Electronic Prognostics System Implementation on Power Actuator Components

Sonia Vohnout
Ridgetop Group, Inc.
6595 N. Oracle Road
Tucson, Arizona 85704
(520) 742-3300
sonia@ridgetop-group.com

Douglas Goodman
Ridgetop Group, Inc.
6595 N. Oracle Road
Tucson, Arizona 85704
(520) 742-3300
doug@ridgetop-group.com

Justin Judkins
Ridgetop Group, Inc.
6595 N. Oracle Road
Tucson, Arizona 85704
(520) 742-3300
justin@ridgetop-group.com

Mladen Kozak
Ridgetop Group, Inc.
6595 N. Oracle Road
Tucson, Arizona 85704
(520) 742-3300
mladen@ridgetop-group.com

Ken Harris
Ridgetop Group, Inc.
6595 N. Oracle Road
Tucson, Arizona 85704
(520) 742-3300
kharris@ridgetop-group.com

Abstract—Prognostics-enablement of power actuator components involves acquisition and processing of multiple data and sensor inputs. Data collection and fusion creates an accurate prognostic prediction. To that end, Ridgetop has developed an extensible Prognostic Analysis System Platform and a companion Prognostics Telemetry Harness.

With an Electro-Mechanical Actuator (EMA) as the focus, this paper describes the extensible architecture for a Prognostics Health Management (PHM) system providing State of Health (SoH) and Remaining Useful Life' (RUL) metrics. The key enabler is the Ridgetop Prognostics Telemetry Harness (RPTH), which collects and preprocesses signals relating to the health of dynamically executing components and subsystems.

With an ultimate target of 100% up-time, prognostics is an effective tool for managing the corrective early actions required to avoid costly down-time events. An example is detailed using a common EMA and further analysis explores the return-on-investment justifying prognostics adoption.[1,2]

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[1] 1-4244-1488-1/08/$25.00 ©2008 IEEE

[2] IEEEAC Paper #1114, Version 1, Submitted Oct. 22, 2007

INTRODUCTION

Actuators are critical components in many aerospace systems. Their failure can lead to catastrophic consequences. Often difficult and expensive to inspect, actuators are frequently removed and replaced for maintenance reasons, whether faulty or not.

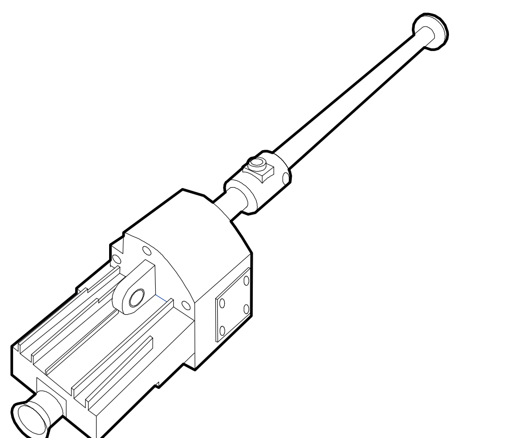

Figure 1: A Linear Actuator

Actuators perform a mechanical motion to a load in response to an input signal. Unfortunately, technicians cannot always replicate problems reported during operation. These problems are termed “No Trouble Found”, “Retest OK”, or “Could Not Duplicate”. The use of Electro-Mechanical Actuators (EMAs) in flight- and mission-critical applications, such as spacecraft, military air vehicles, and commercial aircraft, is increasing and “fly-by-wire” or “drive-by-wire” systems have replaced hydraulic control lines with electrical lines. This eliminates fluid leakage problems while improving control capabilities and reducing weight. EMAs have become ubiquitous in aerospace applications — from robotics to rocket engine control. The trend of all-electric systems makes EMA diagnostic and prognostic-enablement a system design requirement sure to enhance the system reliability of flight- and mission-critical systems. For ease of adoption, non-invasive prognostic solutions for EMAs need development.

Prognostics, or predictive diagnostics, uses observations of measurements to develop a prediction of impending failure of the observed system. In some cases, a precursor event or “signature” is directly measured. In other cases, multivariate inputs are necessary to determine the precursor event, along with the fault-to-failure progression model.

Prognostics methodology can extract pre-cursor information from the EMAs. This predicts failures and provides support to Condition-Based Maintenance (CBM) and Autonomic Logistics Systems (ALS). The concepts from this work have already been applied to a practical and representative EMA design along with associated testing and verification. [3]

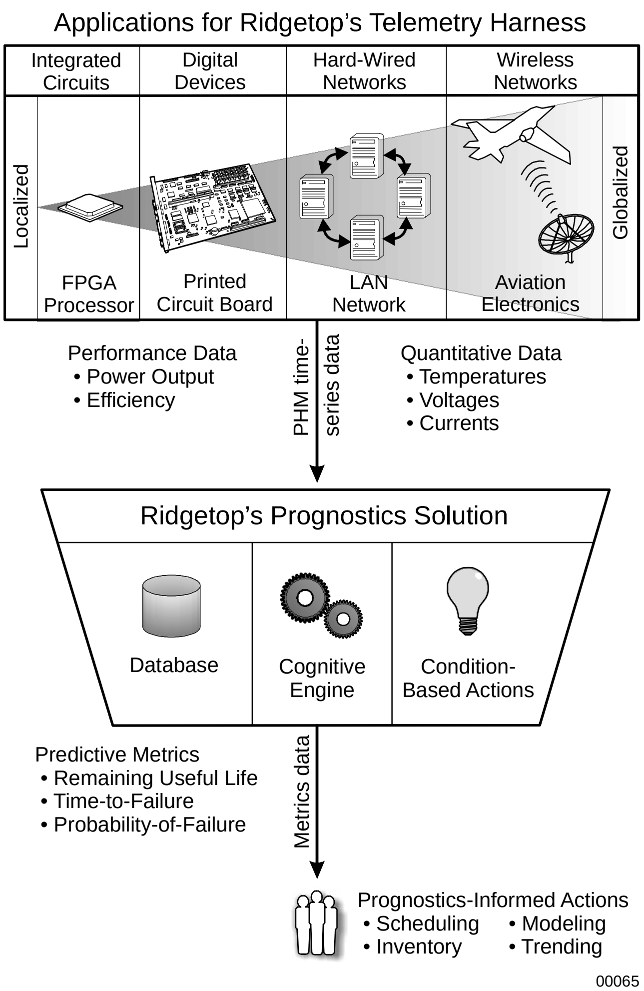

Figure 2: Application, Scalability, and Process Flow of Ridgetop’s Telemetry Harness

ELECTRONIC PROGNOSTIC ENABLEMENT

A properly configured, on-board, prognostic-enabled EMA system:

- Monitors State-of-Health (SoH) during operation
- Extracts prognostic information from SoH
- Reduces overall test costs
- Improves fault coverage through dedicated prognostic circuitry added to EMA circuit design
- Provides SoH and Remaining Useful Life (RUL) metrics through use as remote diagnostics [4]
- Collects data and manages assets with full information on the SOH and RUL from a central collection point linked to the on-board prognostics sensor

With prognostics capabilities now extended to electronic modules, the acquisition of system information must be assembled in a hierarchical manner, assessing failure rates for subassemblies within the modules and determining the modules’ SoH and RUL from a wide range of observations, prognostic sensors, and algorithms .

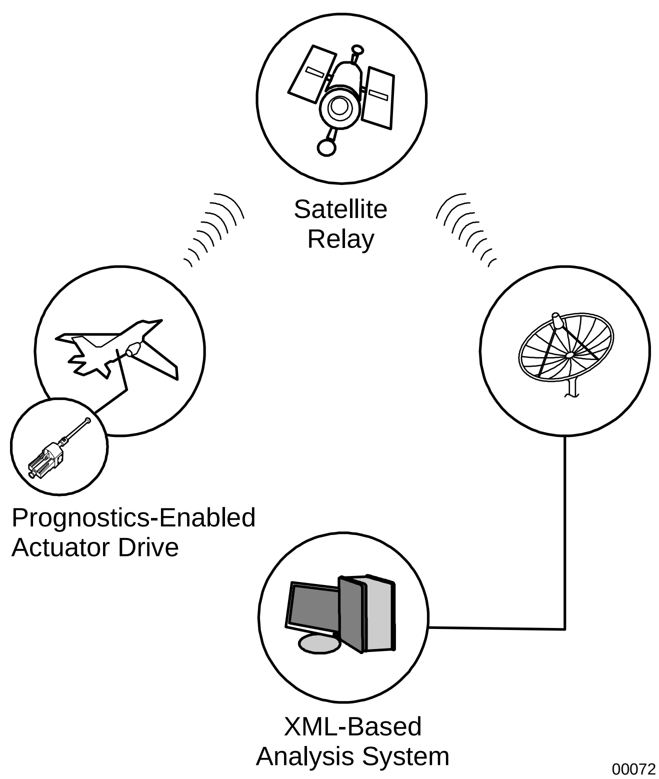

Figure 3: Prognostics Elements Diagram

This information fits into a taxonomy consisting of diagnostics, prognostics, and system-level Integrated Vehicle Health Management (IVHM). To be a versatile analysis platform, the system architecture should be intuitive, easy to use, and simple to interface to other applications. Unlike systems developed for the mechanical world of turbines and engines, this architecture is optimized for electronic systems. This includes short time constants, non-monotonic component degradation, and intermittencies.

Electronic Prognostics and Health Management (ePHM) offers the following benefits:

- Instant determination of the electronic module's SoH
- Prediction of electronic module's RUL
- Advance notice of impending failures
- Integration with the supply chain through ALS

Figure 4 shows the design process or methodology applying prognostics to a general system module. In this application, known problem areas are ranked in a Pareto chart, precursors for "problem" components are derived, and appropriate corresponding observation structures are developed.

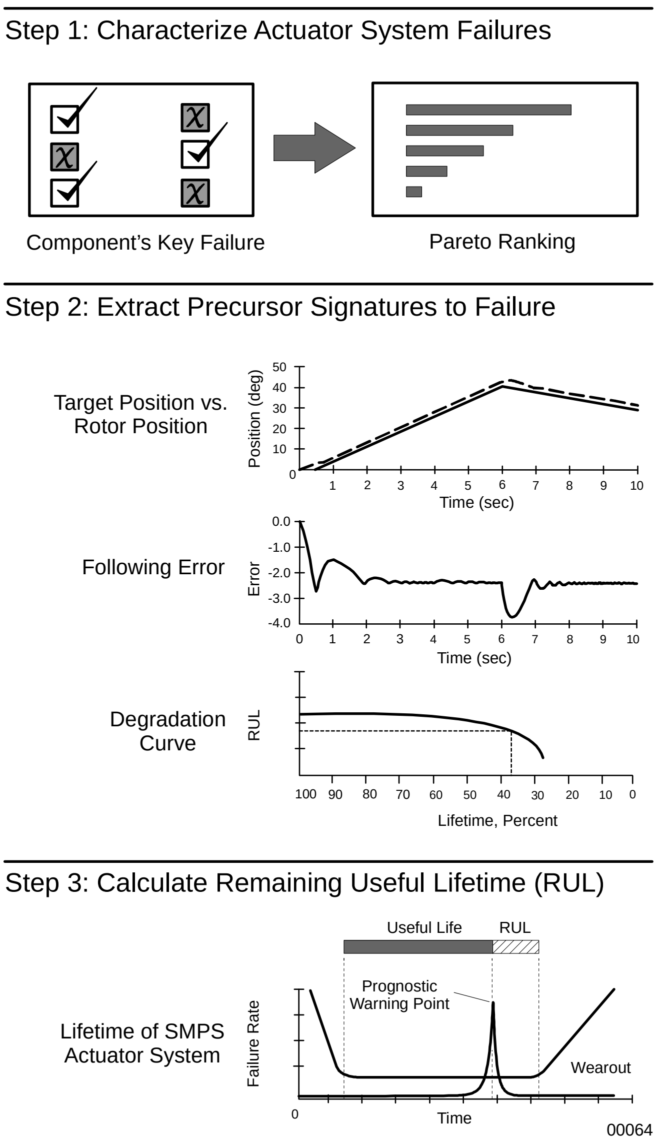

Figure 4: Electronics Prognostics Design Process

A CPU processes the data into meaningful "good/bad" indicators.

Component or Subsystem

The authors describe a prognostics approach that includes both the data collection and the analysis for calculation of SoH and RUL metrics for EMAs.

A PROGNOSTICS ANALYSIS SYSTEM PLATFORM

Ridgetop's architecture supports the prognostics-enablement of a network of distributed assets using wireless transmission technology and a centralized collection point for examining the individual assets' State-of-Health and Remaining Useful Life (see Figure 4). This approach supports CBM strategies reducing the cost of maintaining these systems across a widely dispersed area, improving the overall "up-time" of these assets, and equipping service personnel with correct sets of replacement parts and diagnostic tools to rapidly repair or maintain the systems.

Figure 2 illustrates a multi-level architecture of subsystems and components. Health monitoring occurs at several levels, from IC die- to system-level. For example, an actuator system might consist of power sources, characterized actuator (at various levels of model abstraction), and loads. Each element has its own hierarchically modeled subsystems using an underlying, structured, XML approach.

Data Acquisition and Storage

Ridgetop's electronic prognostics solution provides the ability to store sensor data and applies algorithms to make RUL predictions for on-board electronic systems, subsystems, and components. Through the collection and analysis of time series data, the system monitors quantitative metrics associated with physical variables, performance variables, and various quality of service metrics.

Physical variables include temperatures, voltages, and currents throughout the system. Performance variables include power output and efficiency. Quality of service metrics include RUL, Time-to-Failure (TTF), and Probability of Failure (POF).

These variables provide a rich foundation for building empirical models for system components individually (for example, generators, and batteries) and for individual components in a system.

Benefits of this approach include discovery of root cause, observation of anomalous behavior at the system-level, and early detection of trends toward failure. While independent sensors would show normal operation, trends indicating failure make early detection and preventative action possible.

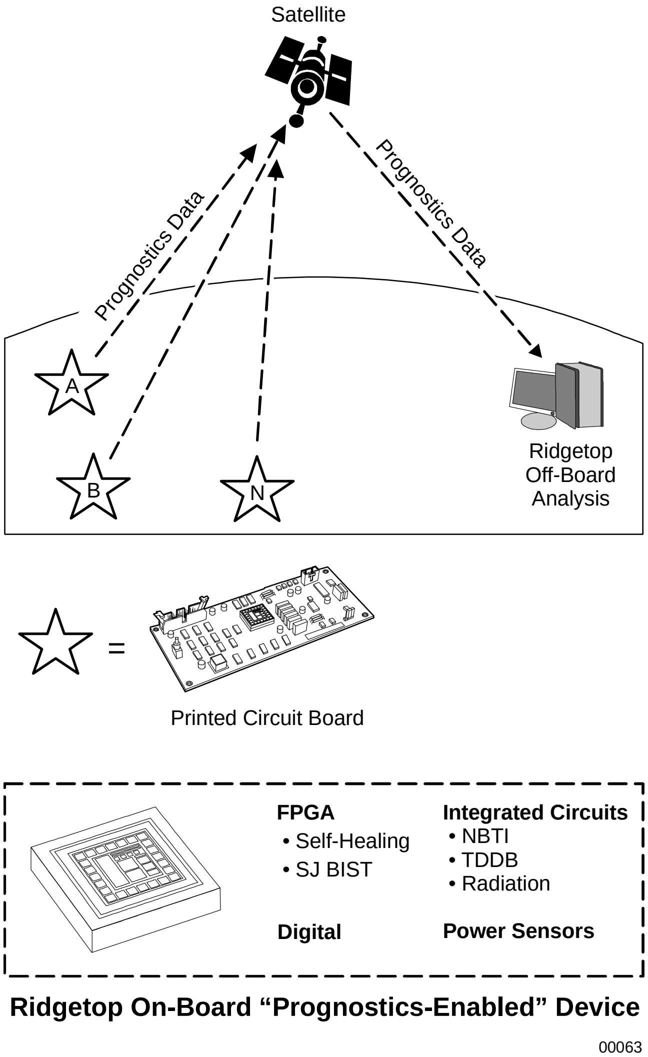

Figure 5: Extensible Prognostics-Enabling Architecture for a Wireless Network of Distributed Assets and Centralized Collection Points

In the deployed system, it is advantageous to obtain information as quickly as possible. So, a real-time link with the deployed system is very powerful benefit. This link can be via satellite, landline, or wireless connection to the central collection point. With the system SoH data, ground support personnel will know exactly what spare parts are needed to maintain a high level of operational readiness.

Data is stored in a hierarchical structure (see Figure 6). An XML-type (Extensible Markup Language) software architecture offers these levels of abstraction as well as compliance with MIMOSA standards. A simple example for an avionics actuator can be represented as a system with subsystems and individual components with XML which is imported into a database platform and used for further diagnostics and prognostics support.

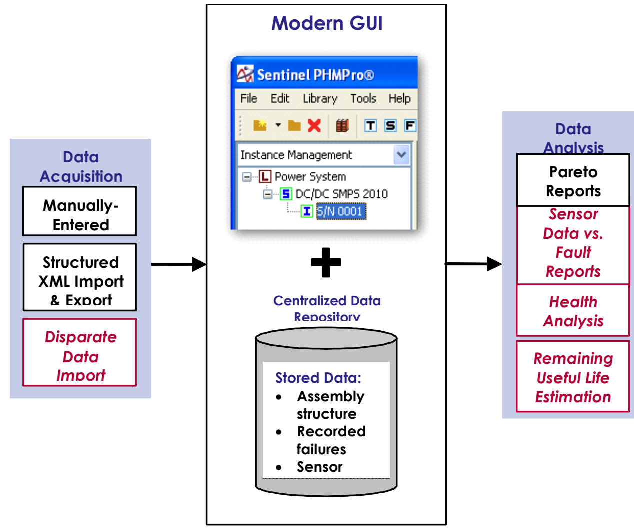

Figure 6: Architectural View Showing an Actuator System at the Top-Level

Cognitive Layer or Engine

The cognitive layer (see Figure 2) provides the necessary fault trend analysis and recommends maintenance actions to the scheduler. An easy-to-use interface with domain experts in the field provides support for engineering changes and equipment recommendations. The primary functions include performing fault isolation via more enhanced diagnostics, prognostic assessments, health management, false alarm mitigation, and data trending. The interface supports optimized maintenance planning and better class-wide management capabilities. Overall, PHM and fault trending analysis reduces total maintenance costs and increases the reliability of in-service actuators.

The Ridgetop State Estimation Technique (RSET) approach uses a self-learning algorithm to compare predicted and measured output of sensors already existing within the monitored system. The residual between the measured and predicted value provides a quantitative basis for incipient fault detection and diagnosis.

Ridgetop Prognostics Telemetry Harness

The key enabler for achieving prognostics capabilities is a Ridgetop Prognostics Telemetry Harness (RPTH). The RPTH collects and preprocesses time series signals relating to the health of dynamically executing components and subsystems in high reliability enterprise servers. The RPTH signals are continuously archived to an offline circular file (the "Black Box Flight Recorder") while being processed in real-time using advanced pattern recognition for proactive anomaly detection and RUL estimation with associated quantitative confidence factors.

Advanced pattern recognition techniques allow sensitive early detection of a wide range of incipient failures in actuator power systems. Even mechanical faults are susceptible to prognostic detection. The electrical perturbations caused by mechanical faults are detectable.

When correlated with a specific condition, a mechanical fault has a precursor signature, same as an incipient fault with an electrical origin.

These mechanical faults or conditions include specific problems such as mechanical wear (bearing aging and lubricant contamination), environmental contributors (thermal anomalies or faults preceded by patterns in wind speed and direction), degraded/failed sensors, and degradation of mechanical and electronic interconnects. These techniques help substantially increase component reliability margins and system availability goals while reducing (through improved root cause analysis) costly troubleshooting-diagnosis-repair cycles that are a significant cost issue for many of these systems.

A particular challenge in setting the prognostic trigger point is the avoidance of false-alarms (detection too early in system's lifetime) and avoidance of late notifications. While the sensors used to acquire SoH information may be both diagnostic and prognostic, neither sensor type provides a prediction of when the failure is likely to occur. One predictive analysis methodology collects sensor data from many sources and conditions the collected data to enable probabilistic calculations, including Bayesian calculations. Bayesian calculations can be quite complex, especially when many variables are involved. After data fusion, it is necessary to run a multiplicity of calculations to predict the likelihood of failure of one of the power subsystems within a specified period. Accordingly, accurate prediction also requires collection, conditioning, and processing of increasingly complex and massive sets of data.

A key benefit of the Ridgetop Electronic Prognostics Platform is the use of collected information to calculate system RUL. There are several techniques employed for such estimates including: analysis of actual operands and measurands, existing diagnostic output vectors, prognostic sensors, and "canaries". Data from the constellation of these inputs is collected and fused. Algorithms yield composite estimates of system health at a particular level within the system hierarchy. The algorithms available include adaptive model-based reasoners, RSET, Bayesian network reasoners, and others. With a platform available for quick analysis, various options can be explored.

For example, at the board and module levels, a Built-In Self-Test (BIST) identifies and isolates faults, as well as providing predictive capability of impending failures. Emphasis is placed on reducing false alarms and identifying prognostic techniques to anticipate system degradation and allow automated recovery. This prognostic approach provides an accurate picture of forthcoming faults and component degradation – the predictive indicators of failure – and is extremely useful to the crew. The solution also allows timely action needed to avoid costly or catastrophic damage to critical Line Replaceable Units (LRUs) and to maintain availability/readiness rates for weapon systems.

ACTUATOR PROGNOSTICS

Prognostic techniques initially developed by Ridgetop for Switch-Mode Power Supplies (SMPS) are applicable to electronic sub-systems, such as the actuator driver in a brushless DC motor system.

The brushless DC motor uses permanent magnets attached to a rotor in place of the armature windings in a conventional DC motor. Field winding are driven by a multi-phase (generally three phase) commutation signal that uses a power drive stage similar to topologies in DC-to-DC power converters.

Typically, three Hall sensors detect rotor position. Commutation is based on the Hall sensor inputs. Two alternative approaches for positioning feedback are 1) taking the back EMF directly from the windings and 2) using an optical sensor for precise position feedback. A microprocessor is generally required to convert position feedback and motion profiles into a commutation signal. The DC brushless motor is common in industrial applications requiring higher performance and reliability. This is due to the motor's brush-free operation, linear current/torque relationship, smoother acceleration, and clean spark-free operation.

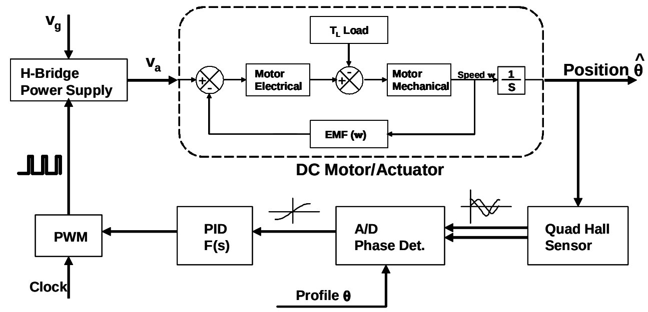

Figure 7: State Diagram of a Close-Loop DC Motor/Actuator System

A closed loop system consisting of an actuator and a position sensing feedback loop (Figure 7) tracks position with a preset motion profile. The system acts as a transfer function responding to perturbations in either set position or motor torque. Critical components – windings, power switches, sensors, and microprocessor – exhibit fault-to-failure progression signatures manifesting in the transfer function of the control loop. The non-invasive prognostic detector is an impulse (either in the motion profile or the load torque) and data register to record the recovery waveform for position, angular speed, or force output. A first-order analysis compares the captured waveform of a suspect motion system against a baseline signature recorded on a new system. Deviations from the baseline suggest an anomaly has been observation of an anomaly.

The simulation shows following error resulting from lead screw in normal and degraded condition (worn bearing).

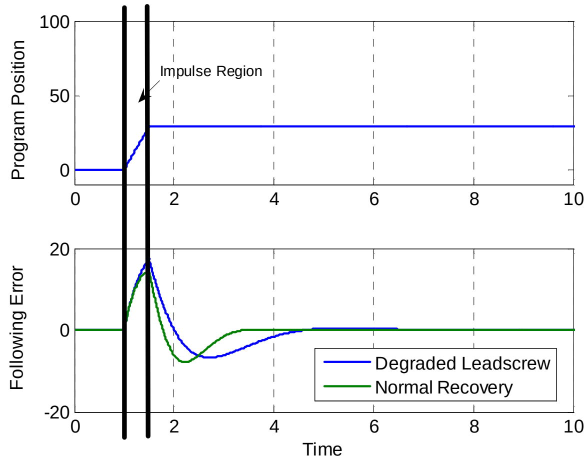

Figure 8: An Impulse Response in an Actuator Caused by a Position Jog

SIMULINK MODEL AND RESULTS

To help better understand the behavior of critical parts in an EMA circuit and to test our hypotheses regarding component degradation, the actuator circuit was simulated using the MATLAB Simulink tool set. The circuit in Figure 9 is the representation of the DC motor, actuator circuit, and the prognostics for the Rotor shaft position.

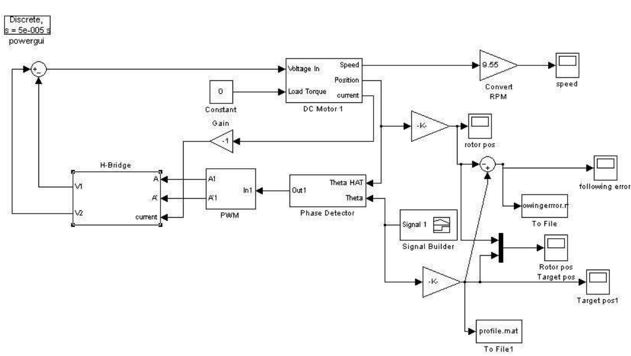

Figure 9: Actuator Circuit (Simulink Model)

The DC motor consists of electrical and mechanical parts as illustrated in Figure 10. The electrical term is made of an inductance and a resistance, with a transfer function:

$$GE(s) = \frac{1}{L_m s + R_m} \tag{1}$$

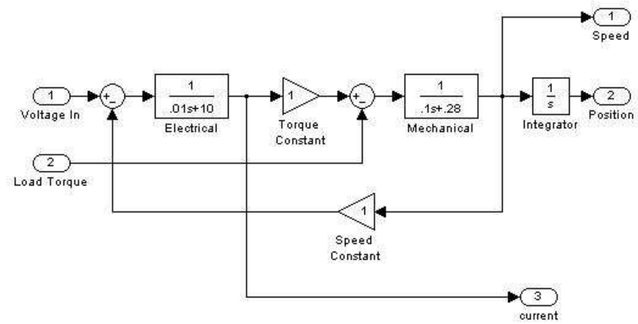

Figure 10: DC Motor (Simulink Model)

Furthermore, the motor converts electrical armature current into mechanical torque of the motor as:

$$T_m = ki_f i_a \tag{2}$$

where i_f is field current, and i_a armature current. The back emf is given by:

$$v_b = k' i_f \omega_m \tag{3}$$

and the supply voltage to the rotor circuit and inertia of the rotor as:

$$v_a = R_a i_a + L_a \frac{di_a}{dt} + v_b \tag{4}$$

$$J_m \frac{d\omega_m}{dt} = T_m - T_L - b_m \omega_m \tag{5}$$

where ω_m is angular speed of the motor, R_a armature resistance, L_a armature inductance, J_m inertia of the rotor, and b_m dampening constant of the rotor, see Figure 11. From these equations the second term, which is of mechanical nature, can be established. Inertia and torque are the main components of this transfer function:

$$G(s) = \frac{1}{J_L s + I_L} \tag{6}$$

The signal coming from the DC motor is fed into Pulse Width Modulator (PWM) and divided into two signals, which are opposite in magnitude (Figure 12). These two different signals are used to turn on and off MOSFETs in the H-bridge (Figure 13).

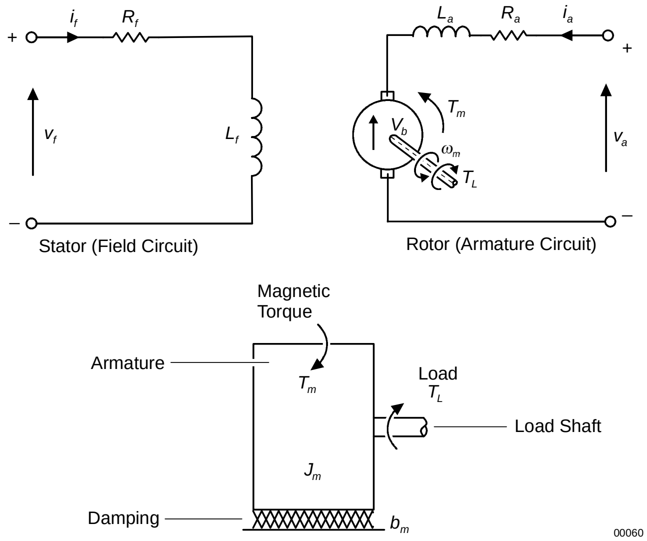

Figure 11: Equivalent Circuit of a DC Motor and Armature Mechanical Loading Arm

The H-bridge consists of four MOSFETs that are connected at the gates diagonally (M1 and M3, and M2 and M4). The outputs of the H-bridge are summed and fed into the DC motor.

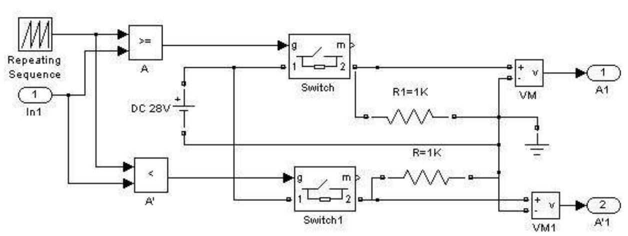

Figure 12: PWM Circuit (Simulink Model)

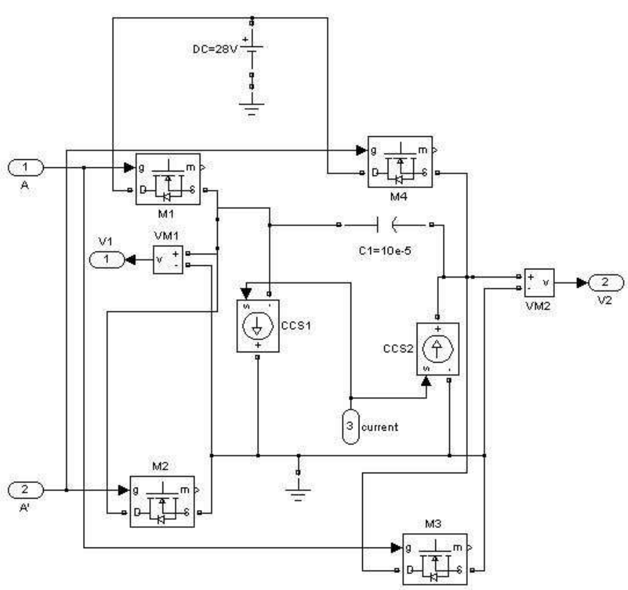

Figure 13: H – Bridge (Simulink Model)

The signal builder, a ramp, was non-invasively induced into the circuit. The signal is used to mimic how the DC motor should behave. It is labeled as Target position (solid line). The Phase Detector detects changes in the position between the Target position and the actual position of the rotor (dashed line). That signal is then summed and displayed as Following Error. Also, the Rotor position, which is directly taken from the DC motor, is compared to the Target position on the same graph.

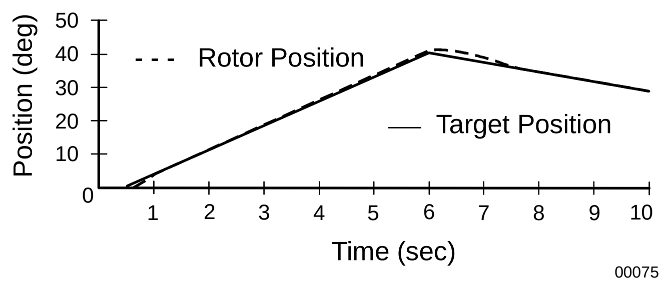

Figure 14: Simulated Target Position vs. Rotor Position (All MOSFETs are good) (Simulink Model)

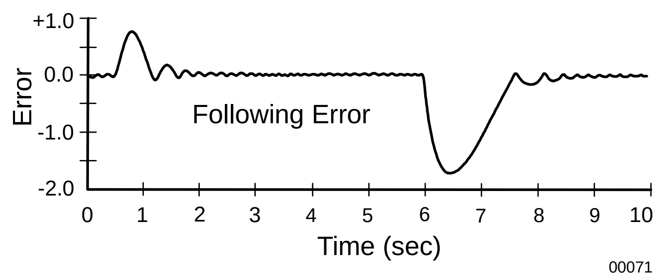

Figure 15. Simulated Following Error (All MOSFETs are good) (Simulink Model)

Figure 14 and Figure 15 are an example of the position and Following Error when all the components in the circuit are in the working condition.

We can observe on Figure 14 that the Rotor position is exactly following the Target position from the start of the simulation until the target position changes direction. At that point the Rotor position overshoots, but it recovers very quickly. The overshoot is due to the slow response time of the Control system. The Following Error or deviation from the target, as seen on Figure 15, is at zero during the whole simulation. As long as the Rotor position follows the Target position the error is at zero. Oscillations from the zero error can be seen at the start of simulation and at the place where the Target position changes direction. This is due to the feedback and its response.

In Figure 16 and Figure 17 one of the MOSFETs, M1 or M3, in the H-bridge breaks down, meaning, that the internal resistance will increase. In Figure 16 the Rotor position is at the higher degree level then the Target position during the entire simulation. At the point of direction change, the Rotor position is overshooting a little, but it compensates and rides again next to the Target position but still with an error.

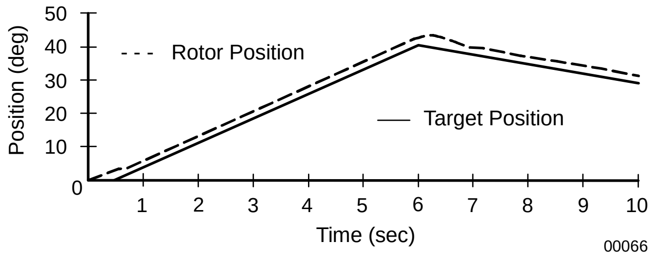

Figure 16: Simulated Target Position vs. Rotor Position (M1 or M3 are damaged) (Simulink Model)

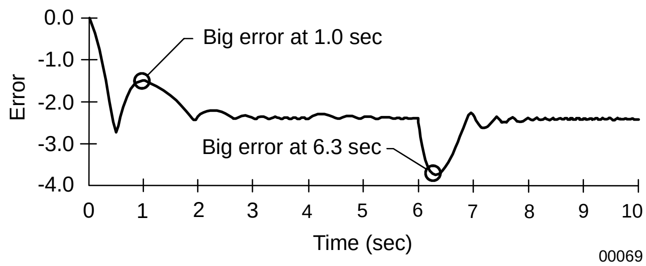

Figure 17: Simulated Following Error (M1 or M3 are damaged) (Simulink Model)

Figure 17 is the representation of the difference between Rotor position and the Target position. If the Rotor position is at the higher degree level from the Target position then the Following Error is negative, meaning the rotor should turn slower. Big errors, at times 1 sec and 6.3 sec, in the Following Error are due to the faster change in the direction of the Target position and the slow response of the Rotor position.

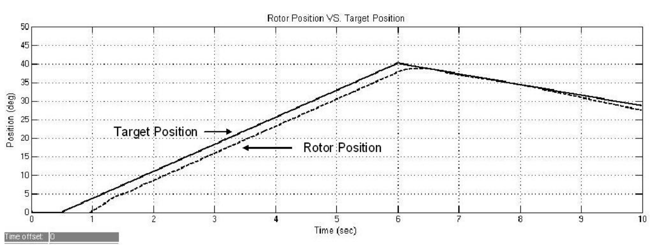

Figure 18: Simulated Target position vs. Rotor position (M2 or M4 are damaged) (Simulink Model)

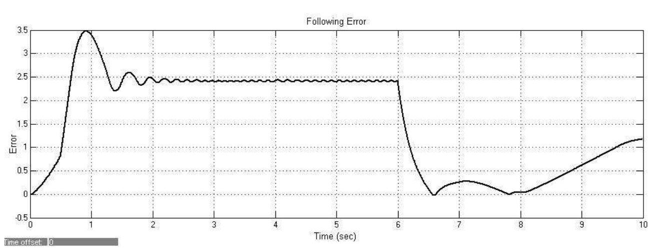

Figure 19: Simulated Following Error (M2 or M4 are damaged) (Simulink Model)

In Figure 18 and Figure 19 one of the other two MOSFETs is degraded. In Figure 18, the output of the Rotor position is below, legging, the Target position all the way, even when the impulse changes its direction. The Following Error in Figure 19 is always positive, but it increases or decreases depending on how close the Rotor position is to the Target position.

When the H-bridge is working properly the Following Error is at zero because the Rotor position is following exactly the Target position. This can be described in the example of the airplane's wing-flap. When the Target position is set to go to 40 degrees and then is lowered to 30 degrees the rotor position should follow the same line. The DC Motor and its control system have a very slow response time and that is why discrepancies in the position graphs can be seen. Every time the direction of the Target position is changed the overshoot of the Rotor position is seen due to the slow response of the control system.

When one of the sides of the H-bridge is not functioning properly, there is higher resistance in one of the MOSFETs, then the response of the circuit is different. If M1 or M3 break down, the DC Motor is going to be driven harder and the Rotor position is going to be at the higher degree then the Target position. The Following Error is going to be positive, meaning the DC Motor should be slowed down. The current in the side that has higher resistance is lower in value then the other side of the H-bridge. However, if one of the other two MOSFETs, M2 or M4, break down then the Rotor position is legging the target position and it does not reach target degrees. In the airplane wing flaps these errors in position can cause airplane to turn slower or faster then expected. Exact functioning of these parts is very crucial for the stability of the airplane.

RETURN ON INVESTMENT

In general, the Return-on-Investment (ROI) for the adoption of electronic prognostics consists of an analysis of the savings associated with the implementation, less the cost of implementation, divided by the investment required. This relationship is mathematically stated:

ROI = (Savings – Implementation costs)/
(Investment required)

For example, in the case of aircraft, the identified sources of savings from prognostics include:

- Increased aircraft availability
- Reduced loss of aircraft
- Reduction in unplanned maintenance (all aircraft not just those in the battlefield) of up to 20% [8]
- Moving spares to the proper place (logistics)
- Better use of inventory
- Better spending controls on spare inventory
- Reduced expenditure in armaments required to accomplish mission
- Increase in mission success rate

The costs of applying prognostics can be separated into three categories:

- Non-recurring engineering (NRE) cost of adding the prognostics to an actuator
- Per unit costs of the prognostic components
- False Alarm Cost (if failure rate of the prognostic circuitry approaches the failure rate of the component being monitored)

In reference [9] it was shown that ROI for prognostics-enabling high efficiency power converters can be up to 20% and is often significantly higher. Separately, Sun Microsystems found that proper adoption of electronic prognostics to their Blade servers reduced their NTF rates from over 50% to less than 10%.[3]

Missed Opportunity: the VW Passat Example

Due to the high cost and complexity involved in purchasing, financing, and servicing aircraft, ROI is often difficult to assess. A more accessible but equally compelling case can be made examining the recent recall and on-going National Highway Traffic Safety Administration (NHTSA) probe of the VW Passat.

An investigation, began in May 2007, revealed there had been 78 reports of engine fires and two injuries involved with the VW Passat. Specifically, the Passat sedans from the 2000-2003 model year equipped with 4- and 6-cylinder engines. The engine fires are attributed to failure of the ignition coil. [10]

Table 1: Statistical Data for VW Passat Recall [11]

Recall Specifics	Data
Total Units	352,668
Affected (Recalled) Units	345,642 [12]
Failure Incidents (to date)	78
Failure Cause (LRU)	Ignition Coil
Warranty Claims	14850
LRU Cost	$173.76
Unit Cost, Low	$21,750
Unit Cost, High	$31,575
Unit Cost, Average	$26,662

Before calculating ROI, an estimate is required for the recall cost. Factors affecting the recall cost include:

- LRUs per unit
- Labor cost per hour
- Labor time
- Recall administrative cost per unit

These factors are the primary assumptions needed to make the recall cost calculation.

Table 2: Recall Cost Assumptions

Recall Cost Assumptions	Value
LRUs per unit	1
Labor cost per hour	$100
Labor time per unit	1 hour
Recall administrative cost per unit	$150

With these factors identified and estimated, the recall cost can be calculated.

Recall Cost (per unit) = $423.76
Recall Cost (total) = $146,469,254

With a $500K investment cost as the price for a corporate prognostics IP license, the ROI calculation is:

ROI = [146,620,960 – 500,000] / 500,000 = 292%

Not bad for an investment of $0.71 per unit (car), particularly when weighted against an estimated $423.76 recall cost per car which does not take into account inestimable values such as customer satisfaction, investor confidence, and positive brand recognition. While damage to these somewhat nebulous values is hard to assess, it's not hard at all to track and tally the losses incurred by businesses suffering from defect-related set-backs.

For VW, a faulty component with a failure rate of 0.02% occurring in 78 cars resulted in the recall of 346,000 cars or 96.1% of all cars manufactured over a four-year period. Or, to put it in another way, $13,000 (approximately one case) of defective ignition coils cost the company $146.6 million dollars. That comes out to $1.9 million dollars per defective ignition coil.

One benefit, yet to be mentioned, of a successful electronic prognostics deployment is the reduction in the very defects and failures that are the root causes of a product buy-backs, refunds, product returns, and recall campaigns.

These ROI calculation demonstrate the tremendous gains possible through a modest investment as well as the cost of missed opportunities. Electronic prognostics are one of those rare value-added propositions customers can easily understand and justify when couched in terms of improved quality, performance, and maintenance reductions.

SUMMARY

This paper shows the efficacy of using electronic prognostics on actuator drive systems used in commercial and mil-aero systems. Electronic prognostics can be linked to larger networks to provide a dynamically updated inventory of assets indicating state-of-health and remaining

[3] Gross, K. "Sun Microsystems Electronic Prognostics Experience", NDIA Conference 2006, Miami, Florida

useful life. This is very beneficial in military and industrial automation settings and can link to larger system level prognostics, such as the generator system in Figure 20, and maintenance ALS.

This incorporates external prognostics extraction blocks multiplexed to external Integrated Health Monitoring System.

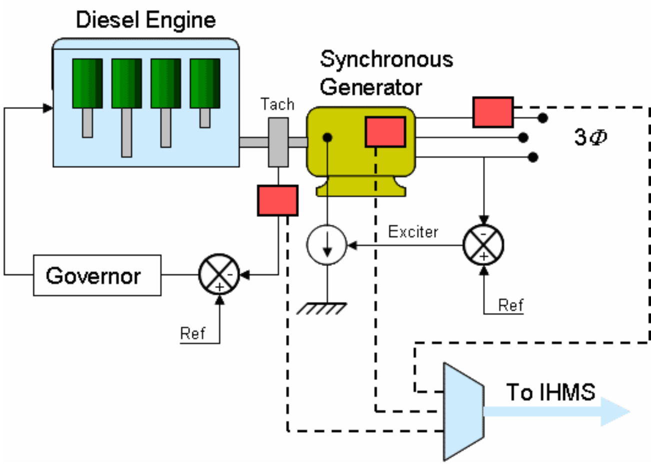

Figure 20: A System-Level Solution for Synchronous Generator

The non-invasive approach to electronic prognostics can be implemented on a variety of power electronic systems where access to internal circuit nodes is not available. Starting with a state diagram description of the system operating with feedback, one can determine the out response to a given input perturbation. Finally, with the understanding of how changes in the condition of interior components affect the response function, component degradation can be measured indirectly. Fault-to-failure progression models are used to derive RUL estimations. This approach has tremendous advantage over direct measurement schemes in which sensors must be added inside the circuit that by virtue of their own reliability can increase the probability of failure and reduce the mean lifetime of the system. High-reliability, high-fault coverage solutions can be implemented for power electronics using existing terminal access.

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[4] Remote diagnostics can facilitate communication between a central diagnostic center with the deployed system. By the time the system is returned to base, a spare can be ready-to-install.

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[10] John Maddox, NHTSA Investigation PE 07-024, "IR to MFR for 2000-2003 Volkswagen Passat," 05/11/2007.

[11] Lee Strickland, NHTSA Investigation PE 07-024, "ODI Resume for 2000-2003 Volkswagen Passat," 05/10/2007.

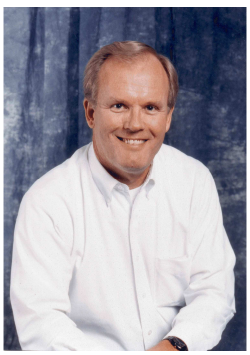
[12] Lee Strickland, NHTSA Investigation PE 07-024, "ODI Resume for 2000-2003 Volkswagen Passat," 09/28/2007.

BIOGRAPHY

Sonia Vohnout

Sonia Vohnout is Systems Engineer at Ridgetop Group, Inc.. She received her Bachelor of Science degree in Computer Science from the University of Costa Rica, and Bachelor of Science and Master of Science degrees in Systems Engineering from the University of Arizona. In the past she has worked for Modular Mining, IBM and AT&T Bell Laboratories. She previously owned and operated a manufacturing facility in Mexico. She is an expert modeler and has extensive expertise in software and computer systems. Ms. Vohnout has over 20 years of experience in systems engineering, quality systems management, and business development and management.

Douglas Goodman



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.

Mr. Goodman is a co-founder and President of Opmaxx, the firm that developed the first commercially available Analog Built-In Self-Test (BIST) product line including self-contained IP for measuring the performance of ADCs, PLLs, Gain Stages, and other mixed signal modules. He has extensive experience in low noise instrumentation design, stemming from a 14-year stint at Tektronix, Inc. He was Vice President of Engineering at Analogy, Inc., an Analog/Mechatronic Simulation Tool firm, which after a successful IPO on the NASDAQ, became part of Synopsys, Inc., a large Electronic Design Automation (EDA) firm.

At Ridgetop Group, Mr. Goodman is the Principal Investigator on a number of electronic prognostics and radiation-hardened IC-related projects in addition to his executive duties.

Justin Judkins

Justin Judkins is Director 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 previously held senior-level engineering positions at Bell Labs and Lucent involving high-reliability telecom transmission. He received a Ph.D. in Electrical Engineering from the University of Arizona.

Mladen Kozak

Mladen Kozak is a Design Engineer and Technical Staff Member for Ridgetop Group, Inc. He is instrumental in developing innovative solutions supporting Ridgetop's prognostic and ePHM efforts related to Power Electronics, Switching Power Supplies, and Electro-Mechanical Actuators. His technical background includes circuit design and complex control system simulations. He received his BSEE from the University of Arizona and is currently pursuing an MS.

Ken Harris

Ken Harris is the senior technical writer at Ridgetop Group. An expert in usability and cross-cultural communication, he has served as plenary speaker and symposium chair for advanced topics in technical communication and information design. Over a 25-year career, he has become an award-winning writer, designer, and illustrator with awards ranging from academic contests to juried national and international competitions. Mr. Harris worked as senior writer, technical illustrator, and information product designer at Lucent, Motorola, NCR, and Cingular Wireless before moving to Arizona and joining Ridgetop Group. He received a BA in English from the University of New Mexico, graduating cum laude and with departmental honors. He has taught graduate technical writing and graphic design at Georgia Tech and Southern Polytechnic State University and is a senior fellow in the Society for Technical Communication.