Proceedings of the 8th European Conference of the Prognostics and Health Management Society 2024 - ISBN – 978-1-936263-40-0

# Machinery Fault Detection using Advanced Machine Learning Techniques

Dhiraj Neupane, Mohamed Reda Bouadjenek, Richard Dazeley, and Sunil Aryal

*School of Information Technology, Deakin University, Waurn Ponds, VIC 3216, Australia*
{*d.neupane, reda.bouadjenek, richard.dazeley, sunil.aryal*} *@deakin.edu.au*

## Abstract

Manufacturing industries are expanding rapidly, making it essential to detect early signs of machine faults for safety and productivity. With the extension of machines' runtime due to industrial automation, breakdown risks have increased, leading to economic and productivity consequences and sometimes even causalities. The surge in industrial big data from low-cost sensing technologies has enabled the development of intelligent data-driven Machinery Fault Detection (MFD) systems based on machine learning techniques in recent years. However, most existing methods are based on supervised pattern classification techniques to detect previously known fault types, which have limitations such as lack of generalization across different operational settings, focusing only on specific machinery and/or data types, and considering the identical and independent distribution of training and testing data. Therefore, my PhD research aims to develop a robust MFD framework for practical use by addressing these limitations.I will explore the potential of ensemble learning, unsupervised and semi-supervised anomaly detection, reinforcement learning, transfer learning, and cross-domain adaptation approaches in MFD. My PhD research will contribute to the field of data-driven MFD by proposing novel, effective solutions that can be applied across various manufacturing applications.

## 1. Background

Rotating machinery holds significant importance in modern industries. These machines often operate longer and under adverse conditions, making them prone to failure. Machine failures result in substantial maintenance costs, production inefficiencies, financial losses, and even risks to human life. Common electric motor failures involve bearings, stators, rotors, and gearboxes. The continuous operation of these machines can lead to wear, cracks, and other defects, emphasizing the need for accurate and timely fault detection and diagnosis to mitigate financial and safety risks (Neupane & Seok, 2020).



## 2. A Brief Discussion on the State-Of-The-Art

Recent developments (Neupane, Kim, & Seok, 2021; Zhong, Zhang, & Ban, 2023) in MFD have mainly focused on classifying the health states of machinery through extensive analysis of samples under normal and faulty conditions. While these studies have contributed to the creation of robust fault diagnosis systems, there is a limited exploration in examining semi-supervised learning (SSL) methods (see Figure 1). Moreover, the prior SSL applications primarily focus on fault classification (Zong et al., 2022; Zhang, Ye, Wang, & Habetler, 2020). Reinforcement Learning (RL) is increasingly being employed in various domains of MFD, such as transmission lines, hydraulic presses, and industrial process controls (Teimourzadeh, Moradzadeh, Shoaran, Mohammadi-Ivatloo, & Razzaghi, 2021; Junhuai, Yunwen, Huaijun, & Jiang, 2023). Although most RL applications treat fault diagnosis as a simple classification task, there are also some innovative approaches that extend its use to complex system management. For instance, (Vos, Peng, & Wang, 2023) employ an RL framework to optimize fleet management in the aviation sector, demonstrating how RL can effectively handle the dynamic decision-making required to maintain high fleet availability and minimize maintenance costs across aircraft with varying ages and degradation paths. Furthermore, data fusion methods play a critical role in enhancing the accuracy of fault detection systems. Techniques range from data-level fusion, such as weighted averaging and Kalman filters, to more complex feature and decision-level fusions that utilize statistical and machine learning methods, such as principal component analysis and Bayesian decision theory (Kibrete, Woldemichael, & Gebremedhen, 2024). Despite these advancements, the integration of multi-level fusion and cross-domain adaptation remains limited, highlighting a significant area for future research.

## 3. Motivations

First, the existing studies on MFD primarily employ supervised learning approaches (over 80%, see Figure 1), which can accurately identify known faults but struggle to detect

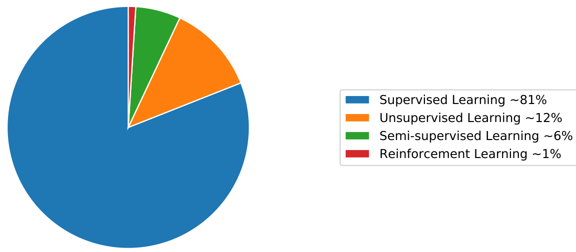


Figure 1. Machine learning techniques used for MFD

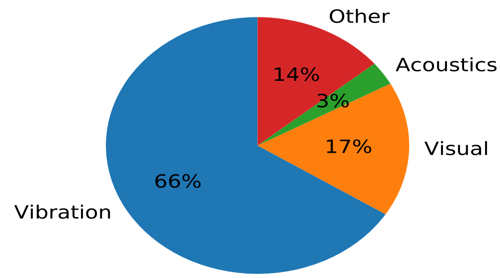


Figure 2. Data types used for MFD

novel or unseen ones (Das, Das, & Birant, 2023). This limitation is problematic in complex industrial settings where modern machines operate, as new fault types can emerge over time. Also, accurately identifying various fault types necessitates a substantial quantity of labelled data, which is a difficult challenge in real-world industrial settings because annotating takes time, expertise, and resources. Moreover, the labelled data may not cover all possible faults, restricting the diversity of the training dataset and hindering the model's ability to generalize to unseen faults.

In supervised learning, the effectiveness of the algorithms heavily relies on the accuracy of the data labels, which are typically derived from expert interpretations of sensor readings or from known operating conditions. This dependency on labeled data also extends to SSL, where limited labeled data can constrain the learning process to the inherent accuracy of these labels, a limitation referred to as the Bayes rate (Nian, Liu, & Huang, 2020). To address this challenge, RL can be used, which is a promising ML framework that learns from trial-and-error interactions using rewards rather than explicit instructions (Wang, Jiang, Li, & Liu, 2020). RL has demonstrated success in various fields, including manufacturing, but its application in MFD is limited. Existing fault detection systems have not thoroughly exploited the potential of RL in optimizing maintenance decisions and fault detection strategies. Current RL algorithms for MFD often treat fault diagnosis as a simple classification task, which may not fully utilize the capabilities of the RL framework. RL can learn the sequence of events leading up to a fault, which can be used to predict when a fault is likely to occur. Moreover, the use of RL algorithms is currently limited to a single machinery or environmental setting. This research aims to explore the application of RL algorithms in MFD and develop specialized RL algorithms that can effectively handle the dynamic nature of fault patterns and machine operational conditions.

Additionally, most existing (about two-thirds, see Figure 2) ML-based MFD techniques use vibration data to predict faults (Das et al., 2023). Vibration signals, however, can be problematic in harsh environments or areas with high background noise, which can decrease the accuracy of collected data. Moreover, traditional vibration sensors may not always be practical for installation in locations that are difficult to access or on specific types of equipment. For example, placing these sensors on ball bearings within centrifugal pumps or on equipment operating under extreme conditions such as low-temperature vacuum pumps can pose significant challenges (Hoang & Kang, 2019). Furthermore, an exclusive reliance on vibration data could potentially limit the performance of ML models. Thus, the incorporation of other data types could offer a richer understanding of the problem and yield improved results. Utilizing diverse data types, such as temperature, current, acoustic, and visual information, into fault diagnosis algorithms can offer a more comprehensive and accurate understanding of machinery health. Combining data from multiple sources not only improves the detection of subtle faults, reducing diagnostic errors but also compensates for potential sensor failures or data inaccuracies due to environmental interference.

Moreover, most existing work on MFD focused on specific machine types and operational environments. Usually, models are trained on data from one type of machine in a particular environment and are expected to perform effectively on similar machines or the same machine under different conditions. This expectation is based on the assumption that the source (training) and target (test) data are independent and identically distributed (*iid*) (Li et al., 2022). However, achieving this *iid* condition in industrial applications is challenging due to several factors: (a) machines can exhibit different behaviors and degradation patterns over time or when operated in varying conditions; (b) differences in machine manufacturing, wear-and-tear, and operational settings can introduce significant variability in the data. These factors contribute to the 'domain-shift' problem, where the training data no longer represents the new conditions under which the model is tested. This domain shift can significantly reduce the effectiveness of fault detection models, as they fail to generalize across different operational scenarios. Thus, addressing this issue is crucial for affecting machine health monitoring and fault diagnosis in diverse environments.

## 4. Research Aim and Objectives

This PhD project aims to develop a robust framework for MFD by addressing identified limitations and research gaps. Defined as 'robust', our framework ensures that various algorithms—-including unsupervised, semi-supervised, and reinforcement learning techniques—-perform effectively in real-world industrial settings. These environments are often complex and noisy, with heterogeneous data. By utilizing diverse data types, our framework anticipates supporting effective applications across different domains. This aim will be achieved through the following objectives:

1. To investigate the potential of unsupervised and semi-supervised anomaly detection (AD) methods for identifying anomalous patterns in MFD. This approach eliminates the need for labeled data and addresses the challenges of class imbalance.
2. Additionally, there is a goal to fully utilize the capabilities of RL for MFD by creating specialized algorithms that can optimize maintenance and fault detection strategies. Apart from fault classification, RL has potential in AD (Arshad et al., 2022), optimizing maintenance strategies (Marugán, 2023) or prediction (Siraskar, Kumar, Patil, Bongale, & Kotecha, 2023). This will help overcome the limitations of treating fault diagnosis as a guessing game and improve performance in diverse operating conditions.
3. Another objective is to explore the potential of using diverse data types for developing MFD algorithms, which can enhance diagnostic efficiency and provide a comprehensive understanding of machinery health status. The study will also investigate the use of ensemble models to improve accuracy and efficiency.
4. Lastly, the aspiration is to bridge the gap between different data types and operational settings using domain adaptation and transfer learning techniques, which can enhance the model's ability to generalize across diverse settings.

## 5. Research Methodology and Timeline

To create an integrated framework for MFD that makes use of robust semi and unsupervised learning-based AD algorithms, our approach encompasses data preprocessing, algorithm selection, and model training, with the aim of generating anomaly scores for predicting faults. We will evaluate the performance of our models using metrics such as precision, recall, F1 score, etc., and compare them with supervised methods. Our work on this project is ongoing, and we submitted an article to "the 8th European Conference of the PHM Society (PHMe2024), presenting the results of our experiments with various AD algorithms on the Case Western Reserve University (CWRU) bearing dataset, Paderborn University (PU) bearing dataset, and Health and Usage Monitoring System (HUMS) datasets. The outcomes of our study so far have been encouraging, demonstrating the efficacy of AD methods.

To achieve our second objective in employing RL in MFD, the formulation of problems, the development of algorithms (including state representation, action space definition, reward function design, and RL algorithm selection), data collection and preprocessing, training and testing, and continuous refinement of the RL algorithm based on evaluation metrics such as performance against baseline models, rewards evaluation, fault detection accuracy, and training convergence progress will be done. Since real-time data collection is limited in our setup, we will focus on employing offline RL techniques (Deng, Sierla, Sun, & Vyatkin, 2023). Offline RL is ideal for situations where learning must be derived from pre-existing datasets rather than from interactions with the environment in real-time. For implementing these techniques, we can utilize well-established libraries, which provide the necessary tools to effectively apply offline RL algorithms to our data.

To accomplish our third objective, we aim to develop a comprehensive MFD algorithm by integrating various data types. Our aim is to improve adaptability, generalization, accuracy, and fault detection capabilities under different machinery conditions. We employ flexible models that can handle heterogeneous data, which are preprocessed for noise and normalization, and utilize ensemble techniques like data, feature, or decision fusion. Evaluation will be based on accuracy, precision, recall, and F1 score metrics. We have made progress by using the PU dataset to fuse vibration and current data, which will gradually advance to the integration of X and Y-axis vibration data, two phases current data, and torque data, ensuring comprehensive feature integration and decision-making.

To effectively enhance MFD in diverse operating conditions and overcome the challenges of limited data by employing domain adaptation and transfer learning techniques, we will apply domain adaptation methods like discrepancy, adversarial, or reconstruction-based approaches (Zhang et al., 2023). Moreover, multi-source domain adaptation is also being explored. The effectiveness of the approach is evaluated using classification and domain discrepancy metrics.

### 5.1. Expected Outcomes and Publications

This project aims to develop a novel, robust, and flexible MFD system for real-world applications. The framework will implement an unsupervised or semi-supervised learning-based fault detection framework, utilizing diverse data types and incorporating RL for fault prediction and cross-domain platforms as well. Apart from these, we have expected to publish a review paper, which is almost ready to submit. Also, a few conference articles and collaboratory publications are also expected.

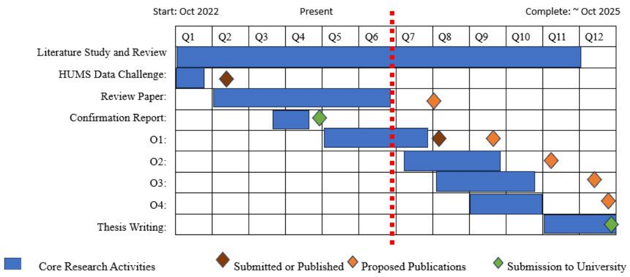


Figure 3. Proposed Timeline for this PhD

### 5.2. Works Done So Far and Timeline

During the course of this research project, significant progress has been made across various aspects of the study.

**Literature Review and Draft Article:** Our initial phase included a comprehensive literature review and a draft of a detailed review paper on significant MFD developments. The paper covers multiple topics and is almost ready for submission.

**Participation in HUMS Data Challenge and Conference Presentation:** We participated in the HUMS Data Challenge and presented our research at the HUMS conference, where our findings were published. Our work involved using signal processing and statistical-based approaches to detect cracks in the provided dataset and the auto-regressive integrated moving average method for predicting fault progression.

**Manuscript Submission in PHMe2024**: We also submitted an abstract and full manuscript for the upcoming conference PHMe2024, going to be held on July 3- 5, in Prague, CZ. The article is related to the use of semi-supervised-based techniques for machinery fault detection, which is objective 1 of this project.

**Objective 1 continued:**The work being carried out for objective 1 is being extended. We are actively engaged in the incorporation of a new dataset and in the application of semi-supervised techniques for anomaly detection. Furthermore, we are exploring various data transformation methods and combinations of features to enhance our results.

This PhD program commenced in October 2022 and is expected to be completed by 2025, within a three-year timeframe. In addition to core research and publication activities, administrative tasks must be carried out throughout the program, as per university and faculty regulations. To facilitate effective planning, the entire three-year period has been divided into twelve three-month periods and is shown in figure 3.

## 6. Conclusion

Implementing a robust machinery fault detection system in real-world settings presents several challenges, such as adaptability to a variety of machines, compatibility with existing infrastructure, and scalability across diverse industrial environments. To tackle these challenges, we aim to develop adaptive algorithms, enhancing system compatibility with current technologies, and ensuring scalability for broad industrial applications. Moving forward, our vision for MFD research encompasses the integration with predictive analytics, aiming to transform MFD systems into comprehensive diagnostic tools that not only detect but also predict faults, significantly reducing downtime and maintenance costs. This future-oriented approach aims to solidify the role of MFD in advancing predictive maintenance strategies and thereby contribute a sustained impact to the field.

## References

Arshad, K., Ali, R. F., Muneer, A., Aziz, I. A., Naseer, S., Khan, N. S., & Taib, S. M. (2022). Deep reinforcement learning for anomaly detection: A systematic review. *IEEE Access*, *10*, 124017–124035.

Das, O., Das, D. B., & Birant, D. (2023). Machine learning for fault analysis in rotating machinery: A comprehensive review. *Heliyon*.

Deng, J., Sierla, S., Sun, J., & Vyatkin, V. (2023). Offline reinforcement learning for industrial process control: A case study from steel industry. *Information Sciences*, *632*, 221–231.

Hoang, D. T., & Kang, H. J. (2019). A motor current signal-based bearing fault diagnosis using deep learning and information fusion. *IEEE Transactions on Instrumentation and Measurement*, *69*(6), 3325–3333.

Junhuai, L., Yunwen, W., Huaijun, W., & Jiang, X. (2023). Fault detection method based on adversarial reinforcement learning. *Frontiers in Computer Science*, *4*, 1007665.

Kibrete, F., Woldemichael, D. E., & Gebremedhen, H. S. (2024). Multi-sensor data fusion in intelligent fault diagnosis of rotating machines: A comprehensive review. *Measurement*, 114658.

Li, W., Huang, R., Li, J., Liao, Y., Chen, Z., He, G., . . . Gryllias, K. (2022). A perspective survey on deep transfer learning for fault diagnosis in industrial scenarios: Theories, applications and challenges. *Mechanical Systems and Signal Processing*, *167*, 108487.

Marugán, A. P. (2023). Applications of reinforcement learning for maintenance of engineering systems: A review. *Advances in Engineering Software*, *183*, 103487.

Neupane, D., Kim, Y., & Seok, J. (2021). Bearing fault detection using scalogram and switchable normalization-based cnn (sn-cnn). *IEEE Access*, *9*, 88151-88166. doi: 10.1109/ACCESS.2021.3089698

Neupane, D., & Seok, J. (2020). Bearing fault detection and diagnosis using case western reserve