Reliability Modeling of NC Machine tools Based on Artificial Intelligence

Guofa Li, Hongxiang Zhu, Jialong He*, Yongchao Huo and Jiancheng Zhang

College of Mechanical Science and Engineering, Jilin University, Changchun, Jilin, 130022, China

*Corresponding author: hjl.star@163.com

Abstract. The level of reliability for NC machine tools represents the development level of the country's manufacturing industry, and its reliability modeling is very important. In order to improve the reliability of NC machine tools, this paper proposes the application of artificial intelligence model for NC machine toolreliability. Firstly, the time history of the NC machine tool reliability is analyzed. Secondly, a reliability evaluation framework based on neural network and bayesian network, intelligent fault diagnosis based on deep learning, and intelligent fault prediction framework based on least squares support vector machine (LS-SVM) are established to achieve remote maintenance of NC machine tools. Finally, with the background of big data, the development vision about the application of artificial intelligence model for NC machine toolreliability is summarized and forecasted.
Keywords: Artificial intelligence; Reliability evaluation; Fault diagnosis; Fault prediction.

1. Introduction

Manufacturing and manufacturing technologies are moving towards the era of Industry 4.0. Intelligent manufacturing has become the main direction for industrial advanced countries to ensure their future competitiveness and status. The manufacturing industry of China faces the opportunities and challenges of innovation-driven development and intelligent transformation and upgrading. The NC machine tool is the "working machine" of equipment manufacturing industry, its reliability level represents the level of development of the manufacturing industry [1]. Its reliability analysis has always been the focus of researchers and users [2-4]. The era of artificial intelligence brings challenges and innovation opportunities to the traditional reliability analysis methods of NC machine tools.

The reliability evaluation technology of NC machine tools is to quantify the reliability level by establishing the reliability model of the machine tool. According to the actual situation, Peng fused the success or failure data, life data, and degenerate data at different system levels, and built a multi-level heterogeneous data index set. The system reliability evaluation and prediction method based on the bayesian network is proposed [5-7]. Graves uses the Bayesian approach to integrate the system's performance degradation data. Genetic algorithms are used to guide the allocation of scarce test resources to reduce the uncertainty, and the bayesian reliability evaluation method based on genetic algorithm is proposed [8]. Reese presented a bayesian model for assessing the reliability of multicomponent systems which the component, subsystem, or system level are integrated with prior information at any level. The model allows pooling of information between similar components, the incorporation of expert opinion, and straightforward handling of censored data [9]. However, the above method didn't consider the influence of the change of operating conditions on the reliability in the actual cutting process of NC machine tools.

With the development of computer technology and signal processing technology, fault diagnosis is developing in the direction of automation and intelligence [10-11]. On the basis of combining the characteristic information collected by various types of sensors for reciprocating compressors, Zhang and Jiang proposed a fault diagnosis method based on multi-source Information fusion to use a combination of multi-source information fusion technology, radial basis neural network, and weighted evidence fusion theory. Reciprocating compressor fault diagnosis method [12]. Che proposed an aero engine fault diagnosis model based on deep learning for a combination of deep neural network and decision fusion algorithms by analyzing a large number of engine performance parameters and working conditions of each component [13]. Lei introduced the characteristics of mechanical intelligent fault diagnosis based on big data. From the aspects of signal acquisition, feature extraction and fault identification, the research progress and development trend of mechanical intelligent fault diagnosis at home and abroad are summarized. Finally, the challenges of mechanical intelligent fault diagnosis theory and method in the context of big data are pointed out [14].

The application of fault prediction technology can prevent maintenance of NC machine tools before the fault occur and improve the reliability of NC machine tools.
Zhang proposed a new method for equipment degradation status recognition and remaining service life prediction based on the hybrid Gaussian output Bayesian belief network model [15]. Tian proposed a method for predicting the remaining service life based on artificial neural network equipment to use the current and previous checkpoint usage times and multiple online state measurement values as input, and the percentage of life as output, which greatly improved the reliability of the equipment and reduced the overall Maintenance costs [16]. Loutas proposed a method for estimating the remaining service life of rolling bearings based on the data-driving method of support vector machines [17]. Sikorska discussed the advantages and disadvantages of fuzzy empirical, neural networks, statistical model and physical models in predicting industrial residual life [18].

This paper discusses the time history of reliability of NC machine tools. A reliability evaluation based on neural network and bayesian network framework, an intelligent fault diagnosis based on deep learning, and an intelligent fault prediction framework based on LS-SVM are proposed.

2. The time history of the NC machine tool reliability

Reliability modeling is a prerequisite to obtain the reliability level of NC machine tools. As shown in Figure 1, the main processes of reliability modeling are reliability evaluation, fault diagnosis, and fault prediction in the life cycle of the NC machine tool. From the assembly completion of the NC machine tool to the end-of-life processing, real-time reliability evaluation of the NC machine tool can accurately obtain the reliability level and understand the dynamic characteristics of the NC machine tool. When the NC machine tool is fault, fault diagnosis is performed to determine the cause of the fault, the location of the fault, and the failure mode to achieve fast and accurate maintenance of the NC machine tool. The fault prediction can determine the time of the next failure for the NC machine tool in advance to perform preventive maintenance. It can reduce the loss caused by the failure of the NC machine tool and improve the reliability of the NC machine tool.

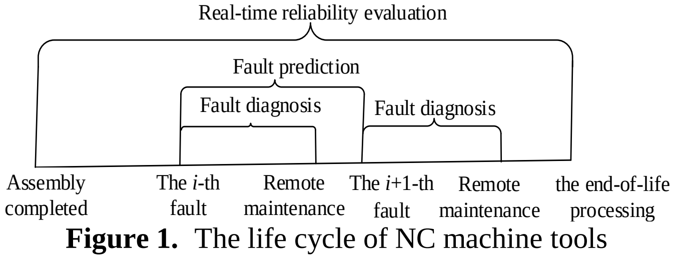

Figure 1. The life cycle of NC machine tools

3. Application of artificial intelligence model for NC machine tool reliability

The data fusion algorithms as bayesian network, deep learning, and support vector machine are the basic methods to realize the reliability analysis of NC machine tools based on artificial intelligence. According to the time history of NC machine tools, this paper proposes an intelligent reliability evaluation framework based on neural network and bayesian network, an intelligent fault diagnosis framework based on deep learning and an intelligent fault prediction framework based on LS-SVM.

3.1. The intelligent reliability evaluation framework based on neural network and bayesian network
The NC machine tool are complex electromechanical-hydraulic integrated systems. The reliability level is one of the most important indicators of its performance. It directly affects the quality and efficiency of processing. The intelligent evaluation of NC machine tools can reflect the reliability level of NC machine tools in real-time, and it has important guiding significance for the reliability design of NC machine tools. Therefore, it is of great significance for real-time reliability evaluation of NC machine tools.

3.1.1. Application of Neural Networks. Due to the large scale and variety of data are collected by sensors, the collected data is the high reproducible and the low data density. The neural network are used to fuse information gathered by multiple sensors, which can improve the credibility of the data.

The data collected by each sensor is very different. The mutual learning is performed through the neural network. The load information with different physical meanings from different sources such as cutting force, current and temperature is converted into values with the same meaning. As shown in Figure 2, the information collected by each sensor X is used as an input of the neural network after preprocessing, and the value Y with the same meaning is obtained after the mutual learning process.

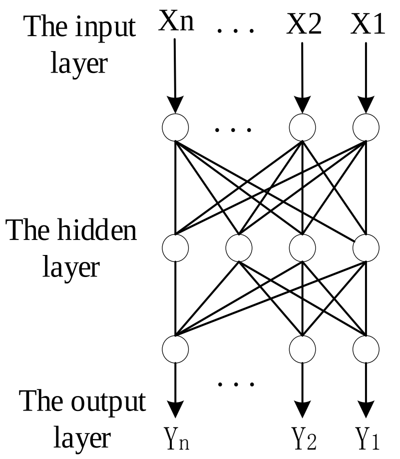

Figure 2. The flowchart of data fusion

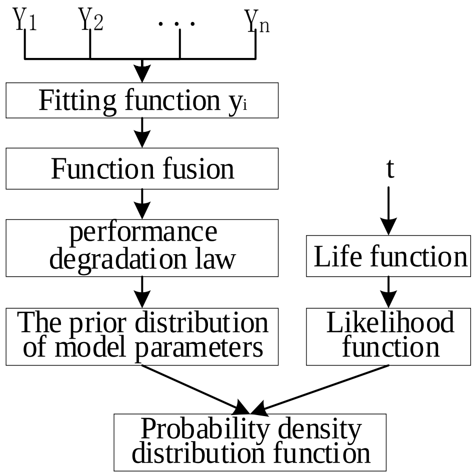

Figure 3. The flowchart of reliability evaluation

3.1.2 Application of bayesian network. As shown in Figure 3, the specific steps of the Bayesian network are as follows.
Step1: the value Y of the output layer for the neural network is fitted with the function, and the performance degradation law of the NC machine tool is obtained, which the prior distribution of reliability model parameters for the NC machine tool is obtained.
Step2: The likelihood function is obtained by using fault data.
Step3: The probability density function is obtained.

The bayesian network is used to fuse operating conditions and fault data, which achieve an accurate evaluation of the reliability for the NC machine tool.

3.2 The intelligent fault diagnosis framework based on deep learning
In the era of big data, failure modes are characterized by coupling, indefiniteness, and concurrency, and the traditional methods have weak self-learning capabilities to result in low fault recognition

accuracy and weak generalization capability. Therefore, in the context of big data, intelligent fault diagnosis of NC machine tools requires new theories and methods.

The deep learning (DL) is a big data processing tool. It builds deep models and simulates the brain learning process to realize automatic feature extraction and fittness of complex mapping relationships. The intelligent fault diagnosis of NC machine tools is realized to excavate the intrinsic information rich in big data and improve the fault recognition accuracy.

The real-time acquisition of operating data for the NC machine tool represents the running state of the NC machine tool, which is the premise of fault diagnosis. The fault information of the NC machine tool is the result of the comprehensive action of vibration, sound source, acoustic emission, and thermodynamics. Therefore, the real-time acquisition of various signal dynamic data provides basic data for the intelligent fault diagnosis of NC machine tools.

The frequency spectrum of the training sample fault feature signal is obtained by using the collected data through a sparse autoencoder (SAE). The hidden layer number of the DL is determined, and the hidden layer output of each SAE is taken as the input of the next layer SAE until completing the training of SAEs, which the output layer is determined. The DL parameters are fine tuned by using the back propagation (BP) algorithm to complete the DL training, the detailed process of intelligent fault diagnosis for NC machine tools is shown in Figure 4.

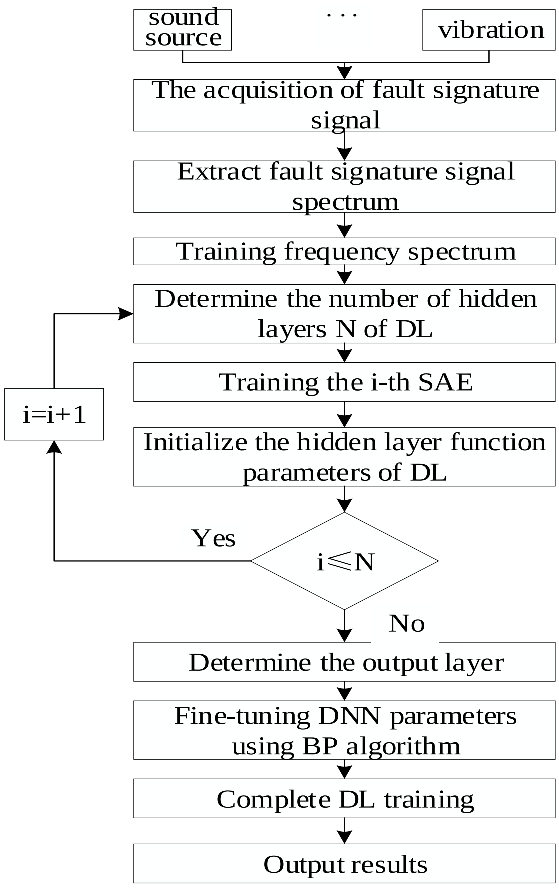

Figure 4. The flowchart of fault diagnosis

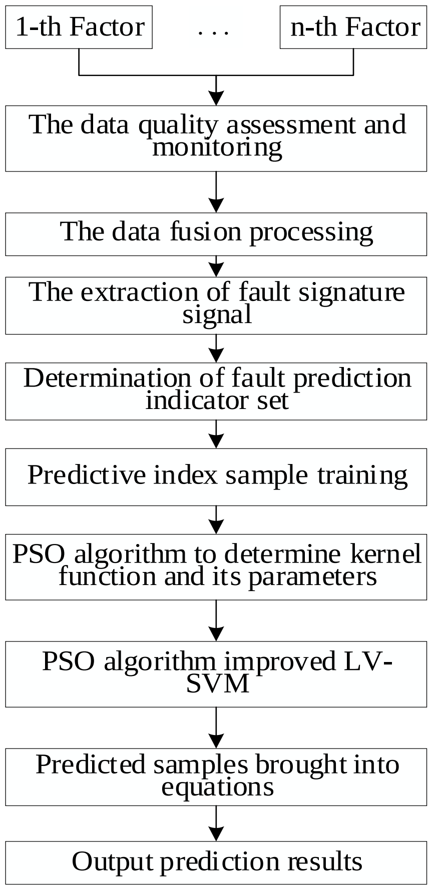

Figure 5. The flowchart of fault prediction

3.3 The intelligent fault prediction framework for NC machine tools based on LS-SVM

In the actual cutting process of NC machine tools, the operating environment is dynamically changing. Therefore, a multi-factor fusion forecasting model should be established to realize intelligent fault prediction under variable operating conditions.The hybrid prediction model considered the relationship of different components and the combination of cutting force, temperature, and other multi-condition factors fusion models can achieve more accurate and intelligent fault prediction of NC machine tools.

The collected real-time data on the multi-condition factors of the subsystem or key component for NC machine tools are evaluated and selected, which fusion processing is performed. The feature signal representing the fault information for the NC machine tool is extracted, the fault prediction index set is constructed, and the hidden fault state information in the data is fully mined. The sample size of the forecasting indicator was trained to determine the SVM kernel function and its parameters using the particle swarm algorithm, and the intelligent fault prediction model for the NC machine tool based on the LS-SVM was obtained as shown in Figure 5.

4. Conclusions

This paper introduces the time history of the reliability for the NC machine tool and proposes the reliability evaluation framework, fault diagnosis framework and failure prediction framework for the NC machine tool based on artificial intelligence.

(1) The neural networks are used to fuse information from a variety of different sources. An intelligent real-time reliability evaluation framework for NC machine tools based on the combination of neural networks and bayesian networks is proposed.

(2) In the era of big data, signals such as vibration, sound source, acoustic emission, and thermodynamics were fused after taking full account of the unique features of failure modes, and an intelligent fault diagnosis framework of NC machine tools based on deep learning was proposed.

(3) The information from a variety of different sources were fused to determine the fault prediction index set. An intelligent fault prediction framework for NC machine tools based on LS-SVM was proposed.

Acknowledgments

This work was supported by the High-level NC machine tools and basic manufacturing equipment (Grant No. 2017ZX04011005), Key Scientific and Technological Project of Jilin Province (Grant No.20170204007G X) and the Doctoral Fund of Ministry of Education of China (Grant No. 2017M621204).

References

[1] Yang Z, Chen C, Chen F,et al 2013 Progress in the Research of Reliability Technology of Machine Tools. Journal of Mechanical Engineering. **49** 130-139

[2] Merrick J R W, Soyer R, Mazzuchi T A. 2003 A Bayesian Semiparametric Analysis of the Reliability and Maintenance of Machine Tools. Technometrics. **45** 58-69.

[3] Zhang Z, Liu Z, Cai L, et al. 2016 An accuracy design approach for a multi-axis NC machine tool based on reliability theory. International Journal of Advanced Manufacturing Technology. **91** 1-20.

[4] W Peng, L Shen, Y Shen, Q Sun. 2018 Reliability Analysis of Repairable Systems with Recurrent Misuse-Induced Failures and Normal-Operation Failures. Reliability Engineering & System Safety. **171** 87-98

[5] Peng W, Huang H Z, Xie M, et al. 2013 A Bayesian Approach for System Reliability Analysis With Multilevel Pass-Fail, Lifetime and Degradation Data Sets. IEEE Transactions on Reliability. **62** 689-699.

[6] Peng W, Huang H Z, Li Y, et al 2013 Life cycle reliability evaluation of new products—A Bayesian model updating approach. Reliability Engineering & System Safety. **112** 109-119.

[7] Peng W, Liu Y, Li Y F, et al. 2014 A Bayesian optimal design for degradation tests based on the inverse Gaussian process. Journal of Mechanical Science & Technology. **28** 3937-3946.

[8] Graves T L, Hamada M S. A 2016 Demonstration of Modern Bayesian Methods for Assessing System Reliability with Multilevel Data and for Allocating Resources. Journal of Quality & Reliability Engineering. **2009**.

[9] Reese C S, Wilson A G, Guo J, et al. 2011 A Bayesian Model for Integrating Multiple Sources of

Lifetime Information in System-Reliability evaluations. Journal of Quality Technology. **9** 489-495.
[10] Niu G, Yang B S. 2010 Intelligent condition monitoring and prognostics system based on data-fusion strategy. Expert Systems with Applications. **37** 8831-8840.
[11] Niu G, Han T, Yang B S, et al. 2007 Multi-agent decision fusion for motor fault diagnosis. Mechanical Systems & Signal Processing. **21** 1285-1299.
[12] Zhang M, Jiang Z. 2017 Reciprocating compressor fault diagnosis technology based on multi-source Information Fusion. Journal of Mechanical Engineering. **53** 46-52.
[13]Che C, Wang H, Ni X, Hong J. 2018 Aeroengine fault fusion diagnosis based on deep learning. Journal of Beijing University of Aeronautic and Astronautic. **44** 621-628.
[14] Lei Y, Jia F, Kong D,Lin J, Xing S. 2018 Opportunities and challenges of machinery intelligent fault diagnosis in big data era. Journal of Mechanical Engineering. **54** 94-104.
[15]Zhang X, Kang J, Zhao J,et.al. 2014 Equipment degradation state identification and residual life prediction based on MoG-BN. Journal of vibration and shock. **33** 171-179.
[16]Zhigang Tian. 2012 An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring. Journal of Intelligent Manufacturing. **23** 227-237.
[17]Loutas T H, Roulias D, Georgoulas G. 2013 Remaining Useful Life Estimation in Rolling Bearings Utilizing Data-Driven Probabilistic E-Support Vectors Regression. IEEE Transactions on Reliability. **62** 821-832.
[18] Sikorska J Z, Hodkiewicz M, Ma L. 2011 Prognostic modelling options for remaining useful life estimation by industry. Mechanical Systems & Signal Processing, **25** 1803-1836.