Integrating Advanced Prognostic Methods for Accurate Remaining Useful Life Prediction in Industrial Systems

ABSTRACT

Accurate remaining useful life (RUL) prediction of industrial system is critical to ensure smooth operation and its safety. Various prognostic methods have been developed but there still exist critical challenges for field applications. One challenge is the unhealth degradation exhibiting the change of state from those of normal degradation. Another is the prediction in the face of severe noise with limited data (i.e., early prediction) using empirical models. Final challenge is the prediction under varying operating conditions, which occurs in practice in various industrial applications. To overcome these challenges, this research proposes advanced prognostics methods with different recipes featured by high adaptability, physical constraints, and monotonic health indicator (HI). The developed methods are validated with specific case studies involved with the challenges.

1. PROBLEM STATEMENT

Prognostic is to predict the RUL of in-service systems based on the condition monitoring data. A variety of algorithms are available to this end such as data-driven (Nguyen et al., 2022), model-based (Chen et al., 2020) and hybrid approaches (Xu et al., 2023). However, obtaining accurate RUL prediction is difficult due to various conditions that can actually occur in practice.

First, there are circumstances when the degradation is accelerated at some point in time to end up with earlier failures. It may occur for example in the unhealthy battery made of poor manufacturing process (Vetter et al., 2005). Without accounting for this, the prediction may be inaccurate, resulting in an incorrect decision for the end of life (EOL).

Second, the accuracy of RUL prediction is significantly affected by the uncertainties such as the measurement noise and the model inaccuracy when the empirical models are employed. These can lead to the poor accuracy of the RUL prediction.

Lastly, when the operating condition fluctuates over time, the health indicator developed by the feature engineering of the sensor signal can fluctuate accordingly, which is hard to use for the prognosis. Therefore, the goal of dissertation is to develop advanced prognostic methods that can solve these issues to achieve prediction accuracy. The advantages of the proposed methods are demonstrated with real case studies.

2. EXPECTED CONTRIBUTIONS

The research is focused on solving three main challenges in RUL prediction: (1) How to enhance the adaptability of prognostic method when the degradation is accelerated (2) How to improve prognostic method by exploiting physical knowledge (3) How to extract monotonic HI under varying operating conditions.

Research for the first challenge focuses on the state change detection and adaptation to the new degradation pattern. Next research investigates on integrating low-fidelity physical information to the prognostic method to reduce the effect of large random noise and uncertainty associated with empirical models, especially in the early stages of degradation. Final research plans to come up with new indicator that is monotonic while minimizing the sensitivity to varying operating conditions.

3. RESEARCH PLAN

Research 1: One of the model-based approaches, Particle filter (PF) algorithm, is utilized to conduct the RUL prediction. The PF uses a physical or empirical degradation model and estimates model parameters recursively by taking one measurements at a time to predict the future state. However, since the particle impoverishment occurs in the original PF, a regularized PF (RPF) is employed in this study which uses the kernel function to transform the discrete particles into the approximate continuous posterior estimates (Orchard et al, 2009). The change point detection technique and way to quickly adjust estimation to the changed degradation are implemented for the RPF process. Then the performance of original RPF and our proposed method is compared for the real battery degradations.

Research 2: In addition to RPF, Bayesian method (BM) is considered in the research 2, which takes all the data until current time to estimate model parameters and to conduct prediction. Physical constraints based on the behavior of low-fidelity physical information are incorporated in the algorithms. The low-fidelity physical information is the lowest level of available physical information that represents the crude behavior of parameters for degradation (Kim et al., 2022). Three different approaches are explored on how to embed physical constraints in the BM and RPF methods. Numerical examples and case study are considered for the study.

Research 3: Focus of this research is on developing more appropriate HI under the time-varying operating conditions while most of previous studies have been made on the constant operating condition. The initial idea is to cluster the operating condition regimes, and develop HI based on the distance method using the optimal features subset in each operating regime. Final goal will be developing HI not only within trained operating conditions but also under unobserved operating conditions. The proposed HI is compared with other features using the bearing run-to-fail datasets.

3.1. Work Performed

Research 1: First step of the research is to detect change point in degradation by introducing decision function in the RPF algorithm. To this end, the likelihoods of each particles are computed in the update step of PF algorithm. Then a decision function (d_k) is defined which is the negative log of mean likelihood as

$$d_k = -ln\left(\frac{1}{N}\sum_{i=1}^{N} L\left(y_k \middle| \boldsymbol{\theta_k}^{\boldsymbol{i}}\right)\right) \quad (1)$$

where k is the time/cycle index, y_k is the measurement data, $\boldsymbol{\theta_k}^{\boldsymbol{i}}$ is model parameters of the ith particle and L is the likelihood. In case the observed state is close to those of the predicted state, the likelihood is high, resulting in the negative value. If the state degrades in a different fashion, e.g., accelerates due to abrupt faults, the decision function value moves toward a positive direction. If it exceeds a set threshold, it is regarded as the change point.

Next step is to shift the kernel functions for the resampling process in the RPF algorithm. If the state change is detected, which means that the degradation deviates from the normal, the resampling is employed with Gaussian kernel function having bandwidth sequentially increased by twice over each cycle until the d_k falls below the threshold. This means the improved RPF adjusted to the new degradation with high likelihood. In the result, the kernel returns to the normal and follows the ordinary RPF with the newly identified model parameters.

Fig. 1 illustrates 12 degradation datasets of the capacity fade of Li-ion batteries used in the study. They were obtained by accelerated life test to the batteries manufactured from different lots. The state-of-health (SOH) represents the health of battery and if it drops below the failure threshold, the battery has reached its EOL. As shown in Fig. 1, while most of the batteries follow a normal capacity fade process, some battery undergoes unexpected state change and its EOL occurs earlier. This battery is defined as an unhealthy battery, and our method is applied for RUL prediction and its performance is compared with those by original RPF.

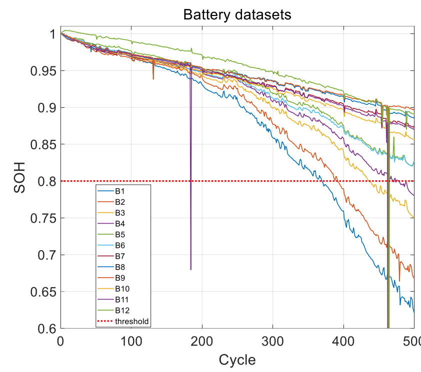


Figure 1. Plot for state-of-health (SOH) data

Research 2: A Bayesian approach with physical constraints is proposed for robust prediction under early prediction scenarios with severe random noise, as shown in Fig. 2. Two algorithms, BM and RPF are considered for the prediction. Physical constraints, such as monotonicity(Mon) and curvature(Cur), are defined with respect to the degradation model. Mon is that the damage state should increase over time (i.e., $dx/dt \geq 0$) and Cur is the slope of degradation should be a positive trend (i.e., non-linearly increasing trend, $dx^2/dt^2 \geq 0$). Three methods are investigated to embed physical constraints: imposing prior distribution, adding acceptance criteria in the sampling, and penalizing the likelihood function. Prediction performance is compared by quantifying the degree of uncertainty due to noise randomness.

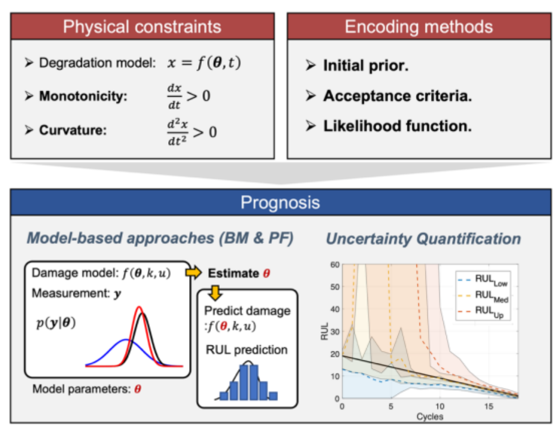


Figure 2. Proposed methodology for prognostics guided by physical constraints

The method 1 is to truncate the initial prior distribution based on the obtained model parameter boundaries. The boundary information is identified by combining monotonicity and curvature grid. Thus, the truncated initial prior information is used to estimate the posterior density function of model parameters.

The method 2 incorporates the physical constraints by the acceptance criteria in the sampling process of BM and RPF. The criteria are set by calculating the monotonicity and curvature values of the new predicted sample not only in the interpolation region (until current time) but also to the extrapolation region (in the future). It means that all the parameters are eliminated that predict the degradation incorrectly in the future, namely, not satisfying the physical constraints: Mon and Cur.

Finally, the method 3 gives penalties in the likelihood function in BM and RPF. The physical constraint is violated whenever the monotonicity and curvature are negative. they are handled by the inequality constraints in the optimization problem, which are turned into an unconstrained problem by using a Lagrange multiplier.

In order to explore and compare the three methods, numerical example is considered, in which the degradation data are generated with different noise level. As shown in Fig. 3, the original BM prediction is unsatisfactory because the estimated posterior state does not accurately reflect the true underlying degradation process and susceptible to the noise. The median of predicted distribution (solid red color) violates the monotonicity and decreases over time. In contrast, the predictions based on the proposed methods are satisfactory since their medians are not only increasing monotonically but also close to the true degradation with reduced uncertainty. The methods are applied to the real case dataset, which are the thrust degradation of each motor in the quadcopter. The results are given in Fig. 4 which the constraint BM show more accurate prediction than the general BM.

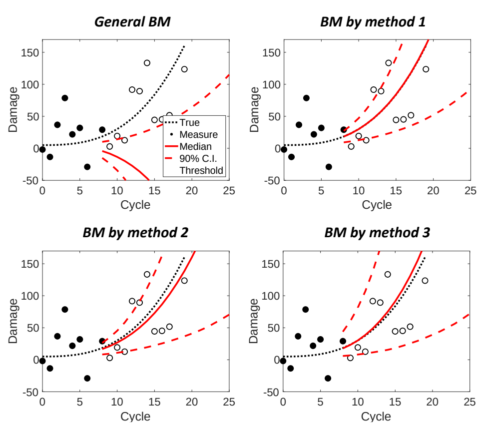


Figure 3. Prediction result using BM and proposed methods

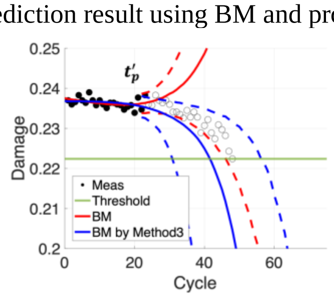
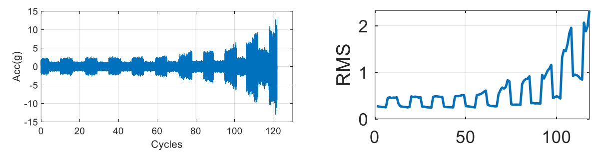


Figure 4. Case study result of BM and BM by method 3

Research 3: A simple RTF experiments are conducted for the bearing in which two operating conditions are applied alternately in terms of load and rotating speed. Fig. 5 shows raw vibration signals and its root-mean square (RMS) which is widely used as a health indicator for monitoring. The figure shows that the raw signals fluctuate between the two conditions, which means that it cannot be used as the HI, since the HI should be monotonic if it represents the degradation over cycles.



(a) (b)

Figure 5. (a) Raw vibration signal (b) RMS value of RTF

In order to construct monotonic HI, one of the RTF datasets is used for the training. In the training, regime clustering is conducted using the k-means algorithm. Features exhibiting monotonicity over cycles are selected for each regime. Then best subset of features are selected from each regime that maximizes the correlation of HI which is defined by the Mahalanobis distance between those at the current and initial normal conditions. Finally, it is validated with the new test RTF dataset. As shown in Fig. 6, the new HI shows the health degradation much better in monotonic way regardless of the regime.

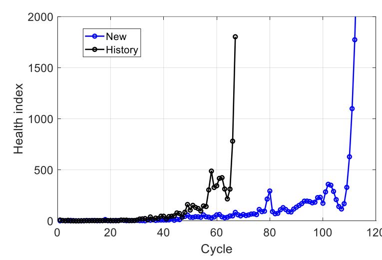


Figure 6. Health indicator of RTF datasets

3.2. Remaining Work

Currently, the research still has a strong assumptions or limitations Therefore the future work will focus on solving these issues as follows:

Research 1: (1) Performance comparison to various RTF datasets of batteries. (2) Proper threshold to detect the anomalies due to state changes

Research 2: (1) Apply to more Bayesian-based algorithms such as Particle Filter (PF) and Kalman Filter (KF) (2) How to optimize the Lagrange multiplier value in various applications.

Research 3: The methodology is largely dependent on the historical operating conditions. In practice, the operating conditions are rather random which might be included in the training set. Thus, developing monotonic HI under unobserved operating conditions is required.

Moreover, integrating proposed solutions and providing overall prognostic strategy from data acquisition will be further studied.

4. CONCLUSION

This research aims to develop advanced prognostic methods to solve three challenges in the RUL predictions. The first method integrates state change detection and kernel transition to enhance the flexibility of prognostic algorithm and adapt to new degradation trend. The second method proposes a Bayesian approach to incorporate physical constraints in the prediction process to improve RUL prediction accuracy with severe noise. Finally, the third method investigates a methodology to construct a monotonic HI under various operating conditions which will enhance prediction performance. These methods have been validated through numerical simulations and real case studies showing promising results. The remaining work will focus on solving limitations of each method and integrating them to further improve prognostics capacity in the field applications.

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