Selected Artificial Intelligence Methods Applied within an Integrated Vehicle Health Management System

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Abstract

The work presented in this paper will highlight selected artificial intelligence approaches as applied within an Integrated Vehicle Health Management (IVHM) system. The selected vehicle subsystem areas to be discussed include electro-mechanical actuators (EMAs), propulsion system performance, vehicle structural integrity and general signal anomaly detection. Artificial intelligence methods including neural networks, fuzzy logic and trained probabilistic classifiers are described within the context of the selected subsystem applications. In addition, discussion on individual subsystem health condition indicators as applied within an intelligent, model-based reasoning approach is presented that examines health state and functional availability of individual components, subsystems, and the overall vehicle. The AI implementations described herein illustrate the integration of detection, diagnostic, and prognostic reasoning capabilities from across critical subsystems on a vehicle platform. The examples provided illustrate how the selected AI technologies can be implemented throughout an end–to–end application, from data signal quality checks to off-board prognostic assessments.

Introduction

The development and evolution of automated fault detection, isolation and prognostic technologies as applied to air vehicle subsystems has enabled continuous advancements in the practice of condition-based maintenance for both military and commercial applications. For air vehicles, this has resulted in increased autonomous operation in flight as well as on the ground; reduced ground maintenance and repairs, facilitated by regular system health checks in flight; and improved safety and reliability via the continuously improving efficacy of the systems monitoring health[1]. IVHM is an integration and coordination of both the embedded aspects of health monitoring and advanced reasoning onboard with the ground based supporting infrastructure all focused on mitigating the impact of detected component failures on mission readiness and safety.

As the name implies, the foundation of IVHM in its true sense is highly integrated into the vehicle, its constituent subsystems, and the supporting ground based infrastructure. An IVHM system is focused on enabling decision support to provide autonomous, timely, and accurate assessments of a vehicle's health and functional availability to operations and maintenance personnel. The greater vision of the system seeks to include utilizing this information on the ground to facilitate decreasing operational costs and increasing operational readiness in order to provide significant life cycle benefits to aerospace systems. As such, a pragmatic view of an IVHM approach would be realized through two distinct areas of functionality: The first, an embedded aspect, facilitating the goal of on-board vehicle health monitoring as summarized by Ofsthun[2]; "to have the vehicle dynamically identify any degradation in functional performance that may affect safety or successful field operations as well as to identify the specific subsystems that require maintenance to restore full operational capability." The knowledge gained from the embedded IVHM functionality must then be forwarded along to a ground-based aspect of the greater system to be used by operations personnel. The ground based system provides the interface between the onboard monitoring and reasoning functionality and operations, maintenance, and logistics personnel and infrastructure, facilitating informed, condition based asset management and support. The scope of this paper is focused on a few selected diagnostic and prognostic approaches as applied to specific subsystems on an air vehicle.

[1] Fox, J.J., Glass, B.J., "Impact of Integrated Vehicle Health Management (IVHM) Technologies on Ground Operations for Reusable Launch Vehicles (RLVs) and Spacecraft", IEEE Proceeding of Aerospace Conference 2000.

[2] Ofsthun, S., "Integrated Vehicle Health Management for Aerospace Platforms," *IEEE Instrumentation & Measurement Magazine*, September 2002, pp. 21 – 24m

Signal Validation and Anomaly Detection

One of the most important areas to consider when implementing an IVHM system is to ensure the reliability of all measured parameters. When automated algorithms are used to identify vehicle subsystem anomalies, the diagnostic and prognostic algorithms must be confident that the anomalies are indeed occurring within the system and are not the result of normal transients or faulty sensors. Therefore, a comprehensive signal validation and anomaly detection module is needed to act as a front-end to validate and call out health status anomalies from the sensed signals prior to further analysis.

One of the AI technologies that can be applied to address this issue is based on a probabilistic neural network (PNN) modeling technique that can use normal system operating data to detect off-nominal behavior. In this approach, a trained PNN data model is used to predict the normal behavior of the system signal data acquired, which can then be used to continuously assess the difference between the actual and predicted data. The overall implementation approach is shown in Figure 1. The benefits of this type of data-driven modeling approach include the ability to detect subtle or abrupt changes in system health signals over a short period of time. Mode detection is also recommended for use with the PNN algorithm to aide in determining the width of the "normal" bands utilized. At the output of the PNN, a residual analysis algorithm evaluates the errors of the current health parameters relative to "expected" values for any given level of operation based on these "normal" bands. The results of the mode detection algorithm will scale the magnitude of the residual being assessed in determining the integrity of the underlying signal.

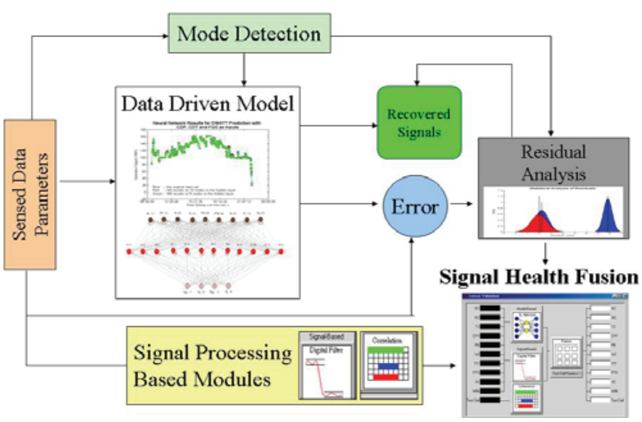

Figure 1 Signal Validation and Anomaly Detection Process

The PNN is trained to predict a signal, with inputs that are correlated to it in some manner over an appropriate dynamic range. The operation of the PNN is simple and can be implemented in real-time without the need for supervised training that makes many neural network applications often difficult to implement and update. As shown in Figure 2, the PNN first compares the inputs to a set of "normal" training vectors contained in database denoted $\mathbf{IW}_{(1,1)}$. The "training data" is simply the data that represent normal behavior for a particular person and is easily substituted based on each persons "normal" condition. Once the data is stored, the second layer of the algorithm sums the contribution of each class of inputs to produce a vector of probabilities. Finally, the prediction is based on the weighting associated with each of the probabilities and the "similarity" associated with the inputs and known "normal" data. Because of the information compression and regeneration, if an anomaly occurs, the output residual will quickly identify it and pass the information to the residual analysis module for further analysis. The PNN has been successfully applied to various anomaly detection implementations for critical systems on the Space Shuttle main engine, gas turbine engines, chemical processing plants, and machinery vibration monitoring applications, just to name a few.

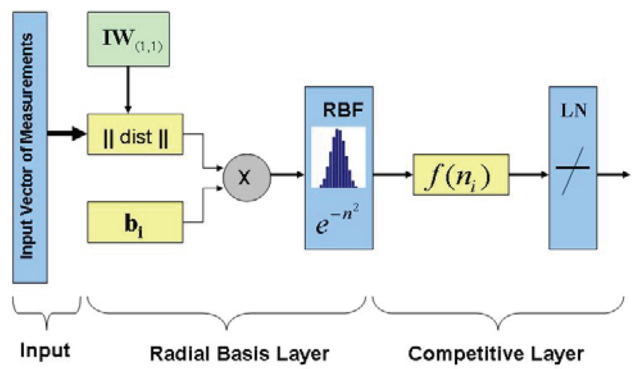

Figure 2 Probabilistic Neural Network (PNN) Model

The residual analysis module assesses the "normal" bands associated with each sensor signal at the current operating condition. When a signal goes outside these bands, while others remain within, an anomaly is detected associated with those specific sensors/data sets. A decision level fusion output determines the final confidence levels that a particular sensor or health feature has anomalies or is corrupted in some way.

Structural Health Monitoring

Structural health monitoring is another significant area of interest in implementing comprehensive vehicle health management functionality. This often includes monitoring the vehicle structure for impact detections, localization of damage events and some form of usage monitoring on key structural and flight control surfaces. Specifically, foreign or domestic object damage (FOD or DOD) impacts may cause damage that ultimately affects the vehicle's ability to complete its required mission. For unmanned vehicle, without a pilot on board to make critical decisions, autonomous assessment of damage becomes even more important to operational success. Various techniques has been developed and implemented that can assess the location and damage level resulting from impacts on structural components that occur during flight[3]. We will discuss the use of combining wavelet transforms and neural networks for determining the impact location and damage severity assessment.

In this structural health monitoring approach, raw vibration signals are acquired from strategically placed accelerometers on a structural member. The continuous monitoring procedure looks for sudden increases in vibration levels. If an impact is suspected to have occurred, further processing takes place to determine the location and estimate the severity of the impact. The analysis is based on using the relative time of arrival of the wave energy propagating away from the point of impact to the sensor locations. Applying a combination of advanced signal processing techniques and neural networks enhances the accuracy of localization and severity estimation.

From a prognostic point of view, the estimated damage severity level can be used in conjunction with pre-run fatigue analysis models to provide a means of estimating the amount of time the vehicle can remain airborne before a damage induced crack grows to a critical, flight-ending size. The approach is based on crack growth formulations and fatigue calculations; implementation requires knowledge of static and cyclic loading profiles on the structural member under consideration.

The wavelet transform is applied to the raw vibration data to provide the threshold for both the timing and maximum energy amplitude encountered. Based on the wavelet analysis, the next step is to extract specific features that can be used for assessing the impact damage characteristics. The features of interest in determining impact location and severity are related to the time of arrival of the propagating dispersive wave and magnitude of energy received at the accelerometer locations, respectively. Figure 3 shows the entire process associated with the feature-based analysis approach, where the block diagram on the left is specifically used in the training stage and the diagram on the right is implemented during the evaluation stage.

Based on the output from the wavelet transform, thresholds are set on the magnitude of the output energy detector in order to calculate the time of arrival of the dispersive wave group velocity. In addition to this time-based feature, an integration of the overall signal magnitude represents an energy feature that is used to locate the approximate area of the impact. The energy features are then calculated from the maximum amplitude experienced from the Kurtosis of the output from the wavelet transform. This maximum amplitude feature is then compared with those experienced by all accelerometers to determine the general area of the applied impact. Next, time of arrival features are calculated from each accelerometer based on when the adaptive energy feature exceeds a particular threshold. Based on the number of known cases used in the training file, a simple back-propagation neural network is used to relate the actual distance of the true impact location to each of the accelerometers. Figure 4 is an illustration of this process as related to the energy and time features.

[3] Roemer, M.J., Ge, J., Liberson, A., Tandon, G.P., Kim, R.Y., Autonomous Impact Damage Detection and Isolation Prediction for Aerospace Structures, IEEE Aerospace Conference, Montana, March 2005.

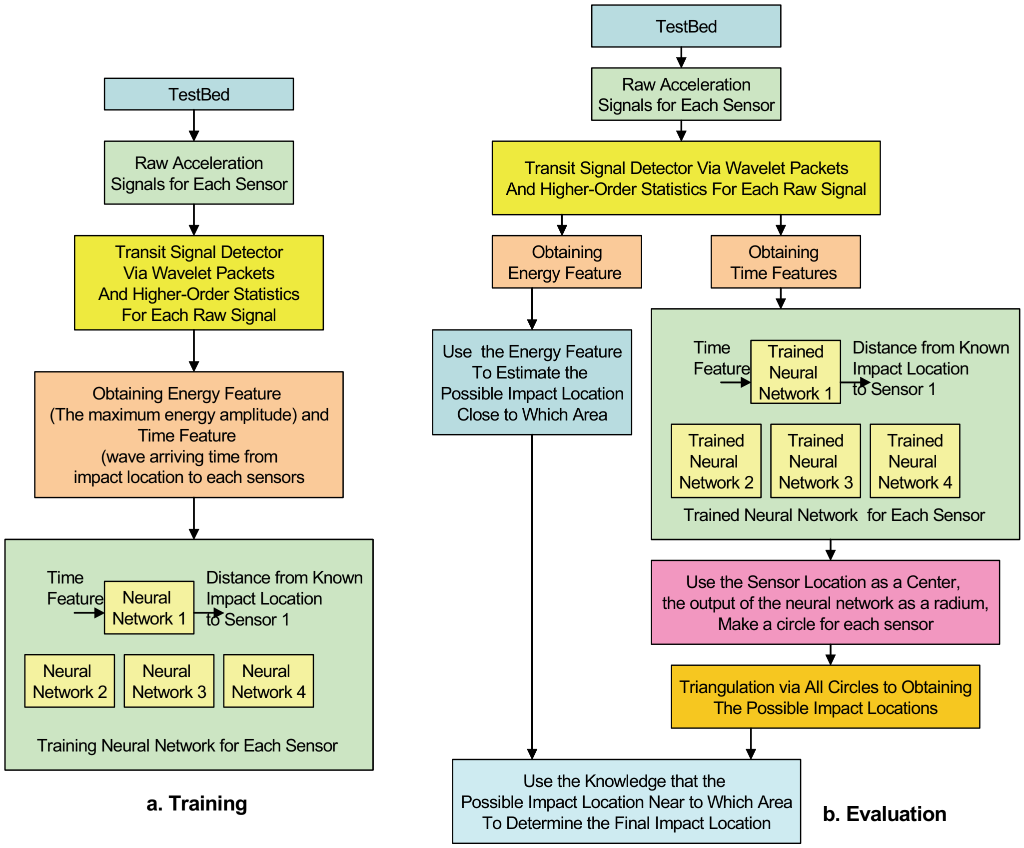

Figure 3 AI Approach for Impact Damage Detection and Localization

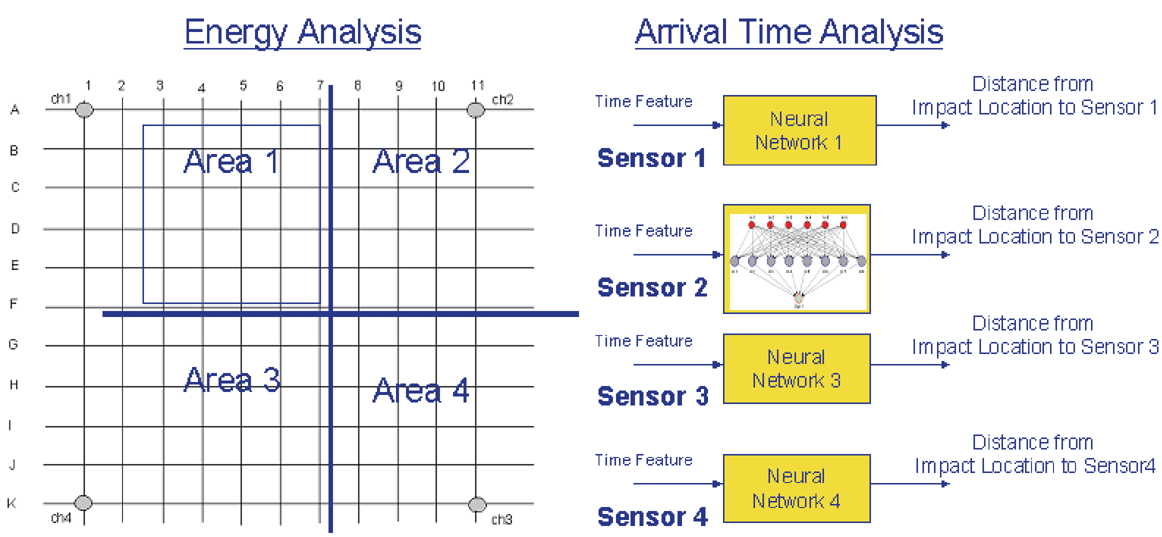

Figure 4 Energy and Time-Based Features Used in Training Algorithms

The neural network data-driven modeling approach uses a training process with initial weights and constants associated with a selected set of basis functions. The approach taken here was to train multiple neural networks with initial weights and basis function constants provided by a Monte Carlo simulation procedure. Therefore, the output of each of these trained neural networks with different initial conditions would provide a distance prediction based on the input group velocity arrival time extracted from threshold crossing. An example of the outputs of these networks for a given example is shown in Figure 5. Finally, a prediction on the location of the impact is made based on the intersection of each of the distances predicted from the accelerometers. These predicted distances are shown as concentric circles, with each of the accelerometers representing the centers.

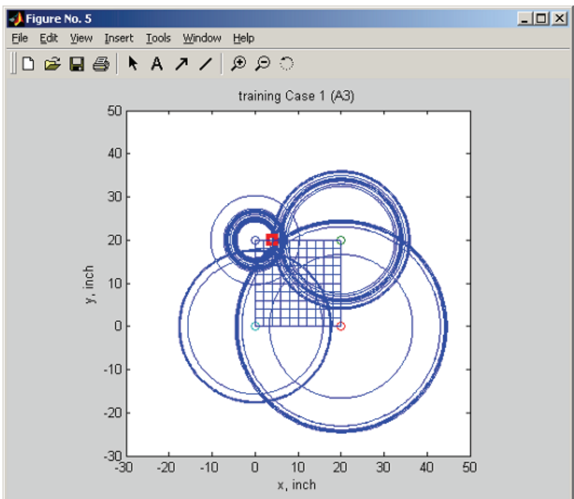

Figure 5 Example Outputs from Trained Neural Network for Distance Prediction

Propulsion System Health Monitoring

Propulsion system performance health is a critical function to be monitored during vehicle operation. To accomplish this, various pressures, temperatures, and flows must be sensed at different points within the gas path, as are any bleed flows, fuel flow, rotor speeds, and any other engine conditions that must be accounted for in performance calculations. In order to perform the on-line performance assessments, specific engine gas path analyses are typically run off-line under off-design conditions to develop a matrix of "error patterns" expected under ideal engine degraded conditions. Measurement and modeling uncertainties are also developed based on the variances in the modeling and measurement acquisition processes.

Using the gas path performance measurements obtained, statistical engine parameter signature curves are developed for a specific engine serial number as well as for a number of engines in the fleet. Hence, engine-to-engine and fleet-to-engine comparisons can be made at any point. Measurement uncertainties are based on this recorded data. The right side of Figure 6 shows the corrected performance curve of compressor discharge pressure as function of N2 speed at pseudo-steady state conditions. The "bands" around the curve represent the 1-sigma distribution (1 standard deviation) levels. The left side of Figure 6 shows a 3-D representation of how the percent deviation in CDPC changes with speed.

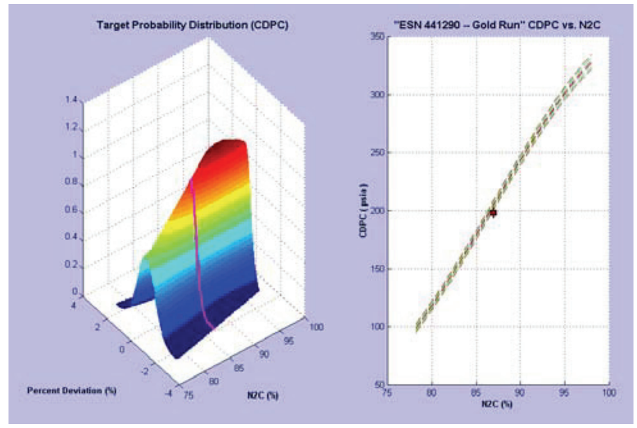

Figure 6 Engine Signature Curve Distributions

Utilizing confidence intervals for the discovery of a statistically significant trend away from "normal" engine operation is a rigorous way to assess engine anomalous events. Utilizing a full set of engine signature curves described above is well suited for this type of analysis. The detection of an anomalous event will trigger the start of a more comprehensive diagnostic treatment of the detected error pattern. The key is to be capable of determining whether the mean measured parameter values have shifted with a high degree of confidence.

This propulsion system performance prognostic approach relies on gauging the proximity and rate of change of the current system deviations to known performance faults based on the GPA model. This multi-parameter, evolutionary technique has been shown to be capable of predicting degraded performance in propulsion systems (Roemer and Ghiocel, 1998). This approach requires that sufficient sensor information be available to assess the current condition of the system in terms of shifted trends in parameters from a baseline condition. Modeling and measurement uncertainty is accounted for with this technique utilizing the distributions on the current parameter shifts and model-based fault conditions. While a physical model, such as a gas path analysis or control system simulation, is beneficial, it is not a requirement for this approach to work. An alternative to the physical model is built in "expert" knowledge of the fault condition.

This AI-based classification and prediction process involves assigning non-normal or normal Probability Density Functions (PDF's) to performance error patterns associated to known faults in N-dimensional space. Similarly, the current error exists as a PDF in the parameter space as well. The probability that the current condition (C, measured parameter shifts), may be attributed to a given fault (F, identified known fault conditions) is determined by the "overlap" (i.e. multi-dimensional integration) of their respective joint probability density functions. Figure 7 shows how this is done in 2-dimensional parameter space. If C and F can be assumed to be normally distributed (not a necessary assumption however), the probability of association (Pa) with a given fault condition F can be found using:

$$p_a = 2\Phi\left(-\frac{\overline{F - C}}{\sqrt{\sigma_f^2 + \sigma_c^2}}\right) = 2\Phi(-\beta)$$

where:

$\overline{F}, \overline{C}$ = the mean of the distributions F and C respectively

σ_f, σ_c = the standard deviation of the F and C distributions

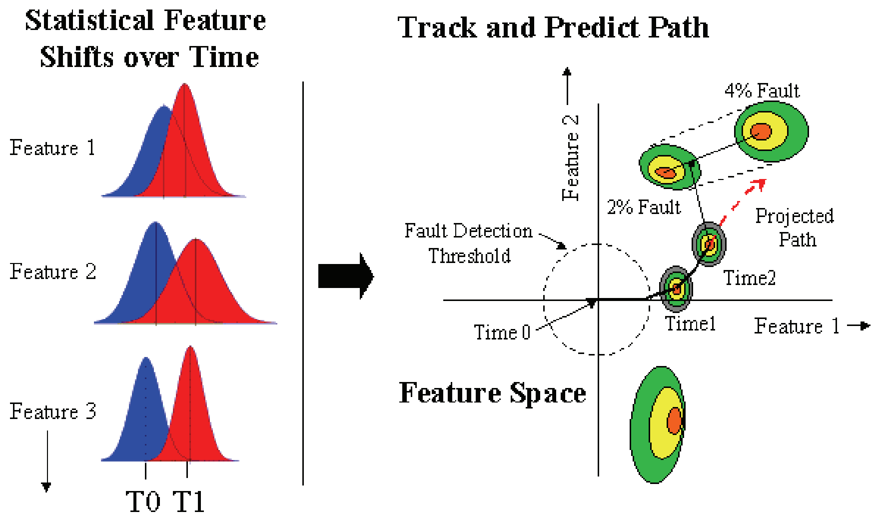

Figure 6 Multi-Parameter Probabilistic Classifier and Predictor

The function Φ( ) is the standard normal cumulative distribution and the β is denoted as the reliability index. The β represents the Euclidean distance between the current conditional distribution (C) and a given fault distribution (F). Hence, this approach performs diagnostics by evaluating the likelihood of the current conditions to known fault conditions and prognostics by extrapolating a fault-weighted, evolutionary path.

Flight Control Actuator Diagnostics

The selected flight control actuator health monitoring and prognostic technique is based on the calculation of features that correspond specifically to the health of the actuator. Hence, a combination of signal processing and neural network generated features were implemented as part of the solution. The developed fault classifier was trained to autonomously map the feature values described briefly next into the correct level of actuator degradation.

Dynamic Pressure

Feature extraction through signal processing is common in the field of prognostics and health management and is a proven technique for tracking damage. Originally developed for vibration monitoring, signal processing techniques have been transitioned to various other technology areas. In previous work, Impact Technologies has demonstrated the ability to detect faults in hydraulic systems using features extracted from the frequency domain [4]. Typically, several frequency bands in the pressure signal are monitored for increased energy content. This increased energy level over these frequency bands is often indicative of wear or damage in the hydraulic system. Figure 7 illustrates the selection of frequency bands where an RMS is calculated and trended over the life of the hydraulic system or component.

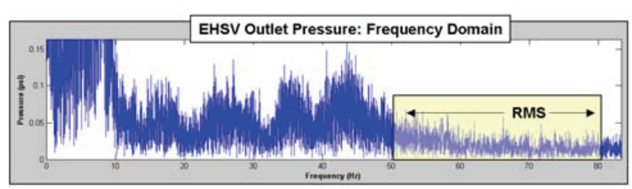

Figure 7 – Frequency Band RMS

[4] Byington, Carl. "In-Line Monitoring System for Hydraulic Pumps and Motors". IEEE Aerospace Conference Procedings. 2003.

The above concept was used to analyze the actuator data and extract a feature related to the dynamic response of the valve's pressure signal. In the analysis, both the inlet and outlet pressures were considered. The output pressure, however, proved to be more sensitive to changes in the health of the valve and was therefore selected for inclusion within the developed automated prognostic module.

The first step in this computation was to calculate the FFT of the output pressure signal. Analysis of the frequency domain identified a noticeable trend in the RMS of the magnitudes in the highest frequency region (50-80 Hz) of the FFT as the valve degrades. The RMS of this region was therefore used to compute the dynamic pressure feature. Typically, frequency bands are selected to be above or between known natural and defect frequencies in the system (and their harmonics). These bands are less affected by mechanical noise and are therefore more sensitive to signal changes caused by degradation. The selection of the high frequency band in this case was chosen because it is above the regions where system noise dominates. As an alternative, adaptive selection of these bands is possible by identifying regions where the band RMS is consistently low under healthy conditions.

Electric Signature Analysis

Similar to the dynamic pressure feature, a servo current feature was also developed that uses the principles of electric current signature analysis (ESA). Electric current signature analysis is another technique that has developed from signal processing for vibration monitoring. Research indicates that this technique is an effective approach for condition monitoring of machinery and several proven techniques exist for feature extraction from electrical current signals [[5,6]].

Using ESA, servo-valve degradation and abnormalities can be observed by monitoring the spectral signature of servo current. Although the servo current data from the tests revealed little evidence of failure through the measurement of a band energy content (like the pressure feature), other significant sources of evidence were present in the signal that could be used as indicators of system health. In particular, several prominent peaks were present in the frequency domain. One such peak, located at 47 Hz, proved to be a good indicator of valve degradation.

Neural Network Error Tracking

The third feature utilized within the data-driven AI approach applies neural network modeling to obtain a prediction of the control valve position. The key element of the neural network paradigm selected here is the novel structure of the information processing system to model the actuator internal dynamics and autonomously predict the control valve position. The network uses only data parameters measured by the control system to make this prediction. The error-tracking feature is then determined by computing the RMS error between the neural network prediction of the valve position and the actual measured position.

Specifically, the neural network used the servo-current and commanded ram position change, both of which are approximately proportional to the valve position, as inputs. As a third input parameter, the feedback (previously measured) valve position was included to improve the accuracy of the prediction. In addition, because of the non-linear nature of the electro-hydraulic servo valve data, a sliding-window of inputs (an input vector, rather that input scalar) was used to improve prediction accuracy. In other words, the 3 previous values of each input parameter were included as inputs along with the values measured at the current time. This results in a total of 12 inputs to the neural network (3 input parameters x 4 data points).

Although several neural network architectures were evaluated, a feed-forward, time-delay neural network was ultimately designed and trained to perform this processing. An illustration of such a network, included within the feature extraction process flow, can be seen in Figure 8.

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[5] Haynes, H. "Electrical Signature Analysis (ESA) Developments at the Oak Ridge Diagnostics Applied Research Center". http://members.aol.com/hayneshd/esapaper.htm

[6] R. C. Kryter, H. D. Haynes, "Condition Monitoring of Machinery Using Motor Current Signature Analysis", Sound and Vibration, September 1989.

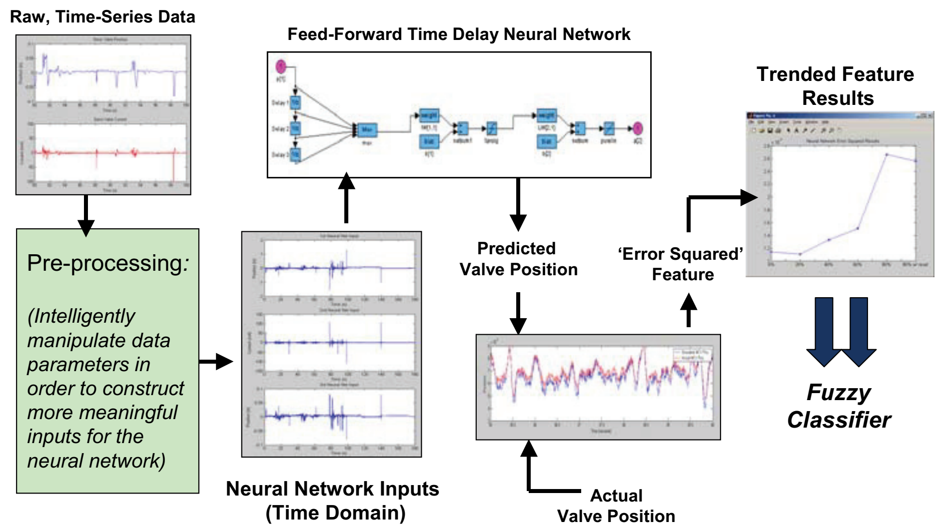

Figure 8 - Neural Network Valve Predictor Process Flow Diagram

Based on the outputs of the neural network and other damage tracking features, additional classification is a critical step for translating the feature values (known evidence) to current and predicted health state for the system. In order to produce an accurate, reliable assessment of system health, the classifier must learn the relationships (usually non-linear) between each feature and the system health state. For the developed automated module, fuzzy logic was selected for the classification system.

The fuzzy logic classification routine operates on the concept of "degree of membership". The routine maps each feature value to a linguistic membership function, assigning varying degrees of membership. Multiple membership functions can be employed for each parameter, representing varying degrees of severity or degradation. A parameter can also simultaneously be assigned to more than one of these membership functions. Rather than a parameter being recognized as "high" or "low", the parameter may share partial membership in both the "high" and "low" membership classes. This ability to represent transition and partial truth is what makes fuzzy logic such a powerful classification system. Additionally, fuzzy logic does not demand excessive computational resources. Impact previously implemented fuzzy classifiers on an embedded system performing hydraulic pump health monitoring[3]. The fuzzy logic classifiers performed exceptionally in the hydraulic pump application, therefore demonstrating fuzzy logic's potential for use in other onboard or at-wing applications.

Figure 9 illustrates the basic process flow of the fuzzy logic classification system employed. As seen in the figure, vital diagnostic information is extracted from a fuzzy classifier once all of the inputs have been analyzed. This routine uses a predetermined set of rules, tailored specific to each application using knowledge of the system and engineering judgment, in order to identify a particular linguistic output. For the prototype actuator monitoring system, the fuzzy system analyzes each data-driven feature and quantifies the level of damage present in the actuator.

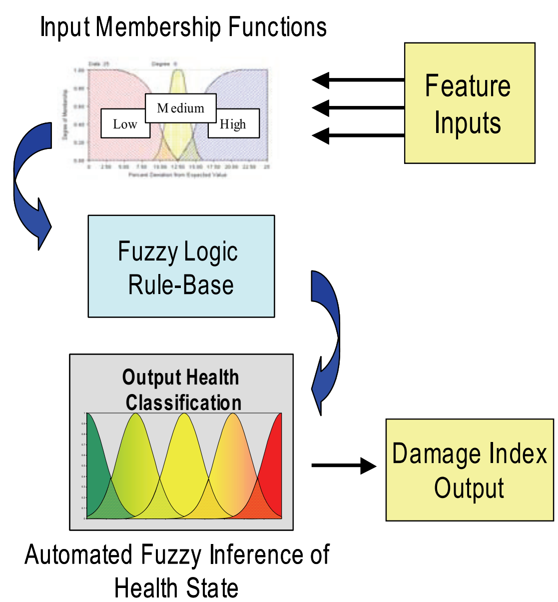

Figure 9 Actuator Health Fuzzy Classification Process

Conclusions

This paper has described a few selected prognostic approaches that were implemented with artificial intelligence technologies within an integrated vehicle health management system framework. Through utilization of AI methodologies, many of the challenges of Prognostics and Health Management (PHM) system developments can be addressed. For example, data driven methods such as neural networks and probabilistic classifiers have been shown to provide accurate prognosis models of fault progression through utilization of statistically sufficient samples of failure data to assist in training, validating and fine tuning the prognostic algorithms. However, the prognosis process by which features and models are integrated to obtain the best possible prediction on remaining useful life still has many remaining challenges. It is a significant challenge to design systems so that measured data can be fused and used in conjunction with physics-based models to estimate current and future damage states. Furthermore, multiple physics of failure models will often be required that may or may not use various feature inputs. Finally, the feedback mechanism in a prognosis system design cannot be ignored. Specifically, the prognosis system must be capable of intelligently calibrating a-priori initial conditions (i.e. humidity, strain and temperature have changed), random variable characteristics or switching prognostic models in an automated yet lucid process to empower better operational and logistical decisions for vehicle platforms.

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