Predict the remaining useful life in HVAC filters using a hybrid strategy

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Abstract.
Introduction: This article discusses an engineering prediction-oriented method to monitor and predict the healthy conditions of air filters in heating, ventilation and air conditioning (HVAC) installations in the construction industry.
Background: In the literature, many researchers have studied hybrid prognostic methods for monitoring and predicting filter clogging, and experimental studies have been conducted to develop degradation models to demonstrate the mechanism of filter clogging. The common methods usually predict residual useful life based on a physics-based degradation model along with a prognostic model based on measured data. However, if there is not run-to-fail data or it is costly to prepare, another method is needed. The method used in the present work is useful when the data of entire operating period is not available, instead part of the operational range is obtained during the operation of the air handling unit (AHU).
Methods: The method described in this article includes a combination of physically-based models and acquired operational data. An appropriate health indicator (HI) is calculated based on measurements. Learning algorithms are used to calibrate a carefully designed filter degradation model. The remaining useful life (RUL) of the filter is estimated using the dimensional reduction method, in particular principal component analysis (PCA) technique. The proposed method has been tested on a real air conditioning unit installed in a building located in Tallinn.
Results: The results show that the selected degradation model provides the best fit based on the data observed from the field. In addition, using dimensional reduction methods to estimate remaining useful life is feasible for HVAC filter clogging prediction. This is based on a comparison between an acceptable remaining useful life estimate and experimental data. The performance analysis results show that predictive maintenance methods can provide accurate prognostic indications.
Conclusion: The application of a hybrid prediction model allows accurate estimation of the characteristics of the remaining useful life of the target component. It should be noted that the use of predictive maintenance strategies in this situation has increased the life of filters in buildings by a significant amount compared to replacement time schedule.

Keywords. predictive health maintenance HVAC filter prognosis, remaining useful life.
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1. Introduction

The building industry needs to focus most on optimizing current maintenance practices, avoiding services that affect failures and reducing related costs. Given recent advances in data technology and science, many companies have made unprecedented efforts to use advanced analytics to improve the operational efficiency of their products and services. Especially in the field of HVAC industry, it is particularly important to develop predictive maintenance (PM) strategies. Many researchers from academia collaborate with industry ones to explore various methods to better plan and manage the maintenance of construction and transportation assets. The development of predictive health maintenance (PHM) solutions for HVAC has been the focus of industrial research [1]. Effective HVAC equipment can lead to increased energy consumption, increased equipment failure, and decreased thermal comfort for occupants, and leading to higher maintenance costs. When ventilation system is affected by faults, the health of the occupants may also be endangered due to the increased possibility of exposure to indoor pollutants. Therefore, PHM is an important tool to ensure efficient operation of HVAC equipment so that air-conditioning assets can achieve their best optimal energy consumption and performance. The health indicator (HI) which is calculated based on a combination of physic-based and data-driven models has been used in this article. This approach leads to the development of degradation model in order to calculate the RUL prediction of working HVAC unit. RUL prediction of degradation is not set explicitly and can be linear, exponential, polynomial or logarithmic, and it depends on the object being studied. In different research cases, the deterioration behaviour of component life may be different. The RUL prediction depends on case study since first, despite the fact that exponential prediction model is used frequently, there are other case studies which concluded that above mentioned model is not appropriate for their systems. For example, Kang et al. [2] used the training datasets which RUL was not provided. They applied a polynomial degradation model and the intersection between the polynomial and the axis of the cycle was calculated as the failure point. Coble et al. [3] implemented the second-order polynomial to model the degradation parameter. While an exponential model may be more physically appropriate, the quadratic model is more resistant to noise and better describes the relevant data for the selected prognostic parameter. Zheng et al. [4] present a RUL of bearing as case study using Hilbert–Huang entropy prediction method with linear degradation model. Second, the exponential degradation model will increase dramatically for predicting over a larger period of time. This is due to the mathematical nature of the exponential function compared to other functions. The third reason is the uncertainty in the RUL models. Celaya et al. [5] discussed the importance and interpretation of uncertainty in RUL prediction of components used in several types of engineering applications and explained why RUL prediction is uncertain. Another influential reason is the existence of unexpected conditions like covid-19 crisis. The main problem is that in the majority of research, the filter behaviour and its pressure drop are based on changes in volumetric or mass flow rate. Those can be described on laboratory conditions. On the contrary, in real conditions, the flow rate is controlled by the controller on a fixed value. These measurements lead to the acquisition of a set of run-to-fail data, which is suitable for use in the survival and similarity based methods. However, this can lead to high costs for laboratory equipment. Another problem is that measuring and having a set of run-to-fail data takes a lot of time. At the same time, run-to-fail data set are sometimes very non-linear with high variations and reduce the prediction accuracy. In the present work, these limitations have been resolved and the measured values from AHU have been used directly.

The organization structure of this article is as follows: The Section 2 provides related work and problem descriptions. Section 3 focuses on the formulation of health indicators and prognostic strategies, and outlines the proposed methods. Section 4 discusses the results of the proposed method to the case study. Finally, conclusions in the Section 5 provide suggestions for future research directions.

2. Background

In many industrial systems, filtration is a key process to achieve the required level of purification of liquids. Filter clogging and pressure drop are the main failure mechanisms that lead to filter replacement or adverse consequences such as reduced performance and efficiency. For HVAC applications, filters are installed to purify the air from particles such as dust, pollen and other airborne materials from windows, kitchens, etc. This accumulates in the filters and can leads to clogging or even blocking, (Figure 1). A clogged air filter will adversely affect the performance of the HVAC system and may cause damage, such as extended compressor running time, reduced energy efficiency, freezing of the evaporator coil, and ultimately damage to the air conditioning system.

Fig. 1 - Samples of new filter (right) and clogged filter (left), [Theengineeringmindset.com]

It is expected that there will be a large amount of articles on HVAC systems. The focus of this paper is to use hybrid methods to detect and predict the pressure drop of air filters in HVAC systems. In the literature, many researchers have studied methods of controlling and predicting filter pressure drop, and conducted experimental studies to establish degradation models to show the mechanism of filter clogging. The authors proposed a simple model-based model for filter clogging by using the Markov model to calculate the remaining useful life in [6]. In the maintenance strategy, three terms are usually used: preventive maintenance, predictive maintenance and reactive (corrective) maintenance, depending on the type and degree of safety of the system. Preventive maintenance usually used on high-precision equipment such as airplanes. The predictive maintenance is usually selected based on the comfort or cost of the residents such as building HVAC. Reactive maintenance is mainly used for consumables such as vehicle parts. Two predicted maintenance cases were found in the literature: Condition-Based Maintenance (CBM) and Prognostics and Health management (PHM). In predictive maintenance, if we are looking for a general strategy, we can use condition-based maintenance to disable component data with the help of a set of executions, and if we only want to maintain components that contain only one data set, we usually use PHM for health prediction. In the process of diagnosis and prognosis, two main approaches can be extracted in the prediction: single model approaches and multiple model approaches. For the single-model approach, there are three types of models are called «knowledge-based models, data-driven models, and physics-based models». The multi-model approach combines at least two of the above three models. Multi-model methods are sometimes referred to as hybrid models, and may have different configurations. In data driven approach, classification and regression algorithms are commonly used for supervised learning. Unsupervised learning algorithms usually use clustering and dimensionality. The third type is reinforcement learning which is used in the absence of training data sets, and learns from its experience. Authors in [7] covered the most complete reviews of predictive maintenance models in 2017 and 2018, respectively. Authors in [8], made studies the comprehensive systematic review in 2019. The main topic was devoted to data-driven methods for prediction work, especially methods related to machine learning and deep learning. Most consulting studies have limited case studies, with few failures (sometimes only one), which is a challenge for extrapolating single-model methods to complex applications of systems. Multi-models usually are used to overcome the complexity of the maintenance predictive task. The author in [9] divided them into 5 specific groups with admirable details. For the research described in this article, a predictive maintenance strategy based on a health indicator has been developed. The health indicator is calculated based on a combination of physics-based models and sensor data collected from working HVAC units, resulting in RUL predictions. Using dimensional reduction methods, it is possible to simulate the future development of the health indicator related to the development of pressure drop due to the clogging. Among dimensionality reduction methods, the PCA is one of the methods that is used for faster and more cost-effective prediction purposes. The reason to use PCA is that in the present case study, the entire execution run-to-fail data is not available, instead a part of the operating range is acquired during the operation of AHU. Lack of information about the final output of failure leads us to used unsupervised learning. The values from the sensors are divided into different parts. This is good idea, especially if we want to upload the new data periodically to the PM algorithm. Each data set can be clustered and extracted based on its own feature.

2.1 case study

The case presented in this paper is based on a real HVAC unit installed on a AHU in the city of Tallinn. Typically, or at least for existing AHUs for current work, filters are replaced periodically based on manufacturer's suggestion. Replacement is often done without assessing the actual retention life of the filter. In addition, inspecting air filters usually requires stopping the building's air conditioning system. Unnecessary filter replacement is costly, time consuming and therefore undesirable. Thus, having the platform that predicts the time of filter replacement is the main idea of doing this work. The proposed method should be easier to implement and also has an acceptable reliability and faster processing speed. The system is equipped with a variable frequency drive, which can adapt the fan motor to the thermal load. In fact, understanding background information is essential to ensure that health indicator is properly assessed. For this reason, it is necessary to consider factors that affect the performance of HVAC components. For the expected situation, it is necessary to control variables such as external temperature, humidity level, fresh air damper position, and HVAC power supply voltage. These factors may affect the failure mechanism.

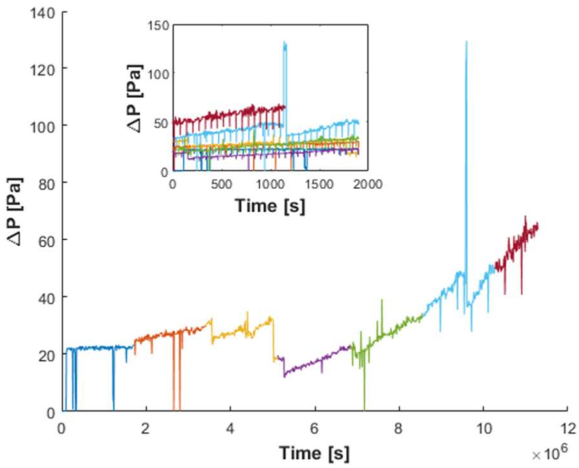

Fig. 2 - Pressure drop measured across the air filter, (top) monthly acquired data, (bottom) assembly of them.

The main health variable that helps to establish health indicators is the pressure difference across the filter. That parameter is not affected by the air flow rate associated with it, because it is controlled by a constant setting point. Figure 2 shows the pressure drop ΔP obtained from BIM from 10th July 2019 to 27th February 2020. The requirement of the original data pre-processing is set, in order to eliminate the influence of the noisy and misprinting data, integrating the pre-processed signal with a time series generated using the most important data features. These feature are the combination of time or frequency features (mainly useful for rotating parts). After processing and filtering, the algorithm will find the most important features. Figure 3 shows the framework used in this work.

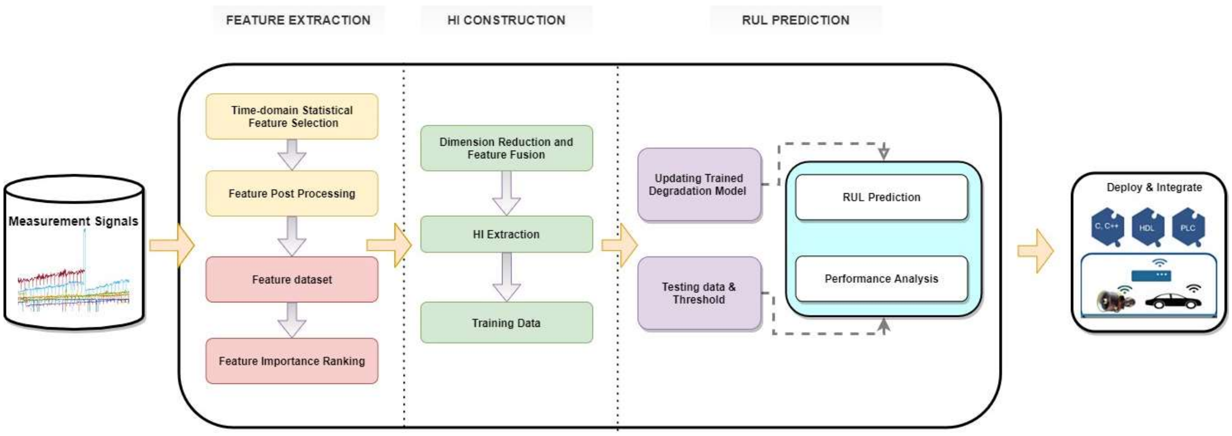

Fig. 3 - The framework of the prediction

The next step is to reduce the dimension of important selected features and extracting the health indicator. Therefore, the proposed method and dimension reduction applied as a hybrid PHM model (with a data-driven model based on a physical model) that relies on a combination of measured data and simulated data. The development of the method is described in the next section. The physic-based model will update with validation data and then will be verified using testing data. The obtained model is used for prediction.

3. Method

This section introduces methods designed for predictive maintenance of HVAC filter. First, a method of extracting relevant information from the original data is proposed. The purpose of this step is to realize the features properly that reflect the filter performance status. Then, the construction of health indicator and the description of related fault threshold are discussed. Finally, a prognostic strategy is described, which involves the use of dimensionality reduction.

3.1 data Preparation and features extraction

As in the majority of machine learning programs, the quality of input data is a key factor in building high-performance predictive models. For not rotating/vibration components usually the time series analysis is performed to extract potentially relevant time series features. In order to eliminate the effect of noise, we can calculate the moving average in a specific attribute window to add them into the feature set. As shown in Figure 2, the raw data collected from this field fluctuates sharply, which makes it difficult to obtain directly the health indicator of the filter from the sensor measurements. For the study carried out in this paper, the following approaches are used to extract the features needed to construct a health indicator: First, pre-processing the original data to eliminate the influence of disturbing variables. Second, extraction of feature importance ranking from the pre-processed signals. Third, generation of PCA based on dimensional reduction of data. Forth, defining the more important principal component for subsequent construction of the health indicator. When the pre-processed pressure drop ΔP is obtained, several features can be calculated including the mean value, the standard deviation, the slope, the maximum/minimum value, the mean square root value, skewness, SNR, and band power. Taking into account the slow changes in the clogging process, in this case, a monthly health assessment can be performed. Therefore, features can be extracted within a time frame of one month. For current case study, seven out of twenty features were found to be sufficient to establish an effective health indicator. There are basically three criteria for extracting the most important features, monotonicity (uniformity), trendability (machinability) and prognosability. Monotonicity is used to quantify whether the features is suitable for prognosis. The monotonicity is obtained using the following equation:

$$Mon(x_i) = \frac{1}{m}\sum_{j=1}^{m}\left|\sum_{k=1}^{n_j-1}\frac{sgn(x_j(k+1)-x_j(k))}{n_j-1}\right| \quad (1)$$

Where x_j represents the measurement vector of a feature on the *jth* system, m is the number of monitored systems, and n_j is the number of measurements in system j. The mean and skewness of the signal is the top feature based on monotonicity.

3.2 dimension reduction

The next step is to reduce the dimension of the selected important features and extract the health indicator. The physics-based model is then updated with validation data and then verify with testing data. The obtained model is used for prediction. Our goal is to build a predictive model for clustering task and reduce its dimension. Due to time constraints in massive data processing, longer computation time, and high storage, dimensional reductions are essential, especially in real-time applications. Feature selection is the first step to reducing dimensions. Many other dimensional algorithms are available through machine learning research, including T-SNE, MDS, multidimensional scaling, missing value ratio, low variance filter, high correlation filter, random forests / ensemble trees, PCA, backward features Elimination, and forward features Construction. The main reasons for selecting the dimension reduction, in particular PCA are: 1) In the modern computer era, large high-dimensional data sets are common; 2) Data visualization is impossible in higher dimensions. As a result, pattern recognition, data pre-processing and model selection must rely heavily on numerical methods; 3) In larger dimensions, the data shows too many edges of the sample distribution, because areas with larger spaces have the largest volume near the surface; 4) In high dimensions, the sampling frequency of internal data points (distribution) is low; 5) The features of high-dimensional data may be irrelevant or redundant; 6) The regression, classification, and clustering algorithms used to process raw data may require a lot of computation time and storage, and even if the algorithm is successful, the resulting model may contain a number of unclear terms. The algorithm provides a linear combination of important features on its first principle axes and the idea is to use these main axes as an important indicator or health indicator for use in training purposes to find a proper physical based model. Its advantages include useful items for the high input dimension (in our case 47 dimensional, 7 month times 7 important features). It also improved algorithm solving speed.

3.3 health assessment

The calculation of the appropriate health indicator (HI) is necessary to establish the relationship between the degradation or deviation of a case and its RUL. Therefore, an accurate HI is a key to more accurate prediction. In this paper, the first component of PCA coordinates is selected as a health indicator. To assess the health status of the filter, it is necessary to select the threshold for the health indicator. For current case study, the failure threshold is $\Delta P = 300$ Pa equal to $HI_{thr} = 30$. Health indicators has been matched on PCA in terms of experimental data, and to mathematical degradation model in terms of prediction.

3.4 prognostics: degradation model and RUL

Once the filter health indictor is determined, the parameters of mathematical prognostic model is updated and is implemented to predict RUL. First, a physics-based mathematical degradation model is used to express the evolution of pressure drop in the filter. Approximately, it is assumed that the filter clogging behaviour is exponential, although it should be noted that the degradation curve can vary or be different depending on the type of machines. For example, Zhao et al. [10] explained that regarding the determination of the empirical data, the different model can be used like exponential model (Table 1).

Tab. 1 - Different mathematical models according to the physical nature of the degradation.

Degradation model	Formula
exponential	$a.exp(b.t)$
quadratic polynomial	$a.t^2+b.t+c$
hybrid	$a.exp(b.t)+ c.t^2+d.t+e$
hybrid	$C=(a/b)/(1+(a/(b.C(t_0))-1).\ exp(-a.(t-t_0)))+ c.exp(d.t)$
Chaos	*due to abnormal conditions such as the Covid period, unintended and sudden breakdown of a part or machine, etc.*

The authors chose the exponential function because due to the fact that in the authors' previous research [5], it was found that the exponential equation gives acceptable results for clogging prediction among existing filters studied. The exponential degradation model for the health index, h (t) is defined as [11].

$$h(t) = \phi + \theta e^{(\beta t + \epsilon - \frac{\sigma^2}{2})} \quad (2)$$

where Φ is a constant deterministic parameter, $\boldsymbol{\theta}$ and β are random variables. These parameters are determining the slope of the model. At each time step t, the distribution of $\boldsymbol{\theta}$ and β is updated to the posterior based on the latest observation of h(t). ε is a Gaussian white noise or a normally distributed random error term with mean 0 and variance σ^2. The variance $\sigma^2/2$ in the exponential is to meet expectation. The model will find the closest training data set in the validation data, fit the probability distribution, and use the median of the distribution as the estimated value of RUL. Using the degradation model in (2), the evolution of health indicators can be obtained. In order to estimate the RUL of the air filter, based on the degradation model, we performed a two-step process: 1) Training phase: Perform model fitting to calibrate and update the degraded model based on pressure drop measurement data collected from the field. 2) Prognosis stage: Use a trained model to simulate changes in pressure drop over time until the air filter's service life is achieved. After finding and updating the model, the future, in particular RUL can be predicted, which could be failure or replacement time. RUL of a machine is the expected life or usage time (cycles, miles, etc) remaining before the machine requires repair or replacement. RUL prediction here is the main purpose of prediction maintenance algorithms.

$$RUL = t_f - t_c \quad (3)$$

Where t_f is a random variable for the time of failure or replacement, and t_c is the current time.

3.5 prognostic performance analysis

In order to prove the performance of the proposed method, the performance algorithm is applied to predict RUL. There is uncertainty in the prediction, which can be represented by a probability density function (PDF). The type of data and the method of predicting RUL based on data are crucial. This uncertainty may occur due to the following reasons: insufficient data, lack of clean data (noise, mispointing, etc), lack of failure data. Therefore, using the set of standards for analysing RUL's predictive performance is required. In these years, many indicators for predictive maintenance performance analysis have been provided. Recently, high robustness metrics for predictive maintenance have been proposed, and four of them have been used in this work, including prognostic Horizon, alpha-lambda performance, relative accuracy, and convergence metrics. The horizon prognosis is obtained from the difference between the end of life (EOL) and the predicted time, *i*. The best result is when the PH(i) reaches zero. We prefer to present the PH results as a percentage of the actual life of the test specimens.

$$PH = EOL - i \tag{4}$$

Obviously, given that we are using a threshold, we must have a real RUL here, so we can use this metric (the point is that our threshold is a health indicator equal to the 300 pa, filter pressure drop). The alpha-lambda diagram is used to analyze the prognostic effect, in which the bound is set to 25%. Alpha-lambda performance evaluates the performance of the prediction inside a shrinking accuracy cone defined by α [12].

$$[1-\alpha].\, r^*(t_\lambda) \le r(t_\lambda) \le [1+\alpha].\, r^*(t_\lambda) \tag{5}$$

$$where \;\; t_\lambda = P + \lambda(EOL - P)$$

where λ is windows modifier, *r* is the estimated RUL at time *t*, *r** is the true RUL at time *t*, *P* is prediction time, t_λ as current time is between conical range of actual RUL. Observing the accuracy of the algorithm with the help of relative accuracy (RA) is another performance evaluation. As shown in the equation, the actual RUL is equal to the predicted RUL if RA tends to 1.

$$RA = 1 - \frac{|r^*(t_\lambda) - r(t_\lambda)|}{r^*(t_\lambda)} \tag{6}$$

Finally, convergence is the ultimate metric that is confirmed. Previously, the algorithm determines whether the accuracy or precise measurement improves over time for true RUL path convergence [13]. The idea of convergence metric is to calculate the center of mass or area of an M which defines as predicted RUL curve. The perfect score for convergence performance metrics is when convergence (CM) tends to zero.

$$CM = \sqrt{(x_c - t_p)^2 + {y_c}^2} \tag{7}$$

$$x_c = \frac{\frac{1}{2}\sum_{t=P}^{EOP}({t_{i+1}}^2 - {t_i}^2)\, M(i)}{\sum_{t=P}^{EOP}(t_{i+1} - t_i)\, M(i)} \tag{8}$$

$$y_c = \frac{\frac{1}{2}\sum_{t=P}^{EOP}(t_{i+1} - t_i)\, M(i)^2}{\sum_{t=P}^{EOP}(t_{i+1} - t_i)\, M(i)} \tag{9}$$

Where (x_c, y_c) is center of area of prediction error accuracy curve *M(i)*, *EOP* is end of prediction and *P* is prediction time.

4. Results and discussion

The predicted maintenance approach is implemented on a filter installed at one of Tallinn's sites. According to the scheduled preventive maintenance plan, the interval for replacing the fresh air filter was 7 months. With new data from this field, the RUL forecast is updated based on new measurements collected from the HVAC unit. Sufficient additional time must be taken to ensure the availability of spare parts and of personnel to operate the replacement as well as to prepare a suitable schedule plan. The results of the application of the proposed algorithm are shown from Figure 4 to Figure 6. The number of months in figures is counted starting from the first prediction date, 10th July 2019. The measured data includes seven data sets due to seven months' data set that contain a combination of the most important features. The selected features were about seven features (mean, skewness, peak2peak, RMS, shape factor, energy and band power), so each of these points is a set of clusters. In fact, there is a 49-dimensional data space that includes seven sets of seven most important features. As mentioned earlier, the main constituent component, PCA_1, is the most important component and is selected as an indicator of health. Bottom plot in Figure 4 shows the results of principal component analysis, which indicates the virtual conversion from multi-dimensional to two-dimensional graph. Each point represents a data set (7 sets) based on the selected important features. From this graph it can be seen that the HVAC filter data of sixth and seventh months is strictly separated from other data sets. So it is quite characteristic that the filter goes to its threshold. The plot indicates that the first principal component is increasing as the machine approaches to failure. Therefore, the first principal component (PCA_1) is a promising candidate for health indicator. In other words, PCA_1 shows that the most important features of filter clogging index approaches the defined critical pressure drop value. The critical pressure drop value is already found in BMS, and is usually calculated based on filter type, manufacturer's data sheet, and etc.

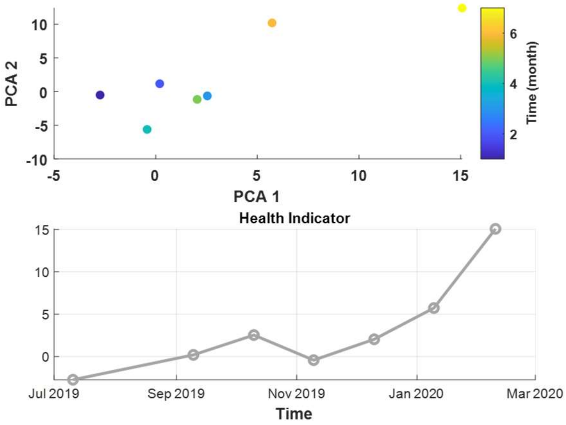

Fig. 4 - The process of filter destruction (up), and Filter health indicator (down)

The health indicator for the monitored filter is shown in Figure 4. If smoothing is needed, the moving average and low pass filter can be used. Possibly using filter can make lag or delay on the signals. The calculated threshold is 30 and it can be seen that the health indicator is still below the threshold. This demonstrates that the preventive schedule to be used in this situation will lead to premature replacement of the filter. In fact, the health indicator clearly shows that the load on the filter pressure drop level is close to the maximum after 7 months. Once the health status of the filter is evaluated, the RUL can be estimated based on the exponential degradation model. Exponential degradation model is fit to the considered health indicator and the model is able to predict the RUL. First, the degradation model (2) is trained to estimate the rate of the pressure drop, so as to minimize the error between the output of the degradation model and the observations collected from the filter. The best degradation model over time related to the health indicator is shown in Figure 5. It should be noted that the hybrid model actually reflects the exponential growth of the health indicator. Using the described method in this article, the RUL shown in upper plot of Figure 5 can be calculated. For each simulation, RUL can be easily predicted and obtained as the difference between end of life and the prediction time. Figure 5 (down) shows the probability density function (PDF) of the predicted results. When the data is updated every month, the PDF will decrease. The confidence interval represents the maximum probability of failure. There will be a lot of variation at the beginning of the prediction, but the more months of training, the more PDFs is obtained. This is advantage since in similarity models, most similar curves are close at the beginning, but when they are close to the breakdown state (threshold), they split and create approximately two states in the RUL distribution. The final RUL estimation is 0.8787 month or 26 days, when the actual life for filter based on measured data was 0.9861 or 29 days.

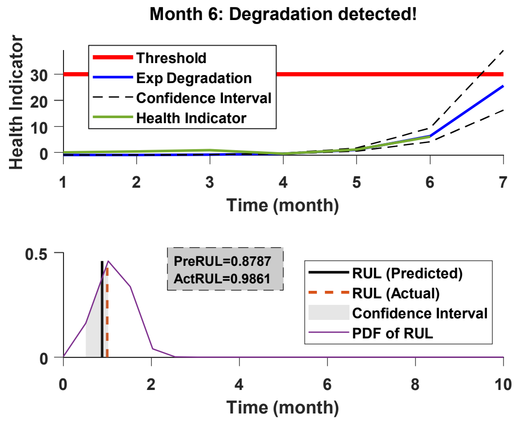

Fig. 5 - Model fitting for degradation model parameters estimation (up); and the probability value of prediction accuracy and final predicted RUL (down)

In order to evaluate the accuracy of the predictions, the prognostic horizon, relative accuracy, alpha-metric and conversion performance analysis has been applied. The alpha performance compares the actual RUL against the predicted RUL, which in Figure 6 (bottom) are indicated as actual RUL and predicted RUL, respectively. For the case illustrated in the figure, considering the slow dynamics of the pressure drop process, the value of alpha has been set to 25%.

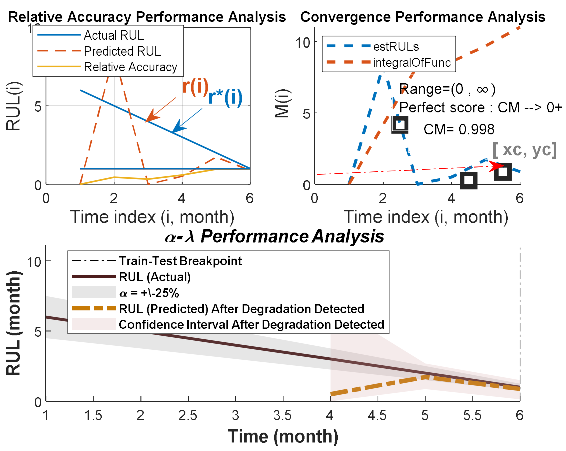

Fig. 6 – Top left: relative accuracy of final prediction, top right: convergence metric of prediction performance, bottom, the α-λ Accuracy metric determines whether predictions are within the cone of desired accuracy levels at a given time instant (t_λ).

It can be seen that after the degradation is detected, the predicted RUL is placed in the safe prediction cone, and the prediction is correct. This means that the relative accuracy of the proposed PHM algorithm (Figure 6, top left) is 100% within the desired prediction range. The convergence metrics is shown in Figure 6 (top right) indicates that the center of mass is shrinking to zero, but due to the type of data, the health indicator rises again over a period of time. As a result, the center of mass is a bit far from ideal, but tended to zero as the prediction continues. Finally, it should be noted that the use of predictive maintenance strategies in this situation has increased the life of filters in buildings by more than 90% compared to replacement time schedule.

5. Conclusions

This article describes the use of maintenance predictive strategies to improve the maintenance of air filters in HVAC systems. First, the appropriate health index is calculated based on the pressure difference measured on the filter. The health indicator can evaluate the actual condition of the filter based on the increase in clogging and pressure drop. Subsequently, a hybrid prognostics method was developed to predict the failure time (time to replace) of the filter on the AHU. The hybrid prediction strategy relies on a physics-based degradation model that uses real data collected from the field. The physics-based model quantitatively describes the degradation process that affects the air filter. The optimization plan is used to determine the parameters of the degradation model, which best matches the observation data in the field. The RUL is then estimated using dimensional reduction approach. This allows to speed up the implementation of algorithms, to help overcome overfitting, and to improves visualization. Finally, the results of performance analysis also show that predictive maintenance methods can provide accurate and accurate prognostic signs.

Future work can be the implementation to all AHUs with the aim of extending the proposed approach as well as different types of inventory and examining the application of health indicators in different situations. Next step is to applying other degradation models. The reason for using other degradation models is that, at least during the Covid crisis period, we realized that the degradation process is not exponential or even linear. However, in practical applications, there are other extras, such as decision time and retention time, which are not usually considered in article prediction calculations.

6. Acknowledgement

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