Online and Offline Fault Detection and Diagnostics in a Nuclear Power Plant Condenser

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ABSTRACT

Nuclear power plants (NPPs) face significant financial pressures due to operational and maintenance costs. This research investigates Fault Detection and Diagnostics (FDD) techniques to optimize maintenance schedules and reduce expenses. The NPP condenser plays a critical role in converting turbine exhaust steam back into water for reuse. Condenser tube fouling, a prevalent fault mode, impedes heat transfer efficiency and can lead to decreased plant efficiency and safety risks. This study proposes an FDD framework that leverages raw signal analyses from temperature and pressure monitoring to detect and diagnose condenser tube fouling in both online and offline settings. The online approach facilitates close-to-real-time predictions, enabling proactive maintenance strategies. Additionally, the framework explores incorporating a condenser's maintenance history for enhanced diagnostics. We employ a dataset obtained from a simulated nuclear power plant condenser using the Asherah Nuclear Power Plant Simulator (ANS). ANS replicates the operational dynamics of a pressurized water reactor (PWR) type NPP. The proposed methodology utilizes an encoder-decoder (E-D) structured 1D-CNN model to analyze the raw signals. The research demonstrates consistent and accurate fault detection and diagnostics for condenser tube fouling in both online and offline scenarios. A high potential for generalization to unseen conditions was observed. However, online detection using small data windows necessitates caution due to potential false alarms around the transition points. Our findings pave the way for further exploration of robust diagnostics by accommodating a wider spectrum of fouling rates within degradation classes using ANS. This combined online and offline FDD approach offers a promising solution for promoting operational safety, efficiency, and cost-effectiveness in NPP condensers.

1. INTRODUCTION

Fault detection and diagnostics (FDD) are critical components of ensuring the safe and efficient operation of complex systems (Abid et al., 2021). FDD involves the continuous monitoring and analysis of system parameters to identify deviations from normal operating conditions, pinpoint potential faults, and diagnose their root causes (Ifeanyi, Dos Santos, et al., 2024). By enabling proactive maintenance and minimizing downtime, FDD plays a pivotal role in enhancing the reliability and performance of energy systems (Ma & Jiang, 2011).

In the context of a nuclear power plant (NPP), the associated operational and maintenance expenses represent a significant financial burden. Even with extended operating licenses, reactors are being decommissioned due to their lack of competitiveness against alternative energy sources, leading to early closures despite their strong safety track record (Walker et al., 2021). Thus, it is crucial to implement cost-saving measures to avert these premature shutdowns. The NPP condenser stands out as a key component where the implementation of FDD holds significant implications. The condenser serves the vital function of converting the steam exiting the turbine into water for reuse in the steam cycle (Attia, 2015). Any faults or inefficiencies in the condenser can have cascading effects on the entire power generation process, leading to decreased efficiency, increased operational costs, and potential safety risks (Webb, 2011a). One prevalent fault mode in condenser systems is condenser tube fouling, which occurs when contaminants such as dirt, debris, or biological growth accumulate on the inner surfaces of the condenser tubes. Fouling impedes heat transfer efficiency, reducing condenser performance and potentially leading to increased turbine backpressure and reduced plant efficiency (Ibrahim & Attia, 2015).

The objectives of this research include leveraging raw signal analyses to detect and diagnose faults in the condenser, with a focus on making close to real-time predictions. Additionally, this research will investigate the potential of incorporating a condenser's maintenance history into the FDD framework. By leveraging past cleaning and repair records, the system's diagnostic capabilities could be further enhanced.

The implementation of both online and offline FDD methodologies offers significant advantages. Online FDD provides continuous monitoring, enabling early detection of faults and facilitating prompt corrective actions. Offline FDD, through periodic in-depth analyses, offers a more comprehensive understanding of the condenser's health and aids in long-term performance optimization. This combined approach ensures a robust FDD system for the NPP condenser, promoting operational safety, efficiency, and cost-effectiveness.

The dataset used in this research was obtained from monitoring the temperature and pressure in the condenser of a simulated NPP. The simulation tool used is the Asherah Nuclear Power Plant Simulator (ANS). ANS is a specialized simulation tool originally developed for conducting cybersecurity evaluations within nuclear power plants. ANS accurately replicates the operational dynamics of a two-loop 2,772 MWt pressurized water reactor (PWR), encompassing primary, secondary, and tertiary loops alongside the control system. Developed using MATLAB/SIMULINK, ANS employs straightforward dynamic models for all components and systems (R. Silva et al., 2020; Hahn et al., 2021). Since ANS reasonably models the physical and operational characteristics of a specific NPP, it could potentially be used to run scenarios that might reveal underlying performance issues that are not immediately apparent due to the aggressive nature of routine NPP inspection and maintenance. By adjusting parameters and introducing fault modes, one could observe how the simulated plant reacts and identify any unexpected behaviors or performance degradations. We have customized ANS with specific modifications incorporated to assess the FDD capabilities of our proposed methodology, as detailed in sections 2 and 4.

Through a comprehensive analysis of raw signal data with different maintenance records, we aim to enhance the reliability and efficiency of condenser operation, contributing to the overall safety and performance of nuclear power generation. The rest of this paper presents a review of previous relevant research to underscore the contribution of this paper (section 2), and thoroughly describes the dataset utilized (section 3). Section 4 elucidates the methodologies adopted to accomplish the research objectives. The results of these methodologies and their implications are discussed in section 5, followed by a summary of the study and suggestions for future research in section 6.

2. BACKGROUND AND LITERATURE REVIEW

FDD is a common practice in various engineering fields including but not limited to building constructions (Shi & O'Brien, 2019), industrial machines and processes (Park et al., 2020), HVAC systems (Z. Chen et al., 2023), aviation (Basora et al., 2019), and energy (Shah, 2011). Across these fields, many methods have been developed for FDD over the years with preferences given to certain methods in some fields. In fields like the manufacturing industry, aviation, and energy where sensors are common or even required components for process monitoring and safety purposes, the abundance of data from these sensors has led to serious investigations into data-driven FDD methods. Some of these data-driven methods are purely statistical while others are Fuzzy logic-based, learned classification-based, clustering-based, and nearest neighbor-based (Chandola & Banerjee, n.d.). In this work, a direct classification learned from samples was preferred for its straightforward application and reduced requirement of expert knowledge.

In this study, we employ a purposefully structured Encoder-Decoder deep learning classification model (see section 4.3) for FDD. Deep learning models offer the distinct advantage of uncovering complex relationships without necessitating explicit feature engineering (Ahmed et al., 2023). Specifically, 1-dimensional convolutional neural network (1D-CNN) classifiers replaced conventional fully connected layer-based classifiers to preserve temporal relationships within the input data. This approach's ability to concurrently capture temporal dependencies of individual sensor variables and nonlinear correlations across multiple sensor variables is a key strength (Ifeanyi, Coble, & Saxena, 2024).

In the nuclear sector, aging plants face a variety of common potential faults. These include degradation in instruments' steady-state performance, such as sensor drift, as well as plant transients from events like control rod ejection. Anomalies in the reactor core, such as undesirable power distribution, and loose parts in the reactor coolant system are also concerns. Additionally, faults in equipment, like motor winding faults, are among the challenges encountered (Ma & Jiang, 2011). Fault modes of particular interest include the loss of cooling accident (LOCA), main steam line break, and steam generator turbine rupture (Elshenawy et al., 2021). Detection methods for issues such as crack detection (F.-C. Chen & Jahanshahi, 2017), pipe corrosion (Chae et al., 2020), sensor faults (Yao et al., 2020), and cybersecurity threats (Vaddi et al., 2020) are also highly studied. These faults can arise from the failure of individual components or a combination of component failures, highlighting the importance of monitoring and detecting component failures. While components like the reactor coolant pump (Di Maio et al., 2013), control rods (Ifeanyi, Coble, & Saxena, 2024), and steam generators (Razavi-Far et al., 2009) have been the focus of FDD research in the past, NPP condensers have received less attention. Over time, some FDD research efforts have been geared toward condenser-related systems such as the condensate-feed system as a whole (Vilkov et al., 2022), and its components like deaerators (Kim & Lee, 2004), and the condensate pump

(Walker et al., 2021) but as emphasized in section 1, the condenser's crucial role in NPP power generation underscores the need to address fault detection in the condensers. Thus, this research aims to detect condenser tube fouling through condenser monitoring, filling an important knowledge gap.

The condenser is a large chamber typically with a cylindrical shape and contains thousands of thin tubes running through its interior. Condenser tubes are the numerous thin tubes that snake through the interior of the condenser. They provide the surface area where the hot, low-pressure steam exiting the turbine condenses into water. Cooling water flows through these tubes' externals, absorbing the heat from the steam in the tubes' internals and carrying it away. The condenser tubes are the workhorses within the condenser, facilitating the transfer of heat from the steam to the cooling water (Webb, 2011b; Sun et al., 2018). Condenser tubes are typically made from strong, corrosion-resistant materials like titanium or stainless steel to withstand the constant flow of hot steam and cooling water (Brodov et al., 2019). These tubes are susceptible to leaks or blockages over time (Choi et al., 2010). NPPs have regular maintenance procedures to clean and inspect the condenser tubes to ensure optimal performance (Fayard, 2008). To optimize these maintenance procedures, monitoring the condition of the tubes and performing FDD is crucial.

Although a previous paper has explored the FDD of condensers in coal power plants (Muñoz & Sanz-Bobi, 1998), investigating FDD in NPPs remains imperative. Unlike coal-fired boilers, the radioactive primary loop of an NPP operates at significantly higher pressure and temperature levels. Consequently, the exhaust steam from a nuclear turbine is hotter compared to that from a coal plant turbine. The condenser in an NPP must efficiently remove heat to maintain optimal turbine performance by sustaining lower pressure levels. In contrast, the operating temperature of coal boilers results in cooler exhaust steam, imposing a less rigorous cooling demand on condensers in coal plants. Therefore, further exploration of FDD in NPPs is essential to ensure the efficient and safe operation of these critical facilities, given the distinct operational challenges and requirements they face compared to coal-fired plants. Recent research attention given to NPP condensers focused on prognostics (Xiao et al., 2023; Zanotelli et al., 2024) which is concerned with estimating the remaining useful life of the investigated system, a different task from FDD.

Several research endeavors have employed the ANS model for NPP cyber security assessment, establishing its usefulness and validity (Lee et al., 2022; R. B. Silva et al., 2021). For example, ANS was used to simulate a nuclear power system to detect false data injection on key equipment such as the control system actuator (Zhang & Coble, 2020). In more recent prognostics applications, ANS has been adapted to include degradation in the condenser caused by tube fouling (Xiao et al., 2023; Zanotelli et al., 2024). Tube fouling was simulated by reducing the number of useful tubes in the condenser over time (Xiao et al., 2023). Fouling hinders the condenser's ability to transfer heat by blocking the tubes and adding a new layer that reduces heat transfer efficiency. This layer also slows down the flow, which further reduces heat transfer. By removing tubes, we can simulate these effects, mimicking the decreased heat transfer and altered flow caused by fouling. This paper builds on these recent modifications of ANS by adding random Gaussian noise across the PWR system to vary the response of the NPP for each simulation run before applying different FDD techniques.

3. DATA SET

As mentioned in section 1, ANS was used to obtain temperature and pressure measurements in the condenser of a simulated NPP. These measurements were obtained under ten operating conditions shown in Table 1. These conditions were generated by varying the final fouling thickness in the condenser tube and the repair history. ANS offers the possibility of immediately restoring the health of a degraded component and this was used to simulate different maintenance histories where a 70% repair mimics partial repairs like incomplete removal of debris and a 100% repair mirrors a replacement with a new and similar component. ANS further allows the user to specify two final fouling thickness values, one before repair and another after repair. For the repaired cases in Table 1, the same values were used before and after repair. As shown in Fig. 1, the final fouling thickness was used as a proxy for varying fouling rates since the degradation is linear over time. Since all simulations had the same period of observation, unrepaired scenarios with higher thicknesses will degrade faster. Fig. 1 demonstrates the fouling thickness profile of an operating scenario of the condenser tubes under varying operating states. As seen, fouling thickness remains at 0 mm during normal operation between 0-3000 seconds but steadily rises after fault onset at 3000 seconds until it reaches an initial final fouling value of 2.5 mm at 6500 seconds. The fouling thickness drops to 30% of 2.5 mm after the simulated instantaneous 70% repair and then rises again at a slower rate than before, eventually reaching a final thickness value of 1.5 mm.

The plant was run for ten thousand seconds during each simulation but multiple simulations were done under each condition to produce multiple sequences of ten thousand seconds. For example, under scenario '10' (normal operation) where there is no degradation and therefore, no repair of the condenser, Fig.2 shows two samples of the generated sequence data. The sampling frequency of the sensors is 10Hz so 100,000 points of data were obtained per sequence. These were however mean-filtered with a window size of '10' without overlap to have one data point per second. The filtered versions were the samples used in the research. The ANS model was created

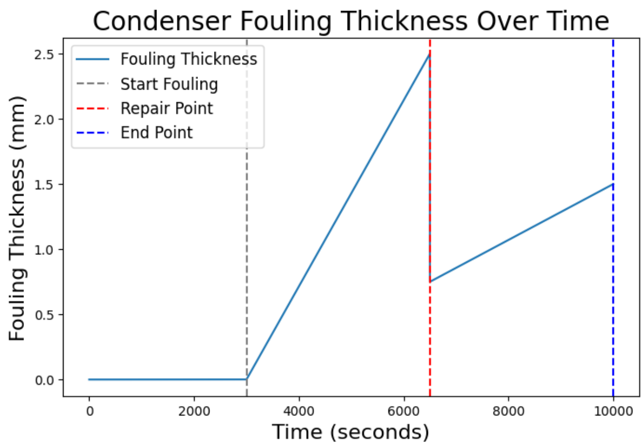
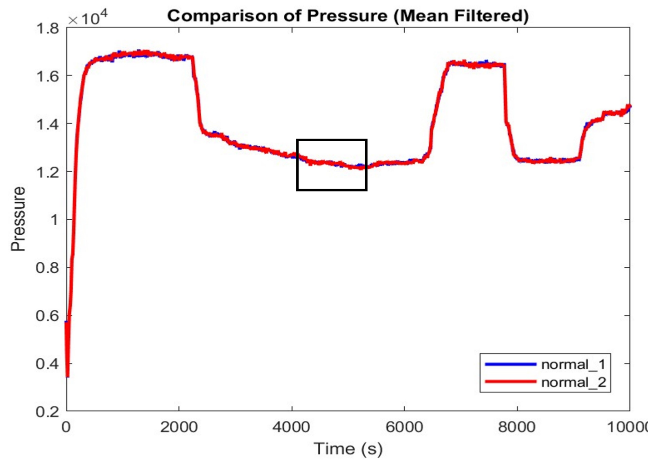


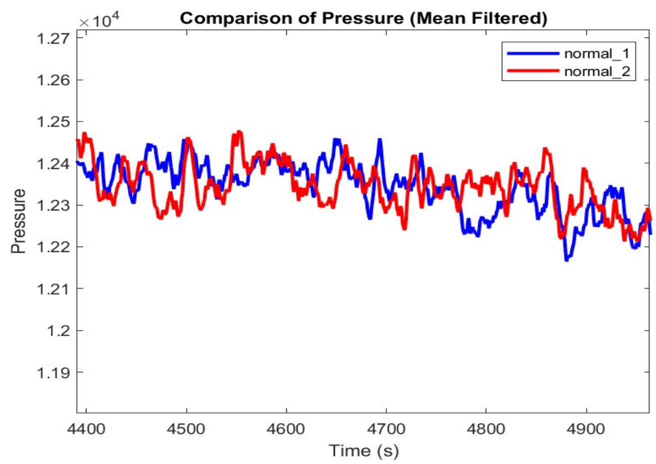
Figure 1. Fouling profile for different operating states

Table 1. Operating Scenarios of the Simulated Data

S/N	Final Fouling Thickness (mm)	Maintenance History
1	2.5	100%
2	3.0	
3	4.0	
4	2.5	70%
5	3.0	
6	4.0	
7	2.5	No Repair
8	3.0	
9	4.0	
10	No Fouling	No Repair



a)



b)

Figure 2. Pressure profile - two normal sequences. a) - mean filtered, and b) - zoomed-in section.

for cyber security assessment tests so repeated simulations did not originally vary. For this research, white noise was added to the ANS model at different points to simulate realistic variations in operations due to measurement and process noise. The marked-out section of Fig.2a (see zoomed-in version (Fig.2b)) emphasizes the variations in the two sequences generated under the same operating scenario. This variation shown for scenario ‘10’ alone is experienced in every other simulated scenario.

The normal operation for all tests in this research is defined as a complete sequence during the 10,000 seconds of observation that does not exhibit signs of degradation (scenario ‘10’). A faulty operation, on the other hand, can take one of any of the other nine scenarios (‘1-9’). For all tests conducted in this research, degradation began at observation 30,000 (3000 seconds), except otherwise stated. Considering the scenarios without any repair history, Fig. 3 shows how the unfiltered pressure profile differs for components with different degradation rates, highlighting the potential of fault detection and diagnostics from raw signal analyses. As shown, significant deviations begin around observation 30,000 with the faster degrading component most deviating from the normal profile.

To summarize this section, it’s crucial to note that each simulation output, post-filtering, comprises two variables, each consisting of 10,000 data points, respectively representing condenser temperature and pressure. In the offline tests conducted in this study, these outputs directly served as samples for the models. The specifics regarding the number of samples utilized for various tests are elaborated in section 5. For the online tests, these sequences were segmented into windows, a procedure detailed in section 4.

4. TECHNICAL APPROACH

There were two general approaches (online and offline) to the detection and diagnostics in this work. Detection concerns classifying samples as faulty or not whereas diagnostics investigates the different fault types. The fault types in this paper refer to the degradation levels since only one fault type was investigated. What a sample means in this paper depends on whether the task is online or offline. The samples of the different tasks are defined in their appropriate sections.

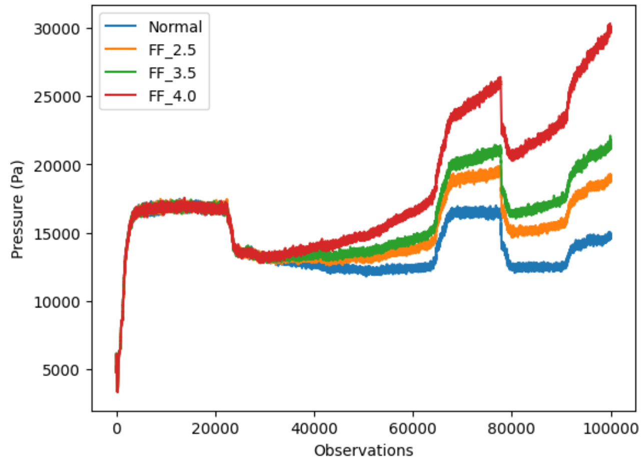


Figure 3. Pressure profile for different fouling rates

4.1. Detection

For offline detection, each sample is a complete sequence with the two monitored variables. In other words, a sample has shape $(10000, 2)$ so that the input to the model is of shape $(n, 10000, 2)$ where n is the chosen batch size. This simulates the real-life scenario where the plant is run up to the point where a scheduled outage is required. The analysis of the monitored signal may be done at this point to check the existence of faults in components that may not have been scheduled for maintenance during that outage period. If a fault exists, the component may be maintained before it is brought back online. This type of detection involves defining what constitutes the faulty class and in this work, the faulty class was defined in three different ways leading to three different tests. In the first case, the faulty class included degraded samples with a final fouling thickness of 3.0 mm and did not undergo any kind of repair (scenario ‘8’ from Table 1). The second test included a mix of samples with the three different simulated degradation rates in its faulty class (scenarios ‘7’, ‘8’, and ‘9’) and the final test had faulty samples with the same degradation rates but different maintenance histories (scenarios ‘2’, ‘5’, and ‘8’).

In the case of online detection, the idea was to make predictions at more granular levels of time so that it is not required to wait for an outage before detecting faults. These online predictions should potentially improve maintenance planning so that the outage period is reduced. To achieve this, the complete sequences were broken into smaller windows of fixed lengths, and in most cases, only one complete sequence was required to train the classifier. This means that the input shape of the model is $(n, window_length, 2)$ where n is the selected number of windows (batch size) processed at a time. Window length was varied to produce multiple tests in this category before varying the degradation start time to better understand the observed behavior of the model. Finally, the generalization capability of a trained model was tested with samples of different degradation rates.

4.2. Diagnostics

In the offline case of diagnostics, the samples were created in the same way as in the offline detection but this task was a multi-class classification where the number of classes depended on the number of fault categories investigated in a particular test. There were three different tests in this category of tests. The first was an attempt to diagnose the different degradation rates of the samples without repair. The second diagnosed degradation rates for the partially repaired components whereas the third repeated the task for replaced components.

The online version of the diagnostics required simulating the operation of a component that degrades at a high rate before undergoing partial repair which restores 70% of its health and leads to the reduction in the rate of degradation. Fixed windows of the described sequence of operation are created and assigned three different classes (normal, high degradation, and low degradation). The model is trained on windows created from two complete sequences before testing on a third sequence. This test could be useful for close to real-time assessment of degradation levels of a component under fault. The component may be allowed to continue to operate under fault until a threshold degradation level is reached.

4.3. Model

In this study, detection and diagnostics were treated as classification tasks, with the offline approach processing full time-series data and the online approach analyzing time-series windows. We employed a 1D-Convolutional Neural Network (1D-CNN) because of its ability to capture local dependencies in time-series data, making it particularly effective for detecting subtle transitions from healthy to faulty states. This is crucial for early fault detection, especially in critical applications, where recognizing evolving patterns is essential. Unlike simpler methods such as decision trees or expert systems, which often rely on static rules or thresholds and may struggle with the temporal dynamics of the data, the 1D-CNN excels by learning and adapting to these changes. Moreover, the 1D-CNN can automatically learn and extract relevant features from raw sensor data, reducing the need for extensive manual feature engineering, which is often required by rules-based methods. While simpler methods like expert systems or decision trees could be applied to fault detection and diagnosis in nuclear power plant condensers, they may lack the flexibility and accuracy required for this critical and dynamic application.

Additionally, we utilized an encoder-decoder (E-D) architecture as illustrated in Figure 4. E-D structures, renowned for their ability to distill essential information from data, have found success in diverse applications, such as denoising with autoencoders (Vincent et al., 2008) and image segmentation using the U-Net CNN architecture (Yin et al., 2022). Given the varied degradation levels within the faulty class, prioritizing the extraction of crucial information aids in generalization within this class while effectively distinguishing it from the healthy class during detection. This choice of the E-D structure is particularly pertinent considering the limited number of examples in each class and the absence of data augmentation in our study.

The input layer can contain either sequences for offline tasks or windows for online tasks. The final layer of the model comprises two dense neurons with a $softmax$ activation function, reflecting the two classes of interest in the detection tests. For other tasks, the number of neurons in the final layer is adjusted to align with the classes under investigation, with most diagnostics tasks necessitating four final neurons. Despite the complexity of the task and the constraint of limited data samples, the employed model remains relatively compact, with approximately 17,000 trainable parameters.

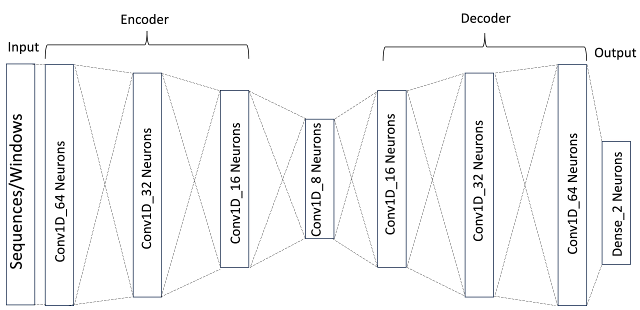


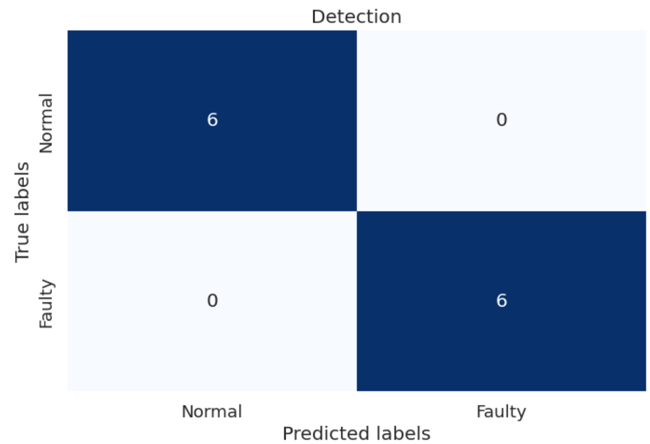
Figure 4. Sample model for detection tasks - Encoder-Decoder structure

5. RESULTS

Having established the methodology for our study in section 4, we now turn our attention to the results, where we present the findings and analyses stemming from the various implemented approaches.

5.1. Detection

This section discusses the findings in both the offline and online detection tests. For the offline set of tests, three versions were conducted as described in section 4.1 and Fig. 5 shows the confusion matrices for the three different tests. For all tests in this category of tests, 30 samples per class were used in total where 80% was for training and 20% for testing. Fig. 5a shows the result when the faulty class only contains samples from scenario '8' in Table 1. As seen, all test samples were correctly classified. When the faulty class contained a mixture of samples from scenarios '7', '8', and '9' in equal proportions, the detection was perfect as seen in Fig. 5b. In the third case, the faulty class was a combination of samples from scenarios '2', '5', and '8' in equal proportions. Again, the fault detection model accurately classified all test samples.



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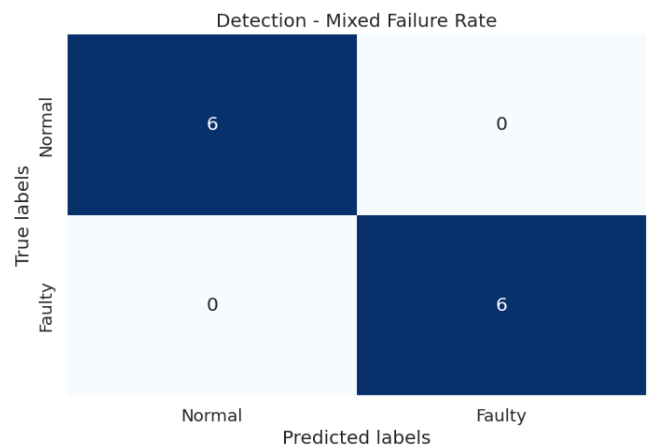

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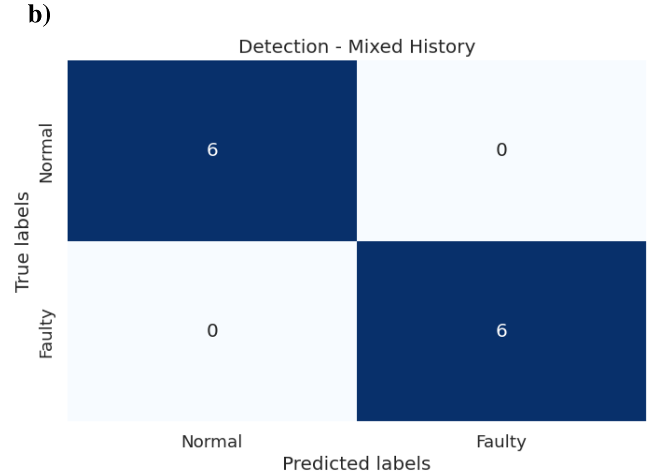
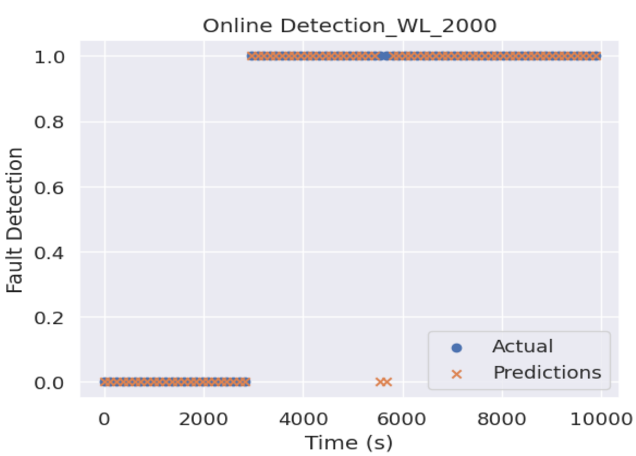


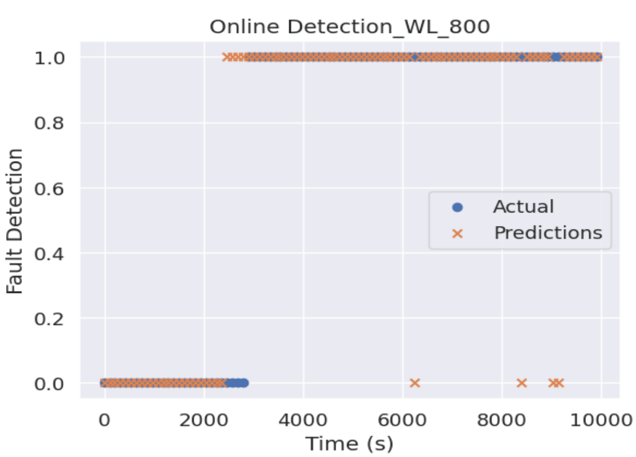
c)

Figure 5. Offline detection. a) - Single fouling rate, b) - Mixed fouling rate, and c) - Mixed maintenance history.

For the online tests, one complete sequence was split into windows for training before testing on a separate sequence split into windows of the same length. Healthy windows are in class '0' whereas faulty windows are in class '1'. The fault detection plot is used to show the classification of the windows over the observed period. The first test investigated the effects of varying window lengths with the same window overlap of 100 points (see Fig.6). For the first case with 2000 points per window (Fig.6a), an almost perfect detection was observed whereas as the window length was decreased to 800 (Fig.6b), misclassification began to occur mostly around the transition point (3000 seconds). In both cases, there were spurious misclassifications of faulty periods as normal. A better prediction from the longer-length windows may be expected because the model is being presented with more example points per window aiding in better identifying the long-term temporal relationships between the data points.



a)



b)

Figure 6. Online detection - Varying window length. a) - Window length 2000, and b) - Window length 800.

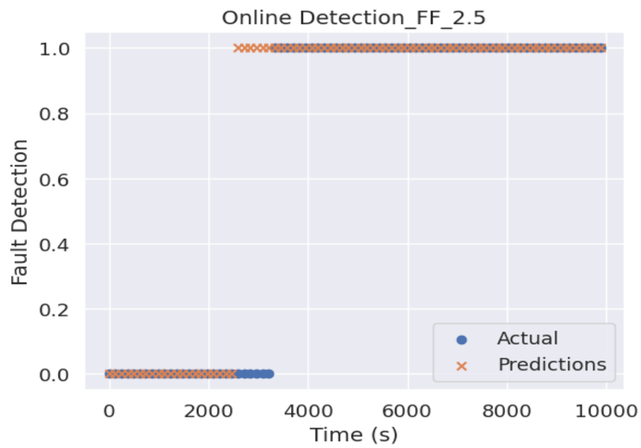
The next online detection test was for generalization capability and a window length of 1000 was used with an overlap of 100. The model was trained on windows from a scenario '7' sequence but tested on sequences from scenarios '7' (Fig. 7a), '8' (Fig. 7b), and '9' (Fig. 7c). The results from Fig. 7 show that the proposed approach and model have a high generalization potential. All tests showed accurate detections except around 3000 seconds. This generalization performance is not unexpected because the model was trained to detect the smaller rates of degradation which should be potentially harder to detect than higher degradation rates. Generalization to lower degradation rates will be tested in the extension of this study.

So far, except for Fig.6a, it is observed that early fault classification occurs around the transition point which is not unexpected since those windows likely contain data points from both normal and faulty operation periods. It is, however, noteworthy that healthy windows are classified as faulty around that point. Although this is undesired in practice because it increases the rate of false alarms, It can be managed by adding a threshold to the number of detected windows before making a final decision. For example, a threshold of 5 consecutive faulty windows before taking corrective actions would eliminate the false alarms in Fig.6b. This false alarm rate is likely because the normal operating points are only about one-third of the total, making the majority of the points faulty. As a result of this imbalance in the training samples, the model may have been slightly more sensitive to faults such that as soon as faulty points are included in the test windows, the observed phenomenon of early fault prediction around the transition point occurs.

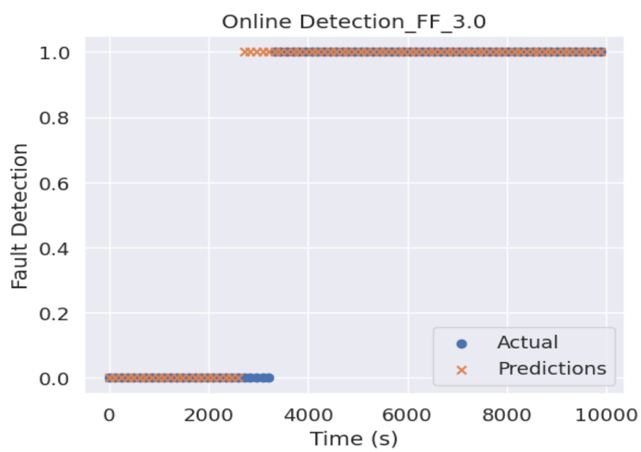
To investigate the hypothesis, two approaches may be taken: First, the operating period could be reduced to 6000 seconds with the degradation start time maintained at 3000 seconds; Second, the degradation start time could be increased to 5000 seconds leaving the operating period at 10,000 seconds. The second approach was taken in this paper to avoid losing training data that could be potentially relevant while balancing the classes. A window length of 1500 was used with an overlap of 100. The model was retrained with balanced samples before testing. As shown in Fig. 8, this approach resulted in misclassifying the faulty periods around the transition point as normal, supporting the suspicion of the effect of class imbalance on the previous models. Now, a slightly delayed fault prediction is observed as opposed to early fault predictions reducing false alarm rates.

5.2. Diagnostics

Offline diagnostics involved one broad test type namely the degradation rate test. For all offline diagnostics in this study, each class had 30 samples (sequences) separated into training and testing with the same strategy employed for offline detection (see section 5.1).



a)



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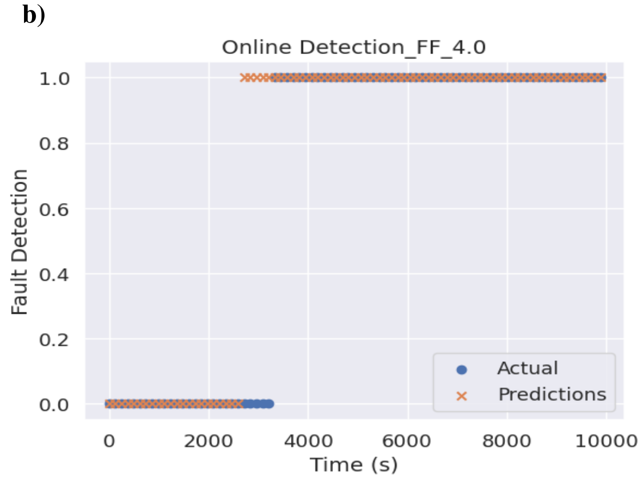

c)

Figure 7. Online detection - Generalization test. a) - Final fouling 2.5 mm, b) - Final fouling 3.0 mm, and c) - Final fouling 4.0 mm.

The task is to differentiate samples from the four different fault classes (no fault, and three degradation rates). It can be considered redundant to diagnose the state as nominal after fault detection but this was done because it could be useful in cases where a fault is falsely detected. In this test category, there were three tests with similar goals of diagnosing the level of degradation of samples. In diagnosing fault levels in components with no prior maintenance (Fig. 9a), classification was excellent in all classes except for a single misclassification in the 2.5 mm final fouling thickness class. Similar fault level classification results were seen for the maintained components (Fig. 9b) and the replaced components (Fig. 9c) with singular misclassifications respectively in the 4.0 mm and 3.0 mm final fouling thickness categories.

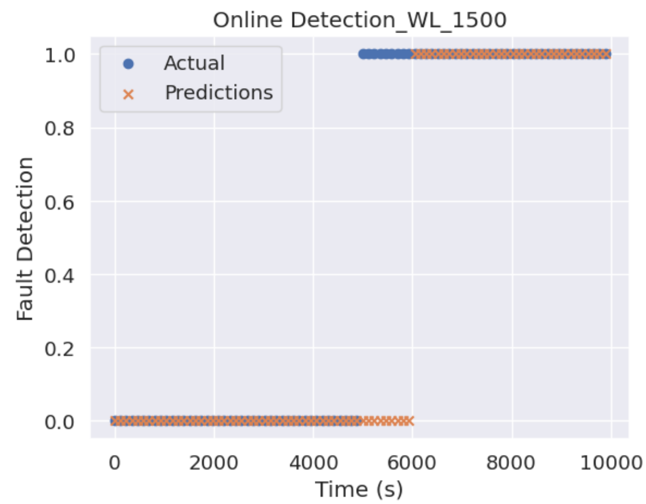

Figure 8. Online detection - Balanced data

Online diagnostics was treated as online detection where one component experiences different rates of degradation before and after repair. In the investigated scenario, at 3000 seconds, a high degradation rate with a final fouling thickness of 3.5 mm was introduced before repair occurred at 6500 seconds followed by a lower degradation rate with a final fouling thickness of 2.0 mm. The pressure profile of the described scenario is shown in Fig 10 with the test result shown in Fig 11. As with other online tests windows were created but in this case, two training sequences were required to provide more example windows to the model. The test was done on a separate third sequence. The window length used in this case was 2500 with an overlap of 200, hence the reduced number of windows. The result shows a single wrong classification out of 38 windows across the three classes.

While the proposed methods and classification models in this paper demonstrate promising performance in simulated environments, their applicability to real-world experimental data necessitates scrutiny. Despite efforts to introduce measurement noise into the simulation for enhanced realism, transitioning from simulated to real-world data poses challenges including additional uncertainties and unforeseen operational conditions. If real-world data become available, the accu-

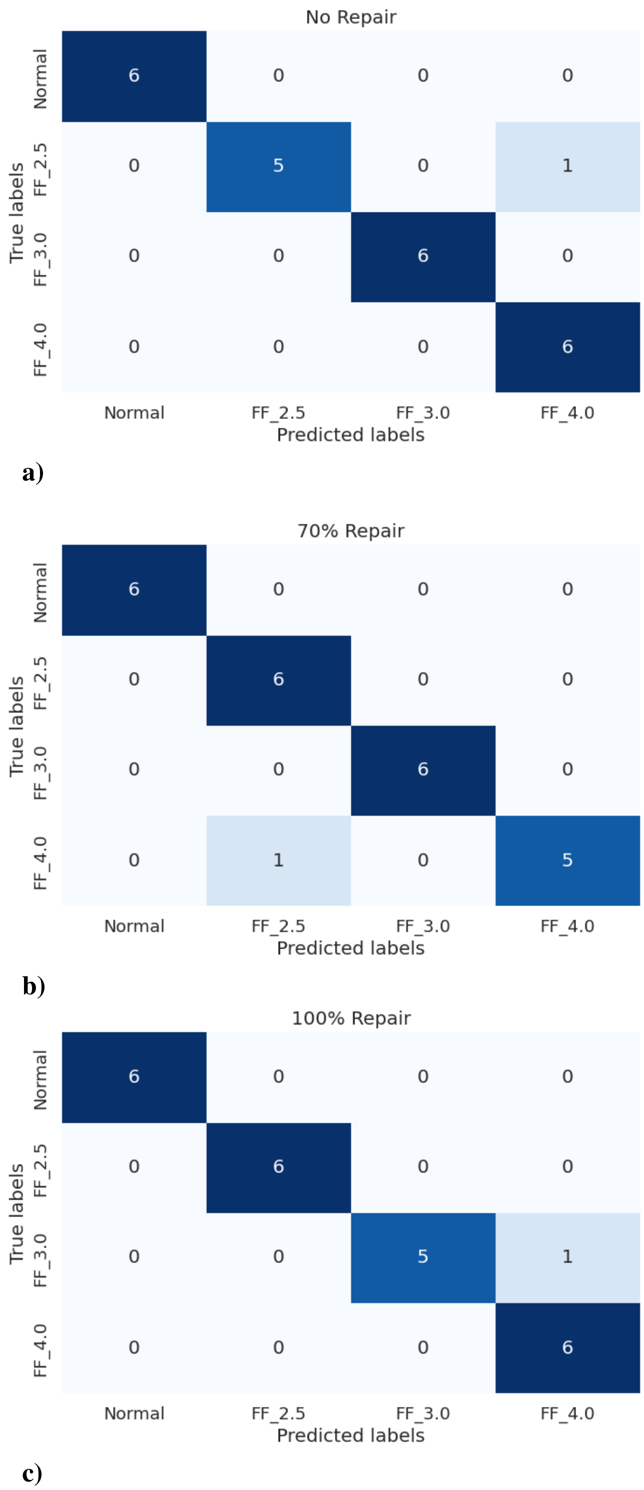

Figure 9. Offline diagnostics - Degradation rate test. a) - No repair, b) - Partial maintenance, and c) - Component replacement.

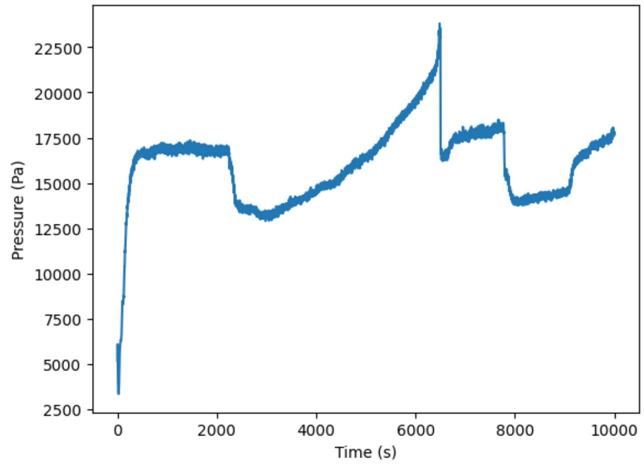

Figure 10. Pressure profile - Mixed rates with repair

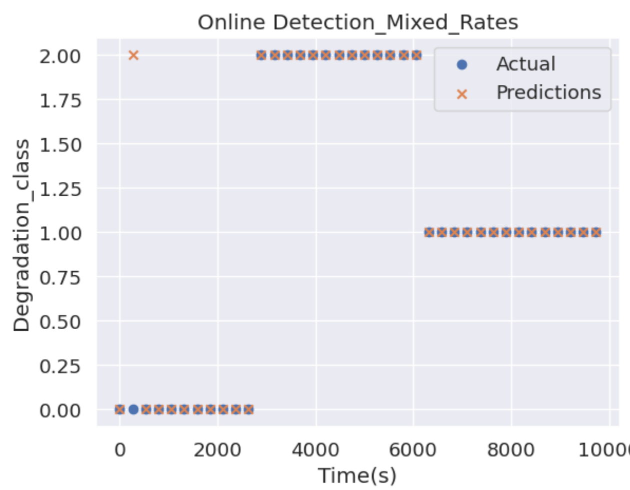

Figure 11. Online diagnostics

racy of the simulated fault scenarios and the resulting analysis could be validated; however, operating NPPs typically perform routine inspection and maintenance at intervals that eliminate fouling before it impacts operation, and real-world data is thus difficult to obtain. Furthermore, accurately replicating fault scenarios encountered in real-world settings within simulations can be intricate.

6. CONCLUSION

Through the utilization of an E-D structured 1D-CNN model to analyze raw temperature and pressure signals, consistent detection of condenser tube fouling faults was achieved both in online and offline scenarios of the simulated operations. Model performance was well generalized to unseen but worse fault conditions. However, it is crucial to exercise caution, particularly in online detection, as predictions derived from small-sized windows may introduce bias stemming from class imbalance. Similarly, employing a comparable strategy, both offline and online diagnostics demonstrated high accuracies with the investigated system, yet there remains an avenue for future exploration regarding online diagnostics with smaller window sizes. In future endeavors, it could be beneficial to enhance the versatility of the simulator (ANS) by customizing it to accommodate a broader spectrum of fouling rates within each degradation class. This adaptation could significantly bolster the robustness of the diagnostics model, allowing for more comprehensive analyses and refined insights into the behavior of the system under varying degrees of fouling.

Overall, this research underscores the importance and substantial potential of embracing a hybrid approach to FDD. By integrating both online and offline methodologies, this approach enables informed short-term maintenance decisions through real-time data analysis, while simultaneously facilitating the development of optimized long-term maintenance plans through comprehensive offline analyses.

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