Literature Review

Paper	Year	Comments	Model	Dataset	Results
[1]	2021	Transformer architecture applied to RUL prediction. Dual Aspect Self-Attention based on Transformer (DAST). DAST consists of two encoders working in parallel to simultaneously extract features of different sensors and time steps (i.e., sensor encoder and time step encoder). *Among the 21 sensors in the C-MAPSS dataset, sensors 1, 5, 6, 10, 16, 18 and 19 always have constant values during the run-to-failure experiments, meaning that data from these sensors cannot characterize the degradation process of the engine. Then, the authors removed these sensor data series and use the data of the remaining 14 sensors for RUL prediction.*	Model based on a Transformer architecture, using encoder and decoder blocks.	C-MAPSS (small) PHM 2008	*RMSE = 11.43 (FD001)* *S = 203.15 (FD001)* *RMSE = 11.32 (FD003)* *S = 154.92 (FD003)* *S = 845 (PHM 2008)*
[2]	2021	Novel feature-attention mechanism applied to the input data to give more attention weights to more important features dynamically in the training process.	Combination of CNN and BGRU (a simpler version of BiLSTM)	NASA C-MAPSS (small)	*RMSE = 12.42 (FD001)*
[3]	2021	They used a multi-head mechanism in which each sensor output is processed on a fully independent head in a multi-head network- Each head is responsible for extracting meaningful features from the sensor data. Employed an attention mechanism on top of the multi-head implementation of different network architectures. They also tested a stand-alone attention model (SAN)	Tested different model architectures. Best results with a fully connected neural network (multi-head FNN).	NASA C-MAPSS (small)	*RMSE = 8.68 (FD001)* *S = 28.43 (FD001)* *RMSE = 9.69 (FD003)* *S = 77.01 (FD003)*
[4]	2019	Investigates the effect of unsupervised pre-training in RUL predictions utilizing a semi-supervised setup. They used a Genetic Algorithm (GA) approach to tune the diverse amount of hyper-parameters in the training procedure.	Restricted Boltzmann Machines as unsupervised algorithm. GA	NASA C-MAPSS (small)	*RMSE = 12.56 (FD001)*
[5]	2018	They used auto encoder as a feature extractor (as kind of a PCA replacement) to compress condition monitoring data. BiLSTM was used to capture features' bidirectional long-range dependencies. They provide a result comparison with other work.	Hybrid autoencoder-BiLSTM	NASA C-MAPSS (small)	*RMSE = 13.63* *Se-3 = 0.261*
[url]	2017	"Deep Learning Basics for Predictive Maintenance"[1]	Basic LSTM	NASA C-MAPSS (small)	*Accuracy: 0.978* *F1-score: 0.96*

[1] https://github.com/Azure/lstms_for_predictive_maintenance

Datasets

Paper	Year	Title	Dataset
[6]	2008	"Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation"	NASA C-MAPSS 1
[7]	2021	"Aircraft Engine Run-to-Failure Dataset under Real Flight Conditions for Prognostics and Diagnostics"	NASA C-MAPSS 2

References:

[1] Z. Zhang, W. Song, and Q. Li, "Dual Aspect Self-Attention based on Transformer for Remaining Useful Life Prediction." 2021.

[2] H. Liu, Z. Liu, W. Jia, and X. Lin, "Remaining Useful Life Prediction Using a Novel Feature-Attention-Based End-to-End Approach," *IEEE Trans. Ind. Informatics*, vol. 17, no. 2, pp. 1197–1207, 2021, doi: 10.1109/TII.2020.2983760.

[3] A. Ayodeji, W. Wang, J. Su, J. Yuan, and X. Liu, "An empirical evaluation of attention-based multi-head models for improved turbofan engine remaining useful life prediction." 2021.

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[5] Y. Song, G. Shi, L. Chen, X. Huang, and T. Xia, "Remaining Useful Life Prediction of Turbofan Engine Using Hybrid Model Based on Autoencoder and Bidirectional Long Short-Term Memory," *J. Shanghai Jiaotong Univ.*, vol. 23, no. 1, pp. 85–94, 2018, doi: 10.1007/s12204-018-2027-5.

[6] 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.

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