DETECTION AND PREDICTION OF DEFECTS IN COMPOSITE MATERIALS USING DI-ELECTRIC CHARACTERIZATION AND NEURAL NETWORKS

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ABSTRACT

The state of art non-destructive inspection techniques for composite materials detect the presence of defects in the composite material, but they do not identify what type of defect it is, and hence, further visual inspection of the details are needed. This visual classification is a costly and time-consuming process, and it’s difficult to distinguish all of the defects effectively.

Broadband Dielectric Spectroscopy (BbDS), has been an established tool for dielectric material characterization in polymer industries for a long time. Dielectric spectra of heterogeneous materials are altered by constituent interfaces, with changes in morphological heterogeneity, electrical and structural interactions between particles, and shape and orientation of the constituent phases of the material system. Machine learning and Artificial Neural Networks (ANN) are computing systems that behave like our brains, storing and learning from previous data (training data) fed into it. In this terminology, classification is identifying the data according to the subset it belongs to.

In this paper, we propose a Non-destructive inspection technique by combining the concepts of the Broadband Dielectric Spectroscopy with Machine Learning Algorithms and Neural Network Computing systems. This technique not only detects the presence of the defects, but can also accurately predict and classify the various defects based on their dielectric properties, as the presence of the various defects varies with the spectra of the interfaces. An experimental procedure for obtaining the dielectric properties of the composite materials with various defects and the classification of the defects by Random Forest Classifier Algorithm and Neural Networks are discussed in this research work.

1. INTRODUCTION

Nondestructive testing (NDT) is defined as a process of inspecting, testing, or evaluating materials, components or assemblies for discontinuities, or differences in characteristics without destroying the serviceability of the part or system. NDT is used to ensure the quality of materials and joining processes during the fabrication and erection phases, and in-service NDT inspections are used to
ensure that the products in use continue to have the integrity necessary to ensure their usefulness and the safety of the public. [1]

Over the past decades, there has been several developments in the NDT for structural integrity evaluation of the composite structures. The growth in these developments are due to the attracted interest to reduce the cost and time to perform damage detection, damage monitoring and predictive maintenance. In particular, detection techniques based on the non-destructive testing (NDT) has been preferable due to the operational aspects of the use of the analyzed structure. [2]

There are many NDT technologies that are available for aircraft inspections. The most common methods are based on visual and optical testing: optical holography, X-ray, ultrasonic wave, infrared detection, X-ray and ultrasonic C-scan. Visual testing is the most commonly used test method in industry. As the name implies, VT involves the visual observation of the surface of a test object to evaluate the presence of surface discontinuities, but it can only detect surface defects and it cannot specify the type of defect. Also, only large discontinuities can be detected.

### 1.1 Broadband Dielectric Spectroscopy (BbDS)

Broadband Dielectric Spectroscopy (BbDS) serves as a robust tool to extract material-level information, which includes the morphology changes caused by micro-defect generation and the orientation of those defects. BbDS deals with the interaction of electromagnetic waves with matter. Hence, this method has become a prominent tool for determining the dielectric properties of a material. Nevertheless, there are several different factors which change the dielectric spectra of a heterogeneous material such as the morphological homogeneity, the interactions of electrical and structural properties between the particles, and the shape as well as the orientation of the combining phases. The dielectric spectra undergoes various alterations from the moment the material is manufactured to the end of its service life. However, during this period, the material experiences gradual damage accumulation.

The dielectric properties of a heterogeneous material are usually obtained in the frequency range of $10^{-6}$ Hz to $10^{12}$ Hz. The data generated in this range are related to the molecular and combined dipolar fluctuation, the effects of polarization, and the charge transport emerging inside the material boundaries as depicted in Figure 1.
1.2 Strength and Quality Measurements on Composites using BbDS

Reifsnider et al., initially proposed BbDS as a non-destructive defect testing method, studying the changes raised in the dielectric response when defects are formed in the heterogeneous material due to mechanical loading [3,4]. Despite typically being used as an NDT method for defect detection, this approach was employed to observe the different modes of damage in the heterogeneous composite systems and to establish their individual strength based on their dielectric spectra [5-9]. Fazzino et al. [4] and Raihan et al. [6] have shown that the association of response to a dielectric field with the response to a mechanical field for a material element is direct. Figure 2 shows the changes that occur in the dielectric properties when a continuous glass fiber reinforced with plain weave coupon is loaded with a quasi-static tensile load.

Figure 2. a) In-Situ tensile test setup, b) Mechanical and Dielectric response of the coupon

Elenchezhian et al., and Banerjee et al., has previously proposed BbDS as a quality measurement tool for measuring the quality and strength of the adhesively bonded composite structures. Figure 3 represents the permittivity and modulus values for different adhesively bonded structures. [10, 11]

Figure 3. Dielectric parameters obtained by quality assessment of adhesive bonds
1.3 Machine Learning and Neural Network in Non-Destructive Testing

Recent developments in the Machine learning and Neural Network algorithms, the usage of the neurons (brain like structures) in supervised learning has developed a presence in the field of structural health monitoring and non-destructive testing.

Angelo, G D., and Rampone, S., proposed a model to classify the aerospace structure defects detected by the eddy current non-destructive testing. They had used the decision trees, neural networks and the naïve bayes models for the classification. [13]. Trtnik, G., et al., modelled an artificial neural network to predict the concrete strength using the ultrasonic pulse velocity measurement. [14]

2. EXPERIMENTATION

2.1 Specimen Preparation

2.1.1 Materials Used

Four composite panels of 254 mm x 254 mm planar dimension were manufactured using 120 Glass Fiber (E-glass) prepreg purchased from Rock West composites. The laminate sequence was [0]_4. The Panels were made with defects induced in them in between mid-layers. Each panel was plotted into 8x8 cell for the experimental readings, as shown in Figure 4.

Table 1. Defects induced in each panel manufactured

<table>
<thead>
<tr>
<th>PANEL No.</th>
<th>DEFECT</th>
<th>Material description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No Defect</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>Release Film</td>
<td>Non-Perforated High Temperature</td>
</tr>
<tr>
<td>3</td>
<td>Backing Paper</td>
<td>Prepreg backing paper attached in Glass Fiber</td>
</tr>
<tr>
<td>4</td>
<td>Release Paper</td>
<td>Top Release paper from the prepreg</td>
</tr>
</tbody>
</table>

Figure 4. Panels manufactured for BbDS Testing
2.1.2 Manufacturing Process

These panels were manufactured as per the manufacturer’s recommended cure cycle at 408 K for the NP301 Resin system, by the WABASH compression molding presses, at the University of Texas at Arlington Research Institute.

2.2 Experimental Setup

2.2.1 Equipment Used

Dielectric permittivity and dielectric strength modulus measurements were measured using the Novo Control Broadband Dielectric Spectrometer at the University of Texas at Arlington Research Institute. A 12.7 mm square electrode was used. The Panels were placed in between electrodes within the closed environmental chamber, and the measurements were observed at each cell for all the four panels. The measurements were obtained by a frequency sweep from 1 MHz to 0.1 Hz, with a scaling factor of 1.4. Figure 5 depicts the setup of the equipment which was used to carry out the experiments.

![Figure 5. Experimental test setup for BbDS measurement](image)

2.2.2 Data Collection

The real permittivity, imaginary permittivity, real modulus and imaginary modulus values for each cell, in each panel were measured. For every single cell measurement, 49 values of each parameter were stored, each value corresponding to a frequency. The following table represents the features and their representations.

<table>
<thead>
<tr>
<th>Feature Number</th>
<th>Feature Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – 49</td>
<td>Real Permittivity at 1 MHz to Real Permittivity at 0.1 Hz</td>
</tr>
<tr>
<td>50-98</td>
<td>Imaginary Permittivity at 1 MHz to Imaginary Permittivity at 0.1 Hz</td>
</tr>
<tr>
<td>99-147</td>
<td>Real Modulus at 1 MHz to Real Modulus at 0.1 Hz</td>
</tr>
<tr>
<td>148-196</td>
<td>Imaginary Modulus at 1 MHz to Imaginary Modulus at 0.1 Hz</td>
</tr>
</tbody>
</table>
These 196 features were obtained from 64 cells of every panel, resulting in 256 cell data points. This data was input into matrix X and Y, where X represents the matrix of size [256,196], representing the total number of cells and the features, Y represents a vector of size [256,1], representing the number of cells and the classes of each cell (typically the classes are the panel number from which the data belongs too). Then the X and Y are shuffled randomly and split into the training and testing sets, which are sent towards the machine learning and neural network algorithms for development of a classification model.

3. MACHINE LEARNING AND NEURAL NETWORKS

3.1 Classification Approach

The Classification algorithm was developed to classify the given data into the classes, obtain decision boundary for the classes, and hence used to predict the class for any new input data. This algorithm is most commonly referred to as the Logistic Regression Algorithm.

For the data we collected, we had a dataset of X[256,196], Y[256,1], XTrain[204,196], YTrain[204,1], XTest[52,196] and YTest[52,1]. The Algorithms are explained with reference to these data set values. ‘m’ represents the number of examples in X, ‘n’ represents the number of features.

![Figure 6. Representation of the Logistic Regression Classifier](image)

3.1.1 Hypothesis

For the given input vector X, we write the predicted output of the logistic regression as

\[
\hat{y} = g(W \ast X + b)
\]  \[1\]

Where W and b are the parameters or weights. W is a vector of size [196,1]\(^T\) and b represents a scalar bias unit. g(z) represents the activation function, discussed later. The structure of the model is shown in figure 6.
3.1.2 Cost function

The aim of the cost function is to minimize and approximate the prediction output $\hat{y}$ to the actual output $y$. Hence, to obtain this, the Loss function is defined as

$$L(\hat{y}, y) = -(y \log \hat{y} + (1 - y) \log(1 - \hat{y}))$$  \[2\]

The cost function $J$ is given by

$$J(W, b) = \frac{1}{m} \sum_{i=1}^{m} L(\hat{y}^i y^i) + \frac{\lambda}{2m} \sum_{j=1}^{n} W_j^2$$  \[3\]

Where $\lambda$ is the L2-Regularization parameter.

3.1.3 Optimization Algorithms

The role of the optimization algorithm lies in obtaining the weight parameters $W$ and $b$, which will minimize the cost function $J$. Gradient Descent Algorithm is the most commonly used algorithm for the logistic regression. There are many optimization algorithms, such as L-BFGS, Adam algorithm which are used later in neural network architectures.

In the batch gradient descent algorithm, every iteration performs the operations

$$W := W - \alpha \frac{\partial J(W, b)}{\partial W}$$

$$b := b - \alpha \frac{\partial J(W, b)}{\partial b}.$$  \[4\]

The batch gradient descent performs simultaneous updates of $W$ and $b$, on all the examples in the training set. The parameters obtained, $W$ and $b$, are used to predict the output class for any new data set.

3.1.4 Activation functions

In the Logistic Regression, we used the function $g(z)$ in our prediction hypothesis. It is called the activation function. There are also many activation functions used by various machine learning methods and data scientists in the industry. The most commonly used functions are linear, sigmoid, Tanh and ReLu, as defined below.

Let $z = W * X + b$ be the input to the activation function

$$Linear = g(z) = z$$
$$Sigmoid = g(z) = \frac{1}{1 + e^{-z}}$$

$$Tanh = g(z) = \tanh(z)$$

$$ReLu = g(z) = \max(0, z)$$

Linear activation functions are used in the linear regression algorithms. For the logistic regression, sigmoid and ReLu functions are used.

### 3.2 Random Forest Classifier

The Random forest algorithm, also called as the Random decision forests, is another algorithm which operates by the construction of multiple decision trees during the training and outputs the mode of classes of the individual decision trees. The Random forest algorithms serves as 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 classification algorithm consists of two primary processes – Tree bagging (also known as Bootstrap aggregate bagging) and creation of the random forests. The number of trees in the model play a vital role, as it increases the average value.

#### 3.2.1 Tree Bagging

Given a dataset of $m$ examples, $b$ number of bags are created where each bag consists of the data of $\bar{m}$ examples. These bags are created by random selection of examples with replacement from the total data set $(X, Y)$ such that an example may repeat in several bags. In general Machine learning usage, $\bar{m} \leq m$

#### 3.2.2 Random Forests

Following the Bootstrap aggregate bagging process, the input data $X(m, n)$ are reduced to $X_1(\bar{m}, n)$ $\ldots$ $X_b(\bar{m}, n)$. To create random forests, the features to be used in each bag is selected in random, creating random subset of features. Hence a massive amount of trees was created to form the forest. Let $\bar{n}$ be the number of features in each tree, where $\bar{n} \leq n$. This process is defined as feature bagging.

The model of random forest regression is depicted in figure 7.

Each of these decision trees consists of a data set, which predicts the class, through the logistic regression or any machine learning classification algorithms. The output of the random forest is computed by the mode of the classes predicted.
3.3 Neural Network Classifier

Artificial Neural Networks (ANN) have been considered as a state of art technique for modeling and predicting non-linear system behavior. This non-linear behavior is obtained using hidden layers, which consist of units called neurons. The neurons in the hidden layers are connected to the input and output data by weights or parameters (W and b). The structure of an artificial neural network used in our model is depicted as follows. An N-layer neural network, consists of N-1 hidden layers.

3.3.1 Feed forward propagation

The forward propagation step is the logistic regression step to calculate the predicted class. The first layer of the ANN is the input layer, which consists of our input of 196 features.

The hypothesis equation is
\[ z^1 = W^1 * X^1 + b^1 \quad [5] \]

The superscript 1 indicates the layer 1. \( a_k \) is used to calculate the values of the neurons in the hidden layer next to the input layer, given by the activation function used.

\[ a_k^1 = g(z^1) \quad [6] \]

Where \( k \) is the number of neurons in the respective hidden layer. \( a_k^1 \) serves as the inputs to the hypothesis function, which is used to calculate the outputs of the next hidden layer. The process is repeated until the output layer, where the final output class \( z^N \) is predicted.

### 3.3.2 Backward propagation

Back-propagation algorithms are used in the design of multilayer neural networks, and are used in various applications in regression, classification problems, speech recognition and image recognition techniques.

It computes the derivatives of the cost function \( J \) with respect to our parameters \( W \) and \( b \) as a method of establishing sensitivity to those parameters.

The Cost Function \( J \) for a Neural Network is given by

\[ J(W^1, b^1, W^2, b^2 ... W^N, b^N) = \frac{1}{2m} \sum_{i=1}^{m} L(\hat{y}^i, y^i) + \frac{\lambda}{2m} \sum_{j=1}^{n} W^2_j \quad [7] \]

The derivatives are given by

\[ \partial z^N = a^N - y \]

\[ \frac{\partial J(W^1, b^1, W^2, b^2 ... W^N, b^N)}{\partial W^N} = \frac{1}{m} * \partial z^N * a^{N-1} + \frac{\lambda}{m} W^N \]

\[ \frac{\partial J(W^1, b^1, W^2, b^2 ... W^N, b^N)}{\partial b^N} = \frac{1}{m} * \partial z^N \quad [8] \]

### 3.4 Evaluation Parameters

Once the classification model is developed by any machine learning architecture, such as the models of logistic regression, random forest classifier, or the artificial neural network classifiers which we have discussed above, and the weight parameters, are obtained, the accuracy of the model can be obtained by using the test set XTest and YTest.

The mean accuracy of the model serves as the evaluation parameter for the proper design and tuning of the model, defined as the percentage of the classes correctly predicted. There are certain other evaluation metrics such as the precision, recall, F1 score which are most commonly used in machine learning architectures.
4. RESULTS

4.1 Data Visualization

The first step in developing a machine learning or neural network model is to visualize our problem and the data set of the problem.

Figure 9 shown below represents a composite laminate with 3 different types of defects in it, and some regions with no-defects. As per our experimental data, measurements were taken for 256 points, represented in the figure by a 16 x 16 cell analysis.

![Figure 9. Composite laminate with the defects](image)

The features that we obtained for each cell measurement are the Real permittivity, Imaginary Permittivity, Real Modulus and Imaginary Modulus. We visualize some of the features at 2-D scale in the figures 10a,10b,11a,11b.

From the Visualization of data in 3-D as shown in figure 12, we observe that the 3-D plot, which indicates that a cell represented by 3 features are more distinguishable, and the classes are more clearly identified. The machine learning algorithms represents 196 features, indicating a 196-dimensional data set for each sample cell.
Figure 10. Real vs Imaginary Permittivity at a) 1 MHz b) 0.1 Hz

Figure 11. Real vs Imaginary Electric Modulus at a) 1 MHz b) 0.1 Hz

Figure 12. Real Permittivity at 0.1 Hz vs 100 Hz vs 1 MHz
4.2 Model Parameters

For the dataset XTrain, YTrain and XTest, YTest which were collected earlier from our experiment, we developed models by the random forest classifier algorithm and Artificial Neural Network Algorithm. The models were developed using the SciKit-Learn package in Python; the Python 3.6 version was used [12-15]. The data were normalized to have the normal distribution of data with zero mean and unit variance.

4.2.1 Random Forest Classifier

The Random Forest Regression algorithm was run with the number of estimators set to 100, and other default parameters of the SciKit-learn random forest classifier were used.

4.2.2 Deep Neural Network

A 4-Layer Neural Network was developed, with 2000 neurons in each of the 3 Hidden layers. The input layer had 196 inputs, and the output layer had four class outputs. The ReLu activation function was used for the hidden layers, and sigmoid activation function was used for the output layer. Optimization was done by the L-BFGS Algorithm. The L2 Regularization Parameter was 0.001.

4.3 Mean Accuracy of the machine learning models

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest Classifier</td>
<td>87.7</td>
</tr>
<tr>
<td>Deep Neural Network Classifier</td>
<td>94.3</td>
</tr>
</tbody>
</table>

From the mean accuracy value of the models we developed, we observe that the neural network architecture performs better than the random forest classifying algorithm. Hereby, we have developed a supervised learning architecture, for the BbDS, which serves as a non-destructive technique for detection and prediction of the occurrence of defects in composite laminates. Also, this model can continuously train on new data, adaptively learn from the new data, and also predict new results as needed.

The accuracy percentage can be improved by varying the parameters input into the model, the L2-Reguralization value, learning rate, and by using different optimization algorithms. More studies on the model can be done by observing the learning curves on the training and the test set, performing hyper parametric studies, and trying various other machine learning, neural network architectures such as the support vector machines and kernels. The limitations of the model developed were that the test set was obtained from the same data set obtained by the same laminates. The accuracy of prediction on an entirely different dielectric constant data, from a similar new laminate might vary. This change in the data, will be considered by introducing a new
data set to the model for the training set. This model can be used only for the laminates manufactured using the same prepreg material and under the same curing conditions.

5. CONCLUSIONS

In this research work, a composite laminate was manufactured with known defects inserted into the laminate. BbDS studies on the laminate identified the dielectric constants of the non-defective and defective locations in the laminate. The dielectric constants at the various cell locations were significant indicators of the type of the defects in laminate material. This data from the dielectric constants was used to build a supervised learning classification algorithms. The random forest algorithm and the neural network algorithm discussed above were developed, giving better accuracy of the models on the test set. Hence, this combination of the BbDS with the supervised learning algorithms is identified as a non-destructive testing methodology to detect and predict the location and type of defects in composite materials.

5.1 Future Work

New supervised learning models are to be developed with the dataset, by varying the model parameters and optimization algorithms. Hyper-Parametric studies are to be conducted in the new models to be developed, to obtain better understanding on the performance and accuracy of the models, as well as importance of the features contributing to these results. This work will be published in a proceeding paper.

6. ACKNOWLEDGMENTS

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7. REFERENCES

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