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RNN-BASED STRESS PREDICTION IN LAMINATED COMPOSITE BEAMS UNDER DIFFERENT BOUNDARY CONDITIONS

Fatih KARAÇAM[*1], Emir ÖZTÜRK[2]

[1] *Trakya University, Engineering Faculty, Mechanical Engineering Department, Edirne, TÜRKİYE*
[2] *Trakya University, Engineering Faculty, Computer Engineering Department, Edirne, TÜRKİYE*

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** Corresponding author: fatihkar@trakya.edu.tr*

Abstract
Accurate prediction of stress responses is important for evaluating the mechanical behavior of laminated composite structures under different loading and support conditions. Recurrent neural networks (RNNs) offer a data-driven approach for estimating such responses without repeatedly performing conventional mechanical calculations. In this study, an RNN-based model is employed to predict the normal and shear stresses of laminated composite beams subjected to clamped-clamped (C-C), clamped-free (C-F), and simply supported-simply supported (S-S) boundary conditions. The predicted stress values are compared with the corresponding analytical results. The results show that the prediction performance varies considerably with the boundary condition and stress component. A close agreement between the analytical and predicted normal stresses is observed for the S-S configuration, while larger deviations occur for the C-C and particularly the C-F cases, especially at extreme stress values. The shear stress predictions generally exhibit greater scatter, although better agreement is obtained for the S-S case within the main stress range. These results demonstrate the importance of considering the characteristics of the stress response when applying RNN-based prediction models to laminated composite beams.

Keywords: Laminated composite beam, recurrent neural network, stress prediction, normal stress, shear stress, boundary conditions.

1. INTRODUCTION

Laminated composite materials are widely used in engineering structures because of their high specific strength and stiffness, low weight, and the possibility of tailoring their mechanical properties through appropriate material selection and stacking sequences. Among structural components, laminated composite beams are encountered in various applications where their mechanical response is influenced by laminate configuration, loading conditions, and support constraints. Accurate determination of normal and shear stresses is therefore important for evaluating their structural behavior and providing reliable information for subsequent design and failure analyses. Analytical and numerical methods, particularly finite element analysis (FEA), are commonly employed to determine the mechanical response of laminated composite structures. Although these approaches provide detailed information on stresses, strains, and deformations, repeated analyses involving different material, geometric, loading, or boundary-condition parameters may require considerable computational effort. This has encouraged the development of data-driven surrogate models capable of learning relationships between structural parameters and corresponding mechanical responses. Artificial neural networks and other machine-learning approaches have consequently received increasing attention for the rapid prediction of composite structural behavior after the initial training stage.

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Several studies have demonstrated the potential of machine-learning approaches for laminated composite structures. Tsiatas et al. [1] compared different machine-learning algorithms for predicting the response of laminated composite beams using datasets generated from a higher-order beam formulation. Zhang et al. [2] combined finite element analysis with machine learning to predict the mechanical properties of composite laminates, demonstrating the applicability of neural-network-based surrogate models. Liu et al. [3] employed ANN-based surrogate models for the design optimization of laminated composite structures, reducing the need for repeated computationally expensive structural evaluations. More recently, Jankovic et al. [4] developed an ANN-based tool for predicting several structural quantities of composite laminates, including maximum stress, displacement, strain, and failure-related parameters. Bagherzadeh et al. [5] investigated the prediction of maximum tensile stress in plain-weave composite laminates using machine-learning algorithms and simulation-generated datasets. These studies demonstrate the potential of data-driven models for approximating complex mechanical responses of laminated composite structures.

Recurrent neural networks provide another data-driven framework and have been applied to composite-material problems involving nonlinear, sequential, or history-dependent responses. Al-Assaf and El Kadi [6] employed recurrent neural networks for fatigue-life prediction of composite materials under different loading conditions. Nguyen et al. [7] applied an RNN-based approach to predict the long-term time-dependent mechanical behavior of laminated composite plates subjected to mechanical and hygrothermal effects. Borkowski et al. [8] subsequently developed a physics-informed recurrent neural-network surrogate model for representing the constitutive behavior of woven ceramic matrix composites. More recently, RNNs have also been applied to the prediction of chaotic vibration responses of laminated composite cantilever beams [9]. Together, these studies indicate that recurrent architectures can provide a useful framework for learning complex relationships between input parameters and mechanical responses of composite systems.

Despite these developments, comparatively limited attention has been given to the RNN-based prediction of normal and shear stresses in laminated composite beams while explicitly comparing different boundary conditions. In the present work, an RNN model is employed to predict the stress response of laminated composite beams under clamped-clamped (C-C), clamped-free (C-F), and simply supported-simply supported (S-S) boundary conditions. Both normal and shear stresses are considered, and the predicted values are compared with the corresponding reference results. Particular attention is given to variations in prediction performance among the three boundary conditions and to the ability of the RNN model to reproduce different ranges of stress response.

2. METHODOLOGY

2.1. Laminated Composite Beam Model

A five-layer laminated composite beam with a rectangular cross-section is considered for the generation of the reference stress dataset. The beam has a length "L", total thickness "h", and unit width, with a slenderness ratio of "$L/h = 100$". The coordinate system is defined such that the x −axis coincides with the longitudinal direction of the beam, while the z −axis extends through the thickness, with the reference plane located at the mid-surface. The beam consists of linearly elastic orthotropic layers and is subjected to a uniformly distributed transverse load of "$q = 1000\ N/m$" acting along its entire length. The five-layer configuration and the three boundary conditions considered in the analysis, namely clamped-clamped (C-C), clamped-free (C-F), and simply supported-simply supported (S-S), are schematically illustrated in Fig. 1.

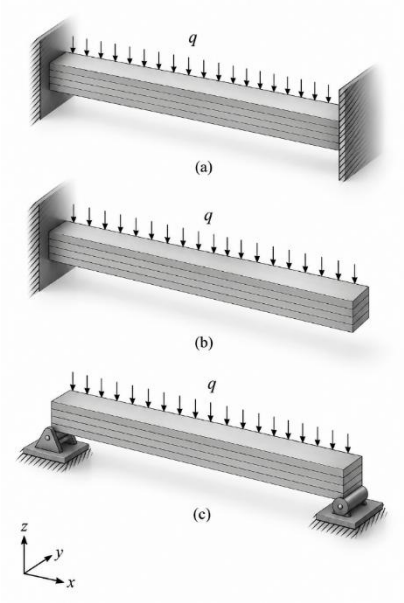


Fig. 1. *Schematic representation of the five-layer laminated composite beam subjected to a uniformly distributed transverse load under different boundary conditions: (a) C-C, (b) C-F, and (c) S-S.*

The mechanical response of the laminated beam is described using a three-degree-of-freedom shear deformation beam theory. The displacement components "U" and "W" in the $x-$ and $z-$directions, respectively, are expressed as

$$U(x,z) = u(x) - z\,w_{,x} + \phi(z)u_1(x)$$
$$W(x,z) = w(x) \tag{1}$$

where "$u(x)$", "$w(x)$", and "$u_1(x)$" are the three unknown displacement functions defined at the middle plane of the beam, and "$,x$" denotes the derivative with respect to "x". The function "$\phi(z)$" is defined as

$$\phi(z) = z\left(1 - \frac{4z^2}{3h^2}\right) \tag{2}$$

where "z" is the thickness coordinate measured from the middle plane. The parabolic shape function "$\phi(z)$" is selected to satisfy the stress-free conditions at the upper and lower surfaces and the continuity of interlaminar stresses through the beam thickness. The non-zero normal and transverse shear strains obtained from the displacement field are expressed as

$$\varepsilon_x = u_{,x} - z\,w_{,xx} + \phi u_{1,x}$$
$$\gamma_{xz} = \left(1 - \frac{4z^2}{h^2}\right)u_1 \tag{3}$$

where "ε_x" and "γ_{xz}" denote the normal strain in the $x-$direction and the transverse shear strain in the $x-z$ plane, respectively. For the kth orthotropic layer, the corresponding normal and transverse shear stresses are obtained from the constitutive relations as

$$\begin{bmatrix}\sigma_x^k \\ \tau_{xz}^k\end{bmatrix} = \begin{bmatrix}Q_{11}^k & 0 \\ 0 & Q_{55}^k\end{bmatrix}\begin{bmatrix}\varepsilon_x \\ \gamma_{xz}\end{bmatrix} \tag{4}$$

where "σ_x^k" and "τ_{xz}^k" are the normal and transverse shear stresses in the kth layer, respectively, while "Q_{11}^k" and "Q_{55}^k" are the corresponding reduced stiffness coefficients of the kth layer, as detailed in Ref. [10]. Based on these constitutive relations, the stress resultants and the governing equations of the laminated beam are obtained using the principle of virtual work. The resulting differential equations are solved analytically by applying the corresponding boundary conditions at "$x = 0$" and "$x = L$". The displacement functions obtained from the analytical solution are then used in Eqs. (3) and (4) to calculate the normal and transverse shear stresses at the specified locations. A graphite/epoxy composite is considered for all layers of the laminated beam. The material properties are $E_{11} = 241.5\ GPa$, $E_{22} = E_{33} = 18.89\ GPa$, $G_{23} = 3.45\ GPa$, $G_{12} = G_{13} = 5.18\ GPa$, $\nu_{23} = 0.25$ and $\nu_{12} = \nu_{13} = 0.24$, where the $1-$, $2-$, and $3-$directions denote the principal material axes of the lamina, with the $1-$direction aligned with the fiber direction. The laminate consists of five layers, and the fiber orientation angles are varied from 0° to 90° in increments of 10°. For each stacking sequence, the normal stresses were determined at "$z = -h/2$", with "$x = 0$" for C-C and C-F and "$x = L/2$" for S-S boundary conditions. The shear stresses were determined at "$z = 0$", with "$x = L/4$" for C-C and C-F and "$x = 0$" for

S-S boundary condition. The stress values obtained for the different stacking sequences and boundary conditions constitute the reference dataset used for the subsequent RNN-based prediction.

2.2. RNN-Based Prediction

The reference datasets generated from the analytical solutions were used to develop the RNN-based stress prediction models. The fiber orientation angles of the five layers, $(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5)$, were used as the input variables, while the corresponding normal or transverse shear stress was considered as the target output. The datasets obtained for the C-C, C-F, and S-S boundary conditions were treated separately to evaluate the prediction performance of the RNN under different support conditions. Prior to training, the dataset was divided into training and test subsets. The RNN was then trained to learn the relationship between the stacking sequence and the corresponding stress response. The main parameters of the RNN model are summarized in Table 1.

Table 1. *Main parameters of the RNN model.*

Parameter	Value
Training–test split	80/20
Number of hidden units	128
Optimizer	AdamW
Number of epochs	500
Batch size	64

3. RESULTS AND DISCUSSION

The performance of the RNN model was evaluated by comparing the predicted normal and transverse shear stresses with the corresponding reference values obtained from the analytical solutions. The results were examined separately for the C-C, C-F, and S-S boundary conditions. Fig. 2 presents the predicted versus analytical normal stress values for all test samples under the three boundary conditions, where the dashed line represents perfect agreement between the predicted and analytical values.

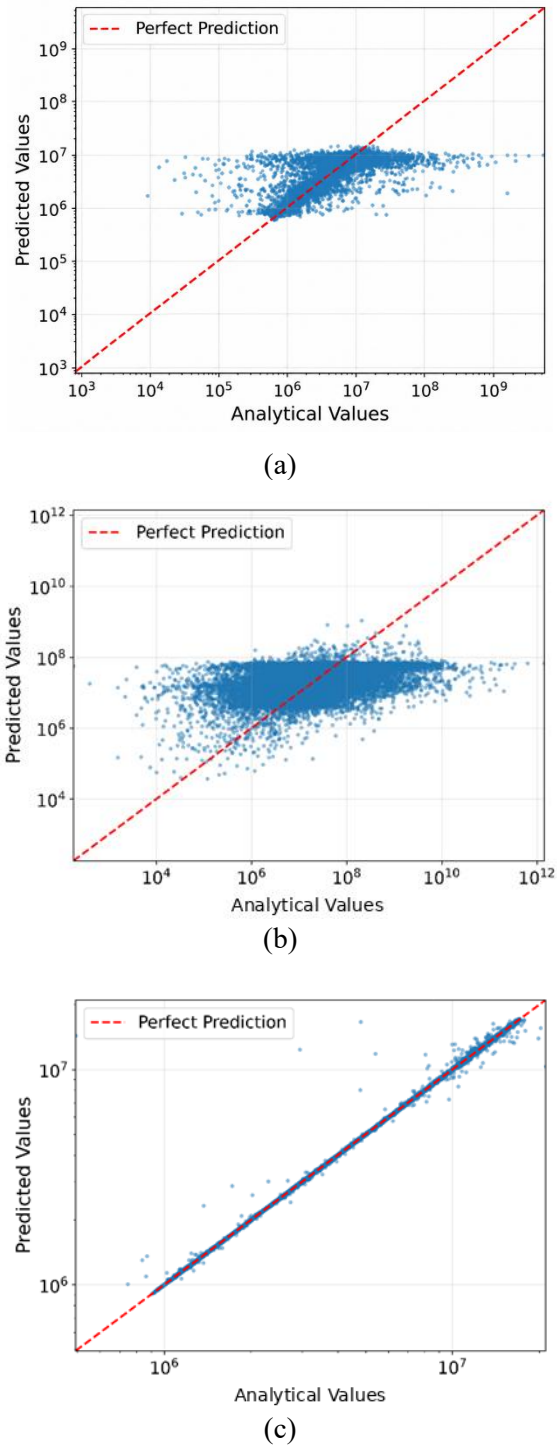
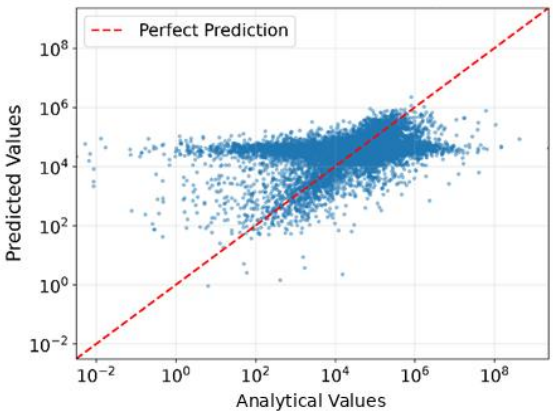


Fig. 2. *Predicted versus analytical normal stress values for different boundary conditions: (a) C-C, (b) C-F, and (c) S-S.*

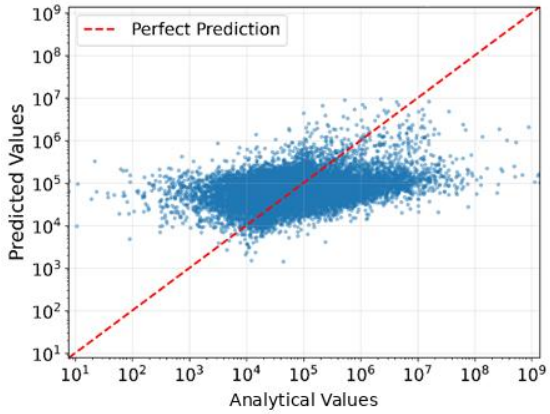
As shown in Fig. 2, the prediction performance of the RNN model varies

considerably among the three boundary conditions. For the C-C case (Fig. 2(a)), the predicted values exhibit noticeable deviations from the perfect-prediction line, particularly as the analytical normal stress increases. Nevertheless, the overall distribution of the predicted values follows the general tendency of the reference data over the main stress range. This behavior becomes more pronounced for the C-F case (Fig. 2(b)), where the analytical stresses span a substantially wider range while the predicted values remain concentrated within a relatively limited range. Consequently, the model is less effective in reproducing the extreme normal stress values under the C-F boundary condition, with the discrepancy becoming particularly evident at the upper end of the stress range. In contrast, the S-S results (Fig. 2(c)) show a close agreement between the predicted and analytical stresses, with most data points distributed along the perfect-prediction line over almost the entire stress range. Only a limited number of scattered points deviate noticeably from this trend. These results indicate that the RNN reproduces the normal stress response most consistently for the S-S case, whereas its prediction accuracy decreases as the range and variability of the stress response increase.

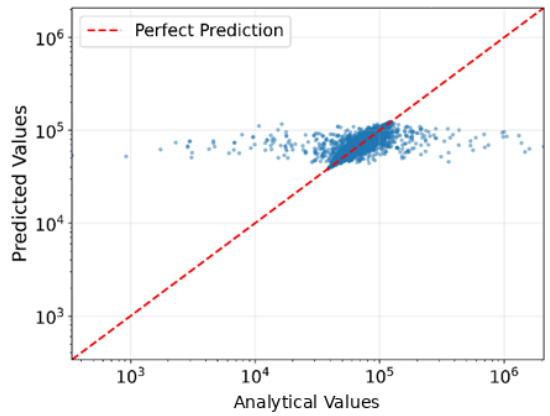
The prediction performance was further examined in terms of transverse shear stress to determine whether the RNN model exhibits a similar behavior for a different stress component. In Fig. 3, the predicted versus analytical transverse shear stress values for all test samples under the C-C, C-F, and S-S boundary conditions are presented. As in the normal stress evaluation, the dashed line represents perfect agreement between the analytical reference values and the RNN predictions. The distributions of the data points relative to this line provide a direct comparison of the model performance for the three boundary conditions.



(a)



(b)



(c)

Fig. 3. *Predicted versus analytical transverse shear stress values for different boundary conditions: (a) C-C, (b) C-F, and (c) S-S.*

As shown in Fig. 3, the transverse shear stress predictions vary considerably among the three boundary conditions. For the C-C and C-F cases (Fig. 3(a) and (b)), the predicted values remain within a relatively

limited range compared with the wider distribution of the analytical stresses, resulting in noticeable deviations from the perfect-prediction line. For the S-S case (Fig. 3(c)), the predictions show closer agreement within the main stress range, although deviations are still observed at lower and higher stress values. Compared with the normal stress results, transverse shear stress prediction is generally more challenging, including for the S-S configuration.

4. CONCLUSION

An RNN model was used to predict the normal and transverse shear stresses of five-layer laminated composite beams under C-C, C-F, and S-S boundary conditions. The normal stress predictions showed the best agreement with the analytical results for the S-S beam, while larger deviations occurred for the C-C and C-F cases, particularly at high stress values. For transverse shear stress, the predictions were generally more scattered, although the S-S case still showed relatively good agreement within the main stress range. The results also showed that the RNN had difficulty reproducing extreme stress values when the analytical results covered a wide range. Therefore, the prediction capability of the model depends not only on the boundary condition but also on the range and distribution of the stress data used for training.

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