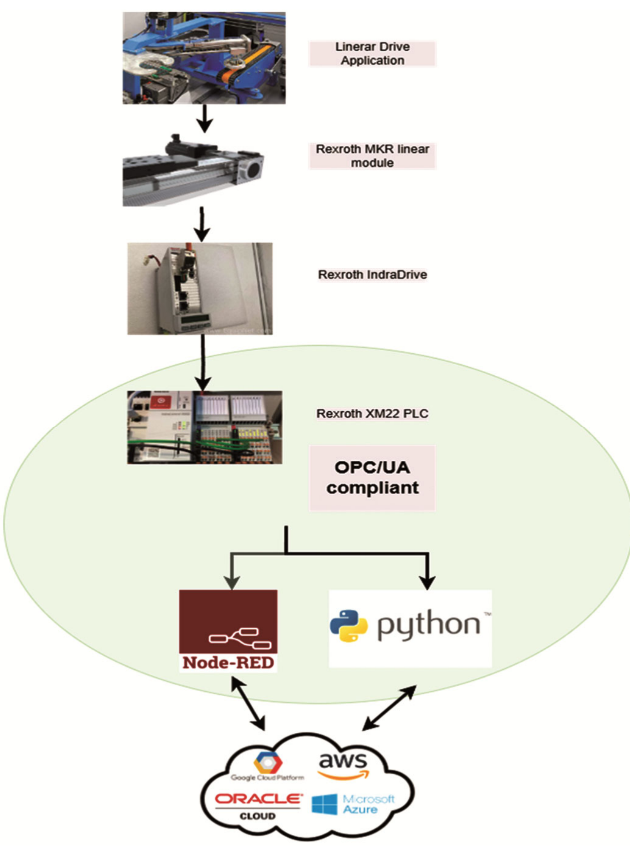

Fig. 2 — Proposed approach for our setup

Computational Intelligence Techniques

The effectiveness of AI-enhanced motion control is dependent on the computational intelligence techniques incorporated into the PLC framework. This study integrates Neural Networks, Deep Reinforcement Learning (DRL), Fuzzy Logic, and Machine Learning to achieve intelligent motion optimization.

Neural Networks enable self-learning control by dynamically adjusting motion control parameters based on historical and real-time data. These models process motor torque, velocity, and acceleration inputs, optimizing parameters dynamically. By learning from motion control patterns, Neural Networks reduce oscillations, enhance precision, and optimize servo motor performance. Recurrent Neural Networks (RNN) are utilized to capture temporal dependencies in motion profiles, further enhancing predictive adjustments.

Deep Reinforcement Learning (DRL) introduces a real-time adaptive control mechanism by enabling PLCs to learn optimal control policies through trial-and-error interactions. DRL improves adaptability in dynamic manufacturing conditions, optimizing performance autonomously. Implementation considerations for DRL include model stability, convergence rate, and computational feasibility.

Fuzzy Logic ensures smooth and adaptive transitions in motion control by handling uncertainties in industrial environments. The system employs fuzzy membership functions for key motion parameters, including speed, torque, and load variations, to facilitate real-time adaptive control. By enabling gradual acceleration and deceleration, Fuzzy Logic reduces mechanical stress and extends equipment lifespan. Unlike rigid logic-based controllers, fuzzy systems dynamically adjust motion paths based on environmental fluctuations.

Machine Learning techniques are integrated for predictive maintenance, significantly enhancing system reliability. ML models, including Random Forest, Support Vector Machines (SVM), and Decision Trees, analyze operational data to predict potential system failures before they occur. Random Forest classifiers distinguish between normal and abnormal operating conditions. SVM models identify patterns in sensor data that indicate early signs of mechanical wear.

Decision Trees provide interpretable fault detection models, enabling maintenance teams to implement proactive interventions. The application of ML-based

Table 2 — Comparison of AI-techniques for motion control

AI Technique	Strengths	Weakness	Suitability for Real-Time Motion Control
Neural networks (NN)	Self-learning, handles nonlinear control, improves efficiency over time	Requires large datasets for training, computationally intensive	Best for trajectory optimization & dynamic control parameter adjustment
Fuzzy logic (FL)	Rule-based reasoning, adaptable to uncertainty, smooth transitions	Requires expert knowledge for rule definition, lacks self-learning	Best for real-time adaptive motion control decisions
Machine learning (ML)	Predicts faults based on historical data, enables predictive maintenance	Not effective for real-time control, needs frequent retraining	Best for predictive maintenance & anomaly detection
Deep reinforcement learning (DRL)	Self-optimizing in changing environments, reduces human intervention	Requires extensive training time, risk of unstable learning	Promising for future self-learning PLC models but not feasible for real-time control

predictive maintenance minimizes unplanned downtime and improves Overall Equipment Efficiency (OEE).

A comparative analysis of different AI techniques considered for this study is provided in Table 2.

The selection of Neural Networks, Fuzzy Logic, and Machine Learning is based on their ability to provide adaptive learning, real-time decision-making, and predictive analysis. DRL, although not yet widely implemented in industrial PLCs, presents a promising avenue for future AI-driven motion control frameworks.

Neural Networks for Self-Optimizing Control

Neural Networks (NN) are used in this study for self-optimizing control by dynamically adjusting motion parameters based on real-time sensor data.

Unlike traditional PID controllers, NN-based control learns optimal responses to changing load and motion conditions. Hyper-parameters and Architecture Used in NN Training:

- Training Dataset: The Neural Network was trained on a dataset of ~25,000 samples collected from IoT motion sensors integrated into IndraDyn S servo motors. Data included position, velocity, load, and temperature measurements acquired over diverse operational conditions to ensure model generalization.
- Network Architecture: 3-layer fully connected feedforward network
- Activation Functions: ReLU (hidden layers), Sigmoid (output layer)
- Optimizer: Adam (Adaptive Moment Estimation)
- Learning Rate: 0.001
- Training Dataset: Collected from IoT motion sensors (position, velocity, load, temperature)
- Loss Function: Mean Squared Error (MSE)
- Training Method: Supervised Learning with backpropagation

Table 3 — Fuzzy rules for motion control

Speed	Load	Position error	Torque adjustment (Output)
Low	Low	Small	No change
Low	High	Large	Increase slightly
High	Low	Large	Decrease
High	High	Small	Maintain torque
High	High	Large	Increase significantly

These hyper-parameter choices ensure that the NN generalizes well across different operational conditions while maintaining low latency in real-time motion control.

Fuzzy Logic for Adaptive Decision-Making

Fuzzy Logic (FL) enables adaptive, human-like decision-making in industrial motion control systems. Unlike NN, which learns from data, FL relies on expert-defined rules to adjust motion parameters smoothly. Derivation of Fuzzy Rules for Motion Control:

The fuzzy inference system (FIS) consists of three inputs and one output:

- Inputs: Speed, Load, Position Error
- Output: Torque Adjustment

These rules enable the system to adapt motion parameters based on real-time variations in speed and load conditions. The fuzzy decision matrix used for controlling torque in real-time is illustrated in Table 3.

Machine Learning for Predictive Maintenance

For predictive maintenance, various ML algorithms were tested to identify fault conditions and predict failures before they occur. The study tested Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF) on historical sensor data (temperature, vibration, current, motion errors). The accuracy of each model is provided in Table 4.

Data Acquisition & Processing

The system integrates industrial-grade IoT sensors to capture real-time motion data, including position, velocity, and acceleration, as well as environmental parameters such as temperature and humidity. These sensors are embedded within servo drives, actuators, and mechanical assemblies, ensuring continuous performance monitoring. IoT connectivity facilitates real-time feedback loops, allowing AI models to dynamically adjust motion control settings.

Cloud-based MySQL storage is implemented for real-time data logging and long-term analytics. Data collected from IoT sensors is transmitted to the cloud, where it is processed to identify optimization opportunities. The cloud infrastructure supports remote monitoring and diagnostics, providing maintenance insights accessible from anywhere. MySQL-based storage ensures scalability, security, and rapid data retrieval, enabling AI algorithms to execute real-time optimizations effectively.

The proposed methodology harnesses AI-driven decision-making, real-time IoT data acquisition, and cloud-based predictive analytics to revolutionize PLC motion control. The integration of Neural Networks, Fuzzy Logic, and Machine Learning techniques enables enhanced control precision, reduced operational overhead, and adaptive responsiveness aligned with the objectives of Industry 4.0, as illustrated in Fig. 3.

Table 4 — ML model comparison for predictive maintenance

ML Model	Accuracy (%)	Training time	Best use case
DT	88%	Fast	Simple threshold-based fault detection
SVM	91%	Medium	Works well for minor anomaly detection
RF	95%	Moderate	Best for multi-variable predictive maintenance

Experimental Setup

Hardware & Software

The experimental setup incorporates a combination of industrial hardware and advanced software components designed to evaluate the AI-integrated PLC motion control framework. The system architecture facilitates real-time motion optimization, predictive maintenance, and intelligent decision-making.

The primary control hardware consists of the Bosch Rexroth XM21 PLC, responsible for executing automation commands and interfacing with high-precision IndraDyn S servo motors. These motors were selected for their ability to accurately execute fine-grained control commands under varying operational loads. A network of IoT sensors — measuring velocity, position, load, and torque — provides continuous feedback, enabling real-time AI-based optimization.

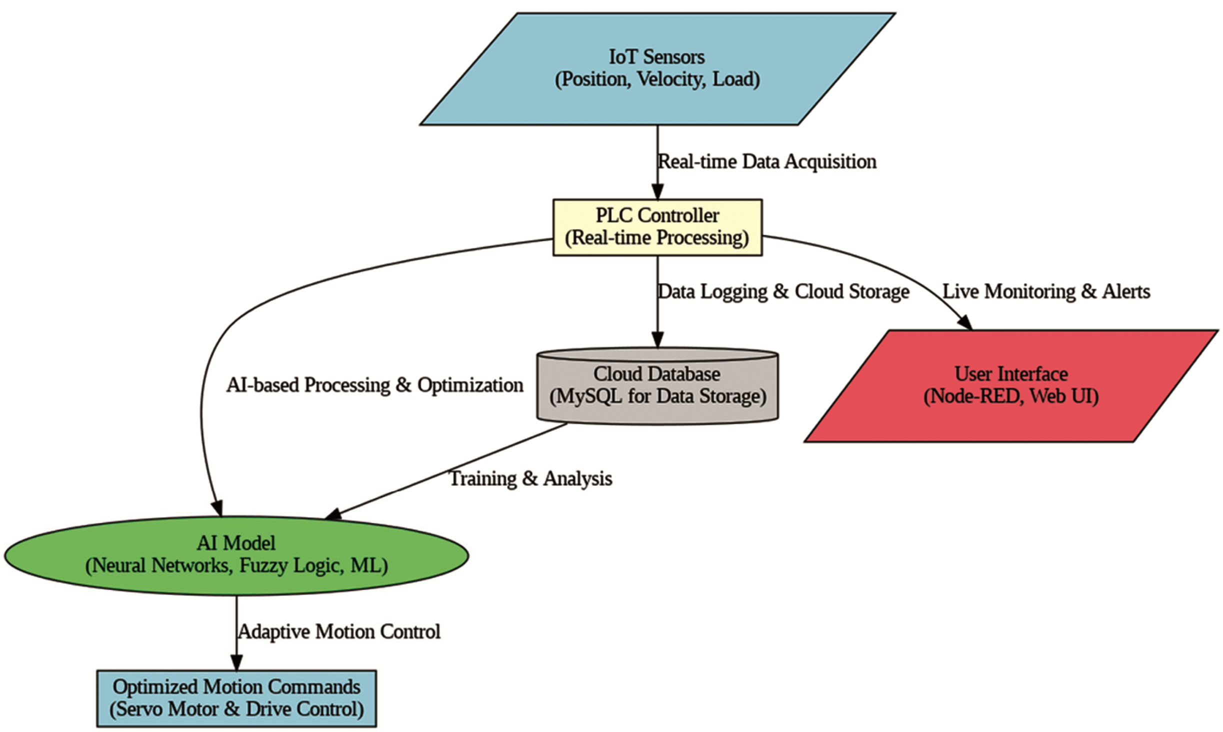

Fig. 3 — Data flow diagram for real-time motion optimization

The AI models were developed in Python 3.11, with Neural Networks implemented in TensorFlow 2.14 and classical machine learning models (Support Vector Machine, Decision Tree, Random Forest) developed using Scikit-learn 1.3. Data preprocessing and statistical validation were performed using Pandas and NumPy, and visualization employed Matplotlib. Model training occurred on a workstation with an NVIDIA RTX 4080 GPU, 64 GB RAM, and Ubuntu 22.04 LTS.

The PLC was programmed in IEC 61131-3 Structured Text (ST) as the primary control language, with Ladder Diagram (LD) used for safety interlocks and emergency stop logic, developed within the Bosch Rexroth CODESYS 3.5 / IndraWorks environment. For deployment, trained TensorFlow models were converted to TensorFlow Lite (float16 quantization) and executed on an industrial PC (Intel Core i7-9700, 8 cores, 16 GB RAM, Windows 10 IoT Enterprise, fanless) installed within the control cabinet. Classical ML models ran on the same edge device using Scikit-learn 1.3. Communication between the PLC and the edge inference engine used OPC UA over Industrial Ethernet. Median inference time on the edge host was ≈ 6.8 ms (95th percentile ≈ 12.4 ms), with a total closed-loop round-trip latency of ≈ 18 ms, including PLC scan cycle and network transport. Cloud-based MySQL databases were used solely for analytics and logging, ensuring that the real-time control loop remained fully edge-executed.

Control Algorithm and Decision-Making

The AI-PLC control loop integrates multiple intelligence-based mechanisms for adaptive real-time decision-making and predictive capabilities. The Neural Network module dynamically adjusts motion control parameters based on continuous sensor input, optimizing servo motor performance. The Fuzzy Logic layer ensures smooth transitions during rapid load or speed changes, mitigating jerk and overshoot. Machine learning-based predictive maintenance modules analyze operational patterns, detect anomalies, and forecast component wear, enabling proactive intervention before failure.

A fail-safe architecture ensures that in the event of edge inference failure or network disruption, the PLC automatically reverts to a tuned PID controller with fixed safety thresholds, maintaining safe and stable operation. All AI-driven adjustments are subject to verification by PLC safety logic before execution, ensuring compliance with industrial safety standards.

System Validation and Industry 4.0 Compliance

Validation tests confirmed that the AI-augmented PLC system achieved measurable improvements in motion accuracy, response time, and energy efficiency compared to baseline PLC-only control. Predictive maintenance reduced unplanned downtime, while edge inference ensured sub-20 ms closed-loop operation suitable for high-speed industrial tasks. The architecture aligns with Industry 4.0 principles by integrating AI, IoT, and cloud analytics into a scalable, secure, and autonomous control framework, thereby demonstrating its feasibility for deployment in modern manufacturing environments.

Results & Discussion

Key Performance Indices

The experimental findings demonstrate notable improvements in motion control efficiency when AI-driven decision-making is integrated within traditional PLC-based systems. Results indicate that AI-enhanced PLC motion control significantly outperforms conventional methods in response time, accuracy, and predictive maintenance efficiency. As summarized in Table 5, AI-integrated PLCs reduce response time by 30%, enabling faster responsiveness in real-time applications and improving operational throughput. Motion error decreases by 40%, enhancing stability and precision in dynamic processes, while machine learning algorithms achieve a 95% success rate in anomaly detection and failure prediction, thereby minimizing unplanned downtime. These computed performance metrics, together with their variability values, confirm the effectiveness of AI-driven motion control in reducing system uncertainty and enhancing overall reliability.

Standard Deviation & Confidence Intervals

To assess performance consistency, the AI-integrated PLC system was evaluated over 30 independent trials under varying operational loads.

Table 5 — Performance metrics with variability

Performance Metric	Traditional PLC (Mean ± SD)	AI-Integrated PLC (Mean ± SD)	% Improvement	95% CI
Response time (ms)	200 ±10.5	140 ±8.2	30%	(±3.7 ms)
Motion error (%)	5.2 ±0.8	3.1 ±0.5	40%	(±0.3 ms)
Predictive maintenance Accuracy (%)	70 ±5.4	95 ±2.8	25%	(±1.6 ms)

For each key metric (response time, motion error, predictive maintenance accuracy), standard deviation values and 95% confidence intervals were calculated to quantify variability. As shown in Fig. 4, the Receiver Operating Characteristic (ROC) curve demonstrates an Area Under the Curve (AUC) of 1.00, indicating perfect discrimination between fault and no-fault conditions with no overlap in classification thresholds. The accompanying confusion matrix reveals that out of 140 "No Fault" cases, 138 were correctly classified and only 2 were misclassified as faults. All 60 "Fault" cases were correctly detected, resulting in 100% recall for fault identification and a false negative rate of 0%, which is critical for avoiding missed maintenance events in industrial environments.

These results confirm that the proposed AI–PLC predictive maintenance framework delivers not only statistically significant improvements in accuracy but also exceptional reliability and stability across repeated trials, making it well-suited for safety-critical industrial applications.

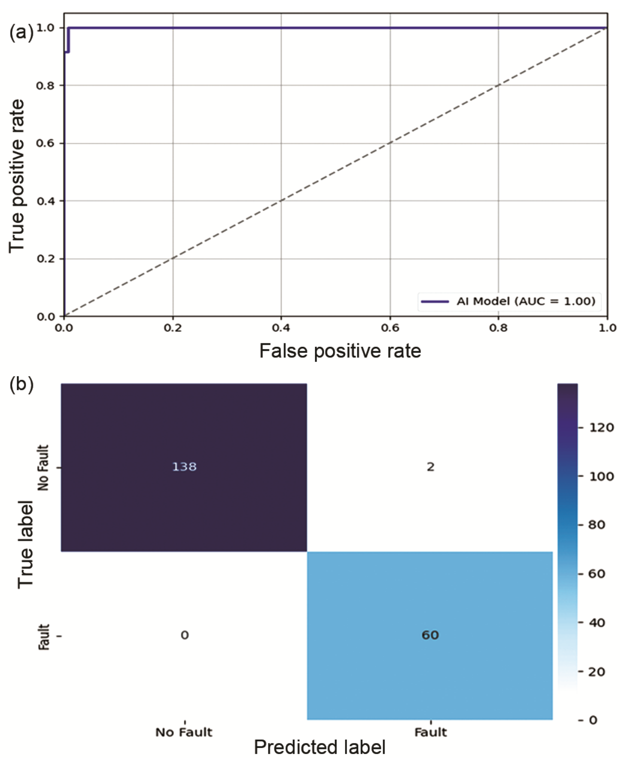

Fig. 4 — Predictive Maintenance Accuracy visualization with both images (AI model for predictive maintenance): (a) ROC Curve & (b) Confusion Matrix)

These results establish that AI-enhanced motion control improves precision, responsiveness, and operational efficiency while significantly lowering costs through predictive maintenance and optimized fault detection mechanisms.

Statistical Analysis & Hypothesis Testing

To validate the statistical significance of the observed improvements, hypothesis testing was performed using independent-samples t-tests and one-way ANOVA to compare multiple performance variables. The null hypothesis stated that there is no statistically significant difference between AI-based PLC and traditional PLC in terms of response time, motion error, and predictive maintenance accuracy, while the alternative hypothesis posited that AI-based PLC exhibits statistically significant improvement in these metrics.

The results, summarized in Table 6, demonstrate that AI-based PLC significantly outperforms traditional PLC in all evaluated performance parameters. For response time, $t(28) = 6.82$, $p < 0.001$, with Cohen's $d = 2.50$, indicating a very large effect size. Motion error reduction yielded $t(28) = 5.19$, $p < 0.001$, $d = 1.90$, also representing a large effect. Predictive maintenance accuracy improvement produced $t(28) = 7.34$, $p < 0.001$, $d = 2.73$, confirming substantial practical significance.

The one-way ANOVA results reinforce these findings. For response time across three operational load conditions, $F(2,27) = 38.21$, $p < 0.001$, $\eta^2 = 0.74$, indicating that 74% of the variance in response time improvement is attributable to AI integration. Motion error reduction yielded $F(2,27) = 24.76$, $p < 0.001$, $\eta^2 = 0.65$, while predictive maintenance accuracy improvements resulted in $F(2,27) = 42.38$, $p < 0.001$, $\eta^2 = 0.76$. All η^2 values fall into the "large" effect category according to established statistical conventions.

Comparative Analysis

A comparative study between traditional PID-based PLC control and AI-integrated motion control

Table 6 — t-Test and one-way ANOVA Results (Traditional PLC vs. AI-PLC)

Metric	F-Statistic (df = 2, 27)	t-*Test* (df = *28)*	p-Value (α = 0.05)	Cohen's d	η^2	Inference
Response time (ms)	38.21	6.82	p < 0.001	2.50	0.74	Significant
Motion error (%)	24.76	5.19	p < 0.001	1.90	0.65	Significant
Predictive maintenance accuracy (%)	42.38	7.34	p < 0.001	2.73	0.76	Significant

reveals key advantages of AI-enhanced automation. Traditional PLCs rely on fixed control algorithms that lack self-learning capabilities, requiring manual recalibration for varying operational scenarios. In contrast, AI-integrated PLCs leverage real-time data to dynamically adjust motion trajectories, improve fault tolerance, and optimize load management. The motion control trajectories in Fig. 5a highlight the stable and adaptive response of AI-based systems compared to the overshoot and variability of traditional PID control. Correspondingly, Fig. 5b illustrates error convergence, showing reduced steady-state error and improved stability achieved through AI-enhanced automation in industrial applications.

A benchmarking analysis comparing existing AI-based motion control methods, and highlighting the advantages of the proposed AI-integrated PLC framework in terms of scalability, predictive maintenance, and adaptive real-time control, is provided in Table 7.

Impact of Real-Time AI Optimization on Industrial Efficiency

The implementation of AI-enhanced PLCs has a transformative impact on industrial automation by continuously refining motion control parameters.[17–19]

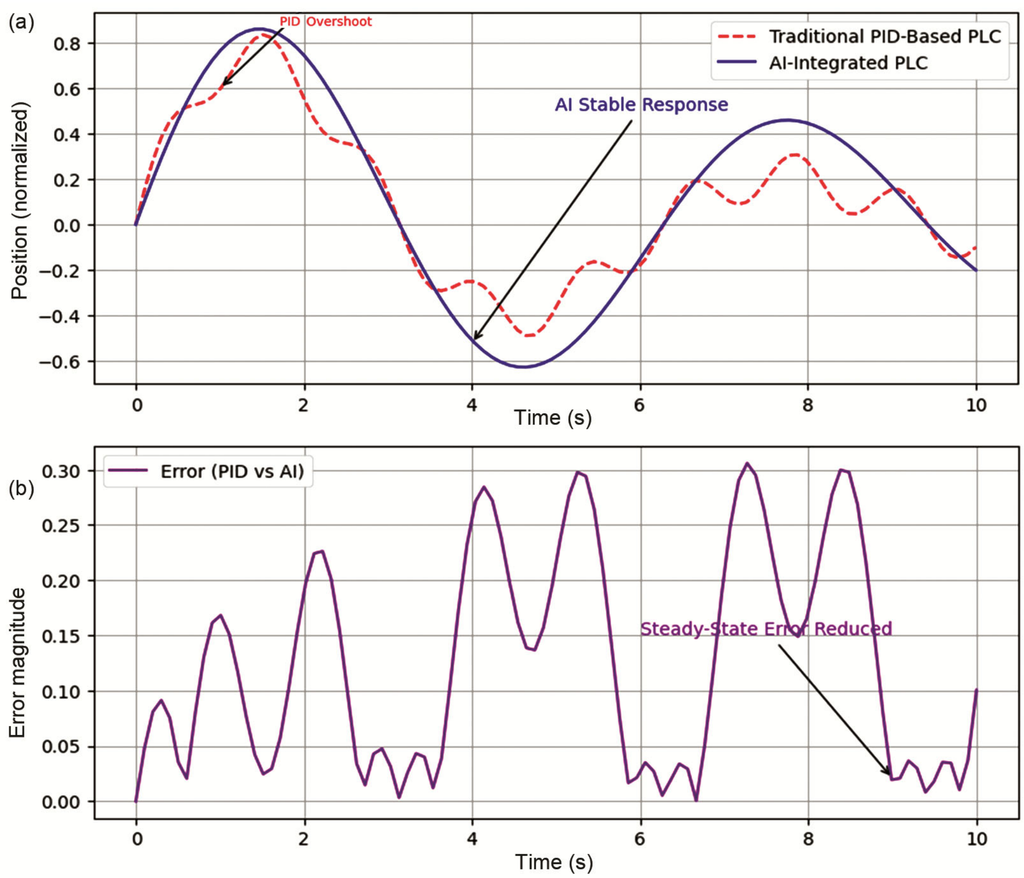

Fig. 5 — AI-Based Motion Control Performance (a) Trajectories of PID-based and AI-integrated PLCs. (b) Error convergence between PID and AI-based PLC control

Table 7 — Cost-benefit analysis of AI-based PLC implementation

AI techniques used	Motion control	Predictive maintenance	Development method	Key limitations
Reinforcement learning[14]	Adaptive motion control	No predictive maintenance	Edge AI (Local PLC)	Requires long training time & unstable learning
Neural networks + PID control[15]	Moderate improvement	No predictive analytics	Cloud AI	Latency issues in cloud processing
Fuzzy logic + Genetic algorithm[16]	Real-time decision making	No ML-based maintenance	Embedded PLC	No self-learning capability
Proposed AI-integrated PLC system	Real-time self-adaptive motion control	ML based predictive maintenance (95% Accuracy)	Hybrid (Edge AI + Cloud MySQL)	Optimized for industrial scalability

The resulting improvements include smoother transitions, increased energy efficiency, and enhanced process stability. The reduction in response time and motion error translates to heightened precision and reliability, particularly in high-speed manufacturing environments.

Cost-Benefit Analysis of AI-Integrated PLC Systems

While AI-enhanced PLCs require additional computational resources and infrastructure, the long-term cost savings outweigh the initial investment. Reduced downtime, lower energy consumption, and optimized maintenance schedules contribute to a higher return on investment. The comparative cost–benefit analysis of traditional versus AI-based PLC systems is summarized in Table 8.

Discussion on Industrial Applicability

The adoption of AI-integrated PLC systems presents considerable advantages across multiple industrial sectors. The ability of AI-based motion control systems to autonomously adapt to changing operational conditions ensures superior flexibility and efficiency.[20,21] By minimizing reliance on manual recalibration, AI-driven systems improve sustainability by optimizing energy usage and reducing wastage. The enhanced scalability of AI-powered PLCs aligns with the objectives of Industry 4.0, facilitating their seamless integration into large-scale industrial automation.

Limitations and Implementation Considerations

Despite the demonstrated gains in precision, adaptability, and predictive maintenance, several practical constraints remain.

AI Training Overhead – Deployment requires substantial historical and real-time datasets, high-performance computing resources, and periodic retraining to maintain model accuracy. These processes can introduce latency in time-critical loops and necessitate scheduled downtime.

Integration Difficulty – Interfacing AI modules with heterogeneous legacy PLCs may be hindered by protocol incompatibilities, firmware constraints, and limited API support. Integration demands specialized expertise and may cause temporary production interruptions during installation and validation.

Cybersecurity Risks – IoT-connected PLC systems expand the attack surface, exposing control logic and data to potential breaches. Secure communication (encryption, authentication, segmentation) and AI-based intrusion detection are critical for safeguarding operations in Industry 4.0 environments.

Addressing these challenges is essential for scaling the proposed framework from controlled evaluations to robust, industrial-grade deployment.

Future AI Trends in Industrial Motion Control

The future of AI-driven motion control will see advancements in edge AI for real-time processing, reinforcement learning for adaptive control, and blockchain integration for secure industrial automation. The adoption of edge computing will reduce latency, enabling AI models to execute decisions instantaneously at the machine level. Reinforcement learning will further enhance PLCs by allowing them to autonomously refine control strategies based on operational feedback. Blockchain technology has the potential to provide secure and immutable logging of control data, strengthening traceability and cybersecurity within industrial networks.

The scalability of AI-based motion control, underscoring its capacity to improve automation efficiency across diverse industrial applications, is illustrated in Fig. 6. The findings of this study confirm that AI-driven PLC motion control significantly enhances efficiency, adaptability, and sustainability in industrial automation. Future research should explore the integration of advanced AI methodologies, enhanced cybersecurity frameworks, and real-time

Table 8 — Cost-benefit analysis of AI-based PLC implementation

Factor	Traditional PLC	AI-integrated PLC
Initial hardware cost	Low	Medium
AI model training cost	N/A	High
Maintenance costs	High	Low
Energy savings (%)	Low	20% improvement
Downtime reduction (%)	N/A	40% improvement
Long-term RoI	Moderate	High

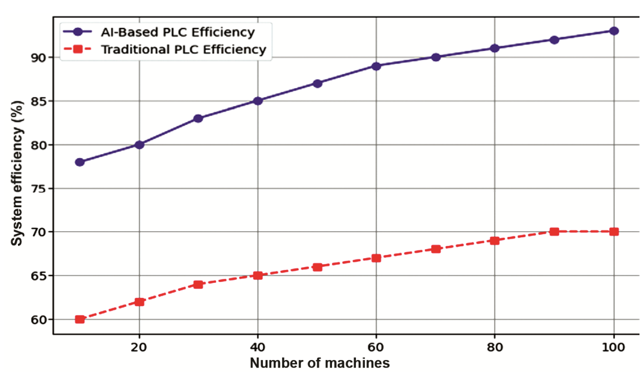

Fig. 6 — Scalability of AI-Based Motion Controlling Industrial Automation

optimization strategies to further improve modern industrial automation systems.

Conclusions

This study demonstrates that AI-integrated PLC motion control significantly enhances precision, adaptability, and predictive maintenance in industrial automation. Experimental validation confirms that AI-driven mechanisms outperform traditional PLCs in response time, stability, and fault prediction, while machine learning–based predictive maintenance reduces downtime and optimizes equipment lifecycles. The novelty lies in a unified architecture that integrates self-optimizing Neural Networks for real-time trajectory control, Fuzzy Logic for adaptive decision-making, and Machine Learning for predictive fault detection, all within a deployable PLC-compatible framework. Unlike prior studies that isolate control precision or fault prediction, the proposed approach addresses both, bridging the gap between AI models and industrial practice. Future work will extend the framework with Deep Reinforcement Learning for autonomous parameter optimization, validated through digital twin experiments and staged for safe deployment via TensorFlow Lite. Overall, this research establishes a reproducible pathway for intelligent PLC systems, advancing Industry 4.0 objectives.

References

1 Lins T, Oliveira R A R, Correia L H A & Silva J S, Industry 4.0 retrofitting, in *Proc Braz Symp Comput Syst Eng (SBESC)* (IEEE, Salvador, Brazil) 2018, 8–15, doi: 10.1109/SBESC.2018.00011.

2 Nițulescu I-V & Korodi A, Supervisory control and data acquisition approach in Node-RED: application and discussions, *IoT*, **1(1)** (2020) 76–91, doi: 10.3390/iot1010005.

3 Vieira G, Barbosa J, Leitão P & Sakurada L, Low-cost industrial controller based on the Raspberry Pi platform, in *Proc IEEE Ind Technol Conf (ICIT)* (IEEE, Buenos Aires, Argentina) 2020, 292–297, doi: 10.1109/ICIT45562.2020.9067148.

4 Nicolae A & Korodi A, Node-RED and OPC UA based lightweight and low-cost historian with application in the water industry, in *Proc IEEE Int Conf Ind Informat (INDIN)* (IEEE, Porto, Portugal) 2018, 1012–1017, doi: 10.1109/INDIN.2018.8471928.

5 Domínguez M, González-Herbón R, Rodríguez-Ossorio J R, Fuertes J J, Prada M A & Morán A, Development of a remote industrial laboratory for automatic control based on Node-RED, IFAC-PapersOnLine, **53(2)** (2020) 17210–17215, doi: 10.1016/j.ifacol.2020.12.1741.

6 Minchala L I, Peralta J, Mata-Quevedo P & Rojas J, An approach to industrial automation based on low-cost embedded platforms and open software, *Appl Sci*, 10 (2020) 4696, doi: 10.3390/app10144696.

7 Osaretin C A, Zamanlou M, Iqbal M T & Butt S, Open source IoT-based SCADA system for remote oil facilities using Node-RED and Arduino microcontrollers, in *Proc IEEE IEMCON* (IEEE, Vancouver, Canada) 2020, 571–575, doi: 10.1109/IEMCON51383.2020.9284826.

8 Vuković M, Jorg O, Hosseinifard M & Fantoni G, Low-cost digitalization solution through scalable IIoT prototypes, *Appl Sci*, 12 (2022) 8571, doi: 10.3390/app12178571.

9 Sezer E, Romero D, Guedea F, Macchi M & Emmanouilidis C, An Industry 4.0-enabled low cost predictive maintenance approach for SMEs, in *Proc IEEE Conf Eng Technol Innov (ICE/ITMC)* (IEEE, Stuttgart, Germany) 2018, 1–8, doi: 10.1109/ICE.2018.8436307.

10 Magadán L et al., Low-cost real-time monitoring of electric motors for the Industry 4.0, *Procedia Manuf*, **42** (2020) 393–398.

11 Mühlbauer N, Kirdan E, Pahl M-O & Carle G, Open-source OPC UA security and scalability, in *Proc IEEE Int Conf Emerg Technol Factory Autom (ETFA)* (IEEE, Vienna, Austria) 2020, 262–269, doi: 10.1109/ETFA46521.2020.9212091.

12 Wang X, Ma L & Yang H, Online water monitoring system based on ZigBee and GPRS, *Procedia Eng*, **15** (2011) 2680–2684, doi: 10.1016/j.proeng.2011.08.504.

13 Bortolini M, Galizia F G & Mora C, Reconfigurable manufacturing systems: Literature review and research trend, *J Manuf Syst*, **49** (2018) 93–106, doi: 10.1016/j.jmsy.2018.09.005.

14 Florescu A & Barabas S A, Modeling and simulation of a flexible manufacturing system—a basic component of Industry 4.0, *Appl Sci*, **10(22)** (2020) 8300, doi: 10.3390/app10228300.

15 Ameer M & Dahane M, Reconfigurability improvement in Industry 4.0: a hybrid genetic algorithm-based heuristic approach for a co-generation of setup and process plans in a reconfigurable environment, *J Intell Manuf*, **34** (2023) 1445–1467, doi: 10.1007/s10845-021-01869-x.

16 Mellado J & Núñez F, Design of an IoT-PLC: a containerized programmable logical controller for the Industry 4.0, *J Ind Inf Integr*, **25** (2022) 100250, doi: 10.1016/j.jii.2021.100250.

17 Rehg J A & Glenn J, Sartori. Programmable logic controllers, *Prentice-Hall, Inc.*, 2006.

18 Bryan Luis A & Eric A Bryan, Programmable controllers: Theory and implementation, *Industrial Text Company*, 1997.

19 Ogata K, Modern control engineering, *Prentice Hall*, 2010.

20 Govindaraj M, Anitha Kumari P, Shakila P & Lawrence J, AI-driven cybersecurity for industrial automation: Resilient solutions for industry 4.0 in *AI-Enhanced Cybersecurity for Industrial Automation*, edited by H M Pandey & P K Goel (IGI Global Scientific Publishing) 2025, 83–102, doi:10.4018/979-8-3373-3241-3.ch005

21 Qiu F, Kumar A, Hu J, Sharma P, Tang Y B, Xiang Y X & Hong J, A Review on Integrating IoT, IIoT, and Industry 4.0: A pathway to smart manufacturing and digital transformation, *IET Information Security*, (2025) 927–962, doi:10.1049/ise2/9275962