In human health care, a medical analysis is made, based on the measurements of some parameters related to health conditions; the examination of the collected measurements aims at detecting anomalies, diagnosing illnesses and predicting their evolution. By analogy, technical procedures of health management are used to capture the functional state of industrial equipment from historical recordings of measurable parameters.

Today, most maintenance actions are carried out by either the preventive or the corrective approach. The preventive approach has fixed maintenance intervals in order to prevent components, sub-systems or systems to degrade. Corrective maintenance is performed after an obvious fault or breakdown has occurred. Both approaches have shown to be costly in many applications due to lost production, cost of keeping spare parts, quality deficiencies, et cetera.

Basically, predictive maintenance or Condition Based Maintenance (CBM) differs from preventive maintenance by basing maintenance need on the actual condition of the machine rather than on some preset schedule. As the preventive maintenance is time-based and activities such as changing lubricant are based on time, like calendar time or equipment run time. For example, most people change the engine oil in their car/jeep at every 3000 to 5000 KMs vehicles traveled. No concern is given to the actual condition and performance capability of the oil. This methodology would be analogous to a preventive maintenance task. If on the other hand, the operator of the car discounted the vehicle run time and had the oil analyzed at some periodicity to determine its actual condition and lubrication properties, he/she may be able to extend the oil change until the vehicle had traveled 10000 KMs. This is the fundamental difference between predictive maintenance and preventive maintenance, whereby predictive maintenance is used to define needed maintenance task based on quantified material/equipment condition.

The objective of CBM is to maintain the correct equipment at the correct time. CBM is based on using real-time Prognostics and Health Management (PHM) data to prioritize and optimize maintenance resources. By observing the state of the system (condition monitoring), the system will determine its health, and act only when maintenance is actually necessary thus minimizing the remaining useful life of the equipment that is thrown away. Using CBM, maintenance personnel are able to decide when the right time to perform maintenance is. Ideally CBM will allow the maintenance personnel to do only the right things, minimizing spare parts cost, system downtime, and time spent on maintenance.

The area of intelligent maintenance and diagnostic and prognostic–enabled CBM of machinery is a vital one for today’s complex systems in industry, aerospace vehicles, military and merchant ships, the automotive industry, and elsewhere. The industrial and military communities are concerned about critical system and component reliability and availability. The goals are both to maximize equipment up time and to minimize maintenance and operating costs. As manning levels are reduced and equipment becomes more complex, intelligent maintenance schemes must replace the old prescheduled and
labor intensive planned maintenance systems to ensure that equipment continues to function. Increased demands on machinery place growing importance on keeping all equipment in service to accommodate mission-critical usage. While fault detection and fault isolation effectiveness with very low false alarm rates continue to improve on these new applications, prognosis requirements are even more ambitious and present very significant challenges to system design teams. These prognostic challenges have been addressed aggressively for mechanical systems for some time but are only recently being explored fully for electronics systems.

Prognosis is one of the more challenging aspects of the modern prognostic and health management (PHM) system. It also has the potential to be the most beneficial in terms of both reduced operational and support cost and life-cycle total ownership cost and improved safety of many types of machinery and complex systems. The evolution of diagnostic monitoring of complex systems has led to the recognition that predictive prognosis is both desired and technically possible.

This book is a collection of chapters that could completely cover the huge coverage that structural health monitoring (SHM) and prognostic health management (PHM) encompasses. The chapters draw from different science fields like mechanical and industrial engineering, information technology, and control engineering in a fruitful effort to bring the state of the art in how SHM and PHM is being established, evaluated, and deployed in industrial machine practice applications.

**Chapter 1.** "Iterative Fault Tolerant Control for General Discrete-Time Stochastic Systems Using Output Probability Density Estimation," presents an ILC-based FTC method for the shape control of the output PDFs for general stochastic systems with non-Gaussian variable using a generalized fixed-structure PI controller with constraints on the state vector that results from the application of square root PDF modeling. The whole control horizon is divided into a number of batches. Within each batch, the state-constrained generalized PI controller is used to shape the output PDF using an LMI approach. Between any two adjacent batches, the parameters of the RBF basis functions are tuned. A P-Type ILC is applied to achieve such tuning between batches, where a sufficient condition for the ILC convergence has been established.

**Chapter 2.** "Intelligent System Monitoring: On-Line Learning and System Condition State," proposes a new intelligent monitoring method for system condition representation. It uses 5 consecutive steps, 1) data acquisition; which in step 3), diagnosis, is compared with a simplified adaptive mode, 2); the degradation hybrid automata flow among degraded modes tracking the system condition, state 4); and, finally EOL or/and RUL forecasting is computed on prognosis step, 5). This chapter addresses an approach for intelligent system monitoring based on a simplified adaptive model in which steps 2) and 4) are studied being out of scope the diagnosis and prognosis part.

**Chapter 3.** "Principles of Classification,” shows that it is possible to develop a continuous learning diagnostic system using neural networks. The system will significantly save an analyst’s time and effort in anomaly and fault detection, which would otherwise require extensive work. There are several ways to enhance the presentation of data on a classifier in order to predict the interpretation of a new data sample. The confidence level of prediction can be estimated using simple terms.

**Chapter 4.** "Generating Indicators for Diagnosis of Fault Levels by Integrating Information from Two or More Sensors,” presents two methods of generating indicators for fault levels by integrating information from possible sensors. The first method regards signals from two sensors and different health conditions as one multivariate signal. Multivariate empirical mode decomposition is adopted to decompose the multivariate signal into a set of IMFs. The fault-sensitive IMF is chosen by a criterion based on mutual information. Then a full spectra based indicator is obtained. The indicator generated by
method 1 reveals the characteristics of planar vibration motions. The second method extracts features from each individual sensor, uses global fuzzy preference approximation quality to select features having better monotonic relevance with fault levels, and utilizes PCA to combine information in selected features into a single indicator. The generated indicator makes use of information among different sensors and features, and outperforms each individual feature. This method is general and can work for multiple sensors. The generated indicator, however, because of the linear transformation induced by PCA, doesn’t keep the physical meaning of the original selected features.

Chapter 5, “Fault Detection and Isolation for Switching Systems using a Parameter-Free Method,” proposes a data-based method for switching detection and mode recognition. Both processes can be achieved successfully in both methods when the system switches between discernible modes. Discernibility between modes requires a necessary condition related to the Markov parameters of the mode. Although when the system switches between non-discernible modes, the switching is detected, which means that the non-discernibility condition does not imply the non-switching detectability is not a sufficient condition for a non-switching detectability.

Chapter 6, “Data Driven Prognostics for Rotating Machinery,” outlines a process for data-driven prognostics by: describing appropriate condition indicators (CIs) for gear fault detection; threshold setting for those CIs through fusion into a component health indicator (HI); using a state space process to estimate the remaining useful life given the current component health; and a state estimate to quantify the confidence in the estimate of the remaining useful life.

Chapter 7, “Identifying Suitable Degradation Parameters for Individual-Based Prognostics,” presents a set of metrics that characterize the suitability of a prognostic parameter. Parameter features such as monotonicity, prognosability, and trendability can be used to compare candidate prognostic parameters to determine which is most useful for individual-based prognosis. Monotonicity characterizes the underlying positive or negative trend of the parameter, which addresses the common assumption that physical systems do not self-heal. Prognosability gives a measure of the variance in the critical failure value of a degradation parameter for a population of systems or components, which improves confidence in the estimate of failure. Finally, trendability indicates the degree to which the developed degradation parameters of a population of systems have the same underlying shape and can be described by the same functional form. These three intuitive metrics can be formalized to give a quantitative measure of prognostic parameter suitableness. The combination of the three measures and the suitability can then be used as a fitness function to optimize the development of a prognostic parameter.

Chapter 8, “Modeling Multi-State Equipment Degradation with Non-Homogeneous Continuous-Time Hidden Semi-Markov Process,” presents a general stochastic model using nonhomogeneous continuous-time hidden semi-Markov process (NHCTHSMP) to model the degradation process and the observation process of a piece of multi-state equipment with unobservable states. The detailed mathematical structure for the NHCTHSMP associated with the multi-state equipment was described. Important measures of a NHCTHSMP based on the associated kernel function and the transition rate function were illustrated. Finally an estimation method was presented which can be used to estimate the unknown parameters of a NHCTHSMP using condition monitoring information. A simple numerical example was provided to describe the application of NHCTHSMP in modeling the degradation process and the observation process of multi-state equipment with unobservable states.

Chapter 9, “Stochastic Fatigue of a Mechanical System Using Random Transformation Technique,” presents a new technique to find the probability density function (pdf) of a stress for a stochastic mechanical system. This technique is based on the combination of the Probabilistic Transformation Method
(PTM) and the Finite Element Method (FEM) to obtain the pdf of the response. The new technique is verified with 10000 Monte-Carlo simulations.

**Chapter 10, “Degradation Based Condition Classification and Prediction in Rotating Machinery Prognostics,”** analyzes the degradation based condition classification and prediction approaches in prognostics. The normal, abnormal, and failure conditions are defined through anomaly determination of the transition stage. The condition classification methods are analyzed with the degradation conditions. Then the probability of failure occurrence is discussed in the transition stage. Finally, considering the degradation processes in rotating machinery, the condition classification and prediction are carried out with the field data.

**Chapter 11, “A Temporal Probabilistic Approach for Continuous Tool Condition Monitoring,”** introduces a hidden semi-Markov model based approach for continuous diagnosis and prognosis. Also, a computationally efficient version of forward-backward algorithm for application of HSMM in continuous health condition monitoring is described. Based on the simplified forward-backward algorithm, diagnostics and prognostics procedures are defined. A comparative study is conducted between the suggested HSMM-based approach and the existing HMM-based approach. Performances of the two approaches are compared in three cases i.e. cross-validation, diagnostics and prognostics. Based on the experimental results, HSMM-based approach outperforms the HMM-based approach in both diagnostics and prognostics. Prognosis ability of the suggested HSMM-based approach is tested in case III. Interestingly, the error rate of the HSMM-based approach predicting 10 time steps ahead is less than the acquired one step ahead average prognosis error rate from the HMM-based approach which indicates how powerful HSMM is compared to HMM in capturing the underlying temporal information.

**Chapter 12, “Combining Health Monitoring and Control,”** proposes the combination of system health monitoring with control and prognosis by the introduction of the HAC paradigm. In this paradigm, the information provided by the prognosis module about the component system health should allow modifying the controller such that the control objectives will consider the system health. In this way, the control actions will be generated to fulfill the control objectives but at the same time to extend the life of the system components. HAC control contrarily to FTC adjusts the controller even when the system is still in non-faulty situation. The prognosis module will estimate on-line the component aging for the specific operating conditions. In the non-faulty situation, the control efforts are distributed to the system based on the proposed health indicator. An example has been used along the chapter to illustrate the ideas and concepts introduced.

**Chapter 13, “A Particle Filtering Based Approach for Gear Prognostics,”** presents a particle filtering based gear prognostics method using a one-dimensional health index for spiral bevel gear subject to pitting failure mode. The presented method effectively addresses the issues in applying particle filtering to mechanical component remaining useful life prognostics by integrating a couple of new components into particle filtering: (1) data mining based techniques to effectively define the degradation state transition and measurement functions using a one-dimensional health index obtained by a whitening transform; (2) an unbiased l-step ahead RUL estimator updated with measurement errors. The presented prognostics method is validated using data from a spiral bevel gear case study. The validation results have shown the effectiveness of the presented method.

**Chapter 14, “Supporting Business Cases for PHM: Return on Investment and Availability Impacts,”** addresses two key capabilities necessary for supporting business cases for the inclusion and optimization of PHM within systems. First the chapter describes the construction of life-cycle cost models that enable return on investment estimations for the inclusion of PHM within systems and the valuation of
maintenance options. Second, the authors address the support of availability-centric requirements (e.g., availability contracts) for critical systems that incorporate PHM; and the resulting value that can be realized. Examples associated with avionics, wind turbines, and wind farms are provided.

**Chapter 15**, “Remote Fault Diagnosis System for Marine Power Machinery System,” reports a new knowledge based remote diagnosis system in the application of condition monitoring and fault diagnosis (CMFD) for marine power machinery systems. The constructed two lever diagnosis system integrates the performance parameters, lubricant oil analysis, vibration, and instantaneous speed analysis to make the remote diagnosis system of marine power machinery systems feasible and available. The gear pump test shows that the proposed system is competent for fault detection. The proposed knowledge based remote diagnosis system has been proven to be feasible in engineering practice, and efficient for failure detection for diesel engines.

**Chapter 16**, “Prognostics and Health Management of Choke Valves Subject to Erosion: A Diagnostic-Prognostic Frame for Optimal Maintenance Scheduling,” analyses a practical case study concerning erosion in choke valves used in oil industries with the aim of defining a diagnostic-prognostic frame for optimizing maintenance scheduling of such components. Two objectives have been identified: 1) the development of a condition monitoring system capable of providing reliable calculations of the erosion state based on collected measurements of physical parameters related to the choke erosion and 2) the development of a prognostic system to accurately estimate the remaining useful life of the choke. An empirical, model-based approach has been used to fulfill the diagnostic objective of providing reliable calculations of the erosion state, whereas a statistical method based on the gamma probability distribution has been adopted to reach the prognostic goal of accurately estimating the remaining useful life of the choke.

**Chapter 17**, “Prognostics and Health Management of Industrial Equipment,” reviews the state of knowledge on the methods for PHM, placing these in context with the different information and data which may be available for performing the task and identifying the current challenges and open issues which must be addressed for achieving reliable deployment in practice. The focus is predominantly on the prognostic part of PHM, which addresses the prediction of equipment failure occurrence and associated residual useful life (RUL).

**Chapter 18**, “Structure Reliability and Response Prognostics under Uncertainty Using Bayesian Analysis and Analytical Approximations,” develops an efficient analytical Bayesian method for reliability and system response updating. The method is capable of incorporating additional information such as inspection data to reduce uncertainties and improve the estimation accuracy. One major difference between the proposed work and the traditional approach is that the proposed method performs all the calculations including Bayesian updating without using MC or MCMC simulations. A twenty-variable numerical example and a structural scale problem are presented for demonstration. Comparisons are made with traditional simulation-based methods to investigate the accuracy and efficiency.

**Chapter 19**, “Fatigue Damage Prognostics and Life Prediction with Dynamic Response Reconstruction Using Indirect Sensor Measurements,” proposes a new methodology for fatigue prognosis integrating usage monitoring system. EMD method is employed to decompose the signal into a series of IMFs with specific filtering process. Those IMFs, which represented the displacement for each mode, are used to extrapolate the dynamic response at critical spot. It should be noticed that the mode shape information is required and can be obtained from classical finite element analysis. The fatigue crack growth prognosis is performed after the extrapolation process using a time-derivative model. Based on the current study, several conclusions are drawn: (1) The presented study provides a concurrent fatigue crack prognosis,
which can be used for on-line fatigue life prediction, and (2) The numerical study demonstrates the proposed reconstruction method can effectively identify the dynamic responses for the critical spot where direct sensor measures are unavailable.

**WHO AND HOW TO READ THIS BOOK**

This book has three groups of people as its potential audience, (i) undergraduate students and postgraduate students conducting research in the areas of system diagnostic and prognostic; (ii) researchers at universities and other institutions working in these fields; and (iii) practitioners in the Research and Development departments of industrial settings. This book differs from other books that have comprehensive case study and real data from industrial settings. The book can be used as an advanced reference for a course taught at the postgraduate level in industrial engineering, electrical engineering, mechanical engineering, manufacturing intelligence, and industrial electronics.

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