AI Based On-Board Diagnostic and Prognostic Health Management System

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ABSTRACT

Health is Wealth, a great fact and growing concern in human context, is equally valid for machines/systems involving complexity and cost and becomes even more critical for manned machines i.e. man in the loop. E.g. Aircraft, car etc. With exponential technological revolutions, systems are no more pure ‘mechanical’ or ‘electrical’ in nature, rather integrated multi-domain 'mechatronics' systems operating in closed-loop/close-interaction. This poses great challenge to system health monitoring as failure of any component can trigger catastrophic system failures. It may be the reason that component failures, as per some aerospace reports, are found to be major contributing factors to aircraft loss-of-control. Essentially, it is either too expensive or impossible to monitor every component or subsystem of a complex machine and the current state of the Integrated Health Monitoring Systems seem to be quite inadequate. In this paper, we propose an approach that combines the best of the diagnostics and feature extraction techniques coupled with Artificial Intelligence as a solution to address the challenges of Prognostics Health Management(PHM) for complex systems in real-time.

In this paper we derive the health status of subsystems by looking at system level responses. Distinguishing features are derived from the overall system level response through feature extraction methodologies and then fed into decision making frameworks that are implemented using Neural Networks. Technology disclosed in this paper is subject matter of pending patent application.

Neural Networks are trained with distinguishable features through system simulations. Employing neural networks provide the ability of classifying the failure modes as well as to analyze system faults/responses. Predictive modeling techniques are applied to the neural network processed data to deliver useful prognostics on the criticality of the failure mode, RUL of the components/subsystems in real time while system is in operation.

The proposed concept can be easily adapted to systems from varying domains and leverages the strength of the ANN for systems health monitoring.

As a case study, the present work demonstrates the AI based DPHM solution applied to a fighter aircraft where failure mode effects of subsystems like lateral and longitudinal control, inertial navigation sensors etc., on the overall flight performance are studied using Modeling and Simulation techniques. A neural network based controller is trained to recognize unique patterns of system responses for various normal and abnormal flight path performances due to subsystem failures and identify failed component triggering a system level failure.

1. INTRODUCTION

In complex engineering systems like aircraft, automotive, turbine engines etc., any faulty sub-system or component has to manifest itself, in some way, in terms of impacting overall system level performance, unless the component has no significant role to play in the overall system functionality. Hence, the question arises, if it is possible to identify a faulty component by monitoring the system level performance with suitable analysis techniques. After all, it doesn't need, while driving on a road, bumping into a speed-breaker or a pothole more than twice to recognize a ‘jerk’ in the drive and tell 'shock absorbers', 'most likely' are the main cause of such response, without requiring any special sensors at shock-absorbers for measuring 'spring constants'!

But, what if the system has identical response for two or more faulty components, as indicated in the Figure 1? Yes, in this situation, it may not be possible to single out the faulty component as there can be identical response for different subsystems failure. Nevertheless, the real-world systems are
seldom single output and even simple systems will have multiple outputs as shown in Figure 2.

**Normal Response**

![Normal Response Diagram](image1)

**Abnormal Response**

![Abnormal Response Diagram](image2)

**Figure 1. A SISO Response Scenario**

**Identical response for different subsystem failures**

**Legend**
- Healthy Subsystem
- Faulty Subsystem

**Identical response for different subsystem failures**

**Figure 2. MIMO system with possible signatures for different subsystem failures**

Essentially, additional system performance can provide more insights with certain ‘uniqueness’ in the response as a whole for any sub-system failures. Still, the challenge remains when systems become very complex, with several outputs. Not any known classical techniques (like search algorithms, decision trees etc.) can be expected to handle such complexity and identify the ‘unique’ signatures in a hard real-time constraints due to processing overhead.

This is where, the present work – **AI Based On-Board Diagnostic & Prognostic Health Management (DPHM)** System demonstrates the methodology for subsystem fault identification, without depending on a physical sensor for every fault, overcoming the limitations of legacy conventional ways of health management system.

The DPHM solution proposed in this work takes model-based approach leveraging Modeling and Simulation tools and techniques for building complex system models and carrying out failure mode studies. AI based algorithms using neural networks and sensor fusion technologies are developed to detect system performance degradation and identify failed sub-system/component. The concept is tested for several subsystem failure scenarios considering the case of a fighter aircraft and results are presented as a proof of concept.

Next section briefly covers the current scenario of DPHM needs of the industry to set the context, followed by discussion on the work done.

**2. DPHM Practice – Industry Scenario**

Based on the industry need, the DPHM/IVHM kind of solutions can be seen to have two different perspectives as shown in Figure 3.

**DPHM/IVHM Solutions - What Industry Needs**

**OFF-LINE DPHM**
- Big Data techniques to analyze system failures - applied to CBM, Improved Operational Decisions etc

**ON-LINE DPHM**
- Real-time techniques for embedded controllers development for on-board implementation - applied to system safety

**Figure 3. DPHM Systems - Industry Need**

Clearly, these are completely two different industry needs with different objectives involving totally different technologies, domain expertise and challenges.

While there is considerable work to be done on off-line DPHM solutions using Big Data kind of analytics for condition-based maintenance, improved operational decisions etc., the market study shows the real-time DPHM solutions are yet to reach maturity levels of industry expectations for deployment. Also, we see there is lot of scope for research and development.

Table 1 captures some major distinguishing features of these solutions.
Motivated by such industry need, the present work focusses on real-time AI Based DPHM solution which can be ported to embedded hardware platforms for the onboard implementation of a machine/plant.

3. AI BASED DPHM - ARCHITECTURE

As discussed in the Section 1, the basic idea behind the AI based DPHM is – How to build an ‘expert controller’ that identifies a failed subsystem by monitoring the system level performance, like an ‘expert technician’ at a car garage identifying a failed component with a couple of test drives.

Essentially, there are two major processing (Intelligence) capabilities involved in this.

1. **Detection**: Ability to distinguish normal and abnormal performance of the system based on domain experience and training (system failure modes and their effects), taking care of many operational conditions.

2. **Identification**: Ability to identify the failed component that can lead to such observable abnormality in the system response (root cause).

4. SOLUTION APPROACH

The solution takes model based approach for generating the normal and abnormal performance data. This data is used to train a neural network for building the Detection and Identification capabilities shown in Figure 4.

The trained neural network is ported to embedded platform. Essentially, the development of the solution has two major phases as shown in Figure 5.

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**Table 1. DPHM Practice - Industry Scenario**

<table>
<thead>
<tr>
<th><strong>OFF-LINE DPHM</strong></th>
<th><strong>ON-LINE DPHM</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-line analysis of the data received from different sources</td>
<td>Real-time analysis of the data acquired while system is in operation</td>
</tr>
<tr>
<td>Analysis targeted more on non-critical / non-critical parameters</td>
<td>Analysis performed on critical parameters, system safety being main focus</td>
</tr>
<tr>
<td>Ability to analyze large data to derive useful info</td>
<td>Focused to work on limited data sets</td>
</tr>
<tr>
<td>Application of statistical data mining and Big data techniques</td>
<td>Real-time techniques feasible for embedded implementation</td>
</tr>
<tr>
<td>Domain independent and more of number crunching/mining exercise</td>
<td>Extensive domain knowledge required due to modeling and simulation</td>
</tr>
</tbody>
</table>

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4.1 ANN for DPHM

The major drivers for choosing the ANN based DPHM solution are:

- ANNs have exhibited their strengths in solving problems that are difficult or in certain cases cannot be solved by using algorithms (David Kriese, 2005).

- Massive parallelism, distributed representation of knowledge, learning ability, generalization ability and fault tolerance capabilities.

Also, the potential of ANNs in the area of fault diagnosis has been demonstrated in various scenarios for different systems (T. Aroui, Y. Koubaa, and A. Touni., 2007 and Bo Li, Mo-Yuen Chow, Yodyium Tipsuwan and James C. Hung, 2000). Pattern recognition method is widely used in the context of varying patterns and the complexity involved in training. It is one of the best training algorithms in the areas of diagnosis and fault analysis. The methodology is used to identify data with respect to regular and irregular conditions and help to manage the impact of the defect efficiently.
(Simani, S., Fantuzzi, C., and Patton, R.J., 2003). Figure 6 shows the DPHM ANN architecture.

![Feature Extraction Diagram]

Figure 6. Architecture of Artificial Neural Network

It was these qualities that triggered the research on how to possibly use the strengths of the neural networks to learn a complex system, as well as, generalize the model so that it could be applied to diagnose unseen cases that are critical and difficult to address through conventional algorithm based approach.

### 4.2 Solution Overview

As shown in the Figure 7, the solution has three major processing modules:

- Data Acquisition & Preparation
- Feature Extraction
- Decision Making

Diagnostics
- Based on Observable Systems States.
- Applying past performance knowledge.
- Based on expertise built over a period.

![DPHM Solution - Overview Diagram]

Figure 7. DPHM Solution – Overview

Following is the Feature Extraction module implementing various algorithms for feature extraction.

As shown in the Figure 8, the plant performance for normal and abnormal scenarios has been simulated and the response is acquired and processed by Data Acquisition modules.

The process involves simulating the failure modes of various subsystems and generating the system response under various normal and abnormal conditions. This data is used for DPHM controller training. In order to learn the impact of various faults in the system, a replica of the system was made where different fault scenarios are introduced for analysis of the system response. The system level outputs of both the reference as well as the fault introduced model are captured continuously in a specified window of time scale and preprocessed to remove trends in data so as to process unique signals.

Statistical and signal processing functions are applied on the data to extract the features that can be used for training. These feature vectors exhibit signatures that could be analyzed for various fault scenarios. The feature vectors are used as inputs to the neural networks and are trained to classify the failures with the associated root causes by leveraging domain knowledge. Once trained extensively and the generalization is achieved, the network is deployed on a target hardware to accept signals in real time.
In view of predicting the failures ahead of time, neural networks are fed with the feature vectors to learn as well as predict the future time series. The failure classification neural network designed earlier is applied to the time predictive neural network to know not only that an anomaly would occur but also which component or components in the subsystem would contribute to the failures.

4.3 Failure Mode Simulation by Fault Injection & Matlab Implementation

In order to generate the flight performance under various subsystem level failure conditions, subsystem faults are simulated at some point of time of flight using fault models for selected subsystems. In this work the control surface actuators/sensor failures are considered for generating necessary failure mode performance data.

In 6DOF ADMIRE model, the subsystems like actuators/sensors are modelled as either first order or second order transfer function where the damping coefficient and speed of response characterise the given subsystem. Essentially any failure in the subsystem, like leakage of hydraulic fluid in case of a hydraulic actuator, manifests in terms of impacting the transfer function parameters. So the faults in the subsystem are simulated by modifying the natural frequency and damping position programmatically in some point of time in the flight path.

In the ADMIRE model, there is implementation for sensors like Air data, Inertial and Attitude, actuators like Rudder, Elevons, Canard and Leasing edge flap. The values of damping frequency and natural frequency are changed dynamically during the simulation which would impact the behaviour of the whole system response.

The user interface developed has the provision for injecting the faults at specific time which is taken as input for the simulation resulting in flight path performance degradation at the time when the fault is specified to occur.

5. Case Study

As the present work is based on Model Based approach, extensive simulations are carried out for generating the training data for various normal and abnormal conditions. To build the case, ADMIRE, the 6DOF aircraft model that leverages SAAB’s Generic Aerodata Model (GAM) with flight control system is used due to open source availability for research (Admire Model).

5.1 System Overview

For a quick reference, this section briefly introduces the system chosen for the present study. As shown in the Figure 10, Gripen is a single seater fighter aircraft with control surfaces for pitch, yaw and roll.

![Gripen Aircraft](image)

**Figure 10.** Gripen Aircraft

The present work leverages the features of the ADMIRE model for creating various failure mode scenarios of selected subsystems and carry out the simulations to study the effect on the aircraft response.

For the sake of training the ANN through feature extraction, we have considered following states out of the available system responses.

\[ V_T = (u_b + u_w)/V_T \]  \( \text{Eq. (1)} \)

\[ \dot{\alpha} = (u_b + u_w)/V_T \]  \( \text{Eq. (2)} \)

\[ \dot{\beta} = (u_b - u_w)/V_T \]  \( \text{Eq. (3)} \)

\[ p_b = (C_1 \cdot \eta_b + C_2 \cdot p_b) \cdot q_b + C_3 \cdot M_x + C_4 \cdot M_z \]  \( \text{Eq. (4)} \)

\[ \dot{q}_b = C_5 \cdot p_b \cdot r_b - C_6 \cdot (p_b^2 - r_b^2) + C_7 \cdot M_y \]  \( \text{Eq. (5)} \)

\[ \dot{r}_b = (C_8 \cdot p_b - C_2 \cdot r_b) \cdot q_b + C_4 \cdot M_x + C_3 \cdot M_z \]  \( \text{Eq. (6)} \)

\[ \psi = (q_b \cdot \sin \phi + r_b \cdot \cos \phi) \]  \( \text{Eq. (7)} \)

\[ \dot{\phi} = q_b \cdot \cos \phi - r_b \cdot \sin \phi \]  \( \text{Eq. (8)} \)

\[ \dot{\psi} = (q_b \cdot \sin \phi - r_b \cdot \cos \phi) \]  \( \text{Eq. (9)} \)

As mentioned, all the above equations are the function of moments acting on the body, which again are the functions of control forces generated by the various control surfaces.
Available control surfaces are left and right canard, leading edge flaps, four elevons, and rudder. The ADMIRE is augmented with Flight Control System that provides stability to the aircraft within the operational envelope.

All the control surfaces are actuated by Hydraulic /Electromechanical actuation systems modeled as first/second order transfer functions as shown in Figure 11.

As discussed in the last section, the DPHM study has been carried out considering effects of failure modes due to actuator faults as a proof of concept.

Canard / Elevon faults were injected in the model simulating the faults and a neural network was trained with these signatures. The neural network was trained iteratively so that the Mean Squared Error (MSE) as well as the Percentage Error (%E) was as minimum as possible. Table 2 captures the training samples, neuron count as well as the performance parameters.

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<tr>
<th></th>
<th>Training</th>
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<th>Testing</th>
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<td>54</td>
</tr>
<tr>
<td>Training</td>
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<td>Session 3</td>
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<tr>
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<td>6.61</td>
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</tr>
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</table>

Table 2. Neural Network Training Results

The trained neural network was deployed on a desktop using the real time windows kernel. The GUI in the Figure 11 was used to introduce the faults once the ADMIRE model was initiated to fly on a pre-defined flight path using the autopilot. The neural network is triggered once the system response deviates from the expected response and starts publishing the diagnostic information in the form of differences in the 6DOF parameter as well as indicates the root cause of the failure on the dash board which is shown in Figure 13 and Figure 14 for right canard and right outer elevon actuators respectively.

Figure 11. Actuator and Sensor Transfer functions

5.2 Failure Mode Simulation

For the study of failure mode effects, control actuators and sensors are chosen as candidate subsystems which develop fault during the flight.

Generally, the fault in these systems due to reasons like leakage of hydraulic fluid and crack in the manifold, result in the dynamics performance parameters like speed of response, damping coefficient. The faults are simulated by varying these parameters beyond the design tolerances. As the simulation is run in non-real time environment, the faults are programmed to occur at some specified time of the flight. A feature rich Matlab GUI has been developed for running the simulation with various failures.

Figure 12. GUI for Failure Mode Simulations

6. DISCUSSION OF RESULTS

Figure 13. ANN Failure Detection and Identification – Right Canard Failure.
ANN Failure Detection and Identification – Right Outer Elevon Failure.

For additional reference, Appendix covers all the software snapshots related to the Model developed as well as the dashboard results presented to the operator/pilot.

7. CONCLUSION

With the industry moving towards ‘Industry 4.0’ in a fast pace, with exponentially growing complexity of systems/machines and built in intelligence, there is a great demand for building Self-Learning, Self-Diagnostics or even Self-Health aware systems like DPHM. In this paper, an AI based DPHM architecture has been presented and the entire design flow to realise a health management system has been demonstrated considering the case of an aircraft. The concept can be implemented for various complex systems ensuring not only safer operation but also avoid catastrophic failures and loss of assets/life.

ACKNOWLEDGEMENT

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NOMENCLATURE

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>ADMIRE</td>
<td>Aero Data Model In Research Environment</td>
</tr>
<tr>
<td>SISO</td>
<td>Single Input and Single Output</td>
</tr>
<tr>
<td>MIMO</td>
<td>Multi-Input and Multi-Output</td>
</tr>
<tr>
<td>RMS</td>
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<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
</tr>
<tr>
<td>STFT</td>
<td>Short –time Fourier Transform</td>
</tr>
<tr>
<td>DWT</td>
<td>Discrete Wavelet Transform</td>
</tr>
<tr>
<td>DTFT</td>
<td>Discrete-time Fourier Transform</td>
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<tr>
<td>ANN</td>
<td>Artificial Neural Networks</td>
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<tr>
<td>NARX</td>
<td>Non-linear autoregressive exogenous model</td>
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<td>Pitch angle (deg)</td>
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<tr>
<td>$\phi$</td>
<td>Bank angle (deg)</td>
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<tr>
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<td>Total aerodynamic force in body x-axis</td>
</tr>
<tr>
<td>$F_y$</td>
<td>Total aerodynamic force in body y-axis</td>
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<tr>
<td>$F_z$</td>
<td>Total aerodynamic force in body z-axis</td>
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<td>Moment about body x axis</td>
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<tr>
<td>$M_z$</td>
<td>Moment about body z axis</td>
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Admire Model. www.foi.se/en/Our-Knowledge/Aeronautics/Admire/

BIOGRAFIES

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Venkateshwar Chindam received a B.Tech (Electrical and Electronics) degree from the JNTU University, Hyderabad. He started a career with HCL technologies working for the validation and verification of Flight Display Systems, BCMS for various Avionics programs. He worked as a System Engineer for A350 XWB and HIL Test Engineer with Daimler India. Currently he is working for TCS in the Research area of Diagnostics and Prognostics.

APPENDIX

All Subsystems are healthy: All subsystems are healthy till the fault has occurred and the dash boards show zero deviations from the expected response for all the 6DOF parameters of the aircraft.
Figure 15. Failure injected at the right canard Actuator

Failure is injected in the right canard between time intervals (50-60 seconds) during simulation. The dashboard alerts the user/pilot about the root cause as well as gives the deviation in response from an expected response on all the 6DOF parameters.

Figure 16. Failure alert of Right Canard

Fault Introduction in the actuator subsystem: The following snapshot showcases the way in which faults were introduced into an actuator subsystem given a time instance in the simulation.

Overall architecture of the Implementation: The overall implementation consists of modularly implemented subsystems like the plant, data acquisition, feature extraction and the neural network subsystems.

Figure 18. Outlook of the simulation