COMPONENT LEVEL HEALTH MONITORING IN FUTURE SHIPBOARD DISTRIBUTED CONTROL SYSTEMS

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Abstract – **Future Navy warships will have high demands for electric power to support electric drive propulsion, high-energy weapon systems, electrical auxiliary systems, and network centric warfare. The future ship Integrated Power System (IPS) will be vital to reliable operations and survivability. Power distribution will involve delivering electric power from multiple generation sources to a dynamic set of load devices whose priority and criticality will vary in real-time with battle/mission situations. These systems will be required to rapidly distinguish between normal and casualty transients, dynamically reconfiguring power distribution under failure conditions to meet changing load priorities. Control system complexity, adaptation timing, and manning constraints necessitate a shift of control functions from human operators to intelligent automatic control systems. Advanced capabilities, such as self-healing reconfiguration of system function and connectivity, will only be possible if system level knowledge of component failures is available under failure mode conditions. Diagnostic and prognostic coverage for system components will be essential for achieving survivability/reliability goals. Component level intelligence, manifested as device-embedded diagnostic and prognostic "software agents", can provide health status reports covering sensors, components, subsystems, and all other mission-critical equipment.**

This paper examines IPS diagnostic requirements and emerging technologies available for insertion into future ship integrated power systems.

Index Terms – **All-electric ship, integrated power systems, diagnostics, prognostics, knowledge management, intelligent software agents, health monitoring, distributed intelligence, component level intelligence.**

I. INTRODUCTION

Future Navy warships will have high demands for electric power to support electric drive propulsion, high-energy weapon systems, electrical auxiliary systems, and network centric warfare. Everything aboard the all-electric ship, from sensors, pumps, motors, advanced weapon systems to computer networks, will depend on electric power. The power distribution network will be vital to reliable operations and survivability. Power distribution will involve delivering electric power from multiple generation sources to a dynamic set of load devices whose priority and criticality will vary in real-time with battle/mission situations. High-speed, solid state switches coupled with advanced power electronics, intelligent controllers, and a communications infrastructure will form a power distribution network fed from multiple generation sources, much like the domestic electric utility power grid. Multiple electric generation and storage devices can be distributed throughout the ship, eliminating dependence on any single power source through dynamic load management and power grid connectivity.

The future ship Integrated Power System (IPS) will be comprised of advanced power electronics, including inverters, rectifiers, and converters. The IPS will be a critical aspect of survivability during major disruptions from battle damage and equipment failures. These systems must rapidly distinguish between normal and casualty transients, dynamically reconfiguring power distribution under failure conditions to meet changing load priorities. The IPS control architecture will be complex, and must be capable of supporting the reconfiguration of the power electronics functionality and network topology based on real-time mission needs. Control system complexity, timing, and manning constraints necessitate a shift of control functions from human operators to intelligent machines. Future power and automation system requirements must support [1]:

1) Reduction of shipboard manpower by 75-90%,
2) Automated situation assessment and casualty response,
3) Robust, survivable control architecture that combines hierarchical structure with distributed, component level intelligence.

From an operational standpoint, embedded diagnostics will be essential to the continuous functioning of future control systems. Intelligent reconfiguration of system function and connectivity will require information on component failures in order to derive satisfactory solutions for power management. Component level intelligence, manifested as embedded diagnostic and prognostic "software agents", can provide health status reports covering sensors, components, subsystems, and all other mission-critical equipment. Existing industrial automation technologies provide a cost-effective way to build a dependable, pervasive computing infrastructure that connects IPS supervisory control functions to the embedded, component level software agents.

From a life-cycle management standpoint, these systems must be economically supportable throughout a 40-50 year life cycle. Their increasing complexity necessitates that equipment manufacturers supply embedded diagnostic intelligence with their devices. New diagnostic engineering paradigms are required to manage and extract maximum value from diagnostic knowledge.

II. EVOLVING INTEGRATED POWER SYSTEM TECHNOLOGIES

A. Power Electronics

A comparison of existing mechanical propulsion and electric power systems to an Integrated Power System (IPS) design is given in [2]. Figure 1 illustrates a zonal architecture designed to control electrical fault propagation by isolating each electrical zone from others, thereby containing any voltage transients within each zone. The ability to contain fault propagation and to intelligently redistribute power dynamically will provide greater design margins and enhance survivability. More complex IPS designs containing far many more power electronic components than illustrated in figure 1 will emerge as “plug-and play” power electronic devices, such as Power Electronic Building Blocks (PEBBs) [3] become more heavily used.

In parallel to the power electronics hardware evolution, advancements in control software are also occurring at a rapid pace. Distributed, modular and open control architectures [4] promise to reduce the design time, development cost, and ongoing software sustainment costs associated with evolving IPS control systems. An open systems strategy employs modular design and defines key interfaces using widely supported standards, where they exist. Traditionally, control software has been closely coupled to the hardware and has been difficult to design and maintain. Open control software architectures that emphasize modularity by encapsulating standard control algorithms into reusable code modules will allow faster development and less costly system maintenance.

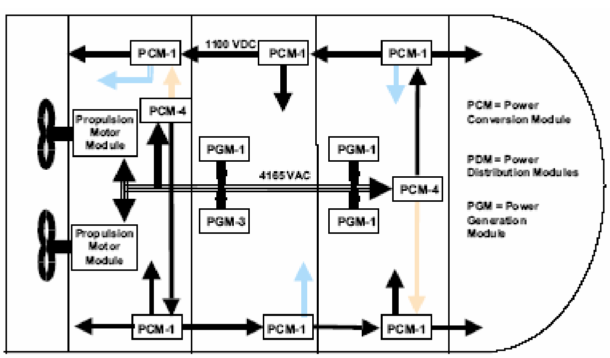

Figure 1 – Zonal IPS Architecture [2]

Large savings in engineering time and cost can be realized if a universal controller [5] is available for evolving standard power electronic devices (PEBBs). A universal controller is typically a multi-function controller board designed to control and reconfigure PEBBs. Based on an open architecture environment, these controllers could be rapidly configured and deployed in scalable, multiprocessor configurations that match the power application. Connectivity of these controllers to supervisory data networks will facilitate higher-level control functions, such as diagnostics and reconfiguration over standard control communications interfaces, such as ControlNet, DeviceNet, LonTalk, etc.

A pervasive controller computing environment will be made possible by messaging protocols that allow control tasks to be distributed across multiple processors on the control network [6]. This capability may allow future control systems to automatically configure themselves for execution on any number of processors, while allocating software control objects to different controllers as may become necessary. This will be an extremely useful capability with respect to creating a fault tolerant environment, whereby a failed node’s control functions may be redeployed across functioning control processors.

Commercial versions of PEBB devices and modular universal controllers optimized for power electronics are available for configuring high-performance integrated power systems [7]. This technology provides high-speed control performance, standard data communications connectivity, and modular I/O, along with a mature suite of software development tools.

B. Reconfigurable Control Systems

Research on software reconfiguration techniques to support self-healing, survivable control networks has been accelerating. Automatic reconfiguration of the shipboard IPS is essential for future survivability requirements. Existing shipboard control systems are not effective in isolating faults and are highly dependent on human intervention. System complexity, timing constraints, and manning reductions necessitate that power restoration through reconfiguration be performed automatically by the IPS control system. Various approaches have been proposed for implementing the required control. A hierarchical system has been suggested that separates high level supervisory and coordination functions from low level safety critical functions [2]. In this approach, the low level or “component level” control would be collocated or embedded within the system devices being controlled. Through interfaces to all critical damage control sensing and response systems, these component level controllers would be somewhat autonomous, not relying on external support or data in order to carry out their intended functions. System faults and failures outside the scope of the component level control would not affect these controllers.

Physical separation of these low level controllers would also serve to enhance survivability. High level supervisory control functions would be carried out at different levels within the hierarchy, with component level controllers within an electrical zone perhaps coordinating with a zone level controller, which, in turn, may coordinate with higher level controllers. Information inputs on mission priorities and plans could to be factored into lower level control algorithms through the appropriate communications channels.

Following a strategy of localized, embedded control within a hierarchical power control network, one can immediately predict that a very large number of these controllers will be necessary for the future all-electric ship. While current research has focused on this distributed intelligence approach, issues of scalability, as well as maintainability, have yet to be adequately addressed. Scalability of similar distributed domestic electric power networks is discussed in [8]. An increasing number of distributed energy resources are augmenting an electric power grid that was once characterized by a relatively few large generation centers. The control and information infrastructure will involve thousands to tens of thousands of distributed generation nodes, instead of just a handful of large utilities. To a large extent, this evolving distributed power network has been made possible by the same power electronics technologies being used in advanced shipboard IPS designs. Power electronics provide for reactive power generation and compensation, power flow control, harmonic compensation, voltage and frequency regulation/control, and real-time switching [8].

C. Intelligent Software Agents

The reconfiguration problem for the all-electric ship IPS can be decomposed into two complex subproblems:

1) detection and localization of multiple system faults, which are likely to occur simultaneously during battle damage, and
2) real-time reconfiguration of the power network.

A multiple software agent paradigm has been outlined as an ideal way to control these large, distributed power networks for high reliability, power quality, and efficient power generation. Multi-agent techniques have been successfully applied to various distributed problem solving, information fusion, computing applications. In addition to localized data processing and computation, reported advantages include scalability, since once an agent's standard data processing, collaboration, and communication functions have been defined, additional agents can be deployed as needed when new equipment is added to an existing configuration.

The case for distributed machine intelligence and decentralized ship system architectures for survivability is presented in [9], which also proposes intelligent software agents as a generic deployment model to control and reconfigure all major ship systems, including power, propulsion, fluid systems, fire suppression, etc. As increases in processing power and advances in control theory make modern controllers more capable, the expected complexity of ships systems will likely increase exponentially in next generation ships. Future ship systems will be comprised of tens of thousands of connect components. Autonomous control appears to be one of the few options available for dealing with an enormous number of possible equipment states. Intelligent, autonomous control has the capability to address large complex systems, but survivability can only be supported by distributing this intelligent control to varying levels of granularity throughout the ship-wide control network. A common theme throughout most recent research is to create component level intelligence by embedding separate device controllers into the devices themselves. Fault diagnostics and reconfiguration control can be performed at the device level. Software agent technology [10, 11] can be used to implement distributed machine intelligence and allow collaborative control during reconfiguration situations. Diagnostics can be performed within the embedded agent intelligence on each device. Health status information can then be propagated over the control network to facilitate system level, real-time, dynamic control. Several researchers are following this development strategy [12, 13].

Figure 2 depicts a conceptual view of sensor data flow and diagnostic processing for a generic diagnostic agent [14]. As indicated, various software components are remotely upgradeable. This architecture can be applied across a range of device complexity. For example, at the simplest level, it can be applied for sensor diagnostics. While historically being deployed primarily for complex devices, such as diesel and gas turbine engines, the underlying diagnostic technology is applicable to any electro-mechanical device and is extensible to large-scale systems. The design also accommodates the implementation of component-level intelligence, as it is amenable to chip-level deployment and provides standard interfaces for reporting device health status.

Referring to figure 2, ***real-time data*** is input to the diagnostic module and is used for both model estimation and residual generation. Sensor inputs can be acquired directly through internal electrical interfaces of the diagnostic module or be obtained via data communications interfaces with existing plant automation (e.g. Ethernet, wireless, etc.).

Model-based diagnostics rely on some type of model for the device under diagnosis. For key diagnostic or performance parameters, the *device model* is used to derive expected device outputs ($\hat{Y}$) from other salient device measurements. The estimated output is then compared to actual device measurements (Y). The difference between expected and measured outputs forms a residual which is key to detecting anomalous device behavior.

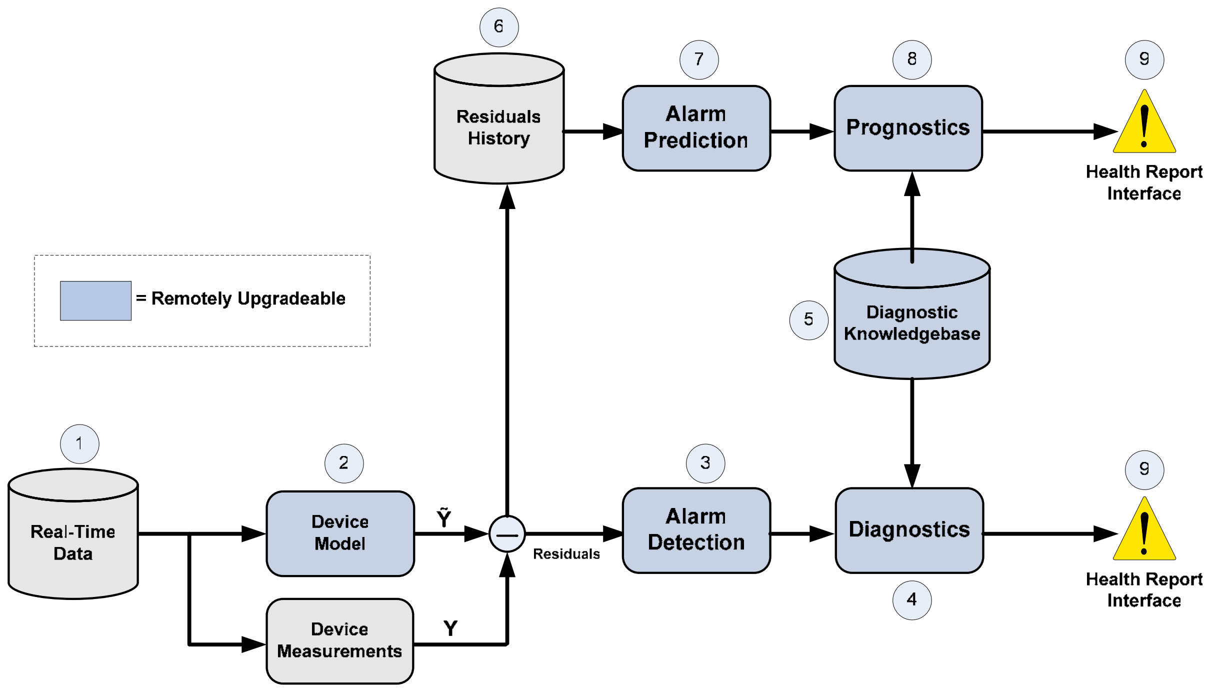

Figure 2 - Diagnostic/Prognostic Software Agent Data Processing

The ***alarm detection*** process detects anomalous conditions for the device. The distribution of residuals for healthy devices is statistically quantified. If the device model accurately reflects the device's behavior, the residuals can be represented by a zero-mean Gaussian process with known variance. Instantaneous residual values exceeding statistically derived confidence regions are classified as anomalous and, along with other similarly classified alarms associated with other device parameters, are input to a diagnostic reasoner for interpretation.

The ***diagnostic reasoner*** performs pattern recognition based on internal representations of diagnostic knowledge acquired from pre-training with the diagnostic knowledgebase. Advanced pattern recognition, neural network algorithms are applied to associate detected residual alarm conditions with known fault conditions *(discussed further in sections E)*. This technique is fast, memory efficient, capable of real-time performance, and produces Bayesian probability estimates based on the quality of match between stored diagnostic knowledge and detected alarm conditions.

The ***diagnostic knowledgebase*** maintains the essential associations between fault conditions and expected alarm conditions. This knowledge can be acquired from a variety of sources, such as device manufacturer or other experts, failure experiments on the actual device, computer simulation experiments, historical customer trouble call or maintenance records, etc. This knowledge is typically derived through a failure mode and effects analysis on the device.

Fault predictions (prognostics) are based on the ***residuals history***. This function manages recording and maintenance of the historical data store. System configuration settings are used to control history length/memory and these are dictated by the prediction horizon of the prognostic (i.e. how far ahead one wishes to predict faults). Prognostic schemes have been developed to predict across multiple prediction horizons (e.g. short, medium, and long-term prediction) using varying time resolutions of residual histories.

Alarm prediction involves quantifying the trends in device residuals over time and using detected trends to predict future alarm conditions. This function analyzes the residuals history through statistical trending techniques to determine if any significant trends are occurring. A residuals trend indicates a discrepancy between the device's actual behavior and its model estimate. These trends are early indicators of an anomaly, either in the device itself or one of its sensors. This function uses the same attributes of the residuals statistical distribution as the alarm detection function to determine if and when a device alarm condition will occur within the prediction horizon.

The ***prognostics*** function performs similarly to the diagnostics function, but inputs predicted alarms instead of current alarms. It relies on the same diagnostic knowledgebase and pattern recognition function as diagnostics, but outputs predicted device faults based on detected trends in its residuals. Trends can also be used to determine remaining time until predicted alarm occurrence. This important information can be relayed to controllers in advance of an equipment failure to avoid disruptions of service, thus improving reliability, mission readiness, and platform availability. While the diagnostics function is more concerned with restoration of service, the prognostic function addresses avoidance of loss of service.

The ***health report interface*** is a standard mechanism for passing diagnostic and prognostic information to other software, such as controllers, as well as other systems such as maintenance management systems, etc.

The agent software is designed to allow remote upgrades to embedded device diagnostic intelligence throughout the ship's life cycle. The blue-shaded components of figure 2 (circles 2, 3, 4, 5, 7, 8) are specifically designed for remote upgrading. To avoid product obsolescence, embedded diagnostic knowledge must be kept current and as accurate as possible. Diagnostic knowledge management is a critical supporting technology and updating onboard intelligence with new experiential knowledge accumulated over time will be required throughout the ship's life cycle. Remote upgrading will also minimize long-term technical support/service costs.

D. Sensor Diagnostics

Sensor diagnostics represents one of the most important and least addressed issues on existing ships. Sensor instrumentation will have elevated importance for higher-level automation and control functions. Sensor accuracy must be qualified as valid prior to executing certain automated control functions. Sensor validation remains an arduous task based on the increasing volume of sensor measurements and the lack of physical sensor redundancy aboard typical ships. Historically, ship monitoring and control systems that rely on sensor measurements throughout the machinery plant have had little to no physical sensor redundancy. In these cases, the failure of a key sensor places the proper functioning of the control system at risk. Sensor diagnostics must be addressed and must be automated in order for advanced functionalities such as intelligent reconfigurable control to be realized.

The number of sensors being incorporated into new ship designs continues to increase significantly over past levels. By some estimates, future all-electric ships will have 20 times the number of sensors as some modern ships, perhaps 100,000 or more. By today's standards, this is a staggering number of sensors to maintain and calibrate. Periodic sensor calibration is currently an expensive, labor-intensive activity. For minimum manned vessels, there may inadequate human resources available to perform continuous sensor monitoring. Automatic, on-line sensor diagnostics represents the only feasible approach to sensor validation aboard future minimally-manned ships.

In the context of ship survivability, sensors represent a weak link in the chain with respect to control system functionality under damage conditions. The ability to detect sensor failure and to provide a corresponding analytical or "soft" estimate to all control functions that rely on the measurement will be an essential requirement. Analytical redundancy costs far less than physical redundancy for critical sensor measurements and can lower the overall cost of the ship.

A significant body of work on sensor validation and data recovery has been developed in industries such as nuclear, chemical processing, and aerospace. Applications are typically reliability critical and require embedded knowledge of sensor accuracy and redundant sensor estimates under failure conditions. A number of techniques have been used to validate sensor measurements against bias, drift, and complete failure [15, 16, 17]. Simple limit checking compares the difference between current sensor readings and the previous validated reading to some maximum possible rate of change. Sensor values can also be validated through comparisons with redundant values either obtained via physical measurements or derived analytically through a system model. In general, a set of residual values is generated and analyzed using an assortment of available statistical methods. The validation methods should be capable of detecting sensor bias and drift, as well as isolating complete failures.

Nearly all past approaches to sensor validation rely on multivariate system models. Analytical or empirical models are built that exploit the relationships amongst correlated sets of sensors. The developed models can generate analytically derived sensor estimates that can be continually compared to measured sensor values to detect statistically significant differences. This generic process for sensor validation is illustrated in figure 3 below.

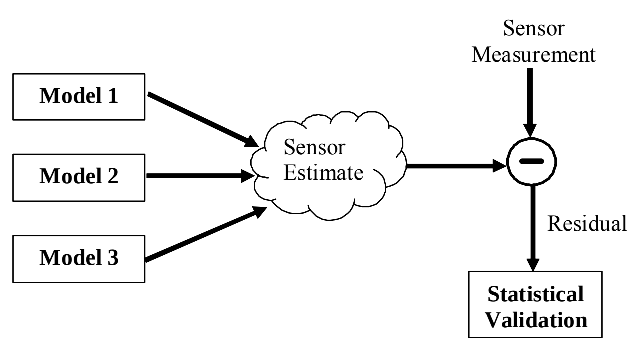

Figure 3 – Generic Approaches to Sensor Diagnostics

Fusing independent model estimates together into one single estimate as shown above can provide a more robust reading than that of any single sensor. Multi-sensor data fusion can provide reduced uncertainty and increased reliability of the system using the sensor signals when a sensor failure occurs. The end goal of the data fusion process is to derive a best estimate of a sensor signal that can be maintained for use by all external process applications, such as higher-level control systems. Various schemes have also been presented for quantifying confidence in the fused estimate, which could also be used in higher-level application decision-making [18, 19, 20].

Recently developed multivariate machine learning techniques have the capability to automatically synthesize sensor models from correlated information in machinery plant data. The models can then generate analytical estimates of various sensor measurements and performance parameters. Support Vector Machine (SVM) regression [21] synthesizes high dimensional models based on strong correlations amongst the model input data, which includes other machinery plant sensor measurements. The technique has been shown to be extremely accurate for both sensor and equipment diagnostics, and can produce analytically redundant estimates of signal values in the case of sensor failure. As an example, figure 4 plots SVM-estimated versus actual Compressor Discharge Pressure based on test data from a Navy gas turbine engine. The estimated values are practically indistinguishable from the actual values, with an average error of less than 0.75%. The SVM technique appears very promising for sensor diagnostics due to its high accuracy.

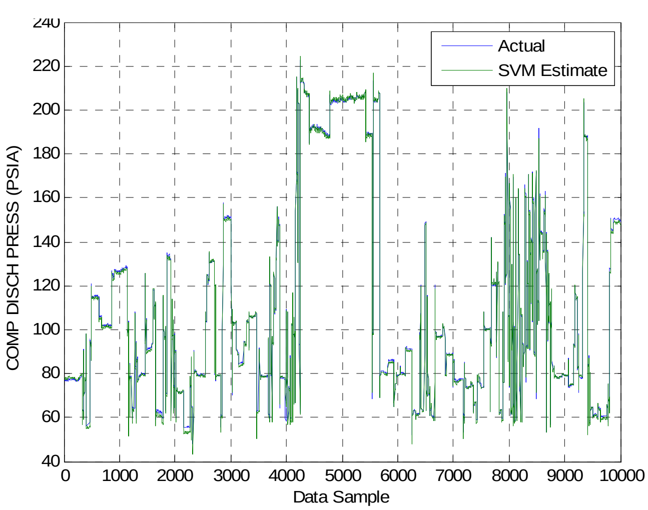

Figure 4 – SVM Modeling of Gas Turbine CDP

E. Neural Network-Based Equipment Diagnostics

A substantial amount of diagnostic algorithm development has been done for equipment and devices that will comprise future IPS. General comparisons of the robustness of the various diagnostic approaches are not forthcoming however, and it can be assumed that more advanced diagnostic algorithms will continue to develop over time. Representative examples of electric machine diagnostics are discussed in the next section in order to expose diagnostic knowledge management issues.

One of the most difficult tasks in building real-time diagnostic systems is dealing with the issue of uncertainty. Uncertainty related to sensor failures and alarm generation can result in erroneous and/or unreliable performance of diagnostic systems. The treatment of uncertainties is, therefore, a serious concern for diagnostics employed for component level intelligence. Diagnostic system robustness is related to its ability to correctly detect specific faults in the system under diagnosis, given process measurements and symptoms (alarm conditions). Diagnostic performance metrics used to assess robustness include the following [22]:

a) Probability of incorrect diagnosis (declaring a fault which is different from the actual fault),
b) Probability of missed diagnosis (not declaring a fault when one is present),
c) Probability of false alarm (declaring a fault when none has occurred), and
d) Probability of correct diagnosis.

A robust diagnostic system will minimize (a) through (c) above and will maximize (d).

Diagnostic robustness is directly related to the extent of process measurements available, as well as to the diagnostic inferencing techniques used. Early expert systems employed rule-based or logic-based reasoning. The strict logic-based reasoning makes these types of systems vulnerable to bad input data, often the result of sensor problems. As a result of the “brittleness” of rule-based systems, they often tend to miss diagnostic calls when one of the rule antecedent conditions is false or missing, as will occur when a sensor problem develops.

An alternative technique particularly well suited to diagnostic applications is artificial neural networks. Neural networks are modeled after biological systems and are known to be good pattern recognition devices. They have several attractive features, including:

- Able to learn from training examples,
- Capable of real-time pattern recognition,

- Capable of classifying novel input patterns not included in training data, and
- Tolerant of noisy or incomplete input patterns.

Neural networks have the ability to learn input/output associations for pattern recognition problems, as are typical of diagnostic and prognostic applications. Because neural networks are tolerant of noisy or incomplete input patterns, they can be used to implement more robust diagnostic systems that those following a rule-based approach. Even if one or more input values are missing, the network is still able to make the closest association to the input/output training data that it has learned.

The critical aspect of deploying neural networks is having access to good training data that is representative of the input/output state space the network is likely to encounter in the application domain. One strategy for deploying diagnostic neural networks for is to train the network from detailed measurement signatures captured in coincident with specific machinery failure events. If the network can learn multi-dimensional signatures of machinery behavior either leading up to or subsequent to a failure event, then the network can serve as a useful prognostic or diagnostic aid.

A more practical alternative is to rely on the experiential and engineering knowledge of domain experts to construct a diagnostic knowledgebase suitable for neural network training. The effect of any inaccuracies in the training knowledgebase can be attenuated by incorporating probabilistic techniques, such as the Probabilistic Neural Network (PNN), into the system design [22].

A Failure Mode and Effects Analysis (FMEA) can precisely define the scope of diagnostic coverage by providing detailed definitions of individual machinery diagnostics. Each machinery system is broken down into its major components. Probable failure modes of the machinery system components are then enumerated. The causes and effects (at the available sensors) are then traced out through the impacted systems. The results of the FMEA will define the diagnostic coverage of the system and will:

- Enumerate the possible failure modes of the machinery systems and components,
- Identify all available sensor measurements, and
- Identify the fault/symptom relationships for automated diagnostics.

For each fault enumerated during the FMEA, a corresponding list of related symptoms is identified and defines a diagnostic. All similar diagnostics are organized into a knowledgebase that can then be used to train the PNN.

A PNN can be used to classify symptom patterns according to the faults that may have generated the alarm conditions. The PNN is pre-trained to learn the associations between a large number of faults and their corresponding symptom patterns, as depicted in figure 5. The input vector, **X**, is comprised of the symptom pattern representing either current alarm conditions or predicted alarm conditions, depending on whether diagnostics or prognostics are being performed. Alarm conditions can be quantized to varying levels of resolution. Once trained, the PNN can be connected to the machinery plant automation system to perform real-time diagnostics. Automated prognostics are a direct extension of diagnostics, coupled with automated trending analysis and prediction functions.

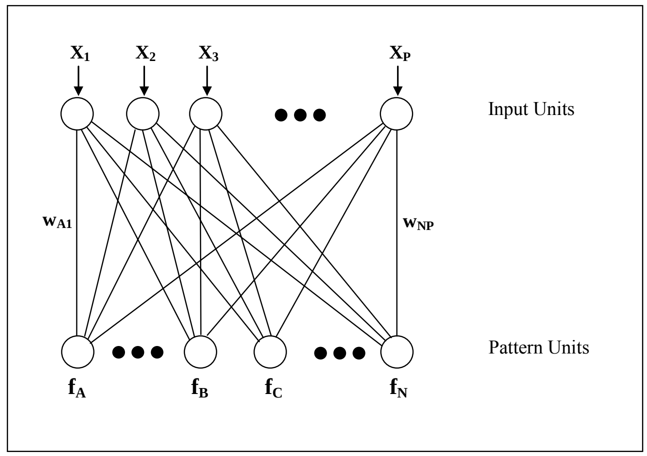

Figure 5 – PNN for Computing Fault Probabilities

The PNN is capable of handling situations in which one or more input variables are missing or are corrupted. This makes the method attractive for real-world applications where sensor failures occur on a regular basis, such as in a shipboard environment.

Classification probabilities are directly output from the PNN, generated by its nonlinear decision surfaces, which approach the Bayes optimal. This is a clear advantage over rule-based approaches incorporating subjective probability estimates or confidence intervals without statistical basis.

The PNN-encoded diagnostic intelligence, as well the computer code implementation of its algorithm, has a small memory footprint that makes it amenable to hardware embedding at the chip-level. Component level PNN-based health monitoring can be readily added to existing equipment microcontrollers with relative ease. “Smart” devices, such as pumps, motors, actuators, valves, etc. can be readily developed with their own customized health monitoring by way of PNN chip level implementations.

III. FUTURE DIAGNOSTIC REQUIREMENTS

A. Diagnostic Knowledge Management

Figure 6 highlights some of the major categories of IPS components for which diagnostic management strategies should be considered. These categories may not be all inclusive, but when reviewing the diagnostics development activities associated with each, the following becomes readily apparent:

- There is an abundance of diagnostic development in progress,
- Most of the diagnostic technologies remain relatively unproven in real-world service,
- Diagnostics will certainly continue to evolve over the lifecycle of the ship, and
- Upgrade mechanisms must be established to exploit new diagnostic technology for continuous improvement in systems reliability and affordability.

For future platforms such as the all-electric ship, the diagnostic knowledge and methods, including embedded procedures, must be managed and maintained current. Standard mechanisms must be established early in the ship lifecycle such that vital systems are designed for diagnosis and continuing knowledge management [23, 24, 25]. Instead of the typical late lifecycle activity, diagnostic knowledge development and management should be integral part of the design and development phase of ship construction. This should include incorporation of diagnostic knowledge specifications and its management mechanisms into equipment solicitations during vendor selection.

Because of survivability issues, it is imperative that embedded diagnostic knowledge be current and as complete and accurate as possible. Updating onboard intelligence with new experiential knowledge accumulated over time will be required to achieve and maintain the highest levels of system performance under all modes of operation. False or missed diagnostic calls will have severe ramifications within the intelligent, automated control environment. Diagnostic knowledge management will become a critical supporting technology for the all-electric ship. Equipment manufacturers can provide initial versions of diagnostic knowledge upon product delivery in a form that can easily be upgraded throughout the ship's lifecycle, preferably in electronic form, fully tested and validated prior to shipboard modification.

Existing diagnostic engineering practices and tools will be ineffective, inefficient, and unsustainable across the complex mix of equipments included in the all-electric ship design. Diagnostic tasks will be more difficult to implement unless approached from a bottoms-up perspective through intelligence embedding into the individual systems and devices, such that they become self-diagnosing. Standards are needed to specify to device manufacturers on just how to do this through common mechanisms designed for long-term knowledge management. Standards are also needed in order for the Navy to enforce compliance by the manufactures such that lifecycle diagnostic management goals are achievable. Today there is no formal methodology within the industry for defining diagnostic requirements, developing diagnostic intelligence, or providing knowledge management tools to maintain, build, and disseminate new diagnostic knowledge. However, methodologies and diagnostic knowledge management toolkits are evolving [26, 27, 28]. Reduced manning initiatives within the Navy will shrink both shipboard and shore side maintenance crews to minimum levels, placing even more value on embedded, upgradeable diagnostic knowledge. Traditional maintenance engineering methodologies, relying on people and paper-based troubleshooting information, must be replaced with a new model for knowledge management. Dynamic, frequently changing diagnostic knowledge must be delivered through electronic support systems that link manufacturers to their products, such that initial failure mode information generated during ship design can be rapidly upgraded throughout the ship's life. These types of electronic support systems are emerging but need to make substantial and rapid progress in order to support future diagnostic and maintenance requirements of the Navy.

B. Power source diagnostics

In the near term, gas turbine generators will be the most likely major power source to the IPS. Alternate power sources include diesel generators, fuel cells, and battery power. There is large body of work involving diagnostics for both gas turbine and diesel engines. New techniques will continue to evolve, as electronic engine control technology becomes more advanced. In general, diagnostic procedures are quite sophisticated, require highly specialized knowledge and substantial computer resources, e.g. advanced vibration and acoustic emission signal processing, artificial neural network algorithms, etc. Research efforts are so broad with respect to gas turbine diagnostics that it is difficult to discern proven and most promising technologies from pure research projects. This situation demonstrates the need to rely on the engine manufacturer to act as a clearinghouse for the implementation of advanced diagnostic technologies for their engines, either by commissioning or carrying out the development internally.

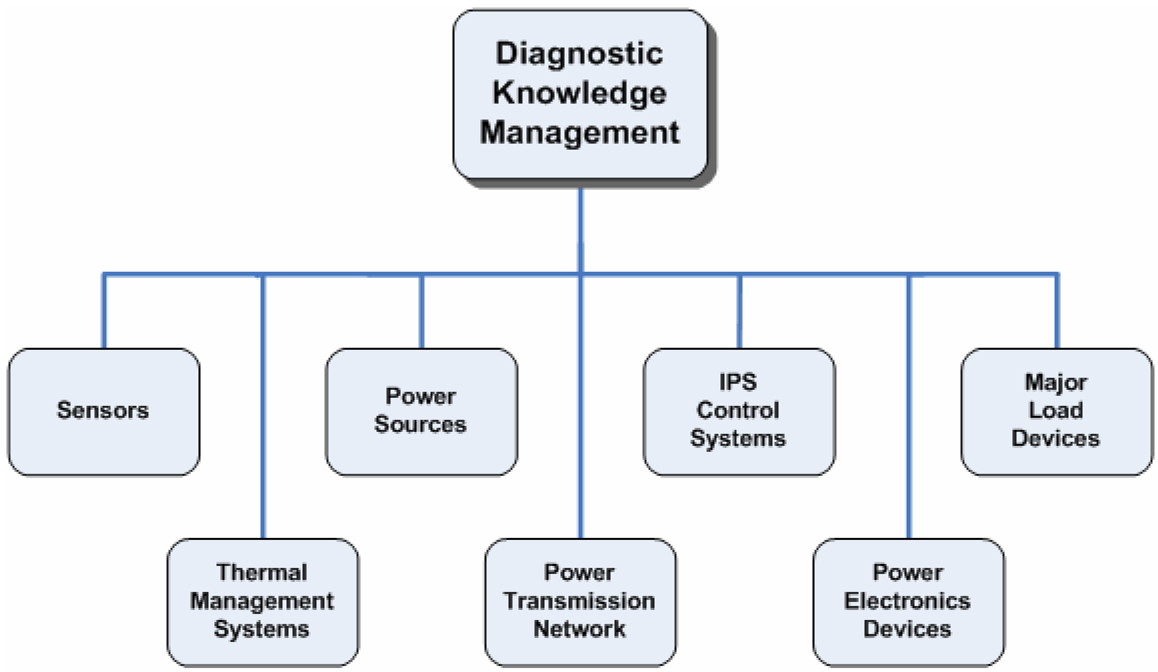

Figure 6 – Diagnostic Knowledge Management of IPS Components

Self-diagnosing engines, instrumented with the best diagnostic knowledge and techniques, are near reality today. In most cases, the existing diagnostics need to be extended for more complete coverage of failure modes and, in particular, upgraded with predictive capabilities. Because engine suppliers are in a position to receive performance feedback on their products and build diagnostic knowledge over time through service experience, common sense dictates that they should assume responsibility of managing onboard diagnostics.

C. IPS controller diagnostics

There appears to be a number of readily available, well developed commercial controller products on the market that can be incorporated into future IPS designs. These products offer mature support in both hardware and software and have a large experience base in electric utility applications with similar requirements as the all-electric ship IPS.

Modern controllers are reliable, fast, and precise computer systems specifically designed for very fast analog and digital I/O control. The controllers are the heart of the power control network to which they are connected and manage. Should they fail, the entire network segment under their control is at greater risk, even with hot swappable back-up controllers in place. The controller should implement its own self diagnostics and be capable of reporting its health status to any interested external "agents" that are connected to it.

D. Electric motor diagnostics

The widespread application of electric motors for power generation, propulsion, thermal management systems, etc. will place a high priority on motor health monitoring as an integral component of IPS diagnostic requirements. A recent symposium offers a glimpse at the state-of the-art in electric machine diagnostic technology developments [29]. The major fault categories include bearing, stator, rotor, and insulation failures.

Advances in signal processing hardware and software have accelerated research in motor diagnostics (prognostics). A multitude of diagnostic techniques have been developed and several may be required to provide more complete fault coverage for the electric motor. Table 1 summarizes some common electric motor faults and related diagnostic techniques being applied to detect those faults. These techniques are highly specialized, requiring significant expertise in their application. As such, many of these advanced techniques are ideal candidates for automation through intelligent software agents.

E. Thermal management system diagnostics

Thermal management will be interdependent with electrical power within the IPS. System level thermal management requirements call for distributed cooling while avoiding additional complexity, cost, and volume. New cooling system architectures must be decentralized, programmable, and capable of autonomous operation in a zonal configuration.

TABLE 1 – Common Motor Faults and Diagnostic Techniques

FAULTS	DIAGNOSTIC TECHNIQUES
• Bearing failures • Stator faults causing opens or shorts of phase winding • Abnormal connection of stator windings • Broken rotor bar • Cracked rotor end-rings • Static or dynamic air-gap irregularities • Bent shaft causing rotor and stator to rub • Shorted rotor field winding • Gearbox failures • Insulation failures	• Motor current signature analysis • Partial discharge pattern analysis • Neural networks • Wavelet packet transform • Genetic algorithms • Spectral analysis • Cross-correlation analysis • Fast Fourier Transforms (FFT) • Leakage flux analysis • Non-parametric power spectrum • Fuzzy logic • Impulse testing • Symmetrical component analysis • Expert systems

High-density electrical power and energy weapons require substantial cooling. The addition of advanced power electronics, advanced radar, dynamic armor, and weapons systems (e.g. EM Railgun, Free Electron Laser, etc.) are predicted to require a 700**%** increase in cooling capacity [30].

Some alternative cooling technologies being investigated include thermoelectric air conditioning, thermoacoustic cooling, and magnetic refrigeration. New heat exchanger designs using new methods and materials are also being explored, including heat pipe technology, through-the-hull heat exchangers, and waste heat recovery systems.

Distributed cooling system designs will require similar intelligence for automatic reconfiguration as that being developed for the IPS. Smart valve technology [31] will allow the development of intelligent fluid systems capable of detecting piping damage, isolating damaged sections, and dynamically reconfiguring the system to restore cooling fluid service through alternative piping paths [32, 33]. Diagnostics on cooling system components, such as valves, heat exchangers, pumps, etc. will play an integral role on reconfigurable control of these and other thermal managements systems.

F. Power electronics device diagnostics

Many of the same diagnostic techniques listed in Table 1 may also be applicable to diagnostics of power electronic devices. However, the time scale at which they must be performed will be very rapid, perhaps within tens of milliseconds. Safe operation of the IPS will require high speed data acquisition, signal processing, and rapid classification of perturbations such that the appropriate protective control actions can be taken to minimize further power system degradation. Once again, diagnostic implementation requires substantial device knowledge and embedded diagnostics or built-in-testing (BIT) will be subject to periodic upgrading. Knowledge management can support long-term sustainment costs for these devices, as well as the other key components of the IPS.

IV. CONCLUSIONS

The Navy seeks both affordability and reliability for the next generation all-electric ship. New diagnostic engineering paradigms will be required to deal with complexity of ship system designs, as well as to manage and extract maximum value from diagnostic knowledge. Previous diagnostic practices and tools applicable to past generations of ships are inadequate for future diagnostic technology delivery, particularly for advanced IPS designs. Integrating diagnostic knowledge into the ship design strategy and delivered systems will facilitate maintenance cost containment over the ship's lifecycle. Diagnostic knowledge management is a dynamic process that begins at the earliest stages of ship design and continues throughout the vessel's life.

Advancements in ship system technologies present significant challenges to the engineering community. The accuracy of embedded diagnostics is essential to implementing advanced reconfigurable control algorithms, of which ship survivability will be dependent. High levels of diagnostic knowledge are also important to isolating and quickly restoring systems to design optimal conditions. Increasing complexity of ship systems, coupled with a multi-vendor supply environment, highlights the shortfalls of existing diagnostic engineering and delivery methods. For future platforms such as the all-electric ship, diagnostic knowledge must be managed and maintained current. Standard mechanisms must be established early in the ship lifecycle such that vital systems are designed for diagnosis and continuous knowledge management.

Equipment manufactures should supply embedded diagnostics within their devices to allow a distributed control strategy. This will support control functions related to ship survivability, such as intelligent reconfiguration of integrated power systems that rely on knowledge of equipment health status. This will also support drastically reduced manning levels for troubleshooting system faults. It is imperative that embedded diagnostic knowledge be current and accurate. False or missed diagnostic calls will have severe ramifications within the intelligent, automated control environment. Diagnostic knowledge management, including onboard updating with new experiential knowledge, will become a critical supporting technology for the all-electric ship.

Reduced manning initiatives will place high value on embedded, upgradeable diagnostic knowledge. Traditional maintenance engineering methodologies, relying on people and paper-based troubleshooting, must be replaced with a new model for knowledge management. Dynamic, frequently changing diagnostic knowledge must be delivered through electronic support systems that link manufacturers to their products, such that initial failure mode information generated during ship design can be rapidly upgraded throughout the ship's life. Knowledge standards are needed to enforce compliance by the manufacturers such that lifecycle diagnostic management goals can be met.

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