ORNL/CP-101277

CONTEXT-DEPENDENT PROGNOSTICS AND HEALTH ASSESSMENT: A CONDITION-BASED MAINTENANCE APPROACH THAT SUPPORTS MISSION COMPLIANCE

Glenn O. Allgood✧
Oak Ridge National Laboratory*
P.O. Box 2008
Oak Ridge, TN 37831-6007

Stephen W. Kercel
Oak Ridge National Laboratory
P.O. Box 2008
Oak Ridge, TN 37831-6011

Abstract: In today's manufacturing environment, plants, systems, and equipment are being asked to perform at levels not thought possible a decade ago. The intent is to improve process operations and equipment reliability, availability, and maintainability without costly upgrades. Of course these gains must be achieved without impacting operational performance. Downsizing is also taking its toll on operations. Loss of personnel, particularly those who represent the corporate history, is depleting US industries of their valuable experiential base which has been relied on so heavily in the past. These realizations are causing companies to rethink their condition-based maintenance policies by moving away from reacting to equipment problems to taking a proactive approach by anticipating needs based on market and customer requirements.

This paper describes a different approach to condition-based maintenance—context-dependent prognostics and health assessment. This diagnostic capability is developed around a context-dependent model that provides a capability to anticipate impending failures and determine machine performance over a protracted period of time. This prognostic capability links operational requirements to an economic performance model. In this context, a system may provide 100% operability with less than 100% functionality. This paradigm is used to facilitate optimal logistic supply and support.

Key Words: Anticipatory systems theory; Bayesian; Context-dependent prognostics and health assessment; Condition-based maintenance; Inductive learning.

Introduction: Condition-based maintenance (CBM) and prognostics have taken on a new meaning in the expanding area of machine reliability and maintainability (see Fig. 1) as a result of advancing technologies and new computational methods. It is no longer sufficient to rely solely on predictive or condition-based scheduling for servicing equipment and systems. As the need arises to maximize system performance (reliability and operational readiness) and reduce life cycle and operational costs, new methods and techniques in CBM must be developed. One such method developed by a team of

✧ Adjunct Professor at The University of Tennessee, Knoxville, TN, in the College of Engineering working for the Maintenance & Reliability Center

* Managed and Operated by Lockheed Martin Energy Research Corporation for the US Department of Energy under Contract DE-AC05-96OR22464

DISCLAIMER

DISCLAIMER

researchers at Oak Ridge National Laboratory is termed context-dependent prognostics and health assessment (CD-P&HA) and is based on anticipatory systems theory. Here, a context-dependent reasoning patterned after a biological paradigm is used to anticipate machine/system needs based on an operational economic model. This approach provides a methodology by which the system is serviced only when needed. These needs being established in terms of the overall system functionality and operational requirements as they relate to economic compliance and system health. Thus optimization is achieved through a hierarchy of command and control modules that support the enterprise operations from systems to components. This is a proactive approach for control that can also reduce inventory queues by projecting equipment and component needs over extended operational periods. This directly supports "just-in-time" equipment and parts delivery as well as optimal service and maintenance support.

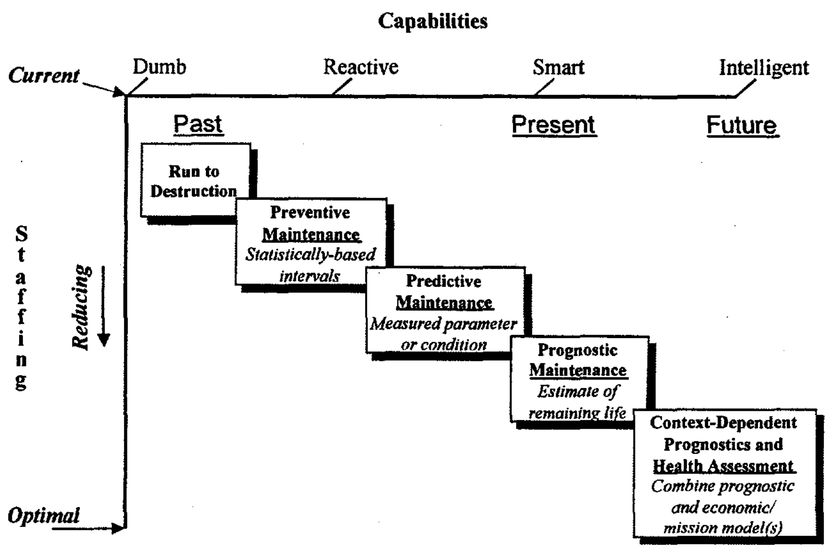

Fig 1. Context-dependent CBM—an evolution of thinking.

To facilitate CD-P&HA, a unifying principle has to be adopted that provides seamless integration of models, sensors, subsystems, and systems into existing infrastructures. As such, the system will have to support such capabilities as sensor driven analysis and self-validation, inductive learning, distributed database and control with inherent communication capabilities (for example: internal to the fault tolerance and self-validating systems and subsystems).

Technology innovations together with advanced computational methods is not capable of achieving the level of performance alluded to in the previous paragraphs. Emerging technologies alone cannot provide the level of support, interaction, or data abstraction necessary to optimize system performance and efficiency. A new approach is needed for asset management and that is CD-P&HA. This paper provides a brief overview of a CD-P&HA system and its application.

Developing a New CBM Paradigm—CD-P&HA: The CD-P&HA paradigm is a culmination of two research projects where each provided basic building blocks for the model. The first project was for the Department of Defense (DoD) and involved the development of a behavioral model to emulate a pilot's physiological response to flight simulator use. The problem was that pilots flying syllabus hops in flight simulators were becoming ill. Whereas, the same flight in an aircraft had no negative impact. What was needed was an effective means to qualify and quantify the level and extent of sickness a pilot would experience in the simulator. It was obvious that the graded mechanism that attends simulator use is related to a pilot's associative behavioral patterns; i.e., those learned traits that color our perception of the environment. A model was developed that provided >90% closure on the graded response.[1] A key factor in its success was the deployment of an anticipatory module that provided error judgments and accommodation (learning) that fed a situational awareness module used to mediate (economic goal) the pilot's activity. Figure 2 shows the block diagram for the model. The key was understanding that a human would change his/her activities in the simulator in anticipation of achieving a stated goal based on his/her perceived well-being and criticality of the mission.

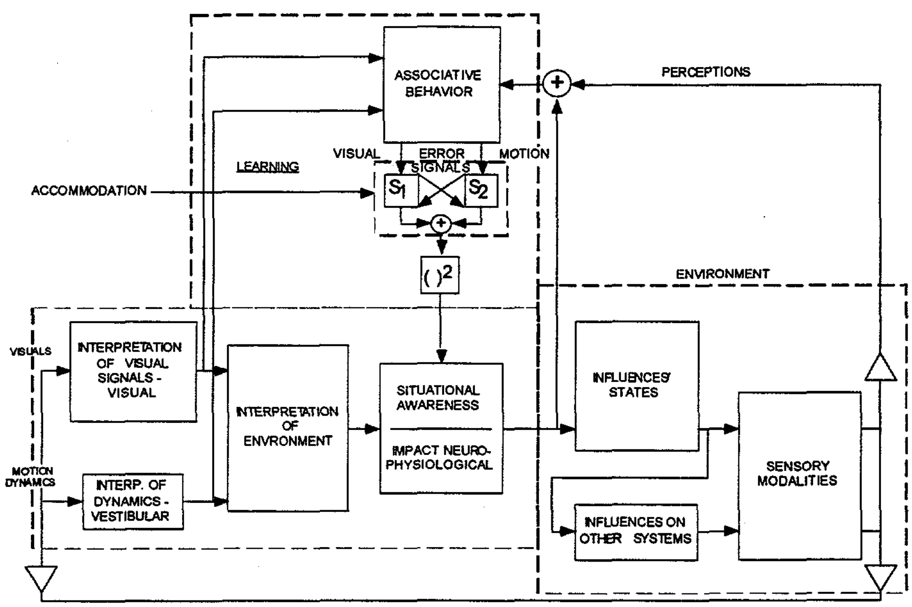

Fig. 2. Hypothesis for the whole-body absorption physiology model.

The second project was the Department of Energy's AMTEX^{TM} Computer-Aided Fabric Evaluation (CAFE) Project. The goal of this research was to identify and insert into the textile manufacturing infrastructure economically-viable technologies that met certain operational and functional performance measures. The performance metrics came as a result of a cost study performed early in the project to determine which technologies could enhance plant operations and profitability. In this study, the health of a weaving machine was identified as one of the major contributors to off-quality products. Thus, a need was established for a cost-effective diagnostic system that could anticipate the maintenance needs of a loom based on customer requirements, raw material supply, inventory and resource allocations, and market draw. This novel, time-managed diagnostics could only be achieved through the deployment of CD-P&HA. Figure 3 shows the basic structure of the system with its associated data flow (feature vectors). As shown, at the heart of the model/method is the CD-P&HA module (model-based – inductive reasoning) that anticipated needs based on market draw (economic compliance), inventory, and process health.

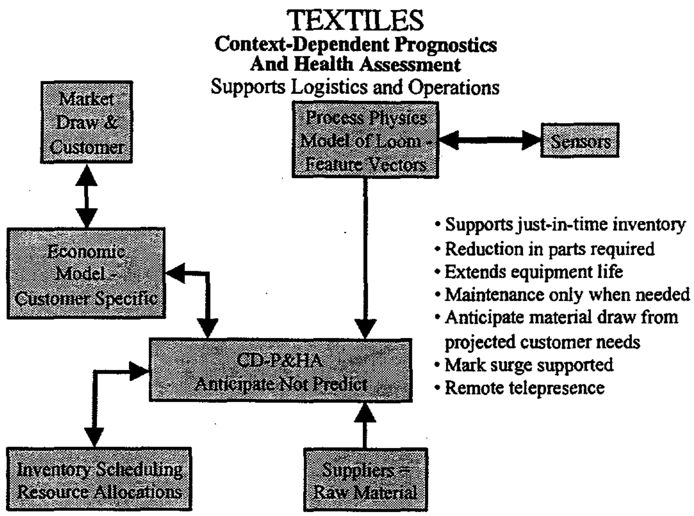

Fig. 3. CD-P&HA applied to the textile industry.

By applying the context-dependent model based on anticipatory precepts, a system was developed that would anticipate impending failures and thus, manage a machine health care program over a protracted period of time based on customer needs and requirements. By adding a performance model that responds to machine health (which provides the necessary functional relationship between the individual machines/systems and the customer requirements and the collective economic impact on the plant), a decision support system was deployed that provides optimal (100%) operability while functioning at less than 100%. Extending this concept to repairs and maintenance provided additional benefits through reduced inventory and an approach for just-in-time inventory control. By making semantic changes to the textile model and integrating the accommodation and reasoning elements of the DoD behavioral model, a general CD-P&HA model was developed that could be used in a manufacturing environment (see Fig. 4). This concept has recently been deployed in a flow loop to sense impending cavitation (i.e., anticipate impending cavitation for the purpose of flow control).[2]

The general CD-P&HA would incorporate a series of nested models (decision support modules, economic, inductive learning, process physics, etc.) (see Fig. 5). The kernel consists of a physical model integrated with the process physics model. This provides the basic physical attributes necessary to determine if the problem is associated with the component (corrosion, fatigue, etc.) or if it is originating from improper use or from the process itself. The economic and inductive reasoning model (anticipatory system) reside at the next level. The economic model gathers knowledge about the process/system health and maps that engine and operational model (economics) which determines resource requirements and allocates them based on current use and contingencies estimated from the mission-dependent closed loop. The context-dependent module makes final recommendations and operational projections across single and multiple missions identifying critical components (short- or near-term failures) and components flagged for incipient failures (future). The key to the model is the anticipatory module, which mediates control decisions and prioritizes tasks through learned expectations.

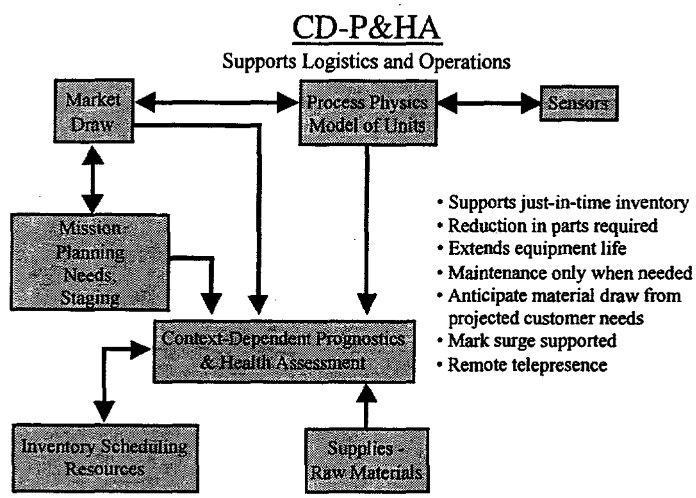

Fig. 4. CD-P&HA System that supports logistics and operations.

Anticipatory Systems: Does the idea of computational emulation of the biological process of anticipating actually provide a practical basis for a novel approach to extracting meaning from data? Recent research by Landauer and Bellman suggests that, in principle it does.[3] Biological systems process signs and symbols to gain awareness of their environment and their processing skill improves with experience. They commonly use the data inferred from these symbols to perform classification and grouping and *they do not do so by identifying boundaries between classes*. The way that biological systems perform classification suggests that there exists a semiotic unifying principle of classification that is applicable to computational systems.[4]

Landauer and Bellman define semiotics as "the study of the appearance (visual or otherwise), meaning, and use of symbols and symbol systems." From their examination of classification by biological systems, they conclude that it would require a radical shift in how symbols are represented in computers to emulate the biological classification process in hardware. However, they argue that semiotic theory should provide the theoretical basis for just such a radical shift. Landauer and Bellman do not claim to have discovered the unifying semiotic principle of pattern-recognition, but they suggest that it must be inductive in character.[5]

Indeed, the development of a unified inductive-learning model is the key to artificial intelligence.[6,7] Induction is defined as a mode of reasoning that increases the information content of a given body of data. The application to pattern-recognition in general is obvious. An inductive pattern recognizer would learn the common characterizing attributes of all (possibly infinitely many) members of a class from observation of a finite (preferably small) set of samples from the class and a finite set of samples not from the class. The problem arises due to the fact that commonly used "learning" paradigms (neural nets, nearest neighbor algorithms, etc.) are based on identifying boundaries between classes and do not directly support inductive learning.

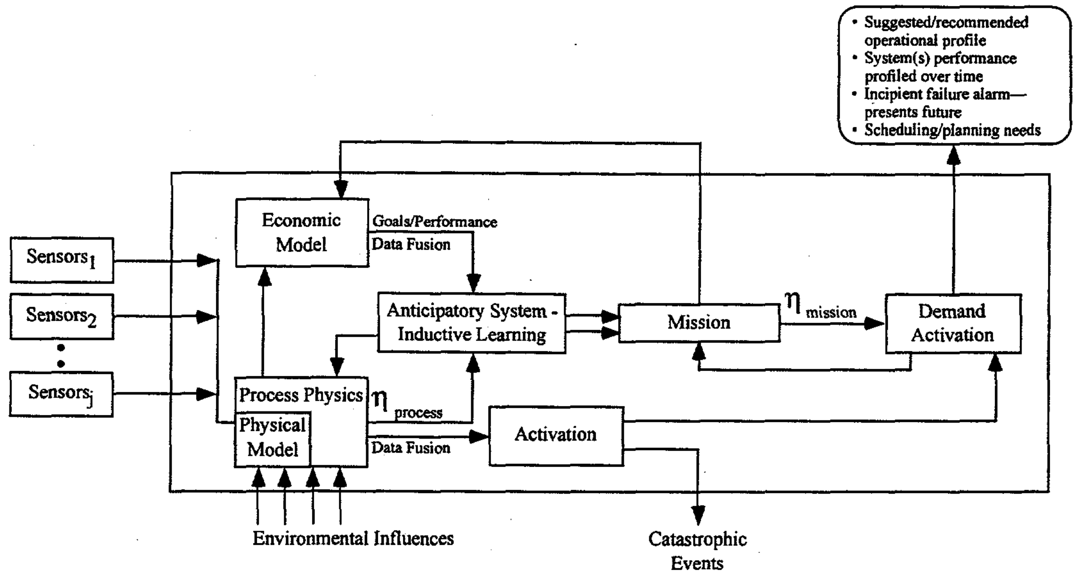

Fig. 5. Context-Dependent Prognostic System. The premise is to provide maintenance *only when the union of economics and process dynamics requires it.*

How then should induction be performed? The leading thinkers in machine intelligence believe it should somehow emulate the process used in biological systems. That process appears to be model-based. Rosen provides an explanation for anticipatory behavior of biological systems in terms of interacting models.

Rosen shows that traditional reductionist modeling does not provide simple explanations for complex behavior. What seems to be complex behavior in such models is in fact an artifact of extrapolating the model outside its effective range. Genuine complex behavior must be described by anticipatory modeling. In Rosen's own words: "In particular, complex systems may contain subsystems which act as predictive models of themselves and/or their environments, whose predictions regarding future behaviors can be utilized for modulation of present change of state. Systems of this type act in a truly anticipatory fashion and possess many novel properties whose properties have never been explored." In other words, genuine complexity is characterized by anticipation.[8]

Rosen defines a formal anticipatory system (AS) (a mathematical formulation that exhibits anticipatory behavior) as having five attributes. An AS, S_2, must contain the model, M, of another system, S_1. The AS, S_2, must contain a set of observable quantities that can be linked mathematically to S_1 and an orthogonal set that cannot. The predictions of the model, M, can cause an observable change in S_2. There must be some observable difference in the interaction between S_1 and S_2 when the model is present and when it is not. Finally, M must be predictive; based on present knowledge, M must change state faster than S_1, such that M's changed state constitutes a prediction about S_1. The point of this discussion is that intelligent behavior is model-based and in the absence of models, there is no intelligent behavior. More to the point, these models must bear some resemblance to physical reality if the behavior of the intelligent system is to have utility in the real world.[9]

What is the best way to obtain the models required for AS? The simple answer is to observe reality to a finite extent and then to generalize from the observations. To do so is inherently to add information to the data or to perform an induction. It requires the generation of a likely principle based on incomplete information and the principle may later be improved in the light of increasing knowledge. Where several possible models might achieve a desired goal, the best choice is driven by the relative economy of different models in reaching the goal.

How might this be done in practice with noisy data? The most powerful method is Bayesian parameter estimation.[10] Bayesian drops irrelevant parameters without loss of precision in describing relevant parameters. It fully exploits prior knowledge. Most important, the computation of the most probable values of a parameter set incidentally includes the measure of the probability. That is, the calculation produces an estimate of its own goodness. By comparing the goodness of alternative models, the best available description of the underlying reality is obtained. This is the optimal method of obtaining a model from experimental data, or of predicting the occurrence of future events given knowledge from the past, and of improving the prediction of the future as knowledge of the past improves.[11] Bayesian parameter estimation is a straightforward method of induction.

Establish a Unifying Integration Principle for the System: The CD-P&HA System architecture was specially designed to observe data and information flow over a wide geographical area (see Fig. 6). The term *wide geographical area* is interpreted as a widely dispersed array of elements, sensors, subsystems, and systems onboard platforms and personnel and located in operating environments and bases, containing distributed data and information. The architecture is comprised of a hardware and software system that provides users information (abstracted data in the form of feature vectors) necessary to make critical decisions with respect to operational readiness and survivability. The architecture includes industry-standard interfaces and protocols (IEEE 1451) with specifically designed object-oriented data structures that allow hardware-independent communication among the nodes in the enterprise network.

The object definitions define the information content of the measurement or control variables. Using information extracted from intelligent sensors reduces the requirements for communication bandwidth, user interface, and data storage. Each layer in the information architecture adds value by integrating, processing, and analyzing the data based on information available at that layer. The user receives information from the system according to object definitions. Allowing more of the abstracted data to pass higher in the architecture accommodates requests for detailed information concerning diagnostics or troubleshooting. Incorporating information from existing databases or components becomes a simple matter of providing an interface module that packages the data into the object data structure.

The architecture embraces an embedded-system concept. This provides the best cost structure for early deployment of sensor/subsystems, rapid prototyping, general platform for all sensors and sensor groups, seamless integration, and a straightforward migration path to a commercially available system. This is especially important in light of recent improvements in the capability to download diagnostic/model routines into digital signal processors (DSPs) and field programmable gate arrays (FPGAs).[12] A logical extension of the embedded system is micro-electro-mechanical systems (MEMS) and thin-film. These systems offer the opportunity for major improvements in near, real-time measurements of the operating environment and conditions affecting component/system integrity.

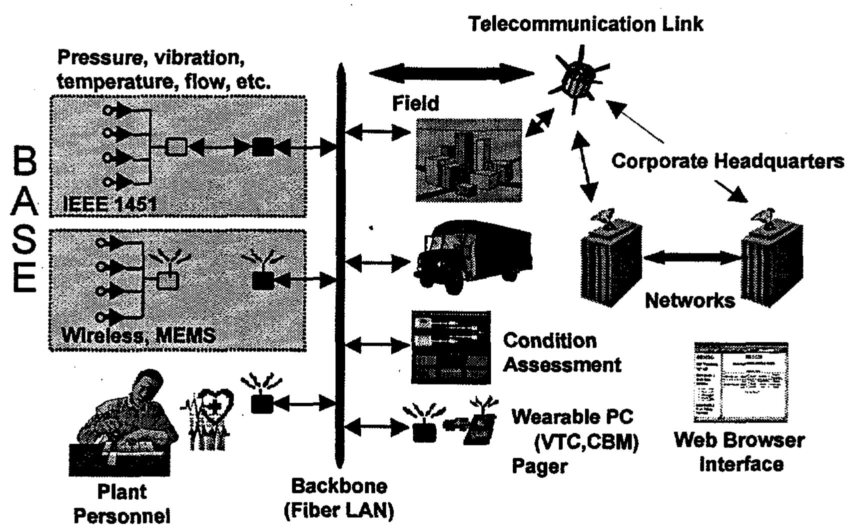

Fig. 6. Dispersed architecture that can observe data over a wide geographical area.

Methodology and Approach for Developing Causal Relationships: The methodology for developing a CD-P&HA System is described below. Its significance is that the process logically builds upon itself and maintains a series of checks and balances.

Baseline Feature Descriptors. In order to define the composition of the CD-P&HA System, it is necessary to describe in detail the operational profile of any candidate system and/or process. This will require the development of feature vectors (operational descriptors) that provide the base-case system identifiers from which operational modes are categorized. Feature vectors are elements that encompass those assigned attributes that characterize a particular system/process and are based on physics and cognitive reasoning. The uniqueness of a feature vector is that it becomes the knowledge for developing intelligent sensors and provides the necessary information for abstracting reasoning. These objects define the information content of a process, fusing measured quantities and variable, human perception and intuition, and influences developed through associative and non-associative reasoning. Once developed, these feature vectors become the protocols invoked for identifying and characterizing current operational states and transition projections in the operational state.

To achieve this, a set of operational descriptors is developed. This requires defining a system's operating profiles and developing data structures as a metaphor for a system's operating signatures. The normal operating modes of the system will be defined in terms of feature vectors and the transition between.

Design and Development of the Monitoring Sensor Suite. Using the feature descriptors, the functional description and requirements document (FD/RD) for each particular system is developed. The FD/RD is based on the process's operational requirements and will detail physical measurements that need to be made (i.e., the set of observable parameters). The sensor suite definitions will come from the physical measurement description. Once the sensor suites have been properly defined in terms of the observables, they will be mapped onto physical sensor capabilities to define the baseline sensor configuration.

Off-operational Feature Descriptors. Once the baseline operational descriptors for the process have been developed, it will then be necessary to develop the off-operational mode descriptors that coincide with degradation and failures of each particular component and element that make up the system. This requires developing procedures by which off-performance and degraded operations in the system can be recorded and analyzed within intelligent sensor/system and enterprise system as a function of a feature vector and mapped as transition points in a Markov process, as an example. In this approach, the parameters for each component/element will be partitioned and sets determined that span a system's operating profile based on mission requirements.

Context-dependent Algorithms. Once the component/element feature vectors and Markov chains are developed, they are integrated into a cohesive, seamless data structure for inclusion into the monitoring system. This provides the mechanism by which the CD-P&HA system is able to discern operating excursions, make quantitative, as well as qualitative judgments about the changes, anticipate needs based on context reasoning, and issue commands and status flags in relation to the global needs. The decisions will be based on the process/system economic model, mission profile, operational constraints, and environmental influences. This step will require cooperation with the enterprise system.

The approach described above has an added benefit. The feature vectors, FD/RD, operational characteristics, cause-and-effect matrix, and system relationship can provide a framework from which embedded training systems and simulators can be developed.

Conclusion: The competition for the US and world market shares will demand that companies embrace new technologies and operational methods in order to keep business prospering in the 21st century. These new business practices will require a holistic view that not only addresses process improvements but also their impact on the enterprise (i.e., operating and support, life-cycle cost, maintenance, inventory scheduling and control, etc.). CD-P&HA has the potential to achieve this. It has been shown in two cases (textiles and flow loop) that this approach is not only feasible but also improves process and enterprise efficiency.

References:

[1] G. O. Allgood, “Development of a Neural Net Paradigm That Predicts Simulator Sickness,” Ph.D. Dissertation, 1991.

[2] G. O. Allgood, S. W. Kercel, W. B. Dress, Jr., “Developing a CD-CBM Anticipatory Approach for Cavitation—Defining a Model-based Descriptor Consistent Across Processes,” Phase I Final Report for SBIR N98-114, November 1998.

[3] C. Landauer and K. L. Bellman, “Semiotics of Constructed Complex Systems,” in *Intelligent Systems: A Semiotic Perspective*, J. Albus, A. Meystel, and R. Quintero, Organizers, pp. 35-40, National Institute of Standards and Technology, Gaithersburg, MD, 1996.

[4] C. Landauer, “Constructing Autonomous Software Systems,” *Workshop on Biologically Inspired Autonomous Systems: Computation, Cognition, and Action*, Durham, NC, March 4-5, 1996.

[5] K. L. Bellman, “When Intelligence is in Control,” in *Intelligent Systems: A Semiotic Perspective*, J. Albus, A. Meystel, and R. Quintero, Organizers, pp. 10-11, National Institute of Standards and Technology, Gaithersburg, MD, 1996.

[6] L. Goldfarb and S. Nigam, “The Unified Learning Paradigm: A Foundation for AI,” in *Artificial Intelligence and Neural Networks: Steps Toward Principled Integration*, V. Honovar and L. Uhr, Editors, Academic Press, Boston, 1994.

[7] L. Goldfarb, “Inductive class representation and its central role in pattern recognition,” in *Intelligent Systems: A Semiotic Perspective*, J. Albus, A. Meystel, and R. Quintero, Organizers, pp. 53-58, National Institute of Standards and Technology, Gaithersburg, MD, 1996.

[8] R. Rosen, “Some Epistemological Issues in Physics and Biology,” in *Quantum Implications Essays in Honour of David Bohm*, Edited by B. J. Hiley and F. D. Peat, Routledge and Kegan Paul, London, pp. 314-327, 1987.

[9] R. Rosen, *Anticipatory Systems: Philosophical, Mathematical, and Methodological Foundations*, Pergammon Press, Oxford, 1985.

[10] L. Bretthorst, *Bayesian Spectrum Analysis and Parameter Estimation*, pp. 1-5, Springer-Verlag, Berlin, 1988.

[11] E. T. Jaynes, “Generalized Scattering,” in *Maximum-Entropy and Bayesian Methods in Inverse Problems*, C. R Smith and W. T. Grandy, Editors, pp. 377-398, D. Reidel Publishing Co., Holland, 1985.

[12] Mango Computers Inc., 83 East Avenue, Norwalk, CT 06851, http://www.mangocom.com.