

A Machine Learning Framework for Predicting Moisture Effects on Active Sensory Piezoelectric Flax Composite Laminates

Vassilis Gkatsis, Antigoni Barouni, Nikolaos A. Chrysochoidis, Georgios Giannakopoulos, Christoforos S. Rekatsinas

Abstract. The increasing use of Flax Fiber-Reinforced Composites (FFRCs) in sustainable engineering applications—particularly in marine environments—demands a deeper understanding of their long-term performance under environmental exposure. In this context, our previous study [1] experimentally investigated how absorbed moisture affects active sensory wave propagation in flax composite laminates. Significant alterations were observed in key signal characteristics, including Time of Flight (ToF), amplitude, and dispersion behavior. Building upon this prior work, the current study extends pitch-and-catch experiments using piezoelectric devices to assess the degradation of mechanical properties over time due to moisture uptake. The experimental campaign includes systematic measurements of stiffness degradation, thickness swelling, and mass gain, which are used to quantify the extent of environmental deterioration in FFRCs. These degradation metrics are then used as inputs to machine learning regression models that aim to predict stiffness loss and dispersion characteristics as functions of moisture uptake. The models are trained on time-resolved experimental data encompassing both moisture diffusion and mechanical response, achieving high accuracy in correlating active-sensory features with material degradation. The proposed methodology establishes a predictive framework for designing environmentally resilient FFRCs with online structural health monitoring capabilities. This work offers valuable insights into moisture-induced degradation mechanisms and contributes to the development of smart, bio-based composite materials for sustainable engineering applications.

Key words: Piezoelectrics, Flax composites, Sustainable composites, Machine Learning, Predictive Modeling

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1 INTRODUCTION

Flax fiber–reinforced polymer (FFRP) composites are emerging as sustainable alternatives to glass-fiber composites in sectors like marine and wind energy. They offer low density and high specific stiffness, with successful use reported in automotive and boat structures [2]. Studies have even explored replacing glass with flax in small wind turbine blades, showing comparable performance and reduced environmental footprint [3], [4]. However, a well-known drawback of flax/epoxy laminates is their sensitivity to moisture. Flax’s hydrophilic lignocellulosic fibers absorb water, leading to fiber swelling, micro-cracking at fiber–matrix interfaces, and overall composite property degradation [5]. Upon water uptake, flax composites can suffer severe stiffness loss – *e.g.*, a >50% drop in Young’s modulus within days of immersion has been observed [6]. Likewise, moisture causes reductions in strength and fracture toughness [7] as the weakened fiber/matrix bonding promotes fiber breakage and pull-out under load [8]. Hybridizing flax with glass or carbon fibers can improve moisture resistance [9], [10], but at the cost of full biodegradability. Given the marine environment’s constant exposure to humidity, there is clear motivation to monitor moisture-induced damage in flax composites to ensure long-term durability.

Non-destructive evaluation (NDE) techniques are being investigated as maintenance tools to track environmental degradation in natural-fiber composites. In particular, ultrasonic wave methods (using piezoelectric transducers) have been widely used for damage detection in conventional composites [11], [12], [13]. Their use as moisture damage indicators, however, has been limited. Only a few studies in the last decade address this gap for flax composites [14]. For example, El-Sabbagh *et al.* showed that ultrasonic longitudinal wave velocity in flax/PP laminates decreases with increasing fiber moisture content, correlating with reduced composite rigidity [15], [16]. Petrone (2018) carried out one of the first Lamb wave dispersion experiments on flax laminates, mapping how flax/polyethylene panels transmit guided waves across frequencies [17]. These foundational studies suggest that wave speed and attenuation are sensitive to the internal state of flax composites.

Recent work has started leveraging minimal piezoelectric sensor setups (pitch–catch configurations) to quantify such changes under environmental aging. Tsitsas *et al.* [1] conducted water-immersion aging of flax/epoxy panels instrumented with just a few surface-mounted piezoelectric wafers. They tracked ultrasonic wave propagation over time and found measurable shifts in wave velocity and signal attenuation as the laminates absorbed moisture, up to saturation. This demonstrates that guided wave speed/attenuation can serve as proxies for stiffness loss during hygrothermal ageing. Similarly, Cinquin *et al.* showed in synthetic composites that the low-frequency Lamb wave (A_0 mode) attenuation increases systematically with moisture content, providing a gauge for moisture levels [18].

Beyond purely hygroscopic effects, guided waves have also been used to monitor mechanical degradation in flax composites. Hana *et al.* (2024) examined static and fatigue loading of flax/epoxy laminates by measuring changes in Lamb wave velocities, successfully correlating wave speed reductions to fatigue-induced damage accumulation [19]. In the context of wind energy, Mat Daud *et al.* embedded piezo-sensors in a flax fiber composite wind turbine blade and demonstrated that damage detection (here, induced by a simulated lightning strike) was as feasible as in a traditional glass-fiber blade [20]. Their comparative study concluded that

flax/epoxy could be a viable replacement for glass in blades without losing structural health monitoring (SHM) capability [21]. These studies consistently use only one or a few transducers in a pitch–catch arrangement to send and receive waves, making the techniques practical for in-situ monitoring.

The above efforts highlight a nascent opportunity: integrating **machine learning (ML)** with piezoelectric sensing to predict material properties or the damage state of flax composites. While still emerging, there are promising examples. Czigány’s acoustic emission work showed that moisture-aged flax composites produce higher-amplitude AE signals during cracking [22], hinting that signal features carry signatures of moisture damage. Modern data-driven approaches can amplify such insights. For instance, researchers have combined acoustic emission data with deep learning to predict the remaining useful life of flax/epoxy specimens under creep loads [23]. Others report successful automated classification of composite fatigue damage using learned features from Lamb wave signals [24]. In addition, ML has been leveraged to address the environmental degradation of composites. Liu *et al.* (2022) developed an XGBoost (extreme gradient boosting) model to predict the residual tensile strength and Young’s modulus of pultruded FRP composites after exposure to water, humidity, and alkaline environments [25]. Another relevant direction is using artificial neural networks (ANNs) for property prediction in aged natural-fiber composites. Nasri *et al.* (2024) recently demonstrated an ANN (multi-layer perceptron) model to assess tensile strength and impact energy of flax/polypropylene biocomposites after UV-aging [26]. In summary, the literature reveals the potential of utilizing machine learning to predict composite mechanical properties under various conditions, including those affected by moisture-induced degradation. Prior studies on flax fiber composites and analogous materials have utilized techniques ranging from linear regression and SVR to decision tree ensembles and MLP neural networks [27].

However, no prior work has focused on using guided wave data to infer stiffness or moisture content in flax fiber laminates directly. This gap in the literature – limited studies applying advanced signal analysis or ML to natural-fiber composite monitoring – represents an opportunity for the present work. By employing a minimal network of piezoelectric sensors and training predictive models on wave speed, time-of-flight, or attenuation features, it is possible to achieve a **real-time assessment of moisture-induced mechanical degradation** in flax-reinforced structures. This approach addresses the sustainability goals (using plant-based materials) and the durability assurance needed for marine and wind energy applications.

2 MATERIALS AND METHODS

2.1 Specimen fabrication

Seven flax/epoxy composite panels were fabricated using non-woven flax fabric impregnated with EL2 epoxy resin (EasyComposites, UK) via hand lay-up and compression molding. Each panel consisted of four fabric layers, which were hot-pressed at 70°C and 100 kN, followed by post-curing in an oven at 80°C for two hours. The final panels measured 200 × 150 mm² and were approximately 3 mm thick, with ~30 wt% fiber content (Figure 1).

2.2 Water immersion

After fabrication, the panels were sealed around the edges with two-part epoxy glue, in order to ensure no moisture would be absorbed from the edges during the immersion of the panels in

the water. In this way, only the top and bottom surfaces will be responsible for absorbing moisture, thereby simulating an actual marine application of flax laminated composites. Six (6) panels were fabricated and immersed in a water tank for different total immersion durations, to facilitate the mechanical testing after these time intervals, namely PF24, PF90, PF180, PF270, PF360 and PF528, as well as a panel PF0, which was the reference panel that was kept dry for comparison purposes. The weight and the average thickness of the final panels were measured and are presented in Table 1.



Figure 1 Flax reinforced panel straight after fabrication, in dry condition.

Table 1 Measured weight of final panels

Plate No.:	PF0	PF24	PF90	PF180	PF270	PF360	PF528
Description	Dry panel	24 hrs immersion	90 hrs immersion	180 hrs immersion	270 hrs immersion	360 hrs immersion	528 hrs immersion
Weight (gr)	135.18	109.56	112.51	101.97	119.38	111.64	121.50
Thickness (mm)	3.70	3.55	3.29	3.05	3.49	3.30	3.45

For the moisture absorption test, the panels PF24 to PF528 were immersed in a container of de-ionised water at a room temperature of $23 \pm 1^\circ\text{C}$, as specified in the ASTM D570 standard. The panels were removed from the container every 24 hours, their surface was dried with absorbent cloth, and measurements of their mass and thickness were taken before they were returned to the water tank. At equal intervals of 90 hours, the panels were sequentially taken out of the container and were cut into tensile samples, according to ASTM D3039 for tensile testing. The total immersion time for the last panel was 528 hours, ensuring that the saturation conditions of the material had been reached. The percentage of gained mass due to water absorption was calculated according to the formula:

$$M(\%) = \frac{M_t - M_0}{M_0} \times 100 \quad (1)$$

where $M(\%)$ is the moisture uptake in percentage, M_t is the weight of the specimen at a given time of the water immersion, and M_0 is the initial weight of the specimen under dry conditions.

2.3 Tensile testing

Tensile tests were carried out according to ASTM D3039 standard using a Zwick/Roell Z30 testing machine equipped with a 30 kN load cell. The tests were conducted by controlling the

displacement using a crosshead speed of 2 mm/min and the Young's modulus (E), the ultimate tensile strength (σ_{UTS}) and the strain at break were determined. Five specimens were used for each water absorption stage and a representative photo of panel PF90 is shown in Figure 2, before and after the tensile testing.



Figure 2 Five tensile samples cut out of panel PF90 after the water immersion for 90 hours (a) samples before tensile testing; (b) samples after tensile testing.

2.4 Effect of water absorption in wave propagation

Based on the experimental procedure outlined previously, Figure 3 illustrates the increase in thickness and mass for each one of the immersed panels over time spent in immersion. It is evident that after approximately 500 hours of immersion, the curve has nearly plateaued, indicating that the water absorption process is essentially complete.

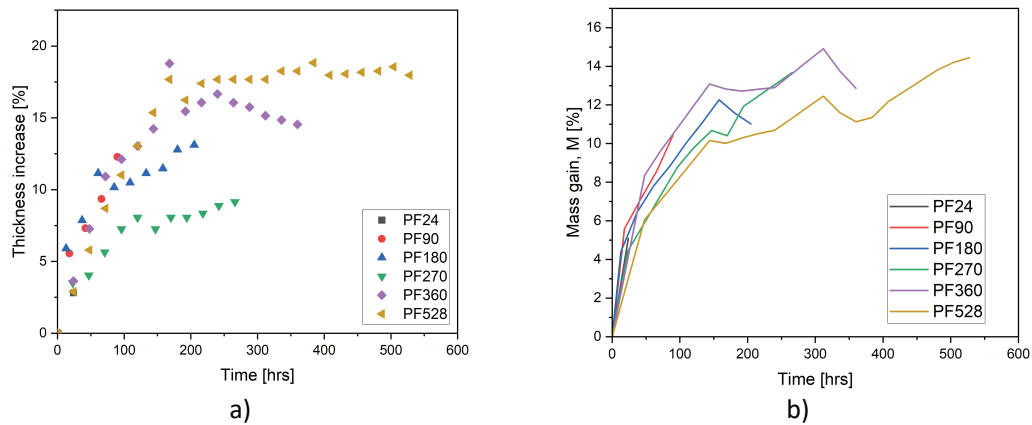


Figure 3. (a) Thickness and (b) mass increase (%) as a function of the immersion time.

Each point on the curve of Figure 3 (a) and (b) represents an interval in the immersion procedure, during which a complete set of measurements was acquired. The initial phase of the experimental campaign aimed to investigate how moisture influences the pitch and catch wave propagation between the piezoelectric elements bonded to the plate surface. In order to evaluate the impact of water uptake, a distinct excitation frequency was chosen, at 130 kHz, based on the calculated dispersion characteristics [28]. More specifically, an excitation frequency at 130

kHz exhibits less dispersive characteristics while the group velocities of the two existing modes, A_0 and S_0 , are easily distinct (Figure 4).

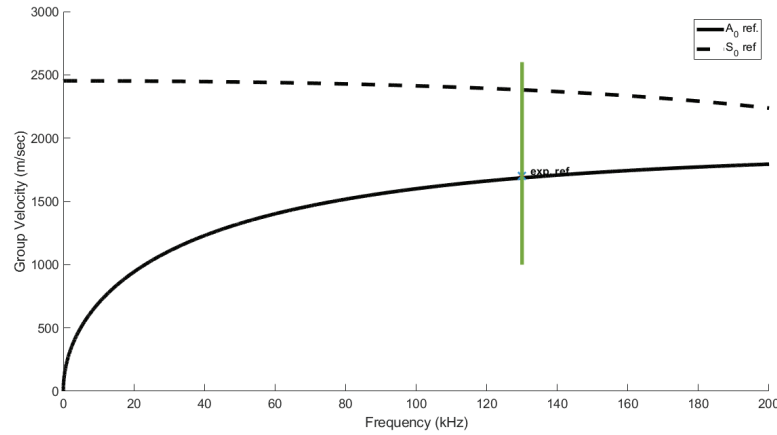


Figure 4. Dispersion characteristics of the fabricated material/laminate of 3mm thickness; group velocity vs frequency.

For the experimental procedure, a set of four rectangular piezoelectric wafers (PZT) was bonded on each panel's surface, in an arrangement as presented in Figure 5, [1]. Each PZT was a square with an edge of 12.7 mm and a thickness of 1 mm. The selection of the piezoelectric wafers' dimensions was based on the dispersion curves demonstrated in Figure 4.

Figure 6 depicts the time response of the sensor voltage and for the actuation-sensing pair 3-4 for each panel used in the study (Figure 5). It is evident from the measurements that the sensor signal undergoes significant distortion due to moisture absorption. Both the amplitude and the time of flight (ToF) are affected, with reductions in amplitude and increases in time of flight observed. This trend intensifies with more extended immersion periods.

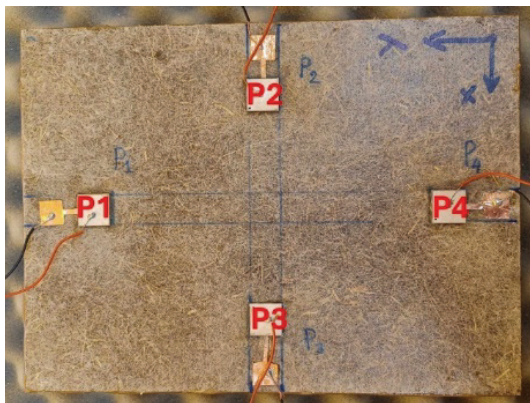


Figure 5. Composite plate equipped with a set of four square piezoelectrics.

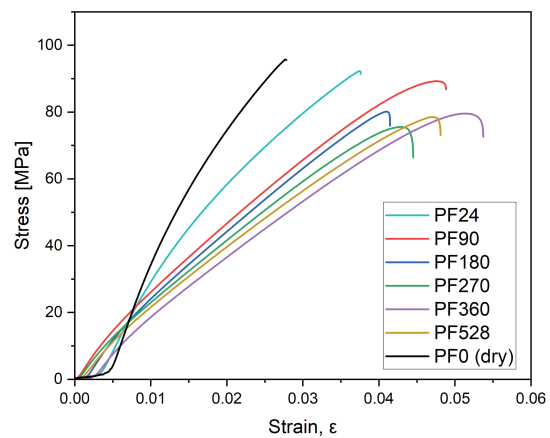


Figure 6. Stress-strain curves derived from tensile testing experiments for each wet and dry panel.

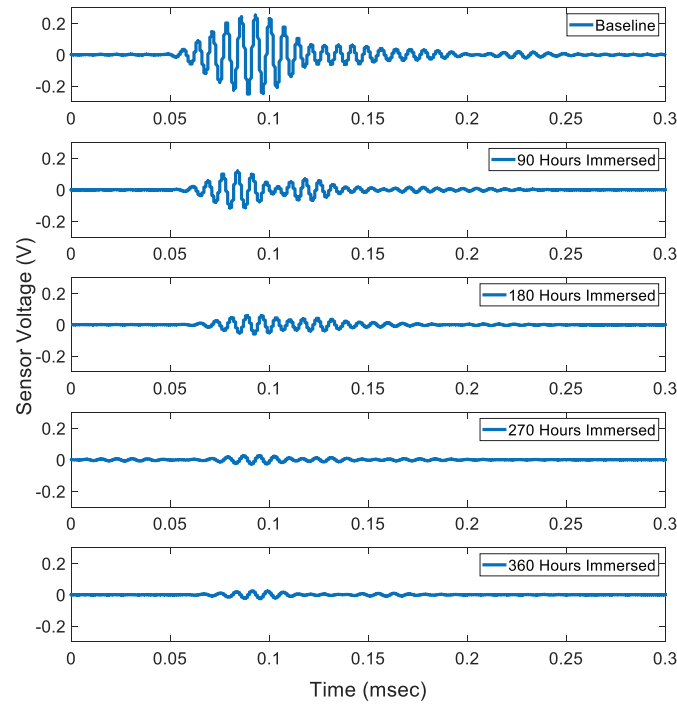


Figure 7. Time response of the sensory voltage for P3 operating as actuator and P4 as sensor. Each plot from the top to the bottom represents a different immersion period starting from the dry baseline condition. Actuation signal set at 130KHz.

A comparison of the stress-strain curves for each wet panel, as well as for the benchmark dry panel (PF0), is given in Figure 7. It is evident that the water uptake from the flax fibres has led to the degradation of the tensile properties and the rate of change of each curve. This is further enhanced by the microstructural degradation mechanisms that take place as the water molecules permeate inside the flax fibres and the composite structure by a diffusion mechanism [29].

As the material is in its dry phase, following the water immersion, the composite material experiences a desorption of water, leading to shrinkage of the flax fibres and, therefore, to local debonding of the flax fibres from the polymer matrix, as evidenced by the morphology of the dry and wet samples (90hrs) through scanning electron microscopy (SEM) images (Figure 8). The variation of the Young's modulus is significant with the minimum water immersion time, due to the hydrophilic nature of the flax fibres and their increase in moisture uptake by the flax/matrix interface. The dry panel PF0 exhibits the highest stiffness of 6.48 *GPa*, with the panel immersed only for 24 hrs (PF24) demonstrating a drop of 34.8% in the Young's modulus and the rest of the panels showing a similar drop compared to the dry panel of 62% on average. This is the reason for moving forward by developing ML models capable of providing critical information regarding the mechanical characteristics of flax-fiber reinforced structures in critical environments.

In the next section, we demonstrate the Young's modulus inference utilising a minimal number of measurements and relatively simple ML models.

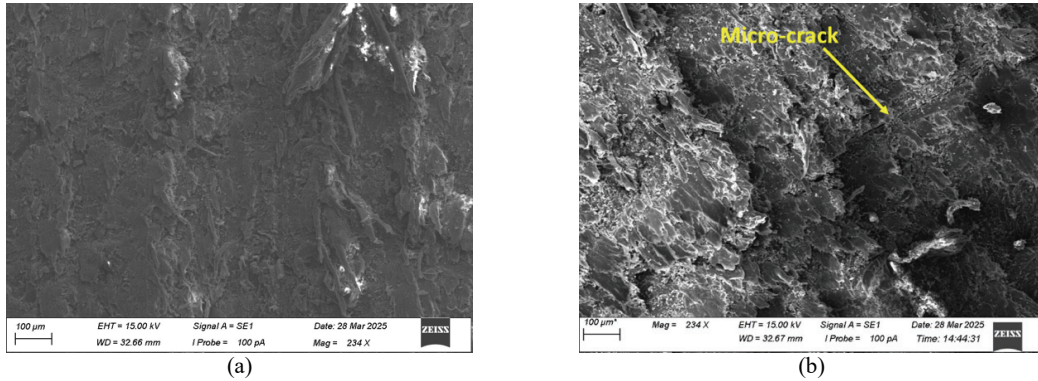


Figure 8. SEM images of composite (a) dry panel, (b) panel immersed in water for 90 hours.

3 RESULTS

3.1 Predictive modelling utilizing ML algorithms

For the ML experiments, we used six models, ranging from simpler to more complex ones. These are *Linear Regressor*, *Stochastic Gradient Descent*, *Support Vector Machines*, *Decision Trees*, *Random Forest*, and *XGBoost predictors*. We have also selected two dummy regressors to be used as a baseline for comparison. These are, the dummy mean and dummy median regressors, which consistently predict the mean and median of the data distribution, respectively.

Table 2 Measured weight of final panels

Hours Underwater	0	90	180	270	360
Weight (gr)	121.5	129.35	132.66	135.2	135.02
Thickness (mm)	3.45	3.63	3.95	4.06	4.08
Youngs Modulus (GPa)	6.479	3.269	2.757	2.774	2.185
Group Velocity Speed (m/sec)	1.70	1.61	1.50	1.34	1.30

As mentioned above, we conducted our prediction evaluations with limited data, namely the five measurements of the panel shown in Table 2. Due to this limitation in numbers, we could not use a proper train–test split of our data, and hence we used the Leave-one-Out technique, which means that we iterated five times over the whole dataset and at each iteration, we kept one measurement as a test set and the remaining four as a train set.

For the evaluation of the models, we have selected Mean Absolute Error (MAE) as the measure, which is defined as:

$$MAE = \frac{1}{n} \times \sum |y_{i,pred} - y_{i,true}| \quad (2)$$

where $y_{i,pred}$ is the predicted value, $y_{i,true}$ is the true target value, and n is the number of predictions. This metric has been selected due to its clarity in measuring the model's efficiency and its simplicity in explanation and comparison with baselines.

We have conducted two inference experiments. In the first step, we use Hours Underwater and Group Velocity Speed as features, and we predict the target values of Weight, Thickness, and Young's Modulus. The MAE scores of these results can be seen in Table 3. In the second experiment, we have used Weight and Group velocity speed as independent variables to predict Young's Modulus, and the results are shown in Table 4. We also provide the MAE scores of the dummy regressors in Table 5, utilizing the same features as training with the respective inference experiments.

Table 3 MAE scores of inference models using Hours Underwater and Group Velocity Speed as features.

Model	Linear Regressor	Stochastic Gradient Descent	Support Vector Machines	Decision Trees	Random Forest	XGBoost
Weight (gr)	8.613	3.65	4.204	3.874	3.401	4.346
Thickness (mm)	0.078	0.344	0.194	0.118	0.127	0.162
Youngs Modulus (GPa)	3.751	1.48	1.081	1.622	1.337	1.507

Table 4 Mean Absolute Error scores of inference models using Weight and Group Velocity Speed as features.

Model	Linear Regressor	Stochastic Gradient Descent	Support Vector Machines	Decision Trees	Random Forest	XGBoost
Youngs Modulus (GPa)	1.186	1.134	1.081	1.523	1.035	1.619

Table 5 MAE scores of dummy models using Hours Underwater and Group Velocity Speed as features.

Model	Dummy Mean	Dummy Median
Weight (gr)	5.321	5.103
Thickness (mm)	0.238	0.303
Youngs Modulus (GPa)	1.493	1.111

Before interpreting the results, it is important to acknowledge the limitations posed by the small dataset. Overfitting is likely, and model generalization is constrained. Nevertheless, several insights can still be drawn.

In **Experiment 1**, predictions for **Weight** and **Thickness** achieved lower MAE scores than the dummy regressors. Notably, the **Linear Regressor** achieved the lowest error in Thickness prediction, suggesting a likely linear relationship between features and thickness response. Additionally, the prediction errors were small relative to the actual value ranges shown in Table 2, indicating model sensitivity to underlying trends.

In contrast, predicting **Young's Modulus** proved more challenging. The regressors' performance was comparable to that of the baseline models, suggesting that the models were unable to extract meaningful patterns from the limited data. The lowest MAE achieved in this task corresponds to 16.7% and 49.5% of the maximum (6.479 GPa) and minimum (2.189 GPa) values of the target property, respectively, a non-trivial error range.

These findings suggest that, although preliminary trends can be observed from limited data, a more comprehensive and diverse dataset is necessary for robust inference of complex

properties, such as Young's Modulus. Nonetheless, the results demonstrate the **potential** of machine learning for efficient, data-driven property prediction in flax composites when paired with smart sensing.

3.2 Feedback of ML predictions and forecasting of Group Velocity

This section presents the integration of machine learning (ML) predictions into a high-fidelity numerical simulation framework to assess wave propagation behavior in water-immersed flax fiber-reinforced composite laminates. The scope of this work is to establish a predictive loop, where ML-inferred mechanical properties—specifically, Young's modulus, thickness, and effective density—are fed into a physics-based model to forecast the resulting group velocities of guided waves. This approach bridges data-driven prediction with mechanistic simulation, enabling structural behavior to be anticipated under varying environmental conditions.

The numerical tool used here is based on the time-domain spectral element framework developed in previous work by Rekatsinas and Saravanos [30], which models the coupled electromechanical response of composite plates with embedded piezoelectric transducers. This high-order model allows the simulation of transient wave propagation generated by active sensing configurations, including pitch-and-catch arrangements typical in structural health monitoring (SHM) systems.

To replicate the experimental protocol described in our earlier study [1], we modeled the actuation of a piezoelectric wafer bonded on the surface of the composite plate. The simulation emulated the propagation of guided waves to a point 45 mm away, matching the experimental measurement position where waveforms were captured using a Laser Doppler Vibrometer (LDV). For each hydration state of the panel, the ML-predicted Young's modulus and thickness were directly incorporated into the numerical tool. The corresponding density was computed via the rule of mixtures, accounting for water content estimated from the measured mass gain. Specifically, the mass increase due to water uptake was used to estimate the water volume fraction, which was then used to calculate the updated composite density based on its revised mass and volume.

Following this data integration step, a series of numerical simulations were conducted, each corresponding to a different moisture exposure time. For each simulation, the group velocity was calculated by dividing the fixed propagation distance (45 mm) by the simulated time-of-flight. These predicted group velocities are presented in Figure 9, alongside the experimentally measured counterparts. The comparison reveals strong agreement between simulation and experiment, indicating that the ML-inferred material parameters, when combined with a high-fidelity numerical solver, can accurately forecast guided wave behavior in environmentally aged flax laminates. While minor discrepancies are observed, particularly at higher moisture contents, these can be attributed to factors such as local inhomogeneities, imperfect boundary conditions, and the limitations of data-driven inference in capturing highly nonlinear degradation effects.

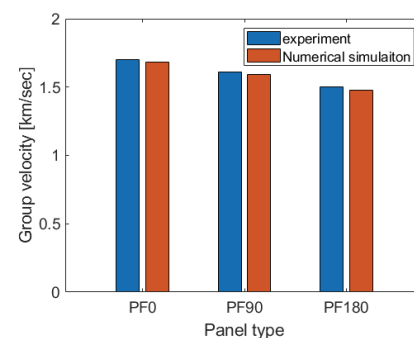


Figure 9 Experimental versus numerically calculated group velocity utilizing the predictive capabilities of ML algorithms

Nonetheless, the results demonstrate the powerful synergy between machine learning and physics-based modeling.

By combining the predictive capacity of trained regressors with advanced spectral element simulation and High-Performance Computing (HPC), it becomes possible to emulate real-world operational conditions and anticipate wave propagation dynamics in smart natural fiber composites. This integrated methodology opens the door to digital twin frameworks for moisture-sensitive structures, where evolving environmental exposure is continuously monitored and simulated.

CONCLUSIONS

This study presented a hybrid experimental–computational framework for predicting moisture-induced degradation in flax fiber-reinforced composites (FFRCs) using minimal piezoelectric sensing and machine learning regression models. By leveraging changes in guided wave features, such as time-of-flight and amplitude, alongside simple geometric and mass measurements, the methodology enabled the inference of key mechanical properties, notably Young’s modulus, during progressive water immersion.

Despite the limitations of a small dataset, several regression models, particularly XGBoost and Support Vector Machines, captured meaningful trends in material degradation. These findings highlight the feasibility of combining active sensing with ML algorithms for effective structural health monitoring of bio-based composites. To further validate the predictive accuracy of the inferred properties, high-fidelity numerical simulations were performed, showing strong correlation with experimental wave propagation results.

Minor discrepancies between simulation and measurement, however, underscore the inherent limitations of purely data-driven models, especially in data-scarce regimes. As a promising direction, future work will explore the development of **physics-informed machine learning (PIML)** frameworks, in which governing physical principles (e.g., wave dispersion, conservation laws, or damage evolution) are embedded directly into the learning process. This integration is expected to improve generalization, reduce data dependency, and enhance robustness, ultimately enabling real-time, closed-loop monitoring and forecasting for smart composite structures in demanding environments such as marine applications and wind turbine blades.

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REFERENCES

- [1] P. Tsitsas, C. Rekatsinas, A. Barouni, and N. Chrysochoidis, “Effect of moisture on the sensing capabilities of piezoelectric actuator/sensor pairs on flax fibre reinforced composite laminates,” *e-Journal of Nondestructive Testing*, vol. 29, no. 7, Jul. 2024, doi: 10.58286/29771.
- [2] A. Moudood, A. Rahman, A. Öchsner, M. Islam, and G. Francucci, “Flax fiber and its composites: An overview of water and moisture absorption impact on their performance,”

- Journal of Reinforced Plastics and Composites*, vol. 38, no. 7, pp. 323–339, Apr. 2019, doi: 10.1177/0731684418818893.
- [3] D. U. Shah, P. J. Schubel, and M. J. Clifford, “Can flax replace E-glass in structural composites? A small wind turbine blade case study,” *Compos B Eng*, vol. 52, pp. 172–181, Sep. 2013, doi: 10.1016/j.compositesb.2013.04.027.
 - [4] K. Pender, K. Bacharoudis, F. Romoli, P. Greaves, and J. Fuller, “Feasibility of Natural Fibre Usage for Wind Turbine Blade Components: A Structural and Environmental Assessment,” *Sustainability*, vol. 16, no. 13, p. 5533, Jun. 2024, doi: 10.3390/su16135533.
 - [5] C. A. Fuentes *et al.*, “Effect of humidity during manufacturing on the interfacial strength of non-pre-dried flax fibre/unsaturated polyester composites,” *Compos Part A Appl Sci Manuf*, vol. 84, pp. 209–215, May 2016, doi: 10.1016/j.compositesa.2016.01.023.
 - [6] F. K. Sodoke, L. Toubal, and L. Laperrière, “Hygrothermal effects on fatigue behavior of quasi-isotropic flax/epoxy composites using principal component analysis,” *J Mater Sci*, vol. 51, no. 24, pp. 10793–10805, Dec. 2016, doi: 10.1007/s10853-016-0291-z.
 - [7] F. A. Almansour, H. N. Dhakal, and Z. Y. Zhang, “Effect of water absorption on Mode I interlaminar fracture toughness of flax/basalt reinforced vinyl ester hybrid composites,” *Compos Struct*, vol. 168, pp. 813–825, May 2017, doi: 10.1016/j.compstruct.2017.02.081.
 - [8] D. Scida, M. Assarar, C. Poilâne, and R. Ayad, “Influence of hygrothermal ageing on the damage mechanisms of flax-fibre reinforced epoxy composite,” *Compos B Eng*, vol. 48, pp. 51–58, May 2013, doi: 10.1016/j.compositesb.2012.12.010.
 - [9] K. Jarukumjorn and N. Suppakarn, “Effect of glass fiber hybridization on properties of sisal fiber–polypropylene composites,” *Compos B Eng*, vol. 40, no. 7, pp. 623–627, Oct. 2009, doi: 10.1016/j.compositesb.2009.04.007.
 - [10] A. K. Barouni and H. N. Dhakal, “Damage investigation and assessment due to low-velocity impact on flax/glass hybrid composite plates,” *Compos Struct*, vol. 226, p. 111224, Oct. 2019, doi: 10.1016/j.compstruct.2019.111224.
 - [11] C. S. Rekatsinas, N. A. Chrysochoidis, and D. A. Saravanos, “Investigation of critical delamination characteristics in composite plates combining cubic spline piezo-layerwise mechanics and time domain spectral finite elements,” *Wave Motion*, vol. 106, p. 102752, Nov. 2021, doi: 10.1016/j.wavemoti.2021.102752.
 - [12] N. A. Chrysochoidis, A. K. Barouni, and D. A. Saravanos, “Delamination detection in composites using wave modulation spectroscopy with a novel active nonlinear acousto-ultrasonic piezoelectric sensor,” *J Intell Mater Syst Struct*, vol. 22, no. 18, pp. 2193–2206, Dec. 2011, doi: 10.1177/1045389X11428363.
 - [13] N. A. Chrysochoidis, T. T. Assimakopoulou, and D. A. Saravanos, “Nonlinear wave structural health monitoring method using an active nonlinear piezoceramic sensor for matrix cracking detection in composites,” *J Intell Mater Syst Struct*, vol. 26, no. 15, pp. 2108–2120, Oct. 2015, doi: 10.1177/1045389X14549865.
 - [14] A. K. Barouni and C. S. Rekatsinas, “Study on the Propagation of Stress Waves in Natural Fiber Composite Strips,” *Journal of Composites Science*, vol. 5, no. 1, p. 34, Jan. 2021, doi: 10.3390/jcs5010034.
 - [15] A. El-Sabbagh, L. Steuernagel, and G. Ziegmann, “Characterisation of flax polypropylene composites using ultrasonic longitudinal sound wave technique,” *Compos B Eng*, vol. 45, no. 1, pp. 1164–1172, Feb. 2013, doi: 10.1016/j.compositesb.2012.06.010.
 - [16] A. El-Sabbagh, L. Steuernagel, and G. Ziegmann, “Ultrasonic testing of natural fibre polymer composites: effect of fibre content, humidity, stress on sound speed and comparison to glass fibre polymer composites,” *Polymer Bulletin*, vol. 70, no. 2, pp. 371–390, Feb. 2013, doi: 10.1007/s00289-012-0797-8.
 - [17] G. Petrone, “Dispersion curves for a natural fibre composite panel: Experimental and numerical investigation,” *Aerosp Sci Technol*, vol. 82–83, pp. 304–311, Nov. 2018, doi: 10.1016/j.ast.2018.08.029.

- [18] M. Cinquin, M. Castaings, B. Hosten, P. Brassier, and P. Pérès, “Monitoring of the moisture content in carbon-epoxy plates using Lamb waves,” *NDT & E International*, vol. 38, no. 1, pp. 37–44, Jan. 2005, doi: 10.1016/j.ndteint.2004.06.006.
- [19] D. Hana *et al.*, “Behavior monitoring of flax fiber reinforced composites by guided waves,” *International Journal of Damage Mechanics*, Aug. 2024, doi: 10.1177/10567895241275365.
- [20] S. Z. Mat Daud, F. Mustapha, and Z. Adzis, “Lightning strike evaluation on composite and biocomposite vertical-axis wind turbine blade using structural health monitoring approach,” *J Intell Mater Syst Struct*, vol. 29, no. 17, pp. 3444–3455, Oct. 2018, doi: 10.1177/1045389X17754259.
- [21] “Structural Health Monitoring of Biocomposites, Fibre-Reinforced Composites.” Accessed: Mar. 26, 2025. [Online]. Available: https://books.google.gr/books?hl=el&lr=&id=7Jp7DwAAQBAJ&oi=fnd&pg=PP1&ots=Ubj8h4InXr&sig=ohf_w-Qkgu4UISGjtosiClgrxjo&redir_esc=y#v=onepage&q&f=false
- [22] T. Czigany, “An Acoustic Emission Study of Flax Fiber-Reinforced Polypropylene Composites,” *J Compos Mater*, vol. 38, no. 9, pp. 769–778, May 2004, doi: 10.1177/0021998304042481.
- [23] J. Hao, M. Rupp, S. V. Lomov, C. A. Fuentes, and A. W. Van Vuure, “Remaining useful life prediction of flax fibre biocomposites under creep load by acoustic emission and deep learning,” *Compos Part A Appl Sci Manuf*, vol. 188, p. 108572, Jan. 2025, doi: 10.1016/j.compositesa.2024.108572.
- [24] H. Lee, H. J. Lim, T. Skinner, A. Chattopadhyay, and A. Hall, “Automated fatigue damage detection and classification technique for composite structures using Lamb waves and deep autoencoder,” *Mech Syst Signal Process*, vol. 163, p. 108148, Jan. 2022, doi: 10.1016/j.ymssp.2021.108148.
- [25] T. Sadat, “Machine Learning-Assisted Tensile Modulus Prediction for Flax Fiber/Shape Memory Epoxy Hygromorph Composites,” *Applied Mechanics*, vol. 4, no. 2, pp. 752–762, Jun. 2023, doi: 10.3390/applmech4020038.
- [26] K. Nasri and L. Toubal, “Artificial Neural Network Approach for Assessing Mechanical Properties and Impact Performance of Natural-Fiber Composites Exposed to UV Radiation,” *Polymers (Basel)*, vol. 16, no. 4, p. 538, Feb. 2024, doi: 10.3390/polym16040538.
- [27] M. V. Pathan *et al.*, “Predictions of the mechanical properties of unidirectional fibre composites by supervised machine learning,” *Sci Rep*, vol. 9, no. 1, p. 13964, Sep. 2019, doi: 10.1038/s41598-019-50144-w.
- [28] C. S. Rekatsinas, C. V. Nastos, T. C. Theodosiou, and D. A. Saravanos, “A time-domain high-order spectral finite element for the simulation of symmetric and anti-symmetric guided waves in laminated composite strips,” *Wave Motion*, vol. 53, pp. 1–19, Mar. 2015, doi: 10.1016/j.wavemoti.2014.11.001.
- [29] V. Fiore *et al.*, “On the response of flax fiber reinforced composites under salt-fog/dry conditions: Reversible and irreversible performances degradation,” *Compos B Eng*, vol. 230, p. 109535, Feb. 2022, doi: 10.1016/j.compositesb.2021.109535.
- [30] C. S. Rekatsinas and D. A. Saravanos, “A cubic spline layerwise time domain spectral FE for guided wave simulation in laminated composite plate structures with physically modeled active piezoelectric sensors,” *Int J Solids Struct*, vol. 124, pp. 176–191, Oct. 2017, doi: 10.1016/j.ijsolstr.2017.06.031.