Mechanical Systems and Signal Processing 107 (2018) 241–265

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Review

A review on the application of deep learning in system health management

Samir Khan *, Takehisa Yairi

Department of Aeronautics and Astronautics, School of Engineering, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan

ARTICLE INFO

Article history:
Received 31 July 2017
Received in revised form 26 October 2017
Accepted 15 November 2017

Keywords:
Artificial intelligence
Deep learning
System health management
Real-time processing
Fault analysis
Maintenance

ABSTRACT

Given the advancements in modern technological capabilities, having an integrated health management and diagnostic strategy becomes an important part of a system's operational life-cycle. This is because it can be used to detect anomalies, analyse failures and predict the future state based on up-to-date information. By utilising condition data and on-site feedback, data models can be trained using machine learning and statistical concepts. Once trained, the logic for data processing can be embedded on on-board controllers whilst enabling real-time health assessment and analysis. However, this integration inevitably faces several difficulties and challenges for the community; indicating the need for novel approaches to address this vexing issue. Deep learning has gained increasing attention due to its potential advantages with data classification and feature extraction problems. It is an evolving research area with diverse application domains and hence its use for system health management applications must been researched if it can be used to increase overall system resilience or potential cost benefits for maintenance, repair, and overhaul activities. This article presents a systematic review of artificial intelligence based system health management with an emphasis on recent trends of deep learning within the field. Various architectures and related theories are discussed to clarify its potential. Based on the reviewed work, deep learning demonstrates plausible benefits for fault diagnosis and prognostics. However, there are a number of limitations that hinder its widespread adoption and require further development. Attention is paid to overcoming these challenges, with future opportunities being enumerated.

Contents

* Corresponding author.
E-mail address: khan@ailab.t.u-tokyo.ac.jp (S. Khan).

https://doi.org/10.1016/j.ymssp.2017.11.024
0888-3270/

1. Introduction

Health management is described as the process of diagnosing and preventing system failures, whilst predicting the reliability and remaining useful life (RUL) of its components [1]. The past few decades have experienced a proliferation of system health management research to help with all kinds of failures occurring at component level and up to the systems level [2] and Lee et al. [3]. However, even though these concepts have been studied extensively [4,5], most methods often require triggering mechanisms that are intelligent enough to collect enough data about the failing component, the nature of the fault, and its severity on the overall system performance. Consequently, efforts are being concentrated on the integration of anomaly, diagnostic and prognostic technologies across systems and related platforms. Such capability to predict and isolate impending failures can help maintain system performance in a cost-effective manner; whilst identifying ongoing issues to mitigate potential risks. Another consequence is the increase in the amount of data collection as an essential component in modern engineering systems. Compared to the typical top-down approaches[1], data-driven methods offer a new paradigm of bottom-up solutions for health management of system failures and prediction. This has made data analytics within diagnostic technologies a high priority research topic.

As the aerospace industry continuously strives to improve its performance[2]; operational pressures expect to reduce the time required for any diagnostic investigations. Here, there is value of having many data collection sources that can be used to provide rich information, e.g. operating variables, environmental conditions, etc., if a disruption occurs during operation. However, most often data sources are disparate. With the ever-increasing size of big data produced by modern systems, coupled with the complexities of contextual components for correlating information; can create barriers that were not anticipated by design engineers during the design phase of the system life-cycle. This eventually results in higher levels of uncertainty during the diagnosis process [6]. In this context, novel approaches are required which can configure applications, as well as mechanisms for making better decisions at the system-level. In the nominal environment, such problems warrant advanced capabilities to monitor in-service operations, record and share expert knowledge, and address critical aspects of on-board software. To address this issue, diagnostic systems based on conventional techniques are being replaced by AI-based ones which can increase the efficiency of the monitoring technology. AI-based approaches can be categorised into (1) knowledge-driven (knowledge-based) approaches including expert system and qualitative-reasoning, and (2) data-driven approaches including statistical process control, machine learning approach and neural networks[3]. Fig. 1 illustrates some of the AI approaches that have been used for system health monitoring applications over the years. One notable development is the application of deep learning. These architectures aim to model high level representations of data and classify (predict) patterns by stacking multiple layers of information processing modules in hierarchical structures. There are advantages of using them, but since it is an evolving research area, its applicability for diagnostic applications must been researched with an aim to increase overall system resilience or potential cost benefits for maintenance, repair, and overhaul activities. The computing science communities have accelerated their research efforts on deep learning in the past few years. However, its knowledge transfer within engineering communities has been scarce [7].

This article provides an overview of AI techniques and focuses its efforts on the application of deep learning methods that have been used for system health management. Deep learning has been applied for fault diagnosis and prediction in the past few years. To date, this expansion has extended from mechanical equipment monitoring to electrical systems, power installations and aerospace disciplines. This includes solutions on electromechanical equipment fault diagnosis, classifying degradation and pattern recognition, and predicting of RUL of components. The presented state-of-the-art is a synthesis of articles that have been reviewed during an ongoing research project on the application of deep learning. The authors have adopted a pragmatic approach and concentrated their efforts on the system health management discipline; rather than providing a comprehensive survey on deep learning. Fortunately, there are other much detailed literature publications that have carried out rigorous reviews on deep learning with the commuting science community (e.g. see [8], LeCun et al. [9], Schmidhuber

[1] These are traditional physics based models whose realisation is often obfuscated by noisy environments and system complexities.
[2] By delivering more reliable assets, with a higher availability.
[3] Some approaches, such as probabilistic reasoning (e.g., Bayesian networks), may belong to both categories, because reasoning and learning cannot be distinguished. Yet, many of them are dependent on obtaining accurate (and sometimes complete) data on system models.