Nano-delamination monitoring of BFRP nano-pipes of electrical potential change with ANNs

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Abstract. In this work, the electrical potential (EP) technique with an artificial neural networks (ANNs) for monitoring of nanostructures are used for the first time. This study employs an expert system to identify size and localize hidden nano-delamination (N.Del) inside layers of nano-pipe (N.P) manufactured from Basalt Fiber Reinforced Polymer (BFRP) laminate composite by using low-cost monitoring method of electrical potential (EP) technique with an artificial neural networks (ANNs), which are combined to decrease detection effort to discern N.Del location/size inside the N.P layers, with high accuracy, simple and low-cost. The dielectric properties of the N.P material are measured before and after N.Del introduced using arrays of electrical contacts and the variation in capacitance values, capacitance change and node potential distribution are analyzed. Using these changes in electrical potential due to N.Del, a finite element (FE) simulation model for N.Del location/size detection is generated by ANSYS and MATLAB, which are combined to simulate sensor characteristic, therefore, FE analyses are employed to make sets of data for the learning of the ANNs. The method is applied for the N.Del monitoring, to minimize the number of FE analysis in order to keep the cost and save the time of the assessment to a minimum. The FE results are in excellent agreement with an ANN and the experimental results available in the literature, thus validating the accuracy and reliability of the proposed technique.

Keywords: nano pipes; nano-delamination monitoring; Electrical Capacitance Sensor (ECS); BFRP; FEM; ANNs

1. Introduction

Nano pipes (N.Ps) manufactured from laminate composite materials are widely used in many nanoelectro-mechanical systems. Thus understanding the mechanical behavior of these nanostructures is much needed for design and development of a new class of nano-systems such as nano-actuators and nano-sensors. But the effect of internal defects may significantly change the stiffness and reduce the strength and lifetime of these composite nanostructures (Altabay 2017a, b).

Delamination is one of the most common damages that can occur between layers in layered composite materials. In general, it can be caused due to manufacturing faults or service process effects such as impact loads, fatigue, etc. Better understanding of delamination mechanism in laminated composite materials will allow to increase use this material in nonstructural applications. The delamination detection in general is a very difficult and expensive job in particular N.Del in N.Ps from laminated composites becomes near impossible. This difficulty of detection indicate to the importance of development of easy and economical technique for monitoring N.Del in that type of N.Ps (Zhao et al. 2017a, 2018a, b, 2019a, Altabay and Noori 2018a, Kost et al. 2019).

Several methods have been found to be useful for in-situ evaluation of composite nanostructures, where the structural integrity of that nanostructures manufactured from laminate composite can be assessed effectively. Recently, various methods have been implemented for that nanostructures monitoring include Ultrasonic; X-Ray Radiography and Thermography (Zhao et al. 2017b, 2018c, 2019b, Noori et al. 2018, Ghiasi et al. 2019).

Although, there is a diverse range of techniques for assessment composite nanostructures, the researchers were found the capabilities and limitations of each method are different, where each technique has its specific field of applicability although there is a level of overlap based on the type and accuracy of detection and the ability to detect more data of damage identification. For instance, it may be necessary to combine information obtained from acoustic emission and X-ray radiography to achieve a three-dimensional map of the complex array of delamination location/size in a composite, however, no single method is capable of easily detecting, or identifying delamination with high level of accuracy, and at a low-cost (Mouritz 2003, Altabay 2017c, d, 2018, Al-Tabey 2014).

ECS is one of the most mature and promising of new
methods, which measures the capacitance change of multi-electrode/nanoelectrode sensor due to the change in dielectric permittivity. It has the characteristics such as being a low cost, fast response, non-intrusive method with a broad range of applications and with a high level of safety (Yang et al. 1995a, b, Li and Huang 2000, Mohamad et al. 2012, Zhang et al. 2014).

As a result in our previous works by Altabey (2017e, f) and Altabey et al. (2018), the present method had been successfully assessment of the delamination location/size, crack identification (Altabey and Noori 2017), water absorption level (Altabey and Noori 2018b) in composite pipes and tensile creep monitoring of composite plates (Altabey et al. 2019). But they found a lot of FE calculations must be performed to obtain a sufficient number of sets of electric potential differences. This is the main drawback of the method identified so far.

In this study, we applied the previous electrical potential (EP) technique in N.Ps manufactured from BFRP laminate composite materials to improve one of most common nanostructures (e.g., nano-diaphragms, nano-pipes), which used in nanoelectro-mechanical systems. In order to avoid main drawback of this method, a FEM is generated with an artificial neural networks (ANNs), which are combined to decrease detection effort to discern N.Del location/size inside the N.P layers, with high accuracy, simple and low-cost. By ANSYS and MATLAB, split into four scenarios only of N.Del location/size and learning of the ANNs under each N.Del scenario. The ANNs are adopted as solvers to obtain relationships between the electric potential differences and the N.Del location/size in order to keep the cost and save the time of the FE assessment data to a minimum. Our presented technique results are showed the excellent agreement between FE and ANN results.

2. Principle of Electrical Capacitance Sensor (ECS)

ECS was first introduced in the 1980s by a group of researchers from the US Department of Energy, at Morgantown Energy Technology Center (METC), to measure fluidized bed systems (Fasching and Smith 1988, 1991, Huang et al. 1989). The technique further developed and advanced rapidly during the past 10 years. It has gained attention and found important applications in monitoring industrial processes, due to its low cost and its operability under harsh environmental conditions.

ECS converts the permittivity of the piping system to inter-electrode capacitance, which is the ECS forward problem. Capacitance measuring circuit takes the capacitance data and transfers that to imaging computer. Imaging computer reconstructs the distribution image with a suitable algorithm, which is called ECS inverse problem.

The need for a more accurate measurement of ECS has led to the study of the factors which influence and affect ECS sensitivity and the sensitive domain of ECS electrodes. In general, there are three factors that have been studied and found that they affect ECS measurements, e.g., Monitoring target manufacturing material (Jaworski and Bolton 2000, Pei and Wang 2009, Al-Tabe 2010, Asencio et al. 2015, Sardeshpande et al. 2015, Mohamad et al. 2016, Altabey 2016a) and Monitoring target thickness (Daoye et al. 2009, Altabey 2016b). Altabey (2016c) found that the environmental temperature also affect ECS sensitivity and sensitive domain of ECS electrodes with high percentage. Therefore, it was concluded that the environmental temperature should be considered as the fourth factor which influences the ECS measurement sensitivity.

Fig. 1 is a schematic representation of an expert system for N.Del assessment using electrical potential (EP) technique with an ANNs, in which R1 is inner N.P radius; R2 is outer N.P radius; R3 is earthed screen radius. The ECS also includes radial guard electrodes to constrain the field lines from the excited nano-electrode (N.E) and to reduce the dependence of spacing between the nano-electrodes (N.Es) and the screen as shown in the Fig. 1. The function of the sensor includes measuring the capacitance between all possible combination pairs of the N.Es and converting the measured capacitance values in the voltage signals. The sensors physical specifications and the permittivity values of BFRP N.Ps are shown in Table 1.

Fig. 1 Schematic representation of the N.Del monitoring method using an ECS method with an ANNs
Table 1 Sensor physical specification

<table>
<thead>
<tr>
<th>ECS system</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Nano-electrodes</td>
<td>12</td>
</tr>
<tr>
<td>Space Nano-electrodes</td>
<td>2 nm</td>
</tr>
<tr>
<td>Nano Pipe diameter (d)</td>
<td>94 nm</td>
</tr>
<tr>
<td>Nano Pipe thickness (h)</td>
<td>6 nm</td>
</tr>
<tr>
<td>Earth Screen diameter</td>
<td>110 nm</td>
</tr>
<tr>
<td>Thickness of Nano-electrodes</td>
<td>1 nm</td>
</tr>
<tr>
<td>height of Nano-electrodes</td>
<td>0.3 μm</td>
</tr>
<tr>
<td>Permittivity Basalt fiber/Polymer</td>
<td>εb = 2.2 Fm⁻¹</td>
</tr>
<tr>
<td>Permittivity of Water</td>
<td>εw = 80 Fm⁻¹</td>
</tr>
<tr>
<td>Permittivity of Air</td>
<td>εa = 1.0 Fm⁻¹</td>
</tr>
<tr>
<td>Excitation voltage</td>
<td>φ = 15 mV</td>
</tr>
</tbody>
</table>

Remark: Other parameters of the electrical property can be found in Zhao et al. (2018a)

The electric potential differences of each segment between N.Es are measured for various scenarios of N.Del location/size. From the measured data, the relationships between electric potential differences and N.Del location/size are obtained using an ANNs.

3. Finite element simulation model

3.1 Physical properties of the BFRP N.P

Table 2 list all the parameters required for physical and mechanical properties of the BFRP laminate composite. These FRP composite properties were tested at the National and Local Joint Engineering Research Center for FRP Production and Application Technology, Nanjing, China, a high-tech company specialized in the research and development, manufacturing, marketing and technical assessment of high-performance fibers and composites. To examine the effect of N.Del on the dielectric properties in BFRP laminated panel, the FE analysis of the electric field intensity of laminated panel were designed using ANSYS ver.15. Suitable finite elements were selected and employed to simulate FRP properties, i.e., PLANE121 element is used to simulate nano-structural property, triangular 6-node, and the element has one degree of freedom, voltage, at each node, and SOLID123 is used to simulate electrical property.

3.2 ECS governing equations

In terms of Electrical Capacitance sensor (ECS), the forward problem is the problem of calculating the capacitance matrix C from a given set of sensor design parameters and a given cross-sectional permittivity distribution $\varepsilon(x, y)$. Thus, the system was governed by the following Poisson equation

$$\nabla \cdot \varepsilon(x, y) \nabla \varphi(x, y) = 0$$

Where: $\varphi(x, y)$ is the potential distribution inside the ECS was determined by solving the Poisson’s equation. For tltkj boundary condition imposed on the ECS head by the measurement system. The electric field vector $E(x, y)$, the electric flux density $D(x, y)$ and the potential function $\varphi(x, y)$ are related as follows

$$E(x, y) = -\nabla \varphi(x, y)$$
$$D = \varepsilon(x, y)E(x, y)$$

The change on the N.Es, and hence the inter N.E capacitances could be found using the definition of the capacitance and Gauss’s law based on the following surface integral

$$Q_{ij} = \oint_{S_j} (\varepsilon(x, y) \nabla \varphi(x, y). \vec{n}) \, ds$$

where: $\nabla \cdot \varepsilon(x, y)$ is the divergence of permittivity distribution, $\nabla \varphi(x, y)$ is the gradient of potential distribution, $S_j$ is a surface enclosing electrode $j$, $ds$ is an infinitesimal area on electrode $j$, $\vec{n}$ is the unit vector normal to $S_j$ and $ds$ is an infinitesimal area on that.

3.3 The boundary conditions

The potential boundary conditions were applied to the sensor-plate (nano-electrodes). For one N.E, the boundary condition of electric potential ($V = V_0$) with 15 mV ($V_0$) was applied and another N.Es was kept at ground ($V = 0$) potential to simulate a 15 mV (RMS) potential gradient across the N.Es. For representing the natural propagation of electric field, the default boundary condition of continuity ($\vec{n}. (D1 - D2) = 0$) was maintained for the internal boundaries.

4. Artificial Neural Network (ANN) Modeling

The RBNN has three layers consisting of an input, a unique hidden layer (function) and an output layer. The input layer is composed of input data and the output layer produces the network response. The function layer is an intermediate layer between the input and the output layer. The activation function of the neurons of the hidden layer is a Gaussian transfer function.

Table 2 Physical and mechanical properties of the BFRP

<table>
<thead>
<tr>
<th>EX</th>
<th>$E_Y = EZ$</th>
<th>$G_{XY} = GXZ$</th>
<th>$G_{YZ}$</th>
<th>$PR_{XY} = PR_{XZ}$</th>
<th>$PR_{YZ}$</th>
<th>$rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>96.74 GPa</td>
<td>22.55 GPa</td>
<td>10.64 GPa</td>
<td>8.73 GPa</td>
<td>0.3</td>
<td>0.6</td>
<td>2700 kg/m³</td>
</tr>
</tbody>
</table>

*Remark: rho is material density, EX, EY, EZ are elastic modulus in the X, Y and Z directions respectively, GXY, GYZ, GXZ are Shear modulus in the XY, YZ and XZ Planes respectively, PRXY, PRYZ, PRXZ are Poisson’s Coefficient in the XY, YZ and XZ Planes respectively*
\[ \Phi(x) = \exp \left[ - \sum_{j=1}^{n} |x_j - c_i|^2 / 2 \sigma_i^2 \right] \] (5)

where \( x \) is the input vector, \( c_i \) is the center of a region called a receptive field, \( \sigma_i \) is the width of the receptive field, \( \Phi(x) \) is the output of the \( i^{th} \) neuron, and \( i \) is the number of neurons.

RBNN Network can learn faster than Feed-Forward Neural Networks (FFNN) and requires less training data. The performance of the RBNN essentially depends on the chosen center where the value of the function is higher and the spread, which indicates the radial distance from the radial basis function (RBF) center, in which the function value resides, is significantly different from zero (Buhmann 2003). The spread value in this work is selected arbitrarily based on the minimum error criteria.

4.2 Performance evaluation measures

It is very useful from the designer’s point of view to have a neural system that helps decide whether its suggested design is appropriate or not by calculating the Mean Square error (MSE) from the equation

\[ \text{MSE} = \frac{1}{n} \sum (E_{ij} - E_{ij})^2 \] (6)

where \( (E_{ij})_{mn} \) the predicted potential differences, \( E_{ij} \) the electric potential differences measured from FE method, and \( n \) is the number of FE measured data values.

Thus, the performance index will have either an overall minimum, depending on the characteristics of the input vectors. The local minimum is the minimum of a function over a limited range of input values. The local minimum is unavoidable when the ANN is installed. Thus, a local minimum may be good or bad depending on the proximity of the local minimum to the global minimum and how much an MSE is required. In any case, the method applied to solve this problem and go down the local minimum with momentum. Momentum allows a network to respond not only to the local gradient, but also to a momentum. Momentum allows a network to respond not only to the local gradient, but also to momentum. Momentum allows a network to respond not only to the local gradient, but also to momentum. Momentum allows a network to respond not only to the local gradient, but also to momentum. Momentum allows a network to respond not only to the local gradient, but also to momentum. Momentum allows a network to respond not only to the local gradient, but also to momentum.

The estimation performances of N.Del location/size is evaluated by the lack of fit with the adjusted coefficient of the multiple determination \( R^2_{adj} \) (Myers and Montgomery 2002, Jang et al. 2014); \( R^2_{adj} \) is defined as

\[ R^2_{adj} = 1 - \frac{SS_G/(n-k-1)}{SS_y/(n-1)} \] (7)

The value of \( R^2_{adj} \) is equal to or less than 1.0. A higher value of \( R^2_{adj} \) implies a better fit. When the ANN shows a very good fit, \( R^2_{adj} \) approaches 1.0. A good fit of the ANN means that the ANN gives good estimates for the change in dielectric properties used for the regression. Lower \( R^2_{adj} \) values mean lower estimations and the error band of the estimated result is wider.

5. Results and discussion

5.1 Convergence study and accuracy

In this subsection, a convergence study is carried out for the proposed method, the differences of electrical potential of delamination between the electrodes due to the delamination are calculated and compared with the experimental results available in the literature. The dataset used for the validation of the presented technique is adapted from Todoroki et al. (2004). The tests were carried out on laminated composite beams made from unidirectional carbon/epoxy (CFRE) layers, the stacking sequence is [0/90]s, and the thickness of the laminates is approximately \( t = 1 \) mm. The volume fraction of fiber is approximately \( V_f = 0.5 \). The beam specimen has a length of 270 mm and a width of 15 mm. Seven electrodes are mounted on the surface of the sample. All of these electrodes are placed on one side of a sample. For the electrode model, the thickness of the electrodes is 10 mm, the space between the electrodes is 45 mm and the limit condition of the electric potential \( V_e = V_0 \) with \(+ 5V\) \((V_0)\). The electrical potential changes of each segment between the electrodes are measured for various cases of location and size of delamination. From the measured data, the relationships between the electrical potential change and the location and size of the delaminations are obtained using the surface response method. Table 3 presents a convergence and comparison study for the proposed method data and the experimental data of Todoroki et al. (2004).

Table 3 presented a comparison between finite element (FE) data and experimental results available in the literature, it can be seen that the numerical results are in excellent agreement with the experimental results of the electrical potential differences of normalization presented by Todoroki et al. (2004). This validates the precision of the technique presented.

5.2 Electrical Potential (EP) technique for Nano-Delamination (N.Del) monitoring

To study the effect of N.Del on the dielectric properties of N.P material, FE analysis of the electric field intensity of the BFRP piping system was performed using commercially available 2D ANSYS software, ANSYS (The Electrostatic Module in the Electromagnetic subsection of ANSYS 2015, Al-Tabey 2012, Altabe et al. 2018a, b). The software calculates the potential and electric field values at the element nodes and interpolates between these nodes to obtain the values of other points in the elements.

The simulations and the potential distribution of the nodes of the N.P before and after the N.Del initiated for the ANSYS 2D simulation, when the N.E (1) is excited, are illustrated in Fig. 2 respectively to the right and to the left. The blue area represents the region of the potential-free N.P i.e., \( \phi = 0 \) but the colored areas represent the region of the N.P having the different potential (different node potential), the area of the electrode can be sensitive or domain detection.
From the FE simulation shown in Fig. 2, we can conclude that this is a significant difference before and after the N.Del introduced into the potential of the node and the intensity of the electric field.

The capacitance values between the N.Es ($C_{ij}$) and the potential differences ($E_{ij}$) of the 2D simulations are calculated before the N.Del$_0$ and after N.Del$_i$, where $i = 1, 2, ..., n$ is the number of scenarios of N.Del (FE models). In general, this study must use at least 66 different FE model of N.Del scenarios (N.Del$_i$) (Eq. (8)) to validate the accuracy and reliability of the proposed technique, which means a great effort and a high cost, also very long time to assess N.Del location/size.

Table 3 Convergence study of normalization electrical potential differences of the CFRE laminated composite beams

| Loca (1) | 127.35 | 113.23 | 81.53 | 68.37 | 18.22 | 7.86 | 19.58 | 67.34 | 97.39 | 108.19 |
| Loca (2) | 127.5 | 113.5 | 82 | 69 | 20 | 8 | 12 | 16 |
| Size (1) | 5.48 | 4.87 | 1.96 | 5.46 | 5.92 | 2.91 | 5.96 | 8.48 | 5.98 | 4.95 |
| Size (2) | 5.5 | 5 | 2 | 5.5 | 6 | 3 | 6 | 8.5 | 6 | 5 |

(1) Proposed method, (2) Todoroki et al. (2004)
\[
M = \frac{N(N - 1)}{2}
\]

where \( N \) is the number of N.Es, and \( M \) is the number of N.Del scenarios.

In this study, an electrical potential (EP) technique is applied with artificial neural networks (ANNs), which are combined to decrease the detection effort to discern the location / size of the N.Del by minimizing the number of FE models in order to keep save the time of the N.Del assessment to a minimum. The method has successfully monitored the N.Del location / size using only four scenarios instead of 66 scenarios, the first scenario (N.Del1) has a size \( \theta = 5^\circ \), is located at \( r = 51 \text{ nm} \) and \( \Psi = 0^\circ \), the second scenario (N.Del2) has the size \( \theta = 10^\circ \), is located at \( r = 51 \text{ nm} \) and \( \Psi = 90^\circ \), the third scenario (N.Del3) has the size \( \theta = 15^\circ \), is located at \( r = 51 \text{ nm} \) and \( \Psi = 180^\circ \) and the final scenario (N.Del4) has the size \( \theta = 20^\circ \), is located at \( r = 51 \text{ nm} \) and \( \Psi = 270^\circ \), respectively, as shown in Table 4.

As shown in Fig. 3 and Table 4 of the node potential differences \( (E_{ij}) \) with different N.Del scenarios when the electrode (1) is excited, we can be seen that the effect of N.Del has occurred on the potential of node distributions the degradation in the potential differences occurred, this degradation is according to the N.E that mounted near the N.Del location occurred (for example the degradation in the value \( E_{1,2} \) is due in the N.Del scenario (N.Del1), value \( E_{1,3} \) is due to the scenario (N.Del2) and the value \( E_{1,10} \) is due to the scenario (N.Del4)), except that the scenario (N.Del2) is influenced by all the values potential differences from \( E_{1,2} \) to \( E_{1,12} \) because the N.Del is located near the N.E (1), and so this behavior will be repeated when the other N.Es are excite (see Fig. 1).

Fig. 4 shows the ECS sensitivity versus N.Del scenarios (N.Del1). The ECS sensitivity is defined as

\[
ECS\ sensitivity\% = \frac{C_{del0} - C_{deli}}{C_{del0}} \times 100
\]

where: \( C_{del0} \) and \( C_{deli} \) are the capacitance measurements for before and after N.Del started respectively.

Fig. 6 The relation between Mean Square error (MSE) and the number of hidden layer neurons
Fig. 7 The relation between Mean Square error (MSE) and selected spread parameters

As shown in Fig. 4, the sensitivity of the ECS depends on the $N.Del$ size ($\theta$), the ECS sensitivity increase with $N.Del$ size increases, the sensitivity of the sensor varies between 6.13 and 26.723% for the scenario ($N.Del_1$) to scenario ($N.Del_4$) respectively and the selected ECS geometry parameters.

**5.3 RBNN structure design and learning**

A RBNN structure is designed based on one input layer, three hidden layers and one output layer respectively as shown in Fig. 1. The first hidden layer with radial basis neurons while the second and third layer with pure linear ones as shown in Fig. 5.

Fig. 8 Training performance of suggested RBNN

Fig. 9 Comparison between the Finite Element (FE) data and Radial Basis neural networks (RBNN) predicted data for nano-delamination scenario ($N.Del_1$)
Learning vectors formed the initial centers of Gaussian RBFs. Determination of the hidden layer, in addition to the number of nodes in the input and output layers, to provide the best training results, was the initial phase of the training procedure. The goal of MSE to reach at the end of the simulations was 0.0001. Since the second step was largely a trial-and-error process, and involved RBNNs with the number of hidden layer neurons more than 13, it did not show any sizeable improvement in prediction accuracy. Thus the number of neurons (the number of RBFs) for the single hidden layer was selected as 13 neurons. Selection of the number of hidden layer neurons, with respect to the MSE term in the presence of different spread parameterized RBNNs is shown in Fig. 6.

Choosing an appropriate spread constant will increase the accuracy of the network. The spread (the width of the RBFs) constant of radial basis function was selected by using Genetic Algorithm (GA). GA may have the tendency to converge towards local optimum (Valle et al. 2008) rather than the global optimum of the problem, if the fitness function is not defined properly. The optimum spread parameter was selected as constant for all group of permittivity, after the trials with the selected hidden layer neurons number, the spread constant was selected as 0.31 as shown in Fig. 7.

5.4 Nano-Delamination (N.Del) location/size estimation using Radial Basis Neural Networks (RBNN)

RBNN is trained by measuring values of \( \Psi \), \( \theta \), \( \varepsilon \) to predict the potential differences (EPD) \( E_{ij} \). In the first RBNN structure is applied for training the data of ECS in Table 4. Fig. 8 shows the training performance of suggested RBNN.

Figs. 9 and 10 represent the comparison between the FE data and the RBNN predicted data for N.Del scenarios (N.Del1) and (N.Del3). The results of the RBNN show much satisfactory predication quality for this case study. The value of mean square error (MSE) between the FE and RBNN predicted data for scenarios (N.Del1) and (N.Del3), in order to obtain the best performances of the present neural network are 0.0964 and 0.044 respectively. The adjusted coefficient \( R^2_{adj} \) of the predicted result is 0.9945 and 0.9985 for scenarios (N.Del1) and (N.Del3) respectively.

Figs. 11 and 12 show the comparison between the FE

![Fig. 10 Comparison between the Finite Element (FE) data and Radial Basis neural networks (RBNN) predicted data for nano-delamination scenario (N.Del3)](image-url)
data and the Radial Basis neural networks (RBNN) expected data for N.Del scenarios (N.Del2) and (N.Del4). From Figs. 11 and 12, we can see the good convergence between the RBNN expected data and FE data. The value of mean square error (MSE) between the RBNN expected data and FE data for scenarios (N.Del2) and (N.Del4), is 0.0695 and 0.0208.

Fig. 11 Comparison between the Finite Element (FE) data and Radial Basis neural networks (RBNN) expected data for nano-delamination scenario (N.Del2)

Fig. 12 Comparison between the Finite Element (FE) data and Radial Basis neural networks (RBNN) expected data for nano-delamination scenario (N.Del4)
Fig. 12 Continued

(a) Location, $\Psi$

(b) Size, $\theta$

Fig. 13 The Radial Basis neural networks (RBNN) Estimation results of nano-delamination (N.Del) in BFRP nano-pipe3 (N.P)
respectively. The $R^2_{adj}$ of the expected result is 0.9978 and 0.9905 for scenarios (N.Del$_i$) and (N.Del$_i$) respectively.

5.5 The use of present RBNN for predicting non-FE data

The main target of artificial neural network design is the prediction of non-FE data. In this section, we will use the suggested RBNN to predict some non-FE data that is not included in the FE assessment. It is selected to use nine random N.Del location / size scenarios for all potential differences (EPD) $E_{ij}$. The three previous parameters $\Psi$, $\theta$, $\epsilon$ are the input vectors for the artificial neural network, while the output is the vector of the signal is the electric potential differences.

Fig. 13 shows the RBNN estimated results of the non-FE N.Del location, $\Psi$ and size, $\theta$. The $R^2_{adj}$ of non-FE result is 0.9733 and 0.9625 for location and size respectively. All of the estimations are plotted on the diagonal line.

The error band is defined as the maximum error of the estimated non-FE N.Del location/size. The error band from the diagonal line is less than 7.75 and 2.25 degrees for location and size, respectively. All of the estimations are plotted on the diagonal line.

The estimated non-FE results of the location $\Psi$ and size $\theta$ by RBNN are presented in Table 5. As a result, a RBNN gave good estimations for non-FE data even for extrapolations N.Del location/size in composite N.P.

6. Conclusions

In the present study, an electrical potential (EP) technique is adopted as an expert system for assessing N.Del location/size in N.P manufactured from Basalt Fiber Reinforced Polymer (BFRP) laminate composite using ECS with ANNs, which are combined to decrease detection effort to discern N.Del location/size inside the N.P layers, in order to keep the cost and save the time of the FE N.Del to keep the cost and save the time of the FE N.Del assessment data to a minimum with high accuracy, simple and low-cost. The results obtained are as follows:

1. Electric potential difference due to different N.Del scenarios can be measured with multiple N.Es mounted on an outer surface of the N.P.

2. The sensor sensitivity and assessment performance was found depend on the N.Del size ($\theta$), as the N.Del size ($\theta$) increases, the sensor sensitivity increased.

3. The methodology has successfully monitored the N.Del location/size using only four scenarios of N.Del location/size are used for training the ANNs to estimate the non-FE results with good performance.

4. The FE results are in excellent agreement with an RBNN results, thus validating the accuracy and reliability of the proposed technique, as shown in Table 5.

5. N.Del size/ location assessment with RBNN can be successfully performed for non-FE N.Del size/ location scenarios in N.P with adjusted coefficient of multiple determination $R^2_{adj}$ is 0. 0.9625 and 0.9733 respectively, see Fig. 13.

6. The electrical potential (EP) technique with ANNs was gave good estimations of non-FE data even for extrapolations within the error band of less than 7.75 and 2.25 degree for N.Del location and size respectively, see Fig. 13.

7. Finally, as a result, the proposed technique was successfully assessing the N.Del for a N.P with low error band, and reduced the scenarios of N.Del to four scenarios only instead of 66 scenarios that must be used in other methods, This represents a significant saving of time and cost reduction associated with the electrical potential (EP) with ANNs method instead of the other methods.

### Table 5: Estimations and errors comparison between RBNN Data (unit degrees)

<table>
<thead>
<tr>
<th>Nano-Delamination Scenario</th>
<th>RBNN Estimated Data</th>
<th>Error of Estimations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>$\Psi$</strong></td>
<td><strong>$\theta$</strong></td>
<td><strong>$\Psi$</strong></td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>5.125$^a$</td>
</tr>
<tr>
<td>6.75</td>
<td>30</td>
<td>7.15$^c$</td>
</tr>
<tr>
<td>8.5</td>
<td>60</td>
<td>8.31$^c$</td>
</tr>
<tr>
<td>10</td>
<td>90</td>
<td>10.666$^b$</td>
</tr>
<tr>
<td>11.75</td>
<td>120</td>
<td>11.02$^c$</td>
</tr>
<tr>
<td>13.5</td>
<td>150</td>
<td>13.21$^c$</td>
</tr>
<tr>
<td>15</td>
<td>180</td>
<td>14.213$^a$</td>
</tr>
<tr>
<td>16.75</td>
<td>210</td>
<td>16.12$^c$</td>
</tr>
<tr>
<td>18.5</td>
<td>240</td>
<td>18.72$^c$</td>
</tr>
<tr>
<td>20</td>
<td>270</td>
<td>21.133$^b$</td>
</tr>
<tr>
<td>21.75</td>
<td>300</td>
<td>22.34$^c$</td>
</tr>
<tr>
<td>23.5</td>
<td>330</td>
<td>23.24$^c$</td>
</tr>
</tbody>
</table>

*a Predicted Data, *b Expected Data, *c Non-FE Data
References


