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RESEARCH ARTICLE

Critical comparison of potential machine learning methods for lightning thermal damage assessment of composite laminates

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The present study assesses the potential of using machine learning (ML) methods to predict the extent of lightning thermal damage in fiber-reinforced composite laminates using three supervised machine learning (SML) algorithms: (1) linear regression (LR), (2) decision tree (DT)-based, and (3) MLP models. These models were based on the 10 most significant factors that influence the severity of lightning damage, including three current waveform parameters, four material configurations, and three orthogonal electrical conductivities of each composite. All models demonstrated good performance with coefficient of determination (R^2) values between 0.84 ~ 0.96. The multilayer perceptron (MLP) regression model trained with the lightning matrix damage dataset showed the most promising results ($R^2 >$ 0.94). Additional hyperparameter optimization was performed to improve the prediction performance of the baseline MLP model. The hyperparameter optimization (Adam optimizer, tanh activation function, and three hidden layers with 234 neurons) slightly improved the performance of the baseline MLP model by ~0.02, but achieved faster convergence. This result suggests that the baseline MLP model trained with the lightning matrix damage dataset is sufficiently accurate and robust. This paper highlights that ML-informed regression models can serve as an efficient first pass-estimator of lightning matrix damage in composite laminates, potentially reducing the amount of extremely time-consuming and expensive laboratory-scale lightning tests or streamlining the development of complex lightning damage models for future design.

Keywords: Lightning damage assessment; supervised machine learning; multilayer perceptron; composites

1. Introduction

Completing experimental lightning strike testing on composite materials is extremely expensive and time-consuming. This means accurate characterization of lightning damage resistance is challenging. In addition, there is no standard measure or method to assess lightning damage. This presents significant challenges in understanding complex lightning interactions and damage mechanisms. As such, this can limit the design of new generation, high-performance aerospace structures.

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Lightning has been standardized into four discrete Waveforms A–D used for both experimental and simulation-based research. Waveform A is characterized as the first return stroke; Waveform B is the intermediate current; Waveform C is the long continuing current; and Waveform D is a subsequent stroke [1]. Each waveform can be defined using six parameters; peak current, I_{peak} (kA), the rise time from 10% to 90% of the maximum current, T_1 (ms), the time to reach the post-peak value of 50% of the maximum current, T_2 (ms), the peak rate-of-rise (kA/ms), the charge transfer (C), and its action integral (A^2s).

Experimental and simulation-based research has been conducted on the effects of lightning strikes on composite materials [2–10], with the greatest volume of works conducted using the component A or D waveforms. Much of this work has been focused on the experimental investigation of new lightning strike protection systems (LSPs) [11–14] or has attempted to replicate experimental conditions with simulations of differing fidelities [6,7,9] due to the high cost of simulated lightning testing. Typical lightning damage in composites can be categorized into three groups: (1) fiber damage, (2) matrix damage, and (3) through-thickness penetration damage [6,9].

In parallel to experimentation, lightning strike simulations, specifically Finite Element Analysis (FEA), have been developed for several years to reduce the amount of experimental testing required [6,7,9]. Broadly speaking there are four types of simulation; thermal-electric [6,9,10], pressure loading [15–18], thermal-expansion [19], and most recently a combination of these approaches [20]. The majority of simulation works have considered only unprotected specimens with no LSP. Conventional lightning damage models are developed using deterministic material properties (i.e. no spatial variation) and predict the severity of lightning damage based on the temperature history of the matrix. For instance, the models predict minor or moderate thermal damage when the maximum temperature of an element reaches matrix thermal decomposition temperatures (i.e. 300 ~ 400°C) and severe damage if the temperature exceeds the decomposition temperature (>500–600°C) [21]. Recently, Shah and Lee [6] proposed a Stochastic Lightning Damage Model (SLDM) to predict lightning thermal damage in carbon fiber/epoxy composites with random material property distributions. The SLDM predicted unsymmetric lightning thermal damage in the composite specimens, which closely matched the experimental results. Charhar et al. [22] investigated the effects of material and geometric uncertainties on lightning damage in composite specimens in a hybrid stochastic modeling framework. The authors concluded that the longitudinal electrical conductivity of the composite was most sensitive to lightning damage, followed by other electrical, thermal, and geometric parameters. While these FE models are less financially expensive than lightning strike tests, some can have significant computational expense and require temperature-dependent material properties, which are challenging to characterize experimentally. Therefore, it can be advantageous to use alternative models, such as machine learning (ML) methods, which may not require the same level of experimental testing or computational expense.

Machine learning models have been used in a variety of applications including drilling [23,24], assessing thermoelectric performance of nanocomposites [25], and structural health monitoring [26]. Supervised machine learning (SML) models are a subset of ML models that use a labeled dataset, which includes input features or independent variables and output label or dependent variables, to train algorithms to predict numeric data (regression [27]) and categorical data (classification [28]). The three most common SML models available in literature for a regression task are linear

regression (LR), decision tree (DT)-based, and multilayer perceptron (MLP) regression models. A LR model [29–31] uses one or more independent variables/features to predict a dependent variable or an output feature. The model seeks to minimize an objective function and avoid overfitting, most commonly by regularization [32], by adding a penalty term. Ribeiro Junior et al. [33] recently conducted a review on the use of ML for damage assessment in composite structures. A DT is a non-parametric SML model [34,35] that has a hierarchical tree-like structure consisting of three types of nodes: root, decision, and leaf nodes. A DT follows a top-down approach with binary splitting from the root to leaf nodes using pre-defined criteria to split the data at each step. Sanz-Corretge et al. [36] used a multi-stage algorithm for the design of composite sandwich panels subjected to multiple manufacturing rules. An MLP model is a fully connected feedforward artificial neural network (ANN), consisting of input, hidden, and output layers, each containing several neurons [37–40]. Weights and biasing are parameters used to scale input values or adjust the input feature before an activate function is applied. Fernández-Fdz et al. [41] used an MLP model to predict the behavior of carbon fiber reinforced polymer (CFRP) during high-velocity impact.

To date, ANNs or other data-driven models have not been implemented extensively to predict lightning damage on composite specimens. The present study, for the first time, investigates the potential use of SML models to predict the extent/area of lightning thermal damage with approaches based on regression analysis. The three most common SML models (Figure 1) are developed to predict the extent of lightning thermal damage in CFRP and glass fiber reinforced polymer (GFRP) composites. Previous works have shown that the current waveform parameters [22,42–44], specimen dimensions [10,45] and specimen electrical conductivity [10,45] are the most influential factors affecting thermal damage post-lightning strike, established either experimentally or via simulation. Recently, Monte Carlo-based simulation of input variables to predict lightning damage was completed [22] and has further informed the choice of input variables herein. It has also been reported in several works that the thermal conductivity has a negligible effect on lightning damage [42–44], therefore this property was ignored in the analyses herein. As such, these SML regression models are based on the 10 most significant factors influencing the severity of lightning damage in composite specimens.

This paper evaluates the reliability of these ML-informed lightning damage prediction models for composite materials and highlights the potential for applying ML in lightning thermal damage assessment.

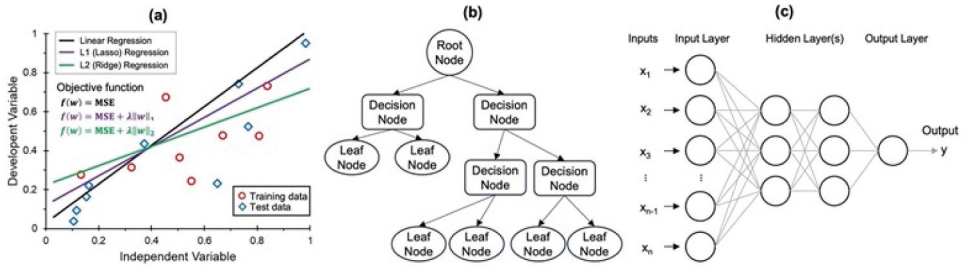

Figure 1. Schematic of three SML models used for lightning damage regression problems: (a) standard and regularized LR models, (b) a DT model, and (c) a MLP model.

2. Model development

2.1. *Database development*

Fiber-reinforced composite laminates, when subjected to lightning strikes or high impulse current waveforms, show three distinct damage modes: (1) fiber damage, (2) matrix damage, and (3) penetration damage. Epoxy matrix degradation typically occurs between 300°C and 800°C while carbon fiber damage occurs at temperatures greater than 3000°C [6,9,46–50]. Therefore, it has been widely acknowledged that so-called matrix damage, indicating lightning thermal damage, is the most significant among various lightning damage modes [20], and a good indication of the overall extent of damage. In general, matrix damage indicates matrix thermal decomposition, melting, burn-out, and char formation, resulting from the lightning strike. This damage mode is illustrated in Figure 2. In order to create a lightning damage dataset for analysis, it was necessary to review the results and data available in open literature. In most cases, the authors quoted values for damage areas directly, therefore, these were taken from the source. However, in cases where only damage images were provided, these were processed to determine numerical values for the damage areas. Differentiating techniques such as image binarization were used on the top-down photographs from literature. Damage regions were highlighted, the image was converted to black and white and a simple script was used in MATLAB to determine the relevant areas in square millimeters. This method is commonly used as a quantitative lightning damage assessment [20].

Lightning damage to polymer matrix composites depends on both interacting and competing factors like the lightning current waveform parameters, material configurations, and the material's intrinsic properties. Note, among various material properties, in-plane and out-of-plane electrical conductivities are found to be the most critical properties in influencing lightning damage development [48]. Therefore, the present study considers only three orthogonal electrical conductivities as representative material properties for damage prediction.

Table 1 provides a summary of an original dataset for lightning damage matrix used in the present study, constructed from 41 sources in literature [4,8,11,12,14,42,43,46,50–83]. This dataset is the first of its kind in the field of lightning strike research and as such, represents a vast quantity of mainstream published lightning test data which can be suitably interpreted for model preparation.

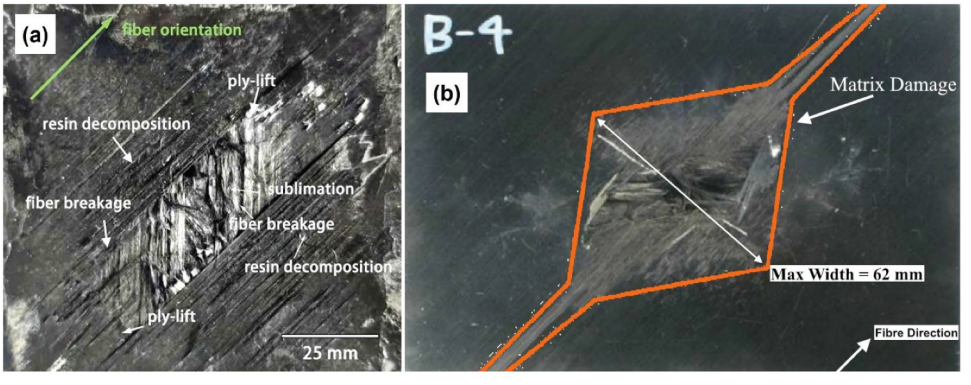

Figure 2. Representative lightning (a) damage types and (b) thermal matrix damage area in fiber-reinforced composites [8,53].

Table 1. Lightning matrix damage dataset used in regression analyses.

Variable	Data Type	Unit	Values*
Peak Current	Numerical	kA	10~189
Rising Time	Numerical	μs	0.5~40.3
Decaying Time	Numerical	μs	10.5~350
Material Type*	Categorical		CF/PA6, CF/BMI, CF/Epoxy, CF/PANI, CF/PEEK, GF/Epoxy
In-plane Dimensions	Numerical	mm^2	13,500~275,000
Laminate Thickness	Numerical	mm	1.84~7
Number of Plies	Numerical		8~48
Longitudinal electrical conductivity	Numerical	S/mm	1.6~36
Transverse electrical conductivity	Numerical	S/mm	3.24×10^{-6} ~ 34.12
Through-thickness electrical conductivity	Numerical	S/mm	7.94×10^{-7} ~ 0.074
Lightning matrix damage area	Numerical	mm^2	20~19,738

*Minimum and maximum values are given for numerical variables and all levels are provided for a categorical variable.

The dataset had a total of 98 data points and consisted of 10 input variables and the corresponding lightning matrix damage area. As shown, the 10 most significant factors that determine the extent of lightning damage in CFRP and GFRP composites were considered as input variables including: (1) *three* current waveform parameters (peak current amplitude, I_{peak} (kA), rising time, T_1 (μs), and decaying time, T_2 (μs)), (2) *four* material configurations (material type, in-plane dimensions, thickness, and the number of plies), and (3) electrical conductivities of composite materials in three orthogonal directions. All input variables, except for the material type, are numerical, so their minimum and maximum values are given. The material type is categorical with six levels, each indicating fiber/matrix composites (i.e. CF/PA6 refers to carbon fiber reinforced PA6 matrix composite). For regression analysis, a categorical variable should be transformed into a dummy numerical variable. In this study, categorical encoding was applied to convert the 'material type' variable into a numerical format (1 ~ 6). The lightning damage dataset used in the present study consisted of 10 input variables (Table 1) and one output variable (lightning matrix damage in composites). Figure 3 shows the relationship between representative input variables and the corresponding lightning matrix damage area. As shown in the figure, the raw data are highly scattered, and there are no clear trends observed between a pair of input and output variables. This poses significant challenges to develop an accurate SML regression model.

A correlation matrix is useful to evaluate the relationship between two input variables in a given dataset. Thus, a correlation matrix was constructed to analyze the relationships among all input variables for lightning thermal damage. Figure 4 shows the correlation matrix developed from the lightning matrix damage dataset. In the figure, each cell in the matrix contains a coefficient (1) ranging from −1 (very strong negative correlation) to +1 (very strong positive correlation) with 0

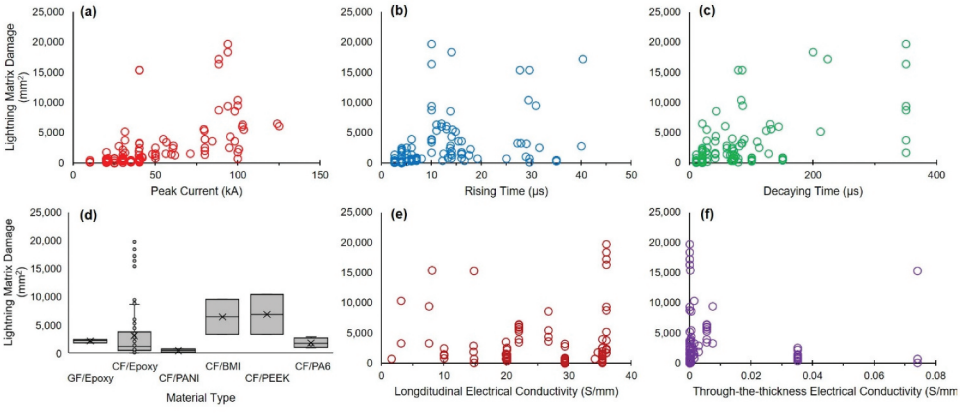

Figure 3. Relationship between representative input variables and lightning matrix damage of an original dataset ($N = 98$): (a) peak current amplitude, (b) rising time, (c) decaying time, (d) material type, (e) longitudinal electrical conductivity, and (f) through-the-thickness electrical conductivity.

indicating no correlation between the two variables. Both correlation matrices show neither high positive nor negative correlation between the input variables. This is important since highly correlated independent variables can cause multicollinearity, which poses challenges to interpret the results of regression analysis [32]. As shown in the figure, there is no correlation between any pair of input variables. Thus, no multicollinearity issues exist in the lightning thermal damage dataset. This implies two significant hypotheses: First, linear ML models (i.e. linear regression) may not be the best choice as they require some level of correlation between input and output variables. Second, no correlation between input variables indicates that any input variable may contribute independently to the output variable, thus feature importance measurement can be straightforward.

2.2. *Dataset cleaning*

Lightning waveform characteristics, material configurations and thermal-electric properties, and a quantitative assessment of lightning damage in the composite specimens are all different across each of the published sources used in this work. The inclusion of potential outliers in the raw dataset can affect the accuracy of a regression model. Thus, the output variable corresponding to measured lightning damage areas may contain intrinsically scattered data points, reducing the reliability of the models. In this work, an interquartile range (IQR) method was applied to detect and remove outliers from a given dataset to enhance modeling reliability. The IQR was calculated as the difference between the third quartile (Q3) and the first quartile (Q1), i.e. IQR = Q3-Q1. Any data points smaller than the lower bound ($Q1 - 1.5 \times IQR$) and greater than the upper bound ($Q3 + 1.5 \times IQR$) were considered to be outliers and were removed from original dataset. In this work, nearly 10% of the original date points were considered as outliers. Therefore, the resulting matrix dataset had a total of 87 data points.

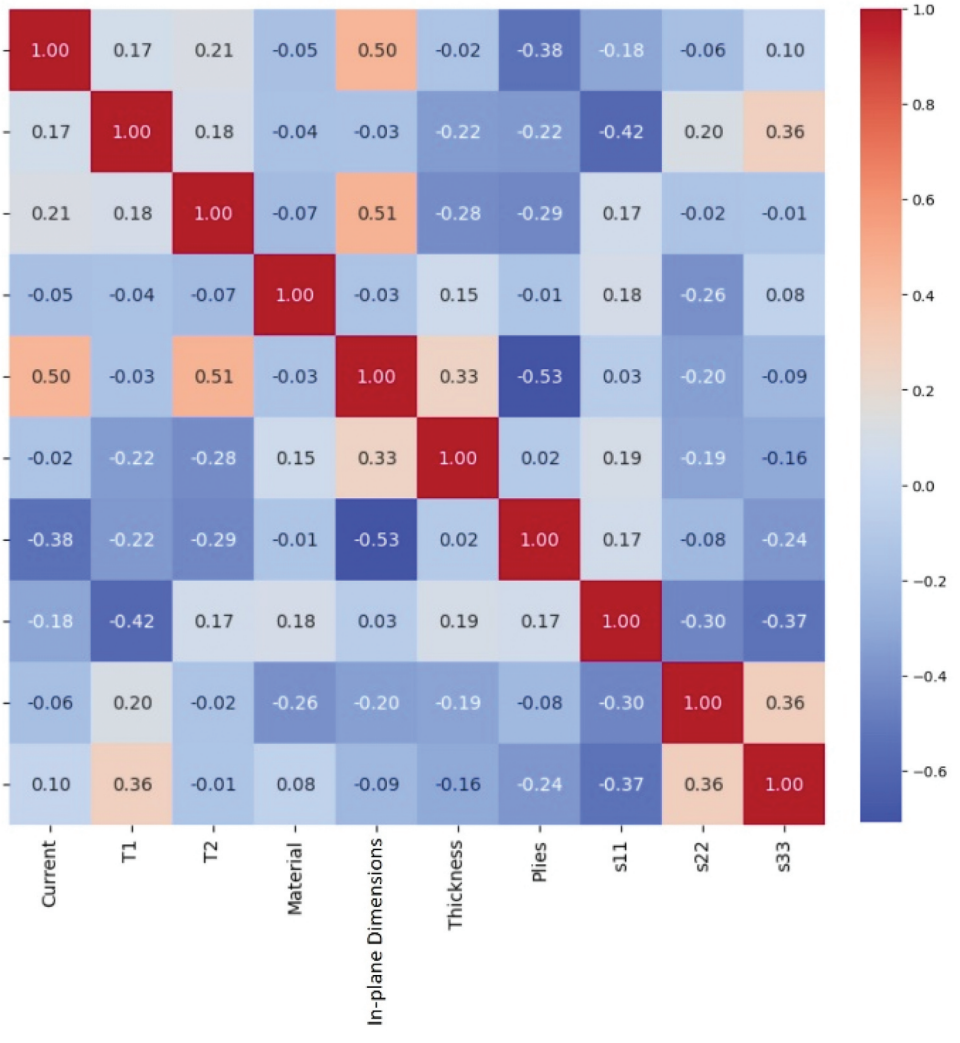

Figure 4. Correlation matrix determined from lightning matrix damage dataset showing interactions between each input variables; a higher positive/negative value refers to strong positive/negative correlation.

2.3. *Regression models*

In this work, all baseline SML regression models were built and tested using a scikit-learn application programming interface (API) [84] with default model parameters. Once the best baseline model was identified, additional hyperparameter optimization was performed based on the best baseline model. Brief details on each SML regression model are now provided, while more details on multiple regression models implemented in scikit-learn API are available in reference [84].

2.3.1. *LR models*

As discussed earlier, a multiple LR model uses more than two independent variables to predict a dependent variable. The prediction is performed based on objective function minimization. Among various objective functions considered in LR models, mean squared error (MSE) is the most common objective function, regardless of univariate or multivariate analysis. Overfitting is a common problem in regression analysis, causing poor generation, and inaccurate prediction on new (untested) data. Overfitting can occur due to various factors, such as the complexity of a regression model, the size of a dataset relative to the number of input variables, and the noise in the dataset. Regularization (i.e. L1 and L2) is a technique to avoid overfitting of a regression model by adding a penalty term to an objective function. In this work, three scikit-learn classes [84] were used to develop standard and regularized LR models, predicting lightning matrix damage in composites: (1) *LinearRegression*, (2) *Lasso* with L1 regularization, and (3) *Ridge* with L2 regularization.

2.3.2. *DT-based models*

Both DT and random forest (RF) models were built using scikit-learn *DecisionTreeRegressor* and *RandomForestRegressor* classes, respectively [84]. In DT-based regression models, key model parameters defined in the decision include (1) an objective function, (2) two data points required to split a decision node, and the maximum depth of the tree (defined as the number of the longest path from root to leaf nodes). Figure 5 shows the DT, constructed using the lightning matrix damage test

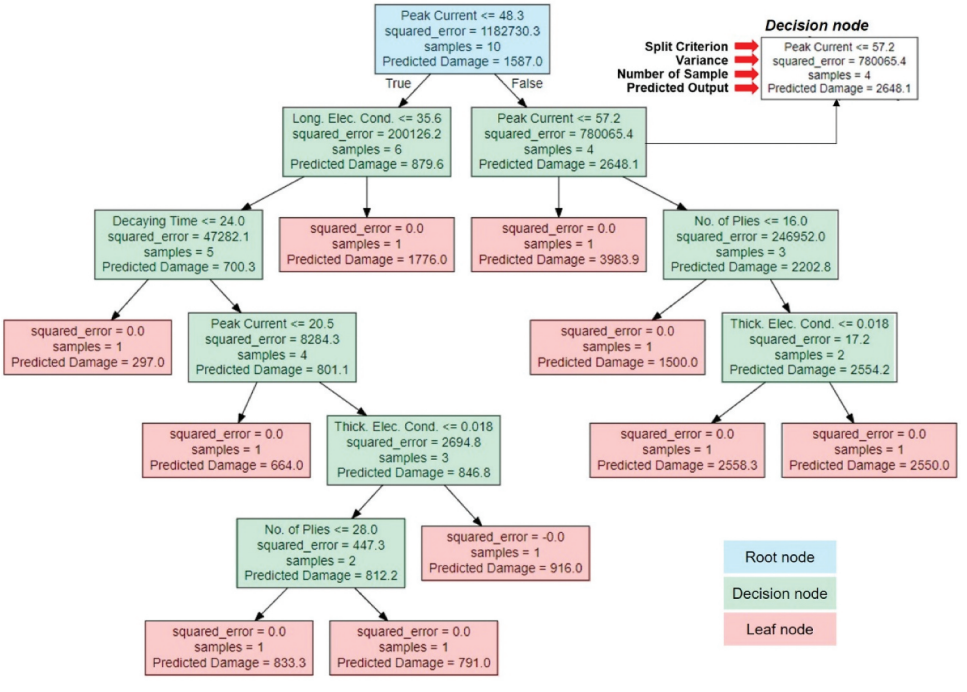

Figure 5. DT architecture constructed using the lightning matrix damage testing data ($N = 10$).

dataset (N = 10) with the maximum tree depth of 6. The weighted average variance of decision nodes was used as a splitting criterion for reference purposes. In this work, an RF regression model was created from 100 decision trees (each hierarchy similar to Figure 5) with identical model parameters under uniform averaging. As shown in Figure 5, root node (blue) has peak current as the input feature with 10 samples; the split criterion is used to find a split point (peak current ≤48.3) that minimizes the variance (some of squared error) of the predicted lighting matrix damage in the resulting subset. This split creates two decision nodes (green), each representing a subset of the data, where the variance in the predicted lightning damage area is reduced compared to before the split. As shown in the figure, the variance decreases from the root to leaf nodes. The split continues recursively. At each decision node, the variance within each subset is minimized until no further splits improve the variance reduction significantly or if other stopping criteria are defined. Lead node (red) includes the predicted lightning matrix damage from a single data point (thus zero variance).

2.3.3. *MLP models*

A baseline MLP regression model (Figure 6) was developed with one input layer, 100 hidden layers, and one output layer. A rectified linear unit function was used as an activation function in the fully connected hidden layers for each lighting damage dataset. A stochastic gradient descent (also called Adam optimizer) was used to update the weights for neurons at each epoch (iteration) in the training process.

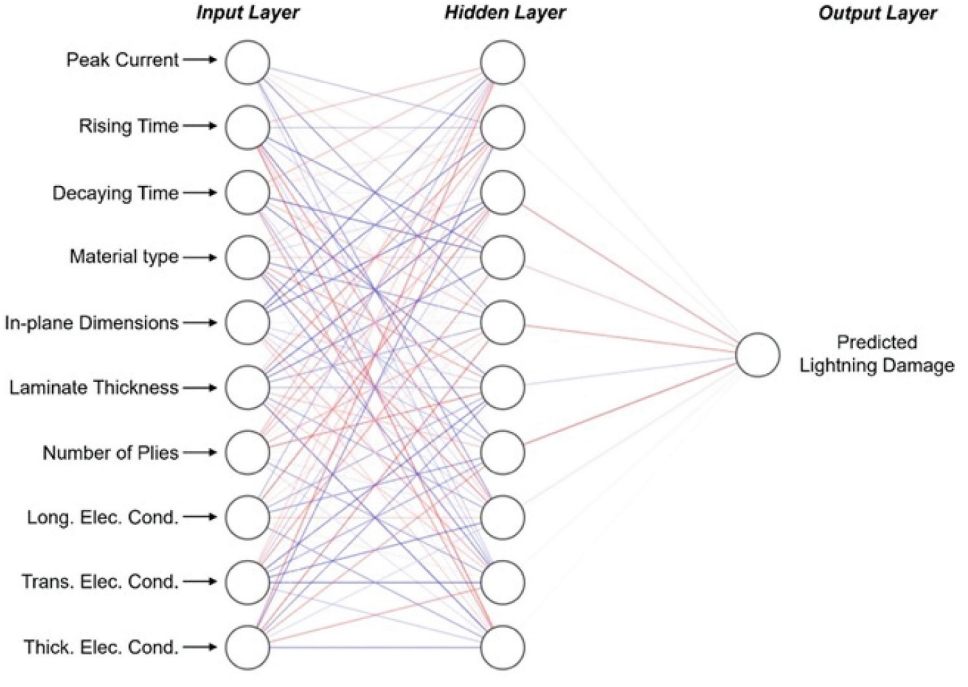

Figure 6. Schematic of a baseline multilayer perceptron model developed for lightning damage prediction in composites.

Some key parameters implemented in this baseline model include a regularization parameter $\lambda_1 = 0.0001$, mini-batch size $|B| = 200$, a constant running rate $\eta = 0.001$, exponential decay rates $\lambda_2 = 0.9$ and 0.999 for two moment vectors, and a numerical stability parameter $\varepsilon = 10^{-8}$.

3. Results and discussion

3.1. *Optimal data splitting*

The processed matrix damage dataset was split into training and testing subsets. Dataset splitting is important and necessary in ML to avoid overfitting of the training dataset. It is well known that small-scale validations (i.e. small training and testing data points) give a greater variance in performance statistics, thus the training-to-testing data ratio must be optimized to ensure good model performance. The rough standard for a training-to-testing data split ratio is 60–90% training data and 10–40% testing data [85]. Figure 7 shows the coefficient of determination (R^2) of the lightning matrix damage test data obtained using the baseline regression models with various train-to-test data split ratios. The optimal training-testing data splitting ratio was found to be 9:1, for all bar one of the models studied. Note that the original lightning matrix dataset had 87 data points after the IQR data filtering (refer Section 2.2 Dataset Cleaning). Thus, the 9:1 training-testing data splitting ratio makes 78 and 9 data points for each training and test datasets. Thus, this ratio was used for all regression analyses presented in the following sections.

3.2. *Feature importance*

Feature importance indicates a technique to determine a score for all features (input variables) for a given SML model. The score is given between 0 and 1, with a higher score indicating a greater contribution to the model prediction (i.e. predicted lightning

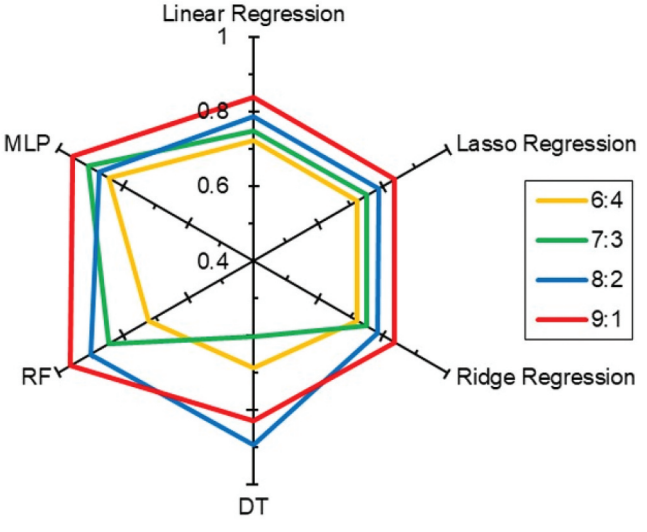

Figure 7. Lightning matrix damage testing dataset R^2 values obtained from various training-to-testing data split ratios.

damage area). The sum of feature importance scores associated with input variables is often normalized to 1, indicating the relative importance of each feature.

In DT and RF models, a feature importance score is calculated based on the amount of each feature (input variable) contributed to reducing the impurity at each node of the tree. For instance, the impurity is variance (i.e. mean absolute error in Scikit learn) for a regression problem. Impurity reduction is calculated when the dataset is split. For a given input variable, the importance is the sum of the impurity reductions across all nodes and normalized by the sum of all feature importance scores. A RF model computes the feature importance score by averaging the importances across all the trees in the forest. The feature importance of a RF model can be calculated as follows [84]:

$$FI_{RF_i} = \frac{1}{T}\sum_{j=1}^{T} FI_{DT_i}^{(j)} \tag{1a}$$

$$FI_{DT_i} = \sum_{t} f_i(t)\Delta I_t \tag{1b}$$

$$\Delta I_t = I_n - \left(\frac{N_{nl}}{N_n} I_{nl} + \frac{N_{nr}}{N_n} I_{nr}\right) \tag{1c}$$

where FI_{RF} and FI_{DT} each refer to the feature importance score of RF and DT models; T is the total number of DTs; ΔI_t is the reduction in impurity due to binary (left and right) child node split; $f_i(t)$ is the indicator function, i.e. 1 if feature is used in split and 0 otherwise; I_n, I_{nl}, I_{nr} and each denote the impurity/variance at the parent node n and the child nodes n_l (left) and n_r (right), respectively; N_n, N_{nl}, and N_{nr} are the number of samples in the parent node and its child nodes, respectively.

Figure 8 compares the feature importance scores of all input variables associated with lightning matrix damage in CFRP and GFRP laminates after outlier removal. Feature importance scores were computed using a baseline RF regression model. Of all input variables, the in-plane dimensions and the peak current amplitude are the two most significant factors determining lightning thermal damage in the composites. One important observation from this feature importance analysis is that lightning thermal damage in composites is more sensitive to current waveform parameters and specimen geometry

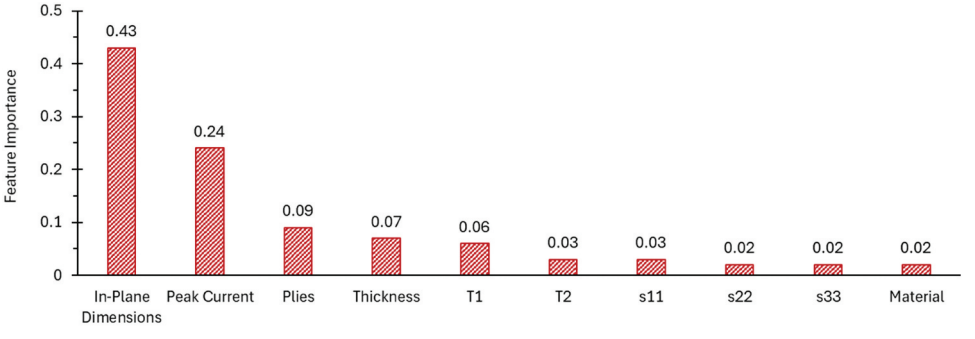

Figure 8. Feature importance analysis performed for lightning thermal damage dataset after outlier removal.

than composite electrical properties. This follows logically since the amount of electrical energy injected into the composite is extremely high and corresponding simultaneous lightning damage is a strong function of several current waveform parameters. It has been reported in open literature that lightning damage evolution in composite materials is highly influenced by in-plane electrical conductivities (s11 and s22 in Figure 4). This statement is true only when the in-plane electrical conductivity varies and other parameters are fixed. As such, the feature importance analysis suggests that overall lightning thermal damage is highly dependent on the current waveform parameters. In addition, the orthotropic nature of composite material properties determines the shape of the lightning damage, which is primarily associated with current and heat conduction paths.

3.3. *Baseline model performance analysis and optimal model selection*

Baseline model performance was evaluated using a testing dataset. Figure 9 compares lightning matrix damage R^2 values from all baseline regression models. All models demonstrated good performance with R^2 values between 0.84 and 0.96. In particular, both RF and MLP regression models exhibited superior regression performance with $R^2 = 0.96$ for lightning matrix damage prediction.

Considering the overall regression model performance for all lightning damage modes, the MLP model was found to be the best baseline model. Thus, this model was taken forward and enhanced using additional hyperparameter optimization to further improve its accuracy and robustness.

3.4. *Hyperparameter optimization of MLP model*

As mentioned earlier, a lightning matrix damage dataset was compiled from 40+ different studies, each with discrete experimental platforms related to lighting testing conditions, specimen configuration, and damage assessment techniques. Therefore, it is challenging to ensure the robustness of the lightning dataset. As such, an additional MLP model was trained and tested on the lightning thermal damage dataset through intensive hyperparameter optimization. Although not included in this paper, the preliminary hyperparameter

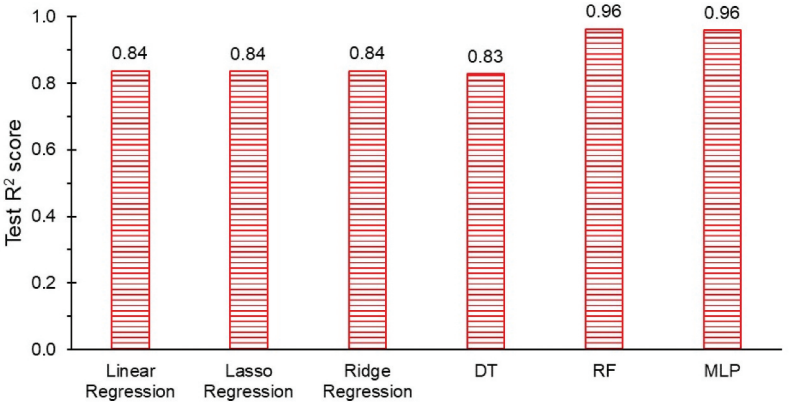

Figure 9. Baseline regression model performance when trained with lightning matrix damage dataset.

optimization was performed with a combination of various optimizers, activation functions, learning rates, and hidden layer architectures (Table 2), selected for potential model performance improvement, with several configurations per hyperparameter, i.e. more activation functions, various numbers of neurons (1 ~ 5* Ntrain), and hidden layers (1 ~ 5). In this work, the three most significant configurations for each hyperparameter were included. The hyperparameters considered herein include (1) three optimizers (lbfgs, sgd, and adam), (2) three activation functions (logistic, relu, and tanh) chosen based on model performance, (3) two learning rates (constant and adaptive), and (4) various hidden layer sizes (three hidden layers with $1 \sim 3 \times N_{train}$ neurons). It is worth noting that a hidden layer size is associated with the number of neurons and hidden layers. The number of neurons in a hidden layer was based on the number of training data points (N_{train}), and thus this was different for each lightning damage model. MLP models with hidden layers ranging from 2 to 4 were considered herein. Table 2 provides the hyperparameter optimization parameters and their values determined from each lightning damage dataset. A detailed description of each hyperparameter can be found from reference [84]. The resulting optimal MLP model is composed of three hidden layers with 234 neurons ($3 \times N_{train} = 78$) and trained with an Adam optimizer, tanh activation function, and adaptive learning algorithm.

Figure 10(a) shows the training loss of the lightning matrix damage dataset with respect to the number of iterations (or epochs), obtained from the optimal MLP models (see Table 2). In this work, the mean squared error (MSE), which measures the average of the squares of the errors, was used as a loss function. During the training process, the loss function was minimized by updating the weight of each layer of the network using a predefined optimization algorithm. The training was terminated if the training loss did not decrease (tolerance $\varepsilon < 10^{-4}$) for over 10

Table 2. Hyperparameter optimization results for the MLP models trained with the lightning matrix damage dataset.

Hyperparameters	Configuration	Optimal Value
Optimizer*	'lbfgs', 'sgd', 'adam'	adam
Activation function	'logistic', 'relu', 'tanh'	tanh
Learning rate	'constant', 'adaptive'	adaptive
hidden layer sizes	N_{train}, 2*N_{train}, 3*N_{train},	(234,234,234)

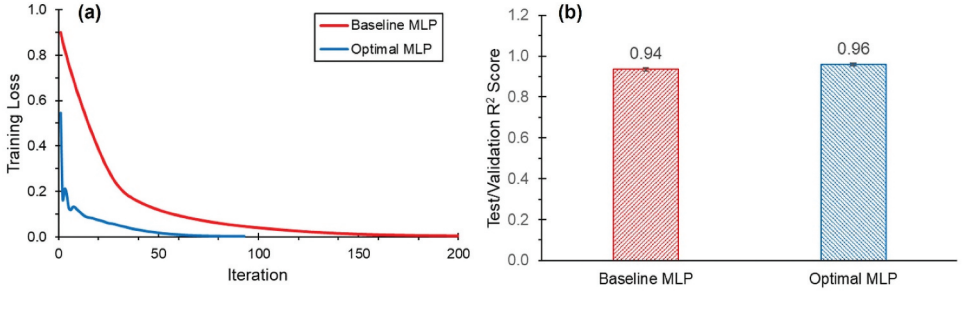

Figure 10. MLP model performance after hyperparameter optimization: (a) training loss versus the number of iterations and (b) validation results.

epochs, otherwise it stopped after 200 epochs. The training loss is known as a common metric used to assess how well a ML model fits the training data. As shown in Figure 10, the training loss curve obtained from the matrix damage dataset exhibited a rapid decrease (faster convergence), ensuring good model accuracy. The effects of hyperparameter optimization on the test/validation scores obtained from the MLP models are shown in Figure 10(b). In the figure, the score was averaged over 5 runs. The matrix damage MLP models showed a superior test/validation score (>0.94) and good reproducibility. Hyperparameter optimization slightly improved the performance of the baseline MLP model by ~0.02, but achieved faster convergence. This result suggests that the baseline MLP model trained with the lightning matrix damage dataset is sufficiently accurate and robust. The benefit of faster convergence achieved from the optimal MLP model becomes important for a larger dataset. For instance, when a training dataset consists of multidimensional (more than 10) input variables with larger data points, the optimal MLP model likely requires significantly less time than the baseline MLP model, while both providing comparable accuracy. This in turn can lead to faster prototyping and development of new lightning-resistant materials.

Figure 11 compares the measured and predicted values of lightning matrix damage from existing literature and the optimal MLP model (see Table 2). The dotted diagonal line with the slope of 1 ($y = x$) represents the ideal scenario, where the predicted damage equals the actual damage (i.e. perfect prediction). The model predicted the R^2 value of 0.96 that demonstrates excellent accuracy in predicting the lightning matrix damage and the results are highly consistent with experimental data. However, the dataset used in model validation is relatively small with only nine data points ($N = 9$). While the high R^2 value of 0.96 suggests a strong correlation between the model prediction and actual lightning damage, it is worth considering the limitations and potential risks associated with small datasets. Future investigations on advanced model validation techniques (i.e. data augmentation, synthetic data generation, transfer learning, and cross-validation) are required to ensure the model's reliability and generalizability.

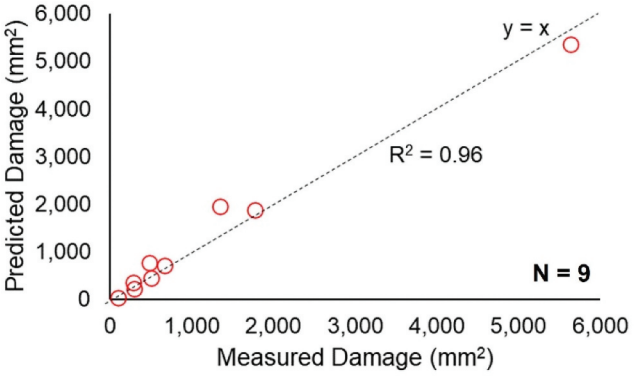

Figure 11. Comparison of actual (from literature) and predicted (from the optimal MLP model) lightning matrix damage in composites.

3.5. *Limitations and suggestions*

It is important to note that the datasets collected from open literature exhibit significant scatter due to the lack of consistent lightning damage assessment standards. In fact, researchers define and quantify lightning damage areas using their own criteria (i.e. rhombic, elliptical, or circular damage domains) and the distinction between various damage domains varies across different studies and is highly subjective. Due to these non-standard measures in quantitative lightning damage, the datasets considered in this study may contain highly nonlinear, non-normal, and multicollinear data points. This intrinsic variability poses a challenge of developing accurate regression models for lightning damage prediction. Naturally, with any data-driven regression model, there is a trade-off between regression performance and data dimension/size. Despite the ever-growing body of lightning strike research, the available datasets are still relatively small when compared with other fields and areas of ML research. The size of the lightning dataset could be increased in the future with further experimental testing campaigns or an FE modeling study in which the most influential parameters are varied within reasonable limits. However, this should be considered carefully as the reliability of simulation data must be ensured with experimental results before use as inputs for any ML model. An increased dataset will reduce the potential for overfitting and bias in the ML predictions, but increasing the dataset is beyond the scope of the present work.

Regardless of the limited and inherently scattered nature of lightning damage datasets, the proposed MLP model could still predict lightning matrix damage with $R^2 = 0.96$. In fact, lightning damage is primarily matrix dominated, for example, typical epoxy matrix degradation occurs between 300°C and 800°C while carbon fiber damage occurs at temperatures greater than 3000°C [5,9,38–42]. Therefore, accurate estimation of matrix damage can be a first indication of the lightning strike damage resistance of a particular specimen.

In this work, the optimal MLP model was developed based on the 10 most significant factors influencing the severity of lightning damage and was trained and tested on a body of published lightning strike experimental literature. Significant further complexity associated with lightning damage in composites would be required to account for other factors such as the layup of the test specimen. In fact, lightning interactions with composites can be also influenced by laboratory testing setup and procedure. For instance, lightning damage to composites can be greatly affected by depending on how and where current waveform is applied (i.e. location of injection, discharge gap, size of the current attachment point, etc).

4. Concluding remarks

This paper is significant as it presents an assessment of the potential use of machine learning (ML) to predict lightning damage, for the first time in literature, within the field of lightning strike direct-effect research. The models were trained with existing datasets from literature. A comprehensive analysis of various regression models was used to evaluate performance across different learning algorithms. Three supervised machine learning (SML) models were developed for predicting lightning-induced matrix damage in composites: (a) standard and regularized linear regression (LR) models, (b) decision tree (DT)-based models, and (c) a Multilayer Perceptron (MLP) model. Several key findings have been identified. First, existing lightning damage datasets contain limited experimental results with large variance. Second, the

regression models trained with the lightning matrix damage dataset show promising results. The MLP model was found to be the best SML model for lightning damage prediction. The optimal MLP model trained with the matrix damage dataset showed a coefficient of determination (R^2) value of 0.96. Hyperparameter optimization (a combination of Adam optimizer, tanh activation function, and three hidden layers with 234 neurons) slightly improved the performance of the baseline MLP model by ~0.02 and achieved faster convergence. The benefit of faster convergence achieved from the optimal MLP model becomes more important for a larger dataset with multidimensional input variables. This in turn leads to faster prototyping and development of new lightning-resistant materials. The models, overarching methodology, and application of ML herein could be applicable to other multi-input datasets.

This paper highlights the challenges of using ML-based regression models for reliable lightning damage assessment of composite laminates. The ML-informed regression models, utilizing advanced optimization algorithms and incorporating more data points after potential outlier removal, can serve as an efficient first pass-estimator of lightning matrix damage in composite laminates. This has the potential to reduce the total amount of extremely time-consuming and expensive laboratory-scale lightning tests or streamline the development of complex lightning damage models for future design. The findings of this paper highlight that future work should include advanced optimization techniques (such as uncertainty analysis for input data, or data augmentation to increase the dataset size) and more reliable lightning damage datasets should be generated (either by experimental testing or well validated, reliable FE modeling) before the models can be finally applied to composite structures. It would also be beneficial to extend the model and methodology herein to the prediction of other lightning damage modes, such as delamination, potentially making the model applicable to other fields of composite research where delamination dominates, such as low-velocity impact.

Nomenclature

ML	Machine Learning
SML	Supervised Machine Learning
MLP	Multilayer Perceptron
LSP	Lightning Strike Protection Systems
FEA	Finite Element Analysis
SLDM	Stochastic Lightning Damage Model
DT	Decision Tree
LR	Linear Regression
ANN	Artificial Neural Network
GFRP	Glass Fiber Reinforced Polymer
CFRP	Carbon Fiber Reinforced Polymer
IQR	Interquartile Range
API	Application Programming Interface
MSE	Mean Squared Error
RF	Random Forest

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Data availability statement

The data that support the findings of this study are available from the corresponding author [JL] upon reasonable request.

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Critical comparison of potential machine learning methods for lightning thermal damage assessment of composite laminates

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