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Vibration Analysis for Fault Diagnosis in Rotating Machinery

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Abstract :

Due to the frequent operation of centrifugal pump machines (CPMs), implementing health-monitoring systems has become essential for advancing the hydraulic machinery sector. During pump operation, monitoring is carried out either manually by operators or through automated online systems. These Health Monitoring Systems (HMS) provide insight into the pump's condition and support maintenance planning. In the CPM industry, common causes of system failure and accidents include impeller damage, bearing faults, cavitation, and shaft misalignment. Therefore, continuous monitoring of key parameters is crucial to extend equipment lifespan and improve plant efficiency, which can be achieved using Data Acquisition (DAQ) systems. To analyse the behaviour of the CPM system, both independent and dependent variables were identified and examined experimentally. It is critical that the process of feature selection and extraction aligns with the chosen DAQ system to minimize data bias and streamline data handling. In this study, the DAQ platform—Arduino Uno was utilized and evaluated using a statistical approach, including five-point summary analysis, standard deviation and maintenance. The paper details, the methods used for data collection from CPMs using each DAQ system and provides a comparative assessment to determine the most suitable option.

Keywords : Centrifugal Pump Machines (CPM), Health Monitoring Systems (HMS), Data Acquisition System (DAQ).

Introduction :

A centrifugal pump machine (CPM) health-monitoring system functions as a predictive maintenance tool for hydraulic and fluid handling applications, designed to evaluate the condition and performance of pumps. Key parameters monitored include faults in bearings and impellers, shaft misalignment, cavitation, electrical current, pressure, and temperature—each measured using dedicated sensors. An effective and adaptable monitoring system must offer flexibility and contribute to minimizing operational downtime in CPM setups. With advancements in CPM monitoring technologies, overall productivity in related industries has significantly improved. These systems often employ sensor-based data extraction techniques to continuously assess equipment conditions and reduce operational losses. intelligent monitoring frameworks. HMS typically relies on multiple sensors to collect data such as vibrations, flow rate, pressure, and electrical current. Raw signals are

gathered through these sensors using structured data extraction methods . In recent years, Machine Learning (ML) and Artificial Intelligence (AI) have been applied to interpret this data for real-time condition monitoring and fault prediction. After comparing different models based on training and testing data, the most accurate one is selected to represent the overall effectiveness of the HMS. This study involves a practical evaluation of system faults, a comparative review of various Data Acquisition (DAQ) systems, and a statistically driven selection of the optimal system.

Literature Survey :

In recent years, the use of low-cost microcontroller platforms like Arduino has gained significant attention in the field of vibration based fault diagnosis for rotating machinery. These systems offer an affordable and accessible solution for real-time condition monitoring, particularly in academic, research, and small-scale industrial settings. Quintero et al. (2019) developed an Arduino based data acquisition system integrated with vibration sensors for monitoring centrifugal pump conditions. Their system demonstrated the capability to detect basic faults such as imbalance and misalignment through time-domain vibration signals. Similarly, Farokhzad (2013) used an Arduino setup with an accelerometer , processing to identify pump bearing faults, showing that even low-cost systems can detect mechanical anomalies when paired with appropriate analytical techniques. Dutta et al. (2022) further explored combining Arduino with external software (such as MATLAB or LabVIEW) to enhance data visualization and processing capabilities, allowing for more precise fault classification. Although Arduino systems are limited by lower sampling rates and processing power compared to industrial-grade DAQ systems, studies have shown they can reliably monitor low- to midfrequency vibration signals, which are sufficient for diagnosing many common faults in rotating equipment.

Moreover, ongoing developments in sensor technology and cloud integration are enabling Arduino-based systems to be part of smart maintenance frameworks aligned with Industry 4.0 principles.

Experimental Setup:

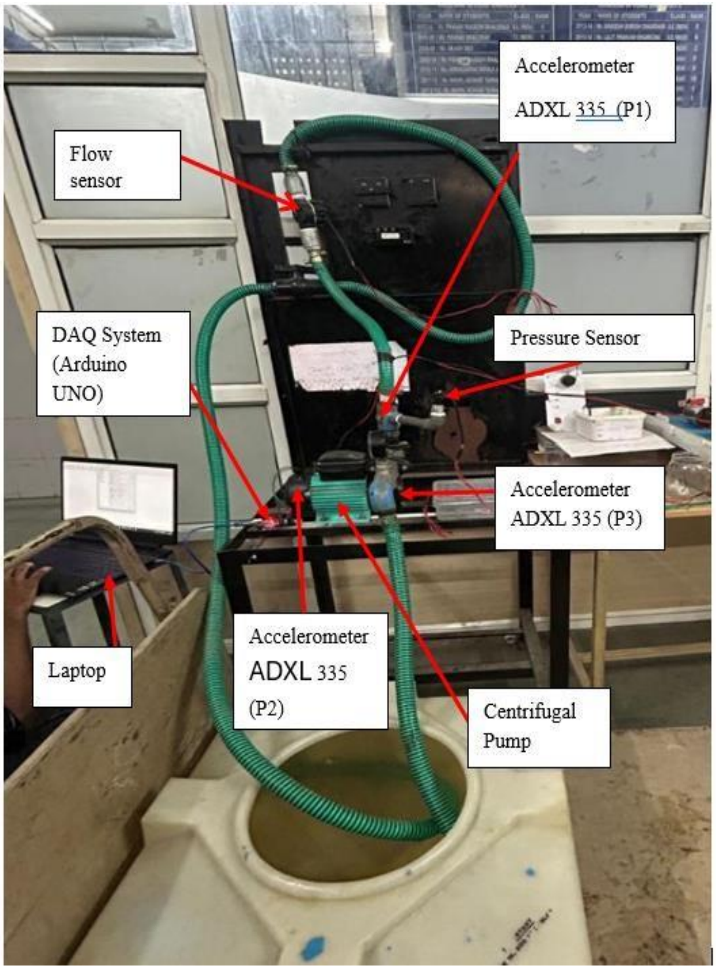


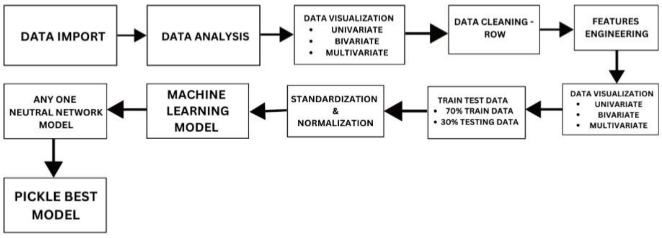
FIG: DAQ System using Arduino

Units :

1. Casing, Bearing and Impeller Vibration – G = 9.8 m/s^2
2. Flow - L/min
3. Pressure - Kpa
4. Current - Ampere
5. Voltage - Volt

Body of Paper :

Methodology Flowchart :



This flowchart illustrates the end-to-end pipeline of a machine learning project. Here's a brief explanation of each step:

1. Data Import: Load the dataset from a source (CSV, database, etc.).

2. Data Analysis: Perform initial examination to understand data patterns and distributions.

3. Data Visualization (Univariate, Bivariate, Multivariate): Use plots to explore individual features, relationships between pairs, and multiple variables together.

4. Data Cleaning – Row: Remove or correct incorrect, missing, or duplicate rows in the dataset.

5. Feature Engineering: Create new features or transform existing ones to improve model performance.

6. Data Visualization (again): Re-analyze with visual tools after feature engineering to assess changes.

7. Train-Test Split: Divide the data into 70% for training and 30% for testing the model.

8. Standardization & Normalization: Scale the data to ensure all features contribute equally to the model.

9. Machine Learning Model: Train a suitable ML algorithm (e.g., decision trees, SVM, etc.).

10. Any One Neural Network Model: Experiment with at least one deep learning/neural network model.

11. Pickle Best Model: Serialize (save) the best-performing model using Python's pickle library for future use.

ML Model Table :

Model	Train Accuracy	Test Accuracy	Precision	True positive rate	True negative rate	False positive rate
Logistic Regression	0.985652	0.987035	0.987273	0.987	0.987	0.013
Logistic Regression Tuned	0.986168	0.987544	0.98765	0.988	0.988	0.012
SVM	0.994384	0.994999	0.995021	0.995	0.995	0.005
SVM Tuned	0.995674	0.996249	0.996261	0.996	0.996	0.004
KNN	0.999603	0.999491	0.999491	0.999	0.999	0.001
KNN Tuned	1	0.999722	0.999722	1	1	0
Neural Network	0.999345	0.999259	0.99926	0.999	0.999	0.001
Neural Network Tuned	0.998988	0.998981	0.998985	0.999	0.999	0.001

Conclusion :

The effectiveness of the feature selection and extraction process largely hinges on how well the DAQ system aligns with the specific requirements of the CPM plant. An ideal DAQ system should be developed as a dedicated solution, tailored through an in-depth analysis of plant characteristics to enable real-time deployment.

Additionally, adopting transfer learning techniques would enable predictive models to adapt to new data trends over time, automatically adjusting their hyperparameters — ultimately extending the model's usefulness and accuracy.

The vibration analysis effectively differentiates between various fault conditions in rotating machinery, especially in centrifugal pumps. Key vibration parameters—casing, bearing, and impeller vibrations—exhibit distinct signatures under different fault types. Misalignment consistently shows the highest vibration levels (700–900), making it easily detectable, while impeller and bearing faults show moderate but distinguishable variations. Flow rate and pressure also correlate with fault severity, offering supporting indicators. Using multivariate analysis and machine learning models, faults were classified with over 99.9% accuracy, achieving precision, recall, and F1-scores of 1.00 across all classes, confirming the reliability of vibration-based diagnostics.

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