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# AN APPROACH TO PROCESSING CONDITION-BASED DATA FOR USE IN PROGNOSTIC ALGORITHMS

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**Abstract:** Modern Prognostic Health Maintenance/Monitoring (PHM) and Integrated Vehicle Health Monitoring (IVHM) systems use algorithms to process Condition-based Data (CBD) to provide prognostic information and actionable imperatives to support Condition-based Maintenance for the system. Prognostic information comprises the following: estimates of remaining useful life (RUL); estimates of state-of-health (SoH); estimates of prognostic horizon (PH) – also called time-to-failure (TTF) or end-of-life (EOL) estimates. Algorithms, such as Kalman Filtering, are used to condition CBD for further processing to accurately project a future time when data reaches an amplitude level indicative of failure. This paper discusses techniques and methods to first transform CBD into a Degradation Progression Signature (DPS) and then into a Functional Failure Signature (FFS): the latter is particularly amenable to processing by prognostic algorithms to produce estimates, such as RUL, that rapidly converge to alpha ( $\alpha$ ) accuracy bounds of ten percent or better with a convergence efficiency ( $\chi$ ) of at least 50% of the prognostic distance (PD).<sup>1</sup> [1]

**Key words:** Prognostics; health management; prognostic distance; alpha accuracy; condition-based data; degradation-progression signature; functional-failure signature; remaining useful life.

**Introduction:** An important objective of PHM/IVHM systems (Prognostic Health Maintenance or Monitoring/Integrated Vehicle Health Monitoring), such as the example in Figure 1, is to monitor selected nodes to collect Condition-based Data (CBD) to produce prognostic information to create actionable imperatives and information useful to maintain health of the system, especially for systems that support condition-based maintenance (CBM). The example system uses a node-based design: monitored nodes are defined; each node definition contains information and pointers; node information is node-sensor specific and, for example, defines the sampling rate, data format and type, and noise margin; pointers identify the modules such as drivers, feature extraction, prediction, and system health and services; and the names of files used for checkpoint/restart, data output, and data input. The heart of the PHM/IVHM system comprises routines that poll and use the node

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definitions to control and manage the flow of the data and system services. Not shown or discussed is a framework to perform health, maintenance, and fault management. [1] [2]

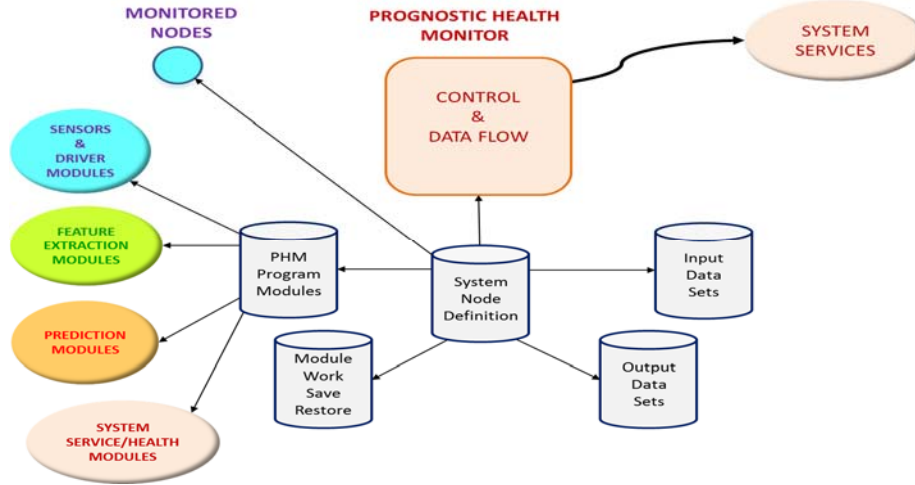


Figure 1: Framework for an Example PHM System.

Referring to Figure 2, sensor CBD is conditioned, fused, and transformed as necessary to extract feature data (FD), to create a CBD-signature. Such signatures are correlated to degradation damage and become data points in a Degradation Progression Signature (DPS), which is further conditioned, fused, and transformed to become data points in a Functional Failure Signature (FFS) that is input to prediction algorithms to produce prognostic information for health management. [2] [3]

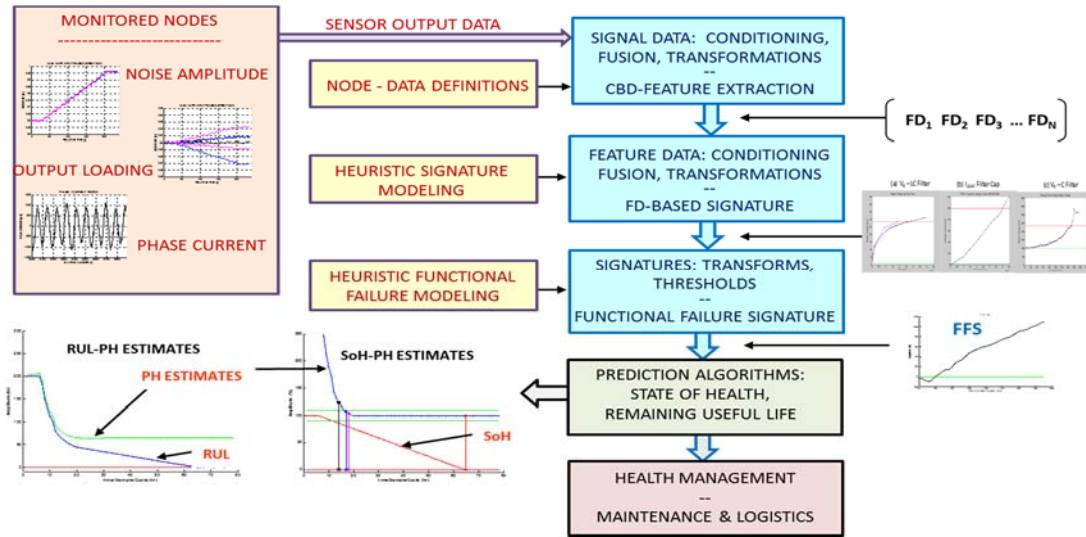


Figure 2: Functional Diagram of an Example PHM System.

**Sensor Conditioning of CBD:** Conditioning of CBD is almost always required because raw sensor data is noisy, distorted, and otherwise varied in ways not related to degradation as illustrated by examples of analog data in Figure 3. Rather than continuous reading and processing of analog signals, data sampling typically consists of “bursts” of digital

sampling wherein analog data is sampled and converted to digital data. For example, a smart sensor might use a stimulus pulse to elicit a damped-ringing response in the output of a DC voltage power supply; capture and convert the analog response (see Figure 4) to digital data; use digital signal processing (DSP) to extract a frequency; average the frequency of a burst of samples; and then produce scalar value of that frequency. That type of sampling is a form of low-pass filtering; and averaging is a form of data smoothing.

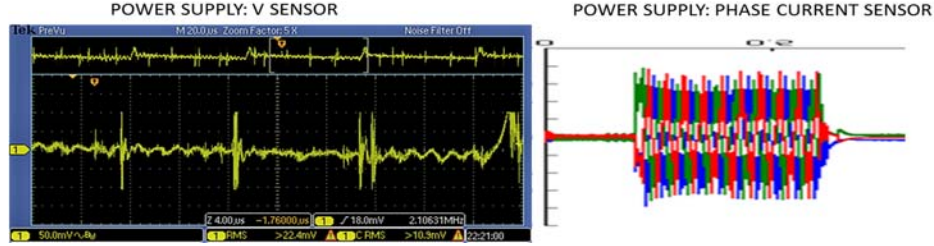


Figure 3: Examples of CBD - Voltage and Current

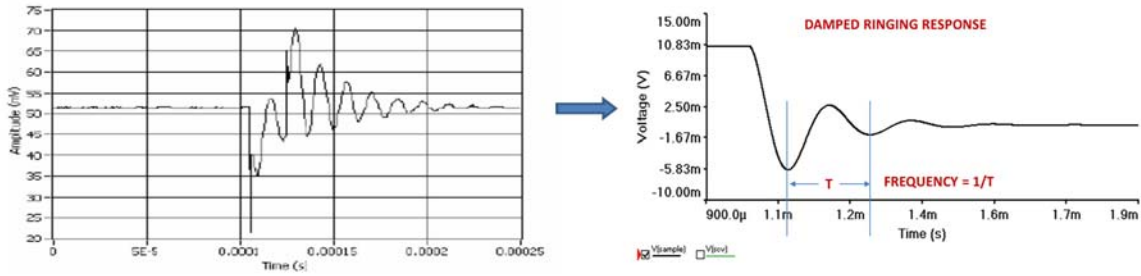


Figure 4: Example of a Damped-ringing Response to a Pulse Excitation

It can be shown that the resonant frequency of a damped-ringing response is highly correlated to the capacitance in the output circuit of, for example, a switch-mode power supply (SMPS). Physics-of-failure (PoF) analysis shows the resonant frequency can be modeled as shown by Equation (1) through Equation (4). [4]

$$V_O = V_{DC} + A_R \{e^{-t/\tau}\} \{\cos(\omega t + \theta)\} + v_{AC} \quad \text{Signal model} \quad (1)$$

$$\omega_0 = \sqrt{A+1} \left( \frac{1}{\sqrt{LC}} \right) \quad \text{Where A is the gain of the feedback loop} \quad (2)$$

$$\omega \approx \omega_0 / \sqrt{(C/(C-dC))} \quad \text{Where dC is the loss in capacitance} \quad (3)$$

$$f = (\omega/2\pi) \quad \text{Where f is the extracted FD} \quad (4)$$

The sampling design might call for a burst of 100 successive samples in a period of 3 ms from which an FD value (frequency) is extracted. Burst sampling might occur once every hour. A collection of FD values (feature data points) forms an FD-based signature: the absolute amplitude of the signature changes as degradation progresses (see Figure 5). Although the FD-based frequency response can be used as input to a prediction algorithm to produce prognostic information, use of the FD-based phase currents is somewhat

problematic. Additional signal conditioning should be performed for both FD-based signatures.

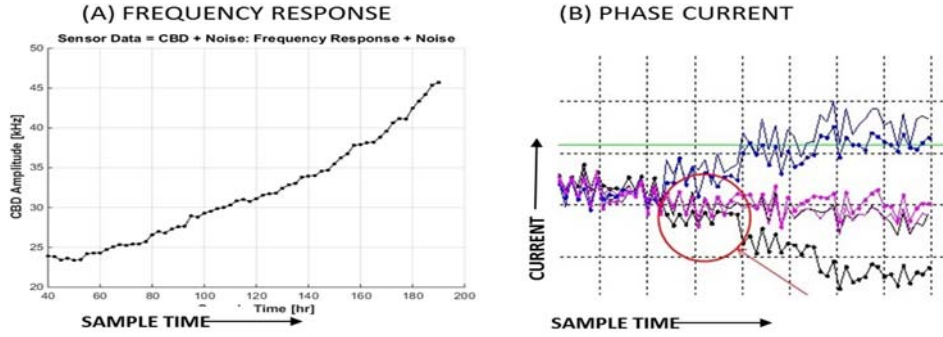


Figure 5: Examples of FD-based Signatures Extracted from CBD

**Conditioning of FD-based Signatures:** We will use the data shown in Figure 5 (A), Frequency Response, as our illustration example. Close examination of that data reveals noise issues/concerns as shown in Figure 6: noise is defined as any variation in a signal not caused by degradation. [2]

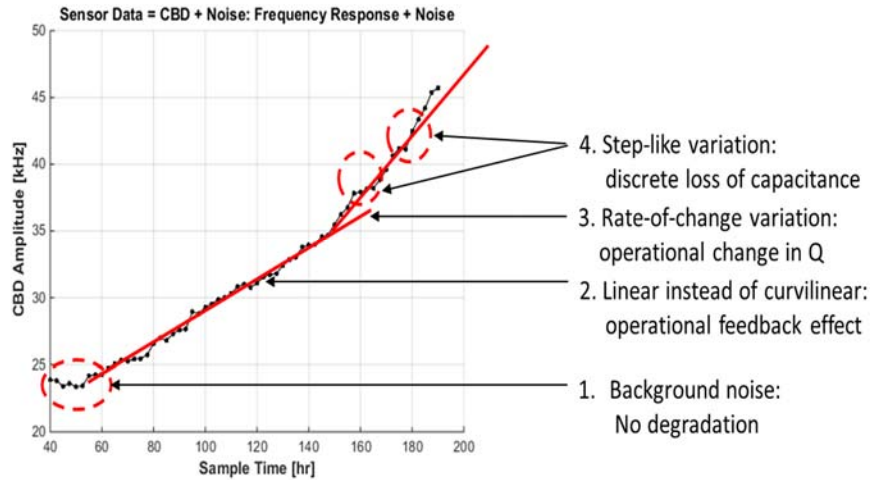


Figure 6: Noise in a FD-based Signature (Frequency Response)

The amplitude (y-axis) and time (x-axis) values of sensor-based FD have differing units of measure such as mA, kHz, V, min, day, and so on, which complicates the processing of such data to produce prognostic information. The first thing we want to do is to account for noise and normalize the data, so after examining experimental and simulated data, we apply data-smoothing (averaging method), we choose a noise margin (NM) of 1.5 kHz and a nominal FD frequency value ( $FD_0$ ) of 24 kHz.

$$FD (conditioned) = [CBD (smoothed) - NM] \quad (5)$$

The result of applying Equation (5) is shown in Figure 7 (A). We then transform FD-based signature data into DPS data by using a  $(dP/P)$  transform:  $dP$  is a change in a

parameter (P) because of degradation. For example, Equation (3) is a power function where  $n = 0.5$  and  $P = C$  (the capacitance). The transform is Equation (6).

$$DPS = dP/P = dC/C_0 = [1 - (FD_0/FD)^2] \quad (6)$$

The result of applying Equation (6) is shown in Figure 7 (B). After examining the original, experimental, and simulation data and performing Failure Mode Effects Analysis (FMEA), you conclude functional failure, operating out of specifications, occurs when the DPS is at or above 0.6 and Equation (7) is used to transform DPS data into Functional Failure Signature (FFS) data, which is plotted in Figure 7 (C).

$$FFS = 100 * (DPS/FL) \quad (7)$$

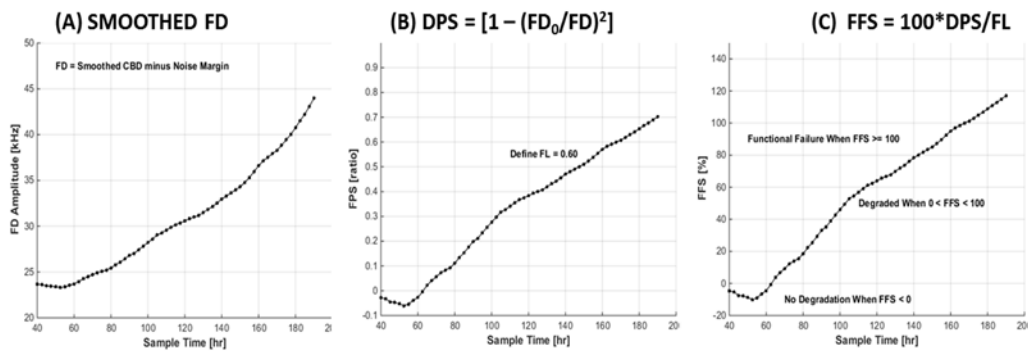


Figure 7: Example of Conditioning and Transforming an FD-signature

**Amenability of an FFS:** We transform data into an FSS because the characteristics of that signature is very amenable to processing by prediction algorithms:

- A transform of ideal linear, power, or exponential data is an ideal straight line
- Non-ideality in the data is “preserved” in the FFS curve – compare Figure 6 to the FFS curve in Figure 8
- All FSS curves have the same y-axis values
  - When a data point is  $< 0$ , state-of-health (SoH) is defined as 100%
  - When a data point is  $\geq 100$ , SoH is defined as 0%
  - Else  $0\% > \text{SoH} < 100\%$
- An FFS transfer curve is more linear compare to its original CBD, which is amenable to prediction algorithms that use Kalman-like filtering and/or random-walk methods to estimate when data is likely to reach a value of 100%.

**DPS Transforms:** CBD curves related to degradation, a change in a parameter  $dP$  are generally the result of power or exponential functions that cause those curves to be convex or concave. To transform decreasing curves to increasing curves, use the following equation:

$$CBD = Data0 - Data \quad \text{Transform decreasing data} \quad (8)$$

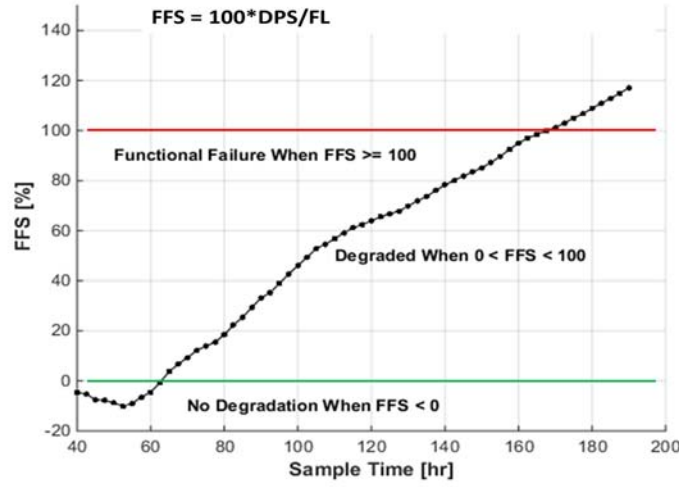


Figure 8: FFS Plot and Degradation Zones

**Power functions:** Directly-proportional functions can be convex, linear ( $n=1$ ), or concave. Inversely-proportional curves are concave. The FD and DPS models are the following:

$$FD = FD_0 [(P + dP)/P]^n \quad \text{Directly proportional} \quad (9)$$

$$DPS = (FD/FD_0 - 1)^{(1/n)} \quad (10)$$

$$FD = FD_0 [P/(P - dP)]^n \quad \text{Inversely proportional} \quad (11)$$

$$DPS = 1 - (FD_0/FD)^{(1/n)} \quad (12)$$

Note the DPS linearity in Figure 9, Figure 10, and Figure 11). When there is no degradation ( $dP = 0$ ), FD equals  $FD_0$ : a constant.

**Exponential functions:** Exponential curves are either concave or convex. The FD and DPS models are the following:

$$FD = FD_0 [\exp(dP/P)] \quad \text{Concave, increasing} \quad (13)$$

$$DPS = \ln(FD/FD_0) \quad (14)$$

$$FD = FD_0 [\exp(-dP/P)] \quad \text{Concave, decreasing} \quad (15)$$

$$DPS = \text{use Equation (8) then apply Equation (17)}$$

$$FD = FD_0 [1 - \exp(-dP/P)] \quad \text{Convex, increasing} \quad (16)$$

$$DPS = \ln[FD_0/(FD_0 - FD)] \quad \text{For } FD \leq FD_0 \quad (17)$$

Note the DPS linearity in Figure 12 and Figure 13. When there is no degradation ( $dP = 0$ ), FD equals  $FD_0$ : a constant.

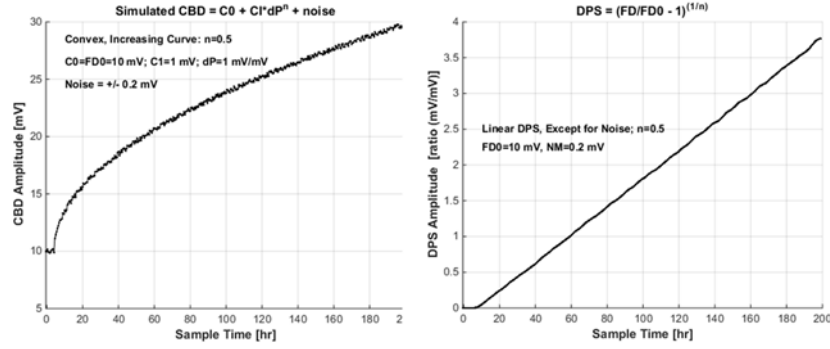


Figure 9: Power Function Example for  $n < 1$ , Directly Proportional

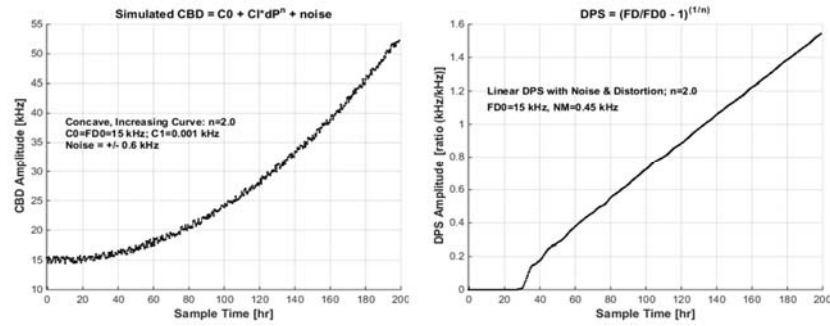


Figure 10: Power Function Example for  $n > 1$ , Directly Proportional

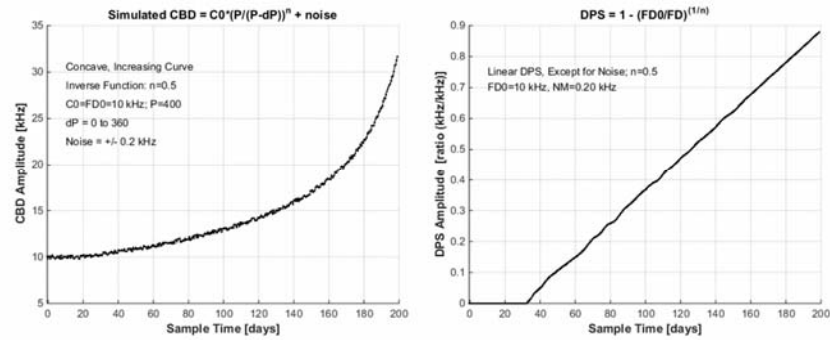


Figure 11: Power Function Example, Inversely Proportional

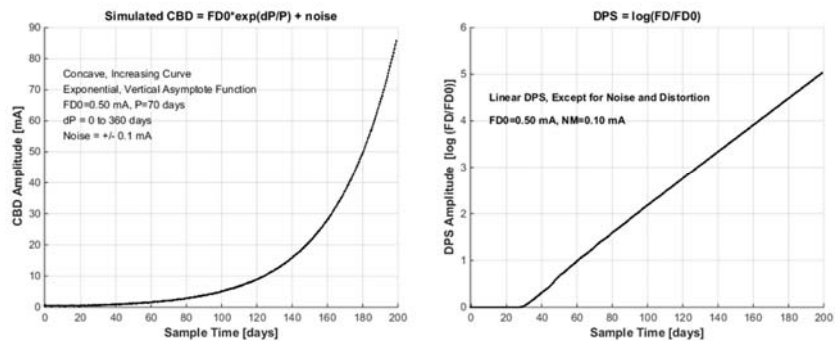


Figure 12: Exponential Function Example, Concave Curve



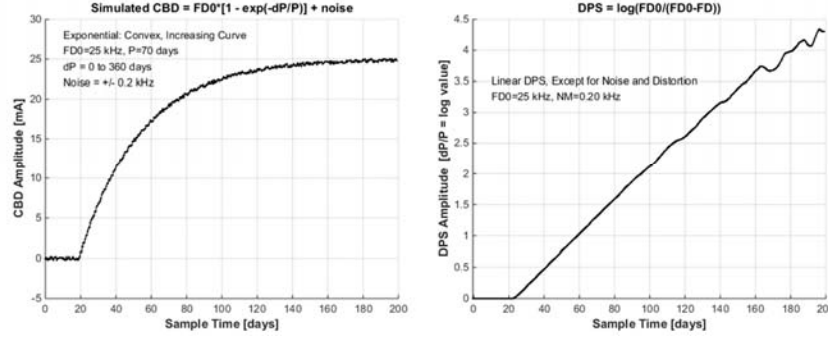


Figure 13: Exponential Function Example, Convex Curve

**Data Fusion and Comparison:** It is often the case that two or more FD-based signatures need to be fused to condition and/or transformed to create a single FD-based signature. For example, the six FD-based current signatures plotted in Figure 5 (B) can be fused and transformed into three different DPS as seen in Figure 14. This state is occurs when one of the six power-switching diodes in an H-bridge power supply driving a rotor degrades.

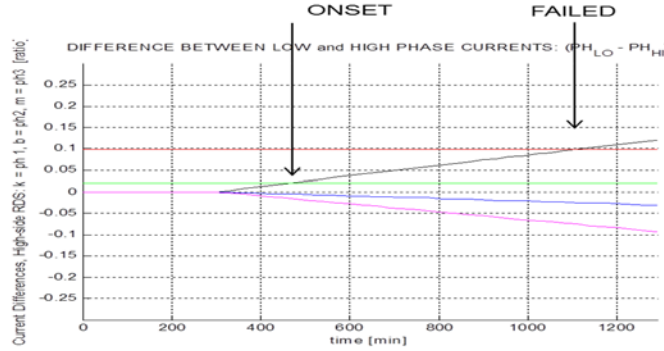


Figure 14: Three FD-based Signatures

**Domain Transform:** It is sometimes necessary to use domain transforms. For example, the voltage and current data in Figure 15 can be transformed into resistance by fusing the two:  $R = V/I$  – but the result, shown in Figure 16 (A), is temperature-dependent. Another transform results in temperature-independent DPS data points, plotted in Figure 16 (B), that is further conditioned (smoothed) and transformed into an FFS as plotted in Figure 16 (C).

**Prognostic Information:** An FFS is input to a prediction algorithm to produce prognostic information: State-of-Health (SoH), Remaining Useful Life (RUL), and Prognostic Horizon (PH): PH is an estimate equal to current relative time of the sampled CBD plus RUL (see Table 1). Figure 17 (A) shows the plots for PH, RUL, and SoH produced from the input FSS shown in Figure 16 (B): the Convergence Efficiency ( $\chi$ ) for a relative accuracy of 10% is better than 98% (refer to Table 1 and Figure 17 (A)).

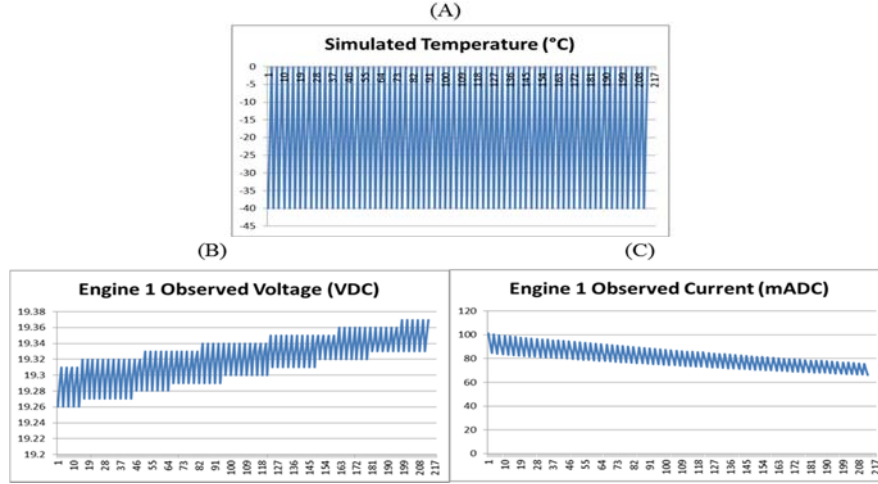


Figure 15: Example of CBD – Temperature, Voltage, and Current.

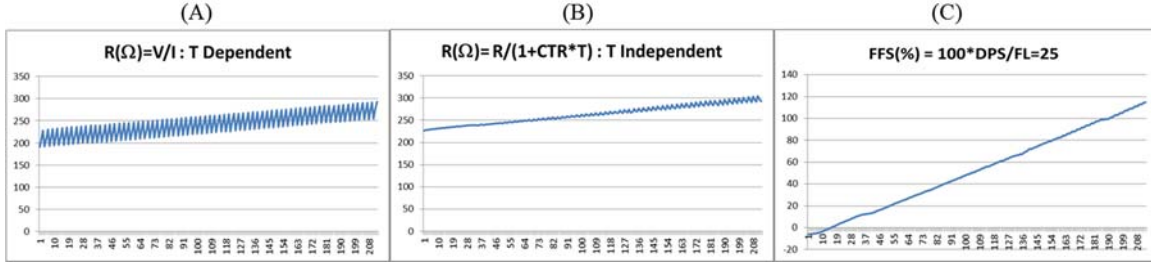


Figure 16: Example of Fusing, Transforming, and Smoothing to Produce an FFS.

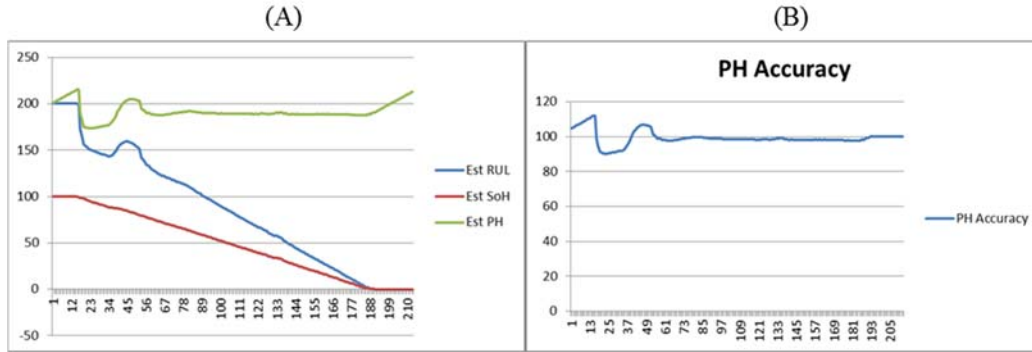


Figure 17: Prognostic Information Plots (A) and PH Accuracy Plot (B)

Table 1: Terminology and Definitions

Term	PHM System Definition
EOL	End-of-Life, time of failure
Prognostic Horizon (PH)	$T_s + RUL$ (sample time + RUL)
Error Margin ( $\alpha$ )	Percent
Relative Accuracy ( $\alpha-\lambda$ )	$(\alpha-\lambda) = (PH / EOL)$
Prognostic Distance (PD)	$PD = EOL - \text{time when degradation first detected}$
Convergence Efficiency ( $\chi$ )	$\chi = (RUL\alpha / PD)$ when RUL within $\alpha$ accuracy

**Conclusion:** In this paper we used an example PHM system based on node definitions and described sensor conditioning of CBD from FD can be extracted. We then described conditioning of FD-based signatures and showed how FD-based signatures are transformed into DPS data and how DPS data is transformed into FFS data. We then described why FFS data is useful as input to prediction algorithms. We asserted that degradation can be modeled as power or exponential functions and we listed the FD and DPS models for those functions. We presented examples of data fusion, comparison, and transforms. We concluded the paper by showing and describing the prognostic information that we obtained using an FFS from example data we used in the paper.

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