

# Feature Extraction Methods for Prognosis Maintenance Model

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**Abstract.** Research in prognosis maintenance, a branch of condition-based maintenance has received more attention from researchers lately. They focus on predicting when is the most suitable time to perform maintenance. Our review suggests that investigation on feature extraction in development of prognosis prediction model is still limited. This paper presents our study to find the most effective method for features extraction from maintenance monitoring data. The chosen features set should effectively improve the prognosis maintenance model performance. There have been several investigations to study feature extraction methods; however, the appropriate one is yet to be identified. In this research, we used datasets publicly available from National Aeronautics and Space Administration (NASA) army research laboratory. These datasets were generated through a simulation of the turbofan engine by using Commercial Modular Aero-Propulsion System Simulation (CMAPSS) software developed by NASA army research laboratory. Features extraction methods such as correlation among sensors, correlation among the outputs, variable weighing and treated data methods were studied in this research. Next, the extracted features were applied to the regression tree for searching an appropriate prognosis model. Based on the Remaining Useful Life (RUL) prediction results, the correlation among sensors method was found as the best method that can represent the most useful features for the prediction model.

## 1. Introduction

In condition-based maintenance, the prognostic method has gained much attention from researchers. This method predicts the remaining period of a machine will operate while it is in good running condition. In contrast, the diagnostic method only recognises the occurrence of faulty machines. The prognosis method is relatively more useful and beneficial to the industry to reduce the maintenance and operating cost. Most of the previous researches investigated a single component system. However, many mechanical systems such as aircraft engines consist of multiple components. Multiple sensors are used to monitor the health condition of mechanical systems and predict their Remaining Useful Life (RUL).

In 2008, NASA prognostic centre organised a prognostic challenge which was opened publicly to researchers. They provide datasets which were generated by stimulation software designed specifically to mimic the aircraft engine behaviour from the initial cycle until failure. Numerous researchers such as Al-Dulaimi et al. (2019) and Moghaddass et al. (2014) have used these datasets to design their RUL prediction models.



An essential element in RUL prediction is to be able to select useful or significant features. These useful features extracted from the collected dataset should improve the prediction model significantly. The performance of machine learning-based model is dependent on the quality of training data. Usually, not all extracted features are significant, and they may overlap with each other. In some cases, the trend may be stagnant or without any particular trends. It is important to select an effective method to extract useful features which can improve the prediction model.

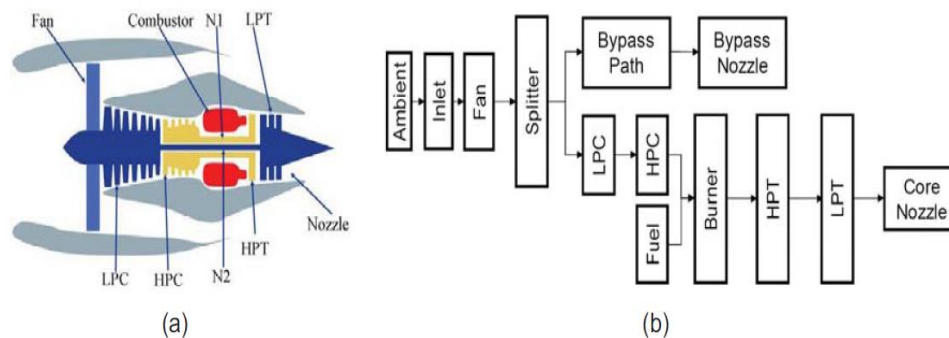
Sensors such as vibration sensor, temperature sensor, acoustic sensor and other sensors are used to gather maintenance data from a machine. The collected data from sensors normally represent the behaviour or health of the equipment. If the machine condition is beyond normal, it will illustrate a unique feature. Feature extraction investigation has two focus research categories, which are feature extraction and degradation assessment. In feature extraction, the research is focusing on health indicators, modelling, and acoustic noise. For health indicator, the research will focus on approach in determining the health indicator. By using a classification supervised machine learning model such as Support Vector Machine (SVM) faults are identified when compared against the health indicator (Benkedjough et al., 2015; Soualhi, Medjaher and Zerhouni, 2015). This method can make the desired prediction. However, they have a problem if the historical data is not complete. The next method is the modelling method. This type of approach has been used by (Mosallam, Medjaher and Zerhouni, 2013) when they try to investigate the advancement of a practical situation where the historical data is not complete. The researchers are using nonparametric time series modelling to resolve this issue. From there, the application of Ridge regression is crucial in RUL prediction. (Scanlon, Kavanagh and Boland, 2013) noted that in acoustic noise analysis, researchers have used feature extraction technique to improve the the quality of monitoring data. The spectral modulation analysis has been applied through the acoustic signal to develop the prediction model. The proposed method has shown significant improvement in RUL prediction over the standard envelope analysis.

The next branch of feature extraction is based on degradation assessment. It can be classified into two subgroups, namely condition assessment and modelling techniques. Condition assessment research is targeting the performance of degradation of bearing component (Hong et al., 2014). They used wavelet packed to extract the required feature for fault and prognosis analysis. Different from previous research, this paper focuses on the data-driven model. Data were collected from the sensor and analysed by using a statistical approach to develop the model. This model is design based on degradation trend and using a Bayesian approach to formulate the model. The rest of this paper will discuss the methodology of the research and presents performance of the investigated feature extraction methods.

## 2. Methodology

The first task is to find suitable dataset for development of the prognostic model. The dataset should have enough quantity and based on mechanical based equipment, which consists of multiple components. The finalised dataset, which can be used to develop the prognostic model is from NASA prognostic repository website. This data is from a simulation of turbofan engine by using CMAPSS simulation software developed by NASA army research laboratory. The user can simulate the effect of faults and deterioration in any engines five rotating components. The components are a fan, LPC (low-pressure compressor), HPC (High-pressure compressor), HPT (High-pressure Turbine) and LPT (low-pressure turbine). There are six types of datasets which four of them also given with true RUL vector. Whereas dataset for PHM2008 (Prognostic Health Management 2008) Challenge, the true RUL vector is not given. From these multiple types of dataset, we have decided to choose only dataset number four, and it was downloaded from NASA prognostic centre of excellence repository website (Center, 2008) on 11 December 2017. This dataset contained 248 train trajectories and 248 test trajectories. The dataset consists adequate amount of data required for extracting features and was given the true RUL value for performance evaluation. In addition, this data has six types of engine condition and two types of degradation which are essential in features extraction studies. Each of datasets is a multivariate type of data, and each of dataset includes training and testing data. The datasets also

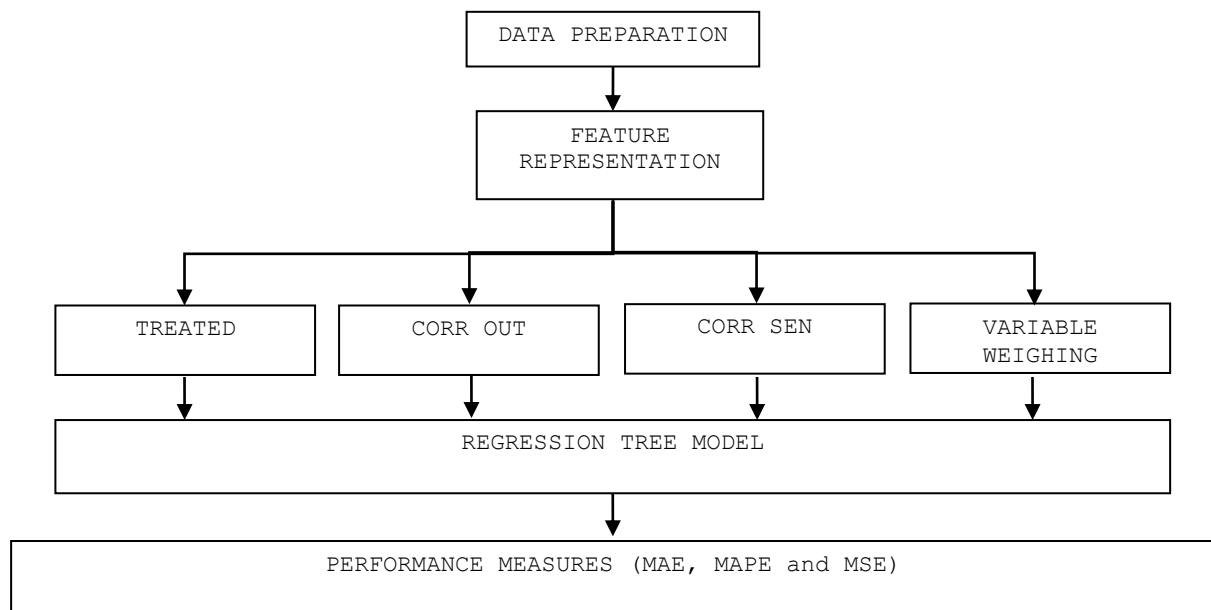
consist of three operating conditions, which are altitude, Mach numbers and throttle resolver angle. In addition, the datasets also included readings from 21 numbers of sensors. These datasets were generated by this simulation software and available for any researcher to use and develop new prognostic model. Furthermore, the researchers are encouraged to participate in PHM 2008 challenge and inspire the researcher to improve on the accuracy of RUL prediction. Figure 1 shows critical components in an air turbine engine. All of these components are required to be in good condition to prevent any catastrophic engine failure. In these datasets, the data representing the sensor readings from the initial runs until just before the failures. There are three sensors which recording the operating condition of the equipment. These operating conditions will indirectly affect the characteristic of 21 sensor readings on different essential engine components. The main components which subjected to failures are a fan, low-pressure compressor (LPC), high-pressure compressor, High-pressure turbine (HPT) and Low-pressure turbine (LPT). The actual remaining useful life (RUL) calculation for the engine can be obtained from the given vector of true RUL values. The highest number of RUL is equivalent to the first cycle, and when the cycle reaches the last value is depicts as zero RUL. The given cycle need to be sorted out was to represent the actual RUL of the engines.



**Figure 1.** Critical components in an air turbo engine and their interconnection (Saxena *et al.*, 2008)

In the next stage, the dataset uses to develop the model as mentioned earlier as training and testing data. There are three main elements in model development, which are data preparation, model development and performance measurements. In data preparations, the raw data need to be processed. First, the data has six different types of condition and requires a method to declutter it. Then the data need to apply normalisation technique to reduce data redundancy and improves data integrity. The last step in data preparation for model training was to select the significant features from the sensors data.

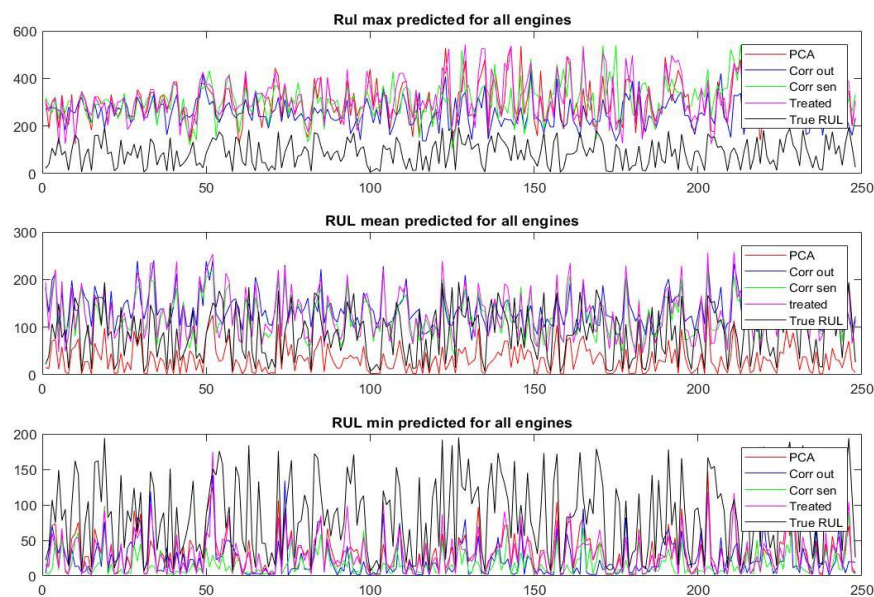
The first strategy was by using variable weighing method to find the signal datasets having the most variance. This method was introduced by (Wang, 2010). The objective of this method was to find the most significant data to obtain an accurate prediction. The second method investigated was to find the highest correlation data between the predicted remaining useful life and the sensor selection (CORR OUT). The third method investigated was to find the lowest correlation among the sensor (CORR SEN) and the highest correlation between the operating settings. The final method investigated was using the treated data from the selected sensors as the benchmark technique. The selected sensors are all sensors except sensors number 1, 5, 6, 10, 16, 17, 18, 19, 20 and 21 that did not show any distinctive trends. The Regression tree used the collected sensors data to develop the prognosis model. First, the training of the model used the training dataset. This dataset consists of sensor readings from first until the end cycles of engines. There were 248 engines where individually having a different cycle of failures. These data were feed into the regression tree model and tested with the testing data. Figure 2 illustrates the general steps in the investigation to select the best feature extraction methods for the prognostic model development.



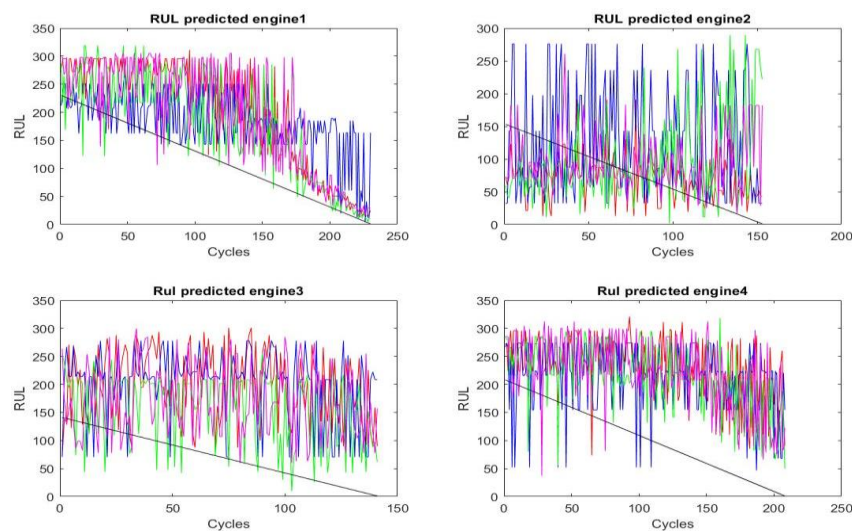
**Figure 2.** General steps to investigate the best feature extraction method in the prognostic model development

### 3. Results

Figure 3 shows the remaining useful life prediction trends for the four investigated feature extraction methods, including the true remaining useful life trend. From here, we compare the performance of feature extraction methods against the actual RUL results. Since the quantity of the data was huge, it was difficult to study for all 249 engines of the same type. Therefore for the general observations, the predicted RUL for four engines were plotted. Figure 4 shows the predictions of remaining useful life for four engines. RUL predictions for Engines one and four show degradation trends which resemble actual remaining useful life. However, engine two and three do not have any specific trends. The prediction of remaining useful life should imitate the true vector of remaining useful life. These results suggest that only some predictions in certain engines are accurate.



**Figure 3.** RUL prediction for all engines



**Figure 4.** RUL predictions for four engines

There are four types of performance measures for error analysis. The first is the average percentage error, where the prediction value of the remaining useful life is compared against the actual value. The next performance measure is known as the average of the mean actual error (MAE). The performance is computed through each cycle for the engines. Then the average of this measure is calculated. Next performance measure is mean actual percentage error (MAPE). The mean absolute percentage error (MAPE) is a measure of prediction accuracy in a forecasting method. A final performance measure is the mean squared error (MSE). The mean squared error (MSE) measures the average of the squared errors or deviations. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. The difference occurs because of randomness or because the

estimator does not account for information that could produce a more accurate estimate. The equations for performance error evaluation are as below:

$$\text{MAE} = \frac{1}{N} \sum_{t=1}^N |x_t - \hat{x}_t| \quad (1)$$

$$\text{MAPE} = \frac{1}{N} \left| \frac{x_t - \hat{x}_t}{x_t} \right| \quad (2)$$

$$\text{MSE} = \frac{1}{N} \sqrt{\sum_{t=1}^N (x_t - \hat{x}_t)^2} \quad (3)$$

Several observations can be made from these results. Firstly, the result of this study shows correlation CORR SEN is the best method whereas variable weighing method from (Wang, 2010) is the second-best method as shown in Table 1. These two methods have the best achievement in performance measures of MEA, MAPE and MSE. Secondly, as illustrated in Figure 3, the prediction of RUL min, mean and max value accuracies against true RUL were different for each method. The third observation is the correct selection of significant sensors plays important roles in predicting RUL.

**Table 1.** The performance measures for different techniques of feature representation

Feature Representation Methods	% Error	MEA	MAPE	MSE
VARIABLE WEIGHING	64.54	71.29	222.39	8938
CORR OUT	60.58	81.61	268.74	10726
CORR SEN	78.39	69.82	222.20	8265
TREATED	67.39	73.26	224.86	9451

#### 4. Conclusion

Even though the correlation among sensors is the best among the investigated methods in preparing the data representation, the errors are still not satisfactory. Further improvement needs to be investigated. RUL min and mean have different accuracy for different techniques. In addition to that, inconsistent RUL predictions were also found among different engines. Three main strategies to rectify these issues are identified. The first strategy is to improve in data preparation, especially in sensor selections or also known as variable selection. The second strategy is to include a health assessment mechanism in the learning phase of the model. In this mechanism each different stages of degradation would be identified. The last strategy is to search for better prediction techniques to improve the performance of RUL prediction.

#### Acknowledgment

The authors would like to thank Ministry of Higher Education Malaysia and Research Management Centre, Universiti Teknologi Malaysia for providing financial support for this project through Grant No: UTM RMC Vot Q.J130000.252418H16.

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