ABSTRACT

Condition based maintenance (CBM) optimizes maintenance by performing it only when necessary, thereby reducing costs and minimizing unplanned downtime. Its effectiveness hinges on solving two key challenges, viz., fault diagnosis and fault prognosis. In fault diagnosis, objective is to identify existing faults, while fault prognosis utilizes historical data to predict remaining useful life (RUL) of the system. Ready availability of large amounts of data has contributed to the widespread adoption and popularity of data-driven methods. Unlike model-based methods, data-driven methods do not require a mathematical formulation of the system thereby making it well-suited for complex systems whose underlying physics is not fully understood or known. Applications vary in their data availability, with some constrained by limited datasets, while others benefit from abundant data resources. This research introduces two distinct approaches for both data-scarce and data-abundant use cases. For fault diagnosis in data scarce applications, feature based methods are commonly used. However, selection of an appropriate subset of features poses a challenge. The present research proposes sparse principal component analysis (SPCA) based feature subset selection and fault classification to address this issue. The validity of proposed method is tested on various faults associated with rotating machinery, including bearing faults, gearbox faults, unbalance, misalignment, and combination of multiple faults occurring simultaneously. For applications where large amounts of data are available, a deep learning based approach to learn data-driven features is proposed. This method eliminates the need for manually crafting features. The use of data-driven features also aids in interpreting the working of deep neural networks. Efficacy of the approach is evaluated on the datasets previously utilized for reduced feature subset-based fault diagnosis. For fault prognosis, where run-to-failure data are available, a deep learning-based attention network is proposed. The attention network only uses raw sensor measurements and achieves competitive results in accurately predicting RUL. The proposed attention-based model is used to predict RUL of CMAPSS dataset made publicly available by NASA. For applications lacking run-to-failure data, a self-supervised learning-based approach is proposed and validated using an induction motor dataset.

Keywords: Data-driven models, fault diagnosis, fault prognosis, sparse principal component analysis, deep learning based attention network, self-supervised learning.