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Distributed Health Monitoring System for Reusable Liquid Rocket Engines

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Extended Abstract:

Problem Statement

The ability to correctly detect and identify any possible failure in the systems, subsystems, or sensors within a reusable liquid rocket engine is a major goal at NASA John C. Stennis Space Center (SSC). A health management (HM) system is required to provide an on-ground operation crew with an integrated awareness of the condition of every element of interest by determining anomalies, examining their causes, and making predictive statements. However, the complexity associated with relevant systems, and the large amount of data typically necessary for proper interpretation and analysis, presents difficulties in implementing complete failure detection, identification, and prognostics (FDI&P). As such, this paper presents a *Distributed Health Monitoring System for Reusable Liquid Rocket Engines* as a solution to these problems through the use of highly intelligent algorithms for real-time FDI&P, and efficient and embedded processing at multiple levels. The end result is the ability to successfully incorporate a comprehensive HM platform despite the complexity of the systems under consideration.

Method of Solution

The method of solution hinges on the use of several critical components that are necessary for enabling the required health management functionality. They include: (a) Optimized Neuro-Genetic Fast Estimator (ONGFE) software for diagnostics and prognostics optimization using pseudogenetic (PG) algorithms; (b) a distributed architecture of Advanced Embedded Smart Sensors (AESS) capable of intelligent functions; (c) non-intrusive energy harvesting vibration sensors; and (d) a user-friendly Man Machine Interface (MMI) for efficient monitoring and maintenance.

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The ONGFE improves neural network (NN) performance by providing: (1) a kernel of fast training algorithms; (2) an interface for conducting training, testing, and real-time FDI&P; and (3) neural network optimization. The ONGFE operates by using processed data and features fed into a kernel with fast and optimized learning algorithms. The resulting NN can then be used for failure detection and identification (FDI). In addition, a population can undergo further optimization using novel algorithms. In this way, two optimization levels are addressed. The ONGFE is then applied for several functions in the HM system, including: (1) system FDI; (2) data-validation and sensor FDI; and (3) auto-calibration.

Due to the throughput and bandwidth computational requirements for rocket engine health monitoring, a distributed and hierarchical system architecture is employed. In this architecture, it is necessary to use a processing scheme in which intelligence is embedded at multiple levels, including the sensors. Initial work has validated an approach with multiple AESS modules; each equipped with one or more transducers (sensor suites) to condition, process, and wirelessly transmit data to a health monitoring node (HMN) or application server man machine interface (AS-MMI). Expansion of the arrangement then consists of using the AESS as a wireless transducer interface module (WTIM), and then sending data to a remote network capable application processor (NCAP in the HMN) for further processing, and in turn, to the health management unit (HMaU) and AS-MMI.

The lowest level of the architecture is noteworthy due to the embedded intelligence of the AESS modules. These smart sensors are equipped with intelligent algorithms that conduct data validation and self-healing. The structure of the AESS is designed for adherence to the IEEE 1451 standards [1][2]. The AESS consists of the blocks shown in Figure 1. A novel addition to the sensor suite is the use of customized piezoelectric sensors with a desirable form factor and power-harvesting capabilities for performing high-quality health monitoring. Both the frequency response and capability to provide features correlated with system behavior are validation criteria for these sensors.

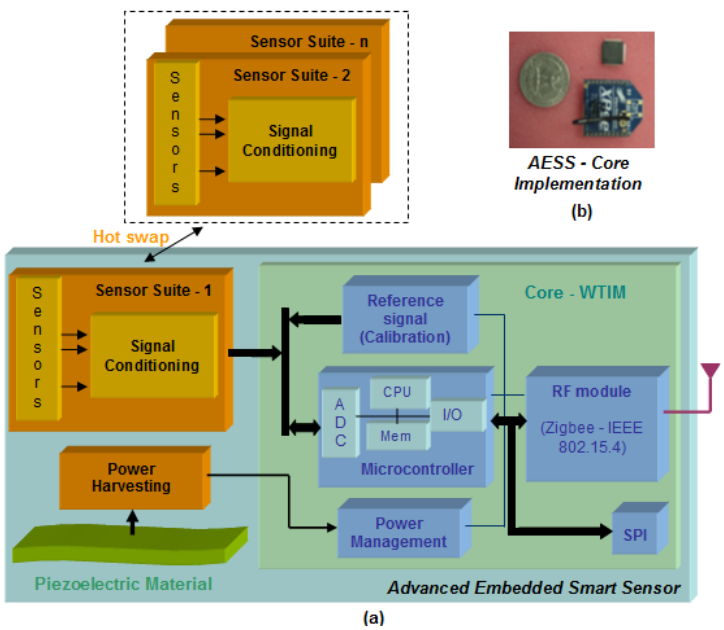

Figure 1: Block Diagram of the AESS

The functions embedded within the AESS modules utilize the ONGFE for sensor validation, self-monitoring, and self-calibration. With these capabilities, the AESS modules are able to detect whether or not the data they are receiving is mostly noise, corrupted, or indeed valid. These abilities are enabled through the ONGFE Neuro-SCST scheme shown in Figure 2. Mapping is provided by an auto-associative process such that a given output can be associated with an input. This mapping includes scenarios in which a certain output must be provided even if the input signal is corrupted and deviates from what is normally expected. A statistical test detects when there is a change in the sensor measurement sequence statistics. The closer the sensor inputs are to the predicted value from the ANN, the higher the confidence value assigned to that sensor. A threshold value is then assigned to determine and isolate any failed sensors.

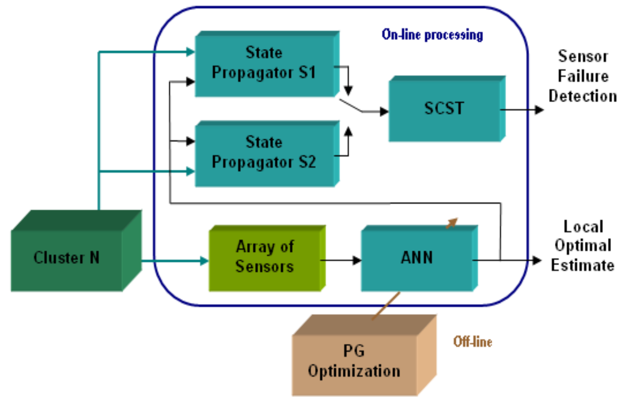

Figure 2: ONGFE Neuro-SCST

The highest level of the distributed architecture is the AS-MMI. This level houses the MMI software which has been specifically catered to meet the needs for rocket engine HM by providing a visual environment in which the user has access and control over the maintenance and health monitoring information. Such software provides information regarding the sensor status, readings, health management, commands, and Transducer Electronic Data Sheets (TEDS). However, in addition to this complete control, the ONGFE is integrated for real-time on-line health monitoring. The ONGFE performs at enhanced speeds with several optimizations in the algorithm, thus successfully circumventing the problem of training with large sets of data.

Obtained Results

The results in this paper verify the success of the ONGFE for performing health monitoring with multiple functions. For conducting FDI, the ONGFE has demonstrated: (a) the ability to be embedded at multiple levels; (b) fast training as is necessary for on-line real-time FDI of complex systems; and (c) optimized learning. In demonstrating the success of the advanced algorithms for conducting FDI&P, a testbed as shown in Figure 3 was constructed with multiple off-nominal bypass lines which, based on the position of valves, simulate the presence and degree of various faults. Studied failures included: (1) damaged pump and reduced flow rate capabilities; (2) pump seal leakage; (3) decreased heating capabilities; (4) stuck valve; (5) reduction of inlet pressure to pump; (6) reduction in heat exchanger efficiency and (7) leakage between heat exchanger plates.

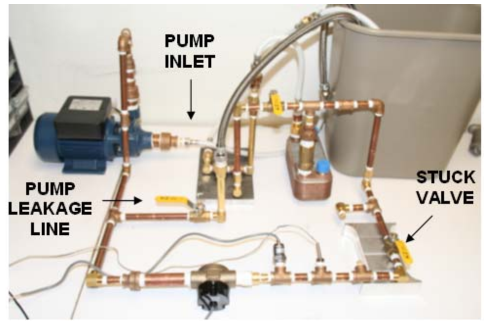

Figure 3: Testbed for System Validation

In order to provide the user with complete access, control, and real-time diagnostic and prognostic information, a user-friendly man machine interface has been developed as shown in Figure 4. The correct prediction and isolation of failures is readily apparent in Figure 5, which shows the MMI software indicating anomalous system operation as opposed to normal operation. Furthermore, features are provided for a Condition Based Maintenance (CBM+) type system [3] by including IEEE 1451 Universal Unique Identification Data (UUID), an FDI&P database, and a configuration management database.

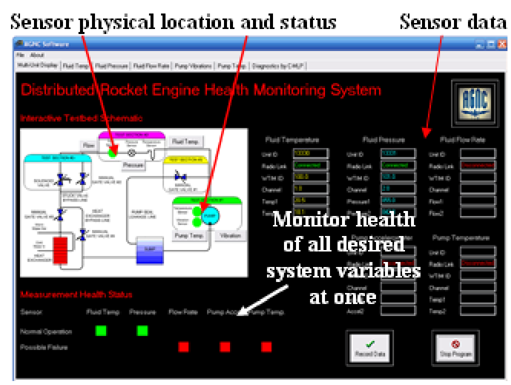

Figure 4: Main Screen of MMI Software

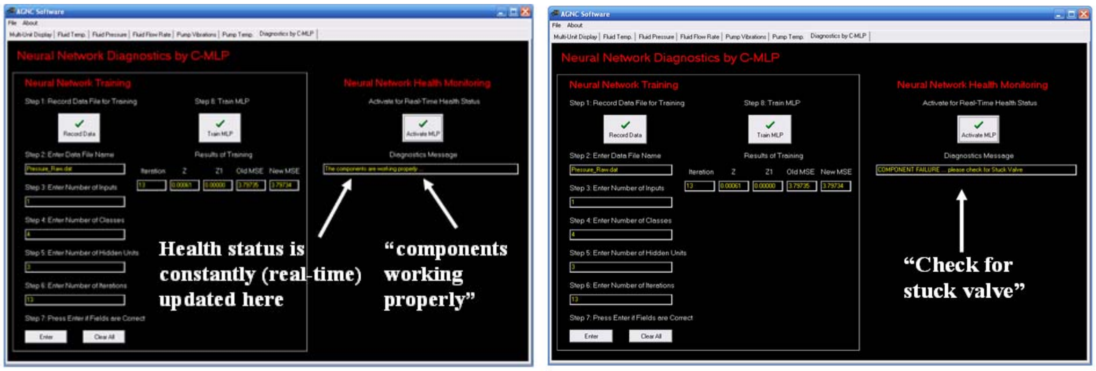

Figure 5: Results of Optimized Neural Network FDI

The demonstration of sensor data validation and self-healing is accomplished by the ONGFE's kernel of fast training algorithms as well as the second optimization level with PG algorithms. In Figure 6, one of the sensors is experiencing both considerable noise and bias. This data is then the input to the neural network which uses the ONGFE and an auto-associative process to produce corrected estimates as shown on the right. In this way, not only is the failing sensor identified, but a self-healing procedure is conducted. The results of this application verified that the embedded NN offers fast computational speed in working on-line and constantly providing information regarding each sensor. Finally, the versatility of the framework is demonstrated in an auto-calibration application in which the ONGFE's function approximation capabilities are utilized. Figure 7 shows an example of the auto-calibration in which resistance values from an RTD are mapped to the appropriate temperature values.

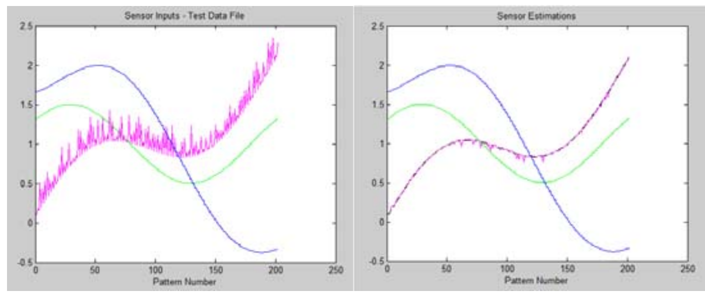

Figure 6: Left: Inputs; Right: Validated Outputs

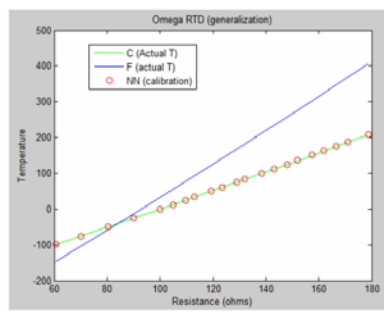

Figure 7: ONGFE Self-Calibration

Another important result discussed in this paper is the use of the piezoelectric sensors for conducting FDI of damaged structures. For failure analysis, the identification of resonance frequencies and the correlation between time domain nominal behavior and anomalies can be utilized. As a failure propagates, the evolution of frequencies can be tracked to provide relevant prognostics information. Figure 8 shows that these sensors provide enough information for detecting and analyzing damage, and by using the main features and frequencies, the ONGFE performs FDI&P.

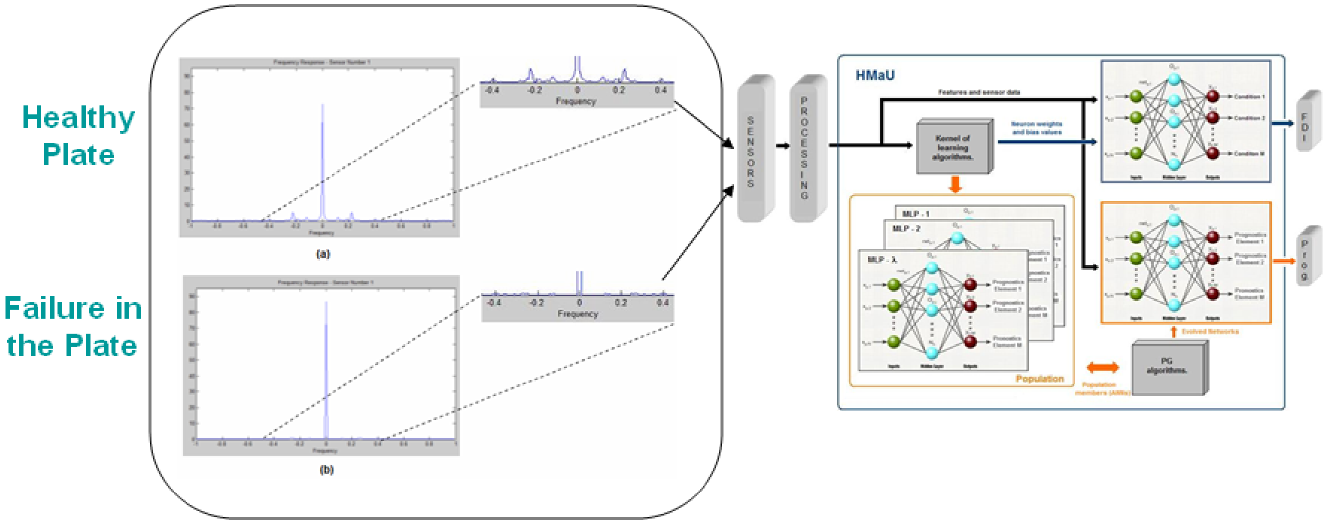

Figure 8: Failure Characterization and FDI&P using the ONGFE

Significance of the Contribution

The optimized learning procedures comprise a major innovation in this paper as they offer significant improvements for diagnostics and prognostics in terms of processing speed, decreased false alarms, and improved detection time. As evident from Figure 9, optimization using the ONGFE (solid blue line) results in lower errors than other approaches. Innovations that highlight the significance of the contribution include:

- Improved neural network performance for FDI and prognostics
- ONGFE flexibility to include a wide array of learning algorithms
- On-line learning for adapting to a dynamically changing system
- ONGFE applicability to a wide array of tasks such as system FDI, data-validation, and auto-calibration
- A distributed architecture with processing at multiple levels
- Sensors capable of intelligent functions
- Non-intrusive self-powered vibration sensors
- Embedded aids for performing maintenance actions, planning, and control of the maintenance cycle

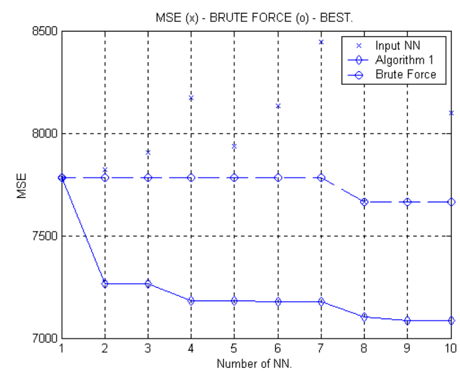

Figure 9: PG Algorithm for Prognostics Optimization

References:

[1] IEEE Std 1451.0 TM-2007. IEEE Standard for a Smart Transducer Interface for Sensors and Actuators - Common Functions, Communication Protocols, and Transducer Electronic Data Sheet (TEDS) Formats. November 2007.

[2] IEEE Std 1451.5 TM-2007, IEEE Standard for a Smart Transducer Interface for Sensors and Actuators - Wireless Communication Protocols and Transducer Electronic Data Sheet (TEDS). October 2007.

[3] K. Navarra, R. Lawton, N. Hearrell, "An Enterprise Strategy for Implementing Conditioned-Based Maintenance Plus (CBM+) Research in the USAF", *in Proc. of the IEEE Aerospace Conference*, pp. 1-7, March 2007.