Applications of Artificial Intelligence/Machine Learning to High-Performance Composites

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Abstract

With the booming prosperity of artificial intelligence (AI) technology, it triggers a paradigm shift in engineering fields including material science. The integration of AI and machine learning (ML) techniques in material science brings significant advancements in understanding and characterizing underlying physics. Due to the overall outstanding properties compared to conventional metallic materials, high-performance fiber reinforced polymer (FRP) composites have attracted great interest. This article aims to provide a comprehensive review of the state-of-the-art works of applying AI/ML methods in high-performance FRP composites, focusing on four critical stages throughout the product life cycle, i.e., design, manufacturing, testing, and monitoring. This present study covers the tasks of material development and selection, process modeling and optimization, material property prediction, and damage diagnosis and prognosis in the four stages, which are conducted with the aid of advanced AI/ML algorithms. An outlook for the incorporation of modern advanced AI/ML models into FRP composite research is provided by the identification of current challenges and potential future research directions.

Keywords: Artificial intelligence; Machine learning; High-performance composites

1. Introduction

Recent advances in material science and engineering with the aid of modern computational algorithms and devices [1] have greatly pushed the need of advanced materials that can be adopted to increasingly complex engineering applications and adapted to multiple functional and safety requirements. Among various types of advanced materials such as crystal, metal alloy, etc., composite material, made up of at least two constituents into a heterogeneous mix [2], is one of the most promising structures. Upon an appropriate combination, the overall material performance will be enhanced, and characteristics of the constituents will be kept simultaneously. Moreover, tailoring material properties can be achieved by adjusting the proportion, composition, structure and manufacturing accordingly [3-5]. Specifically, high-performance composites, which here refer to fiber reinforced polymers (FRPs) usually with carbon/glass fibers (CFRPs/GFRPs) and their joints, stand out due to their extraordinary properties such as higher strength, lighter weight, greater resistance to corrosion compared to conventional metallic materials, with a wide range of structural applications in aerospace [6-9], automobile [10, 11], marine [12, 13], renewable energy [14, 15], and infrastructure industries [16]. For example, in the aircraft design, high-performance FRP composites provide an improvement in fuel-efficiency and emission reduction. In addition to functional benefits such as higher allowable hoop stress and corrosion resistances, a composite fuselage would allow more comfortable levels of cabin pressure and humidity which can effectively improve passenger comfort in modern commercial aircrafts such as Boeing 787 [17], as shown in Fig. 1. Besides, there are many aerospace components made of FRP composites even the primary structures are metallic [18].

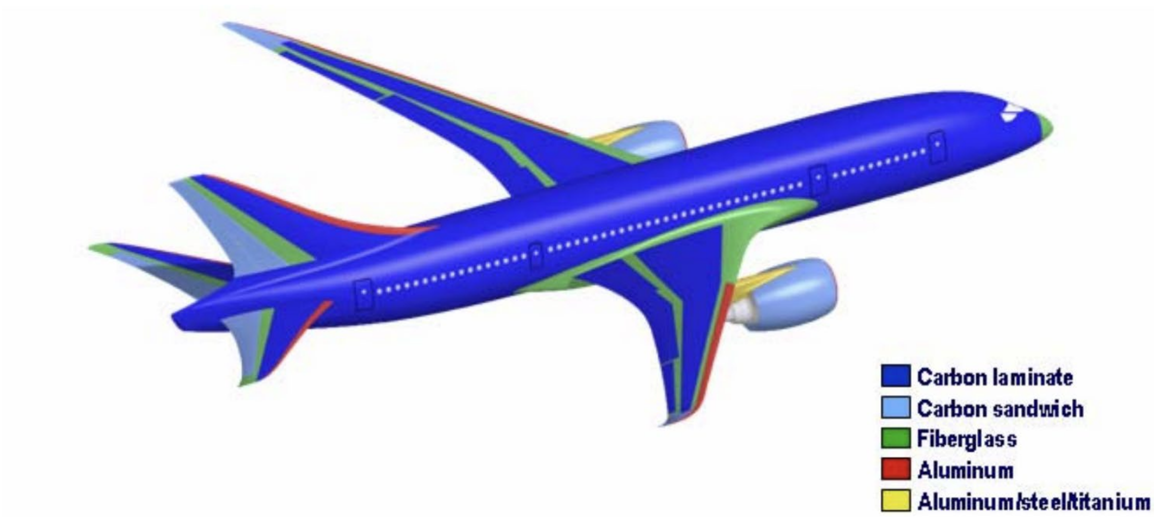

Fig. 1. Material usage in Boeing 787 where nearly 50% of components are composites [17].

The whole product life cycle of high-performance FRP composite structures is shown in Fig. 2, including five main stages: designing, manufacturing (i.e., part generation, machining and post treatment, and joining including curing), testing, monitoring, and recycling. Despite of the outstanding advantages of material properties in various aspects, the complex multi-stage manufacturing process (MMP) and the intricate material structure that leads to material nonlinearity and anisotropy make it a challenging task to understand the material dynamics and physics and characterize material behaviors [19]. Physics-based methods have long been developed to analyze and understand the FRP composite materials in each stage of the MMP, including both analytical models [20-23] and numerical simulations [24-31]. As analytical models easily suffer from over-simplified assumptions, numerical simulations can achieve a reasonable accuracy but often at the cost of computational resources.

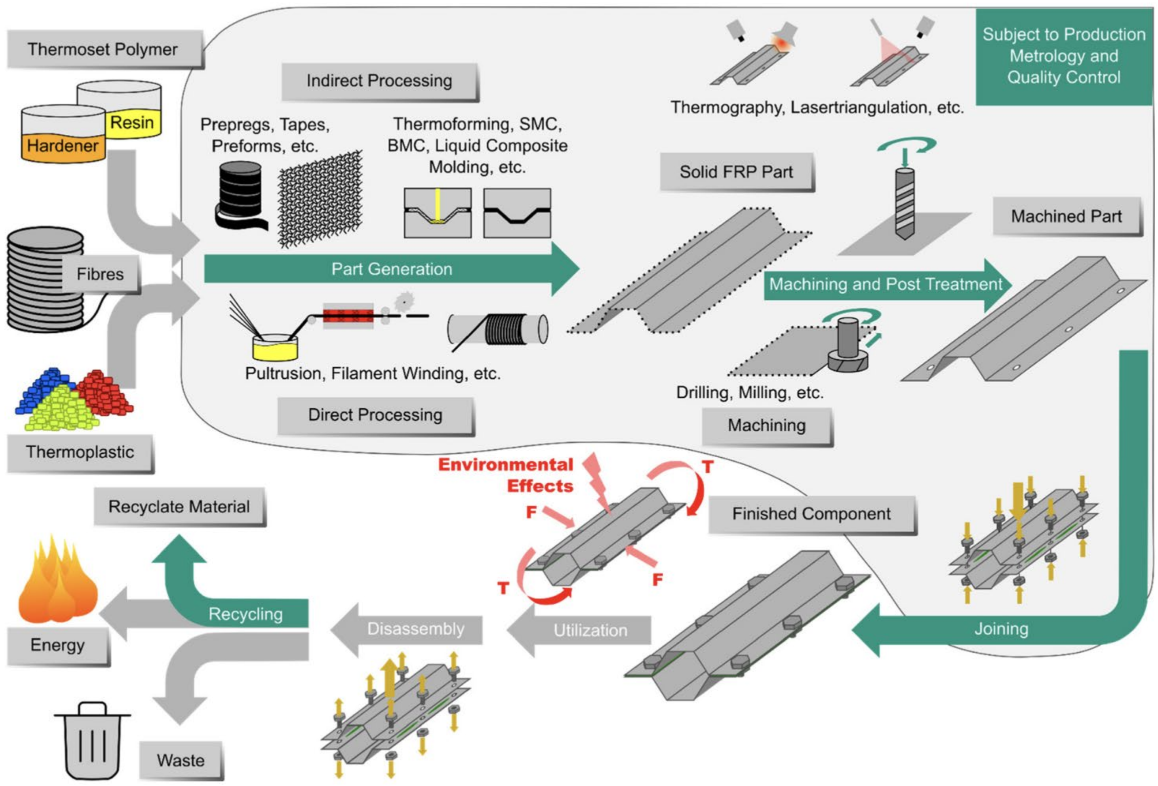

Fig. 2. Product life cycle of FRP composite parts [32].

However, as there is abundant, even excessive, data produced and collected by the rapidly developing sensing technology in all life cycle activities, it has opened the door for artificial intelligence (AI), especially the machine learning (ML) technique due to the powerful data-processing capability. Numerous efforts have been made in applying AI/ML methods to the field of high-performance FRP composites, attempting to take the advantage of data-driven methods to address engineering problems. Existing studies on FRP composite structures with AI/ML techniques have mainly focused on surrogate modeling of finite element methods (FEMs) [33-35], physical process modeling [36-38], regression for property prediction [39-42], and signal/image-based classification [43-45]. Specifically, for instance, in the aerospace application of composite fuselage assembly, sparse learning models [46, 47] were proposed for the optimal placement of actuators and shape adjustment to reduce the maximum gap between two fuselages, significantly improving efficiency compared to traditional manual practice. Zhong et al. [48] further developed a finite element analysis (FEA) model-based automatic optimal shape control (AOSC) framework with model uncertainties addressed by cautious control.

Compared to traditional modeling methods of engineering problems such as analytical derivation and numerical simulations, AI/ML techniques generally require much less domain knowledge and are expected to discover underlying representative patterns in the dataset. For an intricate engineering problem that lacks adequate physical understanding like the adhesive joining of high-performance FRP composite structures, which is currently a common practice in aircraft manufacturing and repair but not fully proved due to its complexity, AI/ML can play a pivotal role in modeling, bypassing the requirement of thorough comprehension of its physical and chemical mechanism. State-of-the-art mechanical analysis of FRP composite adhesive joining is often under a simplified assumption that materials are linear elastic and isotropic [23]. Although one can set a more complex material setting in numerical analysis, e.g., FEA, which is more consistent with reality [49, 50], an accurate result is usually at the cost of computational resources and time. On the other hand, once trained, AI/ML models take only a few seconds for prediction with a new input, which is much faster than traditional numerical simulations. Another prominent advantage of AI/ML methods over conventional ones is that data-driven algorithms have the potential to end-to-end model the whole MMP of high-performance FRP composites and adhesive joining given appropriate data pairs [39, 51]. This is significantly important for quality-critical applications because the manufacturing parameters are control inputs and of great interest. Analytical and numerical models usually cannot capture this relation due to the unknown interactions between stages of MMP. In spite of these advantages, AI/ML models suffer from data-related issues which will be discussed in Section 7.2 in detail.

However, there is still a research gap in thoroughly understanding all the life cycle activities of FRP composite structures, especially the stages of designing, manufacturing, testing, and monitoring which substantially affect the in-service performance of FRP composites. A comprehensive article is highly desired that bridges the widespread and advanced AI/ML techniques for the engineering production and applications of high-performance FRP composites. Therefore, as shown in Fig. 3, this study summarizes current state-of-the-art adoption of AI/ML methods in design, manufacturing, testing, and monitoring stages of high-performance FRP composite structures with tasks of material development and selection, process modeling and optimization, material property prediction, and damage diagnosis and prognosis, respectively.

Hereafter, the rest of this article is organized as follows: section 2 provides a brief history of the development of AI/ML methods and their general applications in engineering. Section 3 describes current utilization of AI/ML models in the material development and selection of composites with a focus on the framework of material genome initiative and inverse design.

The process modeling and optimization for the manufacturing processes including both part generation and curing processes with the aid of AI/ML techniques are reviewed in section 4. Section 5 considers the characterization of FRP composites, especially on the mechanical properties of strength and fatigue, using AI/ML algorithms. Section 6 discusses the state-of-the-art works for damage diagnosis and prognosis of composite structures that are integrated with AI/ML methods. Section 7 concludes this review and looks forward to the prospects and challenges by presenting potential future research directions.

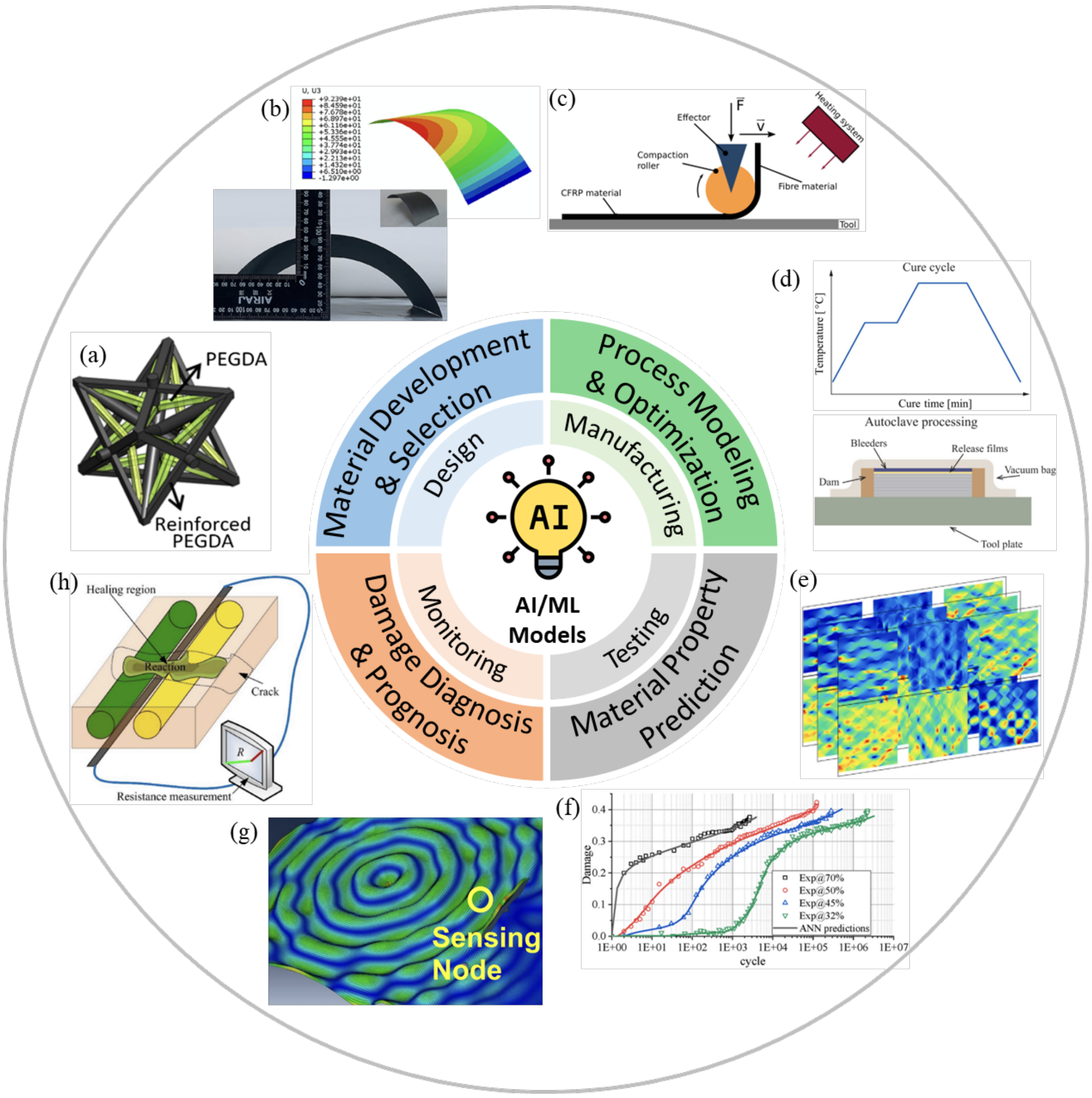

Fig. 3. AI/ML models in design, manufacturing, testing, and monitoring stages of high-performance FRP composite structures with tasks of material development and selection, process modeling and optimization, material property prediction, and damage diagnosis and prognosis, respectively, where (a) Composite structure with tunable negative thermal expansion through computational design [52]; (b) FRP composite structure with simulation result to minimize PID through inverse design [53]; (c) AFP process for FRP composite part generation [54]; (d) Autoclave curing process with cure cycle of FRP composite structure [38]; (e) Microscopic stress tensor field maps of FRP composites for prediction [55]; (f) Stiffness degradation of composite laminates under cyclic loadings predicted by ANN [56]; (g) Simulation of propagating Lamb wave with deformation magnification for NDI of FRP composites [57]; and (h) Integrated self-monitoring and self-healing design of CFRP structure for SHM [58].

2. Development of AI/ML for Engineering

Artificial intelligence (AI) is the field of computer science that studies how machines can be made to act intelligently [59], involving human-like psychological skills such as perception, association, prediction, planning, motor control, etc., with diverse information-processing capacities [60]. With a narrow definition, machine learning (ML), as a subfield of study in AI, investigates algorithms and statistical models that computer systems utilize to perform a specific task, e.g., classification, regression, clustering, etc., without being explicitly programmed [61].

The AI technology has long been developed since McCulloch and Pitts [62] proposed the MP neuron model, connecting nervous activity with computation in 1940s. Classic AI models were later extensively explored such as perceptron [63, 64], back-propagation technique [65], LeNet [66], LeNet-5 [67], support vector machine (SVM) [68, 69], k-nearest neighbor (kNN)

[70], long short-term memory (LSTM) [71], and etc., in which many of the landmark goals had been achieved.

AI, especially ML techniques, thrived when it entered the 21st century. Various concepts derived from ML, e.g., active learning [72], deep learning (DL) [73], physics-informed machine learning (PIML) [74], meta-learning [75], incremental learning [76], and etc., were proposed and developed to strengthen learning ability and deal with real engineering problems. In terms of implementation, one of the most powerful ML models is the neural network (NN). Numerous advanced artificial neural network (ANN) structures were explored including deep neural network (DNN), convolutional neural network (CNN) [66], AlexNet [77], ResNet [78], region-based CNN [79-82], recurrent neural network (RNN) [71, 83-85], generative adversarial network (GAN) [86-88], attention mechanism [89, 90], physics-informed neural network (PINN) [91], generative AI [92] for multiple tasks such as classification, pattern recognition, clustering, prediction and sequence processing.

In addition to the booming development of generic ML models, AI/ML models specifically designed for real engineering problems have also been extensively explored. Generally, the applications of AI/ML models to engineering can be divided into two parts: (1) AI/ML models help in computational modeling of complex physical systems, especially those with multi-physics interactions or unknown physics; and (2) Post-processing of experimental data can be conducted through advanced AI/ML models given their powerful data-mining capabilities.

In the domain of computational modelling, one of the most important goals is to build a simulator with a good balance between computational cost and simulation accuracy. Physics-based simulators by the first principle are usually able to achieve very high accuracy yet suffer from costing huge computational resources. While ML-based models can retain such computational advantage and dramatically reduce the required time when properly trained on related physically-simulated data [93]. ANN has been successfully used to simulate the phase change of crystal materials based on molecular dynamics [94, 95] in the microscale, and turbulent flow dynamics [96, 97] macroscopically. Another significant application of AI/ML methods is surrogate modeling to perform downstream tasks such as real-time prediction, characterization, system health monitoring and control. AI/ML models have been extensively employed for estimating mechanical properties of composite materials and adhesives [39, 51, 98], prediction of compressive strength of concrete [99], real-time anomaly detection on aircrafts [100], understanding transient physics of 2D fluid system [101, 102], and many other aspects. Recent advances in PIML have fostered massive applications to various engineering systems by incorporating known or partially known physics, which can be expressed in a set of ordinary/partial differential equations (ODEs/PDEs) into a machine learning framework. Hot topics are about fluid and thermal dynamics where PIML has great potential to emulate system dynamics for different applications, such as curing of composite systems [37, 38, 103] and weather system [104].

Post-processing of experimental data is also critical in engineering problems. AI/ML algorithms have long been utilized in biology and related fields to analyze large-scale data about molecules, proteins and genes by clustering [105-107] and using CNNs [108, 109]. In other fields such as composites [110-113], astronomy [114], cybersecurity [115], researchers are proactively exploring new applications of AI/ML methods as well.

3. AI/ML in Material Development and Selection of High-Performance Composites

The incorporation of AI/ML into material science has brought new vigor and vitality, enabling more innovation in material development and selection, including the field of high-performance composites. One breakthrough is that deep generative models such as diffusion models are applied to create novel crystal material representations at micro level by exploring latent feature spaces with the aid of fundamental physical law, e.g., quantum mechanics [116, 117]. Although such models have not been extensively employed in the field of composites, it is expected that deep generative models would advance the discovery of better FRP composite materials with appropriate adaptation. The recent applications of AI/ML methods in material genome initiative and inverse design for composites will be discussed in this section.

3.1 *AI/ML in Material Genome Initiative for High-Performance Composites*

Material Genome Initiative (MGI) is a federal multi-agency program that has been advanced to push the development of computational material science since its announcement in 2011 [118]. MGI is designed to accelerate the pace of discovery, design, deployment, and engineering of advanced materials via high-throughput experimentation (HTE) which is a technique that highly integrated with theory, experiment, and computation [119], where AI/ML models can be potentially applied for higher computational efficiency and accuracy. Along with the prosperity of AI/ML over the past decade, MGI has already enabled significant advances in material science with numerous applications. Utilizing high-throughput virtual screening (HTVS) that combines quantum chemical calculations, machine learning techniques, and cheminformatics methods, Gómez-Bombarelli et al. [120] explored over one million candidates in molecular space to identify promising novel design of organic light-emitting diodes (OLEDs). The selected candidates were experimentally demonstrated to reach state-of-the-art external quantum efficiencies.

In addition to advanced materials in the molecular level, MGI has profoundly impacted the progress in many other fields of materials, e.g., composites. Wang et al. [52] designed three-dimensional composite structures with tuneable negative thermal expansion through multi-material projection micro-stereolithography in the framework of computational design that is advanced by MGI. Liu et al. [121] reported an HTE method that was used on functional composite hydrogels to facilitate rapid high-throughput screening of composition-property relationships, enabling accelerated engineering with optimized properties for processability and performance, which was proved by application to different functional composite hydrogel systems.

Although MGI has numerous successes in expediting discovery and development of new advanced functional materials including some composites, there is still a gap in the area of high-performance composites. The HTE method combined with powerful computation ability provided by ML algorithms has a great potential to optimize the design of high-performance FRP composite materials by searching for better combinations of reinforcement and matrix materials in terms of both composition and structure.

3.2 *AI/ML in Inverse Materials Design of High-Performance Composites*

Unlike structure- and element-oriented design that are usually under some constraints, inverse design begins from a required functionality and searches for an ideal material structure [122]. Kim et al. [123] proposed a DNN-RNN-based encoder-decoder structure for the inverse design of organic molecules. The generated molecular structures achieved good agreement with the targeted triplet excitation energy of OLEDs in a later experimental validation.

Not only in design of molecular structures, but researchers also applied inverse design to composite materials, especially high-performance ones. Nomura et al. [124] used topology optimization specifically with tensor field variables on the fiber orientation to obtain beam structures with minimum compliance. Topology optimization was also employed by Jung et al. [125] to search for optimal spatially-varying fiber size and orientation in a multiscale manner in order to minimize structure compliance. AI/ML algorithms were successfully utilized in the inverse design process of high-performance composites, covering more complex physical functionalities. Luo et al. [53] integrated FEM and ANN to perform prediction and inverse design of thermosetting-matrix composites of an asymmetric laminate for a targeted maximum process-induced distortion (PID). The resultant composite of carbon fiber and epoxy agreed with the targeted maximum PID with a root mean square error (RMSE) of 8.01%. Considering random uncertainty, Song et al. [126] firstly developed Kriging surrogate models to learn the transfer functions of both laminated and 2D-woven composites and employed a genetic algorithm (GA) to solve the inverse optimization design to achieve desired mechanical properties with minimum statistical deviation. Liu et al. [40] applied optimization algorithms for inverse design based on a deep operator network (DeepONet) that is designated to bridge the gap between mechanical behaviors and design space of hierarchical composites.

Extensive research works have shown the benefit of incorporating AI/ML algorithms into conventional inverse design and engineering of composite materials. However, this innovative approach demands a great generalization ability of AI/ML methods that can find novel material structures not included in existing databases. Current works in the field of high-performance composites mainly focus on utilizing AI/ML for surrogate modeling to represent the mapping from design space to the desired functionality, and then employing a separate optimization method for inverse design. A holistic approach that integrates these two steps is anticipated to achieve better performance. To this end, generative AI models have great potential to overcome the inherent limitations of finiteness of material choices in material databases. Specifically, combining variational autoencoders (VAEs) with diffusion models can be one of the prospective ML structures, which is able to generate novel material representations in the latent space, as demonstrated in [116]. Translating this strategy into composites domain and incorporating composite-specific physics knowledge is expected to contribute remarkable advances.

4. AI/ML in Manufacturing Process Modeling and Optimization of High-Performance Composites

Manufacturing of high-performance FRP composites parts and components involves part generation process and joining process by various techniques and methods. One of the pioneering works on composite manufacturing process modeling is the utilization of PIML and PINN which integrate physics and engineering knowledge into the framework of data-driven ML modeling, e.g., for composite curing process [37, 38, 103, 127]. This section will introduce both conventional and advanced manufacturing processes of FRP composites and review the state-of-the-art applications of AI/ML methods in it.

4.1 *AI/ML in Part Generation Process Modeling and Optimization of High-Performance Composites*

The part generation process of FRP composites is the process to reinforce matrix material with fiber preforms that are usually made by weaving, knitting, braiding, and stitching of fibers in sheet structure [128]. Conventional generation processes generally include injection molding, compression molding, liquid composite molding (resin transfer molding, rotational molding, and wet pressing), fiber deposition (automated tape/fiber placement), pultrusion, thermoforming, and filament winding. With the integration of AI/ML techniques into the manufacturing processes, higher production efficiency with less defects can be achieved by process modeling, monitoring, and optimization thanks to the powerful data processing capability of AI/ML algorithms.

Image processing techniques have been actively applied into the automated fiber placement (AFP) process for layup defect detection and segmentation [54]. Zambal et al. [129] trained a CNN by images artificially generated by a probabilistic graphical model to mitigate the issue of data scarcity of some new defect types, where the trained model achieved a 95% accuracy on real laser sensor data in AFP process for defect segmentation and classification. Thermal images were employed by Schmidt et al. [45] to comprehensively evaluate CNNs with three various architectures. Sacco et al. [130] presented their Advanced Composite Structures Inspection System (ACSIS) based on ANN for automated AFP defect detection, classification, and documentation. Meister et al. [131] investigated the relevance of certain image pixels regarding the decision-making response of a CNN classifier through explainable AI methods smooth integrated gradients and deep learning important features with Shapley additive explanations (DeepSHAP) to guide monitoring strategies in AFP inspection. In order to find optimized AFP process parameters given desirable mechanical properties, Islam et al. [132] proposed a hybrid approach which combines benefits of ANN, virtual sample generation (VSG) method, and physics-based numerical simulation with real data, as shown in Fig. 4(a).

On the other hand, additive manufacturing (AM) is one of the leading and advanced technologies in composite manufacturing for its flexibility in selection of fiber volume and orientation and ability to adapt to complex geometry. Broadly speaking, FRP composites that are additively manufactured can be categorized into continuous-fiber reinforced composites (by fused filament fabrication, laminated objective manufacturing), short-fiber reinforced composites (by material extrusion processes, vat photopolymerization processes, powder bed fusion processes, binder jetting), and voxelated polymeric composites (uniquely by AM approaches such as multiple jet fusion, and direct ink writing) [133]. AI/ML techniques have significantly improved AM processes, especially in process modeling and optimization. Yanamandra et al. [134] utilized a refined RNN with LSTM architecture to identify the fiber orientation in each layer to capture the tool-path information so as to reverse engineer a FRP composite made by fused filament fabrication (FFF). With the aid of Gaussian process regression (GPR), Hu et al. [135] thoroughly analyzed mechanical properties of polylactic acid (PLA) composites with reinforcement of chopped long carbon fiber (CF) via fused deposition modeling (FDM) fabrication. Wright et al. [136] developed a novel closed-loop DL-integrated extrusion AM system to perform in-situ imaging and process parameter optimization on milled CF-reinforced polymetric composite by several CNNs to maximize material properties and quality, as shown in Fig. 4(b). The composite parts manufactured by direct ink writing (DIW) using the autonomously determined optimal parameters were inspected to be defect-free, demonstrating the effectiveness of the DL-DIW process optimization framework. A similar closed-loop robot-based AM system for real-time defect detection and parameter adjustment of CFRPs enabled by advanced CNN models, e.g., YOLOv4, was proposed by Lu et al. [137].

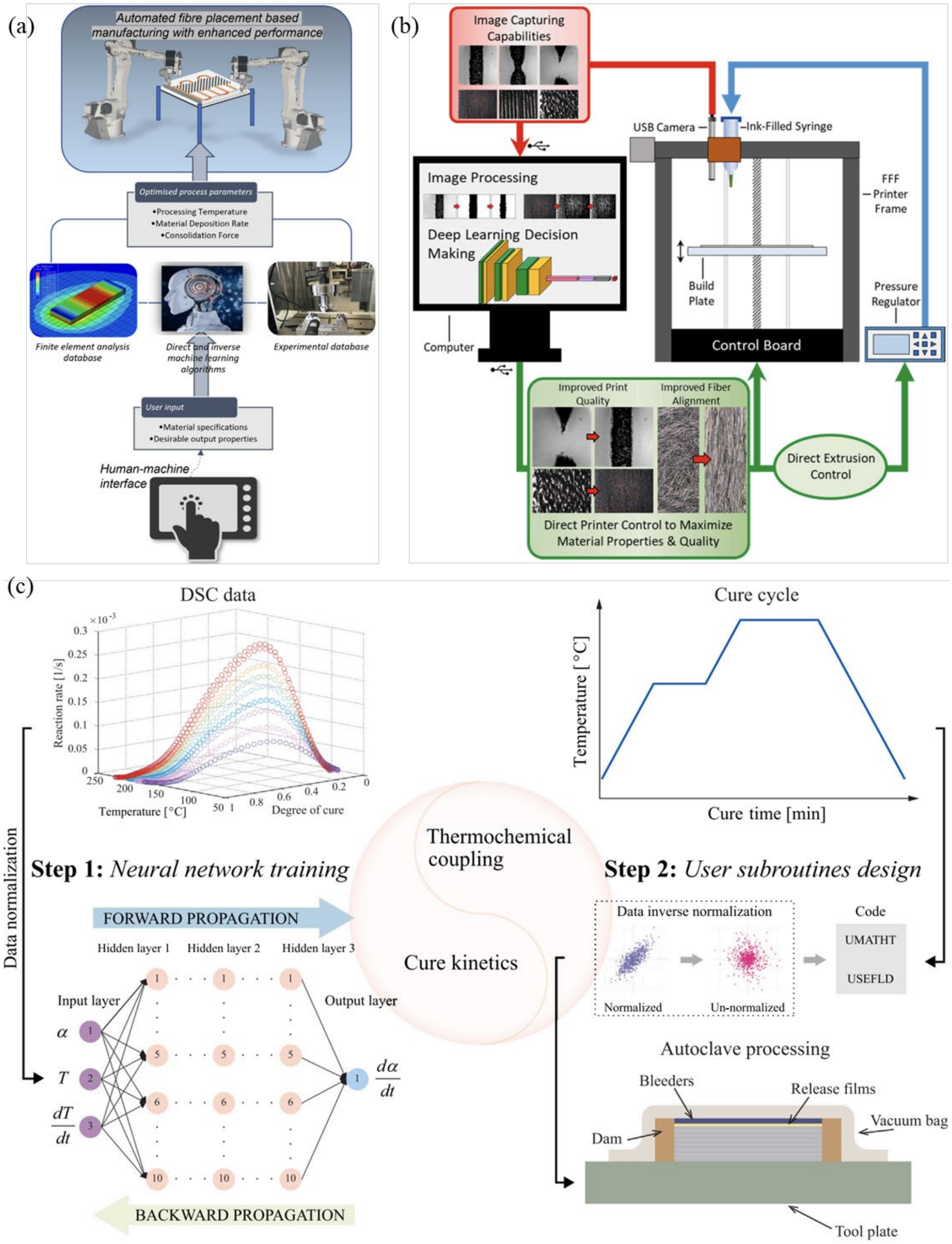

Fig. 4. (a) Process flow diagram indicating the steps from user-input to ML process optimization to AFP-based manufacturing [132]; (b) Overview of the DL-DIW framework showing how a computer, FFF printer, and USB camera are interconnected to perform in-situ parameter optimization [136]; (c) Flow chart of the cure process analysis via ANN including

cure kinetics and thermochemical coupling using non-isothermal differential scanning calorimetry (DSC) data [38].

4.2 *AI/ML in Curing Process Modeling and Optimization of High-Performance Composites*

Once the FRP parts are manufactured, joining them together is the next step to make a component. In addition to traditional joining methods, e.g., mechanical fasteners such as riveted or bolted joints, and welding, adhesive joining is getting increasingly prevalent for composite parts due to its weight reduction and avoiding material damage and stress concentrations. The necessary step to join composite parts with adhesive films or pastes is to cure them. Not only happening during part generation, but the curing process also occurs in the joining processes of polymetric composites. However, residual stress will be generated during this process due to intrinsic factors of material and extrinsic cure conditions, possibly leading to defects like crack, delamination, distortion, and degradation of mechanical performance [138]. Understanding the physics of curing process and evolution of curing-induced residual stress is thus critical to improve the quality of FRP composites. Yet the curing process and corresponding residual stress and process-induced deformation (PID) are often complex interactions between thermal-chemical, flow-compaction, and thermal-mechanical properties of the fiber and matrix materials [139], AI/ML methods play a pivotal role in such research problems, fostering the understanding of complicated physics through a data-driven point of view.

ANNs have already been used in early attempts to model the curing kinetics and predict related parameters such as retained mass [140], degree of cure (DoC) [36], and time derivative of DoC [141]. Kim and Zobeiry [142] developed an ANN to identify equivalent 1-D cases for the 2-D geometry to speed up process simulation considering both geometric and cure cycle parameters. Zobeiry and Poursartip [143] investigated three different scenarios of curing, i.e., to predict thermal lag or exotherm in a curing composite part on an either inert or metallic tool using theory-guided ML which takes physics-based features and uses a physics-based rationale to choose activation functions. Hui et al. [38] considered both cure kinetics and thermochemical coupling in building an ANN to predict the evolution of the DoC. As shown in Fig. 4(c), the predicted curing dynamics can be further used to guide the FE analysis or experiments.

With the advent of PIML and PINN, physical dynamics that are described by ODEs/PDEs can be emulated with higher efficiency and accuracy by incorporating the physics law into the loss function or ML model structure. Zobeiry and Humfeld [127] utilized a PINN to solve the conductive heat transfer PDE along with convective heat transfer PDEs as boundary conditions (BCs) of a heating composite part. Niaki et al. [37] modelled the thermochemical curing process considering exothermic heat transfer by creating two coupled PINNs for a bi-material composite-tool system. One PINN is to predict the DoC that is applicable to the composite material, while the other one is for the temperature distribution for both the tool and the composite part. Losses specially designed for boundary conditions were added to improve the performance of the PINN model. Akhare et al. [103] proposed a physics-informed neural differentiable (PiNDiff) model based on the pioneering PINN model Neural ODE to learn unknown physics from the limited indirect data and to infer unobserved variables and parameters in the application of composite curing. Based on a computational model of cure behaviour of a carbon/epoxy prepreg system proposed by Anandan et al. [22], the PiNDiff model for composite curing was structured as shown in Fig. 5(a) with a great performance on predicting curing dynamics of corner location of a square laminate when trained on temperature data collected at the center, as shown in Fig. 5(b).

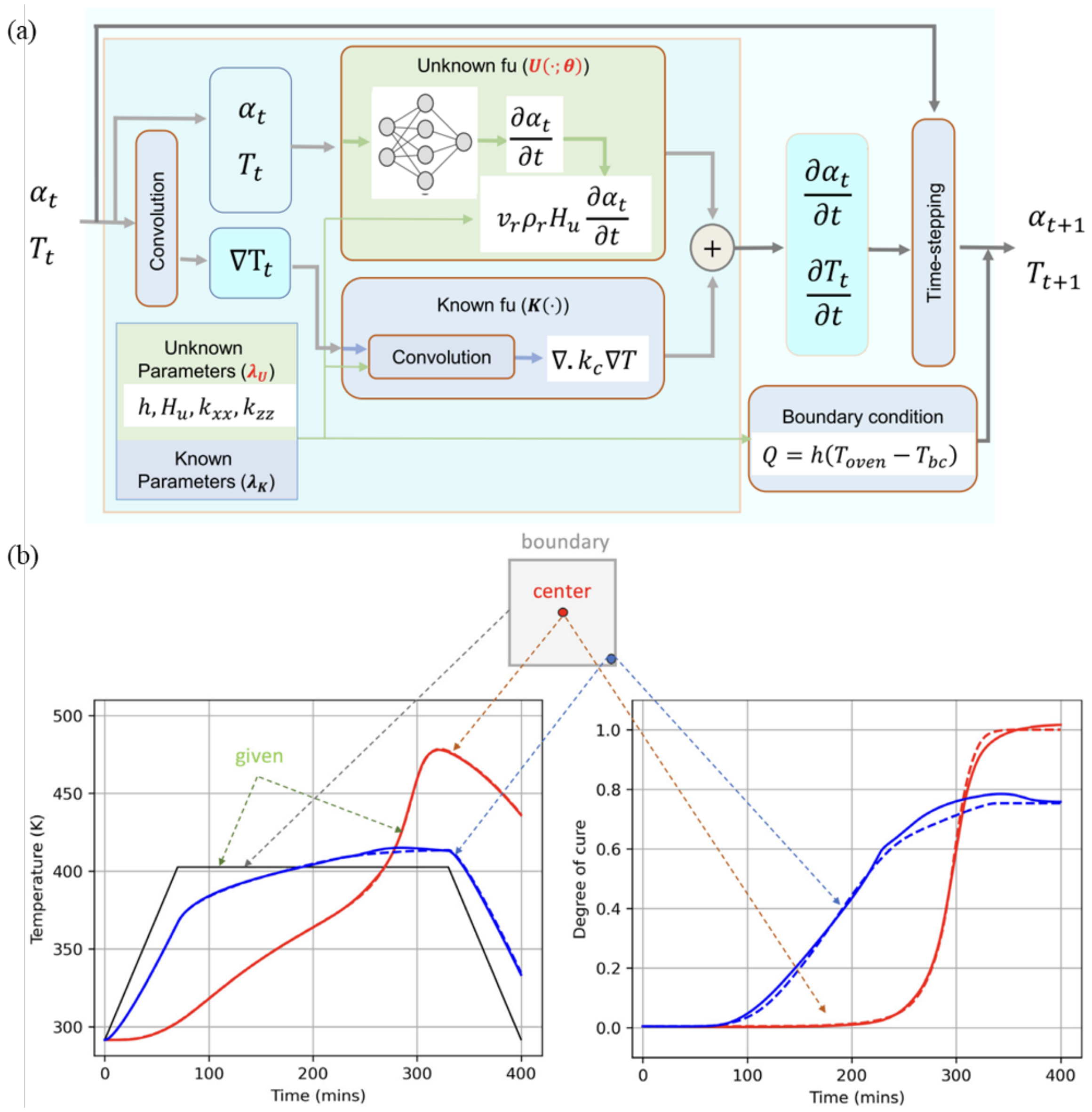

Fig. 5. (a) Schematics of the PiNDiff module for the curing process; (b) PiNDiff predictions on the temperature data collected at the center of the laminate, where black solid line represents autoclave temperature that is the BC, red/blue solid line represents the prediction at the center/corner location, red/blue dashed line represents the ground truth at the center/corner location. (Reproduced from reference [103].)

A natural extension to process modeling is process optimization and control. Jahromi et al. [144] formulated a nonlinear programming (NLP) problem to develop multi-linear-stage cure cycles by minimizing the maximum temperature difference through the cure cycle to improve the mechanical properties and gain a curing uniformity, by using a RNN for surrogate modeling. Struzziero and Teuwen [145] tackled the multi-objective optimization of the cure stage of the vacuum assisted resin transfer molding (VARTM) process for wind turbine blades, aiming to minimizing process time, spring-in, and maximum temperature overshoot by comparing the Pareto front obtained from GA. A ML framework, CompML (Composites Machine Learning), was used by Humfeld and Zobeiry [146] for active control of the composites autoclave processing. Specifically, two LSTM models were trained to solve the forward thermochemical problem to predict temperature histories of the part and tool, then the results were fed into a third ANN to search for an optimal cure cycle. Yuan et al. [33] built a surrogate model through radial basis function (RBF) of multi-field coupled FEM results and utilized a non-dominated sorting genetic algorithm-II (NSGA-II) to search for the global optimum solution where the cure time and maximum gradient of temperature and DoC are minimized to reduce the residual stress and improve production efficiency. Tang et al. [147] employed a multi-objective particle swarm optimization (MOPSO) algorithm to find an optimal cure cycle that minimizes total curing time, maximum difference of DoC, and spring-back angle of a C-shaped composite specimen after curing based on FEM simulations. The optimal cycle was later verified by an experiment to effectively shorten the curing time and reduce the spring-back angle.

Although various advancements have been made by AI/ML methods in the manufacturing and curing processes modeling and optimization of FRP composites, there are still areas not fully touched. One notable domain is to end-to-end model the whole manufacturing process including both part generation and curing processes to better link all related manufacturing parameters with the ultimate performance measures. PIML/PINN are specifically designed to be applied on physics-related problems, having a great potential for understanding the complex interactions during the manufacturing of composite materials.

5. AI/ML in Material Property Prediction of High-Performance Composites

Typically, material properties encompass chemical (chemical composition, atomic bonding, corrosion resistance, etc.), electrical (conductivity, resistivity, dielectricity, etc.), magnetic (ferro/para/diamagnetism, etc.), thermal (thermal conductivity, expansion, diffusivity, etc.), mechanical (strength, stiffness, elasticity, plasticity, toughness, fatigue, ductility, brittleness, etc.), and optical (refection, refraction, diffraction, etc.) aspects [148]. Mechanical properties, among all these aspects, often hold significant importance since they characterize the material in most engineering applications. Traditional methods to determine the mechanical properties of a material rely on repeating mechanical tests laboriously, which is time-consuming and expensive. However, the utilization of AI/ML methods to predict material properties has experienced significant growth and released a large number of efforts from laborious tests for various materials including composites. The capacity to learn intricate nonlinearities has enabled AI/ML methods to encourage researchers to use them to perform these tasks. The main breakthrough in predicting mechanical properties of high-performance composite structures is to forecast the stress/strain tensor field maps instead of merely a value of strength, which requires a more sophisticated design of model to deal with the high-dimensional and multiscale data. CNN-based neural operator with multiscale FEM would be a good candidate [41, 55, 149-151]. This section will focus on the recent advances of AI/ML techniques for prediction of mechanical properties of high-performance composites, especially on strength and fatigue behavior of composites and their joints.

5.1 *AI/ML in Strength Prediction of High-Performance Composites*

Strength of material is often recognized as the most important mechanical characterization for structural parts/components and engineering materials to which FRP composites are usually applied. Rahman et al. [152] built a CNN-based surrogate ML model for molecular dynamics simulations to predict the shear strength of carbon nanotube-polymer interfaces. In addition to the interfacial properties in carbon nanotube (CNT) composites, the geometric deformation was investigated through a model that integrated functional PCA (FPCA) with DNN to ensure predictive performance and interpretability [153]. On the other hand, for general FRP composites, Abuodeh et al. [154] utilized a resilient back-propagating neural network (RBPNN) as a regressor to predict the shear strength of reinforced concrete (RC) beams strengthened with externally bonded FRP sheets. The recursive feature elimination (RFE) algorithm and neural interpretation diagram (NID) were later employed to identify significant parameters to improve predictive efficiency and accuracy. Yin and Liew [155] investigated the application of gradient boosting regressor (GBR) and ANN on evaluating the interfacial properties of FRP composites such as the interfacial shear strength (IFSS) and the maximum force given fiber geometries and basic mechanical properties of fiber and matrix materials. Li et al. [156] predicted the transverse microstructure-property relationship of unidirectional (UD) FRP composites with microvoids through an ML-combined material informatics approach where the principal component analysis (PCA) was used to extract statistical representations and a genetic algorithm optimized back propagation (GABP) neural network was built for prediction. A similar framework but with principal component regression (PCR) was employed by Olfatbakhsh and Milani [157] on fabric composites. Prediction and analysis of dynamic strength [158] and failure criteria [111] in terms of both maximum compressive and tensile stress using AI/ML methods were also explored.

Apart from predicting a single or several strengths that are in the form of scalar, FRP composite stress field prediction has caught great attention and been proactively explored recently [41, 55, 149-151]. Specifically, Rashid et al. [149] utilized the Fourier neural operator (FNO) to predict component-wise stress and strain for two-phase composites. As shown in Fig. 6(a), the FNO learned the constitutive relation between the design geometry and different mechanical responses, predicting the normal and shear components of the stress and strain tensor field in an end-to-end fashion with the material microstructure alone as the input. Notably, the FNO framework was demonstrated to have a decent generalization ability to unseen microstructure geometries. Gupta et al. [55] reported an ML-based approach for multiscale mechanics modeling considering microstructural heterogeneity where a CNN with U-Net architecture was trained to learn the mapping between the spatial arrangement of fibers and corresponding 2D stress tensor fields. Three different approaches for predicting the stress field of a heterogeneous macro-structured composite and a comparison of computational time are shown in Fig. 6(b). The U-Net model trained for stress prediction in the microstructure was tested successfully on three different macro-structures of varying sizes and subjected to different loading and boundary conditions, showing the capability for multiscale analysis.

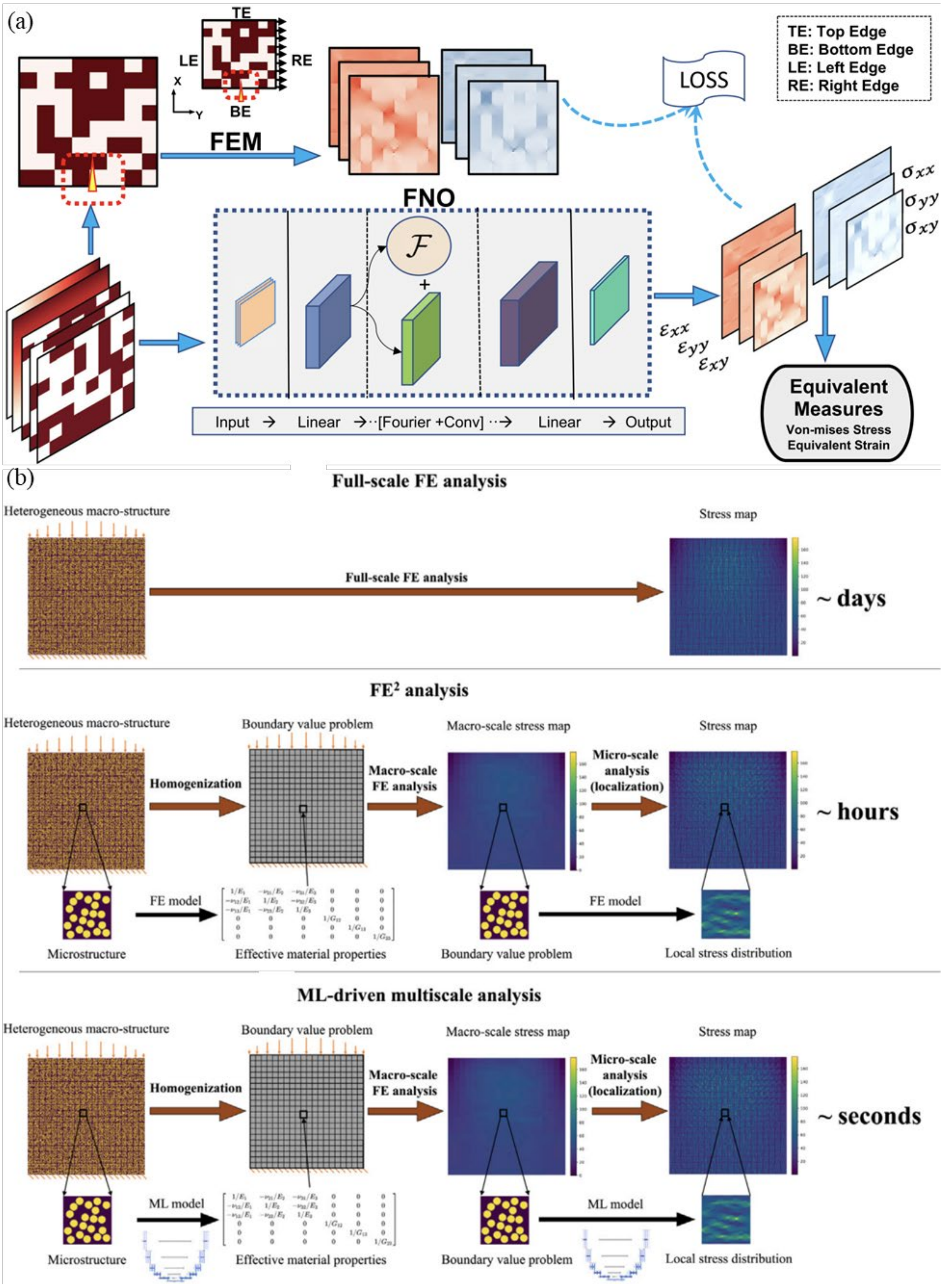

Fig. 6. (a) The workflow of FNO framework for predicting stress and strain field, where the 2D digital composite geometry is analyzed for the mode-I tensile test using FEM with a pre-crack along the x-direction and loading in the y-direction, and the tensor components are

used to derive scalar-valued equivalent measures such as von-mises stress and equivalent strains [149]; (b) Multiscale mechanics modeling of a heterogeneous macro-structure using three different approaches: (i) full-scale FE analysis, (ii) FE^2 analysis, and (iii) ML-driven multiscale analysis. The full-scale FE analysis is the least efficient, the multiscale FE analysis is parallelizable and more efficient, and the ML-driven multiscale analysis is the most efficient [55].

In addition to predicting strength of FRP composite itself, research on forecasting strength and failure analysis on composite adhesive joints has also been extensively explored for its critical significance in multiple engineering applications. Not only the structural epoxy adhesives [39, 159], but also the whole bonded joints, e.g., interfacial properties, are of great research interest, with various types of mechanical testing for different fractures such as mode-I [51], mode-II [160-164], and mixed-mode [113, 165, 166], and the adhesion between different materials [167, 168]. ANN is the most used model among all the AI/ML algorithms, combined with FEM utilizing cohesive zone model (CZM) that describes composite adhesion by a traction-separation law given some certain simplified assumptions, to predict shear and peel strength of composite adhesive joints and perform failure analysis. This combined model directly links nominal material properties (usually from datasheet) and joint geometries to the mechanical characterization, effectively improving the prediction efficiency compared to FEM alone. The potential of applying advanced AI/ML models has been explored as well. Considering the issue of small dataset that is common in engineering applications, Pruksawan et al. [159] utilized an active learning framework with gradient boosting as the regressor and Bayesian optimization for final proposing for a combination of epoxy parameters that yield a maximum adhesive joint strength. This active learning framework will augment the training dataset by adding additional data proposed by the predictive model from the original design space, as shown in Fig. 7, which runs in an iterative supervised manner and would generate a highly uniform set of sample points. This property of active learning is expected to mitigate the issue of lack of training data in a real engineering problem such as FRP composites.

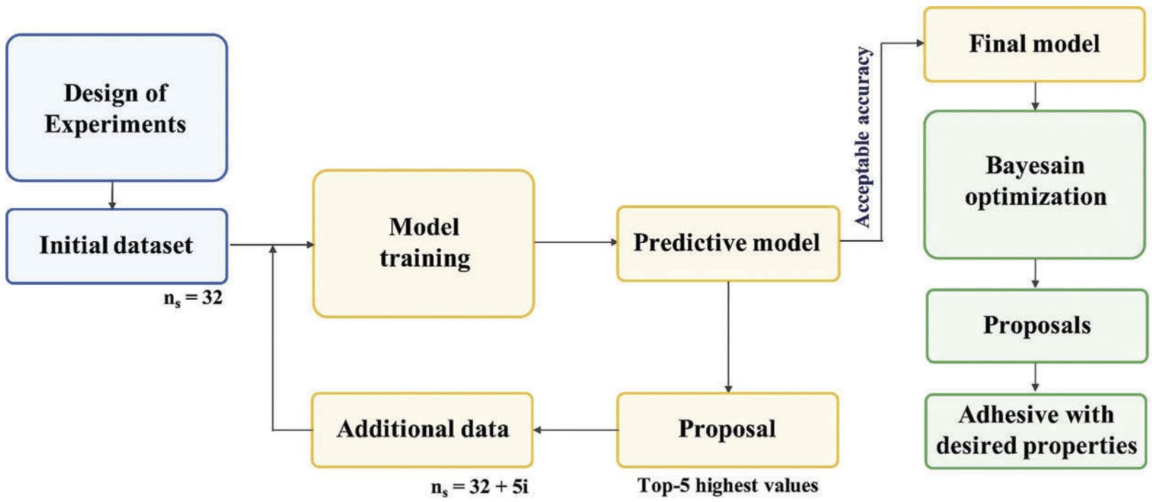

Fig. 7. Flowchart of the active learning approach for modeling and optimization of epoxy adhesive [159].

5.2 *AI/ML in Fatigue Prediction of High-Performance Composites*

Compared to the strength of material, fatigue characterizes the behavior and failure of a material due to a cyclic loading other than a quasi-static one, which is also the most common material failure modes that harm the safety of structural components [169]. Fatigue data is often noisy and unapproachable for physics-based methods to get an accurate result, which is suitable for AI/ML analysis. Fatigue life prediction is a widely studied topic in the literature where researches apply AI/ML models to the fatigue analysis of composites, attempting to bridge material and experimental parameters and the fatigue life [42, 170-174]. Other aspects have also been extensively analyzed, with more concentrations on the fatigue behavior characterization, e.g., damage/crack evolution [112, 175], strength/stiffness degradation [56, 176], and fatigue diagnosis and prognosis [34, 177-179].

Based on the strain pattern obtained from distributed optical fiber sensors bonded on a CFRP double cantilever beam (DCB) specimen under a cyclic loading, Cristiani et al. [175] built a one-dimensional (1D) and a two-dimensional (2D) CNN which were separately trained to predict the delamination length due to fatigue loading to track the crack evolution. Notably, as shown in Fig. 8(a), Tao et al. [56] applied a β-variational autoencoder (β-VAE) firstly to extract and disentangle the latent features to represent the underlying driving mechanism of stiffness degradation, and then adopted the Neural ODE framework to learn the dynamics of the latent features. The Neural ODE framework predicts the stiffness of the composite laminate over the cycle-domain continuously, achieving a better accuracy than a conventional phenomenological model. Lee et al. [179] built a deep autoencoder (DAE)-based model, as shown in Fig. 8(b), to detect and classify fatigue damage in composite structures using the ultrasonic signals collected from the CFRP plate under ultrasonic Lamb waves. The DAE was trained to reconstruct the ultrasonic signals obtained when the sample was intact and for testing, the reconstruction RMSE was selected as an index to detect damage once it exceeded the determined threshold. On the other hand, the feature learned by the hidden layer of the DAE was extracted for damage classification by a density-based spatial clustering of applications with noise (DBSCAN) algorithm after processed by singular value decomposition (SVD) for dimension reduction.

Composite materials exhibit complex hierarchical structures, and thus their mechanical properties depend on interactions at multiple length scales. It is expected to predict material properties with improved accuracy and better understanding of the connection between the structure and properties if an AI/ML model is adopted which considers multi-scales, e.g., from nanoscale to micro- and macroscale, and with considerable interpretability. Additionally, neural operator (NO), other than ordinary neural network, has a great potential on predicting more complex material properties based on material structure and some basic properties, e.g., as demonstrated in [149], because it is able to map between input and output functions on continuous domains and do super-resolution on the output instead of just mapping between input and output points on a fixed, discrete grid [180]. This special nature enables NO overcome the inherent issue of lacking enough continuous data in engineering applications.

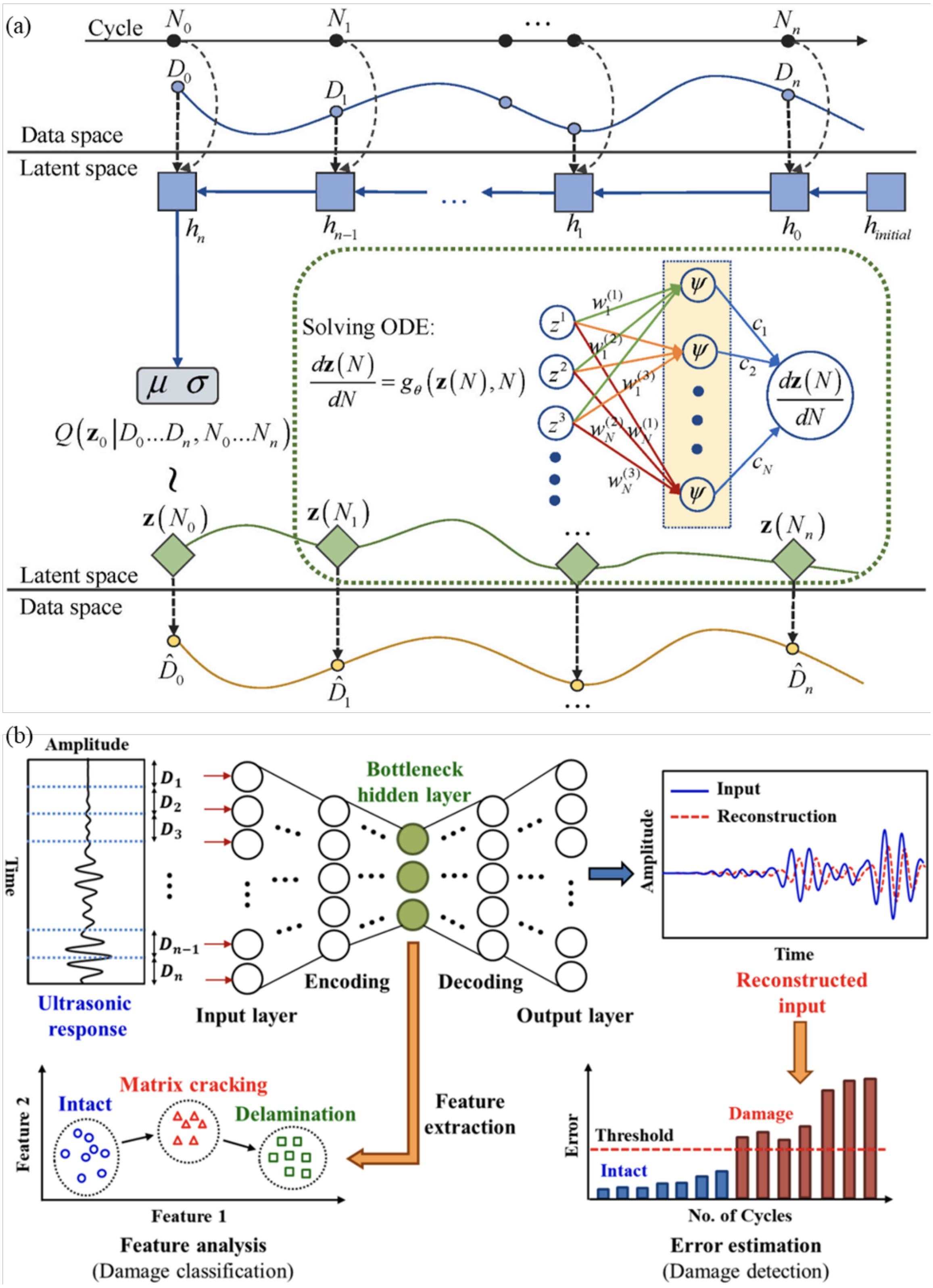

Fig. 8. (a) Computation graph of the ANN model based on the Neural ODE structure with β-variational autoencoder (β-VAE) [56]; (b) Overview of the deep autoencoder-based fatigue damage detection and classification for composite structures [179].

6. AI/ML in Damage Diagnosis and Prognosis of High-Performance Composites

With the increasing use of high-performance composite parts and components in real life, it is of great importance to maintain the structural integrity by damage detection and evaluation not only during manufacturing processes, but also when they are in service. Comprehensive diagnostic and prognostic for FRP composites are critically significant for safety concerns, yet particularly challenging due to non-homogeneity and anisotropy of composite materials [181]. Generally, diagnosis is to obtain a clear picture of the health state of the material, and prognosis will estimate the remaining useful life (RUL) [35]. Therefore, robust and reliable non-destructive inspection (NDI) methods are essential and highly desirable for detection of various types of damages. On the other hand, structural health monitoring (SHM) performs an in-situ and continuous damage evaluation of composite structures, and thus has the potential to identify defects in the early stages, allowing for a timelier maintenance and repair [182]. Although performing a reliable NDI and SHM on FRP composite is difficult because of intricate structural nature, AI/ML methods shed a light by the powerful data analysis capabilities. For example, weak adhesion and kissing bonds are the defects in composite laminates and adhesive joints that are extremely difficult to detect non-destructively through conventional techniques and yet very safety-concerning. AI/ML models, on the other hand, with appropriate feature extraction based on physical knowledge, perform decently on a binary classification task to determine the existence of such defects [110]. Recent advancements in utilizing state-of-the-art AI/ML methods for NDI and SHM on high-performance composites will be reviewed in this section.

6.1 *AI/ML in Non-Destructive Inspection of High-Performance Composites*

Generally, based on the output signal for analysis and its frequency, NDI techniques can be categorized into three main groups: acoustic wave-based, electromagnetic techniques-based, and imaging techniques-based [183]. AI/ML methods, especially ANNs and CNNs, have been applied to these specific fields for composite defect and damage inspection, detection, localization, and classification. Acoustic wave-based NDI mainly includes acoustic emission (AE) [184] and ultrasonic testing (UT) using Lamb waves [185, 186], guided waves [187, 188], and etc., which are suitable for monitoring and locating cracking and delamination in FRP composites. Defects such as crushing and impact that are explicitly on the surface are easily detected by visual inspection (VI), which has also been aided by ANNs/CNNs for automation and better visual detectability for defects that are negligible for naked eyes [189, 190]. Apart from VI and eddy current testing (ECT) [191], another important NDI method in the electromagnetic techniques-based group is infrared thermography (IRT). Combined with different AI/ML methods, e.g., hierarchical clustering [192], kNN [193], Faster R-CNN with attention mechanism [194], IRT is able to detect the size and location of defects in composite laminates based on thermal images in an automated manner. The third group imaging techniques-based NDI generally utilizes the difference between images obtained at different time to highlight changes in defects, including shearography and digital image correlation (DIC) for measuring strain and displacement [195, 196], and X-ray computed tomography (CT) with the capacity to obtain information about internal porosity, pores shape, dimension, and etc. [197]. Additionally, Gillespie et al. [198] utilized the transient thermal conduction profiles to detect delamination in composite laminates based on a supervised support vector classification (SVC) algorithm.

Although AI/ML algorithms have been extensively applied to detect defects and flaws in composite structures, the area of composite adhesive joints, e.g., damages and weak adhesion, has not been fully explored due to its intricate and invisible nature. Kissing bond, defined as a “zero-volume disbond” [199] that the adhesive and adherend are in contact without voids and chemical and/or molecular bonds between the surfaces, is one of the most interested and safety-concerning defects of composite adhesive joints. Because the defect locates in the bondline, i.e., in the interface between two non-transparent materials, and the considerable thickness of adherends compared to that of adhesive, ordinary visual methods and those depending on subtle deformation of a thin part are challenging to be applied. Despite of such difficulties, multiple physics-based methods, especially based on ultrasonic signals, were developed [200-202]. AI/ML methods are also under proactive exploration. Boll et al. [110] employed an ANN to classify kissing bonds made by release agent from pristine samples and defective specimen with a polytetrafluoroethylene (PTFE) film inserted and predict the shear strength of these three types of bonding based on vibroacoustic modulation (VAM) analysis. Specifically, as shown in Fig. 9(a), an ultrasonic Lamb-wave signal f_{Ca} with a high-strain pump wave f_P will result in a signal modulation and sidebands through the bonding area. The material nonlinearity introduced by defects and induced under a high-strain load is expected to further modulate the ultrasonic Lamb wave, revealing higher harmonics than pristine samples. As illustrated in Fig. 9(b), the sidebands and carrier amplitudes after a fast Fourier transform (FFT) were selected as the input of the ANN model for defect classification and shear strength prediction. With the aid of ML classifiers such as SVM, ultrasonic signals that obtained from different NDI methods such as pulse-echo immersion [43], phased array [203] and ordinary UT [204] were utilized to extract physics-based features for classification of adhesive bonding.

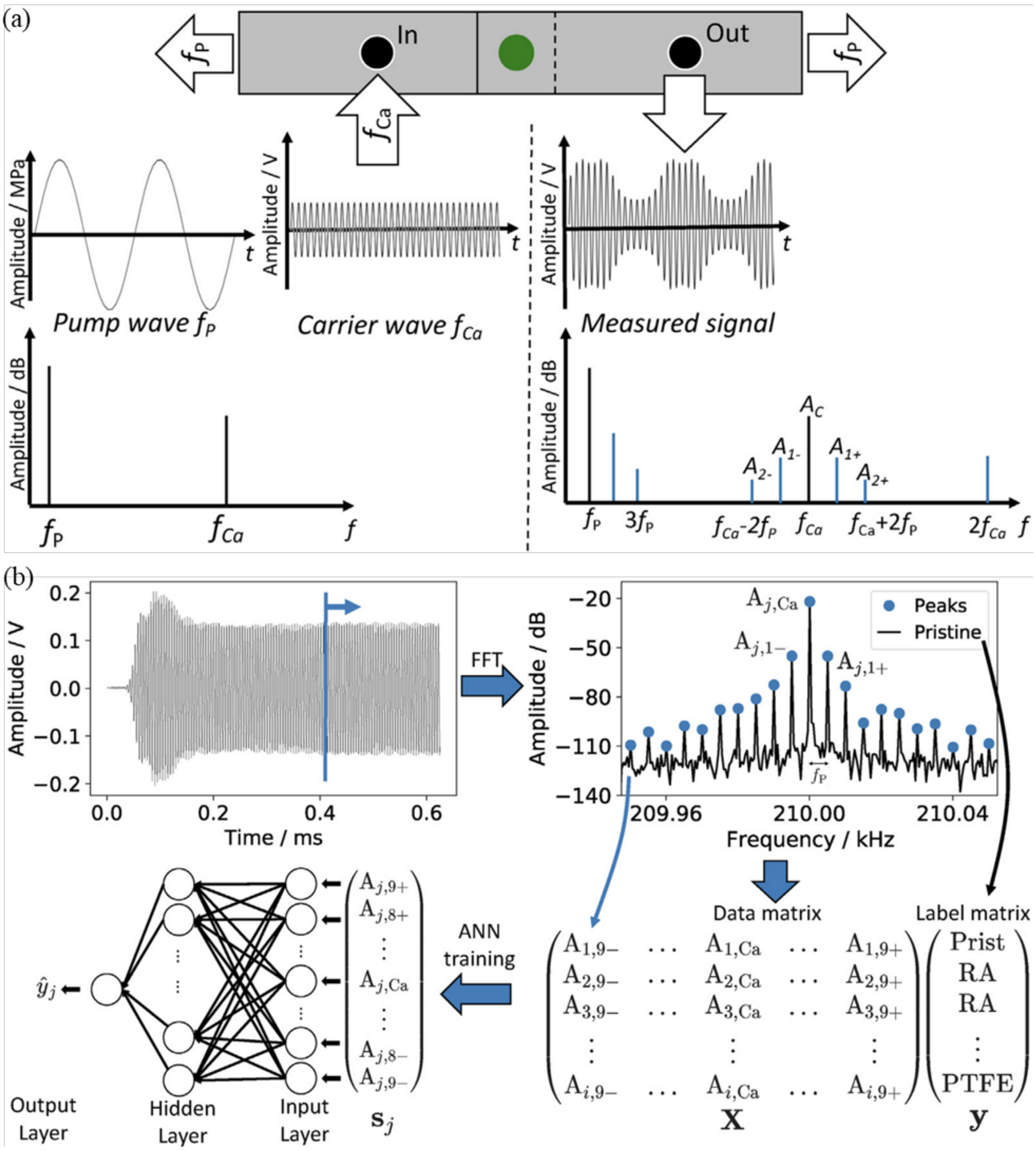

Fig. 9. (a) Schematic representation of a VAM analysis, where combining a high-strain pump wave f_P with an ultrasonic Lamb-wave as signal carrier f_{Ca} results in a signal modulation and sidebands, and the piezoceramic of the carrier signal (In) is excited at f_{Ca} and resulting vibrations are received by another piezoceramic actuator (Out); (b) Exemplary illustration of the ANN approach used to analyse VAM signals, where the Prist, RA and PTFE are corresponding labels of pristine specimen and specimen with release agent contamination or a PTFE-film, respectively. (Reproduced from reference [110].)

6.2 *AI/ML in Structural Health Monitoring of High-Performance Composites*

Taking NDI technique as core a component, SHM provides a continuous and in-situ monitoring of structural loads and damages and environmental parameters, sensing structural state parameters such as stress and/or strain [205]. Selecting a proper sensor and designing an appropriate way to embed the sensor into composite structures without harming structural integrity and strength too much are the primary task and challenge of SHM. The general workflow of SHM is depicted in Fig. 10. The SHM process consists of a diagnostic and a prognostic part where the former one estimates the current state of the structure or the system while the latter one evaluates the damage evolution and forecasts the remaining service life [35]. After diagnosis and prognosis of a system with adequate sensing ability, one can obtain the failure probability for downstream decision making about repair or replacement. There are also four performance levels of SHM defined by Rytter [206], namely, (1) verification of damage presence; (2) determination of damage location; (3) estimation of damage severity; and (4) prediction of remaining service life.

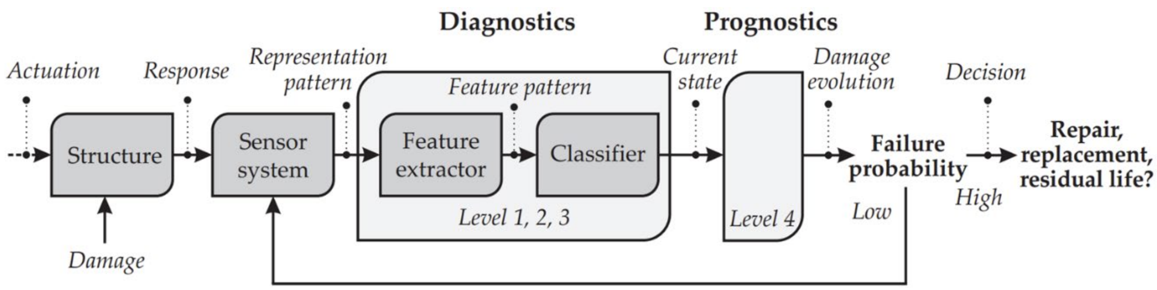

Fig. 10. The multidisciplinary structural health monitoring process [207].

With the development of advanced sensor technology, numerous physics-based SHM research have been done with various design and application of sensing strategies, e.g., electromechanical impedance/resistance-based sensors [208-210], electric time domain reflectometry [211, 212], fiber Bragg grating sensors [213], self-monitoring and self-healing [58], and etc. As shown in Fig. 11(a-c), a smart sensing grid that is comprised of continuous carbon fiber tows were integrated within the polymer matrix to identify the deformation field distribution and detect both micro- and macro-damage according to the dramatic change in the slope of fractional change in electrical resistance with the strain based on the electrical-mechanical behavior [210]. Luan et al. [58] pioneeringly designed a self-monitoring and self-healing composite structure with curing agent embedded using the dual-material AM technology, which is shown in Fig. 11(d), where the continuous carbon fibers serve as both a sensory element and reinforcement. Fig. 11(e) plots the result of three-point bending testing with four obvious stages. Damages can be detected depending on the change of the slope.

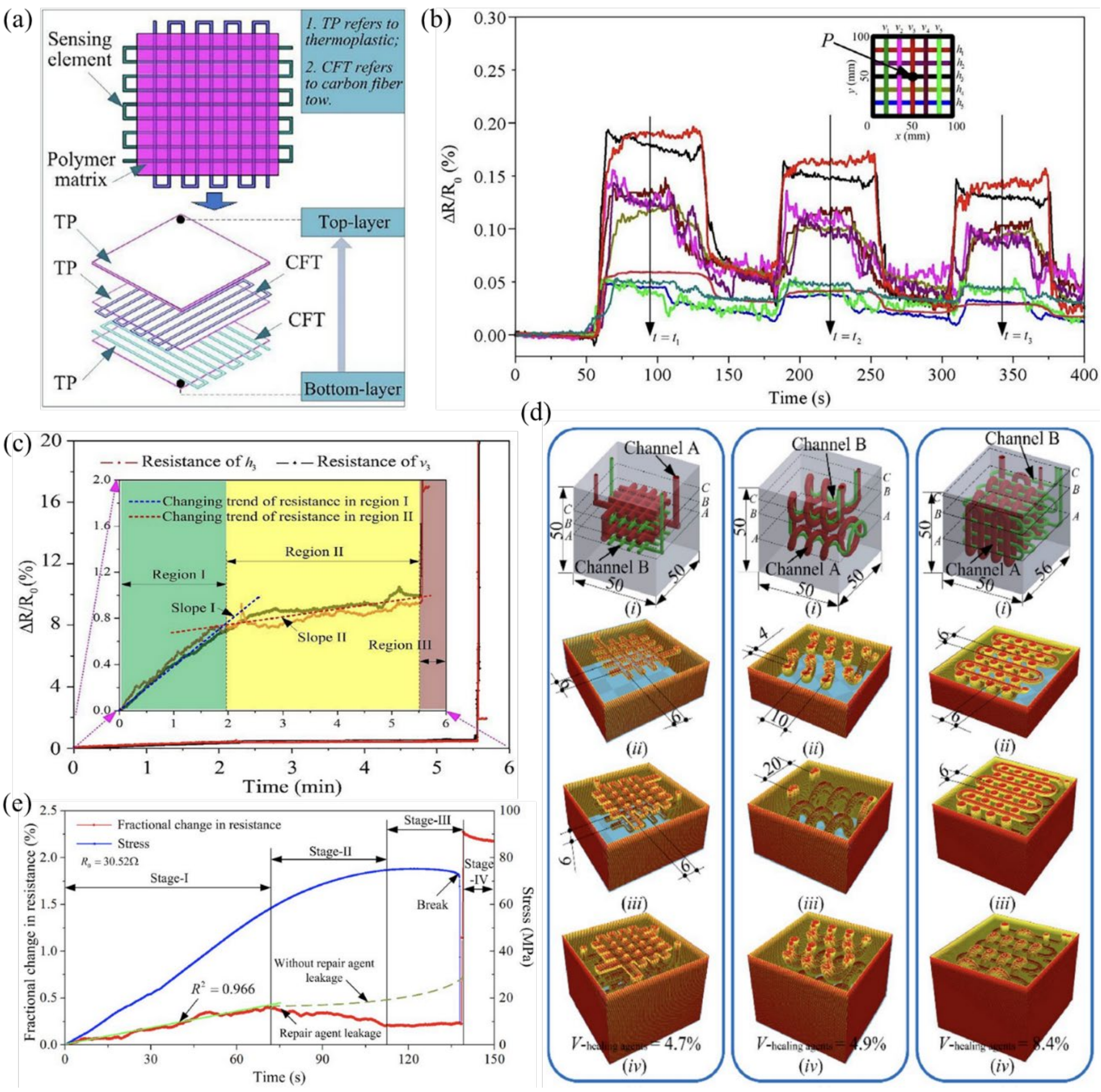

Fig. 11. (a-c) Schematic of a meshed smart structure and fabrication sequence (from bottom-layer to top-layer) with the testing result of fractional change in electrical resistance of each continuous carbon fiber tow, and a detailed look at the relation of middle tows that can be three apparent stages: elastic stage, micro-damage stage, and macro-damage stage [210]; (d, e) Specimens with plane-, spiral-, and interlock-type of self-healing structures, with a testing result of variation of fractional change in resistance and stress versus time for the continuous carbon fiber tow embedded specimen during the entire loading process [58].

AI/ML methods, e.g., ANN, SVM, kNN, etc., have been utilized to analyze the experiment data for downstream tasks such as damage detection, classification, and characterization for different composite structures [44, 57, 214-216]. Ewald et al. [57] proposed a CNN framework called DeepSHM which involves data augmentation of ultrasonic guided wave signals through wavelet transform and formalizes a generic method for end-to-end deep learning for defect classification. Liu et al. [214] performed a clustering analysis using the bisecting K-means algorithm to identify different damage modes for acoustic emission signal sources from a composite wind turbine blade. Khan et al. [215] investigated the classification of two types of delaminated samples from healthy ones using SVM with input of multi-level features extracted from various DL models through transfer learning. The raw structural vibration data was encoded into high-resolution time-frequency images using synchroextracting transforms (SETs). Reis et al. [216] employed an ANN model with input of mini-batches from the high-dimensional vibration data by dislocated series method to detect and classify delamination damage of composite beams. Diaz-Escobar et al. [44] evaluated the performance of different ML models including ANN, kNN, random forest (RF), and SVM on damage identification and characterization in composite laminates using the electrical resistance tomography (ERT) data.

NDI and SHM signals are usually high-dimensional data, leaving a great space for AI/ML algorithms due to their powerful data analysis and processing capabilities. Despite of recent advances in applying AI/ML methods to perform damage and defect detection, localization, and classification, and prediction of RUL for high-performance composite structures, current focuses are mainly on these downstream tasks. Integrating the manufacturing information such as parameters in part generation and curing processes is expected to improve the model performance as these information reveals inherent material properties. NDI and SHM may also benefit from multi-model systems which incorporate multiple sensors and inspection methods.

7. Conclusions and Future Scope

7.1 *Conclusions*

AI/ML technologies have witnessed their rapid development where novel techniques sprout at an unprecedented rate, which triggers a paradigm shift in engineering including material science. How advanced materials are conceptualized, designed, manufactured, and tested is redefined enabled by the great computational power of high-dimensional data analysis and processing. High-performance FRP composite materials, with the advancements in material science and engineering, have been extensively applied to replace conventional structural materials in various industries such as aerospace, marine, automotive, and infrastructure. The intricate structure and complicated interaction inherent in FRP composite structures raise an obstacle to researchers for understanding material behaviors. The utilization and integration of AI/ML algorithms into the science and engineering of high-performance composites marks a pivotal advancement, providing a new understanding from the view of data analytics.

In the current era of innovation with the emergence of AI/ML techniques, this article provides a comprehensive review of recent advances and applications of AI/ML methods in the product cycle life activities of high-performance FRP composites including material development and selection, manufacturing, testing, defect and damage inspection, and in-service monitoring, as summarized in Table 1. The development of AI/ML techniques for science and engineering is briefly reviewed. The AI/ML-based MGI and inverse design of advanced materials are considered when discussing the application of AI/ML methods in material development and selection. Later, this review categorizes the manufacturing of FRP composite structures into part generation and curing processes with an overview of process modeling and optimization using AI/ML techniques. Predicting material properties utilizing AI/ML models is then discussed with the emphasis on two significant mechanical properties, i.e., strength and fatigue. In addition, this study goes over advances of the application of AI/ML methods to the NDI and SHM of composite structures.

Table 1. Details of AI/ML models for design, manufacturing, testing and monitoring stages of high-performance composites in the literature listed in this review.

Stage/Task	Application	Method
Design: Material Development and Selection	Customized material fabrication	MGI [52]
	Composite functionality optimization	High-Throughput Experimentation, Synthesis, Characterization [121]
	Inverse design for required functionality	DeepONet [40], ANN [53], Topology Optimization [124, 125], Kriging with GA [40, 126]
Manufacturing: Process Modeling and Optimization	AFP process optimization	CNN [45, 129, 131], ANN [130, 132]
	AM process modeling and optimization	GPR [135], Refined RNN with LSTM [134], CNN [136, 137]
	Curing process modeling	ANN [36, 38, 140-143], PINN [37, 127], Neural ODE [103]
	Curing process optimization and control	RBF Network with NSGA-II [33], RNN with NLP [144], Multi-Objective GA [145], ANN and LSTM [146], MOPSO Algorithm [147]
Testing: Material Property Prediction	Composite strength prediction	Sparse Regression [111], ANN [154, 155, 158], GABP Network with PCA [156], PCR [157]
	Composite stress field prediction	U-Net-based CNN [41, 55, 150, 151], FNO [149]
	Composite adhesive joint strength prediction	ANN [39, 51, 160, 163-165, 167, 168], GPR [113, 166], Active Learning [159], DNN and Genetic Programming [161], PINN [162, 163]
	Fatigue prediction and characterization	ANN [42, 171, 174], Neural ODE [56, 112], RNN [170], RF [172], Gradient Boosting [173], CNN [175], GA [176]
	Fatigue diagnosis and prognosis	ANN and Particle Filtering [34], SVM and RF [177], DNN [178], DAE [179]
Monitoring: Damage Diagnosis and Prognosis	Composite damage classification and detection	CNN [184, 186, 188, 189, 195-197], SVM and RF [185], ANN [187, 190, 191], Hierarchical Clustering [192], kNN [193], Faster R-CNN [194], SVC [198]
	Composite adhesive joint defect detection	SVM [43, 203, 204], ANN [110]
	Structural health monitoring	ANN [44, 216], CNN [57], K-Means [214], SVM [215]

7.2 *Issues of AI/ML and Potential Solutions*

There are certain drawbacks inherent in data-driven AI/ML models and limitations in the implementation and practice of adopting such algorithms in a complex engineering problem of high-performance composites. These shortcomings are summarized to point out the room for future improvements.

7.2.1 Data Issues and Potential Solutions

Lack of data, especially structured data, often impacts the successful utilization of AI/ML models which are usually data-hungry. Structured data in an appropriate form of input data and output label is highly desired for the application of the standard supervised learning. Because of the expensive cost of physically destructive testing and experiments of high-performance FRP composites, data scarcity and imbalance are one of the most common issues that hinder extensive deployment of AI/ML methods.

Data scarcity occurs generally in each activity during the life cycle of composite structures due to the expensive and time-consuming testing, and data imbalance can be often observed when considering defects and damages in process modeling, material properties prediction, and classification/localization tasks in NDI and SHM. In addition to the ordinary methods that deal with data imbalance such as stratified sampling, a reliable and robust data augmentation strategy is expected to address both issues of scarce and imbalanced data. Such a strategy can be a combination of conventional preprocessing of data, e.g., noise injection, transformation, filtering, etc. and generating synthetic data using advanced AI/ML models such as GAN and its variants.

Another issue related to data is the lack of paired labels. In the framework of supervised learning, it is often assumed that the input data and labels are balanced and paired, which is not reflective of the real-world scenarios where data acquisition and labelling processes are not ideal. Labels can be noisy, incorrect, and/or incomplete, resulting in an inexact, inaccurate, and/or incomplete supervision. To address this issue, weakly-supervised learning is desirable that is designated to train ML models with limited, noisy, and/or imprecise labelling through data-driven methods [217]. Weakly-supervised learning has been applied to a variety of fields [218-221], but its potential in the area of high-performance composite structures has not been fully explored yet.

Considering complex engineering problems of FRP composites, data issues of scarcity, imbalance, labeling pose challenges to the effective and efficient application of AI/ML methods. Low data quality such as inaccurate manufacturing process parameters, testing measurements with large uncertainties requires researchers to cautiously acquire and/or collect data needed. Limited data will degrade AI/ML model performance. However, data augmentation and incorporating physics knowledge, e.g., physical laws, nominal material properties/behaviors, are expected to mitigate such issue for stages of manufacturing, testing and monitoring. With the aid of physical laws, AI/ML algorithms have the potential to comprehend material behaviors with unseen configurations, e.g., fraction of fibers, and predict "A-Basis" and "B-Basis" values for FRP composite design when trained on a moderate size dataset. In summary, techniques such as data augmentation, physics-informed machine learning and weakly-supervised learning are available to alleviate data issues, but it remains to be an open question waiting for further exploration.

7.2.2 Other Issues and Potential Solutions

In addition to data issues, other issues of AI/ML methods such as explainability and interpretability, uncertainty quantification, computational cost, and data privacy are discussed as follows.

(1) Since data-driven methods such as AI/ML models are usually regarded as black-box procedures, the interpretability and explainability of AI/ML models and results have

attracted much research interest, which are also a major drawback especially when an analysis and interpretation of model are desirable which physically makes sense in an engineering application. To address this and facilitate the implementation of black-box models, explainable AI (XAI) that allows users to comprehend results produced by AI/ML algorithms should be investigated to associate with engineering knowledge.

(2) Compared to classic statistical methods, it is more difficult to analyze uncertainty propagation and perform uncertainty quantification in AI/ML, especially DL, models. Uncertainty quantification is significant in considering safety and reliability in any engineering problems. GPR as a cheap-to-evaluate AI/ML model with the capability of uncertainty analysis has been widely used in the field of FRP composites. However, it is not typically utilized for the out-of-distribution (OOD) samples [222], i.e., unseen samples, which are specially interested in the engineering design. Even with more advanced AI/ML models such as Bayesian neural networks and deterministic methods, uncertainty quantification of AI/ML results in high-performance composites is limited and needs more investigation.

(3) One of the practical issues in the implementation of AI/ML methods is the requirement of large amounts of computational resources and time especially for those large-scale models with much data. The computational cost of AI/ML models poses challenges for the extension to large scales and integration with legacy manufacturing systems.

(4) Considering the complexity of high-performance FRP composites such as anisotropy, inhomogeneity, inherent large variability, human factor, etc., adopting AI/ML methods requires more dedicated and special design and more data to ensure the model capture the underlying complicated physics and patterns. End-to-end modeling of the multi-stage manufacturing process of composites using AI/ML techniques remains under-explored.

(5) Regarding safety-critical applications such as aerospace industry, adopting data-extensive

AI/ML models for each stage of high-performance FRP composite cycle life will require additional attention to data privacy concerns and regulatory compliance. While the former one can be addressed by techniques such as federated learning which is a collaboratively decentralized privacy-preserving ML scheme to overcome challenges of data silos [223] and often applied to privacy-sensitive areas such as healthcare, the latter concern requires a much more cautious design of AI/ML algorithms with appropriate constraints to comply with aerospace regulations.

7.3 *Future Research Directions*

Despite of these great advancements and extensive efforts in adopting AI/ML models for engineering problems of high-performance FRP composite structures, there are still some possible future research directions in certain areas that are presented below to provide a clear and systematic overview of current challenges and outlooks in this field.

7.3.1 Exploring and Exploiting Generative Models

There are gaps in designing FRP composite structures based on AI/ML models. The complex material structure and multiple-material system make it challenging to fully understand the relationship between design space and material response merely relying on physical knowledge. In the general framework of material inverse design, VAE is able to learn a stable material representation in the low-dimensional subspace and the decoder produces structures towards the targeted material property when combined with a generative process and predictive model that links to material responses. Novel AI/ML models, especially generative models, have great potential to help design and develop new materials, as demonstrated in [116] where such method has been applied to the crystal materials. When considering FRP composites, a potential direction is to explore structures and/or combinations of fiber and matrix that are more resilient and robust to curing PIDs through the way of inverse design with the aid of generative AI/ML models.

7.3.2 Incorporating Physics and Engineering Knowledge

PIML and PINN generally perform better when solving engineering problems that are related to nonlinear ODEs/PDEs via incorporating physics knowledge into ML and NN frameworks. Such models are suitable for modeling of continuous processes such as manufacturing, curing, and testing processes of composite structures. Based on prior domain knowledge, multiple ways of integrating physics knowledge can be selected when building PIML/PINN models such as adding physics-informed terms that are related to the initial/boundary conditions to loss function, choosing activation functions based on physical rationale, incorporating known or partially known ODEs/PDEs into NN structures, etc. In addition, some advanced PIML/PINN models such as physics-informed neural operators (PINOs) [224-226], Neural ODEs [227], etc. can either map between the input-output space continuously or construct a continuous-depth structure, improving extrapolation performance. This is valuable to some engineering problem where limited experiment data cannot fully cover the input space, which applies to the field of FRP composites. Therefore, hybrid physics-based and data-driven approaches provide opportunities to better understand and model the manufacturing and testing processes of FRP composite structures.

7.3.3 Addressing High-Dimensional and Heterogeneous Data

Considering the high-dimensional data in NDI on composites such as C-scan data from UT and a time-series of image signals, e.g., DIC, thermography, shearography, etc., it is important to process the whole-field spatiotemporal data that is usually in the form of 3-order tensor, whereas most of current works extract features through dimension reduction methods such as PCA, inevitably losing information to some extent. Tensor-based data analytics such as tensor decomposition and tensor-based network can play a role in processing such high-dimensional data by preserving and leveraging the tensor structure and embedded spatiotemporal information, which can also be applied to the scenarios where multiple sensors are distributed and deployed in SHM by fusing sensor signals together. Another potential approach to deal with multiple distributed sensor signals is multi-model method. Meta-learning, which learns from a collection of similar tasks with the goal of generalization and adaptation to a related but new task [228], has the potential to be applied to multiple homogeneous sensors. On the other hand, the SHM with heterogenous sensor setting is expected to be benefited from multi-model meta-learning techniques [229, 230].

7.3.4 End-to-End and Calibration-Free Modeling

Modeling an engineering problem such as FRP composite structures often involves a calibration process on some parameters, e.g., material properties, which are usually unknown and intrinsic property of material. Such parameters vary among different materials yet are constants during manufacturing for each material. Conventional methods for calibration rely on laborious tests that are expensive and time-consuming. An end-to-end modeling is expected to bypass the calibration process of material properties as these properties are also the result of manufacturing parameters. With the aid of AI/ML methods, especially those advanced models such as PINN, etc., complex nonlinearities in the relationship between manufacturing and material response are possible to be revealed. On the other hand, calibration-free algorithm [231] is potential to be applied on continuous processes with multiple sensors, e.g., SHM, to “cancelling out” calibration parameters with an appropriate design.

7.3.5 Multiscale Process Modeling

Multiscale modeling of structural composites for the mechanical performance analysis has been explored in the past through numerical simulations, which often follows the process where one first computes properties of one entity such as individual plies at a small length scale, then homogenizes into a constitutive model and passes to the next level of length scale to estimate the corresponding behavior of a larger entity, e.g., composite laminate, and repeat to the level of structural component afterwards [232]. A local-to-global multiscale simulation strategy composed of computational micromechanics for ply level [233], mesomechanics for laminate level [234], and mechanics for component level [235], however, requires multiple runs of time-consuming numerical simulations. On the other hand, AI/ML methods are being utilized to learn the physics at different length scales and to substitute simulations to improve the efficiency of multiscale analysis of FRP composite structures [55, 236-239]. Generally, AI/ML methods such as MultiScaleGNN [240] serve as surrogate models of numerical ones to reduce simulation efforts in the inference stage and the PINN framework is employed to strengthen the learning capabilities. As a promising alternative for traditional physics-based numerical simulation, AI/ML techniques for the multiscale process modeling can be further improved in the aspects of smoother transition between scales and more robust prediction.

Acknowledgements

This material is based upon work supported by the National Science Foundation (NSF) under Grant EEC-2052714. The authors acknowledge the generous support from NSF and member companies of the Composite and Hybrid Materials Interfacing (CHMI) IUCRC.

References

[1] Butler KT, Davies DW, Cartwright H, Isayev O, Walsh A. Machine learning for molecular and materials science. Nature 2018;559(7715):547-55.

[2] Clyne TW, Hull D. An Introduction to Composite Materials: Cambridge university press; 2019.

[3] Waqar T, Akhtar SS, Arif AFM, Hakeem AS. Design and development of ceramic-based composites with tailored properties for cutting tool inserts. Ceram Int 2018;44(18):22421-31.

[4] Zhang X, Yang W, Wang Q, Huang F, Gao C, Xue L. Tuning the nano-porosity and nano-morphology of nano-filtration (NF) membranes: Divalent metal nitrates modulated inter-facial polymerization. J Membr Sci 2021;640:119780.

[5] Kubota M, Hayakawa K, Todoroki A. Effect of build-up orientations and process parameters on the tensile strength of 3D printed short carbon fiber/PA-6 composites. Adv Compos Mater 2022;31(2):119-36.

[6] McIlhagger A, Archer E, McIlhagger R. Manufacturing processes for composite materials and components for aerospace applications. In: Polymer Composites in the Aerospace Industry: Elsevier; 2020. p. 59-81.

[7] Tiwary A, Kumar R, Chohan JS. A review on characteristics of composite and advanced materials used for aerospace applications. Mater Today Proc 2022;51:865-70.

[8] Davies G, Hitchings D, Ankersen J. Predicting delamination and debonding in modern aerospace composite structures. Compos Sci Technol 2006;66(6):846-54.

[9] Meola C, Boccardi S, Carlomagno GM. Composite material overview and its testing for aerospace components. In: Sustainable Composites for Aerospace Applications: Elsevier; 2018. p. 69-108.

[10] Henning F, Kärger L, Dörr D, Schirmaier FJ, Seuffert J, Bernath A. Fast processing and continuous simulation of automotive structural composite components. Compos Sci Technol 2019;171:261-79.

[11] Rajak DK, Pagar D, Behera A, Menezes PL. Role of composite materials in automotive sector: potential applications. In: Advances in Engine Tribology2022. p. 193-217.

[12] Rubino F, Nisticò A, Tucci F, Carlone P. Marine application of fiber reinforced composites: a review. J Mar Sci Eng 2020;8(1):26.

[13] Goudarzi RH, Khedmati MR. An experimental and numerical investigation of adhesive bond strength in Al-GFRP single lap and double butt lap joints due to applied longitudinal loads. Ships Offshore Struct 2020;15(4):403-16.

[14] Wu W-H, Young W-B. Structural analysis and design of the composite wind turbine blade. Appl Compos Mater 2012;19:247-57.

[15] Murray RE, Beach R, Barnes D, Snowberg D, Berry D, Rooney S, et al. Structural validation of a thermoplastic composite wind turbine blade with comparison to a thermoset composite blade. Renew Energy 2021;164:1100-7.

[16] Prashanth S, Subbaya K, Nithin K, Sachhidananda S. Fiber reinforced composites-a review. J Mater Sci Eng 2017;6(03):2-6.

[17] National Research Council, Division on Engineering Physical Sciences, National Materials Advisory Board, Committee on Durability Life Prediction of Polymer Matrix Composites in Extreme Environments. Going to Extremes: Meeting the Emerging Demand for Durable Polymer Matrix Composites: National Academies Press; 2005.

[18] Kesarwani S. Polymer composites in aviation sector. Int J Eng Res 2017;6(10).

[19] Mortazavian S, Fatemi A. Effects of fiber orientation and anisotropy on tensile strength and elastic modulus of short fiber reinforced polymer composites. Compos B Eng 2015;72:116-29.

[20] Owens JF, Lee-Sullivan P. Stiffness behaviour due to fracture in adhesively bonded composite-to-aluminum joints I. Theoretical model. Int J Adhes Adhes 2000;20(1):39-45.

[21] Deb A, Malvade I, Biswas P, Schroeder J. An experimental and analytical study of the mechanical behaviour of adhesively bonded joints for variable extension rates and temperatures. Int J Adhes Adhes 2008;28(1-2):1-15.

[22] Anandan S, Dhaliwal G, Huo Z, Chandrashekhara K, Apetre N, Iyyer N. Curing of thick thermoset composite laminates: multiphysics modeling and experiments. Appl Compos Mater 2018;25:1155-68.

[23] Zimmermann J, Schalm T, Sadeghi M, Gabener A, Schröder K-U. Analytical stiffness analysis of adhesively bonded single-lap joints subjected to out-of-plane deflection due to tensile loading. J Adhes 2022;98(11):1635-62.

[24] Campilho RD, Banea MD, Neto J, da Silva LF. Modelling adhesive joints with cohesive zone models: effect of the cohesive law shape of the adhesive layer. Int J Adhes Adhes 2013;44:48-56.

[25] Rao GVG, Mahajan P, Bhatnagar N. Machining of UD-GFRP composites chip formation mechanism. Compos Sci Technol 2007;67(11-12):2271-81.

[26] Tan W, Naya F, Yang L, Chang T, Falzon B, Zhan L, et al. The role of interfacial properties on the intralaminar and interlaminar damage behaviour of unidirectional composite laminates: Experimental characterization and multiscale modelling. Compos B Eng 2018;138:206-21.

[27] Mendoza A, Schneider J, Parra E, Roux S. The correlation framework: Bridging the gap between modeling and analysis for 3D woven composites. Compos Struct 2019;229:111468.

[28] Bamane SS, Gaikwad PS, Radue MS, Gowtham S, Odegard GM. Wetting simulations of high-performance polymer resins on carbon surfaces as a function of temperature using molecular dynamics. Polymers 2021;13(13):2162.

[29] Deshpande PP, Radue MS, Gaikwad P, Bamane S, Patil SU, Pisani WA, et al. Prediction of the interfacial properties of high-performance polymers and flattened CNT-reinforced composites using molecular dynamics. Langmuir 2021;37(39):11526-34.

[30] Lin K, Wang Z. Multiscale mechanics and molecular dynamics simulations of the durability of fiber-reinforced polymer composites. Commun Mater 2023;4(1):66.

[31] Bamane SS, Jakubinek MB, Kanhaiya K, Ashrafi B, Heinz H, Odegard GM. Boron nitride nanotubes: force field parameterization, epoxy interactions, and comparison with carbon nanotubes for high-performance composite materials. ACS Appl Nano Mater 2023;6(5):3513-24.

[32] Fleischer J, Teti R, Lanza G, Mativenga P, Möhring H-C, Caggiano A. Composite materials parts manufacturing. CIRP Ann Manuf Technol 2018;67(2):603-26.

[33] Yuan Z, Kong L, Gao D, Tong X, Feng Y, Yang G, et al. Multi-objective approach to optimize cure process for thick composite based on multi-field coupled model with RBF surrogate model. Compos Commun 2021;24:100671.

[34] Cristiani D, Sbarufatti C, Giglio M. Damage diagnosis and prognosis in composite double cantilever beam coupons by particle filtering and surrogate modelling. Struct Health Monit 2021;20(3):1030-50.

[35] Cristiani D, Sbarufatti C, Cadini F, Giglio M. Fatigue damage diagnosis and prognosis of an aeronautical structure based on surrogate modelling and particle filter. Struct Health Monit 2021;20(5):2726-46.

[36] Carlone P, Aleksendrić D, Ćirović V, Palazzo GS. Meta-modeling of the curing process of thermoset matrix composites by means of a FEM–ANN approach. Compos B Eng 2014;67:441-8.

[37] Niaki SA, Haghighat E, Campbell T, Poursartip A, Vaziri R. Physics-informed neural network for modelling the thermochemical curing process of composite-tool systems during manufacture. Comput Methods Appl Mech Eng 2021;384:113959.

[38] Hui X, Xu Y, Zhang W, Zhang W. Cure process evaluation of CFRP composites via neural network: From cure kinetics to thermochemical coupling. Compos Struct 2022;288:115341.

[39] Wang S, Xu Z, Stratford T, Li B, Zeng Q, Su J. Machine learning approach for analysing and predicting the modulus response of the structural epoxy adhesive at elevated temperatures. J Adhes 2023:1-19.

[40] Liu C, He Q, Zhao A, Wu T, Song Z, Liu B, et al. Operator Learning for Predicting Mechanical Response of Hierarchical Composites with Applications of Inverse Design. Int J Appl Mech 2023;15(04):2350028.

[41] Shokrollahi Y, Nikahd MM, Gholami K, Azamirad G. Deep Learning Techniques for Predicting Stress Fields in Composite Materials: A Superior Alternative to Finite Element Analysis. J Compos Sci 2023;7(8):311.

[42] Mital SK, Arnold SM, Murthy PL, Hearley BL. Prediction of Stiffness and Fatigue Lives of Polymer Matrix Composite Laminates Using Artificial Neural Networks. 2023.

[43] Samaitis V, Yilmaz B, Jasiuniene E. Adhesive bond quality classification using machine learning algorithms based on ultrasonic pulse-echo immersion data. J Sound Vib 2023;546:117457.

[44] Diaz-Escobar J, Díaz-Montiel P, Venkataraman S, Díaz-Ramírez A. Classification and characterization of damage in composite laminates using electrical resistance tomography and supervised machine learning. Struct Control Health Monit 2023;2023.

[45] Schmidt C, Hocke T, Denkena B. Deep learning-based classification of production defects in automated-fiber-placement processes. Prod Eng 2019;13:501-9.

[46] Du J, Yue X, Hunt JH, Shi J. Optimal placement of actuators via sparse learning for composite fuselage shape control. J Manuf Sci Eng 2019;141(10):101004.

[47] Du J, Cao S, Hunt JH, Huo X, Shi J. A new sparse-learning model for maximum gap reduction of composite fuselage assembly. Technometrics 2022;64(3):409-18.

[48] Zhong Z, Mou S, Hunt JH, Shi J. Finite Element Analysis Model-Based Cautious Automatic Optimal Shape Control for Fuselage Assembly. J Manuf Sci Eng 2022;144(8):081009.

[49] Carbas RJ, Palmares MP, da Silva LF. Experimental and FE study of hybrid laminates aluminium carbon-fibre joints with different lay-up configurations. Manuf Rev 2020;7:2.

[50] Ye J, Yan Y, Li J, Hong Y, Tian Z. 3D explicit finite element analysis of tensile failure behavior in adhesive-bonded composite single-lap joints. Compos Struct 2018;201:261-75.

[51] Kang H, Lee JH, Choe Y, Lee SG. Prediction of lap shear strength and impact peel strength of epoxy adhesive by machine learning approach. Nanomaterials 2021;11(4):872.

[52] Wang Q, Jackson JA, Ge Q, Hopkins JB, Spadaccini CM, Fang NX. Lightweight mechanical metamaterials with tunable negative thermal expansion. Phys Rev Lett 2016;117(17):175901.

[53] Luo L, Zhang B, Zhang G, Li X, Fang X, Li W, et al. Rapid prediction and inverse design of distortion behaviors of composite materials using artificial neural networks. Polym Adv Technol 2021;32(3):1049-60.

[54] Meister S, Wermes MA, Stüve J, Groves RM. Review of image segmentation techniques for layup defect detection in the Automated Fiber Placement process: A comprehensive study to improve AFP inspection. J Intell Manuf 2021;32(8):2099-119.

[55] Gupta A, Bhaduri A, Graham-Brady L. Accelerated multiscale mechanics modeling in a deep learning framework. Mech Mater 2023:104709.

[56] Tao C, Zhang C, Ji H, Qiu J. Application of neural network to model stiffness degradation for composite laminates under cyclic loadings. Compos Sci Technol 2021;203:108573.

[57] Ewald V, Groves RM, Benedictus R. DeepSHM: A deep learning approach for structural health monitoring based on guided Lamb wave technique. In: Proceedings of Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019. 2019. p. 84-99.

[58] Luan C, Yao X, Zhang C, Fu J, Wang B. Integrated self-monitoring and self-healing continuous carbon fiber reinforced thermoplastic structures using dual-material three-dimensional printing technology. Compos Sci Technol 2020;188:107986.

[59] Ertel W. Introduction to Artificial Intelligence: Springer; 2018.

[60] Boden MA. Artificial Intelligence: A Very Short Introduction: Oxford University Press; 2018.

[61] Mahesh B. Machine learning algorithms-a review. Int J Sci Res 2020;9(1):381-6.

[62] McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. Bull Math biophys 1943;5:115-33.

[63] Rosenblatt F. The perceptron: a probabilistic model for information storage and organization in the brain. Psychol Rev 1958;65(6):386.

[64] Rosenblatt F. Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. Washington, DC: Spartan books 1962.

[65] Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. Nature 1986;323(6088):533-6.

[66] LeCun Y, Boser B, Denker JS, Henderson D, Howard RE, Hubbard W, et al. Backpropagation applied to handwritten zip code recognition. Neural Comput 1989;1(4):541-51.

[67] LeCun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proc IEEE 1998;86(11):2278-324.

[68] Boser BE, Guyon IM, Vapnik VN. A training algorithm for optimal margin classifiers. In: Proceedings of the Fifth Annual Workshop on Computational Learning Theory (COLT). 1992. p. 144-52.

[69] Cortes C, Vapnik V. Support-vector networks. Mach Learn 1995;20:273-97.

[70] Keller JM, Gray MR, Givens JA. A fuzzy k-nearest neighbor algorithm. IEEE Trans Syst Man Cybern Syst 1985(4):580-5.

[71] Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput 1997;9(8):1735-80.

[72] Settles B. Active learning literature survey. 2009.

[73] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521(7553):436-44.

[74] Karniadakis GE, Kevrekidis IG, Lu L, Perdikaris P, Wang S, Yang L. Physics-informed machine learning. Nat Rev Phys 2021;3(6):422-40.

[75] Hospedales T, Antoniou A, Micaelli P, Storkey A. Meta-learning in neural networks: A survey. IEEE PAMI 2021;44(9):5149-69.

[76] van de Ven GM, Tuytelaars T, Tolias AS. Three types of incremental learning. Nat Mach Intell 2022;4(12):1185-97.

[77] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Adv Neural Inf Process Syst 2012;25.

[78] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2016. p. 770-8.

[79] Girshick R, Donahue J, Darrell T, Malik J. Region-based convolutional networks for accurate object detection and segmentation. IEEE PAMI 2015;38(1):142-58.

[80] Girshick R. Fast r-cnn. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV). 2015. p. 1440-8.

[81] Ren S, He K, Girshick R, Sun J. Faster r-cnn: Towards real-time object detection with region proposal networks. Adv Neural Inf Process Syst 2015;28.

[82] He K, Gkioxari G, Dollár P, Girshick R. Mask r-cnn. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV). 2017. p. 2961-9.

[83] Elman JL. Finding structure in time. Cogn Sci 1990;14(2):179-211.

[84] Schuster M, Paliwal KK. Bidirectional recurrent neural networks. IEEE Trans Signal Process 1997;45(11):2673-81.

[85] Pascanu R, Gulcehre C, Cho K, Bengio Y. How to construct deep recurrent neural networks. In: Proceedings of the Second International Conference on Learning Representations (ICLR). 2014.

[86] Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, et al. Generative adversarial nets. Adv Neural Inf Process Syst 2014;27.

[87] Denton EL, Chintala S, Fergus R. Deep generative image models using a laplacian pyramid of adversarial networks. Adv Neural Inf Process Syst 2015;28.

[88] Chen X, Duan Y, Houthooft R, Schulman J, Sutskever I, Abbeel P. Infogan: Interpretable representation learning by information maximizing generative adversarial nets. Adv Neural Inf Process Syst 2016;29.

[89] Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. Adv Neural Inf Process Syst 2017;30.

[90] Fukui H, Hirakawa T, Yamashita T, Fujiyoshi H. Attention branch network: Learning of attention mechanism for visual explanation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2019. p. 10705-14.

[91] Raissi M, Perdikaris P, Karniadakis GE. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J Comput Phys 2019;378:686-707.

[92] Gozalo-Brizuela R, Garrido-Merchan EC. ChatGPT is not all you need. A State of the Art Review of large Generative AI models. arXiv preprint arXiv:230104655 2023.

[93] Frank M, Drikakis D, Charissis V. Machine-learning methods for computational science and engineering. Computation 2020;8(1):15.

[94] Sosso GC, Miceli G, Caravati S, Giberti F, Behler Jr, Bernasconi M. Fast crystallization of the phase change compound GeTe by large-scale molecular dynamics simulations. J Phys Chem Lett 2013;4(24):4241-6.

[95] Gabardi S, Baldi E, Bosoni E, Campi D, Caravati S, Sosso G, et al. Atomistic simulations of the crystallization and aging of GeTe nanowires. J Phys Chem C 2017;121(42):23827-38.

[96] Milano M, Koumoutsakos P. Neural network modeling for near wall turbulent flow. J Comput Phys 2002;182(1):1-26.

[97] Chang FJ, Yang HC, Lu JY, Hong JH. Neural network modelling for mean velocity and turbulence intensities of steep channel flows. Hydrol Process Int J 2008;22(2):265-74.

[98] Ghaderi A, Morovati V, Dargazany R. A physics-informed assembly of feed-forward neural network engines to predict inelasticity in cross-linked polymers. Polymers 2020;12(11):2628.

[99] Yeh I-C. Modeling of strength of high-performance concrete using artificial neural networks. Cem Concr Res 1998;28(12):1797-808.

[100] Nanduri A, Sherry L. Anomaly detection in aircraft data using Recurrent Neural Networks (RNN). In: Proceedings of the 2016 Integrated Communications Navigation and Surveillance (ICNS). 2016. p. 5C2-1-5C2-8.

[101] Smaoui N, Al-Enezi S. Modelling the dynamics of nonlinear partial differential equations using neural networks. J Comput Appl Math 2004;170(1):27-58.

[102] Pan S, Duraisamy K. Long-time predictive modeling of nonlinear dynamical systems using neural networks. Complexity 2018;2018:1-26.

[103] Akhare D, Luo T, Wang J-X. Physics-integrated neural differentiable (PiNDiff) model for composites manufacturing. Comput Methods Appl Mech Eng 2023;406:115902.

[104] Kashinath K, Mustafa M, Albert A, Wu J, Jiang C, Esmaeilzadeh S, et al. Physics-informed machine learning: case studies for weather and climate modelling. Philos Trans R Soc A 2021;379(2194):20200093.

[105] Weber M, Kube S. Robust perron cluster analysis for various applications in computational life science. In: Proceedings of International Symposium on Computational Life Science. 2005. p. 57-66.

[106] Wolf A, Kirschner KN. Principal component and clustering analysis on molecular dynamics data of the ribosomal L11· 23S subdomain. J Mol Model 2013;19:539-49.

[107] Decherchi S, Berteotti A, Bottegoni G, Rocchia W, Cavalli A. The ligand binding mechanism to purine nucleoside phosphorylase elucidated via molecular dynamics and machine learning. Nat Commun 2015;6(1):6155.

[108] Zhou J, Troyanskaya OG. Predicting effects of noncoding variants with deep learning–based sequence model. Nat Methods 2015;12(10):931-4.

[109] Nguyen NG, Tran VA, Phan D, Lumbanraja FR, Faisal MR, Abapihi B, et al. DNA sequence classification by convolutional neural network. J Biomed Sci Eng 2016;9(5):280-6.

[110] Boll B, Willmann E, Fiedler B, Meißner RH. Weak adhesion detection–enhancing the analysis of vibroacoustic modulation by machine learning. Compos Struct 2021;273:114233.

[111] Tao F, Liu X, Du H, Tian S, Yu W. Discover failure criteria of composites from experimental data by sparse regression. Compos B Eng 2022;239:109947.

[112] Tao C, Zhang C, Ji H, Qiu J. Fatigue damage characterization for composite laminates using deep learning and laser ultrasonic. Compos B Eng 2021;216:108816.

[113] Freed Y, Salviato M, Zobeiry N. Implementation of a probabilistic machine learning strategy for failure predictions of adhesively bonded joints using cohesive zone modeling. Int J Adhes Adhes 2022;118:103226.

[114] Pasquet J, Bertin E, Treyer M, Arnouts S, Fouchez D. Photometric redshifts from SDSS images using a convolutional neural network. Astron Astrophys 2019;621:A26.

[115] Narayanan BN, Djaneye-Boundjou O, Kebede TM. Performance analysis of machine learning and pattern recognition algorithms for malware classification. In: Proceedings of 2016 IEEE National Aerospace and Electronics Conference (NAECON) and Ohio Innovation Summit (OIS). 2016. p. 338-42.

[116] Xie T, Fu X, Ganea O-E, Barzilay R, Jaakkola TS. Crystal Diffusion Variational Autoencoder for Periodic Material Generation. International Conference on Learning Representations (ICLR)2021.

[117] Lyngby P, Thygesen KS. Data-driven discovery of 2D materials by deep generative models. Npj Comput Mater 2022;8(1):232.

[118] Nosengo N. The material code. Nature 2016;533(7601):22-5.

[119] de Pablo JJ, Jackson NE, Webb MA, Chen L-Q, Moore JE, Morgan D, et al. New frontiers for the materials genome initiative. Npj Comput Mater 2019;5(1):41.

[120] Gómez-Bombarelli R, Aguilera-Iparraguirre J, Hirzel TD, Duvenaud D, Maclaurin D, Blood-Forsythe MA, et al. Design of efficient molecular organic light-emitting diodes by a high-throughput virtual screening and experimental approach. Nat Mater 2016;15(10):1120-7.

[121] Liu Y, Zhang J, Zhang Y, Yoon HY, Jia X, Roman M, et al. Accelerated Engineering of Optimized Functional Composite Hydrogels via High-Throughput Experimentation. ACS Appl Mater Interfaces 2023.

[122] Wei J, Chu X, Sun XY, Xu K, Deng HX, Chen J, et al. Machine learning in materials science. InfoMat 2019;1(3):338-58.

[123] Kim K, Kang S, Yoo J, Kwon Y, Nam Y, Lee D, et al. Deep-learning-based inverse design model for intelligent discovery of organic molecules. Npj Comput Mater 2018;4(1):67.

[124] Nomura T, Kawamoto A, Kondoh T, Dede EM, Lee J, Song Y, et al. Inverse design of structure and fiber orientation by means of topology optimization with tensor field variables. Compos B Eng 2019;176:107187.

[125] Jung T, Lee J, Nomura T, Dede EM. Inverse design of three-dimensional fiber reinforced composites with spatially-varying fiber size and orientation using multiscale topology optimization. Compos Struct 2022;279:114768.

[126] Song S, Wang Z, Cheng Y. The inverse design and optimization for composite materials with random uncertainty. In: Proceedings of Journal of Physics: Conference Series. 2021. p. 012051.

[127] Zobeiry N, Humfeld KD. A physics-informed machine learning approach for solving heat transfer equation in advanced manufacturing and engineering applications. Eng Appl Artif Intell 2021;101:104232.

[128] Rajak DK, Pagar DD, Menezes PL, Linul E. Fiber-reinforced polymer composites: Manufacturing, properties, and applications. Polymers 2019;11(10):1667.

[129] Zambal S, Heindl C, Eitzinger C, Scharinger J. End-to-end defect detection in automated fiber placement based on artificially generated data. In: Proceedings of Fourteenth International Conference on Quality Control by Artificial Vision. 2019. p. 371-8.

[130] Sacco C, Radwan AB, Anderson A, Harik R, Gregory E. Machine learning in composites manufacturing: A case study of Automated Fiber Placement inspection. Compos Struct 2020;250:112514.

[131] Meister S, Wermes M, Stüve J, Groves RM. Investigations on Explainable Artificial Intelligence methods for the deep learning classification of fibre layup defect in the automated composite manufacturing. Compos B Eng 2021;224:109160.

[132] Islam F, Wanigasekara C, Rajan G, Swain A, Prusty BG. An approach for process optimisation of the Automated Fibre Placement (AFP) based thermoplastic composites manufacturing using Machine Learning, photonic sensing and thermo-mechanics modelling. Manuf Lett 2022;32:10-4.

[133] Yuan S, Li S, Zhu J, Tang Y. Additive manufacturing of polymeric composites from material processing to structural design. Compos B Eng 2021;219:108903.

[134] Yanamandra K, Chen GL, Xu X, Mac G, Gupta N. Reverse engineering of additive manufactured composite part by toolpath reconstruction using imaging and machine learning. Compos Sci Technol 2020;198:108318.

[135] Hu C, Hau WNJ, Chen W, Qin Q-H. The fabrication of long carbon fiber reinforced polylactic acid composites via fused deposition modelling: Experimental analysis and machine learning. J Compos Mater 2021;55(11):1459-72.

[136] Wright WJ, Darville J, Celik N, Koerner H, Celik E. In-situ optimization of thermoset composite additive manufacturing via deep learning and computer vision. Addit Manuf 2022;58:102985.

[137] Lu L, Hou J, Yuan S, Yao X, Li Y, Zhu J. Deep learning-assisted real-time defect detection and closed-loop adjustment for additive manufacturing of continuous fiber-reinforced polymer composites. Robot Comput Integr Manuf 2023;79:102431.

[138] Zhang C, Zhang G, Xu J, Shi XP, Wang X. Review of curing deformation control methods for carbon fiber reinforced resin composites. Polym Compos 2022;43(6):3350-70.

[139] Wang B, Fan S, Chen J, Yang W, Liu W, Li Y. A review on prediction and control of curing process-induced deformation of continuous fiber-reinforced thermosetting composite structures. Compos A Appl Sci Manuf 2023;165:107321.

[140] Bezerra E, Bento M, Rocco J, Iha K, Lourenço V, Pardini L. Artificial neural network (ANN) prediction of kinetic parameters of (CRFC) composites. Comput Mater Sci 2008;44(2):656-63.

[141] Bheemreddy V, Huo Z, Chandrashekhara K, Brack R. Modeling and simulation of cure kinetics and flow in cavity-molded composites. J Am Helicopter Soc 2016;61(2):1-10.

[142] Kim M, Zobeiry N. Machine learning for reduced-order modeling of composites processing. In: Proceedings of the SAMPE Virtual Conference. 2021.

[143] Zobeiry N, Poursartip A. Theory-guided machine learning for process simulation of advanced composites. arXiv preprint arXiv:210316010 2021.

[144] Jahromi PE, Shojaei A, Reza Pishvaie SM. Prediction and optimization of cure cycle of thick fiber-reinforced composite parts using dynamic artificial neural networks. J Reinf Plast Compos 2012;31(18):1201-15.

[145] Struzziero G, Teuwen JJ. A fully coupled thermo-mechanical analysis for the minimisation of spring-in and process time in ultra-thick components for wind turbine blades. Compos A Appl Sci Manuf 2020;139:106105.

[146] Humfeld KD, Zobeiry N. Machine learning-based process simulation approach for real-time optimization and active control of composites autoclave processing. In: Proceedings of the SAMPE Virtual Conference. 2021.

[147] Tang W, Xu Y, Hui X, Zhang W. Multi-objective optimization of curing profile for autoclave processed composites: Simultaneous control of curing time and process-induced defects. Polymers 2022;14(14):2815.

[148] Kibrete F, Trzepieciński T, Gebremedhen HS, Woldemichael DE. Artificial intelligence in predicting mechanical properties of composite materials. J Compos Sci 2023;7(9):364.

[149] Rashid MM, Pittie T, Chakraborty S, Krishnan NA. Learning the stress-strain fields in digital composites using Fourier neural operator. Iscience 2022;25(11).

[150] Bhaduri A, Gupta A, Graham-Brady L. Stress field prediction in fiber-reinforced composite materials using a deep learning approach. Compos B Eng 2022;238:109879.

[151] Khorrami MS, Mianroodi JR, Siboni NH, Goyal P, Svendsen B, Benner P, et al. An artificial neural network for surrogate modeling of stress fields in viscoplastic polycrystalline materials. Npj Comput Mater 2023;9(1):37.

[152] Rahman A, Deshpande P, Radue MS, Odegard GM, Gowtham S, Ghosh S, et al. A machine learning framework for predicting the shear strength of carbon nanotube-

polymer interfaces based on molecular dynamics simulation data. Compos Sci Technol 2021;207:108627.

[153] Yadav U, Pathrudkar S, Ghosh S. Interpretable machine learning model for the deformation of multiwalled carbon nanotubes. Phys Rev B 2021;103(3):035407.

[154] Abuodeh OR, Abdalla JA, Hawileh RA. Prediction of shear strength and behavior of RC beams strengthened with externally bonded FRP sheets using machine learning techniques. Compos Struct 2020;234:111698.

[155] Yin B, Liew K. Machine learning and materials informatics approaches for evaluating the interfacial properties of fiber-reinforced composites. Compos Struct 2021;273:114328.

[156] Li M, Zhang H, Li S, Zhu W, Ke Y. Machine learning and materials informatics approaches for predicting transverse mechanical properties of unidirectional CFRP composites with microvoids. Mater Des 2022;224:111340.

[157] Olfatbakhsh T, Milani AS. A highly interpretable materials informatics approach for predicting microstructure-property relationship in fabric composites. Compos Sci Technol 2022;217:109080.

[158] Cai R, Wang K, Wen W, Peng Y, Baniassadi M, Ahzi S. Application of machine learning methods on dynamic strength analysis for additive manufactured polypropylene-based composites. Polym Test 2022;110:107580.

[159] Pruksawan S, Lambard G, Samitsu S, Sodeyama K, Naito M. Prediction and optimization of epoxy adhesive strength from a small dataset through active learning. Sci Technol Adv Mater 2019;20(1):1010-21.

[160] Rangaswamy H, Sogalad I, Basavarajappa S, Acharya S, Manjunath Patel G. Experimental analysis and prediction of strength of adhesive-bonded single-lap

composite joints: Taguchi and artificial neural network approaches. SN Appl Sci 2020;2:1-15.

[161] Gu Z, Liu Y, Hughes DJ, Ye J, Hou X. A parametric study of adhesive bonded joints with composite material using black-box and grey-box machine learning methods: Deep neuron networks and genetic programming. Compos B Eng 2021;217:108894.

[162] Sharma S, Awasthi R, Sastry YS, Budarapu PR. Physics-informed neural networks for estimating stress transfer mechanics in single lap joints. J Zhejiang Univ Sci A 2021;22(8):621-31.

[163] Kaiser I, Richards N, Ogasawara T, Tan K. Machine learning algorithms for deeper understanding and better design of composite adhesive joints. Mater Today Commun 2023;34:105428.

[164] Mottaghian F, Taheri F. Machine learning/finite element analysis-A collaborative approach for predicting the axial impact response of adhesively bonded joints with unique sandwich composite adherends. Compos Sci Technol 2023;242:110162.

[165] Sommer D, Haufe A, Middendorf P. A machine learning material model for structural adhesives in finite element analysis. Int J Adhes Adhes 2022;117:103160.

[166] Freed Y, Zobeiry N, Salviato M. Development of aviation industry-oriented methodology for failure predictions of brittle bonded joints using probabilistic machine learning. Compos Struct 2022;297:115979.

[167] Su M, Zhong Q, Peng H, Li S. Selected machine learning approaches for predicting the interfacial bond strength between FRPs and concrete. Constr Build Mater 2021;270:121456.

[168] Zhang F, Wang C, Liu J, Zou X, Sneed LH, Bao Y, et al. Prediction of FRP-concrete interfacial bond strength based on machine learning. Eng Struct 2023;274:115156.

[169] Chen J, Liu Y. Fatigue modeling using neural networks: A comprehensive review. Fatigue Fract Eng Mater Struct 2022;45(4):945-79.

[170] Al-Assaf Y, El Kadi H. Fatigue life prediction of composite materials using polynomial classifiers and recurrent neural networks. Compos Struct 2007;77(4):561-9.

[171] Lyathakula KR, Yuan F-G. A probabilistic fatigue life prediction for adhesively bonded joints via ANNs-based hybrid model. Int J Fatigue 2021;151:106352.

[172] Silva GC, Beber VC, Pitz DB. Machine learning and finite element analysis: An integrated approach for fatigue lifetime prediction of adhesively bonded joints. Fatigue Fract Eng Mater Struct 2021;44(12):3334-48.

[173] Fernandes PHE, Silva GC, Pitz DB, Schnelle M, Koschek K, Nagel C, et al. Data-Driven, Physics-Based, or Both: Fatigue Prediction of Structural Adhesive Joints by Artificial Intelligence. Appl Mech 2023;4(1):334-55.

[174] Yao C, Qi Z, Chen W. Fatigue behavior analysis and life prediction of all-composite joint. Thin-Walled Struct 2023;183:110320.

[175] Cristiani D, Falcetelli F, Yue N, Sbarufatti C, Di Sante R, Zarouchas D, et al. Strain-based delamination prediction in fatigue loaded CFRP coupon specimens by deep learning and static loading data. Compos B Eng 2022;241:110020.

[176] Canyurt OE, Meran C. Fatigue strength estimation of adhesively bonded tongue and groove joint of thick woven composite sandwich structures using genetic algorithm approach. Int J Adhes Adhes 2012;33:80-8.

[177] Liu H, Liu S, Liu Z, Mrad N, Dong H. Prognostics of damage growth in composite materials using machine learning techniques. 2017 IEEE International Conference on Industrial Technology (ICIT): IEEE; 2017. p. 1042-7.

[178] Dabetwar S, Ekwaro-Osire S, Dias JP. Fatigue damage diagnostics of composites using data fusion and data augmentation with deep neural networks. J Nondestruct Eval Diagn Progn Eng Syst 2022;5(2):021004.

[179] Lee H, Lim HJ, Skinner T, Chattopadhyay A, Hall A. Automated fatigue damage detection and classification technique for composite structures using Lamb waves and deep autoencoder. Mech Syst Signal Process 2022;163:108148.

[180] Azzizadenesheli K, Kovachki N, Li Z, Liu-Schiaffini M, Kossaifi J, Anandkumar A. Neural Operators for Accelerating Scientific Simulations and Design. arXiv preprint arXiv:230915325 2023.

[181] Wang B, Zhong S, Lee T-L, Fancey KS, Mi J. Non-destructive testing and evaluation of composite materials/structures: A state-of-the-art review. Adv Mech Eng 2020;12(4):1687814020913761.

[182] Azad MM, Kim S, Cheon YB, Kim HS. Intelligent structural health monitoring of composite structures using machine learning, deep learning, and transfer learning: a review. Adv Compos Mater 2023:1-27.

[183] Chen J, Yu Z, Jin H. Nondestructive testing and evaluation techniques of defects in fiber-reinforced polymer composites: A review. Front Mater 2022;9:986645.

[184] Sikdar S, Liu D, Kundu A. Acoustic emission data based deep learning approach for classification and detection of damage-sources in a composite panel. Compos B Eng 2022;228:109450.

[185] Dabetwar S, Ekwaro-Osire S, Dias JP. Damage classification of composites based on analysis of lamb wave signals using machine learning. ASCE-ASME J Risk Uncertain Eng Syst B: Mech Eng 2021;7(1):011002.

[186] Wu J, Xu X, Liu C, Deng C, Shao X. Lamb wave-based damage detection of composite structures using deep convolutional neural network and continuous wavelet transform. Compos Struct 2021;276:114590.

[187] Mardanshahi A, Nasir V, Kazemirad S, Shokrieh M. Detection and classification of matrix cracking in laminated composites using guided wave propagation and artificial neural networks. Compos Struct 2020;246:112403.

[188] Hu C, Yang B, Yang L, Wang Z, Hu W, Biao X, et al. Anti-interference damage localization in composite overwrapped pressure vessels using machine learning and ultrasonic guided waves. NDT & E Int 2023;140:102961.

[189] Fotouhi S, Pashmforoush F, Bodaghi M, Fotouhi M. Autonomous damage recognition in visual inspection of laminated composite structures using deep learning. Compos Struct 2021;268:113960.

[190] Niccolai A, Caputo D, Chieco L, Grimaccia F, Mussetta M. Machine learning-based detection technique for NDT in industrial manufacturing. Mathematics 2021;9(11):1251.

[191] D'Angelo G, Cavaccini G, Rampone S. Shimming analysis of carbon-fiber composite materials with eddy current testing. In: Proceedings of 2018 5th IEEE International Workshop on Metrology for AeroSpace (MetroAeroSpace). 2018. p. 68-73.

[192] Marani R, Palumbo D, Galietti U, Stella E, D'Orazio T. Automatic detection of subsurface defects in composite materials using thermography and unsupervised machine learning. In: Proceedings of 2016 IEEE 8th international conference on intelligent systems (IS). 2016. p. 516-21.

[193] Daghigh V, Naraghi M. Machine learning-based defect characterization in anisotropic materials with IR-thermography synthetic data. Compos Sci Technol 2023;233:109882.

[194] Tong Z, Cheng L, Xie S, Kersemans M. A flexible deep learning framework for thermographic inspection of composites. NDT & E Int 2023;139:102926.

[195] Fröhlich HB, Fantin AV, de Oliveira BCF, Willemann DP, Iervolino LA, Benedet ME, et al. Defect classification in shearography images using convolutional neural networks. In: Proceedings of 2018 International Joint Conference on Neural Networks (IJCNN). 2018. p. 1-7.

[196] Wang Y, Luo Q, Xie H, Li Q, Sun G. Digital image correlation (DIC) based damage detection for CFRP laminates by using machine learning based image semantic segmentation. Int J Mech Sci 2022;230:107529.

[197] Jia Y, Yu G, Du J, Gao X, Song Y, Wang F. Adopting traditional image algorithms and deep learning to build the finite model of a 2.5 D composite based on X-Ray computed tomography. Compos Struct 2021;275:114440.

[198] Gillespie DI, Hamilton AW, Atkinson RC, Bellekens X, Michie C, Andonovic I, et al. Composite laminate delamination detection using transient thermal conduction profiles and machine learning based data analysis. Sensors 2020;20(24):7227.

[199] Brotherhood C, Drinkwater B, Dixon S. The detectability of kissing bonds in adhesive joints using ultrasonic techniques. Ultrasonics 2003;41(7):521-9.

[200] Yılmaz B, Jasiūnienė E. Advanced ultrasonic NDT for weak bond detection in composite-adhesive bonded structures. Int J Adhes Adhes 2020;102:102675.

[201] Yilmaz B, Smagulova D, Jasiuniene E. Model-assisted reliability assessment for adhesive bonding quality evaluation with ultrasonic NDT. NDT & E Int 2022;126:102596.

[202] Attar L, El Kettani MEC, Leduc D, Predoi MV, Galy J. Detection of kissing bond type defects and evaluation of the bonding quality in metal/adhesive/composite structures by a wavenumber-frequency insensitive SH mode. NDT & E Int 2023;137:102841.

[203] Piao G, Mateus J, Li J, Pachha R, Walia P, Deng Y, et al. Phased array ultrasonic imaging and characterization of adhesive bonding between thermoplastic composites aided by machine learning. Nondestruct Test Evaluation 2023;38(3):500-18.

[204] Li J, Gopalakrishnan K, Piao G, Pacha R, Walia P, Deng Y, et al. Classification of adhesive bonding between thermoplastic composites using ultrasonic testing aided by machine learning. Int J Adhes Adhes 2023:103427.

[205] Qing X, Liao Y, Wang Y, Chen B, Zhang F, Wang Y. Machine learning based quantitative damage monitoring of composite structure. Int J Smart Nano Mater 2022;13(2):167-202.

[206] Rytter A. Vibrational based inspection of civil engineering structures [PhD thesis]. Aalborg, North Jutland Region, Denmark: Aalborg University; 1993.

[207] Ooijevaar TH. Vibration based structural health monitoring of composite skin-stiffener structures [PhD thesis]. Enschede, The Netherlands: University of Twente; 2014.

[208] Zhuang Y, Kopsaftopoulos F, Dugnani R, Chang F-K. Integrity monitoring of adhesively bonded joints via an electromechanical impedance-based approach. Struct Health Monit 2018;17(5):1031-45.

[209] Bekas DG, Sharif-Khodaei Z, Baltzis D, Aliabadi MF, Paipetis AS. Quality assessment and damage detection in nanomodified adhesively-bonded composite joints using inkjet-printed interdigital sensors. Compos Struct 2019;211:557-63.

[210] Luan C, Yao X, Zhang C, Wang B, Fu J. Large-scale deformation and damage detection of 3D printed continuous carbon fiber reinforced polymer-matrix composite structures. Compos Struct 2019;212:552-60.

[211] Todoroki A, Yamada K, Mizutani Y, Suzuki Y, Matsuzaki R. Impact damage detection of a carbon-fibre-reinforced-polymer plate employing self-sensing time-domain reflectometry. Compos Struct 2015;130:174-9.

[212] Steinbild PJ, Höhne R, Füßel R, Modler N. A sensor detecting kissing bonds in adhesively bonded joints using electric time domain reflectometry. NDT & E Int 2019;102:114-9.

[213] Shin C-S, Lin T-C. Adhesive Joint Integrity Monitoring Using the Full Spectral Response of Fiber Bragg Grating Sensors. Polymers 2021;13(17):2954.

[214] Liu P, Xu D, Li J, Chen Z, Wang S, Leng J, et al. Damage mode identification of composite wind turbine blade under accelerated fatigue loads using acoustic emission and machine learning. Struct Health Monit 2020;19(4):1092-103.

[215] Khan A, Khalid S, Raouf I, Sohn J-W, Kim H-S. Autonomous assessment of delamination using scarce raw structural vibration and transfer learning. Sensors 2021;21(18):6239.

[216] Reis PA, Iwasaki KM, Voltz LR, Cardoso EL, Medeiros RD. Damage detection of composite beams using vibration response and artificial neural networks. Proc Inst Mech Eng Part L J Mater Des Appl 2022;236(7):1419-30.

[217] Zhou Z-H. A brief introduction to weakly supervised learning. Natl Sci Rev 2018;5(1):44-53.

[218] Marino S, Beauseroy P, Smolarz A. Weakly-supervised learning approach for potato defects segmentation. Eng Appl Artif Intell 2019;85:337-46.

[219] Liu H, Liu Z, Jia W, Zhang D, Tan J. A novel imbalanced data classification method based on weakly supervised learning for fault diagnosis. IEEE Trans Industr Inform 2021;18(3):1583-93.

[220] Alenezi DF, Shi H, Li J. A Ranking-based Weakly Supervised Learning model for telemonitoring of Parkinson’s disease. IISE Trans Healthc Syst Eng 2022;12(4):322-36.

[221] Alenezi DF, Biehler M, Shi J, Li J. Physics-Informed Weakly-Supervised Learning for Quality Prediction of Manufacturing Processes. IEEE Trans Autom Sci Eng 2024.

[222] Nemani V, Biggio L, Huan X, Hu Z, Fink O, Tran A, et al. Uncertainty quantification in machine learning for engineering design and health prognostics: A tutorial. Mech Syst Signal Process 2023;205:110796.

[223] Li L, Fan Y, Tse M, Lin K-Y. A review of applications in federated learning. Comput Ind Eng 2020;149:106854.

[224] Li Z, Zheng H, Kovachki N, Jin D, Chen H, Liu B, et al. Physics-informed neural operator for learning partial differential equations. arXiv preprint arXiv:211103794 2021.

[225] Wang S, Wang H, Perdikaris P. Learning the solution operator of parametric partial differential equations with physics-informed DeepONets. Sci Adv 2021;7(40):8605.

[226] Goswami S, Bora A, Yu Y, Karniadakis GE. Physics-informed deep neural operator networks. In: Machine Learning in Modeling and Simulation: Methods and Applications: Springer; 2023. p. 219-54.

[227] Chen RT, Rubanova Y, Bettencourt J, Duvenaud DK. Neural ordinary differential equations. Adv Neural Inf Process Syst 2018;31.

[228] Finn C, Abbeel P, Levine S. Model-agnostic meta-learning for fast adaptation of deep networks. International Conference on Machine Learning: PMLR; 2017. p. 1126-35.

[229] Vuorio R, Sun S-H, Hu H, Lim JJ. Multimodal model-agnostic meta-learning via task-aware modulation. Adv Neural Inf Process Syst 2019;32.

[230] Abdollahzadeh M, Malekzadeh T, Cheung N-MM. Revisit multimodal meta-learning through the lens of multi-task learning. Adv Neural Inf Process Syst 2021;34:14632-44.

[231] Chen J, Liu Z, Wang K, Jiang C, Zhang C, Wang B. A calibration-free method for biosensing in cell manufacturing. IISE Trans 2021;54(1):29-39.

[232] LLorca J, González C, Molina-Aldareguía JM, Lopes C. Multiscale modeling of composites: toward virtual testing… and beyond. JOM 2013;65:215-25.

[233] Rueda-Ruiz M, Herráez M, Sket F, Gálvez F, González C, Molina-Aldareguia JM. Study of the effect of strain rate on the in-plane shear and transverse compression response of a composite ply using computational micromechanics. Compos A Appl Sci Manuf 2023;168:107482.

[234] Romanowicz M. A mesoscale study of failure mechanisms in angle-ply laminates under tensile loading. Compos B Eng 2016;90:45-57.

[235] Tavares RP, Melro AR, Bessa MA, Turon A, Liu WK, Camanho PP. Mechanics of hybrid polymer composites: analytical and computational study. Comput Mech 2016;57:405-21.

[236] Liu X, Zhou X-Y, Liu B, Gao C. Multiscale modeling of woven composites by deep learning neural networks and its application in design optimization. Compos Struct 2023;324:117553.

[237] Bishara D, Xie Y, Liu WK, Li S. A state-of-the-art review on machine learning-based multiscale modeling, simulation, homogenization and design of materials. Arch Comput Methods Eng 2023;30(1):191-222.

[238] Ghane E, Fagerström M, Mirkhalaf S. A multiscale deep learning model for elastic properties of woven composites. Int J Solids Struct 2023;282:112452.

[239] Wei H, Wu C, Hu W, Su T-H, Oura H, Nishi M, et al. LS-DYNA machine learning–based multiscale method for nonlinear modeling of short fiber–reinforced composites. J Eng Mech 2023;149(3):04023003.

[240] Lino M, Cantwell C, Bharath AA, Fotiadis S. Simulating continuum mechanics with multi-scale graph neural networks. arXiv preprint arXiv:210604900 2021.