AN INVESTIGATION OF AUDIO AND VIBRATION SENSORS FOR PREVENTIVE MAINTENANCE USING THE DRUNKEN FLOWER POLLINATION ALGORITHM

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Abstract:

Unplanned machinery failures remain a persistent challenge in manufacturing, leading to costly downtime, rising maintenance expenses, and operational inefficiencies. While traditional reactive and preventive maintenance strategies offer some mitigation, they often fall short in addressing these issues effectively. This paper investigates a novel approach to fault detection using the *Drunken Flower Pollination Algorithm* (DFPA) combined with audio pattern analysis. By detecting subtle anomalies in sound signatures, the system proactively identifies potential failures, minimizing unplanned outages and optimizing maintenance schedules. For comparison, the DFPA is also tested using traditional vibration-based fault detection methods. The results demonstrate that while audio-based analysis is less conventional than vibration monitoring, it delivers competitively accurate results—offering a viable alternative for predictive maintenance.

Keywords:

Preventive maintenance; Swarm intelligence; Fault detection; Signal analysis

1. Introduction

Malaysia is a vibrant and strategically positioned economy in Asia, known for its diverse industrial base and growing global influence. With a population of 32.98 million and a land area of 330,803 km² [1, 2], Malaysia continues to solidify its role as a manufacturing powerhouse. Industry contributes 36.8% to the nation's GDP, driven by key sectors such as oil and gas, electronics, and palm oil production [4]. In terms of employment, Malaysia relies heavily on its services and industrial sectors, while agriculture, construction, and mining also play significant roles in supporting the economy. As a key player in the global supply chain, Malaysia contributes to a wide range of industries, from electronics and energy to infrastructure and resource-based manufacturing. Manufacturers rely on high-performance machinery to meet production demands. However, unexpected machine failures lead to unplanned downtimes, increased maintenance costs, and reduced operational efficiency. Predictive maintenance is transforming manufacturing by enabling companies to optimize the performance of high-value machinery. Traditional maintenance strategies, such as reactive (failure-based) and preventive (time-based) approaches, often result in unplanned downtime, increased costs, and operational inefficiencies. This paper describes a swarm intelligent preventive maintenance system to analyze real-time acoustic sensor data and the traditional vibration data for early fault detection.

By proactively identifying machine faults before they end in total breakdown, this system can significantly reduce unplanned downtime, ensuring continuous production flow and minimizing costly emergency repairs. This approach also extends machine lifespan by reducing resource waste and enhances workplace safety by preventing potentially hazardous mechanical failures.

2. Problem Statement

Despite advancements in automation and Industry 4.0, unplanned machinery failures remain a significant challenge for manufacturers. These failures disrupt production schedules, halting operations, delaying deliveries, and damaging client trust. They also increase operational expenses due to high maintenance costs, including unscheduled repairs and premature part replacements. Machine downtime carries substantial financial implications for many manufacturers. In Malaysia, unplanned downtime interrupts production, resulting in lost productivity, delayed shipments, and strained customer relationships. This often leads to revenue losses and higher costs from emergency repairs and expedited shipping [5]. Another example is in Taiwan, where downtime has a particularly pronounced impact in industries like semiconductor manufacturing. For example, a temporary halt in operations at Taiwan Semiconductor Manufacturing Company (TSMC) due to unforeseen events on 3 April 2024 was estimated to cost the company US$60 million, underscoring the urgent need for robust disaster management and maintenance strategies [6].

In many of these countries where manufacturing play a very significant role, they will face persistent challenges in minimizing downtime to maintain competitiveness and operational efficiency. Additionally, the absence of real-time condition monitoring accelerates equipment deterioration, shortening machinery lifespan. Sudden mechanical failures not only jeopardize workplace safety and compliance but also cause energy inefficiencies, as malfunctioning equipment consumes excessive power. This drives up costs and contributes to environmental concerns. Addressing these issues requires a proactive, data-driven approach to machine maintenance.

3. Objectives

This paper presents a novel approach that integrates swarm intelligence - a Flower Pollination Algorithm (FPA) enhanced with drunken walk modification to achieve robust fault identification. It addresses data and time scarcity challenges. While machine learning (ML) typically requires large training datasets and training duration, the feature-based FPA compensates for limited data by optimizing feature extraction and improving model generalization in a shorter time. While traditional maintenance aims with schedule, our system enhances this regime by precisely classifying fault types once fault detected. This capability enables targeted interventions, reducing escalation risks and informing future predictive models. By leveraging artificial intelligence, the system can optimize maintenance schedules, predicting the likely timing and location of servicing needs, while eliminating unnecessary inspections. Together, these features bridge reactive and predictive maintenance, minimizing unplanned downtime and laying the groundwork for proactive failure prevention. This project introduces two key contributions, viz

i. A novel framework that uniquely combines swarm intelligence with PCA for superior fault detection,
ii. Utilizing audio data rather than the more common vibration data for better accuracy and overall total system cost.

4. Prior Work

The review of prior work systematically examines preventive maintenance methodologies by focusing on swarm intelligence, anomaly detection, and sensor-based monitoring techniques. It prioritizes AI-enhanced preventive maintenance strategies, emphasizing swarm intelligence models, sensor data integration, and industrial applications. It systematically excludes traditional maintenance strategies, AI research, and purely hardware-focused studies, thus ensuring it will capture the latest advancements in intelligent fault detection, real-time anomaly classification, and AI-driven industrial maintenance. The review is divided into two key areas of conventional AI and sensor-based and vibration analysis.

4.1. Conventional (non-DL) approaches

Traditional machine learning remains vital in predictive maintenance, especially when interpretability or efficiency is needed. Support Vector Machines (SVMs) excel at vibration and acoustic fault detection [15], while Random Forests outperform Decision Trees in sensor data analysis [12]. Bayesian Networks model failure probabilities, KNN detects anomalies in real-time, and PCA isolates key fault indicators. For sequential data, Hidden Markov Models track degradation, and Wavelet Transform precisely locates vibration faults [13]. These methods complement deep learning, offering transparency and effectiveness in resource-constrained scenarios.

4.2. Sensor-Based and Vibration Analysis Approaches

Karrupusamy [12] explored PdM in manufacturing using Industrial Internet-of-Things (IIoT) sensors and Random Forest (RF) models, proving RF's higher accuracy over Decision Trees in fault detection. Pavithra and

Ramachandran [13] focused on vibration analysis, integrating CNN and Wavelet Transform (WT) to reduce false positives and enhance detection accuracy. Tama et al. [14] reviewed deep learning for fault detection in rotating machinery, demonstrating how CNNs and Recurrent Neural Networks (RNNs) effectively classify vibration anomalies. Tambake et al. [15] investigated cutting tool fault diagnosis in CNC machines, utilizing vibration and speed sensors with ML models such as SVM, CNN, and Bayesian classifiers. Lastly, Rajapaksha et al. [16] analyzed acoustic monitoring for induction motors, showcasing how AI-enhanced audio signal processing outperforms traditional vibration-based fault detection. The literature review highlights three dominant approaches in predictive maintenance: (1) deep learning (SAE, CNN, LSTM) for superior anomaly detection, (2) traditional AI (SVM, RF, Bayesian Networks) for interpretability and efficiency with small datasets, and (3) sensor methods (IoT, vibration/acoustic analysis) for fault data collection. Collectively, these advancements underscore the critical synergy of AI, deep learning, and sensor integration in modern predictive maintenance systems.

5. Methodology

This system integrates AI, drunken flower pollination algorithm (DFPA), and real-time sensor data to monitor machine health and prevent failures. The key components are a high sensitivity microphone and vibration sensors connected to a computer laptop for data collection at the same time.

FIGURE 1. Sennheiser MK4 Large-diaphragm Condenser Microphone

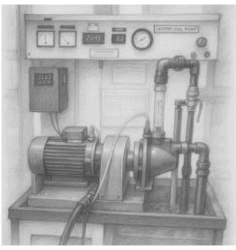


FIGURE 2. Monitoring an electric centrifugal pump

The vibration sensor used here is the '*ifm VVB001*', an industrial-grade microelectromechanical systems (MEMS) sensor type, a tiny device that integrates sensors, actuators, and mechanical structures on a microscopic scale, using semiconductor fabrication techniques. It is designed to monitor machine conditions by detecting vibration levels. It can measure vibrations across a frequency range of 2 to 10,000 Hz and within an acceleration range of 0 to 490.3 m/s², making it effective for detecting both low- and high-frequency mechanical faults. Two of these VVB001 vibration sensors were used to pinpoint two different positions on the centrifugal pump for better detection accuracy. Audio and vibration data will be collected simultaneously to ensure the consistency of the dataset.

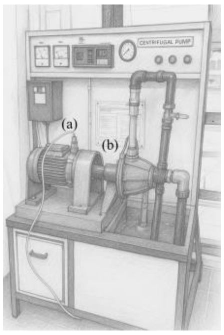


FIGURE 3. Mounting positions of the two vibration sensors

Figure 3 shows the experimental mounting positions of the two vibration sensors at (a) and (b)

5.1. Acoustic Data Collection Setup

The acoustic data collection system uses a Sennheiser MK 4 Large-diaphragm Condenser microphone (figure 1), SSL audio interface, and XLR connections. The microphone is mounted on a stand, connected via XLR, and interfaced with a computer laptop. Proper gain calibration and real-time monitoring are ensured using headphones. The microphone will be positioned at three different locations: top, side, and bottom (figure 4) to analyze the variations. Five-minute recordings are taken for both normal and faulty electric centrifugal pump (figure 2) conditions using a sound recorder. A total of 4 conditions of the pump were collected for audio and vibration based and the snapshot of the normal (a) and the 3 faults classes (b, c, d) of audio data are shown in figure 5.

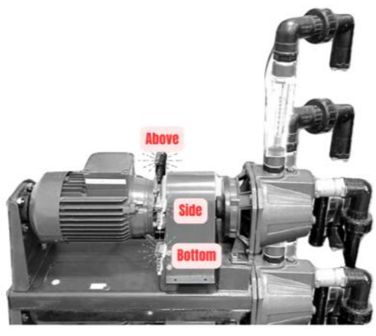
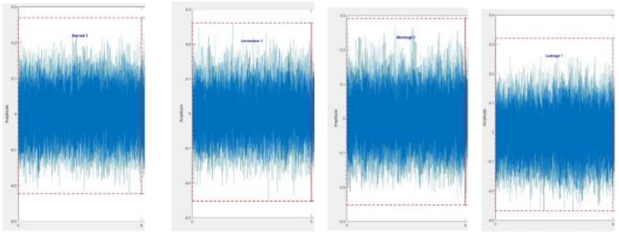


FIGURE 4. Position of Microphone



a) Normal b) Looseness c) Blockage d) Leakage

FIGURE 5. Samples of audio data of the electric pump

5.2. Drunken Flower Pollination Algorithm

The Flower Pollination Algorithm (FPA), introduced by Xin-She Yang in 2012, is a nature-inspired optimization technique based on the principles of flower pollination. Pollination in nature occurs through biotic (cross-pollination) and abiotic (self-pollination) processes, which FPA translates into global and local search strategies. FPA operates on four key principles closely mimicking how pollination occurs in nature —global pollination via Lévy flights for exploration, local pollination for refinement, flower constancy to stabilize solutions, and a switch probability to balance global and local search. These mechanisms allow FPA to efficiently explore and exploit solution spaces, making it effective for solving complex real-world optimization problems. More details can be found in Yang's paper. Nevertheless, while FPA has achieved good convergence rate and results, further improvement can be done by modifying the algorithm to improve the performance of the FPA. Hence, Lee and Lai were motivated to come up with improvements to the FPA by incorporating the intoxication model into the FPA. Since the intoxicated person in the intoxication model is walking in a staggered manner, this inspired the manipulation of the Lévy distribution of the FPA to the intoxication model for the global pollination in the DFPA. This had been tested to successfully identify the correct grade of Edible Birds Nest [8]. As this works on extracted features, a total of 16 types of features were extracted to be used by the DFPA to correctly identify the machine condition. 168 samples are used for training and 72 for testing, with each sample segmented from 5-second intervals.

5.3. Principal Component Analysis (PCA)

To improve classification performance and reduce computational complexity, Principal Component Analysis (PCA) was applied to address the issue of high-dimensional and partially irrelevant feature sets. PCA transforms correlated features into uncorrelated principal components, ranked by the variance they capture. In this study, PCA was applied exclusively to the feature space, excluding class labels, and a cumulative variance approach was used to determine the optimal number of components. An automated hypertuning process evaluated variance thresholds ranging from 50% to 100%, selecting the threshold that achieved the highest average classification accuracy. This adaptive dimensionality reduction strategy enabled the construction of a compact and informative feature set, enhancing both model accuracy and robustness across trials.

5.4. Features Extraction

Unlike image-based tasks, this project focuses on feature extraction from sound waves using the Discrete Flower Pollination Algorithm (DFPA) as a window-based method. Continuous audio signals are segmented into time windows, with DFPA used to extract representative features from each segment for clustering. Each window is reduced to a single point, with DFPA ultimately identifying cluster centroids. Additionally, as categorized by Swapna Mol George et al. [17], acoustic features are classified into continuous, spectral, and TEO-based types.

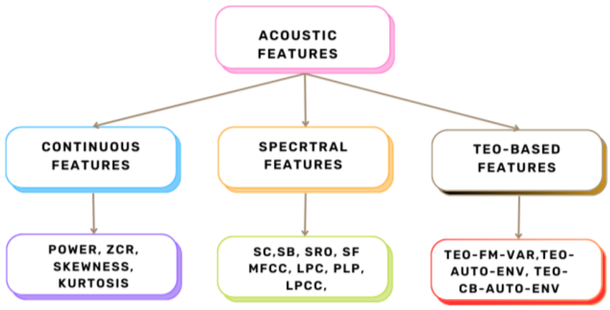


FIGURE 6. Taxonomy of Sound Feature [17]

Table 1 demonstrates that the DFPA+PCA model is effective in recognizing various machine conditions. When comparing audio and vibration data, audio data offer broader and more reliable coverage around the centrifugal pump, leading to more robust results. In contrast, vibration data are captured from fixed positions, making them more sensitive to nearby faults but less effective in detecting faults that occur farther away.

6. Results and Discussion

The synergy between DFPA's chaotic, exploratory nature and PCA's dimensionality reduction and denoising capabilities results in a hybrid method that is not only more accurate but also more stable and interpretable. This

DFPA+PCA method effectively detects centrifugal pump irregularities, with notable differences observed between audio and vibration data. Vibration sensors, mounted at fixed points near the shaft, provide consistent but limited spatial coverage. In contrast, microphones placed above, besides, and especially beneath the pump capture a wider range of acoustic signals, offering richer input for fault detection.

Audio data consistently outperforms vibration data at both 22.2 Hz and 42.2 Hz, particularly when microphones are positioned at the bottom or side of the pump, locations that are more sensitive to airborne cues like pressure shifts and harmonic distortions. Vibration-based detection improves slightly at higher frequencies due to stronger surface resonances but remains less responsive to distributed faults such as looseness or leakage.

TABLE 1. Comparison between Audio and Vibration data at different frequencies and different positions of microphone. (Vibration sensors are fixed)

Frequency (Hz)	**Speed (rpm)**	**Audio**	**Vibration**
		Microphone Positioned Above Pump Shaft (%)	
22.2	1294	97.86	90.12
42.2	2435	99.63	99.019

(a) Positioned above the pump shaft

Frequency (Hz)	**Speed (rpm)**	**Audio**	**Vibration**
		Microphone Placement at Side of Pump Shaft (%)	
22.2	1294	99.52	88.87
42.2	2435	95.611	86.80

(b) Positioned at the side of the pump shaft

Frequency (Hz)	**Audio**	**Vibration**
	Microphone Positioned Beneath Pump Shaft (%)	
22.2	99.80	83.13
42.2	100.00	95.76

(c) Positioned beneath the pump shaft

According to confusion matrix in TABLE 2, misclassification in the audio-based detection system mainly occurred when the microphone was placed at the top of the pump, where its position may be focused more on capturing the operational sounds of the shaft rather than the subtle noises generated by leakage. In leakage conditions, the acoustic changes are often minimal and easily masked by dominant mechanical sounds, especially since the strong suction and operating frequency of the pump can suppress or neutralize the audible cues of small leaks. As a result, the system occasionally failed to differentiate leakage from normal operation, leading to misclassification.

For vibration-based detection, the confusion between fault types such as blockage, leakage, and looseness stemmed from the overlapping vibrational patterns they produced, particularly at lower frequencies. The sensors, positioned above the pump, had limited sensitivity to localized fault vibrations, making it difficult to distinguish between subtle mechanical anomalies. Additionally, structural noise and signal damping through the pump body likely contributed to the ambiguity, causing the model to misinterpret vibration signals and assign incorrect fault classes.

TABLE 2. Confusion Matrix for Microphone Positioned Above Pump Shaft

Data	**Condition**	**Confusion Matrix When Microphone Positioned Above Pump Shaft**			
		Nor.	**Block.**	**Leak.**	**Loos.**
Audio	**Nor.**	17	0	1	0
	Block.	0	18	0	0
	Leak.	4	0	14	0
	Loos.	0	0	0	18
Vibration	**Nor.**	73	0	4	0
	Block.	8	66	3	0
	Leak.	8	2	85	0
	Loos.	0	0	3	91

7. Conclusions

This paper directly addresses manufacturing inefficiencies, unplanned downtimes, and rising maintenance costs by offering a data-driven predictive maintenance solution. By integrating AI and real-time sensor monitoring, manufacturers can significantly reduce disruptions, lower costs, and improve sustainability, ensuring long-term competitiveness in the evolving industrial landscape.

While we have successfully implemented this and tested on an electric centrifugal pump, we plan to expand testing on other types of manufacturing machinery and real-world shop floor environments which will allow us to further refine and optimize the system’s performance

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