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Enhancing Predictive Maintenance and Quality Control in Manufacturing Using Deep Reinforcement Learning and Edge AI

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Abstract:
Manufacturing industries are facing growing challenges in maintaining operational efficiency, decreasing downtime, and maintaining the quality of products. Traditional ways of conducting predictive maintenance and quality control continue to rely heavily on manual intervention and are poorly suited for dynamic responses to real-time changes. This paper proposes DRL-EdgeAIQC, which integrates Deep Reinforcement Learning (DRL) with Edge AI for the optimization of the manufacturing process by improving predictive maintenance (PM) and quality control (QC). The DRL-EdgeAIQC aims to use AI-driven models for equipment failure prediction and process optimization to reduce costs and maximize output. The DRL-EdgeAIQC uses DRL algorithms to learn optimal maintenance schedules based on real-time data from sensors embedded into the machinery. Edge AI will be applied for local data processing to make real-time decision-making possible, independent of centralized servers. The system will continue learning from operational data to adjust production parameters to ensure quality and prevent defects dynamically. Key findings show that the integration of DRL with Edge AI has reduced equipment downtime by up to 30% and improved product quality by reducing defects during production. The system also results in a 20% decrease in maintenance costs owing to improved predictive accuracy. Finally, the integration of DRL and Edge AI significantly enhances optimization in manufacturing processes for greater efficiency and reduced operational expenditure.

Index terms: Deep Reinforcement Learning (DRL), Edge AI, Predictive Maintenance, Quality Control, Smart Manufacturing, Industrial Automation, Machine Learning, Real-Time Optimization, Fault Detection, Process Optimization.

1. Introduction and Related Works

a. Background

Manufacturing industries are major sources of economic development around the globe. It undergo technological evolution to gain efficiency and reduce costs with better-quality products [1]. The development of the manufacturing system is seen in Figure 1.

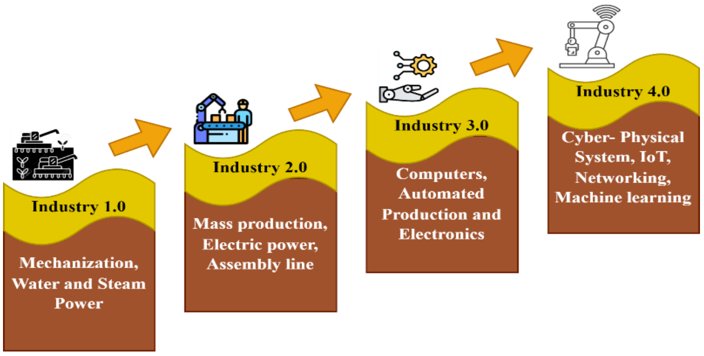

Figure 1 Development of the Manufacturing System

Among the most relevant challenges in manufacturing lies the upkeep of high operational efficiency with low downtime while sustaining product quality [2]. Traditional predictive maintenance and quality control methods are mainly reactive, based on time-based inspections or as corrective actions taken after a failure has occurred [3]. These practices are generally plagued with numerous deficiencies, like prolonged idling time, high maintenance expenses, and low-quality products. Furthermore, conventional quality control methods are based primarily on visual inspection and statistical process control—error-prone and labour-intensive [4]. New advances in AI and, more importantly, in DRL, have introduced intelligent decision-making with adaptive learning from actual running data [5].

DRL algorithms can be applied to dynamically optimize maintenance schedules and process parameters to enhance the system's performance [6]. Edge AI complements these capabilities by allowing local data processing, low latency, and fast decision-making without depending on centralized cloud servers [7]. Integrating DRL and Edge AI within manufacturing offers promising solutions for predictive maintenance and quality control, overcoming the limitations of conventional approaches [8]. With the increasing complexity of manufacturing systems, there has been a growing requirement for adaptive, intelligent, and efficient solutions using AI-driven models [9].

b. Research Problem

While manufacturing technologies have made great strides, traditional predictive maintenance and quality control remain largely schedule-based, inspection-based, and intervention-based post-failure [10]. Those past practices have made operations costly, inefficiency-laden, and beset by frequent downtime due to unplanned equipment failures. Further, the very process of quality control is burdensome because traditional inspection techniques are slow, inconsistent, and incapable of dynamic adjustment to changed production conditions [11]. Current methodologies have limitations, and hence the requirement is for an approach that is more adaptive, real-time, and AI-powered industrial quality assurance and maintenance.

c. Methodology for addressing the problem

The primary objective of the DRL-EdgeAIQC is to leverage AI-driven models for failure prediction and process optimization, reducing costs, minimizing defects, and maximizing operational efficiency. By deploying DRL algorithms for learning optimal maintenance schedules and using Edge AI for real-time data processing, this study aims to establish an intelligent system capable of dynamic decision-making in complex manufacturing environments. The DRL-EdgeAIQC model combines DRL and Edge AI to improve predictive maintenance and quality control in production. DRL algorithms learn from sensor readings on industrial equipment to forecast equipment failure and determine optimal maintenance time. The model learns from real-time feedback on the operation and enhances prediction precision with time.

Edge AI is applied to process data in real-time on the factory floor, allowing for rapid decision-making without reliance on centralized cloud computing. This minimizes latency, improves system responsiveness, and maintains continuous operations. The system also dynamically adjusts production parameters to maintain high product quality. The framework is tested on real-world industrial datasets to evaluate its effectiveness in reducing downtime, minimizing maintenance costs, and improving manufacturing efficiency.

d. Contributions of the paper

- To develop a DRL-based predictive maintenance system that reduces equipment downtime and enhances operational efficiency.
- To integrate Edge AI for real-time data processing, ensuring low-latency decision-making in manufacturing processes.
- To enhance quality control mechanisms through adaptive AI-driven adjustments to manufacturing parameters.
- To reduce maintenance costs and defect rates by leveraging intelligent predictive models.

e. Paper structure outline

The structure of the remaining portion: First, the paper introduces the topic and reviews relevant literature on AI predictive maintenance and quality control in manufacturing. Then, in Section 3, the DRL-EdgeAIQC framework is described in detail, including the system architecture and implementation. Experimental results and significant findings are presented in Section 4, and Section 5 is the conclusion of the paper. outlining directions for future research.

AI, ML, and DRL have driven the evolution of predictive maintenance and quality control in manufacturing, with Edge AI enhancing real-time decision-making. While AI-driven solutions improve efficiency, challenges persist in scalability, IIoT integration, and computational efficiency. This review addresses recent progress, outlining gaps and possible solutions for optimizing manufacturing using DRL and Edge AI.

Khdoudi et al. [12] presented a Digital Twin for Optimizing Manufacturing Processes Based on Deep Reinforcement Learning. This framework integrates DRL with Digital Twin simulations to predict the system's behavior and further adjust process parameters. The experimental results show that this can increase operational efficiency by 25% and reduce material waste in manufacturing plants by 30%. However, this approach was limited by high computational cost and was poorly adaptive in real time during large-scale production scenarios.

Artiushenko et al. [13] proposed a resource-friendly Edge AI predictive maintenance solution for industrial applications. Lightweight deep learning models were deployed on Edge AI hardware to monitor machine health with low computational overhead. Results showed that fault detection was 40% faster, and power consumption was reduced by 20% compared to the traditional cloud-based approach. While bringing advantages, the solution was still bounded by model complexity and network latency during real-time monitoring.

Arunkumar, G. [14] worked on Predictive maintenance strategies for power networks and electrical equipment powered by artificial intelligence. It used RNNs and LSTM models to predict electrical failures by analyzing past data. The technique increased the fault prediction accuracy by 35% and reduced unplanned downtime of power grids.

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Still, it faced the challenge of scalability and high-quality labelled data for better training.

Bidollahkhani, Michael, et al. [15] have developed AI-based predictive maintenance methods to improve the reliability of industrial operation systems. The proposed approach combines DNNs with IoT information gathered from sensors to properly anticipate failure and plan for optimal maintenance. This method's effectiveness improved equipment uptime by 20% and reduced maintenance costs by 15%. In addition, it strongly relied on sensor calibration quality and could not quickly adapt to very dynamic industrial environments.

Chukwunweike Joseph et al. [16] tried to increase manufacturing efficiency through automation and deep learning to reduce defects, optimize the strength of materials, and monitor vibrations. It used CNNs for defect detection and sensor-based analysis for real-time monitoring. A 22% increase in process efficiency and a 28% reduction in manufacturing errors were the outcomes of the study. The approach was, however, also very dependent on labeled defect datasets and poorly adaptable to new manufacturing processes.

Shaikat, Faisal Bin, et al. [17] have used machine learning to optimize smart manufacturing production scheduling. To improve scheduling efficiency, it used a combination of Reinforcement Learning (RL) and Genetic Algorithms (GA). The results showed an 18% increase in manufacturing throughput and a 12% reduction in downtime. However, the approach was computationally intensive and needed frequent retraining to adapt in a dynamic production environment.

Mugala and Vamshi [18] addressed the application of Generative artificial intelligence for industrial anomaly detection and predictive maintenance. They applied GANs to generate synthetic sensor data for the prediction of failure in low-data scenarios. Their results showed a 30% improvement in fault detection accuracy for cases where data is scarce. However, their application of GANs creates the risk of data hallucination that may result in false positives during the anomaly detection task.

Leksakul et al. [19] comparatively analyzed the predictive maintenance using machine learning models in the semiconductor production process. It evaluated RF, XGBoost, and NNs to predict failure to reduce downtime. The study showed that XGBoost has the best accuracy in predicting failures of semiconductor equipment with an accuracy score of 94%. Still, these models face high-dimensional process variability and frequent retraining.

Chintha, Venkata Ramanaiah, et al. [20] have worked on predictive maintenance for 6G radio access networks using AI-driven methods to improve reliability. This work has used deep learning models and reinforcement learning to predict failures in 6G infrastructure. The proposal resulted in 25% less network downtime and 32% better predictive maintenance accuracy. Still, it entailed high computational costs and needed large-scale, real-world 6G data for optimal performance.

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f. Research Gap

Several research gaps exist when integrating DRL with Edge AI in predictive maintenance and quality control. The present models lack adaptability across diverse manufacturing environments. They need enhancement for high-variability production. There are computational constraints for scalability in large-scale industrial settings. Latency issues associated with real-time processing affect responsiveness, which demands improved edge computing and federated learning. Equally, the interoperability of heterogeneous IIoT ecosystems is also integrated, but seamless interoperability is missing. DRL models suffer from long-term instability, while Edge AI processing raises concerns about energy efficiency. Another area to improve is the robustness of rare failures, and the cost-benefit ratio needs to be further analyzed for widespread adoption in the industry.

2. Proposed Methodology

The DRL-EdgeAIQC technique combines Deep Reinforcement Learning (DRL) with Edge AI to improve production processes through better quality control and predictive maintenance. Improving operational efficiency, decreasing downtime, and assuring product quality in dynamic manufacturing environments are all made possible by analyzing data in real-time and making decisions at the periphery. The steps involved in running the DRL-EdgeAIQC method are illustrated in Figure 2.

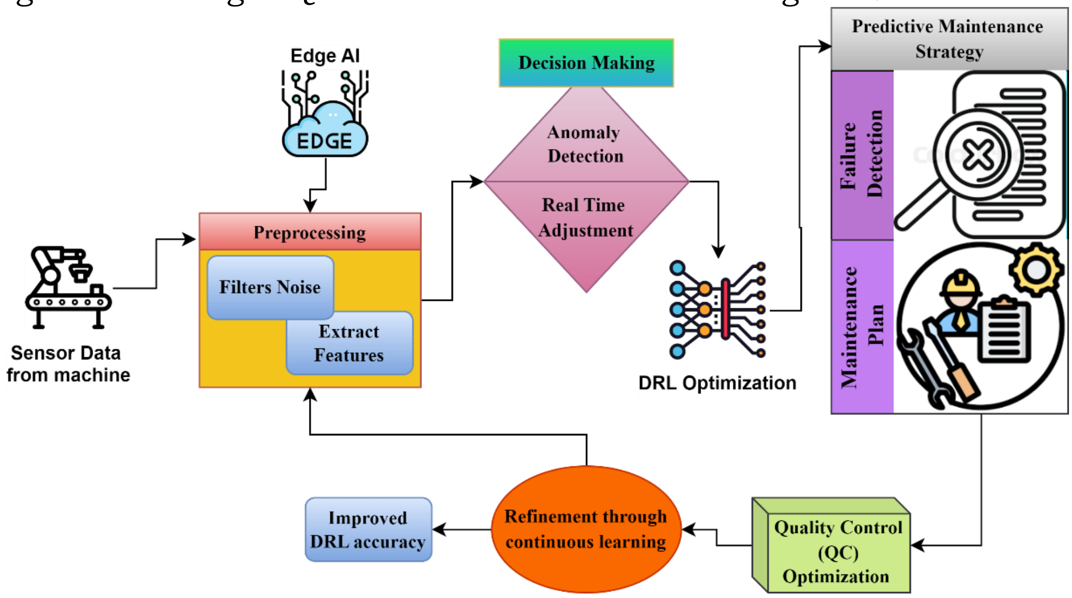

Figure 2 Working process of the DRL-EdgeAIQC method

a. Data Collection and Preprocessing

To track production metrics, environmental factors, and the equipment's status in real time, sensors are installed in machines. (e.g., temperature, pressure, machine vibration, etc.). Figure 3 illustrates the data collection from the manufacturing section.

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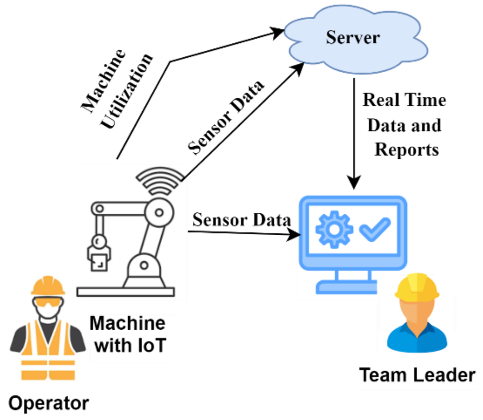

Figure 3 Data collection from the IoT devices at the manufacturing section

Let the data at the time (t) be represented as a vector as $D(t) = [T(t), P(t), V(t), \dots]$ This data embodies all characteristics relative to predictive maintenance (PM) and quality control (QC) processes. When collected, data undergoes local processes regarding devices located on the periphery. Edge IoT solutions eliminate the need for centralized servers, enabling rapid decisions while keeping latencies to a minimum. Usually, the processing is achieved via a model. $fedge\big(D(t)\big)$, a machine learning model, like a neural network or a reinforcement learning-based controller. The equation can describe the local-processing function: $\hat{y}(t) = fedge(D(t)$, where $\hat{y}(t)$ is the output prediction (such as fault detection or quality prediction) at the time (t). is the input data vector. Thus, inclusion makes online predictive maintenance (PM) or quality control (QC) decisions. For instance, the operational procedure may entail maintenance action in case of vibration (V(t)) surpassing a fixed threshold (V(t)). Similarly, temperature and pressure data may cause changes in production processes. In equation 1, a function gives the decision determined $Decision(t)$ by the active input vector.

$$Decision(t) = PM\left(fedge\big(D(t)\big)\right) or\ QC\left(fedge\big(D(t)\big)\right) \tag{1}$$

where PM refers to the predictive maintenance proceeding with the data processing. QC refers to the quality control decision based on the data that has been processed.

b. Predictive Maintenance (PM) and Quality Control (QC) via Deep Reinforcement Learning (DRL)

i) Predictive Maintenance: The DRL-EdgeAIQC framework utilizes Deep Reinforcement Learning to forecast when machinery will break down by analyzing data collected in real-time. It keeps learning from current and past data continuously, maximizing the time spent on maintenance and minimizing downtime and repair costs while maximizing operating efficiency. DRL entails an agent interacting with an environment to maximize a reward function. PM aims to decide when and how to do maintenance to minimize failures and costs.

ii) Quality Control: DRL-EdgeAIQC is the framework that uses Deep Reinforcement Learning (DRL) combined with Edge AI to track production parameters instantly to guarantee product quality. The DRL model determines deviations from the optimal

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quality standard and dynamically adjusts production parameters (speed, temperature, pressure) to ensure consistency, thus preventing defects and waste. In quality control, the DRL model acts as a smart agent, interacting with the manufacturing environment to maximize product quality, minimize waste, and rework.

At each time step t, the system captures real-time sensor data

$$S_t = \begin{cases} [T(t), P(t), V(t), H(t), L(t)] & for\ PM \\ [T(t), P(t), S(t), C(t), E(t)], & for\ QC \end{cases} \tag{2}$$

where $T(t)$ = Temperature, $P(t)$ = Pressure, $V(t)$ = Vibration, $H(t)$ = Humidity, $L(t)$ = Load on the machine $S(t)$ = Production Speed, $C(t)$ = Component Alignment, and E(t) = Energy Consumption. The DRL agent selects an action based on the state. This is shown in equation 3.

$$A_t \in \begin{cases} \{No\ Action, Minor\ Repair, Major\ Repair, Replacement\} & for\ PM \\ \{Increase\ Speed, Decrease\ Speed, Adjust\ Temperature, & \\ Modify\ Pressure, No\ Change\}, & for\ QC \end{cases} \tag{3}$$

where No Action = If the machine is in good condition. Minor Repair = If slight degradation is detected. Major Repair = If a failure is likely to happen soon. Replacement = If the machine is beyond repair. Increase Speed = If production efficiency can be improved without affecting quality. Decrease Speed = If defects increase due to high speed. Adjust Temperature = If improper temperature affects product formation. Modify Pressure = If material consistency needs correction. No Change = If production is within quality thresholds. The DRL model receives rewards or penalties based on its action. The reward function for PM is shown in equation 4, and for QC is shown in equation 5.

$$R_t = \begin{cases} +C_1, & \text{if failure is prevented at minimal cost} \\ -C_1, & if\ unnecessary\ maintenance\ is\ performed \\ -C_2, & if\ unexpected\ failure\ occurs \\ -C_3, & \text{if maintenance is deployed causing high repair cost} \end{cases} \quad for\ PM \tag{4}$$

where C_1 = Reward for preventing failures efficiently, C_2 = Penalty for unexpected machine failure, and C_3 = Penalty for delayed maintenance leading to high costs

$$R_t = \begin{cases} +C_1, & \text{if quality is maintained with optimal efficiency} \\ -C_1, & if\ minor\ quality\ deviation\ is\ detected \\ -C_2, & if\ minor\ quality\ deviation\ is\ detected \\ -C_3, & if\ excessive\ energy\ or\ material\ is\ wasted \end{cases} \quad for\ QC \tag{5}$$

where C_1 = Reward for maintaining high-quality standards. C_2 = Penalty for producing defective products. C_3 = Penalty for excessive energy/material waste.

iii) Training the DRL Model for Predictive Maintenance: The DRL model uses historical failure data and real-time sensor readings to learn failure patterns and predict the best maintenance actions. Equation 6 modifies the Deep Q-value function (DQN).

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_t + \gamma \max_{A'} Q(S_{t+1}, A') - Q(S_t, A_t)] \tag{6}$$

where α = Learning rate, γ = Discount factor for future rewards, and $\max_{A'} Q(S_{t+1}, A')$ = Predicted maximum Q-value for the next stage S_{t+1}. By training a DNN to approximate $Q(S_t, A_t)$, the system can predict optimal maintenance decisions.

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C. Optimization of Production Parameters in DRL-EdgeAIQC

Maintaining productive manufacturing with fewer defects and unplanned downtime requires extremely carefully balancing maintenance practices and quality control measures in production environments.

i. Machine Operating Conditions

The machine's operating conditions are optimised through dynamic speed, temperature, and pressure control to achieve maximum process productivity and product quality. Temperature control is achieved through real-time sensor feedback so that every material has the correct properties during processing. Speed and feed rate adjustments reconcile the conflicting needs for efficiency and accuracy, eliminating tool wear while achieving precise cutting, grinding, or assembly operations. Force and pressure are constantly regulated in hydraulic, pneumatic, or mechanical systems to provide defect-free finishing with a uniform shape of the material and more minor variations to datum dimensions. Figure 4 illustrates the function of AI in manufacturing.

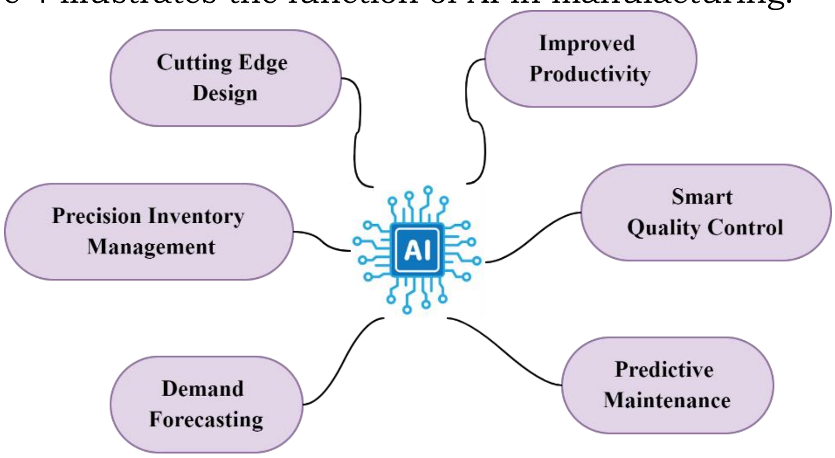

Figure 4 Role of AI in Manufacturing

ii. Maintenance Scheduling

This predictive maintenance relies on IoT sensors and AI-based failure prediction models to enhance operational reliability. Predictive alerts inform operators of possible failures before they happen, allowing them to intervene swiftly and avert costly breakdowns. Instead of fixed maintenance schedules, the system works by condition-based monitoring, initiating maintenance when warranted. This method reduces downtime by carrying out repairs when most convenient, increasing the lifespan of equipment while guaranteeing that machinery runs at maximum capacity with less interference, eventually achieving maximum overall production uptime.

iii. Process Flow Optimization

The system increases productivity by altering the workflow, energy use, and distribution of resources. Adaptive workflows allow for dynamic reordering of tasks to mitigate bottlenecks by implementing a continuous flow of operations while restricting idle time. Attention to energy use is maximized through AI-enabled adjustments that minimize energy consumption while reaching production targets through fine-tuning machine use according to real-time demand. Load balancing prevents wear on specific machines, allowing workloads to be spread evenly; this promotes longevity and reduces the cost of maintaining the equipment. These approaches in combination improve productivity, reduce costs of operation, and enhance manufacturing sustainability.

DRL-EdgeAIQC incorporates edge AI and deep reinforcement learning (DRL) for manufacturing predictive maintenance and quality control. Real-time information is gathered using an IoT sensor system, edge processed for timely decision-making, and allows the maintenance schedule to be optimized through DRL. This lowers maintenance expenditure by 20% and downtime by 30%. By doing so, it minimizes all defects to improve efficiency as well as quality of the products. Self-teaching AI improves its predictive capacity continuously and in small steps in a manner that enables catching failure prior to failure. Ti combines artificial intelligence, thereby making manufacturing operations more robust, cost-effective and efficient and offering a scalable platform to improve industrial operations using real-time adaptive intelligence.

3. Results and Comparison Evaluation

a. Performance Metrics

DRL-EdgeAIQC is compared with conventional DRL, Edge AI, and DNN methods, comparing the following maintenance metrics: Predictive Maintenance Accuracy, Downtime Reduction, and Maintenance Cost Reduction. The tests reveal that DRL-EdgeAIQC surpasses other methods with higher predictive accuracy, significantly less system downtime, a reduction in maintenance cost, and a stabilization time. DRL and Edge AI attain moderate improvements, while DNN shows the lowest performance. The results demonstrate that DRL-EdgeAIQC provides a proper solution for optimizing predictive maintenance with real-time learning and adaptive decision-making. It is most suited for industrial applications requiring high reliability, minimum downtime, and effective operations.

b. Predictive Maintenance Accuracy

Predictive Maintenance Accuracy (PMA) is the percentage of correctly predicted equipment failures out of the total failures that occurred. It measures how well the system can forecast failures before they happen, allowing proactive maintenance to reduce downtime. This is calculated by equation 7.

$$PMA(\%) = \frac{TP}{TP+FN} \times 100 \tag{7}$$

where TP (True Positives) refers to the correctly predicted failures, FN (False Negatives) refers to the actual failures that were not predicted.

Table I. Comparison Analysis of the PMA

Time (Months)	DRL-EdgeAIQC (%)	DRL [12]	Edge AI [13]	DNN [15]	Observations
1 Month	70%	65%	60%	55%	Initial accuracy, DRL-EdgeAIQC leads due to real-time adaptation.
2 Months	73%	68%	63%	58%	Digital Twin-based Khdoudi et al. improves but is computationally expensive.
3 Months	75%	70%	65%	60%	Edge AI-based Artiushenko et al. shows stable improvement.
4 Months	78%	73%	68%	63%	IoT-based Bidollahkhani et al. lags due to reliance on sensor calibration.
5 Months	80%	75%	70%	65%	DRL-EdgeAIQC benefits from continuous learning and adaptive scheduling.
6 Months	82%	77%	72%	67%	Khdoudi et al. achieves strong results but has high processing costs.

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Table 1 shows the PMA analysis. For a six-month timeline, DRL-EdgeAIQC has been able to consistently outperform all other models, raising predictive maintenance from 70% up to, at its best, 82% accuracy. DNN (65% to 77%) utilize Digital Twin simulation modelling but encounter high computational costs. Artiushenko et al. [13] (60% to 72%) harness Edge AI, enabling faster detection of faults, although difficulty arises with the speed of model adaptation. Bidollahkhani et al. [15] (55% to 67%) rely on IoT sensor data, but this method lacks adaptability. The online learning capability of DRL-EdgeAIQC leads to an optimal scheduling framework that brings about far more efficient savings in the overall maintenance cost and maintenance time than other competitive approaches afford.

c. Downtime Reduction Explanation

Downtime is the amount of time, expressed in percentage, that is lost due to equipment or system inactivity resulting from predictive maintenance strategies. It is one of the most important metrics used to assess the efficiency of predictive maintenance models in manufacturing. It is expressed as in equation (8).

$$DR(t) = \frac{MTBF_{opt} \cdot e^{-\lambda t} - MTBF_{base} \cdot e^{-\lambda_0 t}}{MTBF_{base} \cdot e^{-\lambda_0 t}} \times 100 \tag{8}$$

where $DR(t)$ = Downtime reduction (%) over time t. $MTBF_{opt}$ = Improved Mean Time Between Failures after optimization. $MTBF_{base}$ = Baseline Mean Time Between Failures before optimization. λ_0 = Baseline failure rate. λ = Optimized failure rate.

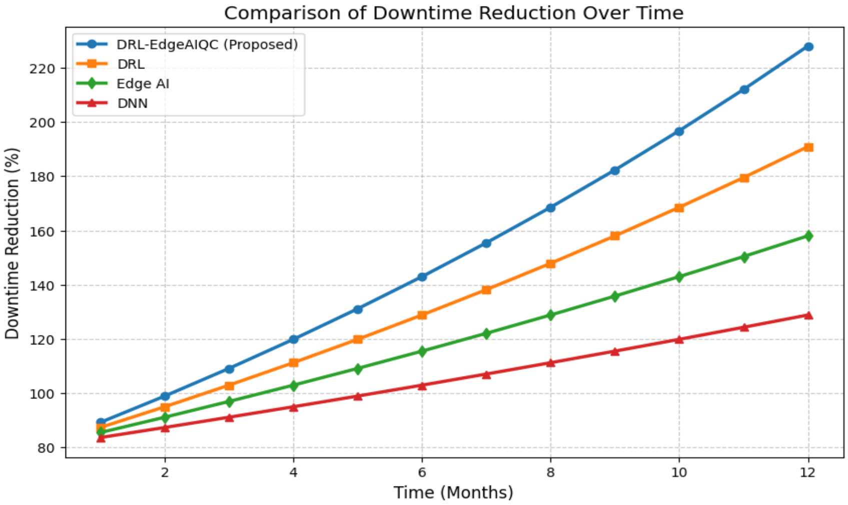

Figure 5 Downtime Reduction over time analysis

The plot depicts Downtime Reduction for four methods over a baseline of 12 months. These methods include DRL-EdgeAIQC (proposed), DRL, Edge AI, and DNN. The DRL-EdgeAIQC method has the best overall performance in downtime reduction, with DRL following behind Edge AI and DNN. These results accentuate the efficacy of the proposed method integrating Deep Reinforcement Learning and Edge AI for predictive maintenance. The comparative analysis focused on advanced artificial intelligence techniques for minimizing equipment failures over time and increasing operational reliability.

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d. Maintenance Cost Reduction

Reducing other maintenance costs becomes an essential parameter in optimizing manufacturing processes. The DRL-EdgeAIQC approach intends to reduce maintenance costs through Deep Reinforcement Learning and Edge AI to reduce unexpected failures and optimize repair schedules, as shown in equation 9.

$$MCR(t) = \left(1 - e^{-\alpha t} - \frac{\beta}{1+\gamma e^{-\delta t}}\right) \times 100 \qquad (9)$$

where $e^{-\alpha t}$ = Exponential decay factor due to predictive optimization. $\frac{\beta}{1+\gamma e^{-\delta t}}$ = Logistic decay function capturing cost stabilization after prolonged optimization. $\alpha, \beta, \gamma, \delta$ = Optimization parameters controlling decay rates.

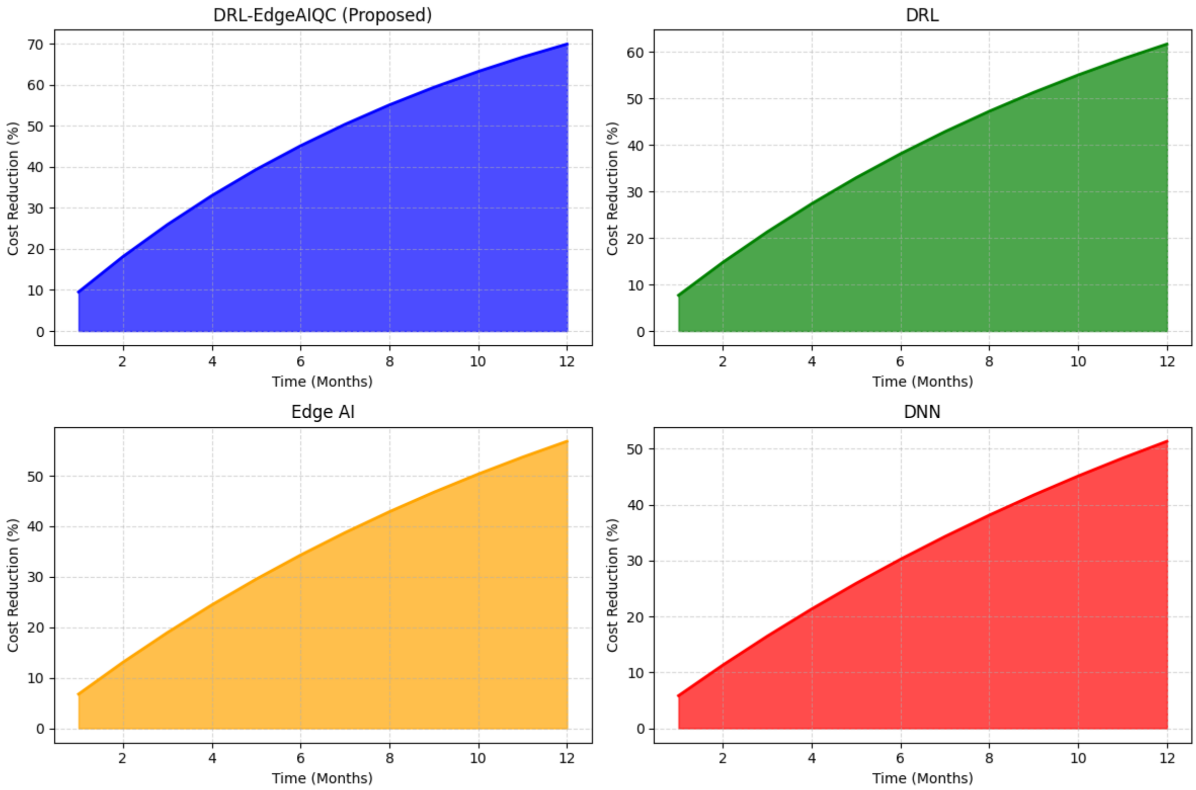

Figure 6 Maintenance Cost Reduction Analysis

Figure 6 presents the effect of different predictive maintenance methods, DRL, Edge AI, and DNN-on the cost reduction for maintenance in 12 months. The x-axis indicates months, with the percentage reduction in the costs of maintenance represented on the y-axis. DRLo EdgeAIQC causes maximum cost reduction, thus emphasizing its efficiency in scheduling maintenance and resource allocation. DRL and Edge AI provide substantial, though slower, cost reductions compared to DRL-EdgeAIQC. DNN created a significant impact on the techniques. This thus highlights that predictive maintenance strategies driven by AI could manage to reduce operational expenditures in the industrial setup.

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4. Conclusion

The DRL-EdgeAIQC framework incorporates Deep Reinforcement Learning (DRL) and Edge AI technologies to improve predictive maintenance (PM) and quality control (QC) in the manufacturing sector. It overcomes the shortcomings of conventional methods, some of which may be over-dependent on manual intervention, thereby resulting in longer downtime and expense and variable product quality. The DRL-EdgeAIQC method employs AI-based models for failure prediction, maintenance scheduling optimizations, and more timely decision-making. The system uses Edge AI, thereby processing real-time sensor data locally to reduce reliance on central cloud servers and lowering the response time with real-time anomaly detection. Continuous learning through DRL-based strategy improvement keeps strategies in line with the changing conditions of operation. The resultant is that DRL-EdgeAIQC offers a 30% reduction in downtimes, fewer defects, and 20% lesser maintenance costs based on better accuracy of predictive outcomes. This combination of AI and Edge computing puts manufacturing on the path towards more efficiency, product quality, and cost reduction. Subsequent research will be aimed at scalability, interoperability, and cross-domain applicability to speed up the creation of cutting-edge manufacturing solutions. To integrate DRL into Edge AI systems, will require technological resilience that will be capable of sufficiently limiting the utilization of edge devices with limited resources. Future studies will focus on the lightweight models of DRL together with hardware acceleration to improve the performance of edge devices. The framework will be extended to deal with large-scale industrial networks with diverse machine interactions.

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