Advances in Reliability, Safety and Security

ESREL 2024
Collection of Extended Abstracts

Stochastic Degradation Modelling Based Monitoring And Predictive Maintenance Framework In Process Industries

Huxiao Shi, Micaela Demichela

Politecnico di Torino, Torino, Italy

Keywords: Stochastic Degradation Process, Monitoring, Predictive Maintenance

Process industries are commonly regarded as being difficult to conduct asset management in because of their complex and non-standard nature, characterized by a variety of unique challenges. These challenges include the continuous production processes, the diversity of specialized equipment and machinery, and the criticality of maintaining quality and safety of the production systems (Aghabegloo et al., 2024). To ensure seamless production continuity, process industries place a high demand on the efficient and safe utilization of a diverse range of expensive and specialized equipment. (Duffuaa et al., 2024). Achieving this goal requires not only an understanding of complex industrial systems but also an awareness of the challenges posed by the dynamic nature of these environments. Consequently, the implementation of effective and appropriate maintenance strategies becomes crucial (Chin et al., 2020). Traditional passive maintenance approaches, such as reactive and preventive maintenance, often fall short in providing dynamic monitoring for systems in process industries due to their limited scope and lack of real-time responsiveness (Demichela et al., 2018; Gutschi et al., 2019; Zio, 2022). This highlights the valuable need to explore more reliable monitoring and maintenance strategies that can adapt to the ever-changing industrial environment.

This research addresses three commonly encountered challenges in process industries:

- the dynamic monitoring strategies which support the proactive maintenance activities;
- the processing of large volumes of data from multiple sensors;
- the variability inherent in the monitoring process;
- the execution of maintenance decisions based on real-time system statuses.

In response to above-mentioned challenges, a stochastic degradation modeling-based monitoring and predictive maintenance framework is proposed as a suitable solution. The framework begins with the application of advanced feature extraction techniques, which are used to extract key features related to system degradation from data monitored by multiple sensors. This data is then used to formulate a health index, a comprehensive measure of the system's current state. One of the common technics applied here is the Principal Component Analysis (PCA), which helps to extract key features from the database which involves the parameters data collected during the system-running period (Yu et al., 2020). PCA is widely used to reduce the target system's complexity and accomplish dimensionality reduction (Chen et al., 2021). In this study, the trending of the PC values (e.g., PC1 in the Figure 1), is appropriate to represent the degradation evolution of the system monitored by multiple sensors.

Next, stochastic degradation modeling techniques are applied to address two types of variability in the health index: temporal variability, which occurs over time (the volatility), and unit-to-unit variability, which occurs between different pieces of equipment (expanded range at each time cycle in Figure 1). These techniques allow for a more nuanced understanding of the health index, enabling more accurate predictions of system performance over the long term (Zhang et al., 2018). Furtherly, Wiener Processes are applied because of its capability of modelling non-monotonous degradation paths, which is more applicable in the real life, within the situations of minor repair, self-healing, or reduced intensity of use, etc.

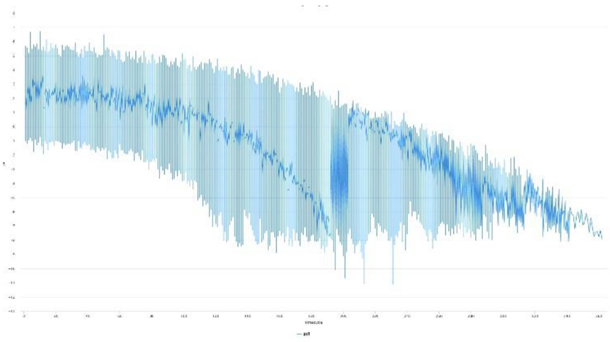

Fig. 1. The Principal Component values from multiple sensors.

The monitoring strategies based on reactive and preventive maintenance always correspond longer or unnecessary checking time consumed, higher costs spent and loss of the production capacity. In this case, Predictive Maintenance (PdM), and its furtherly developed concept ‘Prognostic and Health Management (PHM)’, is considered as a reliable solution in process industries. Through estimating the Residual Performance Lifetime (RPL), or sometimes Remaining Useful Life (RUL) of the component and system, a sequence of maintenance actions/plans can be accordingly made to mitigate the impact of the predicted failure and avoid unexpected system shutdown. In this research, the results from the stochastic degradation modeling support the prediction of system performance, enabling the implementation of agile maintenance strategies that can respond quickly to changing conditions. Given a newly deployed system in process industries, the degradation process of such a system can be simulated according to the estimated model parameters from historical data. Then, maintenance can be specialized according to different running states. For example, for systems in well-running states (the flat stage shown in Figure 1), there is no need to conduct intensive inspections. For systems that have dramatically increased degradation performance (the later stage shown in Figure 1), it is necessary to take more maintenance activities considering the situation of the systems, and even proactively shut down the system or replace components that are close to damage. By conducting the stochastic degradation modeling-based monitoring and making decisions based on predictive maintenance, it is more likely to proactively maintain products and systems, ensuring efficient and safe continuous production in the process industry.

Acknowledgements

This research is supported by China Scholarship Council.

References

Aghabegloo, M., Rezaie, K., Torabi, S.A., Yazdani, M. 2024. Integrating business impact analysis and risk assessment for physical asset criticality analysis: A framework for sustainable operations in process industries. Expert Systems with Applications 241, 122737.

Chen, S., Xu, K., Yao, X., Ge, J., Li, L., Zhu, S., Li, Z. 2021. Information fusion and multi-classifier system for miner fatigue recognition in plateau environments based on electrocardiography and electromyography signals. Computer Methods and Programs in Biomedicine 211, 106451.

Chin, H., Varbanov, S., Klemeš, J., Benjamin, D., Tan, R. 2020. Asset maintenance optimisation approaches in the chemical and process industries – A review. Chemical Engineering Research and Design 164, 162–194.

Demichela, M., Baldissone, G., Darabnia, B. 2018. Using Field Data for Energy Efficiency Based on Maintenance and Operational Optimisation. A Step towards PHM in Process Plants. Processes 6(3), 1-15.

Duffuaa, S., Idris, M., Kolus, A., Al-Turki, U. 2024. A mathematical model for optimal turnaround maintenance planning and scheduling for a network of plants in process industry supply chain. Computers & Chemical Engineering 180, 108477.

Gutschi, C., Furian, N., Suschnigg, J., Neubacher, D., Voessner, S. 2019. Log-based predictive maintenance in discrete parts manufacturing. Procedia CIRP, 12th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 18-20 July 2018, Gulf of Naples, Italy 79, 528–533.

Yu, Y., Peng, M., Wang, H., Ma, Z., Li, W. 2020. Improved PCA model for multiple fault detection, isolation and reconstruction of sensors in nuclear power plant. Annals of Nuclear Energy 148, 107662.

Zhang, Z., Si, X., Hu, C., Lei, Y. 2018. Degradation data analysis and remaining useful life estimation: A review on Wiener-process-based methods. European Journal of Operational Research 271, 775–796.

Zio, E. 2022. Prognostics and Health Management (PHM): Where are we and where do we (need to) go in theory and practice. Reliability Engineering & System Safety 218, 108119.