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A Belief Function Theory Method for Prognostics in Clogging Filters

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This paper presents a similarity-based approach for the prediction of the Remaining Useful Life (RUL) of sea water filters placed upstream the heat exchangers of a nuclear reactor condenser. The prognostic approach is developed considering a library of reference degradation trajectories containing parameter observations taken from a set of similar equipments until their failures. The prediction of the RUL of the a filter is obtained by comparing its degradation trajectory to the reference trajectories and by properly aggregating the RULs of the training trajectories using a weighted sum which takes into account the similarity within test and training trajectories. In order to provide a measure of confidence in the RUL prediction in the form of a prediction interval, we place our work within the framework of belief function theory and we assign to each reference trajectory a belief proportional to its similarity to the test trajectory. A prediction interval is then obtained by properly combining these belief assignments using the Dempster's rule.

1. Introduction

We consider the problem of predicting the Remaining Useful Life (RUL) of filters subjected to clogging, having available few sequences of clogging-related observation collected on similar filters. The real industrial data used in this study are taken from the filters used in the Boiling Water Reactor (BWR) of a Swedish nuclear power plant to clean the sea water pumped through the condenser.

Several data-driven methods have been proposed for predicting the RUL of degrading equipment (Vachtsevanos, 2006; Sikorska et al., 2011), i.e., the time left before the equipment will stop fulfilling its functions. Data-driven methods rely on the availability of observations collected during the degradation of one or more similar equipments. Due to the scarcity of information typically available and the different sources of uncertainty to which the RUL estimate is subject, data-driven models can commit large errors in the RUL estimate and uncertainty management becomes a fundamental task in prognostics (Baraldi et al., 2013): its goal is to provide the maintenance planner with an assessment of the expected mismatch between the real and predicted equipment failure times which allows to confidently plan maintenance actions according to the maximum acceptable failure probability.

In this context, the objective of the present work is to properly represent the uncertainty on the filter RUL prediction provided by a data-driven prognostic model. In practice, the maintenance planner defines the maximum acceptable failure probability, and is informed by the prognostic method of the time at which this probability is exceeded. To this purpose, we consider the similarity-based prognostic model proposed in

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(Zio & Di Maio, 2010) which uses a set of reference degradation trajectories collected in a reference library and performs a data-driven similarity analysis for predicting the RUL of a newly developing degradation trajectory (hereafter called test trajectory). The matching process is based on the evaluation of the distance between the reference and test trajectories. This prognostic model is here extended in order to provide a measure of confidence in the RUL prediction based on the belief function theory (BFT) (also called Dempster-Shafer or evidence theory) (Smets, 1994). The BFT allows combining different pieces of (uncertain) evidence, based on the assignment of basic belief masses to subsets of the space of all possible events, which are, in this case, the possible values that the filter RUL can assume. In practice, the proposed method considers each reference trajectory as a piece of evidence regarding the value of the RUL of the test trajectory. These pieces of evidence are discounted based on their similarity to the test trajectory and pooled using the Dempster's rule of combination [Petit-Renaud & Denoeux, 2004]. The result is a basic belief assignment (BBA) that quantifies one's belief about the value of the RUL for the test trajectory given the reference trajectories. From the BBA, the total belief (i.e., the amount of evidence) supporting the hypothesis that the RUL will fall in any specific interval can be computed. The interval to which a sufficiently large total belief is assigned is retained as prediction interval for the RUL value.

In the remainder of this paper we present the problem of RUL prediction in clogging filters (Section 2), describe the methodology for the similarity-based RUL prediction and the belief function theory–based uncertainty treatment (Section 3), present the results of the numerical application (Section 4) and draw the appropriate conclusions (Section 5).

2. Clogging of BWR condenser filters

We consider the problem of optimizing the maintenance of heat exchanger filters used to clean the sea water entering the condenser of the BWR reactor of a Swedish nuclear power plant. During operations, filters undergo clogging and, once clogged, can cumulate particles, seaweed, and mussels from the cooling water in the heat exchanger. For this reason, prompt and effective cleaning of the filter is desirable; predictive maintenance can help achieving this result, keeping maintenance costs reasonably low.

The clogging process is affected by large uncertainties, due to the variable conditions of the sea water; in this context, the challenge is to provide reliable confidence intervals for the RUL prediction.

From data collected on field, we have available sequences of n^q observations $\mathbf{z}^q_{1:n^q}$, $q = 1{:}8$, taken during the clogging process of $Q = 8$ historical filters up to the last measurement time $\tau^q_{n^q}$ before the failure time, τ^q_F. Each observation $\mathbf{z}^q_i = [\Delta P^q_i, M^q_i, T^q_i]$ contains the measurements of the pressure drop ΔP^q_i, the flow across the filterM^q_i, and the sea water temperature T^q_i collected at time τ^q_i during the clogging process of the q-th filter.

We are interested in predicting the RUL of a filter q at the present time τ^q_I, have available the observation sequences $\mathbf{z}^r_{1:n^r}$, $r = 1{:}7$, for the remaining $R = 7$ reference trajectories, and the sequence of observations $\mathbf{z}^q_{1:I}$, from τ^q_1 to the present time τ^q_I and for the test trajectory q.

3. Methodology

The idea underpinning the RUL estimation method is to evaluate the similarity between the test trajectory and the R reference trajectories, and to use the RULs of these latter to estimate the RUL of the test equipment, taking into account the similarities between the trajectories (Petit-Renaud & Denoeux, 2004; Zio & Di Maio, 2010).

The approach requires defining a measure of similarity between trajectories. This is done by considering the pointwise difference between n-long sequences of observations. At the present time τ^q_I, the distance d^r_i between the sequence of the n latest observations $\mathbf{z}^q_{I-n+1:I}$ of the test trajectory, and all n-long segments $\mathbf{z}^r_{i-n+1:i}$, $j = n{:}n^r$, of all reference trajectories $r = 1{:}R$ is computed as:

$$d_i^r = \sqrt{\sum_{j=1}^{n} \left\| \mathbf{z}_{I-n+j}^q - \mathbf{z}_{i-n+j}^r \right\|^2} \tag{1}$$

Where $\|\mathbf{x} - \mathbf{y}\|^2$ is the square Euclidean distance between vectors $\mathbf{x}$ and $\mathbf{y}$.
The similarity s_i^r of the training trajectory segment $\mathbf{z}_{i-n+1:i}^r$ to the test trajectory is defined as a function of the distance measure d_i^r. In Zio & Di Maio (2010) the following bell-shaped function has turned out to give robust results in similarity-based regression due to its gradual smoothness:

$$s_i^r = \exp\left(-\frac{(d_i^r)^2}{\lambda} \right) \tag{2}$$

The arbitrary parameter λ can be set by the analyst to shape the desired interpretation of similarity: the smaller is the value of λ, the stronger the definition of similarity. A strong definition of similarity implies that the two segments under comparison have to be very close in order to receive a similarity value s_i^r significantly larger than zero.
For the prediction of the test equipment RUL, a RUL value $r\hat{u}l_{i^*}^r$ is assigned to each training trajectory $r = 1{:}R$ by considering the difference between the trajectory failure time τ_F^r and the last time instant $\tau_{i^*}^r$ of the trajectory segment $\mathbf{z}_{i^*-n+1:i^*}^r$ which has the maximum similarity with the test trajectory:

$$r\hat{u}l_{i*}^r = \tau_F^r - \tau_{i*}^r \tag{3}$$

Then, the prediction $rul_I^{SB,q}$ of the test equipment RUL at time τ_I^q is given by the similarity weighted sum of the values $r\hat{u}l_{i^*}^r$.

$$R\hat{U}L_I^{SB,q} = \frac{\sum_{r=1}^{R} s_{i*}^r r\hat{u}l_{i*}^r}{\sum_{r=1}^{R} s_{i*}^r} \tag{4}$$

The ideas behind the weighting of the predictions $r\hat{u}l_{i^*}^r$ supplied by the individual trajectories is that: i) all failure trajectories in the reference library can, in principle, bring useful information for determining the RUL of the trajectory currently developing; ii) those segments of the reference trajectories which are most similar to the latest part of the test trajectory should be more informative about the value of its RUL.

3.1 Credible RUL intervals based on belief function theory

Given the uncertainty to which the RUL estimate is subject, maintenance plans cannot usually be based only on the RUL prediction in eq. (4). In this Section, we assume that the maintenance planner is able to specify a maximum acceptable failure probability, α, and we propose a method to identify the latest time at which, according to the available information, we can guarantee that the probability to have a failure is lower than α. To this aim, we resort to the Belief Function Theory. For the ease of clarity, only the notions of BFT necessary for the understanding of the proposed method will be now presented. For further details about the mathematical developments and the possible interpretations of the theory, the interested reader is referred to the woks of Dempster (1976), Shafer (1976) and Smets (1994).
The belief of an agent about the value of an uncertain variable, in this case rul_I^q, is represented by a basic belief assignment (BBA), which assigns to subsets Y^j, of the domain of $\Omega_{rul_I^q}$ (called frame of discernment in the BFT jargon) a mass $m_{rul_I^q}(Y^j)$ based on the available information. The frame of discernment $\Omega_{rul_I^q}$ is defined as the interval $[0, \tau_F^{\max} - \tau_I^q]$, where $\tau_F^{\max}$ is the maximum possible life duration of the equipment. All the subsets of $\Omega_{rul_I^q}$ with associated a mass $m_{rul_I^q} > 0$ are referred to as focal sets. The BBA should verify the condition that the sum of the masses of all its focal sets is 1.

In our application of the BFT, we assume that each reference trajectory $\mathbf{z}^r_{1:n^r}$, $r = 1{:}\,7$, corresponds to a different agent and that each agent provides a BBA assignment defined by only one focal set $Y^1 = \{r\hat{u}l^r_{i^*}\}$, made of the single element $r\hat{u}l^r_{i^*}$, with associated mass $m^r_{rul^q_I}(\{r\hat{u}l^r_{i^*}\}) = 1$.
The similarity measure $s^r_{i^*}$ defined in eq. (9) is interpreted as a measure about the relevance of the source of information inducing the BBA $m^r_{rul^q_I}$ and the discounting operation is used to reduce the belief assigned by the r-th agent to $\{r\hat{u}l^r_{i^*}\}$ by a factor $(1-\gamma s^r_{i^*})$, with $\gamma \in [0,1]$ representing the dissimilarity between the test and the r-th training trajectory. The discounted BBAs $\tilde{m}^r_{rul^q_I}$, $r = 1{:}\,7$, are thus obtained (Petit-Renaud & Denoeux, 2004):

$$\begin{aligned}&\tilde{m}^r_{rul^q_I}(\{r\hat{u}l^r_{i*}\}) = \gamma \cdot s^r_{i*}\\ &\tilde{m}^r_{rul^q_I}(\Omega_{rul^q_I}) = 1-\gamma \cdot s^r_{i*}\end{aligned} \tag{5}$$

According to the Dempster's rule of combination, two distinct sources of information inducing two BBAs, e.g., $\tilde{m}^1_{rul^q_I}$ and $\tilde{m}^2_{rul^q_I}$, can be combined to give the aggregated BBA $m^{1\oplus 2}_{rul^q_I}$ (Petit-Renaud & Denoeux, 2004):

$$\begin{aligned}&m^{1\oplus 2}_{rul^q_I}(Y^j) = \frac{1}{K}\sum_{Y^{j'}\cap Y^{j''}=Y^j} \tilde{m}^1_{rul^q_I}(Y^{j'})\tilde{m}^2_{rul^q_I}(Y^{j''}), \quad \forall Y^j \in \Omega_{rul^q_I}, \quad Y^j \neq \varnothing\\ &m^{1\oplus 2}_{rul^q_I}(\varnothing) = 0\end{aligned} \tag{6}$$

where the mass $m^{1\oplus 2}_{rul^q_I}(\emptyset) = 0$ is imposed to convert a possibly subnormal BBA (i.e., a BBA assigning a finite mass to the empty set $\emptyset$) into a normal one and where K is a normalization factor introduced to make the masses $m^{1\oplus 2}_{rul^q_I}(Y^j)$ assigned to all focal elements sum up to 1. Then, by aggregating through eq. (5) the R discounted BBAs $\tilde{m}^r_{rul^q_I}$ in eq. (4) one obtains the aggregated BBA $m_{rul^q_I}$.
The information conveyed by a BBA can be represented by a belief $Bel_{rul^q_I}(Y^j)$ or by a plausibility function $Pl_{rul^q_I}(Y^j)$ defined, respectively, as

$$\mathrm{Bel}_{rul^q_I}(Y^j) = \sum_{Y^{j'}\subseteq Y^j} m_{rul^q_I}(Y^{j'}), \qquad \mathrm{Pl}_{rul^q_I}(Y^j) = \sum_{Y^{j'}\cap Y^j\neq\varnothing} m_{RUL_I}(Y^{j'}) \tag{7}$$

The belief associated to an interval $[rul_I^{\inf}, rul_I^{\sup}]$ represents the amount of belief that directly supports the hypothesis $rul^q_I \in [rul_I^{\inf}, rul_I^{\sup}]$, whereas the plausibility represent the maximum belief that could be committed to this hypothesis if further information became available. Then, belief and plausibility can be seen as lower and upper bounds on the probability that hypothesis $rul^q_I \in [rul_I^{\inf}, rul_I^{\sup}]$ is true. Let us consider a left bounded interval $[rul_I^{\inf}, +\infty]$; the belief assigned to such interval is a lower bound for the probability that the RUL of the test equipment is larger than $rul_I^{\inf}$. Thus, if the maintenance planner defines the maximum acceptable failure probability α , the method can provide a value $rul_I^{\inf}(1-\alpha)$ which guarantees that the test equipment will fail before $rul_I^{\inf}(1-\alpha)$ with a probability lower than α. The interval $CI^q_I(1-\alpha) \in [rul_I^{\inf}(1-\alpha), +\infty]$ will be referred to as left bounded prediction interval with belief $1-\alpha$.
To set parameters λ and γ one should take into account the precision of the prediction, which can be evaluated as the mean amplitude $MA_{1-\alpha}$ of the interval $\left[rul_I^{\inf}(1-\alpha), rul_I^{SB,q}\right]$, its coverage $Cov_{1-\alpha}$, defined as the percentage of times the condition $rul^q_I > rul_I^{\inf}(1-\alpha)$ is verified, and its accuracy, measured by the Mean Square prediction Error (MSE). In practice one is interested in two conflicting desiderata: small prediction intervals ($MA_{1-\alpha}$) and high coverage values ($Cov_{1-\alpha}$). Notice that a coverage lower than $(1-\alpha)$ is not acceptable since it would indicate that a too large belief mass has been assigned to the predictions provided by the reference trajectories, and, thus, that the belief $(1-\alpha)$ assigned to the prediction interval is not justified by the experimental evidence.

The following procedure for setting the parameters λ and γ is here adopted: 1) we identify a set of plausible values of λ; 2) for each value of λ in 1), we derive a condition for parameter γ by imposing a coverage $Cov_{1-\alpha}$ greater than $(1-\alpha)$; 3) since the precision tends to monotonically increase as γ increases, we choose, for each value of λ, the maximum γ value which satisfies the condition in 2; 4) within the identified couples of values of λ and γ in 3), we choose the couple with the most satisfactory prediction accuracy (low MSE) and precision (low $MA_{1-\alpha}$) trade-off.

4. Results

According to the procedure proposed in Section 3.1, we have set the method parameters λ and γ to the values of 0.05 and 1, respectively. The prognostic method has then been applied to each available trajectory q at the three life fractions using the remaining $R = 7$ trajectories as reference trajectories. Figure 1 shows the predicted RUL and RUL confidence bound with $(1-\alpha) = 0.8$.

From the point of view of the maintenance planner, the on-line application of the method to trajectory 4 would suggest to perform maintenance on the filters after few days of operation, since the 80% confidence bound reaches the value of zero at time $\tau_3 = 3$ working days. This is due to the fact that the similarity of this trajectory with all reference trajectories is rather low, and thus the prediction is very uncertain. Notice that this filter is actually characterized by a very short life since it is going to fail at time $\tau_{12} = 12$ working days, and, thus, the anticipation of the maintenance action can be acceptable.

On the other side, the application of the method to trajectory 6 would inform the maintenance planner at time 15 working days that the filter life is still long since the 80% RUL confidence bound is 21 working days when actually the filter is going to fail in 10 working days. This incorrect outcome of the method can be ascribed to the fact that trajectory 8 receives a very high belief assignment $m_{rul_l^q}(\{r\hat{u}l_{i^*}^8\}) = 0.937$ due to its high similarity with trajectory 6 around time $\tau_{15} = 15$ although after few working days the parameter evolutions become very different.

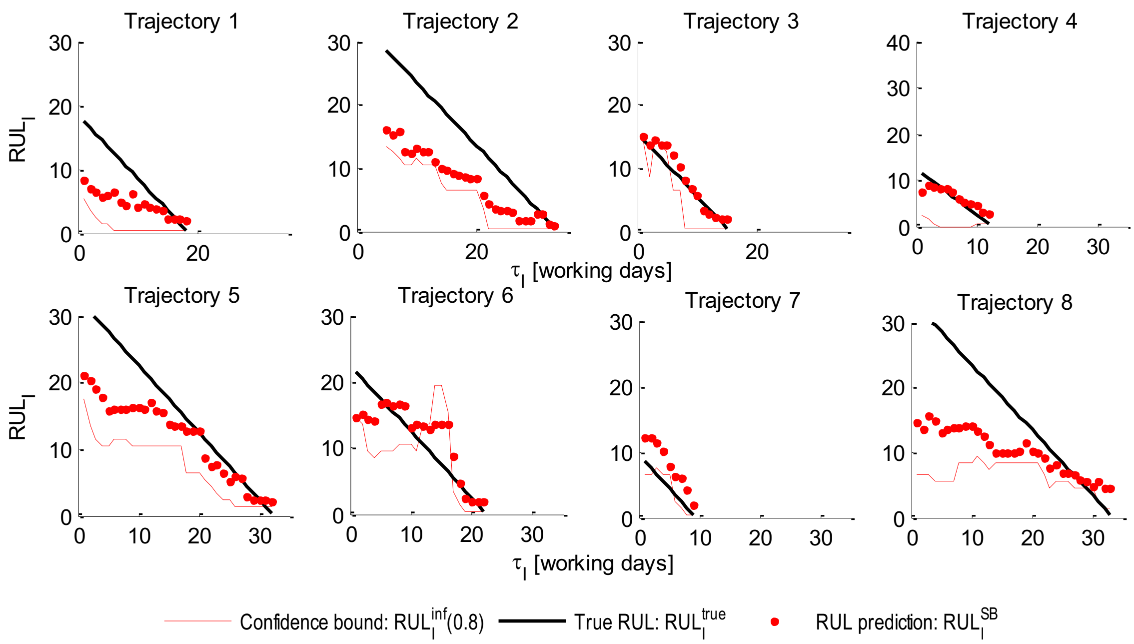

Figure 1: predictions obtained for the $Q = 8$ filter clogging trajectories available using parameters $\lambda = 0.05$ and $\gamma = 1$.

5. Conclusions

In this work, we have considered the problem of predicting the RUL of clogging filters and providing a measure of confidence in the prediction. The information available to perform the prediction is a set of reference degradation trajectories followed by similar filters which have failed in the past. We resorted to a method based on the use of a similarity-based approach for the prediction of equipment RUL and of the belief function theory for the assessment of the RUL uncertainty. Considering the large uncertainties affecting the clogging process and the limited number of available reference degradation trajectories, the obtained results seem to be satisfactory in terms of accuracy, precision and coverage.

Key elements to be considered for the application of the method are the setting of the parameter λ used by the similarity algorithm to define how strong is the interpretation of similarity, and the parameter γ of the BFT discounting operation which defines the degree of trust to be given to the reference trajectories.

A limit of the method is the presence of possibly large oscillations in the provided confidence bound which can be confusing for the maintenance planner. We have shown that such oscillations can be reduced by conveniently setting the parameter values which, however, tends to reduce the precision of the prediction.

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