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Development of a hybrid model for large-scale plant RUL prediction based on data and physical models

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Large plants in the process industry are monitored and maintained at regular intervals, and repeatedly maintenance is either too early or too late. This causes unnecessary costs due to technicians, spare parts procurement as well as delivery issues and to high downtime costs due to unexpected shutdowns. In this context, the Remaining Useful Life (RUL) plays a major role, as it is an indicator of how long a machine or component can run without breakdown, repair or replacement. By predicting RUL using predictive maintenance, maintenance can be better planned, operational efficiency optimized, and unplanned downtime avoided. Optimizing the prediction accuracy should therefore always be in the foreground and is therefore the topic of this abstract.

Lei et al. [1], in a review on data acquisition to RUL prediction, emphasize that predicting the operational behavior of machinery and equipment is one of the major challenges in condition-based maintenance. According to the authors, such a prediction program consists of the following four technical processes: 1. data acquisition; 2. construction of the Health Indicator (HI) of machinery and equipment; 3. subdivision into different stages of the Health Stage (HS); and 4. RUL prediction. The relevance of RUL prediction is also supported by Jimenez-Cortadi et al. [2]. Analogous to Lei et al. [1], Jimenez-Cortadi et al. [2] list different approaches and techniques, but the main contribution is finding a solution to the prediction problem in real machine processes. The results show that preventive maintenance can be transformed into predictive maintenance. In this context, the goal of predictive maintenance is to extend the life of machines and equipment. Jimenez-Cortadi et al. [2] used a CNC milling machine as a real example and used machine-learning techniques to predict the RUL. However, the authors emphasize that the complexity of the model made it difficult to implement in the production machine. Another approach would be a hybrid modeling; this is also emphasized by the authors in Arias Chao et. al [3]. To combine the advantages of both models physical and data-driven, which on the one hand draws on the information of physical models and on the other hand uses deep learning algorithms. The results from the experiment [3] show that the hybrid model outperforms purely data-driven models in terms of predictive power - the prediction horizon could be extended by about 127%.

The hybrid model is enhanced by the physical model to evaluate and prioritize the wear of the plant condition under the given operating conditions and influences. The hybrid model is applied to a real process gas industry. The basic questions are: What was defective and what was repaired? Which components fail most frequently? Which components have to be replaced or repaired at high cost? The prerequisite for this is service and repair data. The physical model describes a functional relationship between operational stress and service life. The remaining service life is finally predicted by determining whether and when the predicted parameters meet the failure criteria from the failure description. The task is to elaborate the technically essential aspects from the point of view of the modeling of mechanical components under the consideration of dynamic quantities and simulation of a large industrial plant. The goal is to correlate the anomalies found by the hybrid model as well as possible with future faults. Such a trained model can be of great importance for industrial real-time applications; after all, the anomalies identified by the model can enable predictive maintenance for complex large-scale plants.

REFERENCES

[1] Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: a systematic review from data acquisition to RUL prediction. Mechanical systems and signal processing, 104, 799-834. doi: /10.1016/j.ymssp.2017.11.016.

[2] Jimenez-Cortadi, A.; Irigoien, I.; Boto, F.; Sierra, B.; Rodriguez, G. (2019). Predictive maintenance on the machining process and machine tool. Applied Sciences, Vol. 10, 224. doi:10.3390/app10010224.

[3] Arias Chao, M., Kulkarni, C., Goebel, K., & Fink, O. (2020). Fusing physics-based and deep learning models for prognostics. Electrical Engineering and Systems Science. Systems and Control. 1-18. arXiv preprint arXiv:2003.00732 [eess.SY].