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Explanatory predictive inference for the maintenance process using a deep learning approach

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Abstract

Monitoring and management of a complex production system is an engineering and business challenge. The concept of Industry 4.0 requires process automation up to a “zero touch” level, where machines autonomously realize production, monitoring and management actions. This triggers development of sensing technology capable of providing useful information about the system state and processes governing its operation. The knowledge retrieved from raw data can be further enhanced with dedicated algorithms, including deterministic, statistical and artificial intelligence (AI)/machine learning (ML) approaches. The content of data and the efficiency of algorithms enable the exploration of more and more complex signals and realization of not only a *post-factum* analysis, but also predictive and/or prescriptive inference. All these paves the way for organization of self-aware and automated technical systems, robust in terms of production and self-maintenance.

The growth of autonomy in technical systems has accelerated significantly in last decade due to advancement in methods of measurement data exploration that mimic human reasoning. Deep learning is a representative strategy for information retrieval from complex data, as it has proven to be very useful in many applications. On the other hand, a drawback of modern AI/ML models is their limited explainability and interpretability.

Following degradation processes in complex manufacturing systems enables planning service actions, improves technical performance and business profitability, and estimates remaining useful life. To date, much of the work in this area is still done using expert knowledge. The bottleneck related to a context-aware operation requires answering at least two questions: a) how new, contextual knowledge on degradation process can be extracted from experimental data, and b) how to inject expert knowledge into procedures designed to manage predictive manufacturing systems.

The goal of the paper is twofold. Firstly, we review the use of AI/ML approaches for prediction of complex degradation processes throughout the whole lifecycle of an engineering system. Secondly, we contribute to the explainable and interpretable prediction of that processes using deep learning and demonstrate robustness of our approach using the exemplary real-world cases and measured data. Namely, we answer the first question formulated above. The work is an extension of the results published in [1].

The methodology is based on data-driven deep learning modelling for a generalised representation of a complex time-varying process expressed in terms of an equation, taking into account trend, time-varying autoregressive components and non-Gaussian disturbances (noise is generically non-Gaussian in nature [2]).

Model complexity is followed adaptively and efficiently throughout the whole lifecycle of the machine, and model parameters are estimated. Obtained inference on the changes in the model structure and parametric profile can be directly associated with the physical properties of the monitored system. Reliable structural-parametric knowledge is an enabler for contextual operation in predictive maintenance system, but can be also extended to applications in other systems, i.e. physical, chemical, biological, financial, etc.

Literature

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