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PREDICTIVE MAINTENANCE SYSTEM FOR ROTATING MACHINERY ONBOARD SHIPS FOR DETECTING PERFORMANCE DEGRADATION

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Abstract. Maintenance of rotating machinery is crucial for extending the lifespan and increasing the reliability of equipment onboard ships. Presently, breakdown and preventive methodologies are used for the maintenance of equipment. Further, dataloggers collect critical machinery parameters, and parameter data is used for real-time parameter monitoring. The availability of such extensive monitoring data has also led to the adoption predictive maintenance methodologies in the industry, wherein machine learning-based analysis of recorded data is used to predict impending defects and prompt required maintenance. In this paper, we propose a predictive maintenance system that records data through a network of sensors installed over multiple electrical motor pump sets onboard the ship and uses statistical analysis to detect equipment degradation. Our system has been deployed onboard a ship to undertake real-time predictive maintenance of electrical motor pump sets used in firemain, AC plants, stabilizers, steering pumps and other auxiliary engine room machinery.

Key words: Predictive maintenance system, vibration and current analysis, Naval ships, Unsupervised learning, Detecting performance degradation, Electrical motors

1. Introduction. The rotating machinery is the lifeline of ships, and specifically, electrical motor pump sets constitute a significant component of critical systems, namely, firemain, air conditioning, steering, stabilizers, propulsion, power generation (alternators) and various auxiliary pumps of circuits of fresh water, seawater and chilled water lines. The ship-board machinery is prone to defects due to exposure to sea climate, moisture and vibrations from the roll/pitch of the ship. Presently, Condition-based Monitoring (CBM) and Planned Preventive Maintenance (PPM) strategies are majorly adopted for the maintenance of equipment. However, these maintenance strategies are affected by more downtime (due to refit and maintenance periods) and are expensive (due to replacement of components) [22]. Predictive maintenance [13] (PdM) harnesses the potential of AI towards increasing the life span of equipment and enhances the reliability of machinery [14] PdM techniques analyze recorded sensor data of machinery to develop cognition for impending failures, and thereby, prompt required maintenance. Predictive maintenance within the shipping industry is in its early stages [5]. Recent research has been undertaken using supervised learning approaches over labelled data from simulated defects on machinery. Vibration analysis can detect abnormal vibration patterns, which may indicate potential machinery defects. PdM techniques using vibration analysis are helpful towards the identification of deviations from normal patterns and resolving issues before major breakdowns occur[18]. Study of vibration analysis [15] using Fast Fourier transform (FFT) has been undertaken by inducing defects in electrical motors. Vibration analysis of gearboxes [10, 2] of electrical motors has been undertaken using SVMs with experimental set-up and inducing defects using faulty bearings. Other than vibration analysis, PdM techniques may be implemented for ship-borne machinery using analysis of running current [1], thermography[4] and oil analysis [8]. In the absence of labelled (labels indicating operational and defective life), real-time datasets of a lifetime of motors and unsupervised learning approaches have also been attempted. Wescoat et al. describe vibration analysis of a paint dosing pump used for Condition Monitoring (CM) based maintenance using unsupervised learning [21]. The work majorly presents techniques to organize data using unsupervised approaches. In both supervised

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and unsupervised approaches, vibration analysis [16, 12] has been found of key importance for undertaking predictive maintenance of rotating machinery. Olesen et al. [3] review state-of-the-art techniques for applying PdM in thermal power plants and pump systems. The review describes various challenges concerning applying PdM for rotating machinery viz unavailability of run-to-failure labelled data set and restriction of state of the art techniques mostly to vibration analysis. Our work utilizes analysis of current parameters in addition to vibration analysis.

During our study, we developed and deployed an AI-based predictive maintenance system onboard a ship to predict the degradation of electrical motor pump sets using a comparative approach. Our contributions are as follows:

- **Data Collection and Exploratory Data Analysis (EDA)** – Dataloggers were installed over one ship to collect data on 16 motors of different ship-borne systems. EDA techniques were used to get insights into patterns of machinery usage and understand the data for further application towards predictive maintenance.
- **Pre-Processing Techniques** – Real-time data received from dataloggers installed on electrical motors may have erroneous values, view accidental grounding of sensor equipment, malfunctioning of sensors or power fluctuations. Our work proposes pre-processing techniques to learn machinery exploitation patterns and segregate erroneous readings. We have used a decision tree-based classifier [7] in our model for filtering erroneous readings.
- **Prediction of Performance Degradation** – To undertake a regression-based analysis of Remaining Useful Life (RUL) [23], we require lifetime data of a motor, i.e. from the installation of a new motor till such time, the motor gets faulty. However, data collection for such rule-based analysis requires recording the parameters of motors for over two years. Our approach circumvents the need to record the parameters of an electrical motor for its lifetime, as we present a methodology for statistical and comparative analysis of motors of similar types, which may be in different stages of their lifetime. Our model determines the Gaussian distribution of data, compares the Gaussian distribution of similar machines and uses empirical rules to predict the degradation of machinery.

Lastly, we demonstrate the efficacy of our system on real-world deployment onboard Naval Ships. We propose future work that can be undertaken to enhance our solution.

2. Application Overview. The application architecture is shown in Fig. 2.1. The system consists mainly of four modules: real-time data collection, pre-processing, data analytics and user interface. During the development of the application, firstly, we used a data collection module to collate data. After that, we used EDA techniques to understand the data. Based on the results of EDA, we developed pre-processing and comparative analytics modules (used for degradation prediction). Subsequently, we deployed the complete application and user interface onboard the ship for real-time predictive maintenance of electrical motor pump sets. In this paper, we briefly explain the data collection module, followed by the results of our EDA techniques. Further, we explain techniques used for pre-processing and prediction of degradation.

3. Data Collection Module. This module comprises a network of sensors (voltage, vibration and current) installed over electrical motor pump sets, a common data bus, and a central polling computer. This rugged system takes data feed from 16 machineries at an interval of one minute. Data were collated for three weeks to design and develop other system modules. The data snapshot is shown in Fig. 3.1 and Table 3.1. The recorded parameters consist of voltage and current in three power supply phases to the machinery and RMS values of vibration (mm/Sec) taken at one-minute intervals. Since information about the state of the machinery, i.e. Degraded/ Operational was not available, our system has been designed to work on unlabelled datasets.

4. Exploratory Data Analysis (EDA). The techniques used for EDA and the results obtained are explained in subsequent paragraphs.

4.1. Analysis using DBSCAN. Density-Based Spatial Clustering Application with Noise (DBSCAN) [17] algorithm and parameters' timeline charts were used over the dataset to undertake EDA. The results of DBSCAN clustering over PCA [11] transformed dataset for one motor are shown in Fig. 4.1 and explained as follows:

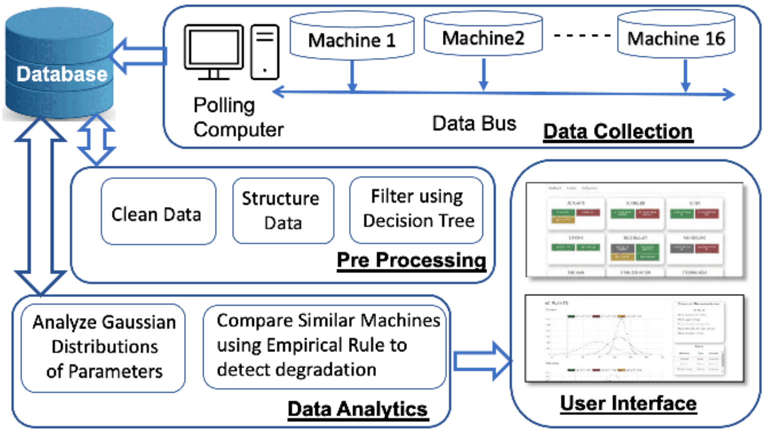

Fig. 2.1: Architecture of Predictive Maintenance System

Table 3.1: Summary of total Data of 16 Machineries

No. of Motors	No. of days	No of Samples per motor	Total No of Samples	Remarks
16	21	31449	5,03,184	One sample per minute 24X7 for 21 days

- The red and blue clusters indicate data points considered normal values by the DBSCAN algorithm, and black dots correspond to anomalies detected by DBSCAN.
- The presence of two clusters was further analyzed in the dataset using timeline plots of current and vibration readings, as shown in Fig. 4.2. Further, the colours (red and blue) of vibration values and current in Fig. 4.2 were mapped with colours of data points in Fig. 4.1 for appreciation of affiche acy of DBSCAN clustering. It was found that zero-valued current readings were grouped in blue clusters, and data points with non-zero values were largely clustered in red clusters. As the motor does not draw current in switched OFF state, it was observed that the red cluster consisted of data points in the ON state of machinery, and the blue cluster indicated the OFF state of machinery.
- Further, it was also observed that anomalies observed by the DBSCAN algorithm were about exceptionally high current values during state transition from OFF state to ON state. It is essential to mention that the datalogger recorded current values at a sampling rate of one datapoint per minute, and therefore, exceptionally high current values were starting current values captured during state transition. It was inferred that though the DBSCAN algorithm detects these points as anomalies, these data points were not anomalous as starting current is consistently higher than the running current during regular operation of the motors. It was also inferred that DBSCAN could not detect graceful degradation, as during a graceful degradation, values will iteratively increase slowly to higher values; therefore, all these density-reachable values would be clustered together.

4.2. Analysis of the running status of the motor. The running status of motors within the group of similar machinery was also studied using histogram analysis. The points with zero current values were labelled OFF state, and non-zero current values were labelled ON state. The histograms of current values concerning two motors are shown in Fig 4.3. This analysis was later used to identify the instances of readings when the current value was zero and filter out readings, as done in Section 5.3.

5. Pre-Processing Techniques. Since the data was recorded from the real-time running of the motors onboard one ship, multiple factors contributed to erroneous values in the data. For example, during the time

1	ser	Current_R	Current_Y	Current_B	Voltage_1	Voltage_2	Voltage_3	Vibration	TimeStamp
2	0	6.5	8.4	8.4	241.2	241.5	240.6	1.7	22-02-2020 00:00
3	1	6.5	8.4	8.4	241.2	241.6	240.7	1.3	22-02-2020 00:01
4	2	6.5	8.4	8.4	241.2	241.5	240.7	1.4	22-02-2020 00:02

COUNTA 31,449

Fig. 3.1: Snapshot of Data from one machinery

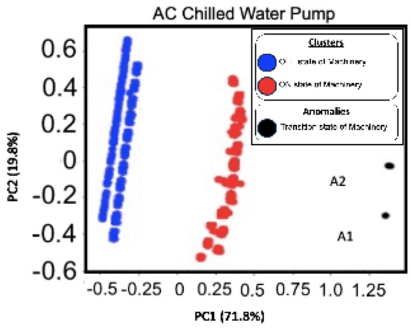

Fig. 4.1: Results of DBSCAN on data from AC sea water pump -1 - (The plot has principal eigenvectors on the X and Y axis, and therefore, no units are indicated)

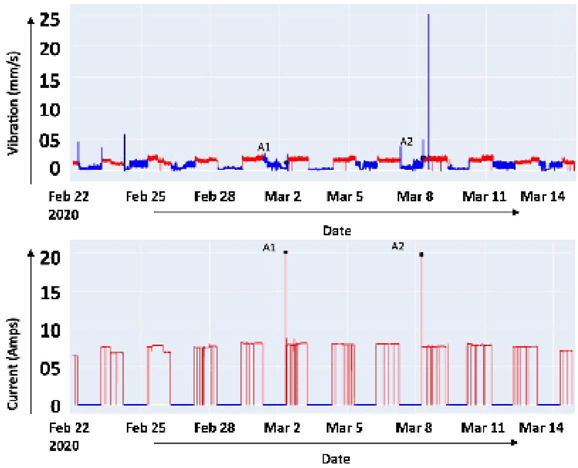

Fig. 4.2: Timeline of vibration and current values of AC chilled water Pump - 1

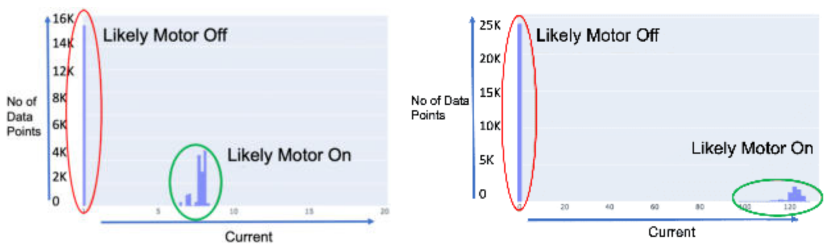

Fig. 4.3: Histogram of current readings – AC Sea Water Pump 1 & AC Plant 2

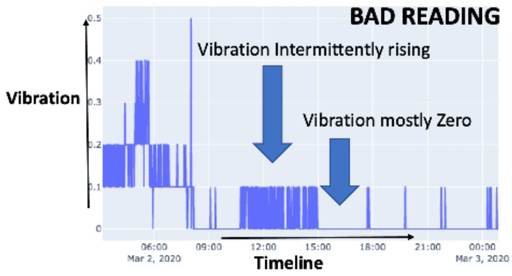

Fig. 5.1: Example of Bad readings from Vibration Sensor

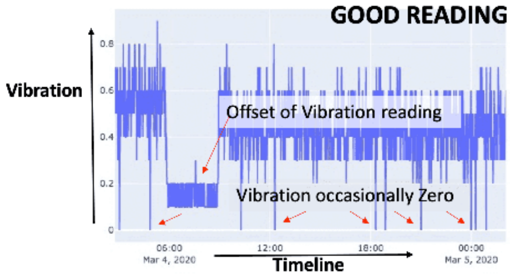

Fig. 5.2: Example of Good readings from Vibration Sensor

series analysis of the readings, it was seen that current values were dropping to zero for three to four consecutive readings due to the accidental grounding of the sensor. Also, there were Direct Current (DC) offsets observed in the readings due to power supply fluctuations [19]. Therefore, the following pre-processing techniques were employed in the AI-based predictive maintenance system (as indicated earlier in fig. 2.1).

5.1. Cleaning of Data. The real-time data generated from dataloggers required data cleaning, including timestamps formatting and removing data files, wherein all readings, viz. current, voltage and vibration, were zero-valued.

5.2. Structuring of Data. The data points were provided with a machine identification number for each machinery. After that, time series data for each machinery was analyzed and observed to be a series of ON-OFF states. It was found that current values remained zero consecutively in the time series when the machinery was OFF and remained non-zero consecutively when running. Therefore, data about each machinery was structured as running instances by scanning the current values in increasing order of time series. The data points about OFF instances of machinery were discarded for further processing.

5.3. Filtering of erroneous readings. During the visualization of timeline charts of vibration and current data for each running instance, it was observed that a few readings needed to be revised and, therefore, required to be discarded. We show an example of a timeline plot of vibration readings of one running instance of one machine in Fig. 5.1. We observed in this example that the vibration readings coming from Sensors were rising intermittently and, at times, continually dropping to Zero. This behaviour may be due to some instantaneous sensor grounding or intermittent contact. We categorized such readings as bad readings. Further, we have shown an example of good reading from another motor in Fig. 5.2. In this example, it can be seen that the vibration occasionally drops to zero, and also, there are DC offsets in readings a few times. However, overall the reading is good compared to readings provided in Fig. 5.1. Therefore, we have applied pre-processing techniques in our work, wherein data points of each running instance were passed through a decision tree-based classifier to accept good readings and reject bad readings. A total of 360 readings were labelled as good and bad readings based on non-linearity and experience of domain experts. The decision tree provided 94%

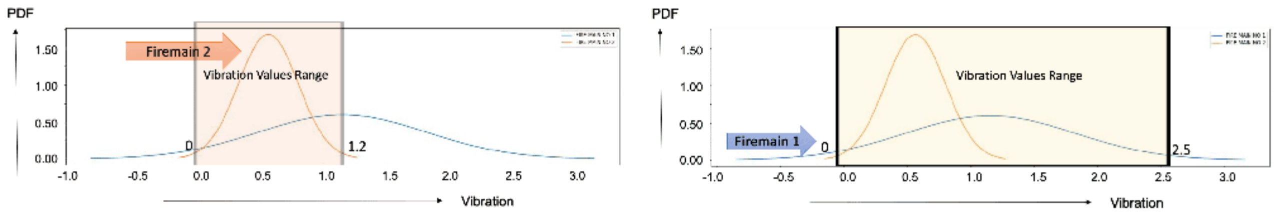

Fig. 6.1: Gaussian distribution on vibration data of Firemain 1 and Firemain 2

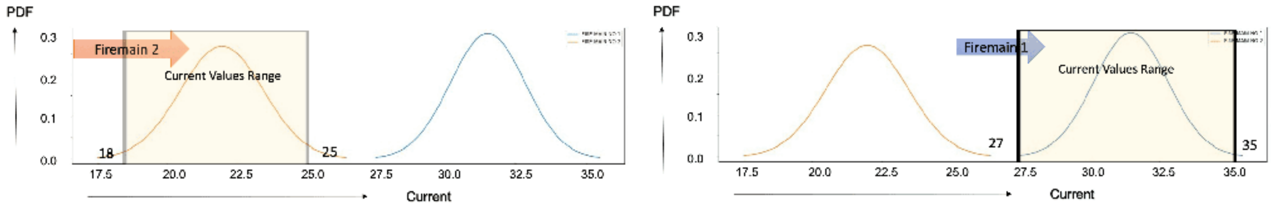

Fig. 6.2: Gaussian distribution on current data of Firemain 1 and Firemain 2

6. Prediction of Degradation. Our algorithm for the degradation prediction is based on a comparative analysis of Gaussian distributions of current and vibration readings of similar types of motors. This module consists of the following two parts:

- Determining the univariate Gaussian distribution of current as well as vibration.
- Comparing the univariate distribution of current and vibration of similar types of motors based on Empirical rule and providing machine status labels as follows:
  - **Satisfactory, Green :** If the Gaussian distribution of vibration and current values of machinery is similar to that of machinery in the same group.
  - **Degradation Likely, Amber :** If the Gaussian distribution of vibration and machinery's current values is higher than that of machinery in the same group.
  - **Degradation Imminent, Red :** If the Gaussian distribution of vibration and machinery's current values is very high compared to the Gaussian distribution of machinery in the same group.

6.1. Examples of functioning of the application. The algorithm's functioning is shown with examples of firemain motors, AC motors and stabilizer motors.

- **Firemain Motors:**There were two Fireman motors in the dataset, i.e., Firemain 1 and 2. Fig. 6.1 shows the probabilistic distribution of vibration readings of both motors, with the Y axis showing the Probability Density Function (PDF). Our algorithm learns that 99.7% of the vibration values from Firemain motor two are spread between 0 and 1.2. Similarly, the algorithm learns that 99.7% of vibration values from Firemain motor 1 are spread between 0 and 2.5. Ideally, the vibration values should be the same for the same type of motor. Our algorithm undertakes a similar analysis of the probabilistic distribution of current readings of both motors. Distributions of current readings are shown in Fig. 6.2. It was observed that the current readings of Firemain 1 were higher than Firemain 2.
- **AC Plants:**The dataset consisted of three AC plants, namely AC plants 1, 2 and 3. The vibration and current analysis of AC plants are shown in Fig. 6.3. It was inferred that the vibration readings of all AC plants were similar, but the current readings of AC plant-1 and AC plant-2 were higher than AC plant-3.
- **Stabiliser Motors:** Our dataset contained data of two stabilizer motors, i.e. port and stabilizer.

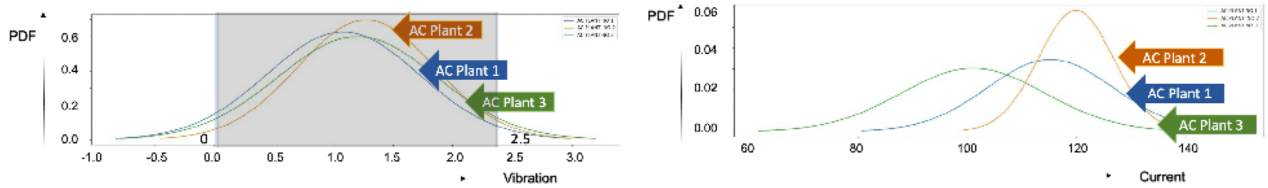

Fig. 6.3: Gaussian distribution on vibration and current data of AC Plants

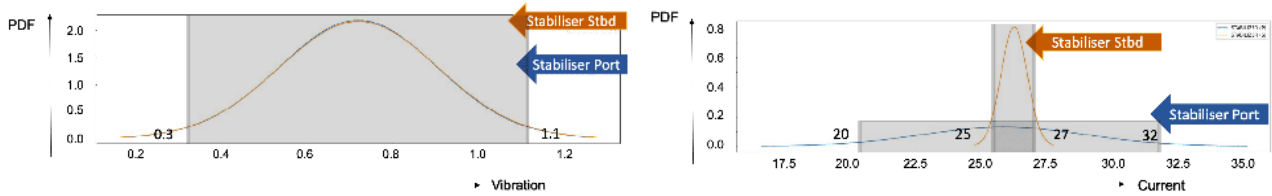

Fig. 6.4: Gaussian distribution on vibration and current data of stabiliser

The vibration and current analysis of stabilizer motors is shown in Fig. 6.4. It was observed that the vibration readings of both stabilizer motors were similar, but the current readings of the port stabilizer were higher than Stbd Stabiliser.

6.2. Evaluation of the Results. In our study, we focused on predicting the performance degradation of rotating machinery using unsupervised techniques. Since labelled data for performance degradation of rotating machinery onboard ships were unavailable, employing traditional measured model quality metrics was challenging. We adopted a practical approach to overcome this limitation, validating our model based on real-world examples and gathering feedback from onboard users. It allowed us to assess the model's performance effectively in real operating conditions. Additionally, we conducted a comparative analysis, contrasting our PdM model with established CBM algorithms. The insights from this comparison offer a comprehensive evaluation of our model's effectiveness and practical utility for predicting performance degradation in rotating machinery. We explain our evaluation with three examples:

- **Firemain :** For example, vibration as well as current values of both Firemain 1 and Firemain 2 were within threshold values as per CBM and therefore, both machineries were working satisfactorily. However, our PdM model compared parameter values of similar machinery, and even though the values were within the threshold, our model observed that parameter readings of Firemain 1 were trending to higher values. Therefore, our model indicated an impending degradation in the state of machinery well in time to prompt maintenance/ overhauling. Based on the results of our model, Firemain 1 landed at the repair yard, and the health of the motor was assessed. It was found that the motor bearings were degraded, and post-greasing of the motor and replacement of bearings, vibration and current readings were similar to that of Firemain 2.
- **AC Plants :** Similarly, values of current drawn by all three AC Plants were within the threshold as per CBM, and the machinery was working satisfactorily. However, our PdM techniques observed that the current drawn by AC Plants 1 and 2 is higher than that of AC Plant 3 during operation. A higher current indicates either higher torque or higher load. In order to rule out the possibility of a higher load, all three AC Plants were disconnected from Ship's AC system and all three AC compressors were tested in full load condition. The current values of AC Plant 1 and 2 in full load condition were also higher than that of AC Plant 3, indicating likely degradation of machinery. Therefore, all three Plants were recommended to be exploited with careful monitoring for further degradation.
- **Stabiliser Motors :** It was observed that values of vibration drawn by both Stabiliser Motors were within the threshold as per CBM, and the machinery was working satisfactorily. However, our PdM

Table 7.1: Recommendation Matrix

Current → Vibration ⇓	Red	Amber	Green
Red	• Check winding insulation. • Check input supply. • Undertake routines of contactors of starter panel. • Check connections of cables and lugs. • Carry out alignment checks of motor and load. • Check vibrations and condition of bearings. • Check fan and motor shaft for any wear and tear.	• Check winding insulation. • Carry out alignment checks of motor and load. • Check vibrations and condition of bearing. • Check fan and motor shaft for any wear and tear. • Check screws of motor foundation.	• Carry out alignment checks of motor and load. • Check vibrations and condition of bearings. • Check fan and motor shaft for wear & tear. • Check screws of motor foundation.
Amber	• Check winding insulation. • Check input supply. • Undertake routines of contactors of starter panel. • Check connections of cables and lugs. • Carry out greasing of bearings. • Check fan and motor shaft for any wear & tear. • Check screws of motor foundation.	• Check starting and running current of motor. • Check vibration readings of driving and non-driving end. • Carry out greasing of bearings. • Check screws of motor foundation.	• Check vibration readings of driving and non-driving end. • Carry out greasing. • Check screws of motor foundation.
Green	• Check winding insulation. • Check input supply. • Undertake routines of contactors of starter panel. • Check connections of the cable and lugs. • Check vibration of driving & non-driving end of motor.	• Check starting and running current of motor. • Check connections of the cable and lugs. • Check screws of motor foundation.	• All Parameters are within threshold.

techniques observed that the current drawn by the port stabilizer motor was higher than that of the stbd stabilizer during operation. Further, it was found that the port stabilizer was operating at a higher torque than the stbd stabilizer during the ship's sailing, owing to the inherent stability of the ship. The same led to higher current usage by the port stabilizer motor. Therefore, the port stabilizer motor was recommended to be exploited with careful monitoring for further degradation.

7. User Interface Design. We have developed an intuitive Graphical User Interface (GUI) for data visualization and prompting the required maintenance based on a decision matrix. The GUI has been developed using Python, Django framework and chart JS. The screenshots of the application are shown in Fig. 7.1.

7.1. Explanation of Results to User. Vollert et al. [20] presents a review of publications addressing PdM problems with a focus on model interpretability. Since explainability is one of the major challenges in the PdM model due to the black-box nature of algorithms. Our model explains results to the end users through charts and decision matrices which is crucial to explain to the user how our model arrived at a specific decision. It ensures that the end users understand and appropriately trust the model's recommendations so that the AI-based Predictive Maintenance System can be deployed confidently. Therefore, we devised a matrix for the explanation of the results of our algorithm to the user. Our model explains the observations of our algorithm and prompts required maintenance for the machinery as per the matrix shown in Table 7.1. The screenshots

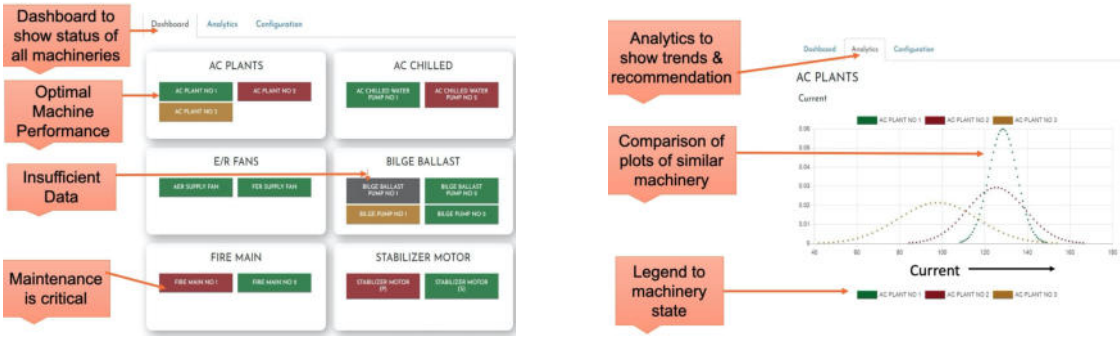

Fig. 7.1: Deployment of the System onboard ship

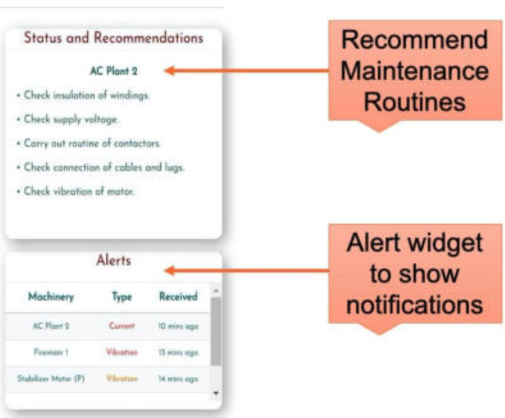

Fig. 7.2: Recommendations to the user

of the application are shown in Fig. 7.2.

8. Deployment of the Application. The application was successfully deployed onboard a ship, and data feeds from dataloggers were integrated into the application to provide a real-time utility for predictive maintenance to users.

9. Conclusion. We have developed a technique to process sensor data from various electrical motor pump sets fitted onboard ships, recorded by a network of sensors. Our application involves pre-processing techniques for cleaning, structuring and filtering data. EDA has allowed us to understand the dataset for its application for predictive maintenance. Further, we incorporated machine learning techniques and empirical rules to perform comparative analytics of data of similar machines [6, 9]. A complete application along with GUI was developed and deployed onboard a ship by combining pre-processing techniques, EDA, and comparative analysis modules.

10. Future Work. Our application may be enhanced by integrating knowledge of the design parameters of machinery for comparing the design and observed parameters. Further, the application can facilitate the collection of more maintenance data by providing functionalities to record details of maintenance routines, downtime of equipment, spares consumed during maintenance and similar data. The availability of detailed maintenance data would facilitate using other AI and ML algorithms for predictive maintenance.

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