Ensemble Learning for Remaining Useful Life Prediction

Zhixiong Li, and Chao Hu

Department of Mechanical Engineering, Iowa State University, Ames, IA, 50011, USA
zhixiong@iastate.edu; chaohu@iastate.edu

ABSTRACT

While significant research has been conducted in model-based and data-driven prognostics, very limited research has been done to investigate the prediction of RUL using an ensemble learning method that combines prediction results from multiple learning algorithms. This research aims to introduce a new ensemble prognostics method with degradation-dependent weights. The performance of the proposed method is evaluated by the C-MAPSS data sets.

1. MOTIVATION

Ensemble learning-based prognostics is among one of the most popular hybrid methods, and has been proven to be capable for improving prediction accuracy by combining multiple learning algorithms [1]. However, how to predict time-dependent degradation due to varying operating conditions is still a challenge [2]. Existing ensemble learning-based prognostics do not take time-dependent degradation into account. In order to address this issue, we propose a new ensemble learning-based prognostic method with degradation-dependent weights. A case study is conducted to demonstrate the effectiveness of this new approach using the C-MAPSS data sets [3].

2. METHODOLOGY

A generic computational framework of the ensemble learning-based prognostic method with degradation-dependent weights is illustrated in Fig. 1. A training data set $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_N]^T$ includes multi-dimensional measurement data from N different run-to-failure units, where $\mathbf{y}_i$ (i = 1, 2, ..., N) denotes the measurement data from the ith training unit. The training data set is used to train a predictive model. A test data set $\mathbf{y}_t$ denotes the measurement data from an online testing unit. The testing data set is used to validate the predictive model. A weight vector $\mathbf{w}^{s_t} = [w_1^{s_t}, w_2^{s_t}, \ldots, w_M^{s_t}]^T$ denotes the weights associated with the degradation stage s_t of the testing unit, where M denotes the number of member algorithms. The predicted RULs of an online testing unit $\mathbf{y}_t$ by M member algorithms are aggregated to generate predictions for RUL using the following weighted-sum formulation [1]:

$$\hat{L} = \sum_{j=1}^{M} w_j^{s_t} \hat{L}_j\left(\mathbf{y}_t, \mathbf{Y}\right) \tag{1}$$

where $\hat{L}$ denotes the ensemble-predicted RUL for $\mathbf{y}_t$; $\hat{L}_j(\mathbf{y}_t, \mathbf{Y})$ denotes the predicted RUL by the j^{th} prognostic member algorithm trained with the data set $\mathbf{Y}$.

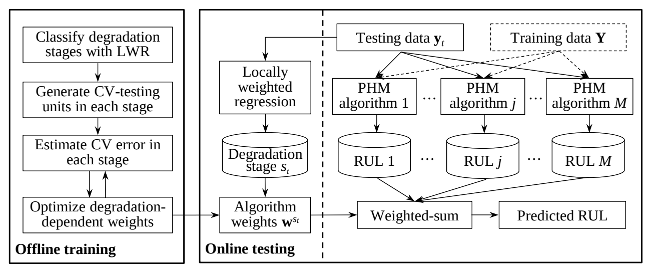

Figure 1. The flowchart of the proposed approach.

Five prognostic algorithms were selected as member algorithms in the ensemble, including the similarity-based interpolation (SBI) with the relevance vector machine (RVM) (RS), SBI with the support vector machine (SVM) (SS), SBI with the least-square exponential fitting (ES), Bayesian linear regression with the least-square quadratic fitting (QB), and recurrent neural network (RNN). The virtual health index (VHI) was used as a data pre-processing scheme for the first four algorithms, while a simple normalization scheme is used for the last algorithm. The theories behind these methods were introduced in [1].

3. PREDICTION OF AERO-ENGINE DEGRADATION

A case study was conducted to evaluate the effectiveness of the proposed approach using the C-MAPSS data sets [3]. The 536 data sets were divided into training and testing data sets, each with 218 data sets.

3.1. Offline Training

Offline training aims to optimize the degradation-dependent weights expressed in Eq. (1). The 10-fold CV strategy [1] is adopted. The offline training is detailed in Steps 1-3.

Step 1: Define the degradation stages. It first calculates the VHI values of the 218 training units. Then LWR is perform on the VHI data for each of the 218 training units to obtain their fitted VHI curves. The red dots in Fig. 2 show the calculated VHI data of the 218 training units, and the blue curves represent their VHI curves. In this example the VHI range was divided into 3 stages: [0.7, 1.2] (stage 1), [0.4, 0.7] (stage 2), and [-0.2, 0.4] (stage 3).

Step 2: Generate partial degradation data via truncations of run-to-failure VHI data [1].

Step 3: perform the 10-fold CV. The degradation-dependent weights are determined for each stage by minimizing the CV error, *S*-metric [1]. Table 2 summarizes the degradation-dependent weights ($\mathbf{w}^{1\text{-}3}$) and degradation-independent weights (**w**).

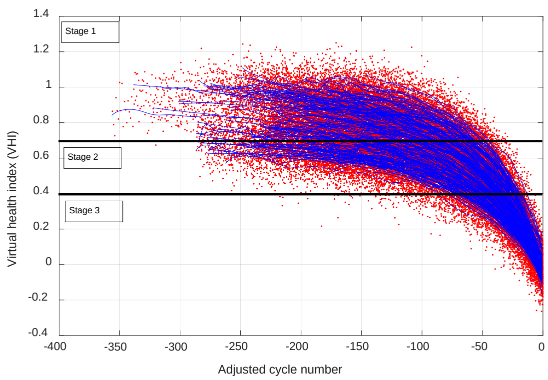

Figure 2. The degradation stage classification.

Table 2. The optimized weight vectors.

Weight vector	RS	ES	SS	QB	RNN
$\mathbf{w}^1$	0.0000	0.7011	0.0000	0.2351	0.0638
$\mathbf{w}^2$	0.0251	0.8302	0.0000	0.1323	0.0123
$\mathbf{w}^3$	0.0000	0.4078	0.2735	0.0000	0.3187
w	0.0000	0.8068	0.0000	0.1226	0.0706

Table 3. Validation errors by EDI and EDD.

Degradation stage	No. of testing units	Validation error		
		EDI	Ref. [1]	EDD
1	85	10.6208	8.6481	**8.0142**
2	87	5.7869	**5.7593**	6.0105
3	46	1.0845	1.1790	**1.0703**
Overall	218	6.6794	6.1955	**5.7493**

3.2. Online testing

In order to evaluate the effectiveness of the proposed ensemble (EDD) method, the 218 testing data sets were used for validation. Table 3 depicts the validation results on the testing data sets using EDD. As can be seen in table 3, the validation errors of EDD in stage 1, stage 2 and overall are smaller than that of the original (EDI) ensemble. Although in stage 2 the best prediction result is generated by [1], the overall prediction precision of the EDD ensemble is higher than that of the EDI ensemble. Hence, it can be safe to conclude that the proposed (EDD) ensemble method is effective and robust for RUL prediction improvement in this case study.

4. CONCLUSION

In this paper, an ensemble learning-based prognostic method with degradation-dependent weights was introduced. In comparison with existing prognostic methods reported in the literature, this method took the effects of system performance degradation into account by partitioning the degradation process into multiple stages. A case study was conducted to predict the RULs of aircraft engines operated under different conditions. The analysis results have shown that this new method outperforms the original (EDI) ensemble method.

REFERENCES

1. Hu, C., Youn, B., Wang, P., & Yoon, J. (2012). Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life. *Reliability Engineering and System Safety*, vol. 103, pp. 120–135. doi: 10.1016/j.ress.2012.03.008
2. Goebel, K., Saha, B., & Saxena, A. (2008). A Comparison of Three Data-Driven Techniques for Prognostics. *Proceedings of MFPT 62*. May 6-8, Virginia Beach, VA.
3. Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008) Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation. *Proceedings of Prognostics and Health Management* 2008. Oct 6-9, Dever, CO. doi: 10.1109/PHM.2008.4711414

BIOGRAPHIES

Zhixiong Li received his Ph.D. degree from Wuhan University of Technology in 2013. He is currently a postdoc fellow in the Department of Mechanical Engineering at the Iowa State University. His research interests include prognostics and health management (PHM).

Chao Hu received his Ph.D. degree in University of Maryland, College Park in Maryland in 2011. He is currently an Assistant Professor in the Department of Mechanical Engineering at the Iowa State University. His research interests are reliability-based design, prognostics and health management (PHM), and design of Li-ion rechargeable battery.