A Novel Architecture for an Integrated Fault Diagnostic/Prognostic System

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Abstract

*Complex dynamical systems, such as aircraft, chemical processes, power plants, shipboard equipment, etc., are required to maintain an acceptable level of operational integrity and availability. Current research aims to maximize uptime by maintaining such systems only when required. A viable and cost-effective diagnostic/prognostic system architecture must integrate a number of functionalities while exhibiting attributes of flexibility and scalability. It must account for fault modes that are inherent to the current operating state of the system and its usage patterns (*Hadden et al. 1999*). Furthermore, it must be able to predict accurately the remaining useful lifetime of failing components and manage effectively uncertainty (*Hadden et al. 1999*). This paper introduces an integrated diagnostic/prognostic architecture that builds upon means to identify the system's operating mode and usage pattern using concepts from hybrid system theory and Petri networks as decision support tools, mechanisms to extract an optimum feature vector based on data-mining and diagnostic/prognostic algorithms that are designed employing a fuzzy logic expert system paradigm and static/dynamic wavelet neural network constructs for fault detection/isolation and for estimation of the remaining useful lifetime of a failing component. Essential elements of the architecture are implemented and validated on a laboratory scale process consisting of multiple tanks, control equipment, sensors and actuators.*

1. State of the Art

A number of approaches to the diagnostic/prognostic problem have been reported in the technical literature. Stochastic Auto-Regressive Integrated Moving Average (ARIMA) models were used on a computerized numerical control (CNC) monitoring and prognosis system to investigate quality of conformity related to the supervision of process control in manufacturing during machining tasks and its implications in the enhancement of the system's efficiency (Jardim-Goncalve et al. 1996). Based on fuzzy pattern recognition principles, a prognostic adaptive system was designed in which the fault detection is achieved by fuzzy classification rules for which a multi-step adaptive Kalman filter updates membership vectors that are suitable for prognosis (Frelicot 1996). CASSANDRA, a knowledge-intensive expert system incorporating shallow knowledge, was designed to continuously monitor the condition/health of industrial equipment through a sensor suite and to predict on-line equipment faults (Lembessis et al. 1989). A nonlinear stochastic model of fatigue crack dynamics was introduced for real-time computation of the time-dependent damage rate and accumulation in mechanical structures so as to estimate the current damage status and predict the remaining service life (Ray and Tangirala 1996). The National Information Infrastructure (NII), a distributed system architecture for electronic delivery of on-line equipment monitoring, diagnostics and prognostics (MD&P) services, was used for predicting the remaining life-time and for real-time constraining of operational parameters for life extension of operating machines (Proha 1996). Polynomial neural networks were employed to construct a generic fault detection, isolation, and estimation (FDIE) algorithm for analysis of normal and defective vibration signatures in helicopter transmissions (Parker et al. 1993). A prognostic maintenance system in which the Hough transform was adopted to extract linear trend features from monitored data was proposed to diagnose incipient fault conditions and to predict the time for the system to reach a critical fault condition (Flint 1994). Based on measurements of operating characteristics and frequency response data of transformers, a number of prognostic methods were investigated for estimation of their coupled overvoltages. An Integrated Diagnostic Support System (IDSS) was initiated by the US Navy, which includes adaptive diagnostics, feedback analysis-precursors and fault prognostic capability. However, these methods have yet to produce a systematic, efficient and robust approach to the prognostic problem. More recently, two main approaches have emerged as potential candidates for prognosis. The first one relies on system models and state estimation techniques (Kalman and Alpha-Beta-Gamma tracking filters) to determine the remaining useful lifetime. The second uses a feature extractor and a learned association method, typically a neural network construct. The first category is hampered by the need for accurate system models while the second requires a sufficient database that covers the dynamic range of the machine or process for training and validation purposes. Model-based state estimation methods were suggested in (Begg 1999). The model-based prognostic framework and an example of a gear tooth crack growth are reported in (Li and Yoo 1998). In (Peebles, Essawy, and Fein-Sabatto 1999), a probabilistic technique called 'symptom reliability' and an empirical, conditional probability argument are called upon to estimate the remaining useful lifetime. A computational example is used to support the thesis of the approach. The authors in [12] are introducing an "intelligent" methodology to the prognostic problem that involves gathering three sources of data, extracting features from the data and developing neural network algorithms based on the extracted features to estimate the RUL. Gearbox test data are used to illustrate the concepts. More recently, testing, monitoring and advanced diagnostic/prognostic activity has been underway regarding helicopter fault modes. The H53 and Commanche programs, among others, conducted by the military involve vibration legacy data and their correlation to flight data recordings such as altitude, air speed, position, etc. The H53 program has been designed to accommodate 23 stations on the vehicle's airframe while a vibralog data acquisition system is collecting vibration data every 120 seconds with a 1 to 2 sec. time window. Probabilistic methods and intelligent techniques are being applied for fault detection and trending purposes. [personal communication]

Critical systems of interest are characterized as large-scale consisting of multiple components. For such systems, traditionally, machine diagnostics/prognostics begins by decoupling the system. This strategy is not always useful, especially when the system is tightly coupled. Moreover, it compromises the diagnostic and prognostic quality even when it considers coupling dynamics. In this paper, a novel integrated architecture is proposed to address these challenges and improve the performance of CBM systems.

A complex dynamic system typically consists of continuous-time dynamics and discrete-event dynamics [13]. It operates in different operating modes, such as startup, normal running mode, shutdown mode, *etc.* Some fault modes may occur in a specific operating state only. It is instructive, therefore, if failure modes are associated with the system's different operating states. Also, the system's operational history includes a variety of usage patterns. For example, heavy load or unloaded, high charged or low charged, *etc.* Failure modes may vary in their features from one usage pattern to another. Considering different operation modes and usage patterns, the system may be divided into several sub-systems in order to implement efficiently and effectively CBM architecture. This paper introduces a flexible, scalable, integrated, and generic architecture for diagnostic and prognostic systems to detect and identify different fault modes and then predict the time-to-failure of critical components. In this architecture, an operating mode and usage pattern detector constitute essential modules. Data mining is used to extract features; fuzzy logic and wavelet neural networks (WNN) function as classifiers; a dynamic wavelet neural networks (DWNN) performs as the prognosticator; a new construct called Confidence Prediction Neural Network (CPNN) represents and manages uncertainty; a Fuzzy Analytic Hierarchy Process (FAHP) adjusts the effects of causal information on the predicted trend. The integrated architecture is implemented and demonstrated on a laboratory scale three-tank process known as the Process Demonstrator.

2. System architecture

2.1 Integrated Diagnostic/Prognostic System (IDPS) Architecture

The role of the diagnostic and prognostic algorithms is to provide continuous on-line fault detection, fault isolation, time-to-failure information, and certainty bounds or prediction intervals. Classical fault detection and isolation (FDI) and prognostic algorithms extract features from raw data, use specific classifiers to identify the fault modes, and accordingly prognose the machine components' remaining useful lifetime. In current diagnostic/prognostic application domains, the focus is on either diagnostics or prognostics, but not both. Also, most of them are interested in continuous dynamics only, which are not well suited for complex systems that have different dynamics related to different operating modes and usage patterns.

The IDPS architecture is illustrated in Figure 1. In this novel system architecture, complete diagnostics and prognostics are implemented. Also, hybrid system theory is employed for different dynamics in different operating modes and usage patterns. A dynamic system is divided into several sub-systems according to the operating modes and usage patterns, so that more than one classifier or prognosticator is used in this architecture. For each sub-system, a fuzzy/WNN classifier and a DWNN/CPNN prognosticator serve in sequence to provide a more accurate trending while bounding uncertainty.

The sub-systems are running in "parallel". The number of inputs to each classifier are limited, contributing to improved speed for failure isolation and detection, thereby reducing not only the number of neurons in the network, but also the run time and training time required for the network. It also reduces the system resource consumption and improves the compuational complexity. Moreoever, rather than training a single classfier for the whole system, by using separate classifiers for each operating mode or usage pattern, additional classifiers may be easily added to the central database as new features are derived or devices are inserted without retraining the existing networks. This feature makes IDPS an open and scalable architecture.

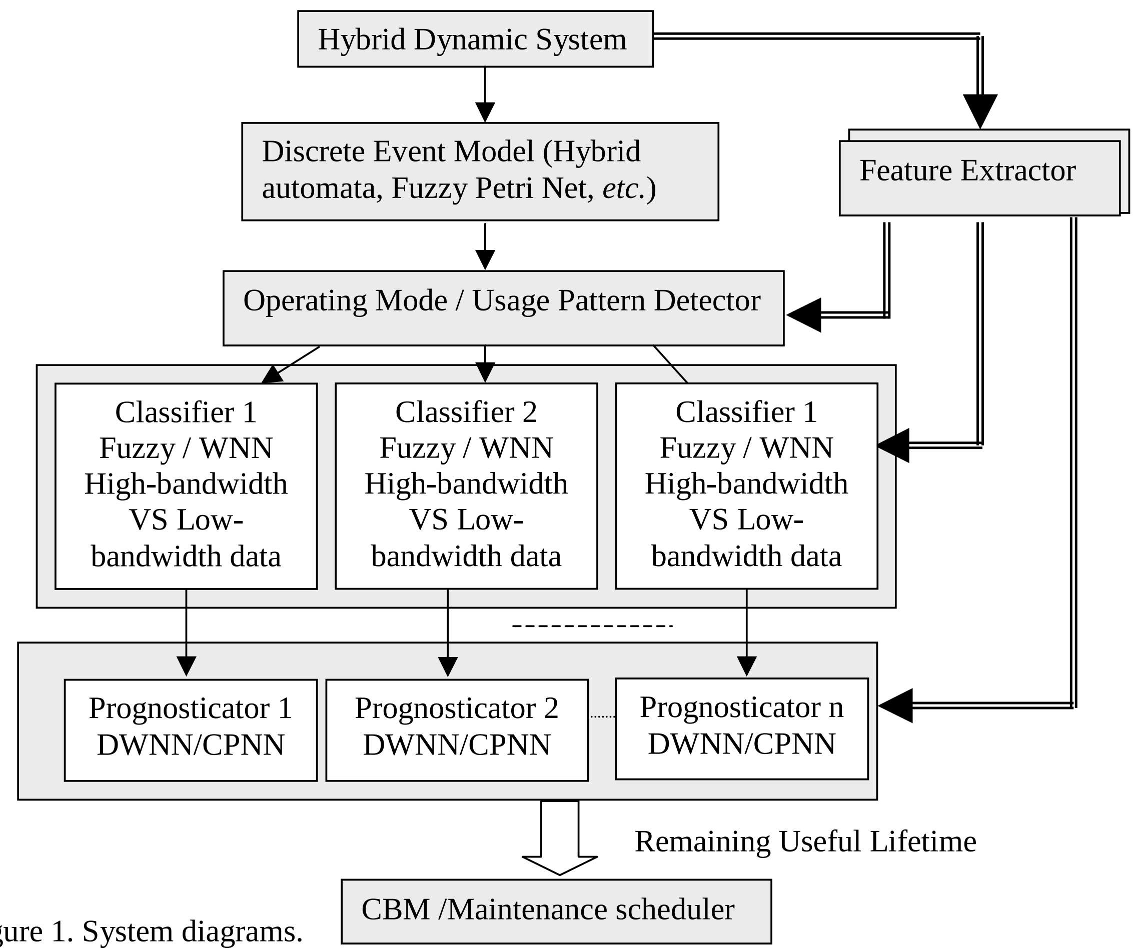

Figure 1. System diagrams.

A brief description of the modules integrated into HDPS follows:

1) Discrete-event model: employs hybrid automata and Petri networks to model the discrete-event dynamics.

2) Feature extractor: receives raw sensor data and relevant historical data, and extracts useful information in the form of a feature vector according to requirements imposed by the diagnostic and prognostic modules.
3) Operating mode / usage pattern detector: decides upon the specific operating mode and usage pattern and directs all the appropriate input to the corresponding classifier.
4) Classifier: employs a fuzzy inference engine and static wavelet neural networks to decide on-line the occurrence of a fault mode and to identify the fault mode.
5) Prognosticator: capitalizes upon a virtual sensor to provide fault dimensions and a dual approach to prediction empolying a DWNN for fault trending and a CPNN assisted by FAHP aimed primarily at accommodating causal adjustments to the prediction curve and managing uncertainty bounds.

2.2 Overview of IDPS Main Modules

2.2.1 Operating Mode and Usage Pattern Detector

Fault modes are often related to specific operating or usage patterns. To diagnose the faults and prognose the time-to-failure of such systems, requires dividing them into several subsystems according to distinct operating modes and usage patterns. An operating mode and usage pattern detector is thus required to accomplish the CBM tasks.

The operating mode and usage pattern detector is implemented using hybrid system theory and Petri networks. In this architecture, the system is divided into several sub-systems according to the prevailing operating state and usage pattern. This reduces the system's complexity, and allows for the design of fault classifiers and prognosticators on the sub-system basis.

2.2.2 Feature Extractor

Measurements of industrial processes are divided into two broad categories: low-bandwidth measurement and high-bandwidth measurements. The former, such as temperature, pressure, level, *etc.* may propagate slowly and data can be sampled at relatively slow rates without loss of historical significance. On the other hand, the latter, such as vibrations, or current spikes, require fast sampling rates in order to capture a reasonable signature of the failure mode.

Component faults can not be readily identified by simply monitoring such measurements. Raw data must be transformed into features, which contain meaningful information in a compressed form. However, since not all features may be applicable in identifying a specific fault mode, a process of recognizing relevant features, which form a feature vector, from all possible features, known as feature selection, is required.

Fault Detection and Identification (FDI) or diagnosis can be viewed as a mapping from a set of given features into one of the predefined fault classes, where irrelevant and redundant features may result in a serious degradation of the efficiency of the fault classifiers.

Different level features act as the main inputs to the other modules of the architecture. Features, such as mean, variance, standard deviation, *etc.*, are extracted from raw data and constitute the first level of the feature vector. "Features of features" are also extracted, and form higher levels of the feature vector. Such derived features as the slope of the mean value, 2nd order moments, *etc.*, are assisting to improve the classification task and increase the signal-to-noise ratio [14].

2.2.3 Diagnostician [15]

To detect and classify the faults, two different methods are implemented. The first one is based on a fuzzy logic paradigm while the second uses a wavelet neural network construct.

The Fuzzy Diagnostic Module

The fuzzy diagnostic module is utilized to detect process fault modes from feature data, i.e. faults, resulting from low-bandwidth events and exhibiting low-frequency signatures. An initiation event begins the fuzzy diagnostic module calculations if receives feature inputs from the database and reports to the database any indications that a fault mode may have occurred, as shown in Figure 2. The Dempster-Shafer module returns a Degree of Certainty (DOC) for detected faults. If a fault mode is detected, the diagnostic output event is triggered with relevant information such as the fault mode name, time of detection, DOC, *etc*. This output event is used for the initiation of various prognostic modules.

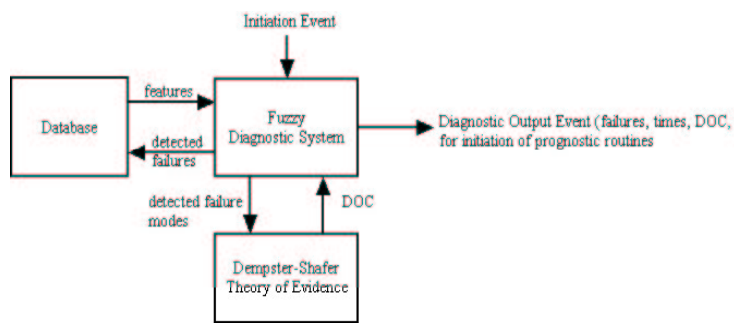

Figure 2. The Fuzzy Diagnostic Module

The fuzzy logic system structure is composed of four blocks: fuzzification, the fuzzy inference engine, the fuzzy rulebase, and defuzzification, as shown in Figure 3.

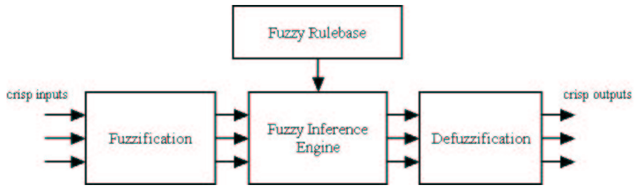

Figure 3. The Fuzzy Logic System Structure

The fuzzification block converts features to degrees of membership within a linguistic label set such as pressure low, pressure high, etc. The fuzzy membership functions are designed through classification techniques from the feature set such as the fuzzy c-Means method. The fuzzy rulebase is constructed from symptoms that indicate a potential fault mode. Two example fuzzy rules for diagnostic detection are shown in Figure 4.

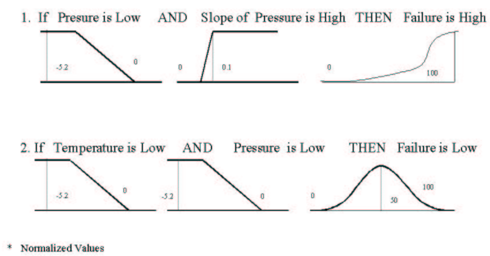

Figure 4. A graphical representation of two rules in a fuzzy rulebase.

The fuzzy rulebase can be developed directly from user experience, simulated models, or experimental data. Fuzzy values are aggregated through a fuzzy inference engine to determine the degree of fullifillment for each rule corresponding to a failure mode (Mandani approach). The defuzzification block outputs between 0 and 100 using the centroid method, as shown in Figure 5. These values are compared to a threshold to determine whether or not a fault mode should be declared as having been detected.

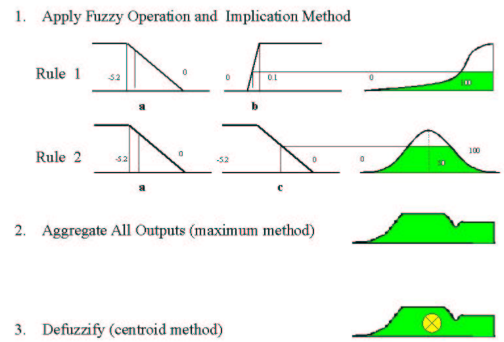

Figure 5. Graphical representation of the fuzzy inference engine and defuzzification.

The Dempster-Shafer Theory of Evidence module is incorporated into the system for uncertainty management purposes. Each input feature has fuzzy membership functions associated with it representing the possibility of a fault mode. Each feature, therefore, represents an expert in this setting. These possibility values are then converted to basic probability assignments for each feature. Dempster's rule of combination is then used to assimilate the evidence contained in the mass functions and to determine the resulting degree of certainty for detected fault modes.

The Wavelet Neural Network Module

The WNN (Figure 6) is used also as one component of the classifier. Potential advantages of the WNN approach include: The resulting neural network is a universal approximator; the time - frequency localization property of wavelets leads to reduced networks at a given level of performance; WNNs offer a good compromise between robust implementations and efficient functional representations; the multi-resolution organization of wavelets provides a heuristic for neural network growth. Furthermore, WNNs may be optimized with respect to structure (number of nodes) and their parameters using a Genetic Algorithm as the optimization tool. The WNN is trained, thus, as a two-step process: the structure and the parameters of the network are determined iteratively until a performance metric is satisfied. The WNN construct suggests a means to parallel-process multiple signals in a multi-tasking environment, thus expediting considerably processing times. Finally, it offers an easy and user-friendly way to "learn" new signal patterns, as long as training data is available.

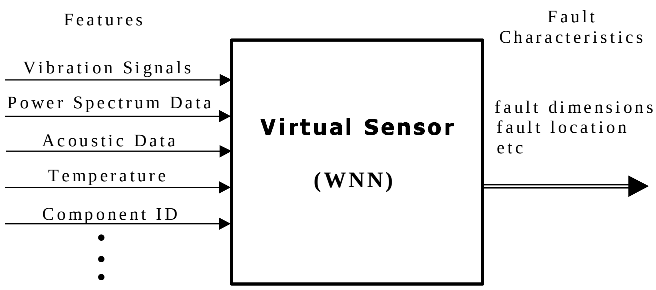

Figure 6. WNN structure.

These classifiers repeatedly scan the incoming feature values. Considering a typical process, the fault modes may include leakage, errosion, crack, *etc.* It is generally possible to break down the sensor values into two categories: low-bandwidth data, such as temperature data, flow rate data, *etc.*, and high-bandwidth data, such as vibration data, acoustic data, *etc.* The data from the first category may vary slowly while those from the second category may change rapidly. The fuzzy logic classifier operates on the incoming low-bandwidth sensor data, while the WNN classifies the fault modes with high-bandwidth data. If one set of data is classified as other than "normal", the classifiers create a fault event and notify the GUI that a fault currently occuring.

2.2.4 Prognosticator

It is well understood that prognostics is the most difficult component of the CBM scheme since it requires prediction in the presence of uncertainty of the remaining useful lifetime of a failing component. It is, therefore, the "Achilles' heel" of the overall system and an effective breakthrough towards its solution may lead to viable CBM implementations and improved equipment uptime. The prognosticator consists of two components: DWNN [16] and CPNN [17, 18].

DWNN module

The DWNN is based on a static "virtual sensor" and a predictor. The static virtual sensor relates known measurements to difficult to acquire failure measurements. The predictor attempts to project the current state of the faulted component into the future thus revealing the time evolution of the fault mode and allowing the estimation of the component's remaining useful lifetime. Both components upon a dynamic wavelet neural network model acting as the mapping tool.

CPNN module

The CPNN represents uncertainties as multiple trends and confidence distributions, and the FAHP adjusts the effects of causal information on the predicted trend.

Classical statistical models for prediction, such as ARIMA, do not provide means to compute uncertainty bounds or prediction intervals. The simple concept of standard deviation of prediction errors is frequently applied to

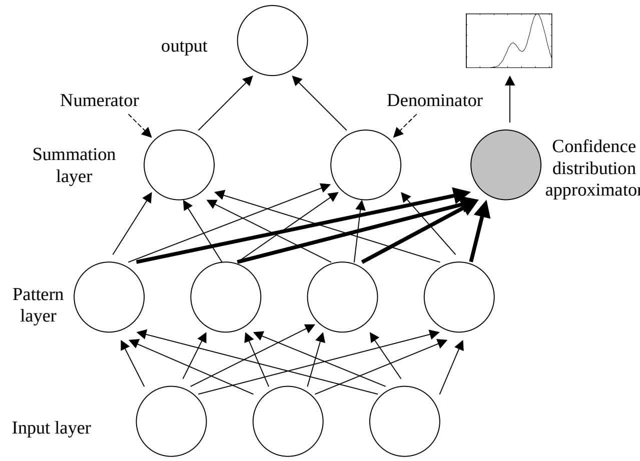

Figure 7. Structure of the Confidence Prediction Neural Network (CPNN)

provide such bounds. While this approach works well for single step prediction, it raises serious concerns when applied to multi-step prediction problems. While the benefits of the uncertainty representation or confidence measure are well understood and have motivated much research, little attention has been paid to an uncertainty distribution of the prediction. We developed a neural network, called Confidence Prediction Neural Network (CPNN) to address this problem (Figure 7). The CPNN accomplishes the goal of representing uncertainty in the form of a confidence distribution by employing a confidence distribution approximator node as shown in Figure 6. Details of this novel development can be found in the cited references [26,27].

2.2.5 Interfacing / Database modules

A central database access management module has been developed to serve the crucial role of storing and accessing raw data, fault features, diagnostic and prognostic results. All CBM modules are built into a COM/DCOM infrastructure in order to be accessed and used in an open and flexible manner accommodating a variety of development languages. The communication between modules is event-based and does not require an overall scheduler to manage all the modules. Each module could be developed separately and independently. This open architecture can be expanded to include additional modules without changing the existing ones. A user-friendly human-machine interface displays all sensor and feature data as real time values and historical records. Thus, the diagnostic/prognostic functions can be accessed through this interface. The software architecture is shown in Figure 8.

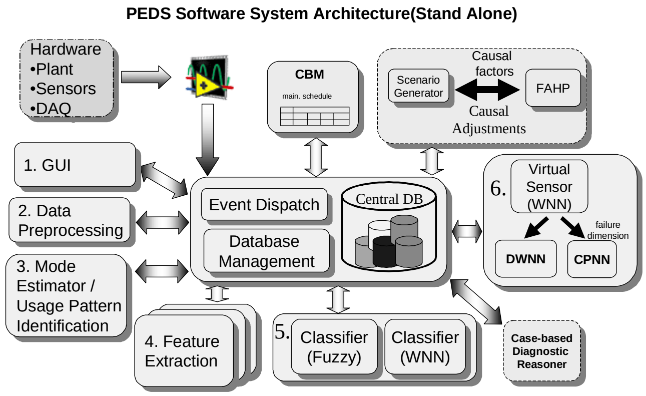

Figure 8. PEDS Software architecture

3. Implementation on a Process Demonstrator

3.1 Testbed Description

The process is a model of a continuous fluid process typical of demonstrator those found in industry (Figure 9). The demonstrator consists of tanks, pipes, valves, pumps, mixers and electric heaters. By activating these devices, fluid can be stirred, heated, and circulated among the tanks. Honeywell Smart Transmitters installed in the system monitor fluid level, fluid flow and fluid temperature.

There are three tanks in the system: two 25-gallon tanks and one 50-gallon tank. Each tank has a pump on the

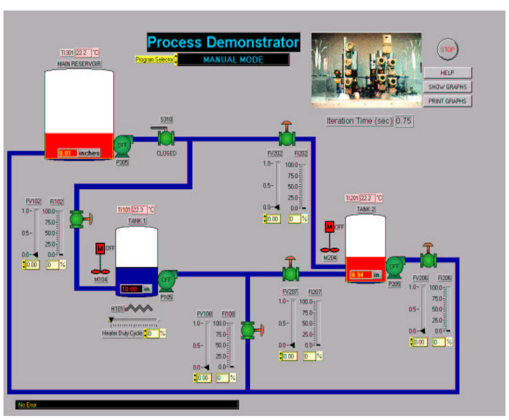

Figure 9. Process Demonstrator.

output line. There are flow valves and flow meters on the lines into and out of tanks 1 and 2. In addition, there is a flow valve and flow meter on the line from tank 1 to tank 2. A solenoid on/off valve is located on the output side of the main tank's pump. There are hand valves into tanks 1 and 2 for introducing disturbances into the system. Tank 1 & Tank 2 have a mixer to stir the fluid in the tank. Finally, there are four heating elements located at the bottom of Tank 1.

3.2 Problem Statement

To simplify the problem, two fault modes are examined: "tank1 leakage" and "stuck outgoing valve FV108" in Tank 1. The fault modes and associated features are shown in Table 1.

The mode detector detects two operating modes in this simulation. Following these two operating modes, two sets of classifiers and prognosticators employed to reduce the system resource consumption and speed up the wavelet training and prediction process.

Table1: Failure modes and features to be examined

Failure Mode	Feature 1	Feature2	Feature3	Operating Mode
Tank1 leakage	Tank1 level slope	Tank2 level slope	Main Tank level slope	System idle
Stuck in FV108	Flow rate between tank 1 and tank 2			Transfer water from tank1 to tank2

3.3 Simulation Results and Analysis

3.3.1 Startup mode

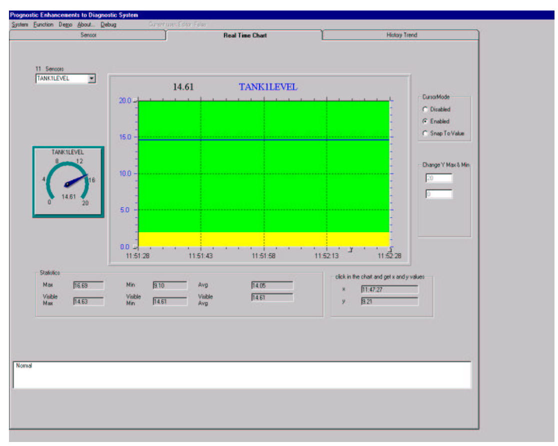

Figure 10: Normal system state.

During this period, the system is running normally: the pumps are off, the valves are in their closed position. The tanks' level is stable (Figure 10). The simulator does not give any warning message.

3.3.2 Operating mode 1 with incipient failure (Figure 11)

At this point, a failure was seeded and detected and an alarm was provided, an alarm message was prompted. Since a failure was detected, the prognostic routine (DWNN) was initiated. The DWNN accessed the fault information from the database and provided the remaining useful lifetime of the failing component, as shown in Figure 12. In this example, 40 seconds is the remaining useful lifetime.

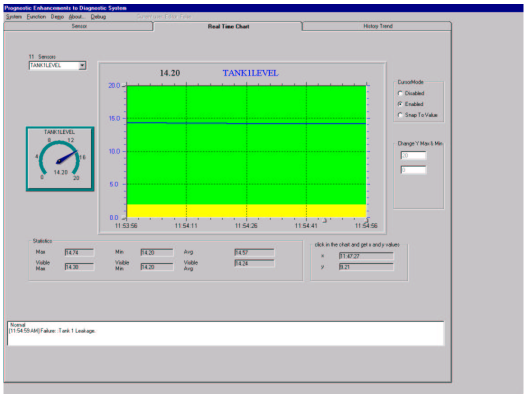

Figure 11. Operating mode 1 with incipient failure.

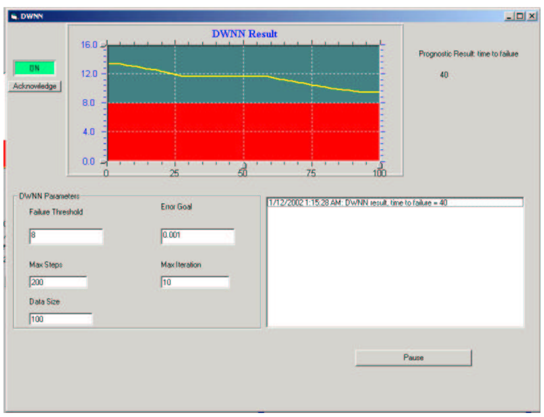

Figure 12. Prognostic result.

4. Conclusions

This paper introduces an open, generic, scalable, and integrated diagnostic / prognostic architecture. The architecture was applied to a 3-tank process where faults were seeded, detected and the remaining useful lifetime of the failing component trended. The results demonstrated that our architecture is useful in obtaining better diagnostic and prognostic results with improvements in speed and reduction in consumption of system resources.

Acknowledgement

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REFERENCES

1. Hadden , G., Bergstrom, P., Bennett, B., Vachtsevanos, G. and Van Dyke, J., 1999. Shipboard Machinery Diagnostics and Prognostics/Condition Based Maintenance: A Progress Report, Maintenance and Reliability Conference, pp. 73.01 – 73.16, Gatlinburg, TN: MARCON 99.
2. Hadden, G., Vachtsevanos, G., Bennett, B. and Van Dyke, J., 1999. Machinery Diagnostics and Prognostics/Condition Based Maintenance: A Progress Report, Failure Analysis: A Foundation for Diagnostics and Prognostics Development, Proceedings of the 53rd Meeting of the Society for Machinery Failure Prevention Technology.
3. Jardim-Goncalves, R., Martins-Barata, M., Alvaro Assis-Lopes, J., and Steiger-Garcao, 1996. Application of stochastic modelling to support predictive maintenance for industrial environments, Proceedings of 1996 IEEE International Conference on Systems, Man and Cybernetics, Information Intelligence and sustems, p. 117-22, vol.1, 14-17.
4. Frelicot, C., 1996. A fuzzy-based prognostic adaptive system, RAIRO-APII-JESA, Journal Europeen des Systemes Automatises, vol. 30, no. 2-3, p. 281-99
5. Lembessis, e., antonopoulos, G., King, R.E., Halatsis, C., and torres, J., 1989. CASSANDRA": an on-line expert system for fault prognosis", Proceedings of the 5th CIM Europe Conference on Computer Integrated Manufacturing, p. 3717, 17-19.
6. Ray, A. and Tangirala, S., 1996. Stochastic modeling of fatigue crack dynamics for on-line failure prognostics, IEEE Transactions on control Systems Technology, vol. 4, no. 4, p. 443-51.
7. Proha, S., 1996. Using the National Information Infrastructure (NII) for monitoring, diagnostics and prognostics of operating machinery, Proceedings of the 35th IEEE Conference on Decision and Control, p. 2583-7, vol. 3, 11-13.
8. Parker, B.E., Jr., Nigor, T.M., Carley, M.P., Barron, R.L., Ward, D.G., Poor, H.V., Rock, D., and DuBois, T.A., 1993. Helicopter gearbox diagnostics and prognostics using vibration signature analysis, Proceedings of the SPIE – The International Society for Optical Engineering, vol. 1965, p. 531-42.
9. Flint, A.D., "A prognostic maintenance system based on the Hough transformation", Transactions of the Institute of Measurement and Control, vol. 16 no. 2, p. 59-65, 1994.
10. Begg, C.D., Merdes, T., Byrington, C., and Maynard, K., "Dynamic Modeling for Mechanical Fault Diagnostics and Prognostics", Proceedigs of MARCON 99, Maintenance and Reliability Conference, pp. 22.01-22.13, May 1999.

11. Li, J. and Yoo, J., “Prognosis of Gear Tooth Crack Growth”, Proceedings of the 52nd Meeting of the Society of Mechanical Failures Prevention Technology, virginia Beach, VA, April 1998.
12. Peebles, T.D., Essawy, M.A., and Fein-Sabatto, S., 1999. An Intelligent Methodology for Remaining Useful Life Estimation of Mechanical Components, Proceedings of MARCON 99, Maintenance and Reliability Conference, pp. 27.01-27.09.
13. Saeks, R., Pooley, J., 1998. A hybrid supervised/unsupervised neural network architecture for health and usage monitoring, Systems, Man, and Cybernetics, 1998. 1998 IEEE International Conference on , Volume: 3 , 1998 Page(s): 2992 -2997 vol.3
14. Wang, P., Propes, N., Khiripet, N., Li, Y., and Vachtsevanos, G., 1999. An integrated approach to machine fault diagnosis, IEEE Annual Textile Fiber and Film Industry Technical Conference, Atlanta.
15. Vachtsevanos, G., Wang. P.,Khiripet, N., 2000. Prognostication:Algorithms and Performance Assessment Methodologies, in *Proc. of MARCON 2000 Conference, pp. 8.01-8.12.*
16. Khiripet, N., Vachtsevanos, G., Thakker, A. and Galie, T., 2001. A New Confidence Prediction Neural Network for Machine Failure Prognosis”, in *Proceedings of Intelligent Ships Symposium IV, Philadelphia, PA.*
17. Khiripet, N. and Vachtsevanos, G., 2001. Machine Failure Prognosis Using a Confidence Prediction Neural Network, In *Proceedings of 8th International Conference on Advances in Communications and Control, Crete, Greece.*