重庆大学
CHONGQING UNIVERSITY

基于稀疏测度的旋转机械故障特征提取研究

侯炳昌

高端装备机械传动全国重点实验室

研究背景

■ 故障监测与诊断是保障高端装备安全运行的核心技术之一

关键旋转部件更容易发生故障

- 轴承和齿轮等关键旋转部件主要用于承载和传递力矩，相对更容易发生故障

旋转部件


轴承


齿轮

典型装备

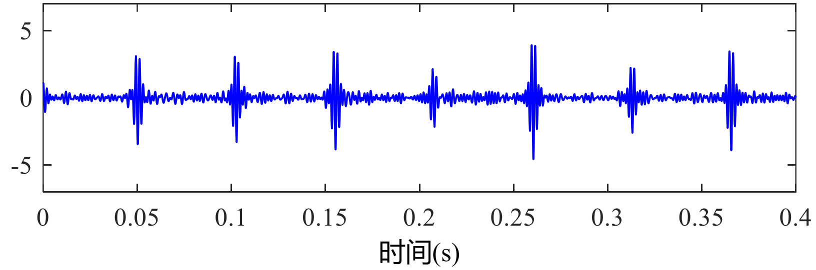
高速动车


风力发电机

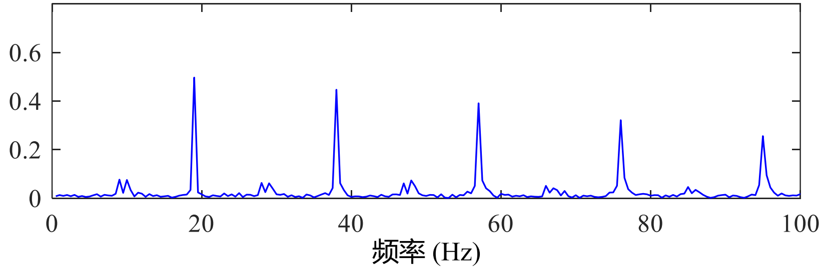
典型故障信号成分具有稀疏性

- 旋转部件的典型故障振动信号为循环脉冲，其在时域和包络谱域具有稀疏性

时域具有稀疏性



包络谱域具有稀疏性



*机械故障诊断主要分析蕴含丰富故障信息的振动信号

***稀疏性**：信号能量分布差异大，能量主要集中在少数信号系数

研究背景->稀疏测度

■ **稀疏测度**能够量化故障信号的稀疏性，被广泛用作故障特征提取方法的优化目标函数，以提取关键故障特征

常用稀疏测度

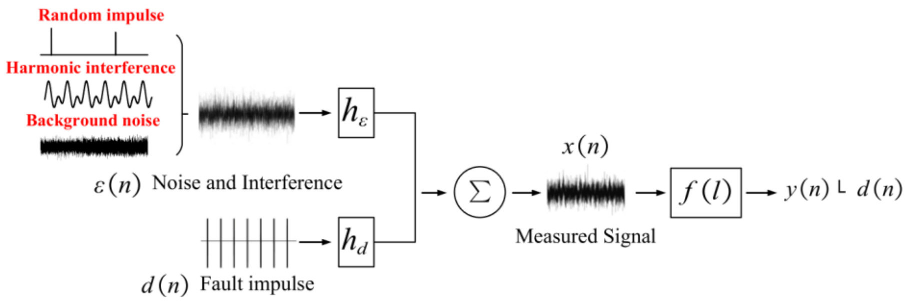
谱峭度： $\mathrm{SK}(\boldsymbol{c})=\sum_{n=1}^{N}(c_n)^2/N\Big/\left(\sum_{n=1}^{N}c_n/N\right)^2$

范数比： $L_{pq}(\boldsymbol{c})=\left(\sum_{n=1}^{N}(c_n)^p\right)^{1/p}\Big/\left(\sum_{n=1}^{N}(c_n)^q\right)^{1/q}$

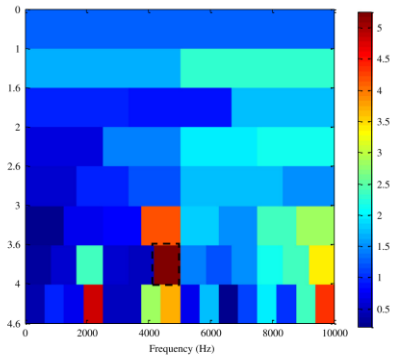
基尼指数： $GI(\boldsymbol{c})=1-2\sum_{n=1}^{N}\frac{c_{n,\uparrow}}{\|\boldsymbol{c}\|_{L1}}\left(\frac{N-n+0.5}{N}\right)$

负熵： $NE(\boldsymbol{c})=\frac{1}{N}\sum_{n=1}^{N}\frac{c_n}{\langle\boldsymbol{c}\rangle}\ln\left(\frac{c_n}{\langle\boldsymbol{c}\rangle}\right)$

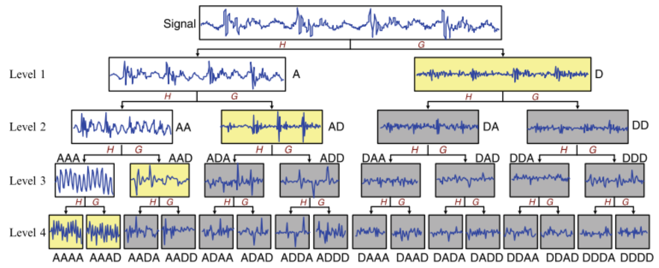
基于稀疏测度的经典机械信号处理方法



盲源去卷积



快速谱峭度图



稀疏测度优化小波分解参数

*稀疏性：信号能量分布差异大，能量主要集中在少数信号系数

代表性成果1—稀疏测度比值共性框架

- **研究挑战**：不同稀疏测度之间的量化共性联系未知
- **代表性成果1**：发现并证明了**稀疏测度的比值共性框架**，进一步构建了**新型稀疏测度**、以及可同时实现故障监测和单调退化评估的**自适应稀疏测度**

稀疏测度的比值共性框架

准算数均值比框架：

$$RQAM(\boldsymbol{c})=M_{f(x)|\boldsymbol{p}'}/M_{g(x)|\boldsymbol{p}''},$$

$$M_{f(x)|\boldsymbol{p}}=f^{-1}\left(\sum_{n=1}^{N}p_n f(c_n)\Big/\sum_{n=1}^{N}p_n\right)$$

框架推广

新型稀疏测度

孪生基尼指数：$GI2(\boldsymbol{c})=1-M_{x^1|\boldsymbol{p}^{(1)}}(\boldsymbol{c})/M_{x^1|\boldsymbol{p}^{(2)}}(\boldsymbol{c})=1-\sum_{n=1}^{N}\frac{2N-2n+1}{N^2}c_{n,\uparrow}\Big/\sum_{n=1}^{N}\frac{2n-1}{N^2}c_{n,\uparrow}$

广义基尼指数：$GGI(\boldsymbol{c})=1-M_{x^1|\boldsymbol{p}^{(3)}}(\boldsymbol{c})/M_{x^1}(\boldsymbol{c}),\ p_n^{(3)}=w[n]\Big/\sum_{n=1}^{N}w[n],\ w[n]=\left[2(N-n)+1\right]^a$

且数学证明满足稀疏测度六大属性要求

应用改进

可同时实现故障监测和单调退化评估的**自适应稀疏测度**

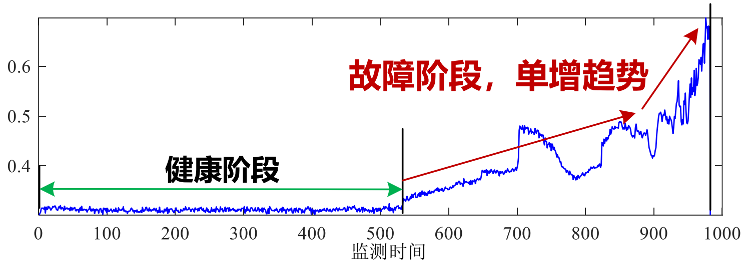
信号自适应变换

$$\boldsymbol{c}^*=(\boldsymbol{c}+m)^{-1},m=-2\sigma^2\ln(1-SP)$$

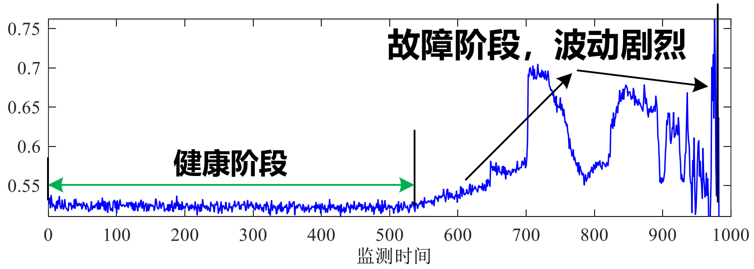
- 稀疏测度量化原始信号$\boldsymbol{c}$；
- 自适应稀疏测度量化信号$\boldsymbol{c}^*$；

轴承退化监测

自适应稀疏测度



原始稀疏测度



代表性成果2—优化权重谱理论及方法

- **研究挑战**：数据驱动稀疏测度模型缺乏可解释性证明
- **代表性成果2：理论证明了模型权重参数可解释性**，并提出了**优化权重谱理论**，其**正负权重可分别指示故障成分和固有成分**，还进一步开发了**多种新型故障特征提取方法**

数据驱动稀疏测度模型

➢ 特征统计量的内积表示：$\boldsymbol{\omega}^{T} NSES$

峭度：$\mathrm{SK} = (\boldsymbol{\omega}_1)^T \boldsymbol{NSES},\ \omega_1[n] = N \times NSES[n]$

基尼指数：$\mathrm{GI} = (\boldsymbol{\omega}_2)^T \boldsymbol{NSES},\ \omega_2[n] = -(-2N+2n-1)/N$

相对熵：$\mathrm{NE} = (\boldsymbol{\omega}_3)^T \boldsymbol{NSES},\ \omega_3[n] = \ln(N \times NSES[n])$

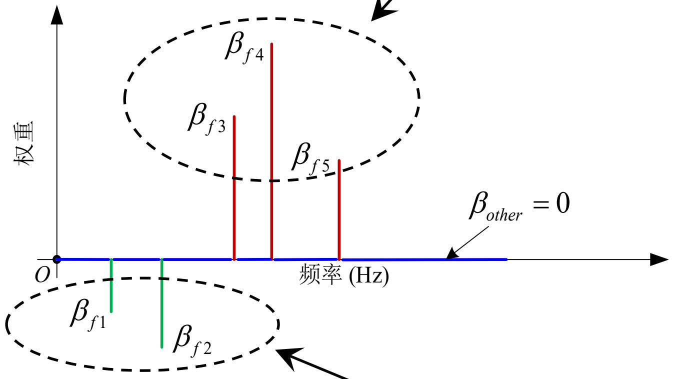
➢ 模型权重优化

健康数据+故障数据+凸优化 ⇒ 最优模型权重 ω^*

模型权重参数研究

可解释优化权重谱

正权重定位故障频率成分

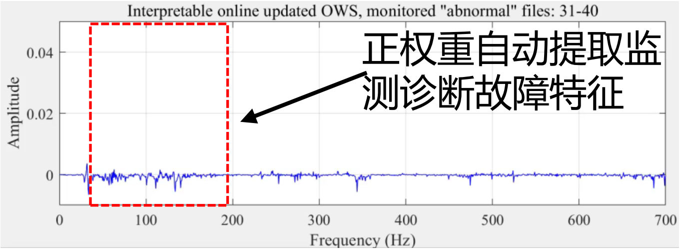


负权重定位基准频率成分

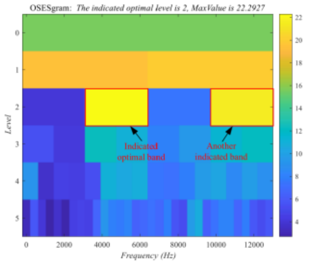
针对在线监测

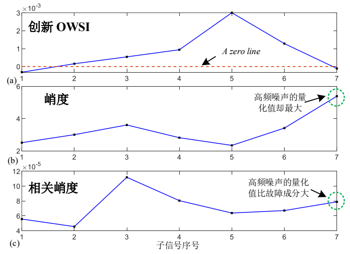
多种新型故障特征提取方法

➢ 优化权重在线更新



➢ OSESgram　➢ 子信号选择方法





代表性成果3——新型脉冲模态分解方法

- **研究挑战**：现存方法难以有效提取和分离复合循环故障脉冲
- **代表性成果3**：提出了基于**新型循环嵌入稀疏测度**的**脉冲模态分解方法**，**突破了自动确定不同循环故障脉冲数量、并准确提取和分离的难题**

新型循环嵌入稀疏测度

定义：

$$CESM(\boldsymbol{SE}) = \sqrt[\alpha]{\sum_{i=1}^{S}\left(SM(\boldsymbol{SE}^{(i)})\right)^{\alpha} / S} \quad \alpha \in \mathbb{R},\ \alpha \neq 0,$$

$$CESM(\boldsymbol{SE}) = \sqrt[S]{\prod_{i=1}^{S} SM(\boldsymbol{SE}^{(i)})} \quad \alpha = 0,$$

1、信号分段

$$\boldsymbol{SE} = [\boldsymbol{SE}^{(1)}, \boldsymbol{SE}^{(2)}, \ldots, \boldsymbol{SE}^{(S)}]$$

定义解析（以幂均值比为例）

2、稀疏测度量化

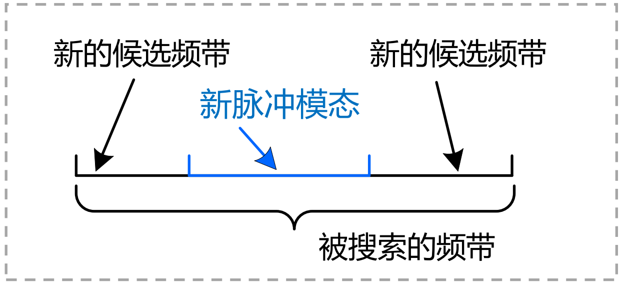
$$M_{2\text{to}1}(\boldsymbol{SE}^{(i)}) = \sqrt{\sum_{n=1}^{L}\left(\boldsymbol{SE}_n^{(i)}\right)^2 / L} \Big/ \left(\sum_{n=1}^{L} \boldsymbol{SE}_n^{(i)} / L\right)$$

3、循环嵌入稀疏测度

$$GM_{2\text{to}1}(\boldsymbol{SE}) = \sqrt[S]{\prod_{i=1}^{S} M_{2\text{to}1}(\boldsymbol{SE}^{(i)})}$$

作为优化目标

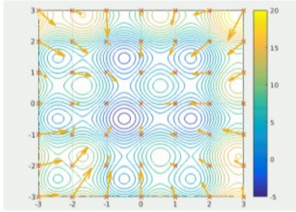
脉冲模态分解



新型滤波频带迭代搜索模型

$$CESM(\boldsymbol{SE}) = \sqrt[\alpha]{\sum_{i=1}^{S}\left(SM(\boldsymbol{SE}^{(i)})\right)^{\alpha} / S}$$

优化目标函数

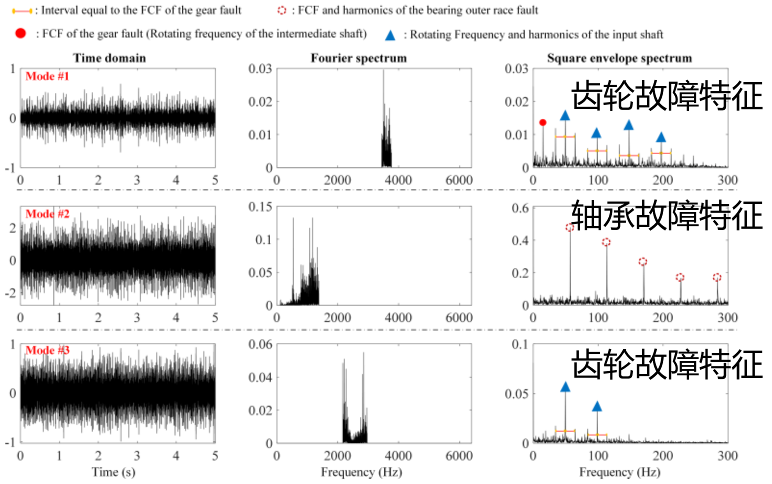


群体智能优化方法

案例效果

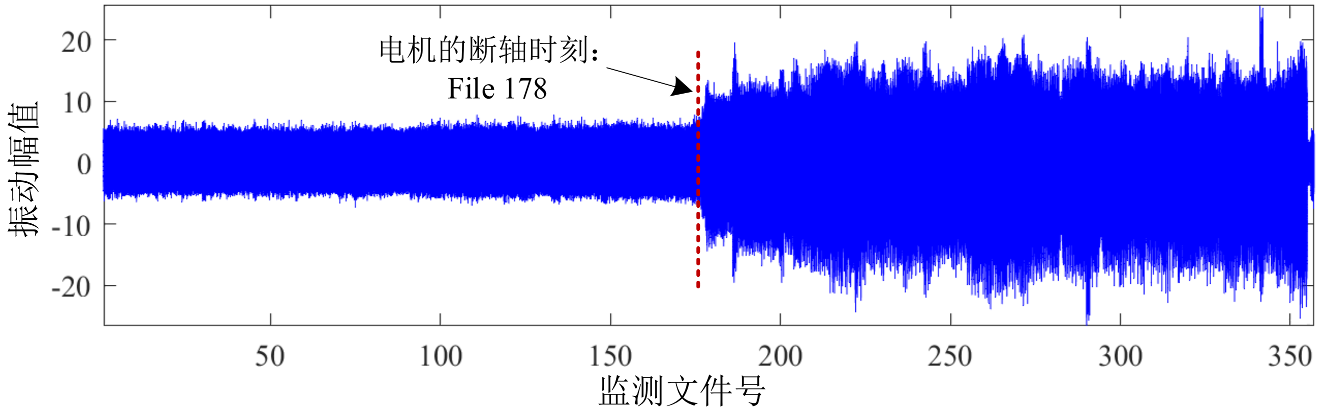
齿轮箱复合故障诊断案例

- 自动确定循环故障脉冲数量为3
- 模态1和3对应齿轮故障成分，模态2对应轴承故障成分



工业验证案例一则：某煤矿电机故障诊断

- **案例背景：**发现某**煤矿电机出现了断轴故障**，并收集到全生命周期监测振动数据，**希望能够分析数据得到早期故障时刻和早期故障类型的信息**
- **数据背景：**电机的转速为1490 rpm (24.83 Hz)，包含357个监测数据文件，人工分析发现断轴故障发生在第178号监测数据附近



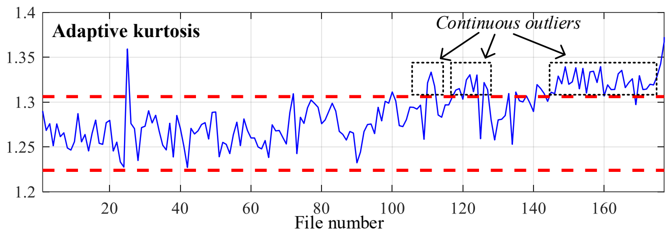
原始振动数据（在178时刻出现严重的断轴事故）

工业验证案例一则：某煤矿电机故障诊断

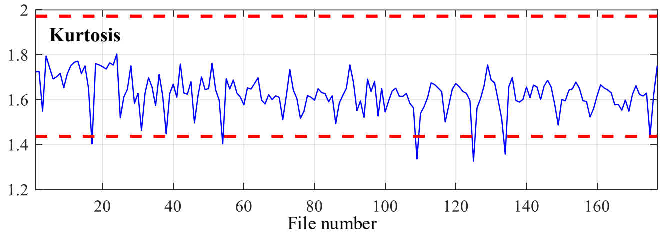
- **自适应稀疏测度**在断轴事故之前8天发现出现异常报警；**在线更新优化权重谱**发现异常时刻出现了50Hz左右的异常频率谱线，对应于轴不对中故障

基于自适应稀疏测度的故障监测 + 基于在线更新优化权重谱的故障诊断

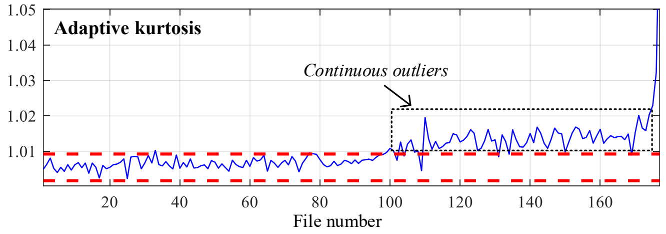
自适应稀疏测度

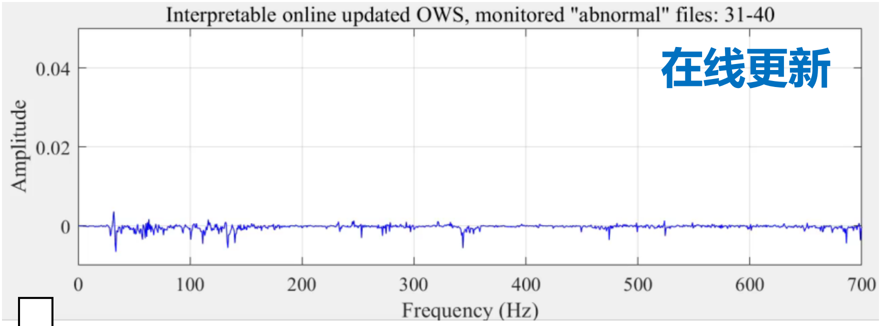


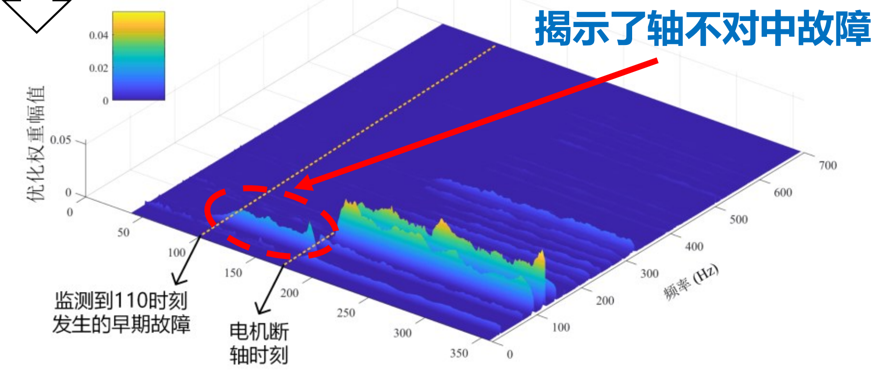
原始稀疏测度



自适应稀疏测度
(量化低通滤波器后的数据)







在线更新优化权重谱提取故障特征

相关**一作论文**获**ESI高被引论文**、ICSMD 2022国际会议论文**Best paper奖**

跟踪研究

■ 前述创新成果已被同行学者**直接应用或持续跟踪研究**

Structural Health Monitoring
OnlineFirst, April 17, 2023
© The Author(s) 2023, Article Reuse Guidelines
https://doi.org/10.1177/14759217231163090
SAGE journals

Original Article

Continuous monitoring of rolling element bearing health by nonlinear weighted squared envelope-based fuzzy entropy

Khandaker Noman[1], Yongbo Li[1], Guangrui Wen[2], Anayet U Patwari[3], and Shun Wang[1]

Mechanical Systems and Signal Processing 206 (2024) 110910
Contents lists available at ScienceDirect
Mechanical Systems and Signal Processing
journal homepage: www.elsevier.com/locate/ymssp

Anomaly detection and multi-step estimation based remaining useful life prediction for rolling element bearings

Junyu Qi[a,b], Rui Zhu[a,b], Chenyu Liu[a,b], Alexandre Mauricio[a,b], Konstantinos Gryllias[a,b,*]

[a] KU Leuven, Department of Mechanical Engineering, Division LMSD - Mecha(tro)nic System Dynamics, Celestijnenlaan 300, BOX 2420, Leuven 3001, Belgium
[b] Flanders Make@KU Leuven, Leuven, Belgium

Expert Systems With Applications 245 (2024) 123051
Contents lists available at ScienceDirect
Expert Systems With Applications
journal homepage: www.elsevier.com/locate/eswa

Differgram: A convex optimization-based method for extracting optimal frequency band for fault diagnosis of rotating machinery

Jianchun Guo[a,b], Yi Liu[b], Ronggang Yang[b], Weifang Sun[b], Jiawei Xiang[b,*]

[a] School of Mechanical Engineering, Guangxi University, Nanning 530004, PR China
[b] College of Mechanical and Electrical Engineering, Wenzhou University, Wenzhou 325035 PR China

---

Contents lists available at ScienceDirect
Reliability Engineering and System Safety
journal homepage: www.elsevier.com/locate/ress

Machinery cross domain degradation prognostics considering compound domain shifts

Peng Ding[a,*], Xiaoli Zhao[b], Haidong Shao[c], Minping Jia[d]

[a] College of Mechanical Engineering, Yangzhou University, Yangzhou 225127, PR China
[b] School of Mechanical Engineering, Nanjing University of Science and Technology, Nanjing 210094, PR China

---

Engineering Applications of Artificial Intelligence 131 (2024) 107872
Contents lists available at ScienceDirect
Engineering Applications of Artificial Intelligence
journal homepage: www.elsevier.com/locate/engappai

Machinery degradation trend prediction considering temporal distribution discrepancy between degradation stages

Shudong Ou, Ming Zhao*, Hao Wu, Yue Zhang, Sen Li

State Key Laboratory for Manufacturing Systems Engineering, School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an, 710049, Shaanxi Province, China

---

Contents lists available at ScienceDirect
Mechanical Systems and Signal Processing
journal homepage: www.elsevier.com/locate/ymssp

A full generalization of the Gini index for bearing condition monitoring

Bingyan Chen[a,b], Dongli Song[a], Fengshou Gu[a,b], Weihua Zhang[a,*], Yao Cheng[a], Andrew D. Ball[b], Adam Bevan[c], James Xi Gu[d]

[a] State Key Laboratory of Traction Power, Southwest Jiaotong University, Chengdu 610031, China
[b] Centre for Efficiency and Performance Engineering, University of Huddersfield, Huddersfield HD1 3DH, UK
[c] Institute of Railway Research, University of Huddersfield, Huddersfield HD1 3DH, UK
[d] School of Engineering, University of Bolton, Bolton BL3 5AB, UK

部分跟踪研究论文

Reliability Engineering and System Safety 238 (2023) 109428
Contents lists available at ScienceDirect
Reliability Engineering and System Safety
journal homepage: www.elsevier.com/locate/ress

A two-phase-based deep neural network for simultaneous health monitoring and prediction of rolling bearings

Rui Bai[a], Khandaker Noman[b], Ke Feng[c], Zhike Peng[d], Yongbo Li[a,*]

[a] School of Aeronautics, Northwestern Polytechnical University, Xi'an, 710072, China

---

IEEE Sensors Council
IEEE SENSORS JOURNAL, VOL. 23, NO. 1, 1 JANUARY 2023 577

Multiscale Sparsity Measure Fusion for Bearing Performance Degradation Assessment

Qian Wang, Qiang Huang, Xingxing Jiang, Qiuyu Song, and Zhongkui Zhu

友情链接

Google Scholar:
https://scholar.google.com/citations?user=O_tweiYAAAAJ&hl=en&oi=sra

ResearchGate:
https://www.researchgate.net/profile/Bingchang-Hou-2