Abstract

This thesis aims to address the challenges of integrating information extraction, degradation modeling, and decision-making in asset health management for complex industrial systems, especially in process industries. For this purpose, an Industrial Monitoring-Oriented Prognostics and Health Management (IM-PHM) framework is proposed to provide system-level health assessment, prediction, and risk-informed decision support.

Within the framework, data-driven approaches are employed on multivariate monitoring data to enhance the system-level health state representation. Specifically, it identifies degradation-related features from high-dimensional monitoring data and transforms them into an interpretable health index (HI) to support degradation behavior characterization and modeling. Building upon them, the functions of anomaly detection, diagnosis, and remaining useful life (RUL) estimation can be supported by considering degradation behavior deviations and degradation state propagation. Stochastic process modeling and Monte Carlo (MC) simulation techniques are employed to support the prognostic function with the consideration of uncertainty. Finally, the Decision Support module is developed to transform prognostic results into risk- and uncertainty-informed decision support information. By combining the evaluation of the current degradation state (through failure risks and behavior deviations) and risk evolutions of systems, recommended actions can be provided regarding action types and timing, and thus support proactive maintenance decision-making.

The effectiveness and applicability of the IM-PHM are cross-validated through multiple case studies, including simulation-based, experimental, and real industrial scenarios. The results demonstrate the IM-PHM's capability to bridge health information extraction, degradation modeling, and decision support through an integrated architecture. In particular, the proposed framework shows advantages in robustness, applicability, and interpretability compared to pure data-driven approaches.

The limitation of the IM-PHM is also highlighted based on results from case studies. The implementation of IM-PHM relies on the availability of sufficient representative failure data, especially run-to-failure data. This limits the use of IM-PHM in real-world industrial scenarios. To address this challenge, the thesis explores the potential of employing surrogate models (such as the digital twin) to enhance the representation of the system and health behavior, and support health assessment under incomplete data conditions.

Overall, the proposed IM-PHM provides an integrated framework linking the monitoring, modeling, and decision support, thereby contributing to the PHM applications in complex industrial systems.