REMAINING USEFUL LIFE PREDICTIONS WITH DEEP LEARNING METHODS

(Bibliography report)

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***Abstract*—The abstract goes here (100 words max).**

I. Context

In recent years deep learning, a subbranch of machine learning, has shown impressive results, especially in the fields of speech recognition, visual object recognition and object detection [9]. One requirement to use deep learning is the presence of sufficient amounts of data [19]. As more data becomes available in the engineering domain there is a recent surge of interest to use deep learning in engineering [22].

One of the strengths of deep learning approaches is their ability to deal with and detect complex relationships in large datasets [14]. This strength makes their usage also interesting in the Prognostics and Health Management (PHM) domain [23]. The potential of deep learning in PHM might not be fully exploited yet [17].

II. Problem statement

The problem to which the deep learning algorithms are applied in this project is the crack growth in precracked aircraft fuselage panels. The Paris-Erdogan Law [3] is used to create a synthetic dataset of the crack growth to train the model. The dataset consists of strain data from virtual strain gauges placed in the area around the crack and the corresponding Remaining Useful Life (RUL) of the fuselage panels.

The goal for this project is to develop different deep learning models for RUL prediction based on different model architectures. The developed models are optimized before a comparison between them is made. Therefore an appropriate evaluation metric must be selected.

III. Prognostics and Health Management

According to Zio [28] PHM is a field of research and application which aims at making use of past, present and future information on the environmental, operational and usage conditions of an equipment in order to detect its degradation, diagnose its faults, predict and proactively manage its failures. In the context of this project only the detection of degradation and prediction of failure are relevant.

PHM models can be divided into single and multi model approaches. Multi model approaches are a combination of different single model approaches. Single model approaches can be further divided into knowledge-based, data-driven and physics-based models. Within the data-driven models there are statistical, stochastic and machine learning models which is the category of deep learning models. [14]

IV. Deep Learning Models

Within the available deep learning models there are two algorithms which are promising for PHM: Recurent Neural Networkss (RNNs) (Little [11] and Hopfield [6]) and Convolutional Neural Networks (CNNs) (Lecun et al. [8]) [17].

The common type of deep learning model for time series prediction are RNNs [7]. Standard RNNs have some major drawbacks (vanishing/exploding gradient problem) which limit their application [2]. Long short-term memory (LSTM) networks (Hochreiter and Schmidhuber) [5] avoid this problem and have established themselves as one of the most used deep learning model type, especially for Natural Language Processing (NLP) [24]. For this reasons LSTMs will be one of the investigated RNN approaches in this project. Another investigated RNN approach are the Gated Recurrent Units (GRUs). It is a simplified version of the LSTM. Due to this simplicity it is gaining in popularity in recent years [16].

Recent results suggest that CNNs can match or even outperform RNNs in time series related tasks [7]. The second major focus of this work are therefore CNN models. Besides the general CNN architectures Temporal Convolutional Networks (TCNs) (Bai et al. [7]) are investigated in this work. A TCN is a specific CNN architecture that tries to replicate some of the best practices for CNN architectures. As depicted in Fig. 1 a TCN is composed of convolutional layers which include dilation. Through dilation TCNs can increase their receptive field and therefore capture relationships over longer time sequences. For more details on TCNs see [7].

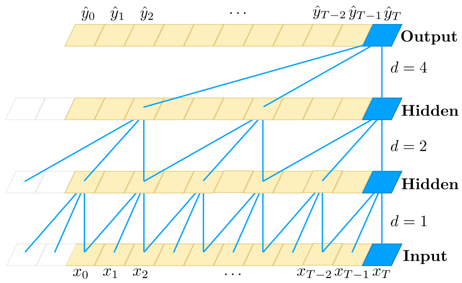

Fig. 1. TCN with dilation factors d = 1; 2; 4 and filter size k = 3 [7]

V. Applications of Deep Learning in Prognostics

RNNs are as stated in chapter IV the common approach for time-dependent relationships and have therefore also achieved great interest in the PHM domain [17].

Pioneers models were developed such as Elman Recurrent Networks (ERMs) or Jordan Networks, outperforming traditional Machine Learning Programs (MLPs) for sequence-prediction [17]. These algorithms were then widely explored by several researchers. Among them can be cited Yan et al. for their work on material degradation evaluation and life prediction in 2007, and Kramti et al. for having used ERMs for high-speed shaft bearing prognostics based on vibration signals [17].

The common CNN models deal with 2-Dimensional data as input such as pictures. The time sequence data used for PHM is in 1-Dimensional format. For this application 1D-CNN have been introduced. The key differences between them and the 2D-CNNs are that their input data is reduced by one dimension and the convolution filter only slides in one dimension. [17]

In one of the first applications of CNNs to PHM Li et al. suggested that CNNs can be used to obtain RUL prognoses for machinery [10]. The model was applied to the C-MAPSS dataset [18] and outperformed state-of-the-art prognostics approaches including RNN and LSTM models. To prepare the data for the CNN a sliding window approach was used. This approach maps the RUL at time t_i to the current and past time steps of the input features $[x_{t-N+1}, x_{t-N+2}, ..., x_{t-1}, x_t]$ where N is the length of the sequence. The resulting input matrix has therefore the dimension $k \times N$ where k is the number of features.

As it showed promising results in other applications of deep learning to PHM ([12], [26]), classification is an interesting alternative to regression for RUL prediction. Instead of trying to predict an exact RUL value the goal is to predict the correct RUL class with a lower and upper bound for the RUL.

VI. Research relevance

The goal of this study is to predict the RUL of precracked aircraft fuselage panels based on strain gauge measurements using deep learning. This approach is driven by the impressive results of deep learning to RUL prediction as shown in [1], [10], [13], [27], [25], [15] and other publications (For an overview see Akrim et al. [17]). Strain gauges play a vital role in PHM in general [21] and specifically for the aircraft domain [20]. According to Fink et al. [4] is the use of simulation environments and adaption to real-life applications a promising future research approach as the data will more likely be sufficient in the source domain. The synthetic dataset used for this study aims at using this advantages. For the application of deep learning to crack growth for RUL prediciton based on strain gauge measurements no results in the literature could be found. This study tries to fill this research gap.

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