FSM Online Internship Report
on

Remaining Usable Life Estimation (NASA Turbine Dataset)
In

Machine Learning

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1. Introduction

1.1 Machine learning

Machine learning (ML) is a type of artificial intelligence (AI) that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. Machine learning algorithms use historical data as input to predict new output values.

Recommendation engines are a common use case for machine learning. Other popular uses include fraud detection, spam filtering, malware threat detection, business process automation (BPA) and Predictive maintenance.

1.2 Predictive Maintenance

Predictive maintenance is a **proactive maintenance strategy** that uses condition monitoring tools to detect various deterioration signs, anomalies, and equipment performance issues. Based on those measurements, the organization can run pre-built predictive algorithms to estimate when a piece of equipment might fail so that maintenance work can be performed **just before that happens**.

The goal of predictive maintenance is to optimize the usage of your maintenance resources. By knowing when a certain part will fail, maintenance managers can schedule maintenance work only when it is actually needed, **simultaneously avoiding excessive maintenance and preventing unexpected equipment breakdown**.

When implemented successfully, predictive maintenance lowers operational costs, minimizes downtime issues, and improves overall asset health and performance.

1.3 Dataset

Given dataset contains simulated data produced by a model-based simulation program, i.e., Commercial Modular Aero-Propulsion System Simulation (C-MAPSS), which was developed by NASA. The C-MAPSS dataset includes 4 sub-datasets that are composed of multi-viriate temporal data obtained from 21 sensors.

Each sub-dataset contains one training set and one test set. The Training datasets include run-to failure sensor records of multiple aero-engines collected under different operational conditions and fault modes. Each engine unit starts with different degrees of initial wear and manufacturing variation that is unknown and considered to be healthy. As time progresses, the engine units begin to degrade until they reach the system failures, i.e., the last data entry corresponds to the time cycle that the engine unit is declared unhealthy.

On the other hand, the sensor records in the testing datasets terminate at some time before system failure, and the goal of this task is to estimate the remaining useful life of each engine in the test dataset. For verification, the actual RUL values for the testing engine units are also provided.

2. Problem Definition

Predict the number of remaining operational cycles before failure in the test set, i.e., the number of operational cycles after the last cycle that the engine will continue to operate.
In simple words aim of this project is to build a machine learning model which can predict the Remaining useful life of engine.

2.1 Problems faced while handling dataset

Main problem faced during handling dataset is it is a large dataset. Over two hundred multivariate time-series datasets were provided.
In the training set for all engines data up to the failure of engine is provided but in test set engine is not getting failed means some life of that engine is remaining.
While training a model it is getting the data up to the failure of engine i.e., zero RUL and in test data there were some remaining life because of this some accuracy related issues raised but in training phase these issues got resolved.

3. Proposed Solution

Built a model which will take the readings of 13 sensors and will predict the remaining useful life of that engine using convolution neural network. All the implementation is done using the Python programming.

4. Literature Review

4.1 RUL Prediction Techniques

Remaining useful life (RUL) is defined as the length from the current time to the failure of a system and its prediction techniques are classified in the following ways: model-based technique (also called physics of failure technique), data driven based technique and hybrid-based technique. The methods are listed in figure 1.

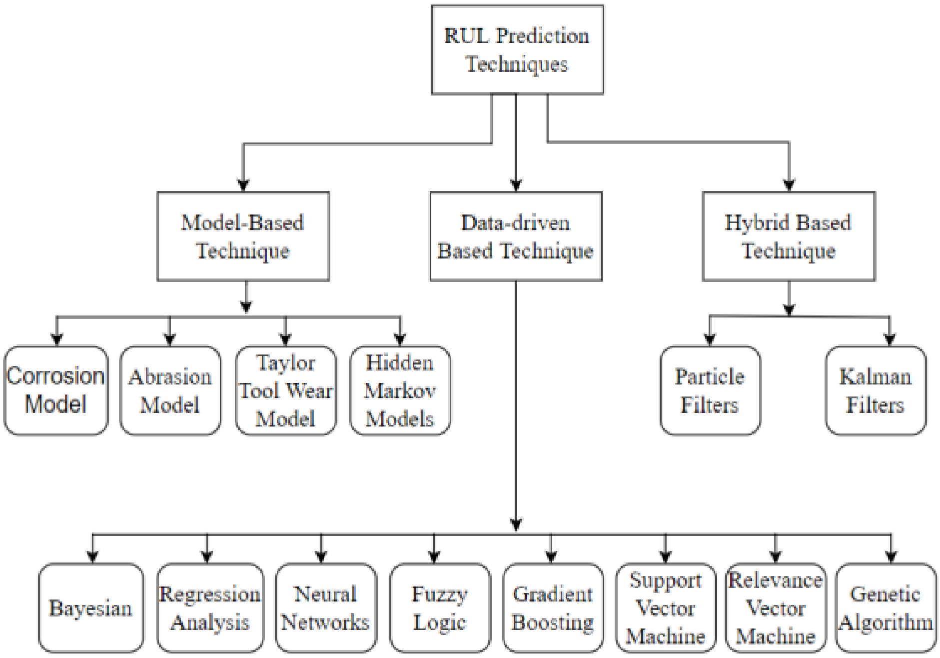

Figure 1 RUL prediction techniques

4.2 Using 1-FCLCNN-LSTM model.

This model adopts the idea of classification and parallel processing; 1-FCLCNN and LSTM network extract spatiotemporal features separately, and the two types of feature are fused and then input to the one-dimensional convolutional neural network and fully connected layer.

Dataset are standardized and divided into two input parts: INP1 and INP2. These two parts are input to the 1-FCLCNN and the LSTM neural network. Among them, the 1-FCLCNN is used to extract the spatial feature of the data set. At the same time, the LSTM is adopted to extract the time series feature of the data set.The overall framework of the model is shown in Figure 2.

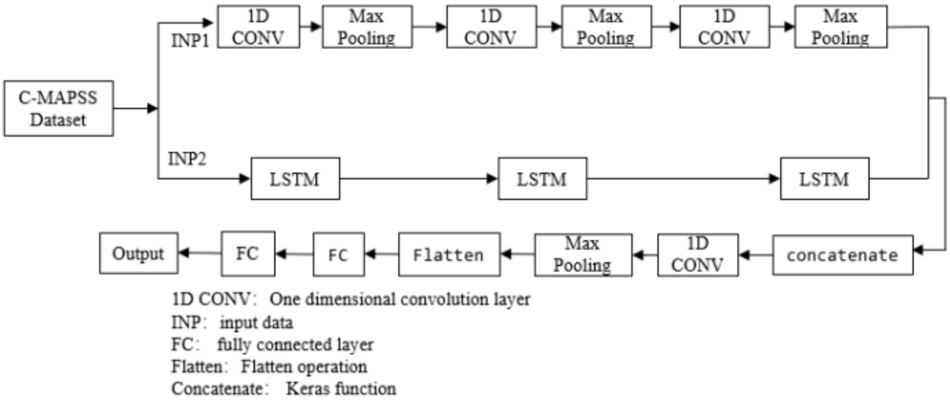

Figure 2 The overall framework of the model

4.2.1] 1**-FCLCNN Network**

There are three 1D-CNN layers, which are used to extract the spatial features. The stacked CNN layers are parsed by three max pooling layers. The first 1D-CNN layers consist of 128 filters ,The second consist of 64 filters, and the third consist of 32 filters (The convolution kernel size of the three 1D-CNN layers is the same (kernel size = 3). "ReLU" activation function is used for the 1D-CNN layers. The Settings of the max pooling layers: pool_size = 2, padding = "same", strides = 2.
Figure 3 shows the detailed architecture of the 1-FCLCNN path.

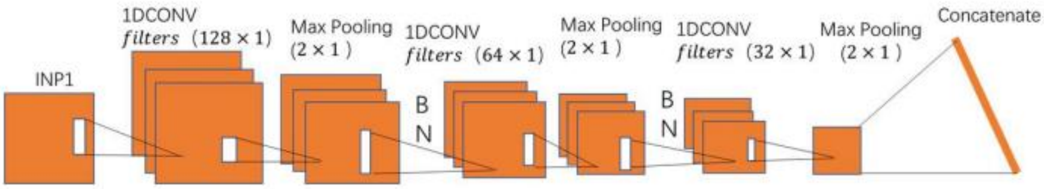

Figure 3 The detailed architecture of the 1-FCLCNN path

4.3 Failure of turbofan engine.

Just like the life of human being is affected by their health same as all systems deteriorate as a result of time, usage, and environmental conditions. Gas-turbine engines may be subjected to severe environmental and operating conditions such as corrosion, wear, buckling, erosion etc. which eventually lead to costly and catastrophic failures if a run-to-failure philosophy is adopted. Hence, in order to monitor the state of gas turbine engine more than two hundred sensors are installed in each gas turbine.
An engine health deteriorates substantially over time. Certain engine 17 variables which are also known as health parameters have significant impact on engine health. Different engines have different health parameters. Hence it becomes important to monitor and evaluate these health parameters in order to improve life, performance, reliability, etc. of engine. However, due to the complexity of aircraft and sometimes due to unavailability of devices to measure certain parameters it is not possible to directly measure the health parameter. Hence it is of great importance to have fault diagnosis and prognostics and health management (PHM) on engine. The prognostics on remaining useful life (RUL) of an engine is the most difficult and challenging part among PHM

5. Understanding the Data

• No missing data in given dataset

• 100 time series in the training set 1, and 100 time series in the test set 1

• the statistics on the number of cycles aren't relevant, because we should only look at the statistics for the maximum number of cycles for each engine. However, the fact that the mean and median number of cycles for the training set are larger than for the test set, agrees with the fact that in the training set, the engines are followed until system failure. In the test set, the time series ends some time prior to system failure

• the following Features are constant, both in the training and in the test set, meaning that the operating condition was fixed or the sensor was broken/inactive: operational setting 3, sensor 1, sensor 5, sensor 10, sensor 16, sensor 18, sensor19. We can discard these variables from the analysis.

• Sensor 6 is oscillating between two values and its corelation with RUL is less so we can discard this feature.

• Sensors 7, 10, 20, 21 are highly corelated with the RUL. These are most important Features.

5.1 Data Preprocessing

The pre-processing of raw data is a required step in any analysis that uses data-driven techniques. NASA published a dataset with 21 sensor signal variables. The spectrum of these signals may be vastly different, having a significant effect on model training. Therefore, signals must be normalized.
There are several normalization techniques like scaling to range, clipping, log scaling and z-score. To normalize the data and prevent overfitting the model over variables with a high order of magnitude, a scaling to range normalization, also known as Min-Max normalization, is applied to both training and testing trajectories of C-MAPSS dataset along each variable.

Equation describes how to evaluate the scaled value $Xscaled$ of a vector X. The minimum and maximum values of each column function are represented by $Xmin$ and $Xmax$, respectively.

$$Xscaled = \frac{X - Xmin}{Xmax - Xmin}$$

In addition, variables that do not alter over time and thus could affect the results are removed. In this project thirteen useful sensor measurements 2,3,4,7,8,11,12,13,15,17,20,21 are selected, and the irregular/unchanged sensor data are abandoned

6. Experiment Setup

To train a model on Nasa turbofan engine dataset In this project Google Colaboratory platform Is used. It provides 13 GB RAM support for model training and 108GB disk space. Collab is a hosted Jupiter notebook service that requires no setup to use, while providing access free of charge to computing resources including GPUs.
For deployment process System should have minimum 1GB disk space and all necessary libraries should be installed.

7. Algorithm Explanation

In this project CNN model is used to predict the RUL on Nasa turbofan dataset. CNN is a type of deep learning model for processing data that has a grid pattern. It is designed to automatically and adaptively learn spatial hierarchies of features, from low- to high-level patterns.

Algorithm:

1. Feature selection of data and standardization of data.

2. Prepare training set and test set; normalization processing of training set and test set

3. Extract input data given the network; Use a sliding window to split the data

4. Use sliding window to extract training set label and test set label.

5. Use Adam optimization algorithm to update weights.

6. The predicted output will be obtained. Calculate the error between the

predicted value and the actual value.

7. Obtain the trained CNN model.

Layers of CNN model is shown in figure 4.

```
model=Sequential()
# CNN
model.add(Conv2D(filters=32, kernel_size=3, activation='relu', input_shape=(win_length,feature_num,1)))
model.add(Conv2D(filters=64, kernel_size=3, activation='relu'))
model.add(Conv2D(filters=128, kernel_size=3, activation='relu'))
model.add(Flatten())
model.add(Dense(1, activation='linear'))

model.compile(loss='mean_squared_error',optimizer='adam',metrics=['mean_squared_error'])
```

Figure 4 CNN model

In the CNN model I have added 5 layers. 1st is input layer, 2nd is 2D convolution layer, 3rd is same as 2nd layer, 4th is flatten layer and 5th is dense and last is compiling layer.

3 convolution layers convolves over the spatial and time dimensions of input data.

Flatten layer is used to convert 2D data into a single 1D array.

Dense layer will receive input from each neuron of previous layer. At last compile is used to

compile all the layers with Adam optimizer.

Using this I got model RMSE 11 on test set 1 and RMSE 18 on test set 3.

8. Evaluating Metrics

In order to better evaluate the prediction effect of the model, this article adopts two currently popular metrics for evaluating the RUL prediction of turbofan engines: root mean square error (RMSE) and R2 scoring function (SF).

RMSE: it is used to measure the deviation between the observed value and the actual value. It is a common evaluation index for error prediction; RMSE has the same penalty for early prediction and late prediction in terms of prediction. The calculation formula is as follows:

$$RMSE = \sqrt{\frac{1}{X_n}\sum_{i=1}^{X_n} Y_i^2}$$

Where Xn Is the total number of test samples of turbofan engine, Yi refers to the difference between the predicted value of RUL and the actual value of RUL.

The R2 score is a very important metric that is used to evaluate the performance of a regression-based machine learning model. It is pronounced as R squared and is also known as the coefficient of determination. It works by measuring the amount of variance in the predictions explained by the dataset.

9. Deployment

Model deployment is the important stage after the model training. For model deployment chosen technology is Flask. To use a Flask for creating a web page flask should be installed on the system.

Frist step for creating a web app is to create two folders titled as templates and static. Templates folder will store the files that will be rendered in the flask app. Static folder will store files that are required in the deployment process and files uploaded by the user for prediction. In flask app created two routes method one is for taking the csv file input from the user it will act as a home page to the flask app and another is to predict route.
When the user uploads a csv file through a post request that file will be catch by the predict route and on that csv file prediction model will applied on that file and results will be displayed.

10.Results

After completion of model training phase now it’s time to check the predicted results and its accuracy Ultimate aim of project is to predict Remaining useful life of each engine so while testing the model prediction on each engine done separately. Initially some engines from test set1 are chosen to check the model’s prediction. Results of some engine are shown in figure 5.

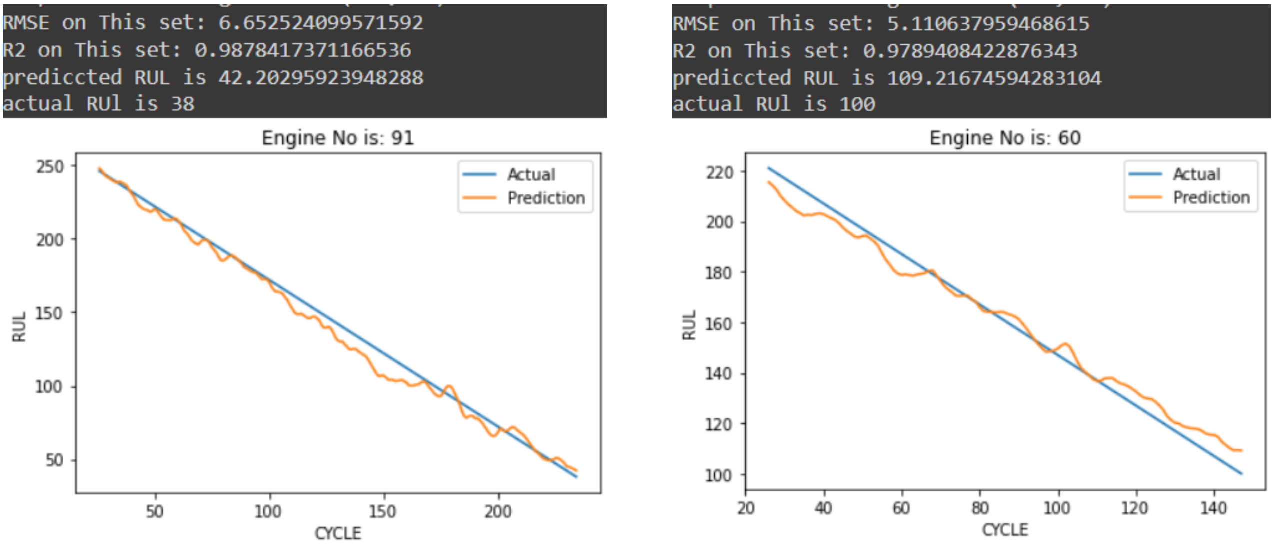

Figure 5 Prediction for engine 91 and 60

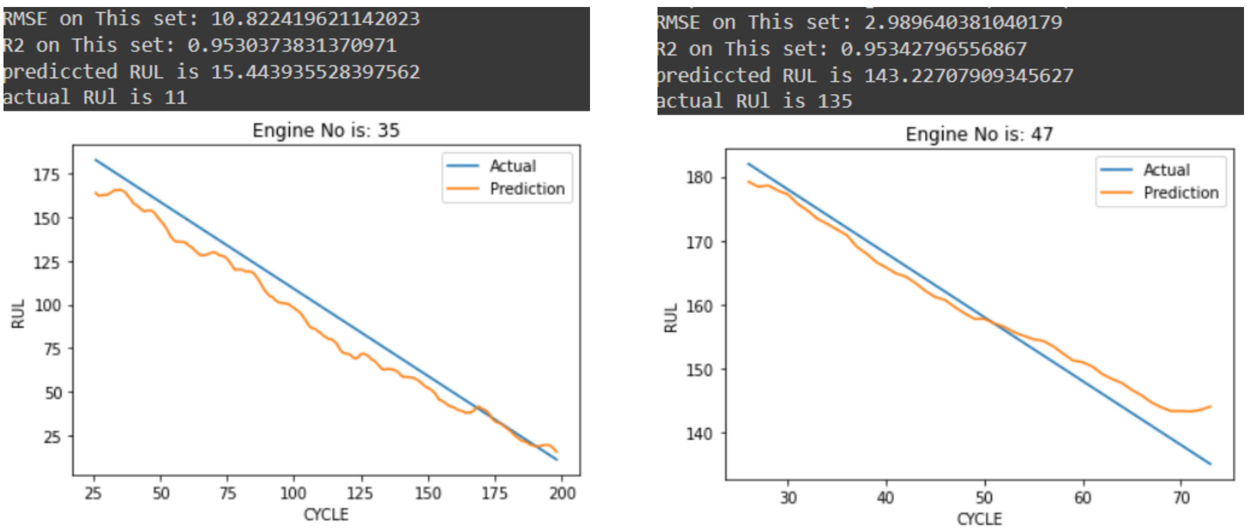

Figure 6 Prediction for engine 35 and 47

Figure 5 and 6 shows the graph of predicted and actual RUL for engine no. 35,47,60,91. From figure 5 and 6 it is clear that the RMSE lies between 0 to 10 and this pattern is followed by all the engines.

When the overall accuracy is taken into the consideration for all the test sets then RMSE for test set 1 is 10, for test set 2 is 3, for test set 3 is 19 and for test set is 3. Figure 7 and 8 shows the graph of predicted and actual RUL and the RMSE on that set.

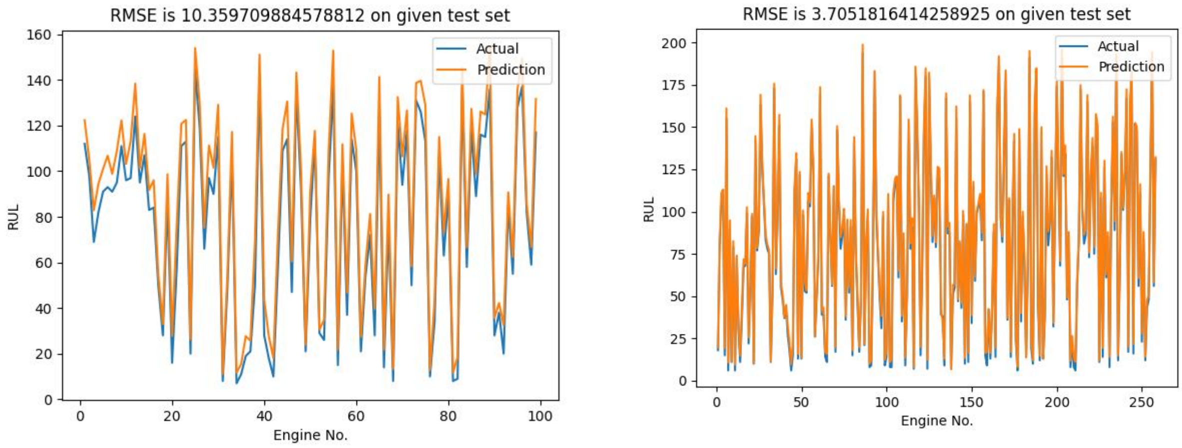

Figure 7 RUL prediction on test set 1 and 2

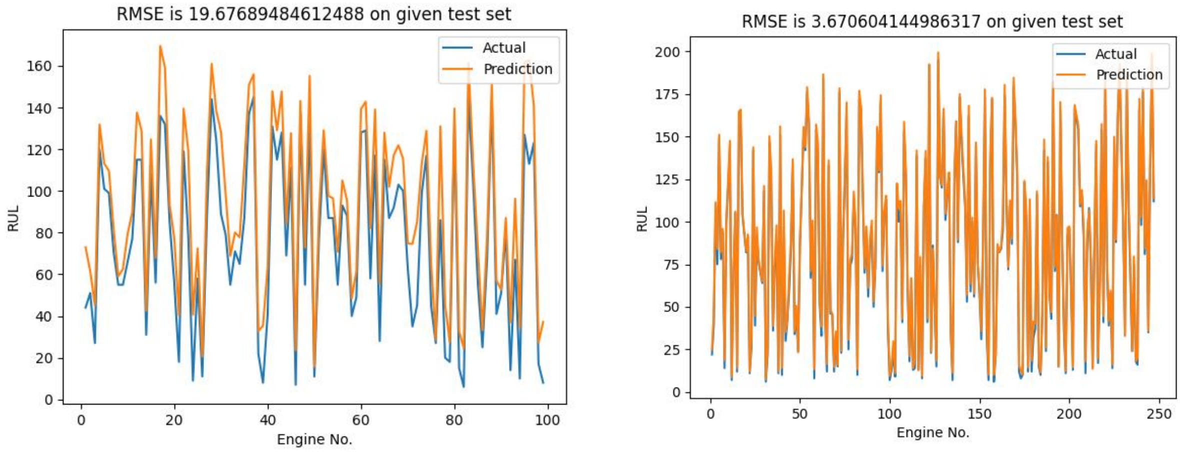

Figure 8 RUL predication on test set 3 and 4

10.1 Deployment

After the deployment of model into a flask app one interface is needed for that purpose created a simple interface to take a csv file input from the user figure 9 shows the user interface of flask app.

Figure 9 User interface

When the user clicks on the choose file button then one window will open and from that user can select the desired file. After choosing the file when user clicks on upload button on uploaded file model will predict the RUL values and will return a table showing the predicted and actual RUL for each engine. Table 1 shows the example of table which will be returned by flask app. This table will be shown on another web page. User will be redirected to the page where table will be shown to user.

	Engine No.	Actual RUL	Predicted RUL
0	1	18	19.799057
1	2	79	80.589832
2	3	106	110.973608
3	4	110	113.065653
4	5	15	19.243987
5	6	155	161.021687
6	7	6	10.731420
7	8	90	94.818706
8	9	11	11.393374
9	10	79	82.528155
10	11	6	9.412874
11	12	73	73.976895
12	13	30	32.790500
13	14	11	14.729936
14	15	37	42.831167
15	16	67	71.753165
16	17	68	69.313349
17	18	99	102.529359
18	19	22	25.437581
19	20	54	56.742673
20	21	97	98.689216
21	22	10	10.416919
22	23	142	144.622028
23	24	77	78.452364
24	25	88	90.429386
25	26	163	169.101468
26	27	126	128.875229
27	29	83	86.326803
28	30	78	80.524387

Table 1 RESULT TABLE

11. Conclusion

This research shows that the machine learning model that can predict the remaining useful life of engine based on data of sensor values. From the results of model, we can conclude that engines in test set 1 and 3 have more RUL than the test set 2 and 4.
Using this model one can predict the remaining useful life of engine will be predicted. Based on the predicted RUL required action can be taken to prevent the breakdown of engine.

12. Reference

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