

Advanced Electrical Signature Analysis of Aircraft Electrical Generators

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ABSTRACT

The electrical and mechanical failures (such as bearing and winding failures) combine to cause premature failures of the generators, which become a flight safety issue forcing the crew to land as soon as practical. Currently, diagnostic / prognostic technologies are not implemented for aircraft generators where repairs are time consuming and its costs are high. This paper presents the development of feature extraction and diagnostic algorithms to ultimately 1) differentiate between these failure modes and normal aircraft operational modes; and 2) determine the degree of damage of a generator. Electrical signature analysis based features were developed to distinguish between healthy and degraded generators while taking into account their operating conditions. The diagnostic algorithms were developed to have a high fault / high-hour detection rate along with a low false alarm rate. The feature extraction and diagnostic algorithms were evaluated against P-3 generator data (phase voltages / currents) collected at various loads and 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 detect and track its health.

INTRODUCTION

The P-3 Navy aircraft uses a Bendix (later AlliedSignal and currently Honeywell) generator that was designed over 30 years ago. The P-3 generator is a salient 8-pole (8 rotor bars), 6,000-rpm, 3-phase brushless ac generator. The running speed of the generator is 5700

rpm to 6,300 rpm (line frequency of 380 Hz to 420 Hz). The rated voltage and power is 115 VAC and 60 kVA (20 kVA/phase), respectively. It has a 12-pole ac exciter and a three-phase, half-wave diode rectifier rotating with the exciter armature and main generator field assembly. A single-phase permanent magnet generator (PMG) furnishes control voltage and power for the voltage regulator.

The electrical and mechanical issues (due to being continuously operated beyond design point and less than optimal drive end bearing support) combine to cause premature failures of the P-3 generators. Repairs are time consuming and its costs are high. Currently, diagnostic / prognostic technologies are not implemented for P-3 generators and other electrical power systems. Although some time series data (such as phase voltage and current) are collected during ground testing, no time series data is collected in-flight for the generators. Figure 1 shows the disassembled parts of a brushless ac generator for the P-3.

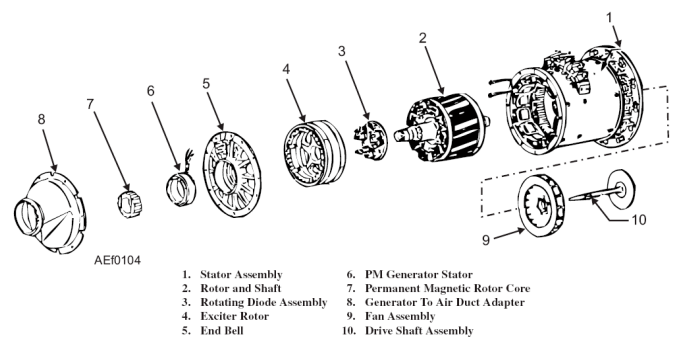


Figure 1: Disassembled brushless ac generator

This paper presents the development of feature extraction and diagnostic algorithms to ultimately 1) differentiate between generator failure modes and normal aircraft operational modes; and 2) determine the degree of damage of a generator. Eventually, the algorithms will account for the GCU when determining the health of generators. This will enhance the reliability of aircraft generators by providing the maintenance personnel with information about the current health state and remaining life of generators so that timely action can be taken.

MAIN SECTION

GENERATOR HEALTH MONITORING ALGORITHMS – Figure 2 depicts the basic modules of the proposed Diagnostic and health management system architecture based upon data-driven algorithms [1][2][3] and also shows how the architecture can provide inputs to the condition-based maintenance (CBM) module for maintenance execution. 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 decides upon the existence of impending or incipient failure conditions. The detection and identification of an impending failure triggers the prognosticator. 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 while certain constraints are satisfied. 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 into the future thus revealing the time evolution of the damage and allowing the estimation of the material’s remaining useful lifetime; and 3) a Confidence Prediction Neural Network (CPNN) [4][5] whose task is to account for uncertainty and manage/shrink the prediction bounds.

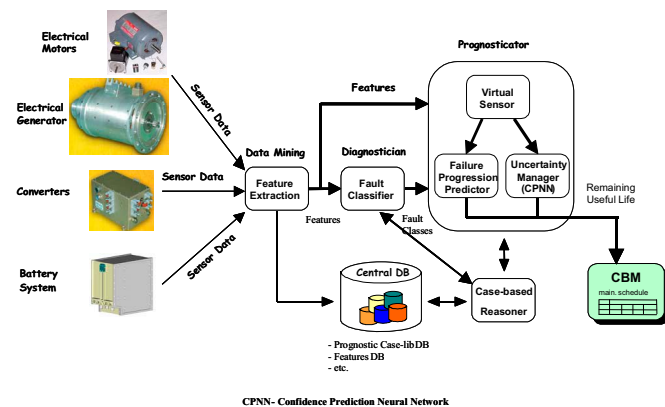


Figure 2: Overall Architecture for Diagnostic and Prognostic Assessment of Aircraft Electric Power Systems

Feature Extraction – Initial time-domain and frequency domain feature extraction algorithms have been developed to distinguish between healthy and common failure modes such as bearing failure. The time domain features (kurtosis, root mean square, etc.) and frequency domain features are calculated from (demodulated) voltage and current. These features are based upon Electrical Signature Analysis (ESA).

Each extracted feature from a set time and frequency domain based features is evaluated separately by statistical comparison with the corresponding feature database. Statistical margins are defined in order to denote the range of healthy / low-hour generators. Values outside of this range indicate the presence of a degraded / high-hour generator.

Consequently, we define the healthy operation range based on separate asymmetrical calculations of high (σ_+) and low (σ_-) margins that are calculated by generalised higher moments of features. The margins are defined for each feature separately by the following equations [6]:

$$\sigma_+ = m + s \cdot \left(\overline{(z_+ - m)^p} \right)^{1/p} \quad (1)$$

$$\sigma_- = m - s \cdot \left(\overline{(m - z_-)^p} \right)^{1/p}$$

where m denotes the median value, z_+ and z_- denote features above and below the median. The asymmetrical margins are controlled by parameters s and p which denote the stretching factor and the generalized higher moment of the feature. For a normal distribution, values $s = 3$ and $p = 2$ correspond to $\pm 3\sigma$ margins. The s value is kept at the default value $s = 3$ and the p value is increased to $p = 4$ which increases the robustness of the feature evaluation with respect to outliers in the feature space.

Demodulation – In this work, two methods are used for amplitude demodulation of voltage and current signals: (1) Hilbert transform and (2) Space vector transform. The Hilbert Transform is used on single phase quantities while the Space vector transform is applied to three-phase quantities. The goal of demodulation is to remove the dominant line frequency component contained in the phase voltage and current signals so that ripple (composed of harmonics and fault signatures) along the line frequency can be analyzed using the envelope of the raw voltage/current signals. This approach allows a clear detection of failure signatures without being swamped by the power in the line frequency [7][8]. The Hilbert transform can be expressed as follow:

$$\hat{x}(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau. \quad (2)$$

The Hilbert transform creates an artificial complex signal $u(t) = x(t) + j\hat{x}(t)$ from input signal $x(t)$. The real part of the analytical signal is the original signal $x(t)$, the imaginary part $\hat{x}(t)$ represents the Hilbert transform of a real part, $x(t)$. The absolute value magnitude of the complex analytical signal forms the signal envelope and demodulates the original signal $x(t)$. The absolute value magnitude of $u(t)$ is given by $|u(t)| = \sqrt{x^2(t) + \hat{x}^2(t)}$.

The Space vector transform creates a complex-valued one-dimensional space vector $P(t)$ from time-dependent real-valued three-phase quantities: $x_a(t)$, $x_b(t)$ and $x_c(t)$. The Space vector transform is defined as follow:

$$\begin{aligned} P(t) &= x_a(t) + \alpha \cdot x_b(t) + \alpha^2 \cdot x_c(t) \\ &= x_d(t) + j \cdot x_q(t) \end{aligned} \quad (3)$$

where $\alpha = e^{2\pi/3}$ and the d-q components are given by

$$\begin{bmatrix} x_d(t) \\ x_q(t) \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & -\frac{\sqrt{3}}{2} & \frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} x_a(t) \\ x_b(t) \\ x_c(t) \end{bmatrix}. \quad (4)$$

The magnitude of $P(t)$, given by $|P(t)| = \sqrt{x_d^2(t) + x_q^2(t)}$, forms the amplitude demodulated signal.

Electrical Signature Analysis – 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. A key consideration when using ESA is that voltage signatures relate to the upstream of the circuit being tested (towards power generation) and current signatures relate to the downstream of the circuit being tested (towards the motor and load) as depicted in Figure 3. ESA uses the machine being tested as a transducer, allowing the user to evaluate the electrical and mechanical condition from the control or switchgear. Typically, ESA is done in the frequency domain, relying upon FFT techniques for accurate analysis [9][10][11][12]. In this work, ESA will be done in the time-domain to assess the health of generators by analyzing the amplitude demodulated signal versus phase angle of the complex signals. Frequency-domain based ESA techniques have been developed to detect and track a seeded bearing failure in a P-3 generator [9], which was not detectable in the vibration signals using visual inspection alone (no large spikes in vibration data were observed). Also the frequency-domain techniques have been used to identify the location / component of degradations in P-3 generators using available phase voltage and current waveforms.

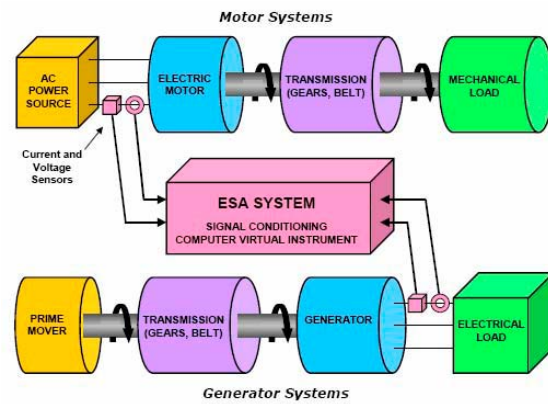


Figure 3: Applying ESA to Motor and Generator Systems

Fault Classifier – The diagnostician, implemented as a multiple-input multiple-output 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.

Virtual Sensor – 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 possible 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).

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: 1) no load, 30 kVA and 60 kVA; 2) operating line frequencies of 395Hz, 400 Hz and 405 Hz. During the testing of P-3 generators at NAVAIR in 2006: Gen 18700071 was a brand new generator with 0 hours of usage, Gen 700 was identified as a high-hour generator with 2,324 hours of usage and Gen 1182 had 2,131 hours of usage. Degradations were identified in Gen 700 and Gen 1182 using frequency-domain based ESA techniques. Although no specific failure was identified for Gen 700, the total power in the odd harmonics of the line frequency was above the other generators. Gen 1182 was significantly higher than the other generators in regards to the total power in even harmonics of the line frequency and the bearing fundamental train frequency fault signature. Also, deviations from the healthy generator were observed for Gen 1182 at the stator and rotating field failure signatures.