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Editorial

Special Issue "Advances in Machine Learning and Deep Learning Based Machine Fault Diagnosis and Prognosis"

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Fault diagnosis and failure prognosis aim to reduce downtime of the systems and to optimise their performance by replacing preventive and corrective maintenance strategies with predictive or conditional ones. The knowledge of the current health state of the systems, provided by diagnostic algorithms, and its time evolution provided by prognosis algorithms, are necessary for the establishment of predictive and conditional maintenance, hence the interest given by the scientific community for the development of monitoring algorithms more and more efficient.

In the literature, there are four main families of approaches for fault diagnosis and failure prognosis: methods based on physical models, data-driven methods, expert methods, and hybrid ones. The fast development of data acquisition and storage tools, processing algorithms, associated with the evolution of instrumentation and process automation techniques that generate large data flows, has fostered the development of data-driven approaches. The papers proposed in this book present new methods of fault diagnosis and failure prognosis which provide solutions to scientific issues such as structured and unstructured uncertainties, the presence of multiple faults, the lack of prior knowledge on the conditions of use, feature extraction and selection, model optimisation and online implementation. The variety of application supports given in this book, ranging from microelectronics devices to large-scale systems, highlights the implementation constraints specific to each field of application and present suitable solutions.

In [1], a deep learning method associating wavelet transform for feature extraction under different frequencies and scales, and a convolutional neural network (CNN) for feature selection and fault classification is presented. The association of the two filtering stages (wavelet transform and convolutional functions) allows the processing of the non-linear mechanism of the processes and the highly correlation among variables. This approach is successfully validated on a refrigerant-producing process. Wavelet transform is also used in [2] as a first data processing step, associated with an improved particle swarm optimization (PSO) and a back propagation (BP) neural network with linearly increasing inertia weight. The idea is to combine the PBNN with the improved PSO algorithm for parameter optimisation, thus giving a better precision of the classification. This method is used for fault diagnosis of a three-phase squirrel cage induction motor, driven by an AC power supply. The considered faults are bearing damage, stator winding, inter-turn short circuit, and broken rotor bar. Induction motor is also considered in [3] which focus their study on the impact of the use of attribute selection methods such as ReliefF, correlation-based feature selection (CFS), and correlation and fitness value-based feature selection (CFFS), on the performance of neural classifiers such as probabilistic neural network (PNN), radial basis function neural network (RBNN), and back propagation neural network (BPNN). This study analyses the current signal of the induction motor for fault diagnosis. The results of the study show that ReliefF, CFS, and CFFS have better efficiency than the unused feature selection approach.

The issue of fault diagnosis under variable operating conditions is dealt in [4] where the data processing is done by a combination of a statistical tool (Empirical Mode Decomposition) and an energetic one based on information entropy theory. Then fault classification is made using a Gaussian mixture model (GMM), which has no need for failure data when building a degradation identification model. To evaluate the effectiveness of this algorithm in presence of different operating conditions, a hydraulic pump is used as a case study, where three kinds of loads are simulated by means of the throttle valve. An axial piston pump is used in [5] as a case study for the validation of state recognition and failure prediction algorithm based on multi-class Gaussian process classification for fault detection and identification, and Gaussian process regression (GPR) for failure prognosis. The vibration signal is first processed variational mode decomposition (VMD) to extract intrinsic mode function (IMF) components, then, multi-scale permutation entropy (MPE) is used for feature selection feature associated with the ReliefF algorithme to reduce the dimension of feature space.

To deal with the issue of the online implementation of deep learning algorithms related to the problems of high-quality data accumulation, high timeliness of the data analysis, and difficulty in embedding deep-learning algorithms directly in real-time systems, [6] proposes a new progressive deep-learning framework, called (TensorFlow), with a high degree of flexibility, portability, and rich library of algorithms.

Other innovative fault diagnosis and failure prognosis techniques are presented in this book [7–9], such as analytical redundancy [10], data-driven analytical redundancy [11], and cyclostationary analysis [12], with applications in microelectronics, rotating machines and polymer electrolyte fuel cell.

The papers presented above show the high scientific quality of the work presented in this book, which gives an overview of the most recent methods used for diagnosis and prognosis, while providing solutions to known problems in this field. The experimental results obtained on various systems show the great potential and relevance of the diagnostic and prognostic tools presented in this book.

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