



Computational Models Of Human–Machine Integration In Automated Systems

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Abstract

Modern automated manufacturing systems require high flexibility to accommodate rapid product customization and dynamic production demands. However, conventional Programmable Logic Controller (PLC)-based automation systems rely on static control logic and manual programming, resulting in long reconfiguration times, high operational complexity, increased human intervention, and susceptibility to errors. The primary objective of this research is to develop an intelligent, adaptive, and interpretable control framework that enables efficient real-time reconfiguration of manufacturing systems while minimizing manual effort and improving operational safety. To achieve this, the proposed Intelligent Adaptive Control Framework (IACF) integrates Knowledge Graph Modeling (KGM) for structured representation of machines, tasks, and dependencies, and a Double Deep Q-Network (DDQN) for optimal decision-making under dynamic conditions. A Human-in-the-Loop Explainable Artificial Intelligence (XAI) module provides transparent and interpretable recommendations, ensuring operator trust and validation. Additionally, a Model-Based Design (MBD) Programmable Logic Controller (PLC) auto-code generation engine automatically generates executable PLC code, while a digital twin simulation layer validates system performance and safety before deployment. Z-score normalization is applied to input features to improve learning stability. Experimental evaluation implemented in Python demonstrates that the proposed IACF achieves strong predictive performance with an Mean Absolute Error (MAE) attained lower value of 0.097. The framework provides precise forecasts with few errors, enhancing flexibility, effectiveness, and dependability in the reconfiguration of intelligent manufacturing systems, making it appropriate for use in practical applications.

Keywords: Human–Machine Integration, Intelligent Manufacturing Systems, Adaptive Automation, Real-Time System Reconfiguration, Industrial Artificial Intelligence, Digital Manufacturing.

1. Introduction

Developing user-friendly Human–Machine Interfaces (HMIs), ensuring that 10 is ethical, managing data complexity, finding a balance between autonomy and control, and establishing successful human-robot collaboration in an Industry 5.0 setting are some of these challenges [1]. Through the use of distributed sensors, digital twins, and cyber-physical systems, Industry 4.0 and the Industrial Internet of Things (IIoT) facilitate human-machine integration, improving process transparency, variability analysis, and decision-making in automated production facilities [2]. Because it connects human cognitive capacities to process control, the Human-Machine Interface makes it easier for operators and automated systems to communicate successfully, increasing efficiency and reducing errors in semi-automated sectors [3]. The Fifth Industrial Revolution emphasizes human–machine collaboration in retail and services, expands stakeholder roles, and integrates digital, physical, and biological technologies to enhance societal well-

being and future innovation [4]. Increasing automation, giving humans less control, data complexity, ethical and legal concerns, unclear future responsibilities, integrating Cyber-Physical Systems (CPS) with AI, and an unclear path forward for the advancement of human-machine cooperation are some of these obstacles [5]. Among the difficulties are striking a balance between human-centric goals and automation, distributing tasks fairly in human-machine collaboration, integrating sociotechnical designs, ensuring worker well-being, and fusing efficiency with sustainability in an Industry 5.0 setting [6]. Compared to Machine Learning (ML) algorithms, traditional rule-based Clinical Decision Support Systems (CDSS) rely on threshold limitations and repeated alerts, which result in reduced accuracy, alert fatigue, lower trustworthiness, lack of flexibility, and an inability to recognize complex patterns [7]. Conventional automation techniques provide predetermined tasks to both humans and robots, but they lack a clear framework for role distribution and cognitive collaboration [8].

Research Aim: The construction of an IACF that would enable better integration between human operators and PLC-based automated manufacturing processes through intelligent and adaptive system reconfiguration is the goal of a suggested research direction. This research uses Double DQN to make optimal decisions in complicated contexts and incorporates KGM to allow structured representation of machines, operations, and product dependencies. Furthermore, interpretable solutions are provided via human-in-the-loop XAI. The construction of an automated PLC code generation process using digital twin technology to simulate performance for system validation and optimization is another goal of the research.

Research Organization: Section 1 offers a background overview of the research's motivations. The research on contemporary methods for XAI, PLC automation, knowledge graph models, human-machine interaction, and RL is given in Section 2. An overview of the suggested IACF is presented in Section 3. The experimental setup and findings are described in Section 4. Conclusions from the performed research are presented in Section 5.

2. Related Works

Table 1 provides an examination of some of the most significant research conducted in the field of industrial automation, with an emphasis on the research goals, methodology, results, and limitations. Human-Cyber-Physical Systems (HCPS), IoT, PLC, and smart systems have all been used in some of the comparisons.

Table 1: Comparative Analysis of Industrial Automation Research Approaches

Ref	Objective	Method	Result	Limitations
[9]	Propose updated automation levels for nuclear reactors	Develop a six-level framework with industry comparisons	Analyse the impact of software automation on industries	Challenges, gaps, and technology requirements remain unresolved
[10]	Analyze the impact of software automation on industries	Review applications using data analytics and ML	Improved efficiency, productivity, reliability, and decision-making capabilities	Integration challenges, training requirements, and change management issues
[11]	Develop a flexible Smart Cyber-Physical Systems (SCPS) architecture for Industry 5.0	Model workflows using Voltage Frequency Islands (VFI) and control techniques	Improved flexibility, integration, and automation efficiency achieved	Complexity, integration challenges, and scalability issues remain
[12]	Analyze the Internet of Things (IoT) role in Industry digital transformation.	Review applications, implementation, and evolution of IIoT	Improved productivity, communication, automation, and operational efficiency	Challenges in implementation, integration, and future scalability
[13]	Enable adaptive PLC-based manufacturing system reconfiguration automatically.	Knowledge graphs and Graph Neural Network (GNN)-based automated PLC generation	Reduced coding effort and improved reconfiguration efficiency	Requires human collaboration for complex reconfiguration tasks
[14]	Analyse PLC development trends for industrial sustainability	Use expert interviews, fuzzy Delphi, and analysis	Identified key PLC components and improvement priorities	Relies on expert opinion, limited empirical validation

[15]	Evaluate PLCnext as an industrial image processing platform	Compare PLC performance with a computer using algorithms	Feasible for low-complexity machine vision applications	Limited processing power restricts high-complexity applications
[16]	Model human-like control behavior in dynamic systems	Nonlinear modeling, machine learning, and reinforcement techniques	Improved understanding of human control in systems	Difficulty unifying diverse modeling approaches effectively
[17]	Explore human-machine collaboration in advanced manufacturing systems	Literature synthesis on CPS, AI, and robotics	Improved efficiency through AI and collaborative robotics integration	Ethical concerns and the need for continuous human training
[18]	Improve safety in human-robot collaborative manufacturing systems	Deep learning (DL)-based Digital Twin with supervised detectors	Accurate detection and classification of human-robot actions	Requires extensive training data and system synchronization

Research gap: Past research has sought to increase automation's flexibility and efficiency [9], although knowledge graphs in PLC automation require humans to accomplish challenging tasks even if they require less coding effort [13]. The proposed IACF framework addresses these gaps by integrating Reinforcement Learning (RL) and XAI to enable real-time adaptive learning, autonomous PLC code generation, and transparent decision-making, thereby reducing human dependency while improving flexibility, interpretability, and system intelligence in dynamic manufacturing environments.

3. Methodology of Intelligent Adaptive Control Framework (IACF)

Figure 1 shows how the IACF works in PLC-based manufacturing systems and covers the entire process, starting from data gathering and standardization through Z-scores to knowledge graph modeling, decision making by the DDQN, and explainability by SHAP values. The IACF includes a digital twin validation step and automatic PLC code generation by MBD technologies.

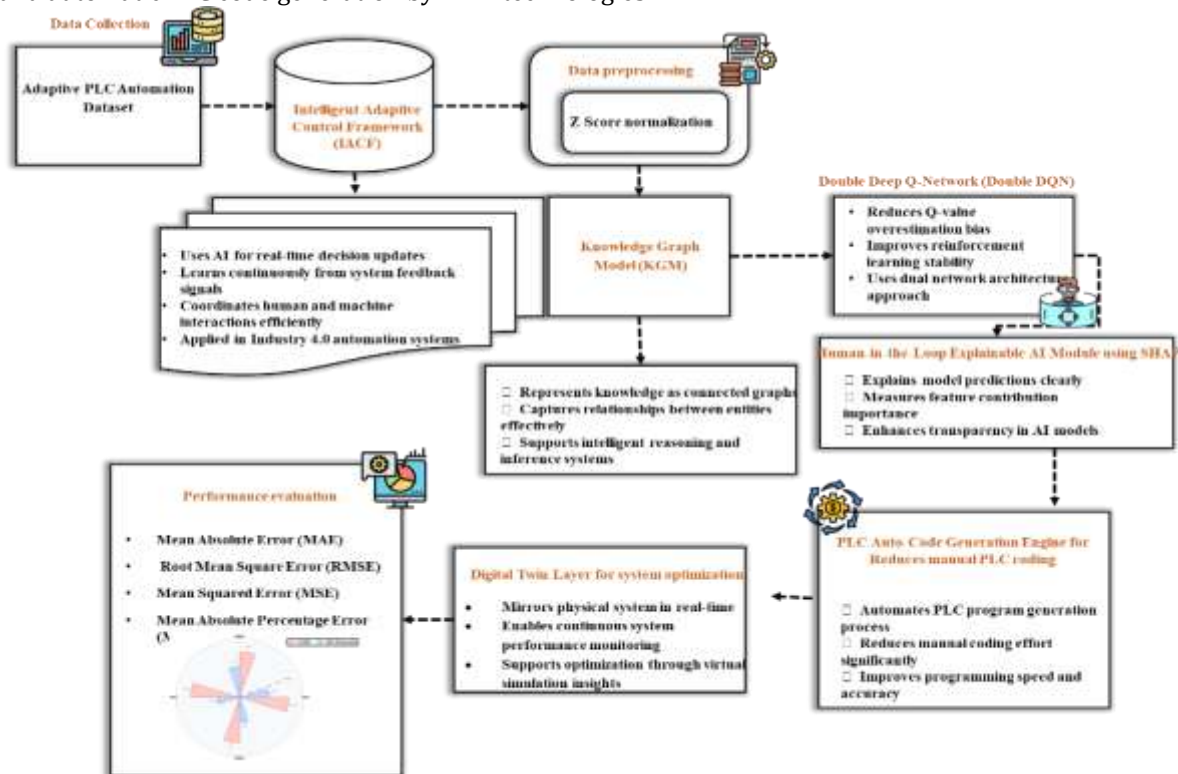


Figure 1: IACF for PLC-Based Smart Manufacturing Systems

3.1 Data collection

The Adaptive PLC Automation Dataset supports intelligent analysis of industrial automation processes controlled by PLC systems for data-driven decision support frameworks. It encompasses 11,500 samples comprising time-series sensor readings, machine operational states, and control signal parameters collected from both the present world and simulated production environments. The attributes considered represent major industrial factors such as equipment status, process conditions, and system response behaviors, and analysis of automation efficiency, fault detection, and optimizing workflow performance in

smart manufacturing systems. The dataset is split into 75% for building the models and 25% for their performance testing.

Kaggle Source: <https://www.kaggle.com/datasets/colabsss/adaptive-plc-automation-dataset>

3.2 Data preprocessing using z-score normalization

The pre-processing of data for this research entails converting the unstructured data collected from industrial automation processes into an appropriate structure that is useful in simulating the interaction between the machines and human operators throughout the automation process. A certain amount of noise, missing data, or measurement inconsistencies may occasionally be present in the data collected from PLC operations, machine status, sensor data, and information from task execution.

$$Z - \text{Scored } EMG_{e,g,j} = (EMG_{e,g,j} - \mu_{train,j}) / \sigma_{train,j} \quad (1)$$

In Equation (1), the standardized representation of a raw industrial signal in the automated systems' human-machine integration framework is called $Z - \text{Scored}$. The value of the raw signal acquired from the industrial automation system is shown by $EMG_{e,g,j}$. e is the manufacturing process's execution instance or event cycle; g is the automated manufacturing plant's machine group or subsystem; and j is a feature index, such as a sensor value or machine status value. The average value of feature j from training samples is represented by $\mu_{train,j}$. The standard deviation of feature j from training samples is represented by $\sigma_{train,j}$.

3.3 Knowledge Graph Model (KGM) for Adaptive Control Systems

KGM is an organized method that uses a graph to model the knowledge utilized in industrial automation operations. In this approach, manufacturing activities, sensors, machines, and control signals are represented as nodes in a graph with distinct relationships to one another. The model's capacity to simulate interactions enables semantic comprehension of the behavior of automated systems. PLC and sensor raw data are transformed into knowledge that is useful for relational reasoning and effective information processing.

3.4 DDQN for Industrial Decision Making

The focus of DDQN is to address the issue of overestimating the action value estimate in the value-based RL method used for adaptive control. In automated industrial processes, overestimation can happen because the adaptive model incorrectly estimates rewards associated with carrying out specific reconfiguration activities. In PLC-based control systems, where numerous operations have almost equal performance results, the effect is more noticeable. By separating action selection from Q-value estimation, DDQN reduces bias in Q-value prediction.

$$R^{estimation}(t, b) = R^{target}(t, b) + Y_t^b \quad (2)$$

Equation (2) represents $R^{estimation}(t, b)$, which is the reward value estimated from the Double DQN Model, and t is the time period in the manufacturing process, and b is a particular manufacturing process, batch, or instance. $R^{target}(t, b)$ is the reward value that is used in training. Y_t^b is the correction factor/error term.

$$Y^{DDQN} = q_t^b + \gamma * R(t', arg \max R(t', b', \theta)\theta') \quad (3)$$

In Equation (3), the double DQN value is Y^{DDQN} to make the best reconfiguration action; it reflects the optimum action value. The Q-value of the current time step t for state b is denoted by q_t^b . The discount factor, denoted by γ , is between 0 and 1 and determines the relative importance of the system's immediate performance and long-term benefits. t' is the future time step following the manufacturing process action. b' is the next production batch or the system's future state. θ The online network's model parameters employed for action assessments. θ' is the target network specifications utilized to determine trustworthy reward values. $arg \max R(t', b', \theta)\theta'$ selects the best course of action depending on the online network. $R(t', arg \max R(t', b', \theta)\theta')$ represents the system's reward function.

$$K(\theta) = F[(Y^{DDQN} - R(t, b, \theta))^2] \quad (4)$$

In Equation (4), the loss function (cost function) is denoted by $K(\theta)$. The expected Q-value from the current network is indicated by $R(t, b, \theta)$. $[(Y^{DDQN} - R(t, b, \theta))^2]$ represents the squared error of the temporal difference, which assesses the disparity in performance and penalizes incorrect action value estimation. The expectancy operator is denoted by F .

3.5 Human-in-the-Loop XAI Module using SHAP

To enhance transparency and interpretability in human-machine integrated automated systems, SHapley Additive exPlanations (SHAP) is utilized to explain the predictions generated by the adaptive control-based computational model. SHAP quantifies the contribution of each input feature, including sensor signals, environmental disturbances, and operator interactions, toward the final decision outcome. This approach enables the identification of critical factors affected by industrial noise and system variability. By filtering

irrelevant disturbances and emphasizing meaningful patterns, SHAP improves decision clarity, consistency, and reliability. Furthermore, it provides both global and local interpretability, strengthening trust and accountability in intelligent PLC-based automation environments.

3.6 Model-Based Design (MBD) PLC auto-code generation engine

By integrating the system dynamics into the control mechanism, MBD transforms tested models into programmable PLC codes. The system is first modeled using differential algebraic equations, and then the model is tested or verified using test data. After the model has been validated, it is utilized to create a controller that maximizes system performance while adhering to the necessary limitations.

$$e\left(\frac{dw(s)}{ds}\right), w(s), v(s), \theta, s = \theta \quad (5)$$

In Equation (5), e is a model function that describes the relationships among system dynamics, input, and parameters. $dw(s)$ is an infinitesimal variation of the function w due to the infinitesimal variation of s . ds refers to an infinitesimal variation of the independent variable s . $\frac{dw(s)}{ds}$ derivative of state $w(s)$ by variable s , measures the state variation relative to the variation of the independent variable s . $v(s)$ is an input or control variable for the system. θ Parameters of the system describe the system. s independent variable of the system. Right-hand side of θ the system output expression indicating the dependence on the parameters.

$$h(w(s), v(s), \theta, s) = \hat{z}(s) \quad (6)$$

Equation (6), h is the output function that converts the system's internal inputs and states into observable outputs. $\hat{z}(s)$ is the model's estimated or anticipated output at s . $h(w(s), v(s), \theta, s)$ function that maps the system's internal state $w(s)$, input $v(s)$, model parameters θ , and independent variable s into a predicted measurable output.

$$\varphi^* = \arg \max_{\varphi \in C} \{\psi\} \quad (7)$$

In Equation (7), represent the φ^* is the optimal value for the design variable φ . $\arg \max_{\varphi \in C} \{\psi\}$ "Argument of the maximum" returns the value of φ and not the maximum value itself, but the argument at which the maximum is obtained. $\max_{\varphi \in C}$ is the design variable φ is belongs to the design space C . $\{\psi\}$ is the objective/design criterion function measuring performance/information/quality.

3.8 Digital Twin Layer for system optimization

With the creation of a virtual, current-time model of the physical manufacturing process, the role played by the Digital Twin layer in the process becomes necessary for achieving optimization. The digital twin is used to create the intelligent interface that is responsible for linking the MBD-generated PLC logic and the MBD_{oE}-based calibration models. Information from sensors can be used to identify defects, predict system failures, and track performance. The performance of the system can also be improved before implementation through proper optimization using the digital twin. Changes in the requirements of the production process can also be accommodated.

Algorithm 1: Intelligent Adaptive Control Framework (IACF)

Input: $D \rightarrow$ Industrial dataset, $G \rightarrow$ Knowledge Graph, $\text{MaxEp} \rightarrow$ Episodes, $\gamma, \epsilon \rightarrow$ RL parameters,

$M \rightarrow$ MBD models, $\text{Sim} \rightarrow$ Digital twin

Output: $C^* \rightarrow$ Optimized reconfiguration strategy, $\text{PLC_code} \rightarrow$ Generated PLC logic

Begin

1. Load dataset D and construct Knowledge Graph G
2. Preprocess data: normalize features, handle noise, and map to state space S using G
3. Initialize Double DQN with Q-network $Q(s,a;\theta)$, target network $Q'(s,a;\theta')$, and replay memory R
4. For each episode (1 to MaxEp):
 - Initialize state s
 - For each step t :
 - Select action a using ϵ -greedy policy
 - Execute action, observe reward r and next state s'
 - Store (s,a,r,s') in R and sample mini-batch
 - Compute target:
 - $Y = r + \gamma Q'(s',a;\theta')$
 - Update Q-network using loss $L = (Y - Q(s,a;\theta))^2$
 - Update state $s \leftarrow s'$
 - Periodically update target network.

5. Generate interpretable decisions using XAI and validate with human-in-the-loop feedback.
6. Convert optimized strategy C^* into model M and auto-generate PLC_code using MBD
7. Validate PLC_code in digital twin Sim; if constraints fail, refine policy
8. Return C^* and PLC_code

End

Algorithm 1 represents facilitating intelligent and adaptive decision-making in automated manufacturing systems. The IACF framework integrates the knowledge graph methodology with DDQN. To identify the best ways to modify these dynamic systems, the IACF framework pre-processes industrial data into states. After that, recommendations are generated by the XAI tool and verified by human experts. MBD is used to incorporate these changes into the PLC code. To confirm the outcomes of the reconfiguration procedure, a simulation is carried out.

4. Result and Discussion

When knowledge graphs, Double DQN, and XAI are combined, the suggested IACF model demonstrates how intelligent and scalable an adaptive reconfiguration mechanism could be in a manufacturing setting. This approach improves decision-making efficiency, adaptability, and overall manufacturing process safety while reducing PLC programming efforts. When MBD is implemented, control logic can be automatically generated. In the meantime, decisions are tested and validated prior to execution using the digital twin. Python is used to create the solution using RL frameworks.

Data feature exploration analysis: In relation to adaptive decision-making and system reconfiguration analysis, Figure 2 illustrates intelligent industrial automation. The DQN confidence score, digital twin safety score, and decision accuracy percentage are correlated in Figure 2 (a), where the adaptability index is displayed using color intensity and confidence values increasing from 0.6 to 1.0 with corresponding accuracy rising from 60% to 95%, while adaptability varies between 50 and 100. Figure 2 (b) displays four different system reconfiguration statuses of successful, unsafe, operator review, and failed, ranging from -150 to 200, highlighting performance fluctuations across multiple reconfiguration conditions and system states.

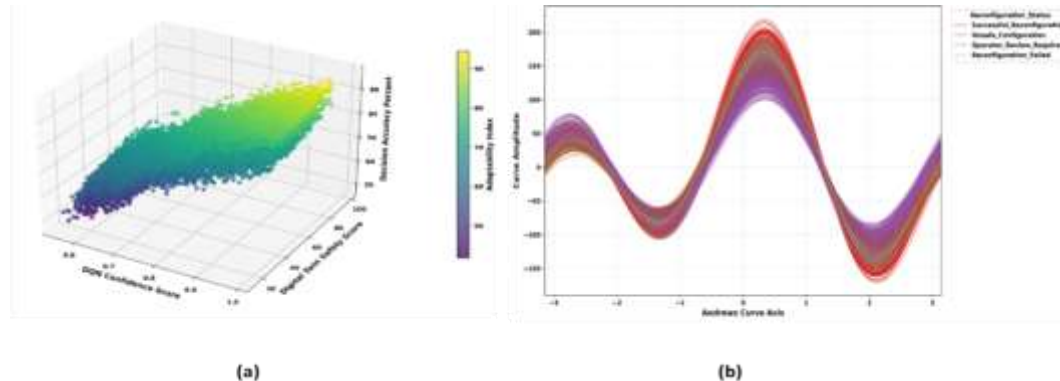


Figure 2: Intelligent reconfiguration analysis of (a) confidence safety accuracy index, (b) curve representation of reconfiguration

Outcome of SHAP analysis: Figure 3, showing the feature importance, illustrates the effects of different system parameters on the predictive outputs. Here, each data point represents the degree and the nature of the impact that is either positive or negative for each feature. Major contributors to the model outputs include the adaptability index, decision accuracy, and confidence scores, among others.

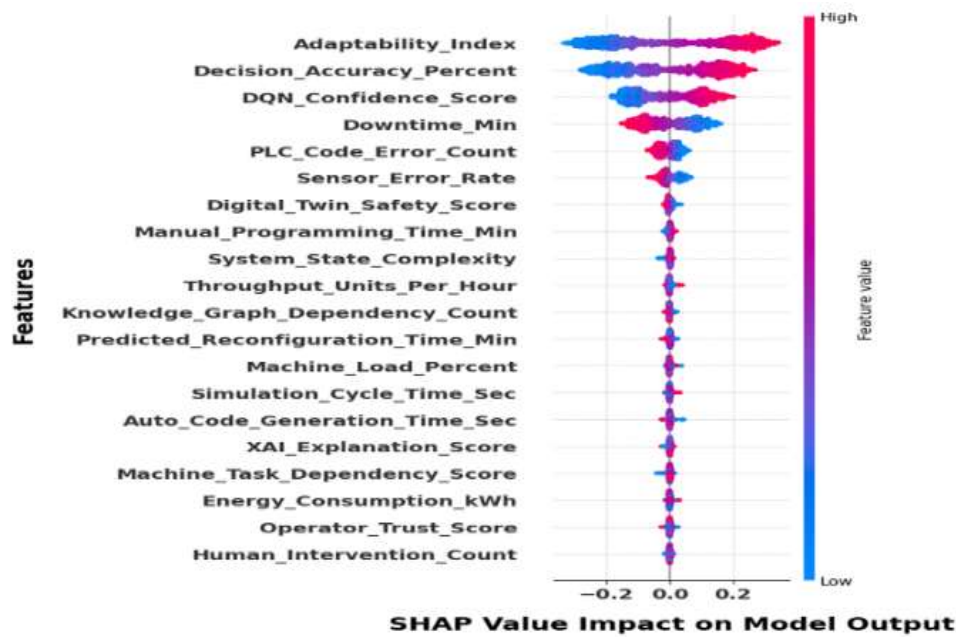


Figure 3: Feature-wise Impact on Model Output Using SHAP Value Distribution

Differentiating analysis: The performance metrics measure the effectiveness of a model in predicting results in human-machine systems. They help assess evaluate model prediction errors, reliability, and capability to identify variation between human-generated inputs and automated processes.

Mean Absolute Error (MAE): Actual and predicted values in a combination of human and machine systems. The statistic shows how well the computer model illustrates the connections between human and automated processes working together.

Root Mean Square Error (RMSE): The square root of the mean of the squared discrepancies between actual and predicted values is shown here. When evaluating crucial errors in human-machine cooperation.

Mean Squared Error (MSE): This metric represents the arithmetic mean of the squared error of forecasts, assessing greater weight to larger differences. MSE serves as a gauge for computer modeling's stability and effectiveness in learning from human and machine operations.

Mean Absolute Percentage Error (MAPE): This is the percentage that separates the actual data from the projections. MAPE serves as a gauge for how well computer models handle differences in automated process output and human input.

Performance evaluation using the Adaptive PLC Automation Dataset: Complete performance comparison of the R-CNN [18] model and the proposed IACF model trained using the Adaptive PLC automation dataset. Several criteria for measuring error values, such as MAE, RMSE, MSE, and MAPE, are considered in the analysis of the accuracy and consistency of prediction by both models, as shown in Table 2 and Figure 4. From the results, the proposed model outperforms the R-CNN terms of error values, hence the capability to learn and generalize.

Table 2: Performance Benchmarking of DL Models for PLC Automation

Methods	MAE	RMSE	MSE	MAPE
R-CNN	0.164	0.221	0.049	8.92
IACF [proposed]	0.097	0.149	0.022	4.87

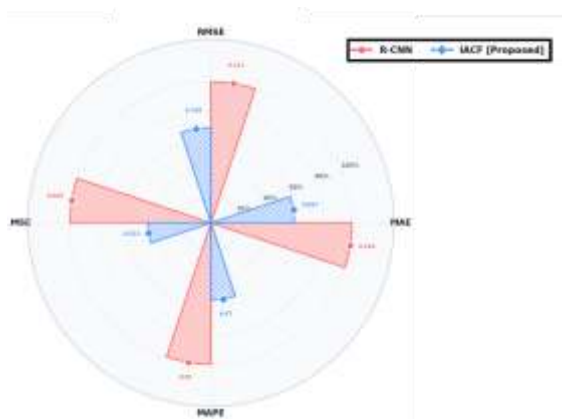


Figure 4: Performance Comparison of R-CNN and Error Metrics

Earlier research [13] and [18] have made great strides, they are still limited in some crucial areas. [13] still requires human intervention for challenging PLC reconfiguration even after automation, and [18] heavily relies on large training sets and strict synchronizations, which increases system complexity. IACF addresses these issues by using digital twin modeling and ML to automatically create PLC codes with minimal human intervention. It encourages flexibility, reduces the need for data, and guarantees improved human-machine collaboration in an industrial setting.

5. Conclusion

Intelligent systems can aid in enhancing human-machine contact's coordination, adaptability, and decision-making process, according to an experiment using computational models of human-machine interaction in automation systems. By using digital twins, intelligent computational models, and learning control models, the system's total performance improves by boosting efficiency and prediction effectiveness. The experimental results show that the suggested IACF is superior to the MAE of 0.164, RMSE of 0.221, MSE of 0.049, and MAPE of 8.92. Scalability, integration, the precision of the sensors employed, and the quality of the dataset used to train the model are all issues with the suggested solution. Dealing with difficult situations that need some human intervention presents difficulties for the suggested approach. Future research tools could involve investigating self-sufficient solutions, enhancing edge-cloud integration, real-time learning, and synchronizing the Digital Twin.

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