

Model Based Diagnostics of an Aircraft Generator Using AAKR and SPRT

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ABSTRACT

Electrical power generation is an important component in the Electrical Power System of an Aircraft (EPS). In this paper we present a model based diagnostic framework for early generator degradation detection and tracking within an Aircraft Generator. The nominal health state is modeled empirically using an Auto-associative Kernel Regression (AAKR) technique using signals extracted from a healthy generator. Later the health state is estimated by comparing sensor observations with the model predictions. Finally, a Sequential Probability Ratio Test (SPRT) is used to detect and track degradation. This model based framework showed excellent degradation tracking performance when it was tested on a unit that was run to failure.

INTRODUCTION

The integrated drive generator (IDG) is an important component of an aircraft electrical power system. Therefore, it is very important to accurately determine and track the health state of the IDG in order to maintain the safety and efficiency of the aircraft EPS. The IDG is such an important component that it requires its own diagnostic and prognostic tools. These unique diagnostic and prognostic tools not only enhance an individual aircrafts operational availability but also provide health condition to enable condition based maintenance (CBM) across fleets of aircraft.

An IDG is a complicated electro-mechanical system that contains many moving and vibrating parts. A functional overview of a typical IDG is shown in [Figure. 1](#).

The constant speed drive is a hydro mechanical device which makes sure that the variations in the speed of the rotor are minimized. The constant speed drive connects to the main generator through a permanent magnet generator and an

exciter. The main duty of the permanent magnet generator and the exciter are to regulate the AC output of the main generator. The generator control unit is a feedback mechanism that is used to regulate the electrical output. Of these components the generator is the most important component and is most susceptible to failure [1]. It itself is made up many different sub-components like windings, rotating diodes, rotors and stators [2]. In this paper we concentrate on the generator health assessment function in particular.

With the presence of multiple components, the generator could degrade in many ways and it is often difficult to ascertain the exact cause of failure or to track it. For this reason it is difficult to design a diagnostic methodology using the typical techniques that search for specific changes in the signals that correspond to specific expected faults and then determine the health state. Further, for the purpose of the maintenance of a generator, there is no real benefit in determining the specific fault as typically a degraded generator is completely (not specific component) removed from the aircraft and sent for overhaul.

Hence, what is needed is an indicator that can accurately track overall health state of the generator. In this paper, we propose a model based method that achieves this objective. The model is generated from signals captured from a healthy generator. Auto-associative Kernel Regression (AAKR) [3,4,5,6] is used for the purpose of model generation from a healthy system. Given a set of input vectors, the model predicts the expected output of a healthy system. This prediction of the model and the observation would be similar if the generator were healthy. However, the predictions and the observations would start to diverge if the system were degraded. This divergence is the indicator of the health state of the system.

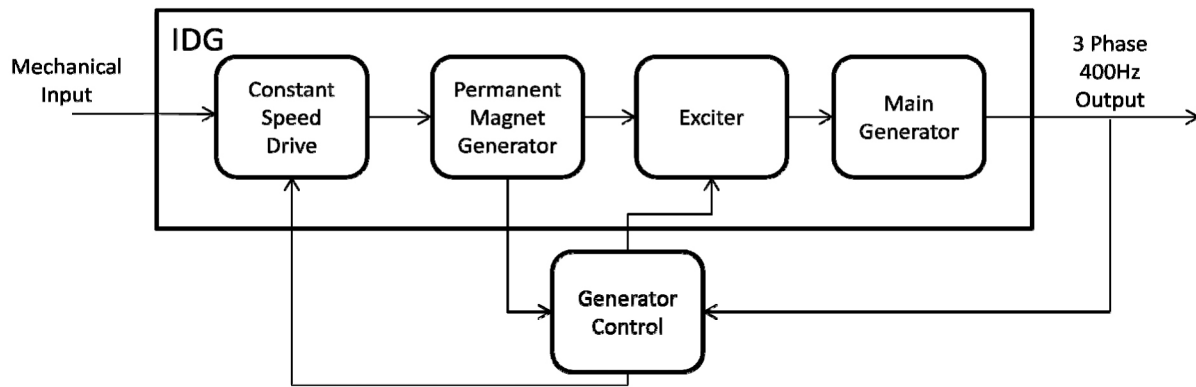


Figure 1. Typical IDG Functional Overview

From this divergence a degradation indicator is extracted to determine and classify the generator as healthy or degraded. Sequential Probability Ratio Test (SPRT) [7,8] is used to identify the changes in the statistical properties of the degradation indicator and classify the system.

The methodology proposed in this paper is explained in the next section. AAKR and SPRT are described in following. The fourth section describes the data on which this methodology was implemented and corresponding performance.

METHODOLOGY

The basic idea behind this methodology is that if a model is generated from a healthy system, then as a system starts degrading the system's performance starts deviating from the predictions of the healthy system model. These deviations can be used for health assessment, diagnostics and prognostics. The assumption is that the observations from a degraded system are dissimilar to the observations from a healthy system. This ideology can be implemented as shown in Figure 2.

First, a model is developed using signals from a healthy generator. Empirical modeling techniques like AAKR can be used for this purpose. The details of AAKR are given in the next section. Now, when the testing begins, the observations from the generator are captured using sensors and compared to the empirical model. The model measures the similarity of the observations with the training data and predicts the expected healthy state given the observations. The deviation between the observations and predictions captures the degradation in the generator; more the degradation greater, greater the deviation. The deviation is calculated as the residual which is simply the difference between the observation and prediction.

Next, to determine the overall health state of the generator the residuals are fused to form one degradation index. From the degradation index the health state of the system can be

assessed using techniques like SPRT (explained in the next section).

AAKR AND SPRT

AAKR is an empirical modeling technique that uses the training data stored in the memory to make predictions. The training data is stored in the memory as a data matrix. Each column vector of the matrix is a sample reading from various sensors at one given instance. The length of the column vector is the dimensionality of model. The column vectors at various instances are grouped together to form the memory matrix. AAKR is a non-parametric technique that makes estimates by taking weighted average over the memory vectors.

Let the dimensionality of the data be n , then n variables can be extracted from the signals collected from the generator. Further, if N samples of the measurements from a healthy system are used to generate the model then the memory data matrix is of size $n \times N$.

In order to predict using AAKR for a given input measurement x_q , first its distance u_j with each of the memory vectors m_j is calculated using measures like the L^2 -norm or the Euclidian distance as shown in Eqn. 1.

$$u_j = \sqrt{\sum_{i=1}^n (x_q^i - m_j^i)^2}$$

Next, the weight w_j of each memory vector is determined from the distance calculated in Eqn. 1 using a Gaussian kernel of bandwidth as shown in Eqn. 2.

$$w_j = \frac{1}{\sqrt{2\pi}h^2} e^{-u_j^2/h^2}$$

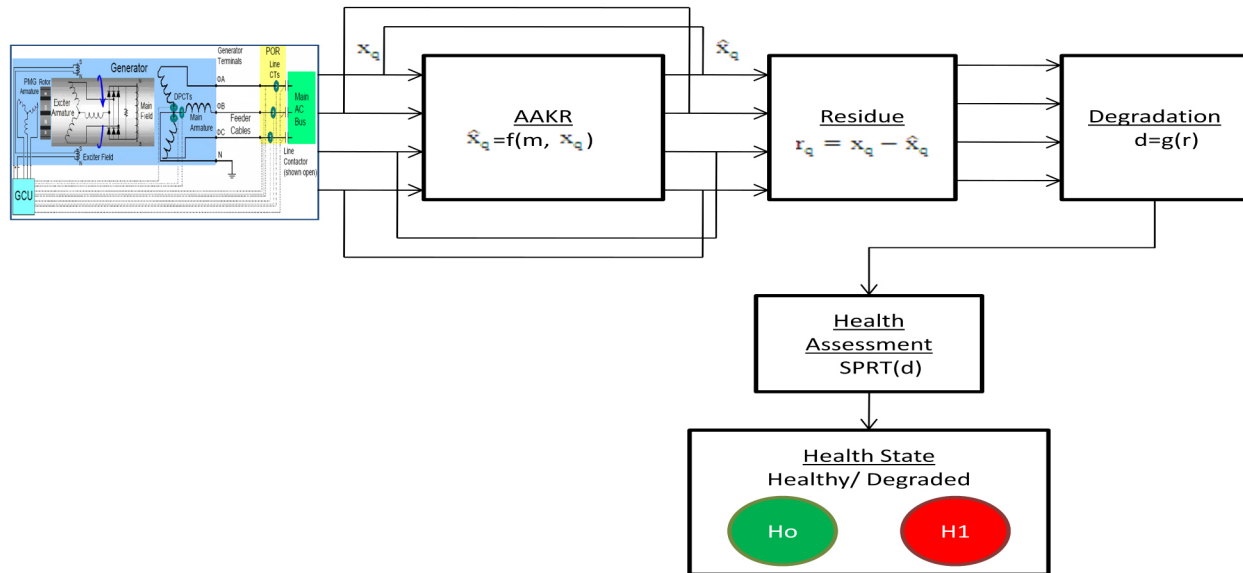


Figure 2. Methodology

Finally, the nominal model prediction and the residual for the given input measurement are given by Eqns. 3 and 4.

$$\hat{x}_q = \frac{\sum_{j=1}^N w_j m_j}{\sum_{j=1}^N w_j}$$

$$r_q = x_q - \hat{x}_q$$

Once the prediction and residual have been calculated by the model, SPRT is used to determine if the deviation from the nominal model can be regarded as degradation.

SPRT is a simple sequential technique that can be used to optimally determine statistical deviation in mean and variance of a sequence of random variable. Given a sequence $r_1, r_2, r_3, \dots, r_q$ SPRT can be used to choose between two Hypotheses H_0 and H_1 with required a probability of $1-\alpha$ or $1-\beta$.

Where,

H_0 : Residuals are drawn from a zero-mean Normal distribution.

H_{01} : Residuals are drawn from a Normal distribution with mean M .

α : False alarm probability.

β : Missed alarm probability.

The underlying assumption here is that the mean of the deviation of a degraded system is significantly different from that of a healthy system.

For a sequence of q observations the likelihood ratio for the two hypotheses can be calculated using Eqn. 5.

$$L_q = \sum_{i=1}^q \frac{\Pr(r_1, r_2, r_3, \dots, r_q | H_1)}{\Pr(r_1, r_2, r_3, \dots, r_q | H_0)}$$

Using Eqn. 5 Hypotheses H_0 is selected whenever $L_q < A$ and H_1 is selected whenever $L_q > B$. A, B are the acceptability thresholds determined using Eqns. 6 and 7.

$$A = \frac{\alpha}{1 - \alpha}$$

$$B = \frac{1 - \beta}{\beta}$$

DATA DESCRIPTION

The generator data used for testing the methodology was obtained from a refurbished P3 aircraft generator. This generator has a maximum rated capacity of 75KVA. According to the log file from the testing, the testing started in November 2008 and continued till the generator failed in April 2009. The generator was operated intermittently and data was collected at each run. When the generator finally failed on April 2009, the cause of failure was not clear. The test performers had no indication of failure until just before the last couple of test runs.

Each test run was composed of a cycle. A cycle included several steps and each step corresponds to a specific operating condition. The operating condition is defined by the