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Next Generation of Process Monitoring and Diagnostics: Applications of AI and Machine Learning to Enable Early Equipment Fault Prediction and Diagnostics

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Abstract: Several rotating equipment such as – centrifugal pumps and positive displacement pumps are extensively used in Water treatment plant for producing potable water from raw water. Centrifugal pumps are required for delivering water from one unit of the plant to the others, while the positive displacement pumps are used for dosing different chemicals at the various stages of water treatment process. Smooth normal operation of these pumps is essential for ensuring both the production quality and quantity. It is extremely important to detect any anomaly or malfunction in this rotating equipment at an early stage. This helps to take the appropriate corrective maintenance actions and prevent any catastrophic failure, equipment down time, quality deviation and/or production loss. However, there are very few methods available in the literature for detecting faults or anomalies in the pumps, particularly for the positive displacement pumps in real industrial application using only routinely available process data -such as: flow, speed, stroke, discharge pressure etc. In this paper, a machine-learning based Early Fault Detection & Diagnostic system is developed to monitor the rotating equipment in operation, detect a fault at initiation, pinpoint the root cause, and to send out alerts for corrective maintenance with suggested remedial actions. The detection works by building a baseline machine learning model of the equipment performance under normal operating conditions which is then used to monitor the health deviation of the equipment in real time and predict a fault at a very early stage, much before it is observed by operations personnel. The proposed fault detection method relies only on routine process data – flow, speed, stroke etc. and does not require any additional measurements like vibration, motor current, acoustic emission data. The diagnostics tool identifies the most probable root causes of the failures and provides the possible failure resolution methods based on the historical maintenance records of similar equipment. The proposed algorithm combines data-driven and knowledge-based approaches. The efficacy of the proposed method was demonstrated to detect and identify incipient faults in positive displacement chemical dosing pumps in a water treatment plant. The detected and identified faults were validated using the maintenance records of the pumps.

Keywords: Anomaly Detection, Machine Learning, Natural Language Processing, Predictive Maintenance, Rotating Equipment, Pumps

1. Introduction

Water treatment plants employ multiple levels of treatment processes to produce potable water from raw water. Most of the individual processes extensively use several critical rotating equipment like positive displacement chemical dosing pumps and centrifugal pumps. Dosing pumps control the release of chemicals at the various stages of water treatment process [1]. Centrifugal pumps deliver water from one unit to discharge pipes or other units within the plant. Getting these pumps to operate efficiently and normally without failures is critical to ensuring the water quality. A minor fault in a pump may eventually develop to a severe one, which may impact the safety and productivity of plants. Therefore, detecting faults in pumps at an early stage is extremely important for efficient plant operation. Such Early fault detection and predictive maintenance algorithm will help in reducing downtime and catastrophic failures down the line. Such a procedure will also help to monitor and compare the performance among similar pumps and provide the operator an option to choose the best performing pump or combination of pumps depending on the operational demand [2].

Fault detection and identification (FDI) methods of pumps can be broadly classified into two categories – (i) model-based and (ii) data-based approaches. Model based FDI approaches rely on explicit mathematical models derived based on first principles. Two main such approaches for pump fault detection are methods based on state observer and parameter estimation [3]. However, in practice, the model-based approaches often fail to work as it is extremely difficult and time consuming to derive accurate first principles-based models for complex equipment/ systems such as pumping system [4, 5]. The data-driven approaches, on the other hand, directly use the monitored variables/ parameters – process variables like flow, speed, inlet/outlet pressures & temperature, vibration measurements at different locations, Electrical signature like motor current, acoustic emission signal etc. to infer the faults. These methods are more suitable for fault detection in complex systems since they do not require any accurate physical mathematical models. Prominent among these data-driven approaches are the (i) frequency and time–domain analysis based [6–8], and (ii) artificial intelligence (AI)/ Machine Learning (ML) based FDI methods [9–13].

Frequency and time domain analysis-based methods are very popular and effective in pump fault detection in which vibration and acoustics emissions signal are analyzed in frequency domain and/or time domain to identify the signatures/patterns of various commonly encountered faults [6-8]. The availability of cost-effective data acquisition systems which enable measurements of several important process variables along with the great advancements in machine learning (ML) techniques paved way for the application of artificial intelligence (AI) in FDI. The AI based data-driven methods mainly rely on ML based and/or statistical based techniques to establish a model that uses historical operational or machine condition data. Zouari et al. [10] proposed a real-time fault detection method for a centrifugal pump using multi-layer perceptron neural network and fuzzy techniques based on vibration measurements. The system was successful to detect various fault types, such as - partial flow rates, loosening of front/rear pump attachments, misalignment, cavitation, and air injection on the inlet, using experimental data. Two different artificial neural network-based approaches were presented in Rajakarunakaran et al. [11] wherein a feed-forward network with back propagation algorithm and a binary adaptive resonance network were developed for the fault detection of a centrifugal pumping systems. Both models showed good performance when applied to simulated data. Ahmed et al. [12] used Principal Component Analysis (PCA) based Squared Prediction Error (SPE), namely Q-statistics on vibration data from a reciprocating compressor for fault detection and diagnosis. In Liang et al. [13], a fault detection and isolation scheme based on Sparse Auto-Encoder (SAE) was developed and applied on centrifugal pumps in a petrochemical plant using industrial multivariate monitoring data set. Robust Mahalanobis distance which combines multiple variables into one system -wide health indicator was applied for fault detection.

However, still there remains some challenges as far as fault detection and identification of pumping system is concerned.

1) Most of the methods proposed in the literature are demonstrated using simulated and experimental data. There are very few methods that were illustrated using real industrial data. Thus, lacking tests in real industrial applications.
2) Majority of the existing FDI methods of pumps rely on ML based classification models which require historical data of both normal and various fault conditions for model development. However, most of the available data belong to normal operating conditions, while faulty data are usually rare and sometimes cannot be obtained. Hence, we need to develop robust anomaly detection models that can take full advantage of the large volume of healthy data and effectively detect the fault.
3) Furthermore, most of the conventional FDI techniques for pump are based on vibration, motor current signature, acoustic emission data, which mainly detect various mechanical and electrical faults such as – bearing damage, looseness, unbalance, broken rotor bar, VFD fault. These methods require additional costly instruments to measure and analyze these vibration, current, acoustic data. All these faults develop gradually over time and needs to be detected at an early stage before the equipment breakdown happens. However, for the positive displacement reciprocating diaphragm pumps which are widely used for properly dosing various chemicals in water treatment plants to control the water quality, it is very important to ensure that the dosing of chemicals happens appropriately. Any underdosing (low flow), overdosing (high flow) or unstable flow conditions in these pumps needs to be detected and rectified as soon as possible. To the best of our knowledge, there is no FDI method available in literature particularly for reciprocating positive displacement pumps which solely relies on routine operation data of a pump such as – speed, stroke length, discharge flowrate and readily detects any anomaly in the pump in the form of underdosing, overdosing, unstable flow etc.

To overcome the above challenges, in this paper, we proposed a novel AI based method for early fault detection and identification which rely on ML models developed solely using routine operation data such as – flow, speed, stroke length of a pump during its normal operating conditions. The ML models thus developed were applied in detecting early fault in various types of real industrial pumps (including both positive displacement and centrifugal types) from a water treatment plant in a real-time manner. The detected faults in the pumps were validated using the maintenance records. Furthermore, to make the diagnosis of the detected fault and to recommend accurate and effective corrective actions to the operators, the proposed data-driven method was complemented by the domain knowledge. The past patterns related to the pump faults were learned from historical maintenance logs and from collective knowledge of the operators. Maintenance logs contain information about type of faults, root causes and repairs carried out on each equipment over its lifetime [14]. The state-of-the-art Natural language processing (NLP) algorithms were applied to combine and utilize all such unstructured data from different sources -such as maintenance records, operators/expert knowledge to build a corpus of knowledge which is then used to find the most probable root cause and resolution for a fault that has been identified.

The rest of the paper is organized as follows – in section 2, the proposed method for detecting and identifying the faults in industrial pumps is presented. The various steps involved in the proposed method – data preparation & feature extraction, model building, model validation, fault prediction, fault resolution tree building for root cause identification and recommendations are discussed in section 2. The effectiveness of the proposed method in detecting and identifying faults in real industrial reciprocating positive displacement type diaphragm pumps are discussed in results section (section 3). Finally, the paper is concluded in section 4 (conclusion section).

2. Method

The proposed algorithm combines data-driven and knowledge-based approaches. Data used can be from multiple sources as represented in the overall workflow in Figure 1. The general flow and contents of the algorithm described above has been represented. The model building happens offline – Process model building is periodic or engineer-selected and the fault tree is built once initially and then updated periodically. The fault prediction and recommendation steps are online and happens as and when sensor data is received.

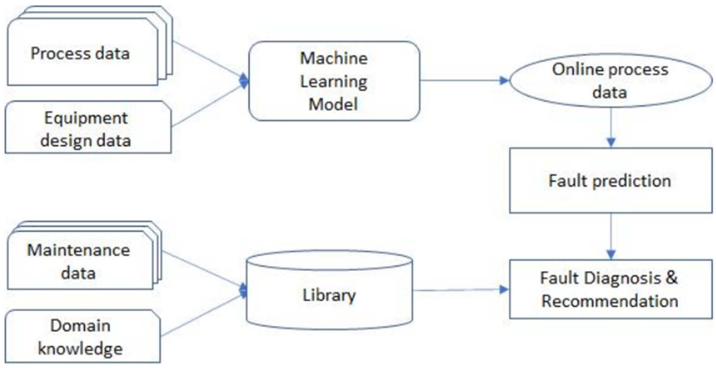


Figure 1. *Schematic Representation of the methodology.*

The process of Early prediction of faults requires multiple processing steps as described below.

2.1. Data Preparation and Feature Identification

To create a comprehensive fault detection and diagnosis model, the data needs to come from multiple sources as listed below.

1) Process/operation data collected from Process Historian.
2) Standard characteristics/performance curves serve as a reference for the expected error limits for a pump in normal operation
3) Pump Calibration data
4) Maintenance logs extracted from Asset Management System
5) Optional addition of domain knowledge-based recommendations for possible failures
6) Equipment and gauge configuration - The rotating equipment may operate in groups or individually. Similarly, there might be sensors that are measuring parameters corresponding to either individual equipment or group of equipment (eg: flow meter, pressure meter). This sensor configuration required to model the pump operation as the input parameters are derived from these individual/group tags.

After data collection, the relevant features that influence the pump flow are identified using Feature Importance calculations on the process data. The data for the model building process is selected from a healthy operation period. The model parameters and the standard pump curves are used to set threshold limits (derived from the typical observed normal operating range) to pump operations and thereby tune the alert settings. Besides incorporating expert knowledge on known corrective actions for commonly diagnosed equipment fault, maintenance logs that have been historized over several years might also provide additional information on the actions to resolve other less common types of failure. However, these are unstructured and contain lots of free-text natural language since they are mostly manual entries without any set standards and therefore require preprocessing before extracting patterns. Text analytics is used to sanitize the data by removing stop words, stemming, etc.

2.2. Model Building

For each equipment group, the features are identified based on the type of equipment, equipment configuration and operation mode. To create the baseline model, we may use the standard calibration curve and/or raw calibration data. For example, the calibration data or a 'reference period' data where the pump was running without any failure can be utilized to model the 'normal' behavior of the pump. Once the reference data is selected, the outliers in the data need to be removed. These outliers occur during changeover of pump or ramping up the speed/stroke which are to be treated as transient data. Once the transient data is removed, the data is equivalent to stable operation/calibration data.

A machine learning model is built using all these features. The model provides an insight on the expected range of stable operation and allows to configure the alert limits. The allowable limits are decided based on the variations observed during stable operation. The model parameters are converted to standard performance index and deviation index to rank the pumps in the same group and identify a best performing pump/group of pumps and alert to the operator/engineer. Thus, the algorithm helps the operator to choose the best pump and combination of pumps at any given time. We will demonstrate one example of model building on reference or calibration data for PD pumps in the coming sections, however, the approach is valid for centrifugal pumps as well.

Figure 2 shows a model built from the reference period data for a PD pump. The model can predict the flow for a given stroke and speed of the pump. Using this the actual behavior of the pump for a selected period is compared with expected behavior to give a quick indication about the current performance of the pump. Once a model is built using pump calibration data or reference period data, we also calculate additional parameters from the model coefficients to create a comparative performance chart of the pump in one equipment group. Such a comparison of 6 pumps in a group is shown in Figure 3. The indices are defined such that a lower deviation index indicates lesser variance in pumping output for any pump. Therefore, the best pump in the group (Pump 4 in the example) should be the one with lower deviation index.

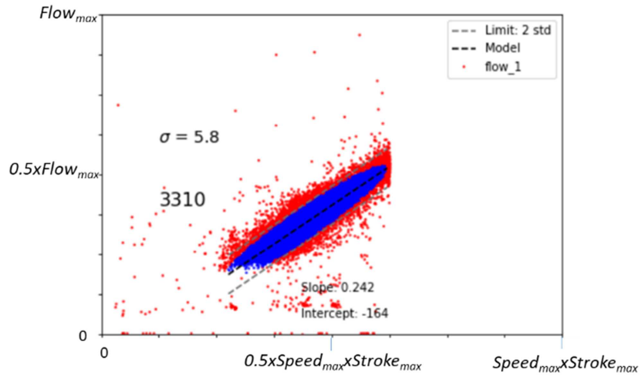


Figure 2. *Model built on normal operation data for a Positive Displacement (PD) pump (#3310).*

Note: Black dotted line represents the model performance; Blue region is the operating points falling within the acceptable 2σ. Red region are the operating points falling outside the acceptable range.

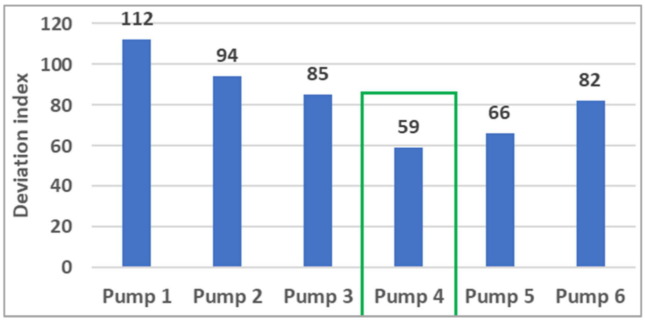
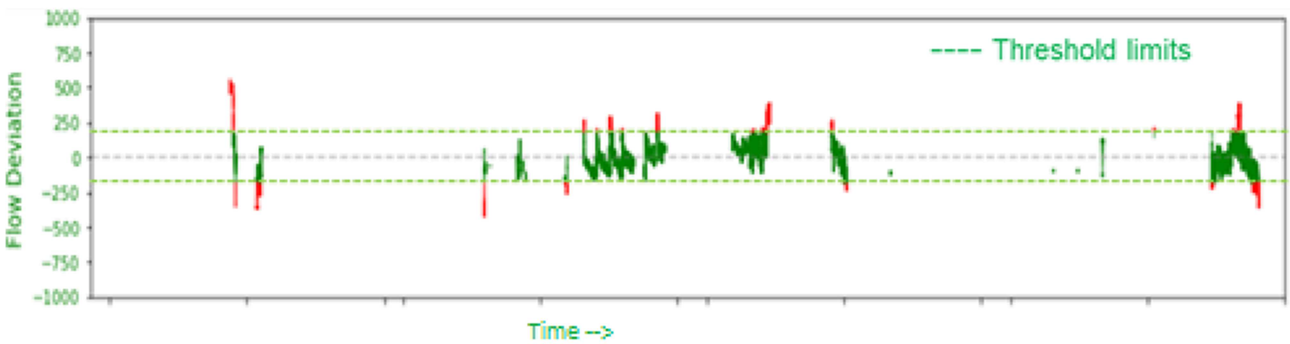


Figure 3. *Comparison of pump performance based on the model coefficients. Selected best pump in the group is marked in green.*

2.3. Model Validation

In the model validation stage, the model is tested on unseen data and any deviation (greater than the allowed threshold) of the output parameter (eg: flow) from the model is considered as a fault. Such faults identified by the algorithm are corroborated using past maintenance records and/or vibration monitoring results. Figure 4 shows the trend of deviation in actual flow from the model/reference period. The threshold limits indicated in green are selected based on reference period or normal operation period. This flow deviation trend is an input to the Early Fault prediction module.



Note: The plot is disconnected because the equipment was stopped intermittently based on the operational demand.

Figure 4. *Monitoring of flow deviation over time indicated in green (within threshold) and red (out of threshold).*

2.4. Fault Prediction

A useful output for the operator/engineer is the alerts from the algorithm. To set the alerts, we use the online flow deviation data and model the trend in flow deviation using an autoregressive model. This model can predict the trends in advance and with the help of the limits/thresholds identified from the stable period model it can identify any faults that are likely to occur much in advance. To avoid false alarms, two additional prediction KPIs were defined on predicted flow deviation. These two KPIs indicate the criticality of the threshold breaches by the predicted flow deviation – magnitude and duration of flow deviation exceeding the threshold. The threshold values of these KPI's can be tuned in the algorithm allowing the user to consider the allowable variations in pumping output such that the alerts are generated only for actual faults. The threshold values of these two KPIs should be tuned accordingly to optimize between false positive and false negative reduction.

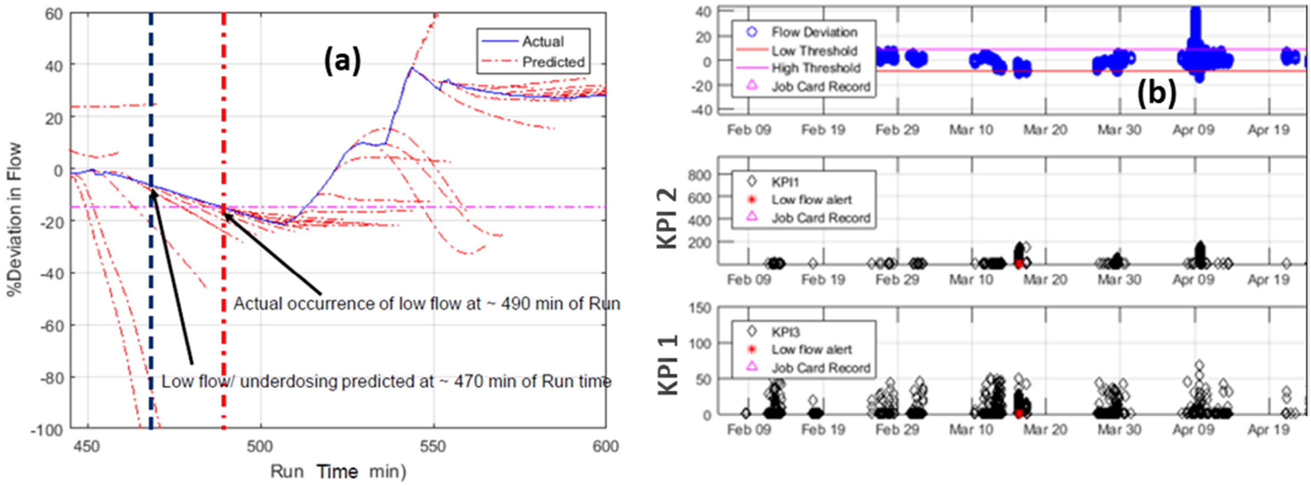


Figure 5. *(a) Prediction of flow deviation for the next x minutes, (b) Monitoring of KPI's for creating advance alerts.*

Figure 5(a) shows the flow deviation (shown in blue solid line) input into autoregressive model which in turn predicts the future trend of the deviation (shown in red dotted lines). The blue solid line indicates the calculated deviation of the flow from the model. The red dotted lines indicate the advance predictions of the flow deviation trend. In the above example, the occurrence of low flow at 490 minutes was detected and alerted at 470 minutes. Two different KPIs based on the magnitude and duration of predicted flow deviation exceeding the threshold limit were used to detect the fault. Figure 5(b) depicts the trends of these two KPIs (see two trend plots at the bottom in Figure 5(b)) computed from the trend of flow deviation (see the trend plot at the top in Figure 5(b)). Red dots indicate threshold breaches in the KPI trends. Alerts to the operator can be triggered when these KPIs breach their threshold limits. This approach was tested on PD pumps but is applicable to centrifugal pumps as well.

2.5. Fault-Resolution Tree Building and Recommendation

Once a fault is detected, an alert must be generated so that the operator can take actions. Instead of providing just an alert on the pump condition, it is of value if the algorithm can provide a list of suggested resolutions to the operator based on the history of the equipment group, domain knowledge and the type of fault identified. When the operator sees an alert for a fault, the Diagnostics algorithm also gives probable root-cause and recommendations for maintenance actions. The main input to this recommendation system is a library established through expert knowledge for known faults and supplemented with past maintenance records from the plant. Additional inputs can also come from knowledge acquired by the operators over the years. The algorithm is built using Natural Language Processing (NLP) methods. Each of the fault and resolution description text is tokenized, vectorized, and mapped. TF-IDF (Term-Frequency Inverse-Document Frequency) is computed to understand the importance of each word in the document. A ranking of TF-IDF allows to recognize the main fault categories from the maintenance data. The algorithm is trained to understand inconsistent vocabulary, industry-specific terms, synonyms, and abbreviations. Whenever a new fault is identified, the algorithm searches for the same fault that has been stored in the corpus and maps the corresponding resolutions ranked by their frequency. These extracted resolutions are provided as suggestion for maintenance along with the fault alerts. This will help the operator to take quick action. The power of this algorithm improves as the size of the data grows. Therefore, this library of information can be continuously/periodically updated as and when new faults occur or updated with expert knowledge-based recommendations, thus improving the variety, and ranking of recommendations the algorithm can provide.

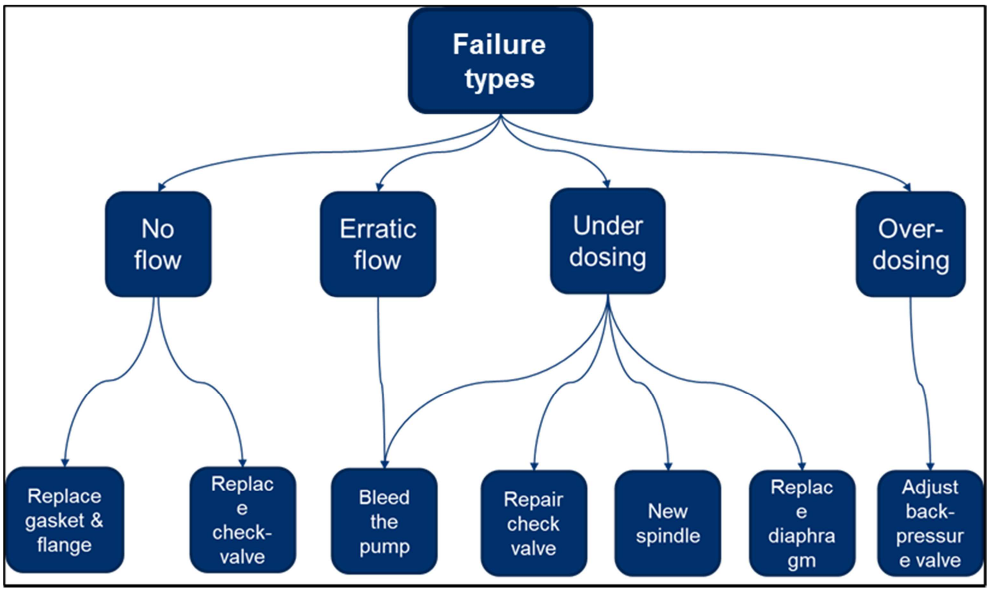


Figure 6. *Fault-resolution tree built from past maintenance records.*

Figure 6 shows a fault-resolution tree identified for the group of pumps. The tree building involves entries of faults and corresponding resolutions by expert recommendation. This information can be supplemented by maintenance record entries in the plant. To prove the concept, we utilized all the possible failures from past records. The first level in the chart lists various modes of failure that can occur for the given group of pumps. In the second level, it shows the corresponding resolutions for each of these faults. This generated mapping combined with the statistical analysis of the fault-resolution branches will be used to create suggestions for root cause and recommendations for maintenance action whenever an alert is generated.

3. Results

The steps discussed in the previous section were applied on multiple PD pump groups and alerts were generated and compared with actual entries in the maintenance record. The threshold values of the two KPIs are tuned such that most of the faults reported in the maintenance record are detected, and the faults were identified as early as possible so that the operator has enough time to act before the pump goes into failure. The Table 1 below shows the summary of fault detections for different pump groups at a Water treatment plant in Singapore with the best KPI threshold settings.

The best threshold setting was selected based on high *true positives* and low *false positive* rates. However, as can been in Table 1 that there were cases of undetected faults (*false negatives*), especially in lime dosing pumps, where the flow deviation was not significant and hence the fault could not be detected. There were also cases where a low flow anomaly was detected, however no maintenance records were raised for months, which indicated that the equipment might not be faulty. These cases were considered as *false positives*.

Table 1. *Summary of alerts detected in 3 selected equipment groups.*

Detection category	Hypo pump group	Lime dosing Pump	Sulphate dosing
Successful detection validated by maintenance records (*True positive*)	5	6	10
Undetected faults recorded in maintenance records (*False negative*)	2	5	0
Additional detections not reported in maintenance record (*False positive*)	2	2	1

4. Conclusion

Most of the FDI methods for rotating equipment (such as – pumps) condition monitoring presented in the literature are demonstrated using simulated and experimental data. Very few available literature methods were illustrated using real industrial data from a pump. Hence, applicability of these literature methods in real industrial applications are limited. To the best of our knowledge, there is not many FDI method proposed in literature particularly for reciprocating positive displacement pumps which solely relies on routine operation data such as – speed, stroke length, discharge flowrate and readily detects any anomaly in the pump in the form of underdosing, overdosing, unstable flow etc. Therefore, there is a strong motivation for developing a novel FDI method for monitoring pumps (particularly, positive displacement pumps) in a real industrial application using only routinely available operation data. In this paper, we propose a novel FDI method by combining the power of machine learning methods complemented with expert knowledge and maintenance history for early fault detection and diagnostics in a pump. The proposed method uses multiple sources of data to provide a comprehensive solution with early identification of problematic "fingerprints" and recommendation for maintenance actions. Such solutions help to optimize plant operation, maintenance, prevent catastrophic failures and downtime. The strength of the solutions lies in the fact that the models can (and need to) be updated over time to make the predictions and recommendations more accurate and able to accommodate for other operational changes over time.

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References

[1] R. Rayner, (1995), Pump Users Handbook, 263-281.

[2] S. Moran. (2015), An Applied Guide to Process and Plant Design, 175-199.

[3] Isermann, R. (2006), Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance; Springer Science & Business Media: Berlin, Germany.

[4] Tinga, T.; Loendersloot, R. (2019), Physical Model-Based Prognostics and Health Monitoring to Enable Predictive Maintenance. In Predictive Maintenance in Dynamic Systems: Advanced Methods, Decision Support Tools, and Real-World Applications; Lughofer, E., Sayed-Mouchaweh, M., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 313–353.

[5] Jiang, G.; Xie, P.; He, H.; Yan, J. (2017), Wind turbine fault detection using a denoising autoencoder with temporal information. IEEE ASME Trans. Mechatron. 2017, 23, 89–100.

[6] Mba, D.; Rao, R. B. Development of acoustic emission technology for condition monitoring and diagnosis of rotating machines; bearings, pumps, gearboxes, engines, and rotating structures. Shock Vibr. Dig. 2006, 38, 3–16.

[7] Alfayez, L.; Mba, D.; Dyson, G. The application of acoustic emission for detecting incipient cavitation and the best efficiency point of a 60 kW centrifugal pump: Case study. NDT E Int. 2005, 38, 354–358.

[8] Sakthivel, N. R.; Sugumaran, V.; Babudevasenapati, S. Vibration based fault diagnosis of monoblock centrifugal pump using decision tree. Expert Syst. Appl. 2010, 37, 4040–4049.

[9] Marton, A. I. Sánchez, S. Carlosa, S. Martorell. (2013), Application of Data Driven Methods for Condition Monitoring Maintenance, Chemical Engineering Transactions, 33: 301-306.

[10] Zouari, R.; Sieg-Zieba, S.; Sidahmed, M. Fault detection system for centrifugal pumps using neural networks and neuro-fuzzy techniques. Surveillance 2004, 5, 11–13.

[11] Rajakarunakaran, S.; Venkumar, P.; Devaraj, D.; Rao, K. S. P. Artificial neural network approach for fault detection in rotary system. Appl. Soft Comput. 2008, 8, 740–748.

[12] Ahmed, M.; Baqqar, M.; Gu, F.; Ball, A. D. Fault detection and diagnosis using Principal Component Analysis of vibration data from a reciprocating compressor. In Proceedings of the 2012 UKACC International Conference on Control, Cardi, UK, 3–5 September 2012; pp. 461–466.

[13] Xiaoxia Liang; Fang Duan 1; Ian Bennett 2 and David Mba, (2020), A Sparse Autoencoder-Based Unsupervised Scheme for Pump Fault Detection and Isolation. Applied Sciences, Applied Sciences, 2020, 10 (19).

[14] M. Devaney, A. Ram, H. Qiu, J. Lee. (2005), Preventing failures by mining maintenance logs with case-based reasoning, 59th Meeting of the Society for Machinery Failure Prevention Technology (MFPT-59).