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Nuclear Power Fault Diagnostics and Preventative Maintenance Optimization

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ABSTRACT

The nuclear industry is beginning to see reactors shut down—even after their operating licenses have been extended—because they are not economically competitive with other energy sources. These early closures happen primarily due to economic reasons, despite excellent safety records. Therefore, it is imperative to reduce costs in order to prevent these early closures. One of the contributors to these economic reasons is the large operations and maintenance costs. This paper showcases recent research on advanced fault diagnostics techniques and preventative maintenance optimization (PMO) for reducing NPP maintenance costs. Specifically, it focuses on the feedwater and condensate system (FWCS) for both pressurized- and boiling-water reactor (BWR) systems. The computerized maintenance management system (CMMS), which contains the plant's digital record of all corrective maintenance (CM) and preventative maintenance (PM) work orders, provided the ground truth for locating potential faults and labeling the process data as either healthy or faulted. Various feature extraction techniques were used to further differentiate the faulted data from the healthy data. Through a cross-validation procedure, support vectors machines were used to label other test sets of process data as either healthy or faulted. With relatively few faults identified in the BWR system, the potential for PMO opens up, since an unnecessary amount of PM leads to inflated maintenance costs. The steps for PMO are summarized, from component health determinations to recommendations for action. An example of PMO assessment is presented for condensate pumps, condensate booster pumps, and the respective motors that drive them.

Key Words: condition-based maintenance, preventative maintenance optimization, support vector machines, feedwater and condensate system.

1 INTRODUCTION

For economic reasons, the nuclear industry is witnessing premature closure of nuclear power plants (NPPs), despite excellent safety records [1]. Operations and maintenance (O&M) activities are some of the largest costs in operating light-water plants [2]. By reducing O&M costs, nuclear energy can become more economically competitive with other energy sources. This can be achieved by transitioning to a

predictive maintenance strategy which takes advantage of advancements in machine-learning (ML) and artificial intelligence technologies to develop data-driven algorithms to better diagnose potential faults within plant systems [3]. Improved accuracy of fault detection can lead to a reduction in unnecessary maintenance, thus reducing costs associated with parts, labor, and unnecessary planned, forced, or extended outages.

The nuclear industry's excellent safety record is partly due to the amount of preventative maintenance (PM) it performs. PM aims to reduce the likelihood of failure through routine tasks. Inspections, replacements, refurbishments, vibration monitoring, oil sampling, and other such tasks are all performed at regular intervals [4]. Each task carries an associated cost but reduces the likelihood of certain component failure modes. The frequencies at which these tasks are performed should be reassessed throughout the life of the plant as a means to reduce O&M costs while still maintaining safety.

The overall goal of this research is to demonstrate how cost reduction associated with the nuclear industry's maintenance practices can be achieved. This is accomplished via a two-prong approach: condition-based monitoring (CBM) and PM optimization (PMO). First, CBM techniques are used to identify potential faults and degradation within the feedwater and condensate system (FWCS)'s condensate pumps (CPs), condensate booster pumps (CBPs), and their associated motors. Heterogenous data are used in combination with information from the computerized maintenance management system (CMMS) to identify potential condition indicators. Next, the application of PMO to update PM frequencies is examined, using component histories and the opinion of subject matter experts to determine whether a component is a PMO candidate. PMO adjusts PM frequencies based on expected fault frequencies to reduce cost without impacting safety.

2 FAULT DETECTION

Faults within a system can accumulate into asset failure. Fault does not necessarily mean that the component is physically broken, just that it may not be performing within the desired ranges. Fault detection is the process of detecting deviations from healthy operating conditions, and fault diagnosis classifies the reason behind such deviations. With pertinent sensor data, anomalies can be detected so that maintenance can be scheduled to remedy the fault [5].

The system of interest here is the FWCS. For BWRs, this system supplies the reactor pressure vessel (RPV) with clean, demineralized water at the desired temperature and pressure, in accordance with the rate of steam production. The water is driven by several CPs, which serve as the driving force for the system. CBPs then provide the motive force to push the condensate through the low-pressure heaters, preheating the coolant before it enters the RPV. The PWR FWCS follows a similar path as the BWR FWCS, but with less conditioning for the condensate, as it does not travel to and from the RPV. The condensate travels from the condenser to the CPs, low-pressure heaters, CBPs, high-pressure heaters, and steam generator. The CPs, CBPs, and their respective motors are the focus of this paper.

Motors convert electrical energy into torque, and potential failures can be found throughout this process. Common failure locations include the frame and mounting, electrical leads, stator windings, shaft, bearings, rotor, and lubricant [6]. Failures within these locations can be found via appropriate discovery methods, such as inspections, oil analysis, electrical tests, bearing temperatures, ultrasonic monitoring, pressure tests, winding resistance, and thermography [7]. No single method can catch every form of degradation, so a suite of methods must be employed. Inspections can uncover most failure types but are often expensive, time-consuming, or require the system to be offline. By using relevant sensors that collect data from heterogenous sources, both common and severe failure mechanisms should be identifiable.

The centrifugal pump uses the motor's rotational energy to increase the flow rate and pressure of the water within the system. Common failure locations for centrifugal pumps include seals, bearings, connections, and gaskets, as well as the impeller, casing, lubricant mounting, shaft, and stuffing box. CBM emphasizes the condition monitoring aspect of maintenance. Data and inspections are used in

combination to infer the health or status of the component. Once a sign of degradation is found and the degradation can be diagnosed, the damage can then be trended. Maintenance can be scheduled and performed prior to the component failing to meet its performance criteria.

Faults can be detected using data-driven or model-based techniques [8]. Data-driven techniques use sensor data collected from the system and do not require expert knowledge of the physics associated with the system. However, data-driven techniques require a sufficient amount of historical data regarding system operations under various conditions. For the data-driven techniques to be most effective, the training data should also include possible failure events. Such data can be difficult to obtain for NPP components since safety is such a key priority. Fault detection in this case may appear similar to anomaly detection, due to the ratio of healthy to faulted data collected. Some data-driven ML techniques include artificial neural networks [9], auto-associative kernel regression [10], and support vector machines (SVMs) [11-14].

Model-based techniques require a priori knowledge about the system and its potential failures [3]. These models can be developed based on first principles such as Newton's laws, but require detailed information about the materials used, the failure mechanisms, and the operating conditions. These types of models can be difficult and costly to create. Model-based techniques are outside the scope of this paper.

This paper specifically focusses on the application of SVM for fault diagnosis. SVMs are classification algorithms that aim to create a hyperplane to separate out two sets of data: healthy and faulted. The core concepts of SVMs are the kernel function and optimization routine [11,12]. In most cases, the healthy and faulted data sets will not be linearly separatable, so the input data must be transformed to a higher-dimensional space via a kernel function. The kernel function returns the inner product between two points for a particular feature space. Common kernel functions include the polynomial, sigmoid, and radial basis functions [13]. An optimization routine is used to find the hyperplane that best separates the datasets in the higher-dimensional space by maximizing the margin between the two classes. The fitted hyperplane is described by the data points closest to the margin's boundary, which are then called "support vectors." These support vectors can be used to classify new sets of data. SVMs are noted for their accuracy, regularization, and generalization abilities [14].

SVM is a supervised learning technique, meaning it requires labeled training data. In practice, such data can be difficult to obtain. For this paper, labeled data is obtained by combining the CMMS with the opinion of subject matter experts. The CMMS catalogues all maintenance actions performed on the system. This includes maintenance to fix faults (e.g., oil leaks) and conduct bearing replacements. Before the system is taken offline for corrective maintenance (CM), the system is assumed to be operating in a degraded state that will be labeled as faulted, as seen in Figure 1. Exactly when this degraded state began is determined via the opinion of subject matter experts, based on deviations in temperature measurements from expected conditions. In many mechanical applications, a rise in temperature correlates with degraded performance, typically through increased vibration or friction.

3 PREVENTATIVE MAINTENANCE OPTIMIZATION

PM includes tasks such as component refurbishments, electrical testing, lubrications, cleanings, and replacements. Initial PM frequencies are typically established through a combination of vendor recommendations, expert opinions, and operating experience. As more experience is obtained, these frequencies should be re-examined and then adjusted accordingly. Poor performance may require more PM in order to reduce in-service failures, whereas excellent performance may suggest that less PM is required, thus leading to reductions in overall O&M costs. This research focuses on an analytical approach for determining which PM task frequencies to extend.

First, the historical health of the component is analyzed to determine whether the component is eligible for PMO. For this project, component health was determined from the CM work orders found in the CMMS. The CM work orders detail every component-associated action that is not a regularly

scheduled activity. Leaks, repairs, and replacements indicate that degraded performance has occurred within the component. If said events occurred frequently, the associated components would be ineligible for PMO since the current rate of maintenance does not seem to be addressing the underlying issues. However, PM is not capable of preventing all faults. The goal of PMO is to optimize resources in order to maximize safety and uptime while also reducing costs. If a component is only experiencing one type of fault, the frequencies of PM unrelated to that particular failure mode can still be potentially extended as well. For example, if the nuisance fault is leaking seals, that is something discovered primarily through inspections. Oil and vibration analyses are unrelated to seal leakage, so the opportunity to extend their PM frequencies may still apply.

Once historical data have been used to identify a component as a potential candidate for PMO, each PM task and the frequency thereof should be evaluated against industry averages or an expert database such as the Electric Power Research Institute (EPRI)'s Preventive Maintenance Basis Database (PMBD). The EPRI PMBD is a maintenance information database containing recommendations on PM frequencies for major components related to power generating facilities. A justification for extending certain PM frequencies can be made by comparing current PM frequencies against those recommendations found in the EPRI PMBD. The PMO process is a delay feedback loop. Effects from extending the PM frequencies will not be seen immediately, so extending them should consist of small, iterative steps.

4 PRELIMINARY RESULTS

This section provides an overview of the sensor data and CMMS information from two different types of operational NPPs.

4.1 Data Description

Different amounts of data were available for the BWR and PWR systems. For the BWR system, sensor data and CBM records were provided for a 5-year period. No PM records were available, so a final PMO cannot be made. However, an assessment of whether PMO is applicable can be made using the data and records available. For the PWR system, a year's worth of sensor data was available for two units, while CM and PM records were available for a 5-year period. This combination is better suited for PMO, since all the maintenance tasks are available. This dataset may be less suitable for fault diagnostics, depending on the signal of interest.

The available sensor data from both systems are similar and include variables such as generator gross load, average feedwater flows, and data on temperatures/pressures for the CPs, CBPs, and their associated motors for multiple pump trains. Each dataset consists of unlabeled data and is sampled hourly. There was no indication as to whether any portion of the data corresponded with equipment failure. The available datasets each encompassed steady-state operation, shutdowns for refueling, and derates of varying sizes. There was insufficient information to determine the cause of each derate.

4.2 Signs of Degradation

In this work, fault diagnostics are analyzed from two perspectives: a data-driven perspective and a CMMS perspective. In the data-driven perspective, the sensor data is analyzed for faults, anomalies, or trends that may indicate degradation or reduced performance. The CMMS is then used to provide the ground truth to verify that a fault occurred, based on any CM work orders remedying the issue. Some changes seen within the FWCS sensor data are not due to faults, but rather changes in operating conditions related to other systems. Diagnosing this behavior is difficult, as sensor data from these other systems were unavailable for this paper.

The fault diagnostics process from the CMMS perspective begins by analyzing the CMMS for CM work orders related to failures and fixes. The sensor data collected prior to the work order being issued are analyzed for signs of incipient degradation or developing trends over a period of time. It should be noted that not all failure modes can be detected using the available process data acquired from in-situ

sensors. Failures concerning seals, shafts, impellers, and oil require some combination of inspection, vibration, and oil analyses. NPPs perform these tasks at regular intervals, but such data were unavailable for this exercise.

The BWR process dataset was first analyzed from a data-driven perspective. The dataset was cleaned, and variables were analyzed individually to observe characteristic features from each signal. Some temperature variables associated with the pumps exhibited seasonal trends: hotter in summer, cooler in winter. Since the dataset covered a period of several years, an expected temperature was calculated for each date, using the average temperature calculated from the other years. These averages were then smoothed using a median filter to remove fluctuations in temperatures due to daily or weekly weather variations. A condition indicator for the pump would then measure the difference between the seasonal average and the current component temperature, as seen in Figure 1. Positive values indicate that the component is running hotter than the seasonal average; negative values indicate that the component is running cooler. Negative values are dismissed in this analysis because degraded components typically run hotter due to increased friction. Positive values above a 6-degree Fahrenheit temperature difference were labeled as faulted. This cutoff was chosen based on the component's history before the outage. Other methods, such as step detection, could be deployed to determine deviations in normal operation. The faulted section can be seen in the red highlighted area in Figure 1. The period of time immediately following the faulted section, and for which no data were collected, represents a regularly scheduled refueling outage.

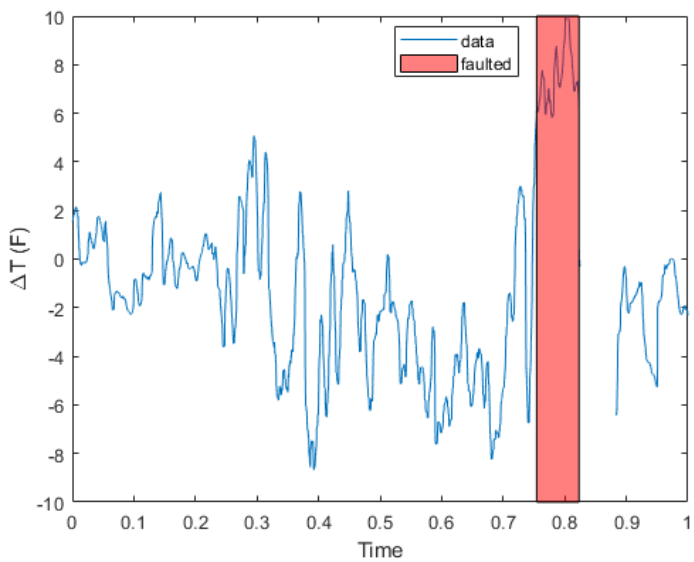

Figure 1. The average seasonal component temperature was subtracted from the current component temperature. Positive values indicate that the component was hotter than the seasonal average. Highlighted in red is the section of training data labeled as faulted.

The temperature condition indicator was combined with other process variables (e.g., gross load, flow, and pressure) to observe the total system response to this potential fault. The high dimensionality of this combination was reduced using principal component (PC) analysis. With just three PCs, 87% of the information within the dataset was represented. These three PCs are seen in Figure 2. Data within the faulted section of Figure 1 are also labeled as faulted in Figure 2, while all other data points are labeled as healthy. Temperature data was not considered when the pump was offline. Figure 2 shows a clear separation between the faulted and healthy data. However, this separation may not be due to the existence of a fault, but rather the ramp down for a planned outage. The temperature difference between the expected and actual temperature values changes in relation to the plant's other process variables. This nonstationary behavior makes it difficult to determine the cause of the separation.

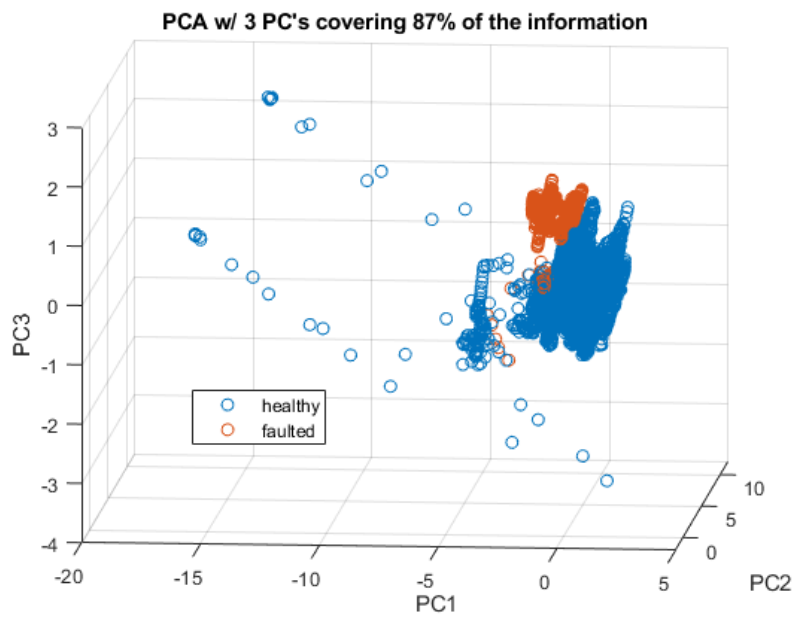

Figure 2. PC analysis was implemented as a preprocessing step to further separate the faulted and healthy datasets.

SVMs use fault labels to search for similar faults in other time periods. To capture the differences between the healthy and faulted data, the SVM was trained on the data presented in Figure 2. Faulted data made up 4.1% of the total training data. The SVM was trained using a linear kernel function, resulting in 242 support vectors. The SVM was then tested on the training data to double-check that it could correctly label that data. On the training data, it proved 99% accurate. The confusion matrix for the training data showed that it labeled 305 out of the 360 faulted data points correctly, while labeling 8,371 out of the 8,400 healthy data points correctly. The SVM was then used to search for similar faults from other years. The test data was normalized and transformed into the same PC space as the training data. The SVM then labeled the test data as either faulted or healthy, as shown in Figure 3 got one year of test data.

The red spikes throughout Figure 3 show each data point that the SVM labeled as faulted. This test year is interesting because no repairs were made to the CP of interest, and a similar de-ramp into an outage was performed. Since no repairs were made to this pump, all data throughout the test year should be labeled as healthy. Under this assumption, the accuracy of the predictions seen in Figure 3 was 81.4%. The accuracy in predicting years involving only healthy, steady-state operation reached as high as 99.7%. This high accuracy can seem misleading, but the system was operating under healthy, steady-state conditions over that entire year, so no faults were expected to be identified.

After the data-driven analysis was completed, maintenance work orders were reviewed to confirm the presence of a fault. Work orders completed during the outage immediately following the labeled faults seen in Figure 1 suggest that the thermocouple experienced a drift or fault.

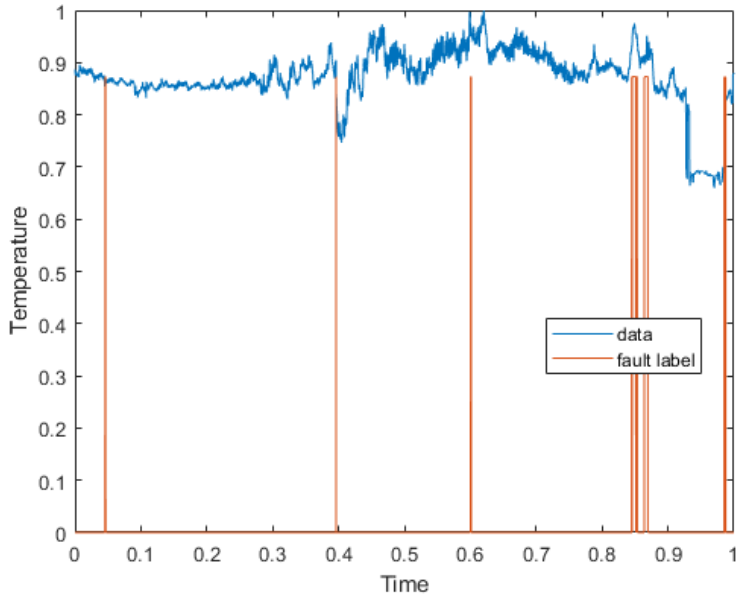

Figure 3. The SVM was used to predict faults in other years. The red spikes indicate either potential faults or inaccurate labels.

Fault diagnostics were then analyzed from the CMMS perspective by reviewing the CM work orders related to failures and fixes. CM work orders generated outside the regularly scheduled refueling outages were given higher priority in this review, since they can immediately affect component uptimes and plant output. One such fault was corroborated using the CMMS. An inboard oil leak was discovered in one of the CPs. This leak was due to a bearing's outer edge riding against the coupling side of the housing. The CP was taken offline during plant operation to fix the bearing leak, causing a 27.5% derate in the plant's output over a 9-hour period.

This leak was most likely discovered during a routine walk-through or via route-based vibration monitoring. The leak was not significant enough to impact those parameters that were being monitored and to which we had access. These parameters included gross load, inboard/outboard bearing temperatures, flow, and pressure. This shows that complete situational awareness is unavailable via the current capabilities of the embedded sensors, causing inspections to remain necessary. A potential way of diagnosing this type of leakage is through the position of the temperature control valve, which might vary as the leakage results in less volume to control. Alternatively, the bearing leakage could potentially be discovered via in situ vibration monitoring. Bearing vibrations may be affected by the size and position of the leak, or by how the bearing's outer edge rode against the housing. In such cases, the change in vibration would be detected in a timelier manner through continuous online monitoring.

4.3 Preventative Maintenance Recommendations

Maintenance plans are established to ensure safety and reliability during plant operation. PM is one aspect of such plans, and it is performed at pre-defined intervals, regardless of the component's current condition. The frequencies at which PM tasks are performed should be reviewed and updated as more operating experience is acquired. This creates a feedback loop in which maintenance frequency impacts component performance—in turn, affecting maintenance frequency. To speed up this feedback loop, current PM frequencies for healthy components are compared against the recommendations in the EPRI PMBD. By reviewing a component's operating history and current PM frequency, a justification can be made for suggesting that the frequency be extended.

Table 1. Example of current PM frequencies and recommendations

Component	PM Task	Current PM Frequency	EPRI PMBD	Recommendation
CP and CBP	Refurbishment	8 years	As required	Good candidate for frequency extension
	Vibration Monitoring	3 months	3 months	Keep
	Oil Analysis	6 months	6 months	Keep
Motor	Vibration Analysis	3 months	3 months	Keep
	Fan Cleaning	6 months	2 months	Keep
	Oil Analysis	6 months	6 months or 1 year	Good candidate for frequency extension
	Electrical Testing/ Inspection	5 years	4 years	Keep

Over the 5-year period, a total of 705 CBM activities were undertaken between the two PWR systems with regards to the FWCS. These activities vary in location and severity, ranging from simple inspections or alignments to bearing failures and equipment replacements. This paper focuses specifically on mechanical issues stemming from the CPs, CBPs, and their respective motors. The CBM work orders were reviewed first, in order to ascertain the historical health of the component.

In unit 1, the CBPs primarily experienced issues concerning mechanical seal leaks. CBP showed three instances of leakage or seal problems. The CPs experienced issues in regard to their connections to the condensate lube oil pump (CLOP). Unit 2 experienced fewer leak issues than unit 1, but included some bearing, sensor, and CLOP issues. The records of the CP and CBP motors for both units 1 and 2 were nearly impeccable. The only recorded issues were dirty filters in the unit 1 motors in 2019. That sort of record can open up opportunities to extend PM frequencies for cost reduction purposes.

A summary of PM tasks and the frequencies at which these tasks are performed for each component is given in Table 1. Next to each component's PM frequency is the EPRI-PMBD-recommended frequency based on subject-matter-expert opinion and component reliability data. Among the seven listed PM tasks, four have current frequencies that differ with those recommended by the EPRI PMBD. Based on CM history and the EPRI-PMBD-recommended frequencies, two tasks were deemed good candidates for PM frequency extensions for the PWR of interest: pump refurbishment and motor oil analysis.

A "refurbishment" is defined as replacing a component with a spare and then sending it off to be overhauled and repaired. Refurbishments are conducted every eight years during a plant outage, thus avoiding any unnecessary downtimes. Overall, the CPs and CBPs had a positive CM work history. With their EPRI-PMBD-recommended PM frequency of "as required," CP/CBP component refurbishment is a good candidate for PM frequency extension, though the final decision should not be based solely on component performance. An appropriate risk assessment and review of available sensors must be undertaken to determine the health of the pumps. To aid in determining when the pumps should be refurbished, it is recommended that the vibration monitoring and oil analysis continue at their current frequencies. These tasks can be used to monitor component health while trending any observable degradation. Additionally, periodic, route-based vibration monitoring can be replaced with online vibration monitoring (where applicable) in order to further aid in this process. The decision of when to refurbish is a complex one, requiring more information than available for this paper.

The motors driving the CPs and CBPs have experienced minimal problems over the last 5 years. The one instance noted in the CM work orders was due to dirty filters in the unit 1 CP motors. Since the

overall health of the components has been good over a significant period of time, PM frequency extensions should be considered in order to reduce the overall cost of maintenance. Since the only issue that the motors faced were dirty filters, and the current PM frequency is already longer than that recommended by the EPRI PMBD, the fan-cleaning frequency should not be adjusted. There is a potential opportunity to extend the frequencies of vibration and/or oil analyses for the motors. Table 1 lists the EPRI-PMBD-recommended frequencies as being 3 months for the vibration analysis and 6 months or a year for the oil analysis, depending on whether the motor is classified as critical or noncritical, respectively. Either of these frequencies could potentially be extended, perhaps even both. Furthermore, the vibration-monitoring PM task could potentially be replaced by continuous online monitoring, which is why Table 1 suggests oil analysis to be the preferred candidate for PM frequency extension. In the PWR system, all four CPs must be running for the system to operate at 100% capacity. The motors that drive the CPs are critical components. The CBPs are operated in a two-out-of-three fashion for 100% capacity. Their operation is alternated regularly in order to evenly spread out the accumulated wear. In this case, a backup CBP is present in case one fails to operate. Even with a potential backup, the CBP motors may still be considered critical, and a 6-month oil analysis may be advisable. With a risk analysis and more information about the oil analysis contents, the PM frequency could likely be extended to 9 months or even a year.

5 CONCLUSIONS

O&M costs for NPPs are very large but could potentially be reduced thanks to advances in fault diagnostics and PMO. The CMMS contains work orders detailing maintenance activities, and these can be used to identify and label faults. ML techniques such as SVM, in combination with feature extraction techniques, can be used to search for similar instances of those faults. Results indicate that not all faults can be identified via the current suite of embedded sensors. Additional sensors or inspections would be required to locate these elusive faults. This paper also showed the analytical steps necessary for PMO, from component health determinations to recommendations for action. This type of analysis can be extended to components within other systems, as long as their performance histories and PM frequencies are known. The final determination as to which PM tasks to extend (and to what frequencies) should be made in light of both the component's performance history and the results of a risk analysis. Further investigation needs to be made into the cause of anomalies observed within the data but not explained by the CMMS. These anomalies could be due to CMMS bookkeeping errors, operational shifts, sensor drift, etc.

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