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To cite this article: M R Prajna et al 2018 J. Phys.: Conf. Ser. 1142 012007

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Machine learning approach for flexural characterization of smart material

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Abstract: The work aims at the comparison of experimental and artificial neural network (ANN) results of smart structures (SWC’s) comprising of three different densities of polyurethane foam (PUF) cored Vinyl ester (VE) SWC’s. As the expected life span of the SWC’s is not properly known yet, the long term durability assessment explores the decay of structural strength of SWC’s. The paper reports the degradation results of PUF cored E-glass mats, i.e., Chopped Strand Stitched Mat (CSM-S) and Stitch Bond Mat (SBM) reinforcement in VE matrix with change in density of PUF for moisture absorption at different temperatures with 95% RH for 180 days. The reduced core shear strength and face bending strength has shown in experimental samples. The verification of the experimental results done using ANN technique with the help of MAT Lab. It is observed that the neural network models are powerful methods for solving the material system issues by determining the complex and nonlinear relationship representing input/output information acquired in the analysis. The observed results infer that the experimental and ANN results are in good convergence.

Keywords: ANN, Smart structures, Core shear strength, bending strength, Degradation.

1 Introduction

The prevalent mechanical properties of the sandwich composites like particular quality, solidness and unbending nature are not by any means the only criteria for the selection of these materials in diverse applications. Additionally, capacity to withstand harsh situations like temperature, moistness and destructive situations dictates their use in real time applications. The toughness of sandwich composites under forceful situations like temperature, humidity, salinity, destructive environment and so on is an essential necessity particularly when these materials are to be utilized under marine ambiance. Be that as it may, it is unfeasible to do constant testing under these conditions as it is not economical [1].

Hence, quickened testing strategies have been connected to think about the solidness of the composites. The life time execution of sandwich composites are unequivocally subject to the properties of the face sheets. Glass reinforced polymer (GRP’s) composites are inclined to degradation when subjected to certain natural conditions [2]. The most broadly acknowledged composite material in the marine fields is FRP because of its toughness, weather ability and cost [3]. In any case, vast scale utilization of FRP is frustrated because of absence of legitimate comprehension of its strength in salt water environment [4, 5, 6, 7]. One of the downsides of plastics in salt water is that the polymer matrix and fiber/network interface get damaged by the hydrolysis [8]. Salt water degradation can bring about swelling and plasticization of polymer network and debonding of the fiber/grid interface that...
may decrease the mechanical properties of the sandwich composites. This issue can be overcome by utilizing vinyl ester based composites that for the most part have predominant substance solidness in marine ambiance [4, 9].

Glass/vinyl ester composites retain their mechanical properties when subjected to sea water for prolonged years [10]. With a specific objective to empower quickened aging can be caused by giving a higher temperature, a higher saline fixation, or a higher measure of mist. In the research performed by Porter and Barnes [11] the accelerate test was conducted by exposing the glass strands to higher pH values and drenching the filaments in a shower at a elevated temperature. It has been demonstrated that sea water submersion and salt-haze introduction are the primary driver of debasement of glass fiber strengthened plastics utilized as a part of maritime applications Aindow et al.[12]. Temperature and stickiness cause hydrothermal crumbling which influences the long haul toughness of the structures. The salt-mist investigations are quickened tests to survey the sturdiness of polymer network composites in marine conditions. Salt-haze can bring about network plasticization at first glance in the underlying stage and harm the interface in the later stage [13, 14]. A specialized report on salt-haze quickened testing of glass fiber reinforced polymer composites has been carried out by Caceres et al. [15]. The salt fog diffusion studies on laminated composites are abundant but the degradation studies on sandwich composites are scare. In the present work salt-fog diffusion test is led to study the strength of sandwich composites, as past studies have demonstrated that it is a standout amongst the most forceful exposures. The composites are orthotropic materials and having dissimilar properties the combination of such would result in an adequate material system. The understanding of such material systems is cumbersome task. Therefore there is a need of computational method to evaluate and verify the materials before they have been selected to the customary applications [16].

Machine learning is a way to deal with design a scrupulous model that permits PCs to collect information without being specifically tailored. It is very easy in large materials data with more properties and using these, predicting the one which has not known. Using known material property estimating the unknown reduced time and cost. There are many algorithms in machine learning. ANN is one such approach which has shown outstanding performance when used with complex linear and non linear material relationships. Artificial neural networks (ANN) have the ability to catch complex input output connections on the premise of experimental data and have been discovered successful in building up a well-mannered belief model for mechanical properties. Use of Artificial Neural Network (ANN) models is considered as a less costly, less monotonous, more productive, and extremely dependable option implies for the estimation of the material weariness properties utilizing the information obtained from the monotonic tests [17]. Besides this, the ANN system was likewise utilized for the parameter estimation identified with the assembling method of materials. The strategy was likewise used to examine and interpret the way in which such material properties are influenced by varieties in the parameters that are the primary administering components of these properties.

In this study the flexural strength of sandwich composites studied. The sandwich composites comprising of three varied densities of polyurethane foams (100, 200 and 300 kg/m³) in vinyl ester matrix with change in test temperature (30°, 40° and 50°C) were assessed for degradation for about 180 days. The primary focus of this article is to predict flexural strength using ANN approach. The results obtained are in good correlation with the experimental data.

2. Materials and Methodology

2.1 Materials

The materials used in the preparation of sandwich composites and their properties presented in Table 2.1 and the Figure 2.1 (a) & (b) shows the various materials and figure 2.1 (c) shows sandwich configuration used in the study.
2.2 Methodology: Long Term Durability tests

The specimens shown in figure 2.2 (a) are studied for long term durability by exposing to salt fog atmosphere. The salt fog chamber Figure 2.2 (b) & (c) of size 0.566 m³ (M/s CM Environ systems, Bangalore) was used to expose the specimens to salt fog as per ASTM B 117. The test specimens were fogged with artificial seawater (salinity 2.9%) and the salt fog chamber being operated at three different temperatures viz. 30°C, 40°C and 50°C and humidity of 95% RH for a maximum duration of 180 days.

The artificial sea water (prepared according to ASTM D1141) is continuously circulated in order to decay. The test samples were regularly measured for the moisture uptake. The percentage mass change in the specimen \( M \) was calculated by the Equation 1.

\[
M = \left( \frac{m_s - m_d}{m_d} \right) \times 100
\]  

Where, \( m_s \) is the mass of the specimen after a given immersion time and \( m_d \) is the original specimen mass. Each test at a specific temperature was performed over a period of 180 days. The test temperatures selected for study are 30°C, 40°C and 50°C. These temperatures are well below the glass transition temperature/degradation of foam and vinyl ester. Specimens were removed at one-month intervals. The flexural test conducted on the specimens to observe the degradation. The properties like core shear strength, facing bending strength were measured for each temperature. The Equation 2.1 gives the face bending strength in any sandwich composites. The ultimate core shear stress is calculated using Equation 2.2, taking maximum peak load from the experiment.
\[
\sigma = \frac{PS}{2r(d + c)b} \quad (2.1)
\]
\[
f_s = \frac{P}{(d + C)b} \quad (2.2)
\]

where:

- \(\sigma\) = Facing Bending Strength, MPa
- \(P\) = Max load prior to failure, N
- \(S\) = span length, mm
- \(t\) = nominal facing thickness, mm
- \(d\) = sandwich thickness, mm
- \(c\) = core thickness, mm
- \(b\) = sandwich width, mm
- \(F_s\) = Core shear ultimate strength, MPa

The experimental data obtained is considered to build ANN model. For the training process, 70% of the data is used as training, 15% for testing and remaining 15% is for validation. The results are discussed in the section 4.2.

3. Artificial neural Network Approach

Artificial neural network is a strategic computing framework made up of various straightforward, profoundly interconnected processing components, which processes the data by their dynamic state as a function of external inputs. Artificial neural systems are utilized as an interdisciplinary tool for numerous sorts of nonlinear applications. Keeping in mind the end result to outline a neural system for a specific issue, one needs a training algorithm [18]. As neural networks task based on samples, it is important to set up an arrangement of illustrations speaking to the issues in the types of framework inputs and yields. Among the training procedure, the weights and biases in the system are acclimated to minimize the error to acquire a better performance. The main components of ANN are processing units, topology and training algorithms. The processing units consists one input, any number of hidden and one output layers. The hidden layer will get the inputs from input layer and it passes the results to the output layer. Choosing the right number of nodes and layers is important; later on when optimizing the neural network to work fairly work for the given problem. There are many training algorithms that can be used. In the present study feed forward network LM algorithm for training is implemented. Because LM training algorithm takes less memory and takes quick time for completing the training process [19, 20].

![Figure 3.1: The typical working model of ANN](image)

The representation of ANN has shown in the figure 2.1. Once the neural system is trained to an agreeable level it might be utilized as an analytical tool on other information. To execute this, the client doesn’t indicate any training rather permits the system to work in forward extended mode as they were. New inputs are displayed to the input pattern where they direct into and are prepared by the hidden layers as if preparing were natural; now the yield is detained and forbids the back propagation. The yield of a forward propagation is the predictable model for the data which can be utilized for further analysis and interpretations [17].

There are different training algorithms utilized as a part of neural system applications. It is regularly not a basic assignment to foresee which of these training algorithms will be the best fit for the issue. Different issues that may likewise be critical could be the data structure and consistency of the training set, as these will influence the framework accuracy and performance. During the preparation procedure, it is vital to refrain from overtraining with an end goal to acquire the best fit.
This is a potential issue with the utilization of capable non-linear regression techniques in neural network demonstration. An over-trained model has a tendency to recollect the relationship amongst input and output variables and thus lacks simplification [19]. For the period of the training session, the network weights are regularly used until the difference between the predicted output and experimental value is minimized. That is the error function defined as the sum of the squares of the difference between predicted and experimental value on all the input patterns reaching a set limit or the number of predetermined training operations or epochs are executed, whichever comes first. The LM algorithm [20] is used for solving the problem of slow convergence of the BP method. The LM method is based on a second order gradient of the network error. The Levenberg–Marquardt training algorithm was indeed found to be the fastest training algorithm to date compared to BP rule which consumes more memory.. Once the training of the network is completed, the ability of the trained neural network to correctly generalize must be checked out using some input-output data which is not incorporated in the training set. This set is commonly known as the test set or validation set. This set is normally prepared by randomly taking some 20 to 25 percent of the original data set. It is noted that each pattern from the validation set must lie within the range defined by the entire training set [21].

4 Results and Discussion

4.1 The Hygrothermal and Diffusion Behavior

The moisture absorption as a function of exposure in days for 100 kg/m³, 200 kg/m³ and 300 kg/m³ PU foam cored CSM-S and SBM sandwich specimens is presented is given Table 4.1. It is observed that the moisture absorption reached a saturation value between 90 to 100 days for all the sandwich composites. Maximum moisture absorption (M∞) by the test specimens at three different temperatures is also shown in Tables 4.1.

Table 4.1: Max. moisture absorption (%) for 100 kg/m³ and 300 kg/m³ of PU foam cored sandwich composites

| Sandwich Type | $M_{\infty}$ at 95% RH (wt %) at 100 kg/m³ | $M_{\infty}$ at 95% RH (wt %) at 300 kg/m³ |
|---------------|------------------------------------------|------------------------------------------|
|               | 30°C          | 40°C          | 50°C          | 30°C          | 40°C          | 50°C          |
| CSM-S         | 1.27          | 1.36          | 1.42          | 1.10          | 1.22          | 1.25          |
| SBM           | 1.35          | 1.70          | 1.99          | 1.14          | 1.28          | 1.43          |

Moisture enters into the composites by the dispersion component and Fick's second law of diffusion has been utilized to examine the dissemination mechanism. Moisture assimilation is a noteworthy hitch of the polymer composites. Consequently, some auxiliary materials are described to disallow the moistness assimilation because of seawater or salt-mist maturing or salt-mist presentation like antacid introduction and concoction presentation, and so forth. As these degradation forms have a tendency to debase their mechanical properties by debilitating the fiber/network bond [22]. The decay because of salt-mist existence in the polymer grid composite is critical due to water retention. Salt water caught in the small scale voids and on the interface is the principle explanation behind the debasement of their mechanical properties. The parameters that influence the water dissemination are volume portion of the fiber, way of the gum framework, temperature, added substances, stickiness, fiber surface interface, fiber size and void volume.

It is observed from Table 4.1, the $M_{\infty}$ decreases with increase in density of the foam core and increases with increase in temperature. Among the 300 series sandwich composites, CSM-S-100 sandwich composites ingested 1.27%, 1.36% and 1.42% though CSM-S-300 sandwich composites demonstrated 1.1%, 1.22% and 1.25% dampness the moisture uptake. Be that as it may, the SBM-100 results in 1.35%, 1.70% and 1.99% against the 1.14%, 1.28 and 1.43% of SBM-300 SWC’s. The rate retention of humidity ($M_{\infty}$) is most noteworthy in SBM and CSM-S sandwich composites reported the least. This might be because of the differed fiber arrangement in these composites. It can likewise property that; the filaments may change the dissemination way of the water atoms in an anisotropic manner by annoying the water from straight dispersion. Since the framework material and the froth
The setback of composites in sea water is breakage of sandwich composites overcome by using of VE (vinylester) composites [4, 9]. The glass ambiance [4, 5, 6, 7] is restricted due to indecent behavior under sea water ambiance [4, 5, 6, 7]. The setback of composites in sea water is breakage of fibre/resin interception due to swelling and cracking leads to weakened physical strength. These observed flaws can be overcome by using of VE (vinylester) composites [4, 9].

The composites subjected to hygrothermal diffusion experience decay in the flexural quality as observed by three point bending tests. The sandwich composites diffuse the humidity and the dampness ingestion is chiefly because of the grid or pitch with the uncovered media. It is seen that the porous strands uptake less humidity [25]. Vinyl ester has a predominant compound dependability, particularly in diffusion and henceforth is the best for the marine applications [26, 27]. Gellet and Turley have done the water inundation aging of glass fiber faceted polymer overlays for marine applications [7,8]. The authors have reported a drop of 15-21% flexural strength of vinyl ester and polyester GRP’s immersed in water and 25% for phenolic GRP’s.

The impacts of ocean water drenching on the toughness of glass/polyster, carbon/polyster, glass/vinylester and carbon/vinylester composites have been studied by Kootsookos and Mouritz [10]. These composites when submerged in salt water at a temperature of 30°C for more than two years, experienced critical dampness retention and endured compound decay of the sap/grid and fiber/network interface area and subsequently suffered in the flexural modulus and quality of the composites. The authors have anticipated the change in the properties of laminates on water ingestion [28].

### 4.2 Degradation in Flexural Strength (CSS &FBS)

Degradation is the debilitation of the quality. The composites subjected to hygrothermal diffusion experience decay in the flexural quality as observed by three point bending tests. The sandwich composites diffuse the humidity and the dampness ingestion is chiefly because of the grid or pitch with the uncovered media. It is seen that the porous strands uptake less humidity [25]. Vinyl ester has a predominant compound dependability, particularly in diffusion and henceforth is the best for the marine applications [26, 27]. Gellet and Turley have done the water inundation aging of glass fiber faceted polymer overlays for marine applications [7,8]. The authors have reported a drop of 15-21% flexural strength of vinyl ester and polyester GRP’s immersed in water and 25% for phenolic GRP’s. The impacts of ocean water drenching on the toughness of glass/polyster, carbon/polyster, glass/vinylester and carbon/vinylester composites have been studied by Kootsookos and Mouritz [10].

From the Table 4.2 it is observe that the CSM-S & SBM fibre faceted sandwich composites showed degradation in flexural strength, due to hygrothermic conditioning. It utilized is the same for every one of the examples, the variety in the measure of assimilation by various sandwich specimens might be because of the variety in the fiber arrangements. SBM mat has 0° or 90° orientations with sewing crosswise over and the customary example is rehashed which advances speedier dispersion of moisture. In CSM-S mats, the strands are haphazardly arranged and are sewed; henceforth the rate of dissemination is less in CSM-S sandwich composites. Additionally, the sporadic course of action of slashed strands alongside sewing smothers the dispersion directs in CSM-S filaments diminishes the procedure of dissemination. The general 0°or 90° orientations of the filaments advance the dispersion along the fiber bearing in SBM sandwich composites. A few researchers have concentrated on the impact of fiber orientations on the humidity dispersion mechanism in the polymer composites. [23,24] have reported that examples with 90° situated strand experienced decay in the properties of the face sheets. SBM mat has 0° or 90° arranged strands particular ingested more elevated amounts of moisture particularly ingested more elevated amounts of diffusion. Thus, higher angle of orientations are desired to lower diffusion rates in composites.

| Composites Type | 300 kg/m³ PU | 100 kg/m³ PU | 300 kg/m³ PU | 100 kg/m³ PU |
|----------------|---------------|---------------|---------------|---------------|
|                | 30°C 40°C 50°C | 30°C 40°C 50°C | 30°C 40°C 50°C | 30°C 40°C 50°C |
| CSM-S          | 6.1 10.7 18.1  | 12.1 15.0 30.1 | 3.99 7.43 12.2  | 20.3 29.7 37.8  |
|                | 5 1 6 5 1 1   |               |               |               |
| SBM            | 16.23.631.7  | 16.623.448.1  | 15.921.225.9  | 25.847.266.3  |
|                | 4 1 4 6 8 1   |               |               |               |

The change in flexural strength of the sandwich composites are detailed in Table 4.2. It is observed that the moisture uptake behavior of the sandwich composites strongly dependent on the properties of the face sheets. It is reported that the glass reinforced polymer composites are prone to degradation when exposed to certain environmental conditions.

But the composites are potential candidate for the structures which are subjected to diverse weather. The most widely accepted composite material in the marine fields is FRP due to its durability, weather ability and cost [3].

However, the wide use of composites is restricted due to indecent behavior under sea water ambiance [4, 5, 6, 7]. The setback of composites in sea water is breakage of fibre/resin interception due to swelling and cracking leads to weakened physical strength. These observed flaws can be overcome by using of VE (vinylester) composites [4, 9]. The glass-vinylester composites shows better properties for many years [10]. From the Table 4.2 it is observe that the CSM-S & SBM fibre faceted sandwich composites showed degradation in flexural strength, due to hygrothermic conditioning. It
was revealed that the bending strength decreases with the increase in the test temperature and the drop in shear and bending strength is found to be predominant in lighter cored composites and the property degradation was higher for SBM facetted composites and least for CSM-S facetted composites. The variation in the strength could be attributed to the moisture uptake and matrix damage.

The comparison of the experimental and predicted results by neural Network showed a good agreement. It is clear that the regression results shown in Table 4.3 shows clear convergence of ANN results with the experimental results. The regression correlation coefficients for CSM-S sandwich composites showed 0.99389 and the best validation performance value observed is 0.01907 at epoch 2 and of SBM revealed 0.83142 and best valid performance being 2.433. The performance graph showed the trained outcomes and is found to be in good consequence with experimental data. The mean square error observed from the ANN results also highlights the acceptance of CSM-S sandwich composites. The experimental results reveal the CSM-S facetted sandwich composites were better material configuration than SBM faceted. The ANN predicted model too revealed the same. Therefore the prediction based on statistical correlation/ANN results can be accepted at 99% confidence level. The network outputs like, mean square error, regression error, performance and correlation coefficient ‘R’ for the different densities like 100 kg/m$^3$, 200 kg/m$^3$ and 300 kg/m$^3$ CSM-S and SBM sandwich composites are detailed in Table 4.3.

| Density (Kg/m$^3$) | Best validation performance | Regression Correlation Coefficient ‘R’ | Mean square Error (MSE) |
|-----------------|-----------------------------|-------------------------------|------------------|
| CSM-S           | SBM                         | CSM-S                         | SBM              |
| 100             | 0.28457                     | 0.21632                       | 0.97939          | 0.9582          | 7.01340e-23    | 1.35458e-26    |
| 200             | 0.056083                    | 1.0817                        | 0.99023          | 0.98862         | 3.398983e-3    | 6.6077e-5      |
| 300             | 0.01907                     | 2.433                         | 0.99389          | 0.83142         | 3.64750e-2     | 4.83029e-6     |

The regression plot in Figures 4.1 and 4.2 shows the output of the network used in the training of the experimental values. If the fit perfect then the outputs are equal to the target sets and the data fall along 45° line. The plots in which the ‘R’ values greater than 0.99 affirms the accepted logical fit. By undergoing change in the initial weights we can also arrive at much higher results so that the network performance can be optimized. The Fig.4.1 and 4.2 shows the best validation performance and regression plots of the CSM-S and SBM sandwich composites for all the chosen densities trained by ANN.

![Regression plots](image)

**Figure 4.1:** Best valid performance and regression analysis plots for experimental and ANN predicted values — CSM-S with verity of densities.
Figure 4.2: Best valid performance and regression analysis plots for experimental and ANN predicted values – SBM with verity of densities.

5. Conclusion
The article claims the advantage of implementing neural network models for the prediction of flexural strength of the sandwich composites. From the analysis we have observed that the flexural behavior of the two types of sandwich composites considered depends on the percentage of moisture absorption. The properties of SBM sandwich compared between 30° degradation to 50° for the face bending strength found to decrease by 53% and core shear strength dropped by 42.78%. The reason for the drop in physical strength could be the moisture uptake and the fiber architecture. The experimental results were compared with ANN methodology using MATLAB. The predicted ANN model merges well with the experimental results. Thus the ANN can be incorporated to outfit the hilarious task of long term experimentations which includes high cost and prolonged testing time. With ANN and experimental observations it is concluded that best performance and regression values obtained are in good agreement test results.

References
1. Manujesh, B.J., Rao, V. and Aan, M.S., 2014. Moisture absorption and mechanical degradation studies of polyurethane foam cored E-glass-reinforced vinyl-ester sandwich composites. Journal of Reinforced Plastics and Composites, 33(5), pp.479-492.
2. Kim, H.Y., Park, Y.H., You, Y.J. and Moon, C.K., 2006. Durability of GFRP composite exposed to various environmental conditions. KSCE Journal of Civil Engineering, 10(4), pp.291-295.
3. Taby, J. and Hoyning, B., 1992, December. Application of multiaxial reinforcements in the marine industry. In La Construction Navale en Composites, Paris (France), 7-9 Dec 1992.
4. Apicella, A., Migliaresi, C., Nicolais, L., Iaccarino, L. and Roccotelli, S., 1983. The water ageing of unsaturated polyester-based composites: influence of resin chemical structure. Composites, 14(4), pp.387-392.
5. Ellis, B. and Found, M.S., 1983. The effects of water absorption on a polyester/chopped strand mat laminate. Composites, 14(3), pp.237-243.
6. Bradley, W.L. and Grant, T.S., 1995. The effect of the moisture absorption on the interfacial strength of polymeric matrix composites. Journal of Materials Science, 30(21), pp.5537-5542.
7. Gellert, E.P. and Turley, D.M., 1999. Seawater immersion ageing of glass-fibre reinforced polymer laminates for marine applications. Composites Part A: Applied Science and Manufacturing, 30(11), pp.1259-1265.
8. Srinivas, M.V., Dvorak, G.J. and Prochazka, P., 1999. Design and fabrication of submerged cylindrical laminates—II. Effect of fiber pre-stress. International journal of solids and structures, 36(26), pp.3945-3976.
9. Dvorak, G.J., Prochazka, P. and Srinivas, M.V., 1999. Design and fabrication of submerged cylindrical laminates—I. International journal of solids and structures, 36(26), pp.3917-3943.
10. Kootsookos, A. and Mouritz, A.P., 2004. Seawater durability of glass-and carbon-polymer composites. Composites Science and Technology, 64(10), pp.1503-1511.
11. Porter, M.L. and Barnes, B.A., 1998, January. Accelerated aging degradation of glass fiber composites. In Second International Conference on Composites in Infrastructure (Vol. 2).
12. Aindow, A.J., Oakley, D.R. and Proctor, B.A., 1984. Comparison of the weathering behaviour of GRC with predictions made from accelerated ageing tests. Cement and Concrete Research, 14(2), pp.271-274.
13. Shen, C.H. and Springer, G.S., 1999. Moisture absorption and desorption of composite materials. Journal of Composite Materials, 10(1), pp.2-20.
14. Roy, S., Xu, W.-X., Park, S.J. and Liechti, K.M., 2000. Anomalous moisture diffusion in viscoelastic polymers: modeling and testing. Journal of Applied Mechanics, 67(2), pp.391-396.
15. Caceres, A., Jamond, R.M., Hoffard, T.A. and Malvar, L.J., 2000. Accelerated Testing of Fiber Reinforced Polymer Matrix Composites–Test Plan. NFESC Special Publication SP-2091-SHR.
16. Sadati, S.H., Kaklar, J.A. and Ghajar, R., 2011. Application of Artificial Neural Networks in the Estimation of Mechanical Properties of Materials. INTECH Open Access Publisher.
17. Atuanya, C.U., Nwobi-Okoye, C.C. and Onukwuli, O.D., 2014. Predicting the mechanical properties of date palm wood fibre-recycled low density polyethylene composite using artificial neural network. International Journal of Mechanical and Materials Engineering, 9(1), pp.1-20.
18. Demuth, H. and Beale, M., 1993. Neural network toolbox for use with MATLAB.
19. Demuth, H.B. and Beale, M.H., 2000. Neural Network Toolbox; for Use with MATLAB; Computation, Visualization, Programming; User’s Guide, Version 4. Math Works.
20. Hagan, M.T. and Menhaj, M.B., 1994. Training feedforward networks with the Marquardt algorithm. IEEE transactions on Neural Networks, 5(6), pp.989-993.
21. Raida, Z., 2002. Modeling EM structures in the neural network toolbox of MATLAB. IEEE Antennas and propagation Magazine, 44(6), pp.46-67.
22. Wong, T.C. and Broutman, L.J., 1985. Moisture diffusion in epoxy resins Part I. Non-Fickian sorption processes. Polymer Engineering & Science, 25(9), pp.521-528.
23. Boukhouida, B.F., Adda-Bedia, E. and Madani, K., 2006. The effect of fiber orientation angle in composite materials on moisture absorption and material degradation after hygrothermal ageing. Composite Structures, 74(4), pp.406-418.
24. De La Osa, O., Alvarez, V. and Avazquez, A., 2006. Effect of hygrothermal history on water and mechanical properties of glass/vinylester composites. Journal of composite materials, 40(22), pp.2009-2023.
25. Choi, H.S., Ahn, K.J., Nam, J.D. and Chun, H.J., 2001. Hygroscopic aspects of epoxy/carbon fiber composite laminates in aircraft environments. Composites Part A: applied science and manufacturing, 32(5), pp.709-720.
26. Thomason, J.L., 1995. The interface region in glass fibre-reinforced epoxy resin composites: 2. Water absorption, voids and the interface. Composites,26(7), pp.477-485.
27. Ishii, O., 1982. Environmental effects on deformation, strength, and degradation of unidirectional glass-fiber-reinforced plastics. II. Experimental study. Polymer Engineering & Science, 15(7), pp.491-499.
28. Pritchard, G. and Speake, S.D., 1987. The use of water absorption kinetic data to predict laminate property changes. Composites, 18(3), pp.227-23