NUCLEAR TECHNOLOGY · VOLUME 210 · 2362–2372 · DECEMBER 2024

DOI: https://doi.org/10.1080/00295450.2024.2342187

Forecasting the Remaining Useful Life of Filters in Nuclear Power Plants

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Received November 20, 2023
Accepted for Publication April 5, 2024

Abstract — *To function effectively, nuclear power plants rely on the effective filtration of air, water, and process fluids, examples of which include inlet sea water, reactor coolant, plant drinking water, and moderator purification. Filtration assets degrade over time, which impairs their filtering performance and reduces the flow rate. Being able to determine the remaining useful life (RUL) of a filter could result in benefits, particularly when moving from a time-based to a condition-based maintenance strategy that would optimize the filter replacement procedure and reduce early replacement of filters that are still fit for purpose. For many filter applications, a time-based strategy is sufficient. For strategically important assets, such as fueling machines, there are benefits to be gained from the development of predictive maintenance strategies.*

In this paper, we propose a predictive condition-based strategy using differential pressure data as a proxy for filter health. The key objective in this work was the creation of a model that could predict a filter asset RUL. The differential pressure for 7 to 14 days is predicted by a heuristic-based regression model of the history of each filter. This approach has been demonstrated using a civil nuclear generation application but could be applied to wider applications. While this model is still undergoing on-site evaluation, it has been estimated that there will be an operationally significant lifetime cost reduction.

Keywords — *Condition-based maintenance, predictive analytics, remaining useful life, nuclear power plants, filters.*

Note — *Some figures may be in color only in the electronic version.*

I. INTRODUCTION

In numerous industrial settings, low-value assets like filters are periodically replaced according to a time-based maintenance approach. This is primarily because these filters lack instrumentation, making it challenging to directly assess their current health status.[1] While it is generally uncomplicated to replace such assets in various applications, the nuclear sector presents unique challenges.[2] Factors such as regulatory constraints, specific replacement timelines, and concerns for engineer safety complicate the replacement process.[3] Consequently, proxy measurements, such as the differential pressure across the filter, are commonly employed to estimate the filter's condition and predict its remaining useful life (RUL).[4] For instance, as the filter degrades, the flow rate decreases, indicating potential

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issues like clogging, or there may be a sudden spike, suggesting filter collapse.[5] Presently, in many applications, the lack of sufficient prognostic information results in the reliance on a time-based maintenance strategy for the routine replacement of these filters.[6]

While current methods in the nuclear sector, particularly for the maintenance of low-value assets like deuterium filters in CANada Deuterium Uranium (CANDU) nuclear reactors, rely heavily on time-based strategies due to a lack of direct health assessment instrumentation, such approaches present inherent limitations. The reliance on time-based maintenance overlooks potential variations in filter degradation rates, leading to either premature replacements, which incur unnecessary costs, or delayed replacements, posing potential safety risks. Additionally, the absence of real-time monitoring and predictive maintenance capabilities hinders proactive intervention, leaving operators reactive to emergent issues. Consequently, there is a pressing need to transition from conventional time-based approaches to condition-based maintenance strategies. Furthermore, the cost implications of raising a work order for an engineer to replace a filter on short notice, such as reallocating resources from other tasks, are substantial compared to scheduling maintenance with advanced notice. This highlights the economic significance of accurately predicting the RUL of deuterium filters, as it allows for efficient allocation of engineering resources and minimizes the financial impact associated with unplanned downtime and reactive maintenance practices.

This paper introduces an approach aimed at transitioning from a time-based maintenance strategy to a condition-based maintenance strategy for the replacement of deuterium filters in CANDU nuclear reactors. The initial step involved extracting information from routinely collected data in the reactor fueling machine log files. To achieve this, a custom parser was developed to suit the specific format of the log data. Initially intended for post-failure analysis, these log data were repurposed for condition monitoring by extracting pertinent attributes based on operational tags. After extracting, processing, and cleansing the log files, the focus shifted to constructing an analytical model for predicting the state of the filters. Utilizing all available historical data for the deuterium filters, a constrained regression model was created to forecast the RUL of the filters. This prediction provides engineers with a 7-day advance notice before the alarm limit is exceeded, enabling the timely issuance of a work order for filter replacement. The novelty of the approach lies in its integration of routine data from fueling machine log files, into a predictive maintenance strategy. Rather than relying solely on traditional time-based maintenance schedules, the approach repurposes these data for condition monitoring, allowing for more precise predictions regarding the state of deuterium filters. Additionally, the development of a custom parser tailored to the specific format of the log data demonstrates a novel solution to data extraction challenges. Furthermore, the construction of an analytical model for predicting the RUL of filters represents a novel application of predictive analytics. Overall, the combination of data extraction and predictive modeling constitutes a novel approach to optimizing maintenance strategies in CANDU nuclear reactors.

II. BACKGROUND

II.A. CANDU Nuclear Reactors

The CANDU nuclear reactor is a unique design renowned for its flexibility and efficiency in generating electricity.[7] Developed in Canada, the CANDU reactor employs natural uranium as fuel and uses heavy water (deuterium oxide) both as moderator and coolant. Unlike most other reactor designs, CANDU reactors can be refueled without shutdown, enabling continuous operation and maximizing efficiency.[8] This design feature, coupled with its inherent safety mechanisms, makes CANDU reactors highly reliable and economically competitive. In the operation of a CANDU nuclear reactor, the refueling process is a critical aspect that ensures continuous power generation. The refueling machine used in CANDU reactors is a sophisticated piece of equipment designed to handle heavy water coolant and fuel channels with precision. These machines are remotely operated to minimize radiation exposure to personnel. One crucial component of the refueling process is the deuterium filters. These filters are responsible for removing impurities from the heavy water coolant. Ensuring the purity of the heavy water coolant is essential for maintaining the efficiency and safety of the reactor operation. Regular maintenance and replacement of these filters are part of the reactor's ongoing maintenance schedule to ensure optimal performance and safety.

The selection of deuterium filters as the component of interest was due to their critical role in ensuring the purity and safety of the heavy water coolant within CANDU nuclear reactors. While it is true that nuclear power plants contain several high-value components, the significance of deuterium filters lies in their direct impact on reactor performance and safety. These filters are integral to maintaining the optimal functioning of the reactor system by removing impurities and contaminants from the coolant, thus preventing potential disruptions to operations and safeguarding against equipment damage or failures.

Considering the cost-effectiveness of implementing a RUL model for deuterium filters, it is crucial to understand the expense associated with predictive maintenance against the potential savings and operational benefits it offers. While the upfront costs of developing and implementing the RUL model may be notable, the long-term benefits outweigh these expenses.[9] By accurately predicting the RUL of deuterium filters, operators can schedule maintenance activities more efficiently, minimizing unplanned downtime and reducing the likelihood of costly reactive repairs or replacements. Additionally, optimizing maintenance schedules based on predictive analytics can lead to improved resource allocation, increased equipment lifespan, and enhanced overall operational reliability.

II.B. Maintenance Strategies

In various industrial applications, two predominant maintenance strategies are commonly employed: time-based maintenance and condition-based maintenance.[10,11]

Time-based maintenance follows a conventional approach, relying on the repair or replacement of assets based on historical failure time analysis. This method operates under the assumption that the asset's failure rate is predictable. The bathtub curve depicted in Fig. 1 illustrates the expected failure rate of an asset throughout its design life. In the nuclear sector, time-based maintenance strategies often incorporate significant conservatism due to the safety and financial implications of failures. Consequently, assets are frequently addressed proactively, even before reaching the point of necessity. Moreover, the lack of available failure data for modeling failure rates is a notable challenge, primarily stemming from the same safety and financial concerns associated with failures.

Condition-based maintenance, also known as predictive maintenance, determines the optimal replacement time for an asset based on its specific operating condition.[12,13] This involves monitoring various process variables, such as vibration, temperature, flow rate, contaminants, and noise levels. By tracking and modeling these variables over time, predictions can be made regarding when maintenance decisions are necessary. The entire process can be divided into three main tasks: data acquisition, data processing, and maintenance decision making (see Fig. 2)[14]:

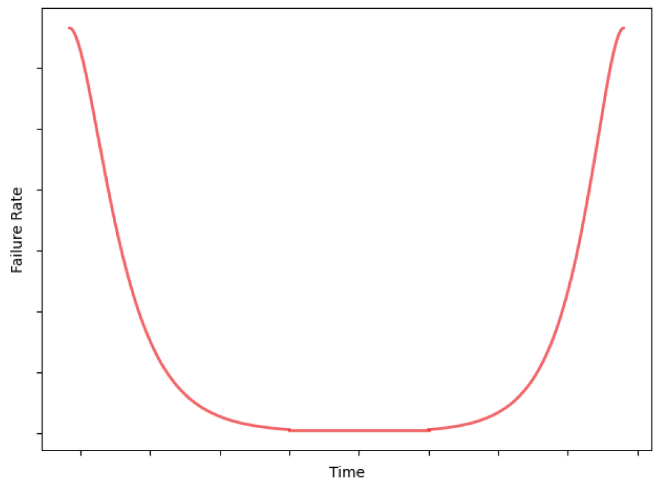

Fig. 1. Bathtub curve representing early life failure, through life incidental failures and wearout.

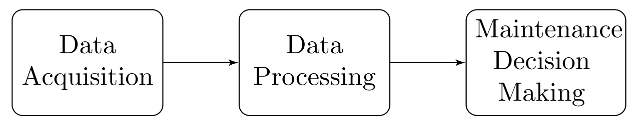

Fig. 2. Three-stage condition-based maintenance approach.

1. *Acquiring data*: In this phase, essential data about the asset's health are collected.

2. *Processing data*: This stage involves the analysis and modeling of relevant data to enhance comprehension and interpretation.

3. Decision making for maintenance: Based on the analyzed data, predictions or recommendations are generated regarding any necessary maintenance interventions.

III. METHODOLOGY

The information stored in the log files of the fueling machine acts as a substitute for machine health measurements in this particular application. These log files are text based and document each operation conducted by the fueling machine. A specific operation within these files provides details about the differential pressure across the deuterium filters. As the filter degrades, the flow rate diminishes to the extent that there is no flow, indicating possible filter clogging. Alternatively, a sudden spike in flow rate could signify filter collapse. Figure 3 illustrates the proposed process for initiating a RUL prediction, beginning with the text-based log files.

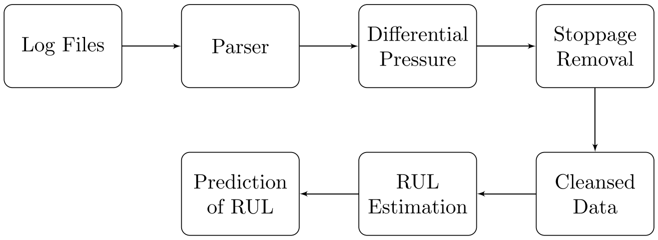

Fig. 3. Methodology for RUL prediction from fueling machine log files.

III.A. Data Extraction

The initial step involved acquiring regularly recorded data from the log files of the reactor fueling machine. This required developing a specialized parser tailored to the complex log data format, enabling the extraction of relevant attributes based on operational tags and revealing a substantial amount of data. Figure 4 provides an example of an entry in the log file, with all sensitive information concealed. By extracting information from each log file entry with the operation tag "1075," details such as date and time, quadrant, and differential pressure could be obtained. These data could then be graphically represented over time for each quadrant of the nuclear reactor, as illustrated in Fig. 5.

The differential pressure information saved in the log files is stored in octal format. To assess the filter's health and make predictions, it was essential to convert these data into decimal kilopascals (kPa) first. Equation (1) provides an illustrative example of the conversion process for differential pressure stored in octal format in the fueling machine log files into the corresponding differential pressure in kilopascals:

$$
\begin{aligned}
P_{octal} &= 2750 \\
P_{decimal} &= (2 \times 8^3) + (7 \times 8^2) + (5 \times 8^1) + (0 \times 8^0) \\
&= 1512 \\
P_{\mathrm{kPa}} &= 0.610 \times P_{decimal} - 749.08 = 173.24 \quad .
\end{aligned}
\tag{1}
$$

Figure 5 illustrates a set of differential pressure measurements for one quadrant of the reactor spanning an entire year. In this representation, abrupt declines in differential pressure correspond to four instances of filter changes. Following a filter replacement, the differential pressure across the filter experiences an exponential increase. According to the current time-based maintenance approach, filters are replaced once this pressure surpasses a predetermined threshold. Examining the third curve in Fig. 5, it is evident that the filter was changed before reaching the alarm limit, indicating that there was still some RUL in that particular filter. The delay between initiating a work order for filter replacement and the actual replacement, which takes approximately 7 days, is a key reason for employing a time-based maintenance strategy rather than changing the filter strictly when it exceeds the alarm limit.

III.B. Data Preprocessing

The data extracted from the fueling machine log files often contain erroneous or abnormal values, which can adversely affect the accuracy of subsequent analyses. One common issue arises from the recording of differential pressure measurements even during periods of reactor outage or when no flow occurs through the filter. These abnormal readings need to be identified and eliminated to ensure the reliability of the dataset.

Initially, the extracted data, including the erroneous data points, are visualized to gain insights into their characteristics. As depicted in Fig. 6, the original data often exhibit spikes or irregularities, indicative of abnormal measurements.

To address this issue, a multistep approach is employed. First, an analysis of the time intervals between consecutive data points is conducted to identify periods of reactor stoppage or no flow. It is observed that during such periods, the time gap between data points significantly exceeds the regular sampling interval, often exceeding 12 h. Upon detecting these intervals, a decision is made to treat them as anomalous and remove the corresponding data points. However, simply removing all data points with time intervals exceeding a predefined threshold may lead to the loss of valuable information, especially if the stoppage is relatively short lived.

Fig. 4. Example log file for single operation.

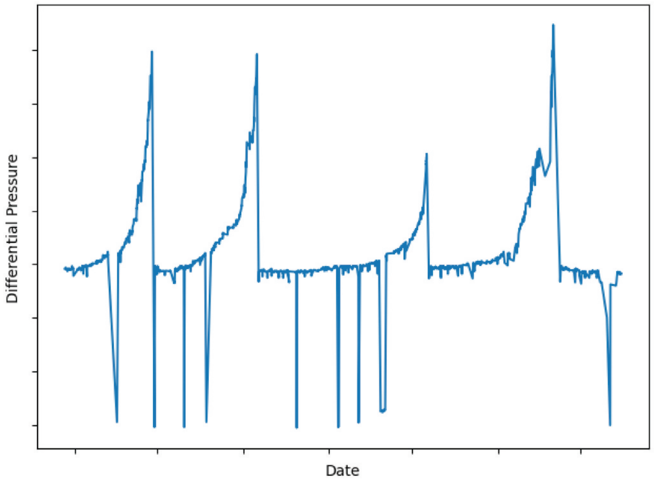

Fig. 5. Data for one quadrant with multiple filter changes. Filter changes are represented by a sudden drop in differential pressure at the end of the degradation curve.

To mitigate this, a more nuanced approach is adopted. Specifically, the time intervals exceeding 12 h are considered as indicative of stoppage periods. However, instead of outright removal, a method is devised to interpolate the missing data points, ensuring that the overall temporal structure of the dataset is preserved. To achieve this, the gap between consecutive data points during stoppage periods is artificially reduced to 1 h. This choice is based on consultation with the engineering team, who determined it to be a close approximation of the actual operational time of the filter between two samples in a no-flow region. The interpolated data points are then smoothed using appropriate filtering techniques to minimize the impact of abrupt changes on

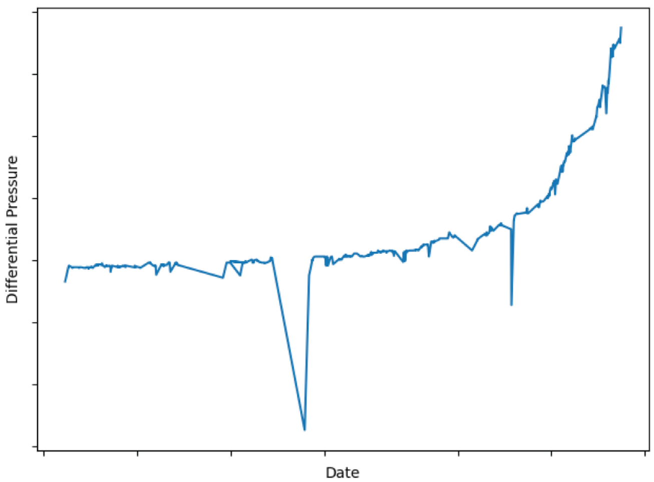

Fig. 6. Original data with erroneous data points.

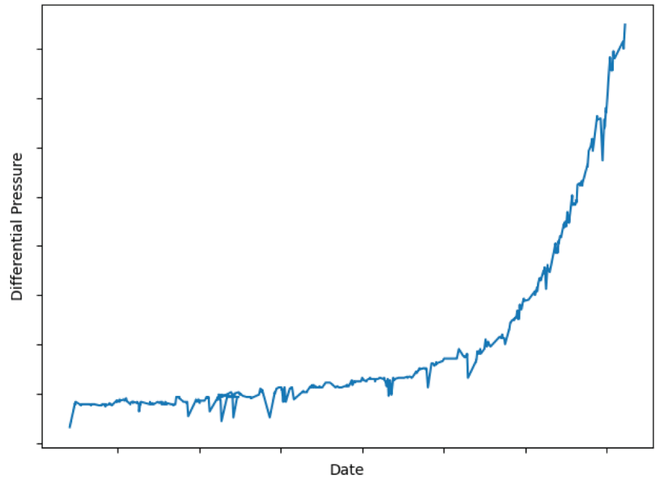

Fig. 7. Processed data after removal of outliers and abnormal values.

subsequent analyses. Finally, the cleansed dataset, devoid of abnormal values, is obtained, as illustrated in Fig. 7.

By identifying and addressing abnormal data points, this preprocessing step ensures the integrity and reliability of the dataset, laying a solid foundation for subsequent analysis and model development.

III.C. RUL Prediction

For a representative dataset, all available data for each quadrant were partitioned to encompass only one filter change, representing a single degradation curve, as exemplified in Fig. 6. Subsequently, only the data corresponding to filters that reached the alarm limit and were not replaced prematurely were retained. As depicted in Fig. 8a, the limited amount of data surpassing the alarm limit aligns with expectations given the current time-based maintenance strategy. To validate any model results, only data exceeding this limit can be utilized for testing. The selection of solely the data surpassing the alarm limit resulted in a constrained dataset comprising only five example degradation curves, illustrated in Fig. 8b. Because of variations in the filters used in the asset, including manufacturing tolerances and filter hole size, there exists an offset in the normal operating differential pressure. To address this, the average value of the first 100 data points for each curve was calculated to normalize the data and eliminate this variance. Subsequently, two models were developed for the RUL prediction.

The initial model employed was an exponential regression model,[15] a statistical approach utilized to fit a curve to data points exhibiting exponential growth or

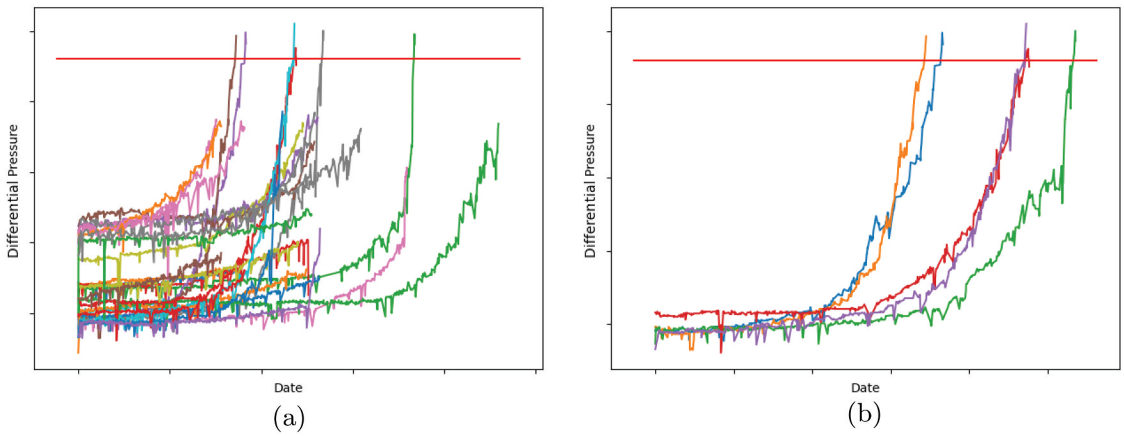

Fig. 8. (a) All degradation curves available for the specific reactor. (b) Selected data used from training and testing the RUL model. The red line indicates the alarm limit.

decay. Equation (2) illustrates the structure of this exponential model:

$$y = ae^{bx} + c \quad , \tag{2}$$

where *a, b*, and *c* = model's coefficients. The variables *a, b*, and *c* are determined through a technique called nonlinear regression, optimized by nonlinear least squares. This method involves minimizing the sum of squared errors between the actual values of y and the predicted values of y. Coefficients were estimated for each curve, and by reducing the dataset used for regression, an RUL prediction was generated for comparison with the ground truth data.

The second model follows many of the same procedures but incorporates the widely recognized technique of leave-one-out cross-validation[16] to enhance prediction accuracy. This method refines prediction accuracy by producing regression models for the dataset, with each iteration excluding one degradation curve for evaluation. The constrained regression process operates by constraining the coefficients of the regression model to fall within the range of coefficients observed in previous instances of degradation curves. By doing so, the model is less susceptible to anomalous data, as it has been trained on prior instances and is inherently limited to realistic parameter values. Equation (3) shows the mathematical representation of this approach:

$$\begin{aligned}&\text{minimize} \sum_{i=1}^{n} (y_i - f(x_i))^2 \\ &\text{subject to } a_{\min} \le a \le a_{\max} \quad , \\ &\text{and } b_{\min} \le b \le b_{\max} \quad , \\ &\text{and } c_{\min} \le c \le c_{\max} \quad ,\end{aligned} \tag{3}$$

where $f(x_i)$ = predicted value of y_i given input x_i; $a_{\min}, a_{\max}, b_{\min}, b_{\max}, c_{\min}$, and$c_{\max}$ = minimum and maximum bounds for coefficients a, b, and c, respectively.

While this approach yields marginal improvements for data in proximity to the alarm limit, it plays a crucial role for data nearing filter change by preventing predictions that would be physically impossible, such as an increase in RUL while the filter is in use.

IV. RESULTS

Both models underwent testing on the five degradation curves, utilizing an expanding dataset ranging from 1 to 13 days for each curve. The error, determined as the difference between the RUL prediction (the time the model forecasts the alarm limit will be exceeded) and the actual time when the alarm limit was surpassed, was computed for each curve at each time interval.

IV.A. Exponential Regression Model

Figure 9 displays the predictions made by the exponential regression model on one of the sample degradation curves while withholding 1 to 13 days of data. In Fig. 9a, it is evident that the model offers a satisfactory estimate of the RUL, aligning with expectations. The estimation remains relatively accurate until Fig. 9d; however, a momentary decrease in differential pressure is observed, suggesting a potential issue with data acquisition or a physical reason for the pressure drop. This occurrence appears to be the contributing factor to the less accurate predictions in Figs. 9d and 9e. It is noteworthy that in Fig. 9f, the prediction is more precise as the data from the preceding section have not been incorporated into the model.

IV.B. Improved Regression Model

The outcomes for the second model are illustrated in Fig. 10 for the same sample degradation curve. Similarly, the estimates for the initial 3 days provide an accurate prediction of RUL. In contrast to the suboptimal predictions of the original model, the improved model, as demonstrated in Figs. 10d and 10e, exhibits predictions much closer to the actual RUL. This improvement is attributed to the constrained nature of the enhanced model. Since the model has been trained on prior instances of degradation curves and since its coefficients are restricted to fall within the coefficients of those previous models, it is less susceptible to anomalous data.

IV.C. Comparison

To assess both approaches, the RUL prediction errors were computed for all degradation curves, withholding data from 1 to 13 days. Figure 11 displays the resulting plots for both models. Up to 4 days before the alarm limit, there is minimal disparity in prediction error between the two models. Beyond this threshold, it becomes evident that the improved regression model exhibits a smaller variance in prediction errors compared to the original regression model. In this case study, the primary objective was to make an accurate prediction of the RUL 7 days before the filter surpasses the alarm limit. This time frame aligns with the duration required to initiate a work order and dispatch an engineer for filter replacement. Specifically, at the 7-day mark, the prediction error is significantly lower with the improved regression model than with the original model. For the original model, the error at this point ranged from a maximum of $\pm$ 6.07 days with an average of $\pm$ 2.46 days, while for the improved regression model, the error was a maximum of $\pm$ 2.83 days with an average of $\pm$ 1.65 days.

The primary challenge in developing a robust model for the case study data stemmed from the limited availability of data surpassing the targeted differential pressure threshold. This scarcity was a direct consequence of the conservative time-based maintenance strategy currently in use for filter replacement. The strategy involved the replacement of filters before reaching the desired threshold, resulting in a small number of instances where the differential pressure exceeded the

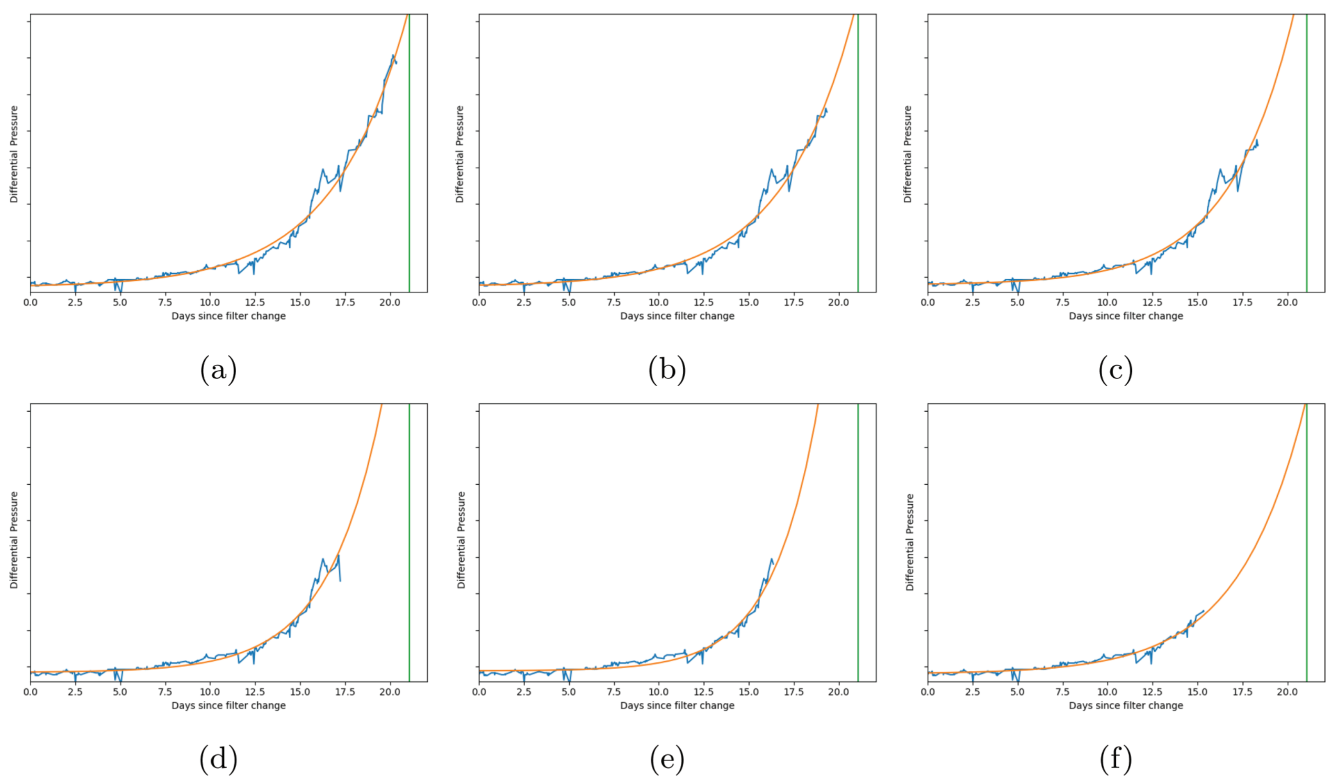

Fig. 9. RUL prediction for an increasing amount of withheld data for the exponential regression model. Day(s) to alarm limit: (a) 1, (b) 2, (c) 3, (d) 4, (e) 5, and (f) 6. The blue line is differential pressure data, the orange line is the prediction, and the green line is the time the alarm limit is exceeded.

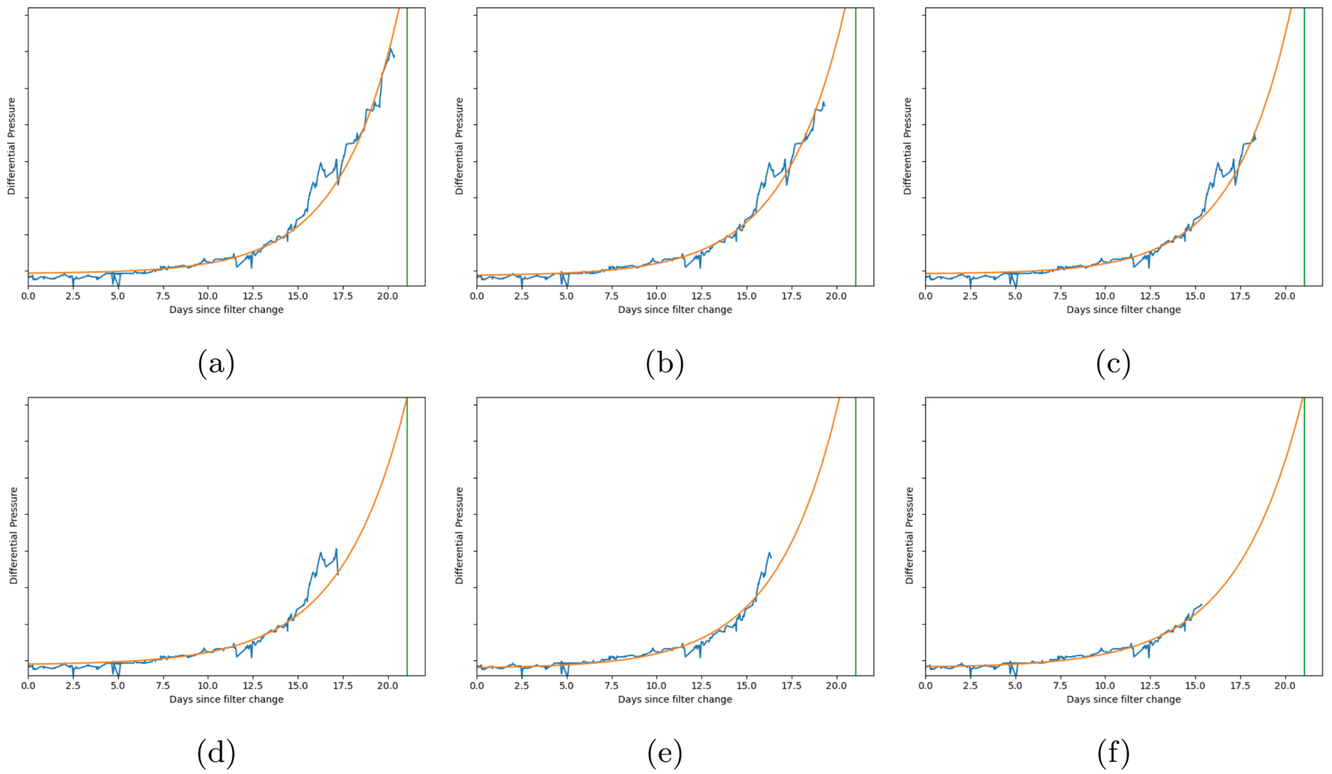

Fig. 10. RUL prediction for an increasing amount of withheld data. Day(s) to alarm limit: (a) 1, (b) 2, (c) 3, (d) 4, (e) 5, and (f) 6. The blue line is differential pressure data, the orange line is the prediction, and the green line is the time the alarm limit is exceeded.

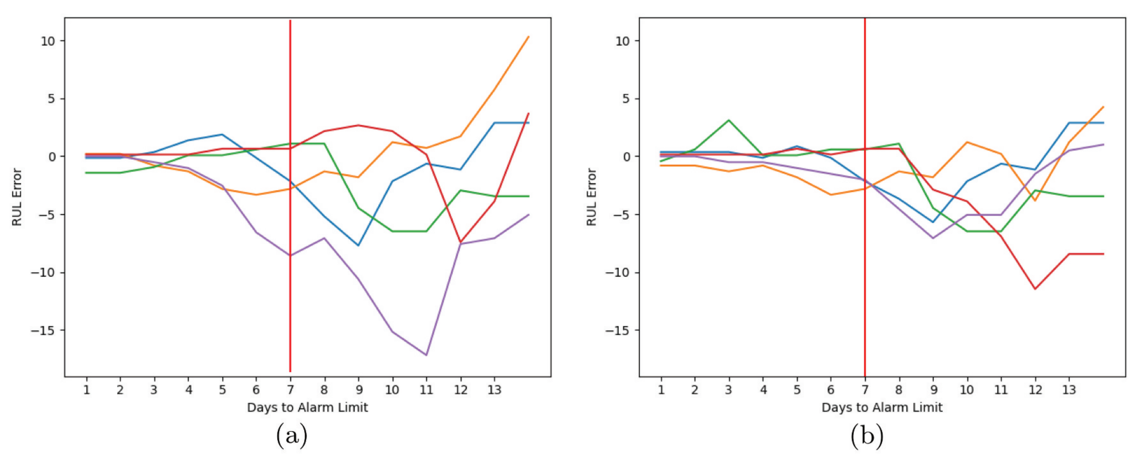

Fig. 11. Prediction error for (a) regression model and (b) improved regression model. The red line indicates the decision point.

desired level, essential for training a reliable predictive model.

To address the limitation posed by the scarcity of data, a proposed solution involves reducing the specified pressure threshold. By doing so, a considerably larger dataset becomes available for model training (Fig. 12). This adjustment in the threshold allows for the inclusion of more instances where the differential pressure reaches levels that were previously considered suboptimal for predictive purposes. The increased diversity in the dataset allows for more accurate learning of the limits in the regression model, ultimately leading to improved predictions and better-informed decision making regarding maintenance interventions. Reducing the pressure threshold to obtain more data represents an approach aimed at enhancing the robustness and generalizability of the developed models. By

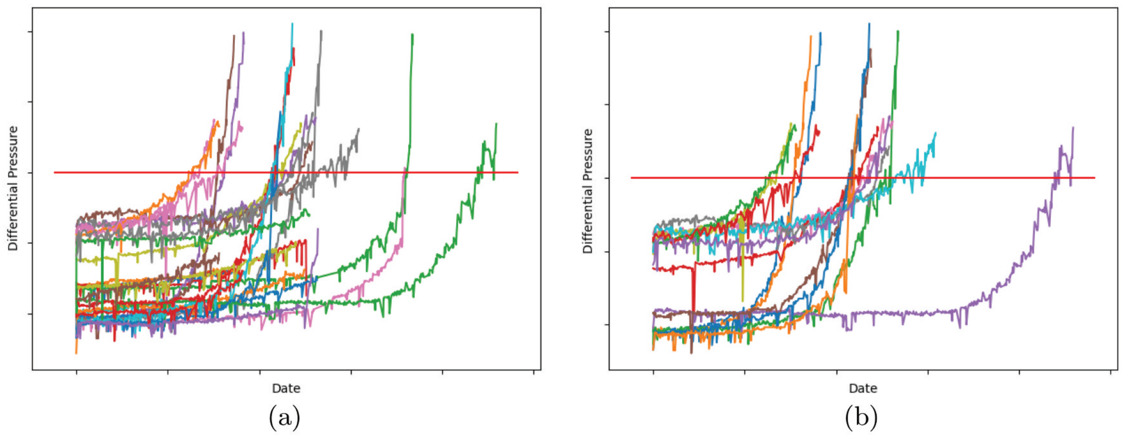

Fig. 12. (a) All degradation curves available for a specific reactor. (b) Selected data used from training and testing the RUL model with the reduced alarm limit.

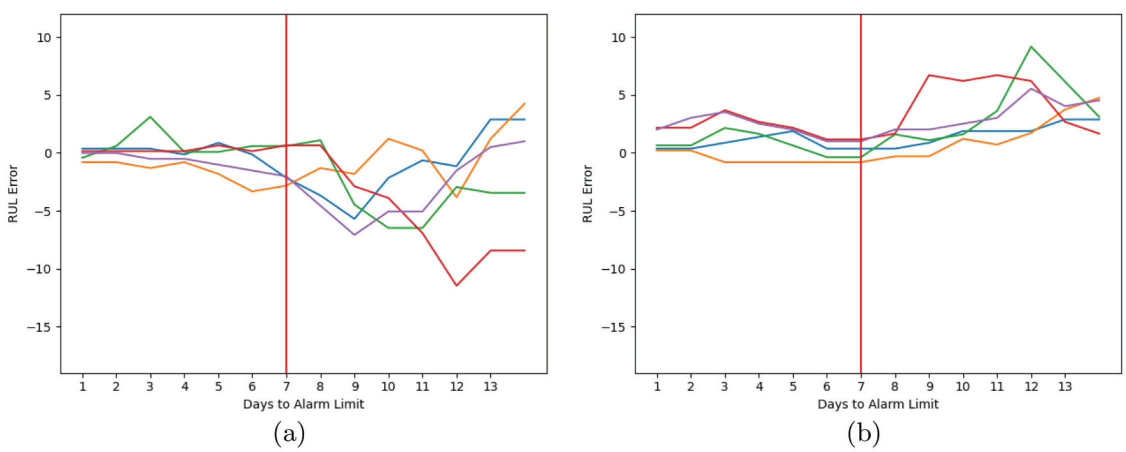

Fig. 13. Prediction error for (a) original dataset and (b) expanded dataset. The red line indicates the decision point.

lowering the pressure threshold, the aim is to capture a broader range of operating conditions and degradation scenarios, thereby enriching the dataset and mitigating the limitation posed by the small sample size. Theoretically, this technique aligns with the principles of statistical inference, where increasing the sample size improves the accuracy and reliability of estimates. This approach attempts to address the data scarcity issue but also contributes to the novelty of the work by offering a theoretically justified method for improving model performance and reliability.

For the initial results for the original model with the limited dataset, both models were tested on five degradation curves, employing an increasing dataset from 1 to 13 days for each curve. The error, representing the difference between the RUL prediction (the time that the model forecasts the alarm limit will be exceeded) and the actual time when the alarm limit was surpassed, was calculated for each curve at various time intervals. With the enriched dataset resulting from the reduced pressure threshold, a similar evaluation process was conducted. Both models were tested on the same five degradation curves, and the error analysis, involving the comparison between the RUL predictions and the actual alarm limit surpassing time, was carried out for each curve across different time intervals.

Figure 13 shows the comparison between results obtained from the original dataset and the augmented dataset. The incorporation of additional data leads to more consistent outcomes and significantly diminishes the occurrence of negative RUL predictions, which represent overestimations of the RUL. These overestimations are more impactful than underestimations of RUL. Around the critical decision point of 7 days, the improved regression model utilizing the original dataset exhibited a maximum error of ± 2.83 days with an average of ± 1.65 days. With the expanded dataset, the maximum error was notably reduced to ± 1.15 days with an average of ± 0.74 days.

While the analysis provides valuable insights into the predictive accuracy of the models up to a 13-day forecast horizon, it is important to note that the chosen evaluation period aligns with the typical degradation behavior of the filters. Filters typically last approximately 4 to 5 weeks, with the first 2 weeks exhibiting no degradation, characterized by stable differential pressure. Only after this initial period does the filter begin to degrade, hence the focus on a 14-day window for evaluation. Given this degradation behavior, the evaluation period captures the critical phase when degradation begins to manifest, allowing for timely maintenance interventions. However, it is recognized that the importance of extending the evaluation period to include longer-term predictions would provide deeper insights into the robustness and reliability of the models over extended operational timelines.

V. CONCLUSIONS

This paper outlines an approach to facilitate the transition from a time-based to a condition-based maintenance strategy for the replacement of deuterium filters in a CANDU nuclear reactor.[17] The methodology involves leveraging routinely collected data from the reactor fueling machine log files, originally designed for purposes other than condition monitoring, to support this transition. The acquired data underwent thorough processing and analysis to predict the RUL of the filters. Introducing an enrichment step to the dataset by reducing the pressure threshold resulted in a more comprehensive and varied dataset.

Two models were introduced for RUL predictions, with results indicating that a constrained exponential regression model yielded the most accurate predictions. The developed analytical model provides engineers with advanced notice, predicting when the alarm limit will be surpassed and allowing 7 days to raise a work order and replace the filter before the limit is breached. Notably, for the test dataset, the RUL prediction exhibited a maximum error of ± 2.83 days and an average error of ± 0.35 days, showcasing enhanced prediction accuracy around the critical 7-day mark with the enriched dataset.

It is important to acknowledge that as a consequence of the reduced pressure threshold and, consequently, a shortened time to failure, the predictions beyond this point exhibit a slight decline in accuracy. While this is a current constraint of the model, in the future when more data are gathered on filters that are run closer to the alarm threshold, it will be possible to mitigate or remove entirely this constraint by updating the model. However, it is also crucial to emphasize that this outcome aligns with the primary objective of achieving a precise prediction at the critical 7-day mark. The overarching aim was to facilitate the timely initiation of a work order for filter replacement. Therefore, while there may be a marginal decrease in predictive accuracy beyond the 7-day threshold, this trade-off is deemed acceptable given the prioritized focus on the targeted time frame for maintenance intervention.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Funding

This work was funded by the Engineering and Physical Sciences Research Council under grant [EP/R004889/1].

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