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REVIEW

Model-Based Mechanical Property and Structural Failure Prediction of Pseudo Ductile Hybrid Composite

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ABSTRACT

Lightweight fiber reinforced composites are widely used in engineering structures, which often fail catastrophically due to the uncertainty of external loads and their brittle nature. The development of pseudo ductile hybrid composites was the proposed solution to create minimal ductility in fiber reinforced composites so that equipment downtime, cost, and loss of lives can be minimized in their structural application. However, the development of pseudo ductile hybrid composites does not guarantee that pseudo ductile hybrid composite is prone to failure. As a result, different models, including Halpin-Tsai, Hashin and Shtrikman, Weibull, and log-normal models, were developed to predict degradation of mechanical properties and structural failure so that prior recognition of failure can be achieved. The current structural health monitoring research trend shows the development of hybrid mechanical property and structural failure prediction models spalling the drawback of data-driven and physics-based models. Physics-based models require detail understanding of the root cause of failure in terms of mathematical or physical model to predict failure progression whereas data-driven

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models rely on historical data or sensor data collected from machineries or structures. While hybrid models combine the strengths of both physics-based and data-driven models providing manageable uncertainty and more accurate prediction. This paper aims to review model-based mechanical property and structural failure prediction strategies with regard to pseudo ductile hybrid composites highlighting future research directions and challenges, and offering insights beneficial to the research and industrial communities.

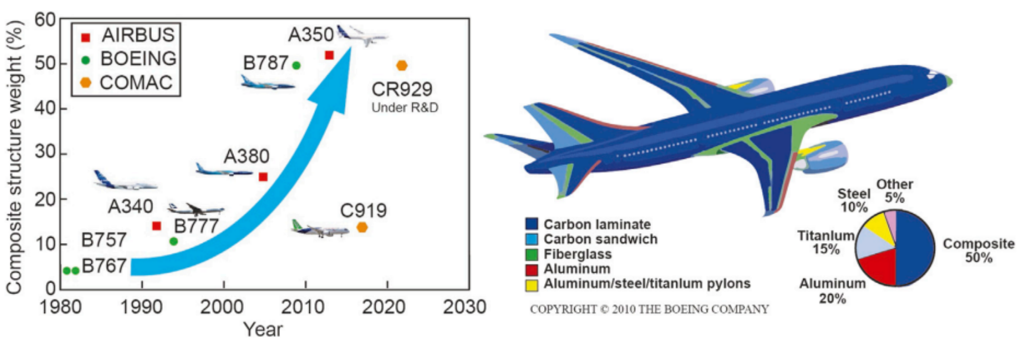
Keywords: Failure Prediction; Mechanical Property Prediction; Pseudo Ductile Hybrid Composite; Data-Driven Models; Physics-Based Models; Hybrid Models; Electric Aircraft

1. Introduction

Predicting mechanical properties, damage and failure of mechanical systems and structures has become critical for researchers and industrialists, especially with the rise of preventive maintenance (PM) [1]. The predictive capability of different methods for composites was evaluated in the first two worldwide failure exercises (WWFE I and II) [2]. In the 2020s, a comprehensive approach to failure prediction and maintenance decision-making was introduced to enhance the reliability and efficiency of composite systems, utilizing advanced deep learning techniques [3].

1.1. Structural Application of Composites

Lightweight design, an extensively explored concept in aerospace and automotive applications, is crucial for reducing fuel consumption and CO_2 global emissions [4]. For example, 10–12% fuel efficiency can be attained for 20% weight reduction in Boeing 787 [5], and 6-8% fuel consumption can be saved for a 10% vehicle weight reduction [6]. Composites, particularly those made from metal fibers, synthetic fibers such as carbon fiber, and metal matrix composites [7], are preferred for such lightweight applications due to their high strength-to-weight ratios. However, natural fiber reinforced polymer (FRP) composites have limited use as primary and secondary structures in these applications because of their instability at high temperatures [8]. Despite this, significant research has been conducted and some progress made in using polymer-based composites in lightweight applications (**Figure 1**), such as spacecraft and electric vertical take-off and landing aircraft (eVTOL), to enhance fuel efficiency [9]. For instance, the International Air Transport Association aimed to save 3925 Kg of fuel and prevent the release of 4 tons of CO_2 for 10 Kg of weight savings [10]. These weight savings focus on increasing the payload capacity and battery life in the case of eVTOL.



(**a**) (**b**)

Figure 1. Composite usage. (**a**) Ratio of structural weight. (**b**) Composites in Boeing 787.

Specifically, due to their fuel efficiency, greater specific stiffness and strength, fiber reinforced laminated composite parts have been successfully installed in automotive sports cars, aerospace and marine systems [11]. For instance, high-strength Euro carbon fiber composite was used for the trailing arm of the F-16 landing gear, BMW electric vehicle project and Airbus A340 horizontal tail, resulting in significant weight and cost reductions, along with enhanced performance[12, 13]. Beachcraft Starship is a business aircraft that was entirely built from composites and remains in operation[14]. Another shift towards composite construction is the development of the eVTOL design concept[15]. In conventional aircraft such as Airbus A350 and Boeing 787 Dreamliner, carbon fiber reinforced plastic composite (CFRPC) is extensively used as an aeronautical structural material[16]. Despite their benefits, the wider adoption of CFRPC in lightweight applications is limited due to the complexity of the manufacturing process, higher cost and brittleness[17].

1.2. Strategies for Enhancing the Ductility of Composites

Brittleness is the main drawback of composites[18]. These factors place composites third in overall material usage (**Figure 2**)[19]. To address these limitations, strategies such as matrix toughening, interfacial toughening and pseudo ductility have been developed[20], with pseudo ductility gaining interest for its potential to reduce brittleness[18]. This is because the ongoing maintenance expenses and capital investment for matrix toughening and interfacial toughening are significant[20]. Pseudo ductile hybrid composites (PDHCs) combine materials with different properties and thicknesses, such as hybridizing low-strain material (LSM) with high-strain material (HSM) or metal fibers with carbon fiber[21]. They can be configured using interlayer, intralayer, and fiber-by-fiber or intra-yarn methods[22]. Another method of achieving pseudo ductility is the use of different weave architectures such as plain weave, satin weave and twill weave[22]. These PDHCs are being used in lightweight fuel-efficient areas including aerospace, medical, automotive, marine, construction, and sports equipment[23].

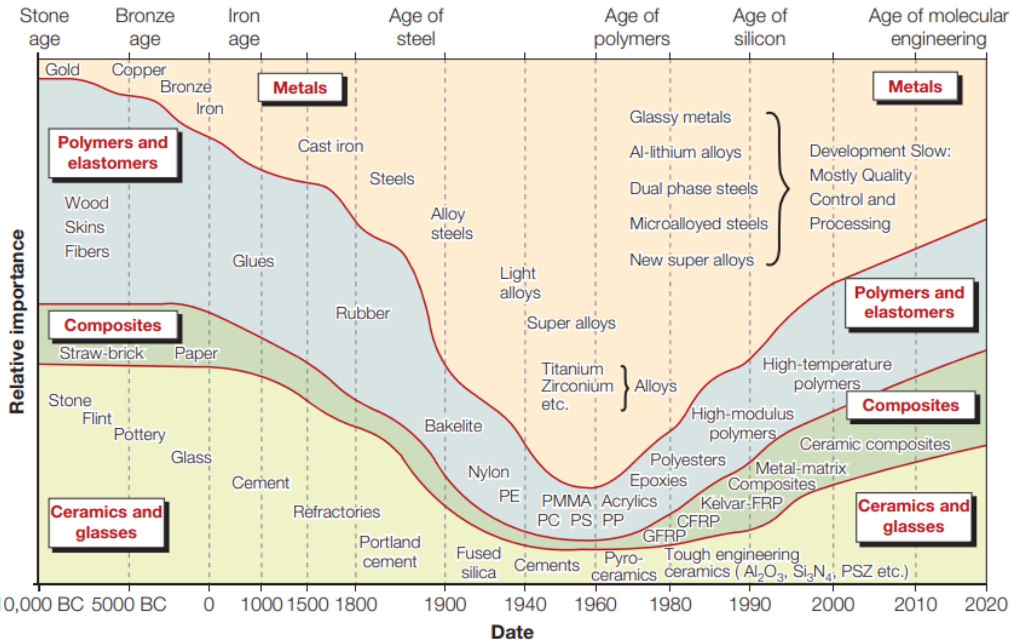


Figure 2. Relative importance of different materials with regard to time.

1.3. Failure Mechanisms of Composites

Laminated composites exhibit complex failure mechanisms, making their behavior challenging to model[24]. Due to quasi-brittleness and lack of ductility, developing computational tools to predict local failures, such as matrix cracking, fiber-matrix debonding, fiber breakage and delamination, is challenging[25]. Composites are anisotropic, meaning they cannot uniformly resist axial, side and shear loads, leading to various failure forms[26]. Developing quasi-isotropic materials that can handle shear, longitudinal and transverse loads is essential[27]. Quasi-isotropic laminates cannot achieve true isotropic performance[28], resulting in failures due to operational, environmental or manufacturing factors[11]. Failure forms include fiber-level microdamage (such as fiber pull-out, fiber breakage, interfacial debonding, fiber failure due to matrix cracking, and transverse matrix cracking), matrix-level damage (such as matrix cracking and fiber interfacial cracking), coupled micro-macro damage, and macro damage (delamination)[29]. These damage forms range from surface scratches to deep grooves and a complete separation of parts, which results in increased stress or premature failure[30]. The damage level starts from micro cracks and voids due to material and manufacturing defects and grows into a macro-level crack leading to final failure[31]. This is not only due to material and manufacturing defects, but also mechanical loading, chemical ingress, thermal gradients, environmental conditions, and deterioration of fiber, matrix, and fiber/matrix interfaces are among the major causes of composite failures[32]. When it comes to secondary structures like seat frames of passenger aircraft, complex variable loads in different directions such as impact force due to unpredictable falling passenger baggage, vertical reaction force due to weight of passenger and gravity, torsional and bending moment due to inertia force, and gear walk and shimmy oscillations affects human machine safety during landing, take-off, maneuvering and other multi-tasks[33]. As a result of all these factors, multiple damage modes can be encountered, especially for carbon glass PDHCs, since the individual fibers have different mechanical properties[34]. For instance, fiber breakage may occur in the carbon fiber as a result of the applied load and glass fiber takes over the remaining external load demonstrating different damage modes such as delamination.

1.3.1. Failure Mechanisms of Pseudo Ductile Hybrid Composites

PDHCs can exhibit various fracture modes depending on the ratio of low strain to high strain. When the ratio is below a critical value, multiple fractures and delamination can occur, while a higher ratio leads to premature failure (**Figure 3**)[34].

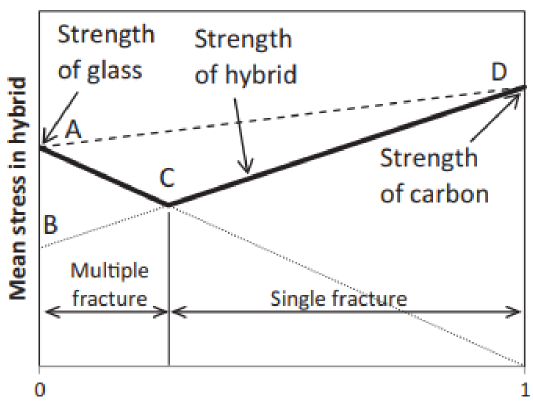


Figure 3. Glass-carbon hybrid theoretical strength.

In a unidirectional (UD) PDHC, after the first crack initiation in the LSM, four possible failure developments could occur[35]. First, fragmentation in the LSM occurs, followed by dispersed delamination and then HSM failure. Second, catastrophic delamination occurs, followed by HSM failure. Third, fragmentation (multiple fractures) in the LSM leads to HSM failure. Finally, premature failure of the hybrid laminate occurs due to the first failure of LSM and a small amount of HSM to withstand the applied stresses[35].

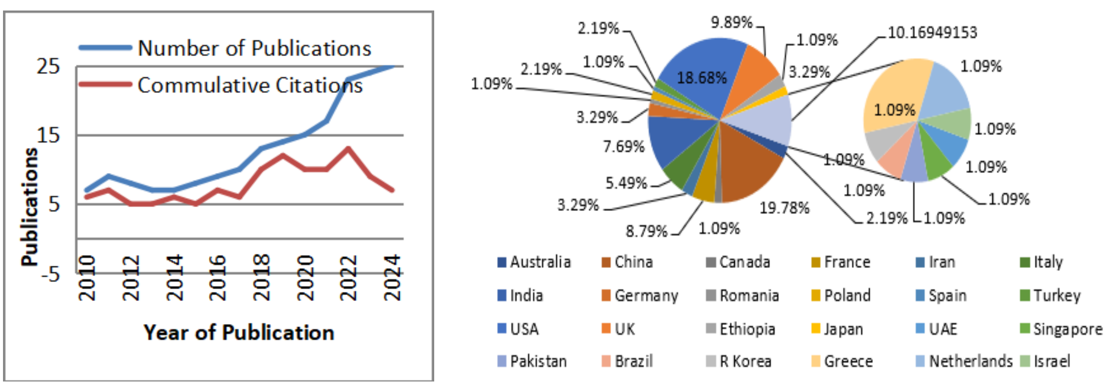
1.4. Motivation of Reviewing in This Area

Fiber reinforced PDHCs although slightly ductile, still fail catastrophically due to small difference in elongation between constituent fibers such as glass and carbon fibers[22]. Both PDHCs and conventional ductile materials deteriorate and can fail catastrophically, leading to significant property loss and fatalities[36, 37].

1.4.1. Typical Examples of Structural Failures

Failure of structures is a lifelong incident recorded through time, resulting in material and life loss. For example, out of a number of failure incidents each year, failure of Quebec steel bridge and failure of Tuojiang bridge are scientifically recorded ones[38]. A number of historical structural buildings, such as Qasr Al-Manar (University of Libya), fail due to severe damage[39]. A total of 1202 events of wind turbine failures were recorded within 156,202h for 600 wind turbines in Sweden from 2000 to 2004[40]. There were also a number of failures of aircraft in the aviation sector[41–44]. For instance, an American Airlines Airbus A300 failed due to delamination[42]. Aircraft companies in the aviation industry face economic burden due to equipment downtime, which disrupts services[45]. Such failures and the resulting costs are thus the major global problem requiring a current, up-to-date solution. As global aviation demand increases, companies are expanding their fleets to meet the growing need for safe and fuel-efficient aircraft. This indicates an increased use of the aviation industry, accompanied by a higher number of failures and accidents, primarily due to structural, battery, or propulsion system failures. Specifically, congested cities and developed urban areas are shifting to use eVTOL, which are entirely built from composites to increase payload capacity and battery life. The rise of eVTOL for urban air mobility (UAM) necessitates analyzing material behavior, mechanical properties and failure mechanisms to prevent economic losses and fatalities. Furthermore, the accident rate is comparably higher. For instance, historical data shows high accident rates for US civil helicopters, 8.09 accidents per 100,000 flight hours in 2004 and 8.52 in 2005, emphasizing the need for improved safety [46]. While significant research has been dedicated to design, manufacturing and crashworthiness of eVTOL, areas such as damage assessment, performance prediction and structural failure prediction are relatively unexplored [47]. In addition, most studies regarding eVTOL have focused on concept design, crashworthiness, battery life optimization, and propulsion systems. Therefore, there is limited research in this area and conducting a review of related research is crucial. The main contribution of this review is to highlight future research directions and challenges, and offer insights beneficial to the research and industrial communities in the area of application of eVTOL. This paper aims to review model-based mechanical property and failure prediction approaches for PDHCs, indicating the knowledge gap.

This review paper was done by searching the keyword on Google Scholar and all the relevant number of publications and cumulative citations to the capability of accessibility of authors were used and presented as in **Figure 4**.



(**a**) (**b**)

Figure 4. Number of publications and cumulative citations on (**a**) year and (**b**) geography basis.

2. Materials and Methods

PDHC materials have recently been familiarized as a new development of fiber reinforced polymer composites (FRPCs) to tackle the abrupt and unpredictable failure [7]. To produce PDHCs, diverse techniques and material amalgamations have been utilized.

2.1. Pseudo Ductile Hybrid Composite Materials

A basic approach to achieving pseudo-ductility is the combination of fresh ductile fibers and matrices, which requires extensive research and validation. Another possibility is the alteration of the construction of FRLCs built from commercially accessible raw materials, such as developing hybrids, which is a much quicker and more straightforward approach. This includes hybridizing conventional composites such as carbon FRPs with metal fibers such as steel [7], or hybridizing thin-ply high-strain FRPCs with thin-ply or conventional low-strain FRPCs.

2.2. Mechanical Property Prediction Models

Researchers have employed various methods, including analytical, numerical and experimental techniques to achieve this goal. Classical micro-mechanics-based analytical methods such as the rule of mixture, Halpin-Tsai equations and Mori-Tanka methods are used to predict the macroscopic properties of composites based on the properties of their constituents [48]. A semi-empirical model called Halpin-Tsai based on the micro-mechanical model developed by Hill helps to estimate the composite modulus of different composite geometries assuming that the composite is a single fiber surrounded by a cylinder [49]. Kamocka et al. [48] used Halpin-Tsai model to analytically estimate the properties of composite materials (fiber metal laminates) evaluating the effective properties of the hybrid layers by considering both matrix and fiber properties. However, it requires proving the suitability of the Halpin-Tsai model for hybrid composites. Nielsen modified the Halpin-Tsai model to represent the maximum packing fraction of the inclusion material [49]. Hashin and Shtrikman developed an analytical model to predict the elastic modulus of two-phase isotropic material based on the change in strain energy using upper and lower theoretical bounds [49], which can be extended to hybrid composites by incorporating multiple phases and their interactions. The Tsai-Wu model achieves accurate predictions for the macroscopic properties of UD composite [50]. This model has accuracy concerns over triaxial stresses compared to uniaxial conditions. All these analytical models developed for solid particle laminated UD composites and Neilson considered a correction factor for hollow particles. Traditionally, FRPC UD laminates impregnated with matrix material offer good in-plane properties but not in the thickness direction [51]. Overcoming the limitations of traditional micromechanics models, Kabir et al. suggest a checkerboard model advancing the evaluation of elastic constants for composites (particularly for composite materials reinforced with graphene nanoplatelets) by incorporating a checkerboard configuration for the dispersion of nanoplatelets within the composite matrix [52]. Whereas, woven FRP composites offer a 3D reinforcement in a single layer and provide better mechanical properties. For a single-layer UD woven composite, a 3D spring element shear lag model can be used to predict mechanical properties using Monte Carlo Simulation (MCS), finite difference successive over-relaxation method, and weak link technique. Okabe et al. have used shear lag model and MCS to examine how micro-damage mechanics affects the mechanical behavior of UD composite and weak link scaling technique to predict ultimate tensile strength (UTS) of macro-composite [53]. Finite element analysis (FEA) numerical method is a powerful tool for simulating the mechanical behavior of composites at various scales, from micro to macro scale [54, 55]. Computational homogenization numerical method is used to derive effective properties of composite materials from the analysis of representative volume element (RVE) [51]. Traditional experimental tests such as tensile, compressive and flexural tests are used to determine the mechanical properties of composites [56, 57]. Machine learning techniques (MLTs), including artificial neural networks (ANNs) and deep learning, are increasingly being used to predict the mechanical properties of composites based on experimental data and simulations [58–61]. Statistical methods such as MCS and reliability analysis are used to quantify uncertainties in the mechanical properties of composites [62–64]. A combination of one or more reliable and accurate models of these techniques was used to predict mechanical properties and structural failure of composites.

2.3. Structural Failure Prediction Models

Predicting structural failure helps maintenance personnel prepare resources in advance [65, 66], reducing unexpected downtime. Failure prediction, particularly in load-bearing structures, has focused on PM, structural health monitoring (SHM), and tracking fatigue damage [67]. Failure prediction falls under PM, aiming to prevent catastrophic equipment failures by using real-time data to signal impending issues [45]. These signals help PM personnel plan repairs and maintenance, reducing operational disruptions. For instance, building rehabilitation is a key PM strategy to reduce structural failure of buildings. For medium level of building damage, cracks up to 3 mm wide, differential settlement of 4–5 cm, and minimal angular rotation, rehabilitation involves repairing and sealing cracks, refinishing surfaces and reinstalling structural elements like doors with the goal of maintaining buildings structural integrity, restore functionality and prevent further deterioration [39]. When the level of damage is characterized by 5–10 mm wide cracks, 5–8 cm differential settlement [39], and collapse structural elements, the goal of rehabilitation, by opening, cleaning and treating cracks and replacing damaged structural elements such as bricks, is to address the series threat to structural integrity and avoid potential failure. If not addressed promptly, structures may show signs of distress such as reduced load carrying capacity, cracks and corrosion over time leading to structural failure [68]. These days, soft computing models such as ANN, Gene Expression Programming (GEP) and Group Method of Data Handling (GMDH) are being incorporated to predict failure of building structural elements including FRP concrete columns [69]. In general, modern failure prediction approaches should answer how and when a failure event can be predicted for given data [45]. Traditional failure estimation methods are based on recorded failure events for identical machine units, including parametric approaches such as Weibull and log-normal models. However, these have limited use in condition-based maintenance (CBM) as they provide minimal system condition insights. Failure prognostic approaches are classified into model-based and non-model-based methods [36, 70], or further divided into model-, data-, and knowledge-based methods (**Figure 5**) [71]. Model-based methods build an accurate mathematical description of systems using physics or first principles and employ statistical techniques to detect, isolate, and predict failure [72]. Knowledge-based methods rely on engineering experience and events, offering intuitive predictions [71]. Experience-based models adjust reliability model parameters using maintenance and operating data [65]. Data-driven methods determine the health status of the system within a certain period of time by analyzing previously observed data. This previously observed data serves as a benchmark in justifying the model performance and guiding algorithm design. The three general damage prognosis methods are data-driven (black box), physics-based (white box), and hybrid methods (gray box) [73–75].

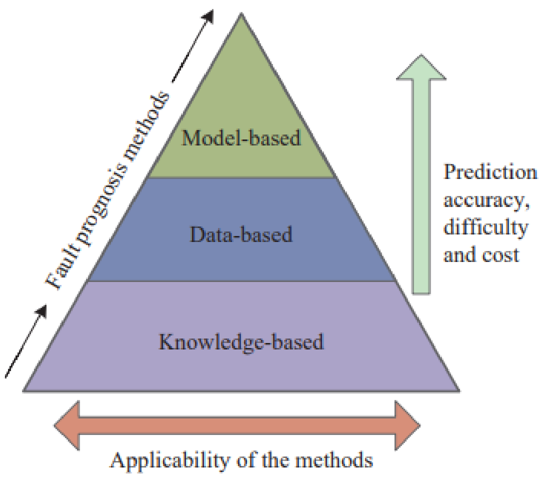


Figure 5. Damage prognosis methods.

2.4. Physics-Based Models

Physics-based approaches use detailed mathematical or physical models to predict failure progression by recognizing failure causes and estimating model parameters [75]. These approaches require extensive information on complex phenomena and are computationally intensive. They predict failure by deeply understanding and modeling systems' thermal, chemical, electrical or mechanical processes [76]. They use data such as pressure, temperature, speed and power data to compute the damage index through local load information. To simplify the computationally expensive physics-based model, a series of attempts have been made recently. However, these simplifications overestimate and are error-prone [77]. Some of the limitations of physics-based models are that they are time-consuming since mathematical or physical models are required for individual failure modes, and it is difficult to model or capture certain phenomena that are not well understood [78]. The requirement for high computational speed in online responses necessarily leads to a limited level of detail in the modeled phenomena, resulting in limited accuracy in representing the actual behavior [70]. The most widely used micromechanical models are shear lag, stress transfer methods and variational methods among the analytical approaches and FEM-based methods such as RVE and periodic unit cell (PUC) [79]. The material modeling in FEA analysis consists of plasticity model (Johnson-Cook model) and damage model (Lemaitre model) [80]. Lemaitre model was used to define damage evolution [81]. Hashin used variational methods to determine stiffness reduction of cross-ply laminates due to cracking [82]. The stiffness reduction method of Hashin was expanded by Nairn, who used the concept of energy release rate to determine the effective modulus of a cross-ply laminate with 900 plies [83]. One of the limitations of these methods is that they are limited to cross-ply laminates and uniaxial tensile loading [79]. The cohesive elements and virtual crack closure technique (VCCT) are mostly suitable for damage simulation in composite laminates. VCCT is employed to simulate crack onset and propagation based on Griffith's theory, a fracture mechanics approach. Both VCCT and cohesive behavior are used to model interfacial shearing, delamination, crack propagation and failure [35]. In both cases, once the damage has initiated and dissipated the same amount of energy between damage initiation and failure, elastic damage constitutive theory can be used to model material response. Modeling adhesives, gaskets, and bonded surfaces of small thicknesses is mostly done using the cohesive behavior approach. Element-based cohesive behaviors and surface-based elements such as slave and master surfaces and contact pairs can be modeled using cohesive behavior. The damage of the ply interface is modeled in such a way that the adhesive layer is considered to be of zero thickness. Finite elements as cohesive elements are characterized by material properties (such as stiffness, strength, and fracture energy) and numerical parameters (such as viscosity and damage variables). Lower viscosity value needs more computational time, whereas higher viscosity value does not represent the damage modeling of FRPC. Surface-based cohesive behavior is a straightforward approach to modeling cohesive connections using the traction-separation interface behavior, where the interface thickness is negligible. In general, cohesive elements are recommended for more detailed adhesive connection modeling. A quadratic failure criterion was used to predict damage initiation for interface cohesive elements inserted between two adjacent layers. Compared to the maximum stress criterion, the quadratic failure criterion is more suitable for predicting delamination onset, as it allows for arbitrary mode interactions. Cohesive zone models were proposed to be the most effective solutions to describe delamination in FEM, simulating the interfaces between plies mainly represented by cohesive elements, which can be regarded as a spring element superimposed between two nodes, with matching solid meshes of upper and lower plies on both sides.

However, use of cohesive zone models has some limitations such as divergence of calculation with implicit algorithms, unstable initiation and propagation of delamination when the energy criteria are fulfilled before the stress criteria, ill-posed problem when there is implicit static and rate-independent formulation and very small lengths of debonding due to onset delamination unless meshed finely [1]. Later in part B of WWFE-II, implicit/explicit algorithms in ABACUS were used to overcome some of these limitations [84].

There are also numerical approaches within the physics-based category that have been used for predicting mechanical properties and failure. For instance, a computer numerical model was created to predict the forces and location of failure of L-shaped joints made from composites subjected to bending load using the ABACUS user subroutine (user-defined material subroutine (UMAT)) [85].

Physics-based multiscale hybrid approach was proposed for prediction of damage and final failure, which the nature, location and evolution of different damages up to final failure precisely defined for higher confidence level, of laminated composites introducing mesoscopic scale of micromechanical aspects (e.g., effect of matrix micro-damage on the strength of mesoscopic scale and non-linear behavior) using a combination of mathematical model and MATLAB for material failure test cases and ZeBuLoN for finite element simulations of open-hole and unnotched specimens subjected to bending load [1].

2.5. Data-Driven Models

A set of black box models that are built on historical data and input sensor data and learn directly from machinery or structural data collected via sensors is the concept of data-driven models [76]. In the context of prognosis, data-driven methods are usually used to predict the failure of a system with the help of sensor data or a combination of sensors and life usage data [86]. Data-driven methods aim to model non-linearities in system behavior, the aging process, and condition monitoring data without requiring physical models [75]. Literature showed that data-driven approaches using MLT and statistical techniques were devised in failure prediction. Data-driven models can be further grouped into single models and combined models based on the number of types of algorithms used [74]. Single models such as conventional exponential smoothing and moving average, statistical regression, autoregression, K-nearest neighbors (KNN), decision trees, support vector machines (SVM), ANN, genetic algorithm (GA), genetic programming (GP), and fuzzy models use a single algorithm for a straight forward predicting process. While combined models, such as ensemble models, and improved frameworks build a framework that manages the strengths and weaknesses of techniques [74]. Data-driven approaches utilize monitored operational data related to system health [70]. For instance, data-driven prognostic and diagnostic models were used for lithium-ion battery health estimation and lifetime prediction, determining how soon the battery performance will become unsatisfactory [87]. These methods can be deployed quickly and cheaply providing wide coverage of system behavior [70]. One should, however, be aware of the limitations of these techniques, which cannot be guaranteed to function properly in situations not included in the database used for training. Unlike physics-based failure models, data-driven approaches attempt to derive models directly from condition monitored (CM) and event data and are grouped into machine learning and statistical approaches. MLTs, both supervised and unsupervised, capture complex relationships between input and output data and learn from them, which can be difficult to describe using physics (**Figure 6**) [88–90].

Supervised MLTs use observational evidence for model construction, whereas unsupervised MLTs do not require any output labels. In both types, various machine learning algorithms (MLAs) are used for regression, classification, or density estimation (clustering). One of the criticisms of the data-driven models is that they require a lot of failure data than the physics-based approaches and it may not be feasible to obtain such data in large quantities [88].

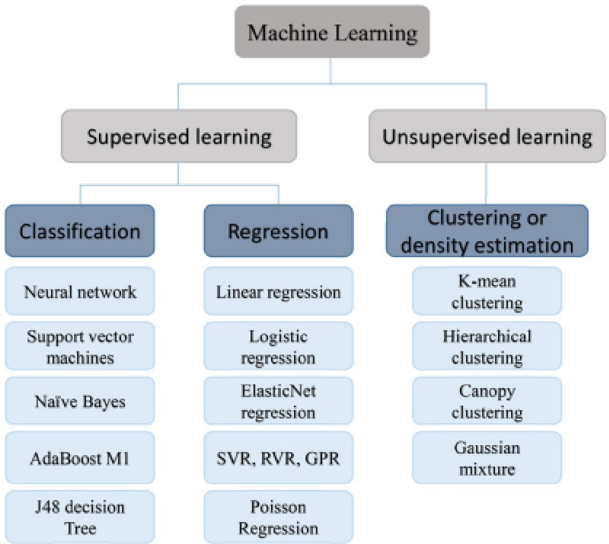


Figure 6. Different types of machine learning algorithms.

Statistical data-driven approaches (SDDAs) rely on the history of data and statistical models. SDDAs can be grouped into models that do and do not rely on directly observed state information of an asset, based on model dependence on state information. They rely on the availability and nature of data. These include both subjective and objective data such as vibration, oil analysis, temperature, moisture, pressure, humidity, loading, speed and environmental data depending on the nature or method of data collection. SVM, ANN, decision trees and other statistical algorithms are the most commonly used supervised MLAs for model training [73]. Statistical approaches are classified into direct and indirect CM data (**Figure 7**) [89]. Some examples of indirect CM data-based statistical approaches are the hidden Markov model (HMM) and hidden semi-Markov model (HSMM) [89].

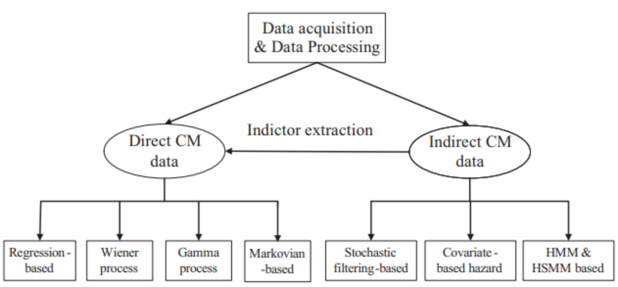


Figure 7. Classification of statistical approaches based on direct and indirect CM data.

The arrow in **Figure 7** indicates that the state of the system can be extracted from indirect CM data using direct CM data-based statistical approaches. Other statistical algorithms include KNN, case-based reasoning (CBR), multivariate adaptive regression spline (MARS), exponential regression, polynomial regression (poly), Bayesian regression, autoregressive integrated moving average (ARIMA), autoregressive (AR), ordinary list square regression (OLS), general linear regression (GLR) and multiple linear regression (MLR).

2.6. Hybrid Models

A hybrid approach is a combination of physics-based and data-driven models that leverages both approaches to achieve finely tuned prediction models with improved quality in managing uncertainty, resulting in more accurate predictions [91]. They integrate physics and data-driven models (**Figure 8**) to detect anomalous behavior or intermittent faults, potential causes of system failure, precursors to failure for effective maintenance planning and the extent and nature of faults for effective maintenance strategies [91]. Physics-based approaches can identify precursors to failure that indicate early announcement and prediction of system failure. Once the failure is defined, as shown in **Figure 8**, time series techniques can be utilized to predict the critical parameter values over time. The first step in the hybrid approach is to determine parameters to monitor, using physics-based models to aid in the analysis of failure modes, mechanisms, and effects [66]. As a second step, monitoring the characteristics of parameters of a product during all stages of its life cycle is performed to understand the health status of the product. In the third step, anomalies can be detected by extracting features of training data and then creating a health baseline with a comparison of monitored data. When anomalies are detected, monitoring commences and proceeds to further steps to predict remaining useful life, showing that the current status of the equipment differs from the healthy baseline. Then, parameter isolation can be carried out using various techniques to identify the parameters that contribute to the abnormal status of the equipment. In the next step, the failure definition can be carried out based on the identification of potential failure mechanisms. A failure definition can be created from physics-based models, historical databases, equipment specifications, or related standards for each potential failure mechanism.

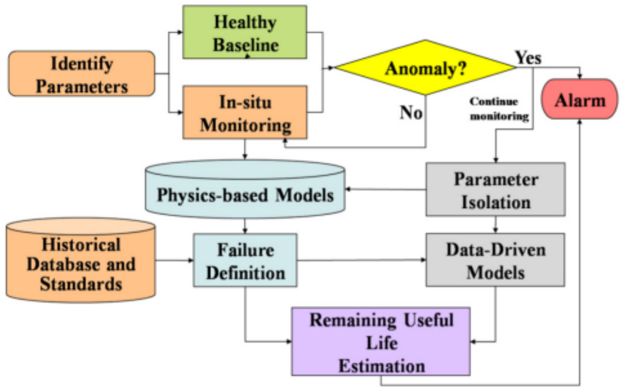


Figure 8. Schematics of Hybrid approach.

The other step is parameter trending, a process of predicting the behavior of parameters in the future based on current and historical trends. For instance, accumulated damage of the actual monitored equipment should be trended if failure is defined by the accumulated damage of an equipment which is a function of an isolated parameter.

In the last step, the time when the trended parameters meet the failure definition is the predicted failure time. The predicted failure times differ because various failure mechanisms have distinct failure definitions and trending parameters. The failure mechanism with the shortest predicted failure time determines the remaining useful life. If not detected, the feature extraction and baseline creation process stage takes over.

There are series or parallel-type hybrid approaches. In a series approach, physics-based and data-driven models are combined to predict process parameters that are uncertain using failure data from the field. However, historical field data raises the issue of inaccuracy, and in situ data is preferable these days [91]. These methods update the tunable parameter when new data is collected, and the core idea behind them is that prediction is not necessarily a direct outcome of tuned parameters, but can be tuned using the crack lengths observed from a borescope inspection.

In the parallel approach, physics-based models can be combined with data from other sources, and MLAs can be trained to predict the errors in prediction that the physics model does not explain. However, integration of model-based methods such as Paris law and data-driven methods such as particle filtering algorithm (PFA) or sequential Monte Carlo technique (MCT) has wider popularity since PFA has a consistent theoretical foundation to handle model non-linearities or non-Gaussian observation noise [92].

Liu et al. used a hybrid approach of Paris law and PFA to predict the residual gear fatigue life (RGFL) incorporating fracture mechanics and prior crack growth information (PCGI) [93]. PFA, effective for non-linear and non-Gaussian systems, employs MCT simulations and Bayesian estimation to predict the posterior probability density function (PDF) [93]. Five implementation steps were proposed by Liu et al. (**Figure 9**), to integrate Paris law and PFA [93].

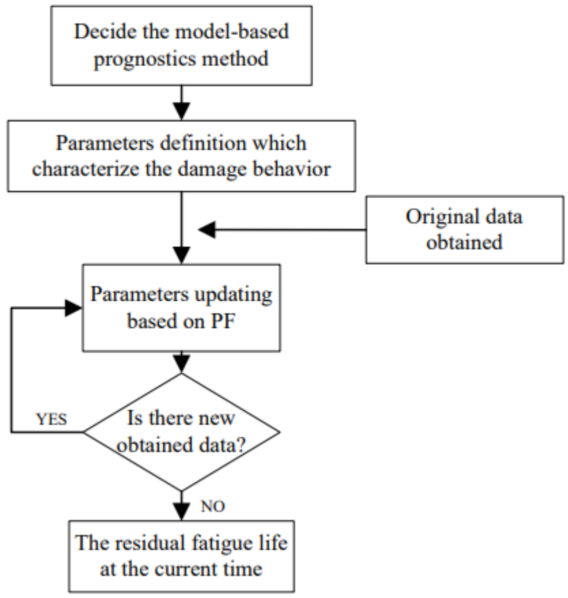


Figure 9. Implementation steps of the hybrid approach using PL and PFA.

By combining the strengths of physics-based and data-driven models [94] while mitigating their individual limitations [66], the hybrid approach improves prediction performance [93]. Balancing physics-based and data-driven components of this approach might lead to challenges in achieving optimal performance. Although hybrid approaches lead to more accurate predictions, the trade-off between the hybrid approach and the effectiveness of the model lies in detailed knowledge of physical processes in the system and choosing the appropriate data-driven techniques for prognosis and diagnosis [94].

2.7. Online Prognostics

Online prognostics, based on runtime monitoring, were used to predict the fault of the aircraft engine bleed valve [86].

Baptista et al. found that SVM outperforms the life usage models on standard deviation, median error, median absolute error and percentage error [86]. Comparing traditional reliability prediction methods (Weibull) with machine learning methods (ANN, SVM, and soft computing methods) yielded the best results in 19 industrial cases [95]. Online prognostic framework (**Figure 10**), using PFA predicted composite laminates fatigue life by varying the PL parameters distribution between the current measurement data and zero [75].

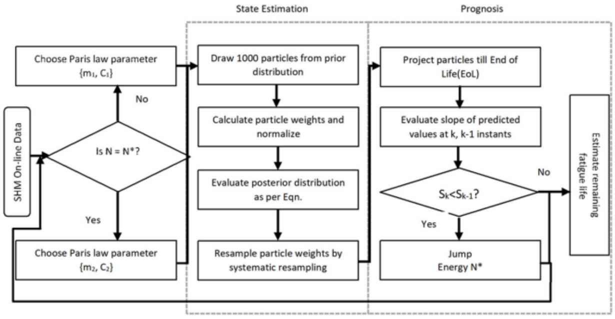


Figure 10. Online prognostic framework using PFA.

3. Implications of Existing Studies

Kazemian et al. predicted damage in non-crimp fabric composites subjected to transverse UD crushing using MAT54 and MAT58 constitutive material models, based on both experimental and numerical analyses [96]. The model's accuracy was verified using numerical simulations in predicting interlaminar damage, delamination and force-displacement response. The implication of this study is that the proposed constitutive models are a reliable simulation approach for predicting damage in non-crimp fabric composites in the areas of aerospace, automotive, and wind energy. However, the multiaxial nature of loads acting in real-life problems means that this study is limited to uniaxial crash loading.

Naderpour et al. employed ANN, GMDH, and GEP soft computing methods to predict the compressive strength of FRP-concrete composite confined columns [69]. This study implies that the proposed soft computing methods, especially ANN, accurately predict the compressive strength of FRP-confined column concrete composite, offering a reliable alternative to traditional empirical methods. However, the proposed methods rely on a limited dataset of 95 experiments, which may not fully capture the variability in real-world conditions, and require further validation with large datasets.

Holmes et al. employed Gaussian process regression MLT to predict loads on landing gear components using flight test and drop test datasets, including measurement of strains, accelerations, shock absorber travel, tyre closure, shock absorber pressure, and wheel speed [97]. This study suggests that, without the need for additional instrumentation on the aircraft, the developed model was able to predict loads on the landing gear component, leading to a more accurate fatigue design criterion, the identification of overloads, and the certification of the landing gear based on actual service life experience. However, further validation with larger datasets and different aircraft configurations is needed to ensure the robustness of the models and measurement data, which may limit the applicability of the model to other landing gear systems.

Hart-Smith et al. employed maximum-strain failure models to predict the failure of fiber/polymer composites [98]. However, their study relies on empirical data requiring further validation with experimental results.

Getahun et al. predicted the tensile and compressive strength of concrete using rice husk ash and Portland cement aggregates, employing an ANN, which implies that the developed model can be applied in sustainable construction materials, streamlining the design process and improving the efficiency of concrete production [99]. However, the study relied on a limited dataset, which may not fully capture the variability in real-world conditions. Furthermore, a large dataset verification with various concrete compositions is necessary to ensure the robustness of the developed model.

Rahimi et al. predicted the failure behavior of composite laminates under uniaxial loading using both ANSYS and a user-developed Fortran-90 FE program using Maximum stress and Tsai-Wu Failure Criteria [100]. However, even if the developed FEM saves cost and ease of modification and manipulation, the model was dependent on a specific failure criterion.

Seon et al. predicted delamination due to non-linear interlaminar shear stress-strain employing non-linear FEM and DIC for short-beam shear tests [101]. This study implies that the proposed model can be used in industries where thick composite materials are practiced, as the non-linear model accurately predicts failure, capturing delamination onset, compared to linear models. However, the model was limited to a specific material configuration.

Cuntze et al. investigated the theoretical failure prediction of UD composite lamina focusing on non-linear progressive failure of 3D stressed laminates until final failure using Puck's and Cuntze's failure theories [102]. However, their study relied on empirical data and requires validation.

Peng et al. introduced impregnated fiber bundle (IFB) elements based on a novel shear-lag model (SLM) to predict the tensile behavior of UD FRPCs, enabling full-field failure simulation that considers the effects of varied constituent properties, hybrid fibers, and initial defects [103]. The study demonstrated that stable IFB strength, higher matrix shear strength, a moderate hybrid ratio and careful packing of fibers achieve optimal composite properties using 6 mm FRP tendons and extending it to different cases. However, although the study uses novel IFB elements that improve computational efficiency, it excludes interfacial sliding in the model.

Khan et al. predicted the residual strength of clay by exploring functional networks and comparing it with ANN and SVM using statistical parameters such as root mean square, maximum average error, absolute average error, correlation coefficient, and Nash-Sutcliffe efficiency coefficient [104]. However, the proposed models require validation with larger datasets.

Alessio et al. developed FEM to evaluate the mechanical performance and failure behavior of aluminum alloy 2024-T3 and CFR-polyphenylene sulfide incorporating cohesive surface behavior to simulate the interface between aluminum and composite with specific traction-separation laws for different bonding zones [105]. The study demonstrated that longer overlap lengths redistribute stress more uniformly, delaying damage evolution in the bonding zones. However, it requires validation with different configurations and stress states.

Ghalehbandi et al. predicted damage and failure of hot work tool steel regarding the thermomechanical fatigue behavior using FEM [106]. In this study, failure was predicted employing a local ductile damage initiation and evolution model based on the hysteresis stress-strain energy concept combined with element removal. It also predicts fatigue crack initiation and growth by simulating thermomechanical fatigue behavior in a hot forging die. However, the study relies on a specific material property.

Aranda et al. investigated different damage mechanisms including translaminar cracking, delamination, and fragmentation in hybrid composites of UD thin layer reinforced with long carbon fibers embedded between two UD layers reinforced with glass fibers under tension using the Coupled Criterion of Finite Fracture Mechanics [107]. The implication of this study is that the proposed method helps to optimize the mechanical properties of hybrid composites and enhance their damage tolerance in areas of aerospace and automotive sector. However, the study was limited to a specific composite configuration.

Zhang et al. predicted failure for magnesium alloy sheet forming using an advanced fully coupled continuum damage mechanics model and implementing it into FE code ABAQUS/Explicit addressing tension-compression asymmetry in yielding and hardening, stress state dependence in damage evolution, and temperature and strain rate effects for metal forming processes at elevated temperatures [108]. However, their study was limited to specific material configurations and may not be applicable to real-world problems.

Yang et al. predicted the stress-strain behavior of binary composites using CNN and principal component analysis [109]. However, the model's robustness is dependent on the amount of data used.

Cheng et al. effectively predicted delamination behavior by measuring moisture parameters of adhesive SY-14M-III and composite T800/AC531, conducting double cantilever beam and end-notched flexure tests in different environments with an established damage model using cohesive zone models [110]. However, the model needs to be tested for new material configurations.

Sun et al. predicted the failure of ductile adhesive of CFRP laminates using FEM and experimental tests [111]. The study compared the user-defined cohesive zone model and the triangular cohesive zone model and examined the influence of adhesive properties. However, the study excludes interfacial debonding.

Deng et al. predicted rock fracture using a novel infrared thermography technique combined with heat diffusion theory, addressing the current limitation of current infrared monitoring techniques, which often capture environmental noise and produce unclear images [112].

Zhang et al. predicted the fault of industrial equipment using a novel back propagation neural network and a dynamic cuckoo search algorithm [113]. This study implies that the proposed method can be applied efficiently in industries. However, it relied on a specific dataset.

Ahn et al. predicted welding-induced residual stresses and distortions employing sequentially coupled thermo-metallurgical-mechanical solutions on 2 mm-thick Ti-6Al-4V sheets welded using a fiber laser [114]. However, the study was dependent on specific material configurations and parameters.

Tura et al. predicted tensile strength by examining process parameters such as raster angle, printing orientation, airgap, raster width and layer height using ANN and adaptive neuro-fuzzy techniques [115]. However, the study relied on a specific amount of data. Kayiran et al. explored stress predictions using Chebyshev Pseudo-spectral method [116].

In general, several factors affect the accuracy of the model to predict mechanical behavior. For instance, material anisotropy, non-locality and van der Waals interactions are the major challenges in modeling carbon nanotubes using continuum mechanics [117]. In addition, most of the studies consider the mechanical behavior with regard to a specific function of a material. However, materials can respond to various stimuli, enabling them to perform multiple functions simultaneously [118]. The implication of most studies is that prediction accuracy is higher; for instance, Zhou et al. obtained 99.4% accuracy, suggesting that these models can be applied in maintenance practices, although a limited dataset was used for training [119].

4. Discussion

PM is transforming traditional maintenance by utilizing techniques like intelligent sensors for real-time monitoring and prediction [3]. Laurin et al. improved the WWFE-II failure prediction model using a physics-based multiscale hybrid damage and failure approach, addressing micro-matrix cracking and inter-ply damage [1]. However, accuracy issues and data dependency limited its effectiveness, requiring precise definitions for accurate predictions. Despite advancements, these studies face limitations, such as accuracy issues due to assumptions in mathematical models and difficulty applying concepts to complex systems and multiple failure modes. A physics-based model combining short beam shear test and DIC with ABAQUS FE-based failure models was used to study delamination prediction in IM7/8552 carbon epoxy laminates [120]. The study correlated failure model predictions with the test data, focusing on locating rather than predicting damage. The results leaned more towards cracking than delamination. The potential of ANN and neuro-fuzzy system (NFS) in predicting pipe failure rates using pipe diameter, age, length, pressure and depth was investigated in a water distribution network of a city in Iran [121]. In this study, a more realistic and accurate prediction was obtained by ANN when compared with multivariate regression and NFS. Comparison was carried out utilizing probabilistic neural network (PNN) and speed up robust features (SURF) and CNN and prediction accuracy was higher than 99% [122]. Although the proposed diagnostic study is a good indication that it can be extended to prognostic analysis, it has a limitation in that it requires GPU hardware (necessitating higher computational cost) to reduce training time, and it cannot predict when input data out of the training domain encounters the sensors.

In general, most predictive models emphasize predicting mechanical properties while others emphasize predicting structural and equipment failures. Most of the multi-physics models, such as shear lag, analytical, fiber bundle models, and their generalizations, fracture mechanics-based models, and numerical micro-mechanical models, predict mechanical properties. In contrast, a combination of experimental and machine learning models predicts structural and mechanical failure such as buckling, fatigue, fracture, wear and creep. Studies show that both mechanical properties and failure modes of polymer composites can be predicted using analytical models and numerical simulations over a wide range of length and time scales. For a known load, estimating mechanical properties can be used to infer mechanical performance. That means, for a known load, developing an accurate mechanical property prediction model is indirectly related to the likelihood of mechanical failure. There is a discussion of the relationships between cracking and stress states that lead to cracking, as well as the potential for using measurements of internal crack growth to quantitatively link bulk material properties such as fracture toughness or damage variables with cracking which could potentially provide a physical basis for a scalar damage variable [123]. However, quantitative relationships between crack parameters and bulk material parameters remain elusive. In addition, a model designed to predict a specific mechanical property or failure has a limitation in being used for another property or failure. There is no accurate predictive model used for universal mechanical properties. Although more emphasis was given to physics-based, data-driven, and hybrid models, an attempt was made to address both deterministic and probabilistic failure modeling, which fall under the three major categories. The probabilistic approaches such as the Weibul distribution, Monte-Carlo simulation, and Bayesian PDF provide a more comprehensive understanding of material behaviour under varying conditions and inherent uncertainties in loading and materials, making them suitable for aerospace structural design [92, 93, 95, 124, 125]; however, they require large data or variability of engineering judgement and provide minimal system condition insights.

4.1. Research Gaps

The implication of existing studies highlights that there is a need for more comprehensive models, larger datasets, and broader validation to address real-world complexities. Dependence on empirical data, material-specific models, dataset restrictions, and loading conditions are the general limitations of recent research studies. In general, **Table 1** presents the contributions and limitations of existing studies in areas related to the mechanical properties and structural failure of pseudo-ductile hybrid composites [69, 94, 96–98, 100–116].

Table 1. Some of the contributions and limitations of existing studies.

Authors	Key Contributions	Gaps/Limitations
Kazemian et al. [96]	Reliable damage prediction in non-crimp fabric composites using MAT58 and MAT54	Limited to uniaxial crash loading; lacks consideration of multiaxial load
Naderpour et al. [69]	Accurate compressive strength predictions using ANN, GEP and GMDH	Accuracy issues are a concern since the study relies on a limited dataset
Holmes et al. [97]	Gaussian process regression for landing gear load prediction	Requires validation with larger datasets and different aircraft configurations
Hart-Smith et al. [98]	Maximum strain failure models for FRPCs	Relies on empirical data; experimental validation required
Getahun et al. [94]	ANN for predicting tensile-compressive strength of concrete with rice husk ash	Accuracy concern due to limited dataset; requires validation
Rahimi et al. [100]	Failure prediction using ANSYS and Fortran-90 FE program	Dependent on specific failure criteria; lacks generalizability
Seon et al. [101]	Non-linear FEM for delamination prediction in thick composites	Limited to a specific material configuration
Cuntze et al. [102]	Theoretical failure prediction using Puck's and Cuntze's failure models	Relies on empirical data; experimental validation required
Peng et al. [103]	Novel shear-lag model (SLM) for tensile behavior prediction	Excludes interfacial sliding; limited applicability
Khan et al. [104]	Residual strength prediction using ANN, SVM and functional networks	Accuracy concerns due to limited datasets
Alessio et al. [105]	Aluminum-CFRP interface performance evaluation	Requires validation with different configurations and stress states
Ghalehbandi et al. [106]	FEM for thermo-mechanical fatigue behavior prediction for steel	Limited to specific material properties
Aranda et al. [107]	Damage mechanism investigation in hybrid composites using finite fracture mechanics	Limited to specific composite configurations
Zhang et al. [108]	Advanced damage mechanics model for magnesium alloy sheet forming	Limited to specific material configurations
Yang et al. [109]	Stress-strain behavior prediction using CNN and principal component analysis	Model robustness depends on dataset size
Cheng et al. [110]	Delamination behavior prediction using cohesive zone models	Needs testing for new material configurations
Sun et al. [111]	FEM for ductile adhesive failure prediction in FRPC laminates	Excludes interfacial debonding
Deng et al. [112]	Novel infrared thermography for rock fracture prediction	The current technique is affected by noise
Zhang et al. [113]	Fault prediction using neural networks and dynamic cuckoo search	Relies on a specific dataset
Ahn et al. [114]	Residual stress and distortion prediction in Ti-6Al-4V welding	Dependent on specific material configurations and parameters
Tura et al. [115]	Tensile strength prediction using ANN and neuro-fuzzy techniques	Relies on a specific dataset
Kayiran et al. [116]	Stress prediction using Chebyshev pseudo-spectral method	Lacks broader applicability due to limited scope

4.2. Challenges

Several challenges face existing studies in the area of model-based mechanical property and structural failure prediction of pseudo-ductile hybrid composites. Physics-based models require individual models for each failure mode and struggle to capture poorly understood phenomena. Although physics-based models are detailed, they are computationally expensive and time-consuming [78]. Overestimations and errors usually occur when researchers try to reduce computational costs. Cohesive zone models and VCCT face issues such as computational divergence, unstable delamination propagation, and sensitivity to mesh refinement, despite being effective for simulating damage. Explicit/implicit algorithms in software like ABAQUS have been used to address these limitations to some extent [84]. Hashin's stiffness reduction method and Lemaitre model have been expanded as a damage modeling technique but remain constrained in scope [83]. Commonly used analytical approaches, such as shear lag, variational, and stress transfer methods, and FEM-based methods, such as RVE and PUC, are limited to specific conditions, including uniaxial tensile loading and cross-ply laminates [79]. MLAs and other data-driven models offer a potential alternative but require extensive failure data. Material anisotropy, non-locality, and interfacial bonds (ssuch as Van der Waals forces) are some of the challenges that complicate the accuracy of data-driven models [117].

4.3. Future Perspectives

Despite the challenges mentioned, some studies, such as the work of Zhou et al., have achieved high prediction accuracy, suggesting practical applicability [119]. However, further advancements in physics-based models, data-driven models and hybrid models are expected from researchers and industrialists to improve computational efficiency, accuracy and applicability across diverse material behaviors and loading scenarios. By combining the strengths of physics-based models and data-driven models, the hybrid approach addresses uncertainties in material behavior and operational conditions, focusing on improving SHM, enhancing prediction accuracy, reducing computer run time, and minimizing aerospace catastrophic failures.

5. Conclusions

Researchers have developed models to predict mechanical properties and failure, enhancing PM. Recent trends focus on improving predictive models, each with its merits and limitations: (1) Most predictive models have limited to the specific type of fiber reinforced polymer composites and face accuracy issues due to dependency on input parameters and boundary conditions; (2) The models do not correlate damage progression with changes in mechanical properties over time or under different environmental conditions, impacting durability and performance; (3) Studies have not confirmed whether certified polymer-based composite components for load bearing structures exist in commercial aircraft, rather than just generalizing the trend of using these composites for fuel efficiency. (4) Additionally, a model designed to predict a specific mechanical property or failure has limitations in being applied to another property or failure. There is no accurate predictive model used for universal mechanical properties. Therefore, this review highlights future research directions and challenges, indicating the implications of existing studies, and offers insights beneficial to both the research and industrial communities.

Author Contributions

Conceptualization, G.A.D.; methodology, G.A.D.; validation, E.G.K., Y.R.; formal analysis, G.A.D.; investigation, G.A.D.; resources, G.A.D.; data curation, G.A.D.; writing—original draft preparation, G.A.D.; writing—review and editing, E.G.K., Y.R.; supervision, E.G.K., Y.R.; project administration, E.G.K., Y.R.; funding acquisition, G.A.D. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The authors declare that data will be available on a request.

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Conflict of Interest

The authors declare that they have no personal relationships or competing financial interests that could affect the publication of this review.

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