An Innovative Approach to Electromechanical Actuator Emulation and Damage Propagation Analysis

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ABSTRACT

As the aviation industry evolves toward next-generation fly-by-wire vehicles, hydraulic and electrohydrostatic actuators (EHA) are replaced with their electro-mechanical counterparts. By eliminating fluid leakage problems while reducing weight and enhancing vehicle control, the feasibility of electromechanical actuators (EMA) in avionic applications has been established. However, due to the inherent nature of electronic components and systems to fail, improved diagnostic and prognostic methods are sought to keep the all-electric aircraft safe. An innovative approach to the emulation of avionic EMA operation is presented. Realistic load profiles can be applied to a scaled-down EMA testbed while executing the in-flight actuator motion commands in real-time. The proposed EMA Emulator is designed to enable the insertion of degraded electronic components, such as the power transistors of the motor drive, to analyze the servo loop response of an aged actuator system. That is, the EMA motion trajectory, or position, data is acquired with various levels of power electronics degradation to populate a fault-to-failure progression (FFP) database of actuator servo loop response signatures. Ultimately, the FFP signature database is leveraged to develop prognostic methods to assess the state of health (SoH), estimate remaining useful life (RUL), and support condition-based maintenance (CBM) of avionic EMA systems.*

1 INTRODUCTION: FLY-BY-WIRE SYSTEMS

Fly-by-wire systems have been heralded as the savior of an industry while also being condemned as unsafe 0. Fly-by-wire aircraft use computerized systems to control engine fuel-flow rate, flight surface movements, and other activities. A computer can make hundreds of flight corrections and updates per second, far more than a human pilot. In theory, this should lead to more economical, smoother, and safer air flight. With the pilot removed from direct connection to the flight control surfaces in a fly-by-wire aircraft, knowledge of component failure modes has become critical in an industry already filled with maintenance issues and mission-critical equipment.

In this paper we define NASA's Integrated Vehicle Health Management (IVHM) project and Ridgetop Group's role supporting it by describing the hardware and software components of their innovative EMA emulator. The final sections of the paper include some preliminary data analysis, the description of an EMA fault dictionary approach, and a brief conclusion that describes future work.

1.1 NASA's IVHM Project

The goal of NASA's Integrated Vehicle Health Management (IVHM) project is to improve the safety of both near-future and next-generation air transportation systems by reducing system and component failures as causal and contributing factors in aircraft accidents and incidents. The IVHM project should develop technologies to determine system/component degradation and damage early enough to prevent or gracefully recover from in-flight failures. These technologies will enable nearly continuous on-board situational awareness of the vehicle health state for use by the flight crew, ground crew, and maintenance depot. A main emphasis of the project is to develop automatic methods for detection, diagnosis, and prognosis of the vehicle at a system and subsystem level. This is accomplished through: analysis of electrical, thermodynamic, and mechanical failures;

the analysis of the interaction of environmental hazards on vehicle systems and subsystems; and the study of damage and degradation mechanisms, to more accurately assess the vehicle's health state.

1.2 Ridgetop Group's Role

Ridgetop's role in the IVHM project is to assist NASA in the development of diagnostic and prognostic methodologies to assess the state of health (SoH) and estimate the remaining useful life (RUL) of the power electronics employed in a typical avionic EMA subsystem. Through quality collaboration with the Ames Research Center (ARC), a model-based laboratory testbed is delivered to identify and characterize the fault-to-failure progression (FFP) signatures of dominant failure modes associated with the EMA servo drive and to analyze the propagation of damage through the drive. A high-fidelity computer model is developed and correlated with the laboratory testbed to enable further analysis of simulated motor drive faults and damage propagation. The Ridgetop testbed is integrated with the ARC Advanced Diagnostics and Prognostics Testbed (ADAPT), shown in Figure 1, and, to simulate in-situ EMA failure modes and logistics. Potentially, the testbed is adapted for in-flight emulation of real-time actuator control signals and load profiles.

2 THE RIDGETOP EMA EMULATOR

Based on the concept that damage or degradation of a servo system is manifested in the control-loop response or "ringing" due to a load change or disturbance stimulus 0, position control or regulation of a Brushless DC (BLDC) motor system is an ideal candidate for application of Ridgetop's patent-pending RingDownTM technology. Specifically, we assert that actuator health can be assessed by measuring the following error, or difference between the target position and actual position, associated with an EMA motion command. The suitcase testbed, shown in Figure 2, was constructed to test our hypothesis on a scaled-down model of an avionic EMA system.

User-programmable motion trajectories and load profiles are applied to the testbed to investigate the servo drive response to various fault conditions. Properly interfaced to an avionic control system, the scaled-down testbed is capable of in-flight emulation of EMA operation under realistic load conditions and actuator damage profiles.

A functional illustration of Ridgetop's EMA Emulator Testbed is provided in Figure 3. Identical BLDC motors are coupled to emulate actuator motion and load behavior. The actuator motor, on the left-hand side of the diagram, is configured in position mode, while the load motor, on the right-hand side of the diagram, is configured in torque mode. Depending on the desired emulation mode, the torque load can be programmed to oppose or assist actuator motion. Sophisticated load profiles, including combinations of static, step and impulse loads, can be created and synchronized with the motion trajectory to emulate actual avionic flight control scenarios.

Once again, matching servo drives and general-purpose Input/Output (I/O) control boards are employed to drive the emulator motors. The prognostics-enabled actuator servo drive has been retrofitted with test sockets to enable insertion of degraded or damaged MOSFET devices into a single phase of the H-bridge. This way, the servo loop response of a damaged actuator can be compared to that of a healthy actuator to develop prognostic analysis methods for the H-bridge power electronics.

3 EMULATOR HARDWARE

A close-up image of the EMA Emulator suitcase top panel is provided in Figure 4. Separate Technosoft ISM4803 Servo Drives provide control of the actuator and torque load NEMA-17 BLDC motors. The ISM4803 utilizes a TI DSP to control International Rectifier (IR) power electronics employed in the three-phase H-bridge. Each H-bridge phase comprises an IR2102S gate driver integrated circuit (IC) and high- and low-side IRFZ44NS MOSFETs. As shown in Figure 4, the IRFZ44NS D2PAKs of Phase A have been replaced with Molex test sockets to facilitate experimentation with ARC-aged MOSFETs.

Along with the actuator and torque load servo drives and motors, each side of the testbed top panel includes a Technosoft IOISM extension board, which provides an external reference source for position/velocity control as well as general-purpose digital I/O pushbuttons for triggering user-defined motion profiles.

As shown in Figure 5, separate 24 VDC supplies are mounted to the bottom side of the EMA Emulator suitcase panel to isolate the motor power of the prognostic-enabled actuator from the torque load motor. A shared 5 VDC supply, on the other hand, provides power for both the actuator and torque load servo drive controller logic. All of the motor power supply and encoder cabling is routed underneath the top panel.

In addition to the power supplies, a commercial USB-to-Serial adapter is included to enable connection to the EMA Emulator Testbed via a standard USB port. Although the USB-to-serial adapter appears as a traditional COM port to the host computer and an RS-232 interface is used to communicate with the servo drives, the USB-to-serial adapter alleviates the requirement of the host computer including a legacy serial port. During setup of the EMA Emulator Testbed, a device driver is installed to enumerate the host computer COM port used to communicate with the testbed.

The ISM4803 controller area network (CAN), depicted in Figure 6, allows multiple servo drives to be configured in a multi-axis motion control application. The EMA Emulator Testbed utilizes this feature of the ISM4803 to synchronize the torque load with the actuator motion trajectory. In this configuration, the actuator drive acts as the CAN bus master with an Axis ID of 255, while the torque load drive acts as a CAN bus slave with an Axis ID of 1.

The actuator master drive receives motion commands from the host via an RS-232 serial interface and transmits them to the torque load slave drive over the CAN bus. A twisted pair cable, also routed underneath the suitcase top panel, is fabricated to connect the master and slave drives with 120-ohm termination at either end of the transmission line.

4 EMULATOR SOFTWARE

Featuring a simple graphical user interface, or GUI, the Ridgetop EMA Emulator application allows the user to select between a Motion tab and Status tab to execute motion profiles and view the servo drive status upon completion. After selecting a Torque Load, the user presses the RUN button to start the actuator emulation. Basically, the actuator servo drive, configured in position mode, executes a standard trapezoidal motion trajectory while the user-selected load profile is applied by the torque load servo drive, configured in current mode. As described in the previous section, the Technosoft Motion Language (TML) includes commands to synchronize the motion of a multi-axis application like Ridgetop's EMA Emulator.

Figure 7 presents a screen capture of the EMA Emulator Motion tab. The Torque Load control has been dropped down to illustrate the available load selections: None, +3A Static, -3A Static, +3A Step, -3A Step, +3A Impulse and -3A Impulse. Static loads emulate constant forces applied to the actuator. The weight of a wing flap is an example of a static load. While raising the wing flap, the weight of the wing flap opposes the actuator motion, resulting in positive static load. While lowering it, on the other hand, the weight of the wing flap assists the actuator motion, resulting in negative static load. Similarly, step and impulse loads can be both positive and negative relative to the actuator motion.

A LabVIEW graph indicator is used to plot the position data acquired from the actuator servo drive. Target Position, in yellow, and Actual Position, in white, are plotted in radians on the left Y-axis, while Following Error, in red, is plotted in radians on the right Y-axis. The motion plot reveals the expected characteristic "ringing" in the Following Error at each position jog or disturbance. Figure 8, Figure 9, and Figure 10 present screen shots of the actuator position servo loop response for positive and negative static, step and impulse load emulation, respectively.

The Store button at the bottom right corner of the Motion tab (refer to Figure 7) is used to log the tab-delimited motion data to an ASCII text file. The format of the data log is shown in Figure 11.

Using a controlled aging process, such as that provided by the ARC's Accelerated Aging and Characterization System, degraded MOSFET devices are inserted into the servo drive test sockets to acquire FFP signatures of the actuator Following Error, from no degradation to total device failure, under various load conditions. The acquired data is recorded in a database and used to develop prognostic methods, or analysis algorithms, to assess the SoH and estimate the RUL of the actuator power stage.

5 DATA ANALYSIS

In pursuit of a method that actively determines the state of health (SoH) and remaining useful life (RUL) of a system, Ridgetop Group developed the platform and methodology described herein. Ridgetop has invested a great deal of time in describing the near-end-of-life behavior of a MOSFET, which has led to exceptional clarity regarding the direction to be taken. The first and most obvious statement is that degradation of the MOSFET does not appear to be linear at this time. The question then naturally arises as to how anyone can determine the age of a system without using extremely invasive methods. The variation in a system is the only reliable indicator of the SoH as it pertains to MOSFET degradation.

The method used by Ridgetop Group was to develop an Electromechanical Actuator Emulator. The EMA Emulator is used to simulate various operational anomalies that a typical EMA would encounter during its life. Several tests are applied to force different types of Following Error plots. The Following Error indicates a system's ability to follow a given command. Variations in Following Error between any two iterations of the same test are difficult to detect with the naked eye, so transformations must be performed to make data more amenable to analysis.

A transformation is required to present the data in a way where similarities are deemphasized and anomalous behavior is exacerbated. The normal operation averaged following error is removed from every following error result. The following error is obviously dependent on several factors such as component age, load profile, and many mechanical factors such as maintenance of the bearings in the drive. To ensure the maximum quality of the data normal maintenance is performed on the drive and tests are always the same.

Aging was performed on multiple IRFZ44N MOSFET devices. The only result seen at the time was the destruction of a few devices, a VT shift, and increasing On-Resistance 0. The desire was that a significant following error change would be measureable before a failure.

Measuring the dissimilarities or changes in the following error of each test and recording the result allows our system to detect if the test result is worth keeping. All results that are pre-failure or post-failure are kept. That is to say that when a seemingly healthy result is found it is not immediately discarded, instead the next test is run and if it shows a significant change then both results are kept; and so on until the motors onboard safeguards are activated.

The current approach is based on the principle that unhealthy system responses are sufficiently different to measure. The difference between a healthy signal (D1) and an unhealthy signal (D2) is calculated using the "Health Distance" of each signal represented with HD. The repetitious behavior of the signals is expected, and each reoccurrence of the same voltage is stored in a matrix vector (Eq. 1):

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

Now an angle can be computed and will represent the overlap of two signals (Eq. 2):

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

$$0 \le \theta \le 2\pi$$

A score of 0 would mean that the two signals are identical and a score of 2π means that there are no similarities at all. The exact implementation of this idea results in large fluctuations in the angle of difference between two signals; so a variation is employed using LabVIEW. The difference is that a statistical distribution of the integral of healthy response signal is called (Eq. 3):

$$D_1 \therefore \int_{\omega_n}^{\omega_{n+1}} D_1 \in D_1(\omega) \tag{3}$$

This introduces memory to the system which decouples the RUL analysis from a single output; this adds accuracy to the system at the price of run time.

This strategy has led Ridgetop to the capture of the last healthy performance of MOSFET, shown in Figure 12, with the trailing faults.

The algorithm to determine the percentage of health is a classical distance algorithm still development but is simply based on the equations above.

After noticing that the motor had failed we proceeded to measure the MOSFET and discovered that the high side of Phase A had become a permanently opened component. Interestingly, several maneuvers were performed perfectly with this totally damaged MOSFET, without tripping the onboard safeguards.

T59 is the name of the device that failed; from the plot in Figure 13 we actually see that 59 was an outlier.

It would be naive to assume that no outliers make it into critical systems, but part qualification tests can mitigate those risks. This plot shows small changes to device physics, yet they have a large impact on the total system performance.

The system described here was the proof of concept that a computer monitoring system could recognize decreasing performance of an EMA and successfully record the data. Also, this has shown that typical operating conditions cause device wear out and failure. With time and a system that can be run autonomously to record motor failure more modes will be developed and a thorough research effort can be mounted to analyze all the fault conditions.

6 AN EMA FAULT DICTIONARY

Leveraging Ridgetop's patent-pending RingDown technology with its flagship prognostic health management software platform, Sentinel PHMPro®, offers an established foundation for developing an EMA fault dictionary tool with considerable benefits to NASA's IVHM initiative. One possible approach for implementing such a tool, employing principal component analysis (PCA), is illustrated in Figure 14.

Essentially, an artificial neural network (ANN) is trained to discriminate FFP signatures stored in a fault dictionary. The optimized ANN is integrated into the EMA Emulator Testbed for evaluation of real-time fault detection and isolation (FDI) effectiveness. The steps involved are summarized as follows:

(1) Transient servo loop response signatures for progressive degradation of selected H-bridge components are acquired and catalogued in a fault dictionary, e.g., MOSFET switch: 0% (healthy), 25%, 50%, 75%, and 100% degradation (catastrophic gate-to-source open circuit fault).

(2) Multidimensional, or multivariate, data (e.g., servo loop following error, motor phase voltages, and/or phase currents) are logged directly from the servo drive controller program.

(3) PCA is used to reduce the multivariate fault signature data to its principal covariance eigenvalue matrix.

(4) Eigenvalues derived from SVD define classification spaces corresponding to target degradation levels (e.g., 0%, 25%, 50%, 75% and 100% degradation) and are used to train an ANN to discriminate damage level and location.

(5) Various ANN algorithms are prototyped and tested with the fault dictionary to achieve optimal performance with maximum FDI accuracy. The goal is to achieve 100% FDI accuracy.

7 CONCLUSION

In this paper, we have presented an innovative approach for EMA emulation designed to enable the insertion of degraded electronic components and to analyze the servo loop response of an aged actuator system. This approach can then be leveraged to develop prognostic methods to assess the State of Health (SoH), estimate Remaining Useful Life (RUL), and support Condition-Based Maintenance (CBM) of avionic EMA systems.

Power system integrity is critically important to the safety and mission-effectiveness of next-generation aerospace vehicles. An innovative, non-intrusive method for identifying failure modes and measuring off-nominal conditions of an avionic EMA power system has been presented. Linked to an IVHM system, corrective actions, such as fault mitigation or load-shedding strategies, are facilitated. System availability is improved while maintenance costs are reduced by combining effective prognostic sensing techniques with advanced fault trending analysis to accurately predict the remaining service life of the EMA power system.

ACKNOWLEDGMENT

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NOMENCLATURE

ANN	artificial neural network
BLDC	brushless DC
CAN	controller area network
EHA	electrohydrostatic actuators
EMA	electromechanical actuator
FDI	fault detection and isolation
FFP	fault-to-failure progression
IVHM	integrated vehicle health management
PCA	principal component analysis
SVD	singular value decomposition
V_T	threshold voltage

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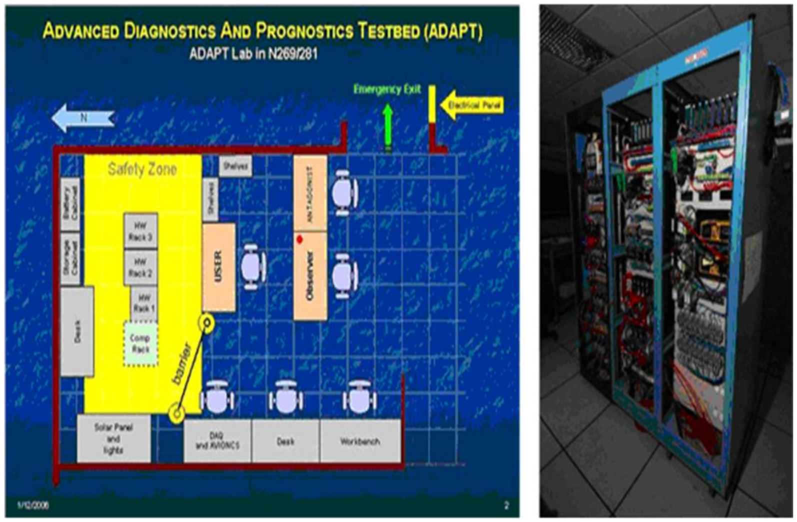


Figure 1: ADAPT Laboratory at NASA/Ames

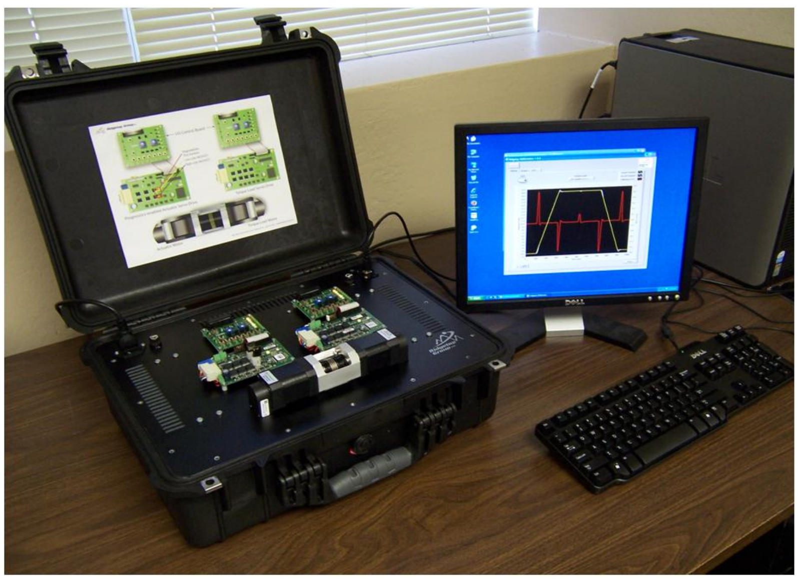


Figure 2: EMA Emulator testbed

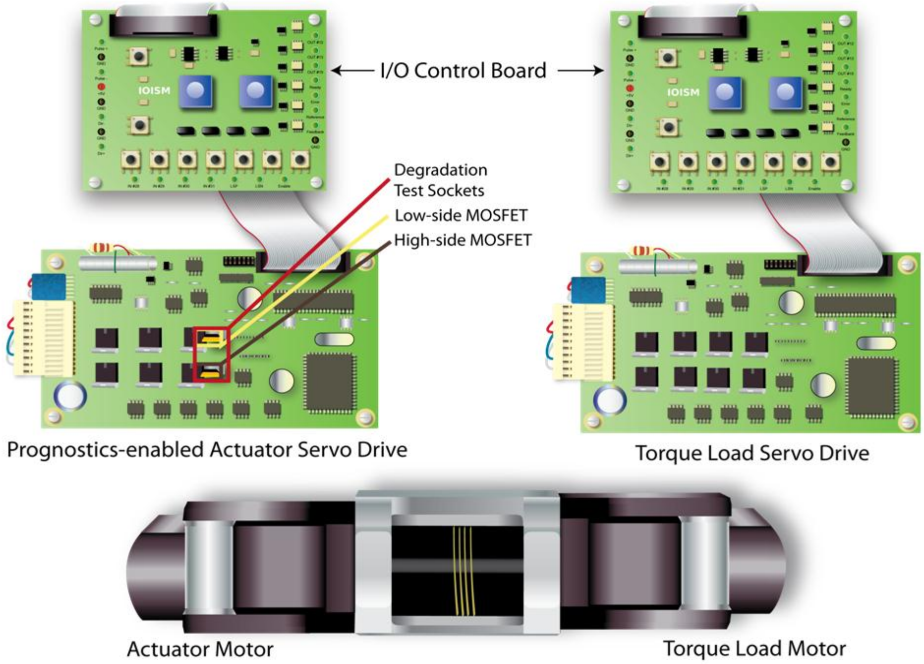


Figure 3: EMA Emulator functional diagram

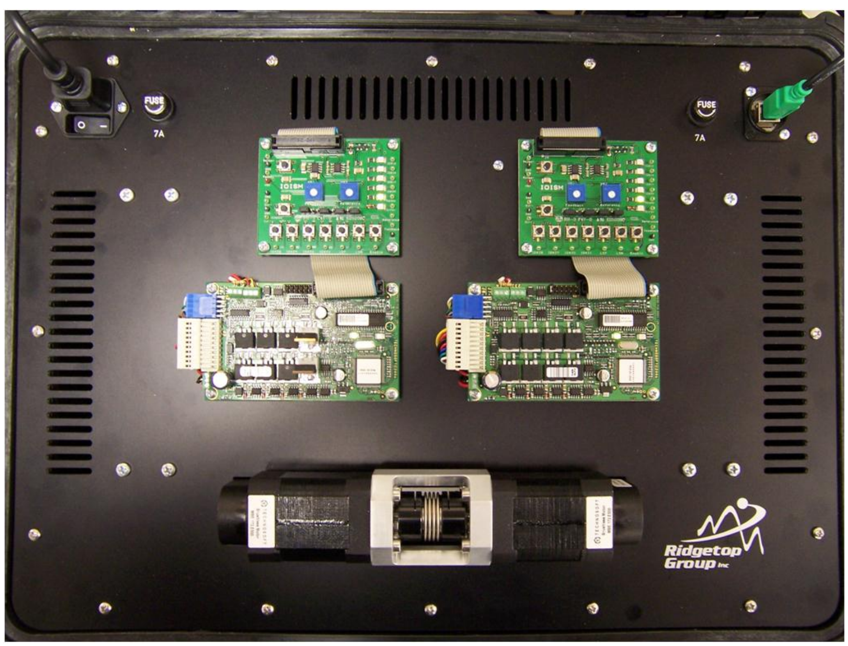


Figure 4: EMA Emulator suitcase panel top view

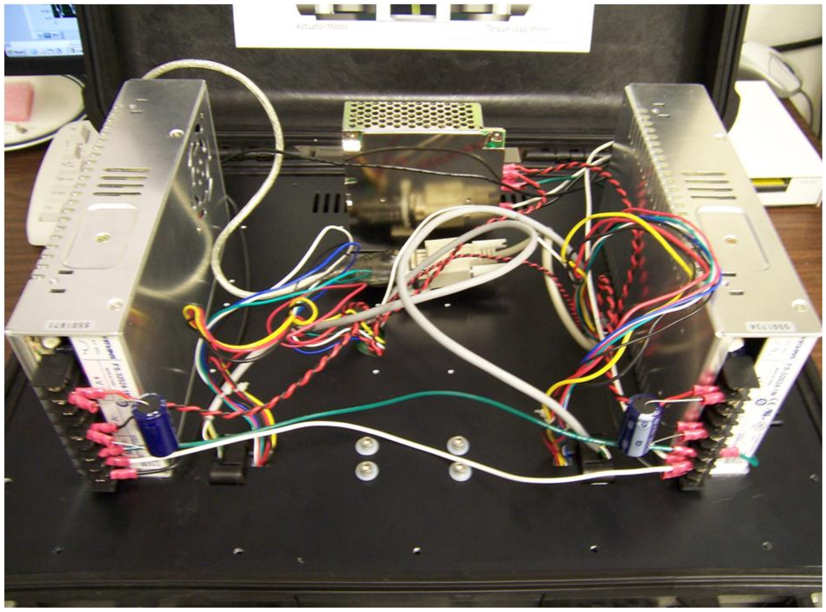


Figure 5: EMA Emulator suitcase panel bottom view

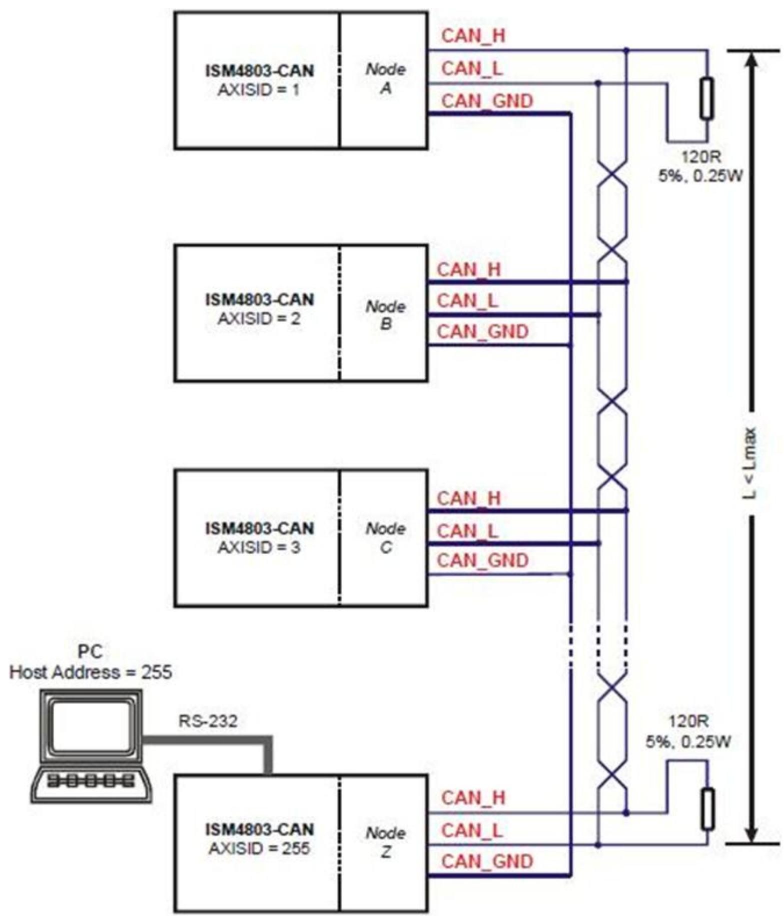


Figure 6: ISM4803 multi-axis CAN bus network

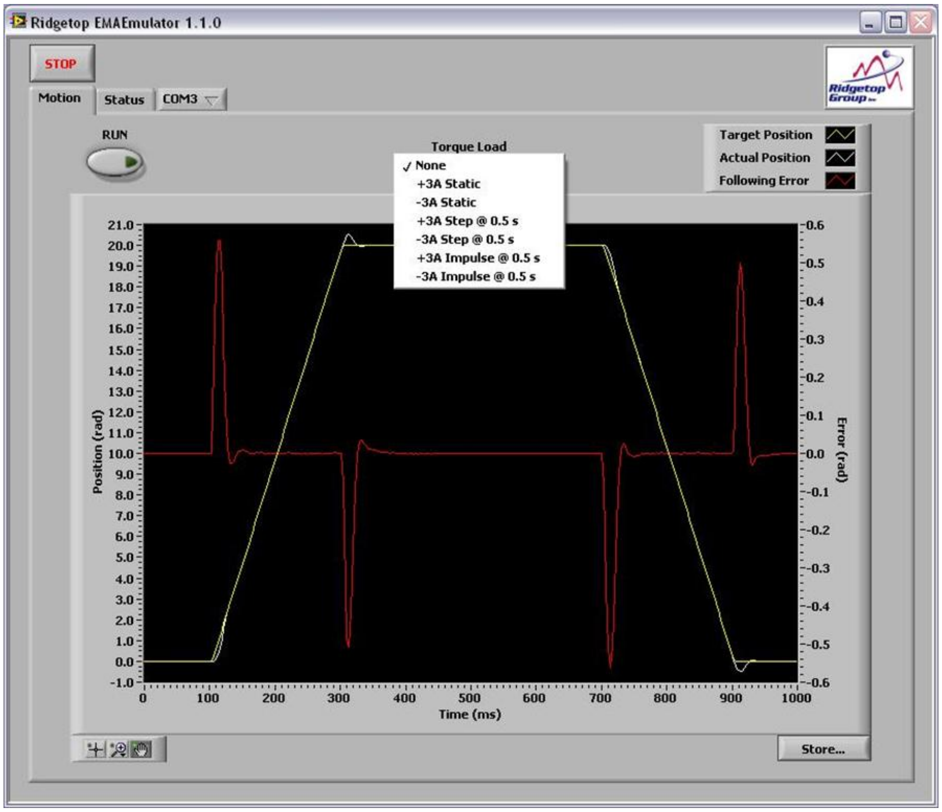


Figure 7: Ridgetop EMA Emulator GUI

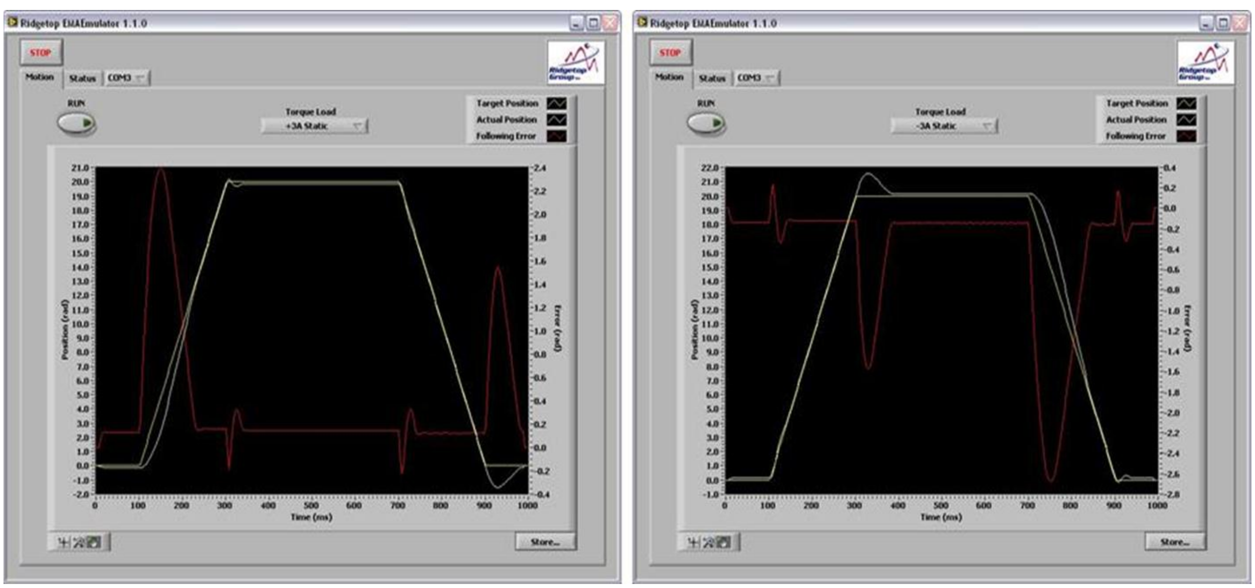


Figure 8: Static load emulation

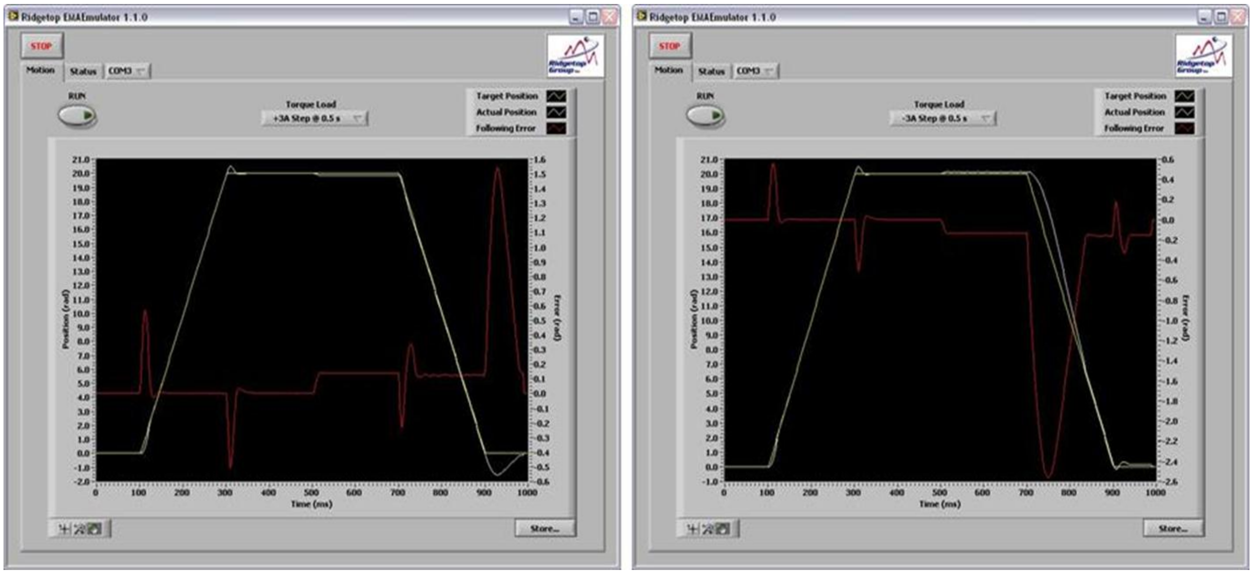


Figure 9: Step load emulation

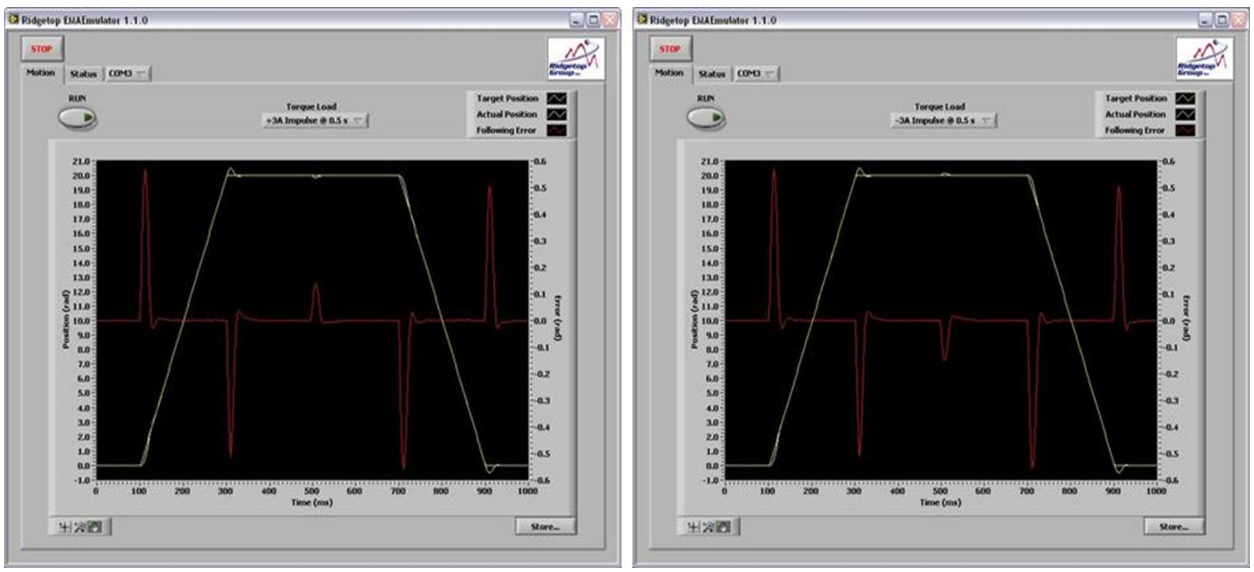


Figure 10: Impulse load emulation

Time (ms)	Target Position (rad)	Actual Position (rad)	Following Error (rad)
0.0000	0.0000	0.0000	0.0000
0.0032	0.0000	0.0000	0.0000
:	:	:	:
0.1056	0.2388	0.0094	0.2293
0.1088	0.5592	0.1131	0.4461
0.1120	0.8796	0.3236	0.5561
0.1152	1.1969	0.6409	0.5561
:	:	:	:
0.9952	0.0000	0.0000	0.0000
0.9984	0.0000	0.0000	0.0000

Figure 11: Ridgetop EMA Emulator data log format

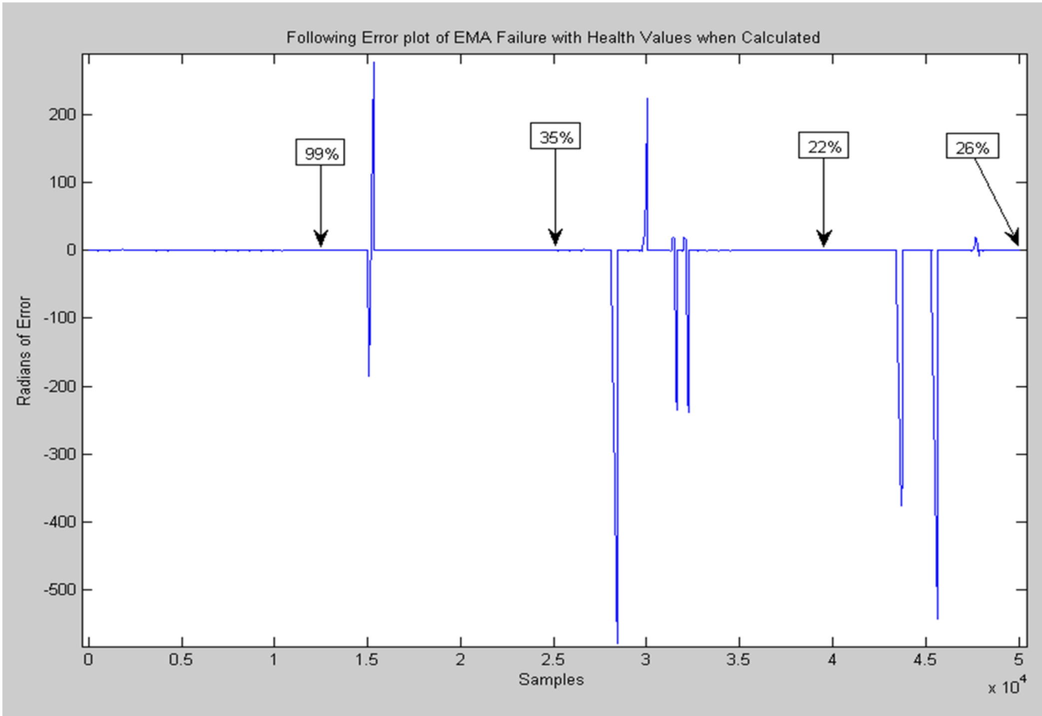


Figure 12: Recorded failures from automated test software

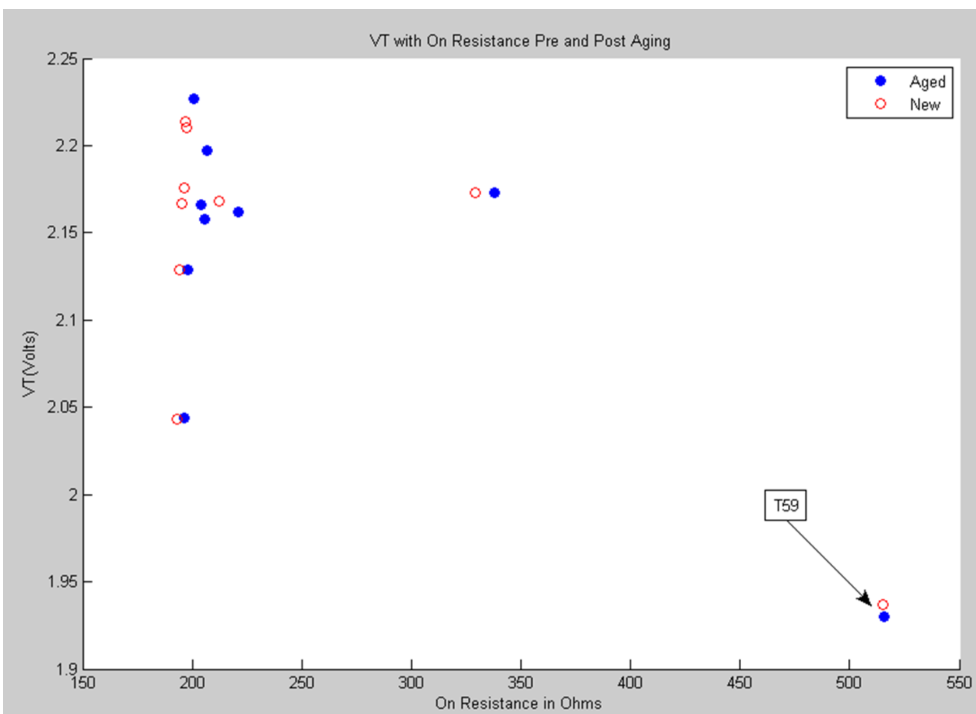
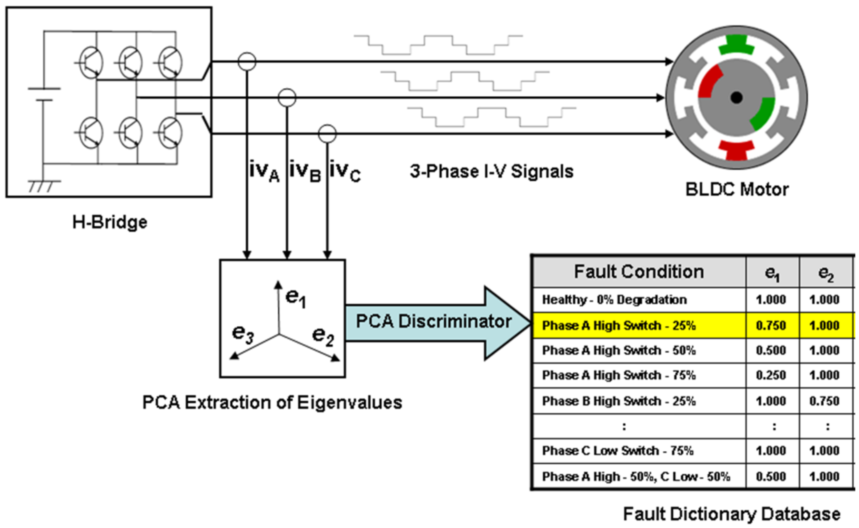


Figure 13: V_T versus On resistance of aged IRFZ44N



Fault Condition	e_1	e_2
Healthy - 0% Degradation	1.000	1.000
Phase A High Switch - 25%	0.750	1.000
Phase A High Switch - 50%	0.500	1.000
Phase A High Switch - 75%	0.250	1.000
Phase B High Switch - 25%	1.000	0.750
:	:	:
Phase C Low Switch - 75%	1.000	1.000
Phase A High - 50%, C Low - 50%	0.500	1.000

Figure 14: Ridgetop EMA Fault Dictionary tool

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