APPLICATION OF LOW-COST SENSORS AND DEEP AUTOENCODERS FOR MONITORING WATER PUMPS IN PARTICLE ACCELERATORS*

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Abstract

In particle accelerator facilities, cooling-water pumps play a critical role in removing substantial amounts (megawatts) of waste heat from numerous high-power accelerator components (e.g., magnets, radio frequency structures, power supplies) and beamline components. Despite their role in daily operations, inspecting hundreds of water pumps is labor-intensive and performed only occasionally. Unexpected pump failures can lead to degradation of beam quality, hardware damage, and costly unplanned downtime. This study introduces an innovative method for real-time monitoring of water pump vibrations to identify anomalies that signal potential mechanical failures. Our approach integrates (i) affordable vibration sensors, which will continuously sample pump vibration data and transmit it to a (ii) deep autoencoder model for detecting anomalies. The planned model will recognize the normal vibration patterns of each pump and identify subtle variations. This developmental monitoring system will help facilitate proactive maintenance by enabling early detection of anomalies, enhancing pump reliability, lowering maintenance expenses, and minimizing costly downtimes.

INTRODUCTION

Cooling-water pumps at the Advanced Photon Source (APS) remove several megawatts of waste heat from accelerator magnets, radio frequency (RF) structures, power supplies, and beamline components. An unplanned pump failure can lead to beam loss and unexpected interruptions. Historical cases at accelerator facilities show that bearing wear or shaft misalignment, undetected between quarterly inspections has led to costly downtimes [1]. Recent advances in low-cost MEMS accelerometers achieving sub-mg resolution and kilohertz (kHz) bandwidth, enable continuous, on-site vibration monitoring at a fraction of the cost of commercial systems [2]. In parallel, transformer-based deep-learning architectures have emerged as powerful tool for modelling long-range temporal dependencies in time-series data, providing improved fault detection over traditional methods [3]. A major barrier to training such models is lack of labelled failure data. To address this, we developed physics-based methods to inject synthetic anomalies into vibration data, creating a ground-truth dataset for training. This paper explores the potential of using affordable sensors, synthetic anomaly generation, and dual-domain (time and frequency) anomaly detection to create low-cost, scalable condition monitoring framework for APS water pumps at Argonne National Laboratory.

METHODS

Low-Cost Vibration Sensor and Data Acquisition

We employed a 3-axis IIS3DWB MEMS accelerometer (STMicroelectronics) housed in an STWIN.box development kit. The sensor, costing approximately $120, offers a wide bandwidth (up to 6 kHz) and low intrinsic noise. Figures 1a-b show the installation on the pump coupler end. An acquisition sampling rate of 10 kHz was chosen to effectively capture relevant high-frequency signals while minimizing noise. The Raspberry Pi edge node stores data locally and forwards it for model training and inference (see Fig. 1c). Representative time-domain acceleration signals in X, Y, and Z under normal operation are shown in Fig. 2a. Since vibration data is routinely analysed in the harmonic orders domain, an in-house FFT-based algorithm automatically detects the fundamental shaft speed (1x order, 44.4 Hz) and harmonics up to 10x (see Fig. 2b). It leverages the fact that motor vibrations display a strong fundamental frequency and harmonic pattern. It achieved a frequency error of less than 0.30 Hz across 1x-10x orders (see Fig. 2b).
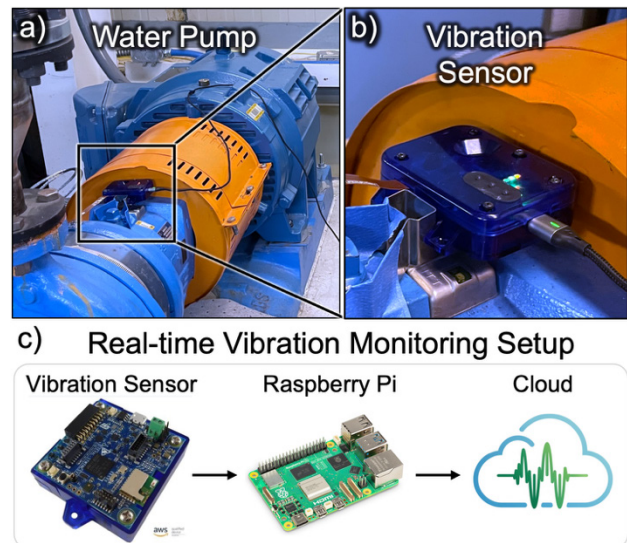

Figure 1: Developmental water pump anomaly detection setup at the Advanced Photon Source. (a) Cooling-water pump with the sensor attached to the pump's coupler end (PCE). (b) Close-up image of the low-cost triaxial MEMS accelerometer on the motor housing. (c) End-to-end data path where the sensor streams vibration data to the Raspberry Pi edge node, which then forwards the data to the PC/cloud for real-time inference.
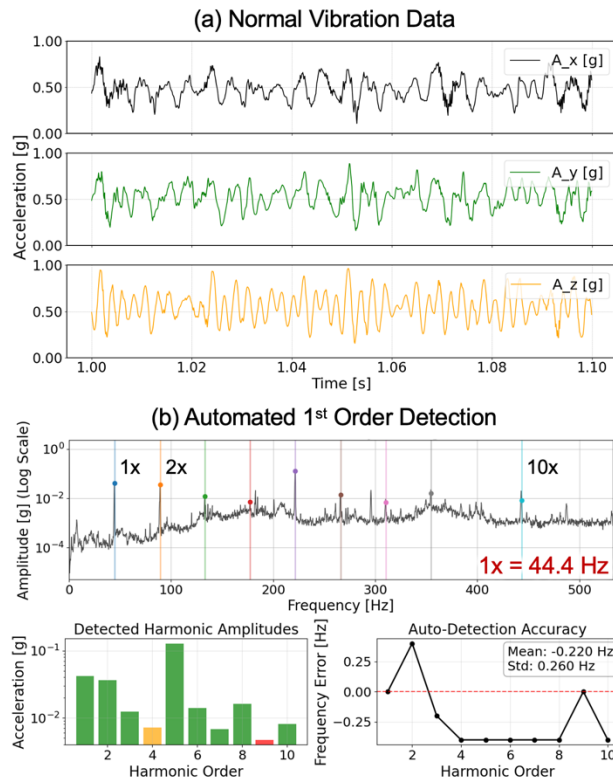
Figure 2: Normal vibration data collected from the water pump and the results of extracting the 1st harmonic order. (a) Pre-processed time-domain plot of acceleration in the X, Y, and Z directions recorded during regular pump operation. (b) Extraction of 1x-10x orders from the FFT spectrum of the time-domain acceleration plot for X-direction acceleration. The 1x order is detected at 44.4 Hz. The measured amplitude of each harmonic order (bottom-left) and the frequency error estimation for these orders (bottom-right) show errors less than approximately 0.30 Hz.

Creating Physics-based Synthetic Anomalies

Due to the absence of historical fault data, synthetic anomalies were created using physics-based models of pump faults, including imbalance, cavitation, misalignment, mechanical looseness, and bearing faults [4]. Figure 3 illustrates some of our physics-based synthetic anomaly generation. The baseline vibration data is presented in Fig 3 with reference normal 1x and 0.5x amplitudes. For instance, bearing defect (see Fig. 3b) has an energy redistribution from 1x into 0.5x, consistent with the outer-race spalling [5]. Shaft misalignment (see Fig. 3c) has the growth of 2x and 3x components due to angular offset at the coupling. Anomalies were injected into normal operating data to produce a 168-hour labelled dataset with mixed normal and faulty sequences.

Transformer Autoencoder and Order Tracking

The time-domain anomaly detection module is a transformer-based autoencoder (see Fig. 4a) with encoder and decoder blocks, eight-head self-attention, positional encoding, residual 'Add & Normalize' layers that stabilize
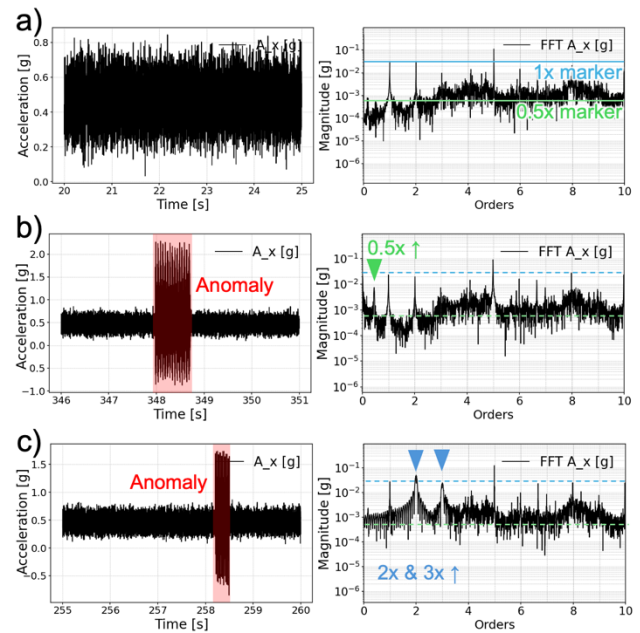

Figure 3: Visualizing synthetic anomalies generated through physics-based simulation of various pump faults. The left panel displays time-domain acceleration data over a span of 5 seconds, while the right panel shows the corresponding order spectra (1-10x), where 1x equals 44.4 Hz. (a) Baseline pump vibration with the acceleration magnitude of 1x and 0.5x order marked for comparison to abnormal vibration data. (b) Simulated bearing fault showing abnormal vibration amplitude in the left panel (encapsulated by a red box) and increased 0.5x order magnitude in the right panel. (c) Simulated shaft misalignment, exhibiting increased levels of 2x and 3x harmonics.

the model training, and a 32-dimensional latent bottleneck [6]. Transformer is demonstrated to outperform recurrent and convolutional auto-encoders on long, quasi-periodic sequences by attending to multiple shaft speed harmonics simultaneously [3]. During the inference the networks reconstructs 512 ms prediction window from a 1s window size or context window (see Fig. 4b). The reconstruction error, normalized by the median absolute deviation, forms the autoencoder anomaly score. Complementing this, a frequency-domain tracker monitors harmonic amplitudes: 1x-10x in 0.5x increments for low orders and in 10x increments for higher order up to 100x. A weighted sum of both metrics yields the final anomaly score.

RESULTS AND DISCUSSIONS

Figure 5a overlays the live vibration spectrum with baseline vibration spectrum. The pronounced deviations at 0.5x and 1.5x are visually evident along the rise of vibration magnitude at 1x. The real-time dashboard in development (Fig. 5b and 5c) streams both raw acceleration and order-domain vdB levels, allowing instant health assessments for each pump. Figure 5c presents a simulated weighted anomaly-score trajectory over one hour. The score crosses the warning and alarm threshold over time with different anomalies occurring being marked down. This proof-of-concept system detects synthetic bearing and misalignment

faults using low-cost sensors. When deployed at the APS, it will provide continuous, automated pump health monitoring, reduce dependence on periodic manual inspections, and improve operational reliability.
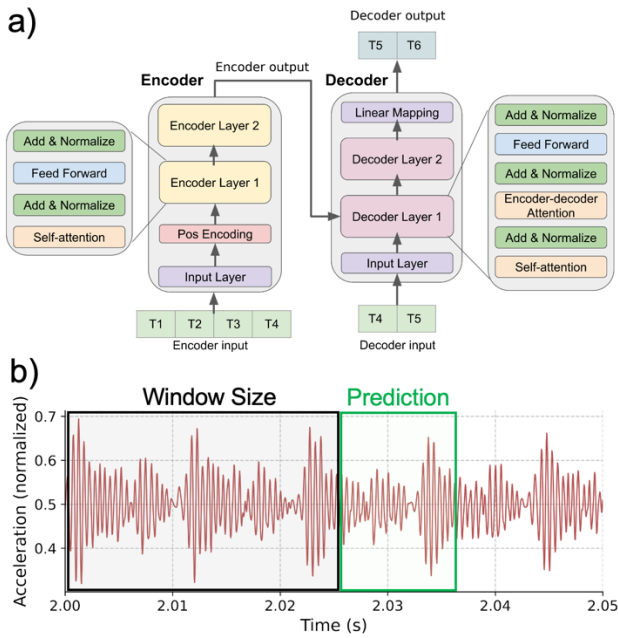

Figure 4: Transformer-based autoencoder for real-time vibration monitoring that detects anomalies in time-domain accelerometer data. (a) Model architecture illustrating the encoder and decoder layers with sinusoidal position encoding, repeating blocks of multi-head self-attention [6]. The bottom panel (b) depicts the inference workflow: the shaded black-box region indicates the input window of raw acceleration, and the prediction box (green) shows the subsequent timestamps reconstructed.

CONCLUSION

This proof-of-principle method shows the usefulness of combining low-cost sensors and transformer-based condition monitoring system for cooling-water pumps in accelerator facilities. Live and continuous component monitoring discussed above possess the ability to prevent costly downtime and experiment interruptions at accelerator facilities. By combining synthetic anomaly generation, and dual-domain anomaly detection, the framework achieves early fault identification Ongoing work focuses on model optimization, field trails across additional APS pumps, and integration into a unified anomaly-detection dashboard for operation deployment.
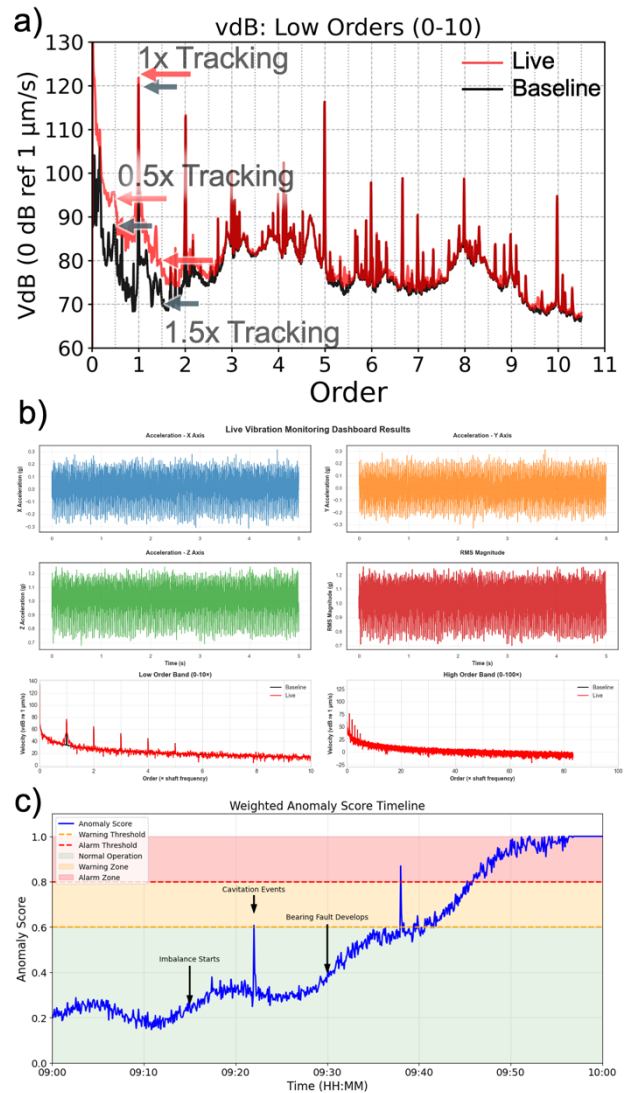
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Figure 5: End-to-end vibration monitoring workflow and dashboard visualization. (a) A standard format comparison plot showing baseline and live data with anomalies present. vdB stands for velocity decibels. The vibration magnitude at 0.5x, 1x, and 1.5x shows a steep change from the baseline level due to anomalies or faults. (b) Real-time dashboard snapshot combines raw triaxial acceleration (top) with vdB spectra for low (1-10) and high (1-100) order to assess the water pump's health. (c) Simulated weighted anomaly-score plot tracks a wear progression. The score is divided into three regions: normal, warning, and alarm.

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