# **Design Approach for a PHM System: Dual Set of Electromechanical Actuator Subsystems**

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**Abstract**: This paper describes a design for an example of a Prognostic Health Monitoring (PHM) system that is able to detect a state of degraded health and make an accurate prediction of when a resulting future failure in the system is likely to occur in a dual set of electromechanical actuators (EMA) subsystems, each comprising a switch-mode power supply (SMPS) and two identical EMAs. Examples of considerations in a design of a PHM system include the following: (1) What is the framework for the PHM system? (2) What units (targets) are to be prognostic enabled? (3) What failure modes are to be monitored? (4) What kind of data conditioning is necessary to isolate and extract condition indicators and/or leading indicators of failure from noisy condition-based data (CBD)? (5) Do special methods of data processing need to be developed and, if so, how? (6) What are the prognostic accuracy requirements? (7) What alerts and alert levels are required to support prognoses? (8) What are the requirements related to starting, stopping, resuming, and recovery of the system? (9) What architecture approach is going to be used to define the target system to the PHM system?

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**Keywords:** condition-based data; CBD; electromechanical actuator; EMA; prognostic health monitoring; PHM; Accelerometer; gear; MEMS; rolling stock; RotoSense; signal quality; train; wheel hub

#### **1.** INTRODUCTION

An important purpose of a Prognostic Health Monitoring/Management (PHM) system is to detect a state of degraded health and accurately predict when functional failure is likely to occur [1]-[2]. This paper presents a design of a PHM system for a dual set of electromechanical actuators (EMA) subsystems, each comprising a switch-mode power supply (SMPS) and two identical EMAs. The design and development of a system to support PHM is complex and there are many approaches to do so. Even though each such system (with the possible exception of demonstrations, test beds, and experiments) is unique, there are important design considerations. Examples of considerations in a design of a PHM system include the following: (1) What is the framework for the PHM system? (2) What units (targets) are to be prognostic enabled? (3) What failure modes are to be monitored? (4) What kind of data conditioning is necessary to isolate and extract condition indicators and/or leading indicators of failure from noisy condition-based data (CBD)? (5) Do special methods of data processing need to be developed and, if so, how? (6) What are

the prognostic accuracy requirements? (7) What alerts and alert levels are required to support prognoses? (8) What are the requirements related to starting, stopping, resuming, and recovery of the system? (9) What architecture approach is going to be used to define the target system to the PHM system?

There are other considerations that are not presented, including but not limited to the following: comparison and selection of sensors; the cost to design, develop, test, verify, field, and maintain a PHM solution for each prognostic target; evaluation of the cost of failure versus the cost of failure prevention; repair versus replacement cost; long-term costs associated with installing, operating, and maintaining a PHM system.

### 2. DESIGN CONSIDERATIONS

# Framework for the PHM System

The framework shown in Figure 1 is selected as the base framework.



#### PHM for ELECTRONICS: FRAMEWORK DIAGRAM

Figure 1: Framework for a PHM System (based on [3]-[5]).

**Health Management Framework.** Health management is very complex and includes decisions that consider risk, deployment, maintenance, reporting and directions (imperatives), procurement and delivery, load shedding, soft shutdown, and much more.

**Performance Validation Framework.** Because predictions are estimates, there is always a question as to how good (accurate) those estimates are. A PHM system could be designed and developed to provide means and methods to evaluate and validate the performance of the prediction algorithms. This paper does not address the design of a Performance Validation Framework.

#### **Prognostic Targets**

The selected prognostic targets are two EMA subsystems, each comprising a power supply and two EMAs as shown in Figure 2.



**Power Supply.** The power supplies are switched-mode power supplies (SMPS) and the identified fault is loss of capacitance in the output filter (block 1 in Figure 3 and Figure 4). That fault is known to result in excessive noise and loss of ability to deliver power, which results in irreversible damage to both a power supply (damaged switching transistors) and a downstream EMA (block 2 in Figure 3) connected to it.



Figure 3: Block Diagram of a Prognostic-Enabled Power Supply in a Test Bed.

**EMA.** Each EMA (block 2 in Figure 3 and Figure 4) comprises a controller (block 11) for a brushless DC (BLDC) motor; the motor has three stator windings (block 13) and a shaft (block 14) to position a load by moving up or down; AC power is delivered by six power-switching transistors (block 12) configured as an H-bridge type of commutation.

The EMA test bed can inject a fault (increase in on-resistance) into any one of the six power-switching branches in the H-bridge. Although not shown are two other fault injection methods: one to simulate a damaged stator winding and another to increase the load on the motor shaft. Three current sensors (block 10) are used to provide CBD for detecting and prognosing faults.



Figure 4: Block Diagram of a Prognostic-Enabled EMA in a Test Bed.

# **Failure Modes**

The PHM system design needs to detect and prognose the failure modes (faults): (i) loss of filtering capacitance in either of the two EMA power supplies; (ii) excessive load/friction on the motor shaft (block 14 in Figure 4); (iii) damage to any of the three stator windings (block 13 in Figure 4); and (iv) damage to any of the six power-switching transistors in the H-bridge connected to the stator windings.

# **Data Conditioning**

You need to collect and analyze sensor data, historical and test, to determine what kind of data conditioning you need – in practical applications, data conditioning, which includes data sampling, is always required.

**Power supply output.** The output of the power supply () comprises ripple voltage, DC voltage, and noise. Noise is anything other than a feature data of interest and includes thermal noise, switching (spikes and glitches) noise, and other features such as droop, harmonic distortion, and damped-ringing responses.

Design is to configure your ripple-voltage sensor to employ bandpass filtering when sampling: frequencies between 200 and 250 kHz.



Figure 5: Noisy Voltage from the Power Supply.

**Phase Currents.** The phase currents of an EMA are also noisy (Figure 6), and they vary depending on positioning direction and load. There is also amplitude variation resulting from the floating reference topology of the EMA motor.



Figure 6: Phase Currents and Position Direction (Left) – Electrical Noise (Right).



Figure 7: Noise & Amplitude - Normal Load (Left) & Heavy Load (Right).



Figure 8: Floating Reference Results in Zero-Sum-Amplitude Variation.

Referring back to Figure 4, a design point is to employ windowing (Figure 9) with a positioning sensor (block 9) and a Window Control (block 20) to sample and measure currents (block 21). The window result is shown in Figure 10.



Figure 9: Sampling Window, Up Positioning for Normal (Left) and Heavy (Right) Loads.



Figure 10: Window Design Employed on the EMA Test Bed.

#### **Special Methods**

Because there are 10 EMA-fault modes to be detected and isolated (six transistors, three motor windings, and a motor shaft) with only three current sensors, special methods of processing phase-current data are required to satisfy the 10 degrees of freedom.

**Positive and negative halves of phase currents.** One design approach is to distinguish changes in the positive halves versus changes in the negative halves of the phase currents (Figure 11, left).

For example, normal values of on-resistance of power-switching transistors range from 0.01 to 0.20  $\Omega$ , so that a value of 2.0  $\Omega$  would be defined as functional failure. Experimentation with the EMA test bed reveals that level of degradation results in decrease of only 25-mA in either the positive or the negative half of the phase current (Figure 11, left): only a 1.4% change in total current – the feature (current change) is lost in the noise (Figure 11, right). Differentiating between peak changes in the current halves improves resolution: but only from 1.4% to 2.8%.



Figure 11: Positive-Negative Difference (Left) & Noisy Data (Right).

**Special-rms calculations.** A design solution does the following: define threshold levels, truncate all current values between the threshold levels, use the remaining values to calculate positive and negative magnitudes, and then sum the magnitudes. This method, called special-rms, emphasizes any differences between peak current values and the defined thresholds: the method overcomes the low-amplitude changes in phase currents.

$$T_{PEAK} = 0.70 \qquad \text{set threshold level} \tag{1}$$

$$I_{PEAK} = 900 \qquad \text{set nominal value of peak current (mA)} \tag{2}$$

$$I_{TRUNC} = T_{PEAK} * I_{PEAK} \tag{3}$$

When (I(n) > 0) &  $(I(n) > I_{TRUNC})$  then letting P = count of true,

$$P_{RMS} = \left[ (1/P) \sum_{1}^{n} (I(n) - I_{TRUNC}) \right] \qquad \text{do not square} \qquad (4)$$

When  $(I(n) < 0 \&\& I(n) < -I_{TRUNC}$  then letting N = count of true,

$$N_{RMS} = \left[ (1/N) \sum_{1}^{n} (I_{TRUNC} - I(n)) \right] \qquad \text{do not square}$$
(5)

$$I_{RMS\_DIFF} = P_{RMS} + N_{RMS}$$
 Sum the magnitudes (6)

The special-rms method significantly improves resolution compared to the normal rms method: about a 5:1 increase for a 0.70 threshold.



Figure 12. Graphical Illustration of Special-rms Method

Figure 13 illustrates the effectiveness of using the special-rms method for both the positive and negative halves of the three phase currents: (1) in the presence of degradation in an Hbridge transistor, there is a change in measured amplitudes of all six halves; (2) there is a significant change in the sum of the current halves for a degraded transistor, while the sums of the other two generally remains unchanged except for noise.



Figure 13: H-Bridge Transistor Fault, Negative Half of the Phase A Current.

**Current offset.** Close examination of the phase currents for a zero-degradation, no-load test (Figure 14) indicates the three phase currents are not centered about zero: this shift in the reference points of phase currents is confirmed by evaluation of plots in Figure 13. Differences in the reference levels is another form of noise of significance when comparing two sets of data, such as the magnitudes of current.

A method to mitigate current-offset noise (a source of error) is the following: (1) Sample and measure the phase currents during a calibration test (position up, no load, no degradation); (2) calculate and save the value of the mean amplitudes; (3) normalize subsequent current measurements.

Let $x = 1:3$	represent a phase current (A, B, C)
Let $z = 1: n$	represent a calibration sample to a design-defined limit

When  $(I_x(n) > 0)$  then letting P = count of true,

$$I_{0ADJ_{P}} = [(1/P)\sum_{1}^{x}\sum_{1}^{n}(I(n) - I_{TRUNC})] \quad \text{do not square}$$
(7)

When  $(I_x(n) < 0)$  then letting N = count of true,

$$I_{0ADJ_N} = [(1/N) \sum_{1}^{x} \sum_{1}^{n} (I_{TRUNC} - I(n))] \text{ do not square}$$
(8)

Then,

$$I_{OFF} = (P_{RMS} + N_{RMS})/2 \qquad \text{Offset adjustment values} \qquad (9)$$

Subsequently,



Figure 14: Phase Currents for Zero Degradation, Normal Load, Position Up.

**Data Smoothing.** The sensor data, pre-conditioned or otherwise, is noisy and is likely to result in noisy feature data (Figure 13). Subsequent experiments confirm that the noisy feature data ultimately results in prognostic information that does not meet accuracy requirements.

The design solution is to smooth the feature data, the transformed fault-to-failure progression (FFP) signature data, and the functional-failure signature (FFS) data that is input to a set of prediction algorithms (Figure 15). Subsequent experimentation confirms that after data smoothing, prognostic accuracy requirements are met.



Figure 15: Smoothed Feature Data (Left), FFP Data (Middle) and FSS Data (Right).

### **Prognostic Accuracy**

**Convergence specifications, initial error.** The specifications call for prognostic information to converge to within 25% when the remaining life is  $\geq 50\%$  (upper blue dots in Figure 16) and to within 10% when the remaining life is  $\geq 30\%$  (lower blue dots in Figure 16). The specifications are for cases where the initial estimated life when degradation begins is within 50% of actual.



Figure 16: RUL Convergence from 50% Error - PD 50% & 10% Points Shown.

Referring to Left-hand plots in Figure 17, a 25% accuracy within 50% RUL is met, but a 10% accuracy within 25% is not met; in the right-hand plots, both the 25% and 10% accuracy specifications are met.

During design, you need to run experiments and/or simulations to indicate the design is likely to result in an implemented PHM system that meets specifications.

# Alerts

The PHM system is designed to issue an alert at the SoH conditions listed in Table 1. The alerts include alert text and actions to be taken as indicated. To do so, the design needs to include the following functionality and methods: (1) prediction algorithms to produce SoH and other prognostic information; (2) support to monitor SoH values and appropriately trigger alerts; and (3) support to include relevant prognostic and failure information such

as RUL, PH, and times to an alert subsystem, such as a Health Management/Services framework (see the lower left of Figure 19).



Figure 17: (Left Plots) Accuracy Within 25% is Met, Accuracy Within 10% is Not Met - (Right Plots) Accuracy Within 25% and Within 10% are Both Met.

State of Health (SoH) Level	Level: Clear Text	Action
< 100%	Warning: xxx is degraded	Monitor
≤ 75%	Warning: xxx is $\leq 75\%$ degraded	Next Maintenance
≤ 50%	Error: xxx is $\leq 50\%$ degraded	Maintenance within RUL/2
≤ 25%	Error: xxx is $\leq 25\%$ degraded	Maint/Repair within RUL/2
≤ 10%	Alarm: xxx failure within RUL	Immediate Repair
≤ 5%	Alarm: imminent failure within RUL	Immediate Repair
0%	Bells/whistles: functional failure	Immediate Repair

Table 1: SoH and Alert Specifications



Figure 18: Example of RUL & PH Estimates (Left) and SoH Estimates with Alert Levels.

#### Start, Stop, Resume

The PHM system is to include the following: (1) support for stopping and restarting health monitoring; (2) support for resuming health monitoring after a planned stop or an unplanned system stop (a crash); (3) when health monitoring is resumed, the state of health of the system shall be the same as that at a checkpoint time; (4) checkpointing shall be at the prognostic-target level – specifically for each of the two power supplies and for each of the four EMAs.

A design solution is the approach shown in Figure 22.

# Architecture to Define Targets to PHM System

Figure 19 is a diagram of a system architecture to support the design of the PHM system presented in this paper. The design approach uses a node-based approach. The design specifications, decisions, and architecture are subject to change as the design is refined, as the system is implemented, and as it is updated during development.



Figure 19: Design Level of Architecture.

### **Node-Based Approach**

Figure 20 diagrams the architecture of Figure 19 to show more details of a node-based architecture as applied to the dual EMA subsystem presented in this paper.



Figure 20: Node-Based Approach for Dual EMA Subsystem.

### Node-Based Control and Data Flow

Figure 21 is a block diagram that illustrates the node-based control and data flow of the PHM system design.



Figure 21: Node-Based Control and Data Flow.

# **Design Approach for Checkpoint/Restart**

Figure 22 is a block diagram that illustrates a design approach to support checkpoint/restart.



Figure 22: Design Approach to Support Checkpoint/Restart.

# **3. Design: Verification**

A critical design process is data analyses: you need to design and run a series of experiments (DoE) using the EMA test that collects sensor data for each of the four selected faults. The data should comprise EMA operation before the onset of degradation, from the onset of degradation through increasing degradation to functional failure. Functional failure is defined as the level of degradation at which the prognostic target (power supply or EMA) no longer operates within specification.

# **Power Supply**

Evaluation of Figure 23 and Figure 24 verifies the design for the power supply.



Figure 23: Power Supply FFS



Figure 24: Power Supply RUL & PH (Left), SoH (Right)

# EMA Winding, Load, Switching Transistor

Evaluation of the results plotted in Figure 25 through Figure 28 verifies the design for the EMAs.



Figure 25: Fault Data for Winding, Friction/Load, and Switching Transistor



Figure 26: Winding Fault - RUL & PH (Left) and SoH (Right)





#### Figure 28: Transistor Fault – $KUL \approx PH$ (Left) and SOH

#### 4. SUMMARY

This paper presented an example of a design for a robust PHM system comprising a dual set of two EMAs and a power supply. The design began with a general framework for a PHM system (Figure 1) and a block diagram description of a dual EMA system to be prognostic enabled. A critical design approach is to collect and analyze data related to the failure modes to be supported. Both the feature data related to failure and the noise in the collected data requires analyses to determine how to process the data to isolated and extract features for creating failure signatures and how to process the data to sufficiently eliminate or otherwise mitigate noise to meet specifications, especially accuracy requirements for detecting the onset of failure and predicting a time of future failure.

The following feature noise considerations were presented for the power supply: ripple voltage is the feature and significant noise such as thermal noise, harmonic distortion, and switching noise. The common noise associated with the EMAs included (1) the positioning of the EMA (up or down and (2) the start and the stop periods – the design solution was to employ a sampling window. Because of magnitude differences, a design for a special-rms method was developed, and a design to mitigate significant offset errors in current references was developed. A third design to mitigate noise was to employ data smoothing of the feature data and the transforms of that feature data into signature data.

An updated framework was presented that would support node-based sensors for monitoring, data conditioning and transformation into signatures, prediction processing of the signature data, detection of alerts and the issuing of alerts. The updated framework included an architecture to support checkpoint-restart to start, stop, resume, and recover the PHM system.

The design was verified by using an EMA testbed and injecting faults into the power supply and the EMAs. Data, from no degradation to degradation and then to functional failure was collected and processed to produce prognostic information. The prognostic information – RUL, PH, and SoH – was plotted, analyzed, and evaluated. The results indicated the design will correctly detect all four of the fault modes and will produce prognostic information that meets the design specifications.

### Acknowledgments

The authors thank Naval Air, Naval Sea, U.S. Army, U.S. Air Force, and NASA research centers for their support and funding of multiple projects that led to the design and development of the prototype solutions and the results described and shown in this paper.

### References

- [1] Pecht, M. (2008) *Prognostics and Health Management of Electronics*. Hoboken, NJ: John Wiley & Sons.
- [2] Goodman, Douglas L.; Hofmeister, James P.; and Szidarovszky, Ferenc (2019); (Pending), *Prognostics and Health Management: A Practical Approach Using Conditioned-Based Data*, 1<sup>st</sup> Edition, John Wiley & Sons, Ltd, The Atrium, Southern Gate, Chichester, West Sussex, PO19 8SQ, United Kingdom, ISBN: 9781119356653, 2019.
- [3] IEEE 1856/D33 (2017), Draft Standard Framework for Prognosis and Health Management (PHM) of Electronic Systems, Mar 2017, IEEE Xplore Digital Library.
- [4] CAVE3 (Accessed 2015, Nov.), Prognostics Health Management for Electronics, Auburn University, Auburn, Alabama. [Online]. Available: <u>http://cave.auburn.edu/rsrch-thrusts/prognostic-health-management-forelectronics.html</u>.
- [5] Hofmeister, James P.; Szidarovszky, Ferenc; and Goodman, Douglas, L. (2017) "An Approach to Processing Condition-based Data for Use in Prognostic Algorithms," 2017 Machine Failure Prevention Technology, Virginia Beach, VA, 15-18 May, 2017.
- [6] Hofmeister, James P.; Wagoner, Robert; and Goodman, Douglas (2019);
   "Electromechanical Actuator Case Study: Multiple Variable Analysis of Phase Currents to Detect Three Types of Faults," 2019 MFPT Conference, King of Prussia, PA, 16-18 May, 2019
- [7] Hofmeister, James P.; Goodman, Douglas, L.; and Szidarovszky, Ferenc (2017)
   "PHM/IVHM: Checkpoint, Restart, and Other Considerations," 2017 Machine Failure Prevention Technology, Virginia Beach, VA, 15-18 May, 2017.