Estimating Remaining Useful Life Under Multiple Operational Conditions Using Ensemble Learning

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Abstract

Prognostics is an important part of advanced manufacturing and maintenance. Recently, many sensors have been adopted for monitoring units before the end of their cycle time. Also, this sensor data is usually noisy and correlated which is challenging for traditional techniques to capture the information and estimate the remaining useful life (RUL). In practical cases, there are many operational conditions that the unit goes through which also complicate the task of estimating RUL. To encounter these challenges, an ensemble learning model could be used to extract the correlated information and predict the RUL. Ensemble learning models produce many weak learners each learns part from the data, and in the end, these weak learners vote to get the best prediction possible.

Keywords
Machine learning, ensemble learning, prognostics, Neural Networks and Remaining life prediction.

1. Introduction
Modern technology enabled a rich-data environment which increased the potential in prognostic. Prognostics activity has been a crucial part to have an effective intelligent manufacturing system by estimating the remaining useful life (RUL). Minimizing the maintenance cost, increasing productivity, and even save people's lives are the outcomes of prognostics activity. Although modern technology-enabled adapting many sensors, this data comes with its unique challenges. First, sensor data is known to be highly correlated where the reading of one sensor affects the other. Also, the noise from the environment affects the reading of the sensors. In some practical cases, not all features are important hence they affect the model accuracy. This paper aims to implement an ensemble learning model which is a type of machine learning model that is known to be powerful. Instead of using a single model, ensemble learning creates many models and aggregates their results to get better accuracy. Also, the data must be preprocessed before using the ensemble method to address the challenges.

1.1 Objectives
The objective of this paper is to identify new methods to model the multiple operational condition and multiple sensor prognostics problem. The model should yield predictions with competing accuracy with fast computational time.

2. Literature Review
In this section, papers related to RUL estimation and prognostics will be reviewed. Yan et al., (2016) introduced the problem with multiple operational conditions and used Data Fusion to fit a statistical model to estimate RUL. Data

fusion is a technique used on data such as the sensor data to combine the sensors readings into a single dimension vector that could be used for data modeling (Hall & Llinas, 1997). Yan et al., (2016) is the only paper which addressed the multiple operational conditions which is a more realistic approach. In Gugulothu et al., (2017); Heimes, (2008) neural networks was (NN) used to model and estimate the RUL with an advanced architecture which is Recurrent Neural Networks (RNN). After using a single layer NN, it shows that the data is separable which serves as a motivation to use advanced NN architecture (Heimes, 2008). An encoder was introduced to model the data that facilitate the task of using RNN on tabular data by having a fixed dimension (Gugulothu et al., 2017). The time series embeddings which were the results of the encoder showed that the model is robust to the noise (Gugulothu et al., 2017). Support vector regression (SVR) could be used to estimate the RUL. Khelif et al., (2017) developed an SVR model that does not need any data preprocessing. The resulted model in Khelif et al., (2017) could take many sensors or a single health index as an input and use it to produces an online estimation for the RUL. Kizito et al., (n.d.) conduct an initial study of applying tree-based models such as random forest to predict failure of machines as a classification and predicting RUL of the machines. The resulted model was very promising for classification and fair enough for regression. Also, it was superior to support vector regression. Also, Paolanti et al., (2018) used the random forest to classify machine states for predictive maintenance on a cutting machine and was able to provide good results. A comparison between random forest regression, neural networks, and support vector regression was done by (Wu et al., 2017). Random forest regression was used with parameters tuning and fed extracted features. Gebraeel & Pan, (2008) uses stochastic models to predict the remaining useful life. It takes into consideration the multiple operational conditions, and multiple sensors. Nonetheless, the model cannot generalize on unseen condition or when more than one component change at the same time.

3. Methods

The Random Forest is a supervised machine learning model that is an extension of decision trees where it would work on both classification and regression tasks (Breiman, 2001). It is an ensemble learning model where it creates many weak learners and combines their results to obtain a better model. The procedure of the model is as follows.

1. bootstrap sample the training set.
2. Select randomly k feature and split on the feature that produces the purest tree. This is the process where weak learners are created.
3. Repeat the process t times.
4. Combine the prediction results of the weak learners.

Note that Random Forest is a bagging algorithm which means that each weak learner is independent of the other.

On the other hand, Gradient Boosting Trees is a boosting algorithm where each learner depends on the previous learner by getting penalized or rewarded based on the accuracy result of the weak learner (Drucker, 1997). The procedure of the model is as follows.

1. Fit a decision tree.
2. Calculate the loss.
3. Based on the loss penalize or reward the model on the prediction
4. Fit another decision tree and add the weight based on the loss
5. Repeat t times.

4. Data Collection

The data is simulated by Saxena et al., (2008) for degradation in aircraft engines. It contains 6 operational conditions such as altitude. Also, 21 sensors readings are highly correlated and noisy based on the description of the dataset. There are 53,759 observations with 260 unique units that ran until failure. The initial preprocessing was creating the RUL feature by finding the maximum cycle-time for each unit then subtract the current cycle-time for each observation per unit. The RUL feature is considered to be the target variable for modeling the problem as cross-sectional data.

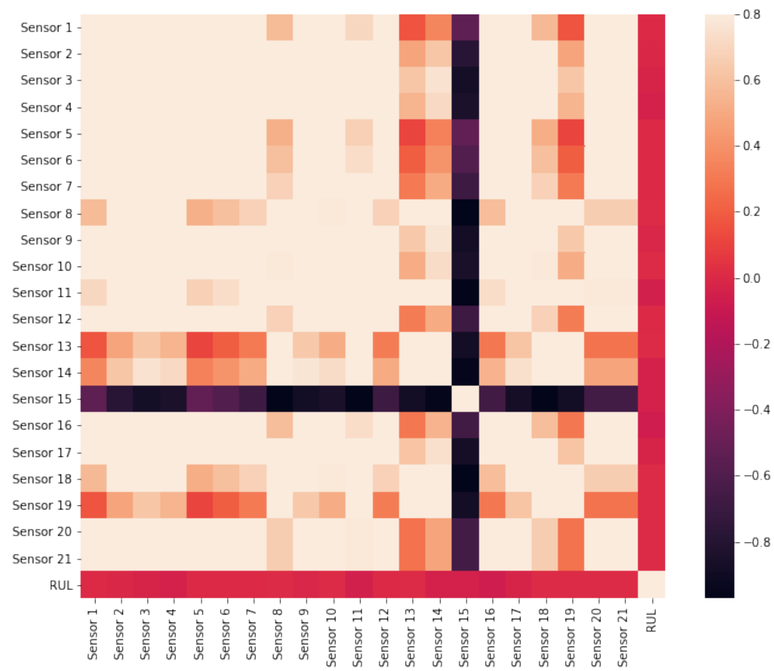

Figure 1. Heatmap of the correlation matrix

Figure 1 shows how the data is highly correlated where the light color in the heatmap represents a high positive correlation, and the dark color represents a negative correlation.

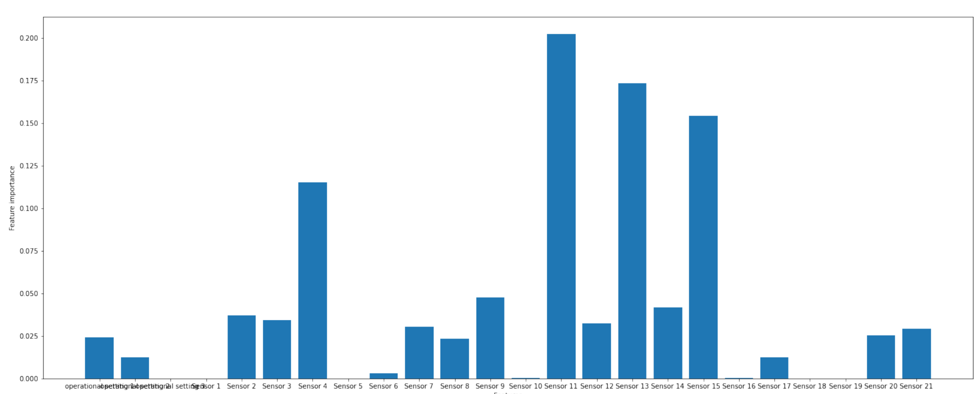

Figure 2. Feature Importance

The above figure 2 shows the importance of the features after the initial fitting of a random forest. The figure motivates to explore two techniques which are Principal Component Analysis (PCA) and feature selection using methods such as regularized regression. Unfortunately, these two techniques are fields to improve the models. PCA showed that the first principal component accounts for 98% of the variability and using this component produced a poor model. Also, after using regularized regression, the features that were chosen produced a poor model.

5. Results and Discussion

A neural network was taken as a base model since there is extensive work in the literature. The architecture of the neural network is in table 1 with a layer to standardize the input since the neural network is a distance-based model. Also, there are 4 dense layers with the stated neurons.

Table 1. The architecture of the used neural network.

Layer (type)	Output Shape	Param #
Standardization	(None, 664)	1,329
Layer 1 (Dense)	(None, 256)	170,240
Layer 2 (Dense)	(None, 128)	32,896
Layer 3 (Dense)	(None, 64)	8,256
Layer 4 (Dense)	(None, 1)	65

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}$$

Equation 1. Mean absolute error

From table 2, it could be observed that neural network has the lowest Mean absolute error as equation 1 (MAE) and the longest computational time. On the other hand, gradient boosting regression has the highest MAE and the lowest computational time. In general, ensemble learning models produced lower accuracy by 26% - 34%, nonetheless, there are significant computational time savings by 39% - 83%. Note that in a larger data set and deeper neural networks may not converge with many wights and biases. Also, Neural Network depends heavily on the hyperparameter tuning meanwhile ensemble learning models are more stable and give better results from the first fit.

Table 2. The results of the models.

Models	Neural Network Regression	Random Forest Regression	Gradient Boosting Regression
MAE (RUL)	25.95	31.59	33.65
Time (min)	5.8	3.5	0.95

6. Conclusion

To sum up, this paper addressed multi-sensor multi-operational condition prognostics using a tree-based ensemble learning models. By using the simulated aircraft engine degradation dataset, ensemble models approach showed significant savings in computational time although there was a small drop in the accuracy. Based on the application required the needs an estimation for RUL, there could be a tradeoff between the accuracy and the computational cost. Note that with highly correlated data, PCA failed to capture the important information and reflect it on the model. Also, feature selection based on regularized regression techniques produced poor models. In the future, the normality assumptions could be checked to build prediction and confidence intervals. Also, the time component in each unit could be exploited and modeled instead of taking the data as cross-sectional data. Moreover, the models introduced could be fitted on a larger dataset to check the accuracy and computational time, especially, finding if the neural network will converge in commodity hardware.

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Firas Alrumaikhany received the B.S. degree in industrial and systems engineering from King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, in 2022. He is interested in scientific research and went through an undergraduate research experience that led to produce a paper. He developed a passion in the application of machine learning. He previously worked with several successful start-up in the region such as Sary and Tamara. Also, he is an active member in IEOM-KFUPM and PyData Khobar. Currently, he is leading the quality team in MisMar one of the fastest growth start-ups in Saudi Arabia.

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