Diagnostic and Prognostic Health Monitoring of Chillers On-board Naval Vessels

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Abstract—Monitoring the health of systems provides important benefits for many operations in the industrial, commercial, and military sectors. When the health state of important machinery is known and can be predicted, maintenance costs are lowered, safety is increased, spare part inventories can be controlled more efficiently, and system downtime due to failures is reduced. Much work has been done in the separate areas of machinery diagnostics and prognostics, however, there was no general framework for the combination of the two ideas. Global Technology in conjunction with Georgia Tech and the Naval Surface Warfare Center (NSWC) has been developing a generic diagnostic/prognostic software and hardware architecture to detect and predict failures applied to York chillers found on Naval vessels. The method utilized is a data-driven system where chiller failures are seeded and sensor information is recorded and stored. The gathered data is then used to train the software modules responsible for diagnosing and prognosing failures. Once the training has been completed, the system is connected on-line to notify the user of incipient failures and the useful life remaining before maintenance must be performed. This information can be utilized in a preventative maintenance program (condition-based maintenance) to optimally schedule maintenance work orders. By scheduling maintenance based on machine health, rather than a periodic timetable, costs are reduced and equipment availability is enhanced. With regards to chillers, future ship systems will require a high degree of thermal management impacted by heavy loads and more automated equipment and electronics aboard. Clearly, Sea Basing can benefit from a condition-based maintenance approach where weight and inventory space is limited, crew safety is a concern, and system downtime is unacceptable.

Index Terms—Diagnostics, Prognostics, Machinery Health Monitoring, Mode Identification

1. INTRODUCTION

Condition based-maintenance (CBM) is the next step in the evolution of maintenance engineering systems. This approach toward maintenance optimally schedules resources and maintenance activities based upon the measured and predicted health status of machinery. Other maintenance approaches such as redundant systems and periodic maintenance often waste money, time, space, materials, etc. CBM provides many benefits such as lowered maintenance costs, increased workplace safety, efficient inventory control, etc. However, the growth of this technology is relatively slow due to lack of failure data, equipment expense, development time, etc. Thus, research continues to develop new CBM technologies in order to make CBM a viable maintenance solution for a wide variety of systems.

CBM approaches often begin with the detection and classification of impending failures from sensor data. This step is called *diagnostics*. After an impending failure has been detected, a prediction is made on the future time-evolution of the failure. This failure behavior prediction is called *prognostics*. The interesting failures are of the variety where the failure grows with time and eventually reaches a critical time where the failure becomes catastrophic. The failure detection and prediction information from both diagnostics and prognostics, respectively, is then used for other purposes such as maintenance scheduling and resource management.

In this paper, we describe a generic, intelligent, data-driven, diagnostic and prognostic software architecture. Section 2 describes the diagnostic and prognostic software architecture. Section 3 discusses the experiments performed on a 363-Ton York AC chiller. Section 4 then concludes with the benefits and drawbacks currently associated with this data-driven approach.

2. PROGNOSTIC ENHANCEMENTS TO DIAGNOSTIC SYSTEMS (PEDS) SOFTWARE ARCHITECTURE

This section describes the main modules of the Prognostic Enhancements to Diagnostic Systems (PEDS) software architecture. Figure 1 shows sensor information that is extracted from the system under study is fed into a computer through a data acquisition device for diagnostic/prognostic software processing. The PEDS system then outputs any detected impending failures and their associated predicted time-to-failure.

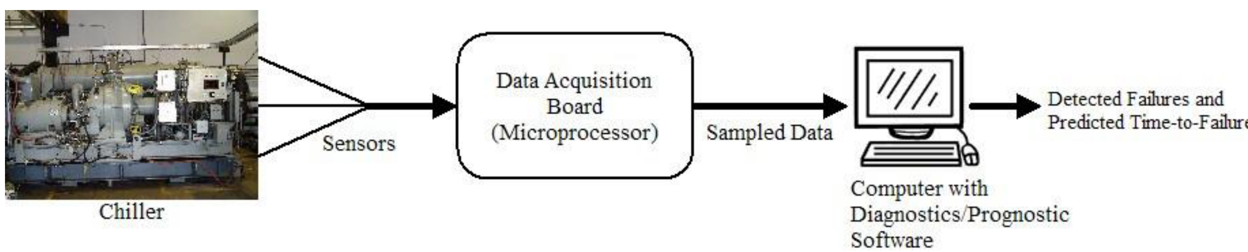

Figure 1. The general diagnostics and prognostics hardware configuration.

Figure 2 shows the different modules of the PEDS software architecture. Central to the architecture are the database and event manager modules which store data and control the execution of the other modules, respectively. The data pre-processing module filters noise and other artifacts to improve signal-to-noise ratio. The mode estimator module identifies the operating mode of the system and declares which sensors should be examined and how they should be processed. Feature extraction is performed on the relievant data to aid in the detection of impending failures. The diagnostic module determines whether or not an impending failure has been detected and identifies the failure through several classifiers (i.e. Fuzzy Logic and WNN). The outputs of these classifiers are fused through use of Dempster-Shafer theory to produce a degree-of-certainty associated with each detected failure. Once a failure has been detected, the event dispatch commands the prognostic module (i.e. DWNN and CPNN) to predict and place bounds on the time-to-failure. The following subsections (2.1-2.4) describe some of these modules in further detail.

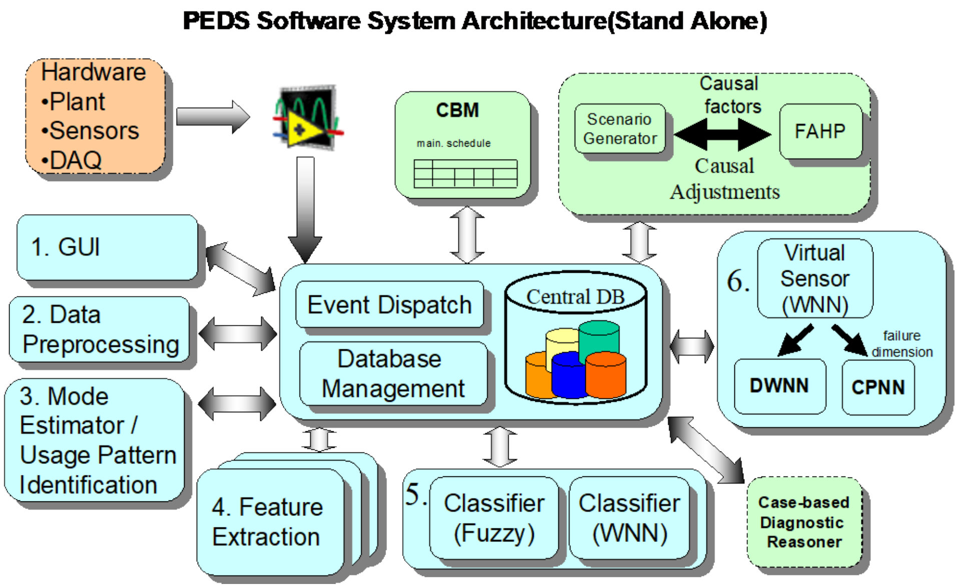

Figure 2. The PEDS software architecture.

2.1 Feature Extraction

In many cases, relevant information is difficult to interpret directly from sensor data. Noise and other artifacts compound the problem of determining which data is important to the task of detecting and predicting failures. Feature extraction is used to aid in separating the relevant and irrelevant information from the gathered data. Some common features are the mean, standard deviation, height of peaks at certain frequencies of spectral data, etc. Typically, several different features are extracted from a window of collected data which defines a feature vector. The feature vector is often optimized by using a method known as feature selection which determines the best features for correctly diagnosing and prognosing failures.

2.2 The Mode Identification Module

Different operating modes such as fast, slow, high load, low load, shutdown, startup, etc. cause failures to evolve in different ways. Therefore, it is important that the operating mode be known in advance in order to accurately detect and predict failures.

The mode identification module presented in this paper takes a hybrid approach where events and dynamics are used to determine the current operating mode separately and then this information is fused to a single identified operating mode as shown in Figure 3. The event-driven part of this model is represented through a fuzzy Petri net where the places represent modes and transitions are mode transition events. The events are represented in rule form with membership functions representing the uncertainty of the event description. The time-driven part of the model uses a fuzzy expert classifier with Mandani inference engine with center-of-mass defuzzification. The output of event- and time-driven models are fused to determine a final identified operating mode.

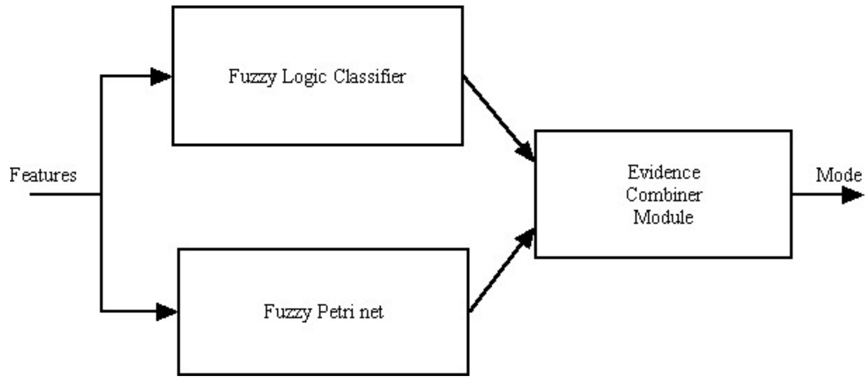

Figure 3. The mode identification module architecture.

2.3 The Diagnostic Module

The diagnostic module which detects and classifies impending failures is composed of two intelligent software modules: fuzzy logic expert and Wavelet Neural Network. The outputs of these modules are fused to give a degree of certainty about the failure mode. Section 2.3.1 describes the fuzzy logic expert diagnostician and section 2.3.2 illustrates the Wavelet Neural Network in more detail.

2.3.1 The Fuzzy Logic Expert 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; it receives feature inputs from the database and reports to the database any indications that a failure mode may have occurred, as shown in Figure 4.

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.

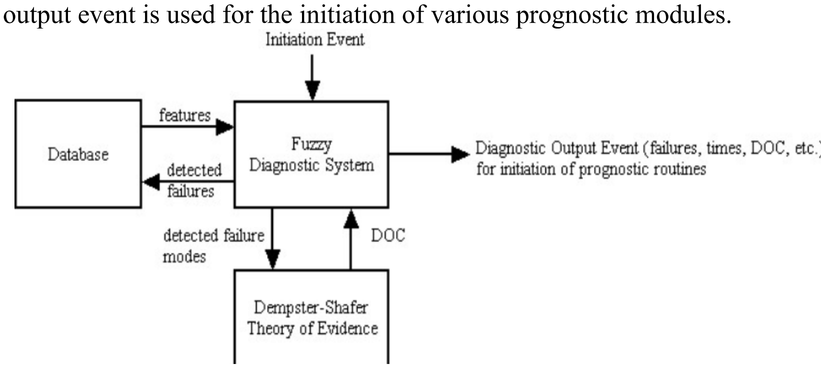

Figure 4. The fuzzy logic expert diagnostic architecture.

The fuzzy logic system structure is composed of four blocks: fuzzification, the fuzzy inference engine, the fuzzy rulebase, and defuzzification, as shown in Figure 5.

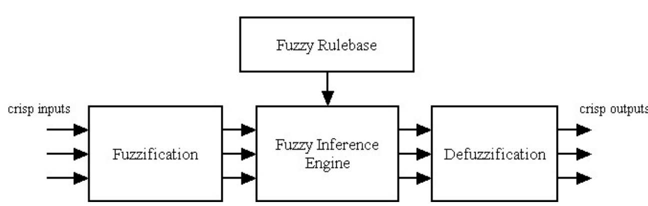

Figure 5. The fuzzy logic system structure.

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 6.

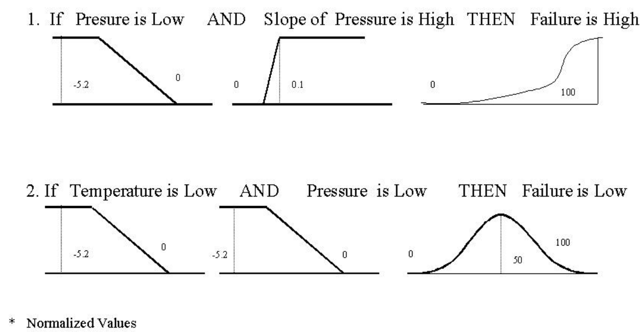

Figure 6. A graphical representation of two rules in a fuzzy rulebase.

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 fulfillment 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 7. These values are compared to a threshold to determine whether or not a fault mode should be declared as having been detected.

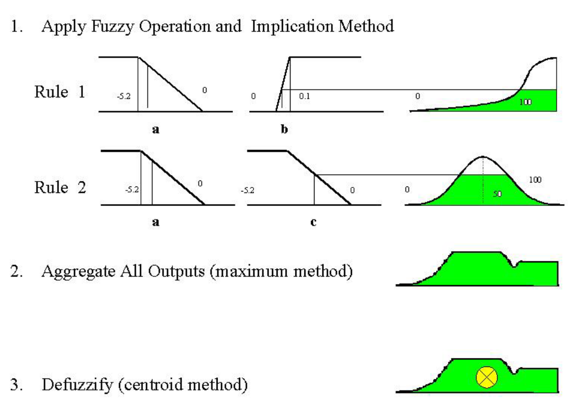

Figure 7. Graphical representation of the fuzzy inference engine and defuzzification.

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.

2.3.2 The Wavelet Neural Network (WNN)

The WNN (Figure 8) 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.

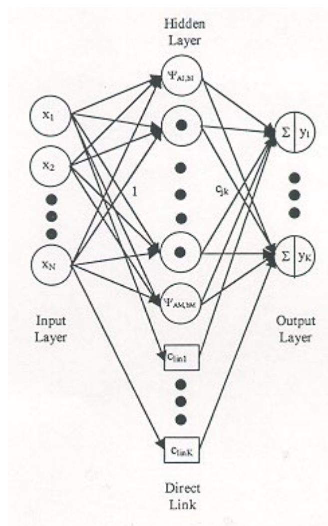

Figure 8. The Wavelet Neural Network structure.

2.4 The Prognostic Module

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 [5] and CPNN [6, 7].

2.4.1 The Dynamic Wavelet Neural Network (DWNN)

The DWNN is based on a static "virtual sensor" (Figure 9) and a predictor. The basic DWNN structure is shown in Figure 10. 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 rely upon a dynamic wavelet neural network model acting as the mapping tool.

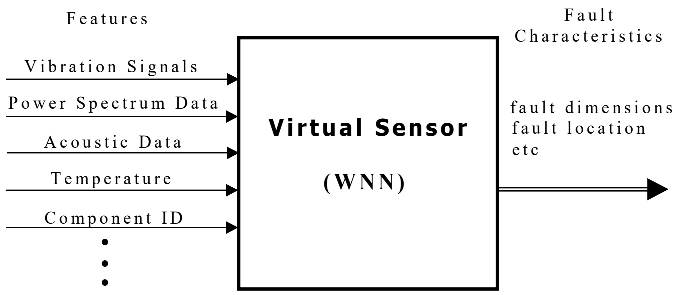

Figure 9. A virtual sensor.

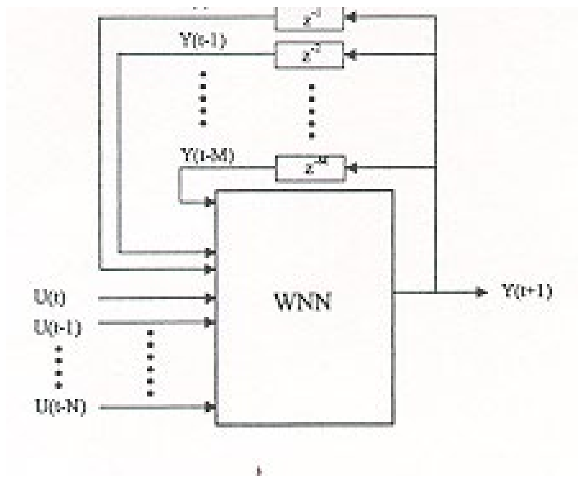

Figure 10. The DWNN structure.

2.4.2 The Confidence Prediction Neural Network (CPNN)

The CPNN represents uncertainties as multiple trends and confidence distributions. 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 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 11). 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 4. Details of this novel development can be found in the cited references [6,7].

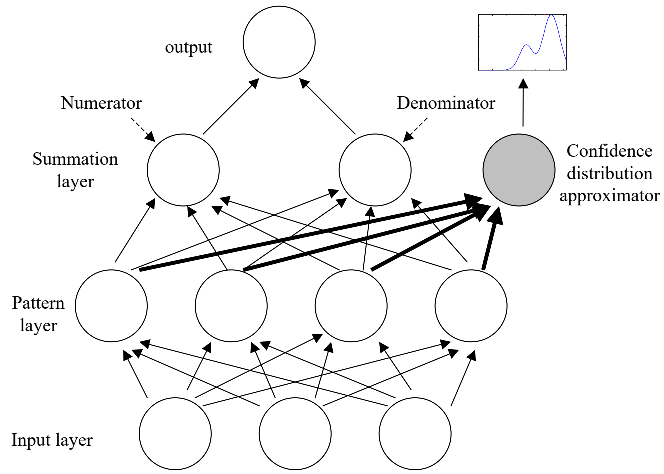

Figure 11. The Confidence Prediction Neural Network.

3. THE CHILLER TESTBED

A 363-Ton York AC Chiller (Figure 12) located at the U.S. Navy HVAC RDT & E testing facility in Philadelphia, PA was used to collect chiller data and test the operation of the diagnostic/prognostic software on-line. The chiller sensors were connected through an embedded microprocessor/data acquisition unit which relayed sensor information to the diagnostic/prognostic computer through a serial port connection. There were 45 sensors readings from the chiller/microprocessor such as pressures, temperatures, valve positions, solenoid states, etc.

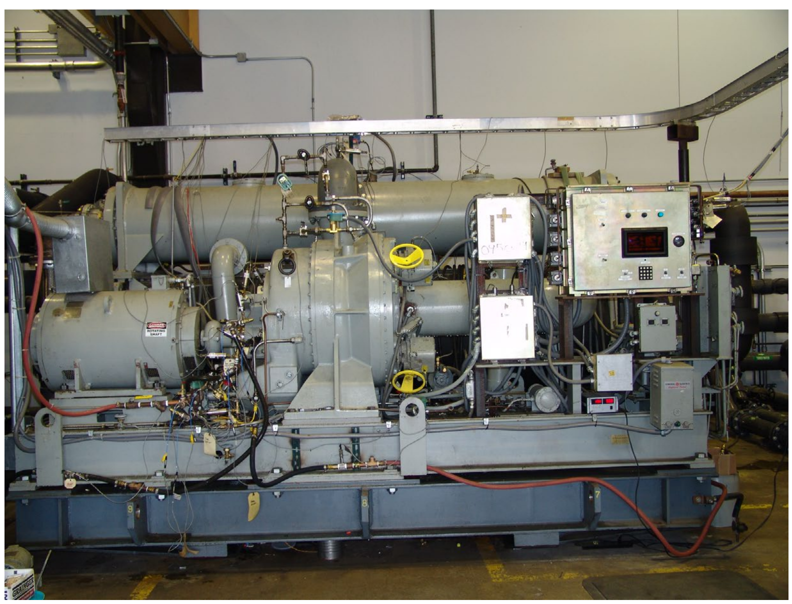

Figure 12. The 363-Ton York chiller at the testing facility.

Experimental data was collected for the following failure modes:

- Refrigerant charge leaking/low (RCL)
- Condenser tube fouling (CTF)
- Compressor Surge (CSurge)
- Compressor Stall (CStall)

The failure experiments were designed so that the chiller would not be damaged. Such experiments where the actual failure does not occur is known as “seeding” failures where one tries to get close to the expected symptoms of the real failure. The failures were “seeded” at different loads and temperatures settings as such:

- RCL – Refrigerant was pumped out at a slow rate (e.g. 50 lbs per hour)
- CTF – The condenser pump rate was reduced slowly
- CSurge – The VGD position was reduced slowly towards 10%
- CStall – The VGD position was increased slowly towards 100%

The retrieved data was analyzed off-line and used to select appropriate features and train the diagnostic and prognostic modules. After training, the diagnostic/prognostic software was connected on-line with the chiller to detect failures and predict time-to-failures.

3.1 EXPERIMENTAL RESULTS

The first interesting aspect of the collected data was the poor resolution that was available from some of the sampled sensor data. Some data were represented by integer values which introduces high signal-to-noise ratio. A graph of the microprocessor data is shown in Figure 13 along with a graph of data taken using LabVIEW (a data acquisition product from National Instruments which had higher data resolution) in Figure 14. Since we intended to utilize the microprocessor data, a low pass filter was designed to smooth out the data so that it resembled that from LabVIEW.

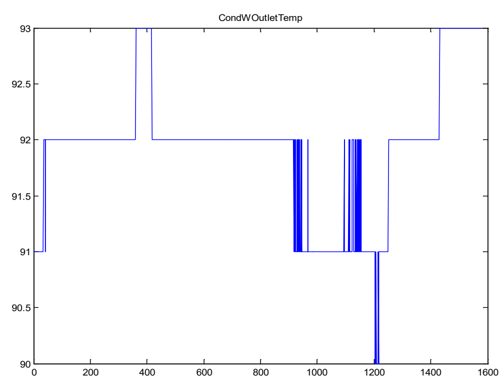

Figure 13. Microprocessor Data

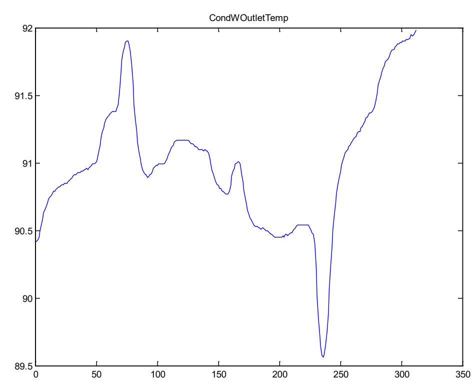

Figure 14. LabVIEW Data

The mode identification module selected four different operating modes of interest: Off, Startup, Normal, and Shutdown modes. Oil valves which were initiated during chiller startup and shutdown operations were measured to determine the mode. The mode identification module worked correctly during off-line and on-line testing by GTC.

The features that were used in the feature extraction module were:

- Chilled Water Inlet Pressure Slope (CTF)
- Condenser Water Inlet Pressure Slope (CTF)
- Compresser Discharge Pressure Slope (RCL)
- Evaporator Liquid Temperature Slope (RCL)
- Motor Current Slope (RCL)
- Surge Load &VGD Boundary Line (CSurge)
- Stall Load & VGD Boundary Line (CStall)

These features were selected from analysis directly from the data collect from the seeded failures.

After the diagnostics and prognostics modules were trained off-line on the data, on-line testing began. On-line operation of the diagnostics/prognostics software consisted of gathering data into the database from the microprocessor periodically (0.5 sample/ sec) and performing the diagnostic/prognostic evaluation while operating the chiller. Modes were changed and failures were seeded while PEDS was running on-line. Only a few on-line tests were performed for each failure mode on the chiller due to time constraints. The software identified the mode and detected seeded failures correctly from these few tests. The prediction result from the DWNN on a seeded refrigerant charge low failure is shown in Figure 15. A CPNN result is shown in Figure 16 demonstrating the bounds on the predicted time-to-failure.

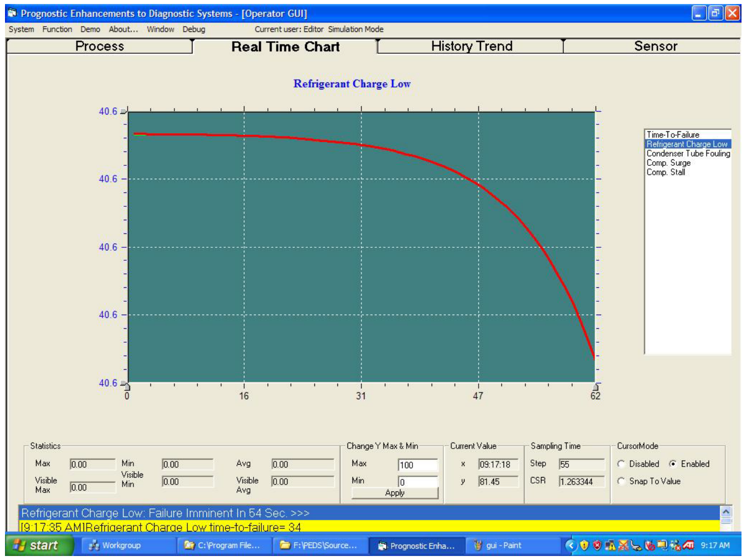

Figure 15. DWNN predicted time-to-failure.

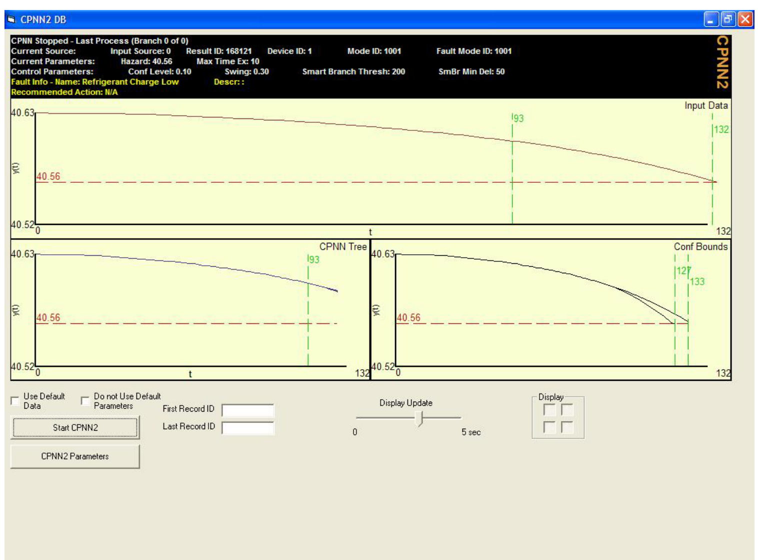

Figure 16. CPNN time bounds on DWNN prediction.

4. CONCLUSIONS

Diagnostics and prognostics systems are essential tools for the CBM approach. It is important not only to detect and identify failures early, but also to predict when impending failures become catastrophic. This prediction information will aid in the optimal scheduling of maintenance actions which is one of the main goals of CBM.

The approach presented in this paper is a data-driven approach where data is collected and prediction algorithm parameters are trained on- and off-line. Unlike statistical approaches which require a plethora of historical data to obtain representative distributions, this intelligent architecture learns from incoming data while operating on-line. Thus, this prediction architecture is adaptive to changes in failure dynamics.

One problem which affects all diagnostic/prognostic systems is that of obtaining failure data. Failure data can be difficult to gather or may not even exist. Thus, seeded failures are an economical solution provided they are designed properly with the aid of experts familiar with the system operation.

Feature selection is an important part of the diagnostic/prognostic design process. Without careful consultation with system experts, the selected features could cause high false failure alarms rates and incorrect prediction results. By utilizing resources such as maintenance personnel expertise, a list of possible features could be selected and fine tuned through automated optimization techniques such as feature selection.

A future enhancement that would increase the reliability of this framework is to merge the results of PEDS with model-based methodologies using appropriate data fusion techniques.

The PEDS architecture provides a generic framework for diagnostics and prognostics for a wide variety of complex systems. It requires off-line training to ensure some degree of immediate performance and then proceeds to learn from new data. The diagnostics and prognostic modules require carefully designed seeded failure experiments to ensure that the correct data was gathered for parameter training. Utilizing both data fusion and expert advice, the confidence in the detection and prediction algorithms will increase. A CBM approach utilizing intelligent systems concepts such as PEDS will ensure economical use of maintenance resources with high degree of flexibility and autonomy.

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