Assessing Health Degradation in Aircraft Generators

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I. MOTIVATION

Electrical and mechanical failures (such as bearing and winding failures) combine to cause premature failures of generators, which become a flight safety issue forcing the crew to land as soon as practical. Based on the Naval Aviation Logistics Data Analysis (NALDA), the generator is the largest degrader of the aircraft's major electrical power system components in terms of Aviation Depot Level Repair (AVDLR) costs, mission aborts, and non-mission capable hours. Currently, diagnostic / prognostic technologies are not implemented for aircraft generators.

Our research presents a methodology including feature extraction and diagnostic algorithms to ultimately: a) differentiate between these failure modes and normal aircraft operational modes; and b) determine the degree of damage/degradation of a generator. Electrical signature analysis based features were developed to distinguish between healthy and degraded generators while taking into account their operating conditions.

II. FEATURE DESCRIPTION

Figure 1 depicts the basic modules of the proposed aircraft health management system. The diagnostic and prognostic health management system architecture utilizes data-driven and physics-based algorithms and also provides inputs to a CBM module. The feature extraction unit takes raw sampled data from a generator and converts it to a form suitable for the diagnostic and prognostic modules. The diagnostician monitors continuously critical feature data and the prognosticator reports the remaining useful lifetime of the failing machine or component to the CBM module. The CBM module schedules the maintenance so that uptime is maximized and long-term maintenance costs are reduced.

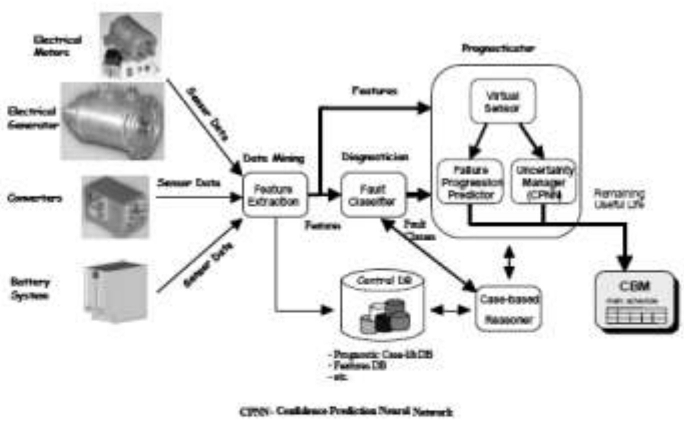

Fig. 1-Overall Architecture for Diagnostic/Prognostic Assessment of Aircraft

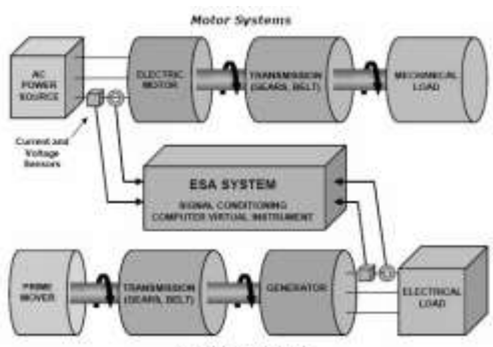

Fig.2 -Applying ESA to Motor & Generator Systems

The prognostic architecture is based on three constructs: 1) a static "virtual sensor" that relates known measurements to material deterioration; 2) a predictor which attempts to project the current state of the damaged material, thus allowing the estimation of the material's remaining useful lifetime (RUL); and 3) a Confidence Prediction Neural Network (CPNN) whose task is to assess the uncertainty in the RUL prediction.

Time and frequency domain features derived from raw sensor data have been developed to distinguish between healthy and common failure modes such as bearing failure. Two methods are used for amplitude demodulation of the 3-phase aircraft generator voltage and current signals: a) Hilbert transform and b) Space vector transform. Features used in estimating the generator degree of degradation are computed from these demodulated signals. Statistical margins based on the features are defined in order to denote the differences between range of healthy/low-hour generators and degraded/high-hour generators. These features are based upon Electrical Signature Analysis (ESA) concepts (Figure 2). ESA is the term used for the evaluation of the voltage and current waveforms. This provides an increased advantage to diagnostics as power-related, motor-related and load-related signals can be quickly compared. The main purpose of incorporating ESA in our work is the fact that ESA uses the generator as a transducer, allowing the user to evaluate the electrical and mechanical condition from the generated electrical signals.

The diagnostician, implemented as a multiple-input multiple-output fuzzy neural network (FNN), serves as a nonlinear discriminator to classify impending faults. The fault classifier is trained to recognize generator faults from a vector of features corresponding to rotor, stator and bearing failures. The virtual sensor calculates a failure measure indirectly through a neural network mapping of features and operating condition. Consider, for example, the case of an electrical generator. No direct measurement of the degree of stator / rotor winding degradation, bearings damage, etc. occurring in a generator is currently available when it is in an operational state. That is, there is no such device as a “fault meter” capable of providing direct measurements of the fault evolution. The fault dimensions take the form of a vector of integer state-of-health (SOH) values where the values range from 100 (healthy) to 0 (fault). A sample SOH is depicted in Figure 4, below.

Generator Classification and Health Estimation Example: NAVAIR provided electrical (voltage and current) data collected at 100 kHz for five P-3 generators (Gen 73-A0255, Gen 1182, Gen 18700071, Gen 700 and Gen 765). The data was collected for the following resistive loads and operating frequency: a). no load, 30 kVA and 60 kVA; b). operating line frequencies of 395Hz, 400 Hz and 405 Hz.

As shown in Figure 3, the brand new generator has less range between the minimum and maximum values of the demodulated signal than Gen 1182. Therefore, the following two general features were selected to detect degradations in P-3 generators:

$$|P(t)|_{max\ diff} = [|P(t)|_{max} - |P(t)|_{min}] \text{ per phase angle bin}$$
$$|P(t)|_{mean} = (1/N)\times\Sigma\, |P(t)| \text{ per phase angle bin}$$

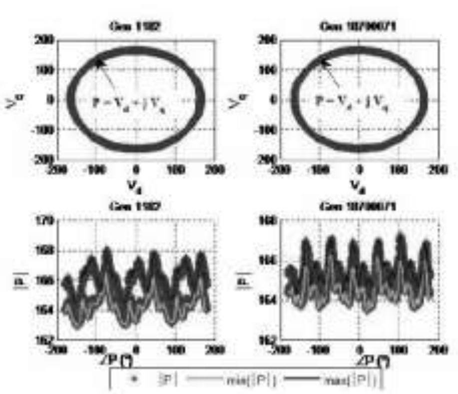

Fig. 3- Demodulated voltage signals as a function of phase angle

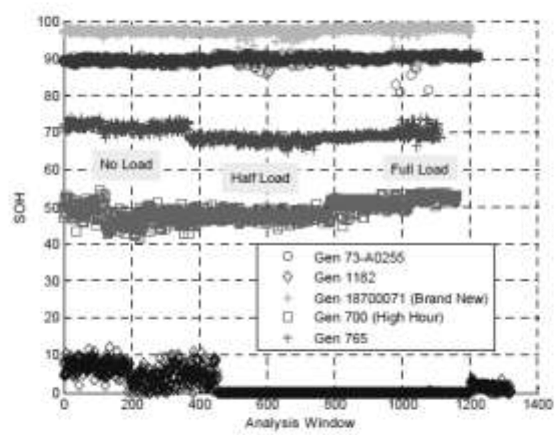

Fig. 4- SOH of P-3 Generators

The diagnostic algorithms were developed to have a low false alarm rate. The feature extraction and diagnostic algorithms were evaluated against P-3 generator data (phase operating line frequencies for healthy, low-hour and high-hour generators). The results show that the electrical signature analysis of the generator's phase voltage(s) can be used to assess and predict its health.

III. CONCLUSION

Time-domain features based upon ESA were developed to distinguish between healthy/low-hour and degraded/high-hour P-3 generators. The detection rate for degraded/high-hour P-3 generators was greater than 99% with less than 0.2% false alarm rate. The brand new P-3 generator was correctly identified as being healthy for more than 99% of the analysis windows. This testifies to the accuracy of the model and the analysis on it. The resulting degradation measure would translate to advantages such as prevention of aircraft loss due to generator failure, a maintenance scheduling strategy that is condition based, readiness evaluation of aircraft fleets, reduced down-time, etc.

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