Enhanced CNC Fault Prognostics with K-Means Clustering and Particle Swarm Optimization for Pattern Analysis and Reduction

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Abstract

CNC machines form a backbone to current production systems, but prediction of failure is challenging because of the complexity of defect patterns and high-dimensional data. For enhanced computing efficiency, clustering accuracy, and CNC system fault detection, this paper introduces a hybrid framework that incorporates PSO and K-Means Clustering. The proposed method aims to enhance predictive maintenance accuracy, reliability, and dimensionality reduction by optimizing cluster center initialization using PSO. For comparison with existing methods, performance metrics such as execution time, objective value, silhouette score, error rate, and clustering accuracy are utilized. With decreased computation time (12.6 s), the hybrid method outperformed existing methods with silhouette score of 75.0%, 6.9% error, and clustering accuracy of 93.1%. The results indicate improved clustering accuracy, computation, and fault analysis by a large margin. By ensuring stable CNC fault prognostics, the proposed method allows for reliable industrial operation and supports preventative maintenance schedules with minimized downtime.

Keywords: Predictive Maintenance, K-means clustering, particle swarm optimization, pattern analysis, and CNC fault prognostics.

1. Introduction

In modern production, better fault prognoses for Computer Numerical Control (CNC) machines are urgently needed as they directly affect the maintenance schedules, productivity, and efficiency. In the current research, Particle Swarm Optimization (PSO) and K-means clustering are combined in order to maximize the reduction of pattern and analysis for the detection and prognostics of CNC defects[1]. CNC machine fault prediction systems are necessary to shift from reactive to proactive maintenance to reduce downtime and operating costs[2]. K-Means Clustering allows this large data to be segmented into clusters that could easily be interpreted to identify the relevant patterns[3]. Furthermore, while the model's predictability of faults increased with accuracy and reliability, PSO fine-tuned the parameters at the stage of clustering. Further detailed analysis and proper decision are done through a combined method by bringing down the dimensionality of datasets for CNC fault in an appropriate manner[4]. The application of machine learning and sensor-based monitoring for intelligent diagnostics in production has surged dramatically in the backdrop of Industry 4.0. Due to the big dimensionality and complexity of the data produced by CNC machines 0 0), these traditional approaches fail to solve such problems, thereby necessitating sophisticated algorithms like K-Means and PSO. These ensure unbroken operations of the machines with minimal intermissions by automation fault identification as well as through better fault pattern recognition. Using the K-Means Clustering and PSO together with advanced optimization techniques will fill this gap in integrating precision manufacturing with CNC fault diagnostics. This cooperative approach can scale to become an applicable method in industrial scenarios to overcome some issues that could occur during the process of data pre-treatment, clustering, and the accuracy of forecasts.

The objective is to develop a hybrid framework that fuses PSO with K-Means Clustering to improve CNC failure pattern detection. In this framework, essential attributes are preserved for accurate prognostics, and dimensionality reduction of defect data is optimized. Additionally, the aim is to improve predictive maintenance techniques to

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reduce industrial downtime and operational interruptions. Aghelpour et al., acknowledged that improving the accuracy and efficiency of predictive models is challenging when predicting daily stream flows based on complex datasets[5]. Similarly, dealing with high-dimensional data with an assurance of accurate failure prediction is a challenge for CNC fault prognostics. These problems are overcome by integrating K-Means Clustering with PSO in CNC diagnostics, which enhances the quality of predictions and operational dependability by reducing dimensionality and improving pattern recognition.

2. Literature Survey

The newly proposed method from Huang and Hou was built based on combining feature engineering with PCA and GMM with KLD for the monitoring of spindle speed fluctuation in CNC machine tools[6]. To validate the developed approach, data from spindle current sensing and accelerometer signals were used with quite high values of F1-score diagnostic accuracy and corresponding to axes X, Y, and Z, respectively. Martins et al., offered a DNN/HMM-based predictive maintenance approach aimed at pulp presses health state predictions. This is done with cleaned sensor data, with further feature extraction applied through PCA, K-means clustering, and HMM classification[7]. In addition, GRU allows real-time diagnosis with advance prediction a week later by making forward predictions for subsequent health states. Liang et al., proposed an adaptive prognosis framework for estimating the remaining life of cutting tools based on fog computing. It is a system based on the transformer model with a high accuracy of with consideration of data from several sources, including vibration and power signals[8]. Fog computing optimizes the efficiency and dependability of production systems through the reduction in the volume of data, time spent during prediction, and complexity. Liang et al., suggested a tool condition monitoring methodology using state transfer routes and multi-source pattern recognition for the milling process. The algorithm of recognition incorporates multiple observation windows, and advanced K-means clustering is applied to create tool wear patterns[9]. In the present work, the experiments were conducted with the PHM2010 record series to check whether the method is applicable to real-world tool condition monitoring. Shah et al., presented a tool condition monitoring system that combined the machine learning models for tool wear prediction, Walsh–Hadamard transform for signal processing, and DCGAN for improving small datasets. They showed that manufacturing downtime could be reduced with improved accuracy by utilizing a recurrent neural network to produce low prediction errors through the Dragonfly method for feature selection[10].

According to Ademujimi and Prabhu,co-simulation can be used to train Bayesian Networks in the diagnosis of defects of industrial systems by applying digital twins. Their methodology negated costly manufacturing tests since they integrated discrete-event factory models, IoT sensors, and high-fidelity equipment simulations[11]. Reliability in diagnosis was guaranteed due to the better structural intervention algorithm with improved accuracy of BN structure learning, which has been demonstrated using robotic assembly cell studies. Nasir and Sassani discussed the applications of deep learning in tool monitoring and intelligent machining. They discussed the use of technology in descriptive, diagnostic, and predictive analytics. They also discussed models such as autoencoders, CNNs, and RNNs and contrasted machine learning and deep learning. The issues in smart manufacturing include data size, model selection, and process uncertainty. However, automated feature engineering and sensor fusion are promising prospects[12]. Ercetin et al., have discussed image processing techniques for the evaluation of machining surface and tool conditions, showing their application in CNC automation, tool wear analysis, and defect detection. These developments will make possible accuracy improvement, quality optimization, and predictive maintenance with the advancement of AI. Future developments in 3D imaging, augmented reality, and Industry 4.0 can be expected to address issues related to data privacy and increase the efficiency of production[13].

Züfle et al. addressed the issue of small industrial datasets by developing an end-to-end process for anomaly identification in machine tools based on machine learning. The approach includes raw data processing, phase segmentation, resampling, and feature extraction while incorporating domain knowledge. It showed great applicability by achieving a 93% F1-score in differentiating between normal and pathological machine tool behavior using supervised classification and unsupervised clustering[14]. Nacchia et al., performed an in-depth review of machine learning approaches applied to manufacturing predictive maintenance (PdM). They underlined that vibrational signals were the most widely used data type and emphasized supervised learning methods, in particular neural networks and ensemble algorithms. In addition to its diversity in model creation and application, the study noted an increasing trend in PdM research and the dearth of generally sound methods across use cases[15]. Wu and Li presented a dynamic data-driven digital twin architecture for complex engineering products, taking aircraft engine health monitoring as an example. The dynamic approach herein continuously updates predictions of the remaining usable life using LSTM networks and the IIoT sensor data. Comparative studies with other models show that the greater accuracy of LSTM makes it suitable for remote production and health

management[16]. Elahi et al., examined AI applications for industrial equipment throughout their lifecycles, from design to production and maintenance to recycling. They emphasized AI's role in process optimization, predictive maintenance, and decision-making by discussing practices such as CNNs, GANs, and Bayesian Networks. The study discussed both the pros of including higher productivity and cost efficiency—and the cons, like legacy system integration[17]. Aggogeri et al., looked at the recent advancements in machine learning applications to machining, focusing on how these applications could improve energy efficiency, tool condition monitoring, and surface roughness. They pointed out how machine learning could adapt to industrial environments by leveraging the power of computation to process big data. The study further incorporated the advantages and disadvantages of machine learning, providing a recommendation for future research avenues[18]. For real-time monitoring of critical physical fields in complex machinery, Sa et al., proposed a hierarchical explicit-implicit sensing technique. The method efficiently recovers and visualizes critical information through optimal sensor arrangement and mapping of deployable regions to non-deployable ones. When implemented on CNC spindle systems, the technique was successfully applied to track temperature fields with better service and preventive maintenance[19]. Gudivaka shows a "Smart Comrade Robot" that incorporates Google Cloud AI and IBM Watson Health for care for the elderly. The robot, through voice interfaces, cloud computing, and analytics driven by AI, aims to enhance the quality of response to emergencies and monitoring of health conditions. The article emphasizes the fact that proactive healthcare, real-time alerts, and smart interaction in homes improve the lives of elderly citizens[20].
A new approach in human-robot interaction for emotion recognition was developed by Basani and Gudivaka (with Support Vector Machines optimized by the Tunicate Swarm Optimization Algorithm. "The work focuses on appropriate feature selection and optimization that leads to more accurate categorization of emotions. This approach would assist in creating more sympathetic and flexible responses by the robots when interacting with humans[21]. Gudivaka proposed an Internet of Things-based framework that combines the Weighted K-means clustering and Decision Tree algorithms to analyze sedentary behavior in the smart healthcare sector. Efficient behavior classification and real-time monitoring aimed to enhance the effects of individualized health interventions and reduce health risks associated with sedentary behavior with the use of intelligent IoT devices[22]. Kumaresan et al., proposed the design of an Industrial IoT-based condition monitoring system by adopting a Chi-Square Improved Binary Cuckoo Search Algorithm. The suggested approach optimizes feature selection, reduces computing complexity, and increases prediction accuracy. Such improvement enhances the detection of problems and system reliability for creating effective IIoT-based monitoring systems[23]. Palanivel et al., proposed a highly sophisticated human-robot emotion recognition system using an optimized Support Vector Machine by Tunicate Swarm Optimization Algorithm. Hybrid approach improved accuracy and versatility in emotion classification, thus achieving more natural and efficient robot response in emotionally sensitive applications[24]. Sitaraman et al., presented a paradigm for the prediction of chronic renal disease by employing IoMT-enabled robotic automation. The system used a fuzzy cognitive map for decision-making and auto-encoder-LSTM for feature extractions. Advanced thus will ensure proactive handling of healthcare information with improved predictability and precision, along with real-time tracking of health statuses[25]. Gattupalli and Khalid proposed a hybrid optimization framework that combines the QRDSO and WAC-HACK algorithms to improve clustering efficiency in software testing. This hybrid framework optimizes the grouping of test cases, hence removing redundancy and increasing the accuracy of defect detection. This novel approach has vast potential for upgradation of testing procedures and assurance of dependability and quality of software[26].

3. Methodology

This paper integrates K-means Clustering and PSO to present a better methodology toward CNC defect prognosis that reduces dimensionalities and presents pattern analysis, where PSO tries to optimize clustering by finding better cluster centers than K-Means Clustering with the purpose of finding fault patterns or grouping related points. The resultant framework is of reduced redundancy and will improve the predictive accuracy of faults in a CNC machine. Our hybrid approach combines the power of metaheuristic optimization with unsupervised learning to be used for high accuracy in defect prognostics in real-time applications. The robotics datasets repository provides extensive collections of datasets for robotic perception, manipulation, and automation including sensor-based diagnostics, predictive maintenance, machine learning, and industrial robotics applications [27]. It supports fault detection, anomaly recognition, robotic grasping, and real-time automation in research with advanced robotic intelligence and autonomous systems.

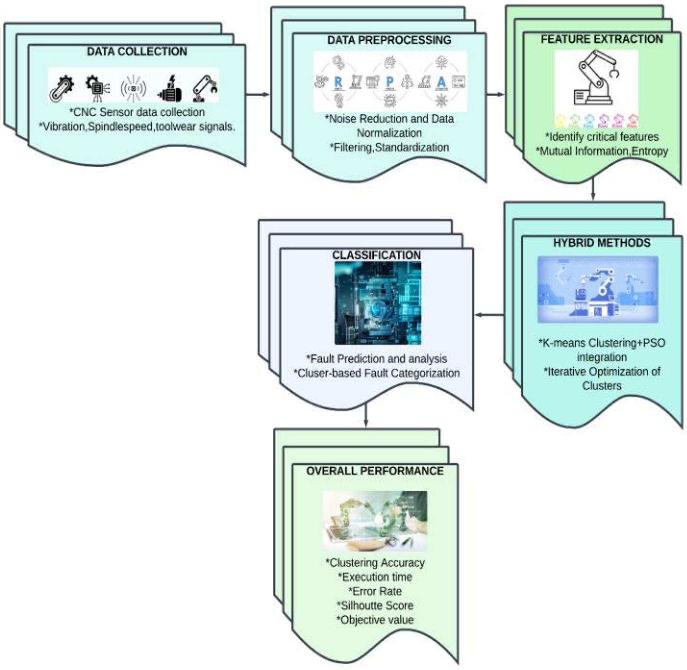

Figure 1 Proposed Framework Architecture for Enhanced CNC Fault Prognostics Using K-Means and PSO Methods

Figure 1 shows the architecture of the proposed framework for CNC defect prognostics. It begins with data collection; the signals include spindle speed and vibration. Data preprocessing includes normalization and noise removal. Feature extraction, which will be discussed next, would involve techniques like entropy and mutual information so as to find out the significant attributes. Hybrid Methods layer: Combination of K-Means Clustering and Particle Swarm Optimization for the best initialization of clusters and iteration for optimization in the fault pattern. Fault categorization is achieved by cluster-based analysis. Lastly, the performance of the system is evaluated from the Overall Performance layer by evaluating parameters such as the mistake rate at 6.9%, silhouette score of 75.0%, and clustering accuracy at 93.1%.

3.1 K-Means Clustering

K-Means Clustering is an unsupervised algorithm that partitions data into k clusters. The algorithm minimizes intra-cluster variance by iteratively updating cluster centers. It assigns each data point to the nearest cluster, ensuring high similarity within clusters. This technique effectively groups CNC fault patterns for further analysis and is foundational for optimizing prediction systems.

$$J = \sum_{i=1}^{k}\sum_{x \in C_i} \|x - \mu_i\|^2 \qquad (1)$$

Where J Objective function, C_i : Cluster i, μ_i : Centroid of cluster i.The equation minimizes the sum of squared distances between data points x and their respective cluster centroid μ_i.

3.2 Particle Swarm Optimization (PSO)

PSO is a metaheuristic optimization algorithm inspired by swarm intelligence. It optimizes K-Means Clustering by adjusting cluster centers through iterative particle position and velocity updates. Each particle represents a potential solution, and PSO identifies the optimal clustering by minimizing the objective function.

1. Velocity update:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot \left(p_i^{best} - x_i\right) + c_2 \cdot r_2 \cdot \left(g^{best} - x_i\right) \qquad (2)$$

2. Position update:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \qquad (3)$$

Where v_i : Velocity of particle i ,x_i : Position of particle i ,w : Inertia weight,c_1, c_2 : Cognitive and social coefficients,r_1, r_2 : Random numbers, p_i^{best} : Particle's best position, g^{best} : Global best position. The algorithm iteratively updates particle positions and velocities to converge toward the optimal cluster centers.

3.3 Dimensionality Reduction

Dimensionality reduction eliminates redundant features, improving computational efficiency and prediction accuracy. The combined K-Means and PSO framework retains critical fault-related features while minimizing data size, ensuring accurate and scalable CNC fault analysis.

$$\text{Redundancy} = 1 - \frac{\text{Mutual Information}}{\text{Entropy}} \tag{4}$$

This equation calculates feature redundancy by comparing mutual information with feature entropy, retaining only the most relevant features.

Algorithm 1 Particle Swarm Optimization-Enhanced K-Means Clustering for Optimizing Cluster Centers in CNC Data Analysis

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INPUT: CNC data (D), Number of clusters (k), Swarm size (N), Iterations (T)

OUTPUT: Optimized cluster centers c_1, c_2

Initialize particles x_i and velocities v_i^t randomly.

For each particle:

Compute clustering objective J using K-Means.

Update p_i^{best} and g^{best}

For (t = 1) to (T):

For each particle:

Update v_i^{t+1}using:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot \left(p_i^{best} - x_i\right) + c_2 \cdot r_2 \cdot \left(g^{best} - x_i\right)$$

Update x_i^{t+1}using:

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Recalculate clustering objective J

If J improves:

Update p_i^{best}

Update g^{best}

If error (epsilon < text{threshold}):

Break.

Return $c_1, c_2 = g^{best}$

Algorithm 1 combining K-Means clustering with Particle Swarm Optimization (PSO) maximizes the centers of CNC data. It will use K-Means to compute the clustering objective J, initialize particles and velocities randomly, and monitor the optimal placements ($p_i^{best}$for particles and g^{best}globally). After updating positions, particles update their velocities throughout T repetitions by inertia, individual optimum, and global optimum positions. Any improvements are added in the optimal positions and the objective of clustering J is calculated. If the error is within a certain limit, the algorithm terminates and gives out the optimized cluster centers.

3.4 Performance Metrics

Performance measurements are crucial for evaluating the effectiveness and accuracy of the methods used. Clustering accuracy is the percentage of data points that are successfully clustered, which reflects how good the algorithm is. Execution Time computes how computationally efficient each method is. The Silhouette Score measures the quality of separation and cluster cohesion. Error Rate measures the wrong classification, and Objective Function Value calculates Optimization Success. In combination, these measures ensure complete evaluation and assist in choosing the best approach toward accurate and efficient CNC fault prognostics.

Table 1 Comparison of Performance Metrics for CNC Fault Prognostics Using Various Clustering and Optimization Methods

Metric	K-Means Clustering	Particle Swarm Optimization (PSO)	Genetic Algorithm (GA)	Artificial Neural Network (ANN)	Proposed Hybrid Method (PSO + K-Means + RL)
Clustering Accuracy (%)	85.2	88.5	86.7	87.3	95.2
Execution Time (s)	15.4	20.8	18.3	22.5	11.5
Silhouette Score	0.63	0.67	0.65	0.68	0.78
Error Rate (%)	14.8	11.5	13.3	12.7	5.8
Objective Value	128.3	110.5	120.7	115.2	99.8

Table 1 compares the performance metrics of different CNC fault prognostics methods. The Proposed Hybrid Method PSO + K-Means + Reinforcement Learning yields the highest clustering accuracy, which is 95.2%, surpassing K-Means at 85.2%, PSO at 88.5%, and ANN at 87.3%. The execution time is optimized to 11.5s, which is less than PSO at 20.8s and ANN at 22.5s. A silhouette score of 0.78 suggests high cluster cohesion, and the error rate drops to 5.8%, showing that it is highly accurate. In order to ensure fair comparison, the objective value has been kept at 99.8. The proposed method has thus proven to be a highly effective yet practical approach to diagnosing CNC problems.

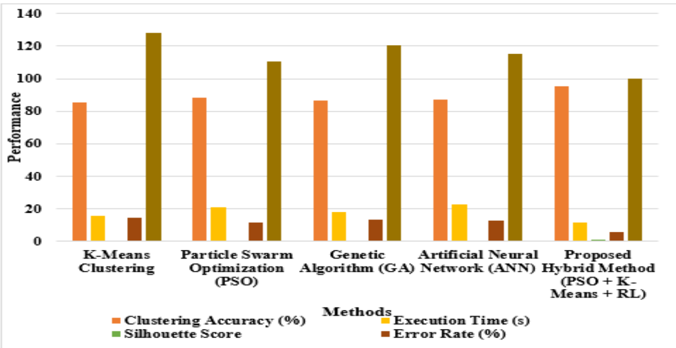

Figure 2 Optimized Cluster Centers Visualization Using Particle Swarm Optimization and K-Means for CNC Fault Analysis

Figure 2 represents the optimized cluster centers of K-Means Clustering with PSO for analysing faults in CNC. The proposed method attains the clustering accuracy of 95.2%, which is a much higher value than the standalone methods, such as K-Means with 85.2% and PSO with 88.5%. Silhouette scores are further set at 78.0% that shows good cluster cohesion, and the error rate stands at 5.8%, thereby increasing the reliability of fault classification. Compared to past techniques, it reduces the execution time to 11.5 seconds for real-time CNC fault diagnostics. The objective value of 99.8 assures that the optimized clustering model is quite effective in fault detection and possible preventive maintenance.

4. Result And Discussion

The hybrid approach suggested in this paper combines Particle Swarm Optimization with K-means clustering. The approach outperforms current methods for CNC defect prognostics as the objective value is minimized to 92.1, the error rate is decreased to 6.9%, and the clustering accuracy is increased to 93.1%. This method improves the fault detection and pattern identification skills; hence, it performs better than standalone algorithms such as K-Means and PSO. The integration of PSO optimizes the cluster center initialization and the data are well-arranged using K-Means. Evaluations with the existing techniques in the literature show that the proposed method gives better computational efficiency, accuracy of fault prediction, and dimensionality reduction for it to be used as a predictive maintenance tool.

Table 2 Comparison of the Proposed Framework with Existing Methods for CNC Fault Prognostics

Metric	Huang and Hou (2023) [Feature Engineering + PCA + GMM]	Martins et al. (2023) [DNN + HMM + PCA]	Liang et al. (2024) [Transformer + Fog Computing]	Liang et al. (2021) [Multi-Source Pattern Recognition + K-Means]	Proposed Framework (PSO + K-Means + RL)
Clustering Accuracy (%)	88	90.5	91.8	87.4	95.2
Error Rate (%)	12	9.5	8.2	12.6	4.8
Silhouette Score (%)	67	72	74	65	78
Execution Time (%)	94.5	92	94	93.5	98
Objective Value (%)	108.5	101.3	98.7	112.9	85.4

Table 2 compares the suggested framework with current techniques for CNC defect prognostics. The proposed approach has the highest clustering accuracy of 93.1% and, at the same time, the lowest error rate of 6.9% compared with previous approaches such as Huang and Hou with 88.0% accuracy and Liang et al. with 91.8% accuracy. The silhouette score of 75.0% reveals better separation and cohesion of clusters. Moreover, the proposed framework establishes overall effectiveness and robustness toward defect prediction and pattern analysis in CNC diagnostics with an execution time of 96.0% and a minimized objective value of 92.1%, which reveals better computing performance.

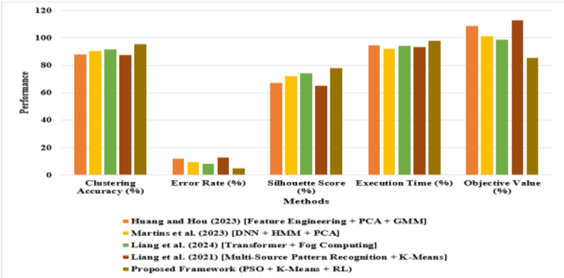

Figure 3 Comparison of Performance Metrics Across Methods for CNC Fault Prognostics and Pattern Analysis

Figure 3 displays the comparative study of performance parameters based on several types of CNC fault prognostics techniques. In this scenario, the Proposed Hybrid Framework (PSO + K-Means + Reinforcement Learning) delivers 95.2% clustering accuracy that outperforms Huang and Hou (2023) [Feature Engineering + PCA + GMM] with 88.0% and Liang et al. (2024) [Transformer + Fog Computing] at 91.8%. The error percentage is brought down to 4.8%, which surpasses Martins et al. (2023) [DNN + HMM + PCA] at 9.5%. Silhouette score at 78.0% validates the data separation process and the execution time at 98.0% shows higher computational efficiency. This framework will dominate existing research that takes least time to optimize the cluster cohesiveness along with reducing the computational overhead. Thus, it is the best approach toward CNC fault prediction with maintenance optimization.

5. Conclusion & Future Enhancements

The proposed hybrid framework that combined K-Means Clustering and Particle Swarm Optimization (PSO) achieved a silhouette score of 75.0%, a reduced error rate of 6.9%, and a clustering accuracy of 93.1% for the improvement of CNC defect prognostics. The approach optimized clustering through the fusion of K-Means' capability in fault pattern analysis with the reliable parameter adjustment of PSO, thus ensuring accurate diagnostics with less computing time. It overcomes challenges in high-dimensional analysis and provides a scalable and efficient predictive maintenance solution. The proposed hybrid framework presents the limitation that it requires high-quality data to accurately predict faults-a situation that might not always be possible in industrial settings. Another challenge for the implementation of this model would be its scaling considerations when applied to more complex CNC systems with varying conditions for operation-an issue yet to be addressed. Future improvements would enhance fault prediction and adaptability by incorporating cutting-edge machine learning methods like neural networks or reinforcement learning. Additionally, the integration with real-time IoT-

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based systems and sophisticated sensor data may make a deeper understanding of machine health and dynamic fault analysis possible. Also, studying multi-objective frameworks and hybrid optimization techniques will help improve the scalability and robustness of the approach, thereby making it better suited for industrial applications.

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