Hybrid Prognostic Approaches of Aircraft Systems and Components

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Contributor: Shuai Fu , Nicolas P. Avdelidis

Prognostic and health management (PHM) plays a vital role in ensuring the safety and reliability of aircraft systems. The process entails the proactive surveillance and evaluation of the state and functional effectiveness of crucial subsystems. The principal aim of PHM is to predict the remaining useful life (RUL) of subsystems and proactively mitigate future breakdowns in order to minimize consequences. The achievement of this objective is helped by employing predictive modeling techniques and doing real-time data analysis. The incorporation of prognostic methodologies is of utmost importance in the execution of condition-based maintenance (CBM), a strategic approach that emphasizes the prioritization of repairing components that have experienced quantifiable damage. Multiple methodologies are employed to support the advancement of prognostics for aviation systems, encompassing physics-based modeling, data-driven techniques, and hybrid prognosis.

prognostics and health management | hybrid model | remaining useful life | physics-based model

1. Introduction

The hybrid prognosis methodology entails the amalgamation of multiple approaches to predict the future state of a certain system. PHM solutions in the aviation sector heavily depend on the exploitation of real-time data to effectively identify potential failures and evaluate the condition of machines. The presented approach is distinguished by its proactive aspect, as it necessitates the application of predictive modeling tools to activate maintenance alerts and anticipate the possibility of faults [1].

Numerous industries have adopted PhM methodologies since they have demonstrated the ability to improve dependability and safety. In the aviation industry, safety requirements are elevated due to the substantial investment and the possible dangers to human life that are linked to aircraft malfunctions or operational disruptions. The utilization of artificial intelligence algorithms is prevalent in commercial operations for the purpose of flight data monitoring systems. Nevertheless, there is a dearth of research that specifically addresses safety-critical systems, such as engine and hydraulic systems [2].

The utilization of hybrid prognosis methodologies within the aviation sector facilitates the augmentation of precision in failure prognostication, thereby making a significant contribution towards the enhancement of dependability and safety within aircraft systems. The incorporation of several methodologies allows for the integration of hybrid prognosis, which in turn facilitates a comprehensive evaluation of the health of a system and enhances the effectiveness of predictive maintenance initiatives [3].

The achievement of a hybrid prognosis can be effectively accomplished using several strategies, such as data-driven, physics-based, and knowledge-based techniques. Data-driven techniques utilize previous data to train machine learning algorithms in order to predict future system behavior. Model-based techniques utilize mathematical models to simulate the dynamics of a specific system and offer predictions regarding its future state. Knowledge-based methodologies utilize expert knowledge and pre-established norms to create predictions on the future state of a specific system. The use of a hybrid prognosis has emerged as a feasible strategy in the aviation industry with the aim of effectively monitoring the operational status of various aircraft systems, encompassing engines, hydraulic systems, and avionics. Sensors are utilized to collect real-time data regarding the operating effectiveness of these systems. Following this, the collected data are then subjected to analysis using hybrid prognostic techniques, with the objective of predicting possible problems and scheduling maintenance measures before their actual occurrence [4].

The application of hybrid prognosis in the aviation sector is of considerable importance as a tool for predictive maintenance. The installation of this technology plays a significant role in improving the safety and reliability of aircraft systems while also reducing maintenance costs and operating disruptions. The hybrid prognosis approach deviates from traditional methodologies by incorporating various strategies to predict the future condition of a system's condition [5]. In contrast, traditional approaches frequently rely on a single strategy for formulating prognostications. An excellent example pertains to the typical prognostic techniques that rely on data-driven approaches, often requiring manual extraction of features from raw sensory input. The process of feature selection can be a laborious undertaking and does not ensure the identification of the most optimal representative attributes in every instance. On the other hand, hybrid prognosis utilizes a hybrid deep neural network structure to extract meaningful features directly from the raw sensory input during the training period.

By using several approaches, hybrid prognosis possesses the ability to provide a comprehensive understanding of the condition of a system and improve the accuracy of predicting failures. The use of this methodology holds promise for improving the reliability and safety of systems while simultaneously reducing costs related to upkeep and operating disruptions.

One such topic is the development of a hybrid prognostic approach for estimating the RUL of aircraft engines using a combination of PCA, classification and regression trees (CART), and MARS techniques [6]. By employing this fitting method, it is possible to determine the future health condition of a given system and to make precise RUL estimates. The simulation results demonstrate that the PCA-CART-MARS-based methodology could anticipate problems well in advance of their occurrence and accurately predicting the RUL. The primary advantage of the proposed model is its independence from the previous operational conditions of the engine's input variables. In recent years, multivariate linear regression and ANNs have also been utilized for the RUL prediction. The effectiveness of the PCA-CART-MARS-based methodology was evaluated in comparison to these established methods. The PCA-CART-MARS-based approach has demonstrated tremendous promise in the field of aircraft engine RUL estimation prognostics. The hybrid model employs elements derived from sensor signals to train itself, thereby representing a variety of aircraft engine health states. Lastly, there is a growing interest in prognostics for autonomous electric-propulsion aircraft, which entails predicting and managing potential system failures [7].

The hybrid prognosis technique is an innovative approach that integrates physics-based modeling and data-driven methodologies to improve the accuracy of predictive results. One example of the application of hybrid prognostics in aircraft systems involves the prediction of fatigue life for metallic components located within the structures of aircraft. The authors of the scholarly research paper developed a hybrid prognosis model to accurately predict the crack growth regime and RUL of aluminum components [6]. A supplementary example is available in a study that introduced a novel hybrid prognostic methodology for predicting the RUL of multi-functional spoiler (MFS) systems. The systems are of utmost importance in facilitating the effective operation of aviation spoiler control systems [8]. Another example of the application of hybrid prognosis may be seen in the evaluation of aviation systems, particularly in the analysis of the effectiveness of hybrid electric and distributed propulsion systems integrated into a light aircraft.

There are several techniques available for the merging of physics-based algorithms with data-driven algorithms within the domain of hybrid prognosis. One possible approach is the utilization of a physics-based model to extract features that can then be employed in a data-driven model. One example that may be used to illustrate this concept is the application of a physics-based model to simulate the dynamics of a system under various situations. The resulting data from this simulation can then be used as input for a data-driven model. The data-driven model possesses the capacity to learn information from the given data and afterward generate predictions. An alternate approach entails employing a data-driven model to improve the precision of predictions given by a physics-based model. An example that serves as an illustration involves the application of a physics-based model to produce the first predictions concerning the behavior of a certain system. Following this, the accuracy of these predictions can be further improved by utilizing a data-driven model that has been trained using data collected from the same system. Both approaches employ a physics-based model to include prior knowledge of the system being modeled and enhance the learning process of the data-driven model. The utilization of a combination of physics-based and data-driven approaches has the potential to boost the precision of forecasts when compared to depending simply on either approach independently.

Prognostics technology encompasses a wide range of facets. For instance, prognostics can provide early indications of potential failures and make estimations for the RUL. This can ultimately lead to enhanced availability, reliability, and safety, while also contributing to decreased maintenance expenses. Prognostics, as stipulated in ISO 13381-1 [9], refers to the process of estimating the TTF and associated risk for one or more existing and potential failure modes. This prediction is based on the current condition of the system and its past operational profile [10]. The application of RUL prediction is extensive, encompassing various domains such as military and aerospace systems, manufacturing equipment, constructions, power systems, and electronics [11].

Generally, prediction models for RUL can be classified into the following three categories: experience-based models, data-driven models, and physics-based models, as depicted in **Figure 1** [11].

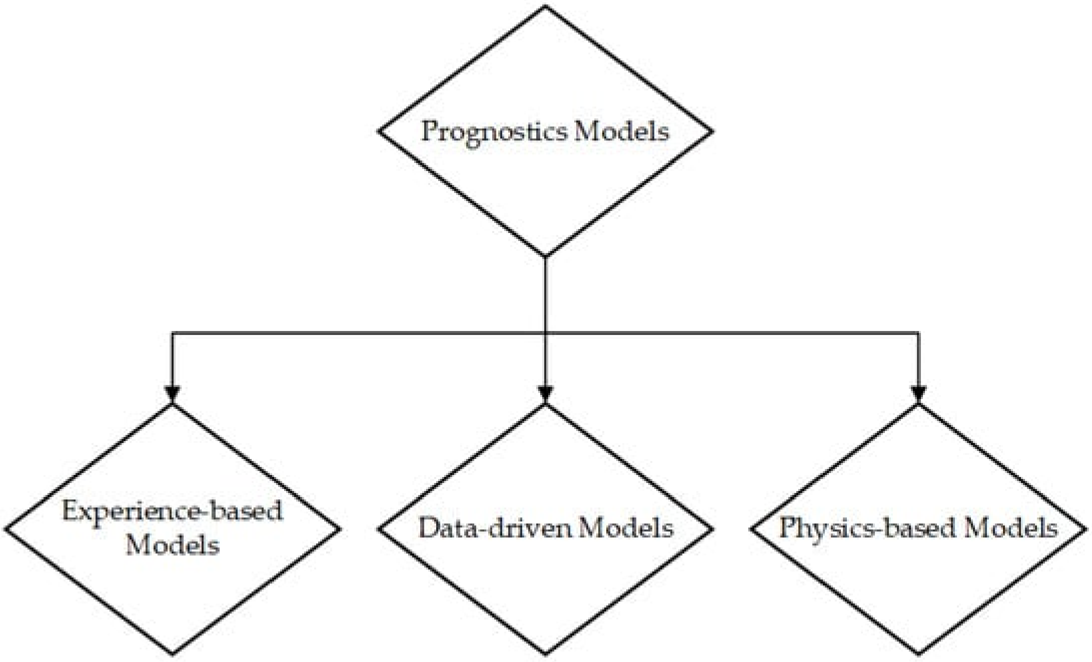

Figure 1. Classification of prognostic models.

There are various methodologies available for the assessment of system conditions. There are two primary strategies commonly employed for prognosis in aviation, namely, physics-based and data-driven methods. Both techniques include distinct advantages and limits, which is why they are frequently utilized with one another [12]. Prognostics is an academic field that focuses on the prediction of the future performance of a system, with a specific focus on identifying the moment when the system will no longer serve its intended purpose, usually known as its TTF. The RUL factor has a key role in the field of PHM, functioning as a critical element in the decision-making process for maintenance and the mitigation of contingencies. Deterioration is a commonly seen phenomenon that can occur during the whole lifespan of a system or component. Numerous methodologies have been devised to predict the future performance of said systems and determine the threshold at which they will no longer serve their original purpose [11].

2. Experience-Based Models

Experience-based approaches, also known as knowledge-based approaches, encompass the utilization of historical data collected over a significant period, encompassing failure times, maintenance data, operational data, and other pertinent information, to predict the TTF or RUL. The main advantage lies in their utilization of simple reliability functions, such as the exponential law and Weibull law, instead of complex mathematical models.

The prognostic outcomes provided by these methodologies demonstrate reduced levels of accuracy in comparison to the prognostics offered by physics-based and data-driven approaches, especially in situations when the operational parameters are well-known or when systems are in their initial phases and have limited failure data available [13]. Experience-based models are subject to limitations as they necessitate a substantial amount of personal knowledge pertaining to a certain component or system.

3. Data-Driven Models

Data-driven methodologies involve the utilization of sensors to acquire online data, which is afterwards transformed into pertinent information. The data are utilized for the purpose of investigating degradation patterns using a range of models and tools, including NNs, Bayesian networks (BNs), and Markovian processes, as well as statistical methods. This analysis aims to forecast the future health condition and the accompanying RUL of the system.

Data-driven approaches possess a notable advantage over both physics-based and experience-based methods. This advantage stems from the fact that, in practical industrial applications, obtaining trustworthy data is a more feasible task compared to developing models that capture physical or analytical behaviors. Furthermore, the behavioral models derived from actual monitoring data yield more accurate predictive outcomes compared to those derived from historical data as mentioned in the previous chapter.

4. Physics-Based Models

The physics-based methodologies employ an analytical framework that incorporates a set of differential or algebraic equations to effectively represent the dynamic characteristics and deterioration of the system. Ref. [14] presented a pioneering study where authors introduced a fatigue life model for ball bearings that relies on stress analysis. The model has improved accuracy in predicting prognosis. Nevertheless, it is crucial to acknowledge that real-world systems often exhibit nonlinearity, and the degradation mechanisms associated with them tend to be inherently stochastic. As a result, the application of analytical models presents difficulties. Hence, the feasibility of using this approach may be limited as aforementioned in Section 2.

5. Hybrid Prognostic Models

Hybrid prognostic methodologies integrate the advantageous aspects of both data-driven and physics-based modeling to enhance the precision and reliability of failure prognostications. Various methodologies can be employed to anticipate and mitigate failures in advance. This can be achieved by carefully picking pertinent hIs and calculating the PDFs of hIs under both optimal and deteriorated conditions [15][16][17]. Hybrid prognostic methodologies may encompass the integration of physics-informed machine learning techniques [18].

One advantage of hybrid prognostics is its capacity to enhance the precision and dependability of failure forecasts through the integration of the robustness of data-driven and physics-based modeling [19]. The hybrid strategy, which combines elements of physics-based and data-driven methodologies, is employed to mitigate the limitations of each approach and leverage their respective advantages. However, it is important to note that the hybrid approach does retain certain downsides associated with both methods.

The section presents a range of ways that utilize different combinations of the three categories. The picture presented in this context is derived from a study conducted by [20] and visually represents five unique combinations.

Hypothesis 1. *Posits the integration of an experience-based model and a data-driven model*.

Hypothesis 2. *Posits the integration of an experience-based model and a physics-based model*.

Hypothesis 3. *posits that the utilization of a data-driven model in conjunction with another data-driven model can yield significant benefits*.

Hypothesis 4. *Posits the integration of a data-driven model and a physics-based model*.

Hypothesis 5. *postulates that the amalgamation of an experiential model, a data-centric model, and a physics-oriented model will yield favorable outcomes*.

One instance of a prognostic application within the aircraft sector can be observed in the Joint Strike Fighter (JSF) [21]. The system is intended for utilization by the United States Air Force, Navy, and Marine Corps, as well as select allied nations inside the United States' sphere of influence. The existing strategy entails implementing a PHM system that offers fault detection and isolation capabilities for all significant systems and subsystems present on the aircraft. Additionally, the system will proceed with prognostics specifically for certain components. PHM constitutes a pivotal factor in substantiating the selection of a singular-engine aircraft, with the primary objective of enhancing safety measures and diminishing maintenance expenses. The architectural design being proposed incorporates an off-board PHM system, which will utilize data mining methodologies [22][23]. Moreover, automated prognostic research has been implemented in a diverse range of systems, encompassing actuators, aerospace structures, aircraft engines, batteries, bearings, clutch systems, cracks in rotating machinery, electronics, gas turbines, hydraulic pumps and motors, military aircraft turbofan oil systems, semiconductor manufacturing, heating, ventilation, and air conditioning, wheeled mobile robots, and UAV propulsion.

Prognostics applications have the capability to operate either in real-time, or near real-time, regardless of whether they are aboard or off-board. Prognostics can also be implemented in an offline manner, independent of the operational duration of the system being monitored. Real-time prognostics involve the utilization of online data obtained from a data-gathering system to estimate the RUL of a system. This calculation enables the system to provide a timely warning regarding an imminent failure, hence facilitating the reconfiguration of the system and the planning of subsequent missions. The offline prognostics system utilizes fleet-wide system data and conducts extensive data mining procedures that are not feasible to be executed onboard in real time due to resource limitations and time constraints. The utilization of outcomes derived from an offline prognostics system holds the potential for informing maintenance planning and facilitating decision-making processes within the realm of logistical support management. The application of prognostics first revolved around the practice of forecasting [24].

5.1. Physics-Based Models or Data-Driven Models

The data-driven model involves gathering monitoring data from sensors to simulate the system's degradation. The data are subjected to pre-processing to find relevant elements that can be utilized in the development of models for health assessment and prediction of RUL. Several machine learning techniques can be identified as aforementioned, including NNs, HMMs, regression analysis, and support vector regression (SVR).

Physics-based model necessitates a comprehensive comprehension of the underlying physical system, encompassing the intricate dynamics of degradation through time. The utilization of physical principles is employed in the construction of a system model that is afterward utilized for the purpose of simulations and RUL prediction [25]. The study conducted by [26] employed a mathematical approach to investigate the deterioration of a vehicle's suspension system, with a focus on physics-based prognostics. In the investigation of the progression of damage in a two-well magneto-mechanical oscillator, the authors [27] adopted a comparable methodology by suggesting a technique rooted in the principles of dynamic systems. It is crucial to recognize that within the realm of physics-based prognostics, the construction of a model necessitates the inclusion of a degradation model, which encompasses factors such as fatigue, corrosion, or wear-induced cracks. It can be observed that data-driven models produce results with lower levels of precision than physics-based methods. Accessibility of the data used to train deterioration models is an additional limitation associated with data-driven prognostics. As stated previously, it is necessary to collect data that accurately represents the degradation's behavior. In practical applications, it is essential to keep in mind that the statistics pertinent to the deterioration of assets under identical operating conditions may exhibit variation. The model derived from this dataset will capture the mean value; consequently, estimates of RUL will be imprecise [28].

Practitioners tend to prefer data-driven solutions due to their cost-effectiveness, versatility, and simplicity. The utilization of physics-based methodologies in industrial systems is impeded by the inherent difficulty of building a physical model that precisely depicts the deterioration of the system. Physics-based approaches can be utilized in systems that have pre-existing models or in certain types of systems, such as mechatronic systems. However, it is necessary to perform empirical investigations to determine the underlying patterns of system degradation. One notable benefit of employing physics-based methodologies is their capacity to yield precise forecasts, especially in scenarios characterized by restricted data availability. Nonetheless, the process of constructing precise models can present difficulties and necessitates a profound comprehension of the system being subjected to modeling. In contrast, data-driven methodologies exhibit a higher level of ease in their implementation, albeit necessitating a substantial volume of historical data for optimal efficacy.

In essence, physics-based methodologies employ mathematical models grounded in fundamental physical principles to provide predictions, whereas data-driven methodologies depend on historical data to acquire knowledge of the system's behavior and generate forecasts. Both methodologies possess their respective merits and demerits, and the selection between them is contingent upon the application and the accessibility of data. The integration of both approaches in a hybrid approach to prognostics can effectively harness their inherent strengths, resulting in improved forecasting capabilities. Concurrently, the hybrid approach possesses the capacity to alleviate the specific drawbacks encountered by individuals [29]. Ensemble learning holds promise for the future use of amalgamating and incorporating diverse data-driven prognostics techniques. The integration of online algorithms and uncertainty poses a significant concern in the context of a hybrid strategy for RUL estimation [28][29].

5.2. Hybrid Approach Integrating Data-Driven Models and Physics-Based Models

There does not exist a flawless prognostics model. Every model has its own set of pros and limitations, and it is more prudent to consider the appropriateness of a model based on the specific scenario being analyzed. In the field of power devices, a research study conducted by [30] introduced a methodology for predicting RUL by employing a combination of data-driven and physics-based prognostics algorithms. The drain-source ON-state resistance was employed by the researchers as a metric for assessing the health status. The methodology employed involved the utilization of Gaussian process regression as the data-driven component. The methodologies employed encompassed two physics-based techniques, namely, an EKF and a PF. The researchers conducted accelerated aging experiments on power devices and employed prognostic performance indicators to evaluate and compare the outcomes of the different methodologies. The PF approach exhibited superior performance in the field of prognostics. The superiority of the physics-based approach can be attributed to the utilization of an exponential deterioration model with two parameters that are computed online within a Bayesian framework. The Gaussian process regression model, which relies on data-driven techniques, was unable to generate accurate RUL forecasts until a distinct degradation behavior, namely, of exponential nature, became evident. On the other hand, in cases when the degradation does not conform to an exponential model due to factors such as noisy data or varying failure modes, the utilization of a data-driven model would provide more precise outcomes. This is because the findings obtained from the data-driven model may be compared to the historical deterioration patterns [20].

In the realm of RUL analysis, it is widely observed that a considerable number of researchers exhibit a preference for a hybrid methodology. This approach entails the integration of both data-driven and physics-based models, with the intention of capitalizing on the unique advantages offered by each model type. The objective behind this integration is to enhance the accuracy and reliability of RUL prediction [20].

5.3. The Prognostics Fusion Framework

The incorporation of data-driven and physics-based approaches into a fusion prognostic framework shows potential for accurately predicting RUL. The physics-based technique, also known as the model-based approach [20], entails leveraging an understanding of the fundamental principles of physics to generate accurate estimations. The approach outlines the procedure for the degradation of a system using an analytical equation known as a degradation model. The degradation model should accurately represent the process of degradation; nevertheless, in practical implementation, deviations from the model may occur. The use of data-driven prediction methods, which utilize past data and the specific system being studied, holds promise for improving the accuracy of forecasts and reducing uncertainty.

The figure depicted above provides a preliminary representation of the intricate relationship that exists between data-driven and physics-based methodologies, as referenced in [11]. The integration of prognostics incorporates two data-driven techniques into the traditional physics-based PF architecture, hence enhancing the precision of predictions. The paper presents a novel approach utilizing data-driven techniques for estimating the measurement model and another for forecasting future measurements in long-term prediction scenarios.

The hybrid prognostics framework extends the applicability of Bayesian state estimation by incorporating two data-driven techniques into a physics-based approach, namely, utilizing the PF method. The sensor readings Yk typically do not provide direct access to the internal system state Xk, such as degradation, in a complex system. This necessitates the utilization of a physics-based approach to indirectly estimate the internal state of the system. The conventional Bayesian state estimation method is based on an analytical measurement model, $Yk=h(Xk)+vk$.

However, in many instances, it is not possible to obtain an analytical representation of the measurement model. As a result, an approach based on data analysis is employed instead. The utilization of the estimated data-driven measurement model enables the execution of state tracking in a conventional manner, employing the system degradation model $Yk=h(Xk-1)+wk$.

5.4. Limitations of Hybrid Prognostic Approaches

Nevertheless, like any other methodology, hybrid prognostics have inherent limitations. One limitation is the challenge associated with developing hybrid models that effectively combine the benefits of data-driven and physics-based modeling techniques [15][31]. The effective integration of the distinct benefits provided by data-driven and physics-based modeling methodologies represents an additional obstacle in the development of hybrid prognostic models in the aviation domain.

Hybrid models are required to possess the ability to accurately predict and prevent failures in advance. This is achieved by carefully selecting the most relevant hIs and accurately calculating the PDFs of hIs for both normal and deteriorated states [17][32]. Another challenge arises from the intricacy of hybrid models, which requires a significant level of expertise for their creation and continuous upkeep. Additionally, it is important to acknowledge that hybrid models may require a significant amount of data for training and validation, which can be difficult to do in certain situations [33].

To tackle these challenges, researchers are presently involved in the exploration of innovative methodologies that combine data-driven and physics-based modeling techniques. Furthermore, their efforts are focused on improving the accuracy and reliability. Within the domain of hybrid prognostics for aircraft systems, PDFs can be utilized to evaluate the probability of a system or component existing in a particular state, such as being in a state of optimal health or experiencing degradation. This estimation is derived by considering the hIs linked to the system or component. Hybrid models possess the capacity to accurately predict and prevent failures by employing the estimate of PDFs for hIs in both healthy and degraded states.

For instance, consider a system comprising two hIs, namely, temperature and vibration. The PDFs of the hIs for both healthy and impaired states can be approximated using historical data. Subsequently, upon the acquisition of novel temperature and vibration data pertaining to the system, the PDFs can be employed to approximate the likelihood of the system being in either a sound or deteriorated condition. If the likelihood of the system being in a deteriorated state is considerable, proactive measures can be implemented to mitigate the risk of a failure prior to its manifestation.

Current studies in hybrid prognostics for aviation have been primarily dedicated to the advancement of novel approaches that integrate data-driven and physics-based modeling techniques. The objective is to enhance the precision and dependability of failure prognostications. An investigation was conducted in a study to examine the utilization of classification methods, as opposed to regression approaches, for the purpose of identifying problems in aircraft systems [15]. Recent papers examined the current advancements in hybrid electric aircraft and the techniques employed for managing their energy [18][34].

These methodologies possess the capability to enhance the safety and reliability of aircraft systems through the precise anticipation and preemptive mitigation of faults prior to their occurrence. A study was conducted to examine the integration of physics-based and deep learning models for the purpose of prognostics [35].

5.5. State of the Art

Reference [1] focuses on prognostics in aircraft systems and presents an overview of contemporary research pertaining to predictive maintenance (PM) techniques employed for the hydraulic system and engine of airplanes. The authors examine the significance of PM and cutting-edge data pre-processing techniques in the context of handling huge datasets. Additionally, they ascertain emerging patterns and obstacles within the realm of project management for aircraft systems.

Reference [36] examines the latest advancements in research and the practical uses of prognostics modeling methods in the field of engineering systems. The study that has been examined is categorized into three primary domains, depending on whether they integrate the understanding of the physics of failure into prognostics. These domains are the data-driven prognostic techniques, the physics-based prognostic methods, and the hybrid prognostic approaches. The technical advantages and limitations of each prognostic approach are analyzed and explained.

Reference [37] elucidates the creation of a novel and authentic dataset comprising run-to-failure trajectories for a fleet of aircraft engines operating in actual flight conditions. This dataset holds significant value for the field of prognostics and diagnostics. The dataset utilized was derived from the Commercial Modular Aero-Propulsion System Simulation (CMAPSS) model, which was originally designed by NASA. The authors emphasize the significance of possessing representative run-to-failure datasets to facilitate the creation of data-driven prognostics models. They also highlight the versatility of their dataset, which may be utilized for both prognostics and fault diagnostics purposes. The paper offers significant insights into the creation of authentic datasets for prognostics in aircraft systems, rendering it a helpful resource for individuals seeking relevant information in this field.

The utilization of data-driven methodologies, particularly ML, has significantly advanced maintenance modeling in recent times, leading to a wide array of practical applications [38]. Several conclusions can be drawn. Firstly, the utilization of publicly accessible data has the potential to enhance research endeavors. Secondly, a significant proportion of academic papers depend on supervised techniques that necessitate annotated data. Thirdly, the amalgamation of multiple data sources has the potential to enhance the accuracy of results. Lastly, the adoption of deep learning methods is expected to rise, but it is contingent upon the development of efficient and interpretable approaches as well as the availability of substantial quantities of labeled data. ML methodologies are currently being utilized for the purpose of mechanical defect detection and prediction within the framework of practical industrial manufacturing scenarios [39]. This analysis demonstrates that there has been a growing number of studies conducted in the manufacturing business in recent years. However, further research is required to effectively tackle the issues posed by real-world situations [39][40].

Reference [41] examines the academic and industry literature to identify the primary technological domains of electric aviation. These domains include battery technology, electric machine technology, airframe technology, and propulsion technologies. The paper discusses the current state of these technologies, their projected advancements in the future, as well as the challenges they face.

Reference [34] provides an overview of the current research progress in the field of hybrid aircraft design and energy management, as well as hybrid propulsion systems. Another instance of a hybrid methodology for prognostics can be observed in the context of micro-electromechanical systems (MEMS), as elucidated by [42]. The proposed methodology consists of the following two distinct stages: an initial offline phase dedicated to the characterization and modeling of the MEMS degradation, and a subsequent online phase where the derived degradation model is employed in conjunction with the available data for prognostic purposes. The offline phase encompasses the utilization of physics-based models to elucidate the behavior of the MEMS and its constituent parts. Conversely, the online phase entails the application of data-driven techniques to revise the model parameters and generate forecasts regarding the system's RUL.

An additional illustration may be found in the form of a model-based hybrid technique utilized for circuit breaker prognostics. This approach effectively integrates the continuous and discrete temporal behavior of the system, as demonstrated in references [43][44]. This combination is well-suited for applications that need the consideration of deterministic system behavior, particularly in cases where the deterioration is observed to increase at specific discrete time intervals. The instances serve as mere illustrations of the potential applications of hybrid methodologies in the field of prognostics. The integration of data-driven and physics-based methodologies provides a robust approach to effectively forecast the future dynamics of a given system, capitalizing on the respective advantages of both approaches.

Reference [45] examines the application of Integrated System Health Management (ISHM) technology in aerospace systems. ISHM technology integrates sensor data and historical state-of-health information of components and subsystems to deliver actionable insights and facilitate intelligent decision-making pertaining to system operation and maintenance. The core foundation of ISHM is predicated on the utilization of evaluations and prognostications pertaining to the overall well-being of a system. This encompasses the timely identification of malfunctions and the calculation of the remaining duration of optimal functionality. Various reasoning techniques, such as model-based, data-driven, or hybrid approaches, can be employed to optimize the promptness and dependability of diagnostic and prognostic data.

References

1. Khan, K.; Sohaib, M.; Rashid, A.; Ali, S.; Akbar, H.; Basit, A.; Ahmad, T. Recent Trends and Challenges in Predictive Maintenance of Aircraft’s Engine and Hydraulic System. J. Braz. Soc. Mech. Sci. Eng. 2021, 43, 403.
2. Hirshman, B.; Milon, T.; Brimmer, A.; Brinkopf, B.; Rabson, M.; Smith, K. How Value Can Take off with Predictive Aircraft Maintenance. Available online: https://www.bcg.com/publications/2020/building-value-with-predictive-aircraft-maintenance (accessed on 30 May 2023).
3. Celikmih, K.; Inan, O.; Uguz, H. Failure Prediction of Aircraft Equipment Using Machine Learning with a Hybrid Data Preparation Method. Sci. Program 2020, 2020, 8616039.
4. Friedrich, C.; Robertson, P.A. Hybrid-Electric Propulsion for Aircraft. J. Aircr. 2015, 52, 176–189.
5. Li, T.; Sbarufatti, C.; Cadini, F.; Chen, J.; Yuan, S. Particle Filter-Based Hybrid Damage Prognosis Considering Measurement Bias. Struct. Control Health Monit. 2022, 29, e2914.
6. Neerukatti, R.K.; Liu, K.C.; Liu, Y.; Chattopadhyay, A. Fatigue Life Prediction Using Hybrid Prognosis for Structural Health Monitoring. In Proceedings of the AIAA Infotech at Aerospace Conference and Exhibit 2012, Garden Grove, CA, USA, 19–21 June 2012.
7. Schumann, J.; Kulkarni, C.; Lowry, M.; Bajwa, A.; Teubert, C.; Watkins, J. Prognostics for Autonomous Electric-Propulsion Aircraft. Int. J. Progn. Health Manag. 2021, 12, 1–15.
8. Kordestani, M.; Samadi, M.F.; Saif, M. A New Hybrid Fault Prognosis Method for MFS Systems Based on Distributed Neural Networks and Recursive Bayesian Algorithm. IEEE Syst. J. 2020, 14, 5407–5416.
9. ISO 13381-1:2015; Condition Monitoring and Diagnostics of Machines—Prognostics—Part 1: General Guidelines. International Standard: Geneva, Switzerland, 2015.
10. Jardine, A.K.S.; Lin, D.; Banjevic, D. A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance. Mech. Syst. Signal Process. 2006, 20, 1483–1510.
11. Liao, L.; Köttig, F. A Hybrid Framework Combining Data-Driven and Model-Based Methods for System Remaining Useful Life Prediction. Appl. Soft Comput. 2016, 44, 191–199.
12. Fornlöf, V.; Galar, D.; Syberfeldt, A.; Almgren, T. RUL Estimation and Maintenance Optimization for Aircraft Engines: A System of System Approach. Int. J. Syst. Assur. Eng. Manag. 2016, 7, 450–461.

13. Singh, J.; Azamfar, M.; Li, F.; Lee, J. A Systematic Review of Machine Learning Algorithms for Prognostics and Health Management of Rolling Element Bearings: Fundamentals, Concepts and Applications. Meas. Sci. Technol. 2021, 32, 012001.
14. Yu, W.K.; Harris, T.A. A New Stress-Based Fatigue Life Model for Ball Bearings. Tribol. Trans. 2001, 44, 11–18.
15. Baptista, M.L.; Henriques, E.M.P.; Prendinger, H. Classification Prognostics Approaches in Aviation. Measurement 2021, 182, 109756.
16. Javed, K.; Gouriveau, R.; Zerhouni, N. State of the Art and Taxonomy of Prognostics Approaches, Trends of Prognostics Applications and Open Issues towards Maturity at Different Technology Readiness Levels. Mech. Syst. Signal Process. 2017, 94, 214–236.
17. Rendón, M.A.; Sánchez, R.C.D.; Gallo, M.J.; Anzai, A.H. Aircraft Hybrid-Electric Propulsion: Development Trends, Challenges and Opportunities. J. Control Autom. Electr. Syst. 2021, 32, 1244–1268.
18. Zainuddin, N.F.; Mohammed, M.N.; Abdelgnei, M.A.H.; Al-Zubaidi, S. The Prognostics Approaches and Applications in Aircraft Maintenance Optimization: Review. In Proceedings of the 2021 IEEE 12th Control and System Graduate Research Colloquium, ICSGRC 2021—Proceedings, Shah Alam, Malaysia, 7 August 2021; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2021; pp. 201–205.
19. Medjaher, K.; Zerhouni, N. Framework for a Hybrid Prognostics. Chem. Eng. Trans. 2013, 33, 91–96.
20. Liao, L.; Köttig, F. Review of Hybrid Prognostics Approaches for Remaining Useful Life Prediction of Engineered Systems, and an Application to Battery Life Prediction. IEEE Trans. Reliab. 2014, 63, 191–207.
21. Wikipedia Contributors Joint Strike Fighter Program; Wikipedia, The Free Encyclopedia: Washington, DC, USA, 2023.
22. Nguyen, K.T.P.; Medjaher, K.; Tran, D.T. A Review of Artificial Intelligence Methods for Engineering Prognostics and Health Management with Implementation Guidelines. Artif. Intell. Rev. 2023, 56, 3659–3709.
23. Schwabacher, M.; Goebel, K. A Survey of Artificial Intelligence for Prognostics. In Proceedings of the 2007 AAAI Fall Symposium—Technical Report, Arlington, VA, USA, 9–11 November 2007.
24. Elattar, H.M.; Elminir, H.K.; Riad, A.M. Prognostics: A Literature Review. Complex Intell. Syst. 2016, 2, 125–154.
25. Medjaher, K.; Zerhouni, N.; Baklouti, J. Data-Driven Prognostics Based on Health Indicator Construction: Application to PRONOSTIA's Data. In Proceedings of the 2013 European Control

Conference (ECC), Zurich, Switzerland, 17–19 July 2013; pp. 1451–1456.

26. Luo, J.; Pattipati, K.R.; Qiao, L.; Chigusa, S. Model-Based Prognostic Techniques Applied to a Suspension System. IEEE Trans. Syst. Man Cybern. Part A Syst. Hum. 2008, 38, 1156–1168.
27. Chelidze, D.; Cusumano, J. A Dynamical Systems Approach to Failure Prognosis. J. Vib. Acoust. 2004, 126, 2–8.
28. Atamuradov, V.; Medjaher, K.; Dersin, P.; Lamoureux, B.; Zerhouni, N. Prognostics and Health Management for Maintenance Practitioners—Review, Implementation and Tools Evaluation. Int. J. Progn. Health Manag. 2017, 8, 31.
29. Su, C.; Chen, H.J. A Review on Prognostics Approaches for Remaining Useful Life of Lithium-Ion Battery. IOP Conf. Ser. Earth Environ. Sci. 2017, 93, 12040.
30. Celaya, J.; Kulkarni, C.; Biswas, G.; Goebel, K. A Model-Based Prognostics Methodology for Electrolytic Capacitors Based on Electrical Overstress Accelerated Aging. In Proceedings of the Annual Conference of the PHM Society, Denver, CO, USA, 20–23 June 2011.
31. Wang, P.; Long, Z.; Wang, G. A Hybrid Prognostics Approach for Estimating Remaining Useful Life of Wind Turbine Bearings. Energy Rep. 2020, 6, 173–182.
32. Schwab, A.; Thomas, A.; Bennett, J.; Robertson, E.; Cary, S. Electrification of Aircraft: Challenges, Barriers, and Potential Impacts; National Renewable Energy Laboratory: Golden, CO, USA, 2018.
33. Cohen, A.P.; Shaheen, S.A.; Farrar, E.M. Urban Air Mobility: History, Ecosystem, Market Potential, and Challenges. IEEE Trans. Intell. Transp. Syst. 2021, 22, 6074–6087.
34. Xie, Y.; Savvarisal, A.; Tsourdos, A.; Zhang, D.; Gu, J. Review of Hybrid Electric Powered Aircraft, Its Conceptual Design and Energy Management Methodologies. Chin. J. Aeronaut. 2021, 34, 432–450.
35. An, D.; Kim, N.H.; Choi, J.H. Practical Options for Selecting Data-Driven or Physics-Based Prognostics Algorithms with Reviews. Reliab. Eng. Syst. Saf. 2015, 133, 223–236.
36. Guo, J.; Li, Z.; Li, M. A Review on Prognostics Methods for Engineering Systems. IEEE Trans. Reliab. 2020, 69, 1110–1129.
37. Chao, M.A.; Kulkarni, C.; Goebel, K.; Fink, O. Aircraft Engine Run-to-Failure Dataset under Real Flight Conditions for Prognostics and Diagnostics. Data 2021, 6, 5.
38. Theissler, A.; Pérez-Velázquez, J.; Kettelgerdes, M.; Elger, G. Predictive Maintenance Enabled by Machine Learning: Use Cases and Challenges in the Automotive Industry. Reliab. Eng. Syst. Saf. 2021, 215, 107864.
39. Fernandes, M.; Corchado, J.M.; Marreiros, G. Machine Learning Techniques Applied to Mechanical Fault Diagnosis and Fault Prognosis in the Context of Real Industrial Manufacturing

Use-Cases: A Systematic Literature Review. Appl. Intell. 2022, 52, 14246–14280.

40. Li, Z.; Wang, Y.; Wang, K.S. Intelligent Predictive Maintenance for Fault Diagnosis and Prognosis in Machine Centers: Industry 4.0 Scenario. Adv. Manuf. 2017, 5, 377–387.
41. Adu-Gyamfi, B.A.; Good, C. Electric Aviation: A Review of Concepts and Enabling Technologies. Transp. Eng. 2022, 9, 100134.
42. Skima, H.; Medjaher, K.; Varnier, C.; Dedu, E.; Bourgeois, J. A Hybrid Prognostics Approach for MEMS: From Real Measurements to Remaining Useful Life Estimation. Microelectron. Reliab. 2016, 65, 79–88.
43. Aizpurua, J.I.; Catterson, V.M.; Abdulhadi, I.F.; Garcia, M.S.; Abdulhadi, I.F.; Segovia Garcia, M. A Model-Based Hybrid Approach for Circuit Breaker Prognostics Encompassing Dynamic Reliability and Uncertainty. IEEE Trans. Syst. Man Cybern. Syst. 2017, 48, 1637–1648.
44. Zio, E. Prognostics and Health Management (PHM): Where Are We and Where Do We (Need to) Go in Theory and Practice. Reliab. Eng. Syst. Saf. 2022, 218, 108119.
45. Ranasinghe, K.; Sabatini, R.; Gardi, A.; Bijjahalli, S.; Kapoor, R.; Fahey, T.; Thangavel, K. Advances in Integrated System Health Management for Mission-Essential and Safety-Critical Aerospace Applications. Prog. Aerosp. Sci. 2022, 128, 100758.