Damage Precursor Identification in Composite Laminates using Data Driven Approach

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Composite materials are rapidly being used in commercial aviation and other day to day applications. The individual damage modes in composites are very well understood but it is the interaction of these local damage modes that leads to global failure. In the current research we intend to identify the damage precursors and the initiation of failure events in off axis unidirectional composite laminates loaded in quasi static uniaxial tension by measuring the dielectric response of the material by an in-situ technique using Broadband Dielectric Spectroscopy (BbDS). Using the variation of permittivity with strain, we are able to classify the stages of damage and predict the current material state. These data were then used to develop artificial intelligence models to identify the material state change and further use this data to predict the damage precursor stage and initiation of failure events. Different artificial intelligence models such as multi-layer perceptron, random forest regression and recurrent neural networks developed are discussed.

I. Nomenclature

\[ \nabla = \text{gradient} \]
\[ J = \text{current density} \]
\[ \rho_v = \text{total charge per unit volume} \]
\[ \sigma = \text{conductivity of the material} \]
\[ \omega = \text{angular frequency} \]
\[ \varepsilon_0 = \text{permittivity of free space} \]
\[ \varepsilon_r = \text{dielectric constant (permittivity) of the material} \]
\[ \varepsilon'_r = \text{real part of permittivity} \]
\[ \varepsilon''_r = \text{imaginary part of permittivity} \]
\[ V = \text{electric potential} \]
\[ E = \text{gradient of electric potential} \]
\[ I = \text{measured current} \]
\[ Z = \text{impedance} \]
\[ C = \text{capacitance of the material system} \]
\[ C_0 = \text{capacitance of free space} \]
\[ A = \text{area under the electrodes} \]

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d = distance between the electrodes  
\( x = \text{input data value} \)  
\( h(x) = \text{predicted output value} \)  
\( y = \text{output data value} \)  
\( L = \text{loss function} \)  
\( \lambda = \text{L2 – regularization parameter} \)  
\( J(W, b) = \text{cost function} \)  
\( W = \text{weights of artificial intelligence model} \)  
\( b = \text{scalar bias term of artificial intelligence model} \)  
\( m = \text{number of samples in dataset} \)

II. Introduction

With increasing demand for composite materials in civil aviation and day to day applications it is important for a design engineer to be able to predict the initiation of failure. Unlike metals, where in the initiation and growth of a single defect is monitored until it becomes unstable, damage in composites is much more complex. It is well defined in literature how the individual damage modes (matrix cracking, delamination, fiber fracture etc.) initiate and progress, however the interaction of these damage modes which creates a critical fracture path that leads to final failure is yet to be clearly understood. Fig. 1 shows the general relationship of material property change to damage development [1].

Recent advances in Non Destructive Evaluation (NDE) have made it possible to map the area of damage and the size of damage. However, none of these techniques are capable to accurately determine the state of the material. Also, a recent report generated by Hall et al., the investigators have stated that by the time any damage is identified, the structure has already lost its critical load bearing capacity which could lead to catastrophic events if it were a primary load carrying structure [2]. Hence it is critical to obtain the real time material state which than can be acted on by engineers to repair or replace the component. To obtain the real time material state, the technique should have the capability to interact with the local details of the material system. Electrochemical Impedance Spectroscopy (EIS), Broadband Dielectric Spectroscopy (BbDS) uses such techniques to extract the material-level information, including the morphology changes caused by micro-defect generation and the orientation and interaction of those defects. For the past 7 years, Broadband Dielectric Spectroscopy (BbDS) has been extensively used by various researchers to detect damage development and final fracture initiation [3-6].

Fig. 1 Relationship of damage development to material properties [1]
BbDS is the interaction of electromagnetic waves with matter in the frequency range from a lower value of 10^{-6} Hz to a higher frequency of 10^{12} Hz. In this regime it is possible to determine the polarization effects that occur at inner and outer boundaries of the material under study. [4]. A vector electric field is applied through the thickness of the specimen as shown in Fig. 2 and the dielectric properties are measured using the Eqs.(1-3) below (derived from maxwell’s laws of electromagnetism)

\[ \nabla \cdot J = -\frac{\partial \rho_v}{\partial t} \]  
(1)

\[ J = (\sigma + j \omega \varepsilon_0 \varepsilon_r) \cdot E \]  
(2)

\[ E = -\nabla V \]  
(3)

Where, \( J \) is the current density (Am^{-2}), \( \rho_v \) is the total charge per unit volume (Cm^{-3}), \( \sigma \) is the conductivity of the material (\Omega^{-1}m^{-1}), \( \omega \) is the angular frequency (rad), \( \varepsilon_0 \) is the permittivity of free space (Fm^{-1}), \( \varepsilon_r \) is the dielectric constant of the material, \( V \) is the electric potential (V) and \( E \) is the gradient of electric potential (Vm^{-1}). By combining Eqs. (2-3) we obtain the Poisson’s equation which can be solved for the electric potential. By measuring the output current I (A) we obtain the impedance \( Z \) (\Omega) of the system by Eq. (4).

\[ Z = \frac{V}{I} \]  
(4)

With impedance data, it is possible to obtain the conductivity and permittivity of the system using Eqs. (5-7)

\[ C = \frac{1}{j \omega Z} \]  
(5)

\[ \varepsilon_r = \frac{C}{C_0} \]  
(6)

\[ C_0 = \varepsilon_0 \frac{A}{d} \]  
(7)

Where, \( C \) is the dielectric Capacitance of the system (F), \( C_0 \) is the dielectric Capacitance of free space, \( A \) is the area between the electrodes (mm^2), \( d \) is the distance between the electrodes (thickness of the sample) (mm).

![Fig. 2 Schematic of the setup for dielectric measurement](image)

Artificial Intelligence is the new “electricity,” which powers millions of digital systems. Recent developments in the machine learning, neural network algorithms and in supervised learning and unsupervised learning, has developed several intelligent systems for aerospace applications. Also, the advancements in sensor technologies and data acquisition methods allow complex structures to be equipped with thousands of sensors which can analyze quantities such as structural responses like deformation and environmental behavior like temperature and humidity. Regardless
of this development of the sensing methods, interpretation of this big data of measurements to obtain useful information on structural conditions remains a challenge. This leads to a massive need for developing a good data-driven system by applying the proper methods to learn and understand such data to make proper decisions.

Since, for heterogeneous structural materials, it is very difficult to measure local compliance changes, or all local crack lengths to estimate strain energy changes, we plan to measure the local dielectric compliance changes through the element thickness using an In situ tensile testing technique [4]. This data can then be used to determine the stage of damage and to find the damage precursors as well as the initiation of failure. Using these data, we plan to use machine learning and develop an algorithm that can predict the state of the material based on the measured dielectric compliance as a function of strain. The hypothesis of the artificial intelligence model developed, its parameters, optimization algorithms, and various learning curves, and error curves that are used to successfully build the model will be discussed. The merits and demerits of this model on wise prediction and classification of damage precursors will enable the intelligent system to make decisions on the stage of material failure, and hence control the testing and interpretation procedures in real-time.

III. Experimental Setup

A. Sample Preparation

In the current work, unidirectional glass fiber reinforced composites (Newport 301 epoxy resin/E-Glass fibers (volume fraction 55%)) were manufactured in house using compression molding technique. In order to induce matrix dominated failure, off axis lamina were chosen and the laminate layup is [+45/-45]s. Two laminate panels were made where in the temperature was ramped up at a rate of 3 °F/min from 70 °F to 275 °F, cured at 275 °F for 60 minutes and cooled at a rate of 3 °F/min from 275 °F to 120 °F, as per the manufacturer recommendations. Cured panels were cut into coupons as per ASTM D 3039 recommendations [7]. The final average dimensions of the unidirectional specimens are 8"*0.73"*0.034".

B. In situ Testing Setup

The coupons will be loaded in tension using MTS Landmark™ unit under displacement control with a 50 KN load frame. Simultaneously, the dielectric properties are measured by attaching an electrode block to the coupon in the form of a parallel plate capacitor and is connected to the analyzer of the Novocontrol™ unit. The schematic of the setup is shown in Fig. 3. A rate of 0.3 mm/min is used for testing the specimens and for the dielectric response a sinusoidal AC signal with a potential of 1 V_RMS at a frequency of 10 Hz was applied. The in situ testing was done in the low frequency regime to capture the redistribution of charges (interfacial polarization) due to local damage mechanisms [4, 8]. Also, edge replication techniques were used to capture the damage patterns developed during loading to correlate the changes in dielectric response to damage growth. Replicas were obtained at every 250 N by holding at that load level for 4 minutes.

Fig. 3 Schematic of the in situ setup for measuring mechanical and dielectric response
IV. Experimental Results and Analysis

A. Experimental Results

The stress-strain curves for the coupons are shown in Fig. 4(a) and Fig. 4(b). The data just before failure is plotted. The mechanical and dielectric response for one specimen is shown below in Fig. 5 [9]. From Fig. 5, it is evident that with increasing strain and damage, there is a variation in the dielectric response. To better understand the variations, the dielectric response data is fitted using a fourth order polynomial as shown in Fig. 5 and the first and second slope of the fitted curves are plotted in Fig. 6 and Fig. 7 [9]. Since, dielectric response varies with damage, the first slope represents the damage growth and second slope indicates the rate of damage. The edge replication images for a coupon is shown below in Fig. 8 and a fractured specimen is shown in Fig. 9 [9].

![Stress-Strain curves for Set A and Set D](image)

**Fig. 4 (a) Stress-Strain curves for Set A, (b) Stress-Strain curves for Set D**

![Mechanical and Dielectric Response of a Sample](image)

**Fig. 5 Mechanical and Dielectric Response of a Sample [9]**
From Fig. 6, the strain at which the first slope changes from positive to negative or the strain at which the real permittivity $\varepsilon'_{\text{r}}$ saturates was determined to be the Characteristic Damage State (CDS) of the material system. Characteristic Damage State (CDS) is a material state where the primary cracks saturate and the secondary cracks initiate in the neighboring plies followed by coupling of those cracks [9]. This can be observed in edge replication images (1750 N) in Fig. 8 [9]. With increasing strain, these secondary cracks initiate at multiple sites leading to interaction of these cracks creating interlaminar cracks or local delamination that are thin strip-like lines shown in Fig. 9. During this stage, the ‘rate’ of these interactions increases at such pace, that the local failures aided by fiber fractures lead to global failure of the material [9]. From Fig. 7, it can be observed that at a certain stage the second slope or ‘rate’ of damage changes shape indicating an accelerating growth of damage events. Also, from Fig. 7, it is evident that the strain at which the rate of damage accelerates is in the zone where there is an inflection in the stress strain curve.

**Fig. 6** Variation of first slope of permittivity with axial strain [9]

**Fig. 7** Variation of second slope of permittivity with axial strain [9]
V. Material State Identification using Artificial Intelligence

In our previous research work, a neural network structure was defined and demonstrated that was successful in learning to predict notched strength, based on training with a data set generated from an average strength concept requiring three material constants. Excellent predictive fidelity was demonstrated from the models developed as shown in Fig. 10(a) and Fig. 10(b) [10]. The statistical uncertainty of the artificial intelligence models being developed plays a major role when we need to predict the defects, remaining life, strength of the composite material, or a new design for the composites structures. The statistical uncertainty is relatively negligible when the data driven model is coupled with a physics-based model.
In another research work, we established a nondestructive evaluation method by using machine learning techniques of random forest classifier and artificial neural network which could detect and predict the defects in the composite materials based on the initial dielectric properties obtained from BbDS. [11]

In this research, we propose to use the dielectric compliance measurements in the artificial intelligence algorithm that can then predict the state of the material, and the initiation of failure based on the experimental observables. A pictorial representation of this research work is shown in Fig. 11.

![Fig. 11 Flowchart of Damage Precursor Identification](image)

**A. Data Visualization**

The first stage of developing a machine learning and neural network model was to understand the data. Visualizing the data, gives a clear overview of what is being expected from the model, and helps to develop the model correctly. The input data set and output data set over time are plotted in Fig. 12(a) and Fig. 12(b) for several samples.

![Fig. 12 (a) Input data of Real Permittivity (b) Output data of 1st slope](image)

**B. Padding due to Variable Length of Data**

Since the data were obtained from the experimental testing of composite materials, the length of the data was not uniform for all the samples. As the data must be of uniform length, all the input and output data was padded with zeros, to make the length of the data set to be a vector of size (1, 1000) for each sample for both input and output.
C. Normalization of the Data
Normalization is defined as the process of scaling individual sample data to have unit norm. This process is useful to quantify the similarity of any pair of samples. Normalization was done by using the scikit-learn normalizer package, by setting the norm parameter as “l2”, to obtain the Euclidian norm and normalizing each sample. By normalizing the data, the optimization algorithm runs better and faster, as the loss value is minimized.

D. Training and Test Set
The total data set was split into training and test sets, by setting the test size parameter to be 0.15, using the scikit-learn[12] python package. Hence the training set size was (9, 1000) and test set size was (2, 1000). Due to the limited number of data, the test set was considered to be the cross validation set as well.

E. Loss Function
For linear regression, the cost function can be calculated from the loss function (also called as error function) as the mean of the squared errors.

For $i^{th}$ example, the Loss Function used in the models is given by Eq. (8) below

$$L(h(x), y) = \frac{1}{2}(h(x^i) - y^i)^2$$  \hspace{1cm} (8)

Hence the Cost Function is given by Eq. (9) below

$$J(W, b) = \frac{1}{2m} \sum_{i=1}^{m} (h(x^i) - y^i)^2 + \frac{\lambda}{2m} \sum_{j=1}^{n} W_j^2$$  \hspace{1cm} (9)

The accurate value of the L2-regularization parameter can be obtained by developing validation curves or error analysis curves.

F. Optimization Algorithm

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**Require:** $\alpha$: Stepsize  
**Require:** $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates  
**Require:** $f(\theta)$: Stochastic objective function with parameters $\theta$  
**Require:** $\theta_0$: Initial parameter vector  

- $m_0 \leftarrow 0$ (Initialize 1$^{st}$ moment vector)  
- $v_0 \leftarrow 0$ (Initialize 2$^{nd}$ moment vector)  
- $t \leftarrow 0$ (Initialize timestep)

**while** $\theta_t$ not converged **do**  

- $t \leftarrow t + 1$  
- $g_t \leftarrow \nabla_{\theta} f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep $t$)  
- $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)  
- $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)  
- $\tilde{m}_t \leftarrow m_t / (1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)  
- $\tilde{v}_t \leftarrow v_t / (1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)  
- $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \tilde{m}_t / (\sqrt{\tilde{v}_t} + \epsilon)$ (Update parameters)

**end while**

**return** $\theta_t$ (Resulting parameters)
---

Fig. 13 Adam Optimization Algorithm from Original Paper [13]
Adam optimization has served to be the best for our models being developed, which is one of the best optimizing algorithms in deep learning inherited from the RMSProp and AdaGrad [13]. The Parameters are updated in this algorithm, invariant to re-scaling of the gradient, hence greater performance is achieved. In the original paper, Adam was demonstrated empirically to show that convergence meets the expectations of the theoretical analysis. Adam was applied to the logistic regression algorithm on the MNIST character recognition and IMDB sentiment analysis datasets, a Multilayer Perceptron algorithm on the MNIST dataset and Convolutional Neural Networks on the CIFAR-10 image recognition dataset. Being computationally efficient, and suitable for large systems in terms of data, Adam is used in both the neural network models being developed. The Algorithm is shown in Fig. 13.

G. Activation Functions

There are many activation functions used most commonly by various machine learning methods and data scientists in the industry. They are linear, sigmoid, Tanh and ReLU – rectified linear unit, as defined below in Eqs. (10-13).

Let \( h(x^i) = z \) be the input to the activation function

\[
\text{Linear} = g(z) = z \tag{10}
\]

\[
\text{Sigmoid} = g(z) = \frac{1}{1 + e^{-z}} \tag{11}
\]

\[
\text{Tanh} = g(z) = \tanh(z) \tag{12}
\]

\[
\text{ReLU} = g(z) = \max(0, z) \tag{13}
\]

ReLU, Sigmoid and Tanh activation functions were used as per the need for the stages of each model that was developed. ReLU was most commonly used, as the problem is a regression model. [14]

H. \( R^2 \) – score

The \( R^2 \) coefficient is defined as the ratio of the residual sum of squares to the total sum of squares of output, subtracted from unity as defined below in Eq. (14). As accuracy for linear regression model is given by \( R^2 \) or Mean Squared Error or Root-Mean Squared Error metrics, \( R^2 \) was chosen as metric for all the models developed.

A \( R^2 \) coefficient of 1 indicates a best model, and a negative \( R^2 \) indicates a worse model. When the \( R^2 \) score tends to 0, it indicates that the model is a constant model, and will always give 0 for any set of input data.

\[
R^2 = 1 - \frac{\sum_{i=1}^{m}(\hat{y}^i - y^i)^2}{\sum_{i=1}^{m}(\text{mean}(y^i) - y^i)^2} \tag{14}
\]

I. Multi-Layer Perceptron Model

Multi-Layer Perceptron (MLP), also called as deep artificial neural network, belongs to a supervised learning algorithm which learns a non-linear function for the regression or classification problems. The important difference of MLP with logistic regression is that, there are one or more than one number of non-linear layers, also called as the hidden layers between in the input and output layer. These are often applied to the supervised learning problems.

For our given dataset, we developed a 3-Layer MLP model, as shown in Fig. 14. As per the dataset, the input and output layers has 1000 values. Both the hidden layers has 1500 neurons in each. Adam optimization algorithm and ReLU activation function was used. The learning rate was 0.001 and L2-regularization parameter was chosen to be 0.0003. This parameter was obtained by plotting the training vs. cross validation curve on various L2-regularization parameter values.

Based on the results obtained and performance of the multi-layer perceptron model, it was easier to understand the behavior of this model and therefore enhance this model, future models were developed.
J. Random Forest Regression Model

With our previous experiments on using random forest regression model to learn about the behavior of the model from the feature importance’s [11], a random forest regression model was developed. It was a part of the error analysis process.

An alternative approach, the random forest algorithm, also called random decision forests operates by the construction of decision trees during the training and outputs the mean of predictions of all the decision trees. The Random forest algorithm is the best fit to avoid the over fitting of the data. It was put forward by Leo Breiman as part of a statistical learning approach. It is an ensemble learning method, which can also predict the value and ranking of each feature [15].

The random forest algorithm involves two primary processes – Tree bagging (also known as bootstrap aggregate bagging) and creation of the random forests. The number of trees in the model plays a vital role, as it increases the average value.

Our model was developed by setting the number of estimators to be 3000, which is thrice the size of our input features. All other parameters was set as default by the scikit-learn [12] python package. The results obtained these models, played a vital role in the development of our next model.

K. Recurrent Neural Network Model

Recurrent Neural Network (RNN) is a supervised learning algorithm, and is a class of the artificial neural network in which the connections between neurons in each layer forms a directed graph along a sequence. RNNs are most commonly used in language modelling and generating text, machine translation, speech recognition, generating image descriptions and time series data, where the model depends on the previous data value to make a prediction.

Long Short-Term Memory (LSTM) networks, are a particular type of recurrent neural networks that has gotten immense attention recently within the data driven community. These networks have an internal contextual state cells that acts as long-term or short-term memory cells. These memory cells are used for predicting a long sequence of data with less memory requirements and achieve greater performance. LSTM networks were discovered by Hochreiter and Schmidhuber in 1997 and set accuracy records in multiple applications domains. [16]

LSTM networks keep contextual information of the inputs by integrating over a loop that allows information to flow from previous step to the current, and further. Hence these loops make RNNs seem magical. The limitation of RNN is the vanishing gradient problem, which is solved by LSTM.

1. Masking Layer

From the results obtained from the previous model, it was realized that padding with zeros had an effect on the models’ performance and hence affected the R²-score of the predictions. RNN or LSTM does not have the requirements for the data to be of the same input length. Also, by masking these network with a masking layer, and by setting the mask value parameter to be zero, the LSTM model skips the particular mask value. Hence the weights are not affected.
2. **3D Input Shape**
   For LSTM, the input needs to be in a 3D shape. Hence the 2D input of \((m, 1000)\) was reshaped into the form of \((m, 1000, 1)\) where the 1000 represents the time steps. Now as per the input data, for every sample \(m\), there are 1000 time steps and each time step has a single feature. In certain other examples, it can have multiple features for a single time step, such as considering the real permittivity, imaginary permittivity, material properties or stress and strain value for a sample.

3. **Our Model**
   The LSTM model was developed using keras\([17]\) package sequential model is shown in Fig. 15. First the input was converted from 2D to 3D, then the masking layer was on the sequential model, which is an embedding layer. The LSTM layer has 1000 units, and the return sequences parameter was set to be false, hence we predict the output as a many to one problem. This is more beneficial in the real time implementation of the model, because the entire input set of values are used to make the prediction at every time step. The model was ran for 2500 epochs, to ensure the convergence of the training loss and testing loss. 4,008,000 parameters were trained.

![Fig. 15 RNN / LSTM model for predicting Characteristic Damage State](image)

VI. **Results from AI models**

A. **Multi-Layer Perceptron Model Results**
   From the MLP model developed, it was observed that the model was over-fitting. It had an excellent R\(^2\)-score on the training data, but a very moderate R\(^2\)-score on the test data. Also, from the results obtained, it was observed that the model predicted outputs even when the input data was zero as observed in Fig. 16(a), which means that the zero padding was inversely affecting the model. Also the R\(^2\)-score on the test data was moderate, because it could very well learn the initial set of data, up to the first 250 features, by which this model still predicts the 1\(^{st}\) slope of permittivity to classify if the specimen has achieved the Characteristic Damage State as shown in Fig. 16(b). Because when the predicted 1\(^{st}\) slope of permittivity reaches zero, and changes from positive to negative, we believe that the material state changes from damage initiation stage to damage accumulation and growth stage.
B. Random Forest Regression Model Results

The Random forest regression model that was developed, did not outperform the MLP model. It had lesser $R^2$-score on both the training and testing compared to the MLP model. Although the $R^2$-score was quite lesser, the model had the same behavior of predicting the output values for the padded region of input data as well. While examining the features importance’s, this behavior was verified that the weights were higher in the regions where there was a change in the length of the data. This is depicted in Fig. 17(a), from which it can observed that the weights are high at approximately 150th feature instance, which is the average instance where the characteristic damage state occurs as seen in Fig. 16(b). It is also high approximately at instances 550, 775 and 890 which are the regions were the input data has no value, and zero padding begins as observed from Fig. 17(b). Once this issue was realized, it was planned to develop the RNN model instead of improving this model to overcome the effect of zero padding and sequential nature of the data.

C. Recurrent Neural Network Model Results

The LSTM model had tremendous performance on our dataset. The training $R^2$-score was much similar to that of the MLP model, and the testing $R^2$-score was significantly improved. Although a highest testing $R^2$-score was not obtained, the LSTM model developed does not have bias and variance issues. The training loss and the test loss was gradually began decreasing after the first few iterations, when our model started learning, as shown in Fig. 18. After 1500 iterations, both the losses converged, and the difference between the losses were of the order of $10^{-5}$.

Also from Fig. 19, it can be observed that the predicted values match closely with the actual test data values. It can also be observed that there is no zero padding effect due to the masking layer in the LSTM model being developed.
D. \( R^2 \) – Score of Data Driven Models

As defined earlier, the model’s accuracy is the \( R^2 \)-score value. Table 1 represents the \( R^2 \) score of the three different models developed.

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Score</th>
<th>Testing Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multi-Layer Perceptron (MLP)</td>
<td>0.9831</td>
<td>0.7322</td>
</tr>
<tr>
<td>Random Forest Regression</td>
<td>0.9168</td>
<td>0.6840</td>
</tr>
<tr>
<td>Long Short Term Memory Network (LSTM)</td>
<td>0.9528</td>
<td>0.8713</td>
</tr>
</tbody>
</table>
VII. Conclusion

An insitu testing technique was used to measure the variation in dielectric response as a function of damage growth in 4 ply unidirectional off axis glass fiber reinforced polymer composites. An increase in normalized real permittivity was observed during micro cracking stage followed by saturation that correlated with the Characteristic Damage State (CDS) of the material system. These were validated using edge replication images and it was observed that when the value of 1st slope of normalized real permittivity was 0, the material state was CDS. Also from the 2nd slope of normalized real permittivity it was observed that the point at which there was a curvature change, there was an inflection point observed in the stress strain response indicating acceleration of damage events.

Three different supervised learning algorithms were developed to predict the 1st slope of real permittivity, for the given real permittivity input values over time. By these predictions, CDS of the material system could be identified from the dielectric data. The Multi-Layer Perceptron and Random Forest Regression model developed reflected in the over fitting of the model. It also lacked success due to the zero padding done on the input data. However these models can be used to classify data between the damage initiation and damage growth stages. The Long-Short Term Memory network model developed as a part of the Recurrent Neural Network, demonstrated better performance on both training and test data and can be used for predicting the CDS of the material system.

VIII. Future Work

The models developed in this research work were for a set of data collected from a constant strain rate. Hence the first slope of permittivity is with respect to that particular strain rate. Future research is to be done on developing RNN models, which can learn the rate of strain, and predict the first slope of permittivity value, with respect to the change in time. By achieving this, a material’s damage initiation and growth accumulation for any particular strain rate can be predicted by just measuring the dielectric permittivity value with time.

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