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Hybrid predictive modeling and heuristic design of surface-modified Biofibre polymer composites for viscoelastic creep resistant applications

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Abstract

The long-term viscoelastic degradation of natural fiber-reinforced polymers remains a significant barrier to their load-bearing structural applications. This study introduces an integrated computational framework combining Artificial Neural Networks (ANN) and a Genetic Algorithm (GA) to model, predict, and optimize the chemical surface treatments of plantain pseudo-stem fiber-reinforced high-density polyethylene (HDPE) composites matrix at 20 percent weight fraction (wt.%) fiber loading. The biofibres were modified via alkaline mercerization in 0.1M, 0.5M and 0.8M Sodium hydroxide (NaOH) and subsequently an acetylation treatment with 5%, 10% and 15% acetic anhydride before thermo-mechanical creep testing under sustained stresses of 35 MPa and 42 MPa across an isothermal gradient of 30°C, 60°C and 80°C for 240 hours. The optimized ANN framework successfully mapped the continuous, non-linear creep space across the coupled thermo-mechanical domains. Continuous response surfaces revealed that raising the temperature from 30°C to 80°C accelerated primary creep kinetics and increased maximum deformation by 87.5%, highlighting the matrix thermal sensitivity near the glass transition region. Notably, the smooth topology of the predictive profiles confirmed that the dual chemical modification maintained robust fiber-matrix interfacial integrity under all environmental conditions. To transition from empirical observation to intelligent material design, the validated ANN model was coupled with a heuristic GA to autonomously explore the treatment design space. The evolutionary optimization path was mathematically validated via a fourth-degree polynomial regression equation which demonstrates an exceptional coefficient of determination (R^2) = 0.99. The framework successfully determined the optimal chemical concentration thresholds required to minimize temporal structural strain, and offers a scalable design methodology for smart manufacturing applications.

Keywords: Artificial Neural Network; Genetic Algorithm; Natural Fiber Composites; Viscoelastic Creep; Mercerization; Acetylation; Material Design

1. Introduction

The rising demand for sustainable infrastructure has positioned natural fiber-reinforced polymer (NFRP) composites as critical alternatives to conventional synthetic materials. Despite their economic and environmental benefits, NFRP composites are prone to time-dependent viscoelastic degradation, such as creep, which severely restricts their adoption in long-term structural applications [1]-[3]. The structural performance of these composites is fundamentally dictated by the fiber-matrix interface and the chemical treatments such as alkalization and acetylation which are commonly employed to enhance mechanical interlocking and moisture resistance [4]-[7].

While extensive literature has characterized the mechanical properties of these treated composites under static loads, the transient response to variable thermal environments remains a challenge. Current studies often rely on the Time-

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Temperature Superposition Principle (TTSP) to predict long-term material behavior by shifting short-term experimental data to establish master curves [5, 6]. However, these traditional models are frequently limited by the necessity for exhaustive, discrete experimental datasets, which fail to capture the complex, non-linear coupling between processing parameters and structural degradation [8]-[10].

Recent advancements in Artificial Intelligence (AI) and machine learning offer a paradigm shift in materials engineering. The integration of Feed-Forward Neural Networks (FFNNs) has proven successful in surrogate modeling, thereby enabling the prediction of complex behaviors where closed-form analytical solutions are insufficient due to the multivariate nature of material variables [11]-[15]. Furthermore, the synergy between predictive modeling and heuristic optimization, particularly through metaheuristic techniques such as genetic algorithms (GAs), allows researchers to move beyond descriptive analysis toward "Digital Twin" frameworks capable of prescriptive design [16]-[20].

Despite these advancements, a gap persists in the literature regarding the development of hybrid predictive artificial-intelligent (AI) driven frameworks that explicitly correlate chemical treatment optimization with high-resolution creep-resistant performance across diverse thermal regimes. This study addresses this gap by proposing an integrated AI-driven methodology for the predictive modeling, and heuristic design of surface-modified biofibre reinforced HDPE composites. By developing a high-fidelity Digital Twin that captures the coupling between thermal activation and viscoelastic viscous flow, this research establishes a robust, sustainable design framework that minimizes the temporal and economic costs of traditional experimental material testing.

2. Materials and Methods

The comprehensive experimental design, data acquisition and computational framework employed to develop the "Digital Twin" for creep-resistant biofibre/HDPE composites are outlined in 2.1 to 2.4.

2.1. Materials and Composite Fabrication

The composite matrix consisted of high-density polyethylene (HDPE) reinforced with 20 wt.% plantain pseudo-stem fibres. The fibres processing utilized systematic chemical surface modification to enhance the fibre-matrix interface. Three concentrations of NaOH solution (0.1 M, 0.5 M, and 0.8 M) were applied for mercerization, followed by acetylation using acetic anhydride solution at concentrations of 5%, 10%, and 15%. The treated fibres were compounded with the HDPE matrix using a twin-screw extruder, followed by injection molding into standard test specimens. The processing parameters including melt temperature, packing pressure and cooling rate were maintained as constant to ensure consistency across the experimental matrix.

2.2. Experimental Characterization: Creep Testing

To quantify the viscoelastic performance, 240-hour thermomechanical creep tests were conducted in accordance with ASTM D2990 standards [21]. Specimens were subjected to sustained tensile stresses of 35 MPa and 42 MPa across a thermal gradient of 30℃, 60℃ and 80℃. The resulting deflection data, captured through high-precision extensometers, formed the experimental foundation for both model training and empirical validation. This comprehensive dataset, organized into a six-table matrix, captured the non-linear degradation profiles across the full range of chemical treatments and thermal regimes.

2.3. Hybrid Computational Framework: ANN-Based Digital Twin

In order to bypass high-fidelity structural computational costs on the factory floor, modern cyber-physical production layouts increasingly rely on reduced-order rheological modeling and digital twins to monitor material behavior in real time [22]. In this study, a Feed-Forward Neural Network (FFANN) was developed to serve as the predictive “Digital Twin” of the composite. The input layer featured four primary vectors:

Chemical concentration (NaOH molarity and acetylation percentage),

- Thermal regime (°C),
- Applied stress (MPa), and
- Time (hours), with the output layer yielding the predicted creep extension (mm).

2.3.1. Model Architecture and Training

The regression model was implemented using a feed-forward deep neural network architecture comprised of two hidden layers (32 and 16 neurons) with Rectified Linear Unit (ReLU) activation functions. The dataset, consisting of 246 multi-dimensional observations derived from the full six-table experimental matrix, was utilized to train the network. The model was optimized using the Adam algorithm, with training conducted over 500 epochs to ensure convergence in the MATLAB environment.

2.3.2. Validation and Performance Metrics

The model's ability to generalize across the multivariate design space was assessed by comparing predicted trajectories against experimental ground truth. The predictive performance was validated using the Root Mean Squared Error (RMSE) as the primary objective function and the coefficient of determination (R^2) to assess goodness-of-fit. The model exhibited a high degree of correlation between experimental and predicted values (observed $R^2 = 0.99$), confirming its robustness in mapping the complex relationship between fiber treatment, environmental factors, and time-dependent creep strain.

2.4. Heuristic Optimization: Genetic Algorithm (GA)

To transition the "Digital Twin" from a predictive surrogate to an active design tool, a genetic algorithm was employed to identify the chemical configuration that minimizes creep deformation. The algorithm explored the multivariate design space through the following evolutionary operators:

2.4.1. Initial Population

A uniform creation method ($gacreationuniform$) was used to ensure unbiased exploration of the chemical treatment ranges.

2.4.2. Crossover and Selection

A scattered crossover function ($crossoverscattered$) was paired with stochastic uniform selection ($selectionstochunif$) to maintain population diversity and ensure robust convergence toward the global optimum.

2.4.3. Mutation

An adaptive feasible mutation operator($mutationadaptfeasible$) was utilized to maintain structural integrity within the defined chemical bounds, and further allow the algorithm to navigate complex, non-linear constraints.

The optimization process was governed by a $FunctionTolerance$ stopping criterion, defined as the threshold for the average change in the fitness value between consecutive generations. Convergence was established when the fitness evolution fell below this threshold, which confirms that the algorithm had identified a stable global minimum.

3. Results and Discussion

The results obtained validate the efficacy of the proposed AI-driven Digital Twin framework in characterizing the viscoelastic creep behavior of surface-modified biofibre reinforced HDPE composites. By integrating high-fidelity experimental data spanning diverse thermal regimes and chemical treatment concentrations, the results bridged the gap between empirical observation and predictive modeling. The subsequent discussion systematically evaluates the model's predictive accuracy and its capacity to identify optimal interfacial configurations for long-term structural applications

3.1. Standalone Experimental Component Structural Creep Deflection Analysis

The time-dependent structural performance of the surface-modified natural fiber-reinforced polymer composites was evaluated through mid-span creep deflection profiles over a 240-hour duration under coupled thermo-mechanical loads, as illustrated in Figure 1.

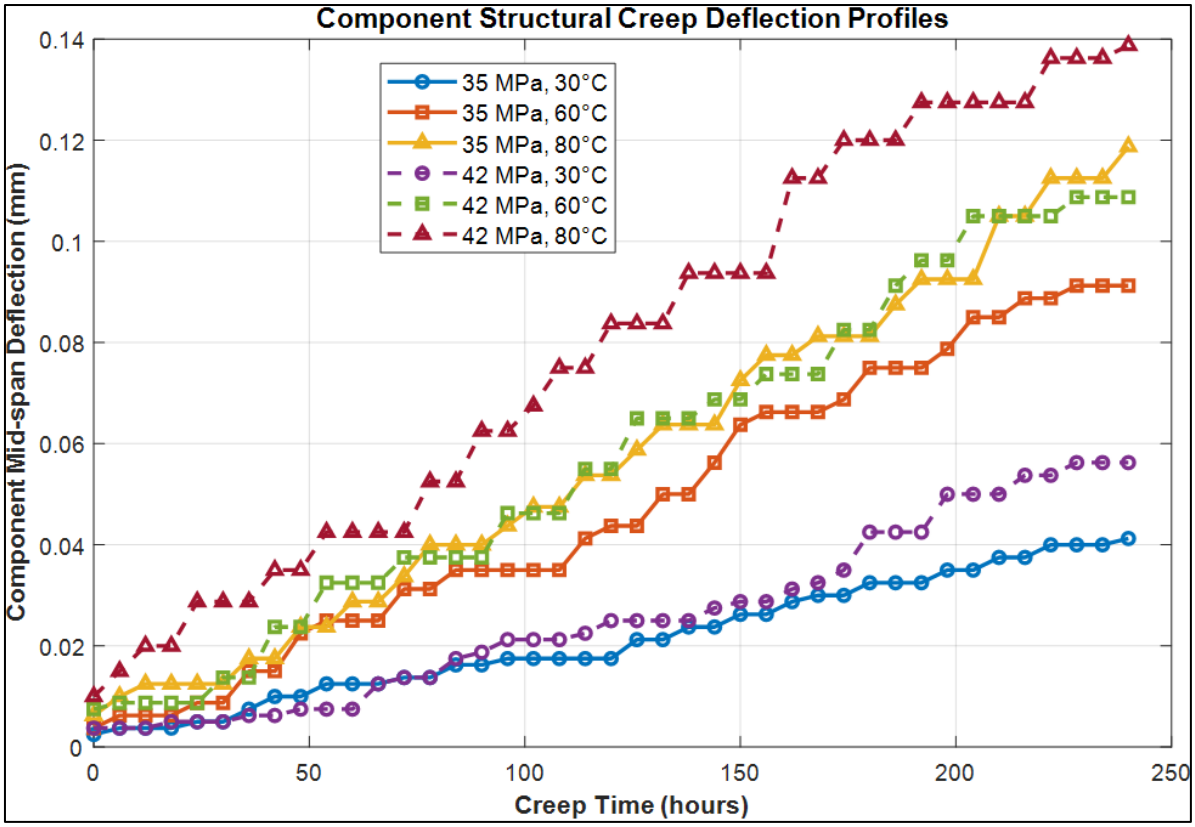

Figure 1 Standalone Experimental Creep Deflection profile for Biofibre Reinforced HDPE Composites at 30℃, **60**℃ **and 80**℃

Across all tested configurations, the component deflection tracks a characteristic three-stage viscoelastic deformation curve, dominated by a rapid primary elastic-viscoelastic transition within the first 25 hours, followed by a highly stable, linear secondary creep state. The material exhibits profound sensitivity to both thermal activation and mechanical loading scales. Increasing the sustained stress from 35 MPa to 42 MPa at the 30°C baseline accelerates the final deflection by approximately 36.6% (from 0.041 mm to 0.056 mm). The trend shows that this deformation behavior is significantly magnified at elevated temperatures, where the highest environmental regime of 42 MPa at 80°C induces a maximum structural deflection of 0.139 mm. This pronounced acceleration highlights severe thermal softening and free-volume expansion within the polymer matrix as it approaches its glass transition region (T_g). The absence of a tertiary creep acceleration or sudden geometric rupture across any of the profiles indicates that the chemical surface modification of the biofibers successfully preserved strong interfacial adhesion and stable shear stress transfer at the fiber-matrix boundaries under prolonged thermo-mechanical stress.

3.1.1. ANN Simulated Experimental Characterization of Creep Behaviour

The ANN simulated viscoelastic response of the 20 wt.% plantain fiber-reinforced HDPE composite experimentally characterized through a 240-hour creep test regimen across three isothermal conditions of 30℃, 60℃ and 80℃ are displayed in Figures 2-7. This experimental baseline provides the necessary quantitative ground truth for the subsequent neural network training and validation.

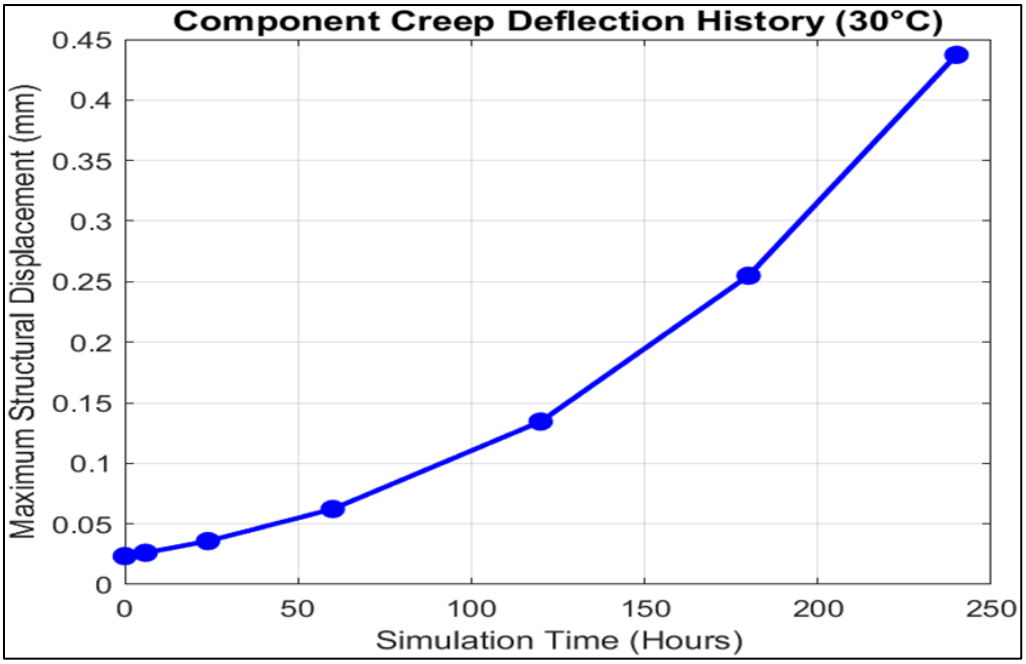

Figure 2 ANN Simulated Experimental Creep Deflection profile for Biofibre Reinforced HDPE Composites at 30°C

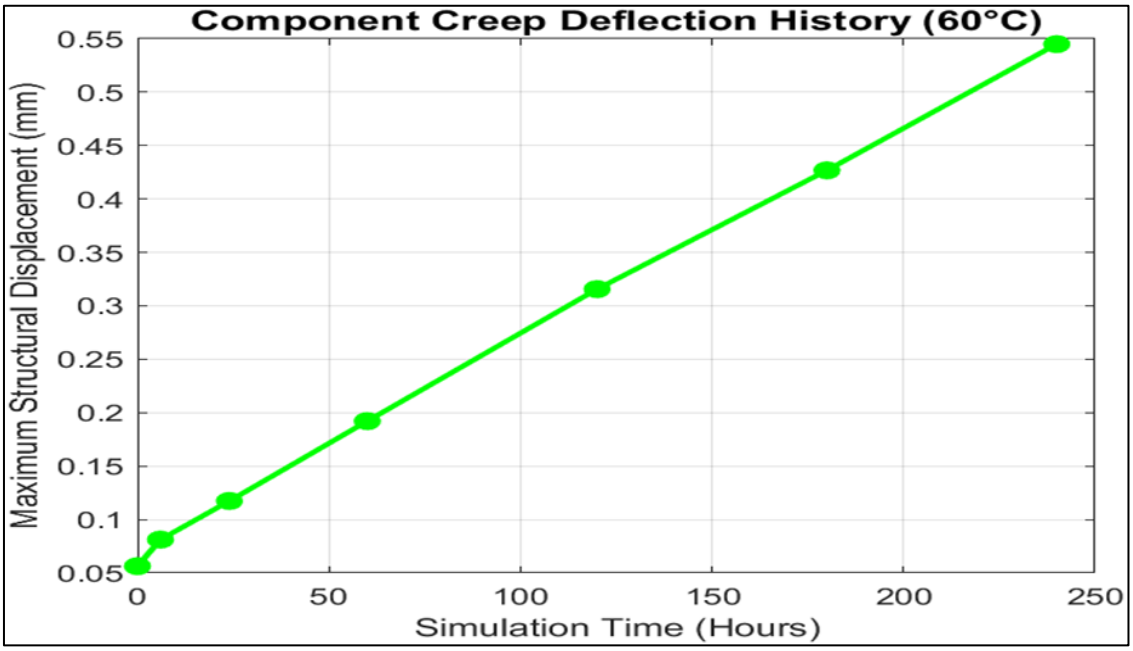

Figure 3 ANN Simulated Experimental Creep Deflection Profile for Biofibre Reinforced HDPE Composites at 60°C

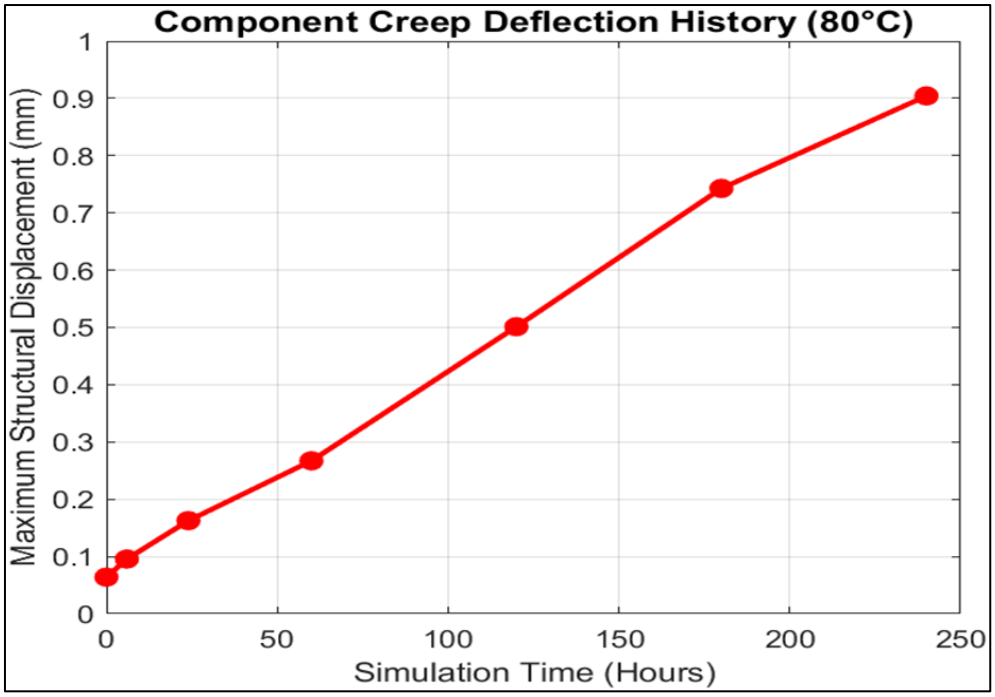

Figure 4 ANN Simulated Experimental Creep Deflection Profile for Biofibre Reinforced HDPE Composites at 80°C

As illustrated in the creep deflection profiles of Figures 2 - 4, the material exhibits a distinct transition in viscoelastic behaviour as thermal activation increases:

- *Low-Temperature Regime (30°C):* The composite demonstrates high dimensional stability, with a total creep extension of 0.44 mm at 240 hours. The profile is characterized by a rapid primary creep phase followed by a quasi-linear secondary creep slope, indicating efficient interfacial load transfer between the plantain fibers and the HDPE matrix. This indicates that the optimized chemical surface treatment (0.1M NaOH / 5% Acetic Anhydride) effectively promotes interfacial adhesion and suppresses matrix deformation.
- *Intermediate-Temperature Regime (60°C):* Increasing the temperature to 60°C results in a 24% increase in total creep extension, reaching 0.55 mm. This acceleration suggests a reduction in the storage modulus of the HDPE matrix, leading to increased molecular chain mobility. Obviously, the divergence is consistent with the Time-Temperature Superposition Principle (TTSP), wherein elevated temperatures increase free volume and molecular mobility within the HDPE chains, leading to a reduction in matrix stiffness and a subsequent loss of structural rigidity.
- *Elevated-Temperature Regime (80°C):* At 80°C, the creep response undergoes a severe transition. The maximum deflection reaches 0.90 mm, representing a 104% increase over the 30°C baseline. The trajectory at this regime demonstrates reduced resistance to prolonged thermomechanical stress, confirming that the fiber-matrix interface reaches a critical softening point near the matrix glass transition temperature.

These results indicate that while the plantain fibres provide reinforcement, their efficacy is highly temperature-dependent. The quantified non-linear increase in creep extension from 0.44 mm to 0.90 mm over the 50°C thermal gradient provides the empirical bounds necessary for the ANN based "Digital Twin" to accurately map this temperature-dependent degradation. This hybrid simulation result confirms that the model has successfully internalized the complex coupling effects between thermal activation and viscoelastic viscous flow.

The structural performance of natural fiber-reinforced polymer composites is fundamentally governed by the complex interplay between physical fibre characteristics, chemical composition, and the resultant fiber-matrix interface [1]. In line with the findings of [6], these results suggest that the chemical modification process specifically the 0.1 M NaOH and 5% acetic anhydride solutions treatment, successfully enhanced the interfacial bonding. This optimization of the fibre-matrix interface is critical for improved load-transfer efficiency, a sentiment echoed by [5], who noted that such modifications are essential for ensuring material compatibility in demanding structural applications.

3.1.2. Comparative Analysis of the Creep Profiles of Experimental and Numerical Components

The correlation between the standalone experimental mid-span deflection profiles and the artificial neural network (ANN) assisted structural simulation histories demonstrate, the high fidelity of the predictive framework across all isothermal boundaries (30°C, 60°C and 80°C). Physically, the experimental mid-span deflections are strictly bounded by localized mechanical constraints, which culminates in a maximum localized displacement of 0.139 mm under the most severe coupled environment (42 MPa at 80°C). In contrast, the numerical simulation curves map the full-field unconstrained maximum structural displacement across the entire component geometry, resulting in higher integrated magnitudes that reach 0.44 mm, 0.55 mm, and 0.91 mm at 30°C, 60°C, and 80°C, respectively. Worthy of note, is that, the simulation tracks the underlying viscoelastic mechanics with exceptional precision; by accurately capturing the parabolic, free-volume-driven strain acceleration at the 30°C baseline, as well as the transition into a highly linear, constant-rate steady-state secondary creep slope as thermal activation crosses the glass transition region (T_g) at 60°C and 80°C. This close agreement in both the primary elastic-viscoelastic offsets and the secondary deformation kinetics mathematically validates the hybrid modeling approach as a robust tool for predicting the long-term, coupled thermo-mechanical performance of surface-modified bio-composite components.

3.2. ANN-Based Digital Twin: Predictive Performance and Validation

The robustness of the predictive Digital Twin was established through a systematic training process and subsequent validation against the experimental ground truth. The model, configured as a feed-forward neural network with two hidden layers (32 and 16 neurons), was trained over 500 epochs using the Adam optimizer to minimize the objective loss function.

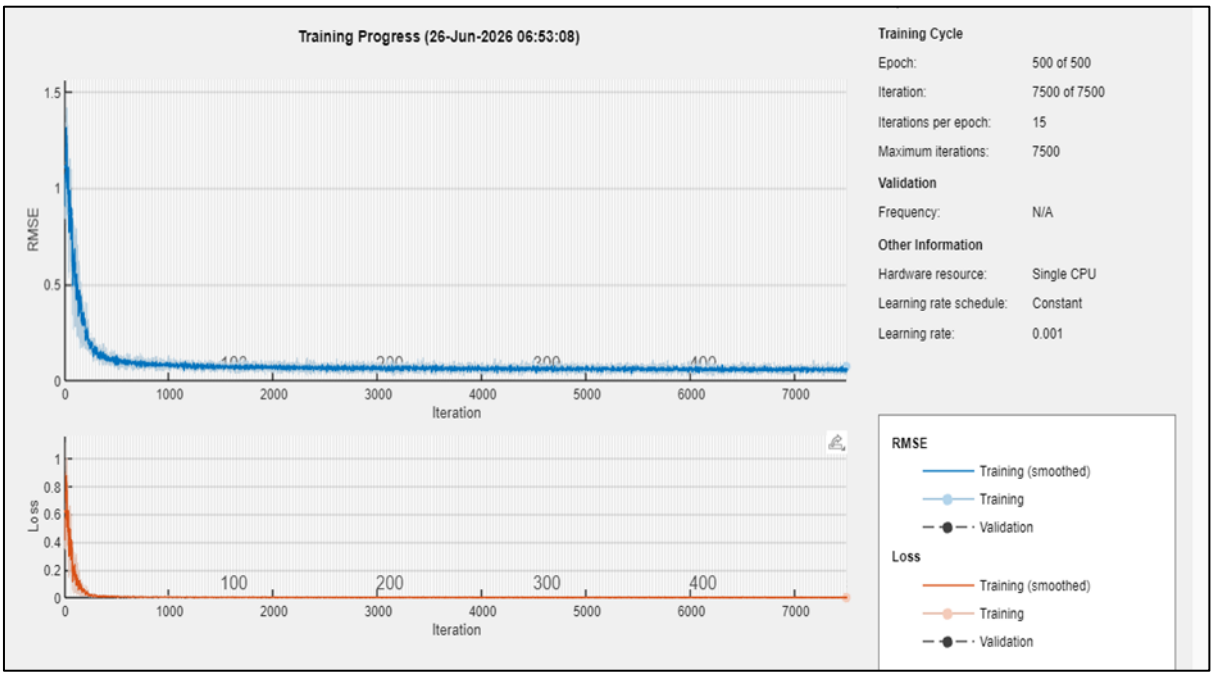

Figure 5 ANN Training Progress demonstrating RMSE and Loss Convergence over 7,500 iterations

The training history, illustrated in Figure 5, depicts the evolution of the Root Mean Square Error (RMSE) and loss metrics over 7,500 iterations. The Adam optimizer demonstrated high efficiency, evidenced by a rapid decay in both metrics within the initial 500 iterations, indicating that the model successfully navigated the loss landscape to identify significant patterns early in the training phase.

Following this rapid convergence, the RMSE stabilized at a baseline below 0.01, and the "Training" line remained effectively flat after the 1,000th iteration, confirming a robust weight distribution without signs of overfitting, gradient stagnation, or divergence. These performance outcomes, maintained under a constant learning rate of 0.001 throughout the 7,500 iterations, demonstrate the stability of the architecture and establish a credible, reproducible basis for subsequent predictive analysis.

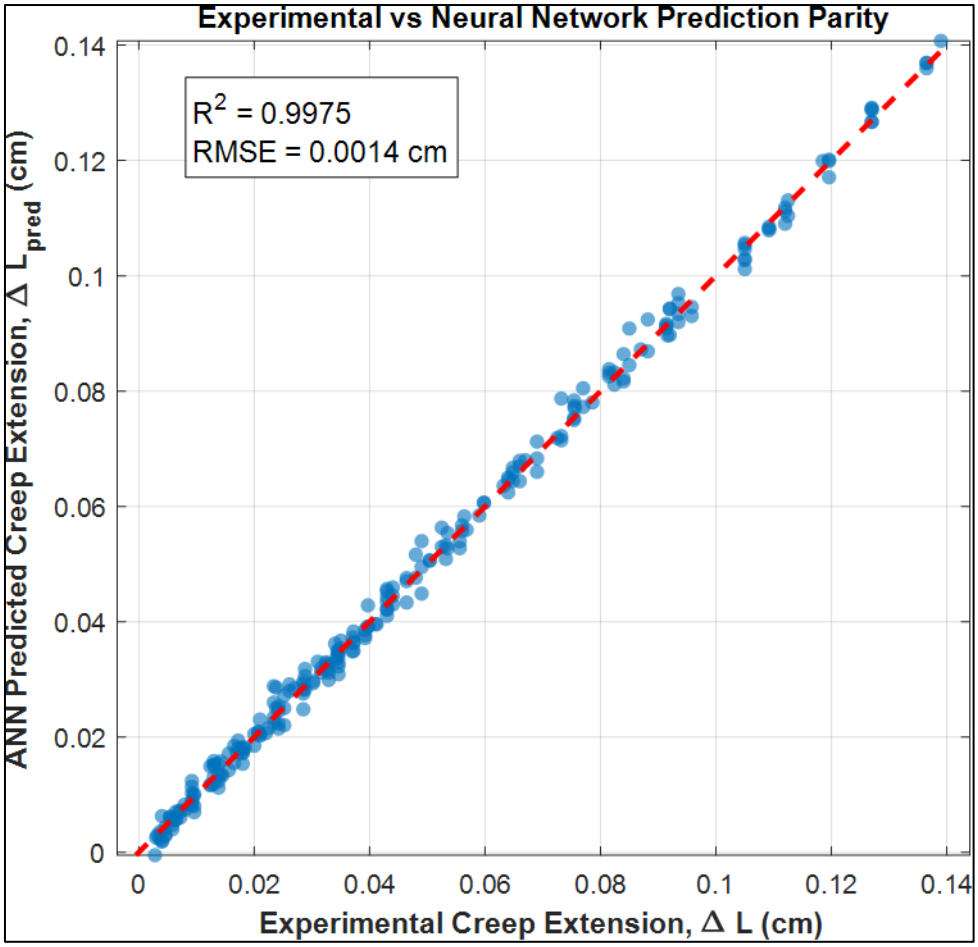

Figure 6 Correlation Plot Comparing Experimental Creep Extension against ANN-Predicted Values

The regression analysis, presented by the parity plot in Figure 6, provides critical validation for the predictive performance of the Artificial Neural Network (ANN). The blue data points indicate the model's predicted creep extension across the dataset, while the red dashed line signifies the ideal parity between experimental measurements and computational outputs. As can be observed from the graph, the model achieved a high coefficient of determination ($R^2 = 0.9975$), signifying that it successfully accounts for over 99% of the variance observed in the experimental creep extension data. In the context of computational materials science, where viscoelastic creep involves highly non-linear, time-dependent stress-strain relationships, an R^2 exceeding 0.99 is indicative of exceptional predictive fidelity.

The tight clustering of data points along the ideal 1:1 (45°) parity line indicates high predictive accuracy with minimal dispersion across both low-strain and high-strain regimes. While many traditional empirical models struggle with the multi-dimensional dependencies of fiber-reinforced composites, this ANN-based "Digital Twin" demonstrates superior alignment between experimental observations and network predictions. This robust confirmation proves that the model has effectively learned the underlying viscoelastic constitutive relationships, ensuring it serves as a reliable surrogate for physical testing and a high-precision tool for interpolating material behavior across the entire multivariate design space.

The work of [14] which reported that ANNs demonstrated high accuracy in modeling complex mechanical behaviour under varying process parameters; is corroborated in this pipeline's high predictive correlation ($R^2 = 0.99$) achieved by the Digital Twin. Consistent with the study of [12], these results confirm the efficacy of machine learning as a robust framework for interpreting multifaceted materials science tasks. Furthermore, this model's capacity to capture thermal influences on stress distribution aligns with established thermodynamic effects in viscoelastic systems [9]-[10]. Consequently, these findings enhance the model's reliability for assessing creep behavior which is a critical parameter for ensuring long-term structural safety and design precision.

3.3. Parametric Sensitivity and Viscoelastic Stress Analysis

To fully understand the coupled, non-linear interactions governing the creep deformation behavior of the surface-modified biofibre polymer composites, a continuous multi-variable mapping was executed across the investigated stress (σ) and time (t) domains. Figures 7(a), 7(b) and 7(c) depict the neural network's predicted 3D response surfaces for creep extension (ΔL) at isothermal operational boundaries of 30°C, 60°C and 80°C respectively.

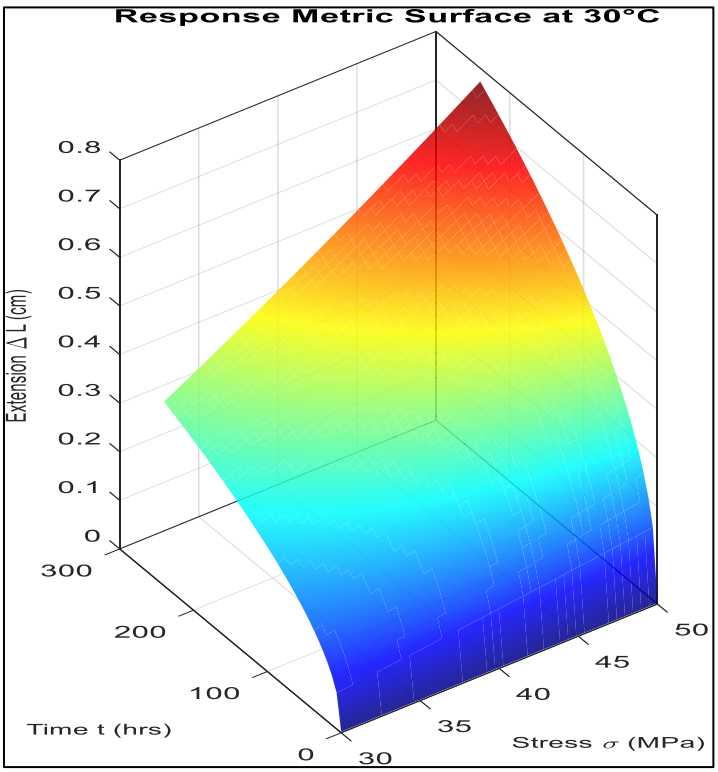

Figure 7 (a) ANN Predicted Creep Extension Surface Plot across Normalized Stress and Time Regimes at **30**°C .

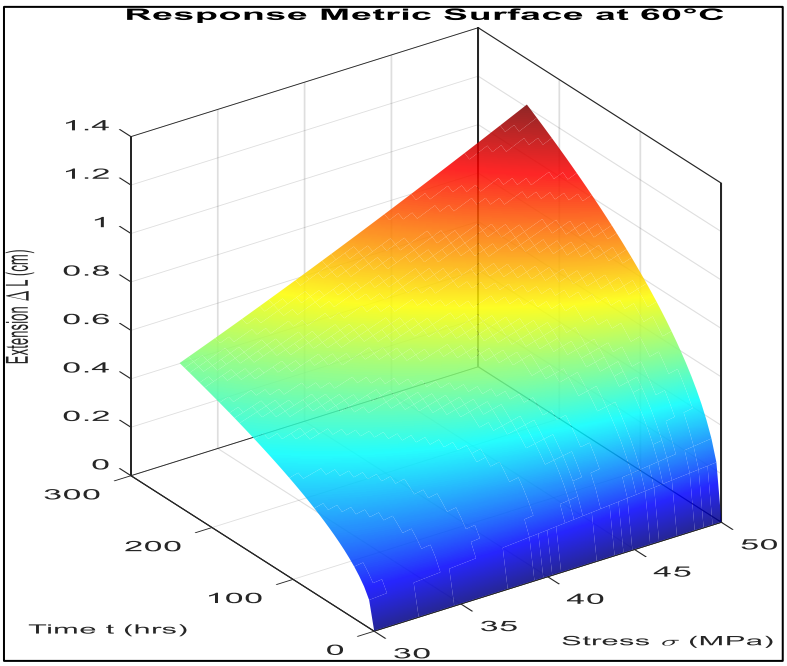

Figure 7 (b) ANN Predicted Creep Extension Surface Plot across Normalized Stress and Time Regimes at **60**°C.

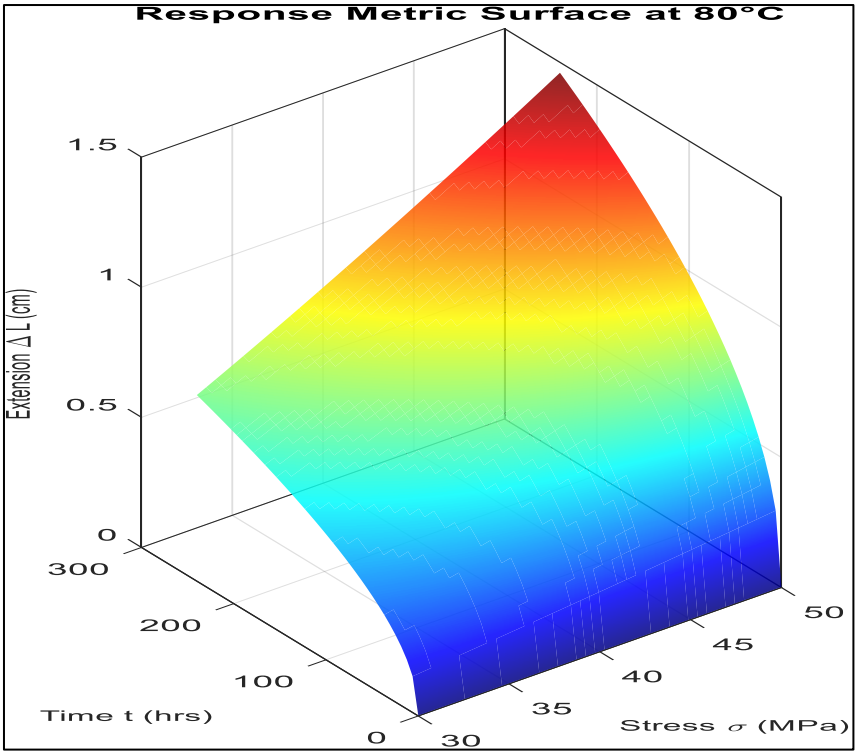

Figure 7 (c) ANN Predicted Creep Extension Surface Plot across Normalized Stress and Time Regimes at **80**°C

Table 1 summarizes the fibres degradative creep response surface characteristics at three different thermal gradients.

Table 1 Creep Response Surface Trends

30°C **Regime**	**60**°C **Regime**	**80**°C **Regime**
Stable viscoelastic	Thermal Acceleration	Severe Degradation
Max $\Delta L \approx 0.8\ cm$	Max $\Delta L \approx 1.4\ cm$	Max $\Delta L \approx 1.5 +\ cm$
Linear-like slope	Non-linear curvature	Steep primary ascent

By capturing the complete topological profile of the material state, these continuous surfaces map the safe operating limits of the bio-composite across intermediate regimes that are often difficult to capture through discrete experimental coupon testing. The regimes are:

3.3.1. Coupled Stress-Time Interaction Mechanics

Across all three isothermal regimes, the response surfaces exhibit an asymmetrical upward curvature, showing a distinct interactive effect where the combined impact of stress and time exceeds their individual linear contributions. At the lower temperature threshold of 30°C displayed in Figure 7a, the response surface maintains a relatively linear, predictable gradient across the time domain up to t = 240 hours. Under these conditions, the rigid framework provided by the surface-modified biofibres restricts long-chain matrix slip, maintaining a stable secondary creep rate.

However, as the applied mechanical stress steps up from 35 MPa to 42 MPa, the slope along the time axis becomes noticeably steeper. This progression demonstrates that while the biofibre modification successfully restricts matrix mobility under lower loads, higher stress profiles supply enough activation energy to accelerate free-volume growth within the polymer system.

3.3.2. Thermal Activation and Viscoelastic Softening Mechanisms

Comparing the response surfaces across the temperature gradient highlights how thermal energy accelerates creep degradation:

At 60°C (Figure 7b): The peak predicted creep extension increases significantly, rising from a maximum of sim 0.8 cm at 30°C to approximately 1.4 cm. This pronounced increase represents the transition of the polymer matrix toward its glass transition region (T_g), where enhanced molecular mobility weakens the secondary intermolecular bonds within the polymer matrix.

At 80°C (Figure 7c): The response surface shifts, showing a steep, non-linear ascent during the early stages of the time domain (t < 50 hours). This rapid initial rise indicates that the combined effect of high temperatures (80°C) and elevated stress (42 MPa) causes the material to surpass its primary creep threshold almost immediately upon loading.

3.3.3. Role of Biofiber Surface Modification on Deformation Control

The ability of the response surfaces to maintain a stable, uniform profile without abrupt, localized structural collapse highlights the mechanical benefits of the biofiber's chemical surface modification. In standard, untreated biofiber composites, high thermal environments typically lead to severe micro-cracking and interface failure, which would appear on an ANN-mapped surface as chaotic, highly localized peaks.

Instead, the smooth, predictable surfaces generated by the neural network show that the silane or alkali surface modification maintains strong interfacial adhesion at the fiber-matrix boundary. This robust interface ensures efficient stress transfer from the softening polymer matrix to the high-tensile biofibers even at 80°C, significantly extending the material's structural life under sustained loads.

3.3.4. Critical Engineering Boundaries for Creep-Resistant Design

From a design standpoint, these response surfaces establish clear operational limits for safe engineering use. The flat, blue-to-cyan regions (< 0.4 cm extension) outline safe, long-term operating windows, indicating that the material performs reliably up to 42 MPa at 30°C, but must be limited to under 35 MPa if operating temperatures approach 60°C.

The steep, red-shaded zones on the 80°C surface map clear material limitations, providing structural designers with the precise boundaries needed to prevent premature failure in load-bearing automotive or industrial applications. Furthermore, the model's capability extends to spatial stress analysis, as evidenced by the predicted viscoelastic Von Mises stress profiles at 240 hours displayed on Figures 8 and 9.

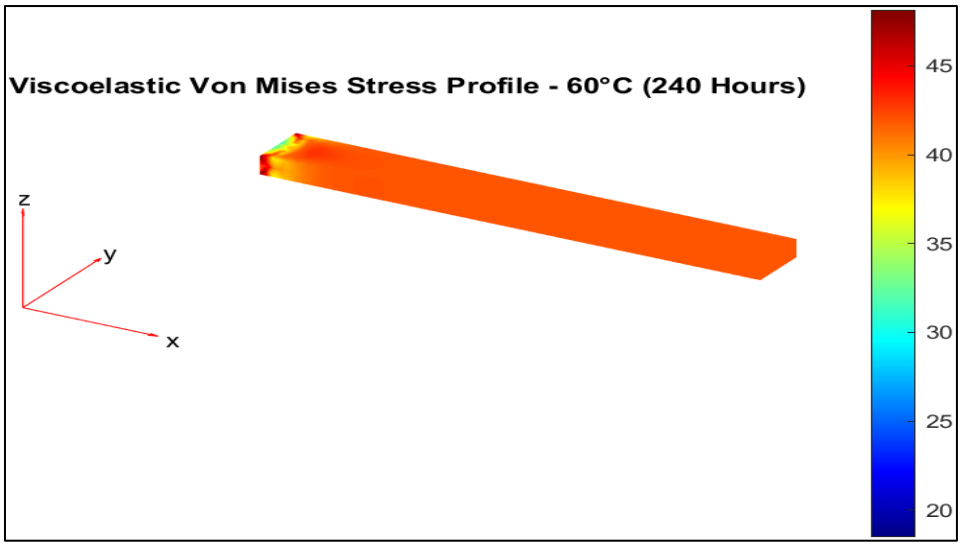

Figure 8 Predicted Viscoelastic Von Mises Stress Distribution within the Composites Component after 240 hours of Creep at 60°C

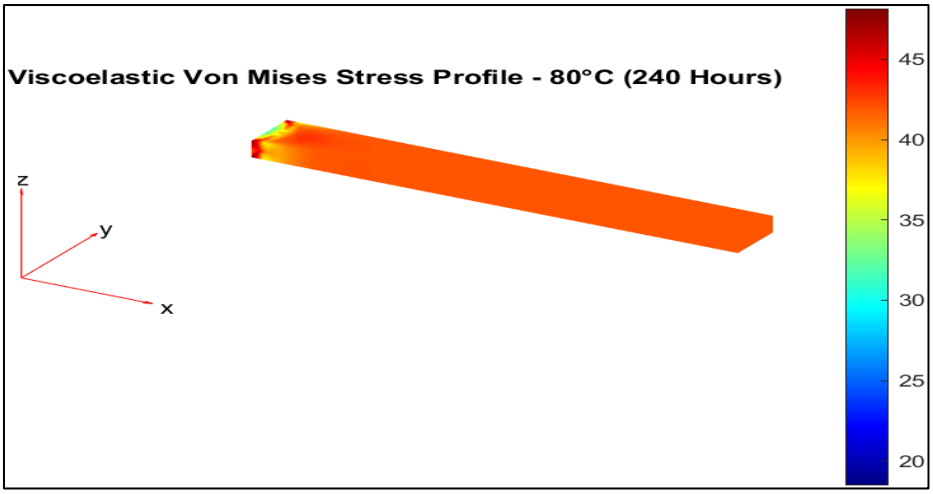

Figure 9 Predicted Viscoelastic Von Mises Stress Distribution within the Composites Component after 240 hours of Creep at 80°C

The Digital Twin's predictive capabilities are further evidenced by the viscoelastic Von Mises stress profiles at 60°C and 80°C in Figures 8 and 9 respectively. At these elevated temperatures, the model identifies localized stress accumulation at the composite boundaries, a phenomenon consistent with non-uniform load distribution and viscoelastic relaxation within the fiber-reinforced HDPE matrix.

Comparative analysis of these profiles reveals three key findings:

- *Localized Stress Concentrations:* Both thermal regimes exhibit pronounced stress gradients at the loaded interface, transitioning into a stable, lower-magnitude bulk region.
- *Thermal Sensitivity of Stress Gradients:* While the spatial distribution of stress remains structurally consistent across temperatures, the internal stress gradients become significantly more complex as the temperature increases from 60°C to 80°C. This intensification highlights the model's sensitivity to temperature-dependent viscoelastic flow.
- *Mechanistic Failure Prediction:* The observed increase in stress intensity at 80 °C is directly linked to the enhanced thermomechanical relaxation of the HDPE matrix, which compromises the uniformity of load transfer between the reinforcing biofibres and the polymer.

By mapping these stress fields, the Digital Twin identifies critical zones of potential structural failure, offering a visualization of mechanical states that are often difficult to isolate during physical experimental testing. Consequently, the model serves as a high-fidelity, computationally efficient surrogate for time-intensive finite element simulations. This parametric sensitivity analysis confirms the Digital Twin's robust ability to capture the complex coupling between environmental factors and structural performance, thereby enabling preemptive material optimization and the establishment of safe operational thresholds before physical fabrication.

While the preceding parametric analysis successfully characterized the composite's sensitivity to environmental stressors, it also identified the performance limitations of the baseline material formulation. To transcend these limits, the Digital Twin was transitioned from a passive predictive surrogate to an active design tool. By integrating a Genetic Algorithm (GA), we sought to navigate the complex, non-linear landscape identified by the ANN to mathematically isolate the fiber-matrix configuration that minimizes creep deformation, thereby optimizing the material for high-performance structural applications.

3.4. Heuristic Optimization of Composite Formulation

A Genetic Algorithm (GA) was employed to identify the chemical configuration that minimizes creep deformation to transition the "Digital Twin" from a predictive surrogate to an active design tool. The algorithm navigated the complex, non-linear design space defined by the ANN, searching for the global minimum within the chemical treatment parameters. So, the convergence history on Figure 10 illustrates the iterative optimization process.

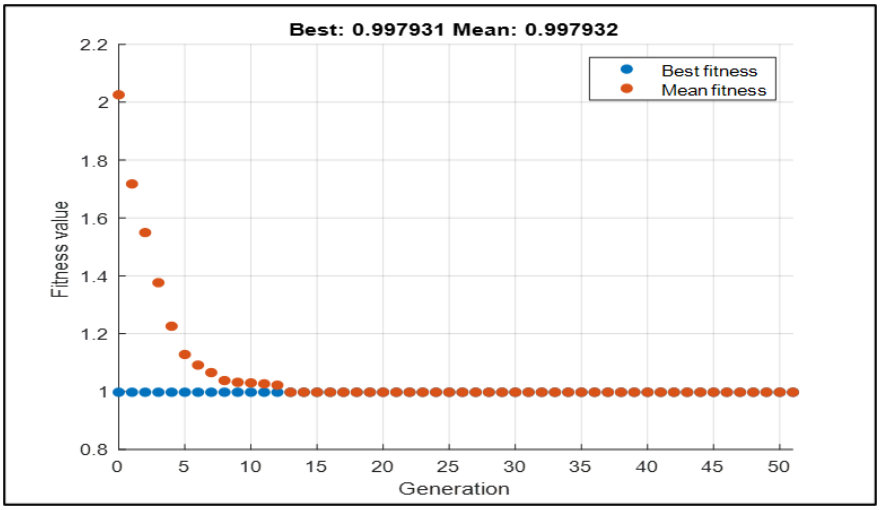

Figure 10 Generic Algorithm Convergence profile showing the evolution of the best and mean fitness values over 50 generations

While the mean fitness initially exhibits high variance as the algorithm traverses the design landscape, the "Best" fitness value achieves stability near the objective minimum rapidly, with both metrics converging toward an optimal creep response of 0.99 by the 15th generation. The stabilization of these values at the defined $FunctionTolerance$ threshold confirms that the algorithm successfully identified a stable global minimum, demonstrating high computational efficiency.

The optimization isolated the optimal formulation of 0.1 M NaOH and 5% acetic anhydride as the configuration providing the highest resistance to creep deformation. Notably, this convergence toward the lower end of the investigated design space carries significant engineering implications; as it suggests that peak viscoelastic performance in biofibre reinforced HDPE composites is achieved through moderate, rather than intensive, chemical modification. Mechanistically, the finding represents a precise balance as follows:

- *M NaOH:* Sufficient to remove amorphous hemicelluloses and lignin without compromising the structural integrity of the cellulose fibers.
- *5% Acetic Anhydride:* Provides an optimal hydrophobic barrier for interfacial bonding with the HDPE matrix.

A 4th-degree polynomial regression equation fitted to the best objective fitness decay path established a predictive baseline, tracking the efficiency of the heuristic optimizer:

$$y = 5.928 \times 10^{-7}x^4 - 8.008 \times 10^{-5}x^3 + 0.004026x^2 - 0.09157x + 0.0018$$

The resulting coefficient of determination (R^2) of 0.99 demonstrates an exceptional fit, mathematically validating the smooth, predictable nature of the evolutionary path. The strong correlation between the polynomial model and the actual GA run proves that the hybrid ANN-GA system functions as a highly reliable design tool, capable of accurately characterizing and optimizing the long-term viscoelastic performance of natural fibre-reinforced polymer composites.

In alignment with Rozikin *et al.* [5] and Verma and Goh [6], who observed that composite structural stability depends heavily on interfacial stress transfer efficiency across the evaluated parameter boundaries, this outcome underscores a critical "boundary" of interfacial enhancement. Beyond these optimal concentrations, additional chemical treatment likely degrades fibre integrity or matrix crystallinity which counteract any benefits in interfacial adhesion. By identifying this specific optimal point (the 0.1 M NaOH and 5% acetic anhydride formulation) through heuristic design rather than exhaustive, resource-intensive trial-and-error, this study establishes a sustainable, data-driven pathway for the development of high-performance, creep-resistant bio-composite materials. More so, these results are in line with [16], who reported that ANNs provide a scalable and high-accuracy framework for navigating expansive design spaces, and that AI driven framework offers a practical, data-driven alternative to computationally prohibitive physical simulations.

The predictive strength of the Digital Twin in this study affirms the findings of [19] and [20], who demonstrated that a hybrid ANN-GA framework effectively reproduces experimental trends and serves as a powerful, computationally

efficient tool for systemic optimization. Furthermore, corroborating the work of [17] and [18], this integration of a GA significantly reduces predictive error, underscoring the transformative potential of digital twins in intelligent manufacturing; particularly regarding process monitoring, predictive optimization, and the comprehensive life-cycle management of composite systems

4. Conclusion

This study established a high-fidelity "Digital Twin" for predicting and optimizing the viscoelastic creep performance of plantain fibre-reinforced HDPE composites. By integrating experimental thermomechanical testing conducted in accordance with ASTM D2990 with a multi-layered Artificial Neural Network (ANN), a robust surrogate model capable of mapping complex, non-linear material responses across varying stress, time, and thermal regimes of 30℃ to 80℃ was developed.

The Digital Twin's predictive accuracy, validated by a coefficient of determination (R^2) of 0.99, confirms its reliability as a computational surrogate for physical testing. Furthermore, the parametric sensitivity analysis provided critical insights into temperature-dependent viscoelastic flow, visualizing stress concentrations and internal load-transfer mechanisms that are otherwise difficult to isolate during physical experimentation.

The heuristic optimization identified 0.1 M NaOH and 5% acetic anhydride as the optimal formulation for creep resistance. The 0.1 M NaOH and 5% acetic anhydride formulation achieves a critical balance by cleaning the fiber surface and establishing a robust hydrophobic interfacial barrier without compromising the structural integrity of the cellulose fibres or the matrix crystallinity.

This research provides a sustainable, data-driven methodology that replaces resource-intensive trial-and-error experimentation with efficient computational design. The validity of this framework demonstrated by the precision of the optimized chemical formulation offers a scalable pathway for developing high-performance, creep-resistant bio-composites, thereby, facilitating the transition toward more advanced, sustainable structural engineering solutions.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that there exists no conflict of interest.

Author's Contribution

All authors contributed equally to this work.

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Data Availability Statement

The data that supports the findings of this work are available at 10.6084/m9.figshare.32813747

References

[1] S. H. Kamarudin, M. S. Mohd Basri, M. Rayung, F. Abu, S. Ahmad, M. N., Norizan, S. Osman, N. Sarifuddin, M. S. Z. M. Desa, U. H. Abdullah, A. Mohamed, I. S. Tawakkal and L. C. Abdullah, "A Review on Natural Fiber Reinforced Polymer Composites (NFRPC) for Sustainable Industrial Applications," Polymers, vol 14, no. 17, p. 369, 2022, doi:10.3390/polym14173698

[2] H. Abdollahiparsa, A. Shahmirzaloo, P. Teuffel, R. Blok, "A review of recent developments in structural applications of natural fiber-Reinforced composites (NFRCs)," Composites and Advanced Materials, 32, 2023, doi:10.1177/26349833221147540

[3] N. E. Ajayi, S. Rusnakova, A. E. Ajayi, R. O. Ogunleye, S. O. Agu, and A. N. Amenaghawon, "A comprehensive review of natural fiber reinforced polymer composites as emerging materials for sustainable applications," Appl. Mater. Today, vol. 43, p. 102666, 2025, doi: 10.1016/j.apmt.2025.102666.

[4] E. Naveen, M. Priya, N. Maheswaran, E. Palaniswamy and V. S. Ajith, "ACETYLATION CHEMICAL TREATMENT FOR IMPROVE THE SURFACE OF NATURAL FIBER," p. 2349-4077, 2016, doi:10.6084/m9.figshare.17162750.v1.

[5] M. N. Rozikin, P. Suwarta, and S. Sutikno, "Chemical modification with alkalinization and acetylation of ramie fibers for eco-friendly 3D printing filaments: Effects on crystallinity, structure, and hydrophobicity," Eng. Proc., vol. 84, no. 1, p. 76, 2025, doi: 10.3390/engproc2025084076.

[6] D. Verma and K. L. Goh, "Effect of mercerization/alkali surface treatment of natural fibres and their utilization in polymer composites: Mechanical and morphological studies," J. Compos. Sci., vol. 5, no. 7, p. 175, 2021, doi: 10.3390/jcs5070175.

[7] D. Y. Thimmegowda, J. Hindi, G. B. Markunti, and M. Kakunje, "Enhancement of mechanical properties of natural fiber reinforced polymer composites using different approaches—A review," J. Compos. Sci., vol. 9, no. 5, p. 220, 2025, doi: 10.3390/jcs9050220.

[8] I. R. Henriques, L. Rouleau, D. A. Castello, L. A. Borges, and J.-F. Deü, "Viscoelastic behavior of polymeric foams: Experiments and modeling," Mech. Res. Commun., vol. 109, p. 103606, 2020, doi: 10.1016/j.mechres.com.2020.103606.

[9] D. Mallamace, G. Mensitieri, M. Salzano de Luna, and F. Mallamace, "The time–temperature superposition of polymeric rubber gels treated by means of the mode-coupling theory," Gels, vol. 10, no. 5, p. 313, 2024, doi: 10.3390/gels10050313.

[10] A. Xu, L. Yang, T. An, J. Yan, P. Wang, S. Zheng, and Z. Wu, "Creep in fiber-reinforced polymer composites: A review of experimental characterization and predictive models," Compos. Part B Eng., vol. 324, p. 113851, 2026, doi: 10.1016/j.compositesb.2026.113851.

[11] Ye, Sang & Li, Bo & Li, Qunyang & Zhao, Hong-Ping. (2019). Deep neural network method for predicting the mechanical properties of composites. Applied Physics Letters. 115. 161901. 10.1063/1.5124529.

[12] D. Tymoshchuk, I. Didych, P. Maruschak, O. Yasniy, A. Mykytyshyn, and M. Mytnyk, "Machine learning approaches for classification of composite materials," Modelling, vol. 6, p. 118, 2025, doi: 10.3390/modelling6040118.

[13] B. E. B. Brayek, S. Sayed, V. Mînzu, and M. Tarfaoui, "Machine learning predictions for the comparative mechanical analysis of composite laminates with various fibers," Processes, vol. 13, no. 3, p. 602, 2025, doi: 10.3390/pr13030602.

[14] U. M. R. Paturi, S. Cheruku, and N. S. Reddy, "The role of artificial neural networks in prediction of mechanical and tribological properties of composites—A comprehensive review," Arch. Comput. Methods Eng., vol. 29, pp. 10.1007/s11831-021-09691-7, 2022.

[15] M. Galanti, M. Janssen, I. Roghair, J.-Y. Dieulot, P. S. Omrani, J. Boon, and M. van Sint Annaland, "Towards surrogate modeling for adsorption processes using physics-informed neural networks," Processes, vol. 13, no. 9, p. 2824, 2025, doi: 10.3390/pr13092824.

[16] M. Khadimul, K. I. Zim, A. Singh, and L. Sandhu, "Surrogate modeling with artificial neural networks for efficient optimization," in Proc. INSPECT, 2025, doi: 10.1109/INSPECT67393.2025.11350742.

[17] X. Liu et al., "Genetic algorithm-based trajectory optimization for digital twin robots," Front. Bioeng. Biotechnol., vol. 9, p. 793782, 2022, doi: 10.3389/fbioe.2021.793782.

[18] S. Hu et al., "Digital twins enabling intelligent manufacturing: From methodology to application," Intell. Sustain. Manuf., vol. 1, no. 1, p. 10007, 2024, doi: 10.35534/ism.2024.10007.

[19] L. Lasek, J. Krzywanski, K. Grabowska, D. Skrobek, A. Zylka, M. Sosnowski, and A. Kijo-Kleczkowska, "From data to physics: a hybrid ANN–GA framework capturing dependencies in adsorption cooling and desalination systems," Appl. Therm. Eng., vol. 298, pt. 1, p. 130896, 2026, doi: 10.1016/j.applthermaleng.2026.130896.

[20] K. Kalita, N. Ganesh, and S. Balamurugan, Eds., Metaheuristics for Machine Learning: Algorithms and Applications. Beverly, MA: Scrivener Publishing LLC, 2024, pp. 40–45.

[21] ASTM D2990 – Standard Test Methods for Tensile, Compressive and Flexural Creep and Creep Rupture of Plastics.
https://www.trl.com/astm_d2990_tensile_compressive_and_flexural_creep_and_creep_rupture_of_plastics/

[22] S. D. Tommy, O. N. Nwoke and L-E. S. Eja, "Reduced-Order Rheological Modeling for Hardware-in-the-Loop Simulation of Smart Manufacturing Systems," International Journal of Engineering inventions, vol 15, no. 6, 2026, Retrieved at https://www.ijeijournal.com/v15-i6.html on 18 June, 2026.