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Dr. Dinkar Mylaraswamy is the Technology Fellow for condition-based maintenance within Honeywell’s Advanced Technology organization. His areas of expertise are fault diagnosis and process monitoring, modeling, and control. In his current role, Dr. Mylaraswamy is responsible for identifying and maturing strategic health management technologies that cut across multiple products and services, providing inputs for strategic technology investments, and mentoring.

Dr. Mylaraswamy joined Honeywell in 1997 after completing his Ph.D. from Purdue University. His Ph.D. thesis on blackboard-based architectures was adopted by the Abnormal Situation Management® Consortium as the basis of an operator tool for addressing the $16B loss suffered by the petrochemical industry from abnormal situations and equipment malfunctions. Dr. Mylaraswamy spent his first six years in Honeywell developing and deploying an Early Abnormal Event Detection application at six refinery sites in North America.

On the Aerospace side, he was the technical lead for Honeywell’s Predictive Trend Monitoring program, a web-based application for monitoring aircraft engines. He continues to serve as the technical lead on various health management programs—within Honeywell as well the U.S. Army, NASA, UK-MOD, and Navair—to support the Aerospace Services business within Honeywell.

As the Technology fellow, he routinely works with academic institutes and small businesses, seeking cutting-edge technologies to support the condition-based service business within Honeywell. Dr. Mylaraswamy has authored over 30 papers and holds 14 patents in the area of fault diagnosis and its applications.

Marcos E. Orchard
Dr. Marcos Orchard is associate professor with the department of electrical engineering at Universidad de Chile, associate researcher at the Advanced Mining Technology Center, and project leader at the Lithium Innovation Center. His research interest is the design, implementation, and testing of real-time frameworks for fault diagnosis and failure
prognosis, with applications to battery management systems, mining industry, and finance. His fields of expertise include statistical process monitoring, parametric/nonparametric modeling, and system identification. His research work at the Georgia Institute of Technology was the foundation of novel real-time fault diagnosis and failure prognosis approaches based on particle filtering algorithms. Orchard received a PhD and MS from The Georgia Institute of Technology, as well as a BS and a civil industrial engineering degree with electrical major from Catholic University of Chile. Dr. Orchard has published numerous papers in his areas of expertise.

**Michael Pecht**
Prof. Michael Pecht is a world-renowned expert in strategic planning, design, test, prognostics, IP, and risk assessment of electronic products and systems. In 2010, he received the IEEE Exceptional Technical Achievement Award for his innovations in the area of prognostics and systems health management. In 2008, he was awarded the highest reliability honor, the IEEE Reliability Society’s Lifetime Achievement Award. Prof. Pecht has an MS in Electrical Engineering and an MS and PhD in Engineering Mechanics from the University of Wisconsin at Madison. He is a Professional Engineer, an IEEE Fellow, an ASME Fellow, an SAE Fellow, and an IMAPS Fellow. He has previously received the European Micro and Nano-Reliability Award for outstanding contributions to reliability research, 3M Research Award for electronics packaging, and the IMAPS William D. Ashman Memorial Achievement Award for his contributions in electronics analysis. He served as chief editor of the IEEE Transactions on Reliability for eight years and on the advisory board of IEEE Spectrum. He is chief editor for Microelectronics Reliability and an associate editor for the IEEE Transactions on Components and Packaging Technology. He is the founder and Director of CALCE (Center for Advanced Life Cycle Engineering) at the University of Maryland, which is funded by over 150 of the world’s leading electronics companies at more than US$6M/year. The CALCE Center received the NSF Innovation Award in 2009. He is also a Visiting Professor in Electronics Engineering at City University of Hong Kong, and a Chair Professor in Mechanical Engineering and a Professor in Applied Mathematics at the University of Maryland. He has written more than twenty books on product reliability, development, use, and supply chain management and over 400 technical articles. He has also written a series of books on the electronics industry in China, Korea, Japan, and India. He consults for 22 international companies.

**Suresh Perinpanayagam**
Dr. Suresh Perinpanayagam is a lecturer at the IVHM Centre, Cranfield University. He leads the Electronic Systems’ Reliability, Prognostics and Health Management (ERPHM) Group at Cranfield University, in the UK. This group develops data-mining techniques for anomaly detection, diagnostics, prognostics, information fusion, predictive maintenance, and logistical support for electronic systems from the aerospace, rail, automotive, critical infrastructure, and renewable energy sectors. Suresh teaches the sensors and instrumentation module for several MSc courses at Cranfield University and has served in industry as a signal processing expert specializing in vehicle systems applications. He has an ME and PhD from Imperial
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Ravi Rajamani
Dr. Ravi Rajamani joined Meggitt in 2011 as an engineering director, after spending nearly 11 years with United Technologies Corporation, first at the Research Center, and then with its Pratt & Whitney division. Before this he was with GE for ten years. His primary focus has been in the area of controls and diagnostics of gas turbines for aerospace and industrial applications. Rajamani has a BTech (ME) from IIT Delhi, an MS (Automation) from IISc, Bangalore, and a PhD (EE) from the University of Minnesota. He also has an MBA from the University of Connecticut. He has published numerous papers in refereed journals and conference proceedings.

Karl Reichard
Dr. Reichard has over 25 years of experience in the design and development of advanced measurement, control, and monitoring systems. He received PhD, MS, and BS degrees in electrical engineering from the Virginia Polytechnic Institute and Virginia Tech. Dr. Reichard is a research associate with the Pennsylvania State University Applied Research Laboratory, and an assistant professor of acoustics with the Penn State graduate program in acoustics. His research experience includes the development of embedded and distributed sensing and control systems for machinery and system health monitoring, acoustic surveillance and detection, active noise and vibration control, and electro-optics. He is the author of numerous papers and articles published in journals and conference proceedings.

Michael J. Roemer
Michael J. Roemer is currently a Technical Fellow with Sikorsky Aircraft with over 20 years’ experience in the development of automated health monitoring, diagnostic, and prognostic systems for a wide range of military and commercial applications. He was previously the co-founder and Director of Engineering at Impact Technologies prior to its acquisition by Sikorsky/UTC. His experience includes a wide range of integrated vehicle health management system implementations to detect and predict system faults in real time and perform automated troubleshooting and maintenance planning. He has developed several diagnostic and prognostic capabilities utilizing technologies such as dynamic signature analysis, artificial intelligence, aero-thermal performance monitoring, finite element modeling, probabilistic remaining life analysis, and risk assessment methods. He is the co-founder and Vice President of the PHM Society, Chairman of the SAE HM-1 Integrated Vehicle Health Management Committee, board member and past Chairman of the Machinery Failure Prevention Technology (MFPT) Society, Prognostic Lead for the SAE E-32 Engine Condition Monitoring Committee, Member of the IGTI Marine Committee and ASME Controls and Diagnostics Committee, and Adjunct Professor of Mechanical Engineering at the Rochester Institute of Technology. He is the co-author of a recent book titled *Intelligent Fault Diagnosis and Prognosis for Engineering Systems* and has written or co-authored more
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Abhinav Saxena
Abhinav Saxena is a research scientist at the Prognostics Center of Excellence, NASA Ames Research Center. He has been involved in the field of IVHM since 2003 and has published numerous research articles in scientific journals, conference proceedings, and book chapters. His research focuses on developing and evaluating health management algorithms for various engineering systems. He also develops systems engineering processes and methods for verification and validation for health management systems. Mr. Saxena is chief editor of the *International Journal of Prognostics and Health Management*. He has a PhD in electrical and computer engineering from Georgia Institute of Technology. He earned his B.Tech. in 2001 from Indian Institute of Technology, Delhi, and his Masters degree in 2003 from Georgia Tech.

Tarapong Sreenuch
Dr. Tarapong Sreenuch is conducting research at the IVHM Centre at Cranfield University in the UK, focusing on projects related to software architecture and systems integration for IVHM systems. He has many years of experience in engineering software design and distributed systems. He is a lead developer at the IVHM Centre in design and development of IVHM-related data processes and software. Tarapong is an instructor in MSc in IVHM and MSc in autonomous vehicle dynamics and control at Cranfield University. He has published in many academic publications. He has a BEng in electronics and electrical engineering from the University of Surrey, and a PhD in control engineering from Cranfield University—Defence College of Management and Technology.

Ashok N. Srivastava
Ashok N. Srivastava, Ph.D. is the Project Manager for the System-Wide Safety and Assurance Technologies Project at NASA. He is formerly the Principal Investigator for the Integrated Vehicle Health Management research project at NASA. His current research focuses on the development of data mining algorithms for anomaly detection in massive data streams, kernel methods in machine learning, and text mining algorithms.

Dr. Srivastava is also the leader of the Intelligent Data Understanding group at NASA Ames Research Center. The group performs research and development of advanced machine learning and data mining algorithms in support of NASA missions. He performs data mining research in a number of areas in aviation safety and application domains such as earth sciences to study global climate processes and astrophysics to help characterize the large-scale structure of the universe.

Dr. Srivastava is the author of many research articles in data mining, machine learning, and text mining and has edited the book, *Text Mining: Classification, Clustering, and Applications* (with Mehran Sahami, 2009). He is currently editing two more books: *Advances in Machine Learning and Data Mining for Astronomy* (with Kamal Ali, Michael Way, and Jeff Scargle) and *Data Mining in Systems Health Management* (with Jiawei Han).
Dr. Srivastava has given seminars at numerous international conferences. He has a broad range of business experience including serving as Senior Consultant at IBM and Senior Director at Blue Martini Software. In these roles, he led engagements with numerous Fortune Global 500 companies including Bank of America, Chrysler Corporation, Saks 5th Avenue, Sprint, Chevron, and LG Semiconductor. He has won numerous awards including the IEEE Computer Society Technical Achievement Award for “pioneering work in Intelligent Information Systems,” the NASA Exceptional Achievement Medal for contributions to state-of-the-art data mining and analysis, the NASA Distinguished Performance Award, several NASA Group Achievement Awards, the IBM Golden Circle Award, and the Department of Education Merit Fellowship.

Kevin Swearingen
Kevin Swearingen has more than fifteen years of experience developing and integrating vehicle health management technologies in the research and technology division of the Boeing Company. Experience as principal investigator includes developing wireless sensor networking hardware for commercial aircraft, conducting maintenance effectiveness analysis for Army helicopters, sensor data interpretation algorithm development, and airborne parametric data management and analysis software production in support of health management. His expertise includes defining and implementing health management system architectures, data analysis, applications of intelligent software (fuzzy logic, neural network, expert rule-based, and Bayesian constructs), and aircraft hardware and software integration. Swearingen is a PhD candidate at the Missouri University of Science & Technology, and holds MS and BS degrees in electrical engineering from the University of Missouri. He is the author of over a dozen technical papers, conference presentations, and technical reports.

George Vachtsevanos
Dr. Vachtsevanos is serving as Chief Scientist at Impact Technologies and is Professor Emeritus at the Georgia Institute of Technology. He directs the Intelligent Control Systems Laboratory at Georgia Tech, where faculty and students are conducting interdisciplinary research in intelligent control, fault diagnosis, and failure prognosis of complex dynamic systems with emphasis on rotorcraft, and hierarchical/intelligent control of Unmanned Aerial Vehicles. His research in fault diagnosis and prognosis for condition-based maintenance began in 1984 with innovative fault detection and control technologies for the space station program. Under Office of Naval Research (ONR) sponsorship, he developed fault detection and fault-tolerant control systems for a turbojet engine. Jointly with Honeywell, he designed diagnostic and prognostic algorithms for shipboard machinery under ONR sponsorship. More recently, he has been an active participant in DARPA’s Prognosis Program, the Aging Aircraft Program, an Advanced Diagnostics Program for U.S. Army vehicles, a U.S. Navy program on Prognostic Enhancements to Diagnostic Systems, an Air Force Space Command Program for CBM Design of Ground Satellite Stations, and other industrial programs. He administers at Georgia Tech and on-site an intensive four-day short course on “Fault Diagnosis and Prognosis for Engineering Systems.” He has published over 350 technical papers.