A data-driven method for estimating the remaining useful life of a Composite Drill Pipe

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***Abstract*—Composite drill pipe has known a big interest in the shortradius drilling industry due to its lightweight, flexibility and the performance properties of steel pipe Despite its benefits, composites suffer from fatigue when subjected to loads, which leads to failure. To prevent this the use of a predictive maintenance monitoring the state and predicting its remaining useful life is needed.**

In this work, we proposed a predictive maintenance method for estimating the remaining useful life of composite drill pipe subjected to cyclic loads. A tension-tension fatigue experiment in a cross-ply Carbon fiber reinforced polymer (CFRP) laminate is used for case study

***Index Terms*—Data-driven approach, composites, drill pipe, neural networks**

I. Introduction

The use of steel drill pipe in short-radius drilling is facing some problems as the inability to withstand stress,which decrease the life time of the drill pipe, and the heavy wight of steel. To overcome this problems one of the best solutions is to replace steel by composites. A composite drill pipe (CDP) have the characteristics of being flexible, lightweight and withstand stress better than steel. This characteristics will extend the drill pipe life as well as reducing the cost of drilling horizontal and directional wells.

The combination of light weight and performance properties (equal to steel pipe) of Composite drill pipe, make it one of the promised resources development technologies, due to both its economic use and its wide application: extended reach (ER), ultra-deep (UD), and deep directional drilling (DDD) applications [1]

Despite CDP benefits, composites can suffer from fatigue when subjected to cyclic loads, which leads to component failure. CDP suffer from two types of damage: matrix micro-cracks and inter-laminar delamination. Matrix micro-cracks develop due to fatigue loading, which appears through the ply thickness direction. The inter-laminar delamination happens when the number of cracks increases. The delamination is considered the main reason for failure in composite structure due its high damage on the structure[2].

Horizontal directional drilling (HDD) product manufacturers indicate the importance of maintenance, especially to directional drilling, Where the failure of the equipment in the field have more sever damage than mean downtime. This due to the difficulty of removing broken-down equipment from below-ground, which can lead to abandoning the hole mid-bore and restarting the process over [3].

Hence, the use of a maintenance strategy monitoring the state of the component and predicting its remaining useful life (RUL) is necessary. The European standard EN 13306 released in 2010, which specifies generic terms and definitions for the technical, administrative and managerial areas of maintenance, defined the predictive maintenance as a condition based maintenance carried out following a forecast derived from the analysis and evaluation of the significant parameters of the degradation of the item[4]. is the most suitable maintenance to solve these problems.

Prognostics and health management (PHM) representing the steps of predictive maintenance and the cycle life of the system (or component) is used in this paper, where we focus on the prognostic step.

The objective of this paper is to propose a predictive maintenance method for estimating the remaining useful life of composite drill pipe subjected to cyclic loads. This method is a data-driven prognostic method which is subdivided on two sequential process: a training (learning) process and a prediction process.

The rest of the paper is divided as follow: in the next section, we present prognostics and health management, in section three we explain the data driven approach and our neural networks method, next we provide a case study for CFRP and finally conclude with a conclusion.

II. Prognostics and health management

PHM is a systematic approach that is used to evaluate the reliability of a system in its actual life-cycle conditions, predict failure progression and mitigate operating risks via management actions [5]. The PHM architecture can be divided into seven steps. Step 1. Data acquisition. Using sensors this module records the state of the monitored machine and provides the PHM application with raw data. In order to provide good data, sensors should be mounted strategically [6].

Step 2. Data processing. The data collected from sensors usually contain noise. To reduce the noise content in these data, denoising techniques must be used. Data processing module aims at filtering noised data and extracting meaningful

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features. This features are then redacted/selected to characterize with precision, the functioning of the system [7].
Step 3. Condition assessment. By detecting and localizing a system fault this module determines the systems current health state [6].
Step 4. Diagnostic. The diagnostic module verify the degradation of the system, and provide the next module with both a diagnostic record and fault causes [8].
Step 5. Prognostics. This module can be considered as the main module of the PHM architecture, where it's main purpose is to predict the future condition of the monitored system and estimate its RUL. The Prognostics module uses data provided by the previous modules in order to predict the future health status and estimate the RUL[9].
Step 6. Decision support. Using the data provided by previous modules the decision support module plan and suggest maintenance actions to prevent failure of the system, while minimizing the cost of maintenance[10].
Step 7. Presentation. This module is interface between the machine and the user to ensure modules communication[6].

III. Data-driven Approach

In the last decades, several prognostics methods and tools were proposed, those methods and tools differ in the type of application considered and the nature of the data and knowledge available, where they can be regrouped in a limited number of approaches. The most used are data-driven approach, model-based approach and hybrid approach of the previous approaches as shown in figure 1.

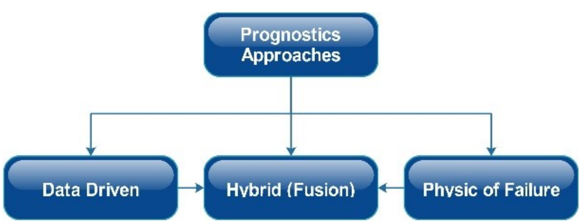

Fig. 1. Prognostics approaches

Using historical and current data. The data-driven prognostics methods probabilistically and statistically estimate, and predict the health and reliability of products. The Data-driven approaches are convenient for monitoring the health of large multivariate systems and allow detection and evaluation of correlated trends in the system dynamics, providing an estimation of the future and current health of the system. Data-driven approaches include fault identification, fault isolation, anomaly detection and prediction of remaining useful life [11]. Due to statistical and probability theory incorporation of Machine learning in addition to feature extraction, cleaning of data, data pre-processing and dimensional reduction, Machine learning is popular in the data-driven approach [12].
In many cases, it is impractical or difficult to determine a physics of failure model for prediction. In such circumstances, the use of nonlinear network approximators is useful, these approximators can provide desired outputs directly in terms of the data [13].
Data-driven method can be classified in artificial intelligence methods (Neural Networks, Bayesian Networks, Wevlet, and Neuro-Fuzzy System) and statistical methods (Parametric and Non-Parametric methods). The neural networks method was used in this paper.

A. Neural networks

Neural networks methods are widely used in different domains as in health care,security and maintenance, and treating a variety of applications problem including, system identification and control classification and time series prediction, due to his strength in capturing the dependency of data.
We can consider the Artificial Neural Network (ANN) as set simple processing units which connected by a large number of weighted connections. The neural network topology focus on the pattern connections between the units and the propagation of data [14]. There are several topologies, the most known topologies are:
i. Feed-forward networks: In the Feed-forward network topology the flow of data between the input and the output units is strictly feed-forward. One of the characteristics of feed-forward networks is that they do not have feedback connections. However, they can contain multiple (layers of) units [15]. ii. Recurrent networks: Contrary to feed-forward networks, recurrent networks contain feedback connections forming a directed cycle, this allows it to exhibit dynamic temporal behavior [16].

In this work we used a recurrent neural network (RNN) to predict the RUL of Composite. The choice of the neural network will solve the complex relationship between the data captured and the RUL. However, using an RNN will improve the prediction due to that the RUL depends not only on the current state but also on the past states.
The architecture of the used recurrent neural network is:

- Three inputs (degradation, Load and Cycles)
- Tow time delay
- Ten neurons in the hidden layer
- Hyperbolic tangent sigmoid transfer function
- One output(RUL)
- Linear transfer function
- Levenberg-Marquardt algorithm

IV. Case Study

In order to evaluate the proposed method, we used a tension-tension fatigue experiment in a cross-ply CFRP laminate for case study. The choice of this composite data set is due to two main reasons, the first reason is that it represent composite data which is the main component of a composite drill pipe, the second reason is that the data are run to failure, which is necessary for the use of a data-driven method. The data was provided from National aeronautics and Space Administration (NASA) Prognostics Center of Excellence Data Repository[18]. This NASA Prognostics Center provides collection of data sets that have been donated by various universities, agencies, or

companies, where composite experiments were conducted at Stanford Structures and Composites Laboratory (SACL) in collaboration with the Prognostic Center of Excellence (PCoE) of NASA Ames Research Center.
The data set is divided on three different layup configurations presenting the ply orientation of the laminated coupons. Each layup folder contains several coupons run to failure. The monitored data consist of lamb wave signals from a network of 16 piezoelectric (PZT) sensors, multiple triaxial strain gages, and periodic x-rays were to describe the internal damage .
For the composite material used, it consist of a Torayca T700G uni-directional carbon-prepreg material, where the coupons dimension is 15.24 cm x 25.4 cm with dogbone geometry and a notch (5.08mm x 19.3mm) to induce stress concentration. To monitor wave propagation through the samples, two six-PZT-sensor (six actuators and six sensors) SMART Layer from Acellent Technologies, Inc. were attached to the surface of each sample. Figure 2 shows the degradation of the path 25 from actuator 5 to sensor 7 with frequency 150 HZ, while the Figure 3 shows the global degradation of all paths. The degradation is calculated by comparing the current signal of the path i with the baseline signal of the same path, the path 25 in figure 2 was presented based on time and not in cycles for a better view of the degradation path. We can observe that the degradation increases as cycles (time) increase, which is expected due the appearance of cracks that alter the signal. The strain gages degradation is shown in Figure 4. This degradation was provided by the data set where we can see it's increases with the increase of the number of cycles. However, the strain gage degradation was not used in the case study due to the missing of several values in the data set.

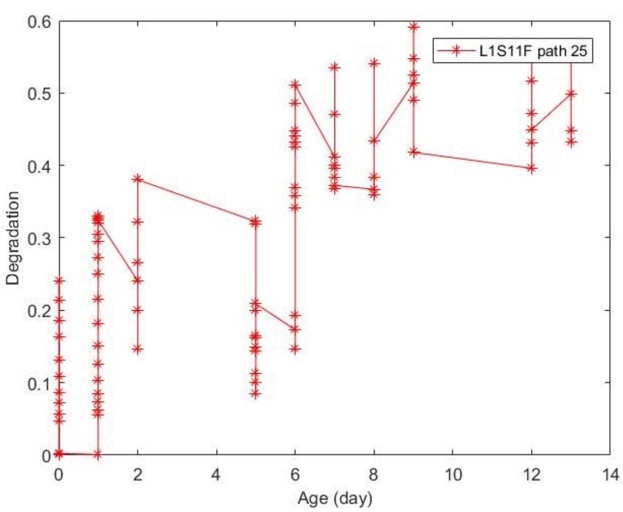

Fig. 2. Degradation of path 25.

In order to compute the RUL we assigned the previous degradation in addition to the loads and cycles as inputs of the recurrent neural network following the architecture described in the neural network subsection. The Figure 5 shows the estimated RUL in red and the real RUL in blue. Here the RUL

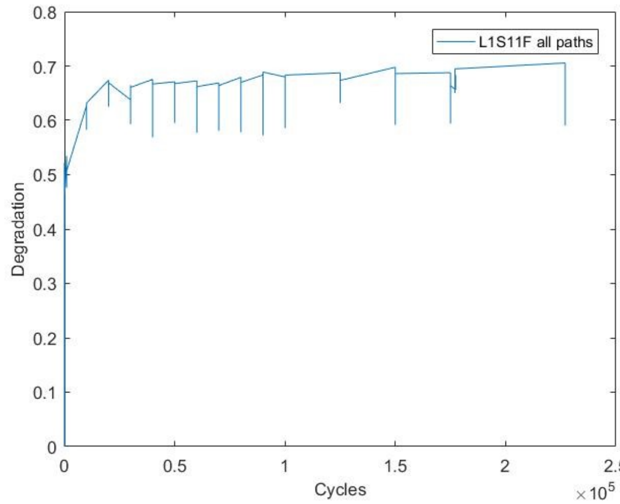

Fig. 3. Degradation of all paths.

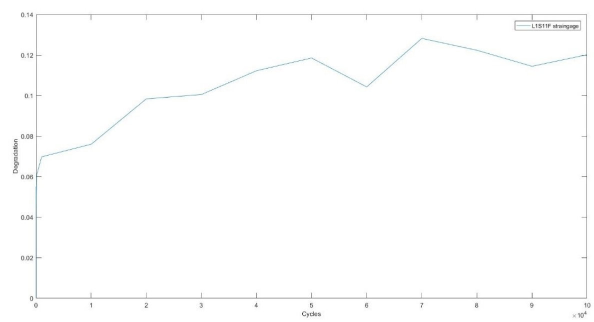

Fig. 4. Strain gage degradation.

corresponds to the number of remaining cycles before failure. The results shows that the estimated RUL is close to the real RUL, which is a good point. The variation of the estimated RUL can be reduced by providing more data.

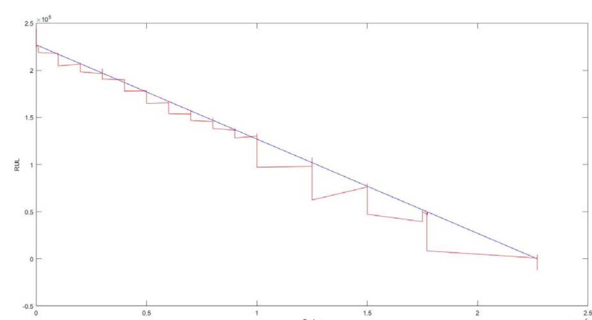

Fig. 5. RUL estimation by neural networks.

A. Conclusion

In this paper, we proposed a predictive maintenance method for estimating the remaining useful life of composite drill pipe subjected to cyclic loads. The prognostic of the RUL was done using neural networks method which is a data-driven method. Composite drill pipe is beneficial compared to steal pipe, however the composites fatigue behavior is complex, hence is difficult to predict. Neural networks with enough data can predict complex behaviors. A case study was done using tension-tension fatigue experiment in a cross-ply CFRP provided by NASA Prognostics Center of Excellence Data Repository. We were able to estimate the RUL with good results. As future works and in order to optimize the method we want to collect data test the method in real machines taking in consideration environment conditions and provide real time prognostics by integrating and communicating with the previous modules.

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