REMAINING USEFUL LIFE PREDICTIONS WITH DEEP LEARNING METHODS

(Final report)

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***Abstract*—This paper aims to compare Deep Learning models to predict the Remaining Useful Life (RUL) of a structure. These models are separated into two families: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Once implemented, their hyperparameters are optimized and the models are compared on the basis of a metric.**

I. BACKGROUND

Deep Learning

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 [1]. One requirement in using Deep Learning is the presence of sufficient amounts of data [2]. As more data becomes available in the engineering domain there is a recent surge of interest in using Deep Learning in engineering [3].

One of the strengths of Deep Learning approaches is their ability to deal with and detect complex relationships in large datasets [4]. This strength makes their usage also interesting in the Prognostics and Health Management (PHM) domain [5]. The potential of Deep Learning in PHM might not be fully exploited yet [6].

Prognostics and Health Management

According to Zio [7] 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 a piece of 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. [4]

II. INTEREST

Deep Learning has shown some impressive results when applied to RUL prediction as shown in **Xu2018**, [8]–[12] and other publications (For an overview see Akrim et al. [6]).

Within the available Deep Learning models there are two algorithms which are promising for RUL prediction: RNNs (Little [13] and Hopfield [14]) and CNNs (Lecun et al. [15]) [6].

RNNs are the common Deep Learning approach for time-dependent relationships and have therefore also achieved great interest in the PHM domain [6]. Pioneers models were developed such as Elman Recurrent Networks (ERMs) [16] or Jordan Networks [17], outperforming traditional Machine Learning Programs (MLPs) for sequence-prediction [6]. These algorithms were then widely explored by several researchers. Among them can be cited Yan et al. [18] for their work on material degradation evaluation and life prediction in 2007, and Kramti et al. [19] for having used ERMs for high-speed shaft bearing prognostics based on vibration signals [6].

An emerging type of Deep Learning network for time-dependent relationships are CNNs which might be able to outperform RNNs [20]. 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 [8]. The model was applied to the C-MAPSS dataset [21] and outperformed state-of-the-art prognostics approaches including RNN and Long short-term memory (LSTM) models.

In this work a synthetic dataset is used as according to Fink et al. [22] the use of simulation environments and adaption to real-life applications is 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 advantage.

The synthetic dataset matches strain gauge data to the RUL. The use of strain gauges as an input to an PHM model is interesting as they play a vital role in PHM in general [23] and specifically for the aircraft domain [24].

III. Aim

The goal of this study is to predict the RUL of precracked plates based on strain gauge measurements using Deep Learning. For the application of Deep Learning to crack growth for RUL prediction based on strain gauge measurements no results in the literature could be found. This study attempts to fill this research gap.

In a work done by Akrim [25] the Paris-Erdogan Law [26] was used to create a synthetic dataset of 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 RUL of the fuselage panels.

The Paris-Erdogan Law is applied to an infinite plate as shown in Figure XXX. The strain gauges are placed in a 45°-Angle at the positions shown in Table XXX relative to the center of the plate. The crack length in the Paris-Erdogan Law is a function of: k number of cylces, $\Delta\sigma$ stress range, m, C material constants, a_0 initial crack length. By calculating the crack growth until the crack length a reaches the critical crack length $a_{crit} = (\frac{K_{IC}}{\Delta\sigma\sqrt{\pi}})^2$ the simulation can determine the RUL for each simulated cycle. For the simulations the stress range $\Delta\sigma$ is kept constant while the initial crack length a_0 and the material parameters m and C are drawn from a normal distribution. 10000 structures are generated this way to form the training and validation dataset. For the testing dataset 100 structures are generated. The output of theses simulations which form the input for the deep learning models is a table matching the strains from the strain gauges to the RUL calculated by the simulations. To reduce the dataset the results are only saved to the table every 500 cycles. Table XXX shows an excerpt of the generated training and validation dataset.

The aim of this work is to predict the RUL based on current and past information from the 3 strain gauges using deep learning models. Different Deep Learning model architectures are to be used for that. The developed models must be trained and optimized before a comparison between them is made.

IV. Methods

Available Dataset

As it showed promising results in other applications of Deep Learning to PHM ([27], [28]), 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. The generated dataset was composed of 80,000 cycles at most. Therefore the chosen strategy has been to create 20 intervals following a parabolic equation. The last class would be for a RUL over 80,000 cycles away.

To prepare the data for the CNN and RNNs models a sliding window approach was used. This approach maps the RUL at time t_i onto 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 therefore has the dimension $k \times N$ where k is the number of features.

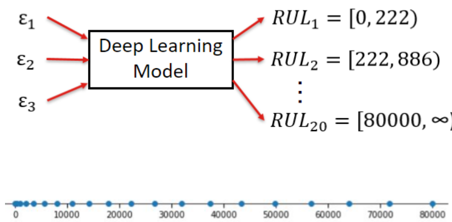

Fig. 1. RUL classification strategy

Recurrent Neural Networks

The common type of Deep Learning model for time series prediction are RNNs [20]. Due to their ability to store information within the cell, it can better remember information of a time-dependant data.

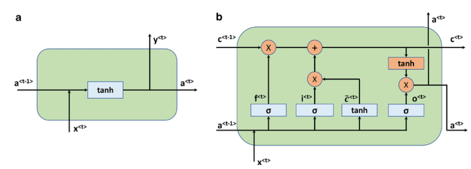

Fig. 2. RNN cell architecture. a A simple RNN unit; b an LSTM unit [29]

However, standard RNNs have some major drawbacks, such as the vanishing or exploding gradient problem, which limit their application [30]. LSTM networks (Hochreiter and Schmidhuber [31]) avoid this problem and have established themselves as one of the most used Deep Learning model types, especially for Natural Language Processing (NLP) [32]. For these 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 has been gaining in popularity in recent years [33]. Then, a simple RNN architecture will be explored to evaluate the possible benefits of more complex structures.

Convolutional Neural Networks

Recent results suggest that CNNs can match or even outperform RNNs in time series related tasks [20]. The second major focus of this work are therefore CNN models.

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. [6]

Besides the general CNN architectures Temporal Convolutional Networks (TCNs) (Bai et al. [20]) 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. 4 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 [20].

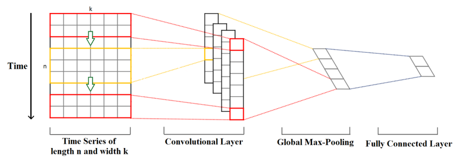

Fig. 3. Example for an 1D-CNN architecture [34]

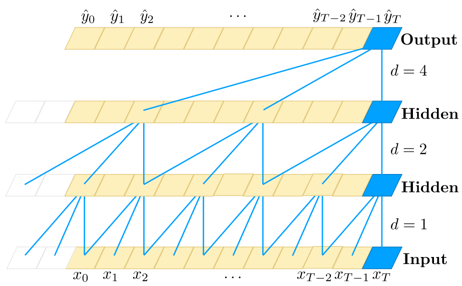

Fig. 4. TCN with dilation factors d = 1; 2; 4 and filter size k = 3 [20]

To evaluate the performance of developed models a metric is needed. As the networks are used to perform classification instead of regression the accuracy metric is used. This metric calculates how many of the predictions made with the dataset are correct (e.g. the right RUL range is predicted)

$$Accuracy = \frac{Number of correct predictions}{Total number of predictions}. \quad (1)$$

This metric is applied during training and validation to compare different models against each other. The final assessment of the models is made by applying the accuracy metric to the testing dataset.

The used loss function which is used as the objective function for minimization by the backpropagation algorithm is the categorical crossentrophy loss function

$$CE = -log(\frac{e^{s_p}}{\sum_j^C e^{s_j}}) \quad (2)$$

where s_j is the output of the network for Class j with s_p beeing the positive class.

V. Results

VI. Conclusions

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