Diagnosis and Prognosis for Complicated Industrial Systems—Part I

DUE to the requirements of the system safety and reliability, the correct diagnosis or prognosis of abnormal condition plays an important role in the maintenance of industrial systems. In the last several decades, based on the well-developed physical model constructing techniques, numerous model-based diagnosis and prognosis approaches have been proposed, and many of them find successful applications in industry [1]–[5]. On the other hand, with the wide application of sensors, the process data reflecting the system operation status can be easily collected. Based on these process data, the data-driven diagnosis and prognosis approaches study using data-mining and machine learning techniques for the purpose of process monitoring of industrial systems. Due to its potentials to boost efficiency and cut costs of industry, the diagnosis and prognosis under the data-driven framework have been an attractive research topic, and lots of related research results have been reported [6]–[10].

With the increasing demands on the production quality, economic operation, as well as system performance, modern industrial systems are becoming more and more complicated. No matter under the model-based or data-driven frameworks, the diagnosis and prognosis of such complicated systems pose new challenges for both the academic and industrial communities. This "Special Section on Diagnosis and Prognosis for Complicated Industrial Systems" of the IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS is motivated to provide a forum for researchers and engineers to report their recent theoretic/application results on modeling, diagnosis, prognosis, and optimization of complicated systems. Since its proposal, this Special Section has drawn great attentions from the academic and industrial communities focused on fault diagnosis, lifetime prognosis, fault detection, and equipment healthy management, and numbers of the research results have been submitted for potential publication.

Considering the large number of significant research works accepted for publication, this Special Section has been divided into two parts for editorial reasons. This first part of the Special Section, i.e., "Diagnosis and Prognosis for Complicated Industrial Systems—Part I," includes 15 papers, which were eventually accepted for publication after a strict peer-reviewer procedure. To give the readers an explicit reference on the contributions of the accepted papers, these 15 papers are summarized as follows in two categories, i.e., "model-based diagnosis and prognosis [11]–[17]" and "data-driven diagnosis and prognosis [18]–[22], [26]–[28]."

The first six papers mainly investigate the model-based diagnosis and prognosis problems for complicated systems. With the well-established system physical model, the diagnosis and prognosis methods are developed in these papers with various industrial applications such as partial-discharge diagnosis and location for the high-voltage insulation system, lifetime prognostic of the proton exchange membrane fuel cell, and fault detection for synchronous machines.

In [11], the authors propose to use the direction-of-arrival estimation algorithm of wideband signals to decide the location of partial-discharge sources in industrial high-voltage insulation systems. The position of PD sources can be decided by the intersecting point of two rays sent from two uniform linear arrays. The received data are represented by a sparse linear combination of potential steering vectors in order to use the technique of multimodal joint sparse representation to improve the performance of direction-of-arrival estimation. In order to reduce the computational complexity of the hard threshold algorithm, an improved soft threshold direction-of-arrival estimation algorithm based on alternating direction methods of multipliers is proposed as well. Simulations and real tests demonstrate that the position of PD sources can be located with a high accuracy based on the cross-location method.

In [12], the authors solve the monitoring problem of interturn short circuits of induction motor stator windings operating under the framework of direct field-oriented control (DFOC). Based on the spectra analysis of the internal signals from the control system, a detection algorithm is introduced to detect the stator winding incipient damages. To design the damage diagnostic algorithm, the increase of the $2f_s$ harmonic amplitude of the internal control and decoupling signals is used. The effectiveness of the proposed monitoring method is verified by the simulations as well as the experimental tests of the induction motor.

In [13], the authors investigate the tracking and optimization problems for a class of industrial processes by utilizing output feedback fault tolerant control and the predictive compensation strategy. A combined fault tolerant and predictive control scheme is developed from the device and operation layers of the industrial process. At the device layer, the tracking problem is studied for systems with both random failures and network-induced delays. At the operation layer, the optimization problem is solved by utilizing the nonlinear model predictive control strategy, and to guarantee the input-to-state practical stability of the resulting system, a compensator is designed. The simulation of a network-based flotation process is used to verify the proposed method.

A simultaneous state and fault estimation technique is proposed based on the unknown input observer for systems subjected to partially decoupled process disturbances or sensor disturbances in [14]. The unknown input observer approach is used to decouple the partial process disturbances, and the LMI

Digital Object Identifier 10.1109/TIE.2016.2522944

optimization technique is to attenuate the process disturbances and sensor disturbances that cannot be decoupled. The simultaneous estimation is realized by the augmented system which is constructed with state vectors and the concerned faults. The effectiveness of the proposed techniques has been illustrated by using two engineering-oriented systems: the three-shaft gas turbine engine and the single link robot. The proposed techniques have the potentials to be applied to various engineering systems.

In [15], the authors present a new algorithm for detecting ground faults in rotor windings in synchronous generators with static excitation. The detection of ground faults is performed under the supervision of the phase angle between two phasor voltages. The first one is the third-harmonic phasor voltage obtained from the measurement of the field voltage, which is used as a reference. The second one is the third-harmonic voltage phasor obtained by the measurement in a grounding resistance placed in the neutral of the excitation transformer. Through the algorithm, not only the fault along the field winding can be detected, but also the cases of the fault can be distinguished. The fault location method is demonstrated to be effective after being tested in a 106-MVA hydro generating unit.

An online parameters' estimation and monitoring system for roll eccentricity is presented in [16]. The performance indicator to assess and monitor product quality is based on product expectations or experiences of the process variables. The online monitoring system for the key parameters of the roll eccentricity includes an adaptive observer for frequency estimation and an adaptive algorithm for amplitude and phase estimation. The rolling model from industrial fields demonstrates the effectiveness and feasibility of the proposed monitoring system. The estimated parameters will later be used for controller design aiming at compensating the effects of the eccentricity on strip thickness.

In [17], the authors propose an observer-based prognostic algorithm to estimate the State of Health and the remaining useful life (RUF) with the inherent uncertainty. An extended Kalman filter is used to estimate the actual state of health and the dynamic of the degradation with the associated uncertainty. Then an inverse first-order reliability method is used to extrapolate the RUF. The global method is validated through a simulation model built from degradation data. The algorithm is demonstrated to be with a high accuracy on a data set gathered from a long-term experimental test on a eight-cell fuel cell stack subjected to a variable power profile.

The second category includes eight papers [18]–[22], [26]–[28] which studied the diagnosis and prognosis under the data-driven framework. Based on the available data set, the data mining and machine learning algorithms, e.g., partial least squares, principal component analysis, and k-nearest neighbor (kNN) algorithm, are used to construct the statistical models for the diagnosis and prognosis purposes.

In [18], a kNN-based fault isolation method is proposed to deal with the problem of isolating sensor faults without using any fault information. According to the contribution analysis methods developed in the frame of principal component analysis, a fault isolation index, i.e., the variable contribution by kNN (VCkNN), is developed by decomposing the kNN distance. VCkNN is defined in the original measurement space, and thus, it is not affected by fault smearing encountered in other existing contribution analysis methods. The theoretical analysis of the isolability for the proposed fault isolation method shows that the proposed method can isolate multiple sensor faults under a less strict condition than that used in the analysis of isolability for other contribution analysis-based fault isolation methods.

In [19], the authors studied the problems of key performance indicator-related prediction and fault diagnosis under the situation that there are outliers existed in process data sets. Based on the improved partial least squares introduced in [9], an advanced partial least squares (APLS) is proposed. To alleviate the negative influences of outliers, the APLS include the weighting scheme, by which the outliers will be assigned with smaller weights than the normal data points. Thus, the influences of the outliers will be mitigated in prediction and fault diagnosis purposes. The effectiveness of the APLS method is verified through the Tennessee Eastman (TE) benchmark process.

In [20], the authors studied the fault diagnosis problem of aluminum electrolysis based on the kernel principal component analysis (KPCA). The traditional KPCA suffers from the loss of the relative importance among each variable after the normalization, and this can lead to misleading interpretations of the principal components for fault diagnosis. To cope with this problem, the optimized relative transformation matrix using bacterial foraging algorithm (BFA-ORTM) is proposed. In the algorithm, the relative transformation matrix (RTM) is introduced into KPCA, and the optimized weights for the best RTM are obtained by the bacterial foraging optimization algorithm. The effectiveness of the proposed BFA-ORTM for fault diagnosis is validated in the real-world aluminum electrolytic production process.

The fault diagnosis problem of the processes with the multimode, nonlinear, and non-Gaussian features is studied in [21]. Different form the commonly used process monitoring methods, e.g., principal component analysis and partial least squares, the independent component analysis can be used for the non-Gaussian processes. To further cope with the nonlinear, multimode characteristics existed in the processes, Zhang *et al.* propose an improved kernel independent component analysis in [21]. With the proposed method, the similarities between different independent modes are extracted, and the independent similar model is constructed. In addition, for each different independent mode, their models are also developed. Then, the process monitoring is simultaneously performed on these constructed models. The TE process is used to verify the effectiveness of the proposed method.

In the practical industrial applications, there are always the indicators which are regarded as the critical ones for the production process, e.g., the final thickness and width of the strip steel products in the hot strip mill rolling process [22]. These critical indicators are named as the key performance indicators or quality indices in research papers. Identifying whether the fault occurred in the process influences these critical indicators is important for improving production quality and maintaining economic operation. Recently, the quality-related fault diagnosis has been a hot research topic, and many research results have been reported [9], [23]–[25]. In this Special Section, several papers focused on quality-related fault diagnosis by using the data-driven techniques are also received. In [22], the authors propose a framework for quality-related fault detection and diagnosis for nonlinear batch processes in the multimode operating environment. The framework can be divided into three parts: multimode clustering, fault diagnosis model constructing, and new measurement classification. The kernel fuzzy C-clustering method is introduced to cluster the modes of the nonlinear data, and the optimal mode number is determined by using the between-within proportion index. To cope with the low fault detection rate problem, an improved kernel partial least squares (KPLS)-based fault diagnosis method is developed. The online new measurement is classified by using the regression abilities of KPLS and Bayes inference. The proposed quality-related fault diagnosis framework is validated in the hot strip mill rolling process. Jiao *et al.* studied the quality-related fault detection approach based on dynamic least squares in [26]. To cope with the dynamic property existed in practical industrial processes, a dynamic least squares method is developed by using the structure of autoregressive moving average exogenous (ARMAX) time series model. In order to achieve the quality-related fault detection, the input matrix is decomposed into two orthogonal parts, i.e., quality-related and unrelated parts, according to their correlations with the output. As aforementioned, the literature [19] deals with the quality-related fault diagnosis problem with the outliers taken into account. An APLS is proposed, and based it, the input matrix is also decomposed into the quality-related and unrelated parts as in [26] for fault diagnosis.

In [27], the RUL prognostics issue of the electrical machine is discussed. With the adaption of a data-driven prognostics framework, a health index (HI)-based prognostics method is proposed. The prognostic procedure of the proposed method can be divided into two steps: calculating HI from the input signals and mapping HI to RUL. The novelty of this method lies in the proposed dynamic HI smoothing approach where three characteristics of HI, namely monotonicity, gradualness, and consistency are incorporated to smooth the current HI values with the previously predicted ones. Real data collected from eight electrical motors are used to evaluate the efficacy of the proposed RUL prognostics method.

A combination of sample entropy and sparse Bayesian predictive modeling (SBPM) has been exploited to synthesize a data-driven battery state-of-health estimator in [28]. The sample entropy of short voltage sequence is used as a signature of capacity loss. The advanced SBPM methodology is employed to capture the underlying correspondence between the capacity loss and sample entropy. The estimator is verified to be accurate and robust by using large amounts of data collected at three different temperatures from multiple cells, outperforming the third-degree polynomial model in both training and validation processes. Besides, compared with the SVM scheme, the multivariate SBPM estimator exhibits comparable (and even slightly better) performance with much simpler topology and additional benefits. Via a combination of SBPM and bootstrap sampling concepts, the forecast of the battery RUL is also performed. The predicted RUL is satisfactory in terms of its average and spread.

To this end, the overview of fifteen papers of this Special Section has been completed. The guest editors expect that this Special Section will help increase more attention in the dynamic data-driven area and will also provide recent advances of related approaches, in particular new ideas and algorithms with industrial applications.

Acknowledgment

The Guest Editors would like to thank all the authors who submitted their valuable contributions, and to extend deep gratitude to all the anonymous reviewers for spending their time and expertise during the review process. They believe that the selected contributions, which represent the current state of the art in the relevant fields, will be of great interest to industrial-related communities. In addition, the Guest Editors are appreciative to the past and present Editors-in-Chief of the IEEE Transactions on Industrial Electronics, Prof. C. Cecati and Prof. L. G. Franquelo, for providing the opportunity to organize this Special Section as well as their continuous support, and to the Journal Administrator, Mrs. S. McLain, for her professional assistance throughout the entire preparation of the Special Section.

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