AI-Based Fault Diagnosis of Centrifugal Pump

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The fault-related impulses in the centrifugal pump (CP) vibration signal are often attenuated due to the background interference noises, thus affecting the sensitivity of the traditional statistical features towards faults. Furthermore, extracting health-sensitive information from the vibration signal needs human expertise and background knowledge.

centrifugal pump | wavelet coherence analysis | fault diagnosis | convolutional neural network | vibrational signals

1. Introduction

CPs play a vital role in various industries including engine manufacturing, air conditioning, electricity generation, and chemical processing, with CPs accounting for approximately 70% of all pump types and consuming around 20% of the world's energy production [1]. Despite their long life span, the sudden failure of CPs can lead to significant disruptions and even catastrophic consequences. These failures result in economic losses, extended costly repairs, and downtime. In order to reduce the potential dangers, it is imperative to regularly monitor the CPs. This monitoring can involve a large workforce or the utilization of signal processing and Artificial Intelligence (AI) techniques, which offer a cost-effective and efficient solution [2]. Recently, AI-based condition monitoring has gained increasing attention, especially for the early detection and diagnosis of CP faults. Therefore, an intelligent framework is proposed for the early detection and diagnosis of faults in CPs, which are prone to various operational concerns due to the rapid rotation of impellers, including issues such as damaged bearings, impeller damage, and cavitation [3]. Defects in CPs can be categorized into fluid-flow-related and mechanical faults (MFs) [4]. Mechanical seal-related defects alone account for 34% of CP defects, while impeller problems can cause mechanical or combined mechanical and flow-related defects [5][6]. Mechanical defects can lead to perilous soft failures, which are difficult to detect due to the gradual decline in the efficiency of CP operation [7]. Early identification of soft flaws in CPs is of primary importance. Researchers focused on the early identification of soft flaws in CPs, often caused by Mechanical Seal Hole (MSH), Mechanical Seal Scratch (MSS), or Impeller Fault (IF) issues. To achieve this, a condition-based monitoring system (CBM) is one of the most effective methods. CBMs collect data from machines under various operating conditions, extending machine runtime at a relatively low cost [8]. Mechanical faults, such as IFs, MSHs, and MSSs, can significantly impact the vibration signals emitted by CPs. These faults can make vibration signals irregular and unpredictable. Signal processing techniques such as time, frequency, and time–frequency-domain (TFD) analyses are commonly used for this purpose.

2. AI-Based Fault Diagnosis of Centrifugal Pumps

AI-based techniques for fault diagnosis consist of signal preprocessing, features preprocessing, and fault identification and classification tasks [9][10][11]. Sakthivel et al. [12] compared dimensionality reduction techniques for CP defect diagnosis and discovered that Principal Component Analysis (PCA) yielded promising results. PCA extracts principal components that contain information about various machinery malfunction symptoms. However, PCA disregards the estimation of intraclass separability. In addition, information loss is a significant disadvantage of PCA. Contrary to PCA, LDA determines the optimal reduced-dimensional representation by considering interclass scatteredness and intraclass separability, given a sufficiently large labeled dataset. Several variants of LDA, such as the trace ratio LDA [13], the local sensitive discriminant analysis [14], and the robust linear optimized LDA [15], have been proposed in recent decades. Li et al. [16] conducted Particle Image Velocimetry (PIV) experiments to examine the correlation between the internal flow field and external characteristics of a low-specific-speed CP. The focus of the investigation was on energy conversion. The findings of the study on the internal flow of CPs have revealed that the rotating impeller's intricate secondary flow results in additional energy loss in the blade channels and an intensified wake-jet structure, leading to further losses at the blade's trailing edge (TE) [17]. Therefore, the primary means of enhancing the energy efficiency of pumps is to minimize the occurrence of secondary flow within the impeller. There are different methods of signal processing, including the Fourier transform (FT), that have proven effective for analyzing stationary signals. However, these methods fail to provide accurate information for nonstationary signals due to the loss of temporal data, though they retain spectral component information [18]. Newer signal processing techniques have been introduced to address this limitation, including the wavelet transform (WT), Short-Term Fourier Transform (STFT), and Stockwell Transform (ST) [19]. The STFT uses fixed sample windows for time–frequency analysis but faces trade-offs between time and frequency resolution [20]. In contrast, the WT solves the problem of resolution by utilizing bigger windows for lower frequencies and smaller windows for higher frequencies. This provides useful data in both the frequency and time domains (TD) [21]. However, the WT method is sensitive to noise and does not provide phase information for the analyzed signals. The WT has garnered significant attention in recent years for its efficacy in processing nonstationary signals, leading to successful applications in various domains [22]. For example, it has been effectively utilized in bearing condition monitoring [23][24][25], detection of machine tool failure [26], knock and misfire detection in spark ignition engines [23], fault detection in washing machines [27], and monitoring of alternating-current drives [28]. Researchers have proposed different approaches using wavelet transforms in machine condition monitoring. For instance, an energy-based method by Ruqiang et al. [29] used wavelet coefficients to identify defects in rotary machinery. Utilizing a Hierarchical Neural Network for Bearing Fault Diagnosis through Dimensionality Reduction and Classification, Delgado et al. [30] employed a nonlinear manifold learning technique. Xia et al. [31] presented a CNN-based approach using data fusion and feature representation for rotatory machinery diagnosis. Ahmad et al. [32] introduced a three-phase technique involving the Walsh Transform, raw statistical features, and cosine linear discriminant analysis (CLDA) for fault classification in CP vibration signatures. Sajjad et al. [33] proposed a technique for fault classification in CP that involves computing kurtogram spectra, utilizing a convolution encoder, and implementing a linear classifier for fault visualization and classification. Kuang et al. [34] identified the vibration source in mechanical specimens using wavelet coherence and Fourier coherence.

The abovementioned techniques improved the reliability and performance of CPs by enabling early detection and diagnosis of faults. However, there exist several limitations. (i) Techniques concerning TD correlation analysis suffer from background noise. (ii) FT is best suited for stationary signals. However, the vibration signals obtained from CPs under defective conditions are highly complex and nonstationary. (iii) Techniques concerning STFT suffer from spectral leakage due to windowing effects. To address these issues, researchers propose an intelligent technique for the fault diagnosis of CP based on wavelet coherence and deep learning. Wavelet coherence analysis is a signal processing technique that is used to measure the degree of linear correlation between two signals as a function of frequency. For Wavelet Coherent Analysis, the selection of a healthy baseline signal is important. For this reason, a proper strategy is adopted for the selection of a healthy baseline signal. The wavelet coherent analysis is calculated between the healthy baseline signal and the signal acquired from the CP under different operating conditions, and coherograms are obtained. The coherograms carry information about the CP's vulnerability to faults. The coherograms are then provided as input to a CNN and a CAE for the extraction of discriminant CP health-sensitive information. The CAE extracts global variations from the coherograms, and the CNN extracts local variations related to CP health. This information is combined into a single latent space. To identify the health conditions of the CP, the latent space is classified using an ANN.

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