

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 (RNN). Once implemented, their hyperparameters are optimized and the models are compared on the basis of a metric.

I. BACKGROUND

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].

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 [8]–[13] 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 [14] and HOPFIELD [15]) and CNNs (LECUN ET AL. [16]) [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) [17] or Jordan Networks [18], 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. [19] for their work on material degradation evaluation and life prediction in 2007, and KRAMTI ET AL. [20] 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 [21]. 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 [9]. The model was applied to the C-MAPSS dataset [22] and outperformed state-of-the-art prognostics approaches including RNN and Long short-term memory (LSTM) models.

III. AIM

The goal of this study is to predict the RUL of precracked plates based on strain gauge measurements using Deep Learning.

The Paris-Erdogan Law [23] is 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.

Strain gauges play a vital role in PHM in general [24] and specifically for the aircraft domain [25].

According to FINK ET AL. [26] 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.

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.

Different Deep Learning model architectures are to be used for RUL prediction. The developed models are optimized before a comparison between them is made. Therefore an appropriate evaluation metric must be selected.

IV. METHODS

The common type of Deep Learning model for time series prediction are RNNs [21]. Standard RNNs have some major drawbacks (vanishing/exploding gradient problem) which limit their application [27]. LSTM networks (HOCHREITER and SCHMIDHUBER) [28] avoid this problem and have established themselves as one of the most used Deep Learning model types, especially for Natural Language Processing (NLP) [29]. 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 [30].

Recent results suggest that CNNs can match or even outperform RNNs in time series related tasks [21]. The second major focus of this work are therefore CNN models. Besides the general CNN architectures Temporal Convolutional Networks (TCNs) (BAI ET AL. [21]) 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 [21].

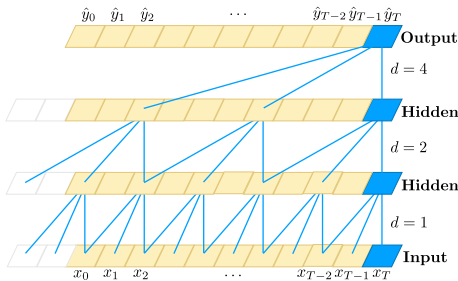


Fig. 1. TCN with dilation factors $d = 1; 2; 4$ and filter size $k = 3$ [21]

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]

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dataset [22] 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 onto the current and past time steps of the input features $[x_{t-N+1}, x_{t-N+2}, \dots, x_{t-1}, x_t]$ 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.

As it showed promising results in other applications of Deep Learning to PHM ([31], [32]), 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.

V. RESULTS

VI. CONCLUSIONS

REFERENCES

- [1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015, ISSN: 1476-4687. DOI: 10.1038/nature14539.
- [2] J. Z. Sikorska, M. Hodkiewicz, and L. Ma, "Prognostic modelling options for remaining useful life estimation by industry," *Mechanical Systems and Signal Processing*, vol. 25, no. 5, pp. 1803–1836, 2011, ISSN: 0888-3270. DOI: 10.1016/j.ymssp.2010.11.018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0888327010004218>.
- [3] A. Voulodimos, N. Doulamis, G. Bebis, and T. Stathaki, "Recent developments in deep learning for engineering applications," *Computational Intelligence and Neuroscience*, vol. 2018, p. 8 141 259, 2018, ISSN: 1687-5265. DOI: 10.1155/2018/8141259.
- [4] J. J. Montero Jimenez, S. Schwartz, R. Vingerhoeds, B. Grabot, and M. Salaün, "Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics," *Journal of Manufacturing Systems*, vol. 56, pp. 539–557, 2020, ISSN: 0278-6125. DOI: 10.1016/j.jmsy.2020.07.008. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0278612520301187>.
- [5] S. Wu, K. L. Tsui, N. Chen, Q. Zhou, Y. Hai, and W. Wang, "Prognostics and health management: A review on data driven approaches," *Mathematical Problems in Engineering*, vol. 2015, p. 793 161, 2015, ISSN: 1024-123X. DOI: 10.1155/2015/793161.
- [6] A. Akrim, C. Gogua, R. Vingerhoeds, and M. Salaun, "Review of prognostics approaches with a particular-focus on the current machine learning algorithms," *Preprint*, 2021.

- [7] E. Zio, "Prognostics and Health Management of Industrial Equipment," in *Diagnostics and Prognostics of Engineering Systems: Methods and Techniques*, S. Kadry, Ed., ISBN13: 9781466620957, IGI Global, Sep. 2012, pp. 333–356. DOI: 10.4018/978-1-4666-2095-7.ch017. [Online]. Available: <https://hal-supelec.archives-ouvertes.fr/hal-00778377>.
- [8] L. X. S. F. Y. J. C. Q. Bao, "Deep learning based fatigue crack diagnosis of aircraft structures," in *7th Asia-Pacific Workshop on Structural Health Monitoring*, 2018. [Online]. Available: <https://www.ndt.net/search/docs.php?id=24093>.
- [9] X. Li, Q. Ding, and J.-Q. Sun, "Remaining useful life estimation in prognostics using deep convolution neural networks," *Reliability Engineering & System Safety*, vol. 172, pp. 1–11, 2018, ISSN: 0951-8320. DOI: 10.1016/j.res.2017.11.021. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0951832017307779>.
- [10] C. Liu, L. Zhang, and C. Wu, "Direct remaining useful life prediction for rolling bearing using temporal convolutional networks," Xiamen, China: IEEE, 2019, pp. 2965–2971, ISBN: 978-1-7281-2486-5. DOI: 10.1109/SSCI44817.2019.9003163.
- [11] M. Yuan, Y. Wu, and L. Lin, "Fault diagnosis and remaining useful life estimation of aero engine using lstm neural network," in *2016 IEEE International Conference on Aircraft Utility Systems (AUS)*, 2016, pp. 135–140. DOI: 10.1109/AUS.2016.7748035.
- [12] Y. Wu, M. Yuan, S. Dong, L. Lin, and Y. Liu, "Remaining useful life estimation of engineered systems using vanilla lstm neural networks," *Neurocomputing*, vol. 275, pp. 167–179, 2018, ISSN: 0925-2312. DOI: 10.1016/j.neucom.2017.05.063. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0925231217309505>.
- [13] K. Park, Y. Choi, W. Choi, H.-Y. Ryu, and H. Kim, "Lstm-based battery remaining useful life prediction with multi-channel charging profiles," *IEEE Access*, vol. PP, pp. 1–1, Jan. 2020. DOI: 10.1109/ACCESS.2020.2968939.
- [14] W. A. Little, "The existence of persistent states in the brain," in *From High-Temperature Superconductivity to Microminiature Refrigeration*, B. Cabrera, H. Gutfreund, and V. Kresin, Eds. Boston, MA: Springer US, 1996, pp. 145–164, ISBN: 978-1-4613-0411-1. DOI: 10.1007/978-1-4613-0411-1_12.
- [15] J. J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities," *Proceedings of the National Academy of Sciences*, vol. 79, no. 8, pp. 2554–2558, 1982, ISSN: 0027-8424. DOI: 10.1073/pnas.79.8.2554. eprint: <https://www.pnas.org/content/79/8/2554.full.pdf>. [Online]. Available: <https://www.pnas.org/content/79/8/2554>.
- [16] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998. DOI: 10.1109/5.726791.
- [17] J. L. Elman, "Finding structure in time," *Cognitive Science*, vol. 14, no. 2, pp. 179–211, 1990, ISSN: 0364-0213. DOI: 10.1016/0364-0213(90)90002-E. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/036402139090002E>.
- [18] M. I. Jordan, "Chapter 25 - serial order: A parallel distributed processing approach," in *Neural-Network Models of Cognition*, ser. Advances in Psychology, J. W. Donahoe and V. Packard Dorsel, Eds., vol. 121, North-Holland, 1997, pp. 471–495. DOI: 10.1016/S0166-4115(97)80111-2. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0166411597801112>.
- [19] J. Yan and P. Wang, "Blade material fatigue assessment using elman neural networks," vol. 2007, Jan. 2007. DOI: 10.1115/IMECE2007-43311.
- [20] S. E. Kramti, J. Ben Ali, L. Saidi, M. Sayadi, and E. Bechhoefer, "Direct wind turbine drivetrain prognosis approach using elman neural network," in *2018 5th International Conference on Control, Decision and Information Technologies (CoDIT)*, 2018, pp. 859–864. DOI: 10.1109/CoDIT.2018.8394926.
- [21] S. Bai, J. Z. Kolter, and V. Koltun, "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling," *CoRR*, vol. abs/1803.01271, 2018. arXiv: 1803.01271. [Online]. Available: <http://arxiv.org/abs/1803.01271>.
- [22] A. Saxena, K. Goebel, D. Simon, and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," in *2008 International Conference on Prognostics and Health Management*, 2008, pp. 1–9. DOI: 10.1109/PHM.2008.4711414.
- [23] P. Paris and F. Erdogan, "A critical analysis of crack propagation laws," *Journal of Basic Engineering*, vol. 85, no. 4, pp. 528–533, Dec. 1963. DOI: 10.1115/1.3656900.
- [24] T. Tinga and R. Loendersloot, "Physical model-based prognostics and health monitoring to enable predictive maintenance," in *Predictive Maintenance in Dynamic Systems: Advanced Methods, Decision Support Tools and Real-World Applications*, E. Lughofer and M. Sayed-Mouchaweh, Eds. Cham: Springer International Publishing, 2019, pp. 313–353, ISBN: 978-3-030-05645-2. DOI: 10.1007/978-3-030-05645-2_11.
- [25] F. Timothy, M. Devinder, and H. Iain, "F-35 joint strike fighter structural prognosis and health management an overview," Jan. 2009. DOI: 10.1007/978-90-481-2746-7_68.
- [26] O. Fink, Q. Wang, M. Svensén, P. Dersin, W.-J. Lee, and M. Ducoffe, "Potential, challenges and future directions for deep learning in prognostics and health management applications," *Engineering Applications of Artificial Intelligence*, vol. 92, p. 103678, 2020, ISSN: 0952-1976. DOI: 10.1016/j.engappai.2020.103678.

[Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0952197620301184>.

- [27] Y. Bengio, P. Simard, and P. Frasconi, "Learning long-term dependencies with gradient descent is difficult," *eng, IEEE transactions on neural networks*, vol. 5, pp. 157–66, 2 1994. DOI: 10.1109/72.279181.
- [28] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, ISSN: 0899-7667. DOI: 10.1162/neco.1997.9.8.1735. eprint: <https://direct.mit.edu/neco/article-pdf/9/8/1735/813796/neco.1997.9.8.1735.pdf>.
- [29] Y. Wu, M. Schuster, Z. Chen, *et al.*, "Google's neural machine translation system: Bridging the gap between human and machine translation," Sep. 2016. arXiv: 1609.08144 [cs.CL].
- [30] R. Rana, "Gated recurrent unit (gru) for emotion classification from noisy speech," Dec. 2016. arXiv: 1612.07778 [cs.HC].
- [31] C.-L. Liu, W.-H. Hsaio, and Y.-C. Tu, "Time series classification with multivariate convolutional neural network," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 6, pp. 4788–4797, 2019. DOI: 10.1109/TIE.2018.2864702.
- [32] W. Xiao, "A probabilistic machine learning approach to detect industrial plant faults," Mar. 2016. arXiv: 1603.05770 [stat.ML].