

Mechanisms and Machine Science

Hao Zhang · Yongjian Ji ·
Tongtong Liu · Xiuquan Sun ·
Andrew David Ball *Editors*

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Hao Zhang · Yongjian Ji · Tongtong Liu ·
Xiuquan Sun · Andrew David Ball
Editors

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Efficiency and Performance Engineering
Network

Editors

Hao Zhang
School of Mechanical Engineering
Hebei University of Technology
Tianjin, China

Yongjian Ji
Beijing Information Science & Technology
University
Beijing, China

Tongtong Liu
Inner Mongolia University of Science
and Technology
Baotou, Nei Mongol, China

Xiuquan Sun
University of Huddersfield
Huddersfield, UK

Andrew David Ball
University of Huddersfield
Huddersfield, UK

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Preface

Beijing Information Science & Technology University and Inner Mongolia University of Science & Technology jointly organised the 2022 International Conference of The Efficiency and Performance Engineering Network (TEPEN 2022) in Baotou City, Inner Mongolia Autonomous Region, China, during 18–21 August 2022.

The goal of TEPEEN 2022 is to provide a common platform by which professionals, engineers, practitioners and researchers working in the field of condition monitoring, plant maintenance and reliability can share their experiences. The scope of the conference covered a broad area with multi-disciplinary interests in the fields of plant maintenance, asset management, reliability, condition monitoring and related areas, ranging from fundamental research to real-world applications.

In this conference, participations and contributions were involved in both theoretical research and practical applications of all aspects of fault detection, diagnostics, prognostics in both the operational and manufacturing processes. In the course of this event, eight keynote speeches and parallel technical sessions were delivered in accordance with key following topics:

- Vibro-acoustics Monitoring
- Asset Management
- Condition-based Maintenance
- Condition Monitoring and Reengineering
- eMaintenance, Mobile Technology
- Health, Safety and Environment
- Sensors and Instrumentation
- Life Cycle Cost Optimisation
- Machine Health Monitoring
- Machine Lube Oil Analysis and Monitoring
- Artificial intelligence, Machine Learning
- Electrical Vehicle Monitoring, Energy Management
- Maintenance Auditing
- Prognostics and Health Management
- Maintenance Organisation
- Maintenance Performance Measurement
- Non-destructive Testing
- Manufacturing Process Monitoring
- Reliability, Maintainability and Risk
- Signal and Image Processing Methods

Despite the challenging circumstances of year 2022, this book consists nonetheless of 98 peer-reviewed papers. The book offers the state of the art of advances in asset management and condition monitoring and also serves as an excellent reference work for academic and industrial scientists and graduate students, working in asset management, condition monitoring and related areas.

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Thank you.

Hao Zhang
Yongjian Ji
Tongtong Liu
Xiuquan Sun
Andrew D. Ball

Contents

Numerical Study of Resistance Projection Welding of Nuts	1
<i>Libin Yang, Wanzhu Xie, and Xuemei Qin</i>	
Fault Diagnosis Method of Planetary Gear Based on FFT-DET and BP Neural Network	12
<i>Zheng Wang, Hongjun Wang, Baisheng Chen, and Zhuangzhuang Zhang</i>	
Continuous Vibration Separation for Fault Diagnosis of Planetary Gear in Equipment Transmission	24
<i>Zhang Lun, Hu Niaoqing, Yin Zhengyang, Hu Jiao, and Yang Yi</i>	
Classification of Sape Soundboard Wood Quality by Employing Machine Learning	32
<i>Tee Hao Wong, Jia Sheng Ng, Muhammad Afif, Agnes Ayang, Ming Foong Soong, Ahmad Saifizul, and Rahizar Ramli</i>	
Design of Airborne Oxygen Pressure Sensor	43
<i>Shupeng Guo, Xiaofei Wang, Tao He, and Guanhuan Chen</i>	
Condition Monitoring of Nozzle Temperature in 3D Printing via Vibro-Acoustic Signals	53
<i>Xinfeng Zou, Zhen Li, Lianghai Zeng, Fengshou Gu, and Andrew D. Ball</i>	
Time Domain Identification Method of Cutting Forces in Robotic Milling Process	64
<i>Maxiao Hou, Hongrui Cao, and Jianghai Shi</i>	
Study on Fault Diagnosis Method of Key Components of the Gearbox Under Variable Working Conditions Based on Improved VMD Algorithm	74
<i>Tongtong Liu, Yanliang Wang, Lingli Cui, and Chao Zhang</i>	
Study on Wear Fault Diagnosis of Planetary Gearbox Based on STOA-VMD Combined with 1.5-Dimensional Envelope Spectrum	90
<i>Jiashuai Zhang, Zhanglei Jiang, Guoxin Wu, and Haocheng Bi</i>	
Intelligent Image Processing for Monitoring Solar Photovoltaic Panels	103
<i>Xing Wang, Wenxian Yang, and Jinxin Wang</i>	

Boiler Wall Temperature Prediction Based on Temporal Convolution Networks	112
<i>Fengbiao Qi, Haiguang Li, and Chao Zhang</i>	
The Extraction of Wind Turbine Condition Related Features Using Air-Borne Acoustic Signals	124
<i>A. Abouhnik, G. Ibrahim, Rongfeng Deng, K. Brethee, A. Badawood, W. Abushanab, X. Zhang, C. Batunlu, and A. Albarbar</i>	
Experimental Investigation of Vibration Signals from an On-Rotor Sensing for Diesel Engine Crankshaft Lubrication Monitoring	138
<i>Solomon Okhionkpmwonyi, Funso Otuyemi, Dawei Shi, Fengshou Gu, and Andrew Ball</i>	
A Study of Electric Current Signal Analysis for Motor Bearing Condition Diagnosis	151
<i>Yinghang He, Kun Feng, Baoshan Huang, Guoji Shen, Dawei Shi, Fengshou Gu, and Andrew D. Ball</i>	
Surface Defect Recognition of NdFeb Raw Materials Based on Improved YOLOX-Tiny Model	172
<i>Changhao Dong, Jianjun Li, Da Lv, and Chao Zhang</i>	
16-Research on Wheel Chassis Motion Control of a Full-Wheel Steering Self-decision Platform Research on Wheel Chassis Motion Control of a Full-Wheel Steering Self-decision Platform	180
<i>Shaoyong Cao, Jingwei Chen, Weijie Tang, and Fen Du</i>	
Advanced Neural Network with Optimized Training Parameters Based on the Cuckoo Search for Detecting and Classifying Faults in PV Power Systems	190
<i>Ghedhan Boubakr, Ann Smith, Fengshou Gu, Andrew Ball, and M. Alrweg</i>	
Summary of Fault Diagnosis of Electric Vehicle Braking System	212
<i>Zheng Lin and Zhou Ziyang</i>	
A Pulse Impedance Technique for Fast State of Health Estimation of EV Lithium-Ion Batteries	220
<i>Xiaoyu Zhao, Zuolu Wang, Li Eric, Fengshou Gu, and Andrew D. Ball</i>	
A Simulation Analysis of the Modal Characteristics and Critical Speeds of a Turbine Rotor System	234
<i>Lei Xue, Jing Liu, and Xiaoyong Dang</i>	

Weak Signal Detection Method with Adaptive Three-Dimensional Coupled Bistable Stochastic Resonance System	245
<i>Mengdi Li, Peiming Shi, Wenyue Zhang, and Fengshou Gu</i>	
On-Line Condition Monitoring of Additive Manufacturing Based on Friction Induced Acoustic Emissions	255
<i>Zhen Li, Xinfeng Zou, Xianzhi Zhang, Fengshou Gu, and Andrew D. Ball</i>	
Tool Wear Monitoring in CNC Milling Process Based on Vibration Signals from an On-Rotor Sensing Method	268
<i>Chun Li, Bing Li, Hongjun Wang, Dawei Shi, Fengshou Gu, and Andrew D. Ball</i>	
Application of a New Finite-Time Tracking Differentiator in Stable Platform	282
<i>Kai Weng, Yan Ren, Chao Zhang, Liyun Zhao, Huimin Wang, and Ning Liu</i>	
Selection of Optimal Mother Wavelet for Acoustic Emission Signal Processing of Gas Pipeline Leakage	294
<i>Lin Gao, Hong Wang, Jiannan Zhou, and Xiaojie Zhou</i>	
Fault Diagnosis of RV Reducers Used in Industrial Robots Based on Vibration Analysis	306
<i>Huanqing Han, Qirong Xu, Dongqin Li, Bing Li, Xiuquan Sun, and Fengshou Gu</i>	
Parameterized Doppler Adaptive Correction for Wayside Acoustic Array Signal	318
<i>Yulan Li, Hongrui Yi, Hao Wang, Xiaoxi Ding, Jiawei Xiao, Huafei Pan, and Yimin Shao</i>	
Research on Bearing Fault Diagnosis Based on 1DCNN with Fault Compound Features	330
<i>Yubin Yue and Hongjun Wang</i>	
Performance Degradation Evaluation Model of Rolling Bearing Based on CAE-SVDD	341
<i>Xinyang Dong, Yunpeng Cao, Hui Li, Xiaoyu Han, and Weixing Feng</i>	
CNN-LSTM-Based Model for Predicting the Remaining Useful Life of Rolling Bearings	354
<i>Xiaopeng Yu, Hao Zhang, Fukai Zhao, Dong Zhen, Kiuhua Lu, and Wei Hu</i>	

Life Prediction of Wind Turbine Based on Attention-BiGRU	367
<i>Da Lv, Chao Zhang, Hongbo Fei, Wentao Zhao, Changhao Dong, and Yongzhi Pang</i>	
Markov Transform Field Coupled with CNN Image Analysis Technology in NIR Detection of Alcohols Diesel	378
<i>Shiyu Liu, Shutao Wang, Chunhai Hu, and Deming Kong</i>	
Temporal Convolutional Network with Attention Mechanism for Bearing Remaining Useful Life Prediction	391
<i>Shuai Wang, Chao Zhang, Da Lv, and Wentao Zhao</i>	
Optimization Design of Welding Fixture Based on Ergonomics	401
<i>Yongyang Zhang, Hanhua Mai, Siqi Wang, Hongming Zhang, Zhuofeng San, and Ruixing Hu</i>	
Quantitative Study of Food Additives Based on Terahertz Spectrum	413
<i>Yi-heng Guo, Fang Yan, Miao-yu Zhao, and Xuan Zhuo</i>	
Securely Similarity Determination of Convex Geometry Graphics Under the Malicious Model	422
<i>Xiaomeng Liu and Xin Liu</i>	
Optimal Repair Time Limit and Replacement Age for a System with Multiple Types of Failures	435
<i>Peirui Qiao, Ming Luo, and Yizhong Ma</i>	
Blind Deconvolution Based on Modified Smoothness Index for Railway Axle Bearing Fault Diagnosis	447
<i>Bingyan Chen, Fengshou Gu, Weihua Zhang, Mengying Tan, Yaping Luo, Zuolu Wang, and Zewen Zhou</i>	
Bearing Fault Diagnosis Method Based on EMD and Multi-channel Convolutional Neural Network	458
<i>Fukai Zhao, Dong Zhen, Xiaopeng Yu, Xiaoang Liu, Wei Hu, and Jin Ding</i>	
Operational Modal Analysis of Journal Bearings Based on Stochastic Subspace Identification	469
<i>Xiaopeng Wang, Guojin Feng, Xiaoxia Liang, Dong Zhen, Hao Zhang, and Zhanqun Shi</i>	
Prediction and Compensation Method of Spindle Thermal Deformation in Five Axis Machining Center	480
<i>Baisheng Chen, Hongjun Wang, Wei Peng, and Zengxin Wang</i>	

Qualitative Detection of Melamine Based on Terahertz Spectrum and Analysis of Absorption Peak Study	492
<i>Miaoyu Zhao and Fang Yan</i>	
A Study of Semantic Map Construction Methods for Power Plant Inspection Robot	500
<i>Yufei Qin, Dongmin Zhang, and Bo Xu</i>	
A Method on Manufacturing Process Monitoring Based on Value Stream Mapping	508
<i>Dongyu Gan, Xinfeng Zou, Xuewei Zhang, Jiaqi Lin, Yongyang Zhang, Jidong Guo, and Dawei Zhou</i>	
Fault Diagnosis of Rolling Element Bearings Based on a Second Order Cyclic Autocorrelation and a Deep Auto-encoder	518
<i>Yajun Shang and Tianran Lin</i>	
Research on Fault Diagnosis Method of Rolling Bearing Based on MobileNet V2	528
<i>Ningkang Dong, Chao Zhang, and Hao Chen</i>	
The Effect of the Cage Clearance on the Lubrication Characteristics of a High-Speed Ball Bearing	534
<i>Ni Hengtai, Liu Jing, and Zhou Ruyi</i>	
Study on Unbalance Method of Rolling Bearing Fault Samples Based on Adversarial Network	544
<i>Li Han, Hao Chen, and WenXing Zhang</i>	
Prediction Reliability Assessment Based on Mahalanobis Distance and GRU in the Application of Bearing RUL Analysis	554
<i>Zhenyu Chen, Shenglan Liu, Hongrui Yi, Xiaoxi Ding, Xin Li, Shanshan Wu, Mingli Hu, and Yimin Shao</i>	
Research on On-line Detection Technology of Lubricating Oil Moisture	568
<i>Bin Fan, Yingjie Gao, Lianfu Wang, Yong Liu, Jianguo Wang, Chao Zhang, and Fengshou Gu</i>	
Rolling Bearing Fault Diagnosis Based on BP Neural Network	576
<i>Chenglong Yu and Hongjun Wang</i>	
A Kalman Filter Based Deep Learning Autoencoder for Induction Motor Broken Rotor Bar Diagnosis	596
<i>Ali Amiri Zaniani, Dong Zhen, Haiyang Li, and Yinghang He</i>	

Preparation and Performance Testing of InAs/GaAs Photodetector	610
<i>Chunhua Yang, Jie Wen, Hongmei Liu, Guodong Wei, Zichao Jiang, and Lei Huang</i>	
Research and Application of Deep Reinforcement Learning in Rotating Machinery Fault Diagnosis Under Unbalanced Samples Condition	615
<i>Cheng Zhe, Wei Lei, Cheng Junsheng, and Hu Niaoqing</i>	
Investigation into Defect Image Segmentation Algorithms for Galvanized Steel Sheets Under Texture Background	628
<i>Rui Pan, Yuda Chen, Guoxin Wu, and Xiaoli Xu</i>	
Low-Cost and Portable Device to Monitor Heart Rate, Blood Oxygen Saturation and Body Temperature with Warning System	641
<i>Cong Guo, Qianhui Ma, Mingyu Shen, Xinghao Dong, Shuaifei Chen, and Fulong Liu</i>	
An SOC Estimation Strategy Considering Lithium-ion Battery Degradation Based on Neural-Network and Equivalent Circuit Model	653
<i>Yuxing Feng, Guojin Feng, Zhaozong Meng, Xiaoxia Liang, Hao Zhang, and Dong Zhen</i>	
Dynamic Modeling Analysis and Experimental Verification of Blade with Breathing Crack	665
<i>Jianfang Cao, Yongmin Yang, and Guoji Shen</i>	
WTBNeRF: Wind Turbine Blade 3D Reconstruction by Neural Radiance Fields	675
<i>Han Yang, Linchuan Tang, Hui Ma, Rongfeng Deng, Kai Wang, and Hui Zhang</i>	
Rolling Bearing Fault Diagnosis Based on Mathematical Morphological Spectrum	688
<i>Wenyan Zhu, Wenxing Zhang, and Chao Zhang</i>	
Dynamic Modeling and Modal Analysis of the Planetary Gear Set-Bevel Gear Set Coupling System	699
<i>Yang Yi, Shen Guoji, Zhang Lun, Cheng Zhe, Hu Jiao, and Hu Niaoqing</i>	
Study of the Dynamic Characteristics of Planetary Gear Systems Under Different Loads	714
<i>Junjie He, Xiaolang Liu, Bowei Fu, Dong Zhen, Kuihua Lu, and Wei Hu</i>	

Research on Production Process Optimization and Improvement Based on a Production Line of Y Company	727
<i>Jidong Guo, Jianying Lu, Xinfeng Zou, Jianxing Zhang, Liangfang Zhu, Xiaoxin Cui, Weihuai Chen, and Dawei Zhou</i>	
Evaluation of the Angular Misalignment on RV Reducer Based on Motor Current Signature Analysis	740
<i>Dongqin Li, Zhexiang Zou, Qirong Xu, Bing Li, Huanqing Han, Xiuquan Sun, Xiaoyu Zhao, Baoshan Huang, Fengshou Gu, and Andrew Ball</i>	
Multi-domain Features Fusion Adaptive Neural Network Tool Wear Recognition Model	751
<i>Hanyang Wang, Ming Luo, and Fengshou Gu</i>	
Simulation and Optimization of Piezoelectric Cantilever Configurations for Energy Harvesting with Multi-modal Vibrations	766
<i>Weiqiang Mo, Yubin Lin, Shiqing Huang, Zuolu Wang, Fengshou Gu, Bo Liang, and Hongjun Wang</i>	
Research on Dynamic Characteristics of Planetary Gear System with Pitting Fault Under Impact Condition	776
<i>Bowei Fu, Jie Yang, Junjie He, Xiaoang Liu, Wei Hu, and Zhuo Yue</i>	
Safety Checking Calculation and Analysis of Flange Sealing Face Bolts of Pressure Vessel	785
<i>Engao Peng, Dandan Wang, Yongyang Zhang, and Zhenkun Luo</i>	
Knowledge Graph Construction in Logistics Based on Multi-source Data Fusion	792
<i>Xinyu Gao, Li Zhang, Wenping Zhang, and Haoxuan Chen</i>	
Investigation of Random Vibration Response of Journal Bearings Under Turbulent Boundary Layer Excitation	803
<i>Fang Zeng, Guojin Feng, Xiaoxia Liang, Dong Zhen, Hao Zhang, Zhanqun Shi, and Hao Zhang</i>	
Dynamic Modeling and Stability Analysis of High-Speed Angular Contact Ball Bearing	818
<i>Yu Tian, Changfeng Yan, Wei Luo, Yaofeng Liu, and Lixiao Wu</i>	
Research on Performance Audit of Air Pollution Prevention and Control: Data from Beijing	829
<i>Chunyu Xing and Xinzhu Feng</i>	

Modelling and Analysis of Internal Excitation of Cracked Spur Gear
Considering Effects of Tooth Errors 841
*Lantao Yang, Desheng Zou, Xiuquan Sun, Yimin Shao, Fengshou Gu,
Andrew Ball, and David Mba*

The Structure Optimization of a Small Linear Friction Welding Machine 853
*Libin Yang, Zeshen Huang, Renjian Su, Mingyou Wu,
and Changshen Song*

A Study of a Novel Acoustic Metamaterial Structure for Signal
Enhancement Based on Fan Blade Fault Diagnosis 865
*Weijie Tang, Shiqing Huang, Rongfeng Deng, David Mba,
Fengshou Gu, and Andrew D. Ball*

Vibration Analysis for Diagnosis of Tribo-Dynamic Interaction
in Journal Bearings 877
*Khaldoon F. Brethee, Jiaojiao Ma, Ghalib R. Ibrahim, Fengshou Gu,
and Andrew D. Ball*

Fault Diagnostics of AC Motor Bearings Based on Envelope Analysis
of Vibration Residual Signal 889
*Jingyan Zhao, Xiuquan Sun, Jianguo Wang, Zewen Zhou,
Yousif Muhamedsalih, Fengshou Gu, and Andrew D. Ball*

Analysis of Fault Characteristics of Planetary Gearbox of Shearer 900
Li Xiaoxue, Guo Yu, and Han Saiwei

Motor Bearing Fault Diagnosis Based on Stochastic Resonance
Enhanced Stator Current Signals 912
*Wenyue Zhang, Peiming Shi, Dongying Han, Yinghang He,
Fengshou Gu, and Andrew Ball*

Fault Diagnosis for Gas Turbine Rotor Using Actor-Critic Network 923
Yingjie Cui and Hongjun Wang

Fault Detection and Diagnosis of Gearbox Oil Shortage Using Motor
Current Signature 936
*Funso Otuyemi, Xiuquan Sun, Jingyan Zhao, Zhexiang Zou,
Jianguo Wang, Fengshou Gu, and Andrew D. Ball*

An Improved Method for Fault Diagnosis of Rolling Bearings
with Optimized Parameters 948
Yu Zhang, Xiwei Zhao, Guoxin Wu, and Chunmei Zhu

Research on Fault Diagnosis of Gas Turbine Rotor System Based on Deep Convolution Generative Adversarial	962
<i>Zhengbo Wang, Hongjun Wang, and Jinglei Su</i>	
Fault Diagnosis of the Ball Screw Pairs in Electromechanical Actuators Based on Empirical Mode Decomposition and Symmetrized Dot Pattern	974
<i>Zhengyang Yin, Niaoqing Hu, Yi Yang, and Ling Chen</i>	
A Support Vector Machine Fault Diagnosis Method for Gas Turbine Fuel System	985
<i>Li Yan, Yunpeng Cao, Rui Liu, Tianrui Zhao, and Shuying Li</i>	
Experimental Investigation on the Internal Clearance Induced Vibrations of Tapered Roller Bearings for Condition Monitoring	995
<i>Zewen Zhou, Bingyan Chen, Fengshou Gu, Rongfeng Deng, Yubin Lin, and Yousif Muhamedsalih</i>	
Gas Turbine Blade Passing Frequency Reconstruction and Its Application for Blade Fracturing Fault Diagnosis	1006
<i>Yuan Xiao, Kun Feng, Zhouzheng Li, Fengshou Gu, and Zhinong Jiang</i>	
AGV Path Planning for Logistics Warehouse by Using an Improved D*Lite Algorithm	1018
<i>Yongyang Zhang, Junhao Luo, Xiaotong Cai, Ying Chen, Engao Peng, and Xinfeng Zou</i>	
An Optimized Modulation Signal Bispectrum for Bearing Fault Diagnosis	1028
<i>Yuandong Xu, Yunpeng Cao, Fengshou Gu, and Andrew Ball</i>	
Analysis on the Application of IE Thought in the Production System of D Company's EM Series Products	1038
<i>Jidong Guo, Xuwei Zhang, Mengjing Chen, Haojun Cai, Wanting Zhang, Mushen Zheng, Rongfeng Deng, and Xinfeng Zou</i>	
Bearing Fault Diagnosis Method Based on STFT Image and AlexNet Network	1056
<i>Wu Guoxin, Wang Ge, Liu Xiuli, and Duan Ruilong</i>	
Intelligent Fault Diagnosis Method Based on CA-ResNet Model	1069
<i>Zhenbao Fu, Zhitao Xu, Liuyang Song, Wenwu Chen, Qingfeng Wang, and Huaqing Wang</i>	

Experimental Investigation on the Propeller Imbalance Detection
via On-Rotor Sensing Vibration for Industrial Drone 1079
*Yubin Lin, Chun Li, Shiqing Huang, Dawei Shi, Rongfeng Deng,
Guojin Feng, and Fengshou Gu*

Fault Diagnosis of Rolling Bearing Based on Laplace Wavelet Sparse
Representation and Teager Energy Operator 1088
Hongfang Li, Rongjia Mo, and Zhifei Wu

Diagnosis of Motor Bearing Faults Using the Vibration of an On-Rotor
Sensing Method 1100
*Dawei Shi, Zuolu Wang, Hongjun Wang, Qishan Chen, Yinghang He,
Guojin Feng, and Fengshou Gu*

Bearing Fault Diagnosis Based on Compressed Data and Supervised
Global-Local/Nonlocal Discriminant Analysis 1113
Xin Wang, Na Yang, and Lingli Cui

Crack Detection of Old Residential Buildings Based on UAV Intelligent
Vision 1126
Jinxin Wang, Shenglei Zhao, Limin Shen, Wenxian Yang, and Jinxin Ma

Author Index 1137



Numerical Study of Resistance Projection Welding of Nuts

Libin Yang^(✉), Wanzhu Xie, and Xuemei Qin

School of Industrial automation, Beijing Institute of Technology, Zhuhai 519088,
Guangdong, China
1394126856@qq.com

Abstract. The resistance projection welding (RPW) of nuts using the pneumatic electrode force system was subjected to thorough numerical and experimental analysis, enabling the identification of the processing window of welding parameters due to its importance of in the auto manufacturing. The purpose of this study is to study the influence of process parameters like welding currents, welding time and electrode pressure on the properties and microstructure of welding joint of nut in resistance projection welding. To enhance the understanding the microstructure transformation of metal structure during welding, a commercial finite element software COMSOL is used to build 2D&3D models for the numerical simulation analysis of the process. Several parameters that affect the microstructure and strength of the joint, such as welding time, welding current and electrode pressure, are analyzed and the optimized values are recommended. The sensitivity of temperature to electrode voltage is found, which can be used to optimize process parameters.

Keywords: Welding parameters · Resistance projection welding · FEM simulation

1 Introduction

Resistance projection welding of bolts and nuts to sheets is an important manufacturing process in the automotive manufacturing. As mentioned by some researchers, advanced car bodies contain approximately 300 welded and clamped fasteners, e.g., bolts and nuts, to which key safety features including seat belts, steering columns or the earthing of electric circuits are fastened. Thus, the quality of the attachment of these fasteners to the stamped body of vehicles is essential as regards the safety and reliability of end products [1, 2]. While the projection welding of nuts is used widely in auto industry for its virtues of high speed, green and limited heat effect on the parts, it is also characterized by some disadvantages and limitations, including narrow window of processing parameters, lack of repeatability, sensitivity to the lack of tolerance in relation to the height of the projection and the hardness of the material subjected to welding [1]. These limitations may cause deteriorated quality of products.

As the quality of resistance projection welding is closely related to some welding variables such as electrode force, welding current, and welding time during welding

process. Low currents cause insufficient heating in weld surface and results in insufficient nugget size, while excessively high current results in defective welding such as surface flash and expulsion. Low electrode force generates expulsion as the small projection collapse leads to concentrated heat generation and expulsion, while a high electrode force leads to insufficient heat generation and small nugget size [2]. Therefore, it is important to understand the welding mechanism of resistance projection welding. Many researchers have contributed lots of efforts in this field. Cunningham and Begeman looked into welding behavior using high-speed photography [3]. Harris and Riley conducted RPW experiments to recommend the suitable values of welding variables and proposed an optimal projection shape with plate thickness [4]. As resistance project welding is a complicated process as the effects of electricity, heat and stress involve simultaneously at the projection; and the nugget along welding surface forms in a few milliseconds, it is hard to capture the changes in the process accurately. To overcome such limitations, it is natural for researchers to simulate the welding process with numerical methods. Sun built a 2D axisymmetric finite element (FE) model simulating projection collapse and nugget forming in the process, the influence of the height of projections on the nugget formation was studied in his paper [5, 6]. C.V. Nielsen et al built a 3D model of projection welding of square nuts to sheets by SORPAS 3D software, focusing on the effect of friction force between nut projection and sheet [7]. Mikno also built 2D&3D models to explore the mechanism during process, with his attention on the difference between the electromechanical and pneumatic electrode force system [1, 8]. Even though many efforts have been put in this field, the results got are usually limited to specific materials and process parameters, there is still no model which has potential of general application. The reason for this may be because the material behavior in the process of RPW is very complicated, involving various factors such as electricity, heat, mechanical deformation, metallurgical elements, and residual stresses around projection after the forming process. And up to now, there is no clear theory about the contact resistance between the projection and the plate, which is important for controlling the temperature near welding line. To understand the variations of the process better, the influence of heat, electricity, stress on the material studied need to be fully coupled. In this paper, a triple coupled model to study the RPW of nuts to sheets is set up using the commercial code COMSOL, which is widely known for its abilities to couple multiple physical fields.

2 Theory of Electro-Thermo-Mechanical Modeling

The numerical modeling of the projection welding of square nuts to sheets was performed by means of the finite element computer program COMSOL multi-physics developed by COMSOL Ltd. The reason for choosing it is because of its open and flexible interface and its reputation on multi-fields modeling ability.

2.1 Mechanical Module

The mechanical module calculates the deformation of the welded part, including the stress and strain along the contact interfaces. The formulation is based on the following

variational form [9],

$$\int_V \bar{\sigma} \delta \dot{\bar{\epsilon}} dV + K \int_V \dot{\bar{\epsilon}}_{ii} \delta \dot{\bar{\epsilon}}_{jj} dV - \int_{st} t_i \delta u_i dS = 0 \quad (1)$$

where V is the domain volume limited by the surfaces S_u and S_t , where velocities u_i and tractions t_i are prescribed, $\bar{\sigma}$ is the effective stress and $\dot{\bar{\epsilon}}$ is the effective plastic strain rate. K is a large positive number, used as a penalty factor to impose incompressibility requirement.

The frictional stress between contact surfaces is modeled by Coulomb law, $\tau_f = \mu \sigma_n$. The direction of the frictional stress is opposite to the relative sliding velocity between the two sliding surfaces.

2.2 Thermal Module

The thermal module calculates heat generation and heat transfer in order to model the effects of temperature increase due to plastic work, heat generated by electrical Joule heating and temperature variation due to exchange of heat with the surrounding environment. The governing equation of the thermal module is built upon the heat transfer equation, which can be written as follows,

$$\int k T_{,i} \delta T_{,i} dV + \int \rho_m C_m \dot{T} \delta T dV - \int \dot{q} \delta T dV - \int k T_{,n} \delta S = 0 \quad (2)$$

where k is the thermal conductivity, ρ_m is the mass density and C_m is the heat capacity, and the rate of heat generation $\dot{q}$ includes the impact of heat flux from electrical heating, convection, radiation and plastic deformation of welding metals.

2.3 Electrical Module

The electrical module calculates the distribution of the electric potential Φ which is necessary to generate the current density through the parts to be welded. The governing equation of the electrical module is built upon integration of Laplace's equation for an arbitrary variation of the electric potential and applying the divergence theorem,

$$\int_V \Phi_{,i} \delta \Phi_{,i} dV = \int_S \Phi_{,n} \delta S \quad (3)$$

where $\Phi_{,n}$ is the normal gradient of the electric potential to the free surfaces, which is zero and thereby leading to a zero right hand side [7].

2.4 Modeling Conditions

The geometry model set up in the FEM software and its picture of corresponding real part are shown in Fig. 1. A total of nearly 10000 tetrahedral elements is adopted for discretizing the nut, the size of which is around $12 \times 12 \times 8.5$ mm.

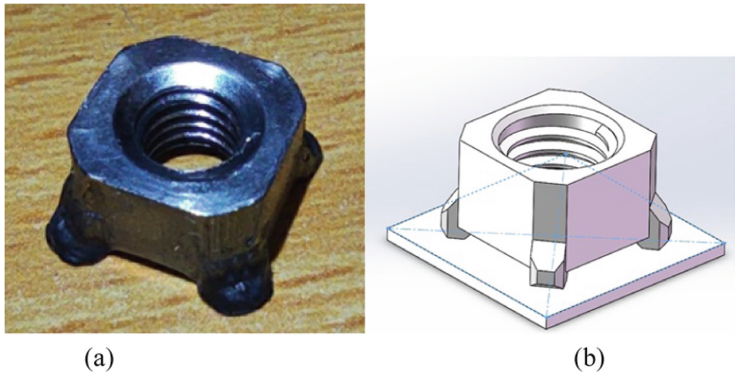


Fig. 1. **a.** A nut frequently used in RPW process. **b.** The 3D geometry model for FEM analysis.

To simplify model and save time of simulation, a 2D axis-symmetrical model is also built, which could give a clear picture about the formation of nugget, as shown in Fig. 2 (Table 1).

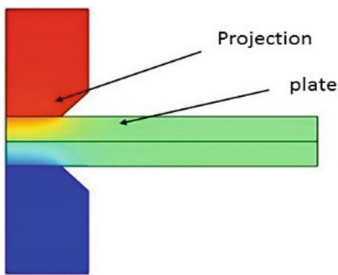


Fig. 2. An axis-symmetrical model of projection welding.

Table 1. The properties of material used in simulation.

Types of materials	Heat conductivity coefficient	Heat capacity	Young's modulus	Electrical conductivity	Poisson ratio	Thermal expansivity
AISI 1010	44.5[W/(m•K)]	475[J/(kg•K)]	200×10^9 [Pa]	9.93×10^6 [S/m]	0.3	$1.28 \times 10^{-5}/^{\circ}\text{C}$

Table 2. Parameters used in simulation.

Initial squeeze	Heating time	Cooling time	Current	Electrode pressure
0.7 s	0.2 s	0.3 s	8KA–10KA	2–5KN

The parameters used in simulation is consistent with those in actual production. The typical scope of parameters for the simulation of RPW is presented in Table 2.

As the projection of the nut will undergo plastic deformation during resistance projection welding, it is necessary to have information of flow stress of mild steel under high temperature during calculation. The relationship of flow stress of mild steel and temperature is described in Fig. 3. The flow stress of material drops significantly with the rise of temperature. To accelerate the convergence of the iteration in calculation of plastic deformation, the hardening effect of strain rate effect is also taken into consideration.

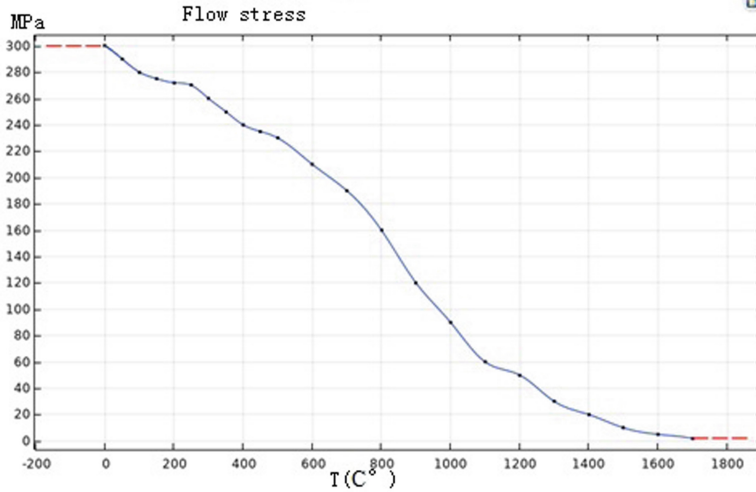


Fig. 3. Flow stress of mild steel vs. temperature.

The numerical simulation was performed through a succession of time increments using transient mode in COMSOL and the overall computing time for a typical analysis was around 10 h on a computer equipped with one Intel Xeon 2.4 GHz processor.

3 Results and Discussion

3.1 Effect of Heating Time

Heating time refers to the time interval when electrical current is applied in the welding process. Increasing the heating time means more energy input into the welding interface, the temperature will be higher. The temperature field is simulated with the voltages is set at 5.5 V and 6 V respectively. The peak temperature increases with the increase of heating time (Fig. 4).

The variation law of molten core diameter with heating time was obtained by simulation as shown in Fig. 5b. The welding current was kept constant, and the heating time t was set as 0.1 s, 0.15 s and 0.2 s respectively. It can be seen from the figure that with the increase of heating time, the generated heat increases and the molten core diameter

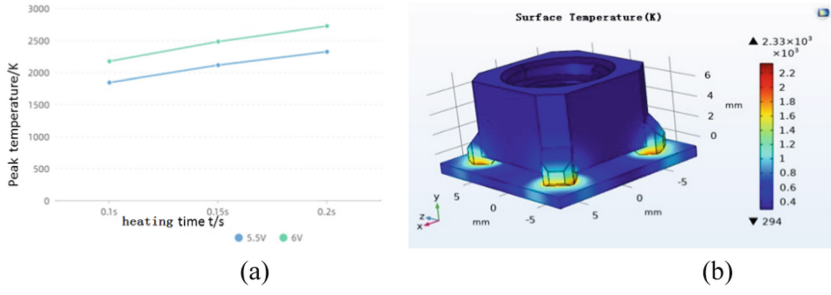


Fig. 4. a. Peak temperature vs. heating time. **b.** Temperature distribution of nut in RPW.

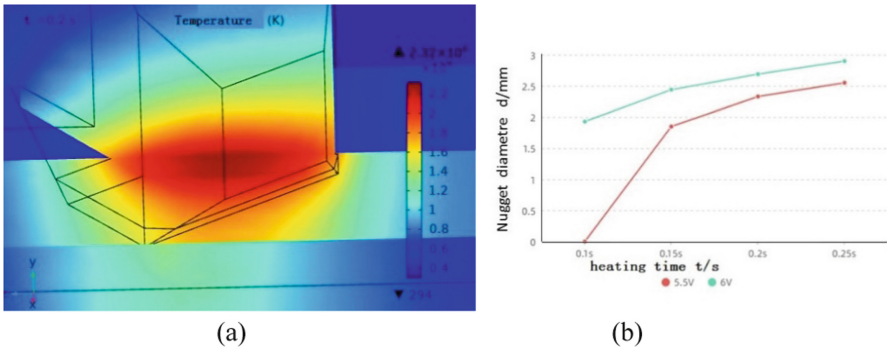


Fig. 5. a. A section of projection near welding surface. **b.** Nugget diameter vs. heating time

increases. When the welding time is the same, the diameter of molten core is larger when the welding voltage is larger.

When the heating time was set as $t = 0.2$ s, the electrode pressure was set as 2000N, and five parameter values from 5 V to 7 V were selected for resistance projection welding experiment. COMSOL software was used to simulate the projection welding with the same parameters, and the simulation results of molten core diameter after welding were obtained. Figure 6 shows the comparison between simulation results experimental results in literature [10]. The nugget diameter grows with the increase of the electrical potential applied. As can be seen from the figure, the change trend of molten core diameter simulated by COMSOL software agrees well that obtained by experiment, and the error between simulation and experimental results is no more than 5%.

Welding heat affected zone (HAZ) refers to the area where, under the influence of a large amount of welding heat input, there is no melting phenomenon on both sides of the weld, which is still in solid state, but has undergone changes in microstructure and performance. Welding heat affected zone (HAZ) is usually small local area, but due to the changes in the microstructure and properties, it is of great significance to explore the HAZ for the performance after welding.

According to the phase diagram of Fe-C alloy, the heat affected zone begins to form when the temperature reaches 727°C . The resistance projection welding is completed in an instant. It can be considered that the time for transformation is not enough at 727°C .

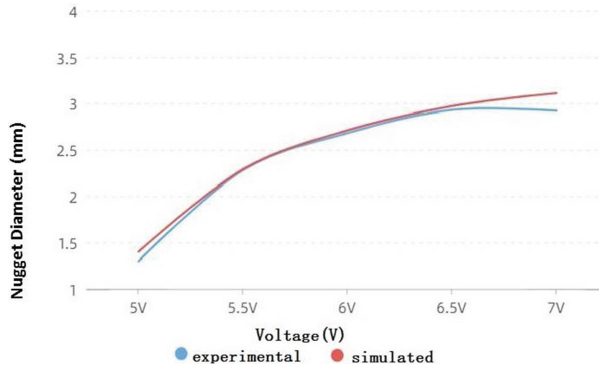


Fig. 6. Comparison of simulated nugget diameter with experimental value.

Therefore, the interval from 800 °C to 1500 °C (1100K to 1800K) is taken as the heat affected zone in this study.

The variation of welding heat affected zone (HAZ) width with heating time was obtained by COMSOL simulation, as shown in Fig. 7. The heating time t takes three values: 0.2 s, 0.25 s and 0.3 s, the welding voltage 5.5 V and 6 V, and the pressure load is 2000N. It can be seen from the figure that with the increase of the welding time, the width of the heat affected zone increases, and the width of the heat affected zone is larger when the welding voltage is small at the same welding time point. The difference between the maximum value and the minimum value is 0.1 mm.

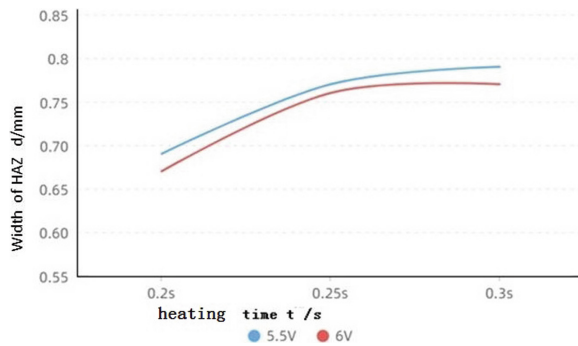


Fig. 7. The width of HAZ vs. welding time.

The heating is stopped when the electricity is cut off and the cooling stage of metals begins. Two points are selected for analysis, point1 in the center of nugget, while point 2 is outside melting area. Their cooling stages are also calculated and illustrated in Fig. 8. As can be seen from the figure, due to the rapid heat conduction of the copper electrode, the temperature at both points drops sharply at the beginning and finally approaches to room temperature, the average cooling rate at the beginning of the cooling stage is around 1000 °C/s.

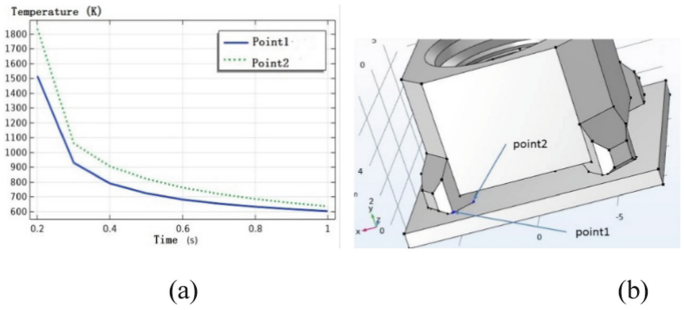


Fig. 8. **a.** Cooling curves for the points in welding area. **b.** Position of the points.

3.2 Effect of Electrode Pressure on Temperature Field

The electrode pressure's effect on the variation of the maximum temperature of the welded joint is also simulated with COMSOL software, as shown in Fig. 9 below. The selected heating time is 0.2 s, the voltage is set as 5.5 V, 4.5 V, and the electrode pressure is as 0N, 333N, 666N, 1000N, 1333N, 1666N, 2000N respectively. As can be seen from the figure, while the maximum welding temperature decreases with the increase of electrode pressure, there is no significant temperature change. The reason may be while the electrode pressure increases, the contact area between the nut and the steel plate increases, the contact resistance decreases, and the input heat Q decreases. Therefore, the overall heating energy input into the process is kept nearly constant. The similar trend can also be found for the nugget diameter and size of HAZ.

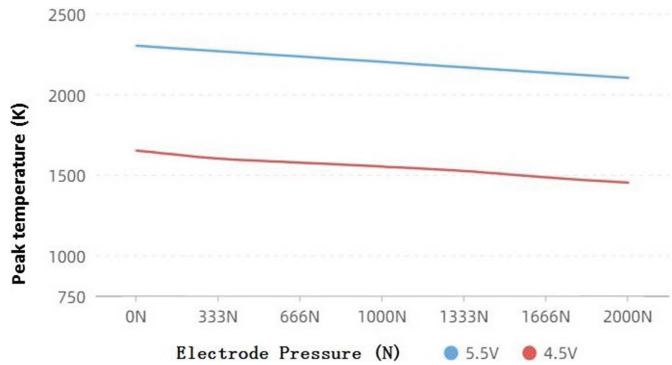


Fig. 9. The peak temperature varies with electrode pressure.

3.3 The Trace of the Point in HAZ

According to some previous study, the properties in HAZ could have important influence to the welding products, it sometimes could even be the weak point. In this study, the point2 in Fig. 8, which is in the area of HAZ, is selected to trace its thermal history

to bring more understanding in this field, as shown in Fig. 10. In the figure, the Ac1 temperature line (1100K) represents the austenization temperature of mild steel. It can be assumed that the longer the austenization time of point2 under a certain welding parameter, the wider the width of the heat affected zone of the welded joint under this parameter, and the wider of the nugget of the weldings. It can also be found that the austenization time becomes longer with the increase of welding electrode voltage, the width of HAZ will be bigger.

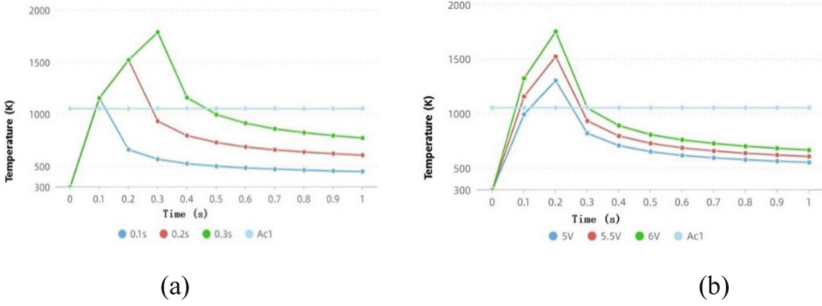


Fig. 10. **a.** Thermal history of HAZ vs. heating time. **b.** Thermal history of HAZ vs. voltage applied.

3.4 Effect of Welding Electrode Voltage on Temperature Field

In this study, it is found that the temperature field is very sensitive to the welding voltage applied on the electrode. According to Joule's law, heat generated by electricity, $= I^2 R t = U^2 t / R$, Heat is proportional to voltage and current during the welding process. When the welding voltage is changed, the welding current is also changed. The temperature field is directly proportional to the welding voltage applied. It can also be seen from the simulated potential diagram of 2D model in Fig. 10 that voltage drop mainly happens near the area of the welding interfaces, that means the biggest part of the electrical energy is consumed at the welding interfaces, so it is reasonable to find that the temperature field is proportional to the welding voltage. When the voltage exceeds a certain value, it will lead to splash and produce the smaller nugget. According to the calculation results in this model, the temperature near the welding surfaces is not sensitive to the electrical current density, which is quite different from other researchers. The possible reason may be the contact resistance between the electrode and nut is not considered in this model. And the results from the calculation may hint that adjusting the electrode voltage instead of current density could be another way to control process parameters (Fig. 11).

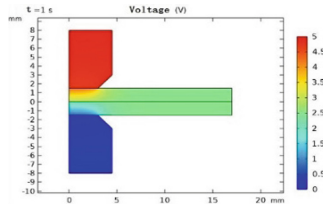


Fig. 11. The voltage distribution of welding parts (time $t = 1$ s).

4 Conclusions

The following points are concluded from the research:

1. The influence of heating time, welding voltage and electrode pressure on the parameters of process like the nugget diameter and width of the heat affected zone of the welded joint is in order from the largest to the smallest. The longer the heating time, the higher the welding voltage, the lower the electrode pressure, the larger the nugget, the wider the heat affected zone.
2. The simulation results show that the ideal welding parameters for the current setting is as follows, heating time, 0.2S, the electric potential of 5.5V, electrode pressure, 2000N, the current density of 10000A/m^2 .
3. The sensitivity of welding interface temperature on the electrode voltage exerted provide possibility to optimize welding conditions through adjusting electrical potential applied.

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Fault Diagnosis Method of Planetary Gear Based on FFT-DET and BP Neural Network

Zheng Wang¹, Hongjun Wang^{1,2,3}(✉), Baisheng Chen¹, and Zhuangzhuang Zhang¹

¹ School of Mechanical Electrical Engineering, Beijing Information Science and Technology University, Beijing 100192, China

wanghj86@163.com

² Beijing International Science Cooperation Base of High-end Equipment Intelligent Perception, Beijing 100192, China

³ Key Laboratory of Modern Measurement and Control Technology, Ministry of Education, Beijing 100192, China

Abstract. A method of effectively extracting fault features from vibration signals of planetary gear system and identifying fault state is kicked out in this paper. Firstly, the fast Fourier transform (FFT) method is used to analyze and extract the fault features of the original vibration signal, and the distance evaluation technology (DET) based on the distance between classes is used to select the sensitive fault features; Then, the fault characteristic data is input into BP neural network to train and test the fault diagnosis model; Finally, the gearbox fault test data set of Southeast University is used for fault identification research. The results show that the proposed method has high identification accuracy for different types of faults. The feasibility and superiority of the fault diagnosis method of planetary gear system based on the combination of fft-det and BP neural network are verified in this study, which can provide technical support for the health state evaluation of rolling bearing.

Keywords: Planetary gear · Fault diagnosis · Fast Fourier transform · Distance assessment technology · BP neural network

1 Introduction

With the rapid development of science and technology, the mechanical equipment in all walks of life is becoming more and more sophisticated, and its internal structure is becoming more and more complex. Due to the increasingly complex structure of these mechanical equipment, the internal parts and components are more closely connected. In the process of machine operation, once a part breaks down and is damaged, if no remedial measures are taken and the damage state is allowed to develop, the equipment will not be able to maintain normal operation, resulting in reduced production efficiency, and the machine will be seriously damaged. In the serious case, it will lead to major safety accidents and endanger people's lives. In 2016, a manned helicopter crashed out of control due to gearbox failure, resulting in 11 deaths and 2 missing [1]. Therefore, if the faults of parts and components can be detected and eliminated in time during the

maintenance of machinery and equipment, so as to ensure the safe and stable continuous operation of the equipment, the occurrence of such accidents can be effectively avoided.

Planetary gearboxes are widely used in many fields such as wind power generation system, mining machinery, agricultural machinery, metallurgical machinery, aviation, ships, automobiles and metal cutting machine tools because of their advantages such as high transmission ratio, high transmission accuracy, strong load capacity, stable operation and compact structure [2, 3]. Because these industrial machinery and equipment generally operate in the outdoor work, the environment is harsh, long time by the sand, corrosive liquid invasion damage, and the gearbox structure is very complex, so its transmission system is prone to failure. When the gear is damaged, it will affect the efficiency of the transmission system and produce adverse vibration and noise. If the fault is not diagnosed in time, the equipment may have a shutdown accident or even a destructive accident. Especially in today's society, with the rapid development of computer technology, electronics and information technology, all kinds of mechanical equipment have the development trend of large-scale, automation and high-speed. The accidents caused by the failure of gear will bring greater losses to production and society. Therefore, planetary gear box fault diagnosis, especially efficient fault feature extraction and analysis method, to reduce and avoid due to component failure of the whole equipment to stop working, the later maintenance, regular maintenance to according the change of situation and lengthen the service life of the gear box service time and has positive significance [4]. It can effectively protect the energy supply, industrial production and other important links of national economic construction, minimize the economic losses caused by machine failure, effectively reduce the probability of major accidents in industrial production, and play an important role in the development of society.

With the rise and development of artificial intelligence, deep learning is widely used in fault monitoring and diagnosis. Many scholars and engineers have used different intelligent algorithms to optimize neural networks to analyze and study the fault diagnosis problem of gearbox, and have achieved a lot of achievements. Zhang Zhiyu et al. [5] proposed an improved deep belief network (DBN) integrated with attention mechanism for gearbox fault diagnosis under variable working conditions, which effectively solved the problems of difficulty in fault identification and reduced classification accuracy of gearbox operating under variable working conditions. Wu Yingjian et al. [6] adopted the method of feature extraction based on multi-scale fuzzy entropy to process signals from multiple scales without prior knowledge of the gearbox, and its fault classification accuracy was better than that of traditional sample entropy and single feature extraction method in time and frequency domain. Liu Jiansheng et al. [7] used the EMD method to intuitively take and analyze the IMF component of gear fault signals, and combined with BP neural network for fault pattern recognition. Compared with the traditional method, the training error was reduced and the iteration speed was accelerated, but the mode aliasing problem of signals was not solved. Chen Lai et al. [8] combined SOM neural network and BP neural network, and adopted the composite neural network method for gear fault diagnosis, which has high reliability, but this method takes a long time to identify fault categories. Xie Chong [9] et al. proposed a method of VMD and multi-scale permutation entropy based on parameter optimization, which can search for a better