Methods and Systems for Hybrid Digital Twin Driven Health Predictions for Aircraft Sub-systems

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ABSTRACT

In the aerospace industry, modern aircraft are increasingly equipped with a growing number of sensors, which enable the development of predictive maintenance solutions utilizing data-driven diagnostic and prognostic (D&P) techniques to enhance operational availability and reduce maintenance costs. However, constructing a purely data-driven D&P solution requires a substantial amount of run-to-fail sensor data, which is often unavailable for highly reliable and safety-critical aircraft systems. This limitation restricts the applicability of purely data-driven D&P solutions for aircraft subsystems. To address this limitation, we developed a novel Hybrid Digital Twin framework that integrates physics-based subsystem models with sensor data, enabling enhanced feature generation for improved fault diagnostics and prognostics. Our approach simultaneously estimates both design and health-related parameters, facilitating accurate model calibration even when some of design data is not available. Sensor features enhanced with estimated health-related parameters enable more accurate data-driven diagnostics and prognostics solutions of a sub-system or a component. The framework is demonstrated on key subsystems of the aircraft Environment Control System (ECS), including the Heat Exchanger and Centrifugal Compressor. Various parameter estimation techniques including nonlinear least squares, particle swarm optimization, and extended Kalman filter, Unscented Kalman filter, Physics-Informed Neural Networks, etc., are evaluated. This Hybrid Digital Twin approach offers a promising pathway for more accurate, robust and scalable health management of aircraft subsystems having limited operational data.

Keywords: Physics-based Model, Hybrid Digital Twin, Model Calibration, Parameter Estimation, Heat Exchanger, Diagnostics & Prognostics.

1. INTRODUCTION

Predictive maintenance has become essential in modern aircraft operations to ensure safety, reliability, and cost efficiency by anticipating faults before failures occur. Prognostics and health management (PHM) techniques leverage sensor data to enable real-time diagnostics and prognostics (D&P), thereby reducing unscheduled downtime and maintenance costs. However, purely data-driven D&P methods require extensive run-to-fail sensor datasets, which are often unavailable for highly reliable, safety-critical aircraft subsystems. This scarcity of data limits the effectiveness and applicability of conventional data-driven approaches in aerospace contexts.

To address these challenges, Digital Twin (DT) technology has emerged as a transformative paradigm. A Digital Twin is a dynamic, virtual replica of a physical asset that continuously integrates real-time sensor data with physics-based models to reflect the asset's current state and predict future behavior. Unlike static digital models or one-way digital shadows, Digital Twins enable bidirectional data exchange and adaptive model updates, supporting enhanced decision-making throughout the asset lifecycle.

The foundation of Digital Twins lies in Model-Based Systems Engineering (MBSE), which formalizes system modeling across requirements, design, analysis, and validation phases (Grieves, 2016). The Digital System Model (DSM) serves as the foundational integrated model from which individual Digital Twins are instantiated (Glaessgen & Stargel, 2012; Gartner Inc, 2019). Digital Twins are characterized by their individuality, adaptability, continuous synchronization with physical assets, and scalability across asset fleets (Redding, 2011; Madni, Madni, & Lucero, 2019).

Recent research highlights (Ezhilarasu et al. 2019, Adhikari et al. 2018) the growing interest in Hybrid Digital Twin approaches that combine physics-based and data-driven modeling to overcome limitations inherent in each method (Jardine et al. 2006; Ezhilarasu et al. 2019). Physics-based models offer interpretability and extrapolation capabilities grounded in physical laws, while data-driven methods excel at capturing complex patterns from operational data. Hybrid approaches, including physics-informed machine learning, provide enhanced robustness and accuracy for health monitoring and prognostics.

In aerospace, several organizations have pioneered Digital Twin applications for vehicle health monitoring. NASA and the United States Air Force developed Digital Twins for airframe health management, with Tuegel (2012) proposing a cradle-to-grave airframe Digital Twin that reduces uncertainty through Bayesian updating of service experience. Zakrajsek and Mall (2017) developed a physics-based Digital Twin for aircraft tire health monitoring during touchdown events.

Among aerospace OEMs, Rolls Royce employs Digital Twins for engine health monitoring, enabling an Intelligent Engine that is highly connected and contextually aware. Their Digital Twin supports analysis of blade-off events in Trent engines (Goldenberg B 2025). Similarly, GE has developed Digital Twins for its GE60 engine family and also aircraft landing gear, using initial physics-based models updated frequently with operational data to detect anomalies, forecast maintenance, and predict remaining useful life (Louise Bonnar, 2019; GE Digital Twin, 2016).

Beyond aerospace, Digital Twins have been widely adopted in automotive, maritime, and railway industries. Tesla Motors creates a Digital Twin for every vehicle, enabling over-the-air fixes, software updates, and maintenance scheduling based on real-time usage and performance data (Schleich, Anwer, Mathieu, & Wartzack, 2017).

Physics-based techniques rely on accurate dynamic Digital System Models (DSM) capable of detecting even unanticipated faults. The prediction results of model-based diagnostic and prognostic solutions are intuitive and grounded in modeled cause-effect relationships; deviations from these predictions during 'nominal' conditions may indicate the need for increased model fidelity or enhanced noise-handling methods. These techniques overcome limitations posed by insufficient sensor data or data inaccessibility in harsh environments by employing high-fidelity models to generate multidomain databases of processed variables, effectively serving as virtual sensors (Liu, Meyendorf, Blasch, Tsukada, Liao, & Mrad, 2025). A key advantage is the ability to combine actual sensor data with model outputs to compute residuals, which, when exceeding defined thresholds, indicate potential fault conditions. Model-based solutions adopt a system-oriented approach characterized by high precision and determinism, allowing failure thresholds to be defined in accordance with system performance.

Pujana et al. (2023) presents a hybrid-model-based Digital Twin methodology for wind turbine power conversion systems that integrate physics-based models with data-driven analytics to enhance failure detection and classification. By generating synthetic failure data from real operational observations and employing machine learning techniques, this approach effectively addresses data scarcity and improves predictive maintenance capabilities.

Building on these advances, this work presents a novel Hybrid Digital Twin framework that integrates physics-based subsystem models with sensor data to generate advanced diagnostic and prognostic features. A key innovation is the simultaneous estimation of design parameters (e.g., mechanical dimensions) and health parameters (e.g., efficiency degradation), enabling accurate model calibration even when original design data is unavailable or affected by operational changes such as aging or environmental stress. This dual-parameter estimation enhances the fidelity of both digital system model and operational Digital Twins for individual aircraft subsystems.

We demonstrate the framework on the Heat exchanger (HX) of the aircraft environment control system (ECS), a critical yet difficult-to-monitor component prone to degradation from clogging, corrosion, and icing. HX's complex design and inaccessibility necessitate accurate prognostics to minimize unscheduled maintenance. Our approach calibrates physics-based HX models using various parameter estimation techniques including nonlinear least squares, particle swarm optimization, and extended Kalman filtering applied after each flight to track degradation trends. Ma, Lu, and Liu (2015) propose a fault diagnosis method for the aircraft environmental control system's HX using a strong tracking filter combined with a modified Bayes classification algorithm. Their approach addresses limitations of traditional filters by adaptively estimating fault-related parameters, enabling accurate and rapid detection and classification of HX faults. Similarly, Jonsson, Lalot, Palsson, and Desmet (2007) demonstrate the use of extended Kalman filtering with nonlinear state-space models for online detection of fouling in HX, showing high sensitivity even during transient operating conditions.

The remainder of this paper is organized as follows: Section 2 reviews related work on Digital Twins and hybrid modeling approaches in aerospace PHM. Section 3 details the proposed Hybrid Digital Twin framework and parameter estimation methodologies. Section 4 presents the case study on HX, including model calibration and prognostics results. Section 5 discusses the implications and potential extensions of the approach. Finally, Section 6 concludes the paper and outlines future research directions.

2. DIGITAL TWIN OVERVIEW

Digital Twin technology has rapidly evolved as a cornerstone for advanced health monitoring and predictive maintenance in aerospace and other industries. By creating a dynamic, data-driven virtual representation of physical assets, Digital Twins enable continuous monitoring, diagnostics, and prognostics throughout the asset lifecycle. To fully appreciate the capabilities and applications of Digital Twins, it is important to understand their foundation within Model-Based Systems Engineering (MBSE) and the role of Digital System Models (DSMs). The following subsections provide a structured overview of these foundational concepts, clarify the unique characteristics of Digital Twins, and explore their methodologies and applications in diagnostics and prognostics.

2.1. Model-Based Systems Engineering and Digital System Models

Model-Based Systems Engineering (MBSE) provides a structured and formalized approach to system development by employing models to support requirements, design, analysis, verification, and validation throughout the system lifecycle. According to Friedenthal, Griego, and Sampson (2007), MBSE utilizes various types of system models, including functional/behavioral, performance, structural/component, and other engineering analysis models. These diverse models collectively contribute to the creation of a comprehensive Digital System Model (DSM), which is a fundamental product of Model-Based Engineering (MBE).

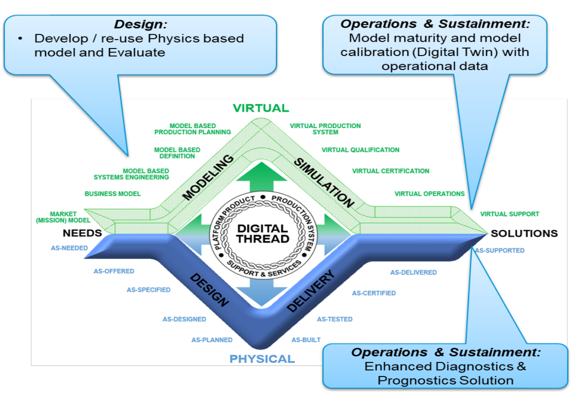

Figure 1. Model Based Engineering Diamond with key enablers

Figure 1 shows key enablers for Digital Twin driven D&P solution, such as model development, calibration, and enhanced diagnostics and prognostics across the product lifecycle.

As described by Reid and Rhodes (2016), the DSM integrates all technical data into a unified framework, serving as the foundation from which individual Digital Twins are instantiated. This integrated model ensures consistency and traceability across the system's lifecycle, enabling seamless collaboration among engineering disciplines.

With this foundational framework in place, it is essential to clearly distinguish the Digital Twin from other digital representations, which we discuss next.

2.2. Defining Digital Twin: Distinction from Digital Model and Digital Shadow

The term "Digital Twin" refers to a dynamic digital replica of a physical system that is continuously updated with real-time data on performance, maintenance, and health status throughout the asset's lifecycle (Madni, Madni, and Lucero, 2019). Unlike static digital models or one-way digital shadows, Digital Twins enable bidirectional, fully integrated, and automatic data exchange between the physical and digital systems, allowing real-time synchronization and interaction.

Figure 2 shows the distinction between a Digital Twin, a Digital Model, and a Digital Shadow. Digital Model is a static digital version of a physical object, such as a CAD model, without automatic data exchange between the physical and digital entities. A Digital Shadow involves a one-way automated data flow from the physical object to the digital counterpart, where changes in the physical asset update the digital shadow but not vice versa. In contrast, a Digital Twin supports bidirectional data flow, enabling the digital model to influence the physical asset and vice versa. This distinction is critical for enabling advanced diagnostics and prognostics capabilities and is emphasized by Fuller, Fan, Day, and Barlow (2020). However, we are not adhering to such a strict definition and also regard Digital Shadow as a form of Digital Twin.

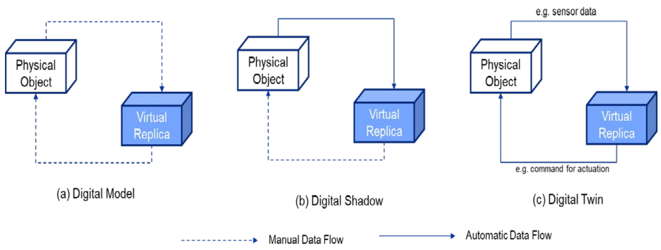

Figure 2. Distinguishing Digital Twin from Digital Model and Digital Shadow

Having established the unique nature of Digital Twins, we now explore their key properties that enable advanced diagnostics and prognostics.

2.3. Key Properties of Digital Twins

Digital Twins possess several essential properties that make them uniquely suited for diagnostics and prognostics in complex systems such as aircraft sub-systems:

- **Individuality:** As defined by Grieves et al. [7], Digital Twins exist in different forms, including the Digital Twin Prototype (DTP) and Digital Twin Instance (DTI). DTP represents the asset at the prototype stage, incorporating design and requirement data, while the DTI corresponds to a specific physical asset in operation, continuously linked to its physical counterpart with real-time sensor data and service records.

- **Adaptability:** Digital Twins must be adaptable to accommodate different asset classes and evolving operational scenarios. Nikula, Paavola, Ruusunen, and Keski-Rahkonen (2020) demonstrated an online adaptation mechanism using differential evolution algorithms to update model parameters in real time, enhancing monitoring and diagnostics accuracy. Madni et al. (2019) introduced the concept of an 'Adaptive Digital Twin' that continuously updates models with real-time and batch data, improving predictive capabilities.

- **Continuity:** Digital Twins are continuously updated with sensor data from physical assets, enabling real-time monitoring and intelligent decision-making. In the Industry 4.0 context, this continuous data flow supports run-to-fail analytics and proactive maintenance strategies.

- **Scalability:** Scalability allows Digital Twins to learn from multiple similar assets and address complex use cases. Jia, Wang, and Zhang (2022) proposed a multi-scale, multi-scenario, and multi-dimensional approach to complex Digital Twin development using a 4-C architecture (composition, context, component, and code). This approach modularizes Digital Twins into reusable components and manages information fusion and multi-context interactions, facilitating scalable and comprehensive digital representations.

These properties collectively empower Digital Twins to serve as powerful tools for health monitoring and predictive maintenance. To realize these capabilities, appropriate methodologies and enabling technologies are required, which we discuss next.

2.4. Methodologies and Technologies for Digital Twin Development

Developing effective Digital Twins involves a combination of physics-based, data-driven, and hybrid modeling approaches. Rasheed, San, and Kvamsdal (2020) provide a comprehensive review of these methodologies, highlighting physics-informed machine learning as a promising hybrid approach that leverages the strengths of both physics-based interpretability and data-driven pattern recognition.

Lim, Zheng, and Chen (2020) further explore the technology stack for Digital Twin implementation, detailing methods and tools across product lifecycle management (PLM) stages. Their work underscores the value of Digital Twins in enabling new business models through enhanced asset management and predictive maintenance, emphasizing the importance of integrating Digital Twins within the broader digital thread.

These methodologies and technologies address challenges related to model accuracy, adaptability, and real-time performance, which are essential for reliable health predictions in aerospace applications.

Building on this foundation, the next subsection highlights the practical application of Digital Twins in diagnostics and prognostics for aircraft subsystems.

3. Diagnostics and Prognostics Driven by Hybrid Digital Twin

Hybrid techniques combine knowledge of the physical process with information extracted from observed data, leveraging the strengths of both model-based and data-driven methods. An important advantage of Hybrid Digital Twins is their ability to calibrate and estimate unknown design parameters or characteristics across multiple components and subsystems, to capture asset-specific behavior of the system and to enhance predictive capability.

The parameters of a Digital System Model can be classified into two categories: design parameters (e.g., mechanical dimensions) and health-related parameters (e.g., efficiency). The estimated health-related parameters are subsequently utilized for diagnostics and prognostics of the subsystem.

Physics-based Digital System Models and their design parameters are typically proprietary to suppliers for the specific assets they manufacture. In many cases, obtaining this design data from suppliers is challenging, creating a bottleneck in developing accurate Digital System Models that define normal system behavior. This paper proposes a novel reverse engineering approach to estimate unavailable design parameters for subsystem Digital Twins using sensor measurements collected under specific nominal operating conditions. Key steps involved in this approach are:

- Physics-based Digital system model (DSM) development (or availability of existing DSMs for system/subsystem)
- Calibration of physics-based Digital System Model using nominal sensor data (transformation to Digital System Model)
- Generation of Advanced Features by comparison of Digital System Model outputs with corresponding sensor data/Operational Digital Twin

Health-related parameters and associated performance characteristics are crucial for subsystem Digital System Models to accurately replicate the nominal behavior of the subsystem. This is achieved by calibrating the Digital System Model using nominal sensor data extracted from comprehensive historical datasets collected across various operators.

The Physics-based Digital System Model (DSM), as depicted in Figure 3, represents the expected behavior of a system during operation, essentially describing "what should happen." This DSM is created from a physics-based model that incorporates the system architecture, component specification sheets, and geometric data, and is continuously updated using nominal operational data. In contrast, operational data captures "what is actually happening." By continuously calibrating the physics-based model with asset-specific operational data, the model evolves into the Operational Digital Twin. Health-related parameters, along with various statistical features derived from the residuals between the Digital System Model and the Operational Digital Twin, combine to form an augmented feature space utilized for failure diagnostics and prognostics.

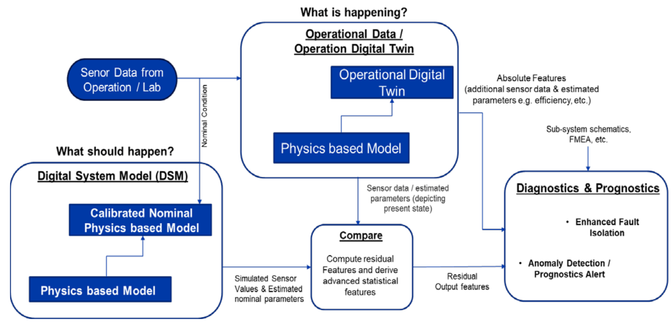

Figure 3. Use of Digital Twin for Diagnostics & Prognostics

The subsequent sections provide a detailed discussion of the aforementioned steps. Step 1 implements physics-based Digital System Model. Step 2 focuses on the calibration of Digital System Models through parameter estimation, supported by a benchmarking study of various techniques using a spring-mass-damper example. Based on this benchmarking, the most effective and efficient approach is identified and subsequently applied to a real-world use case involving HX diagnostics and prognostics, as part of Step 3.

3.1. Physics-Based Digital System Model (DSM)

The physics-based modeling approach involves representing the underlying physical phenomena of a system through mathematical equations. Numerous advanced software packages are available to facilitate the development of such models. Domain knowledge and expertise play a critical role in constructing accurate physics-based models. Unlike data-driven approaches, physics-based models are deterministic and grounded in system dynamics and fundamental physical laws.

An example of a physics-based model is the spring-mass-damper system as shown in Figure 4, commonly used to analyze responses of various engineering applications such as aircraft landing gear operation.

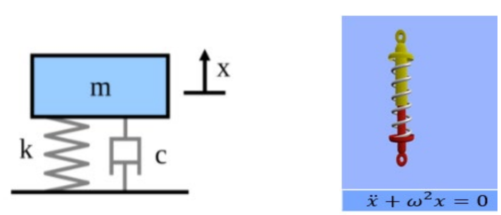

Figure 4. Spring-mass damper system

The spring-mass system parameters include mass (m), stiffness (k), and damping coefficient (c), which govern the system dynamics.

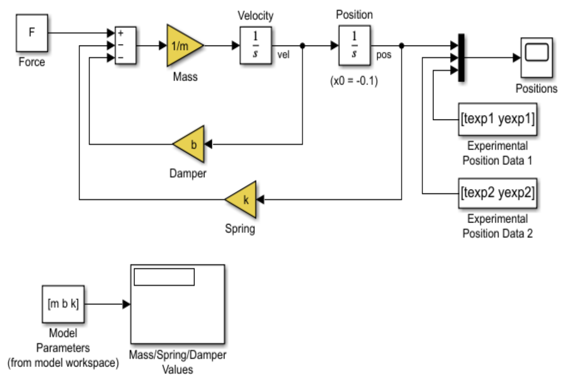

Figure 5. Spring mass damper system physics-based model

The governing equation for the spring-mass-damper system is:

$$m\ddot{x} + bx + k\dot{x} = 0 \tag{1}$$

where (m) is mass, (b) is damping coefficient, and (k) is spring stiffness in the Eq. (1). Figure 5. shows a spring mass damper system physics-based model in Simulink.

3.2. Model Calibration

A Digital Twin of aircraft subsystems constructed using first-principle physics-based models calibrated with operational data, plays a crucial role in enhancing diagnostics and prognostics. For a Digital Twin-driven diagnostic and prognostic (D&P) solution, constructing a Digital System Model for a specific subsystem of an individual asset or platform in operation is a critical step. The parameters of the Digital Twin can be classified into design parameters (e.g., mechanical dimensions) and health-related parameters (e.g., efficiency).

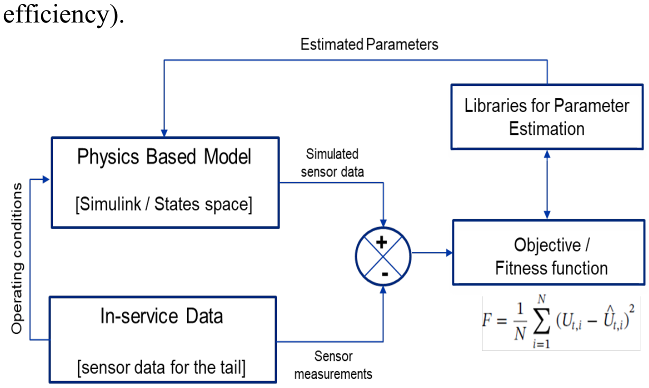

Figure 6. Parameter estimation approach in general

Figure 6 illustrates a general structure of a parameter estimation algorithm, highlighting the integration of physics-based modeling and operational data. A physics-based model, with governing equations (e.g., state-space representation), generates simulated sensor data based on current parameter estimates. This simulated data is compared against actual sensor measurements collected from the asset in operation. The discrepancy between simulated and measured data is quantified using an objective or fitness function, often defined as the sum of squared errors. Parameter estimation algorithms iteratively adjust the model parameters to minimize this objective function, thereby improving the model's accuracy in representing the real system. This closed-loop framework effectively combines model predictions and real-world observations to calibrate parameters, ensuring that the physics-based model remains representative of the asset's true behavior.

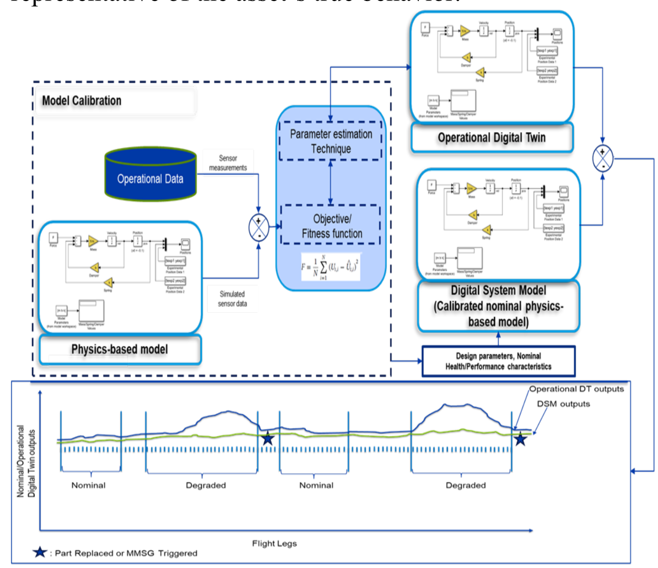

Figure 7. Model calibration and parameter estimation approach in D&P solution

Since the digital system model represents an idealized replica of the actual asset in operation, it is essential to characterize both the design parameters and health/performance-related parameters using nominal data which is free from faults or degradation associated with the real system. The model calibration process, which involves estimating these parameters, is a critical step in developing the Digital System Model (DSM). To accomplish this calibration, the subsystem physics-based model is integrated with a parameter estimation algorithm, such as nonlinear least squares estimation, to convert the physics-based model into a DSM. Figure 7 illustrates the pivotal role of model calibration and parameter estimation in constructing a robust diagnostic and prognostic (D&P) solution.

3.2.1. Overview of Parameter Estimation Techniques for Calibration of Physics-Based Models

Accurate parameter estimation is critical for developing reliable Digital Twins of complex engineering systems, enabling precise characterization of both design and health parameters. A variety of methods have been proposed to address this challenge, each with its own strengths and limitations.

Recursive Estimation Technique:

Among the most widely used are recursive estimation techniques such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), which can estimate system states and parameters simultaneously. The UKF is particularly effective for nonlinear systems because it avoids explicit linearization by using sigma points to approximate the state distribution, often achieving higher accuracy than the EKF. However, this improved accuracy comes with increased computational complexity and the need for careful tuning of noise covariance matrices. The EKF, while simpler and computationally faster, relies on first-order linearization, which can reduce accuracy or cause divergence in highly nonlinear scenarios. Additionally, it requires the derivation of Jacobians, which can be cumbersome for complex models.

Iqbal (2019) explores the application of EKF and its variants in nonlinear mechanics within an experimental physics teaching laboratory, emphasizing their role in filtering noisy data and estimating unknown parameters. The study provides a heuristic understanding of Kalman filtering techniques, highlighting their historical significance and broad applicability across fields such as signal processing and robotics. Yu et al. (2019) propose an improved EKF-based framework for state-of-charge estimation in lithium-ion batteries, combining the Akaike Information Criterion for model optimization with a two-stage estimation process integrating recursive least squares and particle swarm optimization. Their method enhances robustness, accuracy, and convergence speed compared to traditional EKF approaches, as validated experimentally.

Hybrid Physics-Informed Deep Learning Methods:

Beyond classical filtering, hybrid methods like Physics-Informed Neural Networks (PINNs) have gained traction. PINNs incorporate physical laws directly into the training process, offering flexibility in handling noisy and sparse data and enabling simultaneous estimation of states and parameters without model linearization. However, they require significant computational resources, extensive hyperparameter tuning, and expertise in deep learning frameworks, which may limit their practical adoption.

Metaheuristic / Optimization-Based Methods:

Optimization techniques also play a vital role in parameter estimation. Several studies have combined advanced optimization with filtering methods to improve performance. For example, Sun et al. (2018) developed a method integrating EKF with a constrained and improved Particle Swarm Optimization (C&I-PSO) algorithm, effectively incorporating physical constraints and demonstrating superior performance in electromechanical oscillation estimation. Similarly, Xu et al. (2014) proposed a PSO-based approach for multi-parameter estimation in multi-cell biological systems, achieving high accuracy in position tracking and contour estimation while outperforming existing multi-object tracking methods.

Particle Swarm Optimization (PSO), a metaheuristic global optimization technique, excels at exploring complex, multimodal parameter spaces without requiring gradient information. Its simplicity and parallelizability are advantageous, but PSO can be computationally intensive and slow to converge, especially in high-dimensional problems. Moreover, PSO focuses solely on parameter estimation and does not provide state estimates.

Derivative-Based Method:

In contrast, nonlinear least squares estimation (NLSE) leverages gradient-based optimization to achieve fast convergence when residuals are smooth and the model is well-formulated. Supported by robust implementations such as MATLAB's lsqnonlin, NLSE is efficient but sensitive to initial guesses and noise, and like PSO, it estimates parameters only.

Trade-Offs and Method Selection:

Each method presents distinct trade-offs in terms of accuracy, computational demand, and applicability. The choice of an appropriate parameter estimation technique depends on factors such as system nonlinearity, measurement availability, computational resources, and whether simultaneous state and parameter estimation is required. Often, combining complementary approaches or tailoring methods to specific applications enhances estimation performance and model robustness.

Additional Considerations:

Derivative-based methods, including Gradient Descent and nonlinear least squares, rely on gradient information to iteratively minimize error functions but may face challenges like weak observability when measurements are insufficient relative to the number of parameters. Metaheuristic algorithms such as PSO and Genetic Algorithms are population-based, stochastic search methods designed to explore solution spaces globally, improving the likelihood of finding global optima and handling multimodal, nonlinear problems without gradient information.

Online estimation techniques including EKF, UKF, and Particle Filters recursively update parameter and state estimates in real time, accommodating system dynamics and measurement noise. Recent research has also focused on improving parameter estimation efficiency through various strategies. For instance, Le, Zach, Rosten, and Woodford (2020) presented a nonlinear least squares approach that guarantees convergence while significantly reducing computational requirements. Zhao, Qi, and Liu (2017) discussed leveraging information from previous data batches to enhance state estimation using a Bayesian recursive estimation algorithm combined with particle filtering.

3.2.2. Parameter Estimation Benchmarking

Parameter estimation benchmarking using Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Nonlinear Least Squares (NLS) and Particle Swarm Optimization (PSO) were studied before selecting suitable approach for model calibration. Above 5 approaches are implemented on Spring mass damper system, to estimate spring stiffness (k) and Damping coefficient (b). For a given measurement/experimental data, all the above approaches are evaluated against KPIs.

Parameter estimation benchmarking study was conducted using Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Nonlinear Least Squares (NLS), and Particle Swarm Optimization (PSO) to identify the most suitable approach for model calibration. These five methods were applied to a spring-mass-damper system to estimate the spring stiffness (k) and damping coefficient (b). Each approach was evaluated against key performance indicators (KPIs) using the same set of measurement and experimental data.

The spring-mass-damper simulation is designed to generate synthetic data for benchmarking various parameter estimation techniques. The system is modeled as a second-order differential equation representing a mass attached to a spring and damper, with the dynamics governed by the damping coefficient (a) and spring constant (k). The simulation uses a fixed time step (dt = 0.01 seconds) over a total duration of 10 seconds, resulting in a time vector with 1001 points. The true system parameters are set as a damping coefficient of 0.5 and a spring constant of 2.0. An input force, modeled as a sinusoidal function with frequency 0.5 Hz and amplitude 1.0, drives the system. The state variables—position and velocity—are numerically integrated using Euler's method, starting from rest.

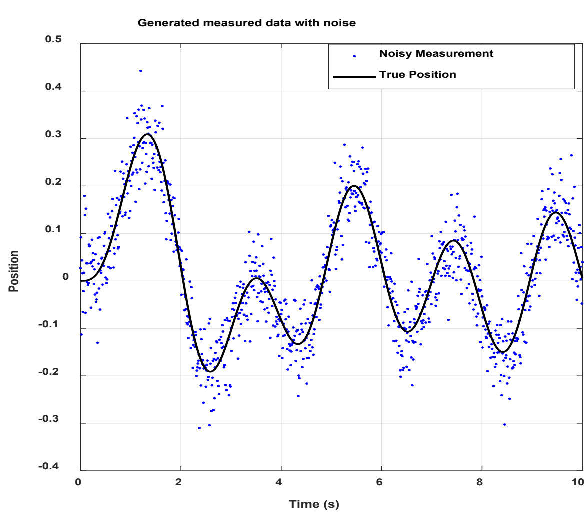

Figure 8. Generated data added with noise using spring-mass-damper simulation

To mimic real-world measurement conditions, zero-mean Gaussian noise with a standard deviation of 0.05 is added to the simulated position data, as shown in Figure 8. This noisy measurement serves as the observed data for parameter estimation. The noise addition ensures that the estimators are tested under realistic conditions where sensor noise and disturbances are present.

All the 5 estimation techniques, uses the noisy position data and known input force to estimate the system states and parameters. Each estimator is configured with specific hyperparameters tailored to its algorithmic nature. For the UKF and EKF, process and measurement noise covariances are carefully tuned to balance model uncertainties and sensor noise, enabling stable and accurate parameter tracking. PSO uses a swarm size of 30 particles and runs for 100 iterations with inertia and cognitive/social coefficients tuned for convergence. NLSE employs the Levenberg-Marquardt algorithm with bounds on parameters and a maximum of 200 iterations. The PINN typically involves network architecture choices, learning rates, and loss weighting between data fidelity and physics constraints.

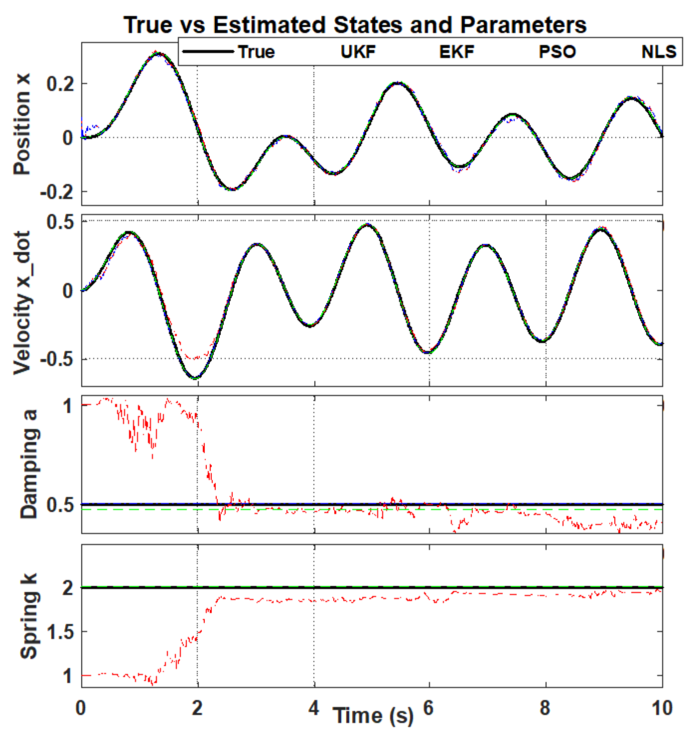

Figure 9. Comparison of results for estimation of various approaches

First 2 subplots in Figure 9 provides the comparison of measured vs computed values against the final estimated parameters of various approaches. Subsequent plots have results for estimated parameters.

Parameter	*UKF*	*EKF*	*PSO*	*NLS*
Damping coefficient	0.404	0.5	0.472	0.472
Stiffness	1.959	2.0	2.008	2.008

Table 1. Comparison of estimated parameter values of various approaches

Table 1 provides the comparison of final estimated parameters of various approaches. Notably, the parameter estimates from the EKF closely match the true system values, with a stiffness of 0.500 and a damping coefficient of 2.000, reflecting its superior accuracy in capturing the system dynamics compared to the other estimators.
To measure the performance of the various approaches it is evaluated against various KPIs as depicted in Table 2.

No	*Metrics*	*UKF*	*EKF*	*PSO*	*NLS*
1	*MSE*	3.2e-4	2.6e-4	3e-5	3e-5
2	*MAPE*	0.553	0.502	0.213	0.213
3	*Computation time (sec)*	0.022	0.027	0.237	0.043

Table 2. Performance comparison of various approaches for position (measured vs. computed)

The benchmarking results demonstrate the comparative performance of the different estimators in terms of accuracy and computational efficiency. The Particle Swarm Optimization (PSO) and Nonlinear Least Squares Estimation (NLSE) methods achieve the lowest Mean Squared Error (MSE) of 0.00003 and Mean Absolute Percentage Error (MAPE) of approximately 0.21%, indicating highly accurate position estimates. However, PSO requires a longer computation time of 0.237 seconds compared to NLSE's 0.043 seconds. The Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) also provide reasonable accuracy, with MSE values of 0.00026 and 0.00032 and MAPE values of 0.50% and 0.55%, respectively, but they are significantly faster, especially the UKF which completes in 0.022 seconds. These results highlight the trade-offs between estimation accuracy and computational cost, guiding the selection of appropriate methods based on application requirements. But the convergence time of all approaches may vary considering the complexity of the systems across various real work use cases.

4. Aircraft System Use Cases: Use of Digital Twin for D&P

A digital system model captures the design intent and expected behavior of a subsystem under healthy or nominal operating conditions. It relies on estimated nominal health parameters to characterize this ideal state. In contrast, an operational Digital Twin reflects the real-time condition and behavior of the physical asset during operation, continuously integrating sensor data and other inputs to derive current health parameters.

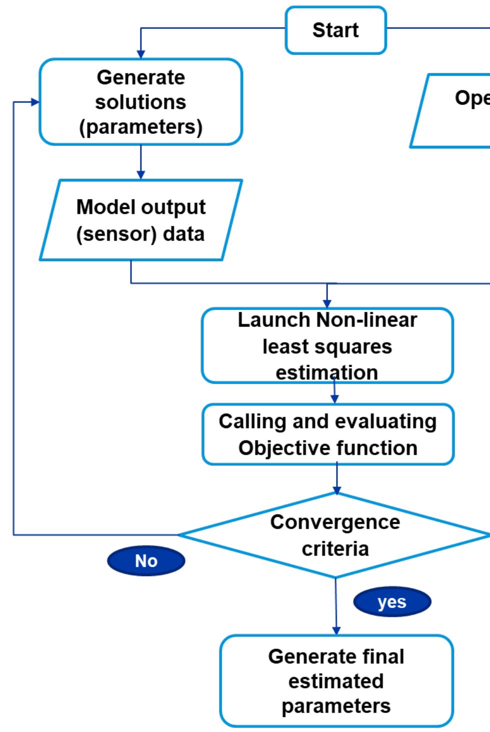

Figure 10. Parameter estimation approach

In this work, a novel two-level filtering approach is employed to identify nominal flight legs of the subsystem. These filtered data segments, representing stable and fault-free operation, are used to calibrate the digital system model, ensuring that the model accurately reflects the subsystem's healthy behavior.

The model calibration process, illustrated in Figure 10, employs a parameter estimation routine based on the Nonlinear Least Squares (NLS) technique. For the initial flight, parameter values within valid ranges are specified as starting points. For subsequent flights, the parameter estimates from the previous flight serve as initial values, enhancing convergence and stability. This iterative calibration against filtered nominal flight data enables precise characterization of nominal health parameters, thereby facilitating the development of a robust and reliable digital system model.

The aircraft Environment Control System (ECS) is vital for maintaining a comfortable and safe cabin environment by regulating temperature, humidity, pressurization, and air circulation. Key components of ECS include the Centrifugal Compressor (CC) and the Heat Exchanger (HX), both of which are critical for effective environmental control and are the focus of this study.

4.1 Design Parameter estimation and characterization for a Centrifugal Compressor in aircraft ECS

A centrifugal compressor is employed in the environmental control systems (ECS) of modern aircraft to compress outside air prior to conditioning and delivery to the cabin. Its main role is to raise the pressure and temperature of the incoming air, facilitating effective cooling, heating, and pressurization of the aircraft cabin. In this use case, we focus on estimating two unknown design parameters the compressor inlet duct area and the impeller effective diameter by utilizing selected nominal operational data.

The governing equations used to estimate these unknown design parameters for the compressor are as follows:
For inlet duct area (which is function of impeller eye diameter) estimation :

$$\mathrm{M_c} = \rho_i * \mathrm{A_i} * \mathrm{V_i} \qquad (2)$$

Where:
Mc = Mass flow rate of air at the inlet (kg/s)
ρ_i = Density of air at the inlet (kg/m³)
$\mathrm{A_i}$ = Cross-sectional area of the inlet (m²)
$\mathrm{V_i}$ = Velocity of air at the inlet (m/s)
Figure 11 shows, a backward swept impeller blade orientation, for which the velocity component at inlet of the compressor can be derived as:

$$\mathrm{V_i} = \mathrm{U_i} * \tan(\beta_i) \qquad (3)$$

Where:
$\mathrm{V_i}$ = Absolute velocity component of the fluid at the inlet (m/s)
$\mathrm{U_i}$ = Blade (or impeller) peripheral velocity at the inlet radius (m/s)
β_i = Blade angle (or flow angle) at the inlet relative to the tangent of the impeller (degrees or radians)

$$\mathrm{U_i} = \frac{\pi * \mathrm{D_i} * \mathrm{N}}{60} \qquad (4)$$

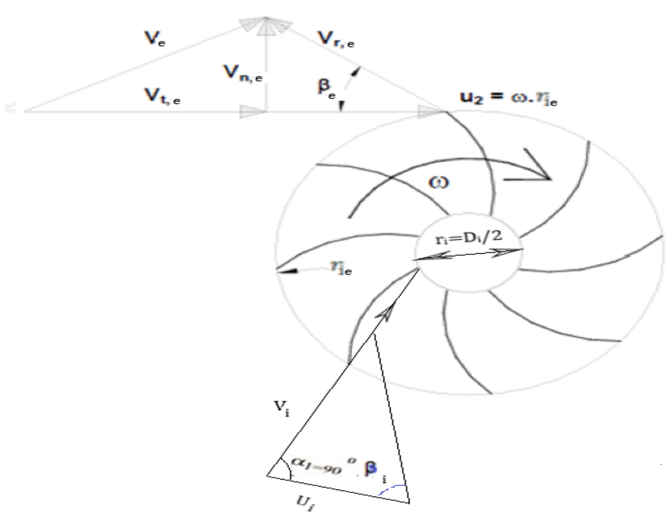

Figure 11. Impeller orientation (backward swept)

For impeller diameter estimation, exit pressure measurement is used.
Governing Equation:

$$r_p = \frac{P_e}{P_i} = \left[1 + \left(\frac{\gamma - 1}{\gamma}\right)\left(\frac{1}{P_i * v_i}\right)(\omega r_{\mathrm{i}})^2\right]^{\left(\frac{\gamma}{\gamma - 1}\right)} \qquad (5)$$

Where:
r_p is pressure ratio (dimensionless)
γ is specific heat ratio (Cp/Cv), constant (dimensionless)
P_i is inlet pressure (pa)
v_i is Specific volume of gas at inlet ($1/\rho_i$) (m³/kg)
ω is $\frac{2*\pi*N}{60}$ is angular velocity in rad/s
r_{ie} is impeller tip radius which is $\mathrm{D_{ie}}/2$ in terms of diameter (effective impeller diameter) in the Eq. (5).
Figure 11 illustrates the impeller orientation, which forms the basis for the above governing equations.

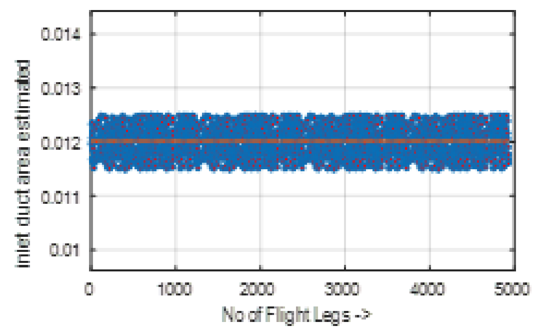

Figure 12. Inlet duct area estimated

Using nonlinear least squares (NLS) parameter estimation on snapshot data from 5345 nominal flights, the results shown in Figure 12 and 13were obtained. To estimate the inlet diameter of the impeller, i.e. the area of the inlet duct which joins at the impeller eye section (shorter section of the impeller), Eq. (2) Eq. (3) and Eq. (4) are used along with the inlet flow rate sensor measurement. Blade angle, β_i is also another estimated parameter. Figure 12 shows the results for Inlet duct area.

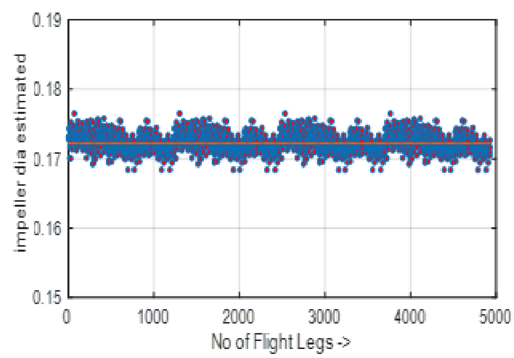

Figure 13. Impeller effective diameter estimation

Impeller effective diameter is characterized as:

$$01731 - 2.9304\text{e-}05 * \text{VDA position} \qquad (6)$$

The above equation provides estimates with a mean absolute error (MAE) of 0.0055, using the Variable Diffuser Actuator (VDA) position measured by a sensor. This is based upon the result shown in Figure 13 for Impeller effective diameter, which is obtained from the estimation using the exit pressure sensor measurement along with the Eq. (5). Once characterization is done, these design parameters are used in the Digital System Model which is used for feature generation for diagnostics & prognostics solution.

4.2 Health Related Parameter Estimation for Aircraft Heat Exchanger

A HX facilitates heat transfer between fluids. Typically designed with a fin-and-tube structure, heat exchangers can face performance issues due to clogging from debris, corrosion, mechanical damage, and ice formation, all of which can lead to reduced efficiency and reliability concerns in associated components. In this paper a HX is considered as a use case for health-related parameter estimation and its characterization for operational Digital Twin development for ECS subsystem.

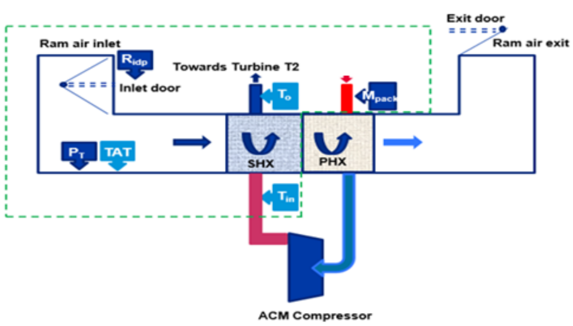

Figure 14. ECS HX and ram air subsystem architecture

Continuous monitoring of heat exchangers is challenging due to their complex design and limited accessibility, making maintenance alert prediction crucial to minimize unscheduled downtime. Jonsson and Palsson (1994) demonstrated the use of an extended Kalman filter for parameter estimation in continuous-time heat exchanger models formulated in state-space form. Their nonlinear model incorporates temperature-dependent parameters and empirical correlations for heat transfer coefficients, enabling accurate dynamic representation and adaptive parameter tuning tailored to the heat exchanger's varying operating conditions.

Newman (2023) presents a scalable approach leveraging engineering Digital System Models (DSMs) and Digital Twins to support and enhance health management activities. He highlights a heat exchanger DSM use case involving time-invariant calculations to determine output temperatures based on inlet temperatures and flow rates.

Guðmundsson (2008) explores statistical methods, including state-space models and Kalman filters, for fouling detection in cross-flow heat exchangers using data collected during normal operation. By dividing the heat exchanger into compartments and applying physical equations alongside Kalman filtering, the study shows effective fouling detection, with offline methods identifying deposits earlier than online approaches.

Zhang et al. (2015) propose a bilinear model-based parameter estimation technique using a multi-input multi-output recursive least squares estimator with a forgetting factor to detect fouling in heat exchangers. Simulation results validate the method's ability to identify early-stage fouling by estimating parameters related to unmeasurable heat transfer coefficients.

Shah, Liu, and Greatrix (2009) introduce a diagnostics, prognostics, and health management (DPHM) solution for online fouling detection in aircraft environmental control system (ECS) cross-flow heat exchangers. Their approach employs a lumped state-space dynamic model combined with extended Kalman filtering to accurately estimate state-dependent parameters, enabling predictive maintenance scheduling based on real-time fouling status. The method is validated through experimental testing.

This paper proposes a Hybrid Digital Twin framework for heat exchanger diagnostics and prognostics. The approach improves fault prediction accuracy by estimating critical parameters, such as heat transfer coefficients, which are difficult to measure directly. Figure 15 illustrates the architecture of the ECS HX and ram air subsystem.

no	Label	Sensor Measurement
1	TAT	Total air temperature
2	PT	Total air pressure
3	T_{in}	Air Cycle Machine (ACM) compressor exit temperature (HX inlet temperature)
4	T_o	HX exit temperature
7	R_{idp}	Ram air duct inlet door position
8	M_{pack}	Pressurized Air Conditioning Kit (PACK) mass flow rate

Table 3. Sensor details of ECS HX

These sensor details of ECS HX are summarized in Table 3. Inputs include Ram air inlet conditions and supply from the centrifugal compressors, in addition to heat transfer coefficients (fouling factors) for the heat exchangers and air cycle machine. Based on these inputs, the temperatures at exits (cold and hot sides) of HX are calculated. Note that the heat transfer coefficients are not recorded in flight sensor data. Governing equation for HX thermal dynamics as shown below:

$$\dot{T}_{ho} = \frac{W_h(T_{hi}-T_{ho})}{m_h} - \frac{H_h(T_{ho}-T_{co})}{m_h C_h} \tag{7}$$

$$\dot{T}_{co} = \frac{W_{ram}(T_{ci}-T_{co})}{m_c} - \frac{H_c(T_{co}-T_{ho})}{m_c C_c} \tag{8}$$

Where,

T_{hi}, T_{ci} — Inlet temperature for hot and cold side

T_{ho}, T_{co} — Outlet temperature for hot and cold side

W_h — Hot side mass flow rate [Pack flow rate]

W_{ram} — Ram air duct mass flow rate

H_h, H_c — Hot and cold side heat transfer coefficients

m_h, m_c — Mass flow corresponding to hot and cold side (product of density and volume for hot and cold side)

C_h, C_c — Specific heats for hot and cold side

It is to be noted that there are two unknown health related parameters (heat transfer coefficients) to be estimated and two equations for solution satisfying observability conditions.

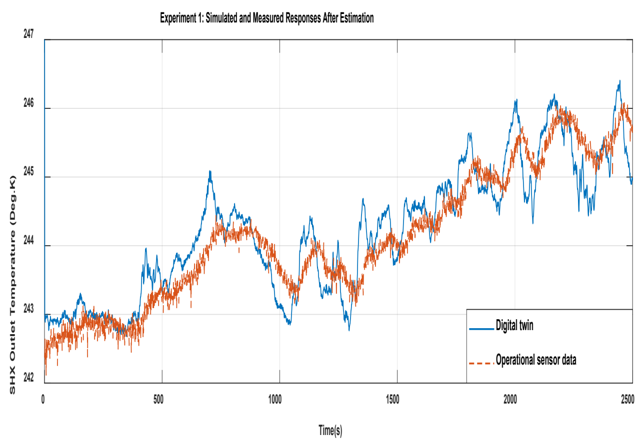

Figure 15. HX Output Temperature vs. Actual Temperature (from CPL Data) for a segment of flight leg using CPL data (time series)

Figure 15 shows the comparison of HX Output Temperature against Sensor measured Temperature after using estimated heat transfer coefficients in the state space model of HX. This is estimated per flight for a selected flight phase, here it is performed on Cruise flight phase where the operating conditions are comparatively stable/steady compared to other phases. Once the estimation of heat transfer coefficients is performed for significant number of flights in the low frequency Aircraft Condition Monitoring System (ACMS) data, it can be also characterized similar to the Design parameter estimation.

Estimated design and health parameters are used for Digital System Model to execute against operational data, which can support deriving advanced features (e.g. Residual features between Digital Twin and Sensor data) for prognostics solution and indicate failure much ahead of warning/maintenance message. Advanced features can be either derived by comparing sensor data or operational Digital Twin features.

4.3 D&P Approach

Advanced feature generation for D&P solution, are mainly based upon the residuals computed from both Operational and Digital System Models. For a selected test data (of any operator) the residual features are generated by comparison of parameters and values computed from Digital System Model to Operational Digital Twin will be used for anomaly detection and can be enhanced by performing various data analytics approaches to the residuals.

Estimated heat transfer coefficient from the HX Operational Digital Twin itself depicted better explainable degradation trend as shown in below figure 16.

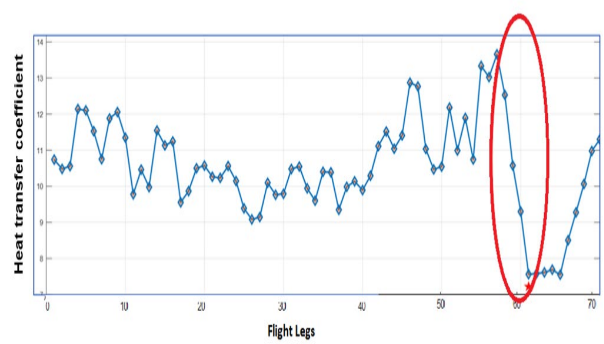

Figure 16. Estimated heat transfer coefficients over successive flights using ACMS data indicating a drift in the heat transfer coefficient at the region of replacement.

The above result is for low frequency ACMS data set, for a window ahead of HX replacement.

5. Conclusion

Digital Twins (DT) have demonstrated significant potential across industries by enabling cost savings in design, testing, inspection, and maintenance, improving knowledge transfer, enhancing data transparency, and integrating supply chains. However, key challenges remain for their implementation in Integrated Vehicle Health Management (IVHM). These include balancing model fidelity with development cost and complexity, optimizing sensor deployment without increasing vehicle weight, managing large-scale data storage and high-speed computation needs, and ensuring cybersecurity against threats inherent in cloud-based data sharing. Additionally, intellectual property concerns limit data sharing, hindering the creation of fully representative DTs.

Despite these challenges, recent advances and decreasing technology costs present opportunities for further research. Most existing DTs focus on components or subsystems, with few addressing integrated system-level models that emulate interactions across entire vehicles. Developing modular, black-box DT representations that can interconnect offers a promising path toward comprehensive vehicle-level Digital Twins. Such integration can enhance IVHM effectiveness and optimize condition-based maintenance strategies, ultimately improving vehicle safety and operational efficiency.

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