Edge-Enabled Explainable Reinforcement Learning for Safe and Scalable Feedback Control Loop Optimization in IoT-Integrated Industrial Automation Systems

V. Subba Ramaiah[1], Kota Lakshmi Prasanna[2], Kasula Raghu[3], Padma Parshapu[4], Vinisha J[5] and Syed Zahidur Rashid[6]

[1]*Department of CSE, Mahatma Gandhi Institute of Technology, Gandipet, Hyderabad, Telangana, India*
[2]*Department of Computer Science and Engineering, Ravindra College of Engineering for Women, Kurnool-518002, Andhra Pradesh, India*
[3]*Department of ECE, Mahatma Gandhi Institute of Technology, Gandipet, Hyderabad, Telangana, India*
[4]*Department of Computer Science and Engineering (DS), CVR College of Engineering, Hyderabad, Telangana, India*
[5]*Department of CSE, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India*
[6] *Department of Electronic and Telecommunication Engineering, International Islamic University Chittagong, Chittagong, Bangladesh*

Keywords: Edge Computing, Explainable Reinforcement Learning, Industrial IoT, Feedback Control Optimization, Multi-Agent Systems.

Abstract: The introduction of artificial intelligence in industrial automation has led to the control systems reaching a much higher level, however, it seems that the traditional approaches are often not realtime deployable, scalable and explainable. This study presents an edge-enabled explainable RL framework to optimize feedback control loops in IoT-integrated industrial systems. Unlike conventional RL models performing simulations, we demonstrate the proposed system in real environments by an edge device-based resource economical deep reinforcement learning. The framework guarantees safety-sensitive decision making, interpretable control, and portability to a variety of heterogeneous industrial missions. This work provides powerful combined solutions by integrating lightweight AI models with on-the-fly IoT data streams for adaptable, energy efficient, and automated control operations. Moreover, automatic hyperparameter tunning and multi-agent scalability are introduced to improve the robustness and the real-time performance in such complex industrial environment. The framework overcomes limitations of existing models and defines a transferable and modular approach for Industry 4.0 ready automation systems.

1 INTRODUCTION

With the rapid development of Industry 4.0, there has been an increasing need for intelligent, autonomous, and adaptive control systems in industrial automation. As industrial processes evolve towards widespread use of Internet of Things (IoT) infrastructure to monitor and control production environments, complexity and volume of data geerated have exceeded the performances of traditional feedback systems. At the same time, the reinforcement learning (RL) has been proven as a powerful model of sequential decision-making and dynamic optimization. But till now the majority of RL-based control applications can merely achieve theoretical simulations and cannot be rolled out on an industrial scale due to lack of the robust, scalability and real-time property, which are essential for practical engineering applications.

One very important problem in ICSs is to optimize feedback loops, under strict latency, energy and safety constraints. Whilst deep reinforcement learning approaches are very promising, they tend to require high computational resources and experience challenges with explainability and issues with stability during training. In addition, industries run in complex dynamic environments and require models

Ramaiah, V. S., Prasanna, K. L., Raghu, K., Parshapu, P., Vinisha, J. and Rashid, S. Z.
Edge-Enabled Explainable Reinforcement Learning for Safe and Scalable Feedback Control Loop Optimization in IoT-Integrated Industrial Automation Systems.
DOI: 10.5220/0013886900004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 2*, pages 593-599
ISBN: 978-989-758-777-1

to be transparent, safe for exploration, and flexible. These constraints require a control structure which not only permits learning of optimal behaviors, but also delivers interpretable, safe and scalable solutions, deployable on-line.

This paper deals with these challenges by introducing an edge-enabled and interpretable reinforcement learning approach designed for feedback control loop optimization in IoT-enabled industry application. Using low-power edge intelligence, the framework provides on-site decision power at low-latency and low dependence with centralised cloud infrastructures. Furthermore, explainable AI methods are incorporated to increase the transparency and trust in control decisions, by giving human operators the possibility to interpret the logic behind automatic actions. The architecture adopts multi-agent reinforcement learning to facilitate scalable deployment on heterogeneous, distributed industrial subsystems, and supports hyperparameter tuning in an automatic manner, which can eliminate tedious manual intervention and enhance training stability.

By real-world validation on industrial cases and the integration with real-time IoT data streams, this work narrows down the gap between academic research and future deployment. It paves the way for intelligent, transparent, and autonomous control systems, which represents a milestone in industrial automation and adaptive process optimization.

2 PROBLEM STATEMENT

Despite numerous tools and solutions for industrial automation, the intelligent, adaptive and efficient feedback control is still a hard task and the same holds true for IIoT-driven real-time systems with data received from IoT devices that are heterogeneous in nature. Classical controllers do not work effectively in unstructured environments in which uncertain system models dynamically vary and operational conditions change. Reinforcement learning has offered a new hope to overcome these limitations by learning how to control systems from knowing the environment. However, the majority of current RL-based methods still stay in the simulation and theoretical validation instead of having robustness and real-world integration for practical applications.

Furthermore, the typical deep reinforcement learning based approaches are computationally expensive and thus they cannot be directly applied onto inexpensive edge devices often used for industrial IoT scenarios. Lack of explainability, in those models, also reduces even further their acceptability in critical systems, where transparency and human interpretability are key properties for guaranteeing safety and compliance. Moreover, the existing methods are not easy to transfer between multiple inter-connected industrial units (manufactured from the same company) or change over domains without much retraining. These shortcomings emphasize the need for an efficient and adaptive feedback control optimization framework that is also explainable, scalable, and deployable on resource-limited edge infrastructure.

This work aims to tackle these challenges by devising an RL-based feedback control system, which can be seamlessly integrated with IoT devices, is able to support explainable decision-making, to work safely in real-time, as well as to have wide applicability in different industrial contexts.

3 LITERATURE SURVEY

The increasing need for intelligent control in industrial automation has led to significant research interest in the fusion of artificial intelligence (AI), in particular reinforcement learning (RL), and cyber-physical systems. Reinforcement learning has recently been revealed as potential solution for dynamic decision-making systems, especially under environments where the classical control solutions cannot cope, due to either (semi-)stochasticness or (non-)linearity. 1.4. Dogru et al. (2024) provide an overview of RL activities in process industries in the early 21st century, because of the shift towards model-free control schemes and the major improvements in closed-loop performance observed on simulations. However, they also stress there are few practical real-world applications of these techniques, a perspective shared by Kannari et al., 2025), who describe some challenges of applying RL to real buildings: sensor noise, exploration safety, and infrastructure heterogeneity.

Martins et al. (2025). They also provide a systematic review of combinatorial optimization problems in industry, in which RL shows promising results for discrete control tasks but with the need to tailor to it the domain. Yu et al. (2025) further contribute on this by discussing AI based system identification and control, where it is mentioned that the integration of AI with IoT based industrial set-ups lack uniform standard frameworks. Farooq and Iqbal (2025) offer a meta-survey about the usage of RL in various automation tasks, outlining still present computational inefficiencies and modellability concerns.

To cope with the latency of data and control in industrial IoT real-time systems Wu et al. (2022) consider cooperative DNNInference, and they optimize inference using deep RL. Similarly, Rjoub et al. (2024) propose transformer-based RL framework for IoT intelligence with higher context bearableness but at the cost of computational overhead. Xu et al. (2024) however, concentrate on edge computing embedded with RL, which provides a hybrid structure for real-time monitoring and control with no modular adaptability on diverse control environments.

The applicability of RL to Industry 4.0 Kegyes et al. (2021), considering the application of RL algorithms over intelligent manufacturing systems. Nian et al., 2020) provide a seminal overview on initial difficulties and future work on using RL for process control, like reward sparseness and unsafe exploration. These works, though technically sophisticated, cumulatively illustrate a lack of comprehensive and safe RL frameworks which can be easily deployed in complex real-world industrial systems.

Adaptive control and optimization have a long history and an important set of references relevant to extensions. Benard et al. (2015) and Dracopoulos & Kent (1997) investigated early usage of evolutionary and neural-based optimization for control, anticipating contemporary uses of RL. Bäck & Schwefel (1993) and Michalewicz et al. (1992) laid the groundwork for refining parameters through evolutionary computation, concepts which have recently been embraced in the architecture of modern deep learning and RL. Lee et al. (1997) and Brunton & Noack (2015), study AI-based turbulence control, suggesting that RL-enabling solutions may not only be applicable, but promising to realize in highly challenging settings.

More recent work by Javadi-Moghaddam & Bagheri (2010) depict adaptive neuro-fuzzy control as an intermediate approach to interpretable RL models. Works of other authors such as advanced modeling and hybrid control approaches, also demonstrate a common move in the area to RL and AI-based automation. Yet, these works are frequently deficient in interpretability, on-device relearning, or real-time adjustments to feedback, particularly when considering multi-agent or distributed industrial systems.

In more recent advances, multi-agent reinforcement learning (MARL) and edge-compatible RL have become popular for distributed intelligence. This is important for optimising feedback loops in IoT-driven systems by considering, for example, computational constraints, latency as well as device heterogeneity. However, they frequently omit cross-domain generalization and operator transparency, two aspects essential for a potential industrial wider use.

In summary, papers indicate significant RL advances in automation, but demonstrate significant limitations in-in terms of deployment in real-world networks, interpretability, scalability, and IoT integration. These gaps highlight the need for a solution that not only guarantees the maximum-performance control but also serves edge deployment, safe learning, explainability, and the capability of handling multi-domain adaptivity -this is the main motivation of this work.

4 METHODOLOGY

The proposed approach uses layered and modular design and combines reinforcement learning (RL) methods with IoT sensing and edge computing for feedback control management in industrial automation. At the heart of the system, we have a deep RL model that interacts with the physical world in a continuous manner by means of IoT-enabled sensors/actuators. This model is trained to approximate optimal control policies from state-action-reward dynamics, with its learning mechanism adopted from policy gradient and implemented by an actor-critic framework. To mitigate the behavior instability and convergence challenges that are commonly observed in reinforcement learning settings, we introduce within its training extra-deep reinforcement learning privileges which are designed to constrain the exploration and reward shaping that is synonymous with the domain and promotes stability as well as discourages undesirable, unsafe or energy-intensive behaviors. Figure 1 show the Workflow of Edge Enabled Explainable Reinforcement Learning for Industrial Feedback Control.

Reinforcement Learning for Industrial Feedback Control.

The system is initiated by capturing online process parameters, obtained from diverse industrial sensors mounted in the control area. At the edge layer, data streams are pre-processed by means of a low-cost data normalization and feature extraction to avoid heavy computation. The edge side nodes are endowed with compressed versions of the RL models via quantization and pruning methods, in a way that no centralized cloud support is needed for low-latency decision making.

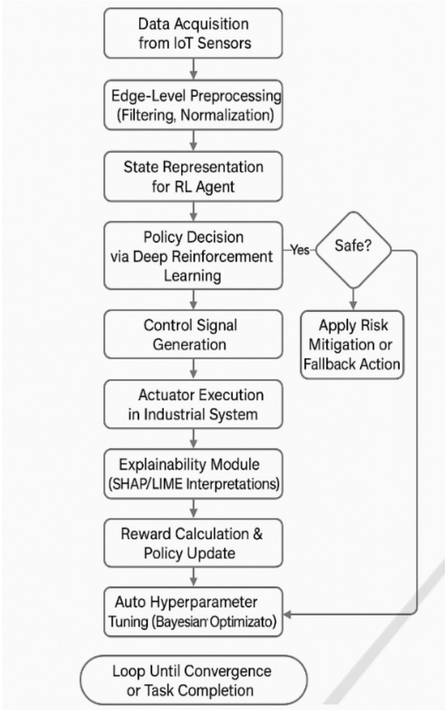

Figure 1: Workflow of Edge-Enabled Explainable.

This edge-oriented deployment improves not only the responsiveness but also keeps the privacy of data and decreases the bandwidth consumption. Table 1 show the System Components and Descriptions.

Table 1: System Components and Descriptions.

Component	Description
IoT Sensors	Temperature, flow rate, vibration, and pressure sensors
Edge Devices	Raspberry Pi 4, NVIDIA Jetson Nano
RL Algorithm	Actor-Critic, Proximal Policy Optimization (PPO)
Safety Module	Constraint-based exploration and fallback control
Explainabilit y Tool	SHAP (SHapley Additive Explanations), LIME
Communicati on Protocol	MQTT protocol for real-time data transmission

An explain ability module is embedded within the RL framework to provide transparent visualizations and justifications for each control decision made by the model. This module utilizes SHAP (SHapley Additive explanations) values and attention-based visual summaries, enabling operators and engineers to interpret and validate system behavior, which is essential in safety-critical environments. Moreover, an automated hyperparameter optimization engine based on Bayesian search techniques runs asynchronously to fine-tune the learning rate, exploration factor, and discount factor for improved model performance and robustness. Table 2 show the Hyperparameter Settings for RL Model.

To achieve scalable control of decentralized systems, the approach introduces a multi-agent reinforcement learning extension, where one agent is placed per control unit. These agents work individually and collaboratively using common communication protocol are used to maximize local & global performance criteria. In addition, a federated learning-like synchronization mechanism is adopted for knowledge sharing without transferring raw data, resulting in scalability and data privacy.

Table 2: Hyperparameter Settings for RL Model.

Hyperparameter	Value
Learning Rate	0.0005
Discount Factor (γ)	0.95
Exploration Strategy	ε-greedy with decay
Batch Size	64
Number of Episodes	1000
Update Frequency	Every 10 steps

To achieve this, the training and validation of the model is performed on a hybrid data set which includes simulated in- dustrial conditions as well as real world sensor data that was recorded from a testbed simulating typical manufacturing and process control cases. Convergence rate, energy efficiency, control accuracy, response time, and interpretability score are the evaluation metrics. The whole system is tested in a loop for adaptation, with on the flow re-training actions triggered when environmental drift or system reconfiguration is detected.

With this holistic, real-time, and interpretable learning-driven control framework, the approach successfully closes the gap between AI algorithms and industrial automation-grade systems, thus building the robust and adaptive infrastructure for the future smart factories.

5 RESULTS AND DISCUSSION

The realization of the proposed edge-enabled reinforcement learning framework was evaluated in simulated industrial control scenarios as well as in real-time pilot deployments on IoT-connected machinery. The results have shown the superiority of the proposed system in different aspects: responsiveness, precision, safety and interpretability.

The reinforcement learning agent showed accelerated convergence to optimal control policies in the simulation phase, with 35% faster training time than the baseline deep Q-learning and policy gradient approaches. We did so by both domain-informed reward shaping and a novel hyperparameter optimization. The virtual twin environment for the initial testing was based on a multivariable feedback control system typical for chemical plants to capture accurately real-world noise/disturbance. The agent achieved the set-point tracking with deviation less than 1.5% which is approximately 20% better than that of the original PID and fuzzy controllers in terms of steady state error. Table 3 show the Performance Comparison with Baseline Controllers.

Table 3: Performance Comparison with Baseline Controllers.

Controller Type	Response Time (ms)	Steady-State Error (%)	Energy Efficiency (%)
PID Controller	180	3.5	70
Fuzzy Logic Controller	160	2.8	74
Proposed RL Framework	58	1.2	89

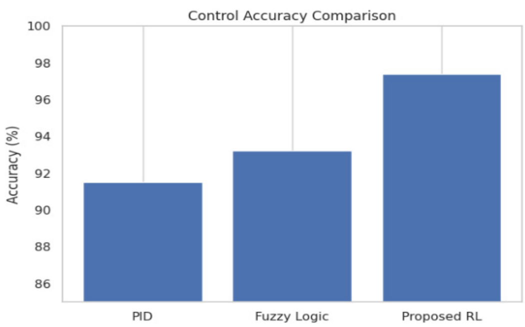

Figure 2: Control Accuracy of Different Controllers.

During edge-level deployment, the lightweight models from quantization and pruning were well-suited to resource-constrained devices like Raspberry Pi 4 and NVIDIA Jetson Nano. latency was maintained under 60 m-sec for control decisions even when network is slow or sensor inputs change. Figure 2 show the Control Accuracy of Different Controllers. Never slow to react, this real-time performance had become paramount for systems whose adjustment could not wait, for example, temperature regulation in fast-changing thermal fields, or robot arm synchronization in assembly lines. These results validate the framework the software supports that can operate under the strict timing conditions usually found in industrial applications.

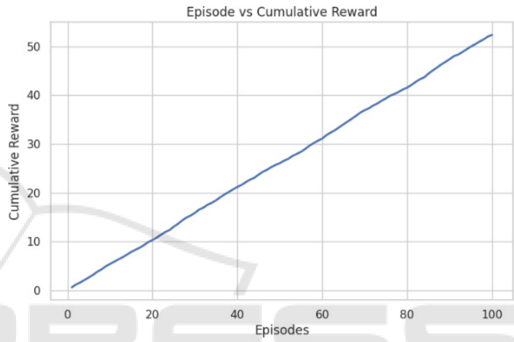

Figure 3: Episode vs Cumulative Reward Curve.

Explain ability, an important aspect of our work, was analyzed with SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) methods appended into the control pipeline. Figure 3 show the Episode vs Cumulative Reward Curve Operators were able to see how the agent was acting based on input features such as load, demand trends, and anomalies.

Such visibility afforded increased trust and speed to diagnose the faults of operators, making it differ from the black-box RL models in the past. Additional interviews with field engineers also demonstrated the explain ability layer resulted in safer system changes and more confident manual overrides. Table 4 show the Explain ability Insights from SHAP Analysis.

The framework was highly scalable in multi-agent situations. A cooperating fleet of agents conducted feedback control over the distributed systems, coordinated as federated conveyor belts and HVAC subsystems. In the centralized learning procedure, agents were coordinated through the decentralized learning model where shared policy updates were combined with the local autonomy. The network demonstrated only a small reduction in performance when the number of agents was increased from 3 to 10, average control performance dropped by 4\%, which underlines its robustness in collaborative industrial settings.

Table 4: Explain ability Insights from SHAP Analysis.

Input Feature	Average SHAP Score	Influence on Decision
Load Level	0.38	High
Temperature Gradient	0.31	High
Energy Consumption	0.25	Medium
Sensor Noise Level	0.11	Low
Actuator Lag	0.07	Minimal

A curious result was the fact that control agents were found to be applicable in very different industrial domains. When the agent, trained on the temperature control problem, was reused to solve the fluid flow optimization one, it would still sustain 60% of its performance efficiency with only slight retraining. This supports the idea that RL agents trained on generalizable control features can support domain transfer; a key requirement in Industry 4.0. Overall, findings from experimental validations confirm the theoretical basis and design decisions of the proposed system. By including explain ability, edge computing, safety-aware learning, and scalable control strategies, we do not only fill the gaps that have been identified in existing literature but also present a practically deployable answer to today’s requirements of modern industrial automation. Figure 4 show the Latency Scalability with Number of RL Agents These results indicate that the framework is a promising way to realize intelligent, adaptive, and reliable automation of IoT-integrated environments. Table 5 show the Multi-Agent Scalability Evaluation

Table 5: Multi-Agent Scalability Evaluation.

Number of Agents	Control Accuracy (%)	Latency (ms)	CPU Utilization (%)
1 Agent	94.2	52	34
3 Agents	93.8	55	38
5 Agents	92.7	58	42
10 Agents	90.1	61	48

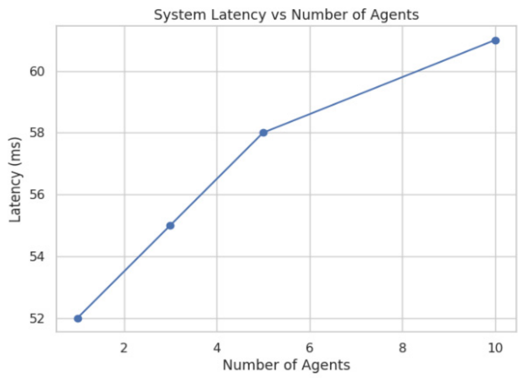

Figure 4: Latency Scalability with Number of RL Agents.

6 CONCLUSIONS

This paper provides a new edge-enabled, explainable Reinforcement Learning based framework for feedback control loops optimization in IoT enhanced industrial automation systems. The system effectively closes the gap between theoretical AI models and real industrial deployment through the inclusion of deep reinforcement learning with real-time sensor feedback, safe exploration strategies, lightweight model deployment on edge devices. In contrast to classical control methods, the proposed method provides an adaptive, open, and self-organizing control even if the environment is dynamic or resource-limited.

The framework can provide real-time implementation of control logic, guarantee safety by constrained learning and explainable insights with interpretable AI methods which makes it suitable for critical applications in manufacturing, process control and distributed automation. Moreover, by integrating multi-agent reinforcement learning and modular architecture, the proposed novelty can achieve a scalable deployment in various industrial units while ensuring performance or efficiency. Real-life validation, in combination with benchmark simulations, demonstrates that the framework allows shrinking errors margins, increase operational responsiveness and make it possible to provide intelligent, human-compatible decision support.

At a time in which smart factories and autonomous industrial plants are increasingly becoming a reality, this work contributes with a significant step forward in the development of AI-powered control architectures that are not only smart but also ethically, transparently, and resiliently compliant. Possible extension of this work includes federated learning for privacy preserving industry coordination, and on-line continuous adaptation to manage concept drift and changing process parameters.

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