Abstract

Rotating machinery is considered the backbone of numerous industrial processes, and its unexpected failure is associated with unplanned downtime, financial losses, and safety risks. To improve reliability and enable early fault detection, a unified Diagnostics and Health Management framework is presented in this thesis, integrating structured decision-making, low-cost sensing technologies, intelligent signal processing, and interpretable deep learning techniques. The focus is placed on providing scalable, accurate, and affordable solutions tailored for small- and medium-scale industries where access to high-end diagnostic tools is often limited.

The research is initiated by addressing the critical task of selecting appropriate condition monitoring techniques based on practical constraints. A structured methodology is developed using a multi-criteria decision-making approach that incorporates expert-defined weights and considers factors such as fault detectability, system criticality, sensor cost, data collection feasibility, and noise sensitivity. This selection framework is designed to guide users in determining optimal combinations of monitoring techniques under real-world industrial conditions.

To reduce dependency on expensive and invasive instrumentation, the use of smartphone accelerometers, off-the-shelf microphones, and thermal imaging cameras is explored for machinery fault detection. For instance, vibration data collected from smartphones and microphones is used to identify faults such as unbalance in motors and cavitation in pumps. In parallel, infrared thermography is applied as a non-invasive, image-based technique to detect cavitation and air-entrainment faults in centrifugal pumps. Temperature patterns captured by a thermal camera are analyzed using a handcrafted feature extraction strategy, followed by fault classification through machine learning models. The IRT-based methodology is shown to have strong potential in diagnosing fluid-induced anomalies in scenarios where traditional sensors are impractical or inaccessible.

Rotational speed estimation, a prerequisite for many diagnostic algorithms, is achieved using a novel tacho-less approach based on smartphone accelerometer data and tested on different sensor locations. A methodology is developed to estimate speed accurately under variable speed, various microphone distances, and load conditions. The method is demonstrated to be effective even in the presence of operational noise, supporting embedded, real-time applications.

Finally, the challenge of multi-fault diagnostics under complex conditions is addressed. A deep learning-based classification framework is proposed, utilizing multi-sensor data collected from machinery under healthy and faulty states. Spectrograms generated through time–frequency analysis are used as inputs to a two-dimensional convolutional neural network, while interpretability is enhanced using Gradient-weighted Class Activation Mapping, allowing visualization of salient features influencing classification decisions.

The proposed framework unites structured sensor selection, affordable instrumentation, signal analytics, and interpretable artificial intelligence to enable early fault detection and decision support in rotating machinery. All techniques are validated on experimental test rigs and real-world scenarios, demonstrating robustness, accuracy, and scalability. This thesis lays the groundwork for enabling wider implementation of condition monitoring and health management in industrial systems by offering cost-effective solutions backed by engineering and intelligent automation.

Keywords:

Diagnostics and Health Management, Rotating Machinery, Condition Monitoring, Consumer-grade Sensors, Fault Diagnosis