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Review

A Comprehensive Review of Emerging Trends in Aircraft Structural Prognostics and Health Management

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Abstract: This review paper addresses the critical need for structural prognostics and health management (SPHM) in aircraft maintenance, highlighting its role in identifying potential structural issues and proactively managing aircraft health. With a comprehensive assessment of various SPHM techniques, the paper contributes by comparing traditional and modern approaches, evaluating their limitations, and showcasing advancements in data-driven and model-based methodologies. It explores the implementation of machine learning and deep learning algorithms, emphasizing their effectiveness in improving prognostic capabilities. Furthermore, it explores model-based approaches, including finite element analysis and damage mechanics, illuminating their potential in the diagnosis and prediction of structural health issues. The impact of digital twin technology in SPHM is also examined, presenting real-life case studies that demonstrate its practical implications and benefits. Overall, this review paper will inform and guide researchers, engineers, and maintenance professionals in developing effective strategies to ensure aircraft safety and structural integrity.

Keywords: structural prognostics; health management; aircraft maintenance; data-driven approaches; model-based approaches; digital twin technology

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1. Introduction

Structural prognostics and health management (SPHM), a vital discipline in aerospace engineering, emphasizes the importance of continuous monitoring, diagnosis, and prediction of the health of aircraft structural systems [1,2]. By capturing and analyzing data from a wide array of sensors and monitoring systems, SPHM systems play an instrumental role in facilitating the real-time evaluation of an aircraft's structural integrity throughout its operational lifespan [3]. These systems offer constant monitoring that delivers insights into the integrity, fatigue, and accumulated damage of various structural elements, including airframes, wings, fuselages, and other crucial structures [4]. The ability to detect and evaluate potential issues empowers these systems to pave the way for prompt maintenance and repair actions, thereby safeguarding the aircraft's optimal performance and safety.

Despite their crucial role in aircraft maintenance via manual inspections, scheduled maintenance activities, and predefined thresholds for component repair or replacement, traditional SPHM approaches face certain limitations [5]. A significant challenge lies in their reactive nature and inability to offer real-time insights into the health of aircraft structures. Visual inspections, while commonly used, remain subjective and are prone to human error, potentially overlooking minor or internal damage that could escalate into catastrophic failure [6]. Reliance on preset maintenance schedules can occasionally lead to unnecessary maintenance actions or oversight of critical indicators, resulting in inefficient resource allocation and heightened maintenance costs [7,8]. To overcome these challenges, it is imperative to augment SPHM practices by capitalizing on technological advancements, thereby fostering proactive and efficient maintenance strategies [9]. In this context, improvements in sensor technology have been pivotal. Modern SPHM systems employ high-precision sensors that accurately measure critical parameters like strain, temperature, vibration, and load conditions from various aircraft structures [10–12]. In the field of aircraft SPHM, the significance of strain and corrosion sensors in maintaining the integrity of aircraft structures is of paramount importance. Strain sensors, with their advanced technology, enable the precise measurement of mechanical deformation and stress distribution across various critical components. By doing so, they facilitate the continuous monitoring of structural responses to diverse operational loads, offering a unique opportunity for the early detection of anomalies that could compromise the structural robustness of the aircraft. These sensors empower engineers and operators with timely information, enabling them to take proactive measures and address potential issues before they escalate [13,14]. Additionally, corrosion sensors leverage techniques like electrochemical or impedance-based measurements to detect and measure corrosion in aircraft structures. Corrosion sensors employ cutting-edge techniques to identify initial corrosion stages and progression, preventing degradation over time. Alongside data acquisition systems and advanced algorithms, these sensors significantly boost the efficiency, reliability, safety, and cost-effectiveness of SPHM, eventually enhancing aircraft operations [15–17].

With the advent of data-driven methodologies and sophisticated technologies, modern SPHM approaches have catalyzed a paradigm shift in aircraft maintenance procedures. These approaches broadly fall into two categories: data-driven approaches [18] and model-based/hybrid approaches [19,20]. Data-driven methods utilize machine learning techniques such as support vector machine (SVM), random forest (RF), and decision trees (DTs), as well as deep learning techniques such as convolutional neural network (CNN), and convolutional autoencoder (CAE). These methods analyze extensive datasets obtained mainly from non-destructive testing (NDT) techniques to detect anomalies and make precise predictions regarding the health and remaining useful life (RUL) of aircraft components [21,22]. However, these methods require extensive labeled datasets and face interpretability challenges. On the contrary, model-based approaches, such as physics-based modeling, finite element analysis (as demonstrated by Yang et al. [23]), and damage mechanics, offer a comprehensive assessment of the structural health of aircraft components [24]. Within the domain of finite element analysis, Tian et al. employed an iterative method to address nonlinear challenges in partial differential equations [25]. This method subsequently demonstrates its effectiveness in solving intricate equations involving fractions and nonlinearity, leading to improved accuracy and reliability, as confirmed through theoretical analysis and numerical experiments [26]. Furthermore, the integration of digital twin technology into SPHM practices provides a significant boost [27–29]. This technology creates virtual replicas of the aircraft systems, enabling real-time monitoring, performance analysis, and condition-based maintenance.

A modern SPHM framework operates via a sequential process that includes technology integration, data acquisition, preprocessing, fault diagnosis, and RUL prediction [30]. Figure 1 shows the SHPM process for aircraft structures. The process initiates with data gathering, wherein high-performance sensors, including strain and corrosion sensors, are employed on the aircraft's critical structural components, such as the aircraft's empennage, wings, cockpit, and fuselage [31]. These sensors capture detailed, real-time data indicative of the structural health of the aircraft. After data gathering, the acquired data undergoes preprocessing, which involves steps such as formatting, normalization, and filtering. This stage is pivotal, as it conditions the raw sensor data, transforming it into a structured format that is suitable for further analysis. It helps in dealing with any discrepancies, noise, or errors in the collected data, ensuring a clean and standardized dataset that is ready for downstream applications [32,33]. The pre-processing step is generally integrated within the feature extraction process, where the pre-processed data are used to extract sensitive features that are able to describe the system's characteristics. The successful integration of pre-processing and feature extraction ensures that the subsequent analysis is based on high-quality and informative features, leading to more accurate and meaningful results. Following feature extraction, the next stage is fault/damage diagnosis. At this stage, the formatted data are subjected to in-depth analysis using advanced algorithms and data analytics techniques. These algorithms sift through the data to identify anomalies, irregular patterns, and potential issues that might be indicative of underlying structural faults. This critical step in the process aids in the timely diagnosis of faults, facilitating prompt remedial actions. The final stage of the SPHM process is the prediction of the RUL of the aircraft components, which employs a combination of predictive models and machine learning techniques [34]. Based on the current health status of the components, their operational conditions, and a rich historical database, these techniques foresee the lifespan of various components. This predictive insight provides invaluable foresight, enabling the formulation of a maintenance plan well ahead of potential failures. By working systematically through these stages, the modern SPHM framework encourages a shift from reactive to proactive maintenance planning. It allows for optimized allocation of resources based on accurate predictions, contributing to improved operational efficiency [35]. Furthermore, it significantly enhances the overall safety of the aircraft by enabling the timely detection and resolution of potential structural issues, thereby mitigating the risk of catastrophic failure.

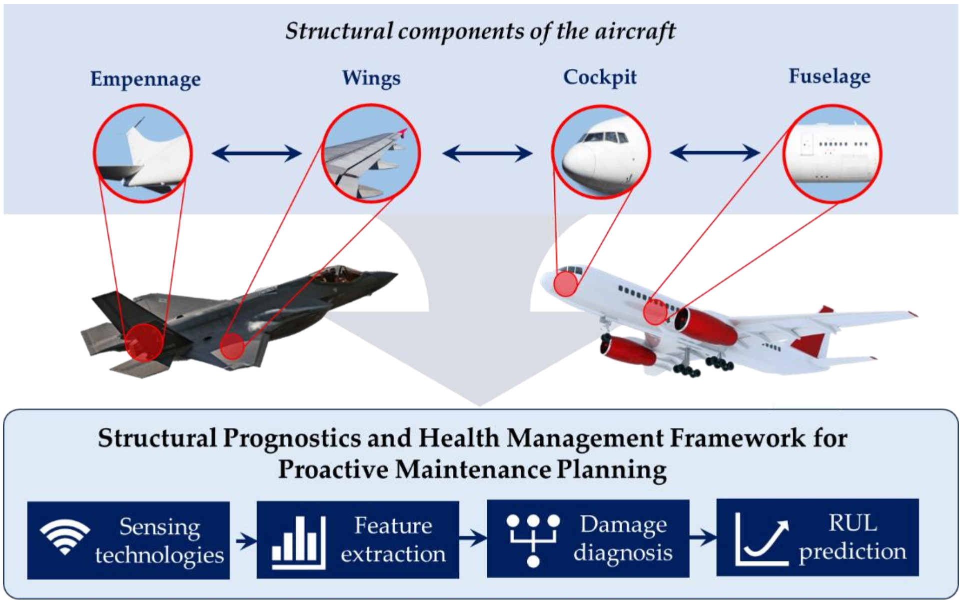


Figure 1. SPHM Framework: Sensor data collection from key aircraft components and its application in fault diagnosis and RUL prediction.

This review paper offers a unique and comprehensive perspective on SPHM in aircraft maintenance. It distinguishes itself by providing an in-depth comparative evaluation of both traditional and contemporary SPHM techniques, shedding light on their individual strengths and weaknesses. Particularly noteworthy is its emphasis on the transformative potential of machine learning and deep learning algorithms, an aspect that has often been overlooked in previous reviews. Moreover, the paper dives deeply into model-based techniques, such as finite element analysis and damage mechanics, providing readers with a fresh understanding of these methods and their implications for SPHM. The review further sets itself apart by thoroughly exploring the role of digital twin technology in SPHM, accompanied by real-world case studies that enhance its practical relevance. The primary objective of this review paper is to enhance comprehension of the diverse SPHM practices and contribute to the further progression of the aviation industry. By providing a comprehensive analysis and comparison of different methodologies, the paper aims to fuel advancements in SPHM and support researchers, engineers, and practitioners in making informed decisions for effective structural health management in the aviation sector.

The structure of this review paper follows a logical flow, beginning with an exploration of traditional SPHM techniques. The limitations of these techniques are examined, providing a foundation for introducing more modern methodologies. The subsequent sections focus on modern approaches that include data-driven techniques, model-based approaches, and hybrid approaches, and revolutionary digital twin technology. Each of these approaches is outlined with a focus on their unique characteristics, implementation strategies, practical applications, and associated advantages and drawbacks. Figure 2 represents the differences between traditional, model-based, hybrid, digital twin, and data-driven approaches. It highlights that traditional, model-based, and hybrid approaches often require significant domain knowledge, while digital twin and data-driven approaches rely heavily on the availability and manipulation of large datasets.

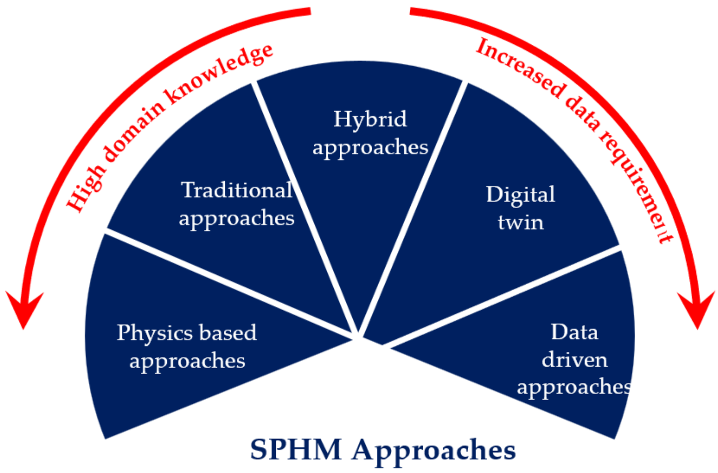


Figure 2. SPHM Approaches: Comparing the knowledge requirements and data dependencies of the traditional, hybrid, data-driven, and digital twin methods.

2. Traditional Approaches to Aircraft SPHM

This comprehensive section thoroughly explores the realm of traditional SPHM approaches and offers an in-depth overview of their crucial role in aircraft health management. Acknowledging their effectiveness, this section also critically examines the inherent limitations and challenges posed by these traditional methodologies. Highlighting the dynamic nature of the aviation industry, the discussion then delves into the significant shift from these conventional tactics toward more sophisticated and predictive strategies. This transformative journey outlines the evolution toward modern SPHM practices, painting a clear and detailed picture of this pivotal transition within the industry.

2.1. Overview of Traditional SPHM Approaches

Aircraft SPHM is an integral aspect of aviation safety and performance. Traditional methods, rooted in the early days of the aviation industry, have primarily revolved around routine inspections, scheduled maintenance, and NDT techniques.

(1) **Inspection and Maintenance Schedules**: In these highly systematic and standardized procedures, technicians conduct meticulous physical examinations of aircraft structures at predetermined intervals [36,37]. The purpose of these checks is to identify any observable signs of structural degradation, such as corrosion, distortion, cracks, or even loose parts [38]. Given the fundamental nature of these inspections, they constitute the primary line of defense against possible structural failure, ensuring the aircraft's physical condition is maintained at its optimal state.

(2) **Non-Destructive Testing (NDT)**: As the aviation industry evolved, the need for more sophisticated methods to inspect structural components without causing damage led to the widespread use of NDT techniques [39]. These encompass ultrasonic testing [40], radiographic testing [41], eddy current testing [42], magnetic particle inspection, and dye penetrant inspection. Through these methods, technicians can detect, locate, and measure defects that may not be visible to the naked eye, enhancing their ability to maintain structural integrity.

(3) **Usage Monitoring Systems (UMS)**: Traditional SPHM also includes the utilization of usage monitoring systems, which record various operational parameters such as load factors, airspeed, and temperature. These parameters, which are critical to understanding the performance and endurance of an aircraft's structure, help in evaluating the health of the aircraft and its components [43,44].

(4) **Damage Assessment and Classification**: Traditional SPHM methodologies involve manual evaluation and classification to ascertain the severity and type of damage or defects. Trained personnel visually inspect and categorize the damage according to set criteria, thereby prioritizing repairs based on the criticality of the identified issues [45–47].

(5) **Structural Health Monitoring (SHM)**: SHM is a fundamental part of traditional SPHM methodologies. Sensors placed at strategic locations monitor various parameters to provide data on structural behavior, allowing operators to detect any deviations from normal behavior, thereby ensuring continuous airworthiness [48–51].

(6) **Experience-based Decision making**: Traditional SPHM methodologies often rely on the expertise of maintenance personnel to make informed decisions about inspections, repairs, or component replacements. Years of operational and maintenance experience underpin the assessment of aircraft structures and appropriate maintenance action [52–54].

2.2. Challenges and Limitations of Traditional SPHM Approaches

While traditional SPHM methodologies are invaluable, they are not devoid of challenges and limitations that can affect their effectiveness and accuracy. Acknowledging and addressing these limitations can improve SPHM implementation overall. Key challenges and limitations include:

- **Reactive Maintenance Strategies and Scheduled Inspections**: Traditional SPHM methodologies often hinge on reactive maintenance, with maintenance actions triggered by scheduled intervals or visible damage detection. This approach can lead to unforeseen failure and the potential for undetected early-stage damage, resulting in heightened costs and safety risks [55,56].
- **Limited Predictive Capabilities**: Traditional methodologies may not accurately project the RUL of components or future degradation. Relying on historical data and scheduled maintenance may lack the necessary insights to optimize maintenance planning or identify critical structural issues [57].
- **Reliance on Human Judgment**: Traditional SPHM methodologies heavily depend on maintenance personnel's expertise and judgment. This dependence introduces variability and subjectivity in the decision-making process, which can affect the consistency and effectiveness of maintenance actions [58].
- **Concealed or Subsurface Damage**: Traditional inspection methods may have difficulty detecting concealed or subsurface damage that is not apparent during routine inspections. Undetected defects beneath coatings or within complex structures could compromise the aircraft's structural integrity [59].
- **Incomplete Exploitation of Advanced Data Analysis Approaches**: Traditional SPHM methodologies may not fully harness the potential of state-of-the-art techniques for data analysis. The analysis of collected data might be restricted to basic trend analysis or manual assessment methods, which can impede the identification of subtle degradation patterns or anomalies [60].

2.3. Evolution from Traditional Methods to Modern Techniques

The inherent limitations of traditional SPHM approaches have sparked a drive toward more advanced methods. With the development of the digital revolution, the aviation sector has seen a paradigm shift in SPHM. Data-driven techniques, propelled by innovations in artificial intelligence (AI), specifically machine learning and deep learning, have ushered in a new era of SPHM. These modern methods provide comprehensive, real-time analysis of aircraft structural health data, enabling the early detection and prediction of potential issues before they turn into significant problems. Consequently, these techniques can drastically reduce unscheduled maintenance and improve aircraft availability. Furthermore, the application of model-based and hybrid methods has added another layer of sophistication to modern SPHM. Model-based methods offer valuable insights into the underlying physics of aircraft structures, while hybrid methods leverage the strengths of both data-driven and model-based approaches to offer further robust predictions and diagnostics. Modern SPHM approaches present a significant leap forward from traditional methods. Figure 3 distinguishes the vital capabilities of modern SPHM approaches, which the following discussion elaborates upon:

- **Use of Digital Twins**: Digital twin technology enables the creation of a virtual replica of an aircraft's structural components. This allows for accurate simulations of various operational scenarios and a better understanding of potential structural issues [61,62].
- **Advanced Diagnostics and Prognostics**: Modern SPHM systems leverage advanced AI algorithms for the real-time analysis of sensor data. These tools provide superior capabilities for predicting and diagnosing potential structural issues well in advance, allowing for more timely maintenance and avoiding unexpected downtime [63].
- **Reduced Costs**: By identifying potential problems early, allowing for predictive maintenance, and minimizing unplanned downtime, modern SPHM methods can lead to significant cost savings in aircraft operations and maintenance [64].
- **Real-time Insight**: Modern SPHM techniques can handle and process large volumes of data from diverse sources and formats, generating comprehensive real-time insights into aircraft structural health [65].
- **Automation**: Modern SPHM approaches offer a high degree of automation. Routine analysis, prognostics, and health reporting can be automated, reducing the possibility of human error and enhancing overall efficiency [66].
- **Adaptability**: As opposed to traditional approaches, modern SPHM systems are adaptable to changing operational conditions and can learn from new data, continuously improving their predictive accuracy [67].
- **Enhanced Safety**: By providing a more accurate understanding of the structural health of an aircraft, modern SPHM methods can significantly improve the safety of aircraft operations [68].

Overall, the evolution from traditional to modern techniques in SPHM represents a significant step towards more proactive and efficient aircraft health management. It demonstrates the potential of emerging technologies and methodologies to enhance the safety and performance of aircraft while minimizing maintenance costs and downtime. This exciting progression sets the stage for future advancements in the field of SPHM, promising a new era in aviation safety and reliability.

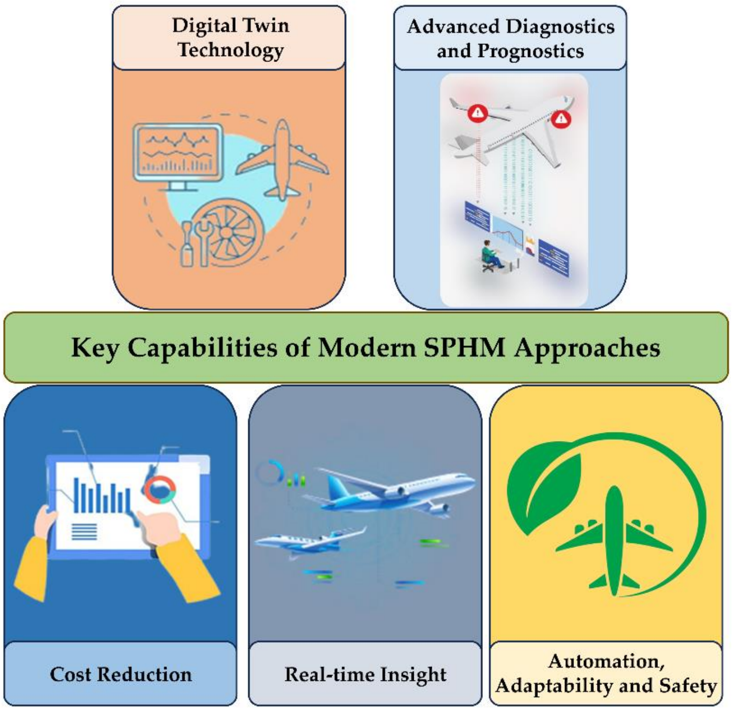


Figure 3. Modern SPHM Approaches: Highlighting the pivotal capabilities and advancements.

3. Modern SPHM Approaches to Aircraft SPHM

The advent of sophisticated computational capabilities and the surge in data collection technologies have paved the way for the emergence of modern SPHM approaches. These revolutionary methodologies, characterized by their data-intensive, predictive, and adaptive nature, offer a robust response to the limitations inherent in traditional SPHM practices. With a focus on data-driven techniques, model-based strategies, hybrid methodologies, and remarkable digital twin technology, modern SPHM approaches have initiated a new era in aircraft maintenance and management. This section delves into the essence of these contemporary methodologies, elaborating on their principles, implementation strategies, and practical applications, as well as their associated advantages and limitations. The discussion will illustrate how these advanced techniques have enhanced the capabilities of SPHM, promising safer, more cost-effective, and more efficient aviation operations.

3.1. Data-Driven Approaches in SPHM

This section provides an extensive exploration of data-driven approaches in SPHM. By thoroughly examining the fundamental principles that form the basis of these methods, the section underscores their reliance on machine learning and deep learning techniques. Through a comprehensive understanding of data-driven approaches, novel prospects emerge for proactive maintenance, knowledgeable decision making, and sophisticated structural health management in the aviation industry.

3.1.1. Introduction to Data-Driven Approaches

Data-driven SPHM for aerospace structures involves collecting and analyzing data from different sensing systems to assess structural health. It offers early fault detection that improves safety and reduces costs by enabling proactive maintenance actions. By continuously monitoring structural health, SPHM enhances operational efficiency, optimizes maintenance schedules, and extends the operational life of the aircraft. Data-driven approaches can be utilized in (a) feature engineering to extract, transform, and filter features for better system representation; (b) decision making, which utilizes AI techniques to decide on the health state of the system; and (c) post-processing to explain the decision-making process [69].

In the realm of data-driven machine learning-based fault diagnosis, the process of feature extraction holds significant importance. This procedure involves capturing specific attributes related to faults from the collected sensor data. Commonly used features span various domains, including time, frequency, and time–frequency. Specifically, in the time domain, pivotal statistical features take center stage, encompassing mean, standard deviation, root amplitude, root mean square, peak value, and other relevant attributes. Similarly, frequency-domain features are acquired by analyzing frequency spectra, incorporating attributes like mean frequency, frequency center, root mean square frequency, and standard deviation frequency. In the time–frequency domain, features such as energy entropy are often derived through techniques like wavelet transform, wavelet package transform, or empirical mode decomposition applied to sensor data [70].

Data-driven techniques rely on massive amounts of data and concentrate on analyzing output signals from the system. These techniques can manage high-dimensional data, making them appropriate for large and complex systems as they do not require physics-based knowledge of the system [71,72]. Even though data-driven techniques are less complex than physics-based approaches, they require a pre-processing phase to extract usable information from data at a significant computing cost [73]. Hence, the performance of the system relies on the training data and may deteriorate when the system encounters uncertainty (beyond the scope of the training data) or is influenced by unidentified flaws. Advancements in AI have boosted data-driven techniques, which are thus being continuously adopted in aircraft SPHM. For intelligent SPHM, both machine learning (ML) and deep learning (DL) approaches have gained popularity [74]; therefore, this section focuses on the latest data-driven technologies adopted for the SPHM of aircraft structures. In the context of SPHM, a significant trend emerges—the abundance of healthy data compared to damaged data. This surplus data arises from the aircraft's robust design and operational conditions, which generate extensive records of healthy flight data. In contrast, obtaining data from actual instances of damage is rare due to stringent safety measures. This is where transfer learning assumes particular relevance. It harnesses the array of healthy data to enhance diagnostic accuracy for rare damage scenarios. This adaptation process utilizes pretrained models, strengthening diagnostic capabilities despite the limited availability of damaged data. In this unique context, the pivotal role of transfer learning in advancing aircraft SPHM becomes evident.

The goal of data-driven techniques is to model relationships between inputs and outputs under specific operational conditions. The model that was developed is subsequently utilized to make predictions and evaluate the health state of the aircraft structures. The model outputs are generally known, as they are acquired from the sensing system, and any deviation of the obtained signal from the normal state demonstrates the presence of a defect. Therefore, numerous techniques exist to analyze the obtained signal and extract features to train the data-driven model to generate a model that is capable of performing better in unseen environments. There are two main types of data-driven techniques utilized for this purpose: supervised learning and unsupervised learning techniques. The supervised learning techniques employ labeled input data, indicating that before the model training, the flaws or defects had been identified and distinguished under different labels. In aircraft structures, physical damage, such as dents, lightning strikes, damaged paint, missing markings, cracks, and holes, can be obtained from visual inspection and labeled according to their respective classes before being used to train a data-driven model [75]. In contrast, unsupervised learning techniques are not trained on labeled datasets; thus, they discover the relevant features in the dataset using unlabeled data. Therefore, predefined defect types that could influence the training process are not employed. More specifically, the extraction of characteristics from input data are independent of the data's physical significance. Both ML and DL have respective models to handle supervised or unsupervised learning tasks. The next sections focus on various ML and DL-based data-driven methods for the SPHM of aircraft structures.

3.1.2. Machine Learning Approaches in SPHM

Machine learning includes data-driven models that allow computers to learn and predict without being explicitly programmed [76]. It entails training a model to recognize patterns and correlations in massive datasets and then applying that knowledge to generate predictions. The SVM, decision trees (DTs), random forest (RF), K-nearest neighbor (KNN), and Naïve Bayes (NB) algorithms are some of the most extensively used ML approaches for SPHM of aircraft structures. The brief description of these ML models is as follows:

SVMs are often used for classification and regression. In SVM classification, a decision boundary known as a hyperplane is obtained by training the dataset. This hyperplane is defined by Equation (1) [77]:

$$w^T x_i + b = 0 \tag{1}$$

where x_i represents the data points of the training dataset ($\mathrm{w}^\mathrm{T} \in \mathrm{R}_\mathrm{d}$, d is some dimension), and b is a real number. The generalization of the SVM model is determined by the hyperplane, and an optimal hyperplane can be obtained by selecting a suitable kernel function such as linear, polynomial, or radial bases, etc. [77].

The DT models use a non-parametric supervised learning approach to perform classification or regression tasks. The DT classifier develops a model that predicts a target variable using basic data-inferred decision rules. It has an upside-down tree-like structure with the roots at the top. The DT splits into branches based on the condition at each node, and a decision is made at the end of the branch with no further splits [78]. The DT algorithm identifies the most valuable feature for classification through the use of appropriate evaluation criteria. The criterion employed to establish the optimal feature encompasses principles such as entropy reduction and maximizing information gain. Information gain (IG) for a feature A with respect to a dataset D is calculated by the following Equation (2) [79].

$$IG(D, A) = H(D) - H((D|A)) \tag{2}$$

where $H(D)$ is the entropy of the original dataset D. It measures the impurity or randomness in the class distribution of the dataset before any split. $H(D \mid A)$ is the conditional entropy of the dataset D given the feature A. It represents the expected entropy of the dataset D after splitting it based on feature A. The higher the value of $IG(D, A)$, the more information the feature A provides in reducing the uncertainty in class predictions after the split. In other words, it quantifies the gain in predictive power achieved by using feature A to split the data.

The RF algorithm, introduced by Breiman [80], is an ensemble learning technique utilized to address classification and regression tasks. The RF classifier combines multiple decision trees to improve the accuracy and stability of predictions. The mathematical representation of an RF classifier includes the consolidation of predictions derived from individual DTs. The final estimate of the RF classifier $H(x)$ is obtained by averaging the predictions of all the DTs, as shown in Equation (3) [81].

$$H(x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \tag{3}$$

where $H(x)$ signifies the final prediction made by the RF for input data x. $h_t(x)$ stands for the prediction of the t-th decision tree for input data x. T represents the total count of decision trees within the random forest.

The KNN is a non-parametric-based ML classification and regression model. The input to the KNN classifier is the k-closest data from the training population, which measures the target's distance from the closest feature space. This distance between the two points is termed the Euclidean distance ($\mathrm{d_E}$), which is an important parameter for the KNN model and can be defined as Equation (4) [82]:

$$d_E = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{4}$$

where x_i is a new point from the training data and y_i is the nearest existing point in the feature space.

The NB classifier is an ML classifier that operates on probabilistic principles, utilizing Bayes' theorem. The NB classifier is frequently employed in scenarios with extensive datasets, where the likelihood of a particular feature (y_h) belonging to a specific class (L_i) may be mathematically represented using the Bayes theorem as shown in Equation (5) [83]:

$$P\left(\frac{L_i}{y_h}\right) = \left(\frac{P\left(y_h/_{L_i}\right) P(L_i)}{P(y_h)}\right) \tag{5}$$

where the probability of each class is represented by $P(L_i)$ and the probability or predictor is represented as $P(y_h)$. The NB algorithm employs maximum likelihood estimation (MLE) and Bayesian probability without the need for training or Bayesian methods. It is often regarded as efficient in terms of storage space and learning time.

Table 1 summarizes case studies that demonstrate the application of machine learning-centric data-driven techniques in the SPHM of aircraft structures. Cortes and Vapnik [84] presented SVMs as a supervised, non-probabilistic binary ML approach for classification and regression tasks. When compared to other ML techniques, SVM performs well with limited data, is resilient to model mistakes, and requires limited computational resources. The SVM method makes use of training data to locate the optimal decision boundary, sometimes referred to as a hyperplane, which separates an n-dimensional space into classes. Escobar et al. examined how to identify matrix cracking and delamination in carbon fiber reinforced polymer (CFRP) composites for aircraft structures using electrical resistance tomography (ERT), incorporating several data-driven models [85]. The results showed that the proposed classification methods, when combined with SVM, can properly assess the degree of delamination and characterize these distinct damage patterns with 94% accuracy. For applications with intrinsic noise in the ERT data, the SVM model outperformed alternative ML methods like KNN and RF. They also determined that combining ERT with ML can result in considerable cost savings in aircraft component inspections and maintenance. The SVM model was also used by Il and Liu to forecast the extent of aircraft damage and personal harm sustained during approach and landing accidents, with a focus on 14 accident characteristics [86]. The SVM models utilizing the radial basis function (RBF) kernel achieved 96% accuracy for aircraft damage prediction and 98% accuracy for personal injury prediction. The research highlighted the effectiveness of the SVM model using the RBF kernel for accident prediction using categorical datasets. The aircraft skin damage recognition method utilizing an image-based method was proposed by Du and Cao to simplify the traditional detection process using a data-driven approach [87]. The wavelet packet decomposition and a gray-level co-occurrence matrix were utilized to ascertain the eigenvalues of the data. Even with a small sample size, the developed SVM training model with optimized RBF kernel function settings displayed good accuracy in recognizing normal skins and unintentional hits, attaining an overall identification rate of 81.5%. Alhammad et al. proposed pulsed thermography (PT) technology to diagnose structural damage in aircraft fuselage CFRP composite structures [88]. Statistical analysis was employed to detect damaged areas, while ML, specifically the SVM algorithm, was used for more accurate detection. The classification models achieved prediction accuracies ranging from 78.7% to 93.5%, demonstrating the potential for developing an automated model for efficient damage evaluation in composite laminates based on NDT techniques.

Decision trees (DTs) are another data-driven method that is commonly employed for the SPHM of aircraft structures. This is a supervised learning model based on a tree-like structure, where a large dataset is decomposed into smaller subsets to develop a root node, named a decision node, and each branch that emerges from the node indicates a decision [78]. For complicated data-driven challenges, DTs calculate the statistical likelihood of a course of action and provide a visual depiction of the chosen decision-making process.

However, with unbalanced or biased data, as is the case of aircraft SPHM, the model may be susceptible to overfitting, making it unreliable on unseen data. Gerdes et al. explored DT based data-driven condition monitoring and prognosis for reducing the unscheduled maintenance of A320 aircraft from Etihad Airways [89]. A DT model was developed to classify system characteristics based on sensor inputs, leading to accurate classification and RUL prediction. The DT model was optimized using a genetic algorithm (GA), and validation was performed on A320 aircraft data. The total useful life (TUL) data were decomposed into 10% groups to obtain 10 class-labeled data points, thus developing a wide range of categories for the supervised learning problem. The proposed method was verified through successful classification of the 10 classes with noise reduction, enhancement of accuracy, and enabling maintenance action detection. Bull et al. used bagged DTs to illustrate the implications of cluster-adaptive active learning for SHM using the Gnat aircraft wing dataset [90]. The results successfully illustrated the benefits of utilizing active learning tools in SHM, highlighting the first use and implementation of active learning methodologies in aircraft structure SPHM.

Random forest is another supervised data-driven model that is often used for the SPHM of aircraft structures. The RF model is composed of multiple DTs, allowing it to make better predictions as it develops correlated forests of the individual DTs and incorporates randomness and ensemble learning to improve performance compared to the DTs [91]. The factors accompanying the aircraft damage probability in bird strike incidents were identified by Misra et al., and classification models were developed to predict aircraft damage [92]. The RF, logistic regression (LR), and XG-Boost classifiers exhibited the best prediction abilities when using the FFA's National Wildlife Strike Database, with accuracy rates of (78.81, 78.51, and 78.35)%, respectively. The RF classifier identified the bird's size, the height of impact, the aircraft's speed, and the aircraft's mass as key factors in predicting aircraft damage. Ai et al. introduced an innovative SHM solution that utilized acoustic emission (AE) monitoring to autonomously detect and localize impacts on aircraft elevators [93]. The aircraft elevator impact data were experimentally obtained using the setup shown in Figure 4. Based on AE signals, regression methods, such as LR and RF, were used to determine impact locations. The RF model outperformed the LR model in predicting impact location with an RMSE of 0.6778, demonstrating its ability to localize impacts on thermoplastic composite aircraft lifts.

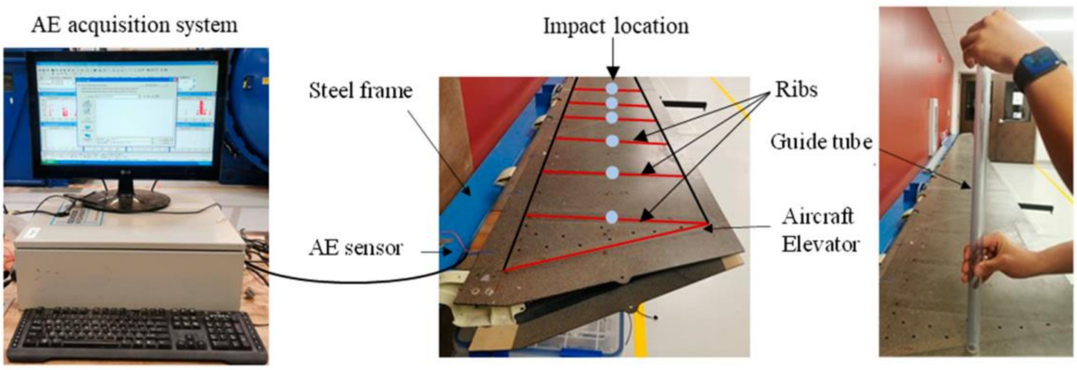


Figure 4. The experimental setup for impact damage characterization of aircraft elevator component [93].

The KNN algorithm is an unsupervised, data-driven model that is commonly used for classification tasks. The model estimates the probability of a new data point and determines the particular group it belongs to, considering the other data points in close proximity [94,95]. As a result, the new data point is assigned a label or group that is highly similar to the given data point. Swischuk and Allaire presented a data-driven strategy for sensor failure detection and the prediction of rectified sensor data in both the online and offline paradigms using ML approaches [34]. Autocorrelation was identified as a global feature that was capable of accurately classifying sensor states and detecting failures. By combining feature selection and KNN regression, the methodology enabled rapid prediction of corrected sensor data during system operation. The method was successfully tested using flight data from a commercial airplane, finding and fixing problems in the pitot static system that resulted in erroneous air-speed estimations.

NB is another supervised data-driven model that is based on counting and conditional probability and is commonly used for classification tasks. The model considers that the characteristics of all data points in the dataset are independent of each other and uses Bayes' theorem to classify the data [94,95]. Dİkbayir and Bülbül used various ML models, such as DT, SVM, and NB, to detect structural damage in aircraft due to bird strikes [96]. They revealed that the NB model with a Gaussian kernel shows superior performance on the versatile dataset obtained from various aircraft structures. Le et al. exploited various ML-based data-driven techniques that included NB, SVM, LR, RF, and KNN, integrating an electromagnetic testing system to effectively characterize hidden corrosion in the riveted joints of aircraft structures [97]. The model is validated on the experimental setup shown in Figure 5. All models showed an accuracy of over 80% for detecting corrosion of numerous sizes and locations, while also exploring training strategies for small datasets.

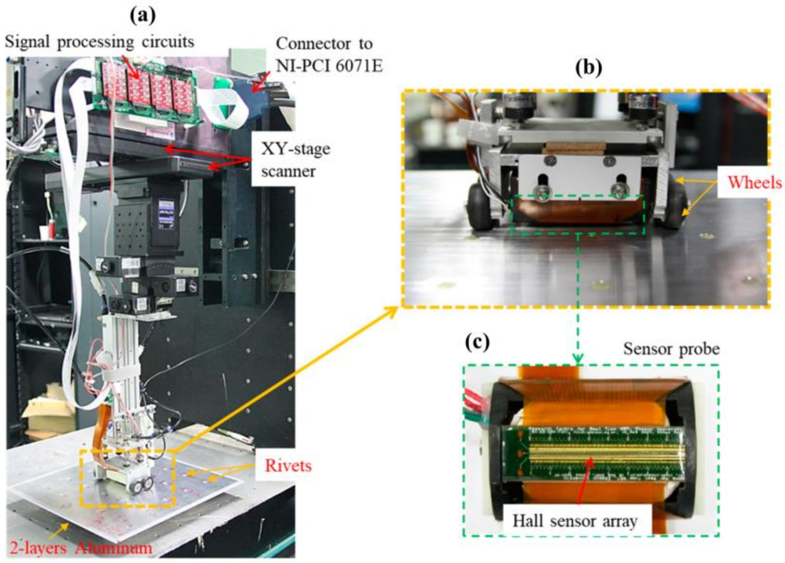


Figure 5. Electromagnetic testing arrangement on a bi-layer aluminum sheet: (**a**) a sensor probe coupled to an XY-stage scanner that contained signal processing circuits; (**b**) the sensor probe placed on the specimen; and (**c**) the sensor probe containing a Hall sensor [97].

Table 1. Machine learning-based data-driven case studies and their key features.

Case Study	Contribution	Application	Proposed Method	Pros and Cons	Ref.
Case 1	Damage detection in CFRP-based aircraft composites using ERT	Aircraft composites	SVM, RF, KNN, and NN	Pros: Multiple damage types Cons: Did not perform full-scale validation	[85]
Case 2	Aircraft damage and personal injury assessment during approach and landing	Entire aircraft structure	SVM	Pros: Aircraft and passenger health injury assessment Cons: Categorical factors introduce complexity	[86]
Case 3	Aircraft skin damage identification using limited data	Entire aircraft structure	SVM	Pros: Efficient for limited data Cons: Tedious pre-processing and feature extraction	[87]

Table 1. *Cont.*

Case Study	Contribution	Application	Proposed Method	Pros and Cons	Ref.
Case 4	Automated Impact Damage Detection Technique using Thermographic Image Processing	Aircraft fuselage	SVM	Pros: Autonomous approach Cons: Low accuracy	[88]
Case 5	A decision tree-based condition monitoring and prognosis for civil aircraft	A320 aircraft	DT	Pros: Includes both condition monitoring and prognosis Cons: Computational complexities	[89]
Case 6	A semi-supervised active learning approach for SHM in aircraft	Gnat aircraft wing dataset	Bagged DT	Pros: Did not consider supervised learning Cons: Model performance is low	[14]
Case 7	Aircraft structural damage due to bird strikes and evaluation of factors with highest contributions towards predicting aircraft damage	Aircraft structural damage using FAA National Wildlife Strike Database	RF, LR, and XGBoost	Pros: Evaluating factors that contribute to aircraft impact damage Cons: Model performance is low	[92]
Case 8	Acoustic emission-based impact damage detection of a thermoplastic composite aircraft elevator	Aircraft elevator component	RF	Pros: Use of thermoplastic resin Cons: Validation required on full-scale aircraft	[93]
Case 9	A proposed ML technique to identify aircraft sensor error and flight data rectification that reliably determines what, if any, problems are happening inside the pitot-static system	Flight data rectification and identification of aircraft sensor errors	KNN regression	Pros: Enhances aircraft system reliability and performance Cons: Feature selection process introduces complexity and high computational resources	[34]
Case 10	Damage detection of aircraft structures due to bird strikes	Aircraft structure extensive set of real bird strike data	NB, SVM, and DTs	Pros: An auto-pilot system for improved safety and decision making Cons: Very low model performance	[96]
Case 11	Aircraft corrosion detection using electromagnetic testing system	Corrosion at riveted joints in aircraft structures	NB, SVM, linear regression, RF, KNN	Pros: Considered corrosion at joints Cons: Requires validation on the actual aircraft joints corrosion	[97]

3.1.3. Deep Learning Approaches in SPHM

Deep learning, a subset of ML inspired by the design and operation of the human brain, entails the construction and training of neural networks with numerous layers of linked artificial neurons to extract complex representations and characteristics from data [98]. These data-driven networks have demonstrated extraordinary effectiveness in multiple domains, including audio and vision recognition, natural language processing (NLP), and autonomous driving. The DL models are continuously replacing conventional ML models for better performance as their deep architecture allows for autonomous feature extraction, which eliminates the need for tedious manual feature extraction. The following section focuses on an overview of the DL-based data-driven models used in the SPHM of aircraft structures.

The artificial neural network (ANN) is the foundational model for deep learning; it consists of artificial neurons, also known as units, which are organized into three distinct layers [99]. The first layer, known as the "input layer", obtains data before forwarding it to the second layer, known as the "hidden layer", which performs mathematical computations. The last layer, the output layer, outputs data. Activation functions serve as fundamental components of neural networks, introducing the crucial non-linearity required to understand complex data patterns. Among these functions, rectified linear activation (ReLU) stands out due to its simplicity. It allows positive inputs to pass through unchanged while converting negatives to zeros, thereby enhancing learning and feature extraction capabilities. In contrast, the Sigmoid function compresses inputs into a range of 0 to 1, making it well-suited for probability-based tasks despite certain gradient limitations. To address these limitations, the hyperbolic tangent (Tanh) function maps inputs from −1 to 1, accommodating a wide range of network architectures. These activation functions empower neural networks to capture intricate patterns, enabling them to excel in various tasks.

Deep neural networks (DNNs) are neural networks with numerous hidden layers. The ANN model follows a forward structure and is taught using the backpropagation technique, which operates in a manner analogous to the human brain or nervous system, characterized by the presence of neural connections that possess many interconnections facilitated by other axons. The formation of each layer of ANN is facilitated by neurons that function as non-linear processing units. However, it is important to note that each neuron inside a given layer is intricately linked to every other neuron in the neighboring layers, establishing complex networks. Furthermore, the interconnection between neurons in consecutive layers is assigned certain weights based on the pattern of the input data. The phenomenon of transmitting information from one neuron to another or from one layer to another is referred to as a forward connection. The process of autonomous learning is achieved by dynamically adjusting the interconnections between neurons within a network. The back-propagation technique is widely used for training ANN and involves minimizing the cost function, which is defined as shown in Equation (6) [99]:

$$m = \frac{1}{2}\sum_{i=1}^{n}(a_i - b_i)^2 \tag{6}$$

where n denotes the number of classes, a_i represents the expected output, and b_i represents the output of the ANN model, namely from the ith neuron out of a total of n neurons in the output layer.

CNN and CAE are commonly employed convolution-based models for aircraft SPHM. These models share a comparable architecture and perform operations across various layers. The essential elements of convolution-based models encompass the convolutional layer, pooling layer, activation layer, batch normalization layer, dropout layer, and global pooling layer [74,100].

The convolutional layer (CL) generates a feature map by convolving filters or kernels of varying sizes with specific segments of the input data. This process involves calculating the dot product between a designated portion of the input data and a matrix of adjustable parameters, namely weights and biases, referred to as a filter or kernel. Typically, filters have smaller dimensions than the input data and are repeatedly applied across the input to capture localized details. The activation of a single filter is commonly used to characterize the output, and multiple filters exhibit activations for various aspects of the input data. The activations of each filter are pooled and organized into a three-dimensional array along the depth dimension. The mathematical representation of the convolution process is depicted in Equation (7).

$$F_k^i = W_k^i * L^i(j) + b_k^i \tag{7}$$

where F represents the feature map generated by the kth filter in the i-th layer, W represents the weights, L denotes the j-th local region of the input data in the ith layer, and b corresponds to the bias of the kth filter in the i-th layer. The terms k and i, respectively, denote the kth filter in the i-th layer.

A pooling layer (PL) is incorporated to reduce the variability of the feature space and network parameters by decreasing the dimensions of its input. The two common pooling functions are maximum pooling and average pooling. Maximum pooling reduces spatial dimensions by selecting the highest value from a set of neighboring pixels or activations, while average pooling achieves this by calculating the mean value of the neighboring pixels or activations.

Activation layers (ALs) introduce non-linearity to input data, enhancing the network's capacity for representation. The ReLU activation function, commonly employed in neural networks, facilitates faster network convergence. Mathematically, the ReLU activation function is expressed as shown in Equation (8):

$$N_i = f(y_i) = \max(0, y_i) \tag{8}$$

where, N_i is the i-th activation of the input y_i. It is noted that the ReLU function allows positive values to pass through unchanged while setting negative values to zero.

The batch normalization layer (BNL) is utilized to address the challenge of internal covariance shift through input normalization. This normalization process speeds up the training procedure and enhances training accuracy. The BNL operates in two distinct stages. In the initial stage, the incoming input is normalized, as depicted in Equation (9):

$$y_{i(norm)} = \frac{y_i - \mu}{\sigma + \varepsilon} \tag{9}$$

where y_i and $y_{i(norm)}$ represent the input from the previous layer, respectively. The symbols μ and σ are used to represent the mean and standard deviation of the input values, while ε is a smoothing factor that ensures numerical stability and avoids division by zero. In the subsequent stage, the normalized values undergo rescaling and offsetting using the rescaling parameter γ and the offsetting parameter β, as shown below in Equation (10):

$$y_i' = \gamma y_{i(norm)} + \beta \tag{10}$$

The parameters γ and β are subject to learning, and their optimal values are found during the training process.

The dropout layer (DL) is integrated into neural networks to combat overfitting. It achieves this by randomly deactivating selected neurons with a dropout probability between 0 and 1 [101]. Adding a DL to the neural network architecture helps mitigate the reliance between neurons during training.

The global pooling layer (GPL) is responsible for feature space pooling, reducing parameters for the fully connected layer. The SoftMax function introduces a probabilistic link between the feature space and classification categories [102,103]. The class output for a specific input is determined by choosing the category with the highest likelihood score in the feature map.

Other commonly employed DL-based data-driven techniques for SPHM of aircraft structures include recurrent neural networks (RNNs) and long short-term memory (LSTM). RNNs are a type of artificial neural network that shares weights across multiple time steps. They are well-suited for processing sequential input data like time-series data due to their incorporation of feedback by feeding the current value back into the network. This feedback mechanism enables RNNs to retain and update information in their memory, leading to cumulative outputs [104]. For a given input sequence $x = (x_1, x_2, \ldots, x_T)$, the hidden state $h = (h_1, h_2, \ldots, h_T)$ of an RNN is updated at each time step as represented in Equation (11) [105]:

$$h_t = \mathrm{H}(W_{\mathrm{xh}} x_t + W_{\mathrm{hh}} \mathrm{h}_{t-1} + b_{\mathrm{h}}) \tag{11}$$

where h_t represents the hidden state or hidden vector at time step "t", W_{xh} is the weight matrix that connects the input vector "x_t" to the hidden state "h_t", W_{hh} is the weight matrix that connects the previous hidden state h_{t-1}" to the current hidden state "h_t", x_t is the input vector at time step "t" and b_h is the bias term added to the weighted sum before applying the activation function. H represents the hidden state or hidden vector at time step "t" and h_{t-1} represents the hidden state or internal memory of a recurrent neural network at the previous time step "t − 1" in a sequence. The output vector y = (y_1, y_2, ..., y_T), is then obtained by iterating the above equation from time t = 1 to T and is given by Equation (12):

$$y_t = W_{\mathrm{hy}} h_t + b_{\mathrm{y}} \tag{12}$$

where y_t represents the output vector at time step "t", and W_{hy} is the weight matrix that connects the hidden state "h_t" to the output "y_t", b_{y} is the bias term added to the weighted sum before obtaining the output "y_t".

The LSTM model stands as a unique iteration of the traditional RNN design, specialized for handling temporal sequences and capturing extended correlations [98]. Employing memory blocks as an alternative to basic RNN units, the LSTM architecture is composed of these blocks, each containing one or more memory cells along with a pair of adaptive multiplicative gates functioning as input and output mechanisms. Within a computational system, the memory block undertakes the task of storing and altering information over varying time intervals, making use of input and output gates. These gates govern the inflow and outflow of data to a memory cell.

Escalonilla et al. conducted tests on ANN to accurately predict strains from flight parameters as part of developing the SPHM method for the A330 Multirole Tanker Transport aircraft [31]. Real flight data from the A310 Boom Demonstrator, equipped with a prototype SPHM system, was utilized for the tests. The results demonstrate the successful application of ANNs in predicting strains for various structural components of the aircraft, including the fuselage, wings, and tailplanes, and also discuss the technologies, strategies, and solutions employed for building and training the ANNs. Lima et al. performed aircraft damage detection using ARTMAP-Fuzzy-Wavelet ANN to assist the inspection process for aircraft structures [106]. For damage assessment, the suggested technique integrates signal modeling and simulation using a numerical model. In the aeronautical structure analysis, the ARTMAP-Fuzzy-Wavelet ANN was proven to be trustworthy and efficient. To classify SPHM data from guided wave sensor networks, Dworakowski et al. proposed ANN-based ensemble models [107]. The method is validated through practical experiments on a full-scale aircraft test, showcasing increased reliability in fatigue crack detection for the load-carrying components of the aircraft structure. The ensemble approach compensates for result variability and provides superior reliability compared to individual classifiers, particularly in challenging monitoring cases; it showed an accuracy of over 95%. While further improvements and ensemble extension were possible, limitations in training data availability and computation time prevented additional experiments.

Long-short-term memory (LSTM), recurrent neural networks (RNNs), deep belief networks (DBNs), and probabilistic neural networks (PNNs) are some of the other NN-based models that have been employed for the SPHM of aircraft structures. Shen et al. focused on the implementation of SPHM systems for aircraft wing structures [108]. They built an FE model of an aircraft wing structure, using natural frequency variations as the features for damage detection. The feature parameters were input into a PNN, which is trained and validated with training and validation datasets of the damaged samples. The results show that the PNN can detect deterioration in the top and lower skins of the wing structure. Tamilselvan et al. suggested a DBN-based multi-sensor health detection approach for quick inference and the capacity to encode higher-order structures [109]. Defining health states, preparing sensory data, constructing DBN-based classification models, and verifying them using testing datasets were all part of the suggested technique. The DBN's performance in health diagnosis is proven by utilizing aircraft wing and engine health diagnostics, demonstrating its efficacy when compared to established ML approaches such as SVM. Hu et al. proposed an NDE approach based on infrared thermography and a LSTM-RNN model for autonomously diagnosing frequently occurring flaws in honeycomb-structured composite materials used in airplanes [110]. The suggested LSTM-RNN algorithm has a sensitivity of more than 90% in diagnosing external flaws and more than 70% in classifying internal flaws, as shown in Figure 6. The technique addresses the need for accurate defect classification in honeycomb materials, providing valuable insights for aircraft maintenance and safety.

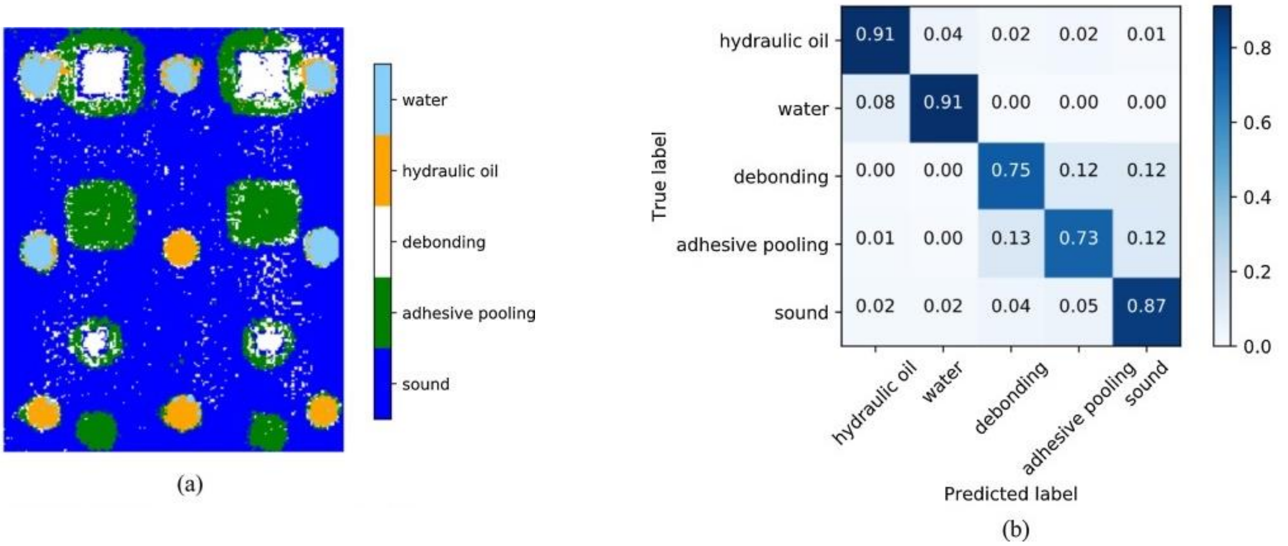


Figure 6. (**a**) The categorization of defects for the training data, and (**b**) the normalized confusion matrix corresponding to the classification results [110].

CNN is a powerful tool that is used for vision-based detection tasks by analyzing patterns. It consists of multiple layers that extract and examine features from the data. These layers encompass the convolutional layer, pooling layer, activation functions like ReLU or LeakyReLU, and the fully connected network (FCN). The convolutional layer employs filters to perform convolutional operations, while the pooling layer down-samples the feature map to reduce its size. The resulting two-dimensional array from the pooled feature map is then flattened into a linear vector. The FCN layer takes this flattened matrix as input, categorizing and identifying images [111,112]. Cui et al. [113] showcased a data-driven deep learning solution utilizing CNNs to detect and locate structural defects in an aircraft's stiffened composite panel [94]. Their CNN algorithm accurately recognizes defects in critical areas of the aircraft panel, such as the skin, flange, and cap. Moreover, the algorithm demonstrates the ability to generalize and detect damage in scenarios that differ from the training data. It also performs reasonably well in probing hard-to-reach regions, such as the stringer region. However, the choice of signal excitation affects the performance of damage imaging, and additional research is necessary to account for environmental factors and incorporate pulse-echo signals to improve the results. In another study by Lin et al., a CNN model was developed for the SPHM of a composite wing using aerodynamic load and strain data [114]. The CNN model was trained using strain data obtained from a digital twin finite element (FE) model (Figure 7) representing a full-scale composite wing with both healthy and damaged elements. The results exhibited strong damage detection with 99% accuracy in noise-free conditions, 97% accuracy in the presence of 2% Gaussian noise, and an overall accuracy of 83% in damage localization using a threshold value of 1.5. The proposed framework showcases the efficiency, accuracy, and robustness of the suggested CNN-based SPHM method.

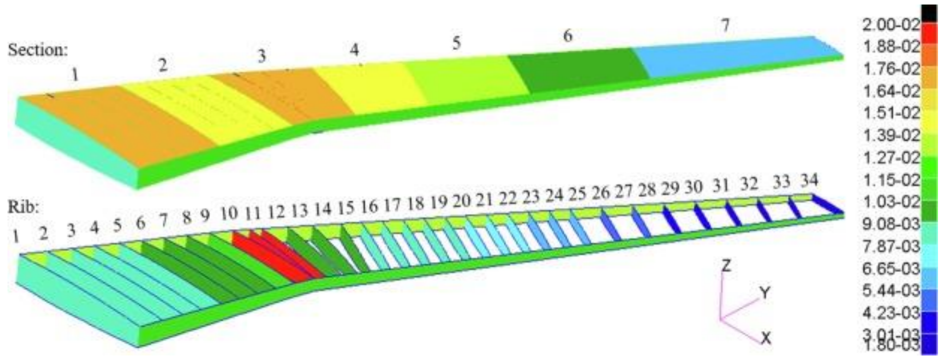
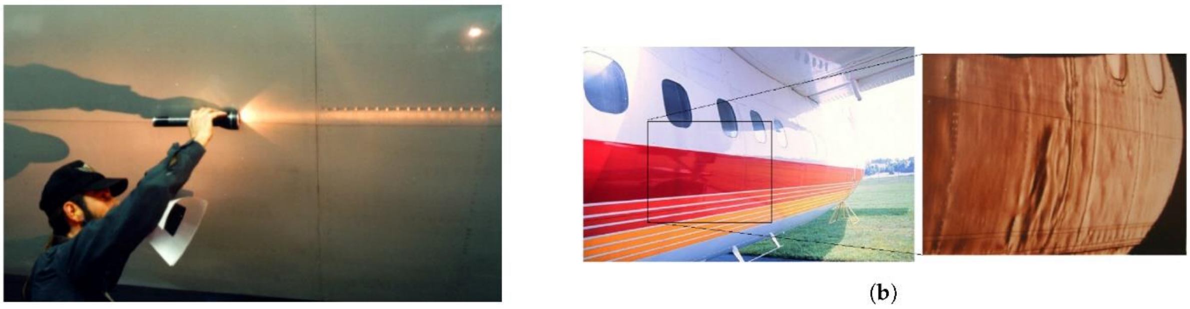


Figure 7. The FE model of a composite wing skin, rib, and spar [114].

Autoencoders are a specific type of unsupervised neural network utilized for learning a compressed representation of input data, enabling the discovery of underlying patterns and structures within the dataset [115]. During the training process, the autoencoder acquires knowledge on how to effectively compress data by capturing its intrinsic characteristics. Essentially, an autoencoder consists of an encoder, decoder, and intermediate feature space. The encoder compresses the input data, while the decoder attempts to reconstruct the original input from the encoded representation. Ai et al. focused on the detection and localization of impact damage in aircraft structures through AE monitoring [116]. Random forest and stacked autoencoder (SAE) models were developed using AE datasets obtained from impact testing on a thermoplastic aircraft elevator. The findings indicated that both the RF and SAE models outperformed a traditional ANN model in terms of impact source localization. The RF model provided insights into feature importance, facilitated feature reduction, and enhanced computational efficiency while maintaining satisfactory localization performance. Conversely, the SAE model achieved slightly superior performance without requiring manual feature extraction. Sarkar et al. proposed a technique for characterizing crack damage in aircraft composite structures [117]. The DAE model demonstrated remarkable accuracy and robustness in characterizing crack damage, even when subjected to varying load conditions. This approach, based on unsupervised learning, was validated using real image data. The results showcased precise damage characterization, even with a limited number of labeled training images, highlighting the potential of deep learning in enabling the autonomous SPHM of aircraft structures.

Transfer learning is another advanced data-driven technique that leverages the advantage of transferring the knowledge gained from one system to another [100]. This enables the challenges associated with the limited available data for training to be overcome. The data-driven techniques are data thirsty, demanding a large amount of data for training. But in practical systems, the availability of data are limited, especially in damaged states, as running the system in a faulty condition may lead to severe consequences. Therefore, in such applications, the transfer learning model is found beneficial. The transfer learning model is trained on large publicly available datasets, and the model weights are then optimized for a given problem by retraining on limited available data. This improves the model's generalization too, and the pre-trained model overcomes the tedious process of developing a model from scratch. In the SPHM of aircraft, in general, healthy data are available in excess; however, damaged data from different types of damage is limited. Therefore, researchers in this domain have explored various transfer learning techniques.

To achieve multi-level damage classification in plate-type structures, Weihan et al. introduced a deep transfer learning network based on Lamb waves. Their approach yielded exceptional accuracy, surpassing 99% [118]. The proposed approach analyzes complicated Lamb wave signals using a 1D-CNN, allowing for deep mining of damage features. A multi-task cascaded architecture is used to detect, localize, and identify the severity of damage while exchanging network structures and weight values to increase computing performance. Experimental results demonstrate a 35% reduction in training time and validate the efficacy and reliability of the suggested method. Corrosion detection in aircraft structures using autonomous images was created by Brandoli et al. using the D-Sight Aircraft Inspection System (DAIS) (Figure 8) using deep transfer learning models such as DenseNet, ResNet, SqueezeNet, and InceptionV3 [16]. The approach demonstrates a precision of over 93% in detecting corrosion, comparable to trained operators, reducing uncertainties associated with operator fatigue and training. The adoption of transfer learning assisted in overcoming the scarcity of corrosion images, and the findings indicate that the approach can support corrosion monitoring and contribute to the automation of maintenance routines in the aerospace sector.



(a) (b)

Figure 8. (**a**) An expert inspects the fuselage visually with a torch; (**b**) the fuselage picture is scanned, revealing surface micro perturbations produced by corrosion [16].

Table 2 presents a compilation of diverse case studies that employ deep learning-based data-driven technologies to advance the SPHM of aircraft structures.

Table 2. Contribution of various researchers to the SPHM of aircraft structures using deep learning.

Case Study	Contribution	Application	Proposed Method	Pros and Cons	Ref.
Case 1	An ANN model has been used to identify the strain at different locations on aircraft using 40 parameters.	Aircraft structure	ANN	Pros: Improves the maintenance process for aircraft Cons: Low performance due to unoptimized model	[31]
Case 2	Integration of various methods to monitor and identify defects in aircraft structures.	Aircraft structure	ARTMAP -Fuzzy- Wavelet ANN	Pros: Hybrid method for better performance Cons: Model is validated only on the simulation data	[106]
Case 3	ANN and its ensemble network classifiers are established for guided wave-based damage detection in aircraft with small-scale and long-term full-scale fatigue experiments	Military turboprop aircraft PZL Orlik TC II	ANN and ensemble network	Pros: High model accuracy Cons: The limitations in training data availability and computation time may pose restrictions on using the proposed method for large aircraft	[107]
Case 4	Based on the wing structure's actual mechanical properties, the fifteen damage patterns were simulated using the aircraft wing structure FE model	Aircraft Wing	PNN	Pros: Multiple damage cases considered Cons: The method requires careful consideration of dissymmetry, geometry, and natural frequency changes, and further research is needed to address these complexities	[108]

Table 2. *Cont.*

Case Study	Contribution	Application	Proposed Method	Pros and Cons	Ref.
Case 5	Deep Belief Networks (DBNs) were used to present a unique multi-sensor health detection technique	Aircraft Wing	DBN	Pros: Multi-sensory data Cons: Model performance needs improvement	[109]
Case 6	Defect classification of honeycomb-based aircraft structures using infrared thermography	Aircraft structure	LSTM-RNN	Pros: Autonomous process Cons: Performance is highly dependent on the accuracy and resolution of the infrared thermography data in practical applications	[110]
Case 7	Ultrasonic guided wave-based damage imaging using a 1D-CNN model applied to a skin-stinging composite aircraft panel	Aircraft panel	CNN	Pros: Multiple damage cases considered Cons: Model did not consider environmental factors	[113]
Case 8	The proposed CNN-based data-driven SHM technique is assessed using strain data from a numerical model, visualizing a network of 324 sensors at the skin-rib joints of an aircraft composite wing under different flight loads	Composite wing skin-rib joints	CNN	Pros: The use of multiple data sources (load and strain data) and noise considerations make the model well suited for real aircraft structures Cons: Model functionality is not interpretable and unable to predict damage location	[114]
Case 9	RF and deep learning-based impact damage detection and localization using AE	Aircraft elevator component	RF and SAE	Pros: Includes damage localization Cons: The validation is based on laboratory environment, and further validation on actual aircraft structures is needed	[116]
Case 10	A new framework based on deep learning was developed and deployed to characterize crack damage in aircraft composite	Thick multi-layer composite sub-elements used in aircraft applications	DAE	Pros: Unsupervised problem Cons: Did not optimize model for better performance	[117]
Case 11	Application of lamb waves and deep transfer learning to multi-level damage classification for aircraft plate structure	Aircraft plate structure	Deep transfer learning	Pros: Multi-level damage with limited data Cons: The applicability and generalization of the technique to different types of aircraft plate structures need investigation	[118]
Case 12	Aircraft fuselage corrosion detection using deep transfer learning models such as InceptionV3 and DenseNet	DAIS photos from various Boeing and Airbus aircraft lap joints	InceptionV3 and DenseNet	Pros: Effective for limited data Cons: The effectiveness of the approach may depend on the availability and diversity of corrosion images for transfer learning	[16]

3.1.4. Advantages and Limitations of Data-Driven Approaches

Data-driven approaches, underpinned by machine learning and deep learning algorithms, have gained significant traction in the realm of SPHM due to their potential to offer robust and adaptable solutions for system health management. This subsection aims to comprehensively evaluate the advantages and inherent limitations associated with these data-driven methodologies.

The advantages of data-driven approaches in SPHM are as follows:

- **Adaptability and Learning Capability**: Data-driven approaches excel in their ability to adapt and learn from large datasets. They leverage complex algorithms to uncover underlying patterns and relationships in the data, allowing them to handle a wide range of scenarios and adapt to dynamic operational conditions.
- **Prediction Accuracy**: Given their capacity to process extensive datasets, data-driven techniques can significantly enhance prediction accuracy. By analyzing diverse operational data, these methods can offer valuable insights into system behavior, aiding in the proactive identification of potential failures.
- **Scalability**: The power of data-driven approaches lies in their scalability. They can effectively handle large volumes of data from diverse sources, making them particularly suitable for complex systems like modern aircraft.

The limitations of data-driven approaches in SPHM are as follows:

- **Data Quality and Availability**: The effectiveness of data-driven approaches largely depends on the quality and quantity of available data. They require substantial amounts of high-quality data to train and validate their models, which can be a challenge in certain environments.
- **Model Transparency**: Data-driven methods, particularly those utilizing deep learning algorithms, often function as "black boxes". It can be challenging to interpret their inner workings, which may hinder understanding and trust in their predictions.
- **Computational Requirements**: These methods can be computationally intensive, requiring substantial processing power and storage capacity. This might limit their application in settings with constrained computational resources.
- **Generalizability**: While data-driven approaches can adapt and learn from the data they are trained on, they may struggle to generalize their learnings to new, unseen scenarios. This can pose challenges in a field as dynamic and unpredictable as SPHM.

3.2. Model-Based Approaches in SPHM

This section offers a detailed exploration of model-based approaches in SPHM. By thoroughly examining the fundamental principles that form the basis of these approaches, the section underscores their reliance on physics and mathematical modeling. By gaining a profound understanding of model-based approaches, new opportunities arise for proactive maintenance, informed decision making, and advanced structural health management in the aviation industry.

3.2.1. Introduction to Model-Based Approaches

Model-based approaches are essential in advancing SPHM for aircraft structures, relying on scientific theories and physics-based models to analyze, assess, and predict structural component health. These methodologies involve developing mathematical equations that capture the physical relationships between parameters such as stress, strain, load, and material properties. By creating accurate models, we can effectively represent the actual structures, encompassing various variables that influence system behavior and performance. This process requires a deep understanding of structural behavior and incorporates the underlying physics and mechanics.

These model-based approaches presuppose the presence of a system behavior model, which, when combined with measured data, identifies system characteristics and predicts the RUL. Three types of models are utilized: physical failure models [24,119], stochastic filtering models [120], and statistical models [121]. Physical failure models are quantitative analytical frameworks that explain the degradation processes of system health indicators by comprehending failure mechanisms. Stochastic filtering models, comprising a process model and an observation model, encompass non-stationary stochastic processes to account for unobserved health indicators and observed Condition Monitoring (CM) data.

In contrast, statistical models are constructed using collected input/output data, with historical data utilized to determine the RUL. The primary advantage of model-based approaches stems from their ability to integrate a fundamental physical comprehension of the monitored system, leading to enhanced accuracy in comparison to data-driven approaches.

These methodologies offer detailed predictive analysis by considering initial conditions, degradation processes, and operational constraints, enabling accurate predictions of potential structural failures and estimations of RUL. As a result, maintenance schedules can be optimized, enhancing the efficiency and cost-effectiveness of aircraft operations. Monitoring and predicting aircraft structural health have become increasingly important in modern aviation, and models for determining RUL have been developed to empower maintenance teams to make informed decisions, improving safety and reliability within the industry. However, model-based approaches face challenges. Creating accurate and reliable models requires extensive domain knowledge, and maintaining and updating these models to reflect real-world conditions demands significant computational resources. Additionally, these approaches may struggle to handle the variability and uncertainty present in real-world conditions [122]. This is where data-driven approaches complement model-based methods by leveraging large datasets and machine learning techniques. Despite these challenges, the ongoing development of model-based approaches demonstrates their significant potential in aircraft health management. Hybrid systems that integrate physics-based modeling with data-driven techniques offer robust and reliable predictions, combining the predictive accuracy of model-based approaches with the adaptability and flexibility of data-driven methods. This fusion enhances the effectiveness of SPHM, ensuring the integrity and safety of aircraft structures.

3.2.2. Implementation and Application of Model-Based Approaches in SPHM

The implementation and application of model-based approaches in SPHM have demonstrated significant potential for enhancing the safety and efficiency of aircraft operations. This section focuses on the practical aspects of implementing and applying model-based methodologies in SPHM, highlighting their effectiveness in predicting the health status and RUL of aircraft structures. One of the key steps in the implementation of model-based approaches is the development of precise and reliable degradation models for the specific components or systems being monitored. For example, in the fatigue crack growth of fuselage panels, researchers have extensively studied fatigue damage models, such as Paris' law [123]. These models describe the crack growth process based on material-specific parameters and provide a foundation for predicting future crack behavior. Paris' law is an equation that relates the crack growth rate (da/dN) to the stress intensity factor range (ΔK) and stress ratio (R), as shown in Equation (13). The crack length is denoted as "a", the number of flight cycles as "N", and the Paris' law parameters associated with material properties as "m" and "C". The material coefficients are obtained experimentally and also depend on the environment, frequency, temperature, and stress ratio.

$$da/dN = C(\Delta K)^m \tag{13}$$

Figure 9 offers insights into the practicality of the fatigue crack growth principle within a designated crack propagation zone. This zone is located between region I, which is near the threshold of crack propagation, and region III, which is near the unstable zone of crack propagation [124].

Kuncham et al. proposed an online model-based method that utilizes an extended Kalman filter (EKF) to estimate the fatigue life of structures [124]. This technique accommodated real-world uncertainties by applying an updated version of the Paris model to simulate fatigue crack growth and propagation. The process included the estimation of model parameters using the history of crack growth and a subsequent crack prognosis based on these estimated parameters. Both numerical analyses and experimental studies validated the method's accuracy in parameter estimation and RUL prediction for structures. Figure 10 shows a flowchart illustrating this methodology. The method was further tested through numerical analysis on a finite plate under a thermo-mechanical load. Crack propagation modeling was carried out with MATLAB, while an ABAQUS-created high-fidelity finite element (FE) model was used for stress intensity factor (SIF) simulation. This technique effectively estimates system parameters and states by incorporating historical data on crack propagation, resulting in the estimated values being much closer to the true values. Finally, the technique's prediction accuracy was assessed under varying levels of measurement noise through a fatigue crack prognosis.

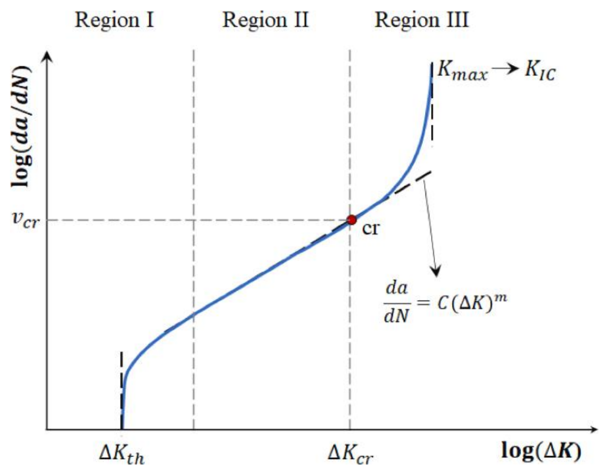


Figure 9. Applicability of Fatigue Crack Growth Rule in Different Crack Propagation Regions [124].

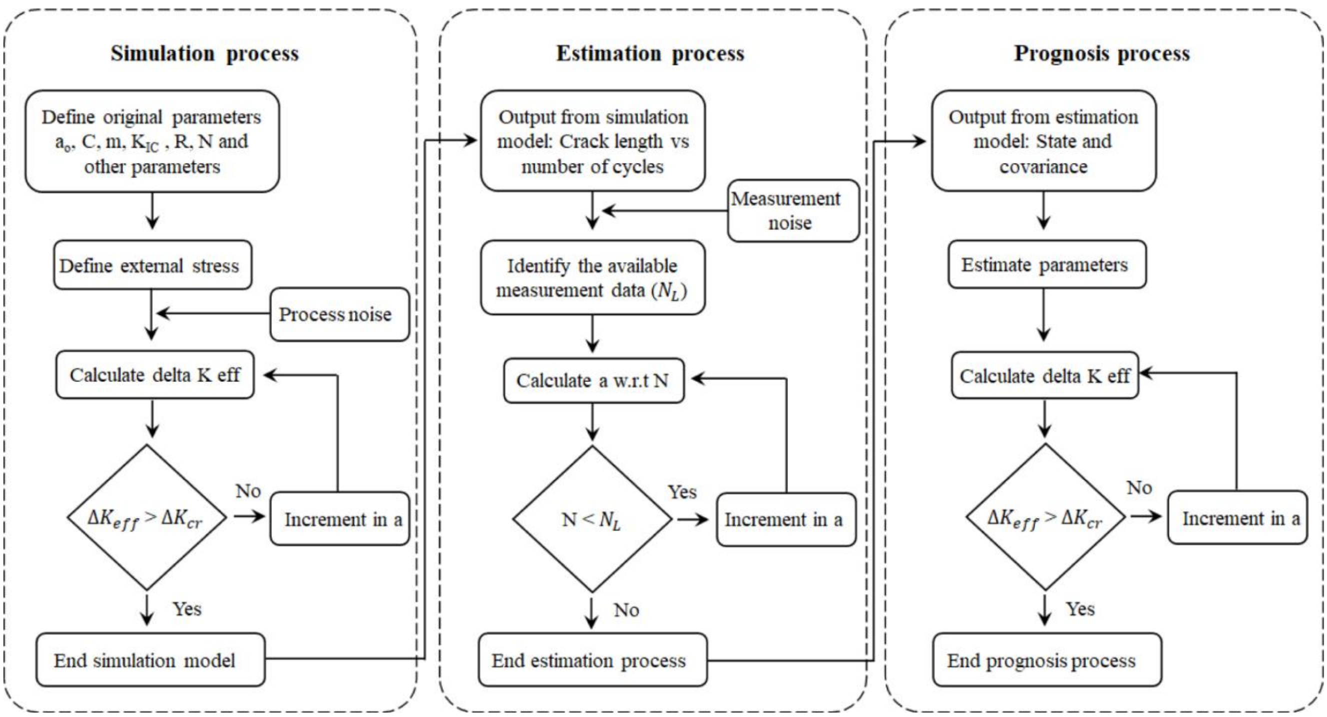


Figure 10. Flowchart of the proposed methodology for online-model-based crack propagation analysis and prognosis [124].

Wang et al. present a model-based prognostic approach to tackle the issues related to fatigue crack propagation in fuselage panels, especially when model parameters are ambiguous and uncertainties influence crack growth. They used Paris' law as their crack growth model and implemented the EKF for state-parameter estimation. The research successfully charted the path of crack growth and computed the RUL by integrating measurement data into the prognostic framework [24]. In another study, Qi et al. proposed a method to estimate the RUL of deteriorating systems under dynamic operational conditions [125]. The method utilizes probabilistic and stochastic approaches and incorporates the influence of specific operational conditions on the degradation rate. Sensor data from a commercial turbofan engine was analyzed using the method, initially with a single sensor. However, the results demonstrate the need for improvement, as there are advancing predictions in the RUL estimations. To address this issue, the paper introduces the integration of multiple sensors through an optimization procedure, leading to enhanced prediction accuracy. The proposed method is compared with existing approaches using the same dataset and showcases superior performance in estimating RUL under dynamic operational conditions. The inclusion of multiple sensors mitigates the issue of advancing estimations observed in the single-sensor approach, providing more reliable and accurate predictions.

Chen et al.'s study focused on failure prognosis, a critical aspect of PHM, as well as condition-based maintenance [126]. The study addressed the challenge posed by multiple sources of uncertainty in real-world scenarios, which can lead to inaccurate predictions. To overcome this challenge, an advanced failure prognosis method utilizing Kalman filtering was proposed. The paper systematically analyzed and classified the various sources of uncertainty, leading to the development of tailored theoretical methods for each specific source. Subsequently, a failure prognosis algorithm was devised, incorporating the identified uncertainties. The effectiveness of the proposed method was demonstrated through a simulation of an aircraft fuel feeding system health monitoring case, showcasing its ability to address real-world uncertainties and its potential for practical applications. Similarly, Chi et al. investigated the use of CM data to predict RUL in aircraft systems. The study addressed the limitations of data-driven approaches by adopting the switching Kalman filter (SKF), a state-space-based method that utilizes multiple models to infer the most probable degradation model from CM data. The SKF approach was demonstrated through a case study, highlighting its potential for practical maintenance decision making [120].

Wang et al. [127] proposed an approach that combines high-performance fatigue mechanics with filtering theories for the diagnosis and prognostication of damaged aircraft structures, as shown in Figure 11a. The approach utilizes the finite element alternating method (FEAM) and the moving least squares (MLS) law for deterministic fatigue crack propagation analysis. Extended Kalman and particle filters are applied to obtain statistically optimal estimates of crack lengths from noisy measurements, as shown in Figure 11b. The approach enables estimation of the probabilistic distribution of the RUL of aerospace structures and demonstrates effectiveness through a simple example, indicating the potential for applications like virtual risk-informed agile maneuver sustainment (VRAMS) and digital twins of aerospace vehicles.

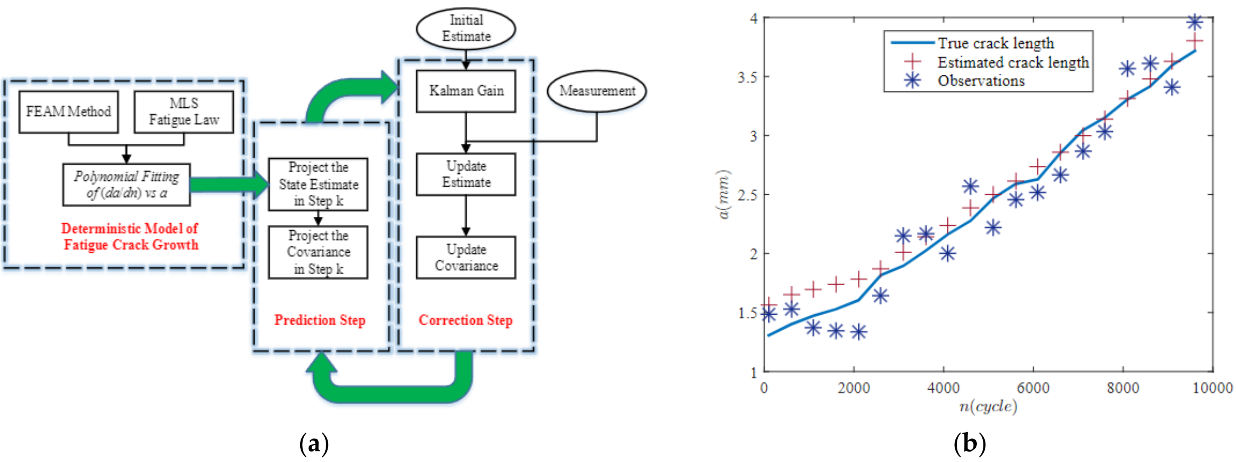


Figure 11. (**a**) A schematic of the EKF application for diagnosing crack length; (**b**) EKF application for the diagnosis of crack length [127].

Table 3 is specifically tailored to showcase studies on model-based approaches for the SPHM of aircraft structures. It offers a comprehensive overview of various case studies, summarizing their potential contributions, application domains, proposed methods, and the corresponding pros and cons:

Table 3. Case studies utilizing model-based approaches and their key features.

Case Study	Contribution	Application	Proposed Method	Pros and Cons	Ref.
Case 1	Studies the effect of model parameters uncertainties on fatigue crack growth	Aircraft fuselage	Paris' law with EKF	Pros: Accurate predictions Cons: Biased initial estimate	[24]
Case 2	Proposes a dynamic probability modeling-based aircraft SHM framework	Aircraft structures	Gaussian Mixture Model	Pros: Reliable monitoring of cracks Cons: Potentially adding complexity	[121]
Case 3	Investigates the use of condition monitoring data for predicting RUL	Aircraft systems	SKF	Pros: Suitability for practical decision making Cons: Increased computational resource	[120]
Case 4	Proposes an approach that combines high-performance fatigue mechanics with filtering theories	Aerospace structures	FEAM and the MLS law	Pros: Effective estimation of RUL Cons: Challenges in terms of implementation and scalability	[127]
Case 5	Introduces new methods for uncertainty management in failure prognosis using particle filters	Aircraft structures	EKF approach	Pros: Reduced uncertainty, reduced computational burden Cons: Dependent on the availability and quality of the data used	[122]
Case 6	Proposes a framework for assessing the safety and efficiency of aircraft maintenance strategies	Aircraft components	Agent-based modeling and Monte Carlo simulation	Pros: Reduction in inspection frequency Cons: accuracy dependent on the quality and availability of the data	[128]
Case 7	Creates a realistic dataset with run-to-failure trajectories	Aircraft engine	Aero-Propulsion System Simulation Model	Pros: Availability of representative run-to-failure dataset Cons: Dataset limitations in terms of its generalizability	[129]
Case 8	Introduces the integration of multiple sensors to enhance prediction accuracy	Turbo fanengine	Kalman Filter	Pros: Enhanced prediction accuracy Cons: Increased complexity, Cost implications	[126]
Case 9	Develops a model-based fault detection	Aircraftcontrolsurfaces	GA	Pros: Early detection, Precision Cons: Complexity, Limited field data	[130]
Case 10	Develops a PHM functional architecture for aircraft avionics systems using a model-based system engineering design approach.	Aircraftavionicssystems	Harmony SE Model-based System	Pros: Systematic development guidance, Simulation-capable Cons: Complexity	[131]

The advantages of model-based approaches are as follows:

- **Accurate Representation**: Model-based approaches provide an accurate representation of the underlying system by incorporating domain knowledge, physical principles, and mathematical equations. They capture the fundamental relationships and dynamics of the system, resulting in accurate predictions and interpretations.
- **Interpretable Results**: Model-based approaches offer interpretability, allowing users to understand the underlying mechanisms and factors influencing the predictions. The explicit mathematical equations and parameters provide insights into the relationships between input variables and the predicted outcomes.
- **Generalizability**: Model-based approaches have the advantage of generalizability. When a model is developed and validated, it can be applied to different scenarios and conditions within the specified range of validity. This enables the transferability of knowledge and predictions to similar systems or applications.
- **Insightful Analysis**: Model-based approaches facilitate in-depth analysis and understanding of the system's behavior. Sensitivity analysis, parameter estimation, and model validation techniques can be employed to assess the impact of different factors, optimize system performance, and gain insights into system dynamics.

Meanwhile, the limitations of model-based approaches are as follows:

- **Assumptions and Simplifications**: Model-based approaches depend on assumptions and simplifications to capture system dynamics. These assumptions may not fully represent the complexity and variability of real-world scenarios, leading to limitations in prediction accuracy and applicability.
- **Limited Adaptability**: Model-based approaches can be less adaptable to changing conditions or situations that were not considered during the model's development. They are often built based on specific assumptions and may not account for unforeseen events or variations outside the scope of the model.
- **Computational Complexity**: Developing and implementing model-based approaches can be computationally intensive, especially for complex systems with numerous variables and interactions. The need to solve mathematical equations and perform numerical simulations can result in longer processing times and resource requirements.
- **Model Uncertainty**: Model-based approaches are subject to inherent uncertainties stemming from model assumptions, parameter estimation, and model structure. These uncertainties can propagate and affect the accuracy and reliability of predictions. Quantifying and managing model uncertainty is a critical challenge in model-based prognostics.

3.3. Hybrid Approaches in Aircraft SPHM

This section provides a comprehensive exploration of hybrid approaches in the SPHM of aircraft structures. This section aims to uncover the development, application, and implications of these hybrid approaches, highlighting their potential to enhance the safety, efficiency, and reliability of aircraft operations.

3.3.1. Introduction to Hybrid Approaches

The emergence of hybrid methodologies, which blend the benefits of model-based and data-driven methods, marks a promising development in the realm of SPHM [65]. These approaches integrate the theoretical foundations and physical understanding provided by model-based methods with the adaptability and learning capabilities of data-driven techniques. By harnessing the synergy between these approaches, hybrid methodologies aim to overcome the limitations of individual methods and achieve a more accurate and comprehensive assessment of structural health. One of the key advantages of hybrid approaches is their ability to leverage the strengths of both model-based and data-driven methods. Model-based approaches incorporate fundamental physical laws, system behavior models, and domain knowledge, enabling them to capture the underlying mechanisms and degradation processes. This allows for a deeper understanding of the system and improves the accuracy of predictions. On the other hand, data-driven methods leverage large datasets and machine learning techniques to extract patterns and correlations from real-world operational data. This enhances the adaptability of the approach and enables it to handle complex and dynamic operational conditions. By combining the advantages of model-based and data-driven methods, hybrid approaches enable a holistic and synergistic approach to SPHM. Such methods can effectively handle uncertainties, adapt to changing conditions, and provide accurate predictions of RUL and potential failure scenarios. The integration of these approaches into a hybrid model creates an advanced SPHM system that is capable of real-time monitoring, in-depth analysis, and predictive forecasting.

While hybrid approaches offer numerous benefits, they also present challenges and limitations. The development and implementation of hybrid models can be complex and resource-intensive, requiring expertise in both model-based and data-driven techniques. The integration of different models and algorithms may introduce additional computational complexities. Additionally, the interpretability of results can be challenging in hybrid approaches, particularly when combining complex mathematical models and machine learning algorithms. Despite these challenges, hybrid approaches hold great promise for enhancing the safety, efficiency, and reliability of aircraft operations. Their ability to combine physical understanding with data-driven insights enables more accurate predictions, proactive maintenance planning, and optimized decision making. By leveraging the strengths of both model-based and data-driven methods, hybrid approaches pave the way for advanced SPHM practices that address the complexities of real-world structural health conditions and contribute to the continuous improvement of aircraft safety and performance.

In the following sections, we explore specific hybrid methodologies, algorithms, and case studies that exemplify the application and effectiveness of these approaches in the SPHM domain. Through these examples, we aim to showcase the benefits and potential of hybrid approaches in enabling proactive and data-informed maintenance strategies for aircraft structures.

3.3.2. Implementation and Application of Hybrid Approaches in SPHM

The development and implementation of hybrid approaches in SPHM require careful consideration of several factors. First, the selection of appropriate models and algorithms is crucial to ensuring the accuracy and reliability of predictions. This may involve the integration of physics-based models, statistical models, machine learning algorithms, and advanced data analytics techniques. Second, the availability and quality of data play a significant role in the success of hybrid approaches. Adequate data collection, preprocessing, and feature selection methods are essential to extract meaningful information and facilitate accurate predictions. Moreover, the merging of data from various sources and sensors can provide a more comprehensive understanding of structural health.

Liao et al. proposed a hybrid prognostics framework combining data-driven and model-based approaches to predict the RUL, which improved the accuracy of the model [132]. The proposed fusion prognostics framework combined data-driven and model-based methods to estimate RUL. The model-based approach utilizes an analytical degradation model, while data-driven methods incorporate historical data to improve prediction accuracy and reduce uncertainty. An interface between the data-driven and model-based approaches is included in the framework, as illustrated in Figure 12, providing a comprehensive and detailed description of each method. This integration allows for more accurate predictions by leveraging the strengths of both approaches.

Yu et al. addressed the limitations of the data-driven techniques by emphasizing the advantages of the physics-based techniques to simulate aircraft dynamics [133]. The proposed approach used deep residual-recurrent neural networks (DR-RNNs), which incorporated aircraft dynamics through a residual function based on an implicit integration scheme. The effectiveness of integrating physics-based modeling with machine learning methods was demonstrated through a case study involving a Boeing 747-100 aircraft. The performance of the hybrid approach was compared to that of a purely data-driven method in terms of prediction accuracy, training costs, and computational efficiency. The study highlights the benefits of the hybrid method, including improved prediction performance, reduced training costs, and the ability to capture the dynamic behaviors of the aircraft.

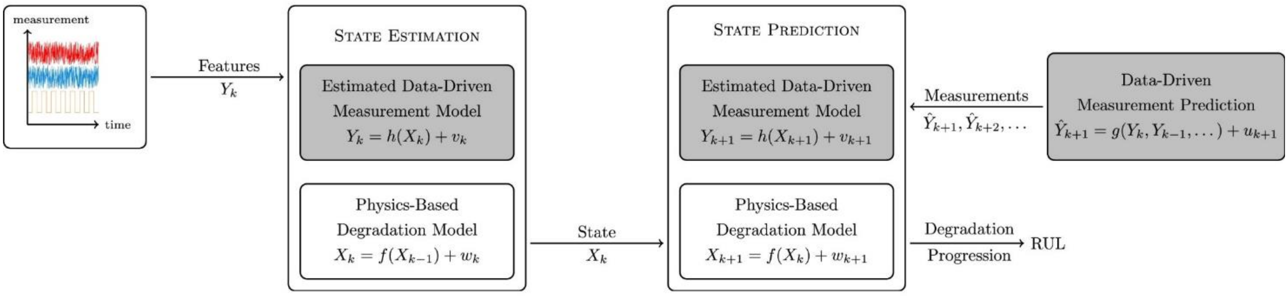


Figure 12. The proposed data-driven and model-based method fusion prognostics framework [132].

Neerukatti et al. proposed another hybrid method to predict crack growth and RUL for aluminum-based components of aircraft wings [134]. The proposed approach overcomes the challenges of fatigue life prediction under different loading conditions by integrating crack growth physics with data-driven techniques. Various regression techniques, such as least absolute shrinkage and selection operator (LASSO) and relevance vector machine (RVM), were used to determine the stress intensity factor for the specimen. The hybrid model exhibited greater accuracy compared to using solely data-driven or physics-based models. Experimental validation confirmed precise RUL predictions for the specimens under different loading conditions, with errors within 5% for constant amplitude loading and reduced errors for random loading conditions. The algorithm was also modified to consider the crack closure phenomenon during overloads, resulting in RUL predictions within 5% error. This research has substantial implications for improving the safety and reliability of aerospace SPHM systems and is backed by support from the U.S. Department of Defense.

Dourado and Viana developed a hybrid model composed of a physics-informed neural network to predict the corrosion-fatigue of aircraft wing aluminum panels [135]. The proposed hybrid approach incorporated physics-informed layers using the Walker model for fracture propagation and data-driven layers to account for the bias in damage buildup caused by corrosion effects. The physics-informed neural network was trained with comprehensive input data, including far-field loads, stress ratios, and a corrosivity index established by an airport, while output data were restricted to crack length observations during inspection for only a small percentage of the fleet. The results demonstrated that the physics-informed neural network effectively compensated for the missing physics of corrosion in the original fatigue model. The hybrid model's predictions can be applied in fleet management for tasks like prioritizing fleet-wide inspections or forecasting the number of planes with damage exceeding a certain threshold.

Data-driven probabilistic methodologies have gained popularity in recent years for predicting the RUL of composite structures using health-monitoring data, as the existing approaches face challenges in dealing with the nonlinear and stochastic nature of composite structure degradation as well as unexpected phenomena that can occur during their lifetime. These phenomena, such as foreign object impacts, pose difficulties for both model-based and data-driven approaches. To address these limitations, Nick et al. proposed an adaptive data-driven prognostic approach that can learn and adapt in real-time based on available data, providing accurate RUL predictions regardless of unexpected events [136]. Open-hole carbon/epoxy specimens were used to demonstrate the effectiveness of the proposed adaptive methodology. Training and testing data were collected using the AE technique, with training specimens subjected to fatigue loading and testing specimens experiencing both fatigue and in situ impact. The adaptive non-homogenous hidden semi Markov model (ANHHSMM) outperformed the non-homogenous hidden semi Markov model

(NHHSMM), indicating its ability to provide more accurate prognostics, as shown in Figure 13.

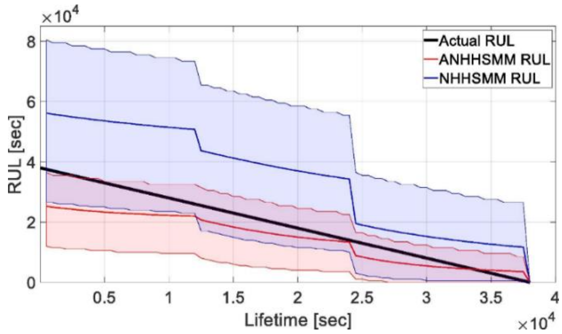


Figure 13. Validation of the adaptive methodology [136].

Giannakeas et al. developed a probabilistic model for the residual strength assessment of aircraft composite panels [137]. The system integrated physics-based and data-driven models, addressing limitations in their completeness and representativeness in training datasets. Detailed FE models were used to create a digital representation of the structure, and an error quantification and propagation program was implemented based on experimental data. A case study involving a 1.6 m composite panel with skin-stringer delamination and 24 piezoelectric transducers demonstrated the framework's prognostic capabilities. Figure 14 shows the experimental setup and the simulation results for the proposed hybrid model. The results indicated a mean absolute percent error (MAPE) of 10% for damage magnitude calculation and 5% for projecting the residual strength of a destructively tested damaged panel.

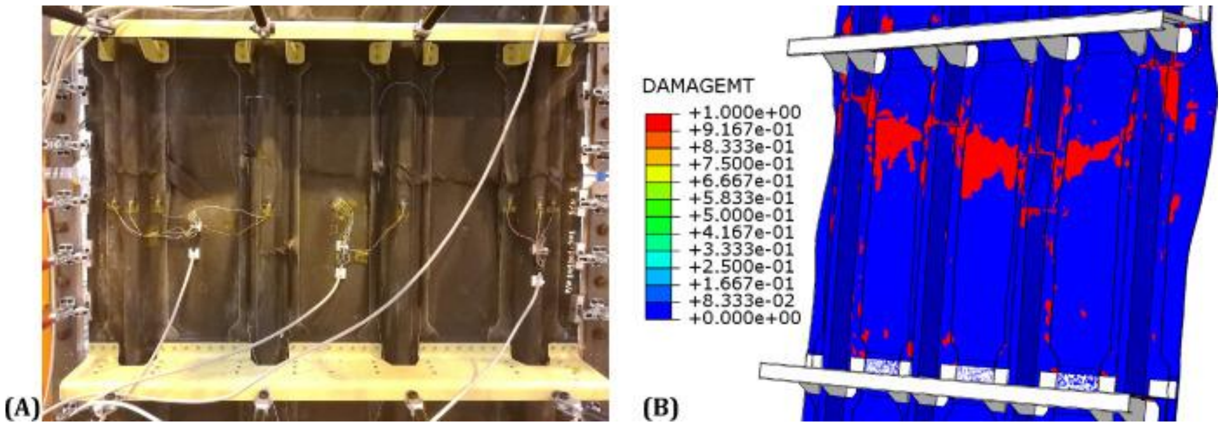


Figure 14. The observed failure of the aircraft composite panel, (**A**) experimental setup with sensor network, and (**B**) the numerical model [137].

Table 4 provides a comprehensive summary of studies on hybrid physics-based and data-driven approaches for the SPHM of aircraft structures. It presents an overview of different case studies, including their potential contributions, application domains, proposed methods, and the associated advantages and disadvantages. This table serves as a valuable resource for understanding the advancements and challenges in the field of SPHM and the potential of hybrid approaches to enhance aircraft SPHM.

Table 4. Case studies utilizing hybrid approaches and their key features.

Case Study	Contribution	Application	Proposed Method	Pros and Cons	Ref.
Case 1	Improved prediction using physics-based learning	Boeing 747-100 aircraft dynamics	Residual function-based implicit integration scheme	Pros: Improved prediction Cons: Potential complexity.	[133]
Case 2	Hybrid approach to predict the crack growth	Aircraft wings	Paris law with RVM model	Pros: Increased accuracy and precision of prognosis model Cons: Only one (Al) material is considered.	[134]
Case 3	Corrosion-fatigue of aircraft wings using physics-informed neural network	Aircraft wing	Integration of Walker model for fracture propagation with neural network	Pros: Accurate modeling of cumulative damage Cons: Limited output observations may reduce model precision	[135]
Case 4	Development of an adaptive data-driven prognostic approach	Aircraft composite structures	ANHHSMM	Pros: Improved RUL estimation, Robustness Cons: Data noise, computational complexity	[136]
Case 5	Probabilistic model for residual strength assessment for aircraft composite panels via a hybrid approach using guided waves	Aircraft composite panel	FE model and an error quantification and propagation program	Pros: Improved residual strength estimation Cons: Relatively high MAPWE	[137]

3.3.3. Advantages and Limitations of Hybrid Approaches

The benefits of hybrid approaches are as follows, highlighting their ability to improve and enhance various aspects:

- ✓ **Enhanced Accuracy**: Hybrid approaches combine the strengths of physics-based models and data-driven techniques, resulting in improved accuracy and predictive capabilities. They leverage both physical principles and historical data to make more reliable predictions.
- ✓ **Flexibility and Adaptability**: Hybrid approaches can accommodate varying levels of data availability and system complexity. They allow for the incorporation of additional data sources and the adjustment of models as new information becomes available, making them adaptable to changing conditions.
- ✓ **Robustness to Uncertainties**: By integrating physics-based models and data-driven techniques, hybrid approaches can handle uncertainties and variations more effectively. They can account for unknown factors and provide more robust predictions in scenarios where either approach alone may fall short.

The limitations of hybrid approaches are as follows, outlining the factors that can restrict their effectiveness and scope:

- ✓ **Increased Complexity**: Implementing hybrid approaches can be more complex than using a single modeling technique. It requires expertise in both physics-based modeling and data analysis, as well as careful integration of the two approaches.
- ✓ **Data Quality and Availability**: Hybrid approaches strongly depend on the accuracy and accessibility of data. Insufficient or inaccurate data can impact the performance and reliability of hybrid models.
- ✓ **Model Interpretability**: Hybrid models might sacrifice some interpretability compared to purely physics-based models. The incorporation of data-driven techniques can introduce black-box elements, making it challenging to understand the reasoning behind predictions.

Table 5 provides a comprehensive overview of the advantages and limitations of data-driven, model-based, and hybrid approaches in the SPHM of aircraft structures. The advantages and challenges associated with each method are compared to aid in the selection of the most suitable approach for different scenarios.

Table 5. Comparison of the Advantages and Limitations of Data-Driven, Model-Based, and Hybrid Approaches for System Analysis.

	Data-Driven	Model-Based	Hybrid Methods
Advantages	• Adaptability and learning capability • Prediction accuracy • Scalability	• Accurate representation • Interpretable results • Generalizability • Insightful analysis	• Enhanced accuracy • Flexibility and adaptability • Robustness to uncertainties
Limitations	• Data quality and availability • Model transparency • Computational requirements • Generalizability	• Assumptions and simplifications • Limited adaptability • Computational complexity • Model uncertainty	• Increased complexity • Data quality and availability • Model interpretability

4. Digital Twin Technology in SPHM

The concept of a digital twin has emerged as a powerful tool in the field of aircraft SPHM. A digital twin refers to a virtual representation of an aircraft's physical structure, enriched with real-time data from sensors and operational inputs. By aligning the behavior of this digital twin with the real aircraft, operators gain the ability to anticipate structural problems, detect anomalies, and forecast maintenance requirements. This proactive approach enhances safety, reduces operational disruptions, and facilitates optimized maintenance planning. The integration of physical and virtual elements through digital twins showcases their potential to revolutionize aircraft structural PHM practices. Using historical load data, condition monitoring, and fault diagnosis-based maintenance, the lifespan of modern aircraft structures may be assessed. However, a set of sensor readings taken early in the life cycle to assess the state of the aircraft structure is frequently insufficient to identify the full structural condition. As a result, adding more sensors is an alternate option to collect a comprehensive dataset; nevertheless, this procedure incurs extra costs. As a result, much effort is being expended to develop a sophisticated methodology and framework to evaluate the entire structure.

By regulating interactive interactions between real items and their virtual models, digital twin technology is evolving. Condition monitoring of aircraft structures is rapidly developing with digital twin technology, with the ultimate goal of a fully simulated model with no physical existence. Total systematic inspection becomes possible with the digitization of an entire dataset. The development of ML and structural condition monitoring frameworks has enabled the introduction of digital twin technology to current aircraft [28]. Giannaros et al. developed a computational model-based digital twin system that can accurately predict the dynamic behavior and delamination area of aircraft composite sandwich structures subjected to bird strikes, with the high-fidelity model matching experimental strain histories and delamination observations [138]. The sensors were integrated into the composites, and the measurements were taken with a sampling rate of 19.2 kHz, while the sensor wavelength was calculated from the strain components using Equation (14):

$$\varepsilon = \frac{1}{P_e}\frac{\Delta\lambda}{\lambda_B} \tag{14}$$

where $\Delta\lambda$ represents the Bragg wavelength shift due to the induced load, λ_B represents the Bragg wavelength reflected from the sensing system, while Pe and ε represent the elasto-optic coefficient and applied strain, respectively. Figure 15 shows the experimental setup of the bird strike test. The low-fidelity model gives quick numerical guidance to determine impact loading situations while cutting computing time by almost a third (to

68%). The numerical model was built using the modified Hashin criterion, as in the original Hashin tensile fiber criteria. When incorporating the shear stress factor, it tends to underestimate the maximum failure load of cross-ply and quasi-isotropic laminates subjected to tension loading [139,140]. The failure equations based on the modified Hashin criterion are as follows:

$$Tensile\ fiber\ mode = \left(\frac{\sigma_{aa}}{X_T}\right)^2 = 1 \quad (15)$$

$$Compressive\ fiber\ mode = \left(\frac{\sigma_{aa}}{X_C}\right)^2 = 1 \quad (16)$$

$$Tensile\ matrix\ mode = \left(\frac{\sigma_{bb}}{Y_T}\right)^2 + \left(\frac{\sigma_{ab}}{S_{ab}}\right)^2 = 1 \quad (17)$$

$$Compressive\ matrix\ mode = \left(\frac{\sigma_{bb}}{2 \times S_{ab}}\right)^2 + \left[\left(\frac{Y_c}{2 \times S_{ab}}\right)^2 - 1\right]\frac{\sigma_{bb}}{Y_c} + \left(\frac{\sigma_{ab}}{S_{ab}}\right)^2 = 1 \quad (18)$$

where σ_{aa} represents normal stress in the fiber direction (longitudinal direction), σ_{bb} represents transverse stress, σ_{ab} represents the in-plane shear stress, and S_{ab} refers to the shear strength between the axial and transverse directions. Whereas X_T, X_C, Y_T, and Y_C denote longitudinal tensile strength, longitudinal compressive strength, transverse tensile strength, and transverse compressive strength, respectively. These models have potential applications in virtual fault detection and damage estimation, and future work will explore the role of strain rate and impact situations.

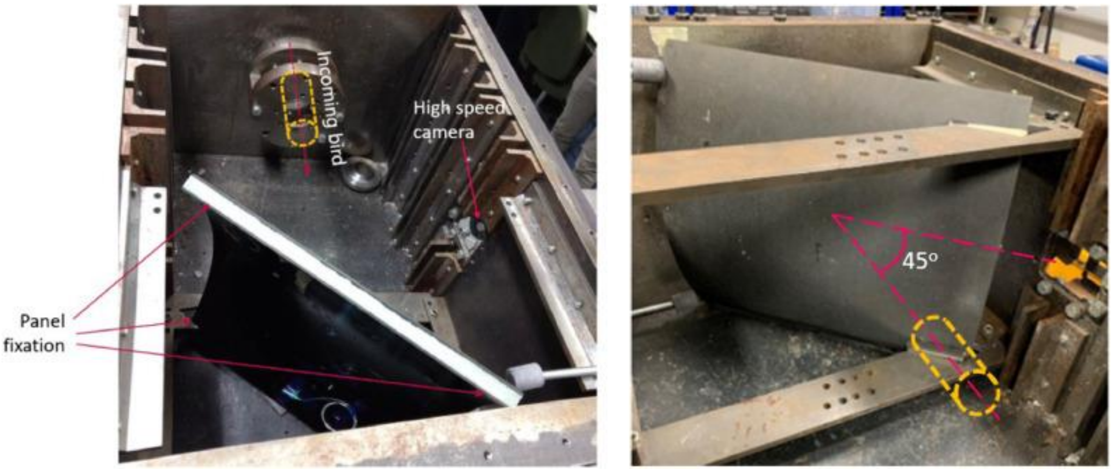


Figure 15. The impact loading experimental setup in the target chamber, which includes a panel position and fixture [138].

Li et al. proposed a digital twin model for fatigue crack propagation in aircraft airframes using the dynamic Bayesian network concept [62]. They integrated various uncertainty sources into their model and handled both discrete and continuous data variables, allowing the model to understand non-linear behavior. The numerical model for fatigue crack growth demonstrated the capacity to track time-dependent factors, minimize uncertainty from time-independent variables, and probabilistically predict future crack growth. The proposed approach is validated on the airframe digital twin program to cut maintenance costs for various aircraft, showing its potential for the SPHM of aircraft structures. Milanoski et al. proposed another digital twin model for aeronautical structures under compressive loading conditions [141]. They first developed an FE model for a single-stinger composite panel under compressive loading to obtain strain and displacement data.

The numerical data were used to develop the digital twin model, which demonstrated good agreement with the experimental data. The validated digital twin model was then used to train a surrogate model, which efficiently mapped the strain values with respect to the compressive loads. The methodology was successfully tested on an artificially debonded panel subjected to fatigue loading, enabling damage identification based on strain measurements from the digital twin.

Lai et al. proposed a measurement–computation combined digital twin (MCC-DT) model for an aircraft wing that integrated various technologies and methodologies, such as sensors, communication technologies, the FE model, and AI [142]. Herein, the load identification was performed through the AI model combining sensor and simulation data, the digital twin performance was improved using the multi-fidelity surrogate (MFS) models, and the online degradation in the digital twin was evaluated using the rainflow counting algorithm. Conclusively, sensor technology and FEM integration have been deployed as viable digital twin frameworks. The damage and defect categories may then be used to evaluate structural condition monitoring and lifespan estimates. Figure 16 is an example of such a notion, in which the aircraft wing model is conceptualized utilizing digital twin technology by merging sensor data with the FEM. Additionally, the contribution of various research efforts in the SPHM of aircraft structures using digital twin technology are summarized in Table 6.

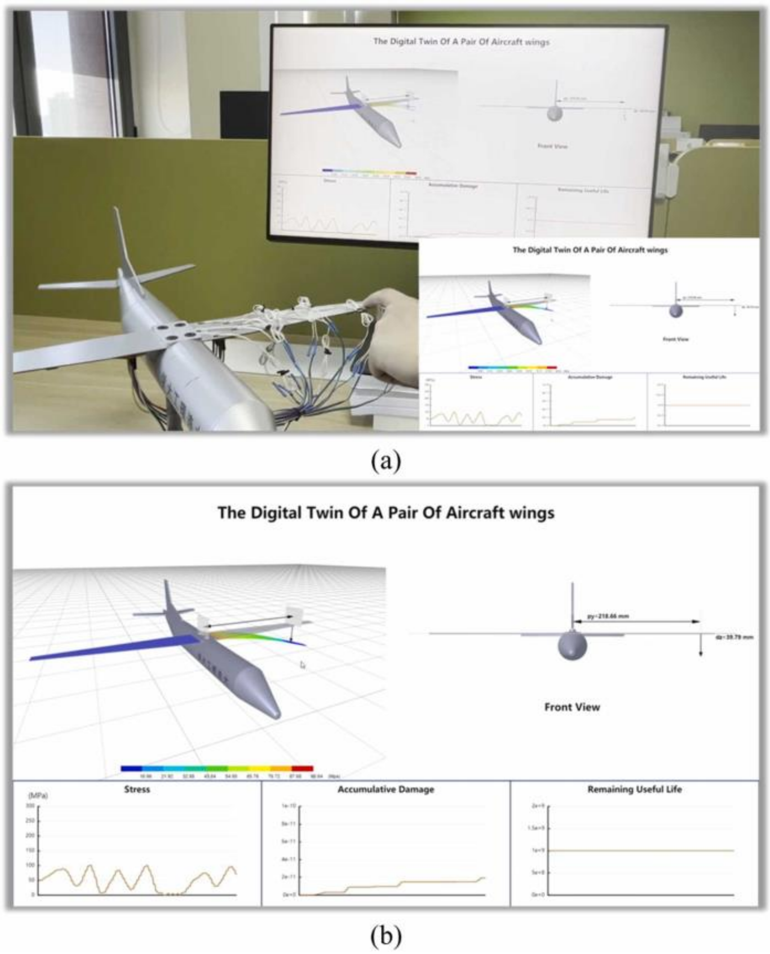


Figure 16. The conceptualization of a digital twin of a small-scale aircraft using WebGL; (**a**) the small-scale aircraft model, and (**b**) the digital twin model of the aircraft [142].

Table 6. Contribution of various research efforts in the SPHM of aircraft structures using digital twin technology.

Case Study	Contribution	Application	Proposed Method	Pros and Cons	Ref.
Case 1	A digital-twin-assisted damage diagnosis of aircraft sandwich structures using low- and high-fidelity modeling	Aircraft sandwich structures	High-fidelity and low-fidelity FE model	Pros: Comprehensive numerical modeling Cons: The study did not address the influence of strain rate and impact conditions, limiting a comprehensive understanding of the model's performance under different scenarios	[138]
Case 2	A versatile airframe fatigue crack propagation-based digital twin model for aircraft wing health monitoring using a dynamic Bayesian network	Aircraft wing	Dynamic Bayesian network	Pros: Integrating various uncertainty sources and handling both discrete and continuous variables improved the model's application to actual aircraft Cons: All results are based on simulation, with no validation	[62]
Case 3	A digital twin model for composite single-stringer panels for an aeronautical structure under compressive loading	Aircraft panel	Surrogate mathematical model	Pros: Data-driven model that did not require comprehensive physical understanding Cons: Uncertainty in input data, modeling techniques, and environmental conditions can lead to uncertainty in the model's predictions	[141]
Case 4	Integration of sensor measurements and FEM to build a digital twin model	Aircraft wing	DNN, CNN, and ResNet	Pros: Integration of multiple technologies and methods helps improve the model's reliability Cons: Structural analysis is considered only in the elastic range, without incorporating any uncertainties	[142]

5. Future Trends in SPHM

The field of SPHM is constantly evolving, driven by technological advancements and the quest for improved aircraft maintenance practices. This section explores the future trends in SPHM, highlighting three key areas that hold tremendous potential: further integration of AI, wider adoption of digital twin technology, and advancements in sensor technologies.

(1) Further Integration of AI

- ✓ The integration of AI is revolutionizing SPHM by enabling more advanced data analysis, pattern recognition, and decision-making capabilities. These technologies have the potential to significantly enhance the accuracy, efficiency, and reliability of structural health monitoring, diagnosis, and prognostics.
- ✓ AI excels at processing vast amounts of sensor data in real-time, allowing for the identification of subtle patterns and anomalies that may indicate potential structural issues. By continuously learning from historical and real-time data, these algorithms can improve their predictive capabilities, enable proactive maintenance, and reduce the risk of unexpected failure.
- ✓ Moreover, the integration of AI with SPHM systems paves the way for automated decision-making processes, including automated decision making using reinforcement learning. This approach allows maintenance schedules to be optimized, component lifetimes to be predicted, and resources to be effectively allocated. By automating these tasks through reinforcement learning, aircraft

operators can improve operational efficiency, reduce costs, and enhance overall safety.

(2) Wider Adoption of Digital Twin Technology

- ✓ Digital twin technology, which involves creating a virtual replica of an aircraft's physical components and systems, offers immense potential for SPHM. By combining real-time sensor data with the virtual twin, engineers and maintenance personnel can gain a comprehensive understanding of the aircraft's current and future health.
- ✓ Digital twins provide a platform for simulating and predicting the behavior of an aircraft under various operating conditions and stress scenarios. This enables proactive maintenance planning and the identification of potential structural issues before they manifest in the physical aircraft. Additionally, digital twins facilitate virtual testing and optimization of maintenance procedures, leading to more efficient and effective maintenance operations.
- ✓ Wider adoption of digital twin technology is expected to significantly improve aircraft safety, reduce maintenance costs, and increase operational availability. By leveraging the insights gained from the virtual twin, operators can make informed decisions, optimize maintenance schedules, and perform condition-based maintenance, ultimately extending the lifespan of critical components and enhancing overall operational reliability.

(3) Advancements in Sensor Technologies

- ✓ The continuous advances in sensor technologies play a pivotal role in enhancing SPHM capabilities. Sensors are the backbone of SPHM systems, providing the necessary data for real-time monitoring, analysis, and decision making.
- ✓ Future trends in sensor technologies include the development of miniaturized sensors, wireless sensor networks, and smart sensor technologies. Miniaturized sensors can be embedded within the aircraft's structural components, enabling continuous monitoring of critical parameters such as strain, temperature, and vibration. This provides a more comprehensive and accurate picture of the structural health of the aircraft.
- ✓ Wireless sensor networks allow for seamless data collection and transmission, providing real-time updates on the structural health of an aircraft. These enable timely decision making and facilitate a proactive approach to maintenance. Smart sensors, equipped with advanced data processing capabilities, can perform on-site analysis and decision making, reducing the need for extensive data transmission, and allowing for rapid response to critical events.
- ✓ These advances in sensor technologies enable more precise and comprehensive monitoring of aircraft structures, facilitating the early detection of potential issues and enabling timely maintenance interventions. By leveraging these advanced sensors, operators can enhance the overall reliability, safety, and performance of their aircraft.

In summary, the future of SPHM holds great promise for the aviation industry. The further integration of AI, the wider adoption of digital twin technology, and advancements in sensor technologies are set to revolutionize aircraft maintenance practices. These trends offer the potential for enhanced safety, improved maintenance efficiency, optimized resource allocation, and ultimately a more reliable and cost-effective aviation industry. Embracing these future trends will undoubtedly pave the way for a new era of proactive, data-driven, and intelligent aircraft maintenance.

6. Conclusions

Structural prognostics and health management continue to revolutionize aircraft maintenance strategies, shifting from traditional reactive practices to proactive, data-driven approaches. The continuous monitoring and real-time evaluation of an aircraft's structural integrity, facilitated by advancements in sensor technology and data analytics, form the core of modern SPHM systems. These technologies permit an in-depth assessment of structural health, aiding in the early detection of potential issues and ensuring timely maintenance actions. The ensuing enhancements in the safety and reliability of aircraft operations are indeed undeniable.

The gradual shift to data-driven methodologies, characterized by the application of machine learning and deep learning techniques, and the creation of digital twin technology, signifies a promising leap in the evolution of SPHM practices. Despite their current limitations, including the need for extensive labeled datasets and the challenges of interpretability, these approaches offer considerable potential. The ability to predict the RUL of aircraft components by analyzing extensive datasets is an advantage that cannot be overstated. Furthermore, the integration of digital twin technology provides a dynamic, real-time representation of the aircraft system, enabling condition-based maintenance. However, it is worth noting that model-based and hybrid approaches maintain their relevance in the SPHM framework. These methods, which incorporate physics-based modeling, finite element analysis, and damage mechanics, provide a comprehensive perspective that complements the insights generated by data-driven approaches.

The landscape of SPHM practices is ripe for further exploration and improvement. Future research endeavors can focus on overcoming the existing limitations of modern SPHM approaches, perhaps by developing methods for generating and labeling large datasets more efficiently or by enhancing interpretability through the creation of explainable AI models. Additionally, further improvements in sensor technology and the integration of more advanced predictive models may enhance the accuracy and efficiency of SPHM systems. Overall, this review underscores the significant progress in the field of aircraft SPHM and its pivotal role in enhancing the safety, reliability, and cost-effectiveness of aircraft operations. By illuminating the current trends and future potential of SPHM practices, it hopes to spark further research and technological innovations in this vital area of aerospace engineering.

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Abbreviations

SPHM	Structural Prognostics and Health Management
SVM	Support Vector Machine
RF	Random Forest
CNN	Convolutional Neural Network
CAE	Convolutional Autoencoder
RUL	Remaining Useful Life
NDT	Non-destructive testing
UMS	Usage Monitoring Systems
SHM	Structural Health Monitoring

AI	Artificial intelligence
ML	Machine learning
DL	Deep learning
DTs	Decision trees
KNN	K-nearest neighbor
NB	Naïve Bayes
CFRP	Carbon fiber reinforced polymer
ERT	Electrical resistance tomography
RBF	Radial basis function
PT	Pulsed thermography
TUL	Total useful life
GA	Genetic algorithm
LR	Logistic regression
AE	Acoustic emission
ANN	Artificial neural network
DNN	Deep neural networks
LSTM	Long short-term memory
RNN	Recurrent neural network
DBN	Deep belief networks
PNN	Probabilistic neural networks
FCN	Fully connected network
SAE	Stacked autoencoder
DAE	Deep autoencoder
DAIS	D-Sight Aircraft Inspection System
CM	Condition Monitoring
EKF	Extended Kalman filter
SIFs	Stress intensity factors
SKF	Switching Kalman Filter
FEAM	Finite Element Alternating Method
VRAMS	Virtual Risk-Informed Agile Maneuver Sustainment
MLS	Moving Least Squares
DIC	Digital Image Correlation
BGOA	Binary grasshopper optimization algorithm
EANNs	Ensemble artificial neural networks
DR-RNN	Deep residual recurrent neural networks
ANHHSMM	Adaptive Non-Homogenous Hidden Semi Markov Model
NHHSMM	Non-Homogenous Hidden Semi Markov Model
MCC-DT	Measurement-computation combined digital twin
MFS	Multi-fidelity surrogate

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