

WROCLAW UNIVERSITY OF SCIENCE AND TECHNOLOGY

Abstract

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Modelling and analysis of long-term historical data of time-varying complex systems in the presence of impulsive noise for condition monitoring

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The field of long-term data analytics has gained considerable interest in recent years due to its crucial role in extracting useful insights, knowledge, and wisdom from long term datasets. In industrial contexts, the development of sensor technology and improvements in information and communication technologies have made it possible to collect large amounts of data, ranging from minutes to years. These carefully selected datasets are extremely helpful resources for informing and improving decision-making processes.

Using long-term data for machine health assessments and prognostics of machine is an important application in the field of condition-based maintenance (CBM). Early identification of system degradation and precise estimation of remaining useful life (RUL) are crucial for preserving the reliability and safety of industrial systems, while also reducing the risks associated with unexpected failures and maintenance expenses.

Complexities in long-term health index data, including non-stationary behavior, non-linearity, and non-Gaussian noise, pose severe challenges for machine health assessments and prognostic applications. The presence of non-stationary behavior in time series can lead to biased parameter estimates, erroneous correlations, and inaccurate predictions due to dynamic changes. This means that such data requires an advanced analysis approach and a complex model. On the other hand, non-Gaussian noise, especially heavy-tailed noise, breaks the Gaussian assumptions in time series models. This can cause estimates to be biased and make them more sensitive to outliers, so robust modeling techniques are needed for accurate analysis and prediction.

The thesis proposes a three-stage model to generate long-term health index degradation data, addressing non-stationary behavior and its non-Gaussian character. It develops a robust framework using techniques capable of handling non-Gaussian noise to analyze and characterize historical degradation data. Additionally, it introduces robust offline and online segmentation methods based on deterministic trends in the health index, followed by the development of a maximum correntropy extended Kalman filter (MCEKF) for probabilistic estimation of RUL, considering the presence of non-Gaussian noise. Analytical studies on synthetic and real datasets with varying levels of non-Gaussian noise demonstrate the effectiveness of these approaches.

Keywords : machine health assessments, prognostics, segmentation, health index, remaining useful life, extended Kalman filter, robust methods, non-Gaussian noise, non-stationary.


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