Chapter 23
Towards Predicting the Life of an Engine:
A Deep Learning Approach

Jayesh Soni
https://orcid.org/0000-0002-5740-4597
Florida International University, USA

ABSTRACT

Predictive maintenance has attracted many researchers with the increased growth in the digitization of industrial, locomotive, and aviation fields. Simultaneously, extensive research in deep learning model development to its deployment has made its way to industrial applications with unprecedented accuracy. The most crucial task in predictive maintenance is to predict the machine's remaining useful life, yet the most beneficial one. In this chapter, the authors address the problem of predicting the remaining lifecycle of an engine using its sensor data. The authors provide practical implementation of predicting the RUL of an engine by proposing a deep learning-based framework on the open-source benchmark NASA's Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) engine dataset, which contains sensor information of around 100 engines with 22 sensors. The proposed framework uses the bi-directional long short term memory algorithm. The authors optimize hyperparameters using advanced deep learning frameworks.

INTRODUCTION

A forecast of equipment failure requirements aids the productions team in planning equipment maintenance. With such a maintenance facility, one can avoid performing unnecessary maintenance checks, called periodical maintenance, and save a lot of energy and time. In modern factories, a huge amount of big data is captured from the sensors attached to equipment and private cloud servers (Yasumoto et al., 2016). Such sensor data contains valuable information about the behavior of equipment during its normal and failed operation. A type of sensor data analysis is termed predictive analytics and is one of the most interesting data analytics problems. A propulsion system generates a thrust for an airplane

DOI: 10.4018/978-1-6684-6937-8.ch023

to move through the air. Turbofan engines are used by modern airliners for such purposes. For aircraft maintenance, it is crucial to predict the turbofan engine's remaining useful lifecycle (RUL). This chapter analyzes the available sensor data to train a deep learning-based algorithm for predicting rul. The dataset is from NASA turbofan jet engine sensor measurements. Predictive maintenance can be performed in a classification or regression way. It predicts the likelihood of failure in subsequent n-steps in its classification approach. Predicting the remaining time left before the subsequent failure is the regression approach. Some of the real-world issues solved using data-driven approaches for RUL prediction are 1) multifaceted chronological dependencies amongst sensors: numerous modules act together with each other in myriad ways leading to complex dependencies amongst sensor readings. For example, an alteration in one sensor may lead to a variation in another sensor after an interval of a few instants. 2) fractional absence of sensor data: some data may be moderately unattainable due to reasons such as loss of communication in the network and broken or defective sensors. 3) health degradation: it is challenging to build physics-based models for complex machines with numerous constituents. 4) noisy sensor readings: varying environmental noise levels affect the sensor readings. The quantity of noise varies across sensors. Learning-based algorithms are one of the growing areas that have a high impact in the predictive maintenance domain, and that is the focus of this chapter.

BACKGROUND

Accurate prediction of the remaining useful life of an engine is one of the crucial parts of predictive maintenance (lee et al., 2017). It can be estimated through convergence rate, relative accuracy, etc. (Djeziri et al. 2020). There are three approaches for RUL prediction: data-driven, physics-based, and hybrid approach (Kim et al., 2016). When a piece of ominously precise information for fatigue crack growth is available, a physics-based approach can be employed (Byington et al. 2004, oh et al. 2010). Nonetheless, significant prior information is required. With no-fault condition data, a data-driven approach to building the model learns the normal behavior. The hybrid method is a combination of a data- and physical-based approach that can give improved results (Zhang et al., 2009; sun et al., 2019). For compound and nonlinear systems, learning-based algorithms have been used for RUL prediction. Decision tree-based Regressor, multilayer perceptron, and support vector regression are machine learning algorithms (TGS et al. 2019, Jayesh soni et al. 2019). Numerous artificial neural network and VM-based approaches are considered as black boxes since they are highly dependent on techniques required for signal processing. To mitigate this issue, several deep learning-based techniques are utilized, which do not require feature crafting from the sensors data and can extract the features automatically for further processing. For example, a recurrent neural network-based long short-term memory (LSTM) algorithm (Jayesh soni et al. 2019) is used to learn the patterns of the sequence. LSTM solves the vanishing gradient descent problem of RNN and is capable of learning the long sequences (Jayesh soni et al. 2019, 2020). LSTM does that by introducing the memory cell (Ellefsen et al., 2019; Al-dulaimi et al., 2019). An LSTM-based neural network is proposed for handling and monitoring multiple data generated from several sources for engine RUL prediction (Wu et al., 2018). With further research, the adaboost algorithm was jointly trained with LSTM for RUL estimate (Zhu et al. 2021). Yuan et al. Researched fault detection using the LSTM approach (Yuan et al., 2016). The author compared vanilla RNN, adaboost-LSTM, gated recurrent unit, and improved performance. To further increase the accuracy, bidirectional LSTM, a variant of LSTM, has been employed that can capture the long sequence dependencies in a bi-directional way and can thus