Pattern Analysis in Real Time with Smart Power Sensor

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Abstract—The current state of the art in electronic prognostic health management systems does not fully support detection, collection, and remediation of real-time faults. As a result, knowledge has not been captured from an actual platform failure mechanism. Thus, point-of-failure feedback cannot be applied by system designers or operators to improve lifecycle weak links in replacement platforms, or to strengthen effectiveness of mission-critical platforms. Our innovation makes it possible to extract and analyze the power system's eigenvalues, which are related to the intrinsic frequencies of the power system that determine correlations between extracted features and state of health (SoH). In-situ electronic prognostics for power systems are crucial for attaining a sound theoretical basis of health status. To provide correlation information such as state of health (SOH) using pattern analysis with real-time data from a non-intrusive smart power sensor, Ridgetop researched using data-driven modeling with a proposed health distance and Support Vector Machines (SVMs) with signatures in a standard IEEE 1451-enabled smart power sensor. Results of this study indicate that a fault pattern analysis methodology overcomes certain disadvantages of the standard failure modes and effects analysis (FMEA) approach, which does not account for the contribution of unobserved failure to a degradation trajectory. The efficacy of the proposed pattern analysis approach is illustrated with test results showing critical distinction in pattern analysis and test data acquired from a real-time IEEE 1451-enabled smart power sensor testbed, and monitored via a testbed with appropriate instrumentation. [1 2]

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1. INTRODUCTION

Fault detection and analysis, coupled with effective monitoring in mission-critical system environments, comprise a challenging research problem due to growth in scale [22] and complexity of applications, the changes in resource configuration [23], and the variety of services being offered and deployed. These capabilities maximize system effectiveness in the presence of anomalies and are defined as health management. Health management technologies have been considered critical for detection and prediction of impending system faults, initiating fault mitigation, and providing valuable information to facilitate proactive logistics planning and fleet-operation decision processes [8].

The pattern analysis approach presented in this paper has foundations in both model-based and model-free analysis. In short, model-based pattern analysis uses prior knowledge of the system to develop mathematical models to process and evaluate the current data. It includes residual-based [15] [6], multiple models [11], decoupling [1] [18], and hypotheses [16]. Model-free approaches, also called data-driven modeling in this paper, rely mainly on observation data without *a priori* knowledge about the system, and include data mining [20] [2] [21], expert system [10] [12] [3], and other methods. In this paper we present data-driven modeling with a proposed health distance and signatures in a standard IEEE 1451-enabled smart power sensor. We also consider one data mining method, the Support Vector Machine (SVM) approach, which has a particular strength to represent boundaries of varying SoH measurements. We then discuss hybrid pattern analysis combining our data-driven analysis as an initial pattern detector in a real-time system and model-based analysis as an advanced pattern detector.

The rest of this paper is organized as follows: In section 2, we explain a real-time IEEE 1451-enabled smart power sensor testbed from which data will be acquired in real time. Section 3 explains the concept of mean time between failures (MTBF) to increase the understanding of prognostics. Section 4 classifies pattern analysis as two approaches with explanation and examples to distinguish the difference and help define concepts used in the following section. Section 5 presents our data-driven analysis development process, and section 6 shows the result, explaining how to apply our data-driven analysis with testing results showing critical distinction in pattern analysis. The opportunity of hybrid pattern analysis is discussed in section 7. Finally, in section 8, we conclude the paper.

2. SMART POWER SENSOR

Non-intrusive monitoring of electronic power systems' SoH can be facilitated by examining the power system response to an impulse load change and extracting the characteristic frequencies of this response. The proposed smart sensor technology, which is based on the extraction and analysis of these eigenvalues, has wide applicability to electronic power systems, including SMPS and electromechanical actuator (EMA) servo drives. A block diagram of the sensor, with implementation of the IEEE 1451.4 interface standard, is shown in Figure 1.

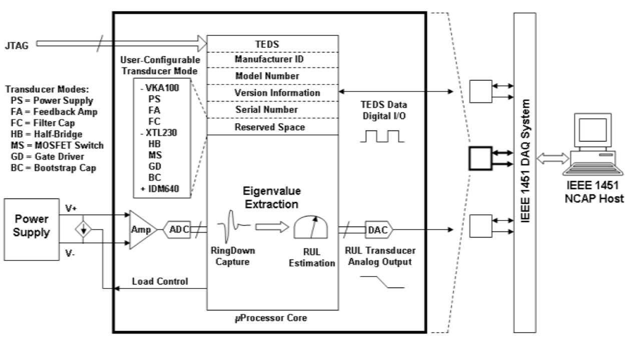

Figure 1 – Programmable IEEE 1451 power sensor architecture

The embedded 400 MHz MPC5200 Freescale processor and Spartan 3 Xilinx FPGA easily satisfy the data acquisition and signal processing needs of our smart power sensor and provide a solid foundation for migration to a single-board solution or system-on-chip (SoC) implementation.

The default measurement mode and transducer output of the smart sensor is the power system SoH. Represented as a fuel gauge in the diagram, the analog transducer output indicates the RUL of the entire system, taking into account the SoH of all individual system components, including the SMPS output filter capacitor, feedback amplifier, PWM controller, etc. The analog output signal is set to a maximum value when the sensor detects that the power system is 100% healthy and a minimal value when the system has completely failed or is 0% healthy.

Flow*To minimize heat dissipation in the static load resistor and allow reduction in power rating, and ultimately size, the smart power sensor provides switching control of the static load as well as the impulse load. The oscilloscope waveform capture provided in Figure 2 illustrates the load control timing. The static load resistor is enabled first for 4 milliseconds (ms). Midway through the static load period, or 2 ms after static load is enabled, the impulse load is enabled for 10 microseconds (μs).

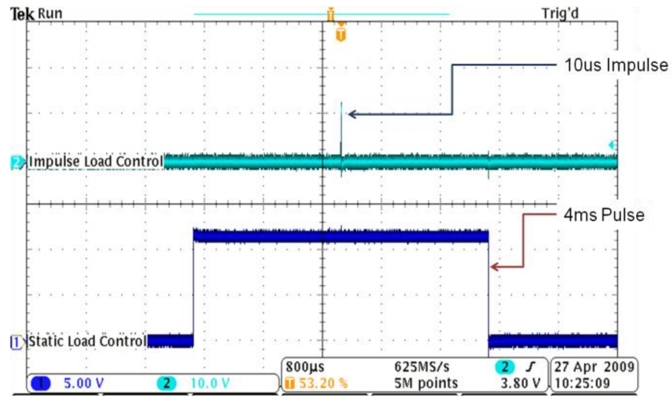

Figure 2 – Load control timing

A block diagram of the advanced load control is provided in Figure 3. Load control functionality has incrementally evolved from a simple hardware switch with an off-board load resistor to more sophisticated programmatic digital control logic. Along with safety benefits, like preventing burn injuries to the user, the advanced load control allows programmatic load insertion for on-line power system health monitoring. Furthermore, the load resistors can easily be changed to adapt the sensor to the target power supply.

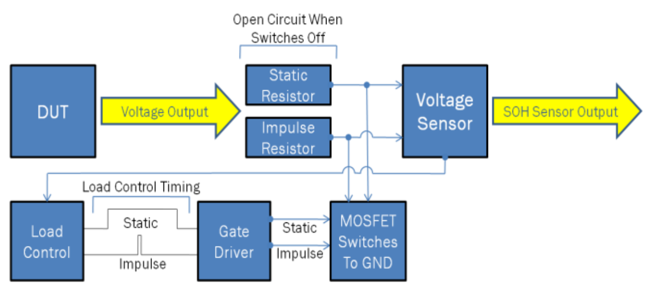

Figure 3 – Advanced load control block diagram

Typical power supply specifications to consider when sizing the load resistors are total output power of the supply and the combined static plus impulse load required to elicit a measurable ringing response. For example a 1 Ω resistor on a 5 V 20A SMPS, like that employed in the RD1000-1, represents a 25% load. This could easily be increased to a 50% load by using a 0.5 Ω resistor, or decreased to 12.5% load using a 2 Ω resistor, as is needed by the specific application.

Another possibility allowed by the replaceable resistors is to add other types of loads. These loads could be capacitive or inductive, or with only slightly more complexity could be introduced as ramp loads rather than the step load currently used.

Another important feature of the load control board design is signal conditioning support. Due to the voltage input limitations of the data acquisition system used in the smart power sensor, it may be necessary to attenuate the input voltage. That is, the input voltage range of the sbRio is ±10 V. Therefore, the user must be able to appropriately scale target power supply voltages greater than 10 V. A simple voltage divider circuit, using 0.1% precision resistors, provides the necessary input voltage scaling. Calibration constants like input voltage attenuation and lead resistance compensation are defined in the Reserved Space of the sensor's TEDS memory, along with the programmable transducer mode. The schematic of the load control board illustrated in Figure 4 details the implementation of the signal conditioning and advanced load control circuitry.

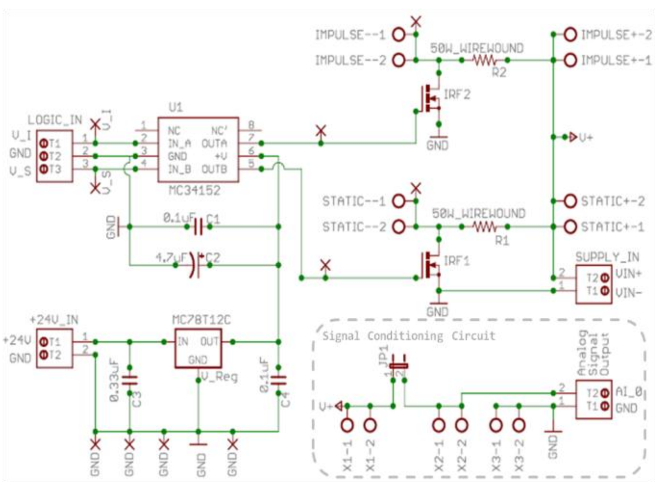

Figure 4 – Advanced load control board schematic

As seen in the schematic, the inputs to the load control board are from three sources. These are the logic input signals, a 24 V input to the voltage regulator, and the input from the supply under test.

The logic inputs, V_I and V_S, are the impulse and static load control signals, respectively. These are amplified using a non-inverting gate driver to drive the MOSFETs that control the signal path of the load resistors. Power for the gate drive is supplied from the 12 V voltage regulator attached to the 24 V input of the load board (lower left in the schematic). The supply under test is then connected to the two loads in parallel fashion. When switched on, the MOSFETs close the circuit that inserts the load resistors across the power supply's output. This in turn causes the ringing response, which is subsequently measured at the output of the load board's signal conditioning circuit.

3. THE FAILURE OF MTBF

In 1995, a cornerstone of reliability was called into question. Mean time between failures (MTBF) is considered the "useful life" of a device, excluding the early failure and wear-out periods as shown in the reliability or "bathtub" curve. The aeronautical industry found use of MTBF questionable because of its inaccuracy when applied to real systems and the nature of the culture it engenders. Because it does not take into account component dependencies, MTBF can overestimate reliability. Some estimates have set MTBF accuracy for component failure rates at only 40%. The difficulty in identifying and correcting MTBF has led to adoption of an "acceptable" level of failures. This corruption of reliability removes the drive to eliminate the root cause and take corrective action. As a result, NASA and other organizations have embraced prognostics.

4. MODEL-BASED AND MODEL-FREE

To achieve prognostics using smart power sensor in electronic power systems, including SMPS and EMA servo drives with acceptable level of failures explained in previous sections, we classify those approaches that we can detect fault: Model-based and Model-free (data-driven).

Model-based pattern analysis for fault detection uses prior knowledge of the system to develop mathematical models that can be used as indications to analyze the current status. One representative method is residual-based model [15] [6] which makes a mathematical model by knowing the input and the output of the system to be used to compare the actual output with those nominal behaviors produced by the model and therefore residuals are formed. This approach requires two steps to detect faults. It first needs to produce inconsistencies, also called residuals, between the real and projected behavior to reflect the potential faults of the system. A decision rule for analysis is then selected. Another example that does not rely on the residual for the detection of faults is multiple models (MM) [11] that use multiple filters in parallel to provide better performance in management of problems with an unknown structure or parameter but without structural or parametric changes. Other model-based methods are found in quantitative model-based methods [19], decoupling methods [1] [18], statistical methods [16].

Model-free pattern analysis methods rely mainly on the availability of the amount of historical data without a priori knowledge about the system. In this approach, there are various ways in that data can be processed and presented as a priori knowledge for detecting process malfunctions. One of the methods is expert systems found in Tirifa's hybrid system [13] utilizing fuzzy logic and signed directed graphs (SDG) to perform qualitative simulation and generate if-then rules to be evaluated by an expert system using fuzzy logic information. Other expert system examples are found in [10], [12], and [3]. Another major method in model-free is quantitative information analysis using statistical methods such as data mining, one of the most active research fields, which can automatically produce succinct and precise detection models from large amounts of data. Data mining techniques such as support vector machines (SVM) [20] [2] [21] divide a set of binary-labeled training data with a maximal margin hyperlane for classification to map nonlinearly the input vector into a high dimensional feature space where the data can be linearly classified. Data mining has been developed with a variety of algorithms concerned with pattern detection, associations, changes, and statistically significant structures and events in data. Other model-free methods are neural network [4] [17] [14] and trend analysis [5] [7] [9].

In this paper, we are initially interested in model-free analysis methods, which do not require an accurate mathematical model of the process and make it possible to detect faults in real time by using the frequency spectrum and data mining based on data collection of both normal and faulty data.

5. DATA-DRIVEN ANALYSIS

The singular assumption made in the data-driven analysis development process is that a power supply's response to a changing load will adjust with its health. First, one needs to understand what a normal or healthy response is. Data collected from the test setup (shown in Figure 5) illustrates a healthy response of the power supply regulating to 5 V.

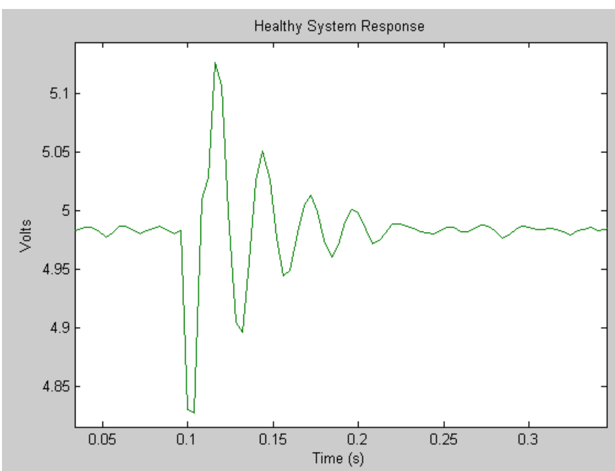

Figure 5 – Healthy system response

This response is ideal since the time in which the device is out of regulation lasts approximately 1/10 of a second and the fluctuation is only 1/10 of a volt. Less healthy systems stay out of regulation longer and their voltages fluctuate comparable to the variation illustrated in Figure 6, for example. Also notice that the voltage fluctuation has increased and the time required for the power supply to re-enter regulation has increased. A performance like this would indicate that the power supply was beginning to suffer from aging, and a computed RUL, along with supporting data, would be displayed to a decision-maker.

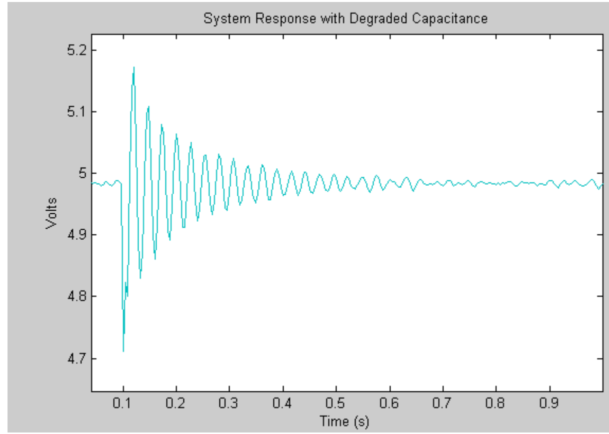

Figure 6 – Increased voltage fluctuation and increased time to re-enter regulation

Difficulty in detecting the decreasing health of a power supply arises when compound failure mechanisms manifest simultaneously. The characteristics of one failure mode may compensate for the characteristics of another. If or when the power supply has a plurality of degradation mechanisms, such as a diminished output capacitance and amplifier gain, the two could mask all obvious visible signs of degradation. A self-imposed requirement of accurately predicting RUL at all times requires the implementation of pattern analysis.

We present the current approach based on the principle that unhealthy system responses can be tested so that they are measurably different. The difference between a healthy signal (D1) and an unhealthy signal (D2) is called the Health Distance™. To be clear, these "signals" at the time of analysis are not in the time domain. This is discussed in further detail in this section.

Health Distance is calculated with D2, relative to a known healthy signal, D1. First, all data is categorized into ω pieces and the sum of all the dot products is equal to that of the dot product over the entire array:

$$\langle D_1(\omega), D_2(\omega)\rangle \therefore D_1 \bullet D_2 = \sum_{\omega} D_1(\omega) \bullet D_2(\omega) \tag{1}$$

Now an angle is introduced to represent the difference between the two arrays:

$$\theta(D_1, D_2) = \cos^{-1}\left(\frac{D_1 \bullet D_2}{\|D_1\| * \|D_2\|}\right) \tag{2}$$

$$0 \leq \theta \leq \pi/2$$

A returned value of 0 would indicate that the two signals are identical; a score of π/2 indicates that there are no similarities at all. The implementation of this process, in the time domain, results in large fluctuations in the angle of difference between two signals. Consequently, a variation is employed using LabVIEW; the difference constitutes a statistical distribution of the integral of a signal's frequency spectrum created and labeled:

$$D_m \therefore \int_{\omega_0}^{\omega_{n+1}} D_m \in D(\omega_n) \tag{3}$$

6. APPLYING DATA-DRIVEN ANALYSIS

The information in the frequency transform lends itself more readily to our data-driven analysis algorithm. The fluctuations in the frequency spectrum are not only a natural function of several environmental conditions (e.g., temperature and vibration) but are also indicative of the system's SoH.

The first step in the signal processing is to remove the DC offset in the signal to allow for removal of zero frequency data from the frequency spectrum. The equation for this is straightforward: $V_1 - V_{DC} = V_2$ where V_2 is a time domain signal, but its average value is 0. This corresponds to the AC coupling of the signal and eliminates the low frequency components that are functions of the Fourier transform.

After this manipulation, the next step is to generate a histogram from the integral of the frequency spectrum. A distribution is needed due to the natural variation in the signal. The advantage of this method is best described with actual data in the following example; note the displays in Figure 7.

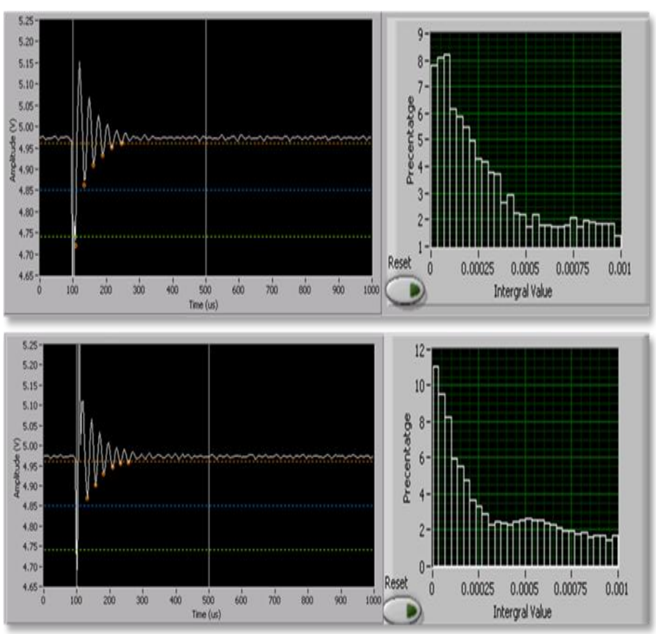

Figure 7 – Time domain signal (l) and results of histogram transform (r)

The preprocessed time domain signal is on the left and its generated histogram of integral values from the frequency spectrum is on the right. The natural variation in the output of every signal leaves the time domain signals (l) nearly indistinguishable. However, after collecting enough data to generate the histogram (r) the difference is more noticeable and the shape much more stable (relative to time domain signal).

The variation in the signal is also characterized in the histogram. This is because the histogram is a probability density function. If the time domain signal was always the same then its frequency spectrum would always be the same and the corresponding histogram would have no variation. That case would produce a single binned histogram and a 100% probability of landing in that bin. Since these signals have significant variation the plot looks like the right half of a Gaussian distribution.

This approach allows us to clearly differentiate between signals that closely resemble a healthy signal, as seen in the upper graphs in Figure 7. This also allows the algorithm processing to function speedily and more reliably than using the time domain signals. The drawback to this method is the overhead in data needed to train the algorithm on a healthy system behavior.

Once the data array has been created from distribution, training of the algorithm can begin. There is no way around the length of the training period without compromising 99% confidence in evaluation; the minimum length for the training is 300 tests (5 minutes). This training performs best with a new system.

In order to train the system, the user must store the fully developed data set, which can be done programmatically with the push of a button. Once the data is collected, it is formatted and stored in a read-only file that remains in nonvolatile memory on the sensor system. This design approach limits the size of the program, keeping the total cost of disk space below 30 kilobytes.

In our experiments, we consider various fault scenarios including compound faults by considering amplifier degradation fault and capacitor degradation fault simultaneously since the characteristics of one failure mode may compensate for the characteristics of another.

Figure 8 is a probability density function (PDF) plot of Ridgetop's fault detection algorithm output from SHM. The x-axis represents the computed output SoH value across multiple induced fault conditions. The expected result was that the SoH value would decrease as more severe faults were injected. The theory, also proven by this plot, is that while health decreases, variation in the computed SoH increases. This asserts that as SMPS health decreases, system dependability breaks down.

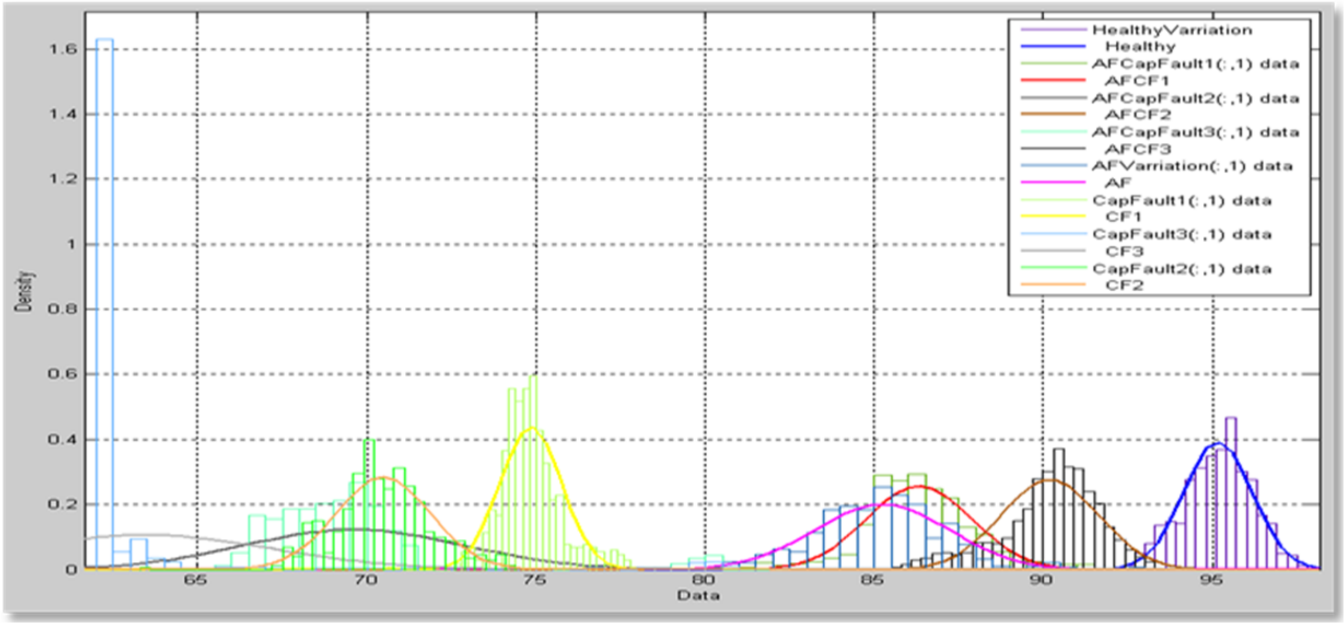

Figure 8 – PDF of SMPS health with multiple fault cases

The blue curve shown in Figure 8 represents the healthy system response which has a standard deviation of 1.0187%; the brown curve represents an early fault case, but already the standard deviation is 1.4454 %.

The increase occurs in all except the first level cap fault, which still rates 75% healthy. These results show the critical distinction between normal and abnormal status.

While the Health Distance is very promising in the initial stages of development, it would be helpful to consider other possible algorithms for this type of work. One that has a particular strength is a data mining approach called the Support Vector Machines (SVM) approach. This methodology is used for multivariate data in the machine learning realm. SVM is best described pictorially along with some preliminary analysis. Figure 9 shows nested rings in green, yellow, and red. These rings represent boundaries of varying SoH measurements.

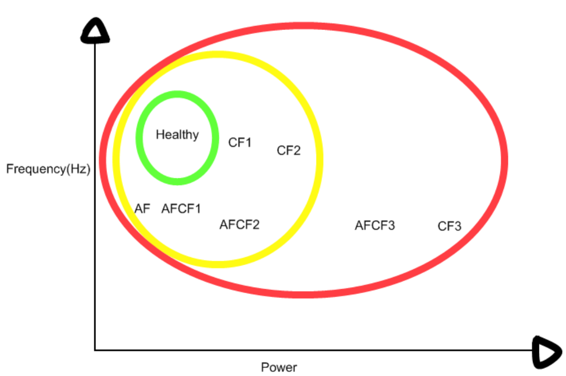

Figure 9 – SVM boundary thresholds

Experimental data of frequency peaks from a SMPS is illustrated in Figure 10. There are a few peaks above the noise floor and in particular a peak at 80 kHz. Output filter capacitance is removed to observe the behavior of the system. Note that, instead of changing the frequency of the peak, the magnitude changed. The actual calculation would be a percentage of points landing inside the threshold ring versus landing outside the ring; over time this percentage should decrease.

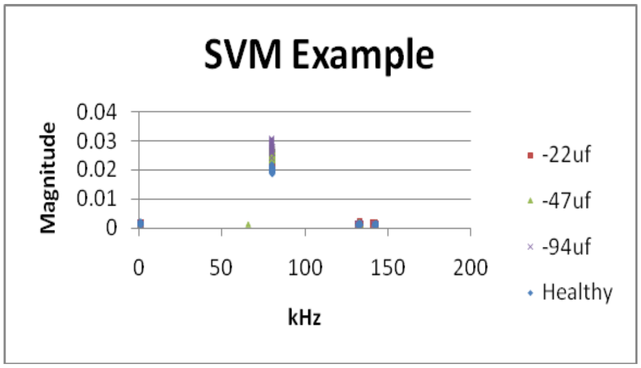

Figure 10 – SVM experimental data set

7. Discussion

We have explained our data-driven analysis and testing results. The proposed approach is very effective in the initial stages of development by providing the critical distinction between normal and abnormal status in real time. Unlike the model-based methods, our approach can be applicable even in the complex real time system since it does not require developing an accurate mathematical model that represents the true system. But if it is possible to know the input to the system, this disadvantage of model-based methods will become the strength in our pattern analysis. From this idea, we propose the hybrid pattern analysis shown in Figure 11 combining our data-driven analysis as an initial pattern detector in a real-time system and model-based analysis as an advanced pattern detector, if we can develop an accurate mathematical model.

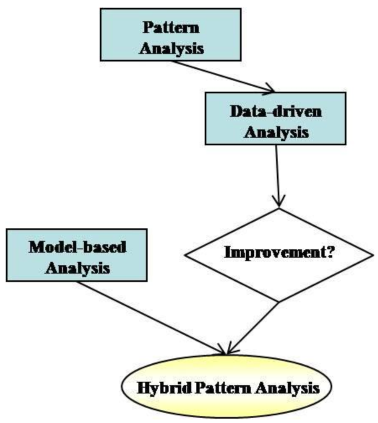

Figure 11 – Hybrid pattern analysis

We are in the stage of development of our pattern analysis methodology and algorithms. To develop the hybrid analysis idea, we may have several questions, for example:

- What kinds of input conditions are needed to decide the applicability of model-based methods?
- What are the benefits that we can get from model-based approach?
- Are the identified benefits valuable compared to the case using only data-driven analysis?
- Can hybrid pattern analysis be efficient in a real-time system?

8. Conclusion

We have presented data-driven pattern analysis with a proposed health distance and signatures in a standard IEEE 1451-enabled smart power sensor and have the result demonstrating the effectiveness of our approach. We also represent boundaries of varying SOH measurements with the SVM approach. These presented data-driven approaches are valuable for showing the critical distinction in pattern analysis. Eventually making a fully functional innovative smart power sensor that supports fault detection and identification would be highly significant. We are currently exploring a variety of algorithms to develop the analysis methodology. Finally, we plan to extend our approach to develop hybrid pattern analysis that combines data-driven and model-based approaches in complex systems.

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BIOGRAPHIES

Byoung Uk Kim, Ph.D. *is a Senior R&D Engineer and a project lead for reliability analysis tool development at Ridgetop Group. The field of interest for his doctoral program was fault detection and root cause analysis systems, electronic prognostics, data mining and data analysis, and self-healing algorithms with autonomic computing. His collegiate repertoire also consists of numerous published papers in reliability analysis and autonomic configuration. Dr. Kim worked on a key NASA reliability/prognostics project in 2006 for Ridgetop. He has contributed to the development of innovative solutions that are currently deployed in the NASA ADAPT program at the Ames Research Center.*

Chris Lynn *is an Electrical Engineer at Ridgetop Group. His focus is in determining reliability of critical systems and predicting their failures. Chris graduated from the University of Arizona where he studied device physics and state-space modeling of physical systems.*

Neil Kunst *is an Engineering Project Manager at Ridgetop Group. He earned his BSEE from the University of Arizona, where he was a member of the Tau Beta Pi National Honor Society. Neil received the Silver Bowl award and awards for outstanding achievement in Physics. He previously worked for Hamilton Test Systems, Intelligent Instrumentation, Inc., Mosaic Design Labs, Inc., Environmental Systems Products, Inc., Dataforth Corp., and SMSC. He also owned and operated his own firm, Palmtree Software, before joining Ridgetop. Mr. Kunst has more than 20 years of experience in product engineering, systems engineering, test engineering, logic design, software development, project management, and consulting.*

Tom Dudgeon *is a Design Engineer at Ridgetop Group. with experience in electrical and mechanical design and integration, as well as PCB Layout and Embedded Systems design. Tom has a BSEE degree from the University of Arizona.*