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Original Article

Vibration Characteristics Prediction of Functionally Graded Material Plates using FEM and Artificial Neural Networks

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Abstract - *The present work proposes a precision model to predict the frequencies of FGM plates using Artificial Neural Network (ANN). The material properties of the ceramic-metal composite change with the thickness using a power-law distribution. The Finite Element Method (FEM) simulation of bending and shear deformation with Third-Order Shear Deformation Theory (TOSDT) was used to generate a comprehensive dataset and depicts the bending and shear deformation without requiring any shear correction factors. The Levenberg-Marquardt algorithm is used to train a feed-forward back propagation network. The 7-26-2 architecture is determined as the most robust in the systematic optimization of the hidden layer architecture, producing regression coefficients that were above 0.9998 with low Mean Squared Errors. Comparison of results with numerical values of various boundary conditions, including all sides clamped, one side clamped, and the rest of the sides free supported showed very good agreement with minimal deviations. The parametric analysis revealed that both plate thickness and index value of power law are the most significant variables, which have a direct proportional relationship with natural frequencies. Conversely, material gradation index and mass density have a negative correlation with the dynamic response. These findings validate the fact that trained ANN model is a very effective surrogate tool which can be used to make near-instantaneous predictions. The strategy is a valuable and fast evaluation measure of engineering design and optimization of advanced FGM structural components.*

Keywords - *ANN, Functionally Graded Materials, Finite Element Method, Natural frequencies.*

1. Introduction

The use of Functionally Graded Material (FGM) plates in aerospace and mechanical engineering has become more popular in minimising stress concentration using continuously varying material properties. The behavior of vibration of FGM plates is highly influenced by different parameters such as the boundary conditions, aspect ratio, thickness ratio, gradation profile and power law index. The principles of classical and higher-order shear deformation, eigenvalue analysis using the finite element method, have been extensively applied to examine the effects of parameters on FGM plates with great precision. It was, however, noted that these methods are computationally prohibitive with respect to multiple analyses in large parametric spaces. Over the past years, Machine Learning (ML) and Artificial Neural Networks (ANN) have been identified to be effective data-oriented methods to describe nonlinear relationships between parameters and structural responses that are complex. AI and ANN methods provide quicker prediction of natural frequencies by providing efficient surrogate models without needing to solve governing equations or eigenvalue problems repeatedly. Being driven by these benefits and the fact that few studies have explored the application of AI ANN technology to vibration characteristics of FGM plates and considered multiple boundary conditions and material parameters simultaneously, the current study aims at predicting vibration characteristics of FGM plates with high precision and significantly lower computational cost.

First, plate-like structural components vibration analysis was conducted through the classical Kirchhoff plate theory, which does not consider shear deformation, and can only be used with thin plates. The necessity to remove the restriction of the Kirchhoff plate theory resulted in the creation of the First-Order Shear Deformation Theory (FSDT) and, subsequently, the Higher-Order Shear Deformation Theories (HSDT), which are more precise and dependable without having to use shear correction factors. One of the most significant advances was Reddy (2000), who solved the problem of FGM plates with power-law material gradation, thermomechanical coupling, time dependence, and geometric nonlinearity, by the application of the Third-Order Shear Deformation Theory (TSDT) and by the use of the Navier and finite element methods, the solution of which was the basis of subsequent analyses. Talha and Singh (2010) also indicated that HSDT was effective in obtaining the free vibration and the statical response of FGM plates where the gradation of the material, ratio of thickness and the boundary conditions had a strong impact on natural frequencies. Other higher-order models and improvements were later documented by Abrate (2006), and Reddy et al. (2000), the need to have refined kinematic models to predict vibrations accurately in moderately thick and thick FGM plates.

Precise and semi-analytic solutions are important in checking up numerical and approximate methods. Vel and Batra (2004) developed a three-dimensional accurate solution of free and forced vibration of simply supported FGM rectangular plates, which can be used in both thin and thick plates. Their findings demonstrated the constraints of CPT and FSDT as the material gradients or thickness get larger. Batra and Jin (2005) applied vibration analysis to anisotropic FGM plates, noting the effects of stiffness coupling by anisotropy of the material. Efraim and Eisenberger developed precise solutions of isotropic annular plates and FGM plates with variable thickness, taking into account the interactions of variation of thickness, material gradation and boundary conditions. These articles are essential sources of justifying FEM, meshless, and data-driven simulations.

The vibration analysis of FGM plates, using Finite Element Methods (FEM), has been extensively used with complex geometries and boundary conditions. Singha et al. suggested a finite element formulation based on FSDT with the consideration of the precise location of the neutral surface and nonlinear effects. Zghal and Dammak (2021) presented advanced shell and plate formulations, proposing an enhanced finite shell element of porous FGM plates and shells with a quadratic shear strain function, removing shear correction factors. This was further applied to thermal free vibration analysis of FGM plates and panels (Zghal et al. 2021). Curved and shell-type FGM structures have also been investigated. Pradyumna and Bandyopadhyay (2008) analyzed free vibration of FGM curved panels using a higher-order finite element formulation. Mohammad Zannon et al. (2020) studied thick FGM spherical shells using TSDT under simply supported and clamped boundary conditions.

Recent studies have also focused on porosity, grading patterns, and thermal conditions. For instance, Xuchu Hu, and Tao Fu (2023) studied the free vibration problem of porous FGM plates under different porosity distributions and grading functions, and they concluded that uneven porosity and sigmoid functions significantly affect frequency characteristics. Zghal et al. (2021) studied temperature-dependent material properties in vibration analysis for FGM plates and panels, and they concluded that temperature has a significant effect on vibration response. Kareem et al. (2025) proposed a new trigonometric displacement function for free vibration analysis of FGM plates, and they compared the results with ANSYS and literature, achieving satisfactory results. Dongze et al. (2025) analyzed vibration characteristics of FGM double-layered cabin-like structures using a Spectro-geometric method, further extending vibration analysis to complex FGM assemblies.

Recent developments have demonstrated the growing importance of artificial intelligence in structural dynamics and vibration prediction. Deep learning, support vector regression, random forest regression, and artificial neural networks have increasingly been employed as surrogate models for computational mechanics problems because of their capability to capture highly nonlinear relationships between structural parameters and dynamic responses. Recent studies by Plevris and Papazafeiropoulos (2024), Spencer Jr et al. (2025), and Scarselli and Nicassio (2025) have emphasized the role of AI in structural health monitoring, digital twins, and predictive maintenance for aerospace and civil infrastructure.

Artificial Intelligence (AI) techniques were initially introduced in civil engineering through vibration-based Structural Health Monitoring (SHM). Neves et al. (2017) proposed a model-free ANN framework for bridge SHM, demonstrating direct damage detection from vibration data. Kourehli (2018) applied least-squares SVM to predict unmeasured mode shapes and detect damage under incomplete modal information. Ghiasi et al. (2018) showed that AI-based models outperform traditional metamodels for nonlinear structural behavior. Improved ANN performance using cuckoo search optimization, while applied ANN models to steel-concrete composite bridges, confirming high sensitivity to stiffness degradation. A comprehensive transition from traditional methods to ML and DL was reviewed by Avci et al. (2021).

Smola and Schölkopf (2004) formalized support vectors regression and improved it by universal kernels by Üstün et al., (2006). Janane Allah et al. (2023) used TSDT, FEM and ANN to predict natural frequencies of FGM plates with high accuracy and low cost of computation. Murat Çelik et al. (2024) validated ANN-based frequency prediction of FGM beams. Mohamed and Kebdani (2022), Domagalski and Kowalczyk (2026) revealed ANN surrogate models used to predict vibrations of cutouts and variable-thickness plates, which allows effective optimization processes. Uncertainty-aware vibration prediction was addressed by Thakkar and Karsh (2025) using ML surrogates trained on Monte Carlo simulation data. Ammu Boban et al. (2024) extended ML-based vibration prediction to confined geomaterials under dynamic loading.

Recent reviews have also emphasized the growing capabilities of AI technology for SHM and vibration analysis. For instance, Plevris and Papazafeiropoulos (2024) have emphasized the predictive maintenance capabilities and intelligent sensor networks through AI technology. Spencer Jr. et al. (2025) have also discussed the evolution of SHM, including vibration analysis, and the emergence of vision-based and digital twin SHM. Scarselli and Nicassio (2025) have also presented a review on AI-based SHM for aerospace applications, including challenges faced due to a lack of data and interpretability.

A few studies have examined vibration characteristics of Functionally Graded Material (FGM) plates with finite element analysis methods, and a few prediction models have been developed based on Artificial Neural Networks (ANN), but most of them are limited to some of the boundary conditions, simplified gradation of material or a small number of design variables. Moreover, the development of comprehensive surrogate models that can predict the natural frequencies when subjected to various boundary conditions with respect to low computation cost is not popular.

It is seen that, therefore, the present study develops an optimized ANN model that is trained using TSDT-based FEM simulation and predict the natural frequencies of the FGM plates accurately and quickly for a wide range of FGM material and geometric parameters. Despite these advances, systematic AI/ANN-based prediction of vibration characteristics of FGM plates considering boundary conditions (CCCC and CFFF), aspect ratio, thickness ratio, material gradation, porosity, and power-law index in a unified framework remains limited. This area motivates the present study.

1.1. Novelty of the Present Study

- Consolidation of a common FEM-ANN approach based on the Third-Order Shear Deformation Theory.
- Optimization of ANN architecture (7-26-2) for the accurate prediction of the first two natural frequencies.
- Multi-parameter geometric, material and boundary conditions optimization simultaneously.
- The significant reduction of computational efforts with respect to repeated FEM simulations and the good predicting accuracy.

2. Materials and Methods

As illustrated in Figure 1, the current study takes into consideration a quadrilateral FGM plate with span a, breadth b, and depth h. The ceramic-metal composition that makes up the plate has measurable characteristics that gradually change along the thickness direction and can be interpreted as a power-law dispersion.

Young's modulus E(z), mass density ρ(z), and Poisson's ratio v(z) are examples of the actual material qualities that are expressed as purposes of the depth direct z with the power index. Changes in the power index can thus provide different gradations from a high ceramic composition to a high metal composition.

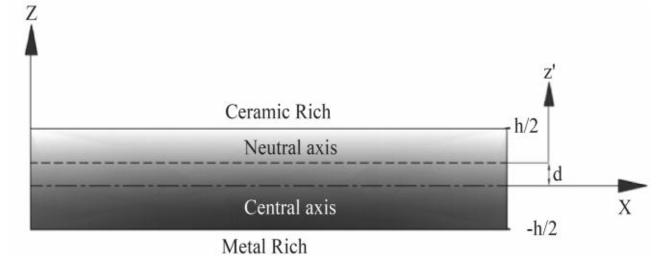

Fig. 1 The design of FG material circulation along the depth of the plate

The modest power rule for changing ceramic size portion labelled as:

$$V_c(z) = \left(\frac{1}{2} + \frac{z}{h}\right)^k, 0 \leq k \leq \infty \tag{1}$$

where k index value of power law.

The following modest rule of combination is used to obtain the active material properties:

$$P(z) = P_c(z)V_c(z) + P_m(z)V_m(z) \tag{2}$$

where the metal and ceramic material components are located roughly at position z of the plate's impartial level that contains FGM material. The active material property, denoted as P (z), could be the FGM plate's mass density (ρ), coefficient of moisture expansion (Poisson's ratio v), or elasticity of modulus (E).

2.1. Finite Element Formulation based on Third-Order Shear Deformation Theory

It uses the Third-Order Shear Deformation Theory (TSDT) to do the free vibration analysis of the FGM plates. This concept takes into account the consequences of transverse shear deformation without needing shear correction factors. This hypothesis is notably useful when investigating thin and moderately thick plates that have different material properties.

The basic constative relation of plate elements is based on the higher progression shear deformation condition. The normal and transverse displacement components of the plate's in-plane transposition components can be written as.

$$u = u_n + z\theta_x - c_1 z^3(\theta_x + w_{n,x}),$$

$$v = v_n + z\theta_y - c_1 z^3(\theta_y + w_{n,y})$$

$$w = w_n \tag{3}$$

where show the displacements with regard to the plate's inactive face and also indicate the functions of x and y. θ_x and $_y$, as a result, are the transverse rotation common about the y and x axes are the rotation of transverse common about the y- and x- axis, consequently.

A four-node quadrilateral plate element is employed in the finite element discretization. Each node possesses seven degrees of freedom, representing the in-plane displacements, transverse displacement, and rotations of the plate mid-surface. The displacement field is defined in accordance with TSDT assumptions, ensuring a realistic representation of bending and shear deformation across the plate thickness.

The in-plane and transverse shear strain displacement relationships are still expressed as follows:

$$\begin{Bmatrix} \varepsilon_x \\ \varepsilon_y \\ \varepsilon_{xy} \end{Bmatrix} = \begin{Bmatrix} \varepsilon_x^{(n)} \\ \varepsilon_y^{(n)} \\ \varepsilon_{xy}^{(n)} \end{Bmatrix} + z \begin{Bmatrix} \varepsilon_x^{(1)} \\ \varepsilon_y^{(1)} \\ \varepsilon_{xy}^{(1)} \end{Bmatrix} - z^3 \begin{Bmatrix} \varepsilon_x^{(3)} \\ \varepsilon_y^{(3)} \\ \varepsilon_{xy}^{(3)} \end{Bmatrix} \quad (4)$$

$$\begin{Bmatrix} \gamma_{yz} \\ \gamma_{xz} \end{Bmatrix} = \begin{Bmatrix} \gamma_{yz}^{(n)} \\ \gamma_{xz}^{(n)} \end{Bmatrix} + z^2 \begin{Bmatrix} \gamma_{yz}^{(3)} \\ \gamma_{xz}^{(3)} \end{Bmatrix} \quad (5)$$

As seen in Figure 2, a rectangular element with four nodes was used in the finite element process to analyze the FGM plate model. There are seven degrees of freedom in each node. The oblique displacement and rotation with the corresponding x and y axes are represented by the normal displacement fields, u, v, and w. The inclinations about the x and y axes are similarly represented.

$$u = \sum_{i=1}^{4} N_i\, u_i, v = \sum_{i=1}^{4} N_i\, v_i, w = \sum_{i=1}^{4} N_i\, w_i,$$

$$\theta_x = \sum_{i=1}^{4} N_i\, \theta_x^i, \theta_y = \sum_{i=1}^{4} N_i\, \theta_y^i,$$

$$\frac{\partial w}{\partial x} = \sum_{i=1}^{4} N_i \frac{\partial w_i}{\partial x}, \frac{\partial w}{\partial y} = \sum_{i=1}^{4} N_i \frac{\partial w_i}{\partial y} \quad (6)$$

Where,

$$\{q_{(e)}\} = \left\{u_i\; v_i\; w_i\; \theta_x^i\; \theta_y^i, \frac{\partial w_i}{\partial x}, \frac{\partial w_i}{\partial y}\right\}_{i=1,2,3,4}$$

node displacement vector.

$N_i, i = 1,2,3,4$ denote the element nodal shape functions.

The element shape function $[N]$can be expressed as

$$[N] = \begin{Bmatrix} [N_{u_n}][N_{v_n}][N_{w_n}] \\ [N_{\theta_x}]\,[N_{\theta_y}] \\ \left[N_{\frac{\partial w}{\partial x}}\right]\left[N_{\frac{\partial w}{\partial y}}\right] \end{Bmatrix}^T \quad (7)$$

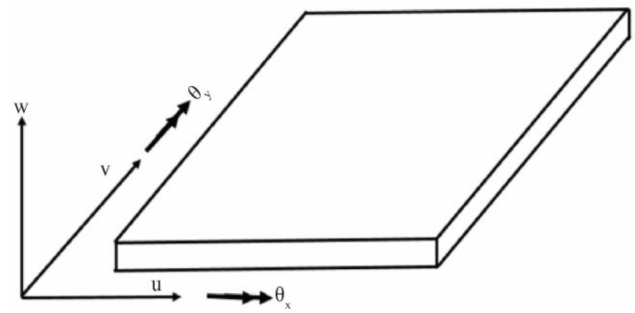

Fig. 2 Rectangular element geometry

By using the higher-order shear deformation condition, the vibratory stresses of the plate element in strain energy can be expressed as:

$$U_{PT}^{(e)} = \frac{1}{2}\{q_{(e)}\}^T\left([K_{(bd)}^{(e)}] + [K_{(sh)}^{(e)}]\right)\{q_{(e)}\} \quad (8)$$

The stiffness matrix of the element can be determined as

$$[K_{(e)}] = [K_{(bd)}^{(e)}] + [K_{(sh)}^{(e)}] \quad (9)$$

The plate element kinetic energy is derived as

$$T^{(el)} = \frac{1}{2}\left[\left\{q_{(e)}\right\}^T [M_{(el)}]\left\{q_{(e)}\right\}\right] \quad (10)$$

where $[M_{(e)}]$ is the matrix of element mass.

A governing equation development of the FGM plate element is represented as:

$$[K_e^e]\{q^e\} - \omega^2[M^e]\{q^e\} = 0 \quad (11)$$

3. Artificial Neural Network Architecture and Training

First and second natural frequencies of FGM plates were predicted using a feed-forward backpropagation ANN, shown in Figure 3. The network had seven input neurons representing Young's modulus (E), density (ρ), Poisson's ratio (ν), power-law index (k), plate length (a), plate width (b), and plate thickness (h), and two output neurons corresponding to the natural frequencies. The Levenberg-Marquardt algorithm was used to train a single hidden layer with a tangent sigmoid (tansig) activation function, and a linear (purelin) output layer. To avoid overfitting, the collected set of 494 samples generated by the FEM were randomly split in three parts: 70% to train the network, 15% to validate the network, and 15% to test the network. Different numbers of hidden neurons (2-34) were used to examine the optimal architecture. The results of Table 1 show that prediction accuracy increased as the number of hidden neurons was increased, with the optimum accuracy obtained at 7-26-2 stage. The regression coefficient was greater than 0.9998, and the prediction error was minimum for all data sets for the optimum architecture 7-26-2. A slight decrease in performance for larger networks (e.g., 7-34-2) suggests that greater network complexity is not associated with better generalization. The results demonstrated that an optimized ANN is able to capture the nonlinear relationship between the input parameters and the vibration characteristics of FGM plates correctly.

The model of FNNN that has an input layer and a hidden layer is based on the following equation.

$$\varsigma^2 = \varphi^2\left[\sum_{i=1}^{n}\Omega_{1i}^2\varphi^1\left\{\sum_{j=1}^{m}\Omega_{j1}^1 x_j + a_i^1\right\} + a^2\right] \tag{12}$$

where ς represents the total output of the network. Consequently, φ^2 and φ^1 are the activation functions of the output layer and the hidden layer, respectively. n and m are the number of inputs and neurons in the hidden layer, respectively. The bias of the neuron in the output layer is represented by a^2. The associated weight between the ith hidden layer resource and the neuron in the output layer is Ω_{1i}.

MSE and the regression correlation coefficient (R) are used to test the convergence of ANN results:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \dot{x})^2 \quad R = \{1 - (\sum_{i=1}^{N}(x_i - \dot{x})^2)/(\sum_{i=1}^{N}(x_i - \ddot{x})^2)\}^{1/2} \tag{13}$$

where x is the actual value, $\dot{x}$ is the predicted value of x, and $\ddot{x}$ is the mean value of x.

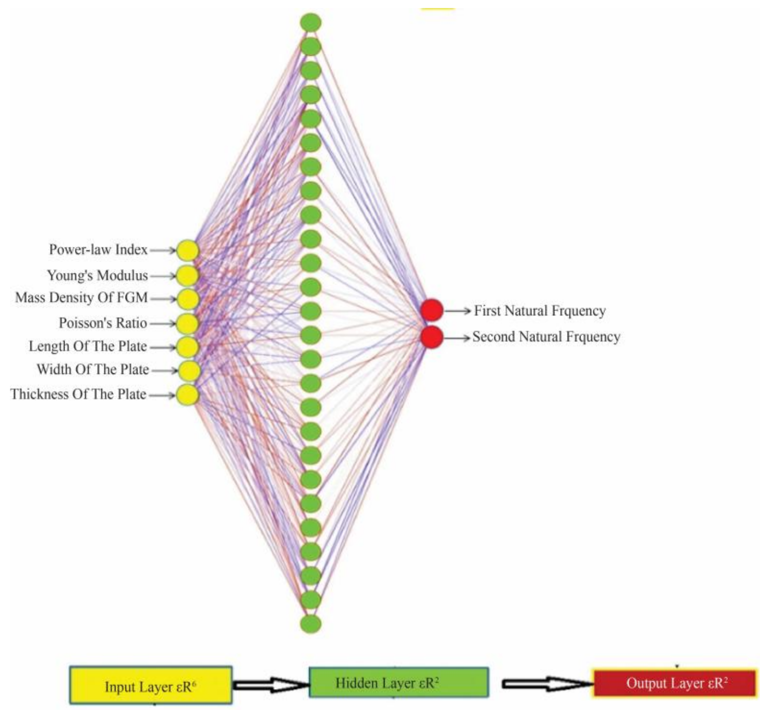

Fig. 3 Layered architecture of the proposed artificial neural network model

A feed-forward backpropagation ANN is used in the current work to estimate the first and second natural frequencies of plates of functionally graded material with all edges clamped, and all sides simply supported boundary conditions. The ANN model acts as a surrogate predictor that learns the complex relationship between material properties, geometric parameters, and vibration characteristics, thereby eliminating the need for repeated computationally expensive numerical simulations.

3.1. Dataset Generation for ANN

The input parameters used in the ANN were chosen as they have significant effects on the dynamic behaviour of FGM plates, such as Young's modulus (E), density (ρ), Poisson's ratio (ν), power-law index (k), length of the plate (a), width of the plate (b), and thickness of the plate (h). The output layer was composed of 2 neurons, corresponding to the first (ω_1) and second (ω_2) natural frequencies for the CCCC boundary condition and CFFF boundary condition, respectively. The dataset was produced by systematically varying the material properties, geometric parameters and boundary conditions in 494 simulation cases with the use of the Third-Order Shear Deformation Theory (TSDT) based finite element simulations. All the input variables were normalized before training to improve convergence and numerical stability. To prevent data leakage and ensure an unbiased evaluation of the model, the data was randomly split into three groups: 70% for training, 15% for validation, and 15% for testing. To avoid overfitting, the early stopping technique using validation performance was used, and the results of training, validation and testing were also well matched, which certified the excellent generalization capability of the developed ANN model. Matlab was used for all the ANN analyses.

4. Results and Discussion

The ANN model proposed was tested in relation to the prediction of the first and second natural frequency of FGM plates. To do this, the proposed model had seven input parameters, i.e. Poisson ratio (ν), gradation index of material (k), Young modulus (E), density (ρ) and geometric parameters, i.e. the length, width and thickness of the plate, with two output parameters using the first and second natural frequency. The systematically varied number of neurons in the hidden layer was used to find the optimal architecture form of 7-n-2.

4.1. ANN Architecture

Effects of the number of hidden neurons on the prediction potential of the ANN model have been given in Table 1 in form of Mean Squared Error (MSE) and regression coefficient (R). The clear conclusion is that the performance of the model becomes much better with the number of hidden neurons increasing to some optimum level.

For the low neuron configurations (7-2-2, 7-4-2), the model shows high values of MSE (on the order of 10^6) along with low regression values ($R \approx 0.98$). With the increased number of neurons (from 7-6-2 to 7-12-2), the values of MSE reduce significantly, along with the improvement in regression values ($R > 0.999$).

As presented in Table 1, low-neuron configurations (e.g., 7-2-2) failed to accurately map the data. The best network performance is noted for configurations such as 7-24-2, 7-26-2, and 7-30-2, wherein the MSE values show the minimum values and regression coefficients tend to unity ($R \approx 0.9998$ to 0.99986) for all the training, validation, and testing datasets. This shows that the ANN model is effectively capturing the complex relationships involved in the dynamic behavior of the FGM plates. But, a slightly decreased network performance is noted for higher neuron configurations, such as 7-34-2.

Table 1. Performance Evaluation (MSE and Regression Coefficient) for Varying Hidden Layer Neurons in the ANN Model

ANN Structure	Training	Validation	Test	All
7-2-2	0.98403	0.99051	0.98451	0.98488
7-4-2	0.98556	0.97819	0.98112	0.98407
7-6-2	0.99631	0.9953	0.99559	0.99605
7-8-2	0.99789	0.99729	0.99724	0.99773
7-10-2	0.99859	0.99699	0.9976	0.99826
7-12-2	0.99939	0.99907	0.99913	0.99931
7-14-2	0.99941	0.99842	0.99925	0.99923
7-16-2	0.99969	0.99966	0.9992	0.9996
7-18-2	0.99974	0.9997	0.99926	0.99964
7-20-2	0.9997	0.99949	0.99966	0.99967
7-22-2	0.9995	0.99869	0.99915	0.99932
7-24-2	0.99984	0.99925	0.99976	0.99974
7-26-2	**0.99987**	**0.99982**	**0.99986**	**0.99986**
7-28-2	0.9997	0.99909	0.99907	0.99952
7-30-2	0.99986	0.99979	0.99971	0.99983
7-32-2	0.99946	0.99915	0.99895	0.99935
7-34-2	0.99976	0.99666	0.99531	0.99856

4.2. Model Accuracy and Generalization

The trained ANN framework could then be retrained with data generated to different material systems, loading conditions, shell geometry and boundary conditions to enable its application to a wide range of FGM structures.

Regression coefficients (R) of training, validation, and test data are always near unity ($R > 0.999$), which means that there is an excellent correlation between predicted and numerical values. In addition, the low MSE values also confirm the high precision of the model. Figure 4 determines the ANN model performance, in relation to MSE, with respect to training epochs. The network had a high convergence rate, with the highest validation accuracy of 36694.48 at epoch 91. This close monitoring of the training, validation and testing curves means that the model is well-generalized and stable. The findings clearly show that the ANN model is an effective alternative to traditional numerical models in predicting the natural frequencies of FGM plates. Although the method of finite element analysis is accurate, it is time-consuming and computationally intensive. On the contrary, the already trained ANN model can make fast predictions with the same accuracy.

The paper has emphasized the need to identify an optimal network structure, especially the size of the hidden neurons, to attain accuracy and generalization. The study has also confirmed that the ANN models are highly suitable for dealing with complex nonlinear relationships, as encountered in structural vibration problems.

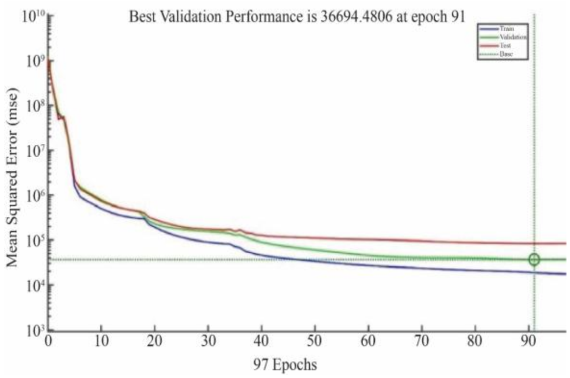

Fig. 4 ANN Model performance on the training dataset

4.3. Regression Analysis of ANN Predictions

Furthermore, the performance of the optimized ANN model in predicting the data is assessed using regression analysis of the training, validation, testing, and combined sets of data, as shown in Fig. 5 below. From the regression plots above, there is a high correlation between the target values generated from the FEM model and the predicted ANN values. The predicted values match the target values well for all data subsets, which shows that the ANN model has been successful in capturing the relation between the inputs and first and second natural frequencies of the FGM plates. The regression analysis results of the training, validation, testing, and combined data sets have indicated the same consistent performance in prediction. The closeness of the target and predicted values indicates the accuracy of the optimized ANN architecture in predicting the data used in this research. Therefore, regression analysis performed in Fig. 5 supports the performance of the optimized ANN architecture of 7–26–2 in predicting the first and second natural frequencies of FGM plates.

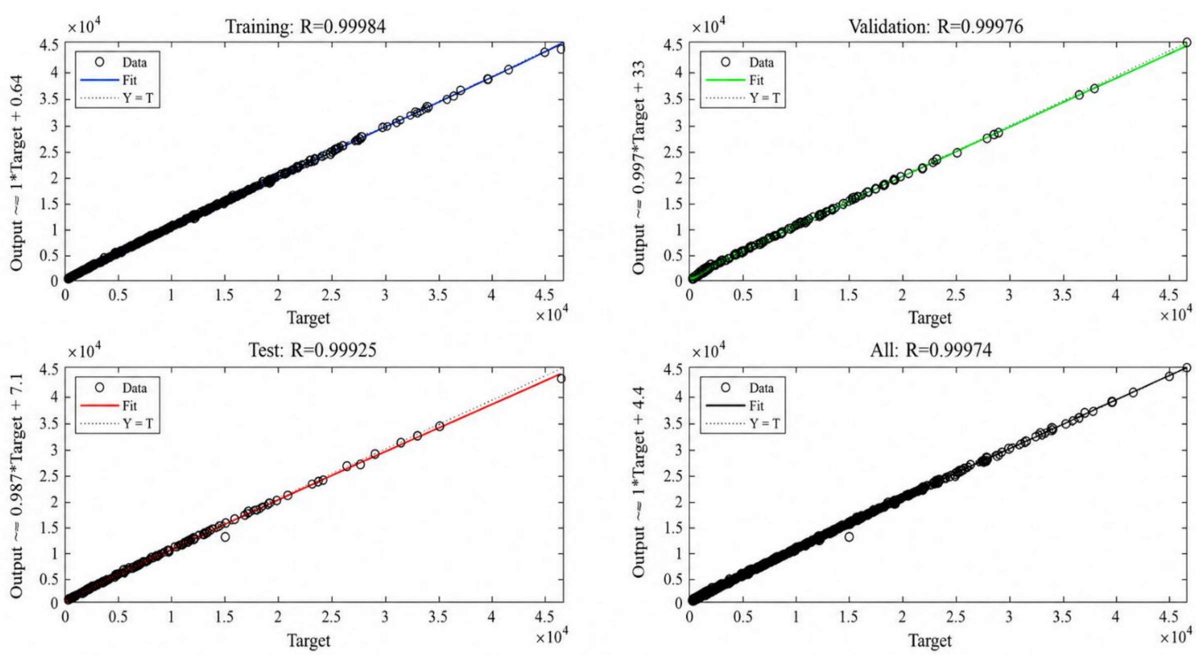

Fig. 5 Regression analysis of ANN predictions across training, validation, test, and combined datasets

4.4. Comparison Between Numerical and ANN Results

A direct comparison between the FEM results and the ANN predictions are performed for the first and second natural frequencies under different boundary conditions.

4.4.1. CFFF Boundary Condition

Comparisons between the FEM results and the results predicted by the optimized ANN model for the first and second natural frequencies are presented in Figures 6 and 7, respectively, for CFFF boundary conditions. It is evident from the two figures that the variation predicted by the ANN model follows the same trend observed in the corresponding FEM results. The close matching between the two datasets implies that the ANN model accurately captures the variation of natural frequency with respect to the material and geometry of the FGM plate. In Figure 6, it is observed that the predictions obtained using the ANN model follow the variation of the FEM results for the first natural frequency. The prediction of the second natural frequency by the ANN model is also depicted in Figure 7, where similar trends have been followed. Some discrepancies may exist between the two sets of results, but in general, the ANN model successfully predicts both vibration modes with the CFFF boundary conditions.

4.4.2. CCCC Boundary Condition

Comparison between the FEM and ANN results of the first and second natural frequencies for the case of CCCC boundary condition can be seen in Figures 8 and 9, respectively. It is clear that the ANN results are in good agreement with the FEM results and represent the variation in both modes of vibration very well.From the comparison presented above, it can be concluded that the trained ANN model is able to predict the natural frequencies of FGM plates with both boundary conditions, i.e., CFFF and CCCC, within the range of input data used in the training and testing processes.

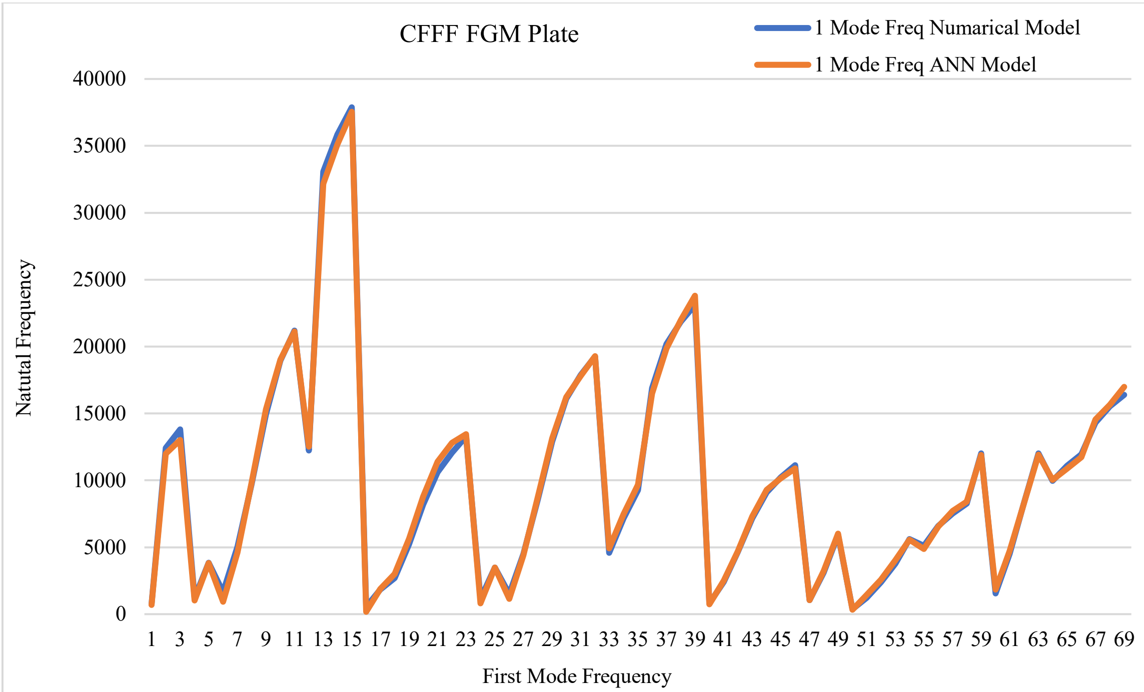

Fig. 6 Comparison of first mode natural frequency of FGM Plate between numerical model and ANN Model (7-26-2) under CFFF boundary condition

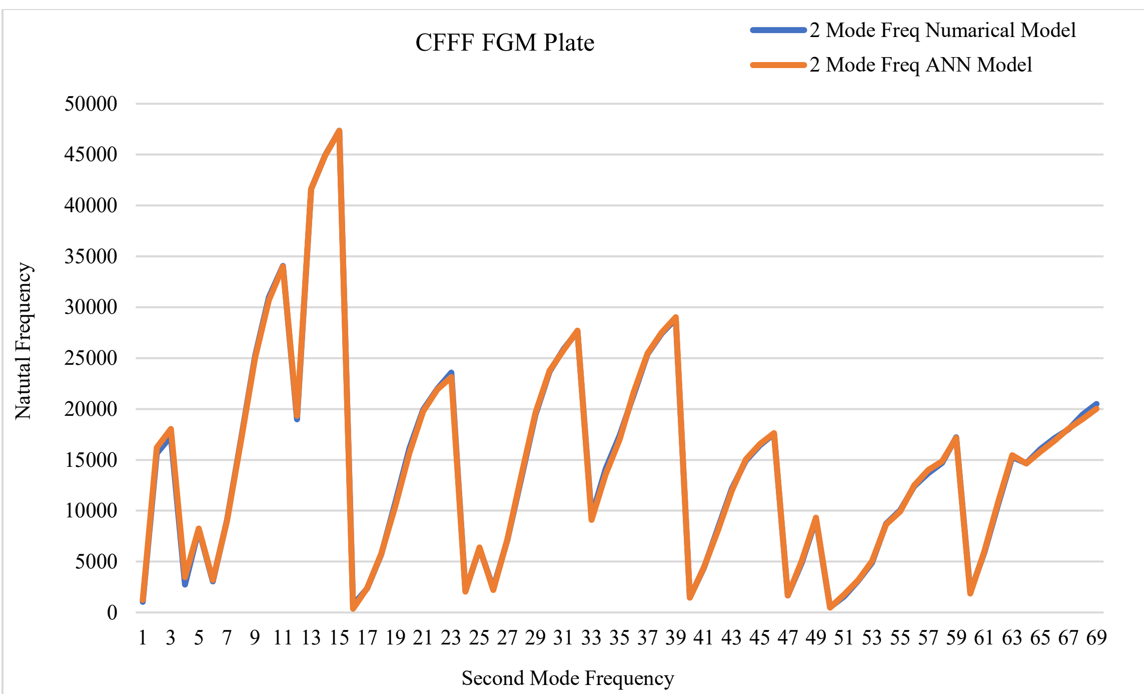

Fig.7 Comparison of second mode natural frequency of FGM Plate between numerical model and ANN model under CFFF boundary condition

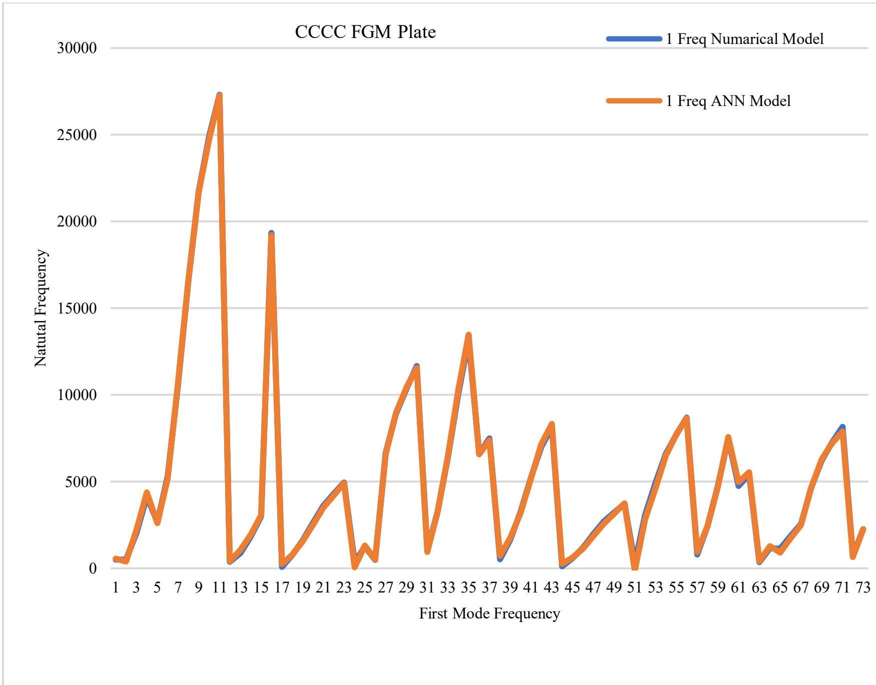

Fig. 8 Comparison of first mode natural frequency of FGM Plate between numerical model and ANN model under CCCC boundary condition

4.5. Influence of Material and Geometric Parameters

Natural frequency characteristics of FGM plates are affected by both geometric parameters and mechanical parameters of FGMs in the FE model. Plate thickness (h) is one of the geometric parameters which have considerable effect on natural frequencies. As plate thickness increases, there will be more stiffness in the system and hence an increase in the natural frequencies. Young's modulus (E) also plays a vital role in the vibration behavior of FGM plates. Increase in the value of Young's modulus makes the plate stiffer and hence natural frequencies become higher. In contrast, increase in density (\rho) increases the inertia of the plate, which leads to a decrease in natural frequencies. Power-law index (k) influences the material gradation in FGMs through thickness direction of the plate and, as a result, has an effect on effective stiffness and mass of the plate. With an increasing power-law index within the investigated parameters range, there will be a decrease in the natural frequencies. Poisson's ratio has less influence on the natural frequencies compared to other parameters.

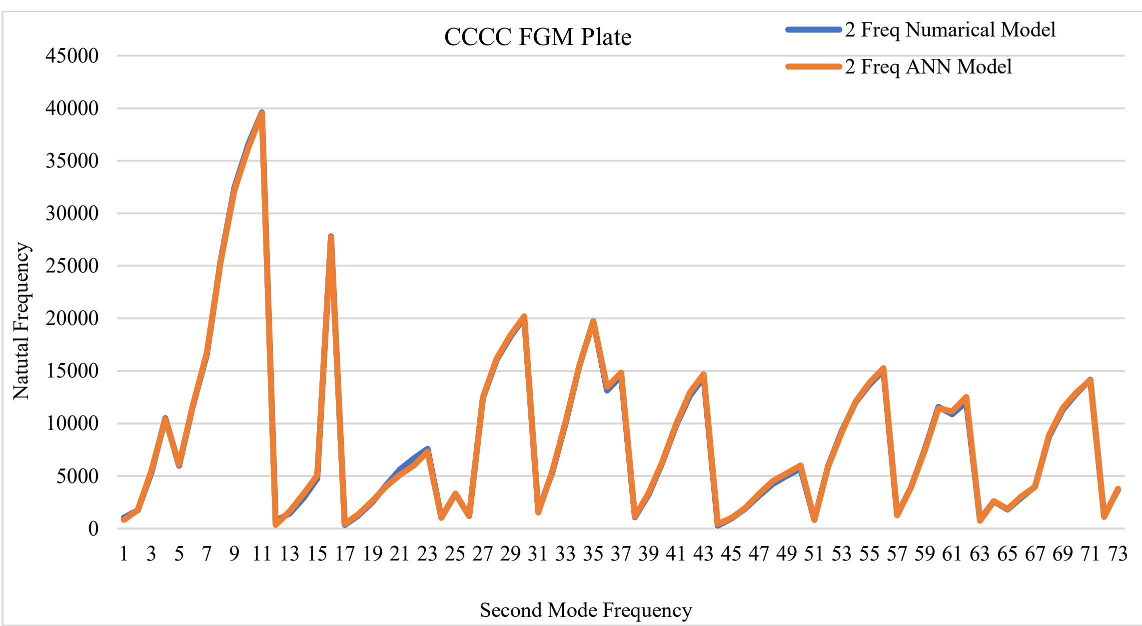

Fig. 9 Comparison of second mode natural frequency of FGM Plate between numerical model and ANN model under CCCC boundary condition

4.6. Benchmarking with State-of-the-Art Method

Optimized ANN decreased the prediction time from several minutes of the FEM to almost instantaneous prediction and still shows good agreement with numerical results shown in table shown in Table 2.

Table 2. Benchmarking

Method	Accuracy	Computational Cost
FEM	Very High	High
ANN	High	Low
Present Study	Very High	Very Low

The proposed surrogate model allows for fast design optimization of aerospace panels, wind turbine blades, marine structures, lightweight vehicles and smart structures with expensive computational cost for repeated FEM simulations. Experimental validation was outside the scope of the present work. Rather, the results of the FEM were compared to the benchmark numerical results reported in the literature. Future work is proposed to validate the experimental results using modal testing.

4.7. Sensitivity and Uncertainty Analysis

The sensitivity of the developed ANN model was investigated by studying the effect of the input parameters on the output of natural frequencies of FGM plates. The input variables taken into account were Young's modulus (E), the density (ρ), the Poisson's ratio (ν) of the plate, the plate dimension (a and b), the thickness of the plate (h) and the power-law index (k). These parameters are, among others, plate thickness and Young's modulus, which have the most significant effect on the values of the natural frequencies. With the increase in the thickness and Young's modulus of the plate, the stiffness of the structure increases, and so does the value of the natural frequency. However, both density and power-law index were inversely related to the natural frequencies, with an increase in mass density or material gradation causing a decrease in the stiffness-to-mass ratio of the plate. The effect of Poisson's ratio was relatively small, suggesting it has a minor effect on the dynamic response. The observations are in line with the physical behaviour of FGM plates, and show that the proposed ANN model is able to capture the effects of the governing material and geometric parameters. The proposed ANN model has yielded an excellent prediction accuracy ($R > 0.9998$), however, there are some uncertainties in the finite element discretization, in the variation of material properties, and in the sampling of the data sets. The dataset was then split into training, validation, and testing data, and the performance of the network was monitored continuously throughout the training phase, so as to prevent overfitting and increase the robustness of the model, which reduces the uncertainty involved in making predictions. The close correspondence between the numerical results and those predicted by the developed ANN model in all datasets confirms the stability, reliability and generalization capacity of the developed ANN model.

4.8. Error Analysis

The statistical error analysis was carried out in terms of Mean Squared Error (MSE) and regression coefficient (R) to assess the prediction performance. The optimized ANN architecture (7-26-2) showed that the regression coefficients for training, validation, and testing sets were >0.9998, respectively, which means that there is a good agreement between the predicted value and the numerical value.

The results of the residual analysis also revealed that there were no systematic trends and the values of the prediction errors were randomly distributed around zero, indicating that there is no significant bias in the ANN model. The lack of any obvious clustering and drift in the residuals suggests that the model is well-suited to the nonlinear relationship between the input parameters and the natural frequencies. The low prediction error in all the data sets indicates that the developed ANN is robust and reliable.

4.9. Engineering Applications

The proposed FEM-ANN framework is a computational efficient method for fast prediction of NFTs of FGM plates, which reduces the number of repeated FEAs in the design optimization process. This developed surrogate model can be used in aerospace structures, gas turbine components, lightweight panels for automobiles, marine structures, and biomedical implants, where vibration characteristics are of concern. The proposed framework can be readily applied to parametric studies, design optimization and real-time engineering decision making, as a result of its high prediction accuracy and low computational cost.

5. Conclusion

The ANN model is developed for predicting first and second natural frequencies of functionally graded material plates. The database for ANN training is created by performing FEM analysis based on the methodology presented in the current research and including different variations in geometrical, material and gradation properties. Among the considered ANN architectures, the 7-26-2 configuration gave the highest accuracy in predictions. The regression analysis and mean squared error values show a good agreement between target and ANN values for the training, validation, testing and total database.

This proves the effectiveness of the proposed ANN model in predicting the dependence of natural frequencies on the inputs. The effect of each input parameter on the frequency has been analyzed. It is found that thickness and Young's modulus have a positive correlation with the frequencies. Also, the density and gradation index are inversely related to the frequency values. The effect of Poisson's ratio is lower compared to the other parameters. In comparison to the FEM simulations, the artificial neural network model trained using the developed algorithm constitutes an efficient way of estimating the natural frequencies of new input cases within the range investigated. Consequently, the suggested approach of FEM and ANN allows for carrying out parametric investigations and analysis of FGM plate vibration problems. The model under investigation has been developed using the FEM data obtained for linear vibration problems. The future development of the framework may include experimental validation as well as taking into account nonlinear vibration and thermo-mechanical loading.

Conflicts of Interest

“The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.”

References

[1] Serge Abrate, “Free Vibration, Buckling and Static Deflections of Functionally Graded Plate,” *Composites Science and Technology*, vol. 66, no. 14, pp. 2383-2394, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[2] Onur Avci et al., “A Review of Vibration-Based Damage Detection in Civil Structures: From Traditional Methods to Machine Learning and Deep Learning Applications,” *Mechanical Systems and Signal Processing*, vol. 147, pp. 1-45, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] R.C. Batra, and J. Jin, “Natural Frequencies of a Functionally Graded Anisotropic Rectangular Plate,” *Journal of Sound and Vibration*, vol. 282, no. 1-2, 509-516, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[4] Ammu Boban et al., “Application of Machine Learning Technique for Dynamic Analysis of Confined Geomaterial Subjected to Vibratory Load,” *AI in Civil Engineering*, vol. 3, no. 1, pp. 1-15, 2024 [CrossRef] [Google Scholar] [Publisher Link]

[5] Leo Breiman, “Random Forests,” *Machine Learning*, vol. 45, no. 1, pp. 5-32, 2001. [CrossRef] [Google Scholar] [Publisher Link]

[6] Murat Çelik et al., “Artificial Neural Network (ANN) Validation Research: Free Vibration Analysis of Functionally Graded Beam via Higher-Order Shear Deformation Theory and Artificial Neural Network Method,” *Applied Sciences*, 14, no. 1, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Łukasz Domagalski, and Izabela Kowalczyk, “Application of Machine Learning Models in Predicting Vibration Frequencies of Thin Variable Thickness Plates,” *Materials*, vol. 19, no. 1, pp. 1-16, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[8] E. Efraim, and M. Eisenberger, “Exact Vibration Analysis of Variable Thickness Annular Isotropic and FGM Plates,” *Journal of Sound and Vibration*, vol. 299, no. 4-5, pp. 720-738, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[9] Ramin Ghiasi, Mohammad Reza Ghasemi, and Mohammad Noori, “Comparative Studies of Metamodeling and AI-Based Techniques in Damage Detection of Structures,” *Advances in Engineering Software*, vol. 125, pp. 101-112, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[10] Trevor Hastie, Jerome Friedman, and Robert Tibshirani, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 1st ed., Springer, pp. 1-536, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[11] Dongze He et al., “Vibration Analysis of Functionally Graded Material Double-Layered Cabin-like Structure by the Spectro-Geometric Method,” *Materials*, vol. 18, no. 6, pp. 1-32, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Xuchu Hu, and Tao Fu, “Free Vibration Analysis of Functionally Graded Plates with Different Porosity Distributions and Grading Pattern,” *Journal of Mechanical Science and Technology*, vol. 37, no. 11, pp. 5725-5738, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Mohamed Janane Allah et al., “Free Vibration Analysis of FGM Plates Using Artificial Neural Networks and Third-Order Shear Deformation Theory,” *Steel and Composite Structures*, vol. 49, no. 6, pp. 633-643, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Marwah Ghazi Kareem et al., “Analysis of the Free Vibration of Functionally Graded Material Plates Using a New Displacement Function,” *Results in Engineering*, vol. 25, pp. 1-12, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Seyed Sina Kourehli, “Prediction of Unmeasured Mode Shapes and Structural Damage Detection Using Least Squares Support Vector Machine,” *Structural Monitoring and Maintenance*, vol. 5, no. 3, pp. 379-390, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[16] A. C. Neves et al., “Structural Health Monitoring of Bridges: A Model-Free ANN-Based Approach to Damage Detection,” *Journal of Civil Structural Health Monitoring*, vol. 7, pp. 689-702, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[17] Mohamed Rida Seba, and Said Kebdani, “Finite Element and Neural Network Based Predictive Model to Determine Natural Frequency of Laminated Composite Plates with Eccentric Cutouts under Free Vibration,” *Advances in Technology Innovation*, vol. 7, no. 2, pp. 131-142, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] Vagelis Plevris, and George Papazafeiropoulos, “AI in Structural Health Monitoring for Infrastructure Maintenance and Safety,” *Infrastructures*, vol. 9, no. 12, pp. 1-25, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] S. Pradyumna, and J.N. Bandyopadhyay, “Free Vibration Analysis of Functionally Graded Curved Panels Using a Higher-Order Finite Element Formulation,” *Journal of Sound and Vibration*, vol. 318, no. 1-2, pp. 176-192, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[20] J.N. Reddy, “Analysis of Functionally Graded Plates,” *International Journal for Numerical Methods in Engineering*, vol. 47, no. 1-3, pp. 663-684, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[21] Gennaro Scarselli, and Francesco Nicassio, “Machine Learning for Structural Health Monitoring of Aerospace Structures: A Review,” *Sensors*, vol. 25, no. 19, pp. 1-46, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[22] M.K. Singha, T. Prakash, and M. Ganapathi, “Finite Element Analysis of Functionally Graded Plates under Transverse Load,” *Finite Elements in Analysis and Design*, vol. 47, no. 4, pp. 453-460, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[23] Alex J. Smola, and Bernhard Schölkopf, “A Tutorial on Support Vector Regression,” *Statistics and Computing*, vol. 14, no. 3, pp. 199-222, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[24] Billie F. Spencer et al., “Advances in Artificial Intelligence for Structural Health Monitoring: A Comprehensive Review,” *KSCE Journal of Civil Engineering*, vol. 29, no. 3, pp. 1-18, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[25] Mohammad Talha, and B.N. Singh, “Static Response and Free Vibration Analysis of Functionally Graded Material Plates Using Higher Order Shear Deformation Theory,” *Applied Mathematical Modelling*, vol. 34, no. 12, pp. 3991-4011, 2010. [CrossRef] [Publisher Link]

[26] Bindi Saurabh Thakkar, and Pradeep Kumar Karsh, “Machine Learning Based Uncertain Free Vibration Analysis of Hybrid Composite Plates,” *Computers, Materials and Continua*, vol. 86, no. 2, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[27] B. Üstün, W.J. Melssen, and L.M.C. Buydens, “Facilitating the Application of Support Vector Regression by Using a Universal Pearson VII Function Based Kernel,” *Chemometrics and Intelligent Laboratory Systems*, vol. 81, no. 1, 29-40, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[28] S. Senthil Vel, and R.C. Batra, “Three-Dimensional Exact Solution for the Vibration of Functionally Graded Rectangular Plates,” *Journal of Sound and Vibration*, vol. 272, no. 3-5, pp. 703-730, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[29] Mohammad Zannon, Abdullah Abu-Rqayiq, and Ammar Al-bdour, “Free Vibration Frequency of Thick FGM Spherical Shells Based on a Third-order Shear Deformation Theory,” *European Journal of Pure and Applied Mathematics*, vol. 13, no. 4, pp. 766-778, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[30] S. Zghal, and F. Dammak, “Vibration Characteristics of Plates and Shells with Functionally Graded Pores Imperfections Using an Enhanced Finite Shell Element,” *Computers & Mathematics with Applications*, vol. 99, pp. 52-72, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[31] S. Zghal et al., “Thermal Free Vibration Analysis of Functionally Graded Plates and Panels with an Improved Finite Shell Element,” *Journal of Thermal Stresses*, vol. 44, no. 3, pp. 315-341, 2021. [CrossRef] [Google Scholar] [Publisher Link]