State-Based Prognostics with State Duration Information of Cracks in Structures

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Abstract

Prognostics is a key process of Condition-Based Maintenance (CBM) having the ability to forecast the expected future performance of the system/component by calculating its Remaining Useful Life (RUL) under degradation process. This paper presents a state-based prognostic method using state duration information to predict the fatigue life or fatigue crack growth in structures. The process of implementing the proposed prognostics algorithm consists of the following two stages: The first stage is identifying the health state of the system, while the second stage is calculating the expected RUL. The presented prognostic method is applied on the Virkler fatigue crack growth dataset and results show that the method efficiently predicts the remaining useful life of aluminium test specimens under constant amplitude fatigue load cycles.

Introduction

The ability to predict the end of life of system/component is critical for system/component continuous operation and can also improve usability and system/component’s safety. In condition-based maintenance (CBM), maintenance is performed based on the analysis of data collected through condition monitoring and assessment of the system/component health instead of its service time. Effective diagnostics and prognostics techniques play an important role in the CBM strategy for helping maintenance engineers to schedule a maintenance and to buy replacement parts before the system completely fail and failure occurs [1, 2].

Prognostics is an essential part of CBM strategy, described as forecasting the remaining useful life of a system/component [3, 4]. A reliable prognostic approach is important in industries to forecast the future states of the system/component or to predict failure propagation trend in system/component. According to the international standard organization [5], prognostics is defined as the predictions of the operating time before the existence or appearance of one or several future failure modes. The difference between the current time and the time of failure is commonly called remaining useful life (RUL). Figure 1 depicts an illustration of a RUL forecasting according to a pre-defined system’s behaviour [6].

Although a vast amount of research of prognostics methodologies have been published recently [7, 8, 9], their application in real-world is still relatively small and mostly focused on the estimation of specific system/component degradation process. Furthermore, they require significant and sufficient number of faulty and degraded dataset to accurately predict the system/component degradations.

According to the literature review, there are two major prognostics approaches:
Physics-based models
Data-driven models

They both have their own advantages and disadvantages, and consequently they are often used in combination in many applications to overcome the individual limitation. Data-driven models employ routinely collected condition monitoring data and/or historical event data instead of building a mathematical model based on system physics or human expertise. They attempt to track the degradation of an asset using forecasting or projection techniques (e.g. regression, exponential smoothing, and neural networks), also rely on the past patterns of deterioration to forecast the future degradation. Since data-driven prognostics have no elaborate information related to asset or system, it has been considered as a black-box operation [10]. A detailed literature review on data-driven prognostics was conducted by [11]. Artificial Neural Networks (ANN) [12], Hidden Markov Models (HMM) and derivations [13], regression models [14], Bayesian & Gaussian Processes [15] are employed in order to estimate the remaining useful of a component or system. Similarity-based prognosis approaches can also be categorized in data-driven prognostics.

Physics-based Models typically involve describing the physics of the equipment and failure mechanism. Mathematical models are usually employed which is directly tied to health degradation. In order to provide knowledge rich prognostics output; physics-based models attempt to combine defect growth formulas, system specific mechanistic knowledge and condition monitoring data. They assume that an accurate mathematical model for component degradation can be constructed from the first principles. Several examples of degradation modelling and physics-based prognostics, specific to the component or system, are found in the literature [16, 17, 18].

Moreover, the prognostics models can be categorized according to the degradation type into two groups: continuous degradation and discrete degradation [19]. Hidden Markov Model (HMM) techniques have been widely proposed as an effective prognostics method in discrete degradation cases [20–24]. However, the proposed HMM approaches significantly increased the complexity of the prognostics algorithms by proposing extra concepts and variables. Therefore, the aim of this paper is to implement a new method of prognostics, developed recently by [19], which can overcomes the drawbacks of HMM techniques. Details of the method are given in the next section.

1. State Based Prognostics With Duration Information (SBPD)

In this section we present briefly the prognostics algorithm in [19] (See [19] for more details), that we used to calculate the RUL. The process of implementing the SBPD approach consists of the following two stages: The first stage is identifying the health state of the system, while the second stage is calculating the expected RUL.

As mentioned above, the first stage of the prognostics method is identifying the health states of the system/component which are defined as the discrete states that present the change from the state of failure-free to the failure state. When the health states are not noticeable, the problem of identifying health states of the system becomes a clustering problem hence k-means clustering method is employed. The K-means clustering method aims to group the samples of the dataset into clusters by optimizing the dispersion between the samples of the dataset and the centre of the identified cluster [25].

In SBPD, the transition probability of a state is described as (p_p) where it is defined as the probability of the system to transit from state i to state j assuming that the system stayed in state i for d many cycles. The k-means clustering method gives the discrete health states number of each training specimen at any time. Transition probabilities are then calculated by counting the numbers of transitions for each state/duration. Once the transition probability of the specimen is identified at a time point, it can be used to predict the expected RUL. The expected RUL is the sum of the total expected time to be spent in the current state of the component as well as the future states until the component reaches the failure as shown in Eq. 2.

\[ E[RUL] = E[T^d_c] + \sum_{s=1}^{c} E[T^f_s] \]  

\[ T^d_c \] is defined as the time to be spent in the health state s, where \( T^d_c \) is the time to be spent in the current health state given the fact that specimen has already spent d cycles in the current health state. \( c \) represents the current state, and \( f \) is the last health state before fault occurs.

To evaluate the effectiveness of the prognostic method, several measures have been proposed in the literature [26, 27]. In this paper the following metrics will be considered as measures of evaluation: prognostic horizon, \( \alpha = \lambda \) accuracy, and Cumulative Relative Accuracy (CRA). The prognostic horizon is defined as the difference between the time when the estimation of the RUL is within the desired error margins and the failure time. The \( \alpha = \lambda \) accuracy metric evaluates the
prediction accuracy in estimating the RUL within the desired error margins at any given time instances. \( \alpha \) indicates the desired accuracy and \( \lambda \) is the time instance. The CRA is defined as the normalized sum of the relative accuracies at given time instances.

In addition to these metrics mentioned above, the Root Mean Square Error (RMSE) and the r-square indicators are employed for evaluating the predicted values of the RUL. The r-square assesses the similarity between the real RUL values and the estimated RUL values. RMSE is defined as the averaged square root of the differences between real RUL values \( (y_i) \) and predicted RUL values \( (f_i) \). R-square and RMSE are calculated using the formulations in Eq. (3) and (4), respectively.

\[
R - \text{square} = 1 - \frac{\sum (y_i - f_i)^2}{\sum (y_i - \bar{y})^2} \tag{2}
\]

\[
\text{RMSE} = \frac{\sqrt{\sum_{i=1}^{n}(y_i - f_i)^2}}{n} \tag{3}
\]

where, \( \bar{y} \) is defined as the mean of real RUL values in Eq. (2), and \( n \) is presents the number of observations in Eq. (3). Both parameters indicate the difference between the estimated RUL values and real RUL values. Therefore, the high values of r-square and low values RMSE indicate better estimation of the RUL.

2. Implementation and Results

In this section, the SBPD implementation results on Virkler fatigue crack growth dataset are discussed.

**Virkler-Dataset**

In the structural health management (SHM) field, fatigue crack is one of the major problems in the structural damage caused by cyclic loadings. Because the crack growths are gradually at the structure surface, it makes the estimation of fatigue crack growth or fatigue life in structures urgent to address.

The Virkler fatigue crack growth data [28] contains 68 run-to-failure specimens. Each specimen used for the experiments is a centre cracked aluminium sheet of 2024-T3. Specimens had a notch of 9mm initial crack and the experiments were stopped once the crack lengths reached around 50mm. Each specimen has 164 crack length observation points. Degradation for all specimens is shown in Figure 2.

![Fig. 2. Crack length propagation samples under the same loading conditions](image)

![Fig. 3. RUL results for test specimens](image)
Total of 68 run-to-failure datasets are used in this paper. 70% of the dataset are used for training, and the rest 30% is used for testing the algorithm.

Figure 3 shows the predicted RUL values of the prognostics method (SBPD) introduced in [19]. The x-axis and y-axis in the Figure 3 are defined as the current life of each test specimen and the RUL for the corresponding to each value of current life, respectively. In Figure 3, the real values of RUL are presented as black dashed line while the SBPD predictions are in red lines. As can be seen from Figure 3, the predicted RUL trajectories are more close to the real RUL when the system is close to its end of life.

Figure 4 displays in detail the RUL predictions for a run-to-failure single specimen and the shrinking \( \alpha \) bounds. The estimated values of the RUL are within the desired error bounds specified by the \( \alpha = 15\% \) cone.

Moreover, Table 1 displays the mean values of the evaluation metric for the SBPD approach (prognostic horizon, \( \alpha - \lambda \) accuracy, and CRA), as well as r-square and RMSE metrics. Higher values or percentages indicate better prognostic results whereas lower RMSE values mean more accurate predictions. Prognostic-Horizon (PH) metric provides binary results by answering if the algorithm predict within desired accuracy around end-of-life (EoL) and sufficiently in advance. 'True' means that the SBPD predictions fall in the desired accuracy bounds half way through the failure. RMSE values have shown in the table fall fewer than 5% error levels.

One can say the SBPD is a well-structured prognostic approach delivering great performance in 5 different performance metrics.

Table 1. Prognostic performance evaluation

| Model/Metric | PH  | \( \alpha - \lambda \) (%) | CRA | RMSE  | R-Square |
|--------------|-----|---------------------------|-----|-------|----------|
| SBPD         | TRUE| 91.994                    | 0.967| 8909.333 | 0.997    |

3. Conclusion & Future Works

This paper presents an implementation of a novel data-driven prognostic approach on a publicly available fatigue crack growth dataset. Prediction results are validated by employing several performance evaluation metrics. Results show that the predictions of RUL by employing SBPD perform reasonably well. However, the model has not been validated on less predictable variable amplitude loading dataset yet. Virkler dataset is a well-controlled set of crack growth experiments where the test specimens are exposed to constant amplitude cyclic fatigue loadings. Dealing with real life fatigue loading cracks with SBPD is anticipated as a future work.

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References

[1] Jardine, A. K. S., Lin, D., Banjevic, D., A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, vol. 20, no. 7, 2006, p.1483-1510.
[2] Yam, R. C. M., Tu, P. W., Li, L., Tu, P., Intelligent predictive decision support system for condition-based maintenance. International Journal of Advanced Manufacturing Technology, vol. 17, no. 5, 2001, p. 383-391.
[3] Kothamasu R, Huang SH., VerDuin WH., System health monitoring and prognostics – a review of current paradigms and practices. International Journal of Advanced Manufacturing Technology , vol. 28, p. 2006, p. 1012-1024.
[4] Peng, Y., Dong, M., Zuo, M.J., Current status of machine prognostics in condition-based maintenance: a review. Int. Journal of Advanced Manufacturing Technology, vol. 50, 2010, p. 297 – 313.
[5] AFNOR, Condition monitoring and diagnostics of machines - prognostics - part 1: General guidelines. NF ISO 13381-1, 2005.
[6] Medjaher, K., Zerhouni N, Hybrid prognostic method applied to mechatronic systems, The International Journal of Advanced Manufacturing Technology, vol. 69, Issue 1-4, 2005, p.823-834.
[7] Heng A., Zhang S., Tan A. C. C., Mathew J., Rotating machinery prognostics: State of the art, challenges and opportunities, Mechanical Systems and Signal Processing, vol. 23, no. 3, 2009, p. 724-739.
[8] Jingliang Z., Jay L., A review on prognostics and health monitoring of Li-ion battery, Journal of Power Sources, vol. 196, no. 15, 2011, p. 6007-6014.
[9] Eker O. F., Camci F., Guclu A., Yiğitoba H., Sevkli M., Baskan S., A Simple Prognostic Method For Railway Turnout Systems, IEEE Transactions on Industrial Electronics, vol. 58, no. 5, 2011, p. 1718-1726.
[10] Zhang, H., Kang, R., Pecht, M., A hybrid prognostics and health management approach for condition-based maintenance, IEEE 2009 - IEEE International Conference on Industrial Engineering and Engineering Management, 2009, p. 1165.
[11] Si, X., Wang, W., Hu, C., Zhou, D., Remaining useful life estimation - A review on the statistical data approaches, European Journal of Operational Research, vol. 213, no. 1, 2011, pp. 1-14.
[12] Gebraeel, N. Z., Lawley, M. A., A neural network degradation model for computing and updating residual life distributions, IEEE Transactions on Automation Science and Engineering, vol. 5, no. 1, 2008, p. 154-163.
[13] Camci, F., Chinnam, R. B., Health-state estimation and prognostics in machining processes, IEEE Transactions on Automation Science and Engineering, vol. 7, no. 3, 2010, p. 581-597.
[14] Guclu, A., Yiğitoba, H., Eker, O. F., Camci, F., Jennions, I., Prognostics with Autoregressive Moving Average for Railway Turnouts, Annual Conference of Prognostics, 2010.
[15] Saha, S., Saha, B., Saxena, A., Goebel, K., Distributed prognostic health management with gaussian process regression, Aerospace Conference, 2010 IEEE, 2010, pp. 1.
[16] Kacprzynski, G. J., Roemer, M. J., Modgil, G., Palladino, A., Maynard, K., Enhancement of physics-of-failure prognostic models with system level features, Aerospace Conference Proceedings, 2002. IEEE, vol. 6, 2002, p. 6-2019.

[17] Qiu, J., Seth, B. B., Liang, S. Y., Zhang, C., Damage mechanics approach for bearing lifetime prognostics, Mechanical Systems and Signal Processing, vol. 16, no. 5, 2002, p. 817-829.

[18] Byington, C. S., Watson, M., Edwards, D., Stoelting, P., A model-based approach to prognostics and health management for flight control actuators, IEEE Aerospace Conference Proceedings, vol. 6, 2004, p. 3551.

[19] Eker, O. F., Camci, F., State-Based Prognostics with State Duration Information, International Journal of Quality and Reliability Engineering, vol. 29, no. 4, 2013, p. 465-476.

[20] Baruah P., Chinnam R. B., HMMs for diagnostics and prognostics in machining processes, International Journal of Production Research, vol. 43, no. 6, 2005, p. 1275–1293.

[21] Chinnam R. B., Baruah P., Autonomous diagnostics and prognostics in machining processes through competitive learning-driven HMM-based clustering, International Journal of Production Research, vol. 47, no. 23, 2009, p. 6739–6758.

[22] Dong M., He D., A segmental hidden semi-Markov model (HSMM)-based diagnostics and prognostics framework and methodology, Mechanical Systems and Signal Processing, vol. 21, 2007, p. 2248-2266.

[23] Ming D., Ying P., Equipment PHM using non-stationary segmental hidden semi-Markov model, Robotics and Computer-Integrated Manufacturing, vol. 27, no. 3, 2011, p. 581-590.

[24] Ying P., Ming D., A prognosis method using age-dependent hidden semi-Markov model for equipment health prediction, Mechanical Systems and Signal Processing, vol. 25, no. 1, 2010, p. 237-252.

[25] Likas A., Vlassis N., Verbeek J. J., The global k-means clustering algorithm, Pattern Recognition, vol. 36, no. 2, 2003, p. 451-461.

[26] Saxena A., Celaya J., Balaban E., Goebel K., Saha B., Schwabacher M., Metrics for evaluating performance of prognostic techniques, IEEE International Conference on Prognostics and Health Management, 2008.

[27] Saxena A., Celaya J., Saha B., Goebel K., Evaluating algorithm Performance metrics tailored for prognostics, IEEE Aerospace Conference, 2009.

[28] Virkler, D. A., Hillberry, B. M., Goel, P. K., The Statistical Nature of Fatigue Crack Propagation, vol. 101, no. 2, 1979, p. 148-153.