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Editorial

Fault Diagnosis and Prognosis of Mechatronic Systems Using Artificial Intelligence and Estimation Theory

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1. Introduction

Industrial processes, manufacturing systems, transportation systems, and related mechatronic systems are becoming more and more complex and may fail, affecting the reliability, safety, and quality of industrial production. Therefore, monitoring, diagnosis, and prognosis of the condition of machines and devices are one of the critical areas that must be taken into account during all changes related to the implementation of Industry 4.0, the fourth industrial revolution in human history.

Diagnostic techniques for the condition monitoring of different mechatronic systems have experienced extraordinary growth and development during the last 30 years. Recently, the data-driven approach and artificial intelligence methods have been widely applied in diagnosis. Among other electrical and electronic systems, it also concerns electrical machines and drives, as can be observed in the increased number of articles on this topic published in scientific journals and related conference proceedings. There are two main reasons for this development:

1. Monitoring and preventive control of machinery condition is becoming more and more important in industry and transport due to the drive to increase the efficiency and safety of processes, which requires the use of advanced noninvasive diagnostic techniques that can be implemented online;
2. The rapid development of applications for "more electric" systems, not only in areas such as industrial automation and robotics but also in transport and wind energy applications, which is due to, inter alia, the global need to minimize carbon dioxide emissions. Systems that consume hydraulic, pneumatic, and mechanical energy, previously used in conventional automation systems or transport devices, are now being replaced by electrical systems that reduce fuel consumption, operating costs, and noise and air pollution. That is why the diagnosis and prognosis of electrical dives is now so important in all applications.

Diagnosis consists of identifying faults that will lead to failure and estimating their severity, while prognosis relies on continuous monitoring of the variables and parameters of the system and uses this information to forecast the evolution of a fault and to predict when the machine will no longer operate as designed or desired. It is known as a prediction of remaining useful life-time (RUL), and it may diminish unnecessary expensive maintenance and unexpected failures and thus decrease the system operating costs.

In particular, obtaining objective diagnostic decisions through the use of methods and techniques of artificial intelligence and estimation theory in fault detectors and damage classifiers, as well as in failure prognostic models for mechatronic systems can facilitate the planning of maintenance and repair inspections of production lines and other devices in industrial plants. It allows diagnosing and classifying damages of individual elements of these systems in real time at the initial stage of their development, as well as to predict failure development and RUL of the failing component/system. Such actions increase the reliability and efficiency of various industrial processes.

Moreover, Industry 4.0 standards (the fourth industrial revolution in human history) assume, among others, an increase in efficiency and a reduction in operating costs associated with the intensive automation of industrial processes. It is obvious that such a massive paradigm shift in the industrial sector will mean that various fields of technology must also change and adapt to be used in a new industry concept.

Therefore, the purpose of this Special Issue was to present current trends, advanced methods, and innovative technical solutions (in the field of hardware and software) used in the diagnosis and prognosis of mechatronic systems and their components (electronic, electrical, and mechanical), with particular regard to artificial intelligence methods: shallow and deep neural networks, as well as estimation theory.

Some of these issues have been addressed in the articles collected here.

2. The Present Issue

This Special Issue consists of fourteen papers covering important progress in the relevant areas. The authors proposed the application of different model-based and signal-based methods supported by machine learning and classical neural networks, as well as deep learning methods, for the diagnosis of mechanical and electrical faults in mechanical transmission of drives, in electrical machine windings, and in static converters (10 articles). The prognosis of electrical devices and industrial processes was also addressed in two articles. The other two papers are related with more general issues related to the digital measurement systems and standards of Industry 4.0 (I4.0). Among these papers, six are focused on diagnosis of mechanical faults of different drive systems using measurements of currents, vibrations, and stray flux. On the other hand, the AC motor winding faults were analyzed using stray flux and stator current signals. The RUL was analyzed for lithium-ion batteries and turbofan engines. The summary of these works is given in Table 1, and more details of these papers are given below.

Table 1. Summary of the work reported in the fourteen papers.

Paper Ref. No.	Field of Application	Type of Data or Information Used	Data Processing Methods or Work Delivered
1	Mechanical transmission fault diagnosis	Current	Parameter estimation via Recursive Least Square algorithm
2	Rotor unbalance fault diagnosis	Vibration	Fast Fourier Transform, Bispectrum Analysis, Full-Spectrum Analysis, Orbit Shape Analysis
3	Rolling bearing fault diagnosis	Vibration	Statistical time-domain features and Gaussian Support Vector Machine
4	Rolling bearing fault diagnosis	Stray flux	Statistical time-domain features and Katz's fractal dimension with Linear Discriminant Analysis supported by Feedforward Neural Network
5	Rolling bearing fault diagnosis	Vibration	Fast Fourier Transform and Multi-Layer Perceptron
6	Rolling bearing fault diagnosis	Vibration	Raw signal and 1D—Convolutional Neural Networks

7	Inter-turn short-circuit fault diagnosis	Stray flux	Fast Fourier Transform and statistical method (Pearson correlation coefficient, belief function)
8	Inter-turn short-circuit fault diagnosis	Current	Fast Fourier Transform of symmetrical current components and K-nearest neighbors
9	Stator and rotor winding fault diagnosis	Stray flux	Fast Fourier Transform and cascaded neural networks: Multi-Layer Perceptron, Self-Organizing Kohonen Map, Recursive Hopfield Network
10	Two-level three-phase PWM rectifier fault diagnosis	Current	Modified Ensemble Empirical Mode Decomposition algorithm and Deep Belief Network
11	Lithium-ion battery monitoring	LiB parameters in time	Two-phase Wiener model and an Extreme Learning Machine
12	Turbofan engine fault diagnosis	Vibration	Recurrent Neural Network and Long Short-Term Memory
13	Measuring electrical quantities	Current and Voltage	Low-frequency sampling method
14	Power supply and control systems	System data	–

In reference [1], Purbowaskito et al. presented a model-based scheme for a permanent magnet synchronous motor (PMSM) driving transmission fault detection and identification (FDI). The proposed background utilizes a PMSM state-space model and an approximated transmission model to construct the regression models for parameter estimation using the Recursive Least Square (RLS) algorithm. This study is limited to steady-state conditions with constant speed and load. Based on the results presented, it can be concluded that as the loading conditions change, the estimated model parameters will also change. Thus, for PMSMs with transient conditions in which the operating condition varies over a short time, this solution may not be applicable. However, this study can be used as a reference to develop a model-based FDI for PMSM under transient conditions.

The next article is related to the signal-based approach to the diagnosis of rotor unbalance in AC drive using vibration signal analysis. In reference [2], Ewert et al. presented and compared the efficiency of four methods of mechanical vibration signal processing applied to the diagnosis of rotor unbalance in a PMSM drive system. The rotor unbalance of a drive system with PMSM was physically modeled using a specially developed shield, with five test masses fixed at the motor shaft. The article evaluates and compares the properties of the diagnostic methods analyzed from the point of view of their usefulness in rotor unbalance diagnosis and determines the basic features that characterize the usefulness of these methods, depending on the operating conditions of the drive. The authors concluded their research by stating that the selection of the best monitoring method to detect PMSM rotor unbalance depends on the operating conditions of the drive system and the available equipment.

Mechanical failures of electrical machines and drives (EM&D) are analyzed using statistical time domain features supported by different machine learning methods [3,4] or fast Fourier transform (FFT) and shallow neural networks.

Lin et al. [3] proposed a medium Gaussian Support Vector Machine (SVM) method for the application of machine learning and constructed a feature space by extracting the characteristic statistical features of the vibration signal such as: maximum and minimum values, average value, standard deviation, RMS, skewness, kurtosis, crest factor, and form factor. Different methods were investigated to group and classify these characteristics to classify motor health. The results show that the Gauss-mean SVM improves the reliability and accuracy of estimating, detecting, and identifying motor bearing failures under conditions of variable crack size and load. This article also provides a detailed overview of the predictive analytics capabilities of machine learning algorithms that can be used as a benchmark for future predictive maintenance analysis of electric vehicle motors.

Zamudio-Ramirez et al. [4] presented a noninvasive gradual wear diagnosis method for bearing outer-race faults. The proposal was based on the application of the Linear Discriminant Analysis (LDA) to statistical and Katz's fractal dimension features obtained from stray flux signals. These fault symptoms are then automatically classified using a feedforward neural network (FFNN). The proposed methodology overcomes a main drawback found in conventional methods, since it does not require prior knowledge related to the installed bearing or the rotor rotational speed information. The proposal may find wide applicability in online schemes with the capability of detecting incipient bearing failures.

The diagnosis of bearings in the induction motor (IM) drive based on the Fast Fourier Transform (FFT) of the vibration signal and the multilayer perceptron network (MLP) is addressed in the work [5]. Ewert et al. proposed and tested a low-cost computer system for monitoring and diagnosing IM rolling bearing conditions. The modular structure of the system supported by an MLP network trained offline guarantees a high operating flexibility and possible extensions by adding other measurements and diagnostic signal processing methods.

Only one work in this set concerns the application of a deep learning method for the mechanical fault diagnosis of EM&D. Chen et al. [6] proposed the architecture of a one-dimensional convolutional neural network (1D-CNN) to improve the precision of rolling bearing diagnosis based on the raw vibration signal. Unlike machine learning and other deep learning models, the 1D-CNN method does not need to pre-process one-dimensional data on the rolling bearing vibration. The number of convolution kernels was shown to decrease with the reducing size of the convolution kernel, and the network structure effectively improves the accuracy of bearing fault diagnosis. The method under study achieved high accuracy and improves generalization ability by introducing an additional dropout layer.

The next four articles in this Special Issue concern detection of electrical faults in EM&D systems, three for AC motor winding faults, and one for power electronic converter.

In the article [7], Irhoumah et al. proposed a new methodology to detect short circuits in the stator winding of synchronous machines based on stray flux analysis. The proposed method is based on the calculation of the Pearson correlation coefficient and the fusion of the Pearson coefficient obtained with belief functions. The tested method has the advantage of being fully noninvasive and does not require knowledge of the initial healthy state of the machines. Using the proposed method enables the detection of an incipient fault in any phase of the tested machine.

The detection of PMSM incipient stator winding faults with the use of the machine learning method is the subject of the next article [8]. Pietrzak et al. investigated the possibility of using spectral analysis of the symmetrical current components and the K-Nearest Neighbors (KNN) algorithm for the detection and classification of the PMSM stator winding fault. The authors presented and discussed in detail the impact of key parameters of this classifier on the effectiveness of stator winding fault detection and classification. Due to the low computational complexity of the KNN classifier, the algorithm described in this paper will be feasible to implement on a low-cost microcontroller.

The easily measurable axial flux was also analyzed as a diagnostic signal in the article [9] for the detection of stator and rotor winding faults of IM supplied from a frequency converter. Skowron et al. presented the efficiency of using cascaded neural structures in the process of detecting damage to electrical circuits in frequency-controlled IM drive based on the FFT analysis of the stray flux. The authors proposed the idea of a sequential connection of classic neural structures (SOM-MLP and SOM-RHN) to increase the efficiency of damage classification and detection. As demonstrated by the authors, this approach improves the efficiency of the detection and classification of mixed failures in the entire range of changes in load torque and supply voltage frequency and allows for the detection of rotor bar faults, even when the IM is not loaded.

The application of a deep learning network supported by a suitable preprocessing method of the measured current in the fault diagnosis of a power electronic converter was presented in the article [10]. Du et al. proposed a novel open-circuit fault diagnosis strategy for a two-level, three-phase pulse width modulating (PWM) rectifier based on Modified Ensemble Empirical Mode Decomposition (MEEMD) and the Beetle Antennae Search (BAS) algorithm optimized Deep Belief Network (DBN). The authors showed that the proposed method, in combination with feature extraction, feature selection, optimization, and fault classification algorithms, significantly improves the diagnosis accuracy.

In the next two articles, the authors address the prognosis issues for lithium-ion batteries and turbofan engines. Chen X. et al. [11] investigated the possibility of the detection of change points and the prediction of the remaining useful life (RUL) of the two-phase Wiener process model (TPWPM) for lithium-ion batteries (LiBs). The authors successfully used the biphasic Wiener model to obtain a mathematical expression of the remaining useful life and the extreme learning machine (ELM) method for adaptive change point detection.

Next, Chui et al. [12] proposed the RUL prediction algorithm in combination with the recurrent neural network (RNN) and long short-term memory (LSTM) of a turbofan engine. The former takes advantage of short-term prediction, whereas the latter manages to improve long-term prediction. The proposal of combining the complete ensemble empirical mode decomposition (EMD) and the wavelet packet transform (WPT) for feature extraction could reduce the average root mean square error (RMSE) by 5.14 to 27.15% compared to existing approaches.

The last two articles in this collection are related with accuracy issues of digital measurements of electrical signals [13] and recent technologies available in I4.0 standards related with protection, control, and power supply of electrical devices [14].

Jaraczewski et al. [13] surveyed methods for measuring electrical quantities using devices with low computational efficiency and low sampling frequency up to 1 kHz. The main advantage of the proposed method is that it achieves a balance between PLC processing power and accuracy in calculating the most important electrical signal indicators such as power, RMS value, and sinusoidal signal distortion factor (e.g., THD). The algorithms presented can be used in devices that monitor the quality of electricity and in devices that protect against overload or distortion of the electric voltage or current.

Finally, Soltysek et al. [14] reviewed the latest technologies available on the market that are part of Industry 4.0 in the field of protection, control, and power supply of devices. The authors compared different solutions that allow for increasing the reliability of the systems with an ethernet connection compared to the classic systems with wired connection. They highlighted that universal protection devices are more flexible compared to classic control equipment but also allow us to make modifications to the structure after commissioning during normal operation of the system without stopping the technological process.

3. Future Trends

From the analysis of the contributions selected for publication in this Special Issue summarized in Table 1, the following conclusions can be drawn.

Firstly, the detection methods and techniques of mechanical [1–6] and electrical [7–10] faults in EM&Ds (including power electronics converters [10]) are still a hot topic in the diagnostics of industrial systems, as predicted in some of the last review papers on EM&D diagnostics [15–18].

Secondly, different diagnostic signals are still used for the analysis of fault symptoms, such as mechanical vibrations [2,3,5,6,12], stray flux [4,7,9], and phase currents [1,8,10,13]. However, it should be noted that the current signal is the most flexible to use in diagnostics, as it is easily accessible in any electrical system, including static converters [10] or battery systems [11]. It is worth mentioning that current and vibration signals can be used not only in diagnostics but also for prognostic purposes [11,12].

Thirdly, various types of machine learning techniques [3,4,8,11] and shallow [5,9,12] and deep [6,10,12] neural networks are being increasingly used for fault detection and classification, which greatly reduces reliance on expert knowledge, according to the tendencies presented in [15–18]. However, the effectiveness of these techniques is highly dependent on the quantity and quality of the data used for training. For machine learning and shallow neural networks, the data sets must be preprocessed first using different signal analysis or statistical methods [2–5,7–9,11]. In the application of deep learning methods for fault detection, two approaches can be used: initially preprocessing the input data, as in [10], or using raw signals as in [6] and some references given in [15] (Section VIII, Table 8).

Finally, the methods and techniques of condition monitoring and fault diagnosis of EM&Ds and other mechatronic systems have recently been expanded to prognostic tasks, as shown in the papers [11,12] of this collection.

Based on the analysis of the works presented in this Special Issue, it can be concluded that, despite the many interesting new ideas presented, few advanced problems, formulated in some review articles, such as in the recent survey [15], have not been adequately addressed. These are as follows:

– Diagnostics in transient states of industrial systems, including low-speed and light-load operation in the case of EM&Ds. Using CNNs or other DNNs without input signal preprocessing is highly recommended in such operating conditions to obtain low-time-consuming solutions;
– Multiple fault diagnosis and classification, which is a difficult task because the same or similar failure symptoms can correspond to different failures of the given system;
– Artificial-intelligence-based, real-time diagnostic systems for greater accuracy and robustness, as well as online operation;
– Transfer learning applications in the case of a lack of experimental data for training AI-based fault detectors and classifiers. Two research directions are possible in this field: transfer learning from mathematical models to real systems and from one system type (e.g., an electric machine) to another (including different power ranges). Moreover, the problems of the universality and scalability of diagnostic systems obtained in this way should also be analyzed.

However, we believe that these issues will soon be developed and presented in forthcoming research papers on diagnostics and prognostics of industrial systems using recently developed AI techniques.

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