PHM/IVHM: CHECKPOINT, RESTART, AND OTHER DESIGN CONSIDERATIONS

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Abstract: An often overlooked set of services associated with Prognostics Health Monitoring and/or Management (PHM)/Integrated Vehicle Health Management (IVHM) are those associated with Checkpoint and Restart (Save and Restore), which is necessary to save and restore operational states. The design of a framework for a PHM system includes consideration of services and support for resource management, such as the following: (1) "What are the considerations for checkpoint/restart?" (2) "How often should nodes be sampled?" (3) "What are the accuracy and precision requirements? (4) "What are the prognostic distance and horizon requirements?" And (5) "How much noise filtering and mitigation is needed to meet requirements?" The answers to these questions and others are especially important for a PHM system using condition-based data (CBD) to support condition-based maintenance (CBM) solutions. In this paper we present concepts and considerations to provide the reader with basic tools and knowledge as a basis to design the framework of a PHM system.[1]

Key words: PHM systems; framework for checkpoint (save) and restart (restore); sampling rate; remaining useful life; prognostic accuracy and precision; prognostic distance; prognostic horizon; noise filtering and mitigation.

Introduction: An often overlooked set of services associated with Prognostics Health Monitoring (Management) are those associated with Checkpoint (Save) and Restart (Restore). We often spend a great deal of time in the design and selection of approaches and algorithms: examples include model-driven versus data-driven versus hybrid; physics of failure and reliability modeling versus statistical modeling versus; and distributions, acceleration factors, and likelihood ratio test (LRT), maximum likelihood estimation (MLE) test, and mean square error (MSE) [1] [2].

We also need to consider how to handle interrupted and resumed operation of subordinate systems, assemblies, and components: (1) "what are the considerations for checkpoint/restart?" Other considerations include, for example, the following: (2) "How often should nodes be sampled?" (3) "What are the accuracy and precision requirements? (4) "What are the prognostic distance and horizon requirements?" And (5) "How much noise filtering and mitigation is needed to meet requirements? The answers to these questions and others are especially important for a PHM system using condition-based data (CBD) for condition-based maintenance (CBM) solutions. This paper uses a hypothetical situation to illustrate checkpoint/restart and other considerations to design a complex PHM system [3].

Hypothetical Example: You are asked to prognostic enable the solenoid to start a turbojet engine; you are informed it has been determined the failure mode is a gradual increase in coil resistance; and you are informed it is not permissible to make direct resistance or impedance measurements – the starter solenoid cannot be removed unless it is replaced.

The customer specifications for the prognostic system include the following: (1) failure is defined to occur when the nominal resistance of the coil of the solenoid changes by 5%; (2) failure must be detected at least 72 flight hours prior to failure; (3) prediction estimates shall have a one-hour precision; and (4) the relative accuracy (α) requirements are (A) within 25% at or before 75% remaining health, (B) within 10% at or before 50% remaining health, and (C) within 5% at or before 25% remaining health.

Reliability Information: You determine (after research, discussions and meetings) some starter solenoids begin to degrade after as little as 200 flight hours, and by 1,000 flight hours all have begun to degrade. After onset of degradation: MTTF (Mean Time to Failure) is 1,200 hours, the smallest TTF is 400 hours, and the largest TTF is 2,700 hours – see the SoH plots in Figure 1. After due consideration, you decide to use CBD to support Condition-based Maintenance (CBM) for the PHM system because you believe reliability-based modeling, usage-base modeling, and/or data-driven methods and approaches will not meet the accuracy and precision requirements of the customer.

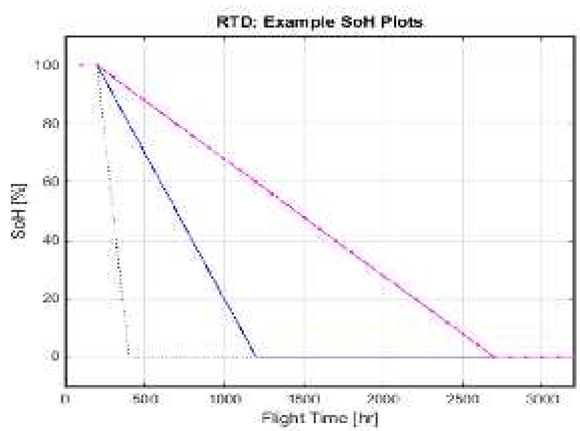

Figure 1: Example of TTF Values Relative to the Time of Onset of Degradation.

Design Approach: You choose to use the design approach shown in Figure 2, in which the framework of the PHM system comprises the following: sensor, feature-vector, prediction, and fault-management [4], which is not shown because you decide to defer that part of the design.

Control and Data Flow: The approach leads you to design a generic PHM system having a data- and control-flow architecture similar to that shown in Figure 3 (after [4]). Data is collected by one or more sensors in a Sensor Framework from one or more monitored nodes; the data comprises one or more leading indicators of failure from which Feature Data (FD) such as voltage, current, and temperature is extracted and input to a Feature Data Framework. Specialized processing such as data fusion, data transforms, and domain transforms are used to produce a Degradation Progression Signature (DPS) and then a Functional Failure Signature (FFS). Each data point in an FFS is passed to a Prediction Framework to produce prognostic information in the form of estimates of State-of-Health (SoH), Remaining Useful Life (RUL), and Prognostic Horizon (PH). Because of the precision and accuracy specifications, you select a sampling rate of twice per hour.

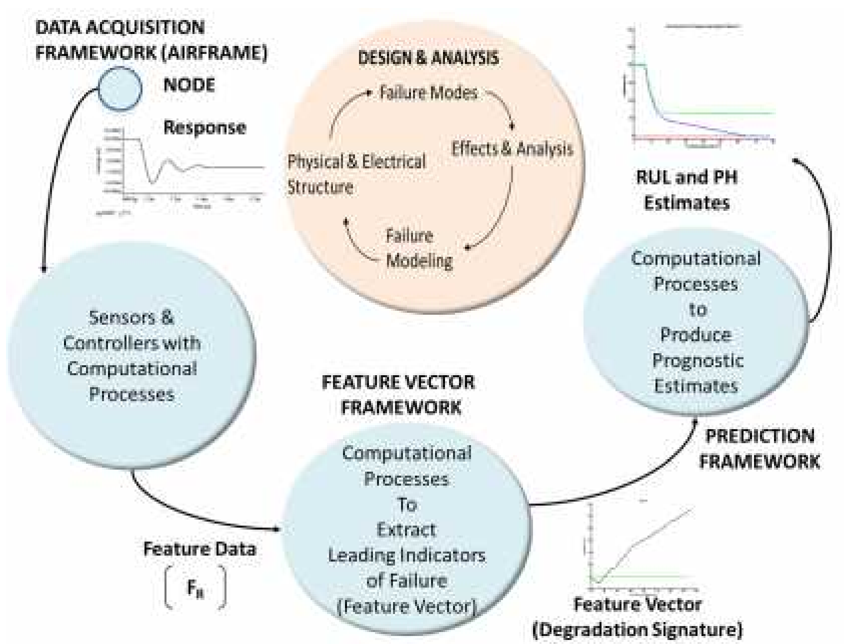

Figure 2: Diagram of an Approach to Designing a PHM Framework.

Prognostic Information: You present your high-level design to customer engineers and you realize those engineers are expecting you to present them with a solution based on their understanding of reliability: Reliability $R(t)$ of a prognostic target is the probability that the prognostic target will operate satisfactorily for a required period of time, and reliability is related to lifetime λ and mean time between failures (MTBF) by the following [5]:

$M = (NT)/F$	Where N = number of test units, T = test time, and F = number of test failures	(1)
$\lambda = 1/M$	Lifetime	(2)
$R(t) = e^{(-t\ )} = e^{(-t/M\ )}$	Reliability	(3)

Performance Metrics: Because your customer is aware of certain performance metrics as defined by NASA [6], you need to explain your PHM system does not use reliability-based modeling; and your need to define and/or explain your prognostic terminology. In addition to RUL and SoH, your terminology includes the following (see Table 1):

Prognostic Horizon (PH) = Estimated EOL = T_S + RUL (4)

Relative Accuracy (α–λ) = (PH / TEOL) (5)

RULα = Estimated TTF - Tα = RUL at Tα (6)

Prognostic Efficiency (χ) = (RULα / PD) (7)

Where T_S = time when data is sampled
Tα = time when estimated EOL is within specified relative accuracy
PD = prognostic distance = PH when degradation is first detected

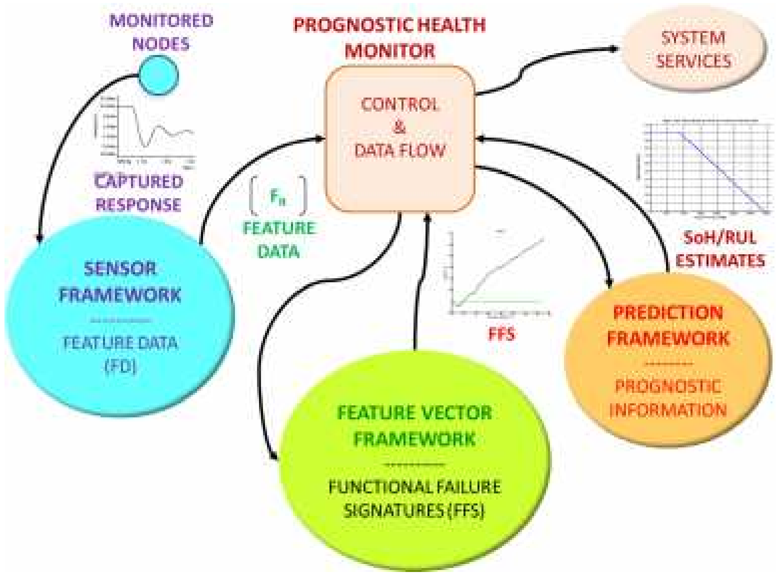

Figure 3: Diagram of a Generic PHM System.

Table 1: Comparison of Terminology and Definitions

Term	NASA Definition	PHM System Definition
EOL	End-of-Life, time of failure	Same
Prognostic Horizon (PH)	EOL – time when RUL estimates are within α accuracy	T_S + RUL
Error Margin (α)	Percent	Same
Relative Accuracy (α–λ)	(α–λ) = (estimated RUL) / (EOL – time of data sample)	(α–λ) = (PH / TEOL)
Prognostic Distance (PD)	Not defined	PD = EOL – time when degradation first detected
Convergence Efficiency (χ)	Not defined	χ = (RULα / PD) When RUL within α accuracy

Rationale for Terminology: The original performance metrics are deficient in two significant ways: initial estimate error and near EOL errors. At the onset of degradation, a

PHM system must make an initial RUL estimate: in our example, a reasonable estimate would be an RUL of 1,200 hours (mean TTF). For a solenoid fails in 400 or 2,700 hours, there is an initial estimate error: an underestimation error of 67% and an overestimation of error of 125%. The NASA-defined relative accuracy results in near EOL errors when estimates occur within a few sampling periods of failure as shown in Figure 4, which is explained as follows: "it may be prudent to evaluate PH on an error band that is limited in extent on the time x-axis by the time instant t_{EoUP}, which denotes the End-of-Useful-Predictions (EoUP), … these predictions are of little or no use practically." [6]

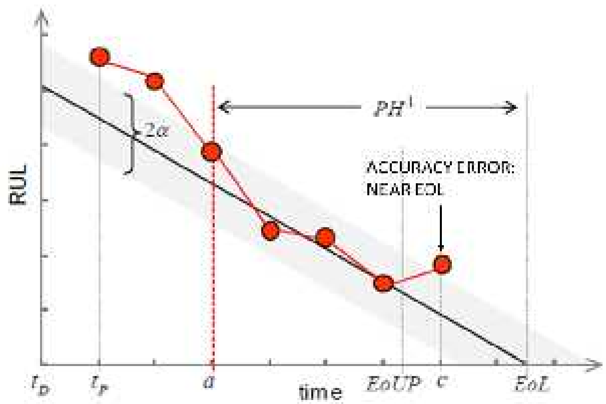

Figure 4: Example of Accuracy Error Near EOL (from [6]).

It is preferable to use a relative accuracy definition that is meaningful, is correct, and does not exhibit such "anomalous" behavior.

Examples of Data and Metrics: To simplify processing, data amplitudes should be normalized by dividing by a nominal value ($D_{NORMALIZED} = D_{MEASURED}/D_{NOMINAL}$) as exemplified by Figure 5. Data should also be made relative to the time when degradation is detected (see Figure 6). The plots in Figure 7 are for ideal PH, ideal RUL, ideal SoH, and ideal PH accuracy; the plots in Figure 8 are examples of initial-estimate errors; and Figure 9 shows examples of non-ideality in FFS transfer curves: signal conditioning such as noise filtering and mitigation is necessary to sufficiently reduce non-ideality. [7]

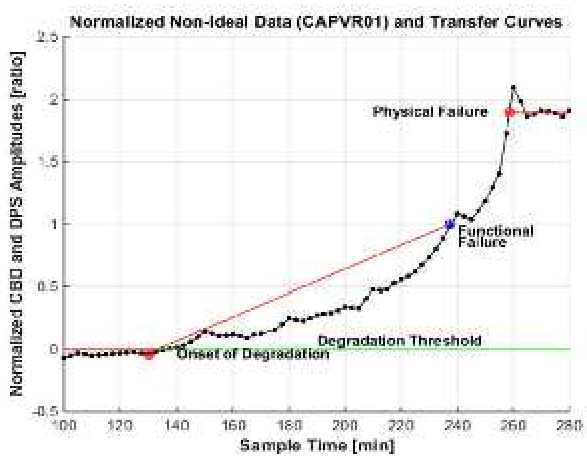

Figure 5: Example of Normalized and Transformed CBD.

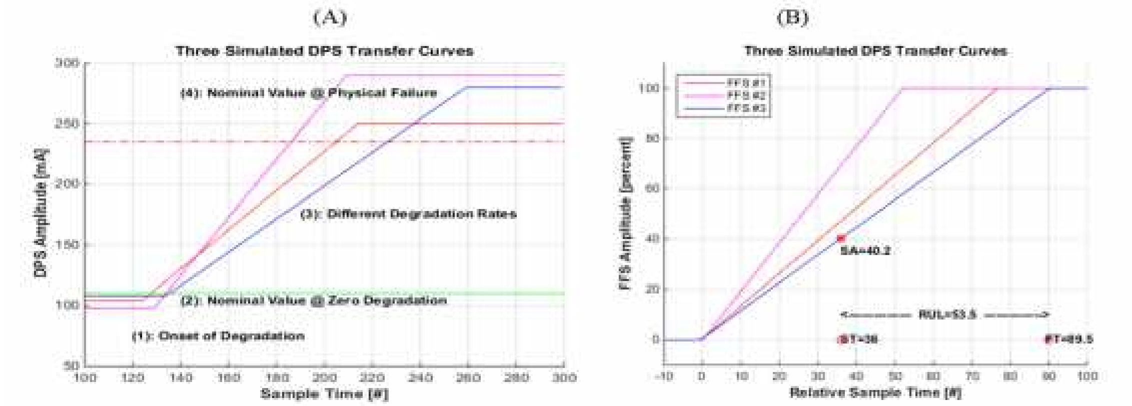

Figure 6: Example of DPS (A) and FFS (B) Transfer Curves.

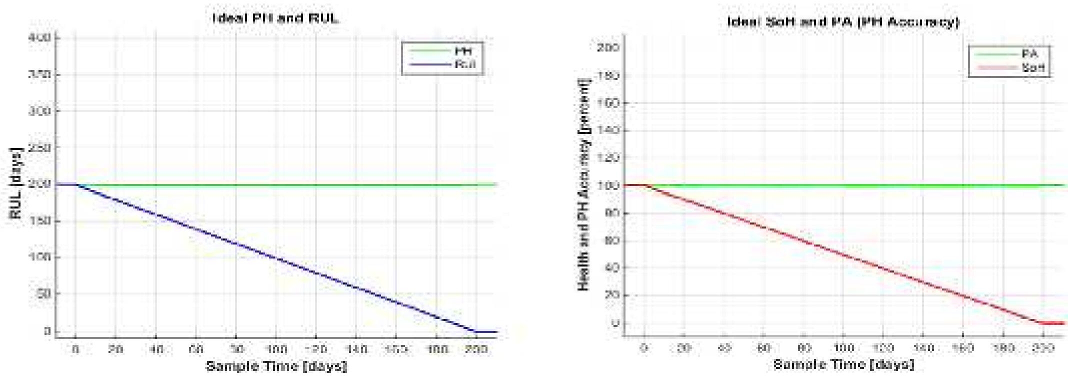

Figure 7: Examples of Ideal Prognostic Information – PH, RUL, SoH, and PH Accuracy.

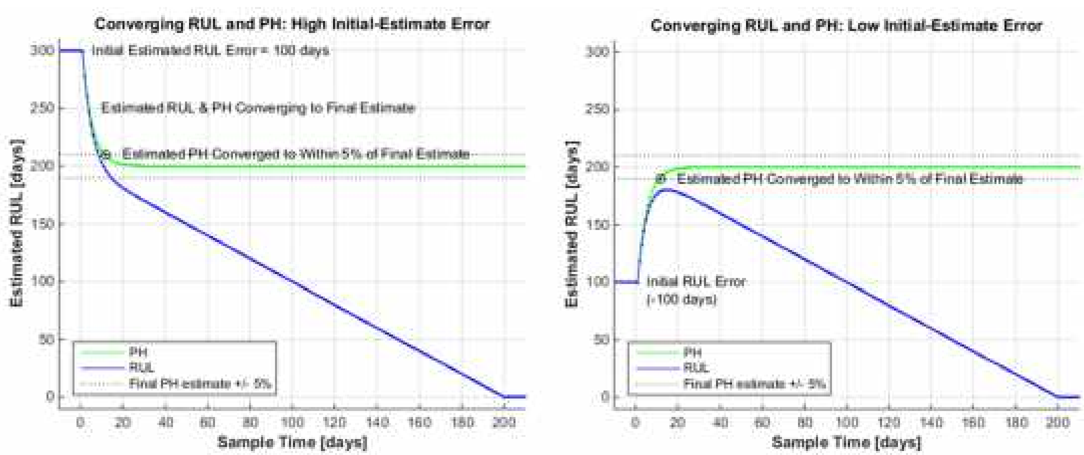

Figure 8: Example of Initial-Estimate Errors and Convergence

FSS Non-ideality: An ideal FSS, straight line, is not achievable in practice due primarily two causes: (1) a change in the failure mode and (2) distortion due to noise which is defined as any variability in CBD not caused by degradation. The first could be addressed by employing a multi-function DPS transform – but experimentation reveals such complexity is not needed. The latter is addressed by employing sufficient noise and distortion filtering and mitigation: see Figure 9. [7]

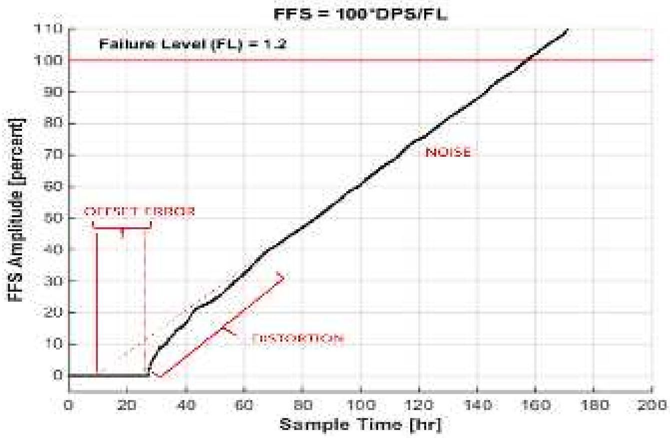

Figure 9: Examples of Non-ideality in FFS Transfer Curves

Experimental FADEC Test Data: You are provided with simulated measurement data obtained from a test bed for a Full Authority Digital Engine Controller (FADEC): see Figure 10. The PHM system performs data conditioning, data fusion, and data transforms with results as shown in Figure 11 and Figure 12 (A).[7]

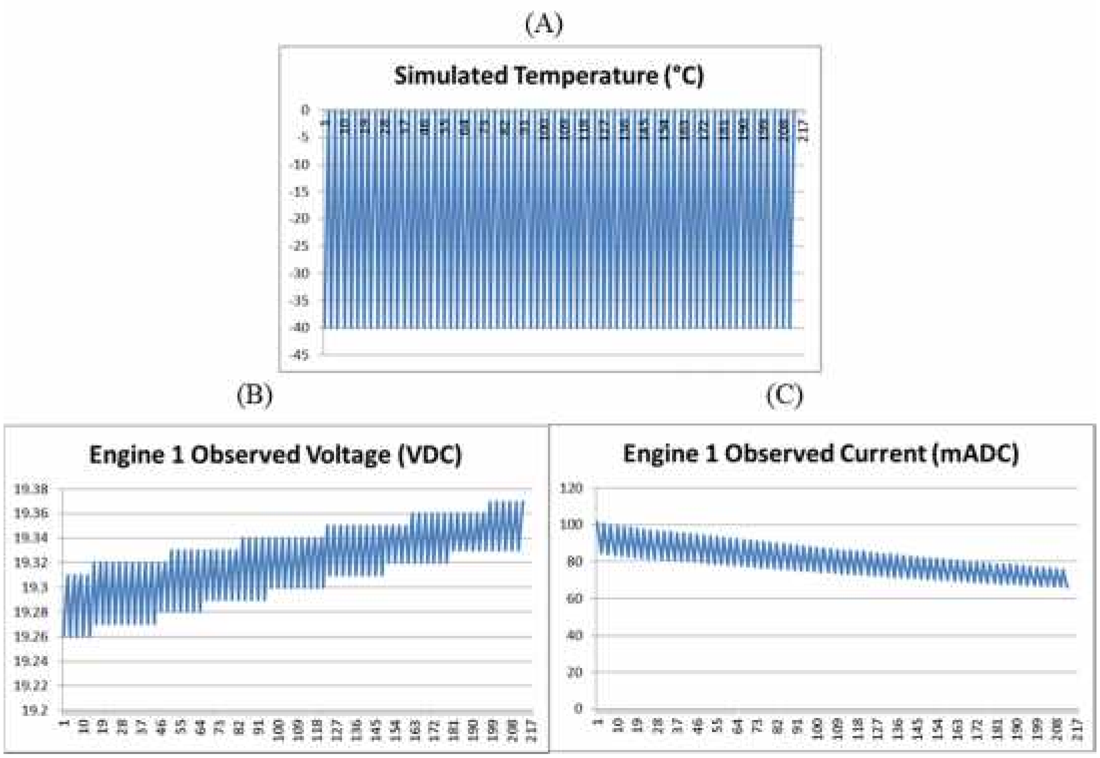

Figure 10: Starter Solenoid Measurements - Temperature, Voltage, and Current.

Prognostic Information – Results: The FFS data is input to your Prognostic Framework with results shown in Figure 12 (B) and (C). The performance is evaluated as “far exceeds requirements” as follows:

- Prognostic Horizon: within 25% at SOH = 99.5%
- Prognostic Horizon: within 10% at SOH = 98.8%
- Prognostic Horizon: < 5% at SOH = 79.4%

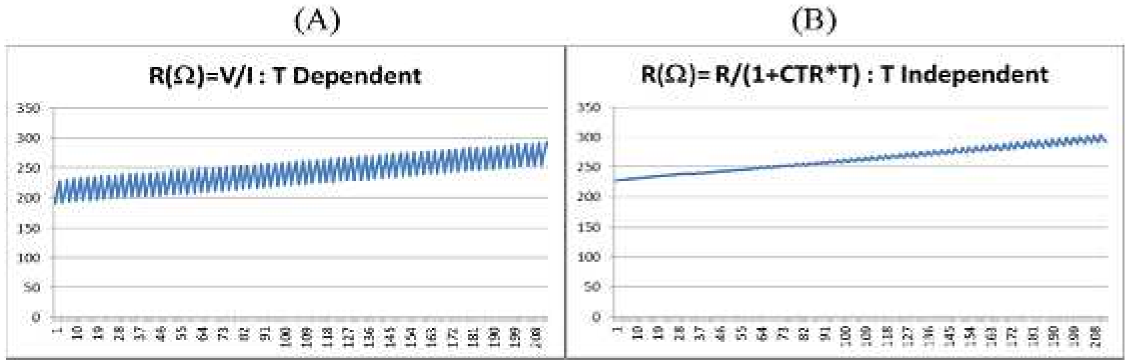

Figure 11: Test Data After Fusing (A) and Transforming (B)

Alpha Test – Revised PHM System: The PHM system is alpha tested and fails because the customer powered off your PHM system between simulated flights: no provisions were made for Check Point/Restart of the system. A redesigned PHM system is necessary: see in Figure 13.

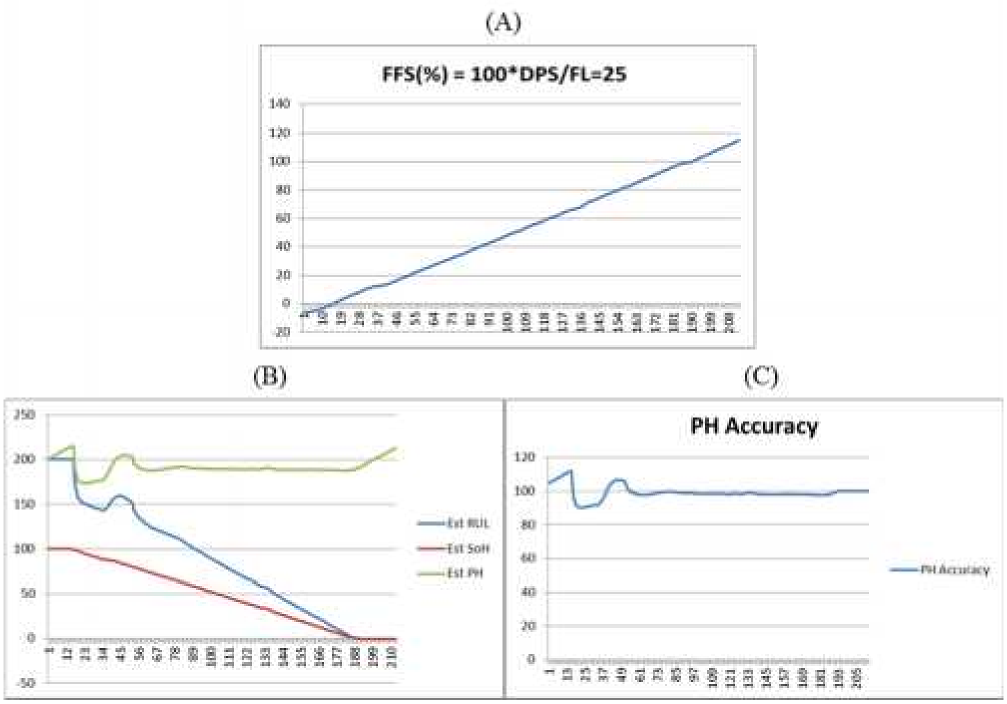

Figure 12: FFS (A); RUL, SOH, and PH (B); and PH Accuracy (C).

Conclusion: This paper used a simple example for a PHM system to present concepts and considerations associated with Prognostics Health Monitoring and/or Management (PHM). Considerations included sampling rate; prognostic information and performance metrics such as RUL, SoH, PH, PD, (α–λ), and χ; data conditioning, including noise and distortion, fusion, and transforming; and Checkpoint/Restart services. [7]

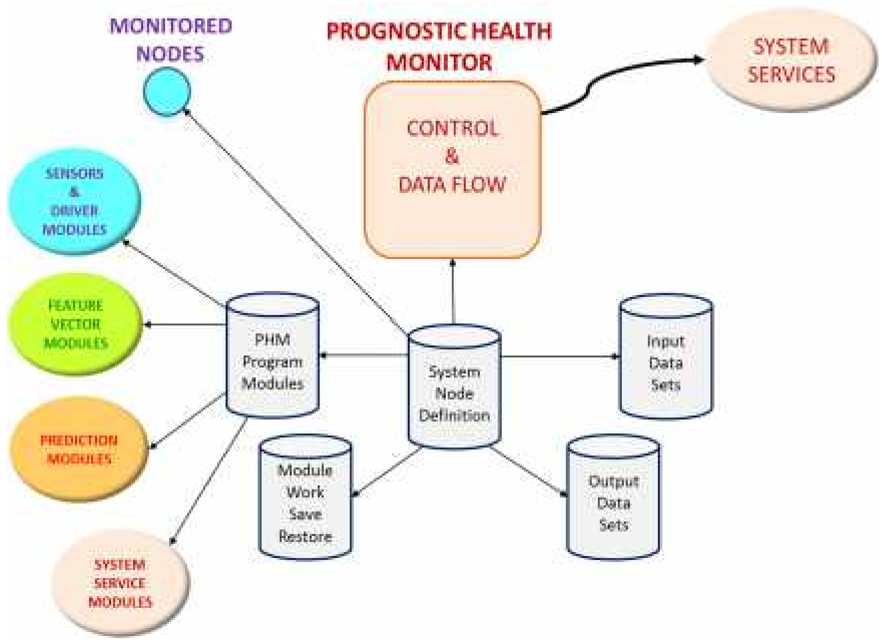

Figure 13: Revised PHM System with Save/Restore (Checkpoint/Restart).

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