Damage Propagation Analysis Methodology for Electromechanical Actuator Prognostics

Neil Kunst
Ridgetop Group, Inc.
3580 West Ina Road
Tucson, AZ 85741
520-742-3300
nkunst@ridgetopgroup.com

Justin Judkins
Ridgetop Group, Inc.
3580 West Ina Road
Tucson, AZ 85741
520-742-3300
justin@ridgetopgroup.com

Chris Lynn
Ridgetop Group, Inc.
3580 West Ina Road
Tucson, AZ 85741
520-742-3300
clynn@ridgetopgroup.com

Doug Goodman
Ridgetop Group, Inc.
3580 West Ina Road
Tucson, AZ 85741
520-742-3300
doug@ridgetopgroup.com

Abstract—Historically in aviation safety, sensor technology intrusion has presented a barrier to enabling prognostic solutions into mission critical, on-board power systems. Without prognostics, catastrophic, intermittent, and damage propagation faults can compromise the integrity of even the best power systems over time. The problem posed by physical limitations, such as size, weight, and wiring, prevents the upgrade of in-flight power systems with prognostic equipment. The solution is development of a non-intrusive prognostic technologies suite designed for minimal impact on existing systems. Specifically, we explore a Hidden Markov Model (HMM) approach to prognosticate the servo loop of an EMA. Results of this study indicate that a fault-progression methodology overcomes some of the disadvantages of the more familiar FMEA approach, which does not account for the contribution of unobserved failure to a degradation trajectory. We show by example how the Ring-down methodology, often used in power systems, can be adapted to servo loop systems employed in aircraft actuator. Adoption of this approach to electronic prognostics improves monitoring of the behavior and health of key or critical components not only ensures safety and success, it makes dynamic switching to back-up systems, fault mitigation, load-shedding, and condition-based maintenance (CBM) technically and economically feasible. [1][2]

TABLE OF CONTENTS

1. INTRODUCTION: FLY-BY-WIRE SYSTEMS

The Airbus A320. The Boeing 777. The Tupolev TU204. These are a few of the commercial aircraft that have joined a much longer list of military aircraft that have sparked a controversy within the reliability profession. Fly-by-wire systems have been heralded as the savior of an industry while also being condemned as unsafe. 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. Greater, more precise control has, in turn, made possible aircraft that are aerodynamically unstable. 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.

2. THE FAILURE OF MTBF

In 1995, a cornerstone of reliability was called into question. Mean Time Between Failure (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. Obtaining age-to-failure data is expensive and not always available. Many MTBF values for components are stored in databases and found to be very inaccurate. 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.

3. LEVELS OF OBSERVABLE INDICATORS

Unlike traditional mechanical components and subsystems, electronic devices provide less observable indicators for making maintenance and diagnostic decisions. That would seem to be a true, straightforward statement. Or is it?

For example, the electronic power systems and electromechanical actuators (EMA) examined in this paper

1———————————

[1] 978-1-4244-2622-5/09/$25.00 ©2009 IEEE.
[2] IEEEAC paper#1728, Final, Updated 2008:12:16

would appear to be typical of solid-state technology. Either they work or they don't work. When viewed through the filters of the human eye, perception, and experience, there seems to be less observable states.

Observable Indicators - Mechanical Vs. Electronic

For maintenance crews at engine depot facilities, degradation such as a worn tooth in a gear can be observed, measured, reported, and scheduled for service. On the other hand, an integrated circuit-based (IC) device either worked or didn't work.

In the 1980s, the first, and only, observable fault indicator of an overstressed electronic component was a puff of smoke and reek of burnt plastic on power-up. When asked what happened, the inevitable reply was, "It let the smoke out." However, experience made more subtle indicators observable. Electricians, in particular, became adept at finding fault indicators. One electrician observed that part of troubleshooting a DC motor involved touching the H-Bridge MOSFETs. A hot one was damaged; the one that took off your fingerprint was shot.

The question, is it true that electronic components provide less observable indicators than mechanical components? Preliminary results suggest that there are just as many observable indicators in electronic systems as there are mechanical, if one knows what to look at.

4. THE HIDDEN MARKOV MODEL

The Hidden Markov Model (HMM) is a statistical modeling technique used when the challenge is to determine hidden parameters affecting an observable state. This is one of the great advantages HMM has over MTBF. Whereas MTBF ignores the dependencies between system components, HMM relies on the play of dependencies to describe and quantify what cannot be directly observed.

The capacity for customization is a strength since an HMM matrix is highly dependent on its particular operational scenario. Due to the sensitivity to changes in component dependencies, HMM-driven engines can be used for different monitoring approaches.

Key Monitoring Approaches

There are two key monitoring approaches to consider when designing an HMM: whether to model for faults selected *a priori* or to model from data-based extrapolation.

The *a priori* monitoring approach is best suited when there is prior knowledge of component fault states. This prior knowledge of system failure modes could be from databases of MTBF, trouble reports, or other reliable historical data. This approach works well with systems using established components and technologies. Its weakness lies in anomalous faults not accounted for in prior knowledge. These faults tend to be placed in a predetermined category, resulting in an error.

The data-extrapolation monitoring approach is best suited when prior knowledge of fault states is not available. This approach uses algorithms to estimate fault probabilities directly from the data with only information needed from the normal operating state. This approach works well for systems using components or technologies that are new. The weakness of this approach is the time needed for the training data to create reliable fault states.

Self-Monitoring of Online Communication Network

Another advantage to HMM is its effectiveness in online health monitoring of communication and network systems. Using an HMM engine to power an online prognostics system would not only allow for health monitoring of geographically distributed electronic assets, but also simultaneous real-time prognostics on the communication network itself.

For example, antennas are the cause of considerable faults within communication networks. Fault detection and isolation is often complicated and lengthy since establishing the root cause in a communication chain is difficult. A dropped carrier lock could be caused by the environment, the positioning EMA, the electronic power supply, defective tachometer, or other faults. A prognostic engine using the Markov process could diagnose itself as well as the targeted components. While accounting for multiple fault conditions is not included in many solutions which, instead, monitor for single-event faults in components, an ideal prognostic network would self-monitor for its own internal failures.

5. APPLYING MARKOV PROCESS TO EMAS

Electro-Mechanical Actuators, or EMAs, such as the linear actuator depicted in Figure 1, are replacing their hydraulic counterparts in many aerospace applications, including military and commercial aircraft. Examination of the servo loop reveals a Markov process well suited for prognostics-enabling. The coil winding of an EMA is dependent on MOSFETs and gate drivers in the H-Bridge. Failure thought to originate at the coil windings is actually a composite of unobserved or "hidden" damage propagated from the MOSFETs and gate drivers. Since EMAs rely on the complex interactions of individual components, MTBF estimates are typically much longer than documented service life. Likewise, Failure Mode Error Analysis (FMEA) techniques are fundamentally flawed since the contribution of unobserved components, in this case MOSFETs and gate drivers, are propagating damage that is not tracked, monitored, or otherwise accounted for.

So, although EMA technology provides advantages to Fly-by-wire aircraft by reducing overall vehicle weight and eliminating fluid leakage problems, there remain reliability issues keeping the true value for contributing to lower operation, lower maintenance costs, and improved flight control from being realized. With the current trend of fly-by-wire subsystems and the critical function aircraft EMAs provide, they have become an obvious candidate for prognostic-enablement.

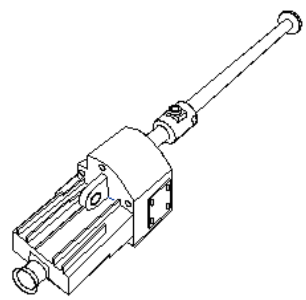


Figure 1. Linear Electromechanical Actuator

For ease of adoption, non-invasive solutions are preferred for prognostic-enablement of electronic subsystems. Toward that end, Ridgetop's patent-pending RingDown^{TM} technology, originally developed for electronic power system prognostics, can be adapted to the servo loops employed in aircraft actuators. More specifically, characteristic ringing can be observed in the following error waveform captured in response to an electrical or mechanical impulse imposed on the EMA.

Efficacy of this approach is demonstrated through simulation. The Brushless DC (BLDC) motor servo loop block diagram shown in Figure 2, which utilizes position feedback provided by a resolver or hall sensors to execute a motion profile, serves as the basis for the simulation model used in this research. For the example presented, disturbances in the electrical and mechanical elements of the actuator system are manifested in the following error, or offset between the actual and commanded shaft position.

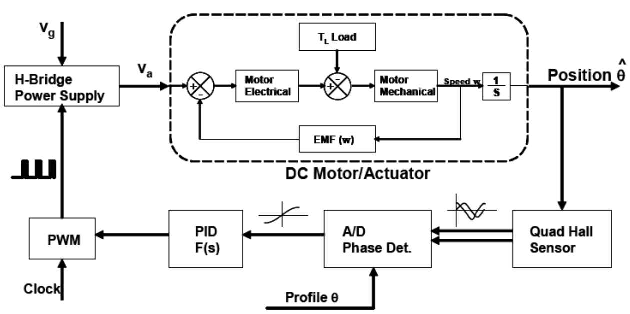


Figure 2. Block Diagram of BLDC Motor/EMA Servo Loop

A non-invasive prognostic sensor applies an electrical or mechanical disturbance to the drive stage or rotor shaft, respectively, while monitoring the system response. In a linear actuator, the rotor is coupled to a lead screw to provide linear motion. Figure 3 illustrates the deviation in following error when a lead screw bearing is degraded, or worn out, compared to a previously recorded baseline response to a position jog.

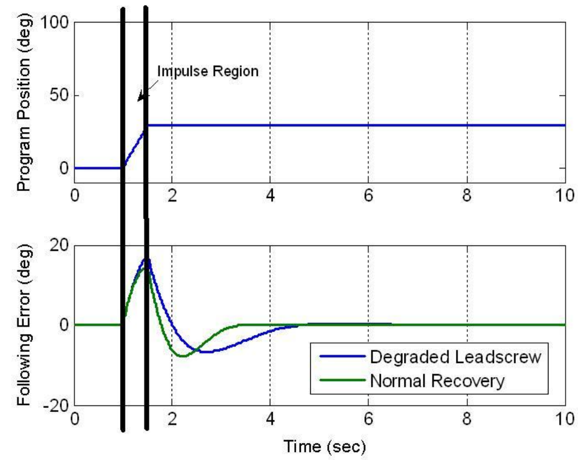


Figure 3. Mechanical Fault Simulation

Similarly, the following error of the motion control system can be analyzed to assess the State of Health (SoH) of the H-Bridge circuit common to brushless DC motor servo drives. Figure 4 provides graphs of the position and following error when all of the components of the H-Bridge circuit are healthy. When the H-Bridge is working normally, the rotor position closely tracks the target position, resulting in nearly zero following error until a change in direction is commanded. The overshoot and oscillations observed at the start of the simulation and the point where the rotor position changes direction are a function of the servo loop damping factor and is normal behavior.

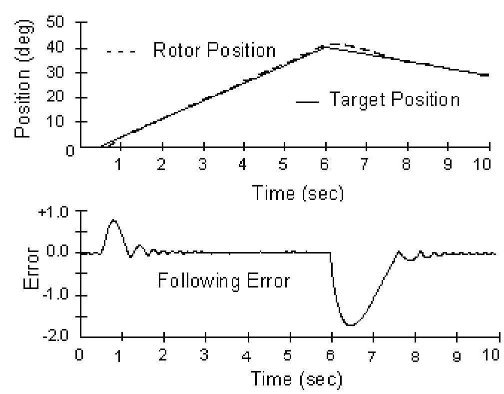


Figure 4. Healthy H-Bridge Simulation

The H-Bridge power stage consists of pairs of MOSFET switches. For a 3-phase BLDC motor, there are three pairs of MOSFET switches, one per winding phase. Using Pulse Width Modulation (PWM) techniques, the MOSFET switches control the current through the coil windings and hence, rotation of the rotor. Essentially, the duty cycle of the

PWM signal is adjusted to change direction of the rotor or to hold it steady at a commanded position. That is, a 50% PWM duty cycle yields no movement; duty cycle less than 50% causes movement in one direction (e.g., clockwise) while duty cycle greater than 50% causes movement in the opposite direction (e.g., counter-clockwise).

Figure 5 illustrates the effect of degradation (e.g., increased internal resistance) on one MOSFET switch in a single phase of the H-Bridge. As can be seen in the top graph, the rotor position is greater than the target position throughout the simulation. When a change in direction is commanded, the rotor position overshoots slightly, compensates and then attempts to follow the target position. The following error graph reveals the anomalous control loop behavior. The increased following error, noted at simulation times of 1.0 and 6.3 seconds, is due to the degraded MOSFET switch, which results in faster than normal rotor response to the commanded position change and the offset observed between the actual rotor position and target position.

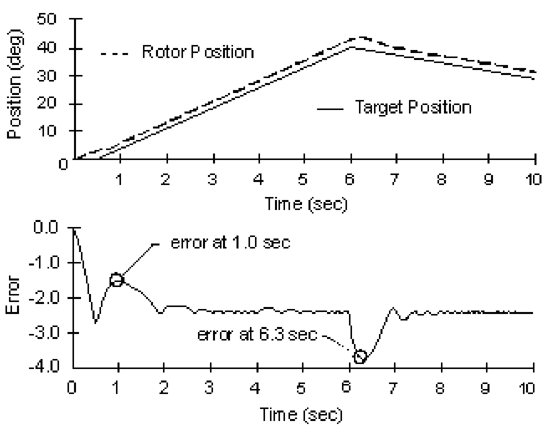


Figure 5. Damaged H-Bridge MOSFET Simulation

The observed system response will be different depending on which MOSFET switch is damaged. For example, if one of the high-side MOSFET switches is degraded, the rotor position leads the target position and positive following error is observed, as shown in Figure 5. If one of the low-side MOSFET switches is degraded, on the other hand, the rotor position will lag the target position and negative following error will be observed.

Clearly, degradation of individual H-Bridge components, like the MOSFET switches, can have a profound effect on the operation of an EMA system. How component damage propagates through the motor drive is a key element of Ridgetop's EMA prognostic research. Our initial H-Bridge damage propagation analysis focuses on the effect of a damaged gate driver amplifier on the MOSFET switch it controls.

As shown in Figure 6, Ridgetop's approach to EMA H-Bridge damage propagation analysis involves:

- Applying various fault conditions to each critical component of the EMA H-Bridge, starting with the gate driver amplifiers (D1) and progressing to the MOSFET switches (D2) and coil windings (D3) of each phase.
- Conducting lab experiments to acquire and characterize the actuator following error associated with each fault condition and the resulting stress effect on the other components in the system.
- Analyzing Fault-to-Failure Progression (FFP) signatures on the acquired test bed data and feeding lab results back into the Simulink model.

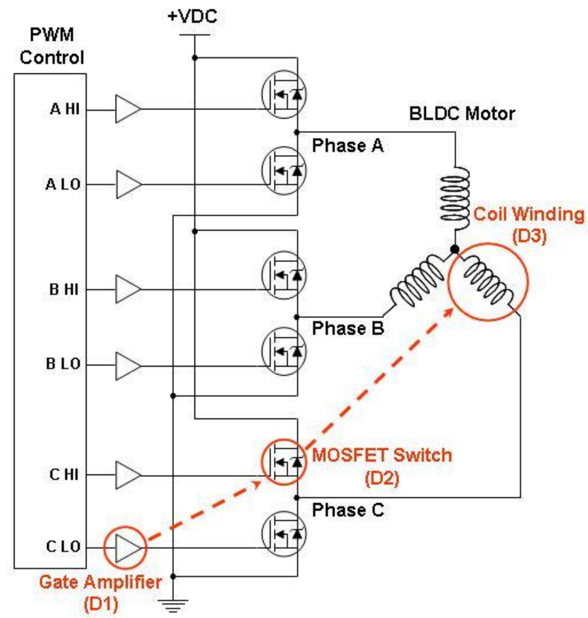


Figure 6. Ridgetop's H-Bridge Damage Propagation Analysis Approach

The purpose of the gate driver, common to servo drive H-Bridge circuits, is to boost the TTL or CMOS low- and high-side PWM commutation signals generated by the motion control logic (for example, microcontroller or DSP) to levels suitable for driving the MOSFET or IGBT switches of the H-Bridge. The gate driver is typically a very stable device; however the bootstrapping configuration of the gate driver circuit introduces a problematic capacitor. Damage or degradation in this part will lead to latch of the high-side MOSFET of the phase with which it is attached. Ridgetop's initial damage propagation research analyzes the effect of the degraded boot-strap capacitor with gate driver failures on the MOSFET switches of the servo drive H-Bridge.

To simulate a bootstrap capacitor failure on the gate driver, a baseline 50% duty cycle was introduced to a single phase of the EMA test bed, with a variable capacitance, and the outputs were recorded. The signals for one phase are shown in Figure 7 with non-degraded capacitance.

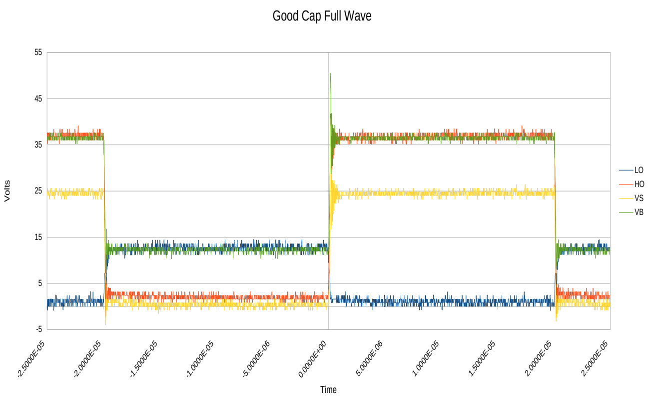


Figure 7. Winding control signals for several values of bootstrap capacitors.

When the capacitor begins to deteriorate the resulting wave form will no longer drive the winding current correctly. Health trending will not predict this kind of error due to the swiftness of the transition. The latch up condition is caused by and under sizing of the boot-strap capacitor. There is a breaking point for this system was determined to be ~70nF, which resulted in the wave form shown in Figure 8. .

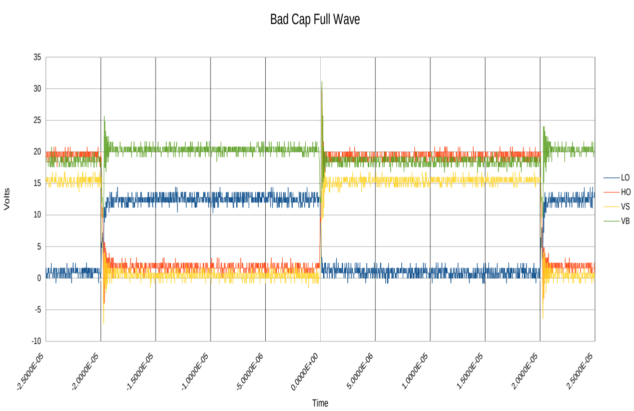


Figure 8. Loss of bootstrap capacitor in H-bridge control signal.

The VB pin on the gate-driver is stuck in the "on- state." This damage then propagates out of the gate driver (D1) in the H-bridge (D2).

When the gate driver behaves likes this, the low-side MOSFET is forced to conduct continuously. This conduction results in large amounts of heat generated in that MOSFET as a result of being operated outside saturation. The actuator system has greatly reduced functionality, and if these symptoms are not recognized the low-side MOSFET will fail. Once it fails the damage will propagate to the high-side MOSFET which will no longer have an attachment to ground. This will cause the output to the motor to always conduct causing possible damage to the motor coil windings. This later stage damage can be observed by the casual inspector.

Figure 9 provides a simple Markov chain used to model the damage propagation from the EMA H-Bridge through the coil windings of the BLDC motor. Each node represents the condition of an individual component's health, while arrows represent the dependencies between component health conditions.

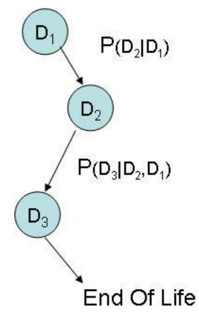


Figure 9. Simple Markov Chain of Damage Propagation

In this model, D1 and D2 are hidden nodes, while D3 is an observable node. Although D3 may be diagnosed as a winding failure, it is dependent upon accumulated wear on the boot-strapped gate drive capacitor and MOSFET switches, D1 and D2, respectively. By collecting samples from the output or observable states one can use predetermined error signatures (specific to each system) to calculate the current health of the system and use HMM to back out the probability of reliability in unobservable states (D1,D2) and extrapolate State-of-Health data.

A methodology, like HMM, that accounts for underlying wear parameters is better suited for analyzing the State-of-Health (SoH) and remaining useful life (RUL) of systems like the EMA.

6. Conclusion

The experimental results and analysis presented herein may best be exemplified with EMA control of an aircraft wing-flap. The actuator shaft controls the position of movable parts on aircraft, such as control surfaces, and as such stability depends mainly on the precise control of each actuator. Errors in the commanded position, due to a boot-strap capacitor, can cause unpredictable performance with possibly catastrophic results. Clearly, prognostic-enabling aircraft EMA systems would help to mitigate this costly risk.

Conventional methods for estimating life consumption are based on over-confident MTBF estimates and often result in a shorter than expected service life. What is too often ignored is that an EMA relies on complex interactions of individual components. That is, EMA health is not simply a sum of unrelated parts. Wear on any one component may affect the life and reliability of another component. A fault can therefore cause a multiplying effect on failure rate that results in a reduction of overall service lifetime.

A novel approach to predicting the SoH of electronic power systems based on a hidden damage propagation model and the analysis of wear-out signatures is proposed. By monitoring impulse responses, the damage level in individual components is extracted from the Eigen values of the transient waveform. Unlike strict trending approaches, application of a HMM fault-to-failure progression methodology considers the interdependence between individual components and provides a more accurate prediction of EMA service life.

One challenge of the proposed methodology is to equip the EMA with a non-invasive prognostic sensor. An elegant solution does exist; a 'virtual' prognostic sensor can be created in the firmware of the servo drive control, as shown in Figure 10. It has been demonstrated, through simulation, that Ridgetop's patent-pending RingDown technology can be adapted for this purpose.

Often difficult and expensive to inspect, aircraft actuators are frequently removed and replaced for maintenance reasons, whether faulty or not [2]. To compound matters, many problems reported in-flight cannot be replicated during on-ground retest and are therefore dismissed as Could Not Duplicate (CND) or No Trouble Found (NTF). At worst, prognostic-enablement would help alleviate this costly diagnostic-repair cycle through support of CBM. At best, prognostic-enabled aircraft EMAs could help pilots avert potential catastrophic disaster. In any event, system availability is improved while maintenance costs are reduced by combining effective prognostic sensing techniques with advanced fault trending analysis, such as HMM, to accurately predict the remaining service life of the actuator system.

7. ACKNOWLEDGMENTS

The authors would like to acknowledge Tom Dabney from the Naval Air System Command (NAVAIR) and David Thompson and Kai Goebel from NASA/Ames Research Center for their support of Ridgetop's work.

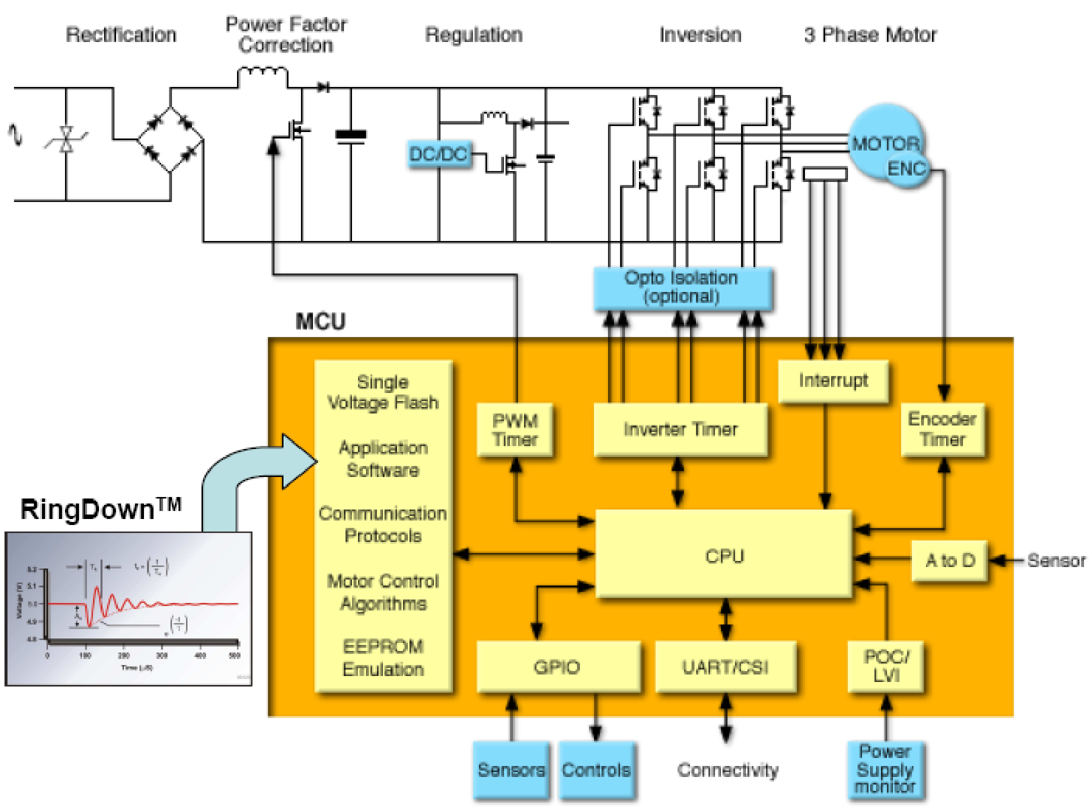


Figure 10. Virtual RingDown Sensor Integrated with MCU [1]

8. REFERENCES

[1]http://www.eu.necel.com/applications/industrial/01_motor_control/030_general_motor_control/020_3_phase_asynchronous/index.html

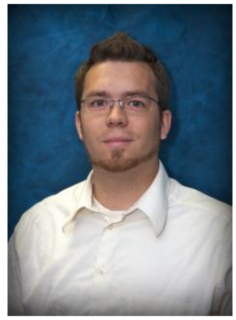
[2]Vohnout, et al, “Electronic Prognostics System Implementation on Power Actuator Components”, IEEE Aerospace Conference, Big Sky Montana, February 2008

9. BIOGRAPHY

Neil Kunst *is an Engineering Project Manager at Ridgetop Group, Inc. He earned his BSEE from the University of Arizona, where he was a member of the Tau Beta Pi National Honor Society. Mr. Kunst 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.*

Justin Judkins *is Vice President of Research and oversees the research and implementations of electronic prognostics. His research interests involve applying sensor array technology to various reasoning engines to provide optimum performance for electronic modules and systems. He is a co-author on three pending Ridgetop Group patents. He previously held senior-level engineering positions at Bell Labs and Lucent involving high-reliability telecom transmission. He received his Ph.D. in electrical engineering from the University of Arizona.*

Doug Goodman *founded Ridgetop Group, Inc. in 2000 and has over 30 years experience as an Electronic Engineer including work at Tektronix and Honeywell. He earned a BSEE from California Polytechnic State University (San Luis Obispo) and an MBA from the University of Portland. He has published over 20 papers on instrumentation and control and was a Member of the Tektronix Patent Review Roundtable.*



Chris Lynn *is an Electrical Engineer at Ridgetop Group, Inc. 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.*