A Systems Engineering Approach to Evolution of Physics-Based Prognostic Health Management of Aging Solid Rocket Motor System Assets

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ABSTRACT

Orbital ATK uses a system's engineering approach to develop diagnostic and prognostic health management (PHM) capability for solid rocket motors (SRM) that replaces empirical methods with mechanistic physics-based methods as necessary. Mechanistic methods are required when empirical methods lack the knowledge of a material's response outside of the measured data. Using a multidisciplinary systems engineering focused approach to motor diagnostic and prognostic predictions is the only approach that allows for successful development of a PHM system that can monitor critical parameters from the motor system and use these to determine current and future performance information of each motor and critical component of the motor system. This PHM system can then determine the current performance of the motor system as well as its future predicted performance and estimate the service life or future time at which the motor system can no longer meet customer performance expectations. This paper outlines the general systems engineering approach, philosophy, and payoff of creating a PHM system, and illustrates when and why mechanistic approaches are best. The paper concludes with a discussion of the results obtained from the process on a demonstration system.

1. INTRODUCTION

Today's environment of shrinking budgets and aging systems has driven the need for more capable sustainment capabilities than those used in the past. In the past and currently, SRMs are managed as a fleet once they are fielded, not as individual assets. The current aging and surveillance approach uses a small number or representative assets taken from the fleet and tested. Empirical data collected from these assets are used to predict fleet service life. Since only a small number of samples are used and the exposure of the fleet to the environments may be different for different assets, data scatter is large resulting in large standard deviations with low confidence, which results in conservative fleet reliability estimates. This results in early retirement of the fleet when a predicted reliability of the fleet falls below its requirement. This process leads to high cost for replacing the assets with no way to identify low reliability assets for removal. In addition, decommissioned assets are being used for missions that can accept a higher risk of failure long after the accepted service life has expired. A potentially better approach is to implement a capability than can monitor individual assets and in an active health management system which can provide insight into each asset.

For a relevant example, decommissioned assets are being used for missions that can accept a higher risk of failure long after the accepted service life has expired. A potentially better approach is to implement a capability than can monitor individual assets and in an active health management system which can provide insight into each asset.

It is fairly safe to conjecture that within months of the earliest Chinese development of solid rockets that they discovered the issue of propellant damage and service life. It usually takes one catastrophic failure of a damaged rocket motor for the warrior to develop a strong sense of caution. Farmers and miners were quick to appreciate the benefits of dynamite, but also quick to learn the hazards associated with old materials. Modern solid rocket technology has continued the healthy respect for the issues of propellant aging and motor service life.

The fundamental challenge of propellant aging and motor service life is to identify bad motors in the inventory and remove them before they can be used or cause harm. The current state-of-the-art is to group the individual motors into production lots, perform an empirical extrapolation of key motor properties associated with a safe motor, and apply that prediction to the full lot of motors. The thinking behind this approach is that the risk of leaving a bad apple in service is greater than the cost of replacing some good motors along with the bad motors.

The current aging and surveillance approach uses a small number or representative assets taken from the fleet and tested. Empirical data collected from these assets are used to predict fleet service life. Since only a small number of samples are used and variability between assets associated with materials and manufacturing processes, as well as, the exposure of the fleet to the environments may be different for different assets; data scatter can be large resulting in large standard deviations with low confidence. This makes accurate individual motor prediction difficult, resulting in conservative fleet reliability estimates.

PHM is an enabling requirement for implementing systems with robust condition-based maintenance plus (CBM+) capability. PHM systems are required when the system is known to change behavior with time and the risk of an inaccurate prediction of future behavior is not acceptable. System behavior changes generally occur by one of the following types of conditions;

1) Cumulative physical damage caused by induced loads

2) Material changes due to chemical aging mechanisms or exposure to environments

3) State or condition changes from material property relaxation or failure such as magnetic decay or optical phase changes over time or by exposure to environments including radiation exposures

PHM systems are typically based on either; a) trend extrapolation or b) fundamental knowledge of what causes the changes in system behavior. Users who rely on trend extrapolations hope past and current system behavior will predict future system behavior. This is often not the case and has led to many significant unanticipated system failures. We introduce a systems engineering approach to develop a PHM system based on fundamental knowledge of what causes changes in systems behavior. We refer to trend extrapolation approaches as empirical, but when the approach is based on knowing the fundamental causes of system performance changes, we refer to that as mechanistic PHM.

Some definitions are required as our use of terms is slightly different than standard convention. Our specific usage has grown out of this effort and enables concise communication of the concepts and applications. Diagnostics here refers to the ability to address and assess material and component current states. Figure 1 illustrates the risk of depending on diagnostics alone. System failures are not found until they exist in the system and failures are experienced or system performance is impacted.

Prognostics refer to the ability to address and predict material or component future states based on assumed boundary conditions that affect those future states. The importance of diagnostics should not be underestimated, since they are required for validation and verification of PHM systems and typically precede PHM system development.

Performance models developed for diagnostic or current state predictions are also useful tools for predicting the behavior of a material or component at some future state given an evolved set of performance characteristics obtained by predicting the physical change in the material or components behavior as a result of time and exposure to boundary condition loads. Mechanistic PHM systems require properly managing the interaction between diagnostics and prognostics.

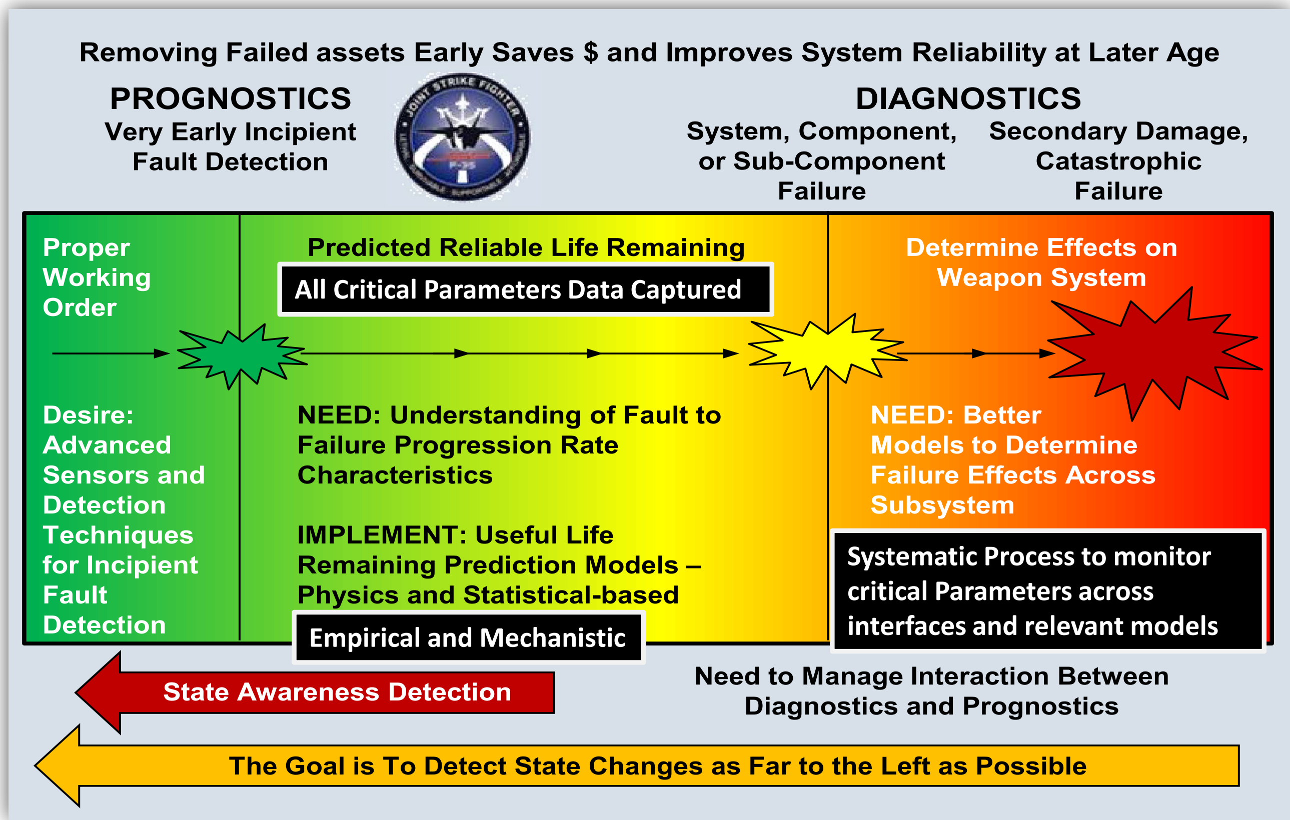

Figure 1. Failure Progression Timeline Example From F-35 Joint Strike Fighter program.[1]

Using individual motor data to predict motor performance is expected to significantly reduce the error in current prediction methods. This allows for the motor's performance prediction at the current time to be more accurate and will provide some improvement in the service life prediction for the motor and in turn the motor sets.

When individual motor management is not practical, a compromise should be considered to provide the most information about the asset that is reasonable to be applied in a fielded system. For example, in a tactical system, smaller assets are typically placed together in storage or in transportation and remain in that configuration throughout most of their useful life. In this case, the pallet or container could be considered the asset and the tracking can be applied to the collection of assets upon the pallet or within the container, since all of the assets will see the same boundary conditions at the same time. Similar assets will most likely experience the same aging effects. If the assets are not of the same type, their response to the environments may be different and this must be taken into account when assessing the conditions of the assets.

Boundary condition history is a key driver in solid rocket motor (SRM) aging. The boundary conditions of an asset refer to those external fields to which it has or will be exposed as a function of time *t*. For example, the temperature history for the i-th asset is $T_i(t)$. The strain tensor field applied may be described by $E(t)$; the magnetic field by $\vec{H}(t)$, a chemical field such as relative humidity by $RH(t)$, and so forth. Note the applied fields are described by tensors, some of rank 0 (scalar fields such as temperature and chemical concentrations), some of rank 1 (vector fields such as acceleration or electromagnetic fields), and some of rank 2 (elastic fields such as stress and strain). Mathematically, the history operator is the full set of relevant boundary condition fields operating on the asset along with their dependence on time.

Orbital ATK used a systems engineering approach to develop diagnostic and prognostic health management (PHM) capability for SRMs that is replacing empirical methods with mechanistic physics-based methods. Mechanistic methods are required when empirical methods lack the knowledge of a material's response outside of the measured data.

Using a multidisciplinary systems engineering focused approach to motor diagnostic and prognostic predictions is the only approach that allows for successful development of a PHM system. This PHM system can determine the current performance of the motor system as well as the future predicted performance of each motor and critical component and estimate the service life or future time at which the motor system can no longer meet customer performance expectations.

The data a PHM system obtains is often not the data used to make decisions. We are typically forced to interpret these data using some form of data reduction, ranging from simple curve fitting to providing constants to a differential equation that describes system behavior. Empiricism (using methods that are data-based analysis methods such as fitting a best-fit line through a cluster of data points and extrapolating to predict future behavior) works well when characterizing the behavior of materials or systems whose structure or behavior does not significantly change under conditions of interest. We are often forced to use empirical methods, however, to predict the behavior of materials and systems even though we know the state of their material structure changes during their life cycle. If we do not understand the most basic cause of the change in state, then we are making blind predictions into the future with empirical methods.

There is great diversity in how engineers define and use empirical versus mechanistic physics-based methods; our goal is to be quite precise here.

An empirical method gathers trends in properties of interest. These trends are obtained from empirical data and do not contain knowledge of why the trends are evolving as they are. In other words, the trends lack causality (Figure 2a and 2b). Therefore, in an empirical PHM solution, an engineer or scientist practitioner gathers data over time, chooses a trend equation that fits the data quite well and that seems a reasonable form for how that data is expected to evolve into the future, and then extrapolates that trend line into the future. This constitutes the heart of an empirical PHM system. Note that the practitioner "chose" the trend line (i.e., the aging model). It was not derived from first principles, and nature is under no obligation to follow that trend line. The reason empirical models often suffer from low fidelity is that nature very often does depart from the chosen trend lines.

A mechanistic physics-based model, on the other hand, seeks to identify the actual physical causes of the asset's evolution in time. Using laws that are well-rooted in universal physical laws, it develops models that describe the evolution of the material's state variables, given a set of applied boundary condition histories. If the model is well-rooted in the universal laws, that is, it can trace its pedigree to the universal laws, and if the model correctly describes the physics of evolution of the asset, then the mechanistic physics-based model is causal. Causality in the models is necessary for the higher fidelity required in future PHM systems. Lack of causality has been the bane of past empirical models and is the reason why attention is turning to mechanistic physics-based PHM.

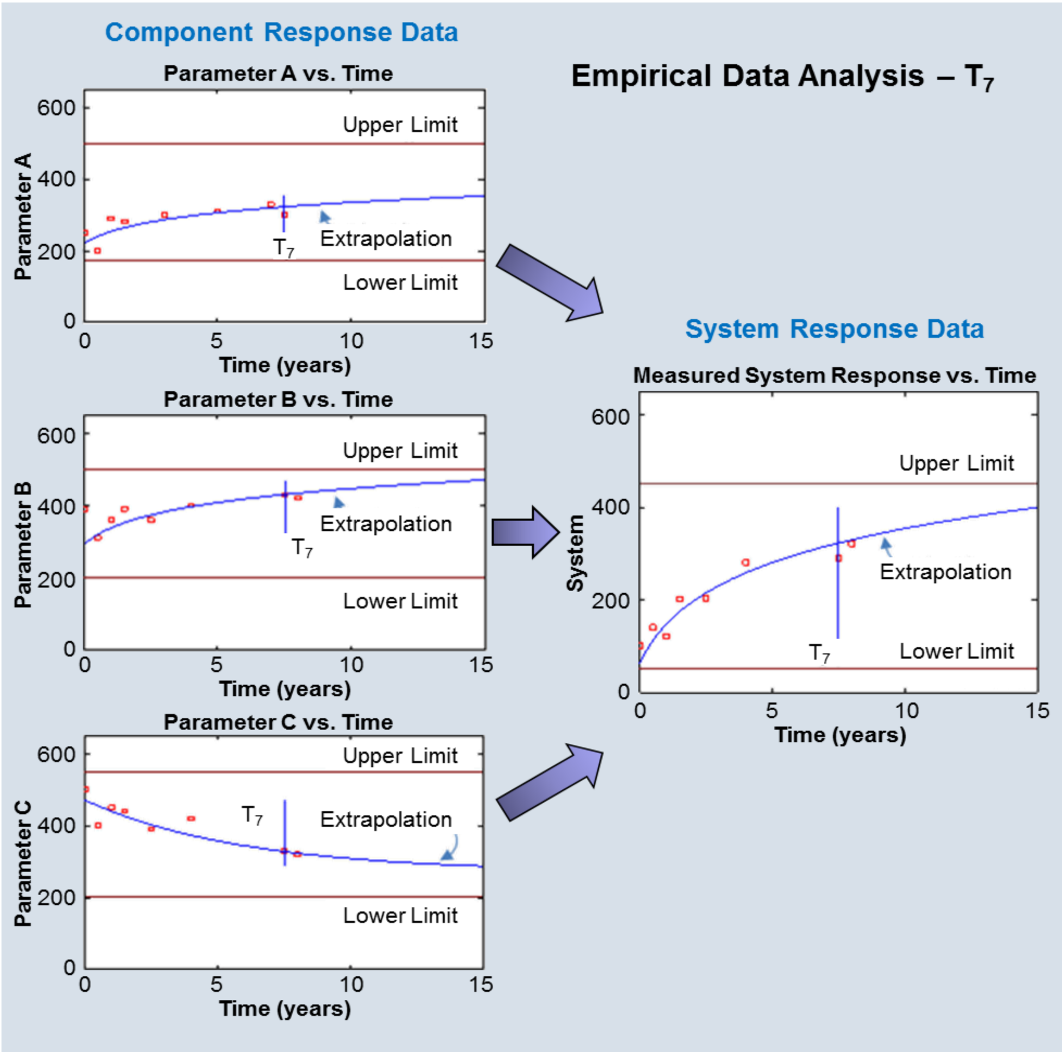

Figure 2(a). Empirical Performance Analysis Example.
Representation of data from time T_0-T_7 and an extrapolation of the data out to time T_{15}.

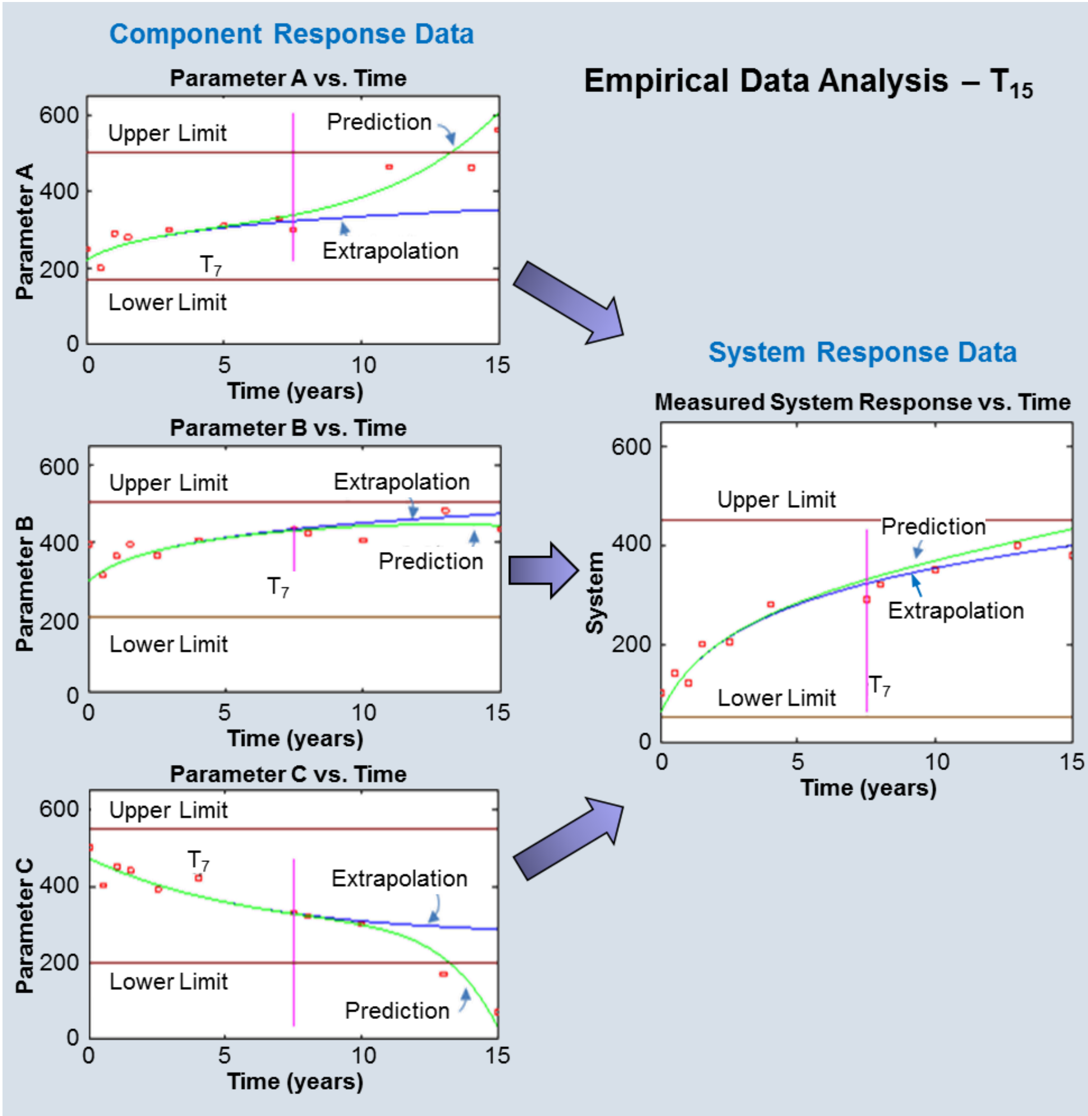

Figure 2(b). Empirical Performance Analysis Example.
The same representation with additional data obtained over time T_7-T_{15} showing prediction lines behaviors changed with respect to the earlier extrapolation. This may indicate a component tolerance is out of specification, whereas, the system response data does not provide indication of such.

The reason for migrating to physics-based PHM systems is because, if executed correctly, this method provides substantially greater accuracy in diagnostic, prognostic, and performance predictions for most asset types. The more complicated the asset is, the greater benefit can be gained from a structured mechanistic approaches to understanding the behavior of the system. If the system, cannot capture the data necessary for monitoring individual critical systems behavior parameters then physics-based PHM systems approaches are needed to accurate understand the system behavior.

We describe conditions when empiricism is adequate for PHM, when it becomes frail, and offer a framework for replacing empiricism with mechanistic methods. The framework consists of developing a predictive train of models that ties the mechanistic methods together into a system prediction. For example, when a product leaves the factory, we know its current state, but from that point forward, we only know the environmental conditions to which it was exposed during its life cycle. We use physics-based models to evolve known zero-time state parameters for the product into its current state at any time during its life cycle using measured environmental data. These evolution models can also predict future states based on assumed environmental conditions. As technology advances, we will use sensors to provide actual measured material properties to determine current state and rely on the evolution models to predict future states.

The benefits of using physics-based methods for complex materials or systems are addressed; particularly a) being able to solve the inverse problem (e.g., material or process optimization) with equal confidence as in the forward solution and b) the ability to segregate and quantify error sources. Solving the inverse problem provides insights on how the system could be improved. Understanding sources of error and their individual effects on PHM allows users to focus on reducing those errors that contribute most to the uncertainty in the system's current and future predicted states.

We discuss an approach for developing PHM systems capable of reliably predicting a complex system's remaining life. We provide a framework to successfully break system requirements down and allocate necessary component requirements down to manageable levels. We also provide a structure that supports the decision process associated with PHM system component development that results in a mechanistic approach. Development of mechanistic PHM systems allows system owners to maintain system reliability and availability by making appropriate repair or replacement decisions with enough lead time to avoid system reliability problems.

This paper outlines the general systems engineering approach, philosophy, and payoff of creating a PHM system and illustrates when and why mechanistic approaches are best. The paper concludes with a discussion of the results obtained from the process on a demonstration system.

2. EMPIRICAL VS. MECHANISTIC METHODS

The ability to predict the viability into the future, however, depends on how well the mathematical models fit motor performance. This presents a problem when the model is a mathematical representation of representative empirical data or the empirical information that is captured does not provide a complete set of the changing parameters. The representative data is obtained by a sample of the fielded boundary conditions applied to the motor set and/or separate accelerated aging samples of materials or components of representative motor constituents.

The approach provides data similar to the data shown in Figures 2a and 2b. This approach has its limitations as indicated by the trending and extrapolation lines within the figures. If the predictions are made within the bounds of the captured data (Figure 2a) for time $\boldsymbol{T_0}$-$\boldsymbol{T_7}$, the data error is limited to the uncertainty in the measurements and how well the data sets from the representative data match real motor performance. Outside of this time, an extrapolation is limited to the behavior of the system matching the same behavior as empirical data contained within the time $\boldsymbol{T_0}$-$\boldsymbol{T_7}$ box. All bets are off, and the error in the predicted performance compared to the actual performance can be huge. This is illustrated by looking at the three components' trends that indicate the effects of the parameters continuing to change over time $\boldsymbol{T_7}$–$\boldsymbol{T_{15}}$ (Figure 2b), two of which are crossing their respective performance limits. This shows a material response that is not captured by a simple empirical extrapolation since the effects of continued exposure to the boundary conditions ultimately result in a physical change in a material or a state change that is not predicted by empirical representations. In other words, the trends lack causality.

Another important concept is also shown in this example, the systems measured performance data still show an acceptable trend, and does not indicate a fault condition is imminent. This is a result of the system's represented data not correctly capturing the critical information about the performance of its components and trending all of this behavior. In this example, two failures exist, but the system data displayed indicate a small offset in the predicted behavior. This is a common problem when the information captured at the system level is some reduced composition of the component parameters and does not accurately indicate change in any given critical parameter. To better understand what the component is doing, and hence reduce the uncertainty in the system, a model needs to be developed based on physical principles that can be used to determine the state of the material at any point in time given specific system-level measurements translated into physical parameters for each components critical performance parameters.

In addition, if one of the components is nearing a cliff where the data drastically shifts over time, this behavior is not accurately predicted by empirical representations. If the interaction of the system component's behavior is affected over time by the exposure to the boundary conditions differently on the different component, then the system'-s response will not be capture by empirical representations of the data since what happened before is not representative of what will happen in the future. These effects could mean the system's capability is nearly exhausted or a trend could actually reverse its effects and leave engineers scratching their heads. The second effect could lead to early retirement of the system when it is not needed, and the first effect would not give system planners time to react to the unpredicted performance degradation. What is needed then is a method to understand how each component affects the system and also what each component contributes to the functional service life of the system.

Empirical and Physics-based Health Management Systems

The following defines the difference between an empirical (or phenomenological) PHM system and a physics-based PHM system. There is great diversity in how engineers define and use empirical versus physics-based models; our goal is to be quite precise here.

An empirical model gathers trends in properties of interest. These trends are obtained from empirical data and do not contain knowledge of why the trends are evolving as they are. In other words, the trends lack causality (Figure 2b). Therefore, in an empirical PHM program, an engineer or scientist practitioner gathers data over time, chooses a trend equation that describes the data quite well and seems a reasonable form for how that data is expected to evolve into the future, and then extrapolates that trend line into the future. This constitutes the heart of an empirical prognostics health management system. Note that the practitioner "chose" the trend line (i.e., the aging model). It was not derived from *first principles,* and nature is under no obligation to follow that trend line. The reason empirical models often suffer from low fidelity is that nature very often does depart from the chosen trend lines.

A physics-based model, on the other hand, seeks to identify the actual physical causes of the asset evolution in time. Using laws that are well-rooted in the universal laws, it develops models that describe the evolution of the material's state variables, given a set of applied boundary condition histories. Given the model is well-rooted in the universal laws, that is, it can trace its pedigree to the universal laws of physics, and the model correctly describes the physics of evolution of the asset, then the physics-based model is causal. Causality in the models is necessary for the higher fidelity required in future PHM systems. Lack of causality has been the bane of past empirical models and is the reason why attention is turning to physics-based PHM.

The reason for migrating to physics-based PHM systems is because, if executed correctly, this method provides substantially greater accuracy in diagnostic, prognostic, and performance predictions for most asset types. The more complicated the asset is, the greater benefit can be gained from a structured mechanistic approaches to understanding the behavior of the system. If the system, cannot capture the data necessary for monitoring individual critical systems behavior parameters then physics-based PHM systems approaches are needed to accurate understand the system behavior.

A systems engineering approach to this problem can provide the necessary structure to understand how each component affects the system. This approach can also reveal the performance indicators at the system level necessary to obtain a valid prediction of component behavior over time. So, development of a system prediction based upon physics-based models provides the best ability to predict system behavior over time.

3. SYSTEMS ENGINEERING APPROACH

Using a multidisciplinary, systems engineering focused approach to motor diagnostic and prognostic predictions is the only approach that allows for successful development of a PHM system that can monitor critical parameters from the motor system and use these to determine current and future performance information of each critical component of the motor system. This PHM system can then determine the current performance of the motor system as well as its future predicted performance and estimate the service life or future time at which the motor system can no longer meet customer performance expectations.

The systems engineering approach first captures all of the customers' functional requirements, desirements, and CONOPS for the desired motor system. Using the captured requirements, desirements, and CONOPS, a functional architecture is defined including functional subcomponent representations necessary to meet the captured criteria and allocate the appropriate requirements to each subcomponent to ensure system performance criteria is met. This process is repeated for each component of the system to determine each subcomponent and its allocated requirements. The process continues until the last subcomponent is defined whose elements are defined by materials or components that are unchanging with respect to the system's exposed environments (Figure 3). Note it is an important part of systems engineering development to capture performance-based parameters at the system and component levels along with any adjustments to functional requirements required by subcomponent capabilities.

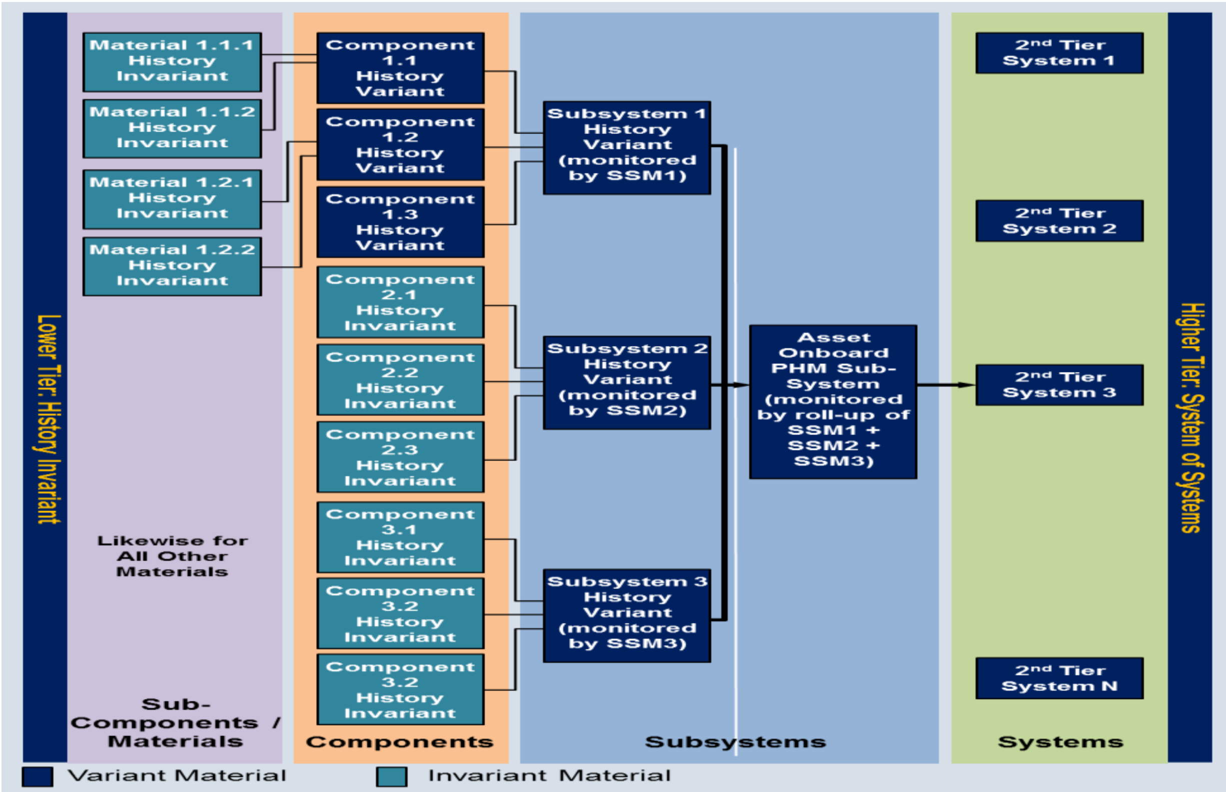

Figure 3. An Asset is Usually Comprised of Various Systems, Which Themselves are Comprised of Still Smaller Subsystems

The asset is usually a component of a larger super-system, which itself is a component of a still larger super-system, and so forth.

Once this deconstruction of the system is accomplished and maintained, including allocating each requirement and defining all interfaces to each component and subcomponent of the system, an understanding can be obtained of what parameters are critical to the performance of each subcomponent and its effect on its parent component. This allows for the systems' critical performance-based parameters to be ascertained and a plan to capture the requisite data to be obtained by a PHM system. This process places an element of component and measurement realism into allocated system functional and performance driven requirements. The verification process is also a necessary and time-consuming process that must be done on the components first and then continue the progression up through the full system. This process is represented by a systems engineering V diagram (Figure **4**) Note it is an important part of systems engineering development to capture performance-based parameters at the system and component levels along with any adjustments to functional requirements required by subcomponent capabilities.

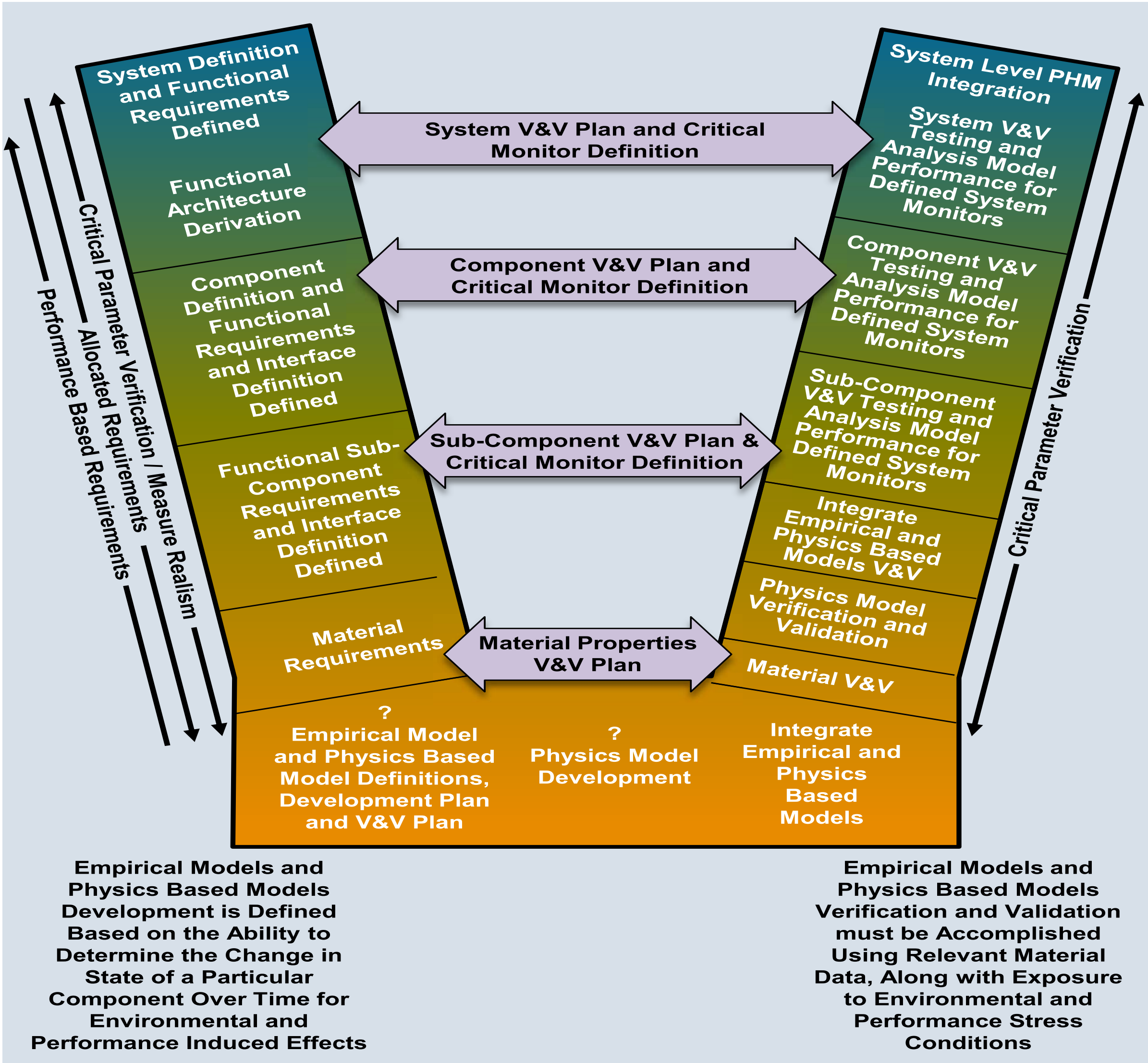

Figure 4. System Engineering V Diagram Showing Requirements Capture, Allocation, and Verification and Validation Process[2]

We now discuss the architecture of a physics-based PHM system that monitors the health of a group of assets (e.g., a fleet of rocket motors, a set of integrated circuits, a set of jet engines). By “monitoring health,” we mean that the PHM system is assessing and communicating the ability of the assets to perform their designed functions.

Major Components of a PHM System

A PHM system’s architecture consists of four main components. The component that assesses the current state of the asset is called *diagnostics*. The component that predicts the time or usage evolution and hence the future state of the asset is called *prognostics*. A third component predicts the performance of the asset given its state, whether that state is the current state or some anticipated future state. Ideally, these three PHM system components are welded together by a data manager, including a cradle-to-grave data warehouse containing all data relevant to evaluate the health for each asset in a group of assets. If the data manager does not exist, coordination among the diagnostic, prognostic, and performance assessment components must be done manually. Figure 5 shows this high-level architecture.

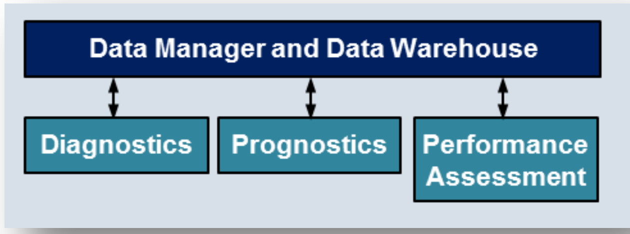

Figure 5. Four Basic Components of a PHM System Architecture.

The State of an Asset—The "state" of an asset is defined by the set of descriptors that the diagnostic, prognostic, and performance assessment models use to predict the evolution and health of that asset. For example, a composite part may have several components of the stiffness matrix and residual strengths as the descriptor set. Note the performance assessment module does not care whether the asset's state comes from the diagnostic or prognostic component – its job is simply to convert a set of asset descriptors defining a state into a performance prediction, whether that state is the current asset state or some projected future asset state.

By the rules of statistical mechanics and laws of thermodynamics, properties of an asset are the ensemble-average over the micro-states of its materials or processes. Physics-based models deal with the micro-states. Empiricism deals with the properties. Since the properties derive from the micro-states, property prediction is not straightforward if micro-state evolution is not straightforward. Later, we discuss when it is appropriate to use empiricism and when physics-based models are needed. For now, we simply define the state variables as those descriptors controlling the micro-states (e.g., radial distribution functions for particulate materials, corrosion chemistry for metals, molecular level dielectric breakdown paths preceding and controlling a macro-breakdown event, cumulative fatigue at the molecular and meso-levels in solder joints subject to vibration). We additionally define causal state variables as those that respond to and evolve with the boundary condition fields applied to the asset.

Group Health vs. Individual Asset Health

The PHM system is most cost effective if it is designed to monitor each individual asset of the group. Group health is always easy to assess if the health of individual assets are known. The converse is not true. If only information about group health is known, individual asset health cannot be known. Therefore, one is in danger of retiring the group from service (a) too early, when many individual assets are or can still operate properly or (b) too late, when some assets of the group will likely fail. If one retires the group too early, unnecessary replacement expenses are incurred; if too late, operations may be compromised.

In many asset groupings, the environmental exposure conditions or operational conditions may be so varied that one would expect some assets to age out before others. PHM systems treating individual assets allow one to "cull" the group, removing those assets that, having seen a harsher set of boundary conditions, have aged out early.

Differences in Architecture: Empiricism vs. Physics-based

The empirical and physics-based material and process models of a PHM system have fundamentally different architectures and the systems engineering tools used to create a physics-based PHM system must be cognizant of these differences. An empirical prognostication is a one-step process; a physics-based prognostication is a two-step process. These differences are most clearly illustrated using a simple operator language as follows.

H = the boundary condition history operator. It consists of the mathematical operations involved in imposing boundary condition fields on the asset's causal state variables.

P = the set of properties needed by the performance prediction models to assess asset viability.

P_{orig} = the original set of properties

P_{future} = the future set of properties at any time past the original time

Empirical prognostication consists of the following step:

$$\text{Step 1: } H(P_{orig}) = P_{future} \qquad (1)$$

In other words, the history operator (mathematical expressions best fitted to trend data as a function of time or of number of uses) transforms the original set of properties into some future set of properties following the trends of the history operator.

Now let us give additional definitions needed for physics-based PHM.

S = the set of causal state variables relevant to the evolution of this asset

S_{orig} = the original values of the causal state variables

S_{future} = the future values of the causal state variables at any time past the original time

EA = the ensemble-averaging operator that averages the ensemble over the set of state variables (micro-states) to obtain the properties of the macro-state. The ensemble-averaging operator usually consists of sums and integrals over micro-states. These sums and integrals are usually quite complicated and often use simplifying assumptions whose validity can and must be tested with simulations and validated by representative sample testing.

Then physics-based prognostication consists of the following two steps:

$$\textbf{Step 1: } H(S_{orig}) = S_{future} \qquad (2)$$

The history operator evolves the original set of causal state variables into some future state whose values are determined by the operation of H on S_{orig}. This step is necessary since it is the causal state variables that are the source of system change(s) with time or use. They are where causality lies; causality does not lie in the properties, but the properties are what the performance assessment models must have to assess asset viability. Hence the next step is:

$$\textbf{Step 2: } EA(S_{future}) = P_{future} \qquad (3)$$

We must ensemble-average over the micro-states whose evolution is dictated by the operation of *H* on the causal state variables and this gives us the properties at any time in the future.

Now the performance assessment models are ready to predict asset viability from these P_{future} properties.

If the causal state variables are history-invariant (do not change with application of *H*), we need only ensemble-average over them once to obtain properties, or easier yet, measure the properties directly. Empiricism is adequate in this case. But if they are history-variant (do change with the application of *H*), empiricism cannot predict their future state because it is ignorant of these causal state variables. The two steps of physics-based models are needed. History variant and invariant materials are discussed in greater detail below.

4. THE ARCHITECTURE OF A PHYSICS-BASED PHM SYSTEM

The architecture of a general physics-based PHM system is shown in Figure 6. We call it the *predictive train*; a sequence of models and data sources that start with the causal state variables on the left and end with predicted asset performance on the right. The physics-based models can be categorized into three groups: (1) the evolution models that describe how the state variables evolve under the influence of the history operator, (2) the conversion models that convert from state variables to the properties required by the performance assessment models, and (3) the performance assessment models that predict how the asset will operate with that given set of properties. The right-most activity is the error roll-up that outputs the desired results of the HM system: when will the asset fail, what component will fail first, and what are the uncertainties and confidence limits in these predictions? We now describe each box in Figure 6 and its function.

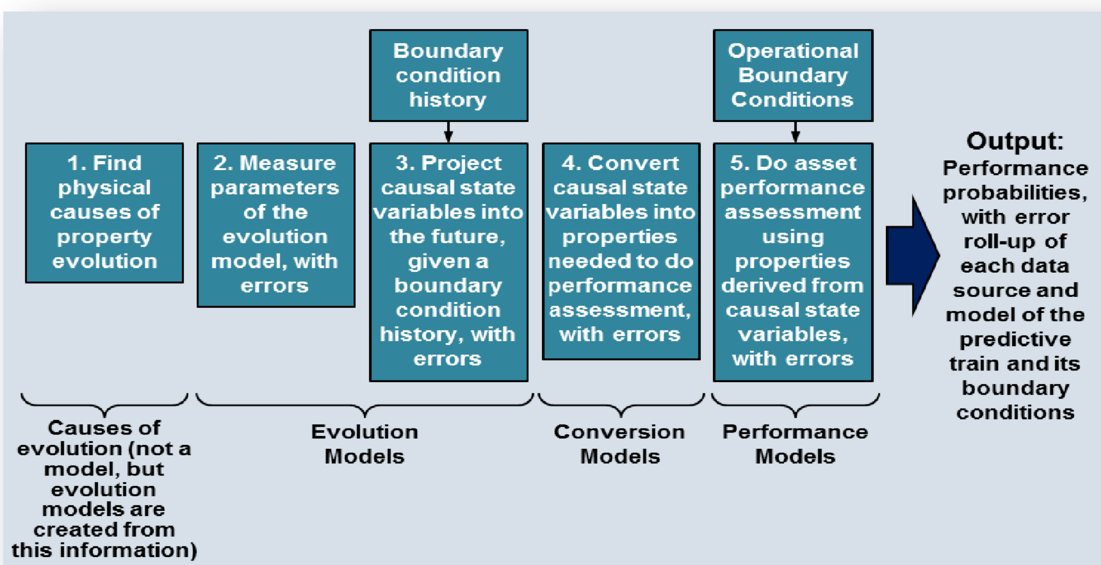

Figure 6. Architecture of a Physics-based PHM System.

The five numbered boxes constitute the predictive train. The error roll-up on the right is the critical activity that provides the desired output – probability of failure with confidence limits.

In Box 1, the causes of property evolution are found at the molecular or meso-level. If an asset component is evolving due to chemical reaction/diffusion processes, chemists will define the causes of evolution. If the evolution is due to cumulative exposure to electromagnetic fields or to mechanical fatigue, other scientists are needed to define the causes of evolution. For most materials, there is a rich literature describing causal processes. The literature is a good starting point, but must usually be adapted and augmented for the specific assets of interest.

In Box 2, carefully designed experiments are conducted, sometimes on idealized as well as real systems, to measure the parameters in the evolution model built from the causal information of Box 1. These experiments must often span several years, since the evolution of many parameters is very slow. Slow evolution is good; otherwise the materials would age out too quickly.

In Box 3, the evolution model is exercised to predict the evolution in time of the causal state variables given an applied set of boundary condition histories (the history operator). We note here that there is generally no such thing as a service life for a set of all assets of a particular type. If some assets have seen a harsher boundary condition history, they age out sooner than other assets from the same set that have not seen the harsher boundary conditions, hence our desire to build PHM systems that monitor individual assets insofar as financially advantageous.

In Box 4, the state variables are converted into the properties needed by the performance assessment models via ensemble-averaging models.

In Box 5, the properties from any point in time are fed into the performance assessment models that predict asset performance.

Lastly, all errors from all data sources and all models are rolled into a final analysis called the error roll-up, which provides probability of failure (or conversely, reliability) versus time or usage. The PHM system may accommodate any desired format for presenting the errors in the predictions and their confidence limits.[3,4]

5. DEMONSTRATION OF AN INTEGRATED MOTOR LIFE MANAGEMENT DATA ACQUISITION AND ANALYSIS SYSTEM

The Integrated Motor Life Management (IMLM) Data Acquisition and Analysis System (DAAS) successfully demonstrates the capability of capturing relevant data from an individual SRM asset, processing this data, and providing a prediction of the asset’s expected performance. IMLM DAAS’ functional architecture is designed to monitor an individual motor in the fleet, record data, and process this data to provide an assessment of the motor's ability to meet its mission today and into the future.

IMLM DAAS uses both the traditional empirical and chemistry based aging surveillance (A&S) methods and an advanced approach that uses physics-based mechanistic models to chemically evolve the materials due to their age and history of environmental exposure capturing the future properties and uncertainties in these properties. This evolution provides a prediction of the future state of the materials based upon physical models of the evolution of the materials. These materials properties are then converted to mechanical properties for prediction of the motor's performance. The empirical and mechanistic information is then used to assess the probability of failure of the motor’s components. This assessment provides the predicted service life of the motor and of the fleet based upon the predictions of each of the motors. This is a defined improvement over the current methods, which provide a prediction of a few sampled motors representative of the fleet and provides no capability to assess environmental exposure or handling effects related to the motors or fleet.

The IMLM DAAS demonstration monitoring system was placed on a SRM (Figure 7) and monitored for boundary condition data. This data was then used to make the thrust prediction for the performance of the motor under operation. The prediction as compared to the measure thrust, and the represented error is shown in Figure 8. The prediction as compared to the motor chamber pressure and the representative error is shown in Figure 9. As can be seen, the performance of the predicted data was well within the uncertainty of the prediction. The IMLM DAAS demonstration showed that a PHM system could be designed, implemented on a motor, and track the motor during both time and space dimensions while collecting, storing and analyzing information relevant to predicting the expected performance of the individual motor. The demonstration used the capabilities developed in the program and diagnostic capabilities that are used in motor design to illustrated the capabilities of an integrated demonstration PHM system giving confidence to the PHM approach.

Figure 7 Full-scale Motor Static Test4

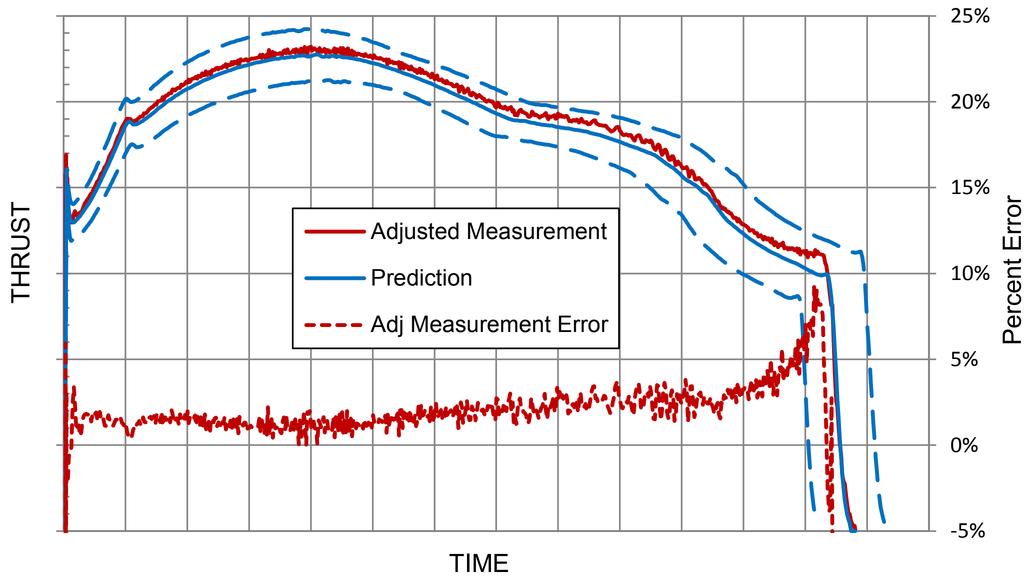

Figure 8. Measured vs. Predicted Thrust and Percent Error

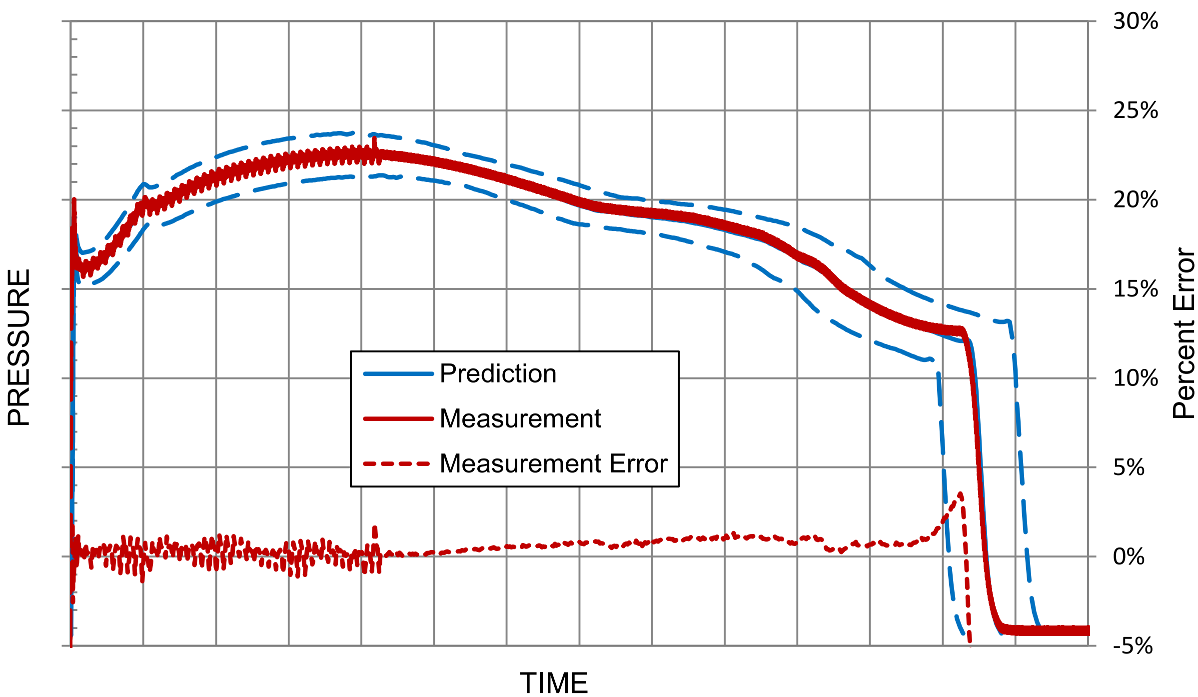

Figure 9. Measured vs. Predicted Pressure and Percent Error Conclusion

This paper has described an approach to PHM that uses physics-based models to enhance the performance of traditional empirical approaches. This approach defines a path to better predict system behavior over time than is currently available and also provides a firm physics-based foundation to develop improved systems in the future. This approach is capable of providing great benefit to systems owners by providing reliable predictions about system performance to within a defined uncertainty as obtained from the error rollup. This allows a system to be monitored for data that can truly provide system performance indicators and allow for early detection of the onset of failure, thereby enabling a more efficient CBM+ capability and extending overall the system life.

6. REFERENCES

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