Remaining useful life prediction of filters in nuclear power plants

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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 remaining useful life (RUL) of a filter could result in benefits, particularly when moving from a time-based to a condition-based maintenance strategy which would optimize filter replacement procedure and reduce early replacement of filters which are still fit for purpose. For many filter types a time based strategy is sufficient, but for strategically important assets, such as fuelling 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 surrogate 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 7-14 days is predicted by a heuristic based regression model the history of each filter. This approach has been demonstrated using a civil nuclear generation application, but could but applied to wider applications. While this model is still undergoing on-site evaluation, it has been estimated that the overall lifetime cost reduction, for this specific application, will be operationally significant once this methodology has been implemented on reactor.

Keywords: Condition-based maintenance, predictive analytics, remaining useful life, nuclear power plants, filters

1. INTRODUCTION

Low value assets such as filters in many industrial applications are often replaced based on a time-based maintenance strategy due to the filters not being instrumented which results in there not being a direct way of measuring the currently health of the filter [1]. In many applications it is usually easy to replace these low value assets, however, in the nuclear sector this is not always the case [2]. This can be due to many factors, for example regulatory considerations, replacement time, and engineer safety. Because of this proxy measurements are often used to infer the status of the filter, and hence make a prediction of RUL [3]. One example of this is the differential pressure across the filter [4], as the filter degrades the flowrate will decrease to the point where there is no flowrate, e.g. the filter is clogged, or a sudden rise spike in the flowrate, e.g. the filter has collapsed. Presently, in many applications, due to insufficient prognostic information, a time-based maintenance strategy is used to routinely remove and replace these filters.

In this paper, we propose an approach that will allow engineers to move from a time-based maintenance strategy to a condition based maintenance strategy for the replacement of deuterium filters in a CANDU

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(CANada Deuterium Uranium) nuclear reactor. The first task was obtaining routinely collected information from the reactor fueling machine log files. This necessitated the creation of a unique parser suited to the bespoke log data format. This log data was originally used for post-failure analysis rather than for condition monitoring purposes. This unlocked a significant amount of data by being able to extract relevant attributes based on operational tags. Following the data extraction from the log files, processing, and cleansing, the work concentrated on creating an analytical model that produce predictions regarding the state of the filters. By using all the historical data available for the deuterium filters it was possible to develop a constrained regression model for predicting the RUL of the filters. This prediction is then used to inform the engineers with seven days advanced notice of when the alarm limit will be exceeded so that the corresponding work order can be raised and the filter change before the alarm limit being exceeded.

2. BACKGROUND

2.1. Maintenance Strategies

There are two main maintenance strategies that are widely used throughout many industrial applications, these are: condition based maintenance and time based maintenance [5].

Time-based maintenance is the traditional maintenance approach that revolves around the repair or replacement of assets based on historical failure time analysis. This is based on the assumption that the failure rate of the asset is predictable. Fig. 1 shows an example of a bathtub curve which shows the expected failure rate of an asset over its design life. In the nuclear sector, there is often a significant amount of conservatism built into these time based maintenance strategies due to the safety and financial affects that failures can have. As a result assets are often repaired or replaced before they are required to be, an additional consideration is the lack of failure data available for modelling the failure rates also due to the same safety and financial effects a failure can have.

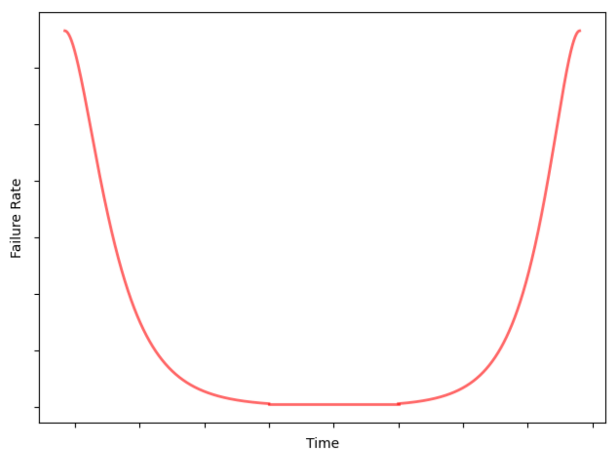


Figure 1: Bathtub curve

Condition-based maintenance, or predictive maintenance, is a maintenance program that determines the replacement time of an asset based on it's specific operating condition [6]. This can be measured based on the monitoring of many process variables such as vibration, temperature, flow rate, contaminants and noise levels. By monitoring these variables over time, and modelling them it is possible to make a prediction on when a maintenance decision needs to be made. This full process can be split up into three main task; data acquisition, data processing and maintenance decision making [7].

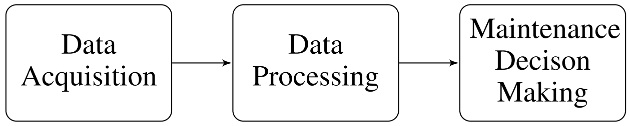


Figure 2: Three stage condition based maintenance approach

1. **Data Acquisition:** This step gathers all the necessary data relating to the health of the asset.
2. **Data Processing:** Analyse and model the relevant data to acquire better understanding and interpretation of the data.
3. **Maintenance Decision Making:** Make a prediction or recommendation based on the data as to any maintenance interventions that need to take place.

3. Methodology

The data stored in the fuelling machine log files serve as a proxy for machine health measurements for this application. These log files are text based and contain an entry for each operation that is performed by the fueling machine. One specific operation contains information relating to the differential pressure across the deuterium filters, as the filter degrades the flowrate will decrease to the point where there is no flowrate, e.g. the filter is clogged, or a sudden rise spike in the flowrate, e.g. the filter has collapsed. Fig. 3 shows the proposed process for making a RUL prediction initially starting with the text based log files.

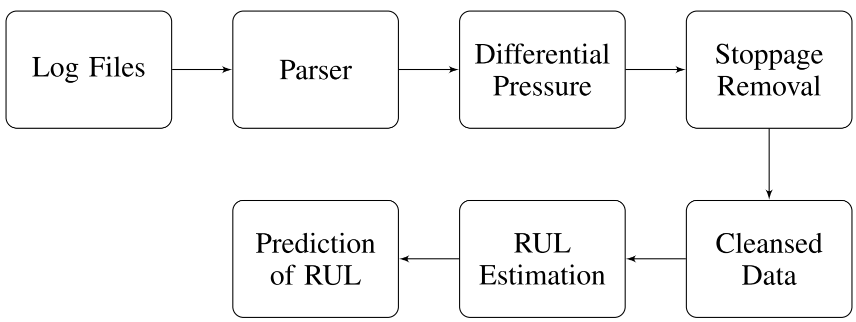


Figure 3: Methodology for RUL prediction from fuelling machine log files

3.1. Data Extraction

The first task was obtaining routinely collected information from the reactor fueling machine log files. This necessitated the creation of a unique parser suited to the intricate log data format which unlocked a significant amount of data by being able to extract relevant attributes based on operational tags. Fig. 4 shows an example of an entry in the log file, with all the sensitive information hidden. By extracting the information from each log file entry for operation tag ”1075” a date and time, a quadrant and differential pressure can be acquired. This data can then be plotted against time for each quadrant of the nuclear reactor, see Fig. 5.

The differential pressure data stored in the log files are stored in octal, so before being able to make any predictions about the health of the filter this had to first be converted into decimal kPA. Eq. (1) shows an example conversion for the differential pressure stored in the fueling machine log files in octal into the differential pressure in kPa.

Figure 4: Example log file for single operation

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

Fig. 5 shows an example of differential pressure measurements for one quadrant of the reactor over a full year. In this example, four filter changes are represented by the sudden drop in the differential pressure. After a filter change, the differential pressure across the filter increases exponentially and based on the current time-based maintenance strategy the filters are replaced. As can be seen by the third curve in Fig. 5 the filter was changed before the differential pressure reached the alarm limit. Therefore, there would still have been some RUL in that filter. Due the time that it takes between raising a work order to replace the filter, and the time the filter is actually changed (approximately 7 days) this is why a time based maintenance strategy is employed rather than changing the filter when it exceeds the alarm limit.

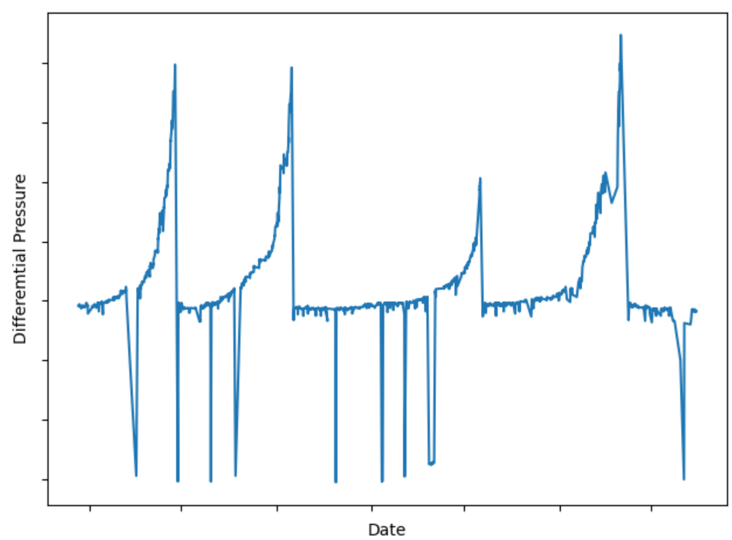
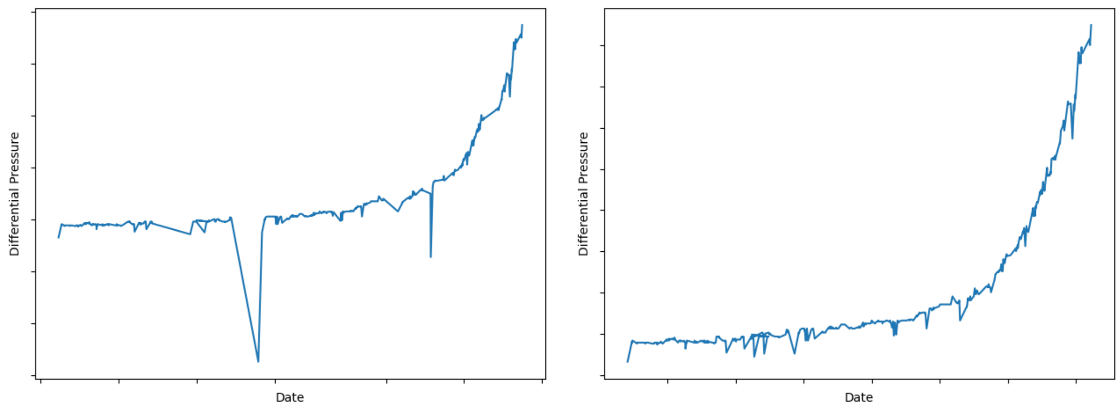


Figure 5: Data for one quadrant with multiple filter changes

3.2. Data Preprocessing

Due to the nature of the data extracted from the log files when there is an outage or no flow passing through the filter if the corresponding operation is performed a differential pressure measurement is still taken, however, this usually results in an incorrect or abnormal value. Fig. 6a shows an example of the original data with the incorrect data included, while Fig. 6b shows the same data after it has the outliers or abnormal data removed.



(a) **(b)**

Figure 6: (a) Original data (b) Processed data

Entries in the fueling machine log file are created every few hours, therefore, to remove the abnormal data shown in Fig. 6 the time between samples is analysed. From the analysis, it was discovered that a gap between data points of greater than 12 hours related to the stoppage or no flow regions of that data. By using this information it was possible to remove these regions by simply setting the gap between data points in these regions to one hour. The one hour used was defined by the engineering team as a close approximation to what the actual operational time of the filter would be between two samples from a no-flow region.

3.3. RUL Prediction

To have a representative dataset all the data for all the quadrants available was segmented to include only one filter change, e.g. one degradation curve, an example of this is shown in Fig. 6a. Next, only the data that reached the alarm limit, those filters that were not replaced early. From Fig. 7a it is clear there is only a small amount of data that has exceeded the alarm limit, this was to be expected due to the current time-based maintenance strategy. To verify the results of any model produced only data that exceeds this limit can be used for testing. Selecting only the data that exceeded the alarm limit produced a limited dataset of only five example degradation curves, see Fig. 7b. Due to the variation in filters that are used in the asset, manufacturing tolerances and filter hole size, there is an offset in the normal operating differential pressure. To remove this for each curve the average value of the first 100 data points was calculated to normalise the data to remove this variance. Following this two models were developed for the RUL prediction.

The first model was an exponential regression model [8], this is a statistical model that is used to fit a curve to data points that exhibit and exponential growth or decay. Eq. (2) shows the form of this exponential model, where a, b, and c are the coefficients of the model. The variables a, b and c are estimated using a method known as nonlinear regression, optimised by non-linear least squares, which involves the minimization of the sum of squares error between the actual values of y and the predicted values of y. The coefficients were estimated for each curve and then by reducing the amount of data used for the regression it was possible to produce an RUL prediction that could be compared with the ground truth data.

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

The second model uses many of the same steps, however, uses the well-known approach of leave-one-out cross-validation [9] to improve the accuracy of the predictions. This works by producing a regression

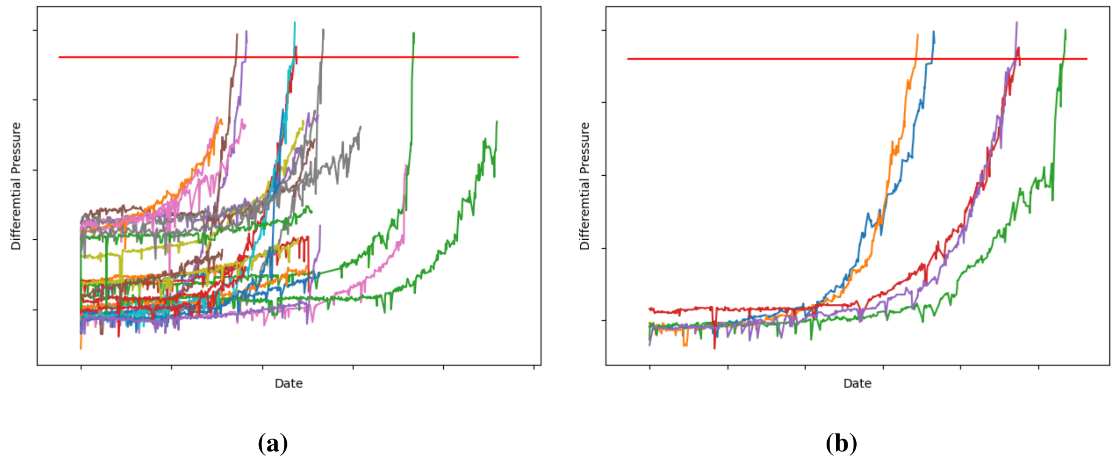


Figure 7: (a) All degradation curves available for specific reactor. (b) Selected data used from training and testing RUL model. Red line indicates alarm limit.

model for all the data except the prediction that is about to be made and using these parameters to constrain the search space of the regression model. For data close to the alarm limit this produces a negligible improvement, however, for data near the filter change this approach prevents any predictions that would not make physical sense, e.g. the RUL increasing as the filter is in use.

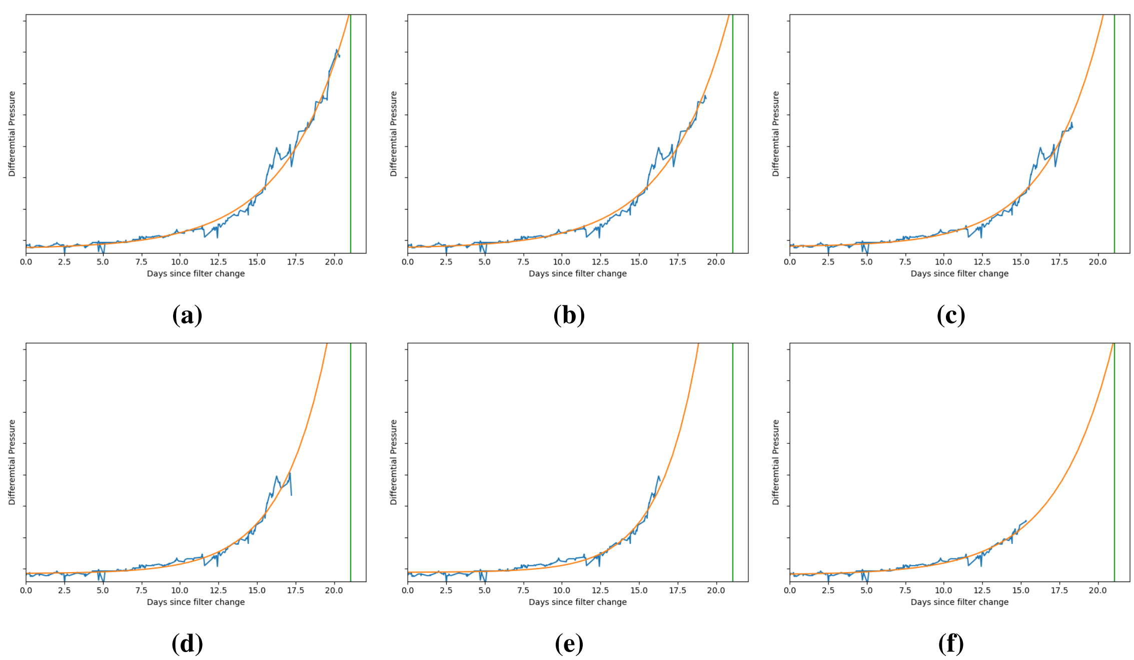


Figure 8: RUL prediction for increasing amount of withheld data for exponential regression model. Day(s) to alarm limit (a) 1 (b) 2 (c) 3 (d) 4 (e) 5 (f) 6. Where the blue line is differential pressure data, orange line is the prediction, and the green line is the time the alarm limit is exceeded.

4. Results

Both models were tested on the five degradation curves available, using an increasing amount of data from one day to thirteen days for each curve. The error between the RUL prediction, the time the model is predicting the alarm limit will be exceeded, and the time the alarm limit was actually exceeded was calculated for each curve for each time interval.

4.1. Exponential Regression Model

Fig. 8 shows the prediction for the exponential regression model on one of the example degradation curves withholding 1 to 6 days of data. From Fig. 8a it can be seen that the model provides a good estimate of the RUL, which is what would be expected. Up until Fig. 8d the estimation is relatively accurate, however, as can be seen the differential pressure momentarily decreases suggesting there was either an issue with the data acquisition or a physical reason why the pressure has decreased. This appears to be the cause of the poor prediction for Fig. 8d and 8e. It should also be noted that in Fig. 8f the prediction is more accurate as the data in the previous section has not been included in the model.

4.2. Improved Regression Model

The results for the second model are presented in Fig. 9 for the same example degradation curve. Similarly the estimation for the first three days provide an accurate RUL estimation. For the poor estimations of the original model, with the improved mode it is shown in Fig. 9d and 9e the prediction is much closer to the actual RUL. This is due to the constrained nature of the improved model, as the model has been trained on previous examples of degradation curves and the model coefficients are constrained to be within the coefficients of those previous models, this model is less affected by anomalous data.

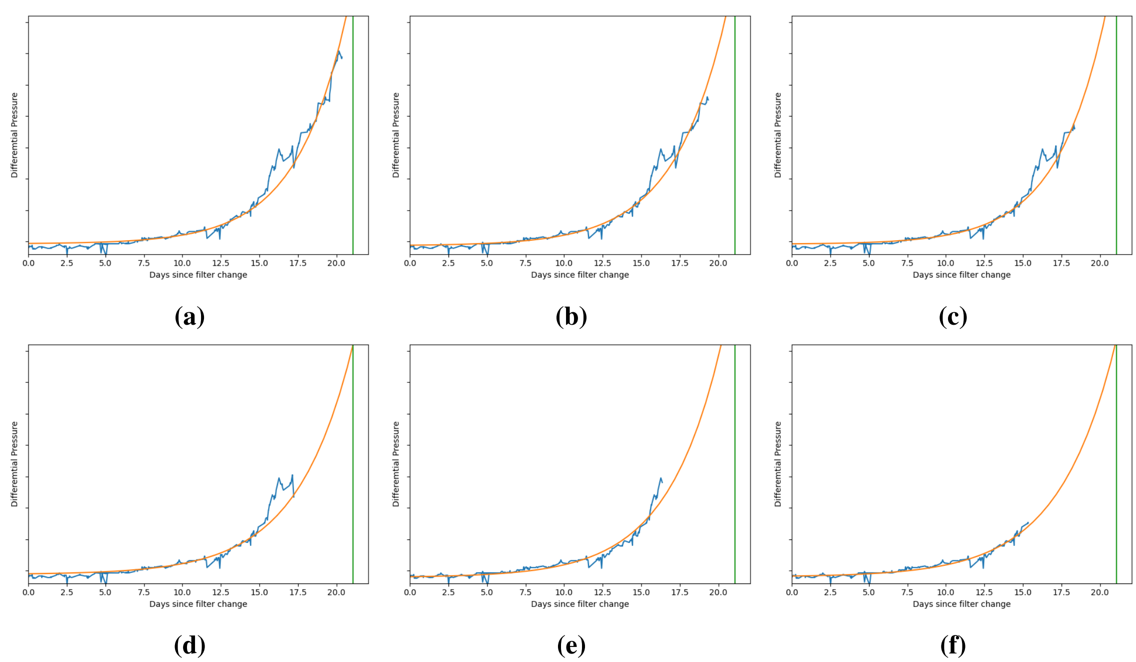
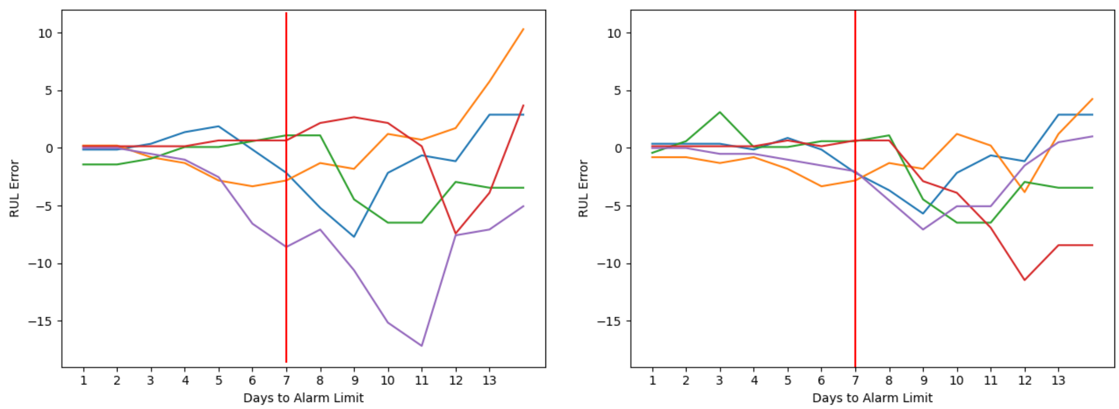


Figure 9: RUL prediction for increasing amount of withheld data. Day(s) to alarm limit (a) 1 (b) 2 (c) 3 (d) 4 (e) 5 (f) 6. Where the blue line is differential pressure data, orange line is the prediction, and the green line is the time the alarm limit is exceeded.

4.3. Comparison

To compare the two approaches the RUL prediction error was calculated for all of the degradation curves withholding one to thirteen days of data. Fig. 10 shows the resulting plots for both models, from one to four days to the alarm limit there is very little difference in the prediction error. Beyond that point, it is clear that the variance in the error is smaller with the improved regression model than with the original regression model. For this case study, the main aim was to make an accurate prediction of the remaining useful life seven days before the filter exceeds the alarm limit. This was because this was the amount of time required to raise a work order and have an engineer sent out to replace the filter. Specifically, at this point, the prediction error is considerably lower with the improved regression model than with the original model. At the 7 days point, for the original model the error was a maximum of $\pm 8.60\ days$ and an average of $\pm 1.07\ days$, and for the improved regression model the error was a maximum of $\pm 2.83\ days$ and an average of $\pm 0.35\ days$.



(a) **(b)**

Figure 10: Prediction error for (a) Regression Model, (b) Improved Regression Model. The red line indicates the decision point.

5. CONCLUSIONS

This paper has described an approach to support the move from a time-based to a condition-based maintenance strategy for the replacement of deuterium filters in a CANDU nuclear reactor. The technique used routinely obtained data from the reactor fuelling machine log files not initially designed for condition monitoring, to support this move. The data gathered was processed and analysed to forecast the RUL of the filters. Two models were proposed to achieve this and the results showed that a constrained exponential regression model provided the most accurate RUL predictions. The analytical model developed provides engineers with a prediction of when the alarm limit will be exceeded, providing them with seven days' advanced notice to raise a work order and change the filter before the limit is exceeded. For the test dataset, the RUL prediction had a maximum error of $\pm 2.83\ days$ and an average error of $\pm 0.35\ days$.

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