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Unsupervised Detection of Abnormal Operating Regimes in Industrial Centrifugal Pumps Using Multivariate Condition Monitoring Data

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ABSTRACT

Industrial centrifugal pumps are critical assets in industrial facilities, where abnormal operating regimes can adversely affect reliability, maintenance efficiency, and process continuity. This study investigated the detection and characterization of abnormal operating regimes in industrial centrifugal pumps using multivariate condition monitoring data and an unsupervised learning framework. A dataset comprising 173,730 observations collected from three centrifugal pumps was analyzed through a workflow that included data preprocessing, sensor-data quality assessment, descriptive statistical analysis, correlation analysis, Isolation Forest-based anomaly detection, and statistical validation. Five operational variables—motor vibration velocity, motor peak acceleration, pump vibration velocity, pump peak acceleration, and outlet pressure—were used for anomaly detection modelling. The results revealed that anomalies were concentrated within specific operating periods rather than being uniformly distributed across the dataset. Pump B on 30 October 2024 exhibited the highest anomaly percentage (59.09%), followed by Pump A on the same date (41.11%), whereas Pump C on 30 October 2024 showed no detected anomalies, indicating a stable inactive operating state. Correlation analysis further demonstrated strong relationships among vibration, acceleration, and pressure measurements, reflecting interconnected mechanical and hydraulic behavior. Anomalous operating conditions were primarily characterized by substantial increases in motor peak acceleration, pump peak acceleration, and outlet pressure. These findings demonstrate that unsupervised anomaly detection can effectively identify abnormal operating regimes in centrifugal pumps without requiring labelled fault information. The proposed framework offers a practical and scalable approach for industrial condition monitoring and supports maintenance decision-making in data-rich operational environments.

1. Introduction

Centrifugal pumps are one of the most widely used fluid-moving devices in industrial systems because of their ability to move fluid reliably and efficiently over a wide range of operating conditions. These are essential elements in industries like power generation, water treatment, chemical processing, manufacturing and food production, where continuous flow is a critical part of the process to ensure smooth operations. In recent years, there has been a great deal of attention paid to the improvement of pumps, both with respect to the design and hydraulic performance, to make them more energy-efficient and less expensive to operate. With the advent of advanced centrifugal pump technologies, broader sustainability, productivity and resource optimization goals for industry have become interwoven (Capurso et al., 2022). In addition, the role of centrifugal pumps in industrial transport processes is evident in their widespread use in the transport of liquids with different process needs (Mohammadi et al., 2023). Centrifugal pumps are directly linked to the reliability of the system, and thus maintenance costs and system performance. Unplanned downtime can result in production downtime, lower equipment availability, higher repair expenses and lower process efficiency. It is hence vital for industrial companies to ensure that pumps are available at high rates to optimize asset utilization and operational performance (Okirie, 2024). Conventional maintenance practices are slowly being complemented by monitoring strategies that constantly assess the condition and performance of equipment through the use of data and increasing automation of industrial facilities. Digital technologies have greatly changed the way industrial pumping systems are now managed. These smart devices are equipped with complicated sensing, control and communication technologies that produce extensive data of their operation. These advancements have allowed data analytics to enhance process control and aid in making informed operational decisions (Johnson et al., 2021). Meanwhile, the smart sensors have enabled the continuous measurement of vibration, temperature, pressure and environmental parameters, providing new opportunities for condition monitoring and predictive maintenance applications in centrifugal pumps (Chen et al., 2022). These technological advancements can be categorized under the Industry 4.0 paradigm that encourages the use of intelligent monitoring systems to enhance reliability, efficiency and maintenance efficacy of industrial assets (de Souza et al., 2022). As more operational data has become available, more interest has arisen in condition monitoring strategies that take advantage of the measurements from sensors and equipment to assess equipment health. Sensor-based monitoring systems can capture several parameters of the pump behavior, such as mechanical vibrations, thermal response, hydraulic parameters and more. These measurements have important information on the operational condition of the pumping system and will allow to continuously monitor performance characteristics. The value of monitoring data, generated by sensors, for assisting the management of an industrial asset has been illustrated in recent studies and the use of data-driven maintenance strategies for centrifugal pump installations (Martone et al., 2025). Of the different monitoring methods, vibration analysis is one of the most commonly used methods due to the fact that vibration behavior can give early signs of degradation, imbalance, cavitation and other abnormal operating conditions. Therefore, the use of vibration monitoring has become a crucial part of troubleshooting and reliability assessment approaches for rotating machinery (Marscher, 2023). With the increasing availability of information on the monitoring data, researchers have shifted their focus to machine learning methods to assess the condition of pumps and detect faults. Previous research has shown that machine learning algorithms can be used to identify faults in centrifugal pump motors and other components, which can be used as a basis for developing more intelligent maintenance systems (Sunal et al., 2022). The work has also been done on how to identify and monitor the cavitation phenomenon, which is one of the most important challenges when working with centrifugal pumps that affects the performance and longevity of the pump (Zhu et al., 2023). Recently, prognostics and health management (PHM) systems have received significant research interest owing to their potential for automated condition assessment, fault prediction and maintenance planning for industrial pumping systems (Khalid et al., 2024). However, there are several gaps in the literature. Many of the machine learning research works are based on supervised learning methods, which need labeled fault information. In industrial settings, however, fault labels may not be available as faults are uncommon, and the operational data may be insufficiently annotated with details about fault conditions. This restriction makes the use of many traditional fault diagnosis methods difficult. For this reason, unsupervised anomaly detection techniques offer a good alternative, as they do not need the knowledge of faults before detection. In recent years, it has been shown that Isolation Forest and its variants of unsupervised learning can be effective in detecting abnormal patterns in engineering systems (Ali et al., 2026). However, the use of such techniques for the characterization of abnormal operating regimes in industrial centrifugal pumps based on multivariate condition monitoring data, collected under real operating conditions, has received limited attention. This existing knowledge thus indicates a definite gap in the literature. Many studies have been conducted on condition monitoring, fault diagnosis, cavitation detection, and predictive maintenance for centrifugal pumps, but few studies have been conducted on the identification of abnormal operating regimes for the centrifugal pumps based on unsupervised learning techniques and real-world industrial monitoring data. In addition, there are many studies available for the classification of faults, but they do not focus on understanding the abnormal operational behavior based on the interaction of several measurements of the same sensor and operating periods.

To address this problem, the present research aims to explore abnormal operating conditions in industrial centrifugal pumps by applying multivariate data from condition monitoring (CM) and an unsupervised anomaly detection framework. The study analyses the nature and quality of the monitoring information, investigates the correlation between the operational variables, uses the Isolation Forest algorithm to detect abnormal operating conditions and statistically compares the normal and abnormal observations.

2. Methodology

2.1 Research Design

The study employed a quantitative data-driven research design to explore abnormal operating regimes and operating behaviour in centrifugal pumps used in industry. Analysis was done using exploratory data analysis, statistical characterization, correlation assessment and unsupervised machine learning methods. The workflow aimed to discover patterns of the operation from multivariate sensor measurements and to detect deviations from the normal operation without any labels for faults. The methodological framework consisted of data preprocessing, descriptive statistical analysis, correlation analysis, anomaly detection, and statistical validation of the detected anomalies.

2.2 Data Source

The data analyzed in this study were provided by a publicly available data set created by Martone and Zazzaro (2025). The data set includes operational data from centrifugal pumps that deliver demineralized water to the boiler systems at an industrial research facility. The variables measured are vibration, acceleration, temperature, pressure and environmental variables recorded with different operating conditions and monitoring periods (Martone & Zazzaro, 2025). This data was obtained from nine monitoring files and three pumps on three different operating dates. The final analytical dataset was 173,730 observations and ten variables of sensor-based monitoring, along with a time stamp and operational identifiers, after data integration.

2.3 Data Preprocessing

The raw data were imported and merged into a single analytical data set. The source files had various delimiters and decimal formats, so a format-detection procedure was used to ensure that the data was ingested in a consistent format. The names of these variables were later standardized to be variable-specific to each pump and to have a common structure for all monitoring files. Timestamp variables were converted to a uniform datetime format, and sensor measurements were converted to numeric. In the first pre-processing step, missing observations were kept to ensure the original features of the monitoring data. Completeness assessment and descriptive inspection were used to assess data quality before modelling. These variables were selected for modelling anomalies because they had relatively low missing values: vibration velocity, peak acceleration, and outlet pressure.

2.4 Descriptive and Correlation Analysis

The means, standard deviations and distributions of the monitoring variables were summarized using descriptive statistical analysis. The mean, standard deviation, median, quartiles, minimum, and maximum values for each sensor variable were calculated. Pearson correlation coefficients were used to explore the relationships between the parameters measured by the continuous sensors. The resulting correlation matrix was plotted to see if there were any correlations between vibration, pressure, temperature, and environmental variables. This analysis served as a preliminary analysis of operational dependencies in the pumping system.

2.5 Anomaly Detection

The Isolation Forest algorithm was used to detect anomalies. Isolation Forest is an unsupervised ensemble-based approach that detects anomalous observations by recursively dividing the data space and separating observations that need fewer partitions than normal observations. Five operating variables were used in the development of the model: motor vibration velocity, motor peak acceleration, pump vibration velocity, pump peak acceleration, and outlet pressure. Missing data were filled with the median value, and variables were scaled to make comparable scales across measurements before modelling. The Isolation Forest model was trained with 300 trees, with the same random seed for reproducibility. Every observation was given an anomaly label and an anomaly score so that abnormal operating regimes could be identified for each pump for each monitoring time.

2.6 Statistical Validation

The Mann–Whitney U test was used to determine if there was a significant difference between the anomalous observations and normal operating conditions. The choice of this test was made because it does not assume a normal distribution, and can be used for comparing independent groups whose distributions may be skewed. The comparisons were made in the variables involved in the anomaly detection. A significance level of 0.05 was used for statistical significance. This procedure gave quantitative evidence for determining if the operating characteristics due to the detected anomalies were statistically different from those during normal operation.

3. Results

3.1 Dataset Characteristics and Data Completeness

Three centrifugal pumps were monitored for 3 monitoring periods, resulting in a final analytical dataset of 173,730 observations. The duration of the monitoring window was different for each pump–date combination, leading to varying numbers of observations. Table 1 presents the composition of the data and completeness of the sensor data for each pump and operating date. The smallest monitoring file had 4,981 observations, while the largest monitoring file had 35,829 observations. For the majority of operating periods, missing sensor values were low (between 0.01% and 2.86%), although Pump B on 30 October 2024 and Pump C on 30 October 2024 had higher values. On 30th October 2024, there were 13.16% missing sensor values in Pump B and 48.84% missing sensor values in Pump C. The high missingness for Pump C is consistent with the reported shutdown status of the pump during that time.

Table 1. Dataset composition and sensor-data completeness

Pump	Operation Date	Observations	Missing Sensor Values (%)
Pump A	2024-04-10	4,981	0.54
Pump A	2024-06-11	21,429	2.86
Pump A	2024-10-30	21,600	0.01
Pump B	2024-04-10	4,981	1.12
Pump B	2024-06-11	35,829	1.69
Pump B	2024-10-30	29,700	13.16
Pump C	2024-04-10	4,981	0.51
Pump C	2024-06-11	21,429	2.75
Pump C	2024-10-30	28,800	48.84

The vibration velocity, peak acceleration, contact temperature, casing temperature, outlet pressure, ambient pressure and ambient temperature were measured. The description of the monitored variables is presented in Table 2. The vibration velocity values were small for motor and pump locations, while the peak acceleration variables had significantly larger dispersions. The mean of the peak acceleration of motors was 22.1595 with a standard deviation of 48.9864, and the mean of the pump peak acceleration was 9.5792 with a standard deviation of 19.7347. The outlet pressure also exhibited a large range of values with a mean of 14.9545 and standard deviation of 19.4523, so that the hydraulic conditions at the time of monitoring the operation of the pump varied widely.

Table 2. Descriptive statistics of pump monitoring variables

Variable	Mean	Standard Deviation	Median	Maximum
Motor Vibration Velocity	0.0013	0.0006	0.0012	0.0039
Motor Peak Acceleration	22.1595	48.9864	0.4997	456.6258
Motor Contact Temperature	36.0236	17.2273	37.0078	300.6250
Pump Vibration Velocity	0.0017	0.0014	0.0009	0.0073
Pump Peak Acceleration	9.5792	19.7347	0.5245	637.1081
Pump Contact Temperature	38.6504	19.9588	40.3672	264.3750
Outlet Pressure	14.9545	19.4523	0.6997	46.7089
Motor Casing Temperature	34.2259	8.8194	35.2242	273.1250
Atmospheric Pressure	1014.6881	4.2821	1011.8811	1022.5323
Ambient Temperature	24.4455	2.4685	25.4339	28.7535

3.2 Relationships Among Monitoring Variables

To analyze the linear associations between the main monitoring variables, correlation analysis was performed. As evident from Figure 1, the monitored variables were mostly positively correlated, which suggested connected mechanical and hydraulic operating behaviour. The highest correlation was found between pump vibration velocity and outlet pressure ($r = 0.88$), indicating that there is a close relationship between the hydraulic loading condition and vibration response. There was also a good correlation between pump vibration velocity and pump peak acceleration ($r = 0.67$) and between motor peak acceleration and pump vibration velocity ($r = 0.66$). There were moderate positive relationships between outlet pressure and motor peak acceleration ($r = 0.57$) and between outlet pressure and pump peak acceleration ($r = 0.55$). Based on these findings, it was deduced that the changes in vibration and acceleration were strongly related to the variations in outlet pressure and, therefore, the mechanical and hydraulic behaviour of the monitored centrifugal pumps are strongly coupled.

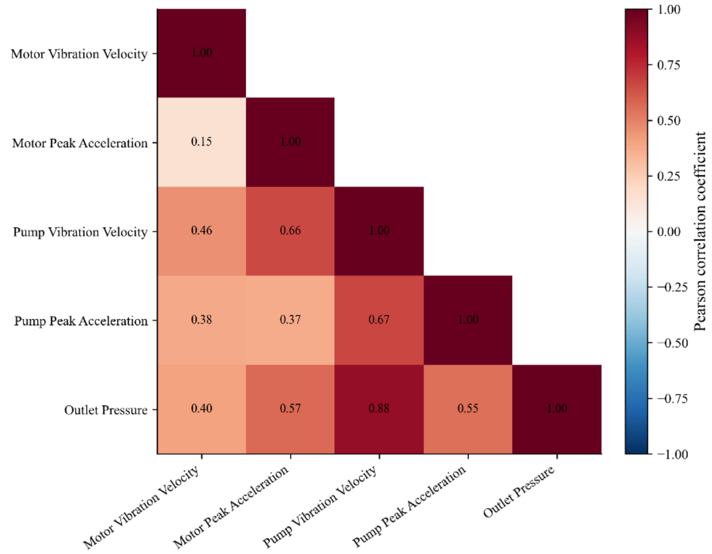

Figure 1. Correlation matrix of pump monitoring variables

To assess if there were significant differences between the normal and anomalous observations, Mann–Whitney U tests were performed on the variables employed in the anomaly detection process. The differences between the two groups in all variables were found statistically significant ($p < 0.001$) and thus supported the hypothesis that the operating characteristics of detected anomalies differed from those observed when operating under normal conditions.

3.3 Distribution of Detected Anomalies Across Operating Conditions

The Isolation Forest model detected a significant difference in the number of anomalies recorded over time and between the different pumps. The detected anomalies were not evenly distributed and were targeted at specific pump–date combinations. As seen in Figure 2, Pump B with the anomaly percentage of 59.09% on 30 October 2024 is the most anomalous pump, followed by Pump A with the anomaly percentage of 41.11% on the same date. Instead, on 30 October 2024, Pump C with 28,800 observations did not show any anomalies. This pattern shows that the model was able to differentiate between the stable inactive state of Pump C and the abnormal operating regimes of Pump A and Pump B on the same monitoring date.

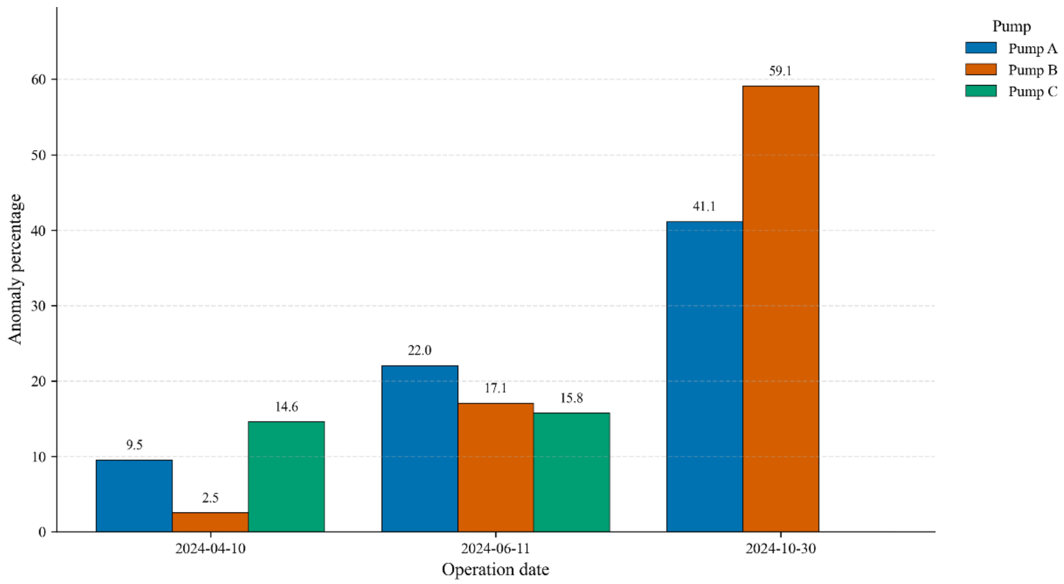

Figure 2. Anomaly percentage across pumps and operating dates

The anomaly detection summary by pump and operating date is provided in Table 3. The maximum number of anomalous observations was recorded during the October monitoring period, for Pumps B (17,549) and A (8,880). The percentage of anomalies was lower during the earlier periods, between 2.53% and 22.04%.

Table 3. Isolation Forest anomaly detection summary by pump and date

Pump	Operation Date	Observations	Detected Anomalies	Anomaly Percentage
Pump B	2024-10-30	29,700	17,549	59.09
Pump A	2024-10-30	21,600	8,880	41.11
Pump A	2024-06-11	21,429	4,724	22.04
Pump B	2024-06-11	35,829	6,110	17.05
Pump C	2024-06-11	21,429	3,376	15.75
Pump C	2024-04-10	4,981	726	14.58
Pump A	2024-04-10	4,981	473	9.50
Pump B	2024-04-10	4,981	126	2.53
Pump C	2024-10-30	28,800	0	0.00

3.4 Temporal Behavior of Anomalous Operating Regimes

The highest anomaly percentages for the two combinations of pump and date were investigated to assess the temporal distribution of abnormal operating regimes. The monitoring period resulted in repeated and prolonged anomalous intervals at Pump B on 30 October 2024, as shown in Figure 3A, which had the highest percentage of anomalous intervals of all operating conditions. For Pump A on 30 October 2024, extended anomalous intervals were also observed (Figure 3B), but the anomalous regions were not as persistent as those observed for Pump B.

Figure 3. Time-series operating regimes with detected anomalous intervals: (A) Pump B on 30 October 2024; (B) Pump A on 30 October 2024

It is found that these temporal patterns suggest that the detected anomalies were not single-point deviations. They instead showed as sustained operating regimes and were interpreted as representing persistent changes in operating behaviour, instead of random variations in measurement noise.

3.5 Characteristics of Anomalous Operating Conditions

The normal and anomalous groups were compared to identify which variables most strongly characterized abnormal operating behavior. The largest differences were observed in acceleration and pressure-related measurements. Figure 4 shows that motor peak acceleration increased by 1001.11% during anomalous operation, followed by pump peak acceleration at 420.43% and outlet pressure at 380.10%. Pump vibration velocity increased by 168.50%, while motor vibration velocity increased by 62.78%.

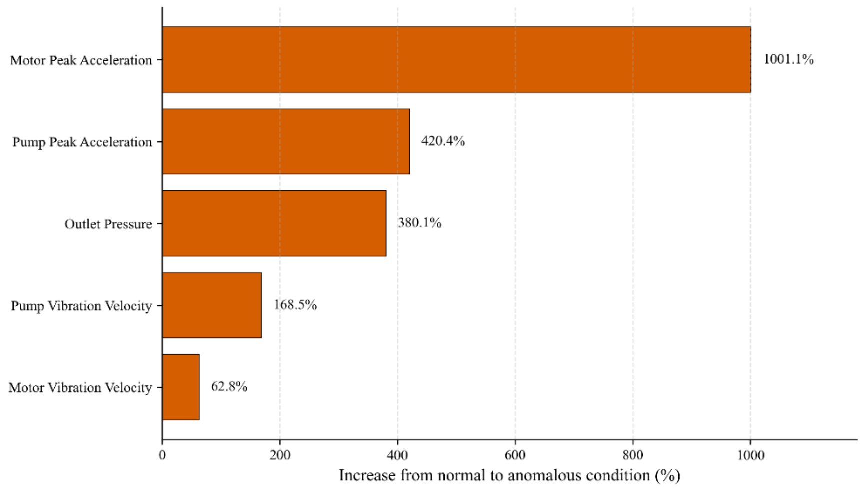

Figure 4. Relative increase of monitoring variables during anomalous operation

The results show that the most significant operating conditions that were considered anomalous were greater acceleration response and more hydraulic loading. It is likely that the simultaneous changes of vibration-related variables and outlet pressure indicated that the investigated abnormal regimes represented mechanically challenging operating conditions, and not sporadic sensor variations.

4. Discussion

The results highlight the effectiveness of identifying abnormal operating regimes in centrifugal pumps, based on multivariate condition monitoring data, without the need to use labelled fault records. The Isolation Forest model did not distribute anomalies randomly across the data; rather, the highest concentrations of anomalies were found in certain combinations of pump and date. Both pumps had their greatest anomalies in 2024, with Pump B having the highest anomaly burden on 30 October 2024, and Pump A on the same date. These suggest that both pumps were operating in conditions that were significantly different from the other monitoring dates. This is also important because there are no anomalies detected for Pump C on 30 October 2024. This file had a large percentage of missing sensor data, but the model predicted that the shutdown state was not a fault state. This indicates that the anomaly detection system was not just detecting the absence of signals due to a shutdown, but rather that it is detecting deviations in the way the system is being operated. Motor peak acceleration, pump peak acceleration and outlet pressure were the most influential variables. The peak acceleration of the motor rose over 1000% during the anomalous operation, and the respective pump peak acceleration and outlet pressure were also increased by considerable values. The results show that the abnormal regimes were primarily related to dynamic mechanical response and hydraulic loading. This strong correlation between pump vibration velocity and outlet pressure will further aid in the interpretation that hydraulic operating conditions affected mechanical vibration behavior. The temporal analysis also revealed that anomalies appeared in the form of extended periods, and not just as a single point, which indicated that the operating regime of the system was abnormal during a long period of time, not just for a short time.

The results are in line with the recent studies focusing on the identification of multivariable operational regimes in pumping systems. The present finding that anomalous behavior of a pump can be explained more effectively using two variables (vibration and pressure) than one variable is consistent with the work of Corrales-Bonilla et al. (2026), who showed the importance of using multivariable frameworks for regime identification and anomaly detection using SCADA. Recent pump fault detection studies also support the importance of electrical and vibration-related monitoring. Adaika et al. (2025) demonstrated that motor current signature analysis can provide meaningful information related to faults in centrifugal pump systems, and Dias et al. (2021) proved that the electric current information available in industrial communication networks can help in the intelligent diagnosis of faults. The present study differs because of the vibration and pressure variables examined, which agrees with the above conclusion that there is potential for abnormal pump behavior to be detected using the signals routinely collected from an industrial process. This is in line with the latest advancements in industrial pump monitoring, which are based on unsupervised modelling. In the context of fault detection, Shaikh et al. (2025) explored an unsupervised method to detect abnormality from multivariate time series, closely related to the present study, which aims to detect the abnormal regimes without a prior label. Likewise, Grašs (2026) suggested a two-layer predictive maintenance system with unsupervised anomaly detection and rule-based interpretation, justifying the relevance of unsupervised methods for the industry, where the labels of faults are limited.

The results are also in line with recent attempts using AI for centrifugal pump diagnostics. Turk et al. (2024) studied the application of AI fault classification and anomaly detection of hydraulic centrifugal pumps, and Chang and Park (2024) used the random forest modelling method for multi-fault classification in intelligent pump systems. The present study does not require the operator to manually classify faults, which is more appropriate when labelled fault classes are not available, as opposed to supervised fault classification. In the last few years, some research with the use of complex learning architectures has demonstrated very good potential for the detection of defects and faults in pumps.

Ullah et al. (2026) proposed an end-to-end deep learning system for the centrifugal pump defect identification, and Garousi et al. (2024) demonstrated the use of vibration analysis and multilayer perceptron modelling for the fault detection under healthy and defective centrifugal pump impeller conditions. The present framework is simpler, interpretable and applicable to unlabeled operational monitoring data as compared to these approaches.

The findings are useful for the industry's condition monitoring and planning of maintenance. Based on the presence of acceleration and outlet pressure as the most dominant variables of the anomalous observations, it is recommended that these variables be prioritized in real-time monitoring dashboards. An increase in peak acceleration and/or pressure may be used as an early warning of abnormal operating regimes that should be inspected or reviewed for operation. The suggested workflow is also applicable when the historical fault labels are not available in the facility. Many industrial plants have sensors providing continuous data, and do not have structured failure annotations. In these environments, unsupervised anomaly detection can serve as a first filter to alert users when an operating interval is abnormal and needs to be interpreted by the engineer. This can help with condition-based maintenance, minimize unnecessary inspections and help prioritize maintenance resources.

There are some caveats to be noted. There were only three pumps and three monitoring dates, and so the analysis was limited in its ability to assess long-term degradation trends. Lack of labelled fault events also results in the anomalies detected being considered as abnormal operating regimes, and not as mechanical faults. Furthermore, the one unsupervised learning model was not compared with other models in the current study. Further studies could investigate longer monitoring time, more pumps and perform a comparison between different unsupervised models with the same preprocessing scheme. Additional work could also incorporate engineering rules and the output of the anomaly detection to aid in the more specific interpretation of abnormal operating states.

5. Conclusion

The multivariate condition monitoring data and unsupervised Isolation Forest framework were effectively applied to the successful identification of abnormal operating regimes in industrial centrifugal pumps. The analysis revealed that anomalies were not distributed randomly but mostly occurred in certain operating periods, such as Pump B and Pump A for 30 October 2024. When the same date was used for Pump C, there were no detected anomalies, which indicates the model was able to tell the difference between a stable inactive state and abnormal active operation. Motor peak acceleration, pump peak acceleration, and outlet pressure were the most significant parameters of anomalous behavior, indicating that most of the abnormal regimes were related to high dynamic response and hydraulic loading. The temporal analysis also revealed that the anomalies appeared as periods of sustained changes in pump operating behavior, suggesting that they were not just isolated fluctuations but rather more of a sustained change. The overall results indicate that unsupervised anomaly detection could be a practical tool for condition monitoring when there is no access to labelled fault data. Future research needs to expand the framework to encompass more monitoring time, more pumps, and an additional comparative anomaly detection model to further enhance the generalizability to operations.

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