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1 Experimental and machine learning models for stress amplitude 2 prediction in damaged GFRP composite pipe

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12
13 **Abstract.** In this paper, a comprehensive modal analysis is conducted, utilizing both experimental and
14 numerical approaches to investigate and predict the influence of the damage size on structural behavior.
15 An FE model is created from different loading conditions of the Glass Fiber Reinforced Polymer (GFRP)
16 composite pipe with a fixed damage size. The model is subjected to three pressure levels (10, 20 and 30
17 bar). Next, a dynamic frequency load is then added to the FE model to visualize the different frequency
18 mode shapes and their values under different loading conditions, on a pressurized and unpressurized
19 composite pipe. The results were collected for the proposed training models. A Kolmogorov Arnold
20 Model (KAM) is employed to develop a robust predictive model that accurately estimates these
21 geometrical and mechanical parameters by analyzing vibration data from various scenarios. The results
22 show a significant correlation between the actual and predicted results across a wide range of test settings
23 and scenarios, and the precision of the predictions is increased by combining data-driven methodologies
24 with classical modal analysis.

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

27

28

29 1. Introduction

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

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

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

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

77 Sebeay and Ahmed (2023) assessed the pressure resistance of GFRP composite pipes with varying fiber
78 angles and wall thicknesses. Finite element analysis reveals that pipes with $[\pm 55^\circ]_3$ angles offer the
79 highest pressure capacity, with an average deformation of 0.37 mm, and results align with previous data.
80 Others research papers focusing in numerical modeling and simulation and addressing different problem

81 in composite materials and composite pipes (Abyaneh Mostafa et al. 2020, Huang et al. 2020, Zhu et al.
82 2020, Gemi et al. 2021, Oulad Brahim et al. 2023).

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

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

107 The Kolmogorov-Arnold Network (KAN), which is based on the Kolmogorov-Arnold theorem (Liu et
108 al. 2024) and produces multivariate functions as sums of univariate ones, is one of the alternative neural
109 networks that researchers have studied. Although deep learning and artificial neural networks (ANNs)
110 have shown impressive results on a variety of tasks, their interpretability and adaptability may be limited
111 by their frequent reliance on set activation functions. KANs use adaptive spline-based activation
112 functions rather than fixed nonlinearities (like ReLU) (Somvanshi et al. 2025), which improve
113 interpretability and flexibility while also assisting in addressing common training problems like
114 vanishing gradients and limited expressiveness in high-dimensional settings (Unser 1999, Kidger et al.
115 2020, Liu et al. 2024). Compared to traditional designs, KANs offer superior generalization and
116 robustness due to their adaptive structure, which allows them to better represent complex functional
117 relationships with fewer parameters. This encouraged us to use this technique to create a robust model
118 for predicting the stress magnitude in a damaged GFRP composite pipe.

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

126 **2. Composite architecture**

127 **2.1 *Fire Loss Test***

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

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

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

$$138 \quad W_f = \frac{w_f}{w_c} \cdot 100 \quad \rightarrow \quad W_m = 100 - W_f \quad (1)$$

$$139 \quad V_f = \frac{\frac{w_f}{\rho_f}}{\frac{w_f}{\rho_f} + \frac{w_m}{\rho_m}} \quad \rightarrow \quad V_m = 100 - V_f \quad (2)$$

$$140 \quad \rho_c = \rho_f \cdot V_f + \rho_m \cdot V_m \quad (3)$$

141 Where w_c and w_f are the mass of samples before and after calcination, w_m is the mass of resin,

142 W_f, W_c are the fiber and composite mass fraction, V_f and V_m are the fiber and matrix volume fraction
 143 in composite, ρ_c , ρ_m and ρ_f are the densities.

144 2.2 Experimental modal analysis

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

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

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

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

165 **2.3 Experimental results**

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

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

174 **3. Numerical simulation**

175 With the aid of the ABAQUS software, a developed 3D model based on the finite element technique
176 (FEM) was created in order to replicate the GFRP laminated composite pipe's modal analysis
177 experiment. First, the model's geometry is constructed using the dimensions shown in **Figure. 3**.
178 Subsequently, the models derived from the experimental results were refined to account for the
179 mechanical properties of the material. Due to their layered structure, laminated composite materials

180 exhibit engineering constants that differ from those of homogeneous materials. These constants—such
 181 as stiffness, strength, and Poisson's ratio—are influenced by the orientation and properties of the
 182 individual plies, as summarized in **Table 3**.

183 The constant parameters used for the numerical model are extracted using the following equations (Chamis
 184 1984, Masoumi et al. 2021):

$$\rho = \rho_f V_f + \rho_r (1 - V_f) \quad (4)$$

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

$$E_{22} = E_{33} = \frac{Er}{1 - \sqrt{V_f} \left(1 - \frac{E_{22f}}{E_r}\right)} \quad (6)$$

$$G_{12} = G_{13} = \frac{Gr}{1 - \sqrt{V_f} \left(1 - \frac{G_{12f}}{G_r}\right)} \quad (7)$$

$$G_{23} = \frac{Gr}{1 - \sqrt{V_f} \left(1 - \frac{G_{23f}}{G_r}\right)} \quad (8)$$

$$v_{12} = v_{13} = V_f v_{12f} + (1 - V_f) v_r \quad (9)$$

$$v_{23} = E_{22}/2G_{23} - 1 \quad (10)$$

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

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

192 An FE model was created based on different loading conditions, and the pipe is subjected to three
 193 pressure levels (10, 20 and 30 bar), a damaged pipe with fixed hole size is chosen to show stress intensity
 194 at the damage location, as we know, an increase in an applied pressure directly influences the increase
 195 in stress intensity, a dynamic frequency loading added to the FE model to see different mode shapes and

196 their values under different loading conditions, the results and a comparison between several cases will
197 be present in the next parts.

198 *3.1 Comparison between experimental and FEM results*

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

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

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

212 *3.2 Pressured composite pipe*

213 **Figure 9** depicts the location of multiple situations of pressured and damaged GFRP composite pipe,
214 excitation point $Sp_{i,1} = 1, \dots, 11$ and an accelerometer point with the position (see **Figure 4**). **Figure. 10**
215 shows the results and mode shapes of the two first mode of pressured and damaged composite pipe. An
216 FE model results in **Figure 9** and **10** was created under 10 bar pressure level and loading conditions,
217 and the pipe is subjected to other three pressure levels (20 and 30 bar), a damaged GFRP composite pipe
218 with fixed hole size in the center location, a dynamic frequency loading added to the FE model under
219 pressure to see different mode shapes and their values under different loading conditions, on this case

220 we keep the first and the second mode shapes for the results and a comparison between several cases of
221 damage sizes and boundary conditions will be present in the collecting dataset.

222 Figure 11 compares the stress distribution under varying applied pressures (10, 20, and 30 bar),
223 highlighting their effect on the first natural frequency for damage sizes of 12 mm, 18 mm, 24 mm, and
224 30 mm. Additionally, Figure 12 illustrates how increasing the damage size from 10 mm to 30 mm
225 influences the stress distribution at the hole location under different pressure levels. Increasing pressure
226 typically leads to higher stress levels across the frequency spectrum. Larger damage sizes (e.g., 24 mm
227 and 30 mm) generally exhibit higher stress concentrations, indicating that an increase in damage size
228 intensifies the system's response to applied pressure. Larger damage sizes increase peak stress levels
229 and may slightly shift the locations of these peaks due to alterations in structural integrity and mass
230 distribution.

231 *3.3 Stress concentration prediction*

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

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

239 **3 Results and discussion**

240 *4.1 ANN model*

241 The damage sizes, the applied pressure, and the frequency values are taken as an input parameter to
242 adjust the ANN and to evaluate the optimal parameter values of training model. To establish the
243 appropriate number of hidden layer sizes (hidden neurons), the outputs and stress concentration are
244 combined. The same parameters are used in all of the proposed ANN models. The PC used for the
245 analysis features a 2.60 GHz Intel(R) Core (TM) i7-6700HQ processor and 16 GB of RAM. The results
246 are shown in **Figures. 14, 15 and 16**. The outputs in **Figure 14** come from 70 % percent of all collected

247 datasets used for the training model, 15 % percent used for the validation mode and 15 % percent used
248 for the test model, in **Figure 15**, the maximum error is equal to 4.455 and 3.655 MPa, a high error
249 density located in the range below 1%.

250 The training performance of an Artificial Neural Network (ANN) with Mean Squared Error
251 (MSE) as the loss function is displayed in the left plot (a). The best validation performance
252 (MSE = 1.4182) is reached at epoch 7, after which the error stabilizes after rapidly declining
253 over the first few epochs. This implies effective convergence and learning without appreciable
254 overfitting. The regression analysis is displayed in the right Figure (b), which illustrates the
255 connection between the target and forecasted values. The $Y = T$ line is closely followed by the
256 data points, suggesting a high degree of agreement between the predicted and actual values.
257 The model's good generalization is confirmed by the strong correlation coefficient ($R =$
258 0.99541).

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

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

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

279 4.2 Kolmogorov-Arnold model for machine learning (KAM)

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

$$284 \quad f(x_1, x_2, \dots, x_n) = \sum_{q=1}^{2n+1} \phi_q \left(\sum_{j=1}^n \psi_{q,j}(x_j) \right) \quad (11)$$

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

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

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

296 A predictive model with KANs that associates these design characteristics with the pipe's inherent
297 frequency response. The network can learn the underlying functional relationship and forecast the

298 optimal composite configurations that maximize the pipe's performance under dynamic loading
299 circumstances given a dataset of simulated or experimentally observed frequency values and stress
300 amplitudes for various composite designs for mechanical and geometrical properties.
301 KANs are superior to conventional deep learning models because they can effectively simulate complex
302 relationships through structured decomposition, which lowers the possibility of overfitting and enhances
303 interpretability. In comparison to traditional finite element simulations, engineers may rapidly find the
304 best GFRP composite pipe designs that display the required vibration characteristics and frequency
305 values while lowering computational costs by utilizing the KAN framework.

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

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

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

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

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

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

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

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

349 **5 Conclusion**

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

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

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

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374 **Data Availability Statement**

375 Data available on request from the authors.

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473 **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 [%]	ρ_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

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Table 2. Geometry of manufactured GFRP composite pipe.

Constants		Value
Composite layer specifications	Layers of fiber-glass	Mat 150 g/m ² + [$\pm 45^\circ$] ₃ + 2*Woven 450 g/m ²
	Total thickness	5 mm

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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 ν_{12} [-]	0.337
	ν_{13} [-]	0.337
	ν_{23} [-]	0.3799
	Shear modulus G_{12} [MPa]	3818.8
	G_{13} [MPa]	3818.8
	G_{23} [MPa]	3762.8

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534 **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		325	345	910	947	1738	1787	1889
FEM	Undamage	323.84	334.17	920	931.74	1775.6	1786.4	1854.3
EXP		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
	Damage = 10 mm	323.55	334.11	917.06	929.29	1765	1776.5	1843.2
	Damage = 12 mm	323.47	334.10	916.90	929.26	1764.8	1776.5	1842.6
	Damage = 14 mm	323.37	334.09	916.73	929.22	1764.6	1776.4	1842.1
	Damage = 16 mm	323.28	334.07	916.55	929.18	1764.3	1776.3	1841.6
	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
	Damage = 22 mm	322.96	334.02	915.99	929.02	1763.8	1776	1840.3
	Damage = 24 mm	322.84	334	915.81	928.96	1763.6	1775.9	1840
	Damage = 26 mm	322.73	333.97	915.63	928.89	1763.4	1775.8	1839.4
	Damage = 28 mm	322.61	333.94	915.47	928.81	1763.2	1775.6	1837.9
	Damage = 30 mm	322.50	333.91	915.31	928.72	1762.6	1775.5	1836.3

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543 **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	
Min. values	10.000	63.160	10.000	354.970	187
Average values	20.000	157.718	20.000	355.417	
STDEV	6.342	53.132	6.140	0.278	

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