JoCoSiR
Journal of Computer Science Research
ISSN 2986-2337 (Online)

Multivariate Analysis and Neural Network-Based Prediction of Compression Molding Behavior in Plantain–Bamboo Fiber Reinforced HDPE Composites

Obiora Jeremiah Obiafudo[a], Joseph Achebo[b], Kessington Obahiagbon[c], Frank. O. Uwoghiren[d], Callistus Nkemjika Chukwu[e]

[a] *Department of Industrial/Production Engineering, Nnamdi Azikiwe University, Awka, Anambra State, Nigeria.*
[b,d] *Department of Production Engineering, University of Benin, Edo State, Nigeria*
[c] *Department of Chemical Engineering, University of Benin, Edo State, Nigeria*
[e] *Department of Industrial/Production, Nnamdi Azikiwe University,Awka, Anambra State, Nigeria*

Email: [a]oj.obiafudo@unizik.edu.ng, [b]joseph.achebo@uniben.edu, [c]kessington.obahiagbon@uniben.edu, [d]frank.uwoghiren@uniben.edu, [e]cn.chukwu@unizik.edu.ng

ARTICLE INFO

Keywords:
Plantain fiber, bamboo fiber, HDPE composites, neural networks, multivariate analysis

IEEE style in citing this article:
O. J. Obiafudo, J. Achebo, K. Obahiagbon, F. O. Uwoghiren, and C. N. Chukwue, " Multivariate Analysis and Neural Network-Based Prediction of Compression Molding Behavior in Plantain–Bamboo Fiber Reinforced HDPE Composites," *JoCoSiR: Jurnal Ilmiah Teknologi Sistem Informasi*, vol. 3, no. 1, pp. 30-36, 2025.

ABSTRACT

The compression molding behavior of plantain–bamboo fiber reinforced high-density polyethylene (HDPE) composites was studied through an integrated multivariate analysis and neural network modelling framework. The study utilized materials for fiber extraction and composite production, including water, alkali (NaOH), acetic acid, acetic anhydride, maleic anhydride grafted PE, hydrogen peroxide, hypochlorite, and caustic soda. The composite matrix was high-density polyethylene with density (0.96 g/cm³), reinforced with activated plantain and bamboo fibers. Methods involved mechanical extraction, chemical treatment using alkali solutions, neutralization, bleaching, and stabilization. Fibers were oven-dried, milled, and sieved to (75 µm) before composite formation. Process variables such as fiber fraction (10–50%) and temperature (150–190°C) informed the experimental design. A feed-forward neural network (5-5-5) was used for modelling system performance. The multivariate analysis used predictive neural network models to study combined process-variable effects during compression molding. Interaction plots were generated by varying fiber volume fraction (VF) against other variables. Results showed that high yield stress near (90 MPa) occurred at low VF (10–20%) when bamboo fiber ratio (BFR) was maintained at (40–60%). Pure plantain fiber outperformed pure bamboo at (0) and (1.0 BFR). Optimal molding temperature ranged (166–174°C), producing high yield stress even at VF (10%). At low temperatures (150°C) and VF (30%), yield stress exceeded (80 MPa). Maximum strength required holding times (>17 min) and low clamping force (<1900 N). Neural network predictions aligned closely with experimental data, demonstrating strong predictive reliability. This integrated statistical–computational approach provides valuable insights for optimizing natural fiber composite manufacturing and reducing experimental cost.

1. Introduction

The growing demand for environmentally friendly composite materials has drawn significant attention to natural fiber reinforced thermoplastics. Among the emerging options, hybrid plantain–bamboo fiber reinforced HDPE composites offer a balance of strength, sustainability, and cost effectiveness. Plantain and bamboo fibers are naturally abundant resources whose potential for sustainable material development remains insufficiently explored. In many Nigerian communities, agricultural residues such as plantain fibers are underutilized despite their availability and cellulose-rich structure, reflecting broader patterns where local resources remain untapped amid structural constraints (Kalu & Okonkwo, 2022; Olonade et al, 2024). Similarly, bamboo is a fast-growing and widely distributed which offers promising mechanical properties but receives limited industrial attention, mirroring national challenges in leveraging indigenous assets for development (Ochi & Brigid, 2022; Ahmad et al, 2025).

Deeper scientific exploration of these fibers can enhance value addition, promote eco-friendly composites, and strengthen resource-based livelihoods. However, the combined variability of natural fibers and the sensitivity of compression molding parameters make it difficult to achieve predictable and reproducible mechanical behavior. Issues such as inconsistent fiber morphology, variable chemical composition, and fluctuating fiber–matrix compatibility complicate performance forecasting, thereby constraining broader

ISSN 2502-3357 (Online)
industrial adoption (Ihueze et al, 2023; Radzi et al., 2022). This challenge creates a clear need for analytical tools capable of modeling complex relationships and predicting molding outcomes with high reliability.

Building on this challenge, researchers increasingly turn to multivariate analysis as a powerful means of deciphering multi-factor interactions that govern composite behavior. Multivariate techniques, particularly Principal Component Analysis (PCA), enable reduction of high-dimensional datasets into interpretable components, making it possible to understand how fiber treatment, loading, and processing variables collectively influence properties (Dauran et al, 2024). RSM and multivariate regression further complement PCA by quantifying main and interaction effects across multiple responses simultaneously (Li et al., 2024). Through these approaches, studies on plantain and bamboo fiber systems have successfully grouped interconnected variables such as fiber fraction, crystallinity, and mechanical outputs, revealing patterns that would otherwise remain hidden (Oladele et al, 2023; Ding et al., 2012). These insights form a foundation for advanced predictive modeling.

As multivariate analysis clarifies structure within composite datasets, artificial neural networks (ANNs) extend this analytical capacity by modeling nonlinearities that traditional regression often fails to capture. ANNs are particularly effective where fiber dispersion, interfacial adhesion, and thermal-mechanical transitions produce highly nonlinear responses during compression molding. Prior research shows their effectiveness in predicting fiber orientation, strength, and viscoelastic behavior in reinforced polymer systems (Sabiston, 2020; Sonawane et al., 2022). Recent ANN optimization studies demonstrate improved accuracy in forecasting composite behavior through better tuning of network architectures and training algorithms (Malashin et al., 2024). For plantain–bamboo–HDPE composites, these capabilities provide a pathway to predicting outcomes such as tensile strength, porosity, and density from processing inputs including pressure, temperature, and dwell time (Hopmann & Sasse, 2024).

While ANNs offer strong predictive power, their effectiveness depends heavily on the quality and structure of input data by linking back to the role of multivariate analysis. Integrating PCA with ANN modeling reduces multicollinearity and enhances training efficiency, especially when experimental datasets are limited, as is common in composite research. Similarly, RSM supports ANN development by defining compact yet comprehensive design matrices that ensure broad coverage of relevant processing conditions (Li et al., 2024). Multivariate outlier detection further enhances ANN performance by eliminating noise and anomalous data that degrade prediction accuracy (Dauran, 2024). Evidence from polymer composite studies confirms that such integrated multivariate–ANN workflows improve both generalization and interpretability (Sonawane et al., 2022; Malashin et al., 2024).

Extending these methodological insights to hybrid plantain–bamboo–HDPE composites highlights both progress and significant research gaps. Plantain fibers, after alkali or chemical treatment, have shown improved stiffness and interfacial bonding, whereas bamboo fibers contribute superior tensile strength and dimensional stability (Oladele, 2023; Radzi et al., 2022). Studies on bamboo–thermoplastic systems indicate that molding temperature, pressure, and hold time critically influence fiber alignment, porosity, and crystallization (Li et al., 2024). Yet, explicit integration of multivariate modeling with ANN-based prediction for hybrid plantain–bamboo–HDPE composites remains scarce, limiting the development of reliable process–property maps needed for industrial scale-up. Thus, literature supports the feasibility of such approaches while underscoring the need for more targeted investigations.

The progression of research clearly shows that combining multivariate analysis and neural network modeling offers a promising framework for improving the predictability and quality of compression-molded natural fiber composites. The present study is justified by the need for reliable prediction tools to manage the complexity inherent in hybrid natural-fiber composites. Existing research acknowledges the variability of plantain and bamboo fibers during processing, yet few studies model their combined behavior in HDPE matrices (Oladele, 2023; Radzi et al., 2022). Although multivariate methods help reveal factor interactions, their application to hybrid fibers remains limited (Dauran, 2024). Similarly, neural networks have shown strong predictive ability in other polymer systems but are rarely applied to plantain–bamboo composites (Sonawane et al., 2022). This gap necessitates an integrated multivariate–ANN approach to optimize compression molding.

2. Methodology

2.1 Materials

The materials applied in this research include materials for extraction/chemical treatment of the biofibers and materials for production of the natural fiber reinforced composite. The materials applied for extraction/chemical treatment of the plantain and bamboo fibers are water, alkali (NaOH) and acetic acid (neutralizer), acetic anhydride(stabilizer), maleic anhydride grafted PE (compatibilizers), hydrogen peroxide, hypochlorite and caustic soda (bleaching agents). Materials applied for production of the composites are: high-density polyethylene (HDPE) resin of density 0.96g/cm, activated plantain fiber, activated bamboo fiber.

2.2 Methods

The extraction and preparation of biofibers for composite formation involve a series of carefully designed mechanical, thermal, and chemical processes intended to enhance fiber quality while maximizing efficiency.

DOI: https://doi.org/10.65126/jocosir.v3i1

ISSN 2502-3357 (Online)
Earlier studies on plantain fiber extraction, such as Ihueze et al (2023), noted that biological retting was traditionally used but was highly inefficient because it required extensive time, energy, and chemical inputs, thereby increasing operational costs. In contrast, the present research adopts a decorticating machine for plantain pseudo-stem fiber extraction, a method that significantly reduces processing time and increases efficiency. The decorticator used in this study is capable of processing approximately two tons/day of dry fiber, completing extraction in a much shorter timeframe than biological retting.

Following extraction, the fibers undergo degumming to remove the substantial amount of gum and non-fibrous parenchyma cells present in plantain fibers, estimated at 30–35% of total mass. These gums, composed mainly of arabans and xylans, are insoluble in water but dissolve effectively in alkaline solutions. The degumming procedure therefore involves several key stages: boiling the fibers in alkaline solution (sometimes under pressure or with reducing agents), washing to neutral pH, bleaching using dilute hydrogen peroxide or hypochlorite, and finally rinsing to remove residual chemicals. While biological retting relies on microbial decomposition for degumming, the mechanical-chemical sequence used in this study yields cleaner fibers more suitable for spinning and composite production.

A similar multi-stage approach was adopted for bamboo fiber extraction, guided by the procedure outlined by Nayak and Mishra (2016). Bamboo culms were first mechanically split using a decorticator and the woody sections rasped off before washing. The crushed strands were then enzymatically treated to separate fibrous components from the lignified culm residues. Subsequent combing isolated individual fibers, which were later spun into yarn-ready formats. This process highlights the distinct structural rigidity of bamboo, a material known for tighter cellulose–lignin bonding compared to many natural fibers. To ensure that both fiber types possessed minimal moisture, oven drying was introduced following ambient sun/air drying, which seldom achieves complete dryness. Drying experiments were carried out across a temperature range of 60–100°C, enabling identification of the temperature that optimizes tensile strength. Fibers dried at this optimal temperature were then used for further processing.

Chemical treatments played a significant role in improving the mechanical and hydrophobic properties of the biofibers. Plantain fibers underwent mercerization in 2% NaOH for about 3 hours, a procedure that removes residual moisture and increases tensile strength. This was followed by neutralization using 1% acetic acid, washing to a pH of 7, and oven-drying at 80°C. Further strengthening and dimensional stabilization were achieved through acetylation using 10% acetic anhydride for about 1 hour, a treatment that protects the cell walls from environmental degradation. Finally, 1.5% MAPE (maleic anhydride grafted polyethylene) was applied as a compatibilizer to improve adhesion between the hydrophilic fibers and the hydrophobic polymer matrix. Tensile and water absorption tests across treatment stages confirmed improvements in fiber strength and surface characteristics.

Bamboo fibers also underwent mercerization. Owing to their dense cellular architecture, effective chemical penetration required mechanical beetling before alkaline treatment. Experiments were conducted using NaOH concentrations in the range of 5–20% to determine optimal conditions for lignin and hemicellulose removal. Tensile strength and water absorption tests were then used to identify the ideal soaking time and alkaline concentration for producing strong, moisture-resistant bamboo fibers.

The plantain pseudo-stems used in the study were sourced from OJ Farms Limited in Anambra State, where residues from harvested plantain trees were transported directly to the decorticator. For composite development, a comprehensive Design of Experiment (DOE) approach was used to ensure systematic evaluation of processing variables. While orthogonal designs such as the Taguchi method were considered, they were deemed unsuitable due to expected variability in the study parameters. Instead, Central Composite Design (CCD) was chosen for its effectiveness in capturing detailed system behavior using a manageable number of experimental runs. The key variables included fiber volume fraction (10–50%), bamboo fiber ratio (0–1.00), mold temperature (150–190°C), clamping force (1500–3500 N), and holding time (5–25 min).

Before molding, treated fibers were milled and sieved to a particle size of 75 μm, identified during preliminary studies as ideal for mechanical performance. Composite samples were produced using collapsible steel molds consistent with ASTM D638-10 standards for tensile testing. The Universal Testing Machine was used to determine yield strength, while production cost was calculated for each experimental iteration, ensuring a comprehensive assessment of performance and economic feasibility throughout the composite manufacturing process.

2.3 Artificial neural network model

The class of neural network model examined in this study is called the feed-forward network (FFN). It allows data to flow from an input layer to the output layer through a hidden layer as illustrated in Figure 1. The connections between the input, hidden and output layers consist of weights (w) and biases (b) that are considered parameters of the model. The neurons in the input layer simply introduce scaled input data via w to the hidden layer. The neurons in the hidden layer sum up the weighted inputs to neurons, including the biases, as shown in equation (1).

ISSN 2502-3357 (Online)

$$sum = \sum_{j=1}^{k} x_j w_j + \mathrm{b} \quad (1)$$

The weighted output is then passed through an appropriate transfer function. A useful transfer function for the FFN is the hyperbolic tangent sigmoidal transfer function (tansig) described by equation (2). The output of the hidden layer becomes an input to the output layer. The neurons in the output layer produce the output by the same method as that of the neurons in the hidden layer. An error function is specified. A standard error function for training the FFN is the mean square error (MSE) described in equation (3). The training ensures that the prescribed error function is minimized by adjusting either 'w' or both 'w' and 'b' appropriately.

$$\mathrm{tansig(n)} = \left[2/1 + e^{(-2n)}\right] - 1 \quad (2)$$

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum_{i=1}^{n} (y_t - y_N)^2 \quad (3)$$

where, y_t is the target output, y_N is the predicted output, and N is the number of system iterations. The schematic of the 5-5-5 feedforward neural network architecture applied in the study is shown in Figure 3.1.

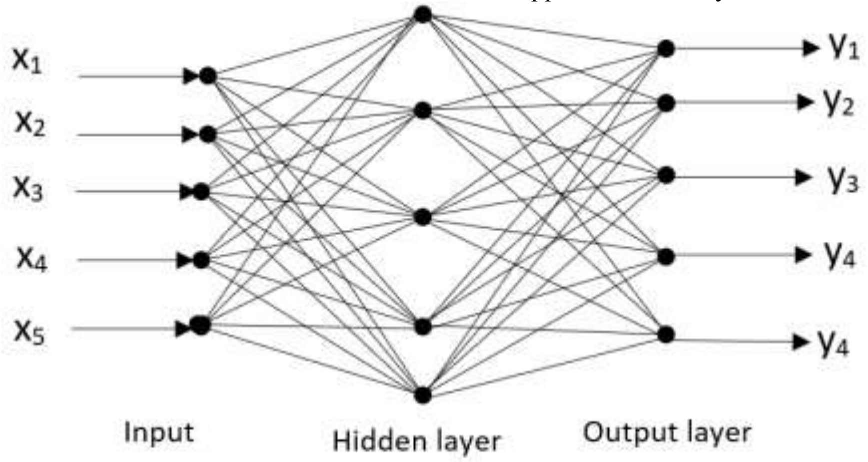

Figure 1. Schematic of a 5-5-5 feed-forward neural network architecture

3. Results

In the multivariate analysis of the compression molding process, the combined effects of the process variables were studied using the predictive neural network models developed from the statistical analysis. Since the effects of the process variables are in reality multi-dimensional, study on the interaction effects of the process variable was conceived to provide more realistic insights into the actual process variability. The results are presented preferably as 2D multiple line plots. At every step, interaction between the volume fraction (VF) of the fiber and one other variable was monitored selectively. To produce the 2D plots, the VF of fiber was varied according to the experimental design on the horizontal axis while the effects of the process adjustment on the performance functions were calibrated on the vertical axis. To account for the coupled effects of any selected variables, the resulting 2D line diagrams were reproduced at different design conditions, resulting in multiple lines on the 2D plane.

The results presented in Figure 2 show the combined effects of the volume fraction (VF) of the fiber and the bamboo fiber ratio (BFR). These results show clearly that although highly reinforced composite material of yield stress close to 90MPa could be obtained with volume fraction of fiber fixed in the range of $10 - 20\%$ as found in the individual process analysis, the choice of a fiber blend in the range of 40 – 60% bamboo actually helps to stabilize this desirable result. The trends seen at 0 BFR and 1.0 BFR as presented in Figure 2(a) and Figure 2(b) suggest that pure plantain fiber is a better reinforcement material for the HDPE compared to pure bamboo fiber at the experimental conditions. However, with the fiber blends in the range of 40 – 60% BFR, products of significantly high/stable yield stress, reduced yield strain and improved elastic modulus are obtainable at low VF.

DOI: https://doi.org/10.65126/jocosir.v3i1

ISSN 2502-3357 (Online)

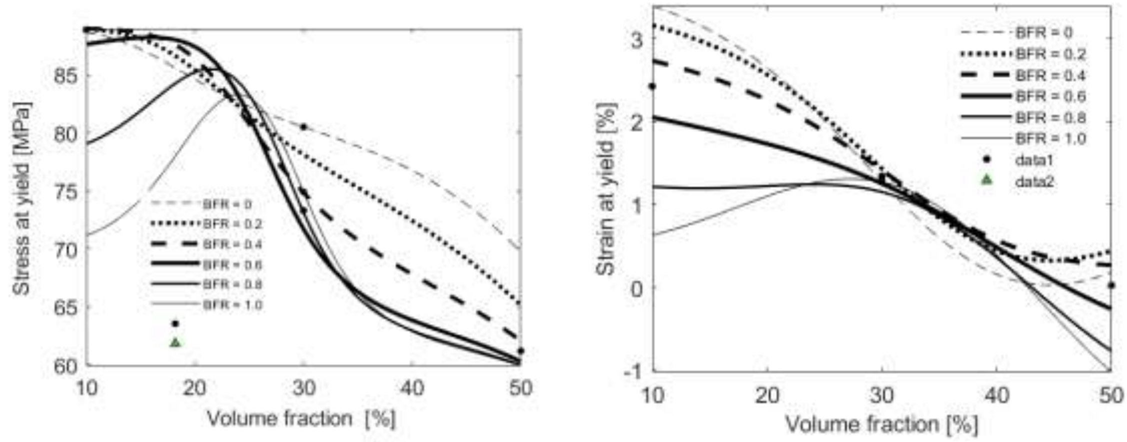

Figure 2: Combined effects of volume fraction of fiber and bamboo fiber ratio on (a) yield stress and (b) yield strain of the composite material

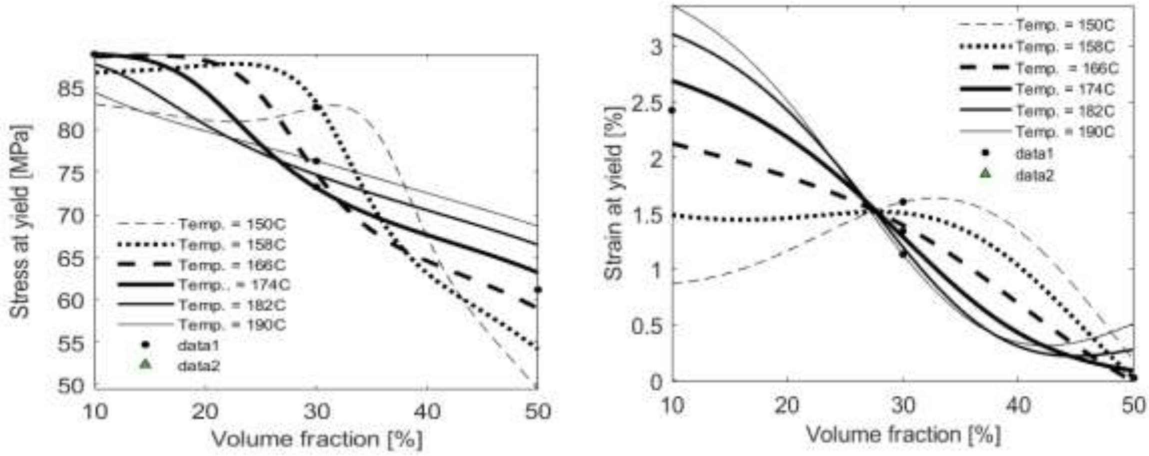

Figure 3: Combined effects of volume fraction of fiber and molding temperature on (a) yield stress and (b) yield strain of the composite material

The best result in terms of what is required to achieve a reinforced material at various molding temperature is witnessed while the molding temperature was adjusted to $166 \leq T \leq 174^0C$. This temperature range was predicted to guarantee maximum yield stress of the material at low VF value of 10% with minimal tradeoff on the yield strain as shown in Figure 3(a) and Figure 3(b). A close look at these results reveals that at higher VF value up to 30% and relatively low mold temperature of 150ºC, a material of significantly high stress at yield > 80MPa and improved elasticity can be obtained. The combined effect of clamping force and volume fraction on the system response is presented in Figure 4. The result indicates that VF value leading to maximum stress at yield was moved away from the axial position when low clamping forces below 1900N was applied.

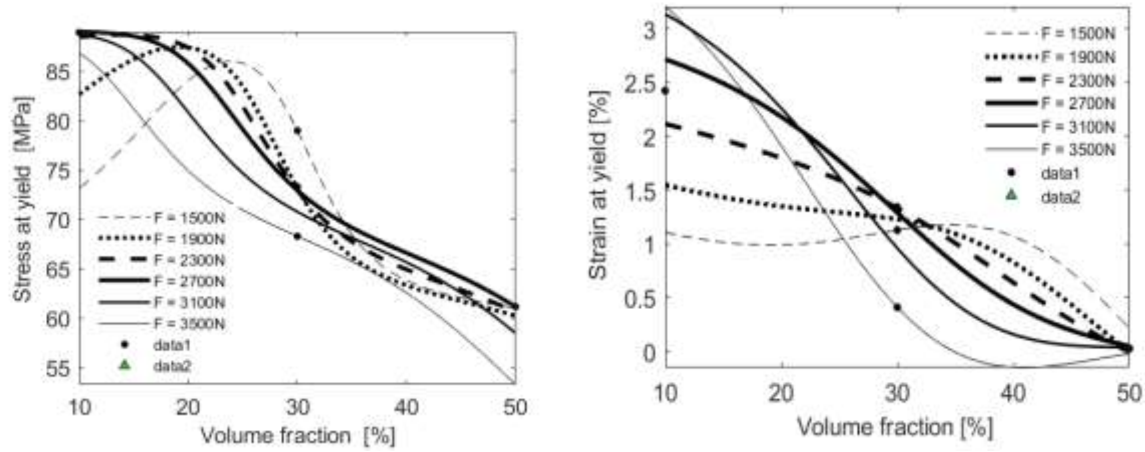

Figure 4: Combined effects of volume fraction of fiber and clamping force on (a) yield stress and (b) yield strain of the composite material

ISSN 2502-3357 (Online)

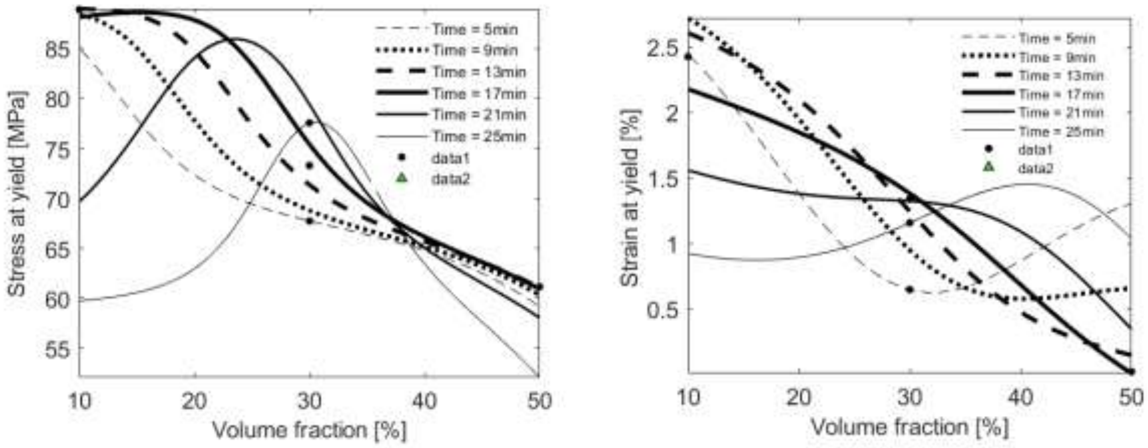

Figure 5: Combined effects of volume fraction of fiber and holding time on (a) yield stress and (b) yield strain of the composite material

Considering the results presented in Figure 5(a), which show that improved material stress at yield is obtainable within 9 – 17 minutes of holding time, there are also indications that the maximum stress at yield could be obtained at higher VF value with higher holding time > 17 minutes. Thus, it could be inferred from the predicted trends that to obtain a highly competitive product showing maximum yield stress at increased fiber concentration in the range of 20 – 30% (say), low clamping force < 1900N combined with high holding time > 17 minutes and mean BFR should be used.

4. Discussion

The multivariate analysis of the compression-molding process using predictive neural-network (ANN) models provided a clearer understanding of the interaction effects among process variables, revealing complex non-linear behaviors typically missed by traditional single-factor approaches. In a related study, Yang et al, (2021) emphasized that ANN-based modelling provides superior sensitivity for detecting multi-dimensional interactions in natural-fiber composites compared to regression-only techniques. This finding agreed with the present results, particularly the 2D interaction plots showing how volume fraction (VF) interacts with bamboo fiber ratio (BFR) to stabilize yield stress. While individual-factor analysis suggested that 10–20% VF was optimal, the combined BFR–VF plots revealed that 40–60% BFR further improved stability of mechanical performance. In contrast, Kumar et al (2022) reported that single-species fiber reinforcement often produces more predictable patterns than blended fibers; however, the present study showed the opposite, as pure plantain fiber outperformed pure bamboo at extreme BFR values, but blended fibers delivered superior balanced properties.

The observed sensitivity of yield stress and strain to molding temperature (Figure 3) also aligns with findings by Yi et al. (2025), who argued that thermal–fiber coupling significantly affects polymer–fiber bonding efficiency. The predicted optimum temperature range of 166–174 °C for achieving maximum yield stress at low VF reinforces this argument, while contrasting with studies where higher temperatures continually improved properties until thermal degradation occurred. Furthermore, the identification of a second performance window of 30% VF at 150 °C which illustrates the ANN model's ability to capture alternative operating regimes within the same process space. The interaction between VF and clamping force (Figure 4) showed that lower clamping forces (<1900 N) shift the optimal VF away from the midpoint, suggesting distortion in melt–fiber orientation equilibrium. This finding agreed with Maheswaran and Kannan (20255), who reported that weak compaction forces in bio-fiber composites encourage heterogeneous stress distribution but may still yield high-strength materials under controlled VF.

The combined effect of VF and holding time (Figure 5) demonstrated that extended holding times (>17 min) progressively improved yield stress at higher VF values. In contrast, Sullins et al (2017) observed diminishing returns at prolonged hold times in hemp–PP composites, highlighting that fiber species and matrix type strongly mediate holding-time effects.

5. Conclusion

This study demonstrated that the integration of multivariate statistical analysis and neural network modelling provides a robust framework for understanding and predicting the complex compression molding behavior of plantain–bamboo fiber reinforced HDPE composites. Examining the combined effects of key variables including fiber volume fraction, bamboo fiber ratio, molding temperature, clamping force, and holding time helped the research to reveal nonlinear interaction patterns that cannot be captured through univariate methods. The results showed that optimal composite performance, particularly high yield stress and improved elastic response, occurs within specific processing windows such as low VF (10–20%), moderate BFR (40–60%), and molding

DOI: https://doi.org/10.65126/jocosir.v3i1

ISSN 2502-3357 (Online)

temperatures between 166–174°C. Neural network models further enhanced predictive accuracy, offering reliable estimations of mechanical responses under varying conditions. The synergy between statistical insights and machine-learning predictions confirmed that plantain fiber, especially when blended strategically with bamboo fiber, significantly enhances composite strength.

6. References

Ahmad, Z., Kumari, R., Mir, B., Saeed, T., Firdaus, F., Vijayakanth, V., Keerthana, K., Ramakrishnan, M. and Wei, Q., 2025. Bamboo for the Future: From Traditional Use to Industry 5.0 Applications. *Plants*, *14*(19), p.3019.

Dauran, N. S., Bashiru, A., Musa, Y., & Raji, A. A. (2024). Enhancing multi response surface methodology through integrating principal component analysis (PCA) for complex parameter design optimization. *Revista O Universo Observável-v*, *1*(8), 1.

Ding, X., Hou, X., Xia, M., Ismail, Y., & Ye, J. (2022). Predictions of macroscopic mechanical properties and microscopic cracks of unidirectional fibre-reinforced polymer composites using deep neural network (DNN). *Composite Structures*, *302*, 116248.

Hopmann, C., & Sasse, J. (2024, May). Development of a decision support system for profile extrusion. In *AIP Conference Proceedings* (Vol. 3012, No. 1, p. 020015). AIP Publishing LLC.

Ihueze, C. C., Okafor, C. E., Onwurah, U. O., Obuka, S. N., & Kingsley-omoyibo, Q. A. (2023). Modelling creep responses of plantain fibre reinforced HDPE (PFRHDPE) for elevated temperature applications. *Advanced Industrial and Engineering Polymer Research*, *6*(1), 49-61.

Kalu, P., & Okonkwo, A. E. (2022). Niger Delta coastal region of Nigeria: Resource control and underdevelopment. Journal of the Management Sciences (JOMAS), 58, 1.

Kumar, S., Manna, A., & Dang, R. (2022). A review on applications of natural Fiber-Reinforced composites (NFRCs). *Materials Today: Proceedings*, *50*, 1632-1636.

Li, W., Feng, T., Lu, T., Zhao, F., Zhao, J., Guo, W., & Hua, L. (2024). Optimization of Compression Molding Parameters and Lifecycle Carbon Impact Assessment of Bamboo Fiber-Reinforced Polypropylene Composites. *Polymers*, *16*(23), 3435.

Maheswaran, C., & Kannan, G. (2025). Effect of elevated temperature on the micro-structure and pore size distribution of sustainable bio-fiber-reinforced ultra-high toughness cementitious composites. *Journal of Sustainable Cement-Based Materials*, 1-21.

Malashin, I., Tynchenko, V., Gantimurov, A., Nelyub, V., & Borodulin, A. (2024). A multi-objective optimization of neural networks for predicting the physical properties of textile polymer composite materials. *Polymers*, *16*(12), 1752.

Nayak, S. K., & Mishra, P. C. (2016). Emission characteristics of diesel fuel composed of linseed oil (Linum Usitatissium) blends utilizing rice husk producer gas. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *38*(14), 2001-2008.

Ochi, A. E. O., & Brigid, I. J. (2022). Crisis of banditry and internally displaced persons in Nigeria: A political economy approach. Scholars Journal of Economics, Business and Management, 9(11), 247–256.

Oladele, I. O., Adelani, O., Oke, S. R., Adewumi, O. A., & Akinbowale, M. K. (2023). Sustainable naturally derived plantain fibers/epoxy based composites for structural applications. *Journal of Natural Fibers*, *20*(1), 2134264.

Olonade, O. Y., George, T. O., Rhodes-Ebetaleye, J., & Imhonopi, D. (2024). Awareness and Utilisation of Natural and Mineral Resources in Selected Communities of Southwest Rural Communities of Nigeria. *SAGE Open*, *14*(3), 21582440241266109.

Radzi, A. M., Zaki, S. A., Hassan, M. Z., Ilyas, R. A., Jamaludin, K. R., Daud, M. Y. M., & Aziz, S. A. A. (2022). Bamboo-fiber-reinforced thermoset and thermoplastic polymer composites: A review of properties, fabrication, and potential applications. *Polymers*, *14*(7), 1387.

Sabiston, T., Inal, K., & Lee-Sullivan, P. (2020). Application of Artificial Neural Networks to predict fibre orientation in long fibre compression moulded composite materials. *Composites Science and Technology*, *190*, 108034.

Sonawane, S. S., Charde, S. J., Malika, M., & Thakur, P. (2022). Artificial neural network model for prediction of viscoelastic behaviour of polycarbonate composites. *Journal of applied research and technology*, *20*(2), 188-202.

Sullins, T., Pillay, S., Komus, A., & Ning, H. (2017). Hemp fiber reinforced polypropylene composites: The effects of material treatments. *Composites Part B: Engineering*, *114*, 15-22.

Yang, B., Fu, K., Lee, J., & Li, Y. (2021). Artificial neural network (ANN)-based residual strength prediction of carbon fibre reinforced composites (CFRCs) after impact. *Applied Composite Materials*, *28*(3), 809-833.

Yi, M., Liu, O., Wen, J., Qiu, Y., Wu, P., Zhu, W., & Wang, L. (2025). Enhanced bonding intensity between the vertically aligned carbon fiber thermal interface material and heat spreader of a flip-chip package through a silane coupling agent. *Physical Chemistry Chemical Physics*, *27*(15), 7629-7639.

DOI: https://doi.org/10.65126/jocosir.v3i1