Diagnosis and Prediction of Typical Faults of Computer Numerical Control Machine Tools Based on Genetic Algorithm

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Abstract: In this piece of writing, we introduce a distinctive approach for diagnosing and anticipating malfunctions in CNC machine tools, leveraging the Genetic Algorithm (GA). Our objective is threefold: enhancing the precision of CNC machine tools' fault diagnosis and prediction, minimizing maintenance expenses and machine downtime, and boosting overall production efficiency. To accomplish this, we employ a model of optimization technique rooted in GA and subject it to rigorous testing. The experimental results underscore the model's commendable performance, exhibiting low false alarm and misdetection rates, alongside swift diagnosis times. These findings collectively attest to the model's reliability and effectiveness in real-world settings. These results prove that the optimization method of this model is effective. It has high practical value and popularization potential, so as to provide strong support for its wide application in the actual production environment.

1. Introduction

With the swift advancement of the manufacturing sector, CNC machine tools have emerged as the linchpin of modern production, greatly influencing both output speed and product quality [1]. Nevertheless, prolonged usage inevitably leads to various malfunctions, disrupting operations, incurring production losses, and posing potential safety risks [2]. Hence, timely diagnosis and prediction of these issues are paramount, ensuring seamless machine operation and optimal productivity [3].

In the recent past, the evolution of artificial intelligence and machine learning has propelled data-driven fault diagnosis and prediction methods to the forefront of research [4]. Among these, the Genetic Algorithm (GA), renowned for its robust global search capabilities and resistance to local optima, holds promise in the domain of fault detection and prognosis [5-6]. Against this backdrop, our article delves into the exemplary fault diagnosis and prediction techniques for CNC machine tools, leveraging the power of GA. Our objective is to enhance diagnostic and predictive accuracy, minimize maintenance expenses and machine downtime, and ultimately boost production efficiency. By exploring this avenue, we aim to pave the way for innovative and effective fault management strategies in the manufacturing industry.

2. Overview of typical faults of CNC machine tools

The CNC machine tool is an advanced automatic device equipped with a sophisticated program control system. This allows the tool to precisely move and process components based on pre-programmed instructions [7]. It seamlessly integrates cutting-edge technologies from various fields such as machinery, automation, computing, measurement, and microelectronics. Additionally, it incorporates a diverse range of sensors, ensuring high machining accuracy, consistent quality, enhanced productivity, and exceptional adaptability. CNC machine tools come in a wide variety, categorized based on processing methods such as metal cutting, metal forming, and special processing. Furthermore, depending on the control trajectory, they can be classified into point control, straight-line control, and contour control [8].

There are various types of faults of CNC machine tools, and the common typical faults mainly include mechanical faults, electrical faults, hydraulic faults and pneumatic faults [9]. Among them,

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mechanical failure is the most common type, mainly manifested in the wear, fracture and deformation of transmission parts; Electrical faults are mainly manifested as short circuit, open circuit and damage of electrical components. Hydraulic failure and pneumatic failure are mainly manifested as abnormal pressure, insufficient flow and leakage. The characteristics of CNC machine tool failures are shown in Table 1:

Table 1 Characteristics of CNC machine tool faults

Characteristic	Describe
Randomness	The time of failure is unpredictable and uncertain.
Transmissibility	The failure of one component may lead to the failure of other components, leading to a chain reaction.
Complexity	The same fault may be caused by multiple reasons, and the same reason may also cause multiple faults.

3. GA theoretical basis

GA is an advanced search technique that mimics the biological evolution process. It borrows principles from natural selection, heredity, and mutation found in biological evolution theory. By simulating biological reproduction, crossover, and mutation, GA strives to locate the most optimal solution [10]. With its robust global search capabilities and resistance to getting trapped in local optima, GA excels in addressing intricate optimization challenges.

In the realm of fault diagnosis and prediction, GA offers promising applications. Initially, GA can assist in extracting and selecting relevant fault features. By refining the selection of feature subsets, the precision of fault diagnosis can be enhanced. Additionally, GA can fine-tune the parameters of fault diagnosis models, leading to improved diagnostic performance.

Furthermore, when GA is combined with other intelligent algorithms, it forms a hybrid approach that elevates the intelligence level of fault diagnosis and prediction. As technologies like deep learning continue to evolve, GA finds new applications in optimizing the architecture and parameters of deep learning models. This synergy further bolsters the accuracy and stability of fault diagnosis, paving the way for more reliable and efficient diagnostic systems.

4. Construction of fault diagnosis and prediction model for CNC machine tools based on GA

When constructing a fault diagnosis and prediction model for CNC machine tools with GA as the basis, a thoughtful model framework is essential. This framework encompasses pivotal modules like data preprocessing, feature extraction and selection, model training and refinement, as well as fault diagnosis and prediction. The data preprocessing module handles the cleansing, transformation, and normalization of the raw data, ensuring its quality for subsequent analysis. The feature extraction and selection module extracts pertinent fault-related features from this preprocessed data. GA is then leveraged to select a subset of features that are most informative, reducing dimensionality and eliminating any superfluous or irrelevant features.

The model training and optimization module takes the curated features and utilizes GA to train and refine the fault diagnosis prediction model, aiming to enhance its diagnostic capabilities. Finally, the fault diagnosis and prediction module employs the trained model to diagnose and predict faults in new data. Feature extraction and selection play a pivotal role in building an effective fault diagnosis and prediction model. In the context of CNC machine tools, common fault indicators include vibration, sound, current, and temperature signals. These signals, while rich in diagnostic information, often contain redundancies and noise. To extract fault-specific characteristics, signal processing techniques are employed. Simultaneously, GA is used for feature selection, ensuring that only the most relevant and non-redundant features are considered, thereby optimizing model performance and reducing computational demands.

In this article, feature extraction involves techniques such as time domain analysis, frequency domain analysis, and time-frequency domain analysis. These methods help extract meaningful features like mean values, variances, peak values, and frequency spectra from the signals. For feature selection, GA's global search and adaptive optimization capabilities are harnessed to identify the optimal feature subset, further optimizing the diagnostic accuracy of the model.

When constructing the fault diagnosis and prediction model of CNC machine tools based on GA, this article designs a reasonable fault diagnosis and prediction method based on GA. When GA is used to optimize the parameters, the fitness function f is set to:

$$f = 1 - \sqrt{\frac{\sum_{j=1}^{l}\sum_{k=1}^{m}\left(desired_{jk} - actual_{jk}\right)^2}{l \cdot m}} \tag{1}$$

$$actual_j = \left[\sum_{i=1}^{n} w_i x_i^p\right]^{1/p} \tag{2}$$

In this context, m denotes the quantity of training patterns that GA necessitates, while n signifies the number of distinct classes within the classification challenge. The execution process of GA comprises several key components, namely:

Initialization Phase: Initially, the evolutionary counter is set to t=0, along with defining the maximum evolutionary count t. Subsequently, m individuals, serving as potential solutions encoded in binary format, are randomly generated to form the initial population P(0).

Individual Assessment: Each individual within the population P(t) undergoes fitness evaluation. The fitness function, often linked to the problem's objective function, assesses the merit of each individual. A higher fitness score increases the likelihood of an individual's survival and subsequent reproduction.

Selection Process: The aim of the selection process is to identify superior individuals from the current population, granting them the opportunity to contribute to the next generation. Selection is guided by individual fitness scores, with common methods including roulette wheel selection and tournament selection.

Crossover Mechanism: The crossover step is pivotal in GA, mimicking the biological process of gene recombination. It involves exchanging genetic material between parent individuals, resulting in offspring with new genetic combinations. This mechanism aids in exploring the search space for better solutions.

Mutation: The mutation step simulates the random genetic mutations that occur in nature. It involves altering the genetic information at specific loci within individual strings. Mutation maintains population diversity, preventing premature convergence to local optima.

Termination Criteria: Following a sequence of genetic operations, the algorithm checks for termination conditions. These may include reaching the maximum evolutionary count t, identifying a satisfactory solution, or achieving a plateau in population fitness. If a termination condition is met, the fittest individual encountered throughout the evolution is designated as the optimal solution, and the algorithm halts.

Leveraging GA: This approach harnesses GA's powerful search capabilities and adaptive adjustment mechanisms for efficient fault diagnosis and prediction. Specifically, it utilizes a GA-based parameter optimization technique to fine-tune the parameters of the fault diagnosis prediction model, thereby enhancing its diagnostic performance. Additionally, GA's parallel search ability facilitates the simultaneous diagnosis and prediction of multiple potential faults, improving both diagnostic efficiency and accuracy.

5. Experimental design and result analysis

To validate the effectiveness of the CNC machine tools' fault diagnosis and prediction model grounded in GA, we must gather a sufficient quantity of operational data from these tools as experimental samples. This data can originate from either the monitoring systems employed during the actual production of CNC machine tools or from publicly accessible fault diagnosis datasets. It is crucial to ensure both the authenticity and completeness of the collected data. Additionally, preprocessing steps such as data cleansing, conversion, and normalization are essential to enhance data quality and uniformity.

During the experimental phase, the initial step involves training the GA-based fault diagnosis and prediction model using the preprocessed data, followed by iterative model optimization. Subsequently, the trained model undergoes testing using a designated test dataset, and we document the model's diagnostic outcomes and performance metrics. To provide a more comprehensive assessment of the model's performance, we employ techniques like cross-validation, repeating the model evaluation multiple times. This allows us to calculate the average performance indices and standard deviations across all experiments. Figure 1 illustrates the model's false alarm rate and missed report rate.

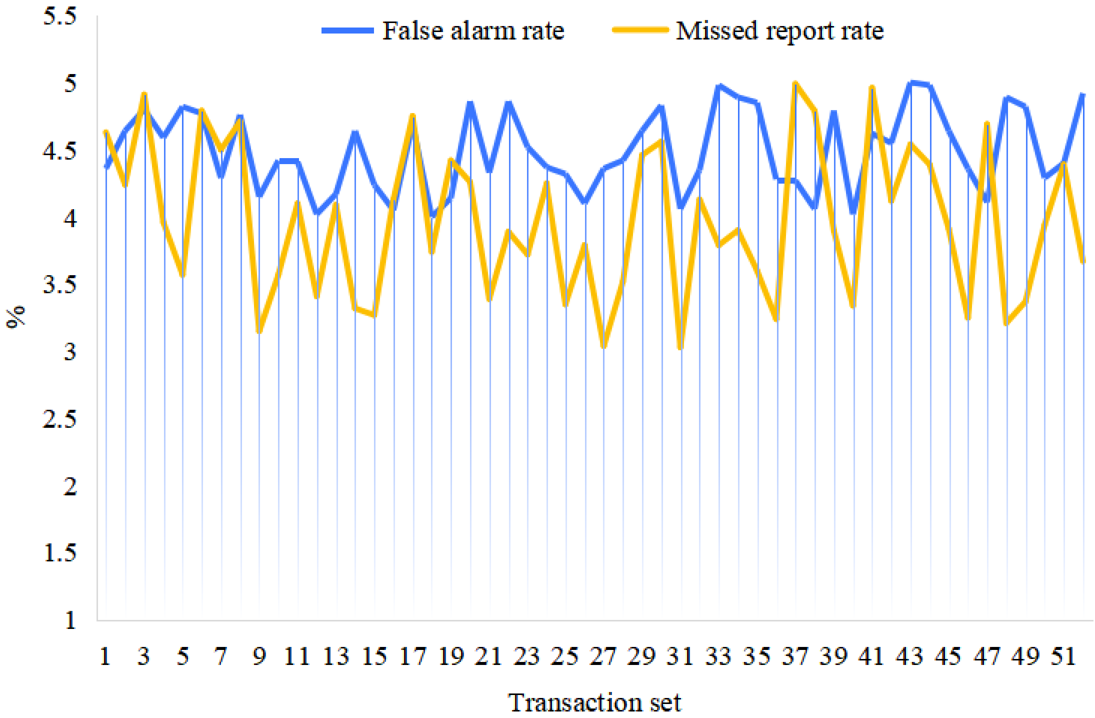

Figure 1 False alarm rate and Missed report rate of the model

The false positive rate refers to the proportion that is actually in a normal state but is wrongly predicted as a fault state by the model. High false positive rate may lead to unnecessary maintenance or downtime, increase operating costs and reduce equipment utilization efficiency. The rate of missing report refers to the proportion that is actually in a fault state but is wrongly predicted as a normal state by the model. A high rate of missing reports may lead to failures that cannot be found and handled in time, increase the risk of equipment damage, and even lead to production accidents. From the results of Figure 1, the low false alarm rate and low missed report rate show that the model has high accuracy and reliability in fault diagnosis. It can effectively capture the real fault signal without frequent false alarms, provide accurate and timely fault information for maintenance personnel, and help to achieve rapid response and effective maintenance.

The diagnosis time of the model is shown in Figure 2.

Diagnostic time refers to the time from data acquisition to model output diagnostic results. The length of diagnosis time directly affects the timeliness of fault response and production efficiency. Shorter diagnosis time means that problems can be found and solved faster and downtime can be reduced. The results show that the diagnosis time of this model is short. Shorter diagnosis time not only helps to find and solve problems in time, reduces downtime, but also improves production efficiency. In addition, rapid diagnosis response can also win valuable maintenance window for maintenance personnel and reduce maintenance cost and complexity.

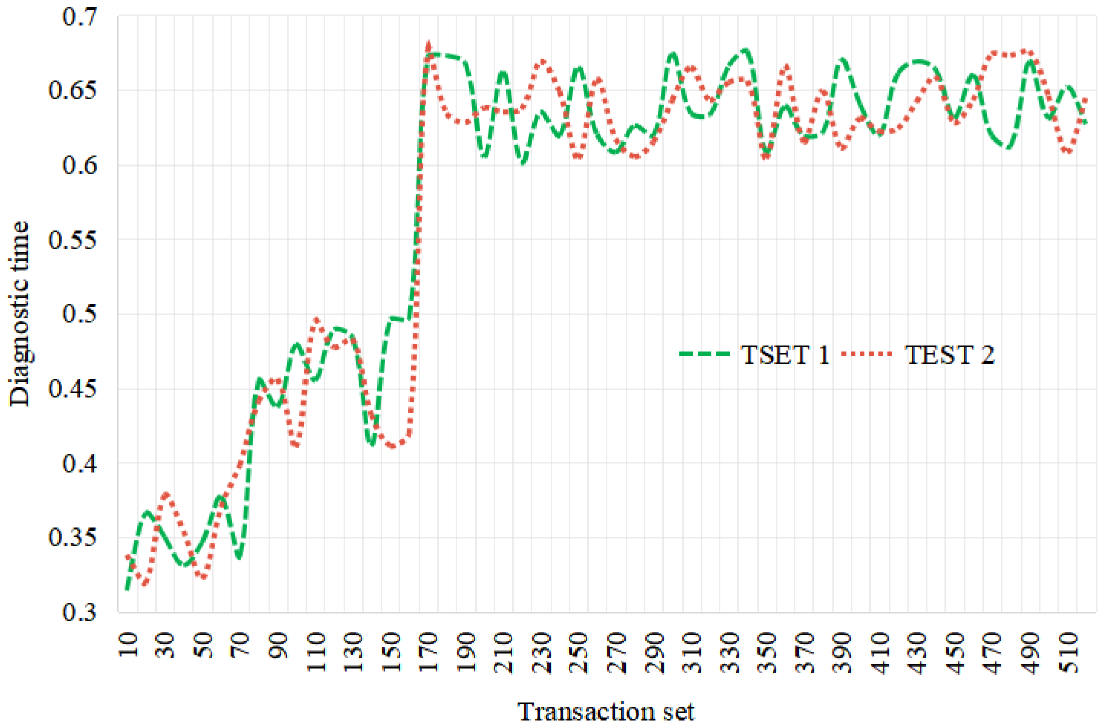

Figure 2 Diagnostic time of the model

6. Conclusions

In this article, a representative fault diagnosis and prediction model for CNC machine tools, rooted in GA, is established. A simulation experiment is conducted to assess the model's efficacy and practicality in diagnosing faults in CNC machine tools. The article delves into the model's performance across three pivotal metrics: false alarm rate, missed detection rate, and diagnosis time. The findings reveal that the model excels in minimizing false alarms, missed detections, and delivering swift diagnostic outcomes. This combination of high diagnostic precision and rapid response time underscores the model's significant practical value and potential for widespread adoption. The insights from this study contribute substantially to advancing fault diagnosis technology and offer valuable guidance for future research endeavors in related domains. Looking ahead, there is scope to explore the adaptability and scalability of this model across a range of equipment types and application scenarios.

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