GUEST EDITORIAL

Special Section: AI in Equipment Service

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This issue of ***AI**EDAM* focuses on AI in equipment service. Recently there has been a strong and renewed emphasis on AI technologies that can be used to monitor products and processes; detect incipient failures; identify possible faults (in various stages of development); determine preventive or corrective action; generate a cost-efficient repair plan and monitor its execution. This renewed emphasis stems from a focus of manufacturing companies on the service market where they hope to grow their market share by offering their customers novel and aggressive service contracts. This service market includes power generation equipment, aircraft engines, medical imaging systems, and locomotives, just to name a few. In some of these new service offerings the old parts and labor billing model is replaced by guaranteed uptime. This in turn places the motivation to maintain equipment in working order on the servicing company. Monitoring can be more efficiently accomplished, in part, by employing remotely monitored systems. Big strides have been taken for in-use monitoring of stationary equipment, such as manufacturing plants or high end appliances, and also mobile systems such as transportation systems (vehicles, aircraft, locomotives, etc). While advances in hardware development make it possible to perform these tasks efficiently, there are new avenues for progress in accompanying AI software techniques. Some of these approaches have their roots in efforts of years past while others arise from new challenges. Characteristics of typical challenges for AI in Monitoring and Diagnosis (M&D) service can be categorized into input, model, and output. In particular, input questions try to deal with real-time data streams resulting from on-line monitoring equipment. They are required to handle: throughput constraints; noise; non-stationary systems (due to linear drifts or chaotic behavior); erroneous data; data compression and information extraction. Process and product modeling tasks attempt to tackle issues involving non-stationary systems which require constant model update (adaptation, learning). In addition, the signature identification in time-series leading to fault detection and identification needs to be addressed. Moreover, the detection of new (unaccounted for) faults/anomalies/state changes has to be dealt with. Models obtained from first principles and from empirical data render different output which can be deterministic or qualified by confidence level, probabilities, and other type of semantics for uncertainty characterization (randomness, imprecision, vagueness, inaccuracy, inconsistency, incompleteness). These different outputs have to be aggregated into a coherent response. This special issue aims to address relevant AI technologies that address segmentation, classification, prediction, and decision making. The papers span the diagnostic cycle from design of a diagnostic system; to processing of textual information for diagnostic purposes; to sensor validation,fusion, and fault detection, to troubleshooting of complex systems, diagnostic information fusion, and fault prognostics.

The first paper by Dr. Piero Bonissone and Dr. Kai Goebel gives an overview of *Soft Computing for Diagnostics in Equipment Service*. It briefly introduces the core constituents of soft computing, describes some of the hybrid uses, and presents several industrial applications of soft computing for equipment diagnostics. The second paper by Burton Lee, *Using FMEA Models and Ontologies to Build Diagnostics Models*, delves into the interrelation of product design and diagnosis. Burton proposes a framework as a possible approach for improved integration of generalized design and diagnostic modeling. He instantiates the framework with a BBN based FMEA modeling approach and a standard Bayes network diagnostic modeling environment. Benoit Farley provides the third paper *Retrieving Information From Free-Text Aircraft Repair Notes*. He describes how natural language techniques are used to analyze the structure and contents of free-form maintenance notes to determine which equipment pieces were involved in the maintenance action and which maintenance action was performed. Benoit uses aircraft engines repair actions as his test bed. The next paper, *A Methodology for Intelligent Sensor Measurement Validation, Fusion, and Sensor Fault Detection for Equipment Monitoring and Diagnostics*, by Dr. Satnam Alag, Professor Alice Agogino, and Dr. Mahesh Morjaria describes how to deal with multiple sensors associated with complex machinery, in this case a gas turbine power plant. The authors show how a hybrid combination of AI and statistical techniques can be effective for monitoring and diagnostics through a sequence of steps: redundancy creation, state prediction, sensor measurement validation and fusion, and fault detection. Professor Finn Jensen, Uffe Kjaerulff, Brian Kristiansen, Helge Langseth, Claus Skaanning, Marta Vomlelova, and Jiri Vomlel present in their paper, *The SACSO Methodology for Troubleshooting Complex Systems*, describe the troubleshooting task of printers using Bayes Belief Networks (BBNs). They focus on how to obtain the best troubleshooting sequence for a given problem. Dr. Kai Goebel describes in his paper *Architecture and Design of a Diagnostic Information Fusion System* how to design a system that is tasked with aggregating the information from several diagnostic tools that are employed on an aircraft engine. Of particular interest for the fusion system is how to deal with conflict resolution, temporal discord and integration of information represented in different domains. Finally, Peng Wang and Professor George Vachtsevanos describe *Fault Prognostics Using Dynamic Wavelet Neural Networks*. Prognosis is at the heart of condition-based maintenance and the integration of temporal information in the forecast of remaining useful life is a fundamental step in this endeavor.

The papers in this special issue represent a well rounded snapshot of AI in equipment service which, from a larger viewpoint, represents classification tasks that are encountered in many other situations as well.