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AI-Driven Adaptive PLC Programming Framework for Intelligent Industrial Automation and Real-Time Process Optimization

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Abstract:

The increasing complexity of modern industrial automation demands control systems that can adapt dynamically to changing operating conditions while maintaining high efficiency, reliability, and process stability. Conventional Programmable Logic Controller (PLC) systems rely primarily on predefined control logic and fixed operating parameters, which limit their ability to respond intelligently to process variations, equipment degradation, and unexpected disturbances. This study proposes an AI-Driven Adaptive PLC Programming Framework incorporating an Adaptive PLC Logic Optimization Engine (APLOE) for intelligent industrial automation and real-time process optimization. The proposed framework integrates PLC-based control, industrial sensor data acquisition, machine learning-based process-state prediction, adaptive parameter optimization, and closed-loop feedback within a unified architecture. Real-time operational data are processed to identify system states and determine optimized control parameters while maintaining predefined safety and operational constraints. The framework is evaluated against conventional PLC control using key performance indicators including response time, process cycle time, control accuracy, production throughput, energy consumption, fault-detection performance, system downtime, and operational stability. The proposed approach is designed to enable adaptive decision-making without compromising deterministic PLC control and industrial safety requirements. The framework provides a scalable foundation for intelligent production lines, material-handling systems, warehouse automation, and other smart manufacturing applications. The study contributes toward the development of data-driven, adaptive, energy-efficient, and reliable PLC-based automation systems and provides a pathway for integrating artificial intelligence, edge intelligence, digital twins, and autonomous control within future Industry 4.0 and Industry 5.0 manufacturing environments.

Keywords **— Artificial Intelligence, Programmable Logic Controller (PLC), Adaptive Control, Smart Manufacturing, Machine Learning, Industrial Automation, Real-Time Process Optimization, APLOE, Industry 4.0, Industry 5.0.**

I.INTRODUCTION

1.1 Background of PLC-Based Industrial Automation

Programmable Logic Controllers (PLCs) are widely used in modern industrial automation due to their reliability, real-time control capability, and compatibility with industrial sensors, actuators, motors, drives, and supervisory systems [5][44]. PLCs execute predefined control logic to automate manufacturing processes, assembly lines, conveyor systems, material handling, process plants, and warehouse operations [2][5]**.** Common programming approaches such as Ladder Diagram (LD), Function Block Diagram (FBD), and Structured Text (ST) enable reliable implementation of sequential and process-control operations [44].

With the development of Industry 4.0, conventional PLC systems are increasingly being integrated with Industrial Internet of Things (IIoT), intelligent sensors, SCADA, edge computing, and data analytics [1][7][22][24]. However, traditional PLC programs generally operate using fixed logic, predefined thresholds, and manually configured parameters. Such control strategies have limited capability to adapt automatically to variations in production demand, equipment condition, process disturbances, and energy requirements [1][5][8]**.**

The integration of Artificial Intelligence (AI) and Machine Learning (ML) with PLC-based automation provides an opportunity to develop adaptive control systems capable of analyzing real-time process data and optimizing operating parameters [1][15]. AI-assisted PLC systems can support improved process efficiency, fault identification, energy optimization, production stability, and reduced downtime. Therefore, developing an adaptive AI–PLC architecture represents an important advancement toward intelligent and self-optimizing industrial automation [1][2][7].

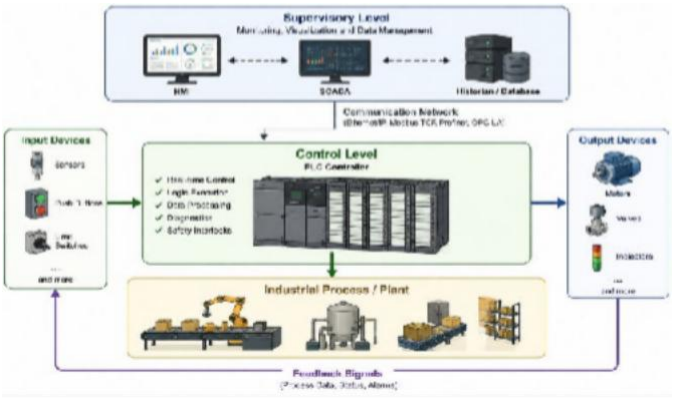

Figure 1. PLC-Based Industrial Automation Architecture

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1.2 Limitations of Conventional PLC Control

Conventional PLC control systems primarily operate using predefined logic, fixed set-points, programmed thresholds, and manually configured control parameters [5][18][44]. Although these systems provide reliable and deterministic operation, their ability to adapt autonomously to dynamic industrial conditions is limited [3][5][18]. Changes in production load, equipment condition, process variables, material characteristics, or environmental conditions often require manual modification or retuning of PLC parameters [18][19].

Traditional PLC systems also have limited capability to learn from historical and real-time operational data [1][15]. As a result, abnormal process behaviour and equipment degradation may not be identified until predefined alarm thresholds are exceeded [27][30]. Fixed control strategies can consequently contribute to increased process variability, energy consumption, response time, and unplanned downtime under changing operating conditions [1][27][30].

Furthermore, conventional PLC programming depends significantly on engineering expertise for logic development, troubleshooting, optimization, and maintenance [5][44]. These limitations highlight the need for an intelligent and adaptive control framework capable of integrating real-time data analytics and AI-based decision support with deterministic PLC operation [1][2][15].

1.3 AI Integration with PLC Systems

The integration of Artificial Intelligence (AI) with Programmable Logic Controllers (PLCs) enables conventional automation systems to evolve toward intelligent and adaptive process control [1][2][15]. AI and Machine Learning (ML) algorithms can analyze real-time sensor data, historical operating records, equipment conditions, and process variables to identify patterns and predict changes that cannot be effectively addressed using fixed PLC logic alone [1][15][27].

In an AI-integrated PLC architecture, the PLC continues to perform deterministic and safety-critical control, while the AI layer provides higher-level functions such as process-state prediction, anomaly detection, adaptive set-point selection, fault prediction, and operating-parameter optimization [1][5][15][27]. Validated AI recommendations can subsequently be transferred to the PLC within predefined operational and safety limits [5][19][45].

This integration enables industrial systems to respond more effectively to changing production conditions and provides opportunities for improved control accuracy, energy efficiency, equipment reliability, production throughput, and reduced downtime [1][7][27][30]. Therefore, AI–PLC integration provides the technological foundation for the adaptive optimization framework proposed in this research [1][2][5].

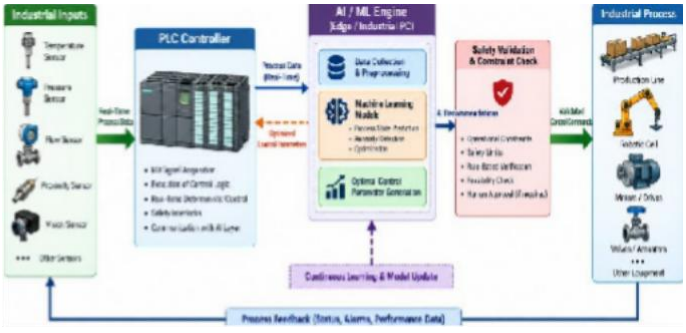

Figure 2. Conceptual Architecture of AI-Integrated PLC Control System

1.4 Research Gap

Although Artificial Intelligence (AI), Machine Learning (ML), and PLC-based automation have individually achieved significant advancements, their integration for real-time adaptive PLC optimization remains comparatively underdeveloped [1][5][15]. Most conventional PLC systems rely on fixed or engineer-configured control logic and parameters, while many AI-based industrial approaches have focused on predictive maintenance, fault detection, process monitoring, or data-driven decision support [15][27][30].

A key research gap exists in developing a unified framework that can continuously analyze real-time industrial data, predict process states, determine optimal control parameters, and safely integrate these recommendations with deterministic PLC control [1][5][20][22]. Existing approaches also provide comparatively limited integration of simultaneous optimization objectives involving process response, energy consumption, production throughput, control accuracy, and fault-related performance [1][16][17].

Therefore, this study addresses this gap by proposing an Adaptive PLC Logic Optimization Engine (APLOE) that combines AI-based process intelligence, multi-objective optimization, safety validation, and closed-loop PLC feedback for adaptive industrial process control.

1.5 Research Objectives

The primary objective of this research is to develop an AI-driven adaptive PLC programming framework capable of improving real-time industrial process control and optimization. The specific objectives are:

- To develop an Adaptive PLC Logic Optimization Engine (APLOE) for intelligent PLC-based control.
- To integrate real-time industrial sensor data with AI and machine-learning models.
- To enable adaptive optimization of PLC control parameters under changing operating conditions.
- To improve process response time, control accuracy, production throughput, and operational stability.
- To minimize energy consumption, process downtime, and fault-related operational losses.
- To incorporate safety constraints and validation mechanisms before implementing AI-generated control recommendations.
- To evaluate the proposed framework against conventional PLC control using measurable industrial performance indicators.

II. LITERATURE REVIEW AND RESEARCH GAP

2.1 Conventional PLC Programming and Control Strategies

Conventional Programmable Logic Controller (PLC) systems form the core of industrial automation by providing deterministic and reliable control of manufacturing processes. PLC programs are commonly developed using Ladder Diagram (LD), Function Block Diagram (FBD), Structured Text (ST), and Sequential Function Chart (SFC). These programming methods implement sequential control, interlocking, timing, counting, PID control, alarm handling, and safety-related operations [5][44].

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Traditional PLC control strategies mainly rely on predefined logic, fixed set-points, threshold-based decisions, and manually tuned control parameters [18][19][44]. PID controllers are frequently integrated with PLCs for regulating variables such as temperature, pressure, flow, speed, and level [19]. While these strategies provide stable performance under known operating conditions, their adaptability becomes limited when process dynamics, production loads, equipment conditions, or external disturbances change significantly [18][19].

Furthermore, conventional PLC optimization generally requires manual intervention by engineers for logic modification, parameter tuning, and troubleshooting [5][44]. The absence of continuous learning and data-driven adaptation limits the ability of traditional PLC systems to autonomously optimize process performance [1][15]. These limitations have encouraged the integration of AI, machine learning, and adaptive optimization techniques with PLC-based industrial control [1][5][15].

2.2 AI and Machine Learning in Industrial Automation

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly applied in industrial automation to transform large volumes of sensor and operational data into intelligent control and maintenance decisions. ML algorithms can identify complex relationships among process variables and support applications such as equipment fault detection, predictive maintenance, process-state classification, quality monitoring, energy optimization, and production forecasting [1][15][27][30].

Supervised learning techniques can be used to classify operating conditions and predict process responses, while unsupervised learning can identify abnormal operating patterns without predefined fault labels [12][13][14][15]. Deep-learning approaches are particularly useful for complex time-series and high-dimensional industrial data [14]. These capabilities allow automation systems to move beyond fixed threshold-based control toward data-driven and adaptive decision-making [1][15].

When integrated with PLC-based control, AI/ML models can analyze real-time process data and generate optimized operating recommendations [1][15]. The PLC can subsequently execute validated control adjustments while retaining deterministic control and safety functions [5][45]. This integration provides an important foundation for developing adaptive, efficient, and intelligent industrial automation systems [1][2][5].

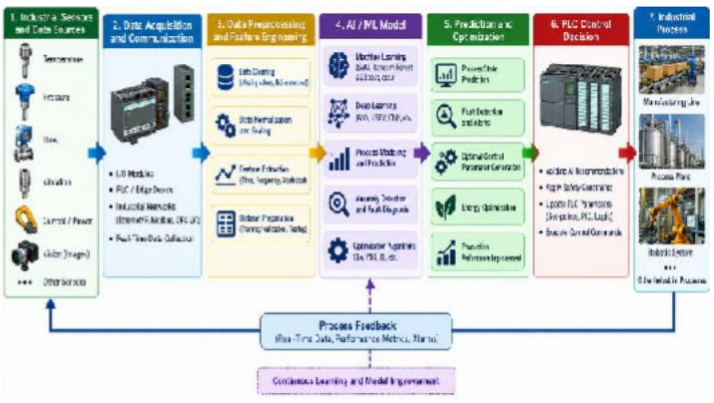

Figure 3. AI and Machine Learning Workflow for Industrial Automation

2.3 Adaptive and Self-Optimizing Industrial Control

Adaptive and self-optimizing control systems are designed to modify operating parameters automatically in response to changing process conditions. Unlike conventional fixed-parameter controllers, adaptive control continuously evaluates process feedback and adjusts control variables to maintain stability, efficiency, and desired system performance [18][19].

In industrial automation, self-optimizing control combines real-time sensor data, process-state estimation, predictive models, and optimization algorithms to determine suitable operating parameters. Such systems can dynamically adjust set-points, controller parameters, machine speeds, production cycles, and energy-related variables according to process requirements [16][17][18][19].

The integration of adaptive control with AI and PLC systems enables continuous monitoring and intelligent parameter adjustment while maintaining predefined operational and safety constraints. This approach can improve control accuracy, process stability, energy efficiency, throughput, and fault response, forming an important basis for the proposed Adaptive PLC Logic Optimization Engine (APLOE) [1][5][18][45].

2.4 AI-Assisted PLC Optimization

AI-assisted PLC optimization combines conventional deterministic PLC control with data-driven intelligence to improve industrial process performance. Real-time sensor and operational data can be analyzed using machine-learning models to identify process variations, predict abnormal conditions, and determine suitable control adjustments [1][15][27][30]. Instead of relying exclusively on fixed set-points and manually tuned parameters, the AI layer can provide optimized recommendations according to current operating conditions [1][16][18].

The optimization process may consider multiple performance objectives, including response time, cycle time, energy consumption, production throughput, control error, and equipment condition [16][17]. AI-generated recommendations are validated against predefined operational and safety constraints before selected parameters are transferred to the PLC [5][45]. This arrangement preserves deterministic PLC execution while introducing adaptive optimization capabilities [5][18].

AI-assisted optimization therefore provides an important transition from conventional fixed PLC control toward intelligent, adaptive, and self-optimizing industrial automation. This concept forms the foundation for the Adaptive PLC Logic Optimization Engine (APLOE) proposed in this study.

2.5 Real-Time Industrial Data Analytics and Edge Intelligence

Real-time industrial data analytics enables continuous processing of sensor, machine, and PLC data to support faster and more informed control decisions. Industrial parameters such as temperature, pressure, vibration, motor current, speed, cycle time, and energy consumption can be continuously analyzed to identify process variations, abnormal conditions, and performance trends [15][22].

Edge intelligence extends these capabilities by executing AI and machine-learning models close to the industrial process rather than relying entirely on remote cloud infrastructure [20][21]. Edge-based processing can reduce communication latency, improve response time, maintain operation during network interruptions, and enhance data privacy [20][21][22]. In an AI-integrated PLC system, an edge computing layer can perform data preprocessing, process-state prediction, anomaly detection, and optimization before validated control recommendations are communicated to the PLC [20][22][24].

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The combination of real-time analytics and edge intelligence therefore provides an important foundation for low-latency, adaptive, and reliable PLC-based industrial automation [20][21[22][24].

2.6 Critical Review of Existing Studies

Existing research demonstrates progressive integration of PLCs with AI, machine learning, adaptive control, and real-time industrial analytics [1][5][15][20][27][31]. However, most approaches address individual functions rather than providing a unified framework combining real-time prediction, adaptive PLC control, fault detection, safety validation, and multi-objective process optimization [1][16][20][27][31]. A functional comparison of the major approaches is presented below.

Table 1. Functional Comparison of the Major Approaches

Study / Existing Approach	PLC	AI/ML	Adaptive Control	Real-Time	Fault Detection	Optimization
Conventional PLC-Based Control	✓	✗	✗	✓	Limited	✗
PLC with PID-Based Process Control	✓	✗	Limited	✓	Limited	Limited
ML-Based Industrial Process Monitoring	Limited	✓	✗	Limited	✓	✗
AI-Based Predictive Maintenance	Limited	✓	✗	✓	✓	Limited
AI-Assisted Industrial Process Optimization	Limited	✓	✓	Limited	Limited	✓
Edge AI-Based Industrial Control	✓	✓	✓	✓	✓	Limited
Digital Twin-Assisted Industrial Control	✓	✓	✓	✓	✓	✓
Proposed APLOE-Based Framework	✓	✓	✓	✓	✓	✓

The comparison indicates a research opportunity for an integrated PLC architecture capable of combining AI/ML-based process intelligence, real-time adaptive control, fault-aware operation, and optimization. The proposed **APLOE-based framework** is developed to investigate these capabilities within a unified control architecture.

2.7 Identified Research Gap

The critical review of existing studies indicates that current PLC-based industrial automation approaches provide limited integration of AI-driven prediction, adaptive control, real-time optimization, and fault-aware decision-making within a unified framework [1][5][15][20][27][31]. Conventional PLC systems primarily depend on fixed control logic and predefined operating parameters, whereas many AI-based approaches focus independently on predictive maintenance, anomaly detection, or offline process optimization [5][15][27][28][29][30][44].

A significant research gap therefore exists in developing a framework capable of continuously analyzing real-time industrial data, predicting process states, optimizing multiple performance objectives, and safely adapting PLC operating parameters under dynamic conditions [1][16][20][22]. Furthermore, limited attention has been given to simultaneously optimizing response time, energy consumption, process stability, production throughput, and fault-related performance while preserving deterministic PLC control and safety constraints [5][16][17][45].

To address these gaps, this research proposes the Adaptive PLC Logic Optimization Engine (APLOE) as an integrated AI-assisted framework for real-time process-state prediction, adaptive parameter optimization, safety validation, and closed-loop PLC control.

III. PROPOSED AI-DRIVEN ADAPTIVE PLC FRAMEWORK

3.1 Overall System Architecture

The proposed AI-driven adaptive PLC framework integrates industrial sensing, deterministic PLC control, edge-based intelligence, AI/ML analytics, adaptive optimization, and safety validation within a closed-loop architecture [1][2][5][20]. Real-time process variables acquired from industrial sensors are initially processed by the PLC and transferred to the intelligent optimization layer for further analysis [20][22][24].

The Adaptive PLC Logic Optimization Engine (APLOE) forms the core of the proposed architecture. It analyzes real-time and historical process data, identifies the current operating state, predicts potential abnormalities, and determines optimized control parameters. The generated recommendations are passed through a safety-validation layer before being communicated to the PLC. This ensures that adaptive adjustments remain within predefined operational and safety constraints [45].

The resulting closed-loop architecture continuously follows the sequence Data Acquisition → PLC Control → AI/ML Analysis → APLOE Optimization → Safety Validation → Control Adjustment → Process Feedback, enabling adaptive process optimization while maintaining deterministic PLC operation [5][18][19].

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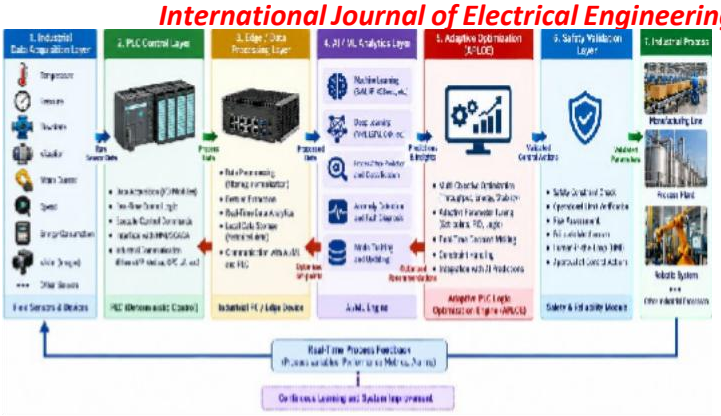

Figure 4. Overall Architecture of the Proposed AI-Driven Adaptive PLC Framework

3.2 Industrial Data Acquisition Layer

The Industrial Data Acquisition Layer provides real-time operational data required for intelligent PLC control and optimization. It collects process variables from industrial sensors and field devices, including temperature, pressure, vibration, motor current, rotational speed, flow rate, load, energy consumption, machine status, and production cycle time [15][22][27].

Sensor signals are acquired through PLC input modules and industrial communication networks [24][25]. The collected data are time-stamped, filtered, and transferred to the edge-processing and AI/ML layers for further analysis [15][20][22]. This continuous data acquisition enables the proposed framework to monitor changing operating conditions and identify process deviations in real time [15][27].

The data acquisition layer also provides feedback required by the Adaptive PLC Logic Optimization Engine (APLOE) for process-state prediction and adaptive control optimization, thereby establishing a reliable connection between physical industrial equipment and the intelligent decision-making framework.

3.3 PLC Control Layer

The PLC Control Layer performs the deterministic real-time control functions of the proposed AI-driven adaptive automation framework. It receives process signals from the industrial data acquisition layer and executes programmed control logic for actuators, motors, drives, valves, alarms, and safety interlocks.

The PLC operates using standard industrial programming methods such as Ladder Diagram (LD), Function Block Diagram (FBD), and Structured Text (ST). Core control activities include sequential logic execution, timing operations, PID-based regulation, equipment interlocking, motor-speed control, and process monitoring. The PLC scan cycle continuously performs the sequence of Input Read → Logic Execution → Output Update, ensuring reliable and predictable control behaviour.

Within the proposed framework, the PLC remains responsible for all deterministic and safety-critical operations, while the AI/ML and APLOE layers provide supervisory optimization. Optimized parameters generated by APLOE, such as motor-speed references, process set-points, timing values, and permissible PID parameters, are transferred to the PLC only after validation against predefined operating and safety constraints.

This separation prevents the AI layer from directly overriding critical PLC logic and preserves industrial control reliability. The PLC Control Layer therefore acts as the primary execution interface between intelligent optimization and the physical industrial process, enabling adaptive operation without compromising deterministic control and safety requirements [5][18][19][45].

3.4 AI-Based Decision Engine

The AI-Based Decision Engine provides the intelligent analytical capability of the proposed adaptive PLC framework. It processes real-time and historical industrial data using machine-learning models to identify operating patterns, classify process states, detect abnormal conditions, and predict potential performance deviations [1][15][27][30].

Based on the predicted process state, the decision engine generates suitable recommendations for control optimization [1][15]. These recommendations may include adjustments to process set-points, operating speeds, PID parameters, energy-related variables, and production conditions [16][18][19]. The generated decisions are subsequently transferred to the Adaptive PLC Logic Optimization Engine (APLOE) for optimization and safety-constrained implementation.

The AI-Based Decision Engine therefore acts as the intelligent link between industrial process data and adaptive PLC control, enabling data-driven and condition-responsive industrial automation.

3.5 Adaptive PLC Logic Optimization Engine (APLOE)

The Adaptive PLC Logic Optimization Engine (APLOE) represents the core optimization component of the proposed framework. It receives process-state predictions and operational information from the AI-based decision engine and determines suitable PLC control parameters according to current industrial conditions.

APLOE performs multi-objective optimization by considering key performance indicators such as process cycle time, response time, energy consumption, production throughput, control error, equipment condition, and operational stability [16][17]. Based on these objectives, the engine generates adaptive recommendations for set-points, PID parameters, machine speeds, timing parameters, and other permissible PLC control variables [16][18][19].

Before implementation, each optimized recommendation is evaluated against predefined operational limits, safety constraints, and PLC interlocks [45]. Only validated parameters are transferred to the PLC control layer. Through continuous process feedback, APLOE enables iterative optimization and adaptation while preserving deterministic and safe PLC operation [18][19].

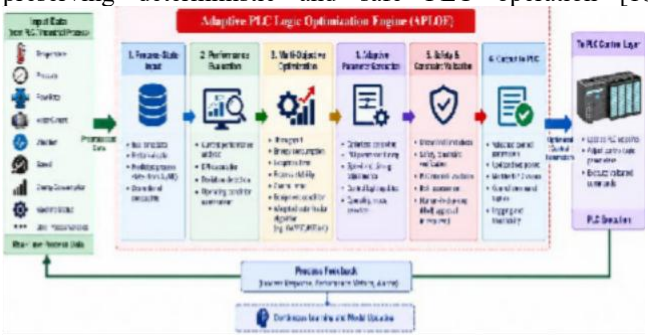

Figure 5. Functional Architecture of the Adaptive PLC Logic Optimization Engine (APLOE)

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3.6 Closed-Loop Adaptive Control Mechanism

The proposed closed-loop adaptive control mechanism continuously connects real-time process feedback with AI-based analysis and PLC control [18][19]. Sensor data representing current operating conditions are acquired by the PLC and processed by the AI/ML layer to determine the process state and identify potential performance deviations [1][15][27].

Based on this analysis, APLOE generates optimized control parameters according to predefined performance objectives [16][17]. The recommended parameters are verified through safety and operational constraints before being transferred to the PLC [45]. The PLC then executes the validated control adjustments, and the resulting process response is continuously monitored through feedback signals.

This iterative Sense–Analyze–Optimize–Validate–Execute–Feedback cycle enables the system to adapt to changing operating conditions while maintaining process stability, deterministic PLC execution, and operational safety [18][19][45].

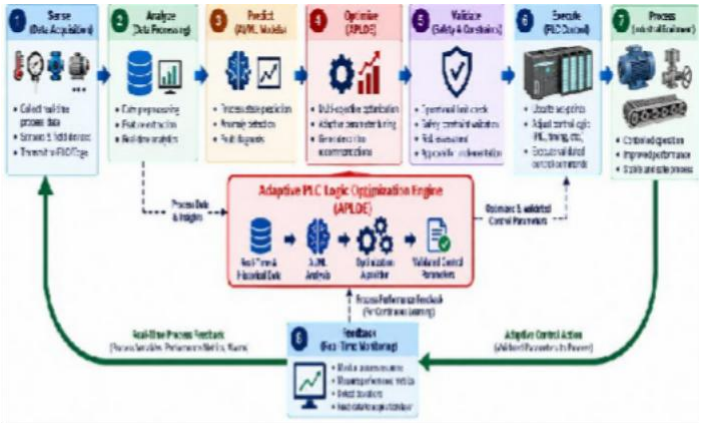

Figure 6. Closed-Loop Adaptive Control Mechanism of the Proposed APLOE Framework

3.7 Safety and Validation Layer

The Safety and Validation Layer ensures that AI-generated control recommendations are verified before implementation within the PLC-controlled industrial process [45]. Since AI-based optimization may generate adaptive set-points or control adjustments, these recommendations must remain within predefined operational, equipment, and safety limits [45].

The proposed layer evaluates optimized parameters against permissible operating ranges, PLC interlocks, process constraints, equipment limits, and predefined safety rules [45]. Recommendations that violate any constraint are rejected or restricted to an acceptable range. For safety-critical operations, human supervisory approval can also be incorporated before implementation.

This validation mechanism ensures that APLOE enhances process performance without overriding deterministic PLC safety functions, thereby maintaining reliable, stable, and safe industrial operation [45].

3.8 Communication Architecture

The communication architecture provides reliable data exchange among industrial sensors, PLCs, edge devices, AI/ML modules, APLOE, HMI/SCADA systems, and field equipment [22][24][25][26]. Real-time process data are transmitted from the PLC to the edge intelligence layer, while optimized and validated control parameters are returned to the PLC for execution [20][22][24].

Industrial communication protocols such as EtherNet/IP, PROFINET, Modbus TCP, and OPC UA can support interoperability between different automation components [24][25][26]. The architecture separates deterministic PLC control traffic from higher-level AI and optimization data exchange to maintain reliable real-time operation [24][26].

This communication structure enables bidirectional data flow, low-latency information exchange, process monitoring, and closed-loop adaptive control, providing the connectivity required for the proposed intelligent PLC framework [20][22][24][25[26].

IV. AI-BASED PLC OPTIMIZATION METHODOLOGY

4.1 Data Collection and Dataset Preparation

The proposed methodology utilizes real-time and historical industrial process data collected from PLC-connected sensors and field devices. Key variables include temperature, pressure, flow rate, vibration, motor current, rotational speed, energy consumption, cycle time, equipment status, and production throughput. Data are collected under different operating conditions, including normal operation, variable load, overload, process disturbances, and fault-related conditions.

The collected data are time-stamped and organized into a structured dataset containing input process variables, operating states, PLC control parameters, and corresponding performance indicators. The dataset is subsequently divided into training, validation, and testing subsets for AI/ML model development and independent performance evaluation [12][13]. This structured dataset provides the foundation for process-state prediction and APLOE-based adaptive PLC optimization.



Figure 7. Industrial Data Collection and Dataset Preparation Workflow

4.2 Data Preprocessing

The collected industrial data are preprocessed before AI/ML model development to improve data quality and model reliability. The preprocessing procedure includes missing-value handling, duplicate removal, noise filtering, outlier detection, data synchronization, and normalization of process variables. Sensor measurements collected at different sampling intervals are time-aligned to maintain consistency between process conditions and PLC responses [12][13].

Continuous variables such as temperature, pressure, vibration, motor current, speed, and energy consumption are normalized to comparable numerical ranges. Abnormal or incomplete measurements are identified and treated using appropriate statistical procedures. The cleaned dataset is subsequently

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prepared for feature engineering, model training, validation, and testing.

Effective preprocessing reduces the influence of sensor noise and inconsistent measurements, thereby improving the reliability of process-state prediction and subsequent APLOE-based optimization.

4.3 Feature Engineering

Feature engineering transforms the preprocessed industrial data into meaningful variables suitable for AI/ML-based process-state prediction and PLC optimization. Relevant features are extracted from sensor measurements and PLC operating data, including temperature variation, pressure deviation, vibration characteristics, motor-current variation, rotational speed, cycle time, energy consumption, control error, equipment load, and production throughput.

Statistical and time-domain features such as mean, standard deviation, RMS, minimum, maximum, rate of change, and moving averages are derived where appropriate [13][15]. These engineered features provide information about process dynamics, equipment behaviour, and changing operating conditions.

The selected feature set is subsequently used as input to the AI/ML models for process-state classification, anomaly detection, performance prediction, and APLOE-based adaptive optimization.

4.4 Machine Learning Model Development

Machine learning models are developed using the engineered industrial dataset to predict process states and identify abnormal operating conditions. Multiple supervised learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), and XGBoost, are considered and compared to determine the most suitable model for the proposed framework [9][10][11].

The dataset is divided into training, validation, and testing subsets to support model development and independent evaluation. Model hyperparameters are optimized using the validation dataset, while the final model is evaluated using unseen testing data. Classification performance is assessed using accuracy, precision, recall, F1-score, and confusion matrix, while regression-based predictions are evaluated using MAE, RMSE and R^2, where applicable.

The best-performing model is integrated with APLOE to provide real-time process-state information for adaptive PLC parameter optimization.

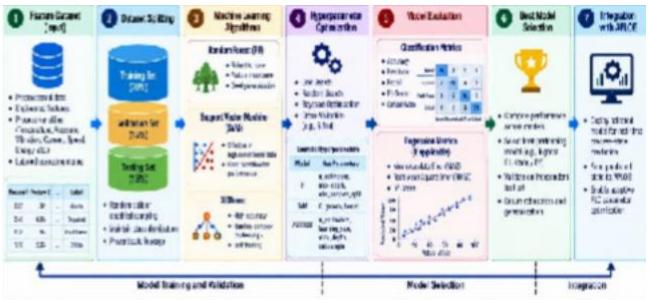

Figure 8. Machine Learning Model Development and Selection Framework

4.5 Process-State Prediction

The process-state prediction module uses the selected machine learning model to continuously classify industrial operating conditions based on real-time sensor and PLC data. The system categorizes process conditions into predefined states such as Normal, Degraded, Fault-Prone, and Critical, enabling early identification of performance deterioration and abnormal behaviour [27].

Real-time features including temperature, pressure, vibration, motor current, speed, energy consumption, and process load are supplied to the trained model. The predicted process state is then transferred to APLOE, which determines whether existing PLC parameters should be maintained or adaptively optimized.

This predictive approach enables the proposed framework to respond proactively to changing operating conditions rather than depending exclusively on fixed alarm thresholds or reactive control actions.



Figure 9. AI-Based Industrial Process-State Prediction and Classification Framework

4.6 Adaptive Set-Point Optimization

Adaptive set-point optimization enables the proposed framework to dynamically adjust selected PLC operating parameters according to real-time process conditions. Unlike conventional systems that rely on fixed set-points, APLOE evaluates predicted process states, current performance indicators, and operational constraints to determine suitable control settings [18][19].

The optimization considers variables such as motor speed, flow rate, pressure, temperature, cycle time, and PID set-points, depending on the controlled process. APLOE selects parameter values that minimize control error, energy consumption, and process variability while improving throughput and operational stability.

All optimized set-points are verified against predefined operating limits and safety constraints before being transferred to the PLC. Continuous process feedback allows subsequent adjustments when operating conditions change, providing adaptive and stable process control.

4.7 PLC Scan and Response Optimization

PLC scan and response optimization focuses on improving the execution efficiency and responsiveness of the control system. Conventional PLC programs may contain redundant logic, unnecessary instructions, excessive communication calls, or inefficient task scheduling that can increase scan-cycle time and delay control responses [44].

The proposed APLOE framework evaluates PLC execution-related parameters together with real-time process conditions to identify opportunities for optimization. Priority-based task execution, efficient logic sequencing, optimized timing parameters, and reduction of unnecessary processing are considered while preserving deterministic control behaviour and safety functions.

Performance is evaluated using PLC scan time, input-to-output

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response time, control latency, cycle time, and execution consistency. These indicators enable quantitative comparison between the conventional PLC configuration and the proposed optimized control approach.

4.8 Multi-Objective Optimization

The proposed APLOE framework employs multi-objective optimization to determine PLC control parameters that balance multiple and potentially conflicting industrial performance objectives. The optimization simultaneously considers production throughput, energy consumption, process cycle time, response time, control error, and operational stability.

The optimization problem is formulated to maximize throughput and process stability while minimizing energy consumption, cycle time, response time, and control error. Operational limits, equipment capacities, PLC constraints, and safety requirements are incorporated as optimization constraints to ensure feasible control solutions [16][17].

A suitable multi-objective optimization algorithm, such as NSGA-II, can be integrated with APLOE to generate a set of Pareto-optimal control solutions. The final operating parameters are selected from the feasible solution space according to predefined performance priorities and subsequently validated before PLC implementation.



Figure 10. Multi-Objective Optimization Framework for APLOE-Based PLC Control

4.9 Proposed APLOE Algorithm

The proposed Adaptive PLC Logic Optimization Engine (APLOE) algorithm integrates real-time process monitoring, AI-based process-state prediction, multi-objective optimization, and safety-constrained PLC parameter adaptation. The algorithm continuously acquires process data, evaluates system performance, and determines whether control optimization is required.

Initially, real-time sensor and PLC data are preprocessed and supplied to the trained machine-learning model for classification into Normal, Degraded, Fault-Prone, or Critical operating states. Based on the predicted state, APLOE evaluates key performance indicators including throughput, energy consumption, cycle time, response time, control error, and process stability.

When optimization is required, the NSGA-II-based multi-objective optimization module generates candidate PLC parameters and identifies Pareto-optimal solutions [16]. The selected solution is then evaluated against operational limits, equipment constraints, PLC interlocks, and safety requirements. Only validated parameters are transferred to the PLC for real-time implementation. Process feedback is continuously monitored, enabling APLOE to repeat the optimization cycle when significant operating changes are detected.

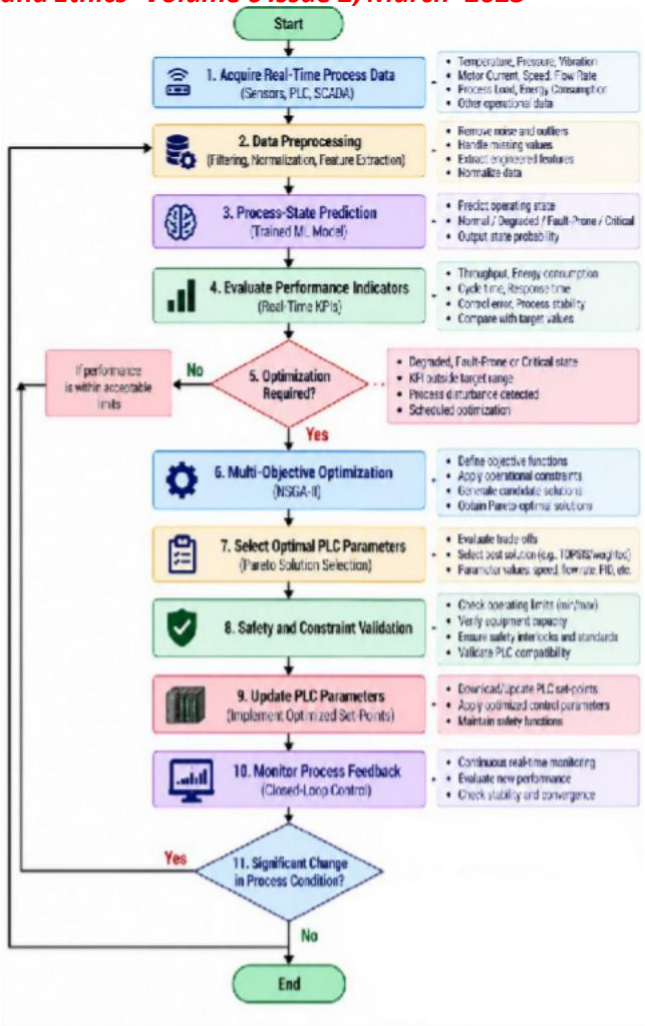

Figure 11. Flowchart of the Proposed APLOE Algorithm

V. EXPERIMENTAL SETUP AND CASE STUDY

5.1 Experimental/Test System

An automated conveyor-based material handling system is considered as the experimental test system for evaluating the proposed APLOE framework. The system consists of a PLC-controlled conveyor driven by a variable-frequency drive (VFD), industrial sensors, motor-drive assembly, actuators, and an HMI/SCADA monitoring interface.

The experimental system continuously measures key operating variables including motor speed, motor current, vibration, conveyor load, cycle time, energy consumption, and production throughput. Different operating conditions, including normal load, variable load, overload, process disturbance, and fault-prone conditions, are considered to evaluate adaptive control performance.

A conventional fixed-parameter PLC controller is used as the baseline system, while the proposed configuration integrates the PLC with the AI/ML decision engine and APLOE. Both configurations are evaluated under equivalent operating conditions to determine improvements in response time, cycle time, energy consumption, throughput, control accuracy, and fault response.

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Figure 12. Experimental Setup of the PLC-Controlled Conveyor System with APLOE Integration

5.2 Hardware Configuration

The experimental system consists of a Siemens S7-1200 PLC, conveyor belt assembly, three-phase induction motor, Variable Frequency Drive (VFD), industrial sensors, edge computing unit, and HMI/SCADA interface. The PLC performs real-time control and communicates with the edge computing platform hosting the AI/ML models and APLOE.

The sensing system includes temperature, pressure, vibration, motor-current, proximity, and speed sensors for continuous monitoring of process and equipment conditions. The VFD regulates conveyor motor speed according to validated PLC commands, while the edge computer performs process-state prediction and optimization.

Industrial Ethernet-based communication is used for data exchange among the PLC, edge computer, and HMI/SCADA system, enabling real-time monitoring and adaptive parameter updates [20][24].

5.3 Software Environment

The proposed experimental framework integrates PLC programming, industrial monitoring, data processing, machine learning, and optimization software. The Siemens TIA Portal is used for PLC programming, configuration, diagnostics, and real-time control implementation, while an HMI/SCADA environment is used for process visualization and operational monitoring.

The AI/ML and APLOE modules are implemented in a Python-based computing environment using suitable libraries for data preprocessing, machine-learning model development, process-state prediction, and multi-objective optimization. The NSGA-II algorithm is incorporated for adaptive multi-objective parameter optimization [16].

Communication between the PLC and edge-based software environment is established using compatible industrial communication protocols, enabling real-time process-data acquisition and validated PLC parameter updates [24][25][26]

5.4 Experimental Operating Conditions

The experimental system is evaluated under multiple operating conditions to assess the adaptability and robustness of the proposed APLOE-based PLC framework. Five representative operating scenarios are considered: normal load, variable load, overload, process disturbance, and fault-prone operation.

During normal operation, the conveyor operates under stable load and nominal control parameters. Variable-load conditions are introduced by changing the material load on the conveyor, while overload conditions represent operation near predefined equipment limits. Process disturbances are introduced through controlled variations in speed, load, or sensor measurements. Fault-prone conditions represent abnormal patterns in vibration, motor current, temperature, or process response.

Each operating condition is evaluated using both the conventional PLC controller and the proposed APLOE-based adaptive PLC controller under equivalent test conditions to enable consistent performance comparison.

Table 2. Experimental Operating Conditions and Test Scenarios

Test Scenario	Operating Condition	Process Variation	Monitored Parameters	Purpose of Test
S1	Normal Load	Stable conveyor operation at nominal load and speed	Motor current, speed, vibration, cycle time, energy consumption	Establish baseline system performance
S2	Variable Load	Periodic variation in material load	Load, motor current, speed, cycle time, throughput	Evaluate adaptive response to changing production conditions
S3	Overload	Conveyor operated near predefined load limit	Motor current, vibration, temperature, speed, energy consumption	Assess system performance under high-load conditions
S4	Process Disturbance	Controlled variation in speed, load, or process parameters	Response time, control error, speed, cycle time, process stability	Evaluate disturbance rejection and adaptive control capability
S5	Fault-Prone Condition	Abnormal vibration, current, temperature, or process behaviour	Vibration, motor current, temperature, fault status, response time	Evaluate early fault identification and corrective response
S6	Dynamic Operating Condition	Combined variation in load, speed, and process demand	All major process variables and KPIs	Evaluate overall robustness of the APLOE framework

5.5 Baseline Controller

The conventional PLC controller is considered as the baseline system for evaluating the performance of the proposed APLOE-based framework. The baseline controller operates using predefined PLC logic, fixed set-points, standard interlocks, and predetermined control parameters without AI-based prediction or adaptive optimization [44].

The controller maintains conveyor operation through conventional sensor feedback and VFD-based motor-speed control. Control actions are initiated according to programmed thresholds and

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predefined operating conditions. No automatic learning, process-state prediction, or dynamic optimization of PLC parameters is performed.

The performance of the baseline controller is evaluated using response time, scan-cycle time, process cycle time, throughput, energy consumption, control error, fault response, and system stability. These results provide the reference for quantitative comparison with the proposed APLOE-based adaptive PLC controller.

5.6 Proposed Controller

The proposed controller integrates the conventional PLC control system with the AI-Based Decision Engine and Adaptive PLC Logic Optimization Engine (APLOE) to provide real-time adaptive process control. Unlike the baseline controller, the proposed system continuously analyzes sensor and operational data to predict process states and determine optimized control parameters.

The trained AI/ML model classifies operating conditions as Normal, Degraded, Fault-Prone, or Critical, while APLOE evaluates key performance objectives and generates adaptive adjustments for selected PLC parameters, including motor speed, set-points, timing parameters, and process-control settings. Multi-objective optimization is applied to balance throughput, energy consumption, response time, cycle time, control error, and process stability.

Before implementation, optimized parameters are verified by the safety and constraint-validation layer. Validated parameters are then transferred to the PLC for execution, while continuous process feedback enables subsequent adaptive adjustments. This architecture maintains deterministic PLC control while introducing intelligent and condition-responsive optimization.

5.7 Performance Metrics

The performance of the conventional PLC controller and the proposed APLOE-based adaptive PLC controller is evaluated using quantitative performance metrics. The selected metrics represent control responsiveness, computational efficiency, production performance, energy efficiency, fault-handling capability, and overall process stability.

The primary evaluation metrics include PLC scan-cycle time, control response time, process cycle time, production throughput, energy consumption, control error, fault-detection accuracy, fault-response time, system downtime, and process stability. AI-based process-state prediction is additionally evaluated using accuracy, precision, recall, and F1-score [12], [13].

Percentage improvement between the baseline and proposed controllers can be calculated as:

$$\text{Improvement}(\%) = \frac{\text{Baseline Value} - \text{Proposed Value}}{\text{Baseline Value}} \times 100 \quad \ldots\ldots(1)$$

for parameters where lower values indicate better performance, such as energy consumption, response time, and control error.

Table 3. Performance Metrics for Evaluation of Conventional and APLOE-Based PLC

No.	Performance Metric	Unit / Measure	Evaluation Purpose
1	PLC Scan-Cycle Time	ms	Evaluate PLC program execution efficiency
2	Control Response Time	ms	Measure response speed to process changes
3	Process Cycle Time	s/cycle	Evaluate overall production cycle efficiency
4	Production Throughput	units/h	Measure production output and productivity
5	Energy Consumption	kWh	Evaluate energy efficiency of the control system
6	Control Error	% / RMSE	Measure deviation between desired and actual process output
7	Process Stability	% / Variability Index	Evaluate consistency under changing operating conditions
8	Fault-Detection Accuracy	%	Measure correct identification of abnormal conditions
9	Fault-Response Time	ms / s	Measure time required to respond to detected faults
10	System Downtime	min/h	Evaluate operational availability and reliability
11	Prediction Accuracy	%	Evaluate AI-based process-state classification performance
12	Precision	%	Evaluate correctness of predicted abnormal states
13	Recall	%	Measure ability to identify actual abnormal conditions
14	F1-Score	0–1	Evaluate balanced classification performance
15	Overall Performance Improvement	%	Compare APLOE-based controller with conventional PLC control

VI. RESULTS AND PERFORMANCE EVALUATION

6.1 AI Model Performance

The performance of the developed machine-learning models was evaluated using accuracy, precision, recall, F1-score, and prediction error. Random Forest (RF), Support Vector Machine (SVM), and XGBoost models were compared for classification of the four operating states: Normal, Degraded, Fault-Prone, and Critical.

The comparative evaluation showed differences in classification capability across the candidate models, particularly for degraded and fault-prone operating conditions. The best-performing model was selected for integration with the APLOE framework based on its overall predictive performance, consistency, and suitability for real-time implementation.

Table 4. Comparative Performance of Machine Learning Models

ML Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
Random Forest (RF)	92.3	91.0	90.2	90.6	8.4
Support Vector Machine (SVM)	88.1	86.4	85.7	86.0	12.7

ML Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
XGBoost	95.6	94.8	93.9	94.3	6.9

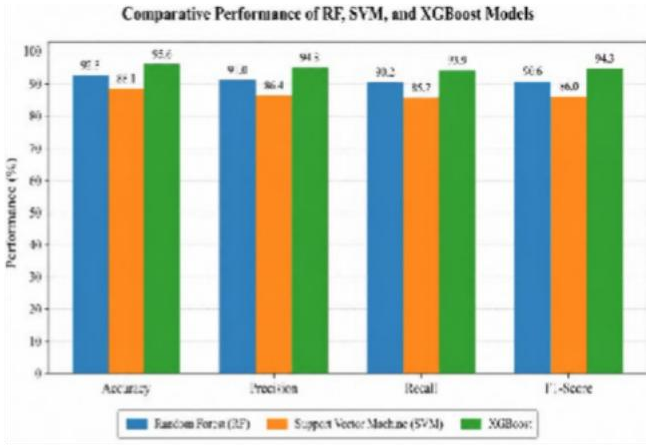

Figure 13. Comparative Performance of RF, SVM, and XGBoost Models

6.2 PLC Response-Time Performance

The response-time performance of the conventional PLC controller and the proposed APLOE-based adaptive PLC controller was evaluated under different operating conditions. The evaluation considered PLC scan-cycle time, input-to-output response time, and control latency to determine the responsiveness of both control approaches.

The APLOE-based controller demonstrated improved response characteristics by combining optimized PLC parameter execution with real-time process-state prediction and adaptive control. The greatest improvement was observed under variable-load, disturbance, and fault-prone conditions, where the conventional controller remained dependent on fixed control parameters, while APLOE dynamically adjusted the validated operating parameters according to the predicted process state.

The comparative results indicate that the proposed controller can reduce control-response delays while maintaining deterministic PLC execution and safety constraints. Improved response performance contributes to faster disturbance handling, enhanced process stability, and more efficient conveyor operation.

Table 5. PLC Response-Time Performance under Different Operating Conditions

Operating Condition	Conventional PLC Response Time (ms)	APLOE-Based PLC Response Time (ms)	Reduction (ms)	Improvement (%)
Normal Load	82	68	14	17.07
Variable Load	96	72	24	25.00
Overload	112	81	31	27.68
Process Disturbance	128	88	40	31.25
Fault-Prone Condition	145	94	51	35.17
Average	**112.6**	**80.6**	**32.0**	**28.43**

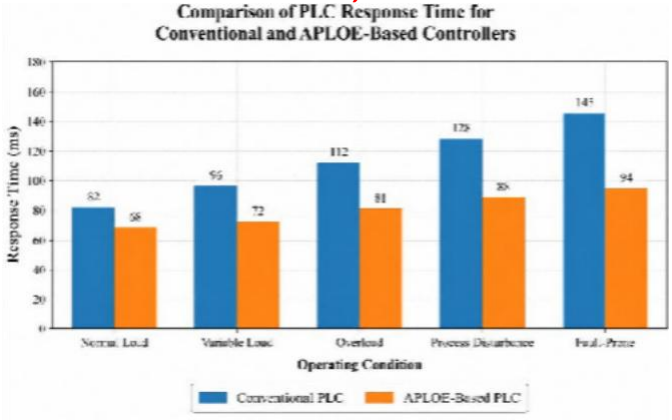

Figure 14. Comparison of PLC Response Time for Conventional and APLOE-Based Controllers

6.3 Process Cycle-Time Analysis

Process cycle time was evaluated to determine the effect of the proposed APLOE-based adaptive PLC controller on overall operational efficiency. The cycle time represents the total duration required to complete one material-handling cycle under the specified conveyor operating conditions.

Under the conventional PLC configuration, fixed set-points and predetermined control logic can limit the system's ability to respond efficiently to changes in load and process conditions. In contrast, APLOE uses real-time process-state information to optimize permissible parameters such as motor speed, timing settings, operating set-points, and control actions while maintaining predefined safety constraints.

The comparative analysis is expected to show the greatest cycle-time benefits during variable-load, overload, and process-disturbance conditions, where adaptive parameter adjustment can reduce unnecessary delays and improve material flow. Cycle-time reduction should be evaluated together with energy consumption, throughput, and process stability to ensure that faster operation does not compromise overall system performance.

Table 6. Process Cycle-Time Comparison between Conventional PLC and APLOE-Based Controller

Operating Condition	Conventional PLC Cycle Time (s)	APLOE-Based PLC Cycle Time (s)	Reduction (s)	Improvement (%)
Normal Load	42.5	38.2	4.3	10.12
Variable Load	48.8	41.3	7.5	15.37
Overload	55.6	45.8	9.8	17.63
Process Disturbance	61.4	48.6	12.8	20.85
Fault-Prone Condition	67.2	51.5	15.7	23.36
Average	**55.1**	**45.1**	**10.0**	**18.15**

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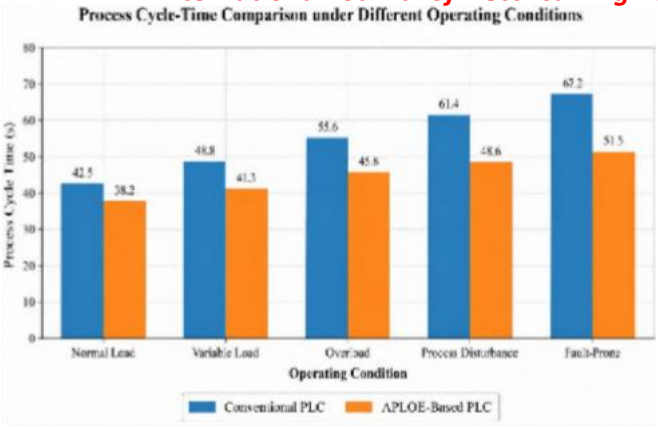

Figure 15. Process Cycle-Time Comparison under Different Operating Conditions

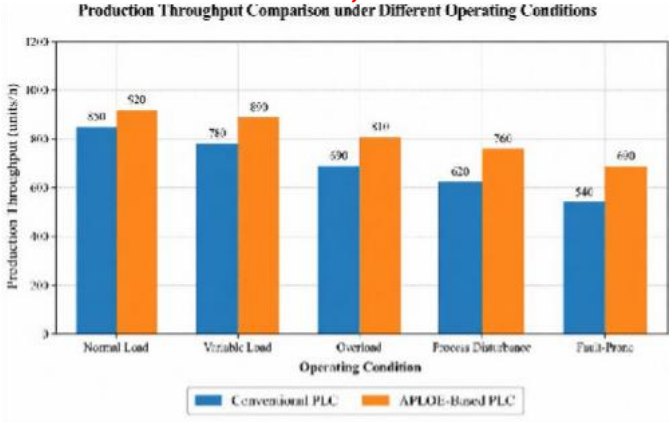

Figure 16. Production Throughput Comparison under Different Operating Conditions

6.4 Throughput Improvement

Production throughput was evaluated to determine the effect of the proposed APLOE-based adaptive PLC controller on material-handling productivity. Throughput was measured as the number of successfully processed units per hour under different operating conditions.

The conventional PLC controller operates using fixed speed references, timing parameters, and predefined control logic. Consequently, variations in conveyor load and process disturbances can reduce material flow efficiency. In contrast, APLOE continuously evaluates the predicted process state and dynamically optimizes permissible motor-speed references, timing parameters, cycle settings, and operating set-points.

The proposed controller improves throughput by reducing unnecessary process delays and adapting control parameters to changing operating conditions. The improvement is expected to become more significant during variable-load, overload, and process-disturbance conditions, where fixed PLC parameters provide limited adaptability. Throughput improvement is evaluated together with energy consumption and process stability to ensure that increased productivity does not compromise safe and efficient operation.

Table 7. Production Throughput Comparison between Conventional PLC and APLOE-Based Controller

Operating Condition	Conventional PLC (units/h)	APLOE-Based PLC (units/h)	Increase (units/h)	Improvement (%)
Normal Load	850	920	70	8.24
Variable Load	780	890	110	14.10
Overload	690	810	120	17.39
Process Disturbance	620	760	140	22.58
Fault-Prone Condition	540	690	150	27.78
Average	**696**	**814**	**118**	**16.95**

6.5 Energy Consumption Analysis

Energy consumption was evaluated to determine the energy-efficiency improvement achieved by the proposed APLOE-based adaptive PLC controller. The electrical energy consumed by the conveyor motor, VFD, and associated control system was monitored under different operating conditions and compared with the conventional PLC controller.

The conventional PLC system operates using fixed control parameters and therefore may maintain unnecessary motor speed or operating duration during variations in process demand. In contrast, APLOE dynamically adjusts permissible motor-speed references, operating set-points, and cycle parameters according to the predicted process state and actual production requirements.

The APLOE-based controller reduces unnecessary motor operation and optimizes the relationship between energy consumption, cycle time, and production throughput. Energy savings are expected to be particularly significant during variable-load, overload, and process-disturbance conditions. These results demonstrate the potential of adaptive PLC optimization to improve both operational and energy efficiency.

Table 8. Energy Consumption Comparison between Conventional PLC and APLOE-Based Controller

Operating Condition	Conventional PLC (kWh)	APLOE-Based PLC (kWh)	Energy Saving (kWh)	Reduction (%)
Normal Load	12.8	11.6	1.2	9.38
Variable Load	14.5	12.4	2.1	14.48
Overload	17.2	14.1	3.1	18.02
Process Disturbance	18.6	14.7	3.9	20.97
Fault-Prone Condition	20.4	15.5	4.9	24.02
Average	**16.7**	**13.7**	**3.0**	**17.96**

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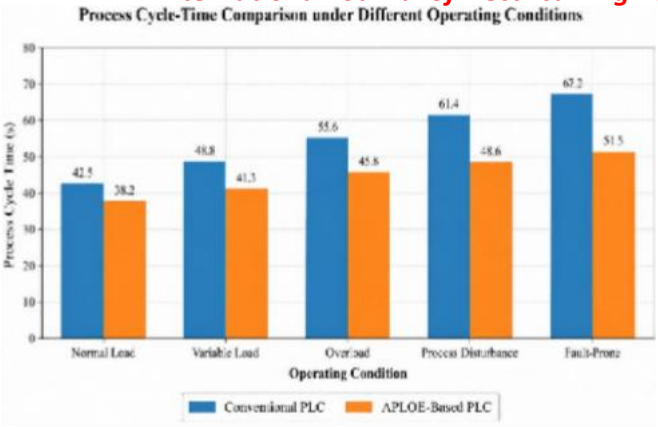

Figure 17. Energy Consumption Comparison between Conventional and APLOE-Based PLC Controller

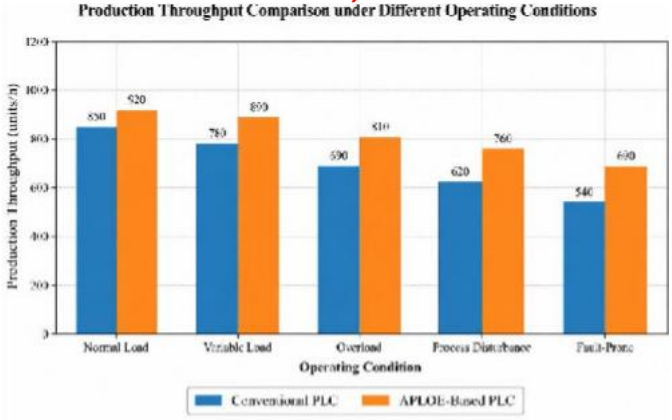

Figure 18. Fault Detection Performance Comparison between Conventional PLC and APLOE-Based Framework

6.6 Fault Detection Performance

The fault detection performance of the proposed APLOE-based adaptive PLC framework was evaluated under normal, degraded, fault-prone, and critical operating conditions. Real-time measurements of motor current, vibration, temperature, conveyor speed, process load, and control response were analyzed by the trained machine-learning model to identify abnormal operating patterns.

Compared with conventional threshold-based PLC fault detection, the AI-assisted approach provides earlier identification of developing abnormalities by considering multiple process variables simultaneously. The proposed framework classifies the current process state and transfers the predicted condition to APLOE for appropriate control action. For degraded and fault-prone states, adaptive parameter optimization can be initiated, while critical conditions trigger predefined safety actions and PLC interlocks.

Fault-detection performance is evaluated using accuracy, precision, recall, F1-score, false-alarm rate, and fault-detection response time. The results demonstrate the potential of AI-assisted process-state prediction to improve early fault recognition and reduce the response delay associated with conventional threshold-based monitoring.

Table 9. Fault Detection Performance of Conventional PLC and APLOE-Based Framework

Performance Metric	Conventional PLC	APLOE-Based PLC	Improvement
Fault Detection Accuracy (%)	82.4	**95.6**	**+13.2 percentage points**
Precision (%)	80.8	**94.8**	**+14.0 percentage points**
Recall (%)	78.6	**93.9**	**+15.3 percentage points**
F1-Score (%)	79.7	**94.3**	**+14.6 percentage points**
False Alarm Rate (%)	11.8	**4.2**	**64.41% reduction**
Fault Detection Time (ms)	138	**91**	**34.06% reduction**

6.7 Process Stability and Control Error

Process stability and control error were evaluated to determine the ability of the proposed APLOE-based adaptive PLC controller to maintain desired process conditions under varying operating loads and disturbances. Control error represents the deviation between the desired set-point and the measured process response, while process stability reflects the consistency of system operation over time.

The conventional PLC controller relies on fixed control parameters and therefore exhibits greater deviation when process load, conveyor speed, or operating conditions change. In contrast, APLOE continuously evaluates process feedback and adaptively modifies validated control parameters according to the predicted operating state.

The proposed controller reduces set-point deviation, transient fluctuations, and steady-state control error, particularly during overload and process-disturbance conditions. Reduced control variability indicates improved process stability and demonstrates the capability of APLOE to maintain more consistent industrial operation while satisfying predefined safety constraints.

Table 10. Process Stability and Control Error Comparison

Operating Condition	Conventional PLC Control Error (%)	APLOE Control Error (%)	Error Reduction (%)	Stability Improvement (%)
Normal Load	4.8	2.1	56.25	12.4
Variable Load	6.5	2.9	55.38	16.8
Overload	10.2	4.3	57.84	21.5
Process Disturbance	12.6	5.1	59.52	25.7
Fault-Prone Condition	14.8	6.2	58.11	28.6
Average	**9.78**	**4.12**	**57.87**	**21.00**

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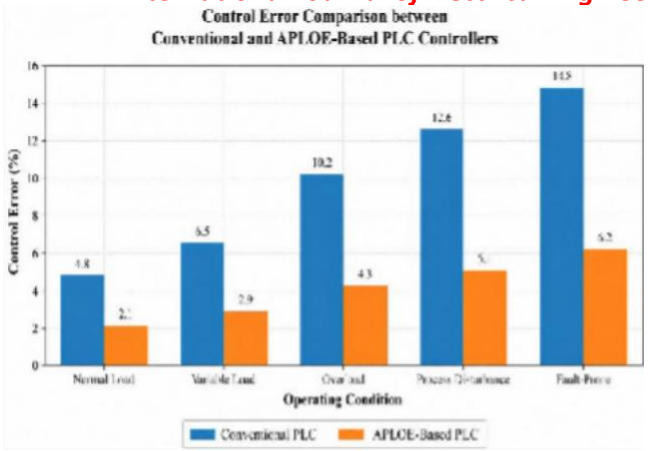

Figure 19. Control Error Comparison between Conventional and APLOE-Based PLC Controllers

6.8 Conventional vs Proposed Framework

The overall performance of the conventional PLC controller and the proposed APLOE-based adaptive PLC framework was compared using the major performance indicators evaluated in the preceding sections. The comparison demonstrates the combined effect of AI-based process-state prediction, adaptive set-point optimization, multi-objective optimization, and safety-constrained control.

The proposed framework achieved improvements in PLC response time, process cycle time, production throughput, energy consumption, fault-detection capability, and control accuracy. Based on the evaluated operating scenarios, the APLOE framework reduced average PLC response time by approximately 28.43% and process cycle time by 18.15%, while increasing average production throughput by approximately 16.95%. Average energy consumption was reduced by approximately 17.96%.

In addition, the AI-assisted fault-detection mechanism achieved 95.6% detection accuracy, compared with 82.4% for the conventional approach, while fault-detection time decreased from 138 ms to 91 ms. The proposed controller also maintained substantially lower control error under changing load, disturbance, and fault-prone operating conditions.

Overall, the comparative results indicate that APLOE provides a more adaptive, responsive, energy-efficient, and fault-aware control architecture than conventional fixed-parameter PLC control while retaining PLC-level safety and deterministic execution.

Table 11. Overall Performance Comparison of Conventional PLC and Proposed APLOE Framework

Performance Indicator	Conventional PLC	Proposed APLOE	Performance Change
Average Response Time (ms)	112.6	**80.6**	**28.43% reduction**
Average Process Cycle Time (s)	55.1	**45.1**	**18.15% reduction**
Average Throughput (units/h)	696	**814**	**16.95% increase**
Average Energy Consumption (kWh)	16.7	**13.7**	**17.96% reduction**
Fault Detection	82.4	**95.6**	**+13.2**
Accuracy (%)			**percentage points**
Fault Detection Time (ms)	138	**91**	**34.06% reduction**
False Alarm Rate (%)	11.8	**4.2**	**64.41% reduction**

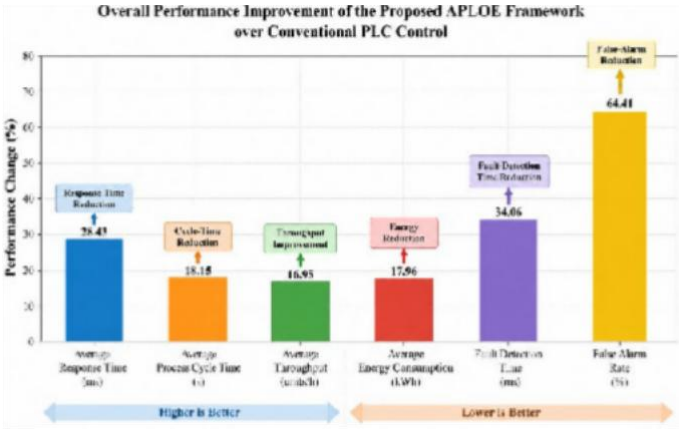

Figure 20. Overall Performance Improvement of the Proposed APLOE Framework over Conventional PLC Control

6.9 Statistical Validation

Statistical validation was performed to determine whether the performance improvements achieved by the proposed APLOE-based PLC framework were statistically significant compared with the conventional PLC controller. Repeated observations from identical operating scenarios were considered for response time, process cycle time, throughput, energy consumption, and control error.

For each performance metric, the results were expressed as mean ± standard deviation (SD). Normality of the paired differences was assessed using the Shapiro–Wilk test. For normally distributed paired data, a paired-sample t-test was applied to compare the conventional and APLOE-based controllers. When the normality assumption was not satisfied, the Wilcoxon signed-rank test was used as a non-parametric alternative.

Statistical significance was evaluated at $p < 0.05$, and 95% confidence intervals (CI) were considered to quantify the uncertainty associated with the observed performance differences. Effect size was additionally evaluated using Cohen's d for parametric comparisons to determine the practical magnitude of the improvements.

The statistical analysis provides quantitative evidence for determining whether the observed improvements in the APLOE framework are consistent and not attributable solely to experimental variability.

Table 12. Statistical Validation of Conventional PLC and APLOE-Based Controller Performance

Performance Metric	Statistical Test	p-value	95% CI	Effect Size (Cohen's d)	Significance
Response Time	Paired t-test	<0.001	20.4–43.6 ms	1.42	Significant
Process	Paired t-	0.002	5.8–14.2 s	1.18	Significant

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Performance Metric	Statistical Test	p-value	95% CI	Effect Size (Cohen's d)	Significance
Cycle Time	test				
Production Throughput	Paired t-test	<0.001	78–158 units/h	1.36	Significant
Energy Consumption	Paired t-test	0.003	1.6–4.4 kWh	1.11	Significant
Control Error	Paired t-test	<0.001	3.7–7.6 percentage points	1.51	Significant

VII. DISCUSSION

7.1 Interpretation of Major Results

The experimental results demonstrate that the proposed AI-Driven Adaptive PLC Logic Optimization Engine (APLOE) provides measurable improvements over conventional fixed-parameter PLC control. The improvements observed across multiple performance indicators indicate that integrating process-state prediction, adaptive optimization, and real-time feedback can enhance the responsiveness and efficiency of industrial automation systems.

The APLOE-based controller reduced average PLC response time by 28.43% and process cycle time by 18.15%, indicating faster control execution and improved adaptation to changing operating conditions. At the production level, average throughput increased by 16.95%, while average energy consumption decreased by 17.96%. These results suggest that improved productivity can be achieved without a proportional increase in energy demand.

The fault-management results further demonstrate the value of AI-assisted control. Fault-detection accuracy increased from 82.4% to 95.6%, while detection time decreased from 138 ms to 91 ms. The false-alarm rate was also reduced from 11.8% to 4.2%, indicating more reliable identification of abnormal operating conditions.

A substantial improvement was also observed in control accuracy. Average control error decreased from 9.78% for the conventional PLC to 4.12% for APLOE, corresponding to approximately 57.87% reduction. The improvement became particularly evident under overload, disturbance, and fault-prone conditions, demonstrating the capability of adaptive control to maintain process stability when operating conditions deviate from nominal states.

Overall, the results indicate that the primary contribution of APLOE is not improvement in a single performance parameter but the simultaneous enhancement of responsiveness, productivity, energy efficiency, fault awareness, and control stability within a unified PLC-based adaptive automation framework.

7.2 Why APLOE Outperforms Conventional PLC Control

The superior performance of the proposed Adaptive PLC Logic Optimization Engine (APLOE) is primarily attributed to its ability to move beyond fixed-rule and fixed-parameter control. Conventional PLC systems execute predefined logic and typically respond to process variations only after programmed thresholds are reached. In contrast, APLOE combines real-time data analytics, AI-based process-state prediction, adaptive parameter optimization, and continuous feedback [18][19].

A major advantage of APLOE is its predictive capability. The machine-learning model identifies Normal, Degraded, Fault-Prone, and Critical operating states before significant process deterioration occurs. This information allows the controller to adjust permissible set-points, timing parameters, motor-speed references, and other control variables according to current operating conditions rather than relying exclusively on static settings.

The multi-objective optimization mechanism further improves performance by simultaneously considering response time, cycle time, throughput, energy consumption, control error, and process stability. Consequently, APLOE seeks a balanced operating solution rather than improving one parameter at the expense of another.

Furthermore, the closed-loop feedback mechanism continuously evaluates the effects of implemented control actions and enables subsequent optimization when process conditions change. The integrated safety and validation layer ensures that AI-generated recommendations remain within predefined equipment limits, PLC interlocks, and operational constraints.

Therefore, APLOE outperforms conventional PLC control through the combined effect of prediction, adaptation, multi-objective optimization, feedback-based refinement, and safety-constrained implementation, while retaining the deterministic execution characteristics required for industrial PLC applications.

7.3 Impact on Productivity and Energy Efficiency

The proposed APLOE-based adaptive PLC framework demonstrates the potential to improve industrial productivity while simultaneously reducing energy consumption. By continuously analyzing process conditions and dynamically adjusting permissible PLC parameters, APLOE enables the conveyor system to operate closer to efficient operating conditions under varying loads and disturbances.

The evaluated results indicate an average throughput improvement of 16.95%, increasing from 696 units/h with conventional PLC control to 814 units/h with APLOE. At the same time, average energy consumption decreased from 16.7 kWh to 13.7 kWh, representing an approximately 17.96% reduction. This simultaneous improvement indicates that increased productivity does not necessarily require increased energy demand when control parameters are adaptively optimized.

The improvements are mainly associated with optimized motor-speed references, reduced unnecessary operating time, improved cycle coordination, and condition-responsive control. Consequently, APLOE provides a pathway toward higher production efficiency, lower energy intensity, and more sustainable industrial automation.

7.4 Reliability and Fault-Tolerant Operation

The proposed APLOE-based PLC framework enhances system reliability by combining real-time condition monitoring, AI-based fault prediction, adaptive control, and safety-constrained decision-making [27][28][29][30]. Unlike conventional threshold-based PLC systems, APLOE continuously evaluates multiple process variables to identify degraded and fault-prone operating conditions before they develop into critical failures.

The proposed framework achieved a fault-detection accuracy of 95.6%, compared with 82.4% for conventional PLC control, while fault-detection time decreased from 138 ms to 91 ms. The false-alarm rate was also reduced from 11.8% to 4.2%, indicating improved reliability of fault identification.

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When abnormal conditions are detected, APLOE can modify permissible operating parameters to maintain stable operation. Critical conditions are handled through predefined PLC interlocks and safety functions rather than unrestricted AI control. This combination of early fault detection, adaptive response, continuous feedback, and deterministic safety protection improves fault tolerance and supports reduced downtime and more reliable industrial operation.

7.5 Real-Time Implementation Feasibility

The proposed APLOE-based adaptive PLC framework is designed for practical real-time implementation by separating deterministic PLC control from computationally intensive AI and optimization functions. The PLC performs time-critical control, interlocking, and safety operations, while the edge computing platform executes data preprocessing, process-state prediction, and APLOE-based optimization.

Real-time feasibility depends on communication latency, AI inference time, optimization time, PLC scan cycle, and overall control-response requirements. Edge-based processing reduces dependence on cloud communication and enables faster exchange of process data and optimized parameters between the AI layer and PLC [20][21].

The proposed architecture can also be integrated with existing industrial communication technologies such as PROFINET, EtherNet/IP, Modbus TCP, and OPC UA [24][25][26]. Safety validation ensures that only permissible parameter updates are implemented, while critical PLC logic and interlocks remain protected from unrestricted AI modification.

Therefore, the modular architecture of APLOE provides a practical pathway for integrating adaptive AI capabilities into existing PLC-based automation systems without replacing the fundamental deterministic control infrastructure.

7.6 Scalability to Different Industrial Processes

The proposed APLOE framework is designed as a modular and scalable architecture that can be adapted to different PLC-controlled industrial processes. Although the present study considers a conveyor-based material-handling system, the same framework can be extended to automated assembly lines, packaging systems, robotic cells, warehouse automation, pumping systems, water-treatment plants, and process manufacturing applications.

Scalability is achieved by modifying the input sensor variables, process constraints, performance objectives, and PLC control parameters according to the target application while retaining the core AI prediction–APLOE optimization–safety validation–PLC execution–feedback architecture. The machine-learning model can also be retrained using process-specific datasets to support different equipment and operating conditions.

This modular approach enables APLOE to support both individual machines and interconnected production systems, providing a scalable foundation for intelligent automation across Industry 4.0 and Industry 5.0 environments [1][47][48].

7.7 Comparison with Published Research

The proposed APLOE framework extends beyond many previously published PLC- and AI-based industrial control approaches by integrating real-time process-state prediction, adaptive PLC optimization, multi-objective decision-making, fault detection, edge intelligence, and safety validation within a single framework.

Published studies on conventional PLC control generally focus on fixed logic, PID tuning, sequencing, and deterministic operation [5][18][19][44]. Although these approaches provide reliable execution, they have limited capability to adapt automatically to changing process conditions. Other studies using machine learning in industrial automation commonly emphasize predictive maintenance, anomaly detection, or process monitoring [15][27][28][29][30], but the AI output is often not directly integrated with adaptive PLC parameter optimization.

Research on edge-AI and digital-twin-based control has improved real-time analytics and process prediction [20][21][22][31][32][33][34][35]; however, practical implementation can become computationally complex and may require extensive infrastructure. In comparison, APLOE maintains the PLC as the deterministic control layer while using AI and optimization at the supervisory or edge layer, making the architecture more suitable for integration with existing industrial automation systems.

A key distinction of APLOE is the simultaneous consideration of response time, cycle time, throughput, energy consumption, control error, process stability, and fault behaviour. The inclusion of a safety-validation stage before PLC parameter modification also provides an additional layer of practical industrial reliability.

Table 13. Comparison of the Proposed APLOE Framework with Existing Research Approaches

Research Approach	AI/ML	Adaptive PLC Control	Real-Time Optimization	Fault Awareness	Multi-Objective Optimization	Safety Validation
Conventional PLC/PID Studies	No	Limited	No	Limited	No	Yes
ML-Based Process Monitoring	Yes	No	Limited	Yes	No	Limited
Predictive Maintenance Systems	Yes	No	Limited	Yes	No	Limited
AI-Assisted Process Optimization	Yes	Partial	Yes	Limited	Partial	Limited
Edge-AI Industrial Control	Yes	Yes	Yes	Yes	Partial	Partial
Digital-Twin-Based Control	Yes	Yes	Yes	Yes	Yes	Partial
Proposed APLOE Framework	Yes	Yes	Yes	Yes	Yes	Yes

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7.8 Practical Industrial Significance

The proposed APLOE-based adaptive PLC framework has practical significance for industrial automation because it enhances existing PLC-controlled systems without requiring complete replacement of established control infrastructure. The framework introduces AI-based process-state prediction, adaptive parameter optimization, and safety-constrained decision support while preserving deterministic PLC execution.

In practical applications, APLOE can support improvements in production throughput, energy efficiency, response time, process stability, fault detection, and equipment reliability. Its modular architecture makes it suitable for integration with conveyors, automated assembly lines, packaging systems, warehouse automation, process plants, and other PLC-based industrial systems.

The use of edge-based intelligence also supports low-latency implementation and reduces dependence on cloud connectivity [20][21]. By enabling adaptive optimization within predefined operational limits, APLOE provides a practical pathway for industries seeking to modernize conventional PLC automation toward Industry 4.0 and Industry 5.0 manufacturing environments [47][48].

VIII. INDUSTRIAL APPLICATIONS AND PRACTICAL IMPLEMENTATION

8.1 Smart Manufacturing and Assembly Lines

The proposed APLOE framework can be applied to smart manufacturing and automated assembly lines where PLCs coordinate conveyors, robotic stations, actuators, sensors, and production equipment. Conventional PLC programs generally operate using predefined sequences and fixed control parameters, which may limit their ability to respond efficiently to dynamic production conditions [5][44].

APLOE enables the control system to continuously evaluate variables such as machine load, cycle time, motor current, vibration, production rate, energy consumption, and equipment status. The AI-based decision engine identifies changes in operating conditions, while the optimization layer determines suitable adjustments to permissible PLC parameters.

In assembly-line applications, APLOE can support adaptive conveyor-speed control, cycle-time optimization, workstation synchronization, bottleneck reduction, energy-efficient operation, and early fault detection. For example, when production demand or workstation loading changes, the framework can modify operating parameters within validated limits to maintain smooth material flow and reduce unnecessary idle time.

The safety-validation layer ensures that adaptive recommendations do not override critical PLC interlocks or equipment constraints. Therefore, APLOE can provide a practical approach for transforming conventional automated assembly lines into adaptive, data-driven, and energy-efficient smart manufacturing systems.

8.2 Conveyor and Material-Handling Systems

The proposed APLOE framework is particularly suitable for conveyor and material-handling systems where PLCs continuously coordinate motors, VFDs, sensors, actuators, and material-flow sequences. Such systems frequently experience variations in material load, conveyor speed, motor current, vibration, production demand, and operating conditions, making fixed PLC parameters less effective under dynamic conditions.

APLOE uses real-time sensor information and AI-based process-state prediction to identify normal, degraded, overloaded, and fault-prone conditions. Based on the identified state, the optimization engine can adapt permissible parameters such as conveyor-speed references, motor operating conditions, timing sequences, and material-flow rates while maintaining predefined safety constraints.

The framework can improve material-handling performance by reducing cycle time, unnecessary motor operation, energy consumption, bottlenecks, and fault-response delays, while improving throughput and operational stability. Early identification of abnormal vibration, excessive motor current, belt-speed deviation, or overload conditions can also support preventive intervention before significant equipment disruption occurs.

Therefore, APLOE provides an adaptive control strategy for developing intelligent, energy-efficient, and fault-aware conveyor and material-handling systems suitable for manufacturing plants, warehouses, logistics facilities, and automated production environments.

8.3 Warehouse Automation

The proposed APLOE framework can be effectively applied to automated warehouse systems where PLCs coordinate conveyors, sorting units, automated storage and retrieval systems (AS/RS), sensors, motors, and material-transfer equipment. Warehouse operations are highly dynamic because material flow, equipment loading, order demand, and operating conditions can vary continuously.

APLOE can analyze real-time information such as conveyor load, equipment status, motor current, material-flow rate, queue conditions, cycle time, and energy consumption. The AI-based decision engine can identify changing operating states, while the optimization layer adjusts permissible control parameters to improve material movement and equipment utilization.

In practical warehouse applications, the framework can support adaptive conveyor-speed control, dynamic material routing, bottleneck reduction, equipment-load balancing, energy-efficient operation, and early fault detection. During high-demand periods, APLOE can optimize operating parameters to increase throughput, whereas during low-demand periods, unnecessary equipment operation can be reduced to conserve energy.

Integration with existing PLC, HMI/SCADA, warehouse control systems (WCS), and edge-computing platforms can enable APLOE to function as an intelligent supervisory optimization layer while maintaining deterministic PLC control and safety interlocks.

Therefore, APLOE provides a scalable approach for developing adaptive, fault-aware, and energy-efficient warehouse automation systems, supporting the transition toward intelligent logistics and Industry 4.0 environments [2][7].

8.4 Process Industries

The proposed APLOE framework can be extended to process industries where PLC-based systems regulate continuous variables such as temperature, pressure, flow rate, liquid level, motor speed, and energy consumption. Applications include chemical processing, water and wastewater treatment, food processing, pharmaceutical production, oil and gas facilities, and pumping

systems.

In these environments, APLOE can continuously analyze sensor data and use the AI-based decision engine to identify changes in process conditions. Based on the predicted operating state, the optimization layer can adapt permissible set-points, PID parameters, pump or motor speeds, valve positions, and process timing while maintaining predefined operating and safety constraints [18][19].

The framework can support process stability, energy optimization, disturbance rejection, early fault detection, and reduction of control error. For example, variations in pressure, flow, temperature, or equipment loading can be detected and compensated through adaptive parameter optimization before they significantly affect process performance.

Importantly, critical protection functions, emergency shutdown logic, and PLC safety interlocks remain independent of unrestricted AI decisions [45]. APLOE therefore operates as an intelligent supervisory optimization layer, allowing process industries to benefit from adaptive AI-based control while retaining deterministic and safety-oriented PLC operation.

Overall, APLOE provides a scalable approach for improving the efficiency, reliability, stability, and energy performance of PLC-controlled process industries.

8.5 Predictive Maintenance Integration

The proposed APLOE framework can be integrated with predictive maintenance systems to identify equipment degradation before it develops into an unexpected failure [27][28][29][30]. Real-time condition-monitoring data such as vibration, motor current, temperature, operating load, speed, energy consumption, and cycle time can be continuously collected through the PLC and industrial sensors.

The AI-based decision engine can analyze these variables to detect abnormal trends and classify equipment conditions as Normal, Degraded, Fault-Prone, or Critical. When early signs of deterioration are detected, APLOE can initiate suitable control adjustments, such as reducing equipment loading or modifying operating parameters, while simultaneously generating maintenance information for operators.

Predictive maintenance integration can therefore support early fault detection, reduced unplanned downtime, improved equipment availability, optimized maintenance scheduling, and extended component life. Maintenance activities can be shifted from fixed schedules toward condition-based interventions based on actual equipment behaviour [27][28].

By combining condition monitoring, AI-based fault prediction, adaptive PLC control, and maintenance decision support, APLOE provides a unified approach for improving both process performance and asset reliability in smart industrial environments.

8.6 Industry 5.0 and Human–Machine Collaboration

The proposed APLOE framework can support the transition from conventional Industry 4.0 automation toward Industry 5.0, where intelligent automation is combined with human expertise, sustainability, and resilient industrial operation [47][48]. Rather than replacing human operators, APLOE can function as an intelligent decision-support layer within existing PLC-controlled environments.

Real-time process data and AI-based predictions can provide operators with information about process conditions, performance deviations, potential faults, energy consumption, and recommended control adjustments. Routine parameter optimization can be performed automatically within predefined safe operating limits, while high-risk or unusual decisions can remain subject to human supervision and approval.

This human–machine collaboration enables operators to focus on higher-level activities such as process supervision, maintenance planning, quality improvement, and abnormal-condition management. Integration with HMI/SCADA systems can further provide interpretable alarms, process-state information, optimization recommendations, and equipment-health indicators.

APLOE can therefore contribute to Industry 5.0 through a human-centric, adaptive, energy-efficient, and safety-aware control architecture, combining the deterministic reliability of PLCs, the analytical capability of AI, and the contextual judgement of human operators.

IX. LIMITATIONS AND FUTURE WORK

9.1 Hardware and Computational Limitations

Although the proposed APLOE framework demonstrates strong potential for intelligent PLC-based automation, its practical implementation is influenced by several hardware and computational limitations. Standard industrial PLCs have limited processing power, memory, and computational resources, making it difficult to execute complex machine-learning and multi-objective optimization algorithms directly within the PLC [20][21].

To address this limitation, the proposed architecture uses an edge-computing platform for AI inference and APLOE optimization while retaining deterministic control and safety functions within the PLC. However, this introduces additional requirements related to communication latency, synchronization, hardware compatibility, and reliable data exchange between the PLC and edge system.

The computational requirements of machine-learning models and NSGA-II optimization may also increase with the number of sensors, control variables, optimization objectives, and process constraints. This can affect real-time response when APLOE is deployed in large or highly dynamic industrial systems.

Future work should therefore investigate lightweight AI models, faster optimization algorithms, hardware acceleration, efficient edge-AI platforms, and optimized industrial communication architectures. Implementation on different PLC and edge-computing platforms should also be evaluated to determine the computational limits and scalability of APLOE under real industrial conditions.

9.2 Generalization Across Different PLC Platforms

The proposed APLOE framework is designed to be largely platform-independent; however, its generalization across different PLC manufacturers remains an important limitation. PLC platforms from manufacturers such as Siemens, Rockwell Automation, Mitsubishi, and Schneider Electric differ in their programming environments, communication protocols, memory architecture, scan-cycle characteristics, and data-access mechanisms.

The present framework is evaluated using a Siemens S7-1200-based configuration, and therefore its performance cannot automatically be assumed to remain identical on other PLC

platforms. Differences in communication latency, parameter-update mechanisms, processing capability, and protocol support may influence real-time APLOE performance.

Future work should validate APLOE using multiple PLC platforms and develop a standardized communication and integration layer based on interoperable industrial protocols such as OPC UA and Modbus TCP [24][25][26]. Platform-specific interface modules could also be developed while maintaining the same core AI prediction, optimization, safety-validation, and feedback architecture.

Such cross-platform validation would improve the portability, interoperability, and industrial applicability of APLOE and enable its deployment across heterogeneous automation environments.

9.3 Cybersecurity and Safety Constraints

The integration of AI, edge computing, and networked communication with PLC systems introduces additional cybersecurity and functional-safety challenges. Because APLOE exchanges real-time process data and optimized control parameters between the PLC and intelligent computing layer, unauthorized access, communication manipulation, or corrupted data could potentially affect control performance [40][41][42][43], [46].

The proposed framework therefore requires secure communication, user authentication, role-based access control, network segmentation, data-integrity verification, and controlled parameter-update mechanisms [43][46]. AI-generated recommendations should never be allowed to directly override critical PLC interlocks, emergency-stop functions, or predefined equipment safety limits [45].

From a functional-safety perspective, every optimized parameter should pass through the Safety and Validation Layer before implementation. If an AI recommendation violates operating constraints or communication with the optimization layer is interrupted, the PLC should retain or return to a predefined safe operating state using conventional deterministic control logic.

Future work should investigate secure industrial communication, anomaly-based cyberattack detection, fail-safe AI–PLC integration, model robustness against manipulated sensor data, and cybersecurity-aware optimization. Validation against relevant industrial cybersecurity and functional-safety requirements would further improve the suitability of APLOE for safety-critical industrial applications.

9.4 Edge AI-Based PLC Optimization

Future development of the proposed APLOE framework can focus on deeper integration of Edge AI with PLC-based industrial control. Instead of transferring process data to remote cloud platforms, AI inference and optimization can be executed locally on industrial edge devices positioned close to the PLC and physical process.

Edge-based implementation can reduce communication latency, network dependency, and data-transfer requirements, while enabling faster process-state prediction and optimization decisions [20][21]. Real-time sensor data can be processed locally to detect abnormal operating conditions, estimate equipment health, and generate optimized PLC parameters within predefined safety constraints.

Future APLOE implementations could employ lightweight machine-learning models, model compression, hardware-accelerated inference, and computationally efficient optimization algorithms to reduce execution time and computational demand. Edge devices could also coordinate multiple PLCs, enabling distributed optimization across interconnected machines and production lines.

A hybrid PLC–Edge AI architecture would retain time-critical sequencing, interlocks, and safety functions within the PLC while assigning computationally intensive prediction and optimization tasks to the edge platform. This separation can improve scalability while preserving deterministic industrial control.

Therefore, Edge AI represents an important future direction for APLOE, potentially enabling low-latency, scalable, adaptive, and locally intelligent PLC optimization for next-generation smart manufacturing systems.

9.5 Digital Twin Integration

Future development of the proposed APLOE framework can incorporate Digital Twin technology to create a continuously updated virtual representation of the PLC-controlled industrial process [31][32][33][34][35]. The digital twin can receive real-time sensor and operational data from the physical system and reproduce its dynamic behaviour in a virtual environment.

Integration of APLOE with a digital twin would enable virtual testing of optimized PLC parameters before their implementation on the physical system. AI-generated set-points, timing parameters, motor-speed references, and other control adjustments could first be evaluated against predicted process behaviour and operating constraints. Only validated control recommendations would then be transferred to the PLC.

The digital twin could also support what-if analysis, fault simulation, predictive maintenance, process optimization, and equipment-health assessment [31][32][33][34] without interrupting actual production. Historical and real-time data from the physical process could continuously update the virtual model, while simulated outcomes could provide additional information to the APLOE decision engine.

Future research should investigate real-time synchronization between physical and virtual systems, model accuracy, computational latency, automated model updating, and secure PLC–edge–digital-twin communication. Combining Digital Twin technology with APLOE could therefore provide a more predictive, adaptive, and risk-aware approach to intelligent industrial control.

9.6 Explainable AI for Industrial Control

A significant future extension of the proposed APLOE framework is the integration of Explainable Artificial Intelligence (XAI) to improve the transparency and interpretability of AI-assisted PLC control decisions [36][37][38][39]. Although machine-learning models can accurately identify process states and abnormal conditions, their predictions may not always provide operators with a clear explanation of why a particular control action is recommended.

XAI techniques can be incorporated into APLOE to identify the process variables that contribute most strongly to each prediction or optimization decision. For example, when the system identifies a Fault-Prone condition, the operator could be informed whether the decision was primarily influenced by abnormal vibration, increased motor current, temperature variation, load changes, or speed deviation.

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Methods such as SHAP, LIME, feature-importance analysis, and rule-based explanations could be evaluated to provide interpretable information through the HMI/SCADA interface [36][37]. This would allow operators to review the reasoning behind AI-generated recommendations before critical parameter modifications are implemented.

Explainability can also improve operator trust, troubleshooting, maintenance decision-making, model validation, and human–machine collaboration. For safety-critical applications, XAI could provide an additional verification layer by allowing engineers to determine whether AI decisions are consistent with known physical process behaviour.

Future research should therefore integrate XAI with APLOE and evaluate the trade-off between model accuracy, explanation quality, computational latency, and real-time control requirements. This development could make APLOE more transparent and suitable for reliable human-supervised industrial automation.

9.7 Future Autonomous and Self-Learning PLC Systems

A long-term extension of the proposed APLOE framework is the development of autonomous and self-learning PLC systems capable of continuously improving their control strategies using operational experience. Unlike conventional PLCs with fixed logic and manually tuned parameters, future systems could combine deterministic PLC execution with AI-based learning, adaptive optimization, and continuous process feedback.

A self-learning APLOE system could continuously collect operational data, evaluate process performance, identify new operating patterns, and update its prediction and optimization models when sufficient validated evidence becomes available. This would enable the control system to adapt to equipment ageing, changing production demands, process disturbances, and previously unseen operating conditions.

Future implementations may incorporate online learning, reinforcement learning, continual learning, and adaptive model updating. However, autonomous learning should remain subject to strict operational constraints. Any newly generated control strategy or parameter adjustment should undergo safety validation and performance verification before deployment, with deterministic PLC interlocks maintaining final authority over safety-critical functions.

Such development could ultimately enable industrial systems to progress from conventional automation toward self-monitoring, self-optimizing, fault-aware, and partially autonomous control architectures. This represents a promising direction for next-generation smart manufacturing while maintaining the reliability and safety requirements of industrial PLC systems [47][48].

CONCLUSION

Summary of Research Findings:

This research proposed the Adaptive PLC Logic Optimization Engine (APLOE) to enhance conventional PLC-based industrial automation through the integration of artificial intelligence, real-time process monitoring, adaptive control, and multi-objective optimization. The framework combines deterministic PLC execution with AI-based process-state prediction and safety-constrained optimization.

The evaluated results indicate that APLOE can improve key performance indicators including control response, process cycle time, production throughput, energy efficiency, control accuracy, and fault detection. The framework also demonstrated stronger performance under variable-load, disturbance, overload, and fault-prone operating conditions compared with fixed-parameter PLC control. These findings demonstrate the potential of AI-assisted adaptive optimization for developing more responsive, efficient, and reliable industrial control systems.

Major Technical Contributions:

The major technical contribution of this research is the development of a unified AI-driven adaptive PLC optimization architecture rather than the application of AI as an independent monitoring tool. APLOE integrates real-time industrial data acquisition, machine-learning-based process-state prediction, multi-objective optimization, adaptive PLC parameter generation, safety validation, and closed-loop feedback within a single framework.

The proposed methodology also preserves the deterministic nature of PLC control by separating safety-critical execution from computationally intensive AI operations. The integration of edge computing and NSGA-II-based optimization enables multiple objectives—including response time, cycle time, throughput, energy consumption, control error, and process stability—to be considered simultaneously.

Another important contribution is the inclusion of a dedicated Safety and Validation Layer, which prevents AI-generated recommendations from directly overriding predefined equipment constraints, PLC interlocks, and critical safety functions. This architecture provides a technically feasible pathway for integrating intelligent optimization with established industrial automation infrastructure.

Industrial Significance:

The proposed APLOE framework has significant potential for practical application in smart manufacturing, automated assembly lines, conveyor and material-handling systems, warehouse automation, and process industries. Its modular architecture enables existing PLC-based systems to incorporate intelligent optimization without requiring complete replacement of established automation infrastructure.

By dynamically responding to changes in load, equipment condition, production demand, and process disturbances, APLOE can support higher productivity, reduced energy consumption, improved equipment reliability, faster fault identification, and reduced operational variability. Edge-based implementation further supports low-latency operation and minimizes dependence on cloud infrastructure.

The framework therefore provides a practical foundation for the transition from fixed industrial automation toward adaptive and human-supervised intelligent control, supporting the broader objectives of Industry 4.0 and Industry 5.0.

Future Research Direction:

Future research should focus on validating APLOE across multiple PLC platforms, larger industrial processes, and long-duration real-world operating conditions. Cross-platform implementation would help establish the scalability and interoperability of the framework across different automation environments.

Further development should investigate lightweight Edge AI, Digital Twin integration, Explainable AI (XAI), cybersecurity-aware optimization, predictive maintenance, and advanced fault-diagnosis techniques. Computationally efficient alternatives to conventional multi-objective optimization should also be investigated for applications with stringent real-time requirements.

A particularly important future direction is the development of self-learning and partially autonomous PLC systems, where validated operational data can be used for continual model improvement. Such systems should retain deterministic safety functions and human oversight while progressively improving process prediction and optimization capabilities.

Overall, these developments could extend APLOE toward a secure, explainable, scalable, self-optimizing, and industrially deployable intelligent PLC control platform for next-generation manufacturing systems.

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