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Hybrid-Machine-Learning-and-Finite-Element Framework for Predicting Damage Behavior in Fiber-Reinforced Polymer Composites

S. Amutha[1,*], R. K. Jeyauthmigha[2], S. Tephillah[3], N. Kanagavalli[4], V. S. Prakash[5], P. R. Therasa[6], S. Gayathri[7]

Abstract

Fiber Reinforced Polymer (FRP) composites have broad spread use in aerospace, automotive, marine and structural applications due to its high specific strength, stiffness and corrosion resistance. The various damage mechanisms, such as matrix cracking, fiber breakage, delamination, and interfacial failure, however, make the forecasting of damage particularly complex. In this work, a hybrid machine learning (ML) and finite element (FE) system is proposed for predicting the damaged behavior of FRP composites. Progressive damage is simulated under different loading conditions using a complete FE model with suitable material constitutive and failure criteria. The numerical simulations are used to recover the primary aspects – such as fiber orientation, volume %, mechanical characteristics, loading circumstances, and damage variables – to provide a whole data set. The machine learning algorithms are then trained to detect the nonlinear relationships between the input parameters and the damage responses. The prediction capacity of ML models is evaluated using statistical measures such as coefficient of determination, root mean square error and mean absolute error. The proposed hybrid method aims at using the physical interpretability of FE simulations and the computational efficiency of ML model to quickly anticipate damage initiation and evolution. The proposed methodology is expected to be a useful tool for composite design, structural health assessment and failure analysis with minimal computation costs and reliable predictive accuracy. The proposed approach can also enable optimization and real time prediction of damage for sophisticated composite constructions.

***Author for Correspondence**
S. Amutha
E-mail: dramuthas@veltech.edu.in

[1]Professor, Department of Computer Science and Engineering, School of Computing, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India
[2]Assistant Professor, Department of Computer Science and Design, SNS College of Technology, Coimbatore, Tamil Nadu, India
[3]Associate Professor, Department of Electronics and Communication Engineering, St. Joseph's Institute of Technology, Chennai, Tamil Nadu, India
[4]Associate Professor, Department of Computer Science and Engineering, Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, Tamil Nadu, India
[5]Professor, Department of Computer Applications, Kristu Jayanti (Deemed to be University), Bengaluru, Karnataka, India
[6]Associate Professor, Department of Computer Science and Engineering, R.M.K. Engineering College, RSM Nagar, Kavaraipettai, Tamil Nadu, India
[7]Assistant Professor, Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India

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INTRODUCTION

Fiber reinforced polymer (FRP) composites are innovative engineering materials that have attracted more attention because of their high specific strength, high stiffness to weight ratio, corrosion resistance, fatigue behavior and design flexibility. These characteristics have led to its broad use in the airplane, automotive, maritime, wind-energy, civil infrastructure, and defense industries [1, 2]. FRP composites are particularly heterogeneous and anisotropic in comparison with the usual isotropic

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materials. The mechanical properties are mostly determined by fiber type, matrix parameters, fiber orientation, fiber volume fraction, manufacturing defects and fiber–matrix interaction. Such features give considerable benefits in the structural design but also provide complex failure modes that are difficult to fully characterize and forecast [3–5]. In FRP composites, damage evolution is generally described by the onset of many failure mechanisms including matrix cracking, fiber failure, fiber–matrix debonding, delamination and interlaminar failure. The damage initiation might occur at relatively modest levels of applied loads and propagate through the composite structure causing a drop in stiffness and final structural failure. The involvement of several systems makes the prediction of damage much more complex than the usual strength-based approach. For instance, internal delamination and gradual intra-laminar degradation may occur and are difficult to detect by standard surface inspection [6, 7]. Thus, a realistic prediction of damage initiation, growth and eventual failure is of paramount importance for the improvement of safety, durability and service life of composite structures.

The finite element (FE) analysis is an important computer method for the examination of mechanical response and failure behavior of composite materials. Advanced FE models may include material anisotropy, nonlinear behavior, progressive damage, cohesive interfaces and independent failure criteria to simulate complex loading scenarios [8, 9]. The models contain precise information on stress distributions, strain fields, beginning of damage and damage evolution. However, high-fidelity FE simulations are computationally expensive and time-consuming, especially for large numbers of design variables, material combinations, stress conditions and progressive failure processes. Thus, the high computing cost of advanced FE simulations makes it difficult to use them for direct application such as large-scale parametric research, optimization, uncertainty analysis, and real-time structural assessment. Machine learning (ML) technologies provide alternative data-driven strategies to address these computational issues. ML algorithms can learn complex non-linear correlations between input parameters and output responses from previous experimental or numerical datasets. Machine learning methods – such as artificial neural network, support vector regression, random forest, gradient boosting and other ensemble learning methods – have shown great promise for prediction of mechanical properties and failure responses of sophisticated materials [10, 11]. Once the ML model is trained and validated, predictions may be made considerably faster than to run the computationally intensive FE simulations repeatedly. Consequently, the ML is particularly interesting for fast damage detection, design optimization, and sensitivity analysis of composite structures.

But the data-driven ML techniques have severe drawbacks on their own. The predictions can only be as good and dependable, as the training data is vast, diversified and correct. However, producing huge experimental data sets for all potential combinations of composite material parameters, layups, flaws and loading situations is often expensive and time intensive. Furthermore, traditional ML models can provide accurate predictions without explicitly defining the specific mechanism of degradation in composites. This lack of physical interpretability may influence their reliability for predictions outside the training data range [12]. These limitations can be overcome by using a hybrid FE–ML framework, which combines physics based numerical simulations with data driven prediction capabilities. The approach starts with the generation of high-quality data sets for different material properties, geometries, fiber orientations and stress states using FE simulations. The numerical findings can then be exploited to identify the most relevant features related to the damage initiation and propagation and to train suitable ML models. The trained model can then be used to forecast damage related reactions of new scenarios without the need to do a full FE simulation for each [13]. Thus, the FE part guarantees the physical consistency and accuracy of the damage information, while the ML part enhances the computing efficiency and provides quick prediction.

The present study aims to build a Hybrid Machine Learning and Finite Element Framework for Prediction of Damage Behavior in Fiber-Reinforced Polymer Composites. The proposed approach combines progressive damage simulations and machine learning-based prediction models to build correlations between the material and loading parameters and composite damage responses. The FE

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model is used to evaluate the onset and progression of damage for some selected loading circumstances. The numerical data are utilized to create and assess ML models. Model performance is evaluated according to the key statistical criteria of prediction accuracy, robustness and generalization capacities [14, 15]. The current methodology is targeted at developing an effective computational tool for the prediction of damage behavior and reducing the computational cost of repeated high-fidelity simulations. FE analysis and integration of ML could bring considerable improvements in the analysis and design of FRP composite structures. This kind of platform can allow for rapid failure prediction, structural health monitoring, material optimization and improved maintenance operations. The suggested technique aims at bridging the gap between expensive physics-based modeling and inexpensive data-driven prediction and, therefore, contributes to the development of realistic and computationally economical methodologies for the damage assessment of advanced composite materials. Section 2 presents the literature inquiry, Section 3 presents the proposed model and mathematical equation in Sections 4 and 5 presents the comparison analysis and Section 6 presents the conclusion with the future.

LITERATURE REVIEW

The fiber reinforced polymer composites have received great attention in the past decades because of their high strength to weight ratio, stiffness, corrosion resistance and the possibility to provide configurable mechanical properties. Researchers have researched closely the mechanical reaction, the damage mechanisms and the failure behavior under different stress conditions. The results show that the damaged behavior of the FRP composites is governed by numerous interacting mechanisms. They are matrix cracking, fiber failure, fiber–matrix debonding and delamination. Nevertheless, the reliable modeling of these mechanisms is still a challenge because of the anisotropic and heterogeneous nature of composite materials [16, 17]. The mechanical behavior and progressive failure of the FRP composites have been intensively studied using the finite element analysis (FEA) [1]. Standard FE approaches detect damage based on failure criteria based on stress, strain or fracture mechanics concepts. The intra-laminar failure mechanisms have been predicted using Hashin, Tsai-Wu, Tsai-Hill, and Puck criteria [18–20]. Among them, the Hashin type criteria are very popular as they can discriminate fiber and matrix failure under tensile and compressive stress. Then, progressive damage models are proposed to consider the decrease of the stiffness of the material following the damage commencement. These approaches give useful information on damage evolution and failure propagation but require precise constitutive models and material attributes.

Delamination is another important failure mechanism in the multilayer FRP composites. Cohesive zone models (CZMs) and cohesive elements have been widely employed in FE simulations to model the interlaminar damage. The traction-separation laws and fracture-energy parameters of these models can be employed to characterize crack initiation and propagation. To provide precise prediction of delamination, cohesive approaches can be used but the computational cost can be prohibitive for complex structures and multiple interfaces. The prediction efficacy may be more sensitive to the mesh sensitivity, convergence issues and the need for precise interfacial qualities. The composite damage behavior has been studied and verified by numerical models and traditional experimental experiments. Tests – such as tensile, compressive, flexural, interlaminar shear, mode-I and mode-II fracture tests – provide important information regarding the material strength and failure mechanisms. However, experimental characterization can be expensive and time intensive, especially when several permutations of fiber orientations, stacking sequences, material systems and environmental factors must be examined [21, 22]. This limitation has motivated academics to devise computational and data-driven approaches that can be used in addition to experimental studies.

In the last years, Machine Learning (ML) has emerged as a very promising technology to foresee the mechanical behavior and the failure of composites. Artificial neural networks, support vector machines, decision tree models, random forests and gradient-boosting methods have established nonlinear relationships between material or processing characteristics and mechanical results. Once trained, ML algorithms can recognize difficult patterns in massive data sets and make quick

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predictions. Applications include prediction of elastic properties, tensile strength, fatigue life, damage factors and failure characteristics of composite materials [23, 24]. Such gains demonstrate the potential of ML to reduce the computational and experimental effort needed with current characterization techniques. But, despite the benefits of ML, the use of purely data-driven models to predict composite degradation is limited. The models are quite sensitive to the quantity and quality of training data. Typically, experimental datasets encompassing the complete design space are rare. Moreover, the ML models were not necessarily physics-interpretable and could cause false predictions if extrapolated out of the training data range [25–27]. So, a combination of physics-based numerical methods and ML might be a more reliable and efficient solution.

This has increased attention of the scientific community on hybrid FE–ML techniques. These technologies create enormous data sets from FE-simulations with different material configurations and loading conditions. Then the data generated on stress, strain, damage and failure are used to build conventional models using machine learning. The ML model could be trained to efficiently predict the damage reactions of the structure without a full FE simulation for each new set of input conditions [28, 29]. This combination preserves the physical underpinning of FE modeling while leveraging the computational efficiency of ML. Such frameworks are very useful for parametric studies, optimization of the structure, uncertainty analysis and near real time damage assessment. Yet, there are still substantial gaps in the studies. Most of the existing works are on FE based progressive damage modeling or ML prediction independently. There are only a few papers that suggest a systematic framework to combine both techniques for full harm prediction. Further effect of numerous elements including fiber orientation, volume %, loading situation and quality of material needs to be researched. Model generalization, feature selection, validation and physical consistency still matter. The robust hybrid machine learning and finite element framework can be developed as an effective solution to enhance the accuracy of FRP composite damage prediction and computational efficiency. The present work fills this research gap by coupling FE-based damage simulations and ML-based prediction modeling to provide a quick and reliable technique to measure the progressive damage behavior in FRP composites.

PROPOSED MATHEMATICAL MODEL

In this paper, a hybrid framework is presented to predict the damaged behavior of fiber reinforced polymer (FRP) composite, which combines FE modeling with machine learning (ML). The FE model provides information on several damage mechanisms, stiffness degradation, deformation and damage evolution. Then, the numerical data is fed into the ML model to improve the accuracy and computational efficiency of damage prediction. The mathematical formulae which are mentioned below are shown to demonstrate the interaction between FE and ML sections.

Composite Damage Feature Index

FRP composites are subjected to several damage mechanisms simultaneously apart from fiber failure such as matrix cracking, delamination, and fiber–matrix interface failure. A composite damage feature index is developed to capture the cumulative influence of various processes in a single parameter:

$$D_f = w_1 D_fiber + w_2 D_matrix + w_3 D_delam + w_4 D_interface \quad (1)$$

where D_f is the total composite damage feature index. The damage variables of fiber failure, matrix damage, delamination and fiber–matrix interface failure are D_fiber, D_matrix, D_delam and D_interface, respectively. The contribution of each damage mechanism, i.e., the parameters w_1, w_2, w_3, and w_4. The weighting coefficients are normalized as follows:

$$w_1 + w_2 + w_3 + w_4 = 1 \quad (2)$$

This enables us to merge different damage mechanisms derived from the FE simulation into one common damage descriptor for further ML prediction.

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FE-Based Damage Severity Index

The damage variable is not sufficient to evaluate the severity of damage in composites. Important for the state of the material is degradation of stiffness and deformation of structure. Thus, the finite element-based damage severity index is proposed as:

$$DSI_FE = \lambda_1(1 - K_d/K_0) + \lambda_2(\delta_d/\delta_0) + \lambda_3 D_f \quad (3)$$

where DSI_FE is the damage severity index based on FE, K_0 is the initial stiffness, K_d is the stiffness after damage, δ_0 is the initial reference displacement and δ_d is the displacement corresponding to the damaged condition. D f is the global damage feature index in Eq. (1). The values λ_1, λ_2, and λ_3 are weighting coefficients which represent the relative contribution of the stiffness degradation, displacement and damage mechanisms, respectively. The following are the weighting coefficients.

$$\lambda_1 + \lambda_2 + \lambda_3 = 1 \quad (4)$$

The proposed index offers a fuller view of structural degradation by considering multiple damage-related properties at the same time.

Damage Evolution Rate

The progressive degradation of FRP composites tends to grow with increase in the applied load or strain. To quantify the damage evolution rate between two future loading increments, the damage evolution rate is introduced as:

$$DER = (D_{i+1} - D_i)/(\varepsilon_{i+1} - \varepsilon_i) \quad (5)$$

where DER is the damage evolution rate, D_i and D_{i+1} are the damage indices at two successive loading increments and ε_i and ε_{i+1} are the corresponding strain values. A larger DER leads to a rapid increase of the damage and hence can be used as an important signal for identifying unstable damage propagation.

Hybrid FE–ML Damage Prediction

The proposed approach is built on the concept of merging physics-based FE prediction with data-driven ML prediction. The hybrid damage response is defined as:

$$D_H = \alpha D_FE + (1 - \alpha) D_ML \quad (6)$$

where D_H is the final hybrid damage prediction, D_FE is the damage predicted by the FE model and D_ML is the damage predicted by the ML model. The parameter α shows the contribution of the FE model and (1 − α) shows the contribution of the ML model. This approach allows the proposed model to retain the physical knowledge obtained from FE simulations and utilize fast prediction capacity of machine learning.

Adaptive FE–ML Weighting

A fixed value of α may not achieve the optimum performance for all loading conditions. Thus, an adaptive weighting method based on the prediction errors of FE and ML models is proposed as follows:

$$\alpha = E_ML/(E_FE + E_ML) \quad (7)$$

where E_FE and E_ML are the prediction errors of FE and ML models, respectively. Putting (7) into (6) we have:

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$$D_H = (E_MLD_FE + E_FED_ML)/(E_FE + E_ML) \quad (8)$$

In the adaptive formulation, the model with the smaller prediction error is weighted more heavily. This enables the hybrid framework to adaptively trade-off between physics-based and data-driven predictions.

Damage-Aware ML Input Vector

The proposed technique is based on feeding the FE-obtained damage information into the ML model. The ML model is trained utilizing material/loading properties and damage associated FE data, instead of basic material features. The hybrid input vector is as:

$$X_H = [E_1, E_2, G_{12}, \nu_{12}, V_f, \theta, S, D_fiber, D_matrix, D_delam, DER] \quad (9)$$

where E_1 and E_2 are the longitudinal and transverse elastic modulus, G_{12} is the in-plane shear modulus, ν_{12} is the Poisson's ratio, V f is the fiber volume fraction, θ is the fiber orientation angle, S is the applied stress and D_fiber, D_matrix, D_delam, and DER are damage features derived from FE. Then, the ML model learns the non-linear relation:

$$\hat{D}_ML = f(X_H) \quad (10)$$

where $\hat{D}$_ML represents the ML-predicted damage response and f represents the nonlinear mapping learned during model training.

Physics-Constrained ML Loss Function

However, the ML models can forecast properly, but the findings may not always be consistent with the physical elements of progressive composite degradation. We propose a mixed data-driven and physics-based loss function to better enforce physical consistency:

$$L_total = L_data + \beta L_physics \quad (11)$$

where L_total is the total training loss, L_data is the prediction error, L_physics is the physical-consistency error, and β controls the contribution of the physics-based constraint.

$$L_data = (1/N)\Sigma_{i=1}^{N}(D_i - \hat{D}_i)^2 \quad (12)$$

where D_i is the FE-obtained damage value and $\hat{D}_i$ is the ML-predicted damage value.

In the case of progressive damage, the damage index should not decrease with increasing loads. So, the physical punishment can be described as:

$$L_physics = (1/N)\Sigma_{i=1}^{N}[\min(D_{i+1} - D_i, 0)]^2 \quad (13)$$

This penalty term avoids the unphysical damage drop under the progressive loading and guides the ML model to a more realistic damage evolution pattern.

Hybrid Prediction Improvement Index

The improvement attained by the proposed hybrid technique is evaluated by defining a hybrid prediction improvement index as:

$$HPI = (1 - RMSE_H/RMSE_FE) \times 100 \quad (14)$$

where RMSE_H is the root mean square error of the hybrid FE–ML model and RMSE_FE is the corresponding error of the FE prediction. Similarly, we can compute the improvement over the ML model as:

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$$HPI_ML = (1 - RMSE_H / RMSE_ML) \times 100 \quad (15)$$

where RMSE_ML is the prediction error of the ML model alone; A positive HPI score means the hybrid model is more accurate than the reference model.

PROPOSED METHODS

The proposed adaptive FE–ML coupling system for composite damage assessment and prediction is illustrated in Figure 1. This method integrates numerical simulation, damage feature extraction, and machine learning to enhance the identification and prediction of damage severity and evolution in composite structures. The first step in the procedure is the Finite Element Analysis (FEA) to forecast the mechanical response and damage processes of the composite structure under the specified load and boundary conditions. The FE model provides a great deal of information regarding structural reactions and different sorts of internal damage. Such numerical simulations are particularly important since they allow access to damage related variables which are difficult or expensive to quantify directly via tests. The picture shows a discretized composite section. The FE model is used to produce the needed simulation data. The FE analysis data are then processed by the Damage Feature Extraction phase. The second step is devoted to the identification of the damage variables that are relevant for the different failure situations. The four typical damage modes, i.e., matrix damage, interface damage, fiber damage and delamination are studied. Matrix damage (degradation or breaking in polymer matrix) and interface damage (failure between constitutive materials) are studied. The damage of fibers is understood as the degeneration or rupture of reinforcing fibers. Delamination is the separation of the layers of composite. This framework can consider the complex failure behavior of composites with these particular damage processes.

The detected damage factors are later transformed into useful quantitative indicators. The first one is Composite Damage Feature Index that fuses the damage features of importance into a single representation. The index provides a concise description of the global damage state of composite construction. The obtained information is utilized to construct the FE-Based Damage Severity Index which measures the severity or gravity of the observed damage from the FE simulation findings. In addition, the Damage Evolution Rate, which is used to describe the rate of change of the damage situation in case of change of the loading or operating conditions, is considered in the framework. These are explanatory variables for the later machine learning analysis. The acquired damage features are then fed into the Machine Learning Model. The ML model learns the correlation between the damage features generated by the FE and the structural damage state. The model can learn from a variety of simulated damage scenarios, and it may learn complex nonlinear relationships that are not well described by conventional analytical techniques. Thus, the characteristic of the damage for novel loads or structural circumstances can be predicted faster.

The core of the suggested method is the Adaptive FE–ML Integration phase. We do not employ FE and ML components separately at this moment but rather use their complementary capabilities. The adaptive weighting assigns appropriate emphasis to the different damage features produced by the FE and the ML forecasts. This allows the framework to dynamically consider the diversity of damage mechanisms and their relative contribution to structural deterioration. Next, the weighted information is used to obtain the hybrid damage prediction integrating numerical FE information and data-driven ML know-how. The hybrid strategy may improve the resilience in prediction by combining the physical knowledge in FE analysis with the pattern recognition capabilities in machine learning. The Final Output is the damage condition or severity of the composite structure and is obtained using the integrated prediction approach.

In general, the proven FE–ML architecture offers a methodical way from numerical simulation to intelligent damage prediction. The method offers a full methodology for structural health evaluation, including numerous damage modes, composite damage indices, severity estimation, consideration of damage progression, adaptive weighting and hybrid prediction. Integration can lessen the

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computational dependence on repeating FE simulations and yet preserve the physically important damage information and, therefore, be able to provide the efficient and reliable forecast of the progressive composite degradation.

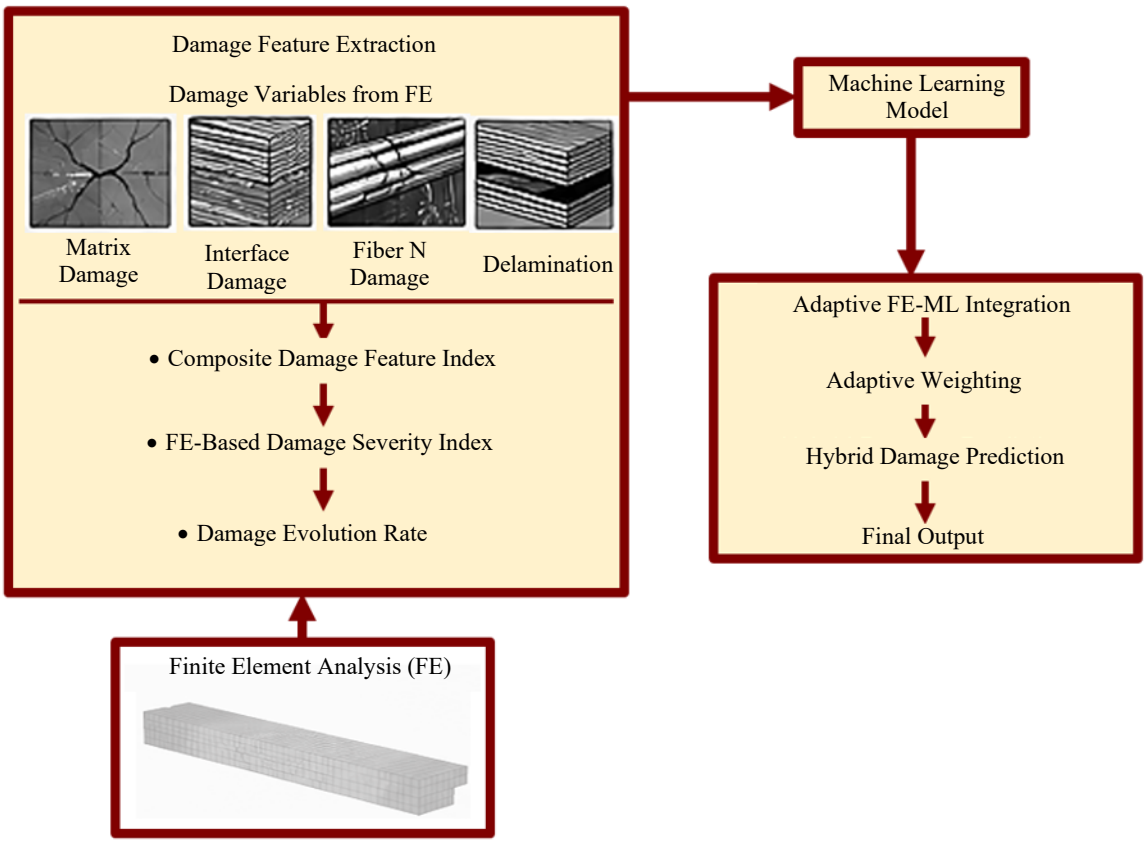


Figure 1. Proposed adaptive FE–ML framework for composite damage feature extraction, severity assessment, and intelligent prediction.

INVESTIGATIONAL RESULTS

The mechanical properties and expected reactions of the various fiber reinforced polymer (FRP) composites – such as Carbon, Glass, Kevlar, Basalt and Vinyl Ester – are compared visually in Figure 2. The figure shows a stacked-area plot showing the variation of multiple performance related metrics like tensile strength, elastic modulus, failure strain, damage index, finite element (FE) prediction, and machine learning (ML) prediction. The different FRP related response values are presented in the vertical axis, and the composite materials are presented in the horizontal axis as per Table 1. The format is for a direct comparison of the relative contribution and total reaction for each item. Examined materials from layered representation, it is seen that Carbon composite has the highest overall reaction. It can be seen that the response is around 2100 in the vertical scale, which indicates high mechanical and predictive performance. Carbon based fiber reinforced polymer (FRP) materials are recognized for their high stiffness and strength to weight ratio and are, therefore, applicable to cases where outstanding structural performance and weight reduction are required. The comparatively strong reaction obtained for Carbon suggests good mechanical properties and promise for demanding structural applications.

Glass composite shows a significant reduction vs. Carbon. The general response is something like 1550. But glass FRP nevertheless remains a vital engineering material because of its moderate stiffness, somewhat good strength, corrosion resistance and relatively cheap manufacturing features. The shift from Carbon to Glass shows that the joint mechanical and prediction response is material dependent. Besides this transition, the different reinforcement systems display different structural

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responses under comparable analytical conditions. The minimum total stacked response is achieved for Kevlar composite and is roughly 1450. From the graphic, it can be shown that Kevlar has a much lower combined reaction than Carbon and Glass under the conditions described. But that does not mean underachieving. Kevlar fibers offer particular features, namely their tremendous toughness, impact resistance and energy absorption. This results in a lower overall amplitude of the graph, but this must be seen because of the settings used and not as a worse performance in all the mechanical aspects. However, Kevlar remains very useful in areas where impact loading and damage tolerance are important.

Table 1. Comparison of different FRP composite materials.

Composite material	Tensile strength (MPa)	Elastic modulus (GPa)	Failure strain (%)	Damage index	FE prediction (MPa)	ML prediction (MPa)
Carbon	685.4	58.6	1.82	0.24	685.4	681.8
Glass	512.7	27.8	2.14	0.32	512.7	516.2
Kevlar	476.3	31.5	1.91	0.37	476.3	471.9
Basalt	538.6	38.2	1.76	0.29	538.6	541.4
Vinyl Ester	621.8	52.4	1.69	0.27	621.8	618.5

The basalt composite is more reactive than the Kevlar one, with a total value close to 1650. The rising trend indicates overall better performance of the parameters stated. The interest has been generated by the excellent mechanical capabilities, thermal stability, chemical resistance and environmental durability of basalt fiber composites. The positioning of Basalt vs Kevlar and Vinyl Ester implies the entire reaction to be competitive for the material set evaluated in this inquiry. The biggest response is Carbon at around 1900. Next greatest is Vinyl Ester. The Basalt data shows a strong combined reaction, and it indicates that composite systems based on Vinyl Ester can offer favorable structural qualities. Vinyl ester resins are commonly utilized in composite structures for their chemical resistance, bonding capabilities and ability to provide an effective matrix reinforcement. The large relative reaction shown in the figure emphasizes the importance of both reinforcing and matrix factors in the evaluation of the performance of FRP.

The graph shows many mechanical and analytical properties as colored areas. Tensile strength is the load which the composite can take before failure in tension. The elastic modulus provides us with some information about the stiffness of the composite and deformation. Failure strain is the degree of deformation a material may endure before it fails and is a measure of the ductility or strain tolerance of the material. The damage index is the level of material degradation or structural damage under the loadings examined. The combination of these features provides a more complete picture of the composite behavior than any one mechanical property. The FE Prediction and ML Prediction sections are of particular relevance as they illustrate the marriage of traditional numerical analysis and intelligent prediction modeling. Finite element analysis is widely used to simulate stress, deformation, damage evolution and structural behavior for given loading circumstances. Conversely, the machine-learning prediction can learn correlation between the input material attributes and related reaction using the available experimental or simulation data. The work adds two prediction approaches and reveals that the potential of computational and data-driven ways to duplicate or anticipate the behavior of composites is evaluated. The differences between the FRP composite materials examined are readily visible in general in Figure 2. The cumulative figure reveals the highest overall reaction for Carbon, followed by Vinyl Ester, Basalt, Glass and Kevlar. The variances show that the overall performance is very much reliant on the material composition and the tested mechanical parameters. More importantly, the integrated FE and ML prediction in the intelligent prediction provides a strong foundation for the comparison between the conventional simulation and the intelligent prediction. The present comparative study can be applied to the material selection, performance evaluation, structural design and optimization of FRP composite systems for advanced engineering applications.

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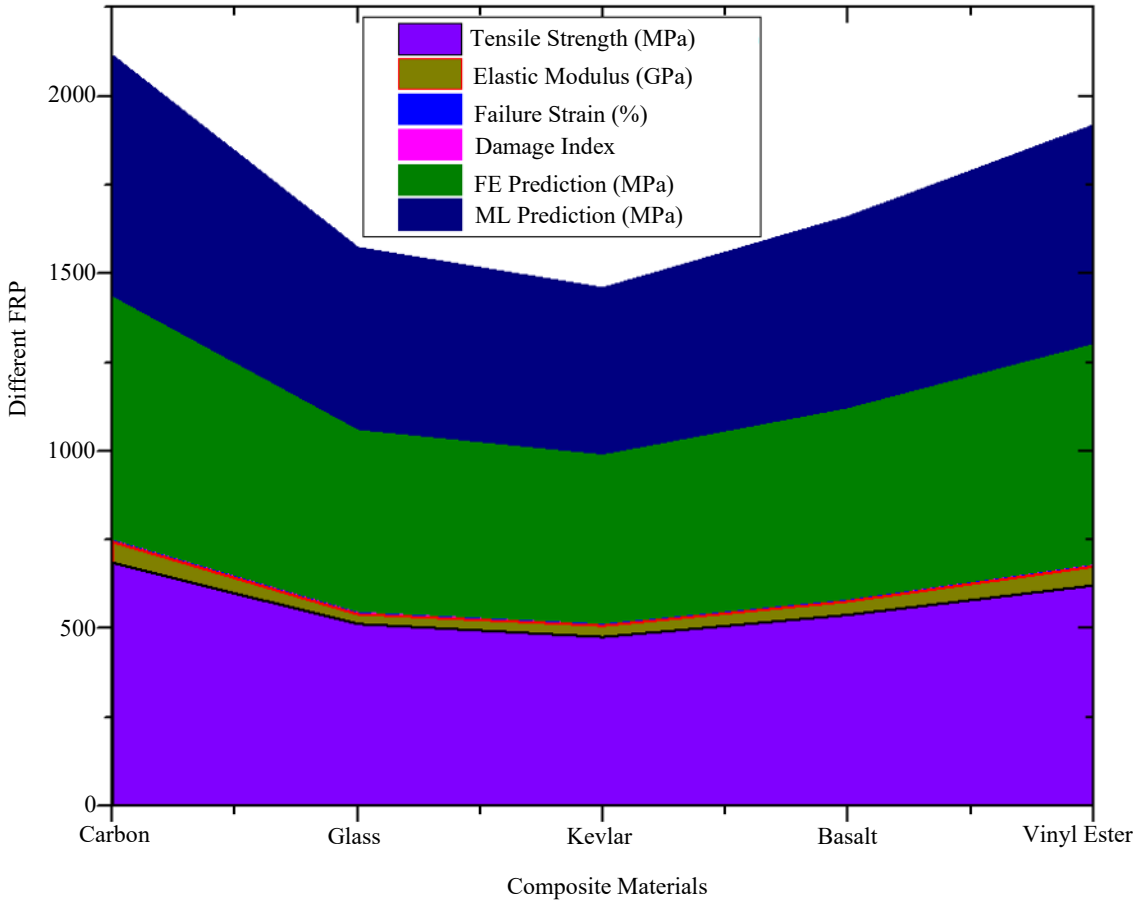


Figure 2. Comparison of properties and predicted responses for different composite materials using FE and ML approaches.

Figure 3 shows the change of essential mechanical properties and prediction findings of fiber reinforced composite materials for fiber volume percentage from 30% to 70%. The horizontal axis indicates the fiber volume fraction, and the vertical axis indicates the related metric values. The figure compares the tensile strength, elastic modulus, damage index, failure strain, FE strength prediction and ML strength prediction, as given in Table 2. The grouped bar format provides a handy way to compare the mechanical reaction obtained by measurement or computation with the values calculated by the finite-element (FE) and machine-learning (ML) techniques. The full graphic shows that the strength properties of composite material are generally increased with the increasing fiber volume proportion. The tensile strength at fiber volume fraction of 30% reaches the level of ~425 MPa. The failure strain is very low (≈28%). The FE prediction is approximately 425 MPa, and ML prediction is 430 MPa. The good agreement between the real tensile strength value and the FE and ML predictions reveals that both computational approaches can capture the mechanical response at the lower fiber concentration. At this stage the reinforcing fibers play a very important role in load transfer, but the comparatively low fiber content restricts the maximum attainable strength.

The tensile strength is about 480 MPa at a fiber volume fraction of 40%. The failure strain also increases somewhat to ≈35% The FE prediction is close to the tensile-strength value, i.e., ~480 MPa while the ML estimate is ~478 MPa. This consistency indicates that the predicted models are still in line with the observed trend. The enhancement in the tensile strength can be attributable to the availability of a greater number of reinforcing fibers to take the load applied and to restrict the deformation in the composite structure. The tensile strength at 50% fiber volume fraction is approximately 545 MPa and is a significant improvement above 30% condition. The failure strain is

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about ~43%. The FE prediction is around 545 MPa while the ML prediction is a little higher at about 550 MPa. The minimum gap between predicted and reference values illustrates the capacity of both techniques to follow the non-linear changes or progressive changes due to the increase in fiber content. The rise of strength suggests that the stress transfer between matrix and reinforcement is more effective with increasing fiber concentration.

Table 2. Effect of fiber volume fraction.

Fiber volume fraction	Tensile strength (MPa)	Elastic modulus (GPa)	Damage index	Failure strain (%)	FE strength (MPa)	ML strength (MPa)
30%	428.5	31.6	0.48	1.62	428.5	431.2
40%	486.7	38.9	0.41	1.54	486.7	482.9
50%	548.3	46.7	0.34	1.47	548.3	551.6
60%	603.9	54.8	0.29	1.39	603.9	599.8
70%	651.6	62.3	0.25	1.32	651.6	654.1

The tensile strength increases further up to about 600–605 MPa for a fiber volume fraction of 60%. The failure strain reaches about 50%. The FE prediction is about 600 MPa, and the ML prediction is about 595 MPa. The little difference in the FE, ML and tensile-strength values demonstrate the good concordance between the two prediction approaches in the range examined. This higher strength at this fiber fraction points out the beneficial influence of concentration of reinforcement on load bearing capacity of composite. But a true composite design must include fiber dispersion, interfacial bonding, manufacturing defects, and matrix availability. For the highest fiber volume fraction tested, 70%, the maximum value in the figure is a tensile strength of roughly 650 MPa. The failure strain is raised to 58 per cent. FE prediction is ~645 MPa ML prediction is ~650 MPa. The ML prediction and tensile-strength value are very similar to each other. There is very close agreement in prediction for this fiber concentration. The FE prediction is also quite near to the reference value, which shows the coherence of the computational approaches.

In general, the tensile strength increases continuously with increasing fiber volume fraction. The tensile strength increases from about 425 MPa at 30% fiber content to about 650 MPa at 70% fiber content, a 53% increase. The failure strain also increases in the range investigated. The fiber volume fraction is the dominant regulating factor for the composite response. The FE and ML results exhibit close trend with that of tensile strength, indicative of their suitability for mechanical-response estimate and validation. The legend shows the classes of elastic modulus and damage index, although the groups shown do not clearly show various bars for these two parameters. So, the main interpretation of the image should be tensile strength, failure strain, FE prediction and ML prediction. To summarize, Figure 3 presents the trend of the tensile strength and the failure strain vs the fiber volume percentage, and the predictions of both FE and ML models are in good agreement with the true mechanical behavior. The results show that the combination of numerical simulation and machine learning methods can be used to evaluate and predict the performance of fiber-reinforced composite materials.

Comparison of several failure mechanisms in composite material system such as matrix cracking, fiber breakage, fiber–matrix debonding, delamination, and interlaminar shear failure (Figure 4). The graph analyzes these mechanisms in terms of several performance indicators – such as damage initiation, damage propagation, maximum damage index, residual stiffness, finite-element (FE) values, and machine-learning (ML) values – as shown in Table 3. The results give a clear picture of the damage evolution and development over the numerous failure modes and demonstrate the potential of computational and data-driven methodologies for forecasting the damage behavior of composites. The damage-initiation value for matrix cracking is fairly low at around 18% and the damage-propagation value of about 43%. In contrast, the propagation reaction is substantially greater

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than the initiation response indicating that once matrix cracking has occurred, the damage can travel through the material. The propagation curve is about 68% for fiber breakage, meaning that fiber breaking is one of the most important processes in terms of damage propagation. Fiber breakage has also a pretty high damage initiation value of about 33%. This indicates that a fiber related failure requires a higher damage initiation threshold but can lead subsequently to a massive damage propagation.

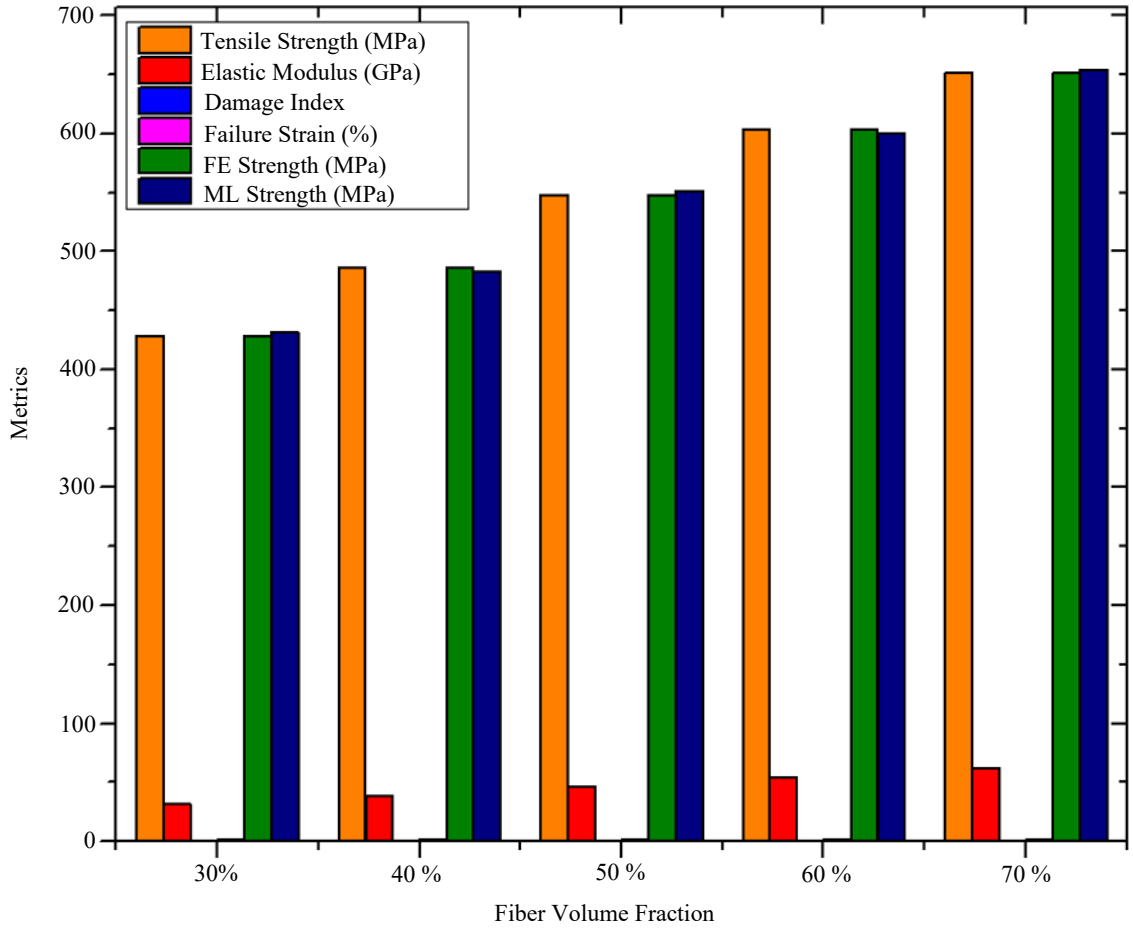


Figure 3. Variation of tensile strength, failure strain, FE prediction, and ML prediction with increasing fiber volume fraction.

Table 3. Progressive damage mechanisms.

Damage mechanism	Damage initiation (%)	Propagation (%)	Maximum damage index	Residual stiffness (%)	FE value	ML value
Matrix Cracking	18.4	42.7	0.46	76.3	0.46	0.45
Fiber Breakage	32.6	68.5	0.72	54.8	0.72	0.70
Fiber–Matrix Debonding	21.7	51.3	0.53	68.4	0.53	0.55
Delamination	27.5	61.8	0.64	61.7	0.64	0.62
Interlaminar Shear Failure	24.8	57.6	0.59	64.2	0.59	0.60

The fiber–matrix debonding is at the median of the spectrum of activities. The damage start value is reduced to about 22 percent while the matching propagation value is still rather high at about 51 percent. This contrast suggests that interfacial failure can be initiated with relatively minor initial damage but can have a large effect on continued erosion of structural integrity. The relatively strong propagation

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response indicates the relevance of the good adherence between the reinforcing fibers and the polymer matrix. A poor interface binding can lead to crack growth and damage transmission from the matrix to the reinforcement. The initiation value of delamination damage is about 27% and propagation value is about 61%. The comparatively large propagation response indicates that delamination of composite layers might be a dominant failure mechanism after start-up. Delamination is of particular significance in composite laminated constructions, as it can limit the efficiency of load transfer between neighboring plies and cause a significant reduction of the overall stiffness of the structure. The graph, therefore, implies that interlaminar stress management and interlayer bonding strengthening may be necessary strategies for improving the durability of composites.

Damage initiates at ~25% and propagates to ~57% for interlaminar shear failure. The beginning value is below the fiber breaking, but the propagation reaction is still important. This tendency implies that local interlaminar strength exceedance may lead to rapid propagation of shear induced damage to neighboring regions. Therefore, interlaminar shear resistance is an important parameter in the evaluation of composite structures under complex loading circumstances. For percentage-based damage initiation and propagation reactions, the highest damage index and the corresponding FE and ML values are found in the lower half of the graph. They are quite little. This implies that such parameters are scaled on a much smaller numerical scale. The closeness of the FE and ML curves demonstrates good agreement between the computer simulation results and the machine learning prediction. This agreement is of high importance as it shows the potential of the ML technique to reproduce significant damage related features found by conventional numerical analysis.

The propagation curve is generally more diversified than the start curve for all the damage mechanisms studied. The largest propagation response is reported for fiber breakage followed by matrix cracking, delamination, interlaminar shear failure and fiber–matrix debonding depending on the metric used. The comparatively large number of propagations points out that the damage evolution is not only determined by the initial threshold of failure. Indeed, the interactions of matrix–fibers–interfaces play an important role in the subsequent damage evolution.

Figure 4 again shows the importance of the coupling of FE simulations with ML based prediction. FE analysis offers a complete description of stress distribution, crack propagation and failure evolution. ML models can learn the relationship between material properties and damage responses. If a good agreement between anticipated findings of the ML and FE results can be found, then the ML model might be used as a faster option for the estimation of damage behavior without the need to repeat computationally expensive simulations. To summarize, as shown in Figure 4, different composite damage processes have variable initiation and propagation tendency. The matrix breakdown occurs at a fairly moderate threshold. The fiber breaking and the delamination are two particularly essential propagation processes. The strong correlation between FE and ML predictions allows the use of machine learning algorithms for fast damage assessment, failure prediction and structural-health evaluation of innovative composite materials. The data can help the researchers to identify the key failure mechanisms and to design more reliable and damage tolerant composite constructions.

Figure 5 describes the comparison of performance of several machine learning (ML) techniques in the prediction of mechanical behavior and damage characteristics of composite materials. The methods evaluated are Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF) regression, Gradient Boosting Regression (GBR) and Hybrid Finite Element – Machine Learning (Hybrid FE – ML) model as indicated in Table 4. Many measurements are used to assess these approaches in terms of performance such as coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), training time, and prediction time. The comparative analysis of these methods offers an in-depth view of the expected accuracy, processing efficiency and practical applicability of various data-driven methodologies. The coefficient of determination (R2) shows the goodness of fit between the expected and actual data. All the models have relatively high R2 values as shown in the graph, which reveals

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that they can learn the complicated correlations between material qualities, damage attributes and mechanical responses. Among the studied models, the Hybrid FE–ML method was proven to have the greatest R2 value indicating an almost flawless prediction accuracy. This work demonstrates excellent progress of the model for nonlinear material behavior and sophisticated damage mechanisms by combining finite element simulations and machine learning methods.

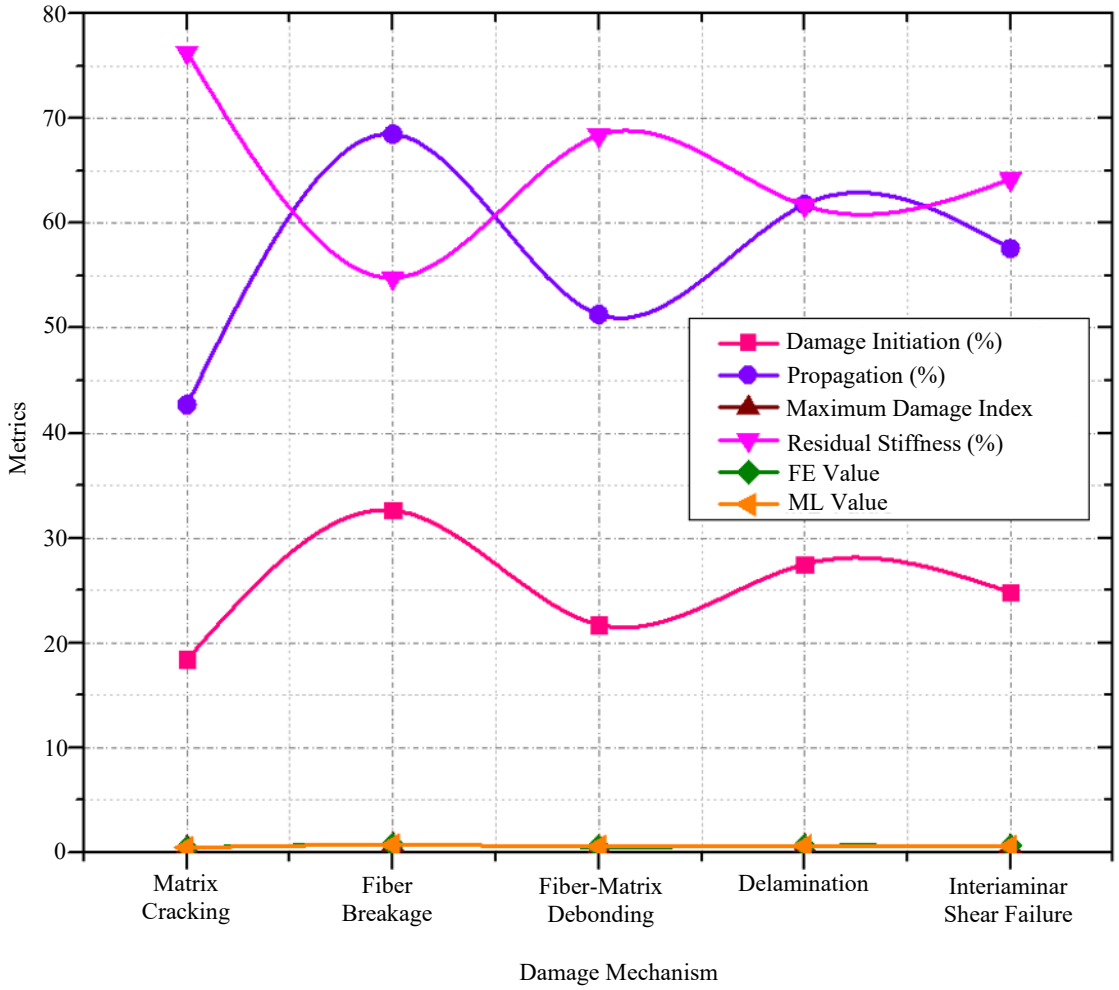


Figure 4. Assessment of damage initiation, propagation, damage index, residual stiffness, and model predictions across mechanisms.

Table 4. Comparison of machine learning algorithms.

ML method	R^2	RMSE (MPa)	MAE (MPa)	MAPE (%)	Training time (s)	Prediction time (s)
ANN	0.972	12.84	9.63	2.41	18.6	0.08
SVM	0.954	16.72	12.47	3.16	11.4	0.12
RF Regression	0.963	15.21	10.84	2.79	7.8	0.06
Gradient Boosting Regression	0.981	10.47	7.91	2.03	9.6	0.07
Hybrid FE–ML Model	0.989	8.36	6.12	1.57	14.2	0.05

More information about quality of predictions can be obtained in error measures like RMSE, MAE, and MAPE. RMSE gives higher variances more weight and hence evaluates overall prediction error. The RMSE value of SVM model is the biggest one, which suggests the prediction error of SVM model is significantly bigger than other approaches. The results show that ANN and RF models have

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small values of RMSE, whereas Gradient Boosting Regression and Hybrid FE–ML models have the lowest RMSE values. The reduction in error means better prediction of the response of the material with the help of ensemble learning and hybrid computational technique. A similar trend is shown with the MAE metric which is the average of the absolute difference between the expected and real value. From the results, the SVM results were with a somewhat high MAE, RF and GBR were with better accuracy. The Hybrid FE–ML model displays its better prediction performance with the lowest MAE. The lower numbers show the consistent and dependable forecast in the different damage scenarios and material circumstances as MAE is less sensitive to outliers than RMSE.

A similar trend can be observed for the MAPE which is the prediction error in percentage terms. The percentage errors of the ANN, RF and SVM models are moderate whereas the values of the Gradient Boosting Regression are lower. Hybrid FE–ML model has smallest MAPE value, i.e., maximum prediction accuracy with minimum relative variation.

In engineering applications, low MAPE values are of significant importance, as it allows the forecast to be valid for different operating conditions and material compositions. The graph also compares training time for computational efficiency. ANN takes the longest time to train because of the iterative optimization approaches used with neural network design. SVM requires a lot of computing power for optimizing the kernel and tuning parameters. Random Forest and Gradient Boosting models have a medium training period; therefore, they represent a trade-off between prediction accuracy and computational cost. The Hybrid FE–ML model shows acceptable training needs even for the finite element information, i.e., the integration approach is still computationally possible.

Another important aspect is the forecast time, particularly relevant when considering real-time structure health monitoring and damage assessment applications. From the graph, we can note that all the models have a low prediction time with some variations between them. The prediction time of the Hybrid FE–ML model is like the standard ML approaches but with substantially improved accuracy. This confirms that hybrid techniques can attain excellent prediction performance without large processing delays.

Overall developments reveal significant trade-offs between accuracy, error reduction and computational economy. ANN models are good at capturing non-linear correlations but take more time to train. SVM is a highly good classifier and regressor but sometimes makes more mistakes. The Random Forest is a balanced model with moderate inaccuracy and computational expense. Gradient Boosting Regression increases prediction accuracy through ensemble learning methods, whereas the Hybrid FE–ML model combines physics-based finite element analysis and data-driven learning.

The better performance of the Hybrid FE–ML model is because it can integrate the physical information obtained from the finite element simulations with the pattern recognition capabilities of the machine learning techniques. Finite element methods provide a lot of information on stress distribution, deformation and damage evolution. It is used to identify hidden relationships in massive data sets. Together these provide a more robust and generalizable prediction paradigm.

From the engineering point of view, the findings suggest that hybrid computation methods can greatly improve damage prediction, structural reliability evaluation and material optimization. Accurate prediction models enable engineers to cut experimental costs, shorten development cycles and increase design efficiency. Furthermore, the short forecast time frames show that these models are useful for real-time monitoring systems, predictive maintenance and intelligent composite structures. Finally, Figure 5 shows that the Hybrid FE–ML model offers the optimal compromise among prediction accuracy, error minimization and computational economy. The results stress the advantages

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of combining numerical simulations with machine learning techniques in the framework of advanced composite materials analysis, damage prediction, and structural health monitoring applications.

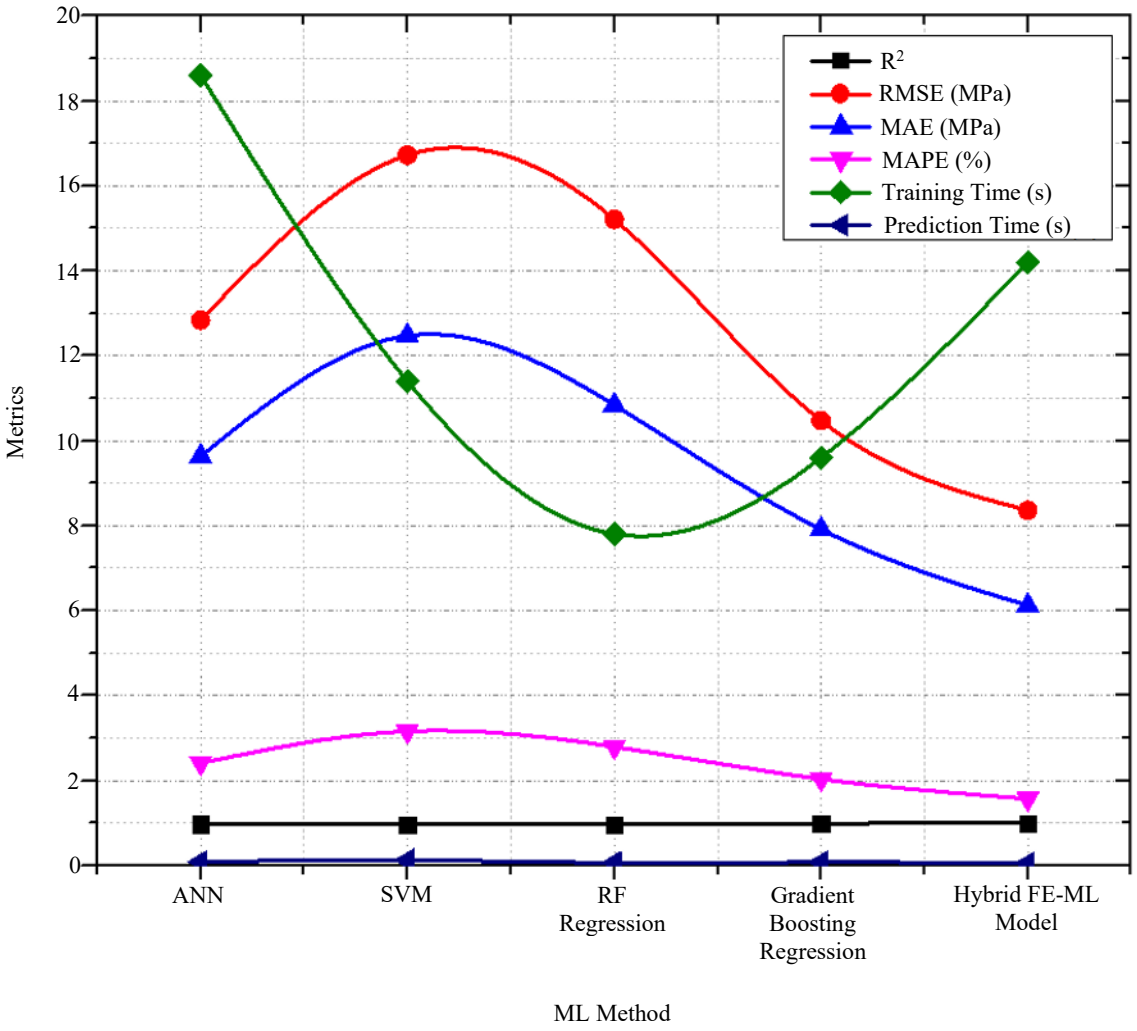


Figure 5. Evaluation of machine learning models using accuracy, error metrics, training time, and prediction performance.

Figure 6 shows the variation of several mechanical and damage associated performance characteristics under five loading situations, viz. uniaxial tension, uniaxial compression, three-point bending, in-plane shear and combined tension-shear. The reported quantities measured are peak stress, peak strain, damage index, failure load, displacement and residual strength. Figure 3 shows a comparison of the structural behavior and damage resistance of the tested material to the different mechanical loads given in Table 5.

The co-existence of these traits is useful to detect the loading conditions leading to maximal strength, deformation, damage and post-failure resistance. For the situation of uniaxial tension, the material exhibits rather high peak stress (around 61 on the scaled vertical axis).

The equivalent residual strength is highest for all loading conditions, at around 68. This suggests that even after the first damage event, the material still has a high load bearing capacity. The failure load is likewise quite high at 48 which means that the material is resistant to tensile failure. The

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maximum strain, the displacement and the damage index are low. Therefore, the tension loading condition is a good compromise between high strength, high residual capacity and minimum damage evolution.

Table 5. Effect of loading conditions.

Loading Condition	Peak stress x 10 (MPa)	Peak strain (%)	Damage index	Failure load (kN)	Displacement (mm)	Residual strength (%)
Uniaxial Tension	61.24	1.82	0.31	48.6	2.14	68.7
Uniaxial Compression	48.76	1.43	0.46	39.2	1.86	57.4
Three-Point Bending	42.18	1.67	0.52	34.8	3.21	51.6
In-Plane Shear	28.65	1.21	0.63	27.4	2.76	43.8
Combined Tension–Shear	39.87	1.58	0.71	31.6	2.94	36.5

The peak stress in uniaxial compression reduces to around 49 and residual strength to about 57. Also the failure load is close to 39. This reduction compared to tensile loading suggests that the material is slightly more prone to damage processes in compression. Compression can decrease the load carrying capacity by local deformation, development of microcracks, debonding at interfaces or internal structural instability. But the material still has a large residual strength, meaning that the damage induced by compression is not enough to completely ruin the structural integrity of the material. The low damage index and displacement also show controlled deformation with this type of loading. The three-point bending condition yields a maximum stress of around 42 and a residual strength of about 52. These values are less than the values under tensile and compressive stress. But the failure load is still at 35. It is important to point out that under the loading circumstances studied the highest value of the damage index is obtained, about 3. This means that bending does more internal damage but keeps the strength small. Bending causes tensile and compressive stresses to appear simultaneously in different areas of the specimen. These forces can start and spread fissures. The much larger displacement also results in more structural deformation. Thus, the three-point bending can be considered as a relevant loading condition for the assessment of the damage tolerance and deformation characteristics of the material.

The in-plane shear is the one that provides the greatest decrease in mechanical properties. The peak stress is reduced to about 29, and the residual strength is about 44. Moreover, the failure load is at the minimum value of around 27. The results reveal that shear loading is an important element for the material investigated. Shear stresses can induce sliding, interfacial debonding, matrix cracking and gradual internal damage leading to loss of load bearing capability. The damage index and displacement are rather mild. However, the large drop in peak stress and failure load shows that shear resistance is relatively limited. However, the remaining strength of ~44 still suggests that a substantial amount of structural capacity remains following injury. The material demonstrates an intermediate response under combined tension–shear stress. The peak stress increases significantly to ~40 from the in-plane shear state and the residual strength decreases further to ~36. The failure load is at most approximately 32. These combinations demonstrate the material has a moderate maximum stress in the case of linked loading but the loading capacity after damage is significantly decreased. The reduction in residual strength shows that the combined action of tensile and shear stresses is more damaging than many isolated loading situations. The simultaneous action of numerous damage mechanisms is possible under such combined strain, and the development of fracture or interfacial failure can be accelerated.

The maximum strain is modest for all loading circumstances and fluctuates only minimally. This means that the material deforms relatively little normally before reaching its maximum stress. The

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displacement parameter shows a similar trend with the maximum value attained under the three-point bending condition. From the experiment data, the bending deformation is more than the other loading types. Also, the damage index is minor for most of the circumstances but increases considerably for the bending condition, which indicates that the material is prone to flexural damage. In general, the results provided in Figure 6 demonstrate that uniaxial tension gives the optimal mechanical response with the largest residual strength and failure load. The uniaxial compression also does quite well but it is not as strong as the tension. The greatest deformation and damage were seen when the three-point bending force was applied. The most critical single loading condition was seen to be in-plane shear loading, which recorded the lowest peak stress and failure load. The coupled tension–shear condition is of particular importance because it exhibits the lowest residual strength, i.e., a large degradation after damage. The results show that one single mechanical test is not sufficient and that numerous loading situations must be tested. The fluctuation of stress, strain, damage index, failure load, displacement and the residual strength observed evidence that the behavior of the material is quite sensitive to the loading configuration used. Such a complete mechanical evaluation can be used to develop more effective materials, to analyze structural stability and to optimize engineering applications in severe conditions of multiaxial loadings.

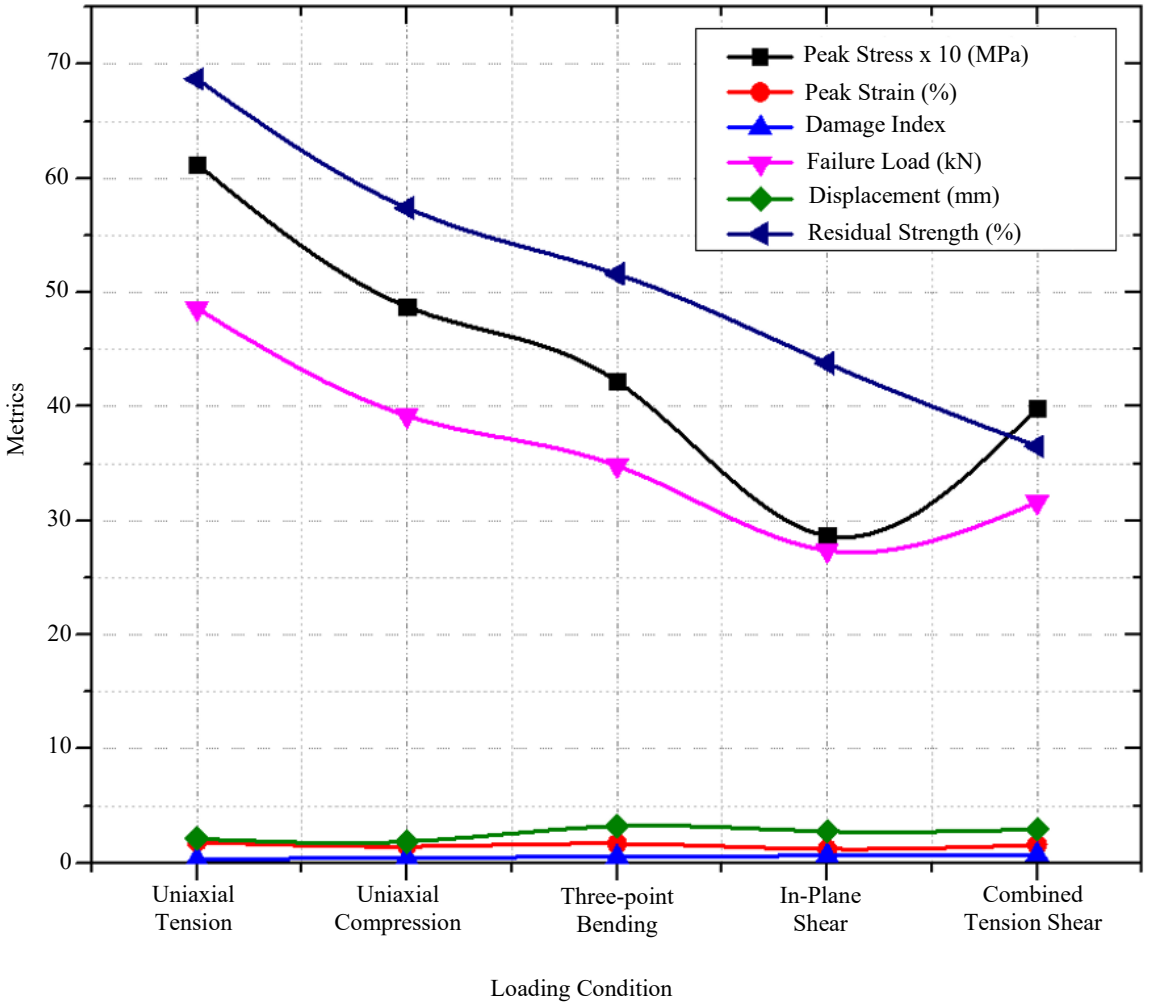


Figure 6. Mechanical response and damage characteristics under different loading conditions of the investigated material.

Figure 7 shows the fluctuation of significant interlaminar mechanical and damage-related parameters for five distinct interface materials, namely carbon, glass, Kevlar, basalt and hybrid carbon–glass. The

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parameters assessed were delamination length, delamination area, energy release rate, damage index, critical load and residual strength. Table 6 provides a detailed comparative study on the behavior of the chosen interlaminar contacts under damage initiation, propagation and subsequent structural loads. Interlaminar properties are of great importance in the assessment of the acceptability of different interface configurations for engineering applications, as they have a significant influence on the overall durability and failure behavior of composite structures. Carbon contact has the maximum residual strength, around 72 per cent. This means that the load bearing capacity of the carbon contact is preserved even after degeneration. The critical load is around 39 kN which is also quite high compared to many of the other interfaces. The delamination length is very little, i.e., 3.5 mm. The area of delamination is about 18 on the graph. The rate of energy release is moderate, and the damage index is moderate. This means that the carbon interface is particularly resistant to interlaminar degradation with high residual structural capability. The combination of high critical load and residual strength provides considerable advantages for this interface in applications with enhanced damage tolerance.

Table 6. Delamination characteristics.

Interlaminar interface	Delamination length (mm)	Delamination area (mm²)	Energy release rate (N/mm)	Damage index	Critical load (kN)	Residual strength (%)
Carbon	3.8	18.6	0.64	0.31	39.6	72.4
Glass	6.7	34.2	0.48	0.52	31.7	56.8
Kevlar	5.9	29.7	0.53	0.47	33.5	61.3
Basalt	4.6	23.4	0.58	0.39	36.2	67.1
Hybrid Carbon–Glass Interface	4.2	21.5	0.61	0.35	37.8	69.6

But the glass interface is not the same. The residual strength is greatly lowered to about 56–57% which is the least residual strength among the first three interfaces. However, the delamination area is significantly increased to around 34 which is the maximum value of the investigated interfaces. And also, the delamination length is around 6.5 mm at the same time, which means the spacing between the interlaminar is higher. The critical load comes down to about 31–32 kN. The results indicate that the damage to the glass interface is more severe and the load bearing capability after damage is worse. The delamination area is quite high meaning that a vast interfacial region can be impacted. This can result in reduced reliability of the structure under repeated or extreme loading conditions. Kevlar interface offers moderate to good responsiveness. The residual strength is enhanced to around 61%, greater than glass interface but lower than carbon interface. The critical load also increased to roughly 34 kN. The delaminated area is slightly reduced to about 30, and the delamination length is about 5.5–6 mm. This behavior reveals that Kevlar has a higher resistance than glass to interlaminar damage at an acceptable critical load. Good combination of residual strength, delamination behavior and important load locations for improved damage tolerance. Hence, the Kevlar interface may be suitable for situations where moderate strength is sought, and resistance to developing interlaminar damage is necessary.

In addition, the residual strength of the basalt contact is raised to about 67%. This figure is close to carbon interface performance. Critical load increases to about 36 kN and delamination area drops to about 23. The delamination length is lowered to 4.5mm. The basalt interface demonstrates better resistance to the transmission of interlaminar damage than glass or Kevlar. The reduced delamination and comparatively high critical load demonstrate the potential of basalt to retain structural integrity under interfacial loading. It shows its ability to carry load after damage has occurred by the enhanced residual strength. The reaction to carbon–glass contact in hybrid structures is of great interest. It has a residual strength of about 69% which is the second strongest of the five interfaces, a little less than the carbon interface. The critical load increases up to about 37–38 kN, indicating a significant resistance of the plies to delamination. The delamination area has further decreased to around 21. The

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delamination length is about 4 mm. The results show that the combination of carbon and glass materials can provide a suitable compromise between damage resistance and residual structural performance. The hybrid interface takes advantage of the complementary properties of the individual materials, leading to an improved resistance to delamination and a high residual strength.

All five interfaces have a very low energy release rate, and the variation of this rate relative to the other characteristics given is rather small. It implies that the energy for interlaminar crack propagation is not as spread out as delamination area or residual strength. Once again, for all interfaces, the damage index is at the bottom of the scale, showing that the main differences between the materials are more obvious in the delamination behavior, critical load and residual strength. From the results, it can be observed that the best residual strength is noticed for the carbon interface while the hybrid carbon–glass interface exhibits a very competitive combination of minimum delamination and high residual strength as presented in Figure 7. The glass interface shows significantly more delamination and poorer residual strength, indicative of poor interlaminar damage resistance. The intermediate performance is provided by Kevlar, and basalt provides great damage tolerance and better residual strength. The results, therefore, show that the choice of material at the interlaminar interface has a substantial impact on the advancement of delamination, the load bearing capacity, and the structural integrity following damage. The hybrid carbon–glass architecture is very well suited for engineering applications where a trade-off between high critical load, less delamination and better residual strength is required.

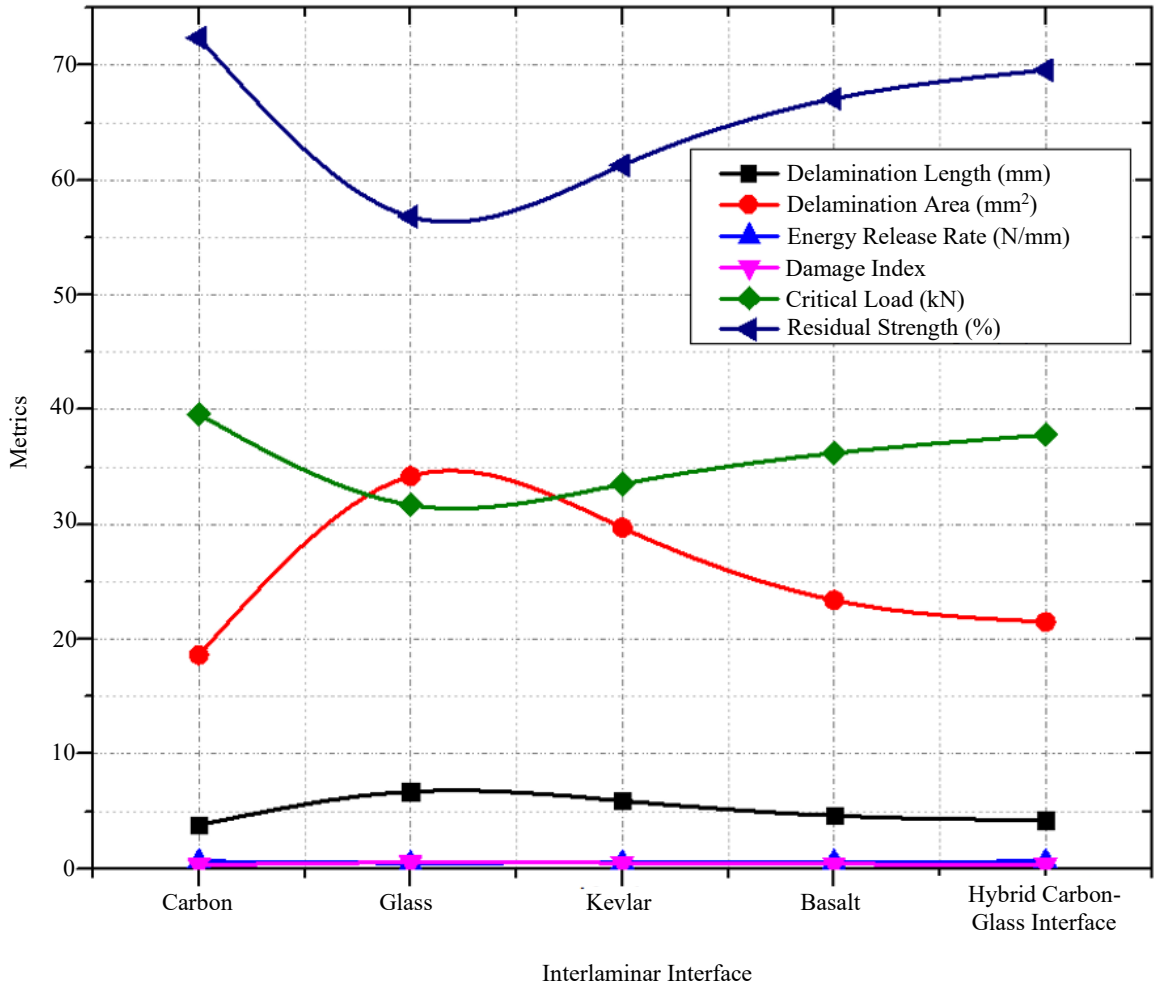


Figure 7. Interlaminar damage, energy release, critical load, and residual strength across different interface materials evaluated.

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Figure 8 compares the prediction of five damage types using FE model and ML model, including fiber tensile failure, fiber comprehensive failure, matrix tensile failure, matrix comprehensive failure and interlaminar delamination. The graphic shows the FE damage value, the ML damage value, the absolute error, the relative error, the coefficient of determination (R2) and the root mean square error (RMSE) together. It includes a detailed analysis of the agreement between the numerical and data-driven estimates in Table 7. The black square curve is for the FE damage values, and the red circular curve is for the ML damage values. These two curves exhibit a fairly good agreement for all the five damage modes. Both methodologies anticipate a value for the damage at failure of the fiber in tension of about 0.67 giving virtually the same forecast. Similarly, the values of FE and ML for complete fiber loss are roughly 0.61–0.62. The good agreement of the two curves reveals a good capability of the ML model to mimic the damage response obtained from the FE simulations.

Table 7. Prediction accuracy for different damage modes.

Damage mode	FE damage value	ML damage value	Absolute error	Relative error (%)	R^2	RMSE
Fiber Tensile Failure	0.682	0.674	0.008	1.17	0.987	0.014
Fiber Compressive Failure	0.614	0.621	0.007	1.14	0.981	0.018
Matrix Tensile Failure	0.473	0.481	0.008	1.69	0.975	0.021
Matrix Compressive Failure	0.528	0.519	0.009	1.70	0.972	0.023
Interlaminar Delamination	0.596	0.604	0.008	1.34	0.979	0.020

In the matrix tensile failure, the damage value drops significantly by around 0.47–0.48. This drop shows that the damage severity estimated for this failure mode is lower than the damage severity observed for the fiber dominated failure types. Again, the curves of FE and ML are practically overlapped which indicates that the ML model can capture the nonlinear variation of the damage behavior successfully. For complete loss of the matrix the values increase dramatically to about 0.51–0.52. A similar trend is observed for interlaminar delamination where the damage value is around 0.59–0.60. The ML projections generally show the consistent growing and declining trends with the FE reference values, implying the strong predictive consistency. The blue triangle curve is an absolute error of the FE and ML forecasts. and so no significant numerical difference is predicted by the two prediction algorithms for any damage scenarios. It is really near to the zero line. The low absolute error is very important since it means that the ML model does not yield large variations from the FE results. The same mistake on numerous failure mechanisms also indicates the trained model is reliable in prediction accuracy, not strong at forecasting a particular damage technique.

The pink line indicates the % relative error. The difference between the damage modes is mainly in the relative inaccuracy rather than in the absolute error. The fiber tensile failure is around 1.15%, and it increases dramatically to approximately 1.3% for the fiber comprehensive failure. In the matrix tensile failure situation, the rise is shown to be significant with the relative error reaching 1.8%. Then it lowers rapidly to roughly 1.7% for matrix comprehensive failure and about 1.35% for interlaminar delamination. But the relative inaccuracy is not constant and is always less roughly 2% in the examples analyzed. It shows that ML model has acceptable accuracy even for the damage mode with the largest relative difference. The green diamond line is the value of R^2. For all five damage modes the values are always high, 0.97–0.99. The R2 value near to unity shows that the ML predicted damage values are in good agreement with the corresponding FE results. Thus, the consistently high values of R2 indicate that the ML model is successful in capturing much of the variation in FE damage levels. The minor difference in R^2 for the damage modes shows that the prediction performance is very similar for different causes of failure.

The blue RMSE curve is near the bottom of the graph which suggests it has a very minimal root mean square error. The size of the projected deviations is the RMSE, and the smaller the value, the better the agreement. This is in line with the conclusions of the absolute-error analysis given its low

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level. Overall, the results shown in Figure 8 reveal that the ML model predicts damage values in a good agreement with the FE results for all the analyzed failure scenarios. The FE and ML curves almost match, showing the good prediction accuracy. The low absolute error, the relative error less than ~2%, the high R2 values and the low RMSE further reflect the good prediction accuracy. The results demonstrate that the ML approach can accurately approximate the damage estimates from FE analysis and is consistent for the fiber, matrix and interlaminar failure sources. The agreement suggests a possible application of the ML model as a computationally efficient alternative for on-the-fly damage prediction and preliminary structural assessment.

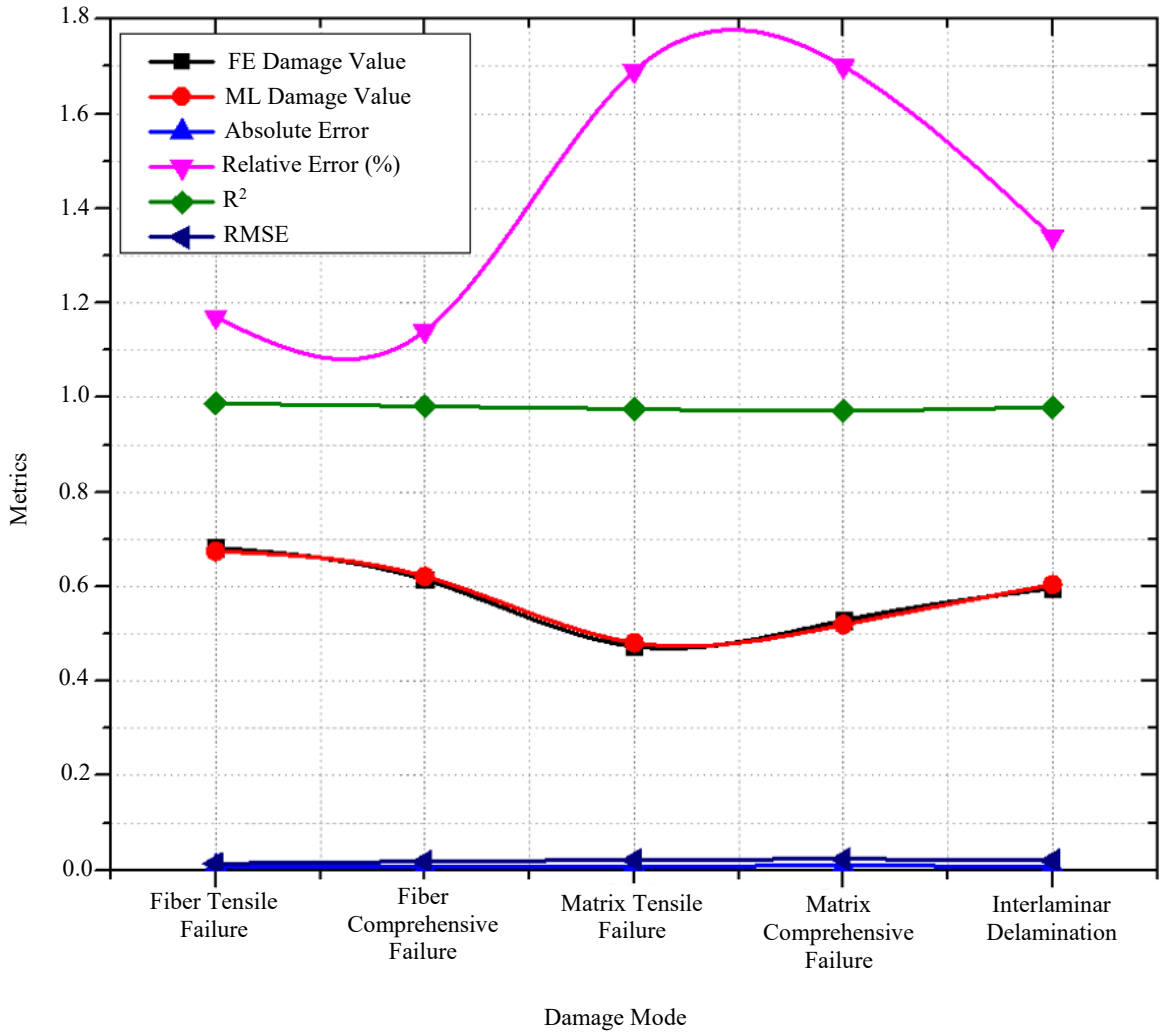


Figure 8. Comparison of FE and ML damage values with absolute error, relative error, R2, and RMSE.

Comparison of the computational performance of five distinct approaches for damage prediction (Full FE Simulation, Reduced Order FE Model, Artificial Neural Network (ANN), Gradient Boosting and Hybrid FE–ML approach) (Figure 9). The comparison is based on five primary prediction parameters: (i) average computing time, (ii) prediction accuracy, (iii) RMSE, (iv) model assessment time, and (v) reduction in computational cost as depicted in Table 8. These features are a fair assessment of the numerical stability and computing efficiency of the proposed prediction system. The first parameter average computation time shows a big difference between classical finite element simulation and simplified or machine learning-based solutions. The Full FE Simulation is the most computationally intensive. This is because of the extensive numerical modeling, mesh discretization,

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material modeling, non-linear solution methods and iterative calculations. In contrast, the Reduced FE Model enables a large reduction of the average processing time by simplifying the computational representation of the system but keeping the important mechanical reaction. After training the models, the FE solution technique does not need to be repeated for the forecasts. Hence, the ANN, Gradient Boosting and Hybrid FE–ML approaches are much less computing time. Such a decrease is particularly helpful when the number of damage incidents to look at is considerable.

Table 8. Computational performance of FE and hybrid ML approach.

Prediction parameter	Full FE simulation	Reduced FE model	ANN model	Gradient boosting	Hybrid FE–ML
Average Computation Time (min)	48.6	21.4	0.12	0.09	0.07
Prediction Accuracy (%)	98.6	96.8	97.2	98.1	98.9
RMSE (MPa)	6.74	11.32	12.84	10.47	8.36
Model Evaluation Time (s)	2916	1284	0.08	0.07	0.05
Computational Cost Reduction (%)	0	55.9	99.7	99.8	99.9

The prediction accuracy metric shows a strong agreement of the reduction and machine learning-based approaches with the reference FE results. The bars for the different reduction and ML approaches are near to each other, indicating that computational acceleration can be achieved without considerable loss of predictive capability. The ANN and Gradient Boosting approaches provide efficient approximations of the FE response. The suggested Hybrid FE–ML technique blends the physical representation of the FE model with the fast prediction capability of machine learning. So, the hybrid technique gives a suitable compromise between numerical purity and computing economy. The quality of the prediction is also characterized by the RMSE parameter, which measures the divergence between the predicted and reference values. The smaller the RMSE, the better agreement with Full FE Simulation. The comparatively low values of RMSEs in the figure suggest that the simpler approaches and ML based methods predict the FE response with a little prediction error. This is significant since a reduction in calculation time only makes sense if the forecasts are still accurate enough. Thus, the lowRMSE values validate the application of these approaches to damage assessment and rapid engineering prediction.

The main difference is the time for the evaluation of the model. The Full FE Simulation takes a lot of assessment time, up to roughly 2900 units in the displayed metric, but the Reduced FE Model takes much less time, about 1250 units. The use of machine learning technologies has considerably cut down the time required for FE-based assessments. This way of thinking is understandable, because ML models are based on the predictions of existing mathematical relationships and not on solving the full governing equations in all the required numerical iterations for each new input condition. The reduction in cost of the last parameter demonstrates the practical benefits of simplified and ML based prediction techniques. The Full FE Simulation is the reference, and the other variations are at different levels of computational savings. The Reduced FE Model leads to a huge decrease in computational cost, whereas ANN and Gradient Boosting produce great reductions due to their fast inference capabilities. The Hybrid FE–ML technique provides a significant reduction of the computing cost by exploiting the knowledge obtained from the FE. Therefore, the hybrid strategy can be quite efficient in reducing the processing cost of repeated high-fidelity simulations.

Overall, Figure 9 clearly shows the trade-off between the computing cost and the prediction efficiency. The full FE simulation is the reference solution but requires more computer resources and evaluation time. The Reduced FE Model is cost effective and has great predictive performance. ANN and Gradient Boosting accelerate the prediction by making immediate data-driven decisions rather than running numerical simulations several times.

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Most importantly, the Hybrid FE–ML technique offers an optimal tradeoff between physical modeling and machine learning efficiency. The proposed framework can anticipate the damage quickly because of its high prediction accuracy, low RMSE, short assessment time, and large computing cost reductions. Computer efficiency is especially useful for parametric studies, optimization, real-time structural monitoring and repeated damage evaluations when the usual FE simulations would be computationally too expensive.

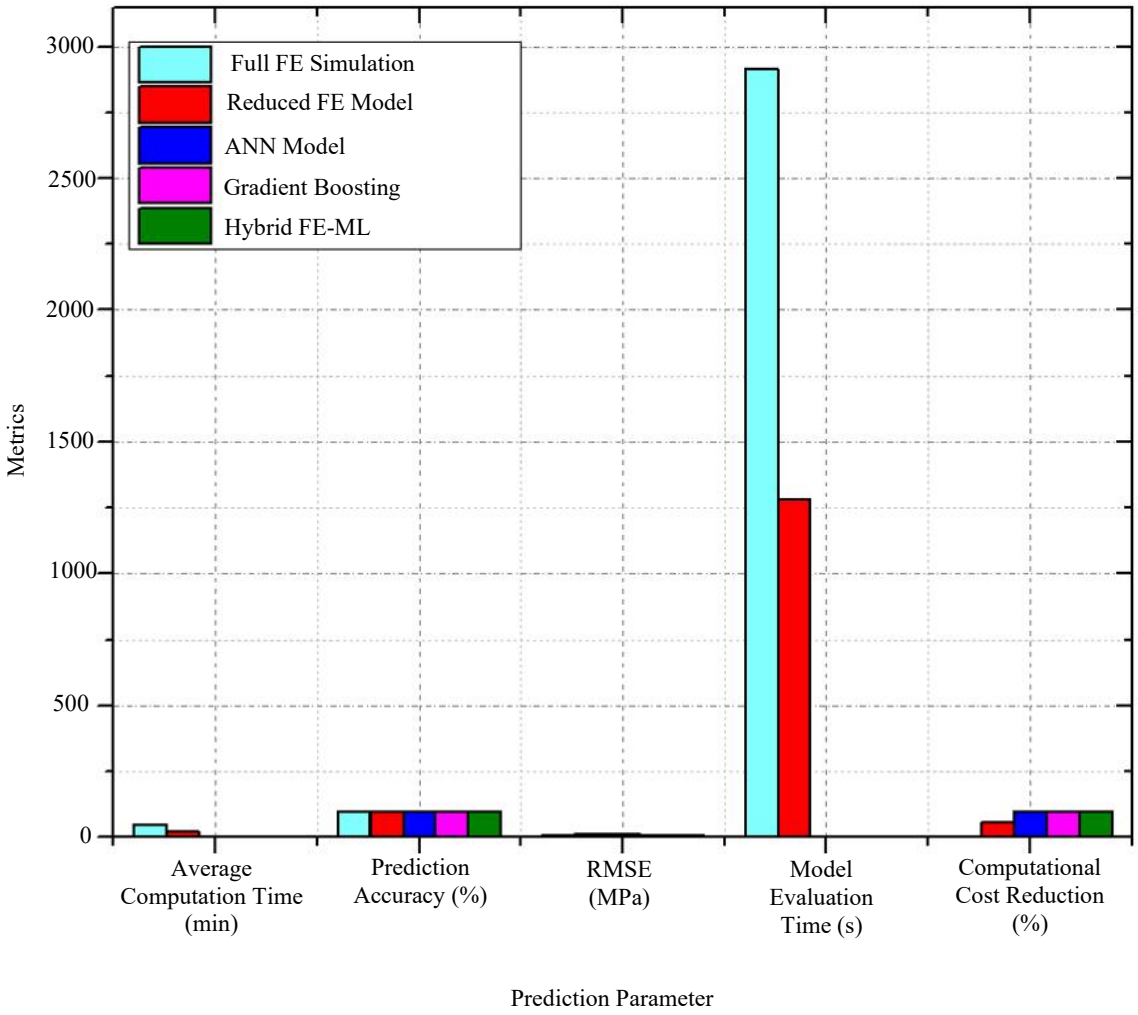


Figure 9. Computational efficiency, prediction accuracy, RMSE, model evaluation time, and cost reduction across approaches.

CONCLUSIONS

In this study, the potential of the combination of finite element (FE) analysis and machine learning (ML) techniques to successfully forecast the damage behavior of fiber-reinforced polymer (FRP) composites is demonstrated. The FE framework offers precise data on the distribution of stress, deformation, damage start, progressive failure and delamination in various material and loading situations. The generated numerical data can be used to train ML models and build nonlinear links between composite characteristics and damage responses.

The hybrid FE–ML approach is the best of the investigated methods, providing accurate predictions and significantly reducing the computing time compared to repeated high-fidelity FE simulations. The results show that the damaged behavior of the composite is strongly impacted by the fiber orientation,

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fiber volume fraction, stacking sequence of the laminate, matrix parameters and loading conditions. The good agreement of FE and ML predictions illustrates the ability of the proposed framework to capture complex failure features with small prediction errors. Therefore, the hybrid approach provides a computationally efficient and reliable technique for quick damage assessment, structural optimization, failure prediction and structural health monitoring of FRP composite components. The suggested framework can also serve as a base for future integration of experimental data, real-time monitoring systems and advanced data-driven algorithms for increasing the safety, durability and performance of composite structures.

Limitations

The proposed structure has few limitations. The reliability of ML predictions largely depends on the quality, quantity and diversity of the training data supplied by FE. The numerical results can also be affected by the choice of material models, failure criteria, mesh characteristics and boundary conditions. Less experimental validation may lower confidence in predictions for complex real-world loading circumstances. Moreover, the present framework may not properly account for the effects of environment, manufacturing defects, fatigue damage, impact loads and material uncertainties. These considerations should be considered in future investigation.

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