A Novel Method for Monitoring Single Variable Systems for Fault Detection, Diagnostics and Prognostics

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Abstract: This paper introduces empirical modeling techniques for process and equipment monitoring, fault detection and diagnostics, and prognostics. The paper first provides a brief background and an overview of the theoretical foundations and presents a new method for applying these methods to systems which only have one useful measured variable. Instead of using a traditional auto-associative model to estimate the fault free parameter values, nominal operating features are inferred from the operating conditions of the system. This newly proposed system is called Stressor-based Univariate Monitoring Method (SUMM). A case study is presented for the application of this method to an aircraft generator that includes normal feature prediction over different operating conditions, actual feature measurement and residual generation, and fault detection and identification. Application of the proposed SUMM system to the simulated aircraft generator data includes fault detection and identification. The results presented here highlight application of the method to data including dynamically changing loads. A methodology for developing a corresponding prognostic model is given.

Keywords: Single variable monitoring, fault detection, fault diagnostics, prognostics

1. Introduction
Condition monitoring and prognostic techniques can play an important role in increasing safety, reducing downtime, increasing mission completion, and improving the corporate bottom line. These techniques are generally components of a larger health monitoring system [[1], [2]]. Health monitoring systems commonly use several modules which monitor a system's performance, detect changes, identify the root cause of the change, and then predict the remaining useful life (RUL) or probability of failure (POF) (Figure 1). The results of the monitoring and RUL estimation may be used to adjust planned operation in order to maximize RUL while minimizing the risk of failure, or to schedule maintenance to prevent in-field failure.

Health monitoring methods for multivariate systems have been well studied. However, analogous methods for single-variable systems are scarce. This paper will present a novel method for system monitoring, fault detection, and diagnostics using a single sensed variable. The following section gives a brief description of the traditional health monitoring methodology for multivariate systems and the new methodology for univariate systems. Established single variable monitoring systems are also discussed, and the key differences that distinguish the new method are highlighted. An application of the proposed method using data from a simulated aircraft generator is given. Finally, conclusions are drawn on the newly proposed method, and areas of future work are outlined.

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2. Methodology

Health monitoring systems commonly utilize a variety of measurements from the system of interest, including operating load information, environmental conditions, and sensed variables. A representative monitoring, fault detection, and prognostic system is shown in Figure 2. Correlated groups of variables are used to develop a monitoring model, such as auto-associative kernel regression (AAKR), to monitor system performance. The AAKR model can be considered an error correction method, which gives the variable values expected for nominal system behavior [3, 4]. Monitoring system residuals are generated by subtracting the actual system behavior from the anticipated nominal behavior. These residuals are evaluated with a Sequential Probability Ratio Test (SPRT) [5] to determine if the system is operating in nominal or anomalous behavior. If a fault is detected in the system, the original data, model residuals, and SPRT results may be used by a diagnostic system to identify the type, and in some cases, severity of the fault. The results of each previous module, condition monitoring, fault detection, and diagnostics, are combined to identify a prognostic parameter which can be extrapolated to a predefined critical failure threshold to make an RUL prediction.

This type of health monitoring system, however, cannot be applied if a set of correlated variables is not available for the system or component of interest. Alternative techniques for monitoring a single-variable system are scarce in the literature. Published research has largely focused on one of two areas: monitoring time based statistics or vibration monitoring of rotating machinery. Marsh and Tucker [6] use statistical process control (SPC) to detect batch-to-batch process variation in chemical industry.
A novel method, Stressor-based Univariate Monitoring Method (SUMM), is proposed for system monitoring and fault detection of a single variable system, as shown in Figure 3 [[16]]. When a set of correlated signals is not available for monitoring, the new method proposes to monitor the frequency characteristics of a single sensed variable. The nominal frequency spectrum is generally dependent on some operating condition, such as load; therefore a hetero-associative model can be used to predict the expected features of the nominal frequency spectrum. These features may be peaks and valleys, or ratios thereof, which change in a significant way with faulted operation. Useful features are identified in an automated way by comparing the nominal frequency spectrum to those of faulted operation. Useful features are those that change in significant way with faulted operation; enough such features are chosen to not only detect faulted operation, but to differentiate different faults using only the resulting residual patterns. The measured signal from the current system is then transformed from the time domain to the frequency domain by taking the Fast Fourier Transform (FFT) of the temporal data, and the desired features of the frequency spectrum are extracted. Residuals between the expected nominal features and the actual system features can be used with a fault detection and diagnostic routine to determine if a fault is present, the type of fault, and possibly the severity of the fault. Fault detection and identification can be accomplished in one of two ways. A traditional fault detection routine, such as the SPRT or simple signal thresholding, can be used to identify which model residuals are the result of faulted operation, with only these residuals passed to a fault detection routine to determine the type of fault experienced. Alternatively, a single classification model can take all residual observations and identify whether the residual vector is the result of nominal operation or some specific faulted operation.
The final component in a full health monitoring system is the prognostic model. In order to develop a meaningful prognostic model, an appropriate definition of failure is needed. In many cases, failure is defined as the point in a fault progression beyond which the system reliability has dropped below the nominal 95% value; that is, the operator can no longer be 95% certain that the system will continue to operate to specifications. Previous work in the SUMM included estimation of the fault severity in the fault diagnostic model ([16]). With an estimate of the current fault severity level and some knowledge of future operating conditions, a Markov Chain prognostic model can be used to simulate possible future fault progressions and a resulting POF curve ([17], [18]). This type of model simulates many possible future operating conditions, relates these conditions to a degradation measure, and then determines the time at which the degradation measure crosses a pre-determined failure threshold. A similar approach, which may also be applied, is the Life Consumption Monitoring (LCM) method, which generally uses first-principle models to determine the amount of “life” which has been used during operation at a given load ([19], [20]). Alternatively, if a parametric model is available or inferable which relates fault severity progression to some measure of duty cycles, such as clock time, run time, cycles, or time spent in different loads, is available then a General Path Model (GPM) prognostic model may be appropriate. This model fits a parametric function to the health progression of the current system and then extrapolates that functional fit to some pre-determined failure threshold. Each of these prognostic models are applicable in different situations, but all are particularly well suited to the information available from the results of the SUMM.

3. Application

The proposed single variable monitoring system is applied to a simulated aircraft generator. An aircraft generator simulator was used by the OEM to generate data for dynamically changing load conditions meant to simulate a short portion of flight. A schematic of the generator simulator is given in Figure 4. Collected data signals include the current and voltage for each of the three legs of the main armature and exciter field current. The data used for this research includes only balanced load conditions on the three legs of the main generator armature, which may change with each duty cycle (1 second) of simulated flight. Data is collected at a rate of 60,000 Hz with a total flight time of 100 seconds. The simulated generator data is clean; that is, no noise is included in the simulations. Actual data collection will, of course, include some amount of random variation about the true value. However, validating the insensitivity of similar methods to nominal levels of process and instrument noise has been successfully performed in
other applications [[21]], which should extend to the SUMM. Application of the method to static, balanced loads was presented in [[16]]; however, the method is also applicable to unbalanced load conditions. In addition, unbalanced loads were simulated for static load conditions of 5, 45, 65, and 85 kW; analysis of this data is an area of future research.

![Figure 4: Schematic of Generator Simulator](image)

4. Results

Analysis of the simulated generator data indicates that the seven available temporal signals, current and voltage for each of three legs of the main armature and exciter field current, are not significantly correlated to allow for a traditional multivariate monitoring approach. In fact, comparison of the nominal and faulted data indicates that the main armature current and voltage variables do not change in any way as small faults are introduced into the system. This is not to imply that a multivariate approach would not be applicable to this system in any situation. Monitoring additional system variables or computed variables may produce a set with sufficient correlation and information about system degradation to apply the multivariate approach. Because such data was not available, the univariate technique was the focus of this analysis. In applying the proposed single variable monitoring methodology, expert opinion provided by the generator OEM suggests that the exciter field current is one of the most useful variables for both fault detection and diagnostics; application of the proposed method to this variable is the focus of the current research.

Because this analysis did not use a set of correlated time-domain signals, the changes due to faulted operation are not detectable with the traditional, empirical monitoring system described. However, the frequency characteristics of the exciter current are determined uniquely from the applied load on the system. Transforming from the time to frequency domain lends significant fault detection ability when the proposed monitoring approach is used. The nominal operation frequency spectrum of the exciter field current is predicted by the load on the main armature, which is determined from the measured current and voltages of the main armature. The three phase loads are used to define the operating condition used in Figure 3. Then, a heteroassociative model is used to predict the normal exciter current spectrum. Peaks in the exciter current frequency spectrum change in an observable and quantifiable way as faults are introduced in the simulated system. For the high fidelity simulated data provided by the OEM, the load on the main armature remains constant for one second of simulated time; the 60,000 observations collected during that second are used to calculate the frequency spectrum during that second for the constant load. In this way, the 6 million time-domain
observations are reduced to 100 joint time-frequency domain observations. Figure 5 shows the frequency spectra for nominal operating conditions and two faulted operating conditions at the same load. The top plot shows the spectrum of the nominal operating condition, the second plot shows the spectrum of fault type A, and the bottom plot shows the spectrum of fault type B. Comparison of these plots shows that additional peaks appear in the frequency spectrum due to the introduction of faults. Similar results are seen at each of the load conditions simulated. As indicated on the plots, six peaks are chosen to detect and identify faulted conditions. Because the location of peaks of interest can shift slightly due to changes in sampling frequency, amount of data available to calculate the frequency spectrum, and noise contamination; frequency ranges are identified about each peak of interest as indicated on the plots, and the peak is chosen to be the maximum value within that range. This small step makes the method more robust to real world data collection concerns.

![Spectrum Example of Normal Current](image)

**Figure 5:** Frequency Spectra of Exciter Field Current for Nominal and Faulted Operation

The chosen peaks of the frequency spectrum are used to generate residual patterns between the expected nominal operation and the actual operation. Figure 6 below shows the exciter current time waveform, frequency spectrum, and spectral residuals resulting from one case of each type of operation: nominal, fault type A, and fault type B. The main plot shows the exciter current measurement for a 14-second interval during the total flight. Each of the segments is from a different operating condition and was provided by the OEM in a blind fashion. The secondary plots summarize the monitoring system execution in three subplots: the exciter current time waveform during a small portion of the one second interval in the top subplot, the frequency spectrum during that interval in the second subplot, and finally the residuals between the calculated frequency spectrum peaks and the expected peaks based on the load. The leftmost plot gives the results for fault type A, the middle plot for nominal
operation, and the rightmost plot for fault type B. It is clear from the residual patterns of the two fault types that they should be easily distinguishable.

![Figure 6: Monitoring Model Results for Nominal and Faulted Operation](image)

After residuals between the nominal and actual operating spectra are obtained for the six peaks of interest, they are run through a fault detection routine to determine if the system is operating in a normal or faulted mode. In this data simulation, faults are simulated to occur for one second and then are "corrected". Because of this simulation method, a simple signal threshold may be used to identify faulted operation. For the peak ranges of interest, nominal operation spectra residuals are below 10 amps while faulted residuals are above 60 – 100 amps, depending on the peak. However, this is not physically realistic; in real-world applications, the faults would likely begin at some small severity level and the progress to greater severity eventually indicating failure. In addition, the noise which would be present in real-world data may muddle the ability to apply a simple signal threshold-based technique. For data of this more realistic type, an SPRT fault detection routine will likely be more useful to detect incipient faults before they become large enough to cross the threshold values used for fault detection here. In the current study, six one-second intervals in the 100-second simulation are correctly identified as operating in a faulted condition, while the remaining 94 seconds are correctly identified as nominal operation.

The six observations of frequency features which have been identified as faulted operation are input to a fault identification module to determine if the system is experiencing fault type A or B. The fault identification module uses an inferential kernel regression function which compares the residual values of the six feature peaks to those seen in the past and determines if the current observation is more likely fault A or fault B. As noted above, the residual patterns for the two fault types are clearly distinguishable. Because only six faulty observations are available (three of fault type A and three of fault type B), a leave-one-out validation method is used to test the diagnostic model. That is,
an inferential model is built using five faulted observations and tested on the remaining one; this is repeated for each of the faulted observations. The diagnostic model gives 100% accuracy in differentiating between fault type A and fault type B for the six available faulted observations. Based on previous studies in which faults of differing severity levels are correctly identified [[16]], effectively increasing the number of fault types identified through the diagnostic model, extension of this method to include more fault types should give acceptable diagnostic coverage.

5. Conclusions

Condition monitoring and state detection (diagnostics) using multivariate systems are ubiquitous in the literature. However, methods for monitoring single variable systems with load-based features are not as prevalent. Available methods focus on monitoring time-based statistics of the single parameter or frequency spectrum statistics for monitoring rotating equipment. This research proposes a novel method for monitoring, fault detection and diagnostics of single variable systems called Stressor-based Univariate Monitoring Method (SUMM) using features extracted from the frequency domain of a selected variable. Corresponding features of the nominal spectrum are estimated based on the system operating conditions. Residuals between the actual frequency features and estimated nominal frequency features can be used in the same fault detection, diagnostic, and prognostic routines used for multivariate systems. The proposed method was applied to an aircraft generator using high fidelity simulated data provided by the OEM. The method was shown to accurately detect and diagnose known faulted operating conditions. Despite some shortcomings in the simulated data available for analysis, this method is believed to be applicable to data which more realistically captures real-world relationships, including sensor noise, faults which grow with time, and unbalanced loads on the main armature.

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References

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