Remaining Useful Life Estimation of Turbofan Engines Using Adaptive Fault Detection Learning

M. Soualhi[1], K. Nguyen[2] K. Medjaher[2], and N. Zerhouni[1]

[1] *FEMTO-ST Institute,*
Université de Bourgogne Franche-Comté CNRS/UFC/ENSMM, CNRS, ENSMM,
24 rue Alain Savary, Besançon cedex, 25000, France
moncef.soualhi@univ-fcomte.fr

[2] *Laboratoire Génie de Production,*
Université de Toulouse, École Nationale d'Ingénieurs de Tarbes, INPT-ENIT,
47 Av. d'Azereix, 65000, Tarbes, France
kamal.medjaher@enit.fr

ABSTRACT

Failure prognostics have greatly enhanced the predictive maintenance of industrial systems by providing the remaining useful life (RUL) information, offering opportunities for high reliability, availability, maintainability and safety. To do so, historical monitoring data are injected into machine learning model to learn how to predict the RUL and then, in an online phase directly estimate the RUL of a new similar system. However, in case of multiple degradation trends representing multiple systems, it lead to different times of anomaly appearance and therefore various RUL values for learning. This situation makes difficult to train the predictor and use in this case an approximated unique RUL value. Hence, this paper proposes an adaptive anomaly detection methodology to identify the times of fault occurrence, and then assign the correct RUL values of each failure trajectory to the train the predictor. This methodology will facilitate the learning task for an accurate prediction of system RUL. The performance of the proposed methodology is highlighted using a long short-term memory (LSTM) network with the accelerated run to failure data of turbofan engines provided by the NASA to estimate the RUL.

Keywords: Prognostics, Condition monitoring, Data processing, Health indicator, Fault detection, Long-Short Term Memory, Remaining useful life, Turbofan engines.

1. INTRODUCTION

System health state prognostics is one the prominent enablers for predictive maintenance strategies. On one hand, it allows

anticipating failures by estimating the Remaining Useful Life (RUL) of a given system (Medjaher et al., 2012). On the other hand, it increases the reliability, availability, maintainability and safety of system (K. T. Nguyen & Medjaher, 2019). In general, prognostics can be classified into three groups, model-based, data-driven and hybrid approaches (M. Soualhi et al., 2022). The first approach uses the physical degradation model, also called (physics-based), to estimate the end of life of the system, it is more accurate than the data-driven (Gouriveau et al., 2016). However, it is difficult to obtain the mathematical representation of the degradation when the system presents stochastic behavior (M. Soualhi, Nguyen, Soualhi, et al., 2019). Besides, the data-driven approach uses sensor measurements to estimate the time of system failure without a priori knowledge on the degradation mechanism (Atamuradov et al., 2017). Indeed, the investigation of artificial intelligence and advanced calculators prompts the use of big data for condition monitoring and facilitates the utilization of data-driven techniques (Fontes & Pereira, 2016). Finally, hybrid approach aims to use the constructed physical model of the system with the real sensor measurements to represent well the system behavior with efficient control. In the context of missing physical knowledge, data-driven is the most suitable, but its performance strictly depends on the amount of historical and representative monitoring data.

For data-driven prognostics, the availability of historical degradation data is the most important prerequisite for developing efficient algorithms. Also, these data should take into account the time of anomaly occurrence to start the prediction and give a reliable estimation of the RUL of the system (A. Soualhi et al., 2020). To this end, the prediction times can be obtained using data processing algorithms to built health indicators (HIs) and detect the faults. The presented works

(K. T. P. Nguyen et al., 2018) extract features in three domains: time, frequency, and time-frequency to diagnose bearing defects while the authors in (Saidi et al., 2017) use frequency analysis, i.e., spectral kurtosis amplitudes to build HIs and detect the fault time. In addition, some researches investigate machine learning (ML) techniques to build efficient indicators which identify well the occurrence of the defect. For illustration, the presented works in (M. Soualhi et al., 2021; Guo et al., 2017) use Recurrent neural Network (RNN) and convolution neural network, respectively, to built the HIs and identify the time of fault occurrence for starting prediction. However, all these studies use less quantity of failure scenarios and may not be efficient in case of operating condition variations. To cope with this situation, the use of big data representing the different failure mechanisms of the system is a promising alternative technique. In fact, investigating more data for the monitoring provides high level of failure mechanism understanding as well as the presented work in (Gouriveau et al., 2016) which uses large failure data of multiple systems to cover various operating conditions of the system for efficient health assessment. However, the variation of operational conditions lead to different time of fault occurrence and therefore makes difficult the prognostic task.

Regarding the prognostics methods for remaining useful estimation, numerous techniques are developed in literature. One can cite the most effective such as Support vector Regression (SVR), Hidden Markov Model (HHM), Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Adaptive Neuro Fuzzy Inference System (ANFIS), Long-Short term Memory (LSTM), etc (Gouriveau et al., 2016). Each of these techniques presents its own advantages and drawbacks. However, as the Long-Short Term Memory network has the capacity of learning large data of different sequences with its memory and forget functions, it allows exploiting all the monitoring data for further accuracy and long term predictions (K. T. Nguyen & Medjaher, 2019).

Considering the synthesis above, one can notice that the availability of large quantity of data from various systems is one of the key issues for improvement of prognostic results. Moreover, because of the numerous factors that impact the operating conditions of the system, the occurrence of faults may be at different instants. Therefore, it is necessary to develop data processing method able to identify the anomaly time of each monitored system and track its evolution. Hence, this paper aims to fill this literature gap. It proposes a data processing methodology that uses different sensor measurements to identify the time of fault occurrence corresponding to each monitored system. Then, the obtained values are used to train an LSTM network to predict the RUL starting from the obtained prediction times. The robustness and the performance of the methodology are verified through the simulated run to failure data set of turbofan (C-MPASS) provided by NASA.

The remainder of this paper is structured as follows. Section 2 presents the methodology for prognostics. In section 3, the performance of the methodology is highlighted through NASA turbofan engines data. Finally, the conclusion and perspectives of this work will be presented in section 4.

2. PROPOSED METHODOLOGY FOR FAULT DETECTION AND PROGNOSTICS

This section presents the proposed methodology of data processing for fault detection and prognostics. The methodology starts with system condition monitoring and passes through data processing for HIs construction to detect the time of fault occurrence, and finally trains the prediction model for the prognostics as shown in Fig. 1.

1. **System condition monitoring:** As mentioned in the introduction, the availability of historical degradation data is one of the key issues for prognostics methods. Therefore, it is necessary to monitor the system over time to detect faults and track their evolution. To do this, appropriate physical parameters that reflect well the degradation of the system are supposed to be monitored. In turbofan aircraft engines, the commonly used sensors are pressure, temperature and speed sensors. These devices collect the monitoring data from the healthy state of the system to its end of life. Once the data are collected, they are in raw form and not suitable for direct use. Therefore, the obtained observations will be injected into processing algorithms to transform them into reliable and exploitable information for the following processes.

2. **Data processing:** In general, it is unable to use the raw data directly for system health state assessment. This unfeasability is due to noises, redundant information, stochastic data, etc. To cope with these limitations, data processing techniques are being developed to transform the raw data into exploitable information. These techniques extract features to build HIs for fault detection, diagnostics and prognostics. Among these techniques, one can cite the time-domain analysis. This method is the most common approach used for processing the raw data thanks to its simplicity and also its fast computation time. In this study, the recorded data are, first, normalized to their dispersion using equation 1. It allows adjusting the different sensor measurements of different scales to a common scale (K. T. Nguyen & Medjaher, 2019), as shown in figure 2.

$$X^{'} = \frac{(X_{ij} - \bar{X}_j)}{StD(X_j)} \quad (1)$$

where X is the total raw data of all the measurements, i and j are number of observations and type sensors, respectively.

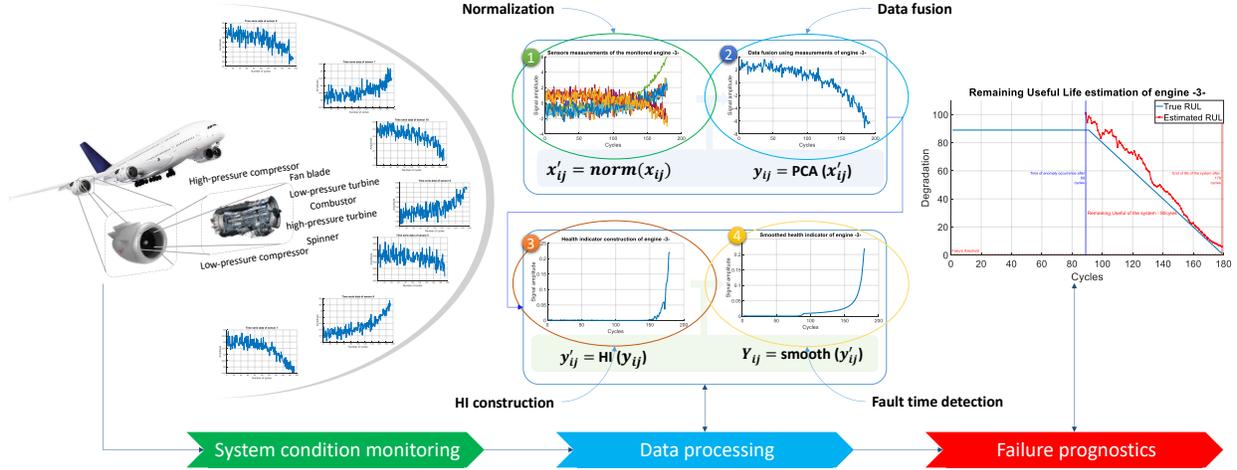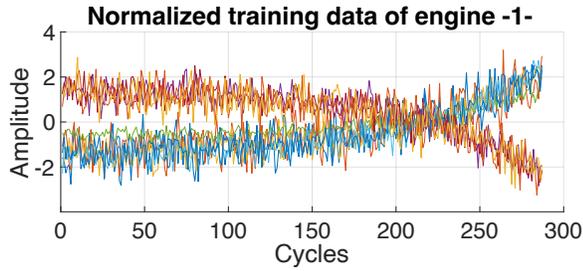The normalized data are then reduced using Principal

Figure 1. Global overview of the proposed methodology.

Figure 2. Raw data normalization by $MEAN$, StD values.

Component Analysis (PCA) function to fuse all the sensor observations into one representative pattern that contains high level of information (equation 2). Figures 3 illustrates the this calculation.

$$F = PCA(X^{'}, n) \qquad (2)$$

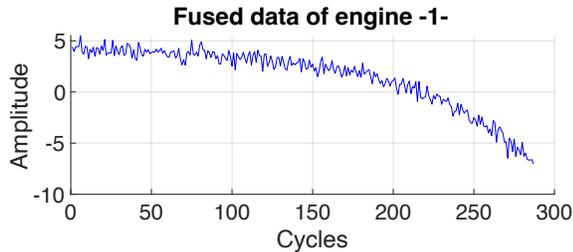where n is the dimension number factor. In this case study n equals to 1.

Figure 3. Data fusion of the different sensor measurements.

The obtained new set of data are used to extract statistical features to construct the HI and detect the time of fault occurrence of each monitored system. The HI is expressed by the following equation.

$$HI = \frac{\left(F_i - \overline{F}\right)^4}{\left(\frac{1}{L} \sum_{i=1}^{L} \left(F_i - \overline{F}\right)^2\right)^2} \qquad (3)$$

where F is the normalized total data of length L with $i \in [1, L]$ points.

The constructed HI is the ratio between the forth order moment of an observation and the global variance of the normalized data. This gain estimates the dispersion of an observation to the overall signal and allows reducing the noises while keeping the main information of the signal (M. Soualhi, Nguyen, Medjaher, et al., 2019). In fact, in the healthy state, the mean value of the signal is approximately equal to 0. In this case, the expressed ratio is lower. Therefore, it can be concluded that in the nominal case where no defects occur, the constructed HI provide a constant trajectory. Otherwise, in the event of a fault appearance, the calculated ratio indicates an increase in the values of the HI representing the occurrence of an anomaly in the system health state evolution, as shown in the figure 4.
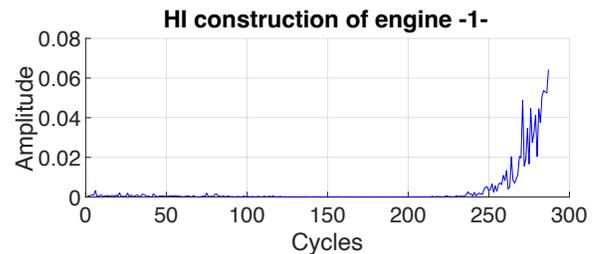

Figure 4. Health indicators construction.

From figure 4, there is two main health states, the healthy state represented by the constant HI curve, and the faulty state represented by the increasing curve of the HI. After

construction of HI of all systems, they are smoothed to reduce the noises and allow to extract the times of fault occurrence. Here, there is a large degradation trends and different time of fault occurrence. For this purpose, algorithm 1 is proposed in this paper to identify the time when the fault occurred. It calculates the distance between HI_{t+1} and HI_t and compare it to a threshold. If the difference at time t is grater than the threshold, the index t is the fault occurrence time (see figure 5).

In this case the threshold is equal to 0.998, which corresponds to the mean value of the constant smoother HI state when normalized between [0,1].

Algorithm 1 Health states division

1: Create an empty variable P
2: Set the sliding window size W
3: Set the number of trends Nbr
4: **for** $j = 1$ to Nbr **do**
5:     Load the data of trend i and normalize it between [0,1] and save in D
6:     Set a variable dropFound as false
7:     Set a starting index Idx (Idx=1)
8:     **while** $dropFound$ is false **do**
9:         **for** $i = 1$ to $length(D)$ **do**
10:             Calculate D(i+W-1)/MEAN(y(i:i+W-2)) and save in Y
11:             Compare Y with a threshold amplitude
12:             Increase the index value (Idx+1)
13:             **if** Idx equal length (D)-W **then**
14:                 Display (No defect)
15:             **else**
16:                 Calculate i+W-2 and save in Drop
17:             **end if**
18:         **end for**
19:     **end while**
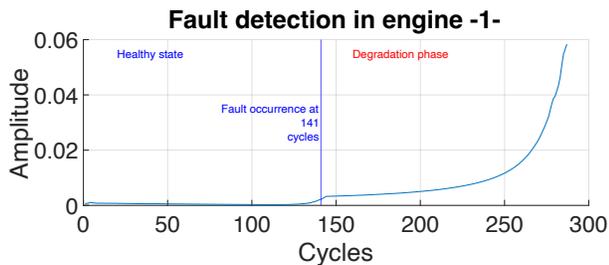20:   Save Drop in P
21: **end for**

Figure 5. Fault detection and health state division.

By using algorithm 1, it is possible to detect the time of anomaly appearance more accurately. Moreover, these times represent the starting point (MAX RUL) for estimating the RUL of the system when training the prediction model. Thanks to this fault detection step, the training process will learn mapping each health indicator observation to the real value of the RUL, and thus with

a minimum of error when using a fixed starting point of RUL for learning.

3. **Prediction models for prognostics:** This step uses the normalized raw data and the obtained prediction times to train a Long-Short Term Memory (LSTM) network for estimating the system RUL. Table 1 show the tuning parameters of the LSTM network.

All the sensor measurements corresponding to each system are injected into the LSTM model as an input and learn the degradation over time as output. This degradation represents the RUL of the system starting from the fault occurrence time.

3. APPLICATION AND RESULTS

This section presents the case study used to verify the performance of the proposed methodology for prognostics. For this purpose, a benchmarking data set of simulated run to failure data, provided by NASA, are used for application. This database allows verifying the developed data-driven prognostics and health management (PHM) algorithms. First, a general overview of the case study is described in subsection (3.1). Then, subsection (3.2) investigates the data processing methodology for fault occurrence detection. Finally, the prognostics of these faults are presented in subsection (3.3).

3.1. Description of the case study

The case study is a simulator of turbofan provided by C-MPASS tool and coded in MATLAB-Simulink environment. Figure 6 shows the simplified diagram of the simulator. This model aims to generate degradation data of the system by providing trajectories representing the system health state from the nominal condition to its end of life. Moreover, multiple failure scenarios can be generated by varying the input setting parameters of the operational profile in different sections of the system. This provide various trajectories where each trajectory represents an engine's degradation scenario. Each simulated scenario generates various sensor measurements, which are mainly temperatures, pressures and speed. Table 2 summarizes the data set used in this paper.
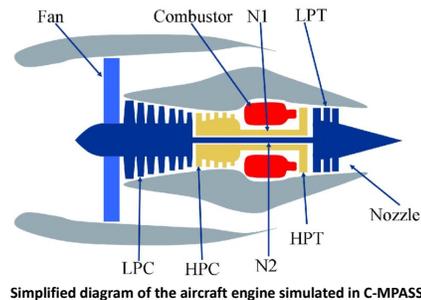

Simplified diagram of the aircraft engine simulated in C-MPASS

Figure 6. C-MPASS simulator case study.

The FD001 training and test datasets consist of 100 trajecto-

LSTM netowrk						
Parameters	Hidden size	Hidden units	Epochs	Optimizer	Learning rate	L2 regularization
values/methods	2	100	100	Adam	0.001	0.0001

Table 1. Tuning parameters of the LSTM network.

Dataset	Train set	Test set	Conditions	Fault mode
FD001	100	100	1	1

Table 2. Dataset description.

ries of unique operating condition with unique fault mode.

3.2. Investigation of the proposed methodology performance

In this subsection, the proposed method for fault detection is applied on the training datasets to detect the time of anomaly appearance of each trajectory. For this purpose, first, the data are normalized by using equation 1 in section 2. After this normalization, each set of engine data is fused into one representative trajectory using the principal component analysis function (PCA) 2. Figure 7 shows an illustration of the global fused data of the total engines.
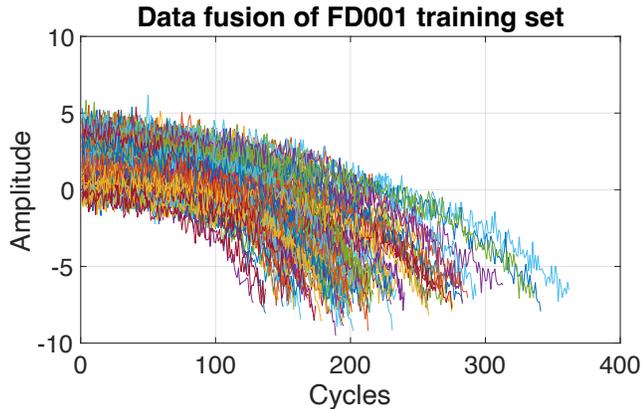

Figure 7. Global fused data of the total trajectories.

Once the data are fused, they are used to construct the HIs. These HIs allow to detect well the healthy state from the faulty states and isolate the time of the anomaly occurrence as shown in figure 8.
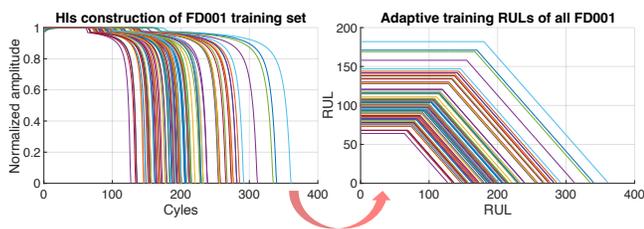

Figure 8. Adaptive prediction times for learning predictors.

By using these HIs and the proposed algorithm 1, the different times of the fault appearance can be detected and isolated automatically. Then, based on these values, it facilitates the learning task of the predictor by providing an accurate RUL values as input in order to correctly map the fused trajectories to their corresponding true RUL.

3.3. Fault prognostics

In this subsection, the raw data of the engines, corresponding to the first test set, are introduced into the LSTM network to estimate their RUL. For this purpose, first, the prognostics is done by using the raw data with the proposed prediction time in the literature and which equals to 130 cycles. Then, the investigation of the proposed method using adaptive prediction times is applied to highlight its efficiency. For this purpose, figure 9 and figure 10 show the estimated RUL of the global test engines using the fixed and adaptive prediction times, respectively.
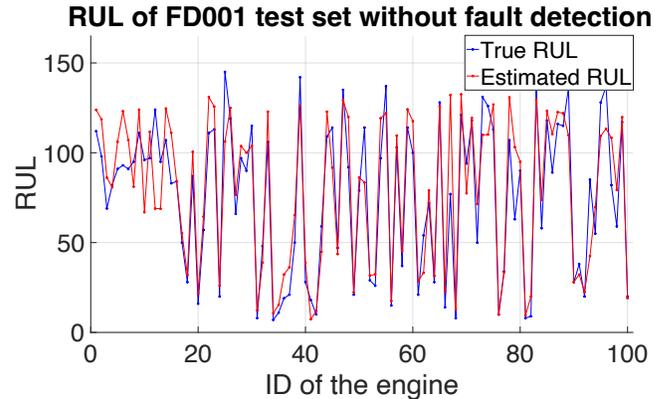

Figure 9. Estimated RUL using unique prediction time.

From the obtained results of the figures above, one can see that the estimated end of life when investigating a fixed prediction time is less accurate compared to when training the model with an adaptive prediction time. In order to show the efficiency of the proposed methodology, the obtained prediction are evaluated through several metrics used in the literature such the Root Mean Square Error (RMSE), Meas Square Error (MSE), Mean Absolute Error (MAE), Accuracy (ACC) and score (S) summarized in table 3.

The results in table 3 show that the proposed methododology, when investigating adaptive prediction times for learning the LSTM network, allows to provide more accurate estimations of the engines' RUL, thanks to the performance of the con-
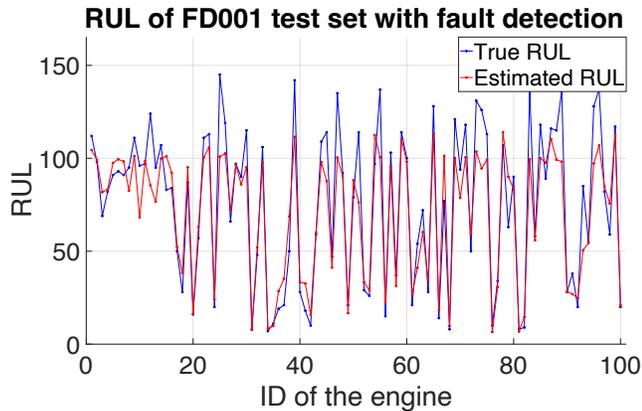
RUL of FD001 test set with fault detection

Figure 10. Estimated RUL using adaptive prediction time.

Metrics	LSTM score	Proposed Methodology score
MAPE	22,46	18,13
MAE	13,48	11,90
MSE	303,12	260,78
RMSE	17,07	15,32
ACC	45	65
Score	696	324

Table 3. Performance comparison using FD001.

structed HIs.

4. CONCLUSION

In this paper, a data processing methodology for fault detection and prognostics has been presented. This methodology used the data of different sensors that represent various degradation scenarios of a given system to detect the times of fault occurrence and estimate its RUL. In detail, the recorded data were processed in time domain by extracting and combining statistical features to construct effective HIs. These HIs allowed separating the healthy state from the faulty state by identifying the times of faults occurrence. The use of the anomaly occurrence time facilitated the learning task of the LSTM network to accurately predict the RUL of the system. The performance of the proposed methodology was highlighted through the C-MPASS data set, showing an improvement of the accuracy of RUL estimation. As future work, a fusion of the estimated RUL from different prediction models will be investigated. This fusion will enhance more the accuracy of the predictions for efficient decision making.

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