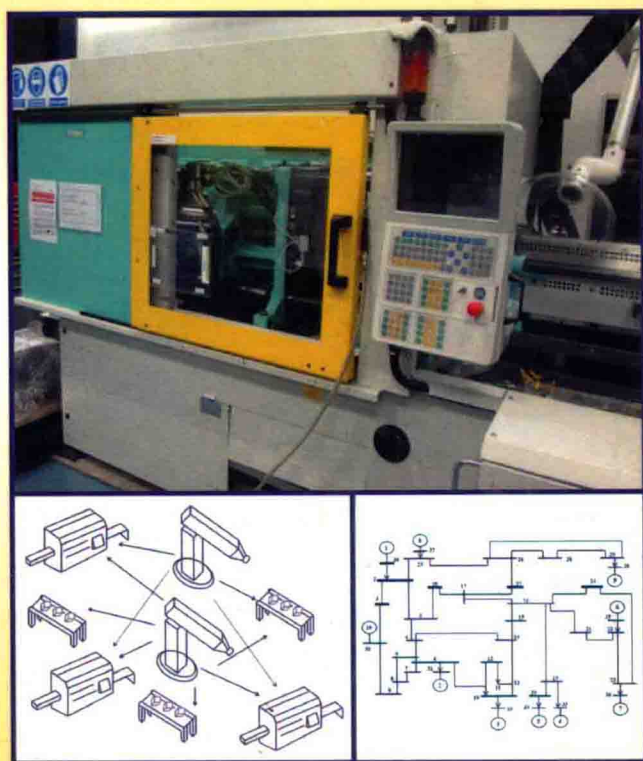


**Automation and Control  
Engineering Series**

# **Intelligent Diagnosis and Prognosis of Industrial Networked Systems**



**Chee Khiang Pang, Frank L. Lewis,  
Tong Heng Lee, Zhao Yang Dong**

**Automation and Control Engineering Series**

# **Intelligent Diagnosis and Prognosis of Industrial Networked Systems**

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# **Intelligent Diagnosis and Prognosis of Industrial Networked Systems**

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# Dedication

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*To those I love, and those who love me.*  
*C. K. Pang*

*To Galina.*  
*F. L. Lewis*

---

# Preface

In an era of intensive competition when asset usage and plant operating efficiencies must be maximized, unexpected downtime due to machinery failure has become more costly and unacceptable than before. To cut operating costs and increase revenues, industries have an urgent need for prediction of fault progression and remaining lifespan of industrial machines, processes, and systems. As such, predictive maintenance has been actively pursued in the manufacturing industries in recent years where equipment outages are forecasted, and maintenance is carried out only when necessary. Prediction leads to improved management and hence effective usage of equipment, and multifaceted guarantees are increasingly being given for industrial machines, processes, products, and services, etc. To ensure successful condition-based maintenance, it is necessary to detect, identify, and classify different kinds of failure modes in the manufacturing processes as early as possible.

With the pushing need for increased longevity in machine lifetime and its early process fault detection, intelligent diagnosis and prognosis have become an important field of interest in engineering. For example, an engineer who mounts an acoustic sensor onto a spindle motor would like to know when the ball bearings will be worn out and need to be changed without having to halt the ongoing milling processes, which decreases the industrial yield. Or a scientist working on sensor networks would like to know which sensors are redundant during process monitoring and can be pruned off to save operational and computational overheads. These realistic scenarios illustrate the need for new or unified perspectives for challenges in system analysis and design for engineering applications.

Currently, most works on Condition-Based Monitoring (CBM), Fault Detection and Isolation (FDI), or even Structural Health Monitoring (SHM) consider solely the integrity of independent modules, even when the complex integrated industrial processes consist of several mutually interacting components interwoven together. Most literature on diagnosis and prognosis is also mathematically involved, which makes it hard for potential readers not working in this field to follow and appreciate the state-of-art technologies. As such, a good intelligent diagnosis and prognosis architecture should consider crosstalk to facilitate actions and decisions among the synergetic integration of composite systems simultaneously, while maintaining overall stability at the same time. This “big-picture” approach will also limit the inherent intrinsic uncertainties and variabilities within the interacting components, while suppressing any possible extrinsic socio-techno intrusion and uncertainties from the human interface layer.

Adding to the current literature available in this research arena, this book provides an overview of linear systems theory and the corresponding matrix operations required for intelligent diagnosis and prognosis of industrial networked systems. With the essential theoretical fundamentals covered, automated mathematical machineries are developed and applied to targeted realistic engineering systems. Our results show

the effectiveness of these tool sets for many *time-triggered* and *event-triggered* industrial applications, which include forecasting machine tool wear in industrial cutting machines, sensors and features reduction for industrial FDI, identification of critical resonant modes in mechatronic systems for systems design of research and development (R&D), probabilistic small signal stability in large-scale interconnected power systems, discrete event command and control for military applications, etc., just to name a few. It should be noted that these developed tool sets are highly portable, and can be readily adopted and applied to many other engineering applications.

## Outline

This book is intended primarily as a bridge between academics in universities, practicing engineers in industries, and also scientists working in research institutes. The book is carefully organized into chapters, each providing an introductory section tailored to cover the essential background materials, followed by specific industrial applications to realistic engineering systems and processes. To reach out to a wider audience, linear matrix operators and indices are used to formulate mathematical machineries and provide formal decision software tools that can be readily appreciated and applied. The book is carefully crafted into seven chapters with the following contents:

- Chapter 1: *Introduction*  
Intelligent diagnosis and prognosis using model-based and non-model-based methods in current existing literature are discussed. The various application domains in realistic industrial networked systems are also introduced.
- Chapter 2: *Vectors, Matrices, and Linear Systems*  
Fundamental concepts of linear algebra and linear systems are reviewed along with eigenvalue and singular value decompositions. The usage of both real and binary matrices for diagnosis and prognosis applications are also discussed.
- Chapter 3: *Modal Parametric Identification (MPI)*  
Proposes a Modal Parametric Identification (MPI) algorithm for fast identification of critical modal parameters in R&D of mechatronic systems. A systems design approach with enhanced MPI is proposed for mechatronic systems and verified with frequency responses of dual-stage actuators in commercial hard disk drives (HDDs).
- Chapter 4: *Dominant Feature Identification (DFI)*  
Proposes a Dominant Feature Identification (DFI) software framework for advanced feature selection when using inferential sensing in online monitoring of industrial systems and processes. A mathematical tool set which guarantees minimized least squares error in feature reduction and clustering is developed. The proposed techniques are verified with experiments on tool wear prediction in industrial high speed milling machines and fault detection in a machine fault simulator.
- Chapter 5: *Probabilistic Small-Signal Stability Assessment*  
Proposes analytical and numerical methods to obtain eigenvalue sensitivities with respect to non-deterministic system parameters and load models



for large-scale interconnected power systems. A probabilistic small-signal stability assessment method is proposed, and verified with extensive simulations on the New England 39-Bus Test System.

- Chapter 6: *Discrete Event Command and Control*

Proposes the use of binary matrices and algebra for command and control of discrete event-triggered systems. A mathematically justified framework is provided for distributed networked teams on multiple missions. This is verified with simulations and experiments on a wireless sensor network (WSN), as well as simulation on a military ambush attack mission.

- Chapter 7: *Future Challenges*

Provides conclusion and future work directions for intelligent diagnosis and prognosis in areas of energy-efficient manufacturing, life cycle assessment, and systems of systems architecture.

## Learning Outcomes

The developed tools allow for higher level decision making and command in synergistic integration between several industrial processes and stages, thereby achieving shorter time in failure and fault analysis in the entire industrial production life cycle. This shortens production time while reducing failure through early identification and detection of the key factors that can lead to potential faults. As such, engineers and managers are empowered with the knowledge and know-how to make important decisions and policies. They can also be used to educate fellow researchers and the public about the advantages of various technologies.

Potential readers not working in the relevant fields can also appreciate the literature therein even without prior knowledge and exposure, and are still be able to apply the tool sets proposed therein to address industrial problems arising from evolving or even emerging behavior in networked systems or processes, e.g., sensor fusion, pattern recognition, and reliability studies, etc. The mathematical machineries proposed aim to analyze methodologies to make autonomous decisions that meet present and uncertain future needs quantitatively, without compromising the ad-hoc “add-on” flexibility of network-centered operations.

Many universities also have established programs and courses in this new field, with cross-faculty and inter-discipline research going on in this arena as well. As such, this book can also serve as a textbook for an intermediate to advanced module as part of control engineering, systems reliability, diagnosis and prognosis, etc. We also hope that the book is concise enough to be used for self-study, or as a recommended text, for a single advanced undergraduate or postgraduate module on intelligent diagnosis and prognosis, FDI, CBM, or SHM, etc.

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Chee Khiang Pang  
Frank L. Lewis  
Tong Heng Lee  
Zhao Yang Dong

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# Nomenclature

ADFI	Augmented Dominant Feature Identification
AE	Acoustic Emission
ARFIMA	AutoRegressive Fractionally Integrated Moving Average
ARIMA	AutoRegressive Integrated Moving Average
ARMAX	Auto-Regressive Moving-Average with eXogenous input/s
AVR	Automatic Voltage Regulator
BEP	Best Efficiency Point
BIBO	Bounded-Input-Bounded-Output
BU	Business Unit
C2	Command and Control
CAD	Computer-Aided Design
CAPEX	CAPital EXpenditure
CBM	Condition-Based Monitoring
CDF	Cumulative Distribution Function
CF	Characteristic Function
CNC	Computer Numerical Control
dRAM	disjunctive-input Resource Assignment Matrix
DAE	Differential and Algebraic Equation
DDFI	Decentralized Dominant Feature Identification
DEC	Discrete Event Control
DFI	Dominant Feature Identification
DSA	Dynamic Signal Analyzer
DSP	Digital Signal Processing
EA	Evolutionary Algorithm
ELS	Extended Least Squares
EPRI	Electric Power Research Institute
FACTS	Flexible Alternating Current Transmission Systems
FCS	Future Combat System
FDI	Fault Detection and Isolation
FEA	Finite Element Analysis
FEM	Finite Element Modeling
FFBD	Functional Flow Block Diagram
FFT	Fast Fourier Transform
GA	Genetic Algorithm
GHG	Green House Gas
HDD	Hard Disk Drive
HHT	Hilbert–Huang Transform
HMM	Hidden Markov Model
HTN	Hierarchical Task Network
HVDC	High-Voltage Direct Current
IM	Induction Motor
IPP	Independent Power Producer
ISO	Independent System Operator
JAUGS	Joint Architecture for Unmanned Ground System
KLT	Karhunen–Loève Transform

LCA	Life Cycle Assessment
LDV	Laser Doppler Vibrometer
LS	Least Squares
LSE	Least Square Error
LITP	Linear-In-The-Parameter
LTi	Linear Time-Invariant
MIMO	Multi-Input-Multi-Output
MPI	Modal Parametric Identification
MRE	Mean Relative Error
MRM	Multiple Regression Model
MSE	Mean Square Error
MTBF	Mean Time Between Failure
NN	Neural Network
OODA	Observe, Orient, Decide, and Act
OPEX	OPerations EXpense
OS	Overall Sensitivity
O&S	Operation and Support
PCA	Principal Component Analysis
PDA	Personal Digital Assistant
PDF	Probability Density Function
PFA	Principal Feature Analysis
PHM	Prognostic Health Management
PN	Petri Net
PSS	Power System Stabilizer
PZT	Lead-Zirconate-Titanate (Pb-Zr-Ti)
R&D	Research & Development
RAM	Resource Assignment Matrix
RBF	Radial Basis Function
RBS	Rule-Based System
RDM	Resource Dependency Matrix
RLS	Recursive Least Squares
RMS	Root Mean Square
RTO	Regional Transmission Organization
SD	Standard Deviation
SHM	Structural Health Monitoring
SISO	Single-Input-Single-Output
SNR	Signal-to-Noise Ratio
SoS	System-of-Systems
SVD	Singular Value Decomposition
TCM	Tool Condition Monitoring
TIA	Totally Integrated Automation
TOC	Total Ownership Cost
TPM	Technical Performance Metric
TRADOC	TRAIning and DOCTRine command
TSM	Task Sequencing Matrix
UAV	Unmanned Aerial Vehicle
UGS	Unattended Ground Sensor
UGV	Unmanned Ground Vehicle
VCM	Voice Coil Motor
WSN	Wireless Sensor Network
ZIP	Constant impedance (Z), current (I), and power (P)

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