

Applying Poincaré Plots for Evaluating the Health State of Aircraft Generators

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ABSTRACT

This paper explores the use of Poincaré plots to study signal variability of Navy P-3 aircraft generators. The method, which was inspired from nonlinear dynamics for analyzing interval sequences, is a technique used to plot each interval against the subsequent interval of the signal from different points of view. The geometry of the plots reveals salient features among new, low-usage, and high-usage generators. In addition to its simple visual interpretation, quantitative descriptors were explored to assess the degree of degradation of the overall system health state. The results suggest that accurate health state predictions can be achieved if baseline data can be collected.

INTRODUCTION

System health management technology is critical for an aircraft's Electrical Power Generation System (EPGS), the source of power for all navigation and mission systems on modern military aircraft. Because failures in the EPGS can lead to catastrophic results, distinguishing the aging features of in-service units is important, as it may allow for monitoring, early detection of impending faults, prognostics, and enabling the decision process for replacing components safely before failures occur. In this study, measures are sought to differentiate the status of system health among Navy P-3 aircraft generators. By identifying potential indicators to quantify the state of health, the measures may be used for re-certifying generators during depot repair and overhaul.

In pure scientific research, the criterion for excellence is primarily aesthetic, and applicability to the real-world is not required. However, while aesthetics is important, the

criterion for research excellence shifts to one of usefulness in helping solve important real-world problems for a business. Therefore, we set two goals for the study:

1. To devise a simpler data processing method for possible technology transition in the future.
2. To find quantitative descriptors to provide degradation evidence of the generators' state of health.

It is worth noting that the first goal about applicability is essential from a business perspective. As such, acquisition of real-world data and platform integration issues related to technology transition (e.g., computing power and weight, data storage, communication bandwidth, and cost) were factors being considered in this work.

DATA ANALYSIS APPROACH AND RESULTS

DATA DESCRIPTION – The data sets used in this study were obtained from the U.S. Naval Air Systems Command (NAVAIR) at Patuxent River, MD. NAVAIR collected the data from an electrical signature analysis (ESA) test performed on five P-3 aircraft generators. The P-3 electric generator is a 3-phase, 400 Hz, 115 VAC, 60 kVA, air cooled generator. The operating speed is 5700 to 6300 rpm with nominal frequency from 380 to 420 Hz. During the test, the frequency was varied with different running loads (0, 30, and 60 kVA). Both vibration and electrical data are available in the data sets, but only electrical data were used in this study. The electrical data sets consist of 14 variables.

Among the five generators, there is one brand new generator, one high hour generator, one generator used in the auxiliary power unit (APU), and two other low

usage generators as shown in Table 1. Because examining the signal quality is one of NAVAIR's original goals in the ESA test, the data were collected at high sampling rates at 100 kHz. From NAVAIR's standpoint, these five generators were all considered to be “good” generators because they all passed the ESA test; nevertheless, our aim was to differentiate and quantify the degree of degradation due to “aging” or “in-service use” among them. Consequently, the methods developed in this study focus more on prognostics than on diagnostics.

Table 1: P-3 aircraft generators used in the data sets

1	73-A0255	Low usage generator
2	1182	APU generator
3	18700071	Brand new generator
4	700	High hour generator
5	765	Low usage generator

POINCARÉ PLOT AND DATA REDUCTION - Several data-driven techniques were investigated. The Poincaré plot method reported here is one of the techniques used in analyzing the data. The technique was taken from nonlinear dynamics to reveal aspects of the interval sequence and has been an emerging analytic technique in the field of heart rate variability (HRV) for nervous system studies [1]. A Poincaré plot of an interval sequence is a diagram in which each interval is plotted against the previous interval [2]. In nonlinear dynamics, it is a first recurrence plot to quantify self-similar or recurrent behavior in processes. We focused on the interval sequence because the method can shed light on the changes of a signal without the burden of storing a huge amount of continuous time series data in-flight. In addition, the method does not require intensive data processing resources. After examining the data and consulting with some generator manufacturers, the exciter current was suggested as a potentially good health indicator and was used as the starting point for this analysis.

THE OBSERVED RAW DATA – For each generator, the collected data were roughly split into several data files based on the combination of frequency and load conditions. From these data files, we selected the cases of maximum load with 400 Hz output frequency and sliced about one-third of the data with total length 500,000 points to perform the analysis. Figure 1, shows a 0.1 s sample of the gathered data points for Generator-3 (brand new) and 4 (high hour). At first glance, it is apparent that the signal patterns of these two extremes exhibit a certain difference. Beyond the visual inspection of the raw data, our focus was on exploring a way to distinguish clearly the aging features. Given that the difference among the other low usage generators, such as Generator-1 and 5, were not as obvious, we needed to explore feature extraction

methods to characterizing the degree of degradation due to in-service use.

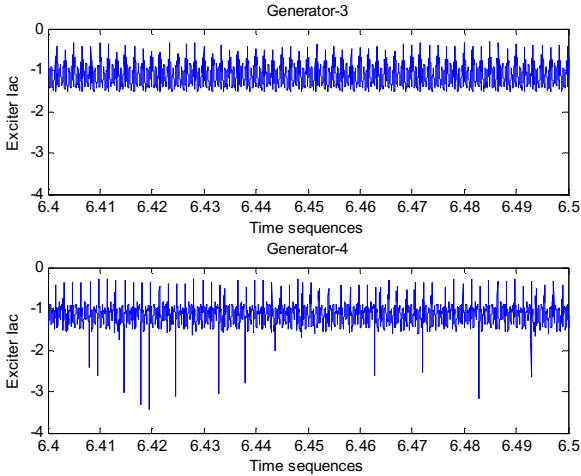


Figure 1: Raw values of exciter current.

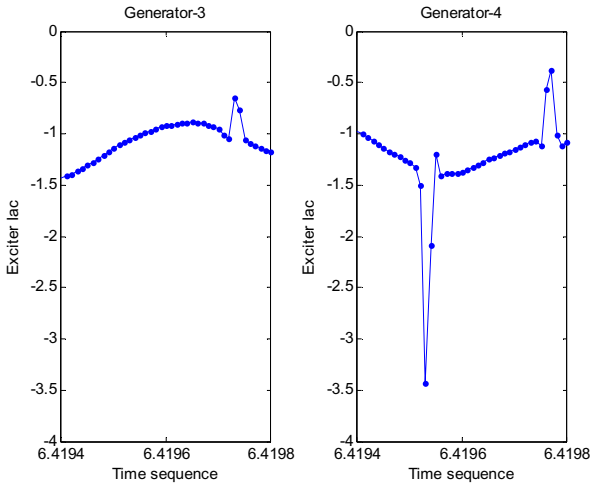


Figure 2: Close-up view of the raw data.

LOG-RETURNS AND SPIKE DETECTION – Figure 2 shows a close-up view of a sample of data points in a 0.0004 s interval. Examining the data closely, we found that, even when the sampling rate is high, a spike or a valley was just one or two data points. With so few data points to represent a spike or a valley, it is not effective to directly transform the signal to a frequency domain for analysis. Although, theoretically, it is possible to remove the dominant frequency components through certain demodulation methods to reveal the spikes or valleys, these approaches require more computing power and storage. Our goal was to seek a simpler and less demanding method to obtain the interval sequence in time domain. Therefore, we applied the following: Let $\{ s_i; i = 1, \dots, N \}$ denote the time series, here we are concerned with the logarithmic returns (log-returns), a terminology from finance, defined as

$$x_t = \ln (s_t + 1) - \ln (s_{t-1}), t \in \mathbb{N}$$