Recent Approaches in Prognostics: State of the Art

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Abstract— *The need for Prognostics and Health Management (PHM) systems has increased along with an increase in domains that require intelligent predictive systems, which can help in decreasing the downtime of the assets thereby curbing increasing maintenance costs, to manage asset inventories and customer satisfaction. Many techniques have been developed in the field of Prognostics Maintenance. This paper reviews the recent approaches that were developed and implemented on NASA's turbofan engine dataset, which was developed as a part of PHM'08 challenge and C-MAPSS dataset [1] [2].*

Keywords: Prognostics, Intelligent Prediction, PHM, C-MAPSS, NASA TurboFan Engine

1. Introduction

With an increasing need for efficiency and increasing maintenance costs due to premature failures, many industries are using Predictive Maintenance (PM) to find solutions for predicting the failure of an asset beforehand, thereby reducing the downtime of the asset by performing a maintenance operation on it. Asset management and Inventory management domains are also looking towards PM systems, which can help them predict the need for stocking assets or asset components, thereby controlling the inventory costs.

The Prognostics and Health Management (PHM) systems have become instrumental for predictive maintenance support since a decade ago. PHM systems play a pivotal role in the development of predictive maintenance and support systems. They can help in predicting the failure beforehand, failure identification and isolation, anomaly detection, etc. An essential feature of PHM is the estimation of Remaining Useful Life (RUL), a piece of quantitative information about how long the asset can be in a working condition which helps in planning maintenance operations [3].

According to many studies, prognostic approaches are categorized into: Model-Driven approaches, Data-Driven approaches, and Hybrid approaches [4]. Model-based approaches are mathematical models based on modelling the physical behaviour of the system by understanding the dependencies and interrelationships which can result in acceptable results. However, it requires an in-depth knowledge of the system to build such models, which makes them difficult to implement. Data-driven methods are most sought-after methods due to their ease of implementation. These methods use machine learning to derive the degradation process from the data. They proved to be reliable in conditions where sufficient historical data for training exists and in-depth system knowledge is not required [5], making them computationally less expensive compared to model-driven methods. Popular data-driven approaches include deep learning methods such as recurrent neural networks, convolutional neural networks, deep belief networks, and other approaches such as support vector machines, regression trees, ensemble methods, genetic algorithms, and fuzzy networks for PHM. Hybrid approaches are a combination of data-based and model-based approaches, which use the best features in each approach [6].

In this work, we present a review of the most recent approaches for prognostics and health management, specifically on NASA's turbofan engine dataset. In section II, we discuss NASA's turbofan engine dataset. Section III explains different types of applications on C-MAPSS dataset. Next, section IV introduces different techniques applied to the applications in Section III. Finally, section V provides a direction for future research opportunities and concludes the paper.

2. NASA TurboFan Engine Dataset

The NASA turboFan engine degradation simulation dataset [1] was developed by NASA using Commercial Modular Aero Propulsion System Simulation tool (C-MAPSS) [7], [8]. It was developed in order to encourage developments in Prognostics. The dataset contains multivariate time series data from a simulated large commercial turbofan engine instances using C-MAPSS. The C-MAPSS dataset consists of five sub-datasets, which are named as FD001, FD002, FD003, FD004, FD005T and FD005V. The first four sub-datasets contain training and test data along with the actual RUL values for test data. The dataset FD005T, used as a part of PHM Challenge'08 also contains training and test files except that the Actual RUL values for the test data was not provided. FD005V was used as a validation data set in the PHM'08 challenge.

The dataset consists of 26 columns. The first column indicate the engine identification number. The seconds column denotes the run-cycle of the engine. The next three columns denote the operational settings followed by 21 sensor values. The engines in the training files are till failure, while the engines in test files are run till a random point prior to failure. Table 1 shows more information about the attributes of the data.

Table 1: Attributes of Turbo Fan Degradation Simulation Dataset from NASA's repository

	C-MAPSS Simulation Data				PHM2008 Challenge	
	#1	#2	#3	#4	#5T	#5V
#Conditions	1	6	1	6	6	6
#Fault Modes	1	1	2	2	1	1
#Train Units	100	260	100	249	218	218
#Test Units	100	259	100	248	218	435

3. Prognostics Domains

The following are the different application domains in which the C-MAPSS dataset is used since 2018, based on the best knowledge of the authors.

3.1 Prediction of Remaining Useful Life

Prediction of remaining useful life of the engine is a major goal of the works discussed in this paper. Remaining Useful Life is the remaining time for a system/component to perform its functions until it fails. Estimating the remaining useful life helps in reducing the downtime of the device by planning maintenance actions in advance

Prediction of RUL can be achieved in various approaches, which are generally categorized into [9]:

- Mapping between input and RUL
- Mapping between health-index and RUL
- Similarity-based methods

Prediction of RUL using input signals and the ground truth RUL values involve modeling a relationship between data features which include both raw as well as extracted features and the labeled RUL [9]. These methods learn the underlying patterns and interrelationships between these features and the RUL and predict the RUL of new, unseen test instances using these patterns.

The other category of approaches involve learning the mapping between a developed feature called Health-Index (HI), which represents the health status of the component, and RUL. It is developed by fusing the input signals into a one-dimensional feature that is mapped to the labeled remaining useful life of the training instances. The methods in this approach learn the relationship between the HI and RUL and are used to predict the RUL of the test instances. Previous works have used methods such as linear regression [10] and logistic regression [11] for converting the multi-dimensional inputs to health index.

Similarity-based prediction methods [9],[10] use similarity comparison between a library of degradation models of instances of training data and test data [9]. The library of degradation pattern is created directly from the raw data or by using HI. The trajectories of the test data are compared with the patterns in the library and distance measures are used to compare the similarity between them. Different methods are later used to infer the RUL from the most similar model in the library.

By estimating the Remaining Useful Life of a system, maintenance activities can be planned and spare parts that are required for the maintenance can be ordered and stored based on RUL. Costs involved in managing inventory can be minimized if the spare parts are ordered with a minimal time between their use, instead of storing them. This paper discusses the recent works which, have proposed approaches for inventory maintenance using the prediction of RUL.

3.2 Anomaly Detection and Sensor Recovery

Anomaly detection is the concept of the discovery of sudden changes in the running pattern of the component, which in this case is the turbofan engine[12]. This concept can be utilized to obtain a variety of information such as change-point, fault source identification, and fault isolation. With developments in the area of Internet of Things (IoT), the use of sensors has increased in the past decade. Sometimes anomalies can be caused due to the faulty working of the sensors. The sensor values emitted from anomalous sensors can have a significant influence on the prediction of remaining useful life and degradation modeling tasks. So, it is essential to recover the actual data from anomalous sensors instead of discarding it [13]. Training the RUL prediction methods by retrieving the data can have a significant impact on the prediction accuracy.

3.3 Real-time Prognostics and Online Learning

Most of the works in the field of PHM deal with Prediction of RUL and estimation of the health status of the asset in offline mode, that is the predicting methods are trained on a entire batch of data at once. To implement the system in real-time, Online Training is needed.Online-Learning methods are useful to train the methods on new data and learn new patterns from the dynamic data. Online Learning can enable implementing the prediction systems in real-time domain. Latest developments in PHM are aimed at real time applications where the methods are trained sequentially as the data comes in. With changing environments and operating conditions in which the system is run, Online Training is useful solution for real-time diagnostics.

4. Prognostics Methods

4.1 Convolutional Neural Networks

Convolutional Neural networks (CNNs) [14], [15], [16] are one of the most popular methods for image data processing. Two characteristics of CNNs are: spatially shared weights and spatial pooling[17]. The shared weights between several functions in the architecture help in minimizing the memory requirement and the complexity of the neural network. CNNs are also capable of handling raw input data which makes less dependent on prior knowledge. The first implementation of CNN for predicting RUL of jet engines was proposed in [18]. The results were better than all the earlier prediction techniques such as multi-layer perceptron, support vector regression, and relevance vector regression.

Recent approaches like [19], [20] have performed well on RUL estimation task. [19] proposes Deep Convolutional Neural Network (DCNN) with five Convolutional layers and one fully connected Layer, all with *tanh* activation for better extraction of sensor signals. It also introduced a time window which helped in better feature extraction. The model performed better than all the state-of-art papers at that time, namely [18], [21], [22] to name a few. [20] proposes a CNN, added a Residual Building Block (RBB) along with piece-wise linear degradation [23]. By using K-fold cross validation, K number of models are trained and grouped to form an ensemble. This method gave a better accuracy than [18], [19], [24].

4.2 Recurrent Neural Networks and its Variants

Recurrent Neural Networks (RNN) [14], [17] are a group of neural networks for processing sequential data. They have been applied to many domains such as natural language processing, sequence-to-sequence translation, heathcare, etc. Below we review the RNN variants applied to this problem.

4.2.1 Long Short-Term Memory

Long Short-Term Memory (LSTM) is a variant of RNN developed by Sepp Hochreiter and JÃijrgen Schmidhuber [25] to avoid the problem of vanishing or exploding gradient in a traditional RNN [26]. It uses gate functions, namely input gate, forget gate, and output gate, as well as a cell which acts as a memory unit [27]. Information can be written into, stored, and read from the cell. The gates decide what information to preserve and what information to forget in the cell. The forget gate decides which historical data to discard from the cell state, input gate decides which states should be updated, and the output gate decides which part of the cell state should be given as output [28]. LSTM has been formerly applied on NASA turboFan jet engine dataset [21], [24], [28], [29] and yielded promising performance.

Recent studies [30], [31], [32], [33], [34] have utilized LSTM to this problem as well. [30] predicts the probability of an error in different time intervals instead of a particular RUL. This helps in planning maintenance actions during those intervals. [31] proposes an LSTM implementation for predicting RUL, which uses the Piece-Wise linear degradation concept [23]. An LSTM which takes the advantage of training on censored instances along with failed instances is proposed in [32]. In terms of Mean Squared Error (MSE) and score(S), it performs better than [24], [29], which only uses failed instances for training.

While the above discussed works are aimed at either prediction of RUL through direct mapping of input and RUL, or mapping of health index and RUL, [33] proposes a dual-task LSTM, which performs the degradation assessment and RUL prediction at the same time. Feature extraction is performed using the Kernal Principal Component Analysis (KPCA) [35]. The Root Mean Square Error (RMSE) reported was better than that of [24]. In another research project, Vanilla LSTM was used and it outperformed Gated Recurrent Units (GRU) and the regular RNN [34].

Additionally, in [36], LSTM is used for modeling long-sequence trends and gradient boosting regression. [37] models the short-term trends in different time windows. Finally, a neural network combines the results from long-term and short-term estimators and yields a hybrid prediction result. Using an ensemble of LSTMs and a feature augmentation method, which adds the forward difference of current and previous values of the sensors in [38], the RUL is estimated. Besides it provides further information on the prediction interval of RUL that can be utilized in deciding the upcoming strategy of maintenance. As a variation to using sole LSTM, [39] have added an unsupervised layer of Restricted Boltzman machines [40] in order to capture the latent features of raw sensor data and then the LSTM is trained with labeled data. This semi-supervised approach not only results in better estimation compared to that of supervised methods, but also makes the model capable of handling data not fully labeled. As in real-life cases of PHM, applications with fully labeled data is not easily obtained.

4.2.2 Bi-Directional Long Short-Term Memory Recurrent Neural Network

Bi-directional Long Short-Term Memory Recurrent Neural Network (BiLSTM) is a variant of LSTM that connects two hidden layers of opposite directions to the same output. The BiLSTM network can learn the dependencies of sensor data in both forward and backward direction, thereby having an added advantage. They were introduced in [41]. The increased capability of bi-directional LSTMs in prediction and classification has made it a suitable tool for the problem of RUL. Bi-directional LSTMs have been applied to the RUL problem in [42], [43], [44]. BiLSTMs outperform RNN, LSTM, GRU, and BiGRU in this class of problems.

AutoEncoder (AE) is essentially an unsupervised method of extracting features from higher dimensions of data and representing them in lower dimensions. Studies have shown the advantages of using auto encoders alongside BiLSTMs in estimation of RUL [45], [46]. Lowering the dimension of input data using an AE, and then passing the data to BiLSTM to capture the temporal dependencies, seems to improve the RUL estimation results [46]. Using an AE made of bi-directional LSTMs, decreases the multidimensional sensor data to lower dimension, and then generates a single dimensional health index afterwards, using a similarity based curve matching approach to estimate RUL [45].

4.2.3 Gated-Recurrent Unit

Gated Recurrent Unit (GRU) is a variant of RNN which also follows the gate concept as in LSTM. Except that the GRU only has 2 gates and it does not use a memory cell unit [47]. In many of the proposed approaches discussed in section 4.2, the LSTM methods tend to outperform their GRU counterparts. However, [48] has shown that adding a kernel principle component analysis [35] layer that lowers the dimensions of the data, by extracting features from it, improves the performance of GRU in terms of RUL estimation error. That outperforms its LSTM based counterparts. Besides, the time required to train the model is decreased significantly.

4.3 Hybrid variants of CNN and RNN

Along the major approaches to CNN and RNN, learning architectures have been proposed that make use of both methods. In [49], a 1D layer of CNN is used to capture low level representations of sensor readings. These representations are then sent to an LSTM layer in order to capture long-term dependencies. Then the fully connected network layer maps the RUL to the inputs from previous layer. Another architecture that first applies a CNN and then uses and LSTM for estimating RUL is [50]. They have proposed a method of data augmentation that improves the performance of their approach. Another instance of this category combines CNN and RNN in parallel [51]. A hybrid deep neural network is proposed that takes in the input data in two separate paths. One path is a CNN, and the other one is a LSTM. Then, the outputs of these paths are passed through a multi-layered neural network that acts as the fusion path. In [26], CNN and LSTM extract features in parallel paths. And then their outputs are fused using another LSTM. At the end, a fully connected neural network maps these features to RUL.

4.4 Echo State Networks

Though RNN's possess a huge potential in modelling sequential data, they also possess certain drawbacks such as the need to train lots of parameters and the computational burden it causes. Also, a single parameter update can be computationally expensive and will require many cycles. As a result, training times increase, which is not preferred. Echo State Networks (ESN) rise from a concept called "Reservoir Computing". They were developed by [52].

In an ESN, an RNN is created whose weights are generated randomly. This RNN, which is called the reservoir, remains unchanged during the course of the training. It is passively excited by the input signal [53]. Only weights of the connections among the reservoir internal states and the output are optimized, while the weights of the reservoir and input remain unchanged, which makes them less computational expensive to train. Past implementations of ESN on the C-MAPSS dataset of turbo fan engine degradation simulation dataset have performed well [54], [55].

Works such as [56], [57], [58] have used ESN in recent times for different tasks on the C-MAPSS dataset. [56] proposes an ensemble of ESN's aimed at predicting the remaining useful life on C-MAPSS dataset. Additional methods such as optimization of the ensemble architecture parameters using multi-objective differential evolution algorithm, which is an optimization algorithm [59], and local aggregation of the ensemble ESNs, which assigns different weights to the individual models based on their performance on a subset of the training data, have been also introduced. [57] uses an attention-based ESN using a genetic algorithm to optimize the hyperparameters, which reported a better MSE compared to [22], [24]. [58] proposes an echo state network implementation for online training, where the inputs come sequentially, and the ESN must be trained on them as the input arrives. This work uses an online kernel-Based learning method, called Kernel Recursive Least Squares (KRLS) algorithm, for training the output weights in the ESN [60].

4.5 Hidden Markov Models

Hidden Markov Models (HMM) are probabilistic models that can be used to model/predict a sequence of signals. HMMs are built on the assumption of markov process, which states that future states are independent of the past states, given the present states [61]. HMM can model the degradation of a component, each state of the model representing a health state of the component. By modelling the health state of the component, the RUL of the component can be estimated. [61], [62]are some well-known implementations of HMM on the NASA turboFan engine dataset.

Recent approaches using HMM for predicting the RUL such as [63], [64], [65] have introduced some novel methodologies. [63] uses a cluster-based HMM which predicts the RUL through a mapping with the degradation pattern. The RMSE reported was better than some of the state-of-art works such as [19]. Another similar approach uses HMM with clustering [65]. This approach uses three HMM's where one of them is used to predict the RUL, while the other two HMM's are used to output the lower and upper bounds for the RUL, which can help in maintenance planning decisions.

4.6 Other Approaches

In the recent years, we have seen the rise of many novel approaches developed for RUL prediction, anomaly detection, change point detection, fault isolation, sensor recovery from anomalous sensors, online training, and distributed training.

A hybrid of Auto-Regressive Integrated Moving Average (ARIMA) and SVM for the prediction of RUL is proposed in [66]. The ARIMA is used to forecast the input values and SVM is used for RUL prediction using the forecasted values. [67] employs an artificial neural network to perform similarity-based RUL estimation on NASA turboFan engine dataset. In this work, the raw sensor data are normalized and clustered based on operational regimes. A joint-approach for predicting the RUL as well as prediction of failure within a specific interval was proposed in [68] using Deep Weibull Recurrent Neural Network (DW-RNN) and Multi-Task Learning (MTL-RNN).[69] used a Regression-Tree Approach for RUL prediction. Regression using Relevance Vector Machine (RVM), a machine learning technique which works similar to SVM but gives a probability distributions instead of point estimates, is used by [70]. Multi-Layer Perceptrons (MLP) are known to work well with nonlinear data and with the fact that they are computationally inexpensive to train when compared to other deep networks like RNN, a RUL prediction method using MLP with striding time window was proposed in [5], and it performed better than [18], [54], coming close to the performance of [22], [19]. Another implementation of MLP was introduced in [71], which used an MLP with functional data analysis [72].

Filtering methods are generally used to filter out noise in sensor data, but in most cases, filtering methods are specific to a particular type of data. Some examples of known filtering methods are moving average, exponential smoothing, linear Fourier smoothing, and wavelet smoothing methods [73]. A recent work, [73], proposes utilizing a group of filtering methods and using the extracted features for training, after performing Principal Component Analysis (PCA) to reduce the dimensions of the input space. In this work, an MLP and Random Forest (RF) were trained using the output from PCA, which was reported to be robust on different types of datasets such as C-MAPSS dataset.

Operating conditions of the components have a major influence on the working of the components. So [74] proposes an approach for RUL prediction which considers the effect of the operating conditions on the degradation pattern. This method works robustly on non-linear continuously degrading systems such as the NASA turbofan engine dataset. Extreme Learning Machine (ELM) [75], a kind of neural network in which the input weights and hidden weights are not trained, is used in some of the latest works such as [76], [77].

The ensemble is a concept by which the results of multiple methods are combined to yield better prediction accuracy. The performance of different base learners is compared and combined to give better accuracy. In [78], gradient boosting Trees and random forest techniques, which are a kind of ensemble methods is used for predicting the RUL. They are trained on data that has been normalized and clustered based on the operating conditions. Ensemble learning is also used for distributed prognostics and in edge computing environments. Instead of performing operations on data collected in a centralized cloud repository (or global repository), edge computing involves performing operations at the local data repository itself. [79] uses ensemble method with different base models, namely K-Nearest Neighbours (KNN) [80], Decision Trees (DTs) [80], SVM [80] and MLP [80]. Another ensemble-based approach method was implemented in [81] that uses a parallel ensemble of RFs, Classification and Regression Tree (CART), RNN, Autoregressive (AR), Adaptive-Network-Based Fuzzy Inference (ANFIS), Relevance Vector Machine (RVM), and Elastic Net (EN). In [82], a decision tree based gradient boosting approach, named Light Gradient Boosting Machine (LightGBM) [83] is used for RUL prediction. It displayed better RMSE values when compared with existing state-of-art approaches such as [24], [18], [22].

Anomaly detection is an important task for predictive maintenance. It helps in identifying a problem and necessary steps to solve the malfunction before any actual damage happens to the asset or its components. Anomaly detection using data-driven methods is generally considered to be unsupervised due to reasons such as: 1) Not all faults are known in advance. They are dependent on many factors such as operating conditions and environment, wear-and-tear of the asset/component, etc. 2) Accurate labelled data cannot be found in most of the conditions. Discussion on the state-of-art papers in anomaly detection can be found in [12]. Interesting developments in the anomaly detection have been introduced using NASA turbofan engine dataset in recent works such as [84]. In traditional clustering algorithms such as k-means, k-medoids and self-organizing maps, the cluster centre is used to measure the similarity distance to a new point [84]. These techniques involve heavy memory and computational expenses since every new data point has to be compared with each and every cluster centre, which is computationally demanding in case of large datasets. [84] proposes construction of a non-convex hull, using an algorithm called DINA [84], around the generated cluster to represent all the similar data points. Using a non-convex hull to cluster the data points, anomalies can be detected by comparing the new data points to the nearest non-convex hull. Sometimes sensors may fail or malfunction, causing anomalous behaviour. Values generated by an anomalous sensor have a major influence on the prediction values. The anomalous sensors should be identified and the actual data should be recovered, which can be used for training. Some recent approaches such as [85] are aimed at sensor anomaly detection and recovery of data from anomalous sensors by using mutual information of the sensors. KPCA [35] is used for anomaly detection followed by Least Square-Support Vector Machine (LS-SVM) to recover the data.

Finally, inventory management is a classical domain, where RUL prediction can be used to minimize the costs involved in storing the assets or its components by ordering/storing the components only for short time, thereby cutting down the storing costs. Application of PHM for this purpose is discussed in [86]. Application of real-time prognostics in a distributed manner for management of a fleet of assets is discussed in [87] in which an RNN is used as the prediction method by online training. Systems in daily life are used in dynamic operating conditions and environments, which would require online training of the data to adapt to the new patterns of the data.

5. Discussion and Conclusion

This paper provided a bird view analysis of the very recent approaches developed in prognostics and health management domain using the NASA turboFan engine degradation dataset. The works are discussed based on the type of methods applied to achieve tasks, namely, estimation of remaining useful life, anomaly detection, sensor recovery, and online and real-time prognostics.

The intention of this survey paper is to guide future researchers by providing them information regarding the latest trends in the field of prognostics and health management of industrial systems. The techniques developed using the C-MAPSS dataset can be used for developments in other complex systems as well. We intend to provide a more comprehensive analysis of the recent trends, discussing the pros and cons of each method, and a more detailed comparison of them in a follow up journal paper.

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