Prediction of remaining useful life for mech equipment using regression

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Abstract. Maintenance has always been an important function in any manufacturing operations. Recently, Condition Based Maintenance (CBM) prognosis approach is gaining popularity in prediction of mechanical equipment remaining useful life (RUL). However, there is a need to improve the existing RUL prediction approach for mechanical equipment with multiple components. In this paper regression tree is used for developing the RUL prediction model of multiple components. A widely investigated dataset, PHM 2008 from NASA Prognostic Center was used in this study. Seven out of 21 sensors data were selected and used for prediction modeling. Before the data can be used, it must be filtered, clustered and normalized. Then the regression tree approach was used to develop the prediction model. The proposed regression tree model gave almost comparable results to other prediction methods such as Dempster-Shafer Regression (DSR), Support Vector machine (SVM) and Recurrent Neural Network (RNN). Besides, regression tree provides simplicity and the ability to manage large dataset.

1.0 Introduction

In manufacturing, maintenance plays an important role to ensure the success of the entire production operation. Maintenance influences the operation cost, asset value and product quality. The maintenance planning is a part of operation policies that affecting the performance of the entire manufacturing system [1]. The oldest approach in the maintenance system is known as breakdown maintenance which repair when the equipment has a breakdown. This method is not economical as it may cause an interruption in the production operation and quality. As the technology improved, preventive maintenance was introduced. This method uses a periodic time frame to plan the maintenance activity and generally it can improve machine reliability. However, this approach can lead to excessive maintenance and increase the operation cost if not properly planned. To overcome this limitation, a relatively newer approach known as condition-based maintenance (CBM) has been introduced.

CBM monitors the equipment's condition and only performs the maintenance if the machine condition is found to be below the healthy condition. The CBM approach which are diagnostic, and prognostic are more suitable for modern machines [2]. The significance of the CBM approach was due to the enhancement of technology [3]. Recently, the prognostic method has gained popularity among researchers. This approach predicts the duration of the equipment operates in good running condition. Thus, it predicts when the machine will breakdown. On the other hand, the diagnostic approach only recognized the occurrence of faults in equipment. Generally, prognosis approach is more effective and attractive to industry. Overall existing RUL studies are mainly limited to the single component system [4].

In 2008, NASA Prognostic Center organized a prognostic challenge opened to the public. The organizer provided simulated dataset to mimic the aircraft engine behavior from initial cycle until

failure. Numerous researchers have used this dataset to design and propose RUL prediction models. Various techniques have been investigated including similarity-based approach [5]. The data from multiple sets of engines were used to create a collection of degradation trends. New data from sensors will be matched with the collection of degradation trends and it will be the basis estimation for RUL. Kalman filter also has been investigated to fuse multiple neural networks in developing RUL prediction model [6]. Besides that, Heimes [7] has proposed recurrent neural network in developing RUL model. However, the recurrent neural network was reported to have flaws in the modeling sequence. To overcome this, Zheng and his colleagues [8] have proposed a long-short-term memory for RUL prediction. The existing RUL prediction model needs further improvement, especially in handling high dimensional data, incomplete data and improving the accuracy of prediction.

This paper aims to propose an improved RUL prediction model by using regression tree (RT) technique. RT has been used in other research areas such as in medical research, marketing research and much more especially when the data has high independence variables. To best of our knowledge, application of regression tree technique for RUL prediction has not been reported in journal publication. The rest of this paper is organized as follows. Section 2 discusses on the methodology of model development. Next in section 3, the result of model simulation is presented and finally, in Section 4 concludes the paper.

2. Methodology

2.1. Background of regression tree
Regression tree (RT) is one of the classification techniques that can be used for prediction based on growing and pruning tree method. This method was initiated by Automatic Interaction Detection (AIA) technique9 and later it was improved by a group of researchers which established the RT technique [10]. Linear and multiple regressions can handle a limited number of features in the dataset. If the number of the feature is small, regression method can handle it well for prediction. However, when the number of features increases the model will become complex to interaction between features. To overcome this limitation, RT applies partitioning method where it reduces the number of features into a small segment which is more manageable.

2.2 Development of regression tree for RUL prediction
In one of most recent research by Johansson et al [11], RT was incorporated into the conformal prediction. One of the findings is the determination of interval range of data is important in RT model to improve the interpretability of conformal prediction11. In another research area presented by Yuh-juh et al [12], RT also has been used for prediction with multiple factors and the dataset are in time series. Yuh-juh et al [12] were investigating in the medical area to develop a prediction model for patient pain and analgesic consumption by using RT. They have found this method has the best prediction capability compare to other regression methods [12]. In addition to that, RT method also has high potential in predicting blood pressure cases. In a research performed by Zhang et al [13], used RT to develop a prediction model for blood pressure cases by analyzing various factors. This method has outperformed other methods such as linear regression, ridge regression, support vector machine and neural network in terms of accuracy rate.

RT has the capability of making good prediction based on the available data. In this model, three main sections of the framework are explained in detail. Figure 1 illustrates the steps in the development of RT model for RUL prediction. Three main approaches model development are data preparation, model preparation and performance measures are explained in detail. In Data preparation, the source of data and how the data is prepared for next procedure are specified. In addition to that, the condition of the data and the nature of data measurements are also discussed. The next approach is the remaining useful life model preparation. The method used in developing the model is discussed in this approach. How the selection of sensors and techniques used to build the model are deliberated. The last approach is the performance measures. Three type of performance measures which are used to evaluate the model.

2.3 Experimental data

The case study dataset was obtained from National Aeronautics and Space Administration (NASA) Prognostic Center of excellence data repository (https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/) which was generated through stimulation of air turbine engine via C-MAPSS software. In this paper, The PHM 2008 Challenge dataset reported by Saxena and Simon [14] was chosen to evaluate the effectiveness of the RT model. All critical components such as fan, low-pressure compressor (LPC), high-pressure compressor (HPC), High-pressure turbine (HPT) and Low-pressure turbine (LPT) are required to perform in good condition to prevent any catastrophic engine failure. In this dataset, the data representing the sensor readings from initial run until just before failure. Three sensors were designated to record the operating condition of the equipment. These operating conditions indirectly affect the characteristic of 21 sensor readings on different essential engine components.

In dataset PHM 2008 Challenge, 218 engines which run at the same time but with different manufacturing variability. Therefore, each engine will fail at different cycles. For this stimulation, the cycle can be considered as time elements in this study. However, we have decided to use only 80 engines for training model and others 20 engines are were used for testing the performance. The reason for this data selection is to match with the Jiuping et al.[15] previous work as benchmark to our RT model performance.
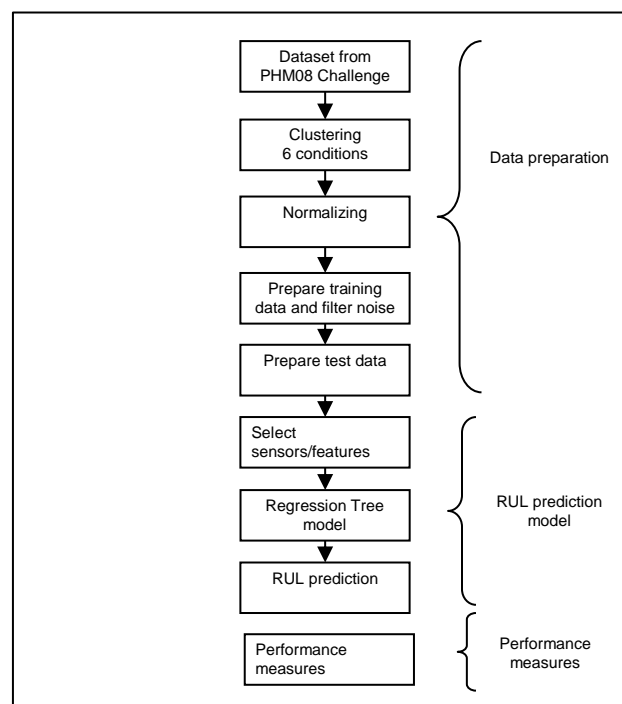

Figure 1: Steps in the development of RT model

2.4 Data preparation

The PHM 2008 challenge data consists of 218 engines for training and testing data. The data has one type of failure and has six conditions embedded within these data. For each engine, it consists of a group of cycles which run from initial stage until it reaches the failure stage. In this dataset also, consist sensor reading from three operating conditions and 21 readings from sensors. As mentioned before, the dataset is enclosed with six conditions. As the result, we need to cluster the data into six segments which can be presented as conditions. To perform the clustering, K-means clustering technique was used to group the data into six regions. Then each data in each group are normalized against the operating conditions.

This method was proposed by the Wang[5] who also used the similar data. The equation for normalizing [9] is as below.

$$x^p = Mean(\{x\}^p) \tag{1}$$
$$s^p = Std(\{x\}^p) \tag{2}$$
$$Yn = \frac{\sum_{p=1}^{p} Cp \cdot (xn - \hat{x}^p)/ sn^p}{\sum_{p=1}^{p} Cp} \tag{3}$$

n=1,…,N

2.5 Model preparation

Training data is prepared to train the model with the relation between input from sensors and target values which are the sorted cycles for each engine. In order, to increase the learning capability of the model, randomization of training data is applied. Only data from 80 engines are used and for each engine will be selected randomly. Then the selected data is grouped back according to their respective engine number and then the median filter is applied to the data. This filter is used to minimize the noise effect from the raw data.

RT model is developed by using MATLAB program which involved RT fit function which is the core of the model development and prediction function of the developed model. In RT fit function, input and target data are load into the function for model training purposes. For model training, data from 80 engines are selected. Whereas in prediction function of model is used to predict the RUL based on the provided testing data. In this stimulation, only data from 20 engines are extracted for testing data. The testing data come from engine 81 until 100. In contrast, testing data is not selected at random and without any filter applied.

Another important element in model preparation is the sensor selections. Selection of sensors will affect the accuracy of prediction. For this exercise, sensors 2, 3, 4, 7, 11, 12 and 15 are proposed because they have significant trends.

2.6 Performance measures

Performance measurements are important to determine the effectiveness of the proposed model. After collecting the prediction of RUL from the model, the prediction value is compared against the true value. The true value is the cycle value in testing data. Then for measuring the error performance of our prediction, we used mean absolute error (MEA), mean absolute percentage error (MAPE) and mean squared error (MSE). The equations for the performance errors are as below:

$$\text{MAE} = \frac{1}{N} \sum_{t=1}^{N} |xt - \widehat{xt}| \tag{4}$$
$$\text{MAPE} = \frac{1}{N} \left| \frac{xt - \widehat{xt}}{xt} \right| \tag{5}$$
$$\text{MSE} = \frac{1}{N} \sqrt{\sum_{t=1}^{N} (xt - \widehat{xt})^2} \tag{6}$$

3. Experimental Results

From the prediction results, data are plotted against the true value. As illustrated in Figure 2, the predicted values trend is resembling to true values trend pattern. This show that the newly developed model is functioning well and able to learn based on the sensory input data. In details, there are several segments in the cycles which have some discrepancy. Those segments are between cycle 2 until 6, cycle 8 until 11, cycle 11 until 15 and cycle 17 until 20.

Table 1 shows the results of RUL prediction against the true value. Whereas, Table 2 shows three other methods which have good performance in predicting RUL, especially the Comentropy based fusion method. In contrary, the proposed RT model performance gave promising results for RUL

prediction. However, the proposed model needs further improvement. We believe decision three has high potential in RUL prediction. Besides, it provides the simplicity and ability to handle high dimension.

Table 1: RUL prediction for 20 testing engines

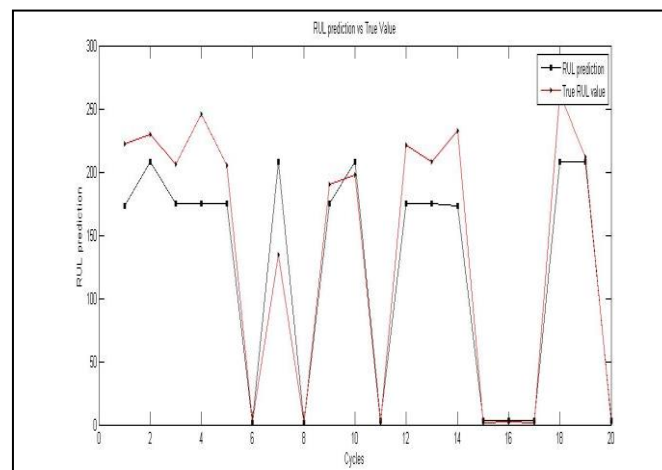| Engine	RUL prediction	True value
1	172.75	222.00
2	207.67	230.00
3	175.00	206.00
4	175.00	246.00
5	175.00	205.00
6	1.25	2.00
7	207.67	134.00
8	1.25	1.00
9	175.00	190.00
10	207.67	198.00
11	3.00	1.00
12	175.00	221.00
13	175.00	208.00
14	172.75	233.00
15	3.00	1.00
16	3.00	2.00
17	3.00	1.00
18	207.67	262.00
19	207.67	212.00
20	3.00	1

Figure 2: RUL prediction versus True value

Table 2: Performance of regression tree (RT) against existing RUL prediction model namely, Dempster-Shafer regression (DSR), Support vector machine (SVM), Recurrent neural network (RNN) and Comentrophy based fusion.

Method	MSE	MAE	MAPE
*DSR	6.21	26.30	0.14
*SVM	7.50	31.14	0.15
*RNN	6.80	29.01	0.14
*Comentropy based fusion	3.50	14.20	0.07
Regression tree (RT) (This study)	25.50	25.50	0.58

4. Conclusions

The RT model gave promising results especially in learning capability and in MEA. In MEA, the RT prediction performance outperforms the DSR, RNN and SVM techniques. However, for mean absolute percentage error (MAPE) and mean square error (MSE), prediction techniques DSR, RNN, SVM, and fusion gave better performance compared to the RT. Generally, RT is simple and able to perform well even for the small dataset. Currently we are improving the RT model by investigating selected significant sensors to improve the RUL prediction.

Acknowledgments

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