2025 | 471

Change point detection method for estimating the remaining useful lifetime of engine filters

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ABSTRACT

Predictive maintenance aims to anticipate component failures in order to replace the components at the optimal time. In this context, methods for estimating the remaining useful life (RUL) of engine filters are being developed at Liebherr Component Colmar.

The pressure signals upstream and downstream of the filters are measured by test bench sensors, allowing to obtain a time series for the pressure difference across the filter, denoted by the differential pressure, Delta_P. The pressure drop is considered as the best indicator of the filter's status in terms of clogging. The visual analysis of such time series shows two phases of distinct behavior. In a first period corresponding to a healthy filter, the Delta_P oscillates around a filter-dependent constant value. At some point, however, the Delta_P shows an inflexion and starts a growth trajectory of increasing slope until clogging.

The method presented is two-fold, combining a change point detection algorithm to identify the inflexion with a RUL-estimation model during the second phase. The cumulative sum control chart (CUSUM) algorithm is a widely used and robust algorithm to detect changes of average value in times series. It relies on the computation of a likelihood-based score that tells how far observations are from a reference model. This score moreover grows cumulatively when successive observations deviate from the reference model. The first step of the proposed method is an adaptation of that procedure, based on linear model likelihoods, to detect changes in slope when considering time windows of the Delta_P. Using the inflexion point identified by the CUSUM algorithm, a polynomial/exponential curve fit is then applied to the Delta_P curve to predict its future values. This allows a prediction of the RUL which is defined as the remaining time left before the Delta_P reaches a pre-defined level considered as filter clogging.

The developed method has the advantage to be online, not to rely on a nominal mean value for the Delta_P, and to be computationally frugal as it relies only on linear models and polynomial fits. Those characteristics make it a good candidate for an embarked system ringing an alarm several days before a clogging occurs. It however depends on several parameters (reference slope, window size, score threshold used for inflexion detection, degree of the polynomial fit) that must be optimized. Training and test data obtained on bench engines at Liebherr Component Colmar are used to learn those parameters and evaluate the resulting performance.

1 INTRODUCTION

Technological and electronic progress in modern sensors allow for the collection of vast amounts of data on mechanical and industrial equipment, particularly time series measuring their evolution over time. The definition of the maintenance schedule, which is crucial in the industry, is moving towards predictive maintenance, also known as condition-based monitoring (CBM) based on measurement of the industrial system. This approach is distinct from traditional preventive maintenance, where maintenance schedules are predefined, and components are replaced at fixed intervals. CBM avoids replacing functional components, thereby reducing costs, by establishing a dynamic schedule that evolves based on real-time system monitoring. A critical step in this process is the estimation of the remaining useful life of a component, considering the actual system usage, i.e., the time until its failure. It's also important to address the question of who is responsible if a component fails despite being declared valid by the monitoring system.

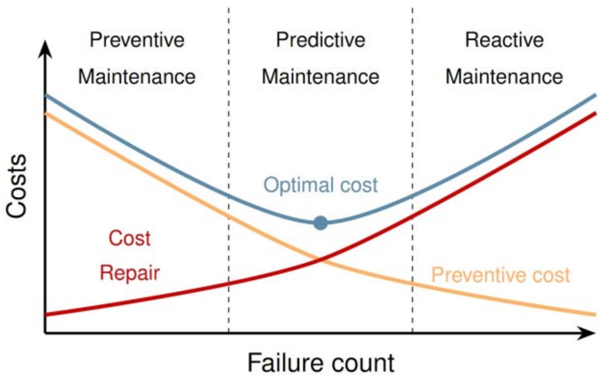

Figure 1 Predictive maintenance

The most commonly found approaches in the literature to design predictive maintenance models are physic-based methods, data-driven methods (statistical, machine learning, deep learning) or hybridisation of those approaches [1].

Physical methods are based on the physical modeling of the phenomena involved in the degradation of a system until failure, such as corrosion or fatigue. A mathematical model is used to simulate the degradation of the system under study and allows for the prediction of the Remaining Useful Life (RUL) [2]. Physical based methods need a strong physical and mechanical knowledge of the studied system. These methods have the advantage of being tunable in case of hardware changes, unlike statistical approaches. In particular, [3] proposes a physics-based approach to model the filter clogging phenomena, which will be used as a reference to build the models used in the present article. [4] presents a framework that combines physics-based models with degradation curves to simulate and predict the behavior and the RUL of industrial robots. Using the Digital Twin concept, it provides real-time alignment between simulated and actual system behaviors.

Data-driven methods include approaches that rely on stochastic models or statistical analysis to develop fault detection models that do not directly mimic the underlying physics. These methods may include statistical algorithms like in [5] where unsupervised learning and Monte Carlo simulations are used to mimic the degradation process and perform fault detection on real devices from the automobile production. Another example can be found in [6] with an application of evolving fuzzy models for semiconductor health management. In [7], statistical algorithms based on the Gaussian distribution are used combined with neural network to diagnose battery fault.

Data-driven method also includes machine learning and deep learning algorithms, which have been extensively used by the Prediction and Health Management community to develop predictive maintenance strategies. Such methods, enable analysis without the need for physical or mechanical knowledge of the studied system. In recent years, numerous articles have demonstrated the effectiveness of those methods for RUL prediction. For instance, multiple linear regression durability models were used to predict the fatigue life of automotive coil in [8]. In [9] SVM classifiers allow for fault detection in vehicle suspensions. The data being primarily time series, the developed methods focus on architectures commonly used for sequential data processing. Recurrent Neural Networks (RNNs), such as Long-Short-Term-Memory (LSTM) networks [10], Convolutional Neural Networks (CNNs) [11], and more recently, Transformers [12], which have been adapted from the original Transformer architecture [13] to handle time series, are popular methods for performing Remaining Useful Life (RUL) predictions.

The estimation of the RUL of clogged filters is an area of research within predictive maintenance, particularly for filtration systems in various industrial applications. Several studies have focused on the modeling and prediction of filter clogging, exploring different methodological approaches. For instance, in [14] an experimental setup to collect data on filter clogging mechanisms has been developed, providing a foundational basis for degradation predictions. In [15] a state-based model analyzes phase transitions in clogging and estimates RUL with increased accuracy. In a different context, [16] applied a Gaussian Process Regression model to predict the RUL of air filters, comparing it to neural networks to demonstrate the effectiveness of this approach in handling small datasets. Additionally, [17] proposed a data-driven approach for liquid filtration systems, where they developed a health index to predict filter RUL. Lastly, in [18] the use of machine learning, particularly neural networks, to predict filter clogging in maritime systems is investigated, illustrating the potential of these techniques for filter monitoring in real-world scenarios. These works underscore the importance of integrating advanced techniques to enhance the accuracy of filter RUL estimations and ensure optimal maintenance of filtration systems.

2 INDUSTRIAL CONTEXT AND PROBLEMATIC

2.1 Industrial Context

The present paper focuses on predictive maintenance applied to engine oil filters of heavy-duty engines produced by Liebherr Components Colmar (COC). Liebherr is an equipment manufacturer comprising over 150 companies, organized into various divisions such as earthmoving, mining, household appliances, engine components, and more. COC factory is specialized in producing high-power diesel engines (> 1 MW). The engines produced by Liebherr have various applications from genset and mining trucks to mining excavators and rail applications.

Over the lifespan of an engine, approximately fifty oil filter replacements are performed, leading to maintenance costs. The study targets the genset application, with a particular emphasis on the twelve-cylinder displacement configuration because of the data availability. The primary objective is to estimate the Remaining Useful Life (RUL) of the engine filters.

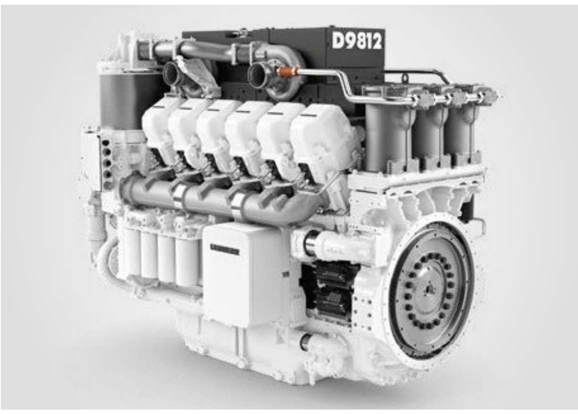

Figure 2 D9812 Liebherr diesel engine

Liebherr is investigating the possibility of estimating Remaining Useful Life (RUL) for their components. Starting with oil filters is an initial focus for developing and testing these predictive maintenance algorithms as their lifetime is dependent on the engine's operating conditions. The goal is to maintain the integrity and reliability of the machines by accurately estimating the RUL of components. Liebherr aims to ensure that their equipment continues to operate smoothly and efficiently, preventing unexpected breakdowns and optimizing maintenance schedules.

2.2 Problematic: RUL estimation of oil filters

Liebherr’s oil filters are cartridge filters, which are a type of filtration system widely used in industrial and mechanical applications. These filters consist of a cylindrical housing containing a pleated filter element made of accordion-folded filter media like in Figure 3.

Figure 3 shows the pleated structure increases the surface area, enhancing filtration efficiency while maintaining a compact design.

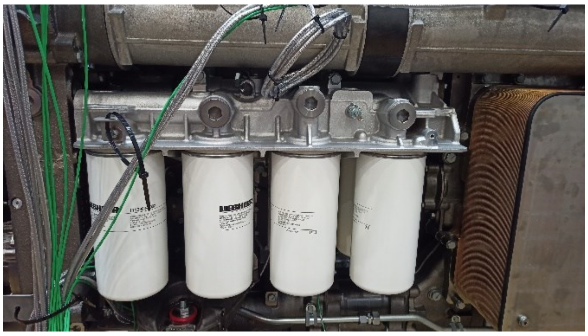
Figure 4 Oil filters connected to the engine

On Liebherr diesel engines, multiple oil filters are arranged in series like in Figure 4 and their number depends on the engine displacement.

The primary function of cartridge filters is to remove contaminants from fluids, such as oil, fuel, or hydraulic fluids, ensuring the longevity and performance of the machinery. Their design allows for easy replacement and maintenance, making them an ideal choice for applications requiring high-performance filtration under varying operational conditions.

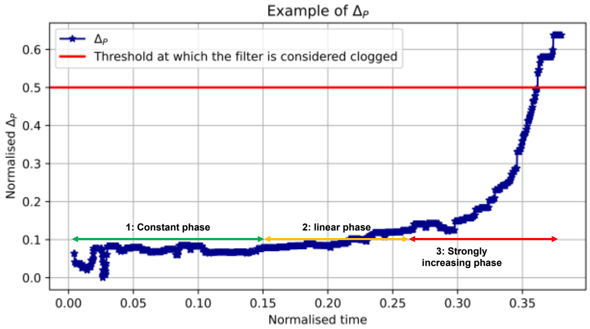

Figure 5 Example of $\Delta_P(t)$ over the lifetime of a filter with the clogging threshold and the three clogging phases

Oil filters remove contaminants and impurities from the oil to protect the engine. The notation Δ_P refers to the pressure difference between the upstream and downstream sides of the filters. It is computed with two pressure sensors placed before and after the filter. The Δ_P measure indicates the filter's state (healthy, partially clogged or clogged) and is used to estimate the RUL of the oil filters. A significant increase in Δ_P suggests that the filter is clogged or nearing its capacity, while a low and constant Δ_P value usually indicates a clean and effective filter. The objective of the method developed in the present paper is to be able to anticipate the oil filters clogging i.e. to predict the filter end of life.

The lifespan of a filter is characterized by three distinct filtration phases as shown in [3]. In the first phase, Δ_P remains constant. This phase corresponds to the filtration of a clean filter, where most particles pass through the mesh without being retained. During the second phase, known as the linear or cake filtration phase, particles begin to accumulate in the filter. As a result, Δ_P increases gradually and linearly over time. The third phase, which corresponds to the filter clogging stage, is marked by a sharp increase in Δ_P. This rapid rise is due to the reduction in the effective filtration surface area as the filter becomes more clogged.

It is quite impossible to capture the very different behaviour of the three phases in a modelling of Δ_P as a single smooth time series. Preliminary work was made in that direction and gave very poor results in terms of RUL prediction. This is due to the fact that the difference in the Δ_P slope is such between phases 2 and 3 that no precise RUL can be obtained without proper detection of the time on which the third phase begins. This moment will be denoted as the change point for Δ_P

The present paper proposes a strategy that allows a RUL prediction once Δ_P entered the third phase, which corresponds roughly to a couple of days before filter clogging. The method relies on the detection of the change point followed by a data-driven modelling of Δ_P in the third phase.

3 CHANGE POINT DETECTION METHODS

The objective of this section is to develop two methods to automatically monitor the change point detection in the time series of Δ_P. The first one is based on the evolution of the Δ_P as a function of engine load and engine speed, while the second uses only the Δ_P time series and an adaptation of the cumulative sum control chart (CUSUM) algorithm.

3.1 Automatic labeling method

The first proposed method relies on the idea that when the filter is functioning properly, the observed Δ_P should be within a certain range depending on the current speed and load of the motor, and a significant deviation persisting over time indicates that the clogging phase has begun. The method therefore proceeds in two steps for any given filter.

1. The linear regression of Δ_P is computed as function of *engine speed* and *load* on the beginning of the filter lifetime which can be considered as a period where the filter is healthy. The variance of the residuals of the linear regression denoted σ is computed on this period. Δ_P is expressed as:

$$\Delta_{P(t)} = \alpha_2 \times speed(t) + \alpha_1 \times load(t) + \alpha_0 \qquad (1)$$

2. The residuals of the regression (denoted $\epsilon(t)$), are then computed which allows to calculate the standardized residuals $\frac{\epsilon(t)}{\sigma}$.

The change point is considered to be reached when the standardized residuals exceed a specified threshold for a predefined number of consecutive time steps. The condition on the consecutive time steps has been set up to avoid false detection. When these conditions are met, Δ_P is considered to deviate significantly from its expected distribution when the filter is functioning in healthy state.

3.2 CUSUM method

The second change point detection method relies on the Cumulative Sum Control Chart (CUSUM) algorithm, which is a sequential analysis technique developed by Page in 1954 [19] to dynamically detect changes in the mean of time series [20]. An adaptation of the method is proposed to detect a change in the slope of Δ_P, indicating the beginning of the third phase without using additional data than Δ_P.

The first step of the proposed method consists in dividing the time in fixed windows W_i dynamically, a new window being created whenever a sufficient time interval has been observed. Two models are then compared on each window, corresponding respectively to small or high slopes. To do so, let α_{ref} be a reference slope to be chosen by the user.

The first model M_0 corresponds to a null slope on W_i. It assigns to W_i the likelihood $L_0(i)$ of the gaussian linear model with null slope

$$M_0: \quad \Delta_P(t) = \beta + \epsilon \tag{2}$$

where β is an intercept and ϵ a gaussian noise. Both β and the variance of ϵ are estimated to compute the likelihood.

The second model M_1 corresponds to a slope on W_i at least equal to α_{ref}. To compute a likelihood, the gaussian model

$$M_1: \quad \Delta_P(t) = \alpha\, t + \beta + \epsilon \tag{3}$$

is adjusted to obtain an estimation of its parameters, and in particular an estimation $\hat{\alpha}_i$ of the slope on W_i. The considered likelihood $L_1(i)$ is then computed from the model

$$M_1: \quad \Delta_P(t) = \alpha_i^* t + \beta + \epsilon \tag{4}$$

with α_i^* fixed to $\alpha_i^* = \max(\alpha_{ref}, \hat{\alpha}_i)$ while β and the variance of ϵ are estimated.

Finally, S_i is given the score

$$s_i = log\left(\frac{L_1(i)}{L_0(i)}\right) \tag{5}$$

The rationale behind this score is that windows showing no significant increase in Δ_P will have a higher likelihood in M_0 compared to M_1 and therefore a negative score. Conversely, windows with a slope close to or greater than α_{ref} will have a positive score, which large values when the increase is important and $\hat{\alpha}_i$ is far from 0.

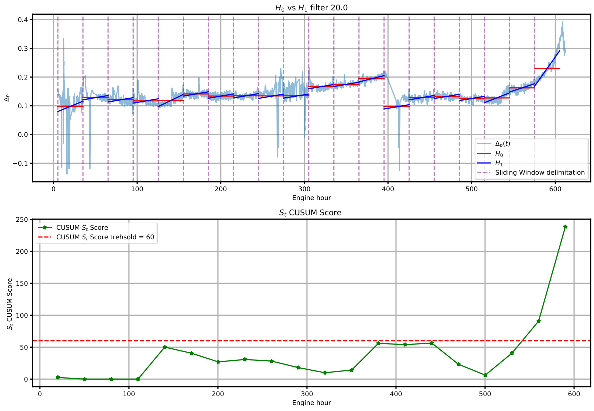

Figure 6 Example of CUSUM Score for filter 20 with the two hypotheses H_0 and H_1.

This behaviour is illustrated Figure 6 for a given filter. It shows an example of visualisation of the two models M_0 and M_1 on the time windows of a given filter, as well as their scores.

As in the original CUSUM method, the cumulative sum of the scores is then considered, that is

$$S_i = max(S_{i-1} + s_i, 0) \tag{6}$$

While the filter is in phases 1 or 2 where model M_0 is more likely, $E(s_i) < 0$. Thus, Formula (4) ensures that the cumulative sum is pulled back to 0 whenever it may be positive but never becomes negative. The expected behaviour during that phase is therefore a generally null sequence S_i with some limited positive excursions. However, once the filter enters the third phase, several successive values of s_i are positive and potentially large and the cumulative sum grows fast.

A rule is defined to determine the change point by choosing the first time the cumulative sum S_i exceeds a predefined threshold h.

Figure 6 illustrates the cumulative sum behavior on a given filter. One can see that small variations are mainly smoothened out by the likelihood comparisons on time windows and that the small positive excursion around time 410 engine hours is pulled back to 0. However, after phase three has started, the cumulative sum rapidly becomes very large.

3.3 Automatic labeling and CUSUM comparison

Both methods aim to identify the transition to the clogging phase in the Δ_P time series, they differ in their underlying principles, data requirements, and computational efficiency.

The advantage of automatic labeling is that it takes engine operating conditions (speed and injection) into account for breakpoint detection. However, this requires having the corresponding speed and injection data in addition to the Δ_P signal. In contrast, the CUSUM method relies solely on the Δ_P signal making it more applicable in scenarios where supplementary engine data is not available.

The Automatic Labeling Method is robust against short-term fluctuations, as the regression-based approach accounts for variations in engine conditions. The CUSUM Method with the cumulative sum mechanism mitigates false alarms by smoothing out small variations and also makes the method robust against short-term fluctuations.

Both methods were developed with the same objective, but the computation time for automatic labeling is reduced compared to the CUSUM method. The two methods were optimized based on the same breakpoints manually annotated, the results of the CUSUM method show better performance on the studied cases.

While both methods aim to detect the transition to the clogging phase, the choice between them depends on data availability and computational constraints.

4 EXPONENTIAL CONSTRAINT-BASED OPTIMIZATION

This section focuses on the second part of the method presented in the article, that is the modelling Δ_P and RUL estimation in the third phase. It is therefore assumed in this section that the change point t_{change} has been estimated by one of the methods of the previous section.

Due to the sharp increase of Δ_P during phase 3, the chosen model is the following:

$$\Delta_P(t) = f_1(t) = a \times exp(bt^2) + c \quad (7)$$

where a, b and c must be estimated.

The choice of such a functional model may seem arbitrary. However, an analysis was conducted to determine which functions best fit the data for accurate approximations. Several functions were investigated, including polynomials of degrees 4 to 20 and exponential functions. Among these, the exponential function of t^2 was found to provide the most accurate results on our available data.

Modelling step: For each time t after the change point, coefficients a, b and c are estimated using only the values of Δ_P up to t. To ensure that $f_1(t)$ is increasing, this estimation problem is considered as a constrained optimization problem with constraints $a \geq 0$ and $b \geq 0$. To do so, the `minimize` function from the Python library SciPy [21] is used, with The BFGS (Broyden–Fletcher–Goldfarb–Shanno) algorithm as selected optimisation method. The algorithm is an iterative method for solving unconstrained nonlinear optimization problems.

Not all available points are used to reduce computation time and simplify deployment on an embedded controller. Points are selected from the beginning (older points) and end (more recent points) of the increasing phase to optimize prediction accuracy.

The following parameters are optimized:

1. $\boldsymbol{c_{norm}}$**:** The normalization constant, used to scale time and prevent numerical instability in the exponential term. The normalized time is calculated as $t_{norm} = \frac{t}{c_{norm}}$.

2. $\boldsymbol{c_{begin}}$**:** A constant ranging from 0 to 1 to determine the starting point for the estimation algorithm. It is defined as $t_{begin} = t_{change} - c_{begin} * (t_{change} - t_0)$ where t_0 is the beginning of the oil filter lifetime.

3. **h_begin:** the number of hours used to obtain the *first points*: the data from t_{begin} to $t_{begin} + h_{begin}$is used for the estimation procedure.

4. **h_end:** the number of hours used to obtain the *last points*: the data from $t_{present} - h_{end}$ to $t_{present}$ is used for the estimation procedure.

RUL Estimation Step: Once the coefficients are obtained, Δ_P is predicted using the estimated coefficients. The time at which the predefined threshold is reached is calculated by projecting Δ_P. The estimated RUL is the time difference between the present time and the time when the threshold is reached.

5 EXPERIMENTAL RESULTS ON LIEBHERR'S APPLICATION

5.1 Dataset presentation

The dataset used to develop and validate this method is composed of six oil filters complete lifetime on Liebherr high powered diesel engines, originating from two engines of the same type operating on the test bench. Complete lifetime data of oil filters is only available on the test bench, as the Δ_P value is monitored in real-time. This allows for filter replacements at the most appropriate moments, specifically when the filter is clogged because the Δ_P has exceeded the predefined threshold. The current study is therefore limited to the small sample of bench data for which the complete data until clogging is available.

For field test engines, filters are currently replaced preventively according to a predefined maintenance schedule.

The method presented has been developed and optimised on the six oil filters presented in table 2. The method may however be extended to other engine types and/or on other filter types (fuel filters, air filters…) as the clogging phenomenon is similar and also other component with similar end of life behaviour.

Table 1 Available data

Filter ID	Engine	Lifespan*
20	1	612.2
28	1	297.5
32	1	191.2
153	1	126.5
201	2	434.6
204	2	159

*Lifespan in engine hours.

The dataset contains the time series of Δ_P, for each filter, as well as the speed and load times series needed for the first change point detection method.

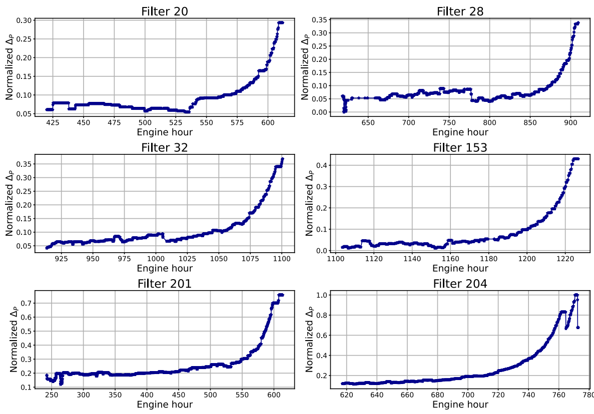

Figure 7 Δ_P of the six oil filters available

5.2 Choice of the parameters value

The two change-point detection methods are optimized using the available data, with manually annotated change points serving as a reference for this optimization. To do so, a grid of threshold values is tested for each method, and the one achieving the best mean distance between predicted and annotated change points is selected. A leave-one-out procedure is used to avoid overfitting.

Table 2 Parameter values for RUL estimation

Parameter	Value
c_norm	750
c_begin	0.2
h_begin	2 hours
h_end	40 hours

A grid search is also conducted on the available data to optimize the parameters for the RUL estimation step. It tests all possible combinations within the parameter grid and selects the best ones, which are shown in Table 2.

An initialisation of the coefficients a, b and c is also needed for the optimisation method used. c is initialised as the mean of the Δ_P on the first points, while a and b are randomly initialised taking values ranging respectively between $[1^{-20}; 1]$ and $[1; 150]$. Moreover, studies conducted on the initial conditions show that they have little impact on the estimated RUL. To reduce the randomness of the results, we compute the predictions for 10 random initialisations of a and b and take the average prediction of the 6 best-performing models among them.

5.3 Results

The results, i.e., the predictions of Δ_P that allow the filter RUL estimation, depend significantly depending on the change point time used for constrained optimization. If the rupture time is too early in the filter's lifetime, the estimated RUL may be inconsistent as it is physically not possible because of the three clogging phases. Conversely, if it is too late, it will hinder for predictive maintenance of the filters. It is important to determine the appropriate rupture time. Both change point detection methods are therefore tested in combination with the RUL Estimation procedure and the corresponding results are presented.

The results are shown on sixth oil filters for both methods.

The colored lines shown in the lower graphs part 5.3.1 and 5.3.2 represent the predictions of Δ_P at specific time points, and the RMSE displayed in the figures are computed from the change point time.

5.3.1 Results from the change point based on automatic labeling method

In this section, the rupture time is determined using the automatic labelling method and is indicated by a red vertical line in the figures. The RUL starts to be estimated once the rupture time is identified, which is why the figures do not display the entire lifetime of the filters, but only the data corresponding approximately to phase 3. The choice of α_{ref} (corresponding to the reference slope) was made using leave-one-out cross-validation on a grid of possible values for the parameter, selecting the parameter that yielded the best average results on the filters from the test set.

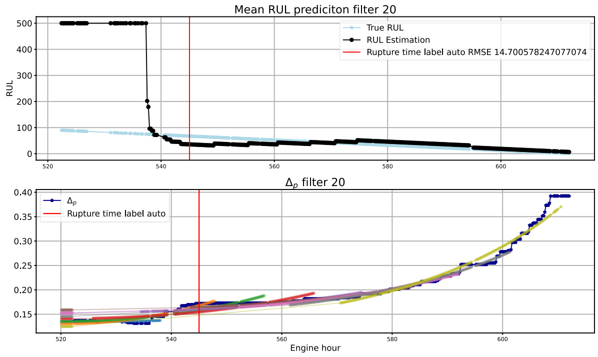

Figure 8 Results filter 20

In Figure 8, the RUL is initially overestimated; however, the predictions become more precise over time.

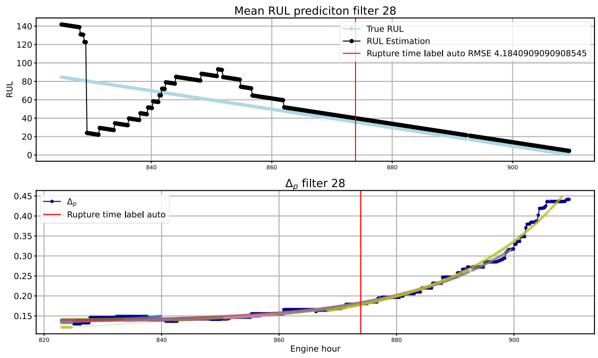

Figure 9 Results filter 28

Accurate predictions are observed in the latter part of Figure 9. However, prior to stabilization, significant fluctuations in the RUL values are evident, consistent with observations from other filters.

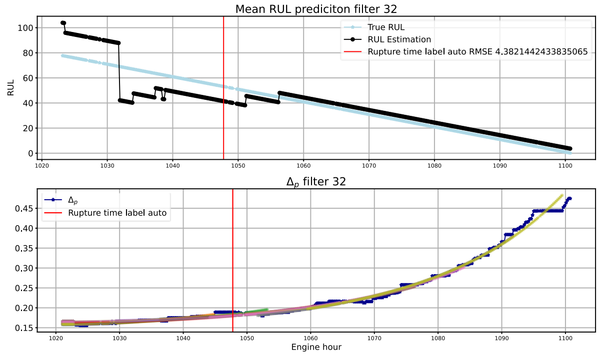

Figure 10 Results filter 32

In Figure 10 the RUL is slightly overestimated at the outset; however, the predictions stabilize and closely align with the true RUL values as the filter progresses through its lifespan.

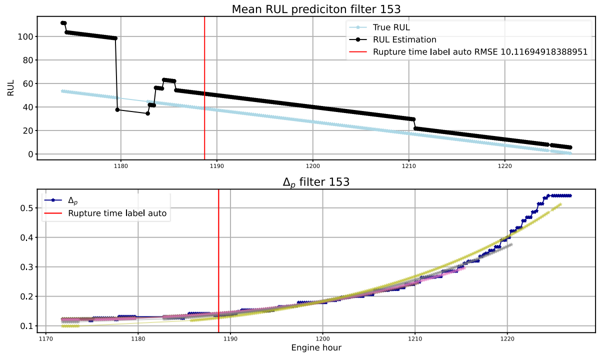

Figure 11 results filter 153

Figure 11 shows RUL predictions that closely align with the true values following an initial phase of fluctuation.

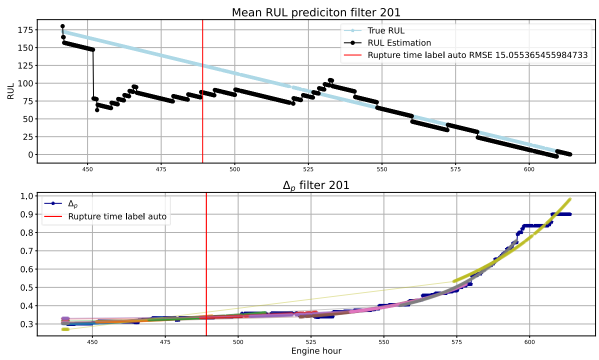

Figure 12 Results filter 201

In Figure 12, the predictions in the latter part of this figure are accurate. However, prior to stabilization, significant fluctuations in the RUL values are observed, consistent with trends identified in other filters.

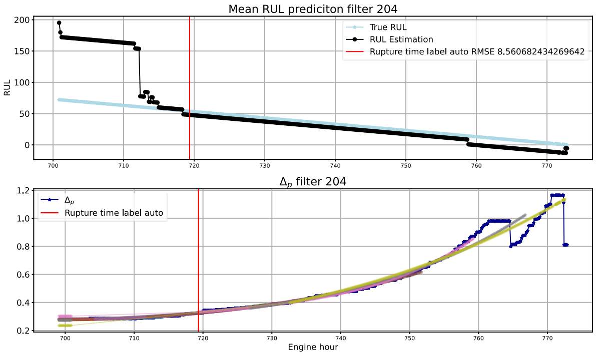

Figure 13 Results filter 204

In Figure 13 the RUL predictions exhibit a stable trend after an initial phase of overestimation. As the rupture point nears.

5.3.2 Results from the change point based on the CUSUM method

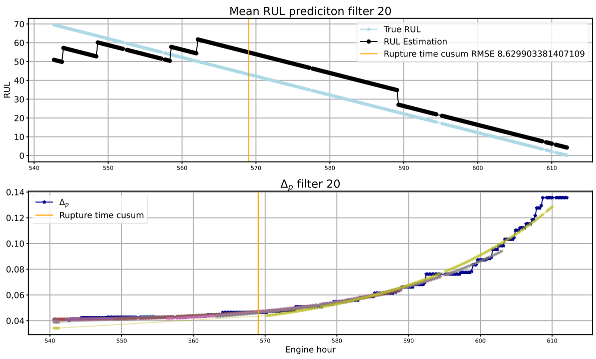

Figure 14 Results filter 20

In Figure 14 the change point time is detected early in the data, with Δ_P just beginning its sharp increase.

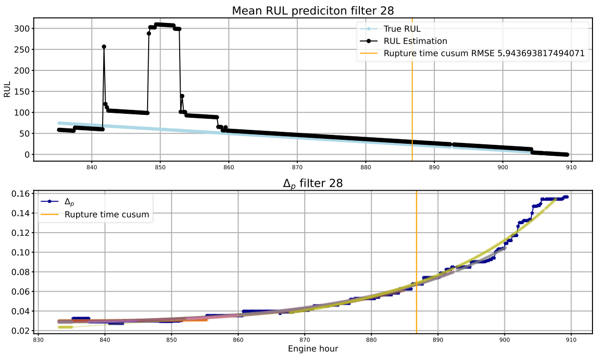

Figure 15 Results filter 28

In Figure 15 the estimated RUL stabilizes around the true RUL prior to the rupture point. These results indicate highly accurate predictions for the end of the oil filter's lifetime.

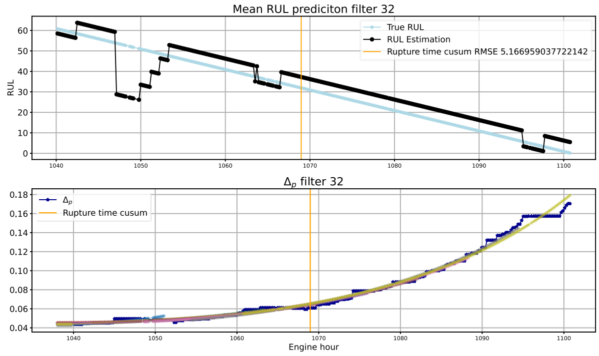

Figure 16 Results filter 32

In Figure 16 the RUL fluctuates initially but stabilizes effectively around the true RUL as the change point approaches.

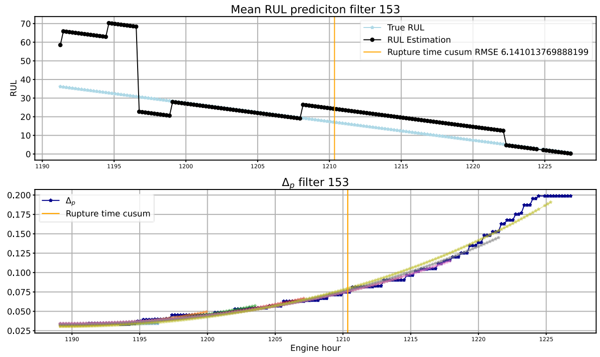

Figure 17 Results filter 153

In Figure 17 the RUL is initially overestimated but converges closer to the true RUL before the change point.

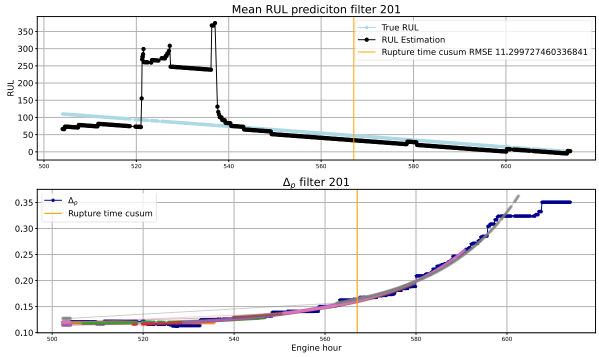

Figure 18 Results filter 201

The initial estimations are consistent; however, they deviate from the true RUL before stabilizing around it as the change point approaches.

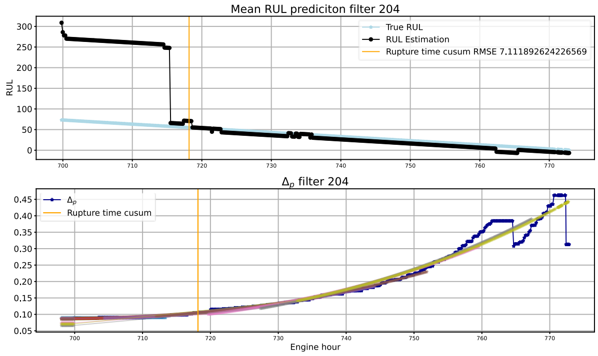

Figure 19 Results filter 204

At the outset, the RUL is overestimated, but it subsequently stabilizes around the true RUL shortly before the rupture point.

5.3.3 Results synthesis

An analysis of the figures reveals that the predictions closely match the observed values when they are made after the change point. Additionally, it highlights that the change point is detected between 40 and 110 hours prior to clogging. This demonstrates the robustness of the proposed method, enabling clogging to be predicted with a precision of less than ten hours, typically within two to four days before it occurs.

Regarding the comparison between change point detection methods, a general trend is that the automatic labeling detects change points earlier than the CUSUM method, aligning better with the goal of identifying the rupture point as soon as possible after the actual event.

The RMSE values displayed in the Figures are computed from the change points, which differ depending on the method used. Therefore, it does not make sense to compare the performance of the two methods based on these RMSE values. To address this, we compare the RMSE values using the same start point.

We denote t_c as the rupture time obtained with CUSUM and t_l as the rupture time obtained with automatic labeling and M_{tc} as the model that uses t_c as rupture time and M_{tl} as the model that uses t_l as rupture time.

The rupture time obtained from CUSUM, or automatic labeling are respectively denoted t_c and t_l.as the model that uses t_c or t_l as rupture time are respectively denoted M_{tc} andM_{tl}.

Table 3 RMSE computed from t_l

ID filter	M_{tc}	M_{tl}
Filter 20	**8.5**	14.7
Filter 28	6.3	**4.2**
Filter 32	7.1	**4.4**
Filter 153	13.9	**10.1**
Filter 201	68.5	**15.1**
Filter 204	**7.1**	8.6
Mean	18.6	**9.5**

Apart from filter 201, the results obtained with the automatic labeling and CUSUM methods are comparable. For filter 201, using CUSUM, the predictions stabilize after the rupture point detected by the automatic labeling method, which explains the very high RMSE value.

Table 4 RMSE computed from t_c

	M_{tc}	M_{tl}
Filter 20	8.6	**10.6**
Filter 28	5.9	**4.2**
Filter 32	5.2	**3.5**
Filter 153	6.1	**5.2**
Filter 201	11.3	**6.2**
Filter 204	**7.1**	8.5
Mean	7.4	**6.4**

There are few differences between the RMSE calculated from the CUSUM rupture point. The results obtained using automatic labeling are however better, except for filter 204. Furthermore, the average RMSE is also better with the automatic labeling method.

The results presented in section 4 demonstrate that, beyond a certain point, the model predictions are accurate and enable the dynamic estimation of the filters' RUL, allowing for predictive replacement schedule.

6 CONCLUSIONS

This study presents a comprehensive framework for predicting the RUL of engine filters through the combined use of two complementary methodologies: change-point detection and RUL estimation. The first method, change-point detection, plays a crucial role in identifying key moments when the system undergoes significant changes in behavior or performance (phase 3), which are indicative of the onset of degradation. By accurately detecting these rupture points, this approach enables the timely characterization of critical transitions in the lifecycle of engine filters, providing valuable insights into their performance under operational conditions.

The second method, RUL estimation, further refines this analysis by quantifying the time remaining before the filter reaches the end of its useful life. The RUL estimations are based on constrained estimation methods. This predictive approach leverages the information gathered from change-point detection to make informed predictions about the degradation trajectory, enabling maintenance teams to plan interventions effectively. The accuracy of the RUL predictions, as reflected in the low RMSE values observed across multiple oil filters corresponding to different scenarios, underscores the robustness and reliability of the proposed framework and demonstrates a proof of concept for the hybrid approach presented.

The method presented here combines breakpoint detection and constrained optimization to overcome the issue of poor prediction quality at the beginning of the filter's lifespan, since the Δ_P signal contains little information during phases 1 and 2 (constant and linear). This is made possible by breakpoint detection, which is usually not used for RUL estimation.

The integration of these two methodologies offers a significant advantage in predictive maintenance. By combining the early warning capabilities of change-point detection with the actionable insights provided by RUL estimation, this framework ensures both the prevention of unexpected failures and the optimization of maintenance schedules. This dual-method approach reduces operational risks and costs, minimizes downtime, and optimise the lifespan of critical components.

Future work could expand on these findings by incorporating advanced machine learning models to enhance the precision and adaptability of both methods. Additionally, integrating real-time sensor data and exploring other operational contexts could broaden the applicability of this framework across different industries. While this study focused on oil filters, the proposed approach could also be extended to other applications, such as engine filters or critical components in various mechanical and industrial systems. Ultimately, this hybrid methodology serves as a promising step toward the implementation of smarter, data-driven maintenance strategies that align with the principles of Industry 4.0.

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