Prediction of Remaining Useful Life of anAircraft Engine under Unknown Initial Wear

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Abstract

Effectiveness of Condition Based Maintenance (CBM) strategy depends on accuracy in prediction of Remaining Useful Life (RUL).Data driven prognosisapproaches are generally used to estimate the RUL of the system. Presence of noise in the system monitored data may affect the accuracy of prediction. One of the sources of data noise is the presence of unknown initial wear in the samples. Present paper illustrates the effect of such initial wear on prediction accuracy and presents the guidelines to handle such initial wears. Two Artificial Neural Network (ANN)models are developed. First model is developed with the help of completedata; while the second model is developed after removing samples with abnormal initial wear.$\bar{x}$and R control chart is used to screen the samples with abnormal initial wear. It is found that the presence of initial wear significantly affects the prediction accuracy. Also, it is found that RUL estimation for a unit with short history tends to produce great uncertainty.Hence, it is recommended that RUL prediction should be continuously updated with age of the unit to increase the effectiveness of CBM policy.

Keywords: *Prognosis, Remaining Useful Life,Artificial Neural Network, Control Chart.*

I.Introduction

Condition Based Maintenance (CBM) strategy can produce cost savings by reducing scheduled maintenance cost. However, CBM systems can be leveraged into far great cost savings by developing a prognostics capability. Implementation of prognostic technology can facilitate in reducing life cycle cost through optimizing system performance, minimizing unplanned failures, reducing maintenance costs and improving system logistic support (Kumar et al., 2008). Prognosis approaches are mainly classified as Physics of Failure(PoF) based approaches and data driven approaches. PoF approachesare based on identification of potential failure modes, failure mechanisms and failure sites for the product as a function of the product life cycle loading conditions. The stress at each failure site is obtained as a function of both the loading conditions and the product geometry and material properties. Damage models are thenused to determine fault generation and propagation (Pecht and Gu, 2009).The drawback of PoF approach is that model development requires a thorough understanding of the system and high-fidelity models can be computationally intensive, which make this approach difficult or even impossible to implement in many real life systems. Whereas data driven prognosis approaches use historical and current data statistically and probabilistically deriveprediction of RUL of a system (Pecht, 2008).Condition monitoring data, such as vibration data, oil analysis data, acoustic emission data, etc., are collected, processed and used for predicting the RUL. However, such approaches often suffer from poor prediction accuracy because of noise in the data. One of the major sources for noise in the data is the presence of unknown initial wear due to manufacturing inefficiencies.

In the present paper an Artificial Neural Network based data driven approach is presented for RUL prediction of an aircraft engine under unknown initial wear. It further examines the severity of such initial wear in terms of prediction accuracy. $\bar{x}$and R control chart is used with ANN for the same. Finally, it provides guidelines to handle such initial wear in condition based maintenance planning.

The paper is organized in the following manner. In the next section, the problem description for this study is outlined. Section IIIdescribes the development of the proposed ANN based RUL prediction models.SectionVIpresents the results and discussesthe effects of initial wear on prediction accuracy. It also provides guidelines to handle such initial wear. Section V concludes the paper.

II. Problem Description

Predicting the progression of damage in aircraft engine turbo machineryunder unknown initial wear is very important task for condition based maintenance planning. Aircraft engine condition monitoring has received a great deal of attention from researchers (Kurosaki et al., 2004). In the present work we have taken the problem which was reported in PHM 2008 prognostics data challenge (Saxena and Simon, 2008). Aim of the challenge was to estimate RUL of an aircraft engine using historical data only, irrespective of the underlying physical process.System monitored data of an aircraft engine is taken from National Aeronautics and Space Administration (NASA) Prognostics Center of Excellence Data Repository(http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository),which consist of multiple multivariate time series.Each time series is from a different engine; i.e., the data can be considered to be from a fleet of engines of the same type. There are three operational settings and 21 sensor measurements that have a substantial effect on engine performance. Table 1 gives the details of operational settings and sensor measurements (Saxena and Simon, 2008).

Table 1 Operational settings and sensor measurements description

Operational Settings(OS)		
S.No.	**Description**	**Range**
1	Altitude	0-42K ft.
2	Mach number	0-0.84
3	Throttle resolver angle	20-100
Sensor Measurements(SM)		
S.No.	**Description**	
1	Total temperature at fan inlet (°R)	
2	Total temperature at LPC outlet (°R)	
3	Total temperature at HPC outlet (°R)	
4	Total temperature at LPT outlet (°R)	
5	Pressure at fan inlet (psia)	
6	Total pressure in bypass-duct (psia)	
7	Total pressure at HPC outlet(psia)	
8	Physical fan speed (rpm)	
9	Physical core speed (rpm)	
10	Engine pressure ratio (P50/P2)	
11	Static pressure at HPC outlet (psia)	
12	Ratio of fuel flow to Ps30 (pps/psi)	
13	Corrected fan speed (rpm)	
14	Corrected core speed (rpm)	
15	Bypass Ratio	
16	Burner fuel-air ratio	
17	Bleed Enthalpy	
18	Demanded fan speed (rpm)	
19	Demanded corrected fan speed (rpm)	
20	HPT coolant bleed (lbm/s)	
21	LPT coolant bleed (lbm/s)	

Initial wear can occur due to manufacturing inefficiencies and are commonly observed in real systems. In the given data set,damage modeling process was done using Commercial Modular Aero Propulsion System Simulation (C-MAPSS). The engine is operating normally at the start of each time series, and starts to degrade at some point during the series.The initial wear is modeled by variations in flow and efficiencies of the various modules.The system monitored data includes operational data from 218 different units.Table 2 shows the sample of system monitored data (Note: The values shown in table 2 are round off values of the original values).In the present paper variable data is divided in two subsets: training data (160 units) and test data(58 units).Operational cycles of each units in the test data are made to end sometime (randomly) prior to complete failure. So,the developed model can be tested for its prediction accuracy.The main challenge with this data is the presence of initial wear in the system monitored data, as it may make a difference in useful operational life of a component. The objective is to predict the number of remaining operational cycles in the test set, i.e., the number of operational cycles after the last cycle that the engine will continue to operate properly.

Table 2 Sample of system monitored data from 218 different units

Unit No.	t_i	**OS 1…**	**SM 1**	**…SM 21**	R_l
1	1	10	489.1	17.1	0.99
1	2	0	518.6	23.3	0.99
1	3	34.9	449.4	8.8	0.98
1	222	20	491.1	14.5	0.004
1	223	34.9	449.4	8.6	0
2	1	0	518.6	23.4	0.99
2	2	35	449.4	8.9	0.98
2	164	25	462.5	8.3	0
100	1	0	518.6	23.3	0.99
100	2	20	491.1	14.8	0.99
100	213	42	445	6.2	0
160	1	10	489.1	17.2	0.99
160	2	0	518.6	23.3	0.98
160	146	41.9	445	6.31	0.006
160	147	10	489.1	17	0
176	1	42	445	6.36	0.99
176	2	20	491.1	14.78	0.98
176	197	41.9	445	6.29	0
218	1	0	518.6	23.36	0.99
218	2	0	518.6	23.38	0.98
218	133	25	462.5	8.51	0

where, t_i is the time in cycles,
R_l is the percentage residual life of engine.

III. The Proposed ANN RUL Prediction Models

ANN has been considered to be one of the most promising approaches for prediction of RUL due to their adaptability, nonlinearity, and ability of arbitrary function approximation (Tian and Zuo, 2009).Three layers Feedforward Neural Networkis used for RUL prediction in this work. Figure 1 shows the configuration of the network. The network is divided into three layers; input, hidden and output layers.

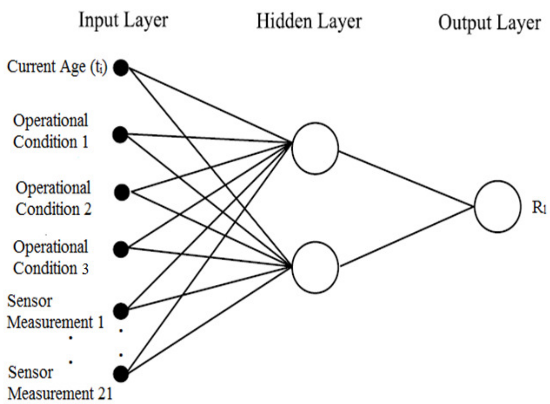

Figure 1 Feedforward Neural Networkmodel

For ANN training, there are 25 inputs fed into the network, out of which one is current age(t_i), three are operational conditions and 21 aresensor measurements. The percentage residual lifeof engine R_l is used as the output of the network. R_l is calculated as follows:

$$R_l = \frac{(\text{Time to Failure} - \text{Current Age})}{\text{Time to Failure}} \quad (1)$$

The output is normalized between 0 and 1, which gives same order of magnitude variables to avoid numerical instability (Rajakarunakaran et al., 2008). 1 indicates that 100% life is remaining (i.e. component is new) andthe unit is failed when the residual life percentage reaches 0.

Levenberg Marquardt (LM) learning algorithm (Tian, 2009) is used to train the network. MATLAB(Version: 8.0.0.783 (R2012b)) neural network toolboxis used for the training of ANN model.The configuration of ANN model uses tansig (Hyperbolic tangent sigmoid) transfer function in its hidden and output layer.

In order to avoid over fitting of data,two different sets of data are required for training and validating the network. In the training set, the degradation grows in magnitude until a predefined threshold is reached beyond which it is not preferable to operate the engine. In the validation set, the time series ends some time prior to complete degradation. During over fitsituation, Mean Squared Error (MSE) for the validation set decreases first and comes to a minimum value and later increases,though the MSE of the training set continues to decrease. When the MSE of the validation set increases, it is assumed thatthe regression algorithm is over fitting the training data (Mahamad et al., 2010). Thus, the training is stopped as soon as MSE in the validation setbegins to increase. For the selection of Feedforward Neural Network topology, there is no specific method. Trial and error search method is the bestoption to select the optimum topology for the prediction.

In this work, the training set uses the original data from input feed to the network but, the validation set is perturbed with +10% of the fed.The ANN model is train and validated in order to find the minimum validation error. The training and validation for ANN are setup from two to thirty nodes or neurons. The network which gives minimum validation error is selected as the optimum model.

The trained ANN model is tested with test data set and performance of the model is evaluated.For performance assessment Mean Squared Error (MSE) in RUL cycles and average score indices are calculated. These are defined as follows:

*Mean Squared Error:*MSE is the average of the squares of the difference between the actual observations and predicted values.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \quad (2)$$

where,
t_i= Predicted value, a_i= Actual value, N= Number of data points.

*Score:*The score for one prediction is defined as the exponential penalty to the prediction error; and the score of an algorithm is defined as the total score S from all the predictions for the units in the testing data set(Wang et al., 2008).

$$S = \begin{cases} \sum_{i=1}^{n} e^{-(d/13)} - 1\,, & d < 0 \\ \sum_{i=1}^{n} e^{(d/10)} - 1\,, & d \geq 0 \end{cases} \quad (3)$$

where,
S is the computed score,
d is the difference between estimated RUL andactual RUL,
n is the number of units under test.

The penalty function is asymmetric as if give more penalty to late predictions. Lower scores are better; a perfect algorithm would score zero. Average of the calculated score for the given units in test data set is used for performance assessment in this paper.

The overall procedure of the proposed method can be illustrated in a flowchart asshown in figure 2.

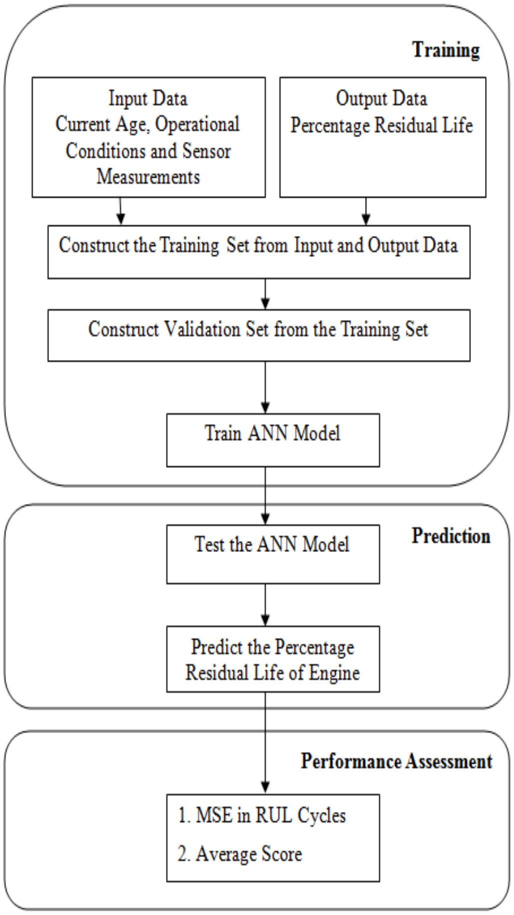

Figure 2Flowchart of the proposed method

IV. Results and Discussion

Table3presents the results of the ANN model.

Table 3 Results of ANN model

Validation Error	0.00451
No. of Neurons	13
MSE in RUL Cycles	1256
Average Score	130

Study of the Effect of Initial Wear: As the data was subjected to unknown initial wear, it is important to study the effect of the same on the prediction accuracy. In the present paper statisticalcontrol chart technique is used to screen the data with abnormal initial wear. Statistical control charts aregenerally used to monitor variables data from production machinery and identify the presence of abnormal process behavior because of chance causes (Montgomery, 2005). In the present case, time to failure of units is considered as the variable monitored through control chart. $\bar{x}$and R chart is used in the present study. Abnormal initial wear isconsidered as the presence of chance cause.Figure 3 shows $\bar{x}$ and R chart obtained for the given data. Statistical control limit on $\bar{x}$ chart are:upper control limit=275 and lower control limit=146.Thus, after removing units that fall above or below the control limit on $\bar{x}$chart187 units are obtained for further analysis. These 187 units are further divided into training set (137 units) and test set (50 units).

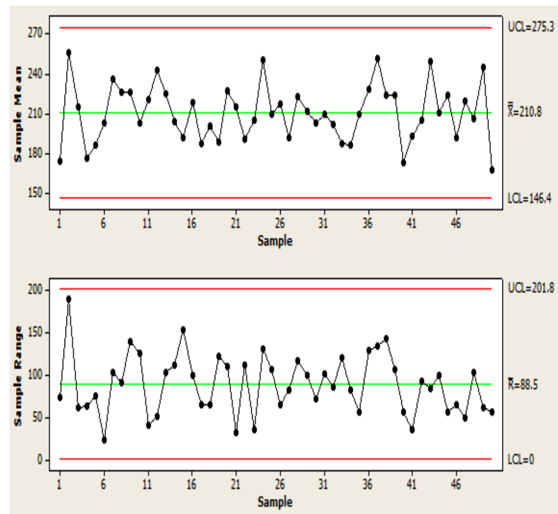

Figure 3$\bar{x}$and R chart

Table 4 shows the results of ANN model applied after screening of sample data.On comparing the results of table 3 and 4, it can be concluded that the prediction performance is significantly affected by the presence of the abnormal initial wear in the data. Hence, adequate measures should be taken before maintenance planning to handle such effects.

Table 4 Results of ANN model after screening abnormal initial wear samples

Validation Error	0.00306
No. of Neurons	13
MSE in RUL Cycles	708
Average Score	14

Guidelines to Handle the Effects of Initial Wear: As the presence of abnormal initial wear in the data may lead to poor prediction performance, the same needs to be quantify as accurately as possible. However, it may not be possible many times to quantify such initial wear. In such cases updating the prediction with age of the component will be useful; as the prediction accuracy late in the life of the unit is more important than that early in its life. This will more likely affect the decision on whether or not preventive replacement should be performed at the current inspection point (Tian, 2009). To investigate the prediction accuracy late in the unit life, we tested the prediction performance of units which have completed less than 50% of its life and which have completed more than 50% of its life.Table 5indicates that theunits which have completed less than 50% of its lifehave very high MSE andaverage score.On the other hand,units which have completed more than 50% of its life have very low MSEand average score. Thus,a unit with short history tends to produce great uncertainty or variance, which results in unreasonably long or short estimation. The RUL prediction becomes more accurate when it is close to the failure time. Thus, continuously updating the RUL prediction will help in reducing the effects of abnormal initial wear on CBM planning.

Table 5Prediction accuracy late in the life of the unit and early in its life

ANN Model 1		
MSE in RUL Cycles (>50%)	535	Count 27
AverageScore (>50%)	32	
MSE in RUL Cycles (<50%)	1885	Count 31
Average Score (<50%)	221	

V. Conclusions

This paper has presented an ANN approach for RUL prediction of an aircraft engine under unknown initial wear.Two ANN models were developed.First model uses complete data which have unknown initial wear, while the second model is developed after removing samples with abnormal initial wear.Thestatistical quality control$\bar{x}$and R chart was used to screen the samples with abnormal initial wear.

It is evident from test results that a unit with abnormal initial wear significantly affects the RUL prediction performance.It is also concluded that RUL estimation of a unit with short history tends to produce great uncertainty which leads to inaccurate prediction.Hence, updating the RUL prediction is the key to effective CBM planning.

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