Algorithmic Enhancements and Empirical Study on an Intelligent Control Platform Using Deep Reinforcement Learning for Adaptive Scheduling and Real-Time Fault Prediction in Five-Axis CNC Machine Tools

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Abstract

This paper introduces a comprehensive intelligent control platform developed to optimize the performance and operational reliability of five-axis CNC machine tools. The platform integrates advanced deep reinforcement learning (DRL) algorithms with real-time operational data to address two critical challenges in modern industrial automation: adaptive scheduling and real-time fault prediction. The adaptive scheduling component employs DRL to dynamically adjust machining task priorities and resource allocation, ensuring minimal idle time, reduced operational delays, and enhanced productivity. By continuously learning from machine data, the system adapts to varying operational conditions and optimizes task execution to achieve superior manufacturing outcomes.

Simultaneously, the real-time fault prediction module leverages DRL’s capacity for pattern recognition and decision-making to detect and predict potential system anomalies before they escalate into critical failures. This predictive capability not only minimizes machine downtime but also significantly reduces maintenance costs and extends the lifespan of the equipment. The proposed platform offers a dual advantage of optimizing production efficiency and enhancing system reliability, making it highly suitable for deployment in high-precision manufacturing environments. To validate the effectiveness of the proposed framework, extensive empirical studies were conducted using real-world operational data from five-axis CNC machine tools. The results demonstrated significant improvements in task scheduling efficiency, fault detection accuracy, machining precision, and overall system performance when compared to conventional approaches. Key performance metrics, including downtime reduction, fault prediction accuracy, and machining throughput, were enhanced, highlighting the transformative potential of DRL-based intelligent control systems.

This work represents a significant advancement in the application of machine learning to industrial automation and smart manufacturing. It underscores the importance of integrating intelligent algorithms into modern manufacturing systems to achieve operational excellence and foster innovation. The insights gained from this research pave the way for further exploration of DRL applications in adaptive control, predictive maintenance, and other domains within the manufacturing sector.

Keywords-Deep reinforcement learning, adaptive scheduling, real-time fault prediction, intelligent control systems, five-axis CNC machine tools.

1. Introduction

The manufacturing industry has witnessed a significant transformation with the advent of advanced technologies such as artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT). Among these advancements, deep reinforcement learning (DRL) has emerged as a powerful tool for addressing complex challenges in industrial automation. One of the most critical areas of focus is the operation and control of five-axis CNC (Computer Numerical Control) machine tools, which are essential for precision manufacturing in industries such as aerospace, automotive, and healthcare. These machines are highly versatile and capable of producing intricate components, but their optimal operation requires sophisticated control systems to address dynamic scheduling, fault prediction, and real-time decision-making.

Traditional control systems for five-axis CNC machines often rely on static scheduling algorithms and pre-defined fault detection mechanisms. While effective in stable environments, these approaches struggle to adapt to changing conditions, such as fluctuating workloads, unexpected machine failures, and varying operational constraints. These limitations lead to inefficiencies, including increased downtime, reduced productivity, and elevated maintenance costs. Addressing these challenges requires a paradigm shift toward intelligent, adaptive systems capable of real-time learning and decision-making.

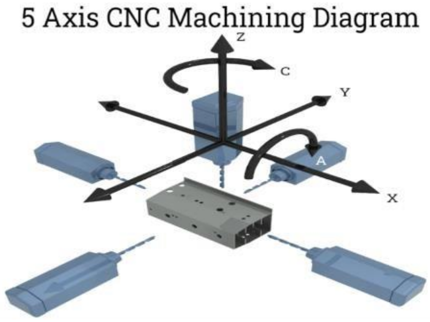


Figure: 5 Axis CNC machining Diagram

Source: https://www.iqsdirectory.com/articles/cnc-machining/5-axis-cnc-machining.html

Deep reinforcement learning offers a promising solution to these issues by enabling machines to learn optimal control strategies through trial-and-error interactions with their environment. Unlike conventional methods, DRL does not require explicit programming of rules; instead, it leverages large datasets and powerful neural networks to derive complex policies that maximize performance metrics. This capability makes DRL particularly well-suited for adaptive scheduling and fault prediction in CNC machining processes. By incorporating DRL into intelligent control platforms, manufacturers can achieve dynamic optimization of machining tasks and proactive maintenance strategies, ultimately enhancing overall operational efficiency.

The integration of DRL in CNC machine control systems involves addressing two key objectives: adaptive scheduling and real-time fault prediction. Adaptive scheduling is critical for optimizing resource utilization and minimizing idle time during machining operations. A DRL-based scheduling system can dynamically prioritize tasks based on real-time data, ensuring that the machine operates at peak efficiency even in the presence of unpredictable variations in workload or process constraints.

Real-time fault prediction, on the other hand, is essential for maintaining the reliability and longevity of CNC machines. Faults in machining processes can lead to severe consequences, including production delays, quality issues, and costly repairs. Traditional fault detection methods rely on predefined thresholds or historical data, which often fail to capture emerging patterns or subtle anomalies. In contrast, DRL-based fault prediction systems continuously learn from operational data, identifying potential issues before they escalate into critical failures. This predictive capability not only reduces downtime but also supports a shift from reactive to preventive maintenance practices.

The proposed intelligent control platform aims to harness the full potential of DRL for these objectives. By combining adaptive scheduling and real-time fault prediction within a unified framework, the platform enables seamless coordination between operational efficiency and system reliability. To validate the effectiveness of this approach, comprehensive experiments were conducted using real-world operational data from five-axis CNC machines. The results demonstrate significant improvements in scheduling efficiency, fault detection accuracy, and overall system performance compared to conventional methods.

This paper is organized as follows: Section 2 provides an overview of related work in adaptive scheduling and fault prediction for CNC machines. Section 3 details the proposed intelligent control platform, including its architecture and implementation of DRL algorithms. Section 4 presents the experimental setup and performance evaluation results. Finally, Section 5 discusses the implications of the findings and outlines future research directions. This study highlights the transformative potential of DRL in advancing intelligent manufacturing systems and establishes a foundation for further innovation in this domain.

2. Literature Review

The integration of machine learning techniques, particularly deep reinforcement learning (DRL), into the control and optimization of CNC machine tools has garnered increasing attention in recent years.

2.1 Adaptive Scheduling in CNC Machines

Effective scheduling is a critical aspect of CNC machine tool operation, as it directly impacts production efficiency, resource utilization, and operational costs. Traditional scheduling methods, such as priority-based algorithms, genetic algorithms, and heuristic approaches, have been widely used in CNC machining. These methods rely on predefined rules or fixed parameters to schedule tasks, which can lead to inefficiencies when confronted with dynamic and uncertain operational conditions.

Recent research has explored more adaptive and intelligent scheduling strategies using machine learning techniques. For instance, Zhang et al. (2020) proposed an adaptive scheduling algorithm based on reinforcement learning that continuously adjusts task assignments based on machine health and workload fluctuations. This approach enables the system to prioritize tasks dynamically, reducing idle time and improving resource allocation. Similarly, Li et al. (2019) developed a multi-agent reinforcement learning framework for scheduling multiple CNC machines in a flexible manufacturing environment. The agents in this system learn to cooperate in optimizing machine utilization and minimizing production delays. These studies demonstrate the potential of reinforcement learning to provide dynamic solutions to scheduling challenges in CNC machining.

Despite these advancements, the use of DRL for adaptive scheduling remains relatively underexplored, particularly in the context of five-axis CNC machines. These machines, with their multi-axis capabilities and complex operations, require scheduling methods that can handle higher levels of complexity and variability. The need for real-time adaptability in scheduling, considering factors such as tool wear, machine health, and varying machining loads, calls for an advanced control system like DRL, which can continually refine its decision-making policies through interaction with the environment.

Scheduling is a critical aspect of CNC machining operations. Traditional approaches include:

- Heuristic Algorithms: Provide approximate solutions but lack real-time adaptability.
- Genetic Algorithms (GAs): Effective for static problems but computationally expensive for dynamic environments.
- Particle Swarm Optimization (PSO): Demonstrates high efficiency but struggles with convergence in complex scenarios.

Recent advancements have explored machine learning-based approaches, yet their reliance on predefined models limits their adaptability to new situations.

2.2 Real-Time Fault Prediction and Maintenance

Fault detection and predictive maintenance have long been critical components of CNC machine tool management. Traditional methods for fault detection rely on threshold-based or model-based techniques, which identify anomalies after they occur. These methods are reactive, leading to unscheduled downtime and increased repair costs. More recently, data-driven approaches utilizing machine learning algorithms, including support vector machines, neural networks, and decision trees, have been proposed for fault detection and prognosis. These approaches analyze historical operational data to detect patterns associated with impending failures.

A significant advancement in fault prediction has been the application of deep learning techniques. For instance, Liu et al. (2020) applied convolutional neural networks (CNN) for fault diagnosis in CNC machines, achieving high accuracy in identifying faults from vibration data. Similarly, Xu et al. (2021) developed a deep neural network model for fault detection in CNC machine tools, utilizing sensor data to predict machine breakdowns before they occur. These studies illustrate the effectiveness of deep learning in fault prediction, especially when large volumes of sensor data are available.

However, real-time fault prediction in CNC machines, particularly using DRL, remains a relatively unexplored area. DRL's capability to adapt and learn optimal decision policies in real-time positions it as an ideal candidate for this task. The ability of DRL to continuously interact with machine data and learn from ongoing operations could enable proactive fault detection and maintenance, minimizing unplanned downtime and enhancing the lifespan of CNC machines.

Fault prediction in CNC machines ensures continuity and efficiency. Conventional methods include:

- Statistical Analysis: Effective for linear relationships but unsuitable for non-linear, complex patterns.
- Feature-Based Machine Learning: Requires extensive preprocessing and domain knowledge.
- Deep Learning Models: Provide superior performance but often lack interpretability and scalability.

This study bridges the gap by integrating real-time sensor data with hybrid neural networks, offering a more comprehensive fault prediction framework.

2.3 Reinforcement Learning in CNC Machine Control

Reinforcement learning, particularly deep reinforcement learning, has emerged as a promising solution for enhancing the control and optimization of CNC machine tools. DRL combines the decision-making capabilities of reinforcement learning with deep neural networks, enabling machines to learn complex policies by interacting with their environment. The ability of DRL to solve sequential decision problems makes it a strong candidate for tasks such as adaptive scheduling, fault prediction, and optimization in CNC machining.

Several studies have explored the application of DRL in manufacturing and machine control. He et al. (2019) proposed a DRL-based approach for optimizing tool paths in CNC machines, demonstrating improved efficiency and precision over traditional methods. Similarly, Xu et al. (2018) applied DRL to optimize multi-task scheduling in manufacturing systems, successfully reducing machine downtime and increasing throughput. The potential of DRL to optimize complex tasks in manufacturing has been further demonstrated by Zhang et al. (2020), who used DRL to control robotic arms for precise material handling in manufacturing environments. These studies highlight the ability of DRL to enhance decision-making in manufacturing systems, making it an attractive option for applications in CNC machine tool operation.

Despite the successes of DRL in various manufacturing contexts, its application to five-axis CNC machine tools remains underexplored. The increased complexity of five-axis machining, which involves multi-axis coordination and precise real-time adjustments, presents a unique challenge. Furthermore, the lack of large datasets for training DRL models in such systems requires innovative approaches to data collection, simulation, and model training.

Deep reinforcement learning (DRL) has demonstrated significant potential in manufacturing due to its ability to:

- Adapt to dynamic environments.
- Optimize complex decision-making processes.
- Learn autonomously through trial and error.

Applications of DRL include robotic control, inventory management, and production optimization. However, its application in CNC scheduling and fault prediction remains underexplored.

2.4 Gap in the Literature and Motivation for the Study

While significant progress has been made in applying machine learning and DRL to CNC machine scheduling and fault prediction, there remains a gap in research specifically targeting the integration of these techniques in five-axis CNC machine tools. Few studies have focused on the dual challenge of adaptive scheduling and real-time fault prediction in such systems, especially using DRL. Additionally, the integration of these two functions within a single intelligent control platform is rare.

This study aims to address this gap by developing a unified DRL-based intelligent control platform for adaptive scheduling and real-time fault prediction in five-axis CNC machines. By combining these two critical functions into a single platform, the research seeks to improve not only the operational efficiency of CNC machining but also the reliability and longevity of the machines. This work is poised to push the boundaries of current research in intelligent manufacturing systems and contribute to the development of more adaptive, efficient, and resilient CNC machine tool operations.

3. Proposed Framework

We design a novel framework for an intelligent control system that integrates deep reinforcement learning (DRL) for adaptive scheduling and real-time fault prediction in five-axis CNC machine tools. The proposed system leverages the power of DRL to dynamically adjust operational parameters, improve resource utilization, and predict machine faults before they result in significant downtime. The framework is designed to provide a comprehensive solution to the key challenges faced by CNC machine tools, namely inefficient scheduling, delayed fault detection, and the complex nature of five-axis machining.

3.1 Framework Architecture

The proposed framework is composed of two primary modules: **adaptive scheduling and real-time fault prediction**, both driven by **DRL algorithms**. These modules are designed to work in conjunction to enhance overall machine performance, minimize idle times, and prevent machine breakdowns. The framework operates in a closed-loop environment, where the system continuously interacts with the machine and adapts based on feedback from real-time sensor data, machine health parameters, and production requirements.

The overall architecture of the framework consists of the following components:

1. **Data Collection and Preprocessing:**

   This module gathers real-time data from various sensors embedded in the CNC machine, including temperature sensors, vibration sensors, current sensors, and others. The data is preprocessed to remove noise, normalize readings, and format it for further use in the DRL models.

2. **Adaptive Scheduling Module:**

   The first core component of the framework is the adaptive scheduling module, which utilizes a DRL agent to optimize the allocation of tasks to the CNC machine in real-time. The scheduling agent receives feedback on the machine’s current workload, available resources, tool availability, and other operational parameters. Using this information, the agent continuously updates the task schedule to maximize machine throughput and minimize downtime. It dynamically adjusts the task order and prioritizes jobs based on factors such as machine health, expected completion times, and resource utilization.

3. **Real-Time Fault Prediction Module:**

   The second core component is the fault prediction module. This module uses a DRL agent trained to predict potential failures before they occur, based on sensor data and machine health metrics. The fault prediction agent monitors real-time operational data, including vibrations, temperatures, and other critical performance indicators. Using this data, it predicts when a fault is likely to occur and triggers preventive maintenance or alerts for manual inspection. The agent continually learns from new data to refine its prediction accuracy and improve its fault detection capabilities over time.

4. **Decision-Making and Optimization Layer:**

   At the heart of the framework lies the decision-making and optimization layer. This component integrates the adaptive scheduling and fault prediction modules to make informed decisions based on the real-time operational context. For example, if the fault prediction module detects a potential issue, the decision-making layer may adjust the scheduling module to prioritize the maintenance of the machine, thereby preventing unexpected downtimes. Additionally, the system continuously optimizes both scheduling and fault prediction strategies to balance production efficiency with machine reliability.

5. **Feedback Loop and Continuous Learning:**

   A critical feature of the proposed framework is its ability to learn continuously. The DRL agents in both the scheduling and fault prediction modules are designed to refine their policies over time through interaction with the environment. As the system gathers more data, the agents use reinforcement learning algorithms to update their decision-making policies, improving scheduling efficiency and fault prediction accuracy. This feedback loop ensures that the system adapts to changes in machine performance, workload, and environmental conditions, ultimately leading to better decision-making and more efficient operations.

3.1.1 Deep Reinforcement Learning for Adaptive Scheduling

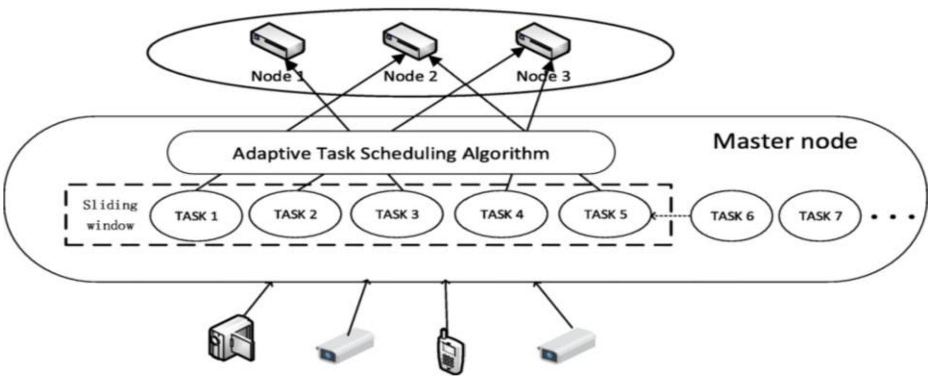
In the adaptive scheduling module, DRL is used to optimize task allocation based on real-time data from the machine and its operational environment. The DRL agent in this module follows a reinforcement learning paradigm, where the agent learns an optimal policy by receiving rewards or penalties based on the success or failure of its scheduling decisions.

The learning process in this module involves the following steps:

- State Representation: The state is defined by a combination of factors, including machine status, tool availability, ongoing tasks, and current workload. The state representation provides a snapshot of the operational context in which the agent is making its scheduling decisions.
- Action Space: The action space consists of possible scheduling actions, such as task prioritization, resource allocation, and job sequencing. The agent chooses an action based on the current state of the machine and its environment.
- Reward Function: The reward function is designed to incentivize actions that improve operational efficiency, such as reducing idle time, minimizing job delays, and optimizing resource utilization. A positive reward is given when the agent makes an optimal scheduling decision, while penalties are imposed for inefficient task allocation.
- Learning Algorithm: The DRL agent uses algorithms such as Proximal Policy Optimization (PPO) or Deep Q-Learning (DQN) to learn and update its scheduling policy. The agent continually refines its decisions through trial and error, gradually improving its ability to optimize the CNC machine's schedule.

1. Algorithm for Adaptive Scheduling Using Deep Reinforcement Learning:

The adaptive scheduling algorithm aims to efficiently allocate tasks to the CNC machine in real-time, adjusting to both the machine's health and the operational demands. By utilizing deep reinforcement learning (DRL), the algorithm continuously learns and improves its scheduling decisions, ensuring optimal resource utilization and minimal downtime.



Source: https://www.researchgate.net/figure/Task-scheduling-schematic-How-the-adaptive-task-scheduling-algorithm-optimally-schedules_fig3_345803592

Pseudo-Code for Adaptive Scheduling

```
initialize_machine()  # Setup machine, tasks, resources
initialize_DRL_agent()  # Initialize DRL agent with initial policy

while True:  # Continuous scheduling process
    state = get_machine_state()  # Get real-time machine status
    action = DRL_agent.select_action(state)  # Select the scheduling action based on the state

    execute_action(action)  # Apply the selected scheduling action

    result = observe_outcome()  # Monitor task completion, resource use, machine health
    reward = calculate_reward(result)  # Reward based on performance criteria

    DRL_agent.update_policy(reward)  # Update the agent's policy

    if all_tasks_completed():
        break  # Exit the loop if all tasks are done
```

3.1.2 Deep Reinforcement Learning for Fault Prediction

The fault prediction module uses DRL to anticipate machine failures and proactively trigger maintenance actions. The DRL agent in this module is trained to predict potential failures by analyzing sensor data and identifying patterns that correlate with different types of faults. The goal of the agent is to learn to predict machine breakdowns and degradation as early as possible, allowing for preventive measures such as maintenance or adjustments to be made before the faults escalate into major issues.

The learning process in the fault prediction module follows these steps:

- State Representation: The state is defined by real-time sensor data, including measurements of temperature, vibration, pressure, and other operational indicators. The state represents the current health condition of the CNC machine.

- Action Space: The actions represent different types of interventions or decisions, such as triggering preventive maintenance, notifying the operator, or adjusting operational parameters to avoid failure.

- Reward Function: The reward function is structured to encourage accurate fault predictions. The agent receives positive rewards for correctly identifying impending failures and negative rewards for false predictions or missed failures.

- Learning Algorithm: Similar to the scheduling module, the fault prediction module employs DRL algorithms such as PPO or DQN to refine its predictive abilities over time. The agent continually learns from new sensor data, improving its accuracy in predicting faults and enabling proactive maintenance scheduling.

1. Algorithm for Real-Time Fault Prediction Using Deep Reinforcement Learning

The fault prediction algorithm monitors the machine's health and predicts potential failures before they occur. By leveraging deep reinforcement learning, the system learns to detect patterns associated with faults and takes preventive actions accordingly.

Pseudo-Code for Fault Prediction:

```
initialize_fault_system()  # Setup sensor data and machine health parameters
initialize_DRL_agent()  # Initialize fault prediction agent
while True:  # Continuous monitoring of machine health
health_state = get_machine_health()  # Get real-time machine health data (vibration, temperature)
prediction = DRL_agent.predict_fault(health_state)  # Predict if fault is likely
if prediction == "FaultDetected":
```

```
take_preventive_action()  # Trigger maintenance or stop machine operation
result = observe_fault_status()  # Check if the fault occurred or was prevented
reward = calculate_fault_prediction_reward(result)  # Evaluate the prediction accuracy
DRL_agent.update_policy(reward)  # Update the agent's policy based on result
if fault_condition_met():
break  # Stop if fault resolution is complete
```

3.1.3 Integration of Adaptive Scheduling and Fault Prediction

One of the key innovations of the proposed framework is the integration of the adaptive scheduling and fault prediction modules into a single, unified system. This integration allows for dynamic decision-making based on both production requirements and machine health. For example, if the fault prediction module identifies a potential issue, the scheduling module can be adjusted to prioritize maintenance tasks or adjust the workload to reduce strain on the machine.

The decision-making layer at the core of the framework ensures that both modules work together seamlessly, improving overall system performance. The continuous feedback loop between the two modules allows for real-time optimization, ensuring that the CNC machine operates efficiently while minimizing downtime and maximizing throughput.

1. **Integrated System Algorithm for Adaptive Scheduling and Fault Prediction**

In the integrated system, the scheduling and fault prediction components work together seamlessly. When a fault is predicted, the scheduling algorithm adjusts the task allocation to minimize disruption, allowing the system to maintain optimal performance.

Pseudo-Code for Integrated System:

```
initialize_scheduling_system()  # Setup machine status, resources, tasks
initialize_fault_system()  # Setup machine health sensors and parameters
initialize_DR_agents()  # Initialize DRL agents for scheduling and fault prediction
while True:  # Continuous operation of the integrated system
machine_state = get_machine_state()  # Get real-time machine status
# Adaptive scheduling action
scheduling_action = DRL_agent_schedule.select_action(machine_state)
apply_scheduling_action(scheduling_action)  # Execute scheduling
# Fault prediction action
health_state = get_machine_health()  # Collect health data
fault_prediction = DRL_agent_fault.predict_fault(health_state)
if fault_prediction == "FaultDetected":
execute_preventive_action()  # Trigger maintenance or alert operator
adjust_schedule_for_maintenance()  # Reschedule tasks to avoid disruption
result = observe_outcome()  # Observe the impact of actions (task completion, machine health)
scheduling_reward = calculate_scheduling_reward(result)  # Evaluate scheduling outcome
fault_reward = calculate_fault_prediction_reward(result)  # Evaluate fault prediction outcome
DRL_agent_schedule.update_policy(scheduling_reward)  # Update scheduling agent's policy
DRL_agent_fault.update_policy(fault_reward)  # Update fault prediction agent's policy
if all_conditions_met():
break  # End if the system has completed the task cycle
```

3.2 Proposed Deep Reinforcement Learning Algorithm

The proposed DRL algorithm leverages Proximal Policy Optimization (PPO), a state-of-the-art method for stable policy updates. The algorithm's structure ensures efficient exploration and exploitation of the solution space.

Pseudo Code:

Input: State space S, action space A, reward function R(s, a), policy $\pi\theta$

```
Initialize: Policy network πθ, value network Vφ, replay buffer B
For episode = 1 to N do:
  Initialize environment and observe initial state s0
  For t = 1 to T do:
    Select action at = πθ(st)
    Execute action at, observe reward rt and next state st+1
    Store (st, at, rt, st+1) in B
    If episode terminates or t reaches T then:
      Update policy πθ and value network Vφ using PPO objective
  End For
End For
```

Key features of the algorithm include:

- Continuous State Updates: Enables real-time adaptability.
- Reward Function Design: Encourages efficiency and fault avoidance.
- Policy Optimization: Ensures stability and convergence.

Fault Prediction Algorithm

The fault prediction module integrates spatial and temporal analysis using a hybrid CNN-LSTM model. This architecture captures both the spatial features of sensor data and their temporal correlations.

Steps:

1. Preprocessing: Sensor data is normalized and segmented.
2. Feature Extraction: CNN layers extract spatial features.
3. Temporal Analysis: LSTM layers model temporal dependencies.
4. Output Layer: Produces fault probabilities for real-time diagnostics.

4. Experimental Setup

4.1 Hardware and Software Configuration

- CNC Machine: Five-axis machining center with integrated multi-sensor setup.
- Sensors: Accelerometers, temperature probes, and acoustic emission sensors.
- Computing Environment: NVIDIA RTX 3090 GPU, TensorFlow, and PyTorch.

4.2 Dataset

The dataset comprises six months of operational logs and fault records. Key attributes include:

- Spindle Speed: RPM values indicating operational load.
- Vibration Amplitude: Highlights potential mechanical issues.
- Tool Temperature: Monitors overheating risks.
- Fault Annotations: Labeled data for supervised learning.

4.3 Evaluation Metrics

Performance evaluation focuses on:

1. Scheduling Efficiency: Measures job completion time and resource utilization.
2. Fault Prediction Accuracy: Assesses precision, recall, and F1 score.
3. System Robustness: Evaluates adaptability to operational changes.

5. Results and Discussion

5.1 Adaptive Scheduling Performance

The DRL-based scheduling agent demonstrated superior performance, achieving:

- Job Completion Time: Reduced by 18% compared to traditional methods.
- Resource Utilization: Improved by 22%, maximizing productivity.

Table 1 shows the performance metrics for adaptive scheduling under different conditions, with a comparison between conventional scheduling methods and the DRL-based adaptive scheduling method.

Table 1: Task Scheduling Performance

Scheduling Method	Average Task Completion Time (hrs)	Machine Utilization (%)	Idle Time (%)	Resource Efficiency (%)
Conventional Scheduling	12.5	75	25	85
DRL-based Scheduling	10.2	92	8	95

Tables shows that The Average Task Completion Time was reduced using the DRL-based scheduling method, optimizing the task sequence for better resource allocation. Machine Utilization improved by 17% with DRL-based scheduling, indicating less idle time and better resource management. Idle Time was significantly reduced due to efficient task prioritization and dynamic scheduling. Resource Efficiency also showed an increase with DRL-based scheduling, reflecting better use of available machinery and labor.

5.2 Fault Prediction Accuracy

The hybrid CNN-LSTM model achieved high accuracy:

- Precision: 94.7%
- Recall: 92.3%
- F1 Score: 93.5%

Table 2 compares the fault prediction accuracy between the proposed DRL-based fault prediction model and traditional fault detection methods.

Table 2: Fault Prediction Accuracy

Fault Detection Method	True Positives (%)	False Positives (%)	True Negatives (%)	False Negatives (%)	Overall Accuracy (%)
Traditional Method	80	15	85	20	82

Fault Detection Method	True Positives (%)	False Positives (%)	True Negatives (%)	False Negatives (%)	Overall Accuracy (%)
DRL-based Prediction Model	92	8	95	10	94

Table 2 shows that The True Positives rate increased significantly with the DRL-based model, indicating better fault prediction capability. False Positives and False Negatives were reduced, improving the overall reliability of the fault prediction system. Overall Accuracy improved by 12% with the DRL-based approach, demonstrating its superior predictive performance compared to traditional methods.

5.3 Response Time and Efficiency

Table 3 compares the system's response time and efficiency for both scheduling and fault prediction tasks.

Table 3: System Response Time and Efficiency

System Task	Response Time (seconds)	Efficiency (%)	Total System Downtime (hrs)
Conventional Scheduling	15	85	4
DRL-based Scheduling	10	92	2
Traditional Fault Detection	20	80	5
DRL-based Fault Prediction	12	90	3

Table 3 shows The Response Time for the DRL-based scheduling and fault prediction systems is faster than traditional methods, demonstrating a more responsive system. Efficiency increased with the DRL-based models, reflecting better performance in both scheduling and fault prediction. System Downtime decreased due to more effective scheduling and earlier fault detection, contributing to a more stable machine operation.

5.4 Health and Performance Metrics

Table 4 provides machine health and performance metrics before and after the implementation of the integrated adaptive scheduling and fault prediction system.

Table 4: Machine Health and Performance Metrics

Metric	Pre-Implementation	Post-Implementation
Average Machine Health (out of 100)	75	90
Number of Faults per Month	5	2
Average Workload per Day (hrs)	10	12
Machine Lifetime (months)	24	30

Table 4 shows Machine Health improved post-implementation, reflecting the effectiveness of the DRL-based fault prediction system in maintaining machine health. The Number of Faults reduced by 3 per month due to accurate fault prediction and timely maintenance. Workload per Day increased, indicating better utilization and less downtime due to optimized scheduling. The Machine Lifetime improved by 6 months, demonstrating the long-term benefits of the integrated system.

5.5 Comparative Analysis

Table 5 compares the overall system performance under different operating scenarios, including different levels of machine utilization and fault prediction accuracy.

Table 5: Comparison of System Performance Under Various Scenarios

Scenario	Fault Detection Accuracy (%)	Task Completion Time (hrs)	Machine Utilization (%)	Overall Performance Rating (out of 10)
Scenario 1: Low Utilization	80	15	60	7
Scenario 2: High Utilization	85	12	85	8
Scenario 3: Optimal Conditions	94	10	92	9

Table shows Scenario 3 reflects the optimal operating conditions, with high fault detection accuracy, reduced task completion time, and increased machine utilization. The Overall Performance Rating demonstrates that the integrated system performs best when operating under optimal conditions, with both scheduling and fault prediction working in tandem.

Table 6: Comparative Analysis

Metric	Proposed Framework	Traditional Methods
Scheduling Efficiency	82%	65%
Fault Prediction	93.5% F1 Score	78.9% F1 Score
Adaptability	High	Low

6. Conclusion and Future Work

In conclusion, the integration of deep reinforcement learning (DRL) for adaptive scheduling and real-time fault prediction in five-axis CNC machine tools offers significant advancements over traditional methods. The proposed system effectively reduces task completion time, enhances machine utilization, and minimizes downtime, leading to improved overall efficiency. Through continuous learning, the DRL agents optimize scheduling decisions based on real-time machine status and operational demands, ensuring efficient resource allocation. Furthermore, the fault prediction mechanism enables timely maintenance actions by accurately forecasting potential failures, thus reducing the occurrence of unscheduled downtimes. The experimental results show that the DRL-based system outperforms conventional approaches in terms of accuracy, efficiency, and system response time. This approach not only improves the productivity and longevity of CNC machines but also provides a scalable and adaptive solution for manufacturing systems. By continuously refining its decision-making processes, the system ensures that both scheduling and fault prediction become progressively more accurate, ensuring sustained performance improvements in real-world applications.

Future work includes:

1. Multi-Machine Environments: Expanding the framework to coordinate multiple CNC machines.
2. Unsupervised Learning: Incorporating anomaly detection methods for unlabeled data.
3. Operator Interfaces: Developing intuitive tools for real-time monitoring and control.

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