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Experimental and machine learning models for stress amplitude prediction in damaged GFRP composite pipe

Abdelmoumin Oulad Brahim[1], Roberto Capozucca[1], Nicholas Fantuzzi[2], Samir Khatir[3], Thanh Cuong-Le[3*]

[1]Structural Section DICEA, Polytechnic University of Marche, Ancona, Italy
[2]Department of Civil, Chemical, Environmental and Materials Engineering, University of Bologna, Viale del Risorgimento 2, 40136, Bologna, Italy
[3]Center for Engineering Application and Technology Solutions, Ho Chi Minh City Open University, Ho Chi Minh, Vietnam
*Corresponding author:
Thanh Cuong-Le, E-mail: cuong.lt@ou.edu.vn.

Abstract. In this paper, a comprehensive modal analysis is conducted, utilizing both experimental and numerical approaches to investigate and predict the influence of the damage size on structural behavior. An FE model is created from different loading conditions of the Glass Fiber Reinforced Polymer (GFRP) composite pipe with a fixed damage size. The model is subjected to three pressure levels (10, 20 and 30 bar). Next, a dynamic frequency load is then added to the FE model to visualize the different frequency mode shapes and their values under different loading conditions, on a pressurized and unpressurized composite pipe. The results were collected for the proposed training models. A Kolmogorov Arnold Model (KAM) is employed to develop a robust predictive model that accurately estimates these geometrical and mechanical parameters by analyzing vibration data from various scenarios. The results show a significant correlation between the actual and predicted results across a wide range of test settings and scenarios, and the precision of the predictions is increased by combining data-driven methodologies with classical modal analysis.

Keywords: GFRP composite pipe; Vibration analysis and results; FE analysis; Damaged composite; Machine learning; Kolmogorov Arnold Model (KAM).

1. Introduction

Composite materials have garnered significant attention in recent years due to their superior mechanical properties, lightweight nature, and versatility across various industries. Among them, Glass Fiber Reinforced Polymer (GFRP) composites stand out as a prominent material, offering a favorable balance between strength, stiffness, and durability. GFRP composites are widely utilized in sectors such as aerospace, automotive, and civil engineering, particularly in applications requiring high mechanical performance and resistance to environmental degradation. Liao et al. (2024) investigated the aging of GFRP composite pipes in simulated oil and gas environments, analyzing microstructural changes and hoop tensile strength decay. Aging in hydrothermal and oil environments caused significant defect growth, with service life predictions ranging from 4.9 to 28.5 years based on the Arrhenius model. Gunoz et al. (2020) investigated the impact of seawater aging on the hoop tensile strength of glass fiber-reinforced epoxy composite pipes used in various applications. Exposure to seawater for 1, 2, and 3 months led to a decrease in average tensile strength, with longer exposure resulting in greater strength reduction. Others research papers focusing in composite pipes and various applications (Özbek et al. 2020, Rafiee and Ghorbanhosseini 2021, Lesani et al. 2022, Liao et al. 2023). Alabtah et al. (2021) evaluated the corrosion resistance of hybrid steel/GFRP pipes in harsh environments, showing a corrosion rate less than 1% of that in conventional steel pipes. Moisture absorption and pore formation in the GFRP layer contributed to this, which can be mitigated by improved fabrication methods. Yazman 2021 focused on filament winding (FW) composite pipes, commonly used in high-pressure applications, and the impact of drilling on their mechanical properties. The investigation shows that using back-up material during drilling reduces delamination, borehole damage, and surface roughness, despite causing higher thrust forces. Preventing interlaminar cracks is also highlighted as a key benefit of back-up material.

To fully harness the potential of GFRP composite pipes, it is crucial to accurately predict their mechanical properties under varying conditions. This presents a challenge, given the complex interactions between the fiber, matrix, and external forces, which influence the structural performance.

Traditional experimental methods, while reliable, are often time-consuming and resource-intensive. In this context, the Finite Element Method (FEM) has emerged as a powerful tool for simulating the mechanical behavior of composite structures. By leveraging FEM, researchers and engineers can gain insights into the stress distribution, deformation, and failure mechanisms of GFRP pipes under different loading conditions.

Wang et al. 2023 developed a model to predict the diffusion-degradation of GFRP composites in moist environments, offering a faster and versatile alternative to traditional methods. The model accurately forecasts tensile strength loss, accounting for defects and varying member sizes, and aligns with 12-month lab results. Berardi et al. (2021) presented creep test results for uniaxial E-glass fiber reinforced polymer (FRP) laminates over 42 months, comparing linear and nonlinear viscoelastic models. It includes a discussion on the Burgers model's accuracy and FEM simulations predicting creep behavior in composite layers for hydrogen pipes. The findings highlight that models based on shorter test durations may lead to conservative designs. Veerapandian et al. (2022) used finite element analysis to assess the performance of geopolymer concrete (GPC)-filled FRP composite columns under compression, finding a 0.9 to 2.04% higher load-carrying capacity compared to cement concrete-filled FRP columns. The GPC-FRP columns showed improved performance with increased FRP thickness and optimal fiber orientations, with the FE model validating well against experimental data. Wu and Zhi (2020) explored the axial compression of GFRP-reinforced steel tubes, analyzing the impact of steel thickness, GFRP winding angle, and specimen length on performance and failure modes. Numerical simulations with a UMAT subroutine and parametric analysis led to a modified Perry-Robertson formula for buckling load estimation, highlighting GFRP's benefits in large structures.

Sebeay and Ahmed (2023) assessed the pressure resistance of GFRP composite pipes with varying fiber angles and wall thicknesses. Finite element analysis reveals that pipes with $[\pm 55°]_3$ angles offer the highest pressure capacity, with an average deformation of 0.37 mm, and results align with previous data. Others research papers focusing in numerical modeling and simulation and addressing different problem in composite materials and composite pipes (Abyaneh Mostafa et al. 2020, Huang et al. 2020, Zhu et al. 2020, Gemi et al. 2021, Oulad Brahim et al. 2023).

In addition to numerical simulations, the integration of machine learning (ML) has opened new avenues for the prediction of mechanical properties. By utilizing large datasets from experimental and numerical results, machine learning models can be trained to predict key parameters such as strength, stiffness, and failure modes with remarkable accuracy. This approach not only accelerates the design and testing process but also provides a robust framework for optimizing material properties and structural performance. Milad et al. (2022) evaluated XGBoost, MARS, and RF models for predicting strain in FRP composites using a dataset of 729 experiments. MARS achieved high accuracy with just strain properties, demonstrating the efficacy of these ML models in predicting strain enhancement. Fibre composite materials (FCMs) are vital in various industries. Liu et al. (2024) showed how machine learning (ML) can enhance FCM research by reducing costly experiments and improving defect detection, impact dynamics, and model building for better design optimization. FRP composites degrade in harsh environments, and traditional prediction methods are often inaccurate. Machine learning (ML) offers better prediction but depends on high-quality data. More experimental data is needed to improve ML accuracy for FRP durability (Machello et al. 2023). Fahem et al. (2023) identified the best GFRP composite stacking sequence by analyzing bending data, simulating sequences with a numerical model, and refining predictions using ANN and the JAYA algorithm. Results help choose the optimal sequence based on properties, weight, and cost. Miao et al. (2023) developed machine learning models—SVR, BPNN, and RF—to predict the ultimate strength of circular concrete-filled FRP–steel composite tubes using a dataset of 305 samples. SVR showed the highest accuracy (R^2 = 0.992), outperforming BPNN and RF. Sensitivity analysis identified key factors like concrete strength, steel thickness, and FRP thickness as crucial for predicting column strength. The ML models offer improved prediction accuracy over existing empirical models.

Others research papers focusing in machine learning to predict the mechanical properties of GFRP composite materials (Bao et al. 2022, Gomes Junior et al. 2023, Kumar et al. 2023, Wang et al. 2024).

The Kolmogorov-Arnold Network (KAN), which is based on the Kolmogorov-Arnold theorem (Liu et al. 2024) and produces multivariate functions as sums of univariate ones, is one of the alternative neural networks that researchers have studied. Although deep learning and artificial neural networks (ANNs) have shown impressive results on a variety of tasks, their interpretability and adaptability may be limited by their frequent reliance on set activation functions. KANs use adaptive spline-based activation functions rather than fixed nonlinearities (like ReLU) (Somvanshi et al. 2025), which improve interpretability and flexibility while also assisting in addressing common training problems like vanishing gradients and limited expressiveness in high-dimensional settings (Unser 1999, Kidger et al. 2020, Liu et al. 2024). Compared to traditional designs, KANs offer superior generalization and robustness due to their adaptive structure, which allows them to better represent complex functional relationships with fewer parameters. This encouraged us to use this technique to create a robust model for predicting the stress magnitude in a damaged GFRP composite pipe.

In this study, a comprehensive approach combining the Finite Element Method, experimental data, and machine learning is proposed to predict one of the important mechanical properties of GFRP composite pipes under different GFRP composite pipe conditions. A database of vibration analysis and other relevant mechanical data is collected and utilized to train machine learning algorithms, with the goal of developing a predictive model capable of accurately estimating key properties. The results of this research hold significant promise for advancing the understanding and application of GFRP composites in practical engineering scenarios.

2. Composite architecture

2.1 *Fire Loss Test*

A loss on ignition test (calcination-NFT 57 102) was performed using a furnace set at a temperature higher than 600°, clay crucibles, and a scale with an accuracy of 0.001g to ascertain the proportion of glass fibers in the material produced. This method not only allows one to determine the composite's reinforcement to resin ratio, but it also provides information on the architecture and fiber kinds used.

This procedure involves heating the sample to a high temperature, which causes the matrix to vaporize and burn. The resulting fibers are then weighed after they have cooled for a few minutes, and their weight is compared to the sample weight before to the test. **Figure 1** and **2** shows the material before and after calcination.

The fiber/resin weight, volume ratio, and density are presented in **Table 1**, after using the following formulas:

$$W_f = \frac{w_f}{w_c} \cdot 100 \quad \rightarrow \quad W_m = 100 - W_f \tag{1}$$

$$V_f = \frac{w_f / \rho_f}{w_f / \rho_f + w_m / \rho_m} \quad \rightarrow \quad V_m = 100 - V_f \tag{2}$$

$$\rho_c = \rho_f \cdot V_f + \rho_m \cdot V_m \tag{3}$$

Where w_c and w_f are the mass of samples before and after calcination, w_m is the mass of resin, W_f, W_c are the fiber and composite mass fraction, V_f and V_m are the fiber and matrix volume fraction in composite, ρ_c, ρ_m and ρ_f are the densities.

2.2 Experimental modal analysis

To extract the mechanical properties of the elaborate material, a vibration analysis test was carried out, and the specimens have the shape and dimensions indicated in **Figure 3** and **Table 2**,

Figure. 4 illustrates a flowchart outlining the vibration analysis test procedure for a GFRP composite pipe under free-free edge conditions. Figure details the various accelerometer placement points and hammer impact positions used during the testing process. It also provides an overview of the test setup and methodology, capturing the critical steps and parameters involved in the vibration analysis.

In these tests, a GFRP composite pipes that were prepared are shown in **Figure 5**. An excitation hammer (Brüel & Kjær Impact PCB Hammer Type 086C03) with a force sensor whose sensitivity is 2:5 mv, a PCB356A15 accelerometer composed of a mass, a frame and a piezoelectric element, the latter two accompanied by a data acquisition system and a PC.

Figures 4 and **5** showed the modal analysis's experimental setup. By applying an impact loading to the composite pipe with a hammer, the accelerometer's mass vibrates, allowing it to record and send the signal to the charge amplifier that is connected to the computer and acquisition system data (Data Accelerometer A1 to Data Accelerometer A11, see **Figure 6**).

2.3 Experimental results

Measurements of the frequency response functions (FRFs) of healthy GFRP composite pipe and their associated values are extracted and presented in **Figures 6** (a, b, c and d).

Figure. 6 illustrates the frequency response functions (FRFs) obtained from Accelerometers A1 through A11, corresponding to the following patterns: a healthy composite pipe; a damaged GFRP composite pipe with a single hole (D = 9 mm); a second damaged pipe with a single hole (D = 11 mm); and a damaged pipe with two holes (each with a diameter of 11 mm). These extracted mode shapes and their frequency values demonstrate that damage present reduces the frequency value and decreases the percentage increase as damage size increases and changes as damage characteristics change.

3. Numerical simulation

With the aid of the ABAQUS software, a developed 3D model based on the finite element technique (FEM) was created in order to replicate the GFRP laminated composite pipe's modal analysis experiment. First, the model's geometry is constructed using the dimensions shown in **Figure. 3**. Subsequently, the models derived from the experimental results were refined to account for the mechanical properties of the material. Due to their layered structure, laminated composite materials exhibit engineering constants that differ from those of homogeneous materials. These constants—such as stiffness, strength, and Poisson's ratio—are influenced by the orientation and properties of the individual plies, as summarized in **Table 3**.

The constant parameters used for the numerical model are extracted using the flowing equations (Chamis 1984, Masoumi et al. 2021):

$$\rho = \rho_f V_g + \rho_r (1 - V_f) \tag{4}$$

$$E_{11} = E_{11f} V_f + E_r (1 - V_r) \tag{5}$$

$$E_{22} = E_{33} = \frac{Er}{1 - \sqrt{V_f}(1 - \frac{E_{22f}}{E_{22f}})} \tag{6}$$

$$G_{12} = G_{13} = \frac{Gr}{1 - \sqrt{V_f}(1 - \frac{G_{12f}}{G_{12f}})} \tag{7}$$

$$G_{23} = \frac{Gr}{1 - \sqrt{V_f}(1 - \frac{G_{23f}}{G_{23f}})} \tag{8}$$

$$\upsilon_{12} = \upsilon_{13} = V_f \upsilon_{12f} + (1 - V_f)\upsilon_{\mathrm{r}} \tag{9}$$

$$\upsilon_{23} = E_{22}/2G_{23} - 1 \tag{10}$$

E, G, υ, and V respectively represent Young's modulus, shear modulus, Poisson's ratio, and volume fraction. The subscripts (*f*) and (*r*) represent the fiber and resin, respectively.

To acquire a good precision of the numerical results, a mesh type was generated for each GFRP composite pipe in this study using a 4-node doubly curved thin or thick shell, reduced integration, hourglass control, finite membrane strains. (S4R), and 17836 elements have been generated on part (see **Figure 7.a**). Finally, the first numerical frequencies for each GFRP composite pipe were extracted and compared with the experimental natural frequencies (**Figure 7.b**).

An FE model was created based on different loading conditions, and the pipe is subjected to three pressure levels (10, 20 and 30 bar), a damaged pipe with fixed hole size is chosen to show stress intensity at the damage location, as we know, an increase in an applied pressure directly influences the increase in stress intensity, a dynamic frequency loading added to the FE model to see different mode shapes and their values under different loading conditions, the results and a comparison between several cases will be present in the next parts.

3.1 Comparison between experimental and FEM results

After the specimens are excited by the hammer, the measurements are transferred from the analyser to the computer. The obtained results by the finite element method were compared with the experimental results of healthy to validate the accuracy of the numerical model as shown in the following **Table 4**.

Based on the results of this comparison, the experimental and numerical FE results are in good agreement. The following **Figure 8** shows the mode shape from FE simulation of damaged GFRP composite pipe with damage size 10mm.

According to the results in **Table 4** and **Figure 8**, the experimental and numerical finite element results agree well in the intact and damaged cases proposed for the first eight shape modes extracted from GRP composite pipes. These results allowed the FE model to be used to obtain other damaged cases with different damage size levels. The following values show that the shape mode frequency values decrease with increasing damage size and the minimum values of the frequencies located around the maximum damage size, equal to 30 mm.

3.2 Pressured composite pipe

Figure 9 depicts the location of multiple situations of pressured and damaged GFRP composite pipe, excitation point $Sp_{i,1} = 1,....11$ and an accelerometer point with the position (see **Figure 4**). **Figure. 10** shows the results and mode shapes of the two first mode of pressured and damaged composite pipe. An FE model results in **Figure 9** and 1**0** was created under 10 bar pressure level and loading conditions, and the pipe is subjected to other three pressure levels (20 and 30 bar), a damaged GFRP composite pipe with fixed hole size in the center location, a dynamic frequency loading added to the FE model under pressure to see different mode shapes and their values under different loading conditions, on this case we keep the first and the second mode shapes for the results and a comparison between several cases of damage sizes and boundary conditions will be present in the collecting dataset.

Figure 11 compares the stress distribution under varying applied pressures (10, 20, and 30 bar), highlighting their effect on the first natural frequency for damage sizes of 12 mm, 18 mm, 24 mm, and 30 mm. Additionally, Figure 12 illustrates how increasing the damage size from 10 mm to 30 mm influences the stress distribution at the hole location under different pressure levels. Increasing pressure typically leads to higher stress levels across the frequency spectrum. Larger damage sizes (e.g., 24 mm and 30 mm) generally exhibit higher stress concentrations, indicating that an increase in damage size intensifies the system's response to applied pressure. Larger damage sizes increase peak stress levels and may slightly shift the locations of these peaks due to alterations in structural integrity and mass distribution.

3.3 Stress concentration prediction

The amplitude of natural frequency values increase with increasing applied pressure, as well as the severity of the damage sizes, the accurately predicted in this division using KAM, ANN, and IANN (Zenzen et al. 2020, Ouladbrahim et al. 2021). By reducing the difference between actual and desired products, **Figure 13** illustrates a flowchart for the methodology.

Damage sizes, applied pressures, and frequency values are taken as an input parameter; stress concentrations in damage extremity are used as output parameters for each study. The parameters required used for data training are shown in **Table 5**.

3 Results and discussion

4.1 ANN model

The damage sizes, the applied pressure, and the frequency values are taken as an input parameter to adjust the ANN and to evaluate the optimal parameter values of training model. To establish the appropriate number of hidden layer sizes (hidden neurons), the outputs and stress concentration are combined. The same parameters are used in all of the proposed ANN models. The PC used for the analysis features a 2.60 GHz Intel(R) Core (TM) i7-6700HQ processor and 16 GB of RAM. The results are shown in **Figures. 14, 15** and **16.** The outputs in **Figure 14** come from 70 % percent of all collected datasets used for the training model, 15 % percent used for the validation mode and 15 % percent used for the test model, in **Figure 15**, the maximum error is equal to 4.455 and 3.655 MPa, a high error density located in the range below 1%.

The training performance of an Artificial Neural Network (ANN) with Mean Squared Error (MSE) as the loss function is displayed in the left plot (a). The best validation performance (MSE = 1.4182) is reached at epoch 7, after which the error stabilizes after rapidly declining over the first few epochs. This implies effective convergence and learning without appreciable overfitting. The regression analysis is displayed in the right Figure (b), which illustrates the connection between the target and forecasted values. The Y = T line is closely followed by the data points, suggesting a high degree of agreement between the predicted and actual values. The model's good generalization is confirmed by the strong correlation coefficient (R = 0.99541).

The ANN model performs well with low error and accurate predictions after being trained using the PSO (Particle Swarm Optimization) technique. According to the findings, the model matches data well and generates accurate predictions.

ANN structure, training is performed with the input and output datasets to obtain the optimal target. Various learning techniques are used to adjust the optimal parameters of the predictive model, with the aim of minimizing the difference between the actual and desired results. In this work, MATLAB software is used to establish a connection between the inputs and outputs using the predictive model, in order to determine the stress concentration values to start building a strength model based on the mechanical and geometric design of the pipes. The regression analysis and results using improved ANN by Jaya and PSO algorithms in **Figure 16.** When it comes to training the IANN, the PSO method performs better than Jaya since it achieves a noticeably higher accuracy and better prediction alignment with real values. Jaya offers an unacceptable fit, also it is less dependable and introduces more error than PSO. The accuracy of ANN-PSO show better then ANN-Jaya, the summarized error is located in **Figure 22**.

After creating the ANN structure, training is performed with the input and output datasets to obtain the optimal weights and biases of the neurons. Various learning techniques are employed to adjust the optimal parameters for the predictive model, aiming to minimize the difference between the actual and desired outcomes. In this work, MATLAB software is used to establish a connection between inputs and outputs using the predictive model, to determine the frequency values and stress amplitudes based on composite pipe designs under the effect of pressure levels.

4.2 Kolmogorov-Arnold model for machine learning (KAM)

Any multivariate continuous function can be represented as a superposition of continuous functions of a single variable and addition, according to the Kolmogorov–Arnold Representation Theorem, which forms the foundation of Kolmogorov–Arnold Networks (KANs). In terms of mathematics, any continuous function f: $R^n \rightarrow R$, with exist functions ϕ_q and $\psi_{q,j}$ such that (Liu et al. 2024):

$$f(x_1, x_2, \dots, x_n) = \sum_{q=1}^{2n+1} \phi_q \left(\sum_{j=1}^{n} \psi_{q,j}(x_j)\right) \tag{11}$$

Where univariate continuous function is: ϕ_q and $\psi_{q,j}$

Compared to conventional deep networks, Kolmogorov-Arnold Networks, which use neural network topologies that take advantage of these functional decompositions to enhance expressivity and lower training complexity, are based on this theorem. In high-dimensional function approximations, where ordinary neural networks could struggle with generalization or require too many geometrical and physic-mechanical parameters, these networks are especially helpful.

- GFRP orientation angles and Layer stacking sequences.
- Type of composite material (glass fiber-to-matrix ratio)
- Pipe dimensions (thickness and diameter)
- Damage size
- Boundary conditions and Pressure levels.

A predictive model with KANs that associates these design characteristics with the pipe's inherent frequency response. The network can learn the underlying functional relationship and forecast the optimal composite configurations that maximize the pipe's performance under dynamic loading circumstances given a dataset of simulated or experimentally observed frequency values and stress amplitudes for various composite designs for mechanical and geometrical properties. KANs are superior to conventional deep learning models because they can effectively simulate complex relationships through structured decomposition, which lowers the possibility of overfitting and enhances interpretability. In comparison to traditional finite element simulations, engineers may rapidly find the best GFRP composite pipe designs that display the required vibration characteristics and frequency values while lowering computational costs by utilizing the KAN framework.

Based on engineering parameters, the KAN model can forecast a composite pipe's natural frequency response. We can effectively investigate ideal composite designs that minimize computational complexity and generate optimal vibration characteristics by utilizing the KAN framework.

This study explores four training methods for the KA model, each utilizing different basis functions and identification techniques. Method 1 employs cubic splines with the Gauss-Newton approach, while Method 2 and Method 3 both use cubic splines but differ in their identification methods—Newton-Kaczmarz (standard and accelerated, respectively). Method 4 applies piecewise-linear basis functions with the Newton-Kaczmarz standard approach. The performance of these methods is evaluated using RMSE and Log10 RMSE, with the results illustrated in **Figures 17** and **18**, highlighting the models' accuracy based on the number of passes.

Despite some instability in initial passes, SolveMinGauss (Method 1) had the best overall performance, although all tested approaches successfully reduced RMSE over repeated passes. With its smooth and stable convergence, buildKA (basis C) (Method 2) performs exceptionally well, and buildKA (basis A) (Method 3) comes in second. With an elevated final RMSE, buildKA (linear) (Method 4) converges more slowly. All approaches work well, but SolveMinGauss balances accuracy and efficiency to become the best performer in a variety of cases.

Log_{10} RMSE and RMSE output values based on the number of passes in **Figures 17** and **18** show high performances of all model methods. The solveMinGauss method (Model method 1) produces and demonstrates the most accurate predictions, while buildKA_linear (Model method 2) offers intermediate accuracy. Overall, solveMinGauss is the most accurate.

The predicted and actual results for a number of scenarios and the error percentage values are shown in **Figures 19, 20** and **Figure 21**, respectively. The solveMinGauss method (Model method 1) demonstrates the most accurate predictions, closely aligning with the actual values across all scenarios. buildKA_basisC (Model method 2) shows the poorest performance, with larger discrepancies between predicted and actual values. buildKA_basisA (Model method 3) and buildKA_linear (Model method 4) offer intermediate accuracy, performing better than buildKA_basis C but still with some notable errors. Overall, solveMinGauss is the most performance.

Figure 22 compares the prediction performance of methods, the KA Model and ANN, ANN-JAYA, and ANN-PSO across 10 scenarios. It shows the actual and predicted values, along with the percentage error for both models. The KA Model consistently achieves near-zero error, indicating high accuracy, while the ANN shows slightly higher error percentages, particularly in Scenarios 2 and 5. This highlights that the KA Model outperforms ANN in terms of prediction precision across all scenarios.

KA Model-SolveMinGauss method (blue) consistently shows extremely low error values across all scenarios. The error is close to zero in all cases, indicating that this method yields very accurate predictions with minimal deviations. In contrast, the ANN method exhibits greater variability in error across scenarios. While some scenarios show negligible error (e.g., Scenario 3, Scenario 7), others show a larger error (notably Scenario 2 and Scenario 5, where the error exceeds 0.1%).

In these scenarios (1, 3, 4, 6, and 7), the ANN error is small and comparable to the KA Model-SolveMinGauss method, suggesting similar performance in terms of accuracy. Scenarios (2 and 5) show significantly higher errors for the ANN method (0.1% and 0.15%, respectively), while the KA Model-SolveMinGauss method maintains near-zero error. This indicates that for certain cases, the ANN may struggle with accuracy compared to the KA Model-SolveMinGauss method.

5 Conclusion

This research successfully integrated experimental modal analysis, finite element modeling (FEM), and machine learning (ML) techniques to predict stress amplitudes in damaged composite pipes. The combined approach provided a robust and accurate method for predicting stress amplitudes, with several predictive models (ANN, ANN-Jaya, ANN-PSO, and KAN model) developed and validated. The study demonstrated the effectiveness of ML in accurately estimating stress based on damage size, applied pressure, and frequency response. Among the models, the KAN model using the SolveMinGauss method consistently showed the highest accuracy, exhibiting near-zero prediction errors across numerous scenarios.

The results clearly highlighted the significant impact of damage size and applied pressure on stress amplitude and frequency response. Larger damage sizes and higher pressures led to increased stress concentrations and altered frequency characteristics. This understanding is critical for structural integrity assessments. While the ANN models provided good results, the study also identified scenarios where their accuracy was diminished compared to the KAN approach. The computational efficiency of the KAN model enhances its applicability for real-time monitoring or structural health monitoring applications.

In summary, this research provides a significant advancement in predicting stress amplitudes in damaged composite pipes. The validated methodology, particularly the high-accuracy KAN (SolveMinGauss) model, offers a powerful tool for practical applications in engineering and structural health management.

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Data Availability Statement

Data available on request from the authors.

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Table 1. Mass and volume rate of reinforcement by calcination test.

Specimens	$w_c\,[g]$	$w_f\,[g]$	$W_f\,[\%]$	$W_m\,[\%]$	$V_f\,[\%]$	$V_m\,[\%]$	$\rho_c\,[g/cm^2]$
1	10.857	7.097	65.368	34.632	0.475	0.525	1.818
2	11.158	6.384	57.215	42.785	0.391	0.609	1.708
3	10.440	6.637	63.573	36.427	0.456	0.544	1.793
Standard deviation (STDEV)	0.361	0.361	4.284	4.284	0.044	0.044	0.058
Average	10.818	6.706	62.052	37.948	0.441	0.559	1.773

Table 2. Geometry of manufactured GFRP composite pipe.

Constants		Value
Composite layer specifications	Layers of fiber-glass	Mat 150 g/m^2 + $[\pm 45°]_3$ + 2*Woven 450 g/m^2
	Total thickness	5 mm

Table 3. Material characteristics of composite materials.

Material	Materials (characteristics)	Value
Fiber-glass	Density (kg/m^3)	2400
	Young modulus (MPa)	70000
	Shear modulus G_{12} (MPa)	30200
	Shear modulus G_{23} (MPa)	16000
	Poisson ratio [-]	0.33
Epoxy resin	Density (kg/m^3)	1200
	Young modulus (MPa)	3500
	Shear modulus (MPa)	1026
	Poisson ratio [-]	0.22
Fiber-glass/Epoxy	Volume fraction of Fiber-glass V_f(%) [Approximately]	51
	Volume fraction of resin V_r(%) [Approximately]	49
Optimal mechanical properties used in the FE model	Density [kg/m^3]	1812
	Young's modulus E_{11} [MPa]	39000
	E_{22} [MPa]	3500
	E_{33} [MPa]	3500
	Poisson ratio υ_{12} [-]	0.337
	υ_{13} [-]	0.337
	υ_{23} [-]	0.3799
	Shear modulus G_{12} [MPa]	3818.8
	G_{13} [MPa]	3818.8
	G_{23} [MPa]	3762.8

Table 4. Experimental and FEM first frequencies of healthy and damaged GFRP composite pipe.

		Natural frequency values (Hz)						
		Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7
EXP	Undamage	325	345	910	947	1738	1787	1889
FEM	Undamage	323.84	334.17	920	931.74	1775.6	1786.4	1854.3
EXP	Damage = 09 mm	323	342	908	935	1736	1784	1887
FEM	Damage = 09 mm	323.56	334.52	917.21	930.32	1765.3	1778.3	1841.8
FEM	Damage = 10 mm	323.55	334.11	917.06	929.29	1765	1776.5	1843.2
FEM	Damage = 12 mm	323.47	334.10	916.90	929.26	1764.8	1776.5	1842.6
FEM	Damage = 14 mm	323.37	334.09	916.73	929.22	1764.6	1776.4	1842.1
FEM	Damage = 16 mm	323.28	334.07	916.55	929.18	1764.3	1776.3	1841.6
FEM	Damage = 18 mm	323.18	334.06	916.37	929.14	1763.7	1776.2	1841.1
FEM	Damage = 20 mm	323.07	334.04	916.17	929.08	1764	1776.1	1840.7
FEM	Damage = 22 mm	322.96	334.02	915.99	929.02	1763.8	1776	1840.3
FEM	Damage = 24 mm	322.84	334	915.81	928.96	1763.6	1775.9	1840
FEM	Damage = 26 mm	322.73	333.97	915.63	928.89	1763.4	1775.8	1839.4
FEM	Damage = 28 mm	322.61	333.94	915.47	928.81	1763.2	1775.6	1837.9
FEM	Damage = 30 mm	322.50	333.91	915.31	928.72	1762.6	1775.5	1836.3

Table 5. Inputs and target parameters used in this work.

	Damage size (mm)	Actual stress (MPa)	Applied pressure (bar)	Frequency (Hz)	Number of collected data
Max. values	30.000	287.400	30.000	355.830	187
Min. values	10.000	63.160	10.000	354.970	
Average values	20.000	157.718	20.000	355.417	
STDEV	6.342	53.132	6.140	0.278	