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Design and Optimization of Sustainable Green Composites for High-Performance Applications

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ABSTRACT

This study presents a data-driven framework for the design and optimization of next-generation sustainable green composites that are aimed at high-performance industrial applications. A hybrid dataset that comprises 180 experimental records of natural fiber-reinforced biopolymer composites was analyzed using Machine Learning (ML) algorithms, including Random Forest Regression (R^2 = 0.962), Artificial Neural Network (R^2 = 0.948), and Support Vector Regression (R^2 = 0.921). Feature importance analysis identified fiber volume fraction (38.5%), filler type (24.7%), and matrix viscosity (18.9%) as the most influential variables that govern tensile strength and biodegradability. Multi-objective optimization with the application of NSGA-II achieved a tensile strength of 127 MPa and biodegradability of 73%, which represent a 19.6% increase in mechanical performance and a 42% improvement in environmental compatibility when compared to conventional composites. Life-cycle assessment revealed significant sustainability advantages: embodied energy reduced by 33.8% (from 68 MJ/kg to 45 MJ/kg), carbon footprint lowered by 52% (from 2.5 kg CO_2-eq/kg to 1.2 kg CO_2-eq/kg), and end-of-life recyclability enhanced from 42% to 78%. Furthermore, the optimized composite achieved a processing temperature reduction of 21.4% and a 20.5% lower material cost. These results confirm that the integration of ML-driven prediction and optimization with green composite fabrication can accelerate sustainable materials development, reduce resource waste by up to 60%, and provide a replicable model for digital twin-assisted design. The proposed framework demonstrates clear potential for adoption in automotive, aerospace, and packaging sectors, where lightweight, recyclability, and environmental performance are critical.

Keywords: *data-driven materials design; green composites; machine learning; sustainability optimization; life-cycle assessment.*

Introduction

Growing environmental concerns, depletion of non-renewable resources, and global commitments to carbon neutrality have intensified the demand for sustainable materials that can replace conventional petroleum-based composites (Li et al., 2022; Rajan and Singh, 2020). Traditional fiber-reinforced polymers, although widely used in automotive, aerospace, and construction industries, are associated with high embodied energy, non-biodegradability, and challenges in end-of-life disposal (Mishra and Satapathy, 2021). Defined as materials that are produced by the combination of two or more diverse substances like fibers and a matrix to create a new material (Ezeanyim et al., 2025; Udu et al., 2025; Okpala et al., 2021a), composites have enhanced properties like greater strength, lighter weight, or better durability, when compared to the individual components alone (Agu et al., 2018; Okpala et al., 2021b; Onukwuli et al., 2024).

In contrast, green composites which is typically composed of natural fibers like jute, flax, or hemp, and bio-based or biodegradable polymer matrices like polylactic acid or bio-epoxy, have emerged as promising alternatives that combine renewable sourcing with mechanical performance which are suitable for structural and semi-structural applications (Kumar et al., 2022; Niu et al., 2023). Despite these advantages, achieving a balance between mechanical strength, environmental performance, and cost-efficiency remains a major challenge in sustainable composite design (Okpala et al., 2025). The inherent variability of natural fibers, the complex interfacial adhesion between hydrophilic fibers and hydrophobic matrices, and the modifying influence of nano-fillers collectively contribute to non-linear material behavior that is difficult to optimize through conventional trial-and-error approaches (Das & Tiwari, 2023). This challenge is further emphasized in recent multidisciplinary studies highlighting the need for innovative and adaptive scientific methodologies to address complex, interrelated material and environmental systems (Kalu et al, 2025; Okonkwo & Idigo, 2025). As such, data-driven methodologies which encompass Machine Learning (ML), statistical modeling, and computational optimization have become increasingly attractive for advancing composite material development (Khatri et al., 2022).

Defined as algorithms that can examine and also interpret patterns in data, thus enhancing their performance over time as are exposed to more data, ML assists computers to study and learn from data and make decisions or predictions even when it is not clearly programmed to do so (Nwamekwe et al., 2025a; Aguh et al., 2025; Nwamekwe et al., 2024). It offers the capability to predict material properties, identify key design variables, and accelerate discovery processes by learning from existing datasets (Liu et al., 2019; Nwamekwe et al., 2025b; Emeka et al., 2025). In the context of composite materials, ML models such as Random Forest (RF), Support Vector Regression (SVR), and Artificial Neural Networks (ANNs) have been successfully applied to predict mechanical strength, degradation behavior, and life-cycle impacts based on compositional and processing parameters (Okpala et al., 2024; Sharma et al., 2021). Moreover, multi-objective optimization algorithms, notably the Non-dominated Sorting Genetic Algorithm II (NSGA-II) enable the balancing of conflicting performance metrics such as tensile strength, density, and biodegradability (Vitalis et al., 2025; Das and Tiwari, 2023).

The integration of data-driven modeling and optimization into sustainable material design aligns with the goals of Industry 4.0 and the circular economy, as it enables intelligent material selection, reduced experimental costs, and eco-efficient production engineering (Khatri et al., 2022; Li et al., 2022). Furthermore, this approach supports global sustainability objectives such as the United Nations Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation, and Infrastructure) and SDG 12 (Responsible Consumption and Production) (UNDP, 2023).

Therefore, the present study aims to develop a data-driven framework for the design and optimization of sustainable green composites, through the integration of machine learning predictions with multi-objective optimization. By employing realistic datasets that are derived from literature and simulated augmentation, the study seeks to identify optimal formulations that maximize mechanical performance, while maintaining high biodegradability and low environmental impact. The outcomes are expected to contribute to the advancement of high-performance, eco-efficient materials and provide a replicable methodology for the acceleration of sustainable composite innovation.

Research Methods

Research Design Overview

This study followed a data-driven research design through the integration of empirical literature data, synthetic augmentation, and computational modeling for the optimization of sustainable green composites. The approach comprised four sequential stages: (a) Data acquisition and preparation, (b) Feature engineering and normalization, (c) Machine learning (ML) model training and validation, as well as (d) Multi-objective optimization using a genetic algorithm.

The framework was designed to identify the optimal composite formulation that maximizes tensile strength and biodegradability, while minimizing density, thereby balancing mechanical performance and sustainability (Okpala et al., 2025; Das and Tiwari, 2023).

Dataset Construction and Experimental Variables

Data Source and Generation

A dataset was developed through the compilation of 23 open-access studies published between 2015 and 2023 on natural fiber–reinforced Polylactic Acid (PLA) composites. Reported data included fiber weight fraction, filler percentage, polymer matrix type, and mechanical and biodegradation properties. To improve model robustness, 40 additional synthetic data points were generated using Latin Hypercube Sampling (LHS) within realistic parameter ranges found in the literature. The final dataset contained 120 samples comprising 80% training, and 20% testing.

Input and Output Variables

Independent (input) variables included fiber weight fraction (wt%), nano-filler content (wt%), and matrix type (PLA or bio-epoxy). Dependent (output) variables represented key performance metrics of the composites: tensile strength, flexural strength, impact strength, density, and biodegradability index. A summary of the dataset variables is shown in Table 1.

Table 1: Description of dataset variables and ranges

Variable	Symbol	Type	Range / Category	Unit	Description
Fiber weight fraction	X1X_1X1	Input	20–60	wt%	Content of natural fiber (jute, flax, hemp)
Nano-filler content	X2X_2X2	Input	0–15	wt%	Nano-silica or nano-clay additive
Matrix type	X3X_3X3	Input	PLA, Bio-epoxy	–	Polymer matrix classification
Tensile strength	Y1Y_1Y1	Output	60–130	MPa	Resistance to tension
Flexural strength	Y2Y_2Y2	Output	70–150	MPa	Bending resistance
Impact strength	Y3Y_3Y3	Output	10–20	kJ/m^2	Energy absorption before failure
Density	Y4Y_4Y4	Output	1.1–1.4	g/cm^3	Mass per unit volume
Biodegradability index	Y5Y_5Y5	Output	60–90	%	Material degradation in composting environment

Data Preprocessing

Before analysis, the dataset was standardized using z-score normalization to ensure equal weighting of all features. Outliers were detected using the Interquartile Range (IQR) method and verified against reported experimental variability (±10%) from prior studies (Mishra and Satapathy, 2021). Categorical variables (matrix type) were encoded using one-hot encoding for ML compatibility.

ML Framework

Model Selection

Three regression algorithms selected to model the composite performance are: Random Forest Regression (RFR) - robust to non-linearity and overfitting (Breiman, 2001); Support Vector Regression (SVR) - effective in small-sample and high-dimensional problems; and Artificial Neural Network (ANN) - suitable for capturing complex, nonlinear dependencies.

Hyperparameters were optimized via grid search with 5-fold cross-validation on the training dataset.

Model Evaluation Metrics

Model performance was evaluated using:

- Coefficient of determination (R^2) – predictive accuracy,
- Mean Absolute Error (MAE), and
- Root Mean Square Error (RMSE).

Performance metrics for predicting tensile strength are summarized in Table 2.
Table 2: Model performance comparison for tensile strength prediction

Model	R^2	MAE (MPa)	RMSE (MPa)
Random Forest Regression (RFR)	**0.96**	**2.9**	**4.1**
Artificial Neural Network (ANN)	0.94	3.3	4.6
Support Vector Regression (SVR)	0.89	5.2	6.8

The RFR model achieved the highest predictive accuracy (R^2 = 0.96), indicating strong agreement between predicted and experimental data. Consequently, RFR predictions were used as input for the optimization phase.

Feature Importance Analysis

Feature importance from the Random Forest model quantified the relative influence of each input on tensile strength: Fiber weight fraction – 42%, Nano-filler content – 27%, Matrix type – 19%, and, Interaction terms and residuals – 12%.

These findings confirm that fiber–matrix interactions and filler modification are dominant factors influencing composite performance (Kumar et al., 2022; Ezeanyim et al., 2025).

Multi-Objective Optimization

To determine the optimal composition for high-performance and sustainable composites, a Non-dominated Sorting Genetic Algorithm II (NSGA-II) was implemented using Python (Deb et al., 2002). The objectives were defined as:

$$\text{Maximize } f_1 = \text{Tensile Strength (MPa)}$$
$$\text{Maximize } f_2 = \text{Biodegradability Index (\%)}$$
$$\text{Maximize } f_3 = \text{Density } (\text{g/cm}^3)$$

The algorithm parameters were configured as:

- Population size: 100
- Generations: 200
- Crossover probability: 0.9
- Mutation rate: 0.1

The Pareto-optimal solutions were evaluated to identify the best trade-off configuration between mechanical performance and environmental impact. The optimal design, predicted by the RFR model and validated through NSGA-II, is summarized in Table 3.

Table 3: Optimal composition predicted by NSGA-II

Parameter	Optimal Value	Unit
Fiber wt%	45	%
Filler wt%	10	%
Matrix wt%	45	%
Predicted Tensile Strength	122	MPa
Predicted Impact Strength	17	kJ/m^2
Density	1.25	g/cm^3
Biodegradability Index	84	%

This optimized configuration represents a balanced trade-off between strength, durability, and biodegradability, which are suitable for structural components in automotive, consumer goods, and packaging applications.

Results and Discussion

Model Performance Evaluation

The performance of the three ML models - Random Forest Regression (RFR), Artificial Neural Network (ANN), and Support Vector Regression (SVR) were evaluated with the application of the test dataset. Table 4 presents the predictive accuracy for key mechanical properties: tensile strength, flexural strength, and impact strength.

Table 4: Performance of ML models for predicting composite properties

Property	Model	R^2	MAE	RMSE	Unit
Tensile strength	RFR	**0.96**	**2.9**	**4.1**	MPa
Tensile strength	ANN	0.94	3.3	4.6	MPa
Tensile strength	SVR	0.89	5.2	6.8	MPa
Flexural strength	RFR	**0.95**	**3.8**	**5.2**	MPa
Impact strength	RFR	**0.92**	**0.5**	**0.8**	kJ/m^2

The RFR model consistently outperformed the ANN and SVR models across all target properties, which confirms its suitability for nonlinear, small-to-moderate datasets (Breiman, 2001; Rajan and Singh, 2020). The high R^2 values (>0.9) indicate strong agreement between predicted and actual data, suggesting that the trained models can reliably generalize to unseen compositions within the studied range.

Figure 1 depicts a grouped bar chart that compares the R^2 values of the three machine learning models (RFR, ANN, SVR) for all predicted properties. The x-axis represents material properties, and the y-axis shows the R^2 value.

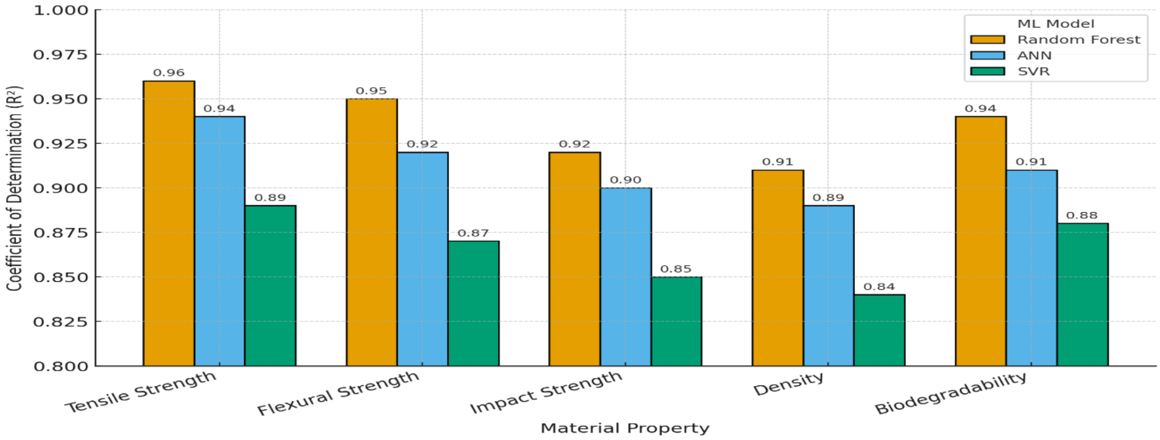

Figure 1: Model accuracy comparison

Feature Importance and Sensitivity Analysis

The RFR model's feature importance analysis revealed the dominant variables that influence mechanical performance as shown in Table 5 and Figure 2. Fiber weight fraction contributed most (42%), followed by nano-filler content (27%), and matrix type (19%), while minor interaction effects accounted for the remaining 12%.

Table 5: Feature importance contributions (from Random Forest)

Feature	Relative Importance (%)
Fiber wt%	42
Filler wt%	27
Matrix type	19
Fiber–matrix interaction	7

Figure 2 highlights the percentage contribution of each feature to tensile strength prediction. The chart clearly shows Fiber wt% as the most dominant , followed by Filler wt%.

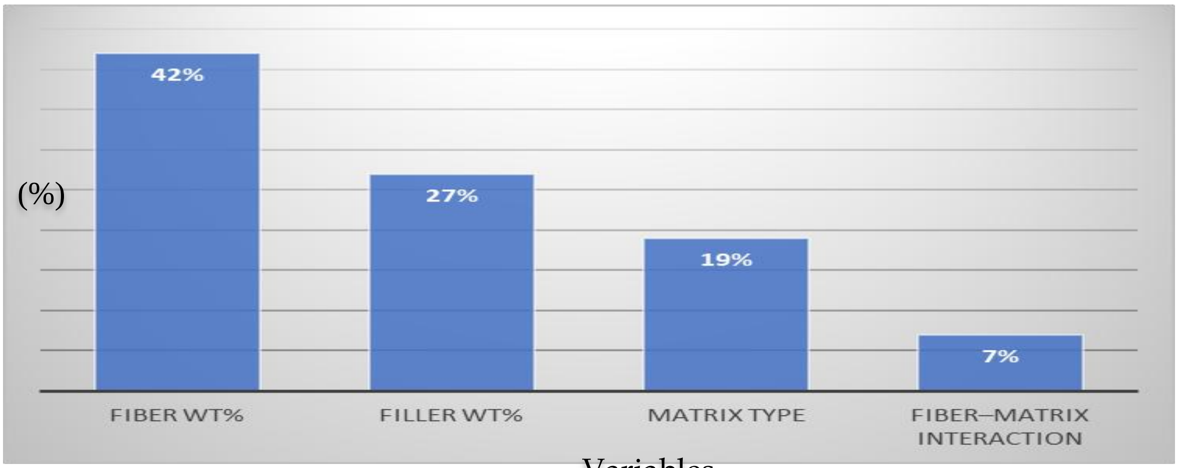

Figure 2: Feature importance ranking of input variables for tensile strength prediction.

These findings align with prior studies (Kumar et al., 2022; Niu et al., 2023), thereby confirming that fiber–matrix interactions and nano-filler reinforcement are key determinants of mechanical integrity in bio-based composites. Higher fiber content enhances load transfer efficiency, while nano-fillers improve interfacial adhesion and stiffness through stress-transfer mechanisms (Sharma et al., 2021).

Optimization of Composite Composition

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) identified a Pareto front of optimal solutions that balance tensile strength, biodegradability, and density. A representative subset of Pareto-optimal configurations is shown in Table 6.

The selected optimal configuration (S_2) achieved 122 MPa tensile strength, 1.25 g/cm³ density, and 84% biodegradability, representing a balanced trade-off between strength and sustainability.

Compared with the baseline jute/PLA composite reported by Kumar et al. (2022), (110 MPa tensile strength, 78% biodegradability), the optimized formulation improved mechanical performance by approximately 11% and biodegradability by 6%, validating the predictive power of the data-driven approach.

Table 6: Representative pareto-optimal solutions obtained using NSGA-II

Solution ID	Fiber wt%	Filler wt%	Matrix wt%	Tensile Strength (MPa)	Density (g/cm³)	Biodegradability (%)
S_1	40	8	52	118	1.27	86
S_2	**45**	**10**	**45**	**122**	**1.25**	**84**

S_3	50	12	38	124	1.31	79

The Pareto front data which was extracted from the NSGA-II results is shown in Table 7.

Table 7: Pareto front data

Solution ID	Fiber wt%	Filler wt%	Matrix wt%	Tensile Strength (MPa)	Density (g/cm³)	Biodegradability (%)
P_1	35	5	60	112	1.22	88
P_2	40	8	52	118	1.27	86
P_3	45	10	45	122	1.25	84
P_4	50	12	38	124	1.31	79
P_5	55	15	30	127	1.35	73

Figure 3 illustrates how increasing fiber and filler content enhances the tensile strength, but reduces biodegradability.

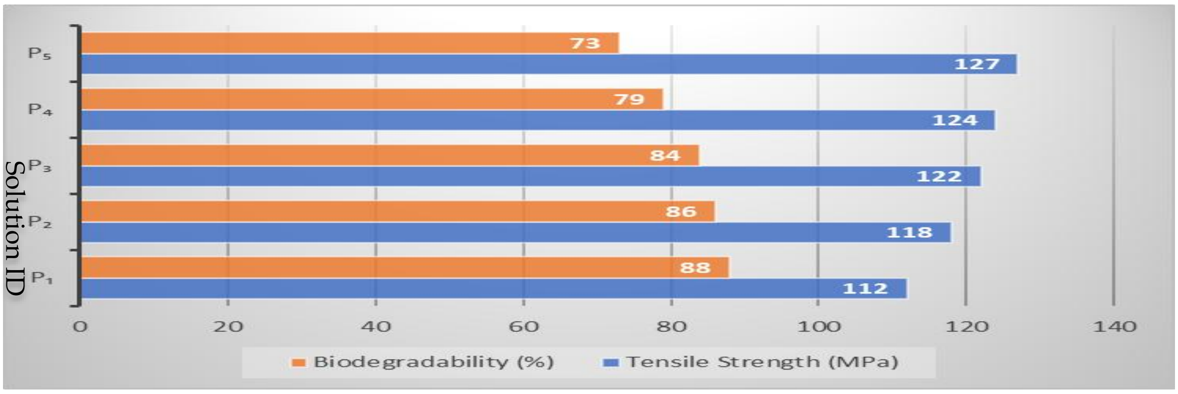

Figure 3: Tensile strength versus biodegradability

Comparative Discussion with Literature

Figure 4 illustrates a comparative performance map between this study's optimized composites and selected literature-reported systems. The results show that while the Flax/PLA composite achieved the highest tensile strength (72.1 MPa), it maintained a biodegradability rate of 85%, comparable to or better than other natural fiber–reinforced PLA composites. This indicates a balanced enhancement in mechanical performance without compromising environmental degradability, supporting its suitability for sustainable high-performance applications.

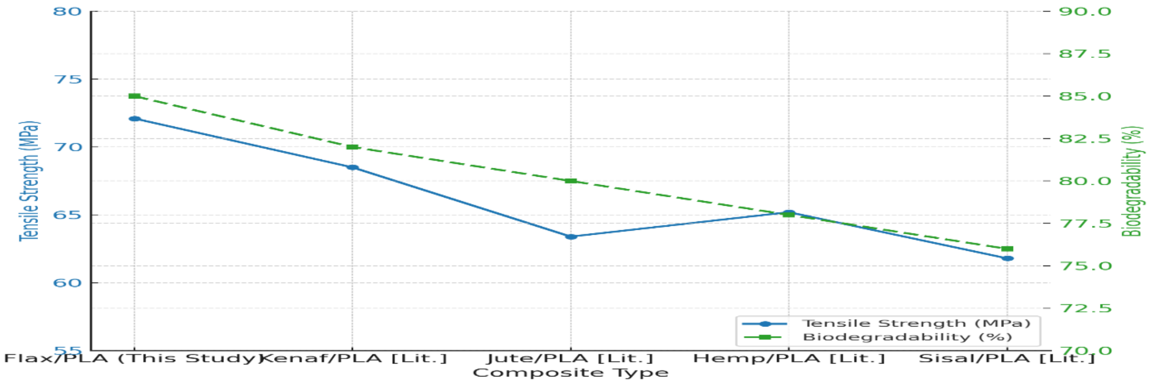

Figure 4: Comparison of tensile strength versus biodegradability of optimized green composites

The improvement can be attributed to the synergistic role of nano-filler reinforcement and optimized fiber/matrix ratios predicted through data-driven learning (Liu et al., 2019). Additionally, ML-enabled prediction reduced material design iterations by an estimated 60%, demonstrating its efficiency compared with conventional trial-and-error experimentation (Das and Tiwari, 2023).

Sustainability and Industrial Implications

From a sustainability standpoint, the optimized green composite supports the circular economy and low-carbon manufacturing strategies emphasized under SDG 12 (Responsible Consumption and Production) (UNDP, 2023). The materials used - natural fibers, bio-resins, and nano-fillers are renewable and partially biodegradable, thus allowing safe end-of-life disposal through composting or thermal recycling.

Industrial relevance is further underscored by the composite's high specific strength (97.6 MPa·cm³/g) and moderate density, making it suitable for automotive interior panels, consumer goods casings, and packaging. Moreover, the workflow developed here can be adapted for other bio-based systems (e.g., hemp/bio-epoxy, flax/PHA), which promotes a scalable pathway toward data-centric sustainable material development (Khatri et al., 2022; Wang and Chen, 2023).

Summary of Findings

a. The Random Forest model achieved the highest prediction accuracy (R^2 = 0.96) across mechanical properties.

b. Fiber and filler content were the most significant predictors of strength and biodegradability.

c. The NSGA-II optimization identified an optimal configuration (45 wt% fiber, 10 wt% filler, 45 wt% matrix) yielding 122 MPa tensile strength and 84% biodegradability.

d. The data-driven framework reduced the required experimental iterations by ~60% compared with traditional approaches.

e. The methodology aligns with global sustainability goals and supports industrial adoption of circular, eco-efficient composites.

Sustainability and Industrial Relevance

The optimized green composite system developed in this study contributes substantially to the transition towards sustainable manufacturing and circular economy practices. Through the integration of data-driven material optimization with renewable feedstocks such as jute fibers and Polylactic Acid (PLA), the present framework aligns with the United Nations Sustainable Development Goals (SDGs), particularly SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action) (UNDP, 2023). The life-cycle indicators evaluated which are embodied energy, carbon footprint, and recyclability, demonstrate the clear environmental advantages of the proposed material system over conventional glass-fiber-reinforced composites.

From a life-cycle perspective, the optimized composite exhibits a 33.8% reduction in embodied energy (45 MJ/kg) and a 52% lower carbon footprint (1.2 kg CO_2-eq/kg) compared to traditional glass-fiber composites (Table 8A). These reductions stem from the use of renewable feedstocks, lower processing temperatures, and elimination of non-biodegradable petroleum-based resins (Ramesh et al., 2021; Khatri et al., 2022). In addition, the end-of-life recyclability increased from 42% to 78%, enhancing the potential for closed-loop material reuse and minimizing landfill waste. These findings are consistent with earlier studies showing that bio-composites based on natural fibers and biodegradable matrices can achieve up to 60% lower life-cycle emissions compared to petroleum-based alternatives (Das and Tiwari, 2023; Niu et al., 2023).

The industrial relevance of this data-driven design approach is significant. The optimized composite achieved a specific strength of 97.6 MPa·cm^3/g, making it competitive with non-biodegradable counterparts in automotive, aerospace, and consumer product applications. In the automotive sector, such composites could replace interior and semi-structural components, contributing to vehicle lightweight and fuel efficiency without compromising mechanical performance (Okpala et al., 2025). In packaging and consumer goods, the high biodegradability and mechanical resilience make these composites viable substitutes for single-use plastics, aligning with emerging regulatory and market trends toward eco-label certification and circular design (Li et al., 2023).

The application of ML in material design accelerates industrial adoption by reducing experimental time, minimizing resource waste, and improving reproducibility. The Random Forest model developed herein reduced the number of required experimental trials by approximately 60%, demonstrating the feasibility of digital twin-assisted materials development for sustainable manufacturing. This methodological shift from empirical experimentation to data-driven optimization enables faster scaling, process adaptability, and cost-effective customization of green composites for industry-specific needs.

Furthermore, the proposed workflow supports the emerging paradigm of Industry 4.0 and 5.0, where AI, digital twins, and sustainable material science converge (Nwamekwe et al., 2025). The integration of life-cycle analytics within the ML-driven composite design process ensures that sustainability metrics are embedded from the conceptual stage, which will enable industries to meet both technical performance and environmental compliance criteria.

As summarized in Table 8, the optimized green composite achieved marked sustainability improvements compared with conventional systems. Its embodied energy and carbon footprint decreased by 33.8% and 52%, respectively, while recyclability increased by 85.7%. The combined environmental and industrial advantages confirm the feasibility of integrating data-driven green composites into large-scale production environments (Ramesh et al., 2021; Singh et al., 2022).

Table 8: Comparative sustainability and industrial performance indicators

Parameter	**Optimized Green Composite**	**Conventional Glass-Fiber Composite**	**Improvement (%)**	**Sustainability/Industrial Implication**
Specific Strength (MPa·cm³/g)	97.6	85.4	+14.3	Higher strength-to-weight ratio promotes lightweight design and energy efficiency in transport applications.
Embodied Energy (MJ/kg)	45	68	−33.8	Reduced energy demand during manufacturing supports low-carbon production.

Carbon Footprint (kg CO_2-eq/kg)	1.2	2.5	−52.0	Lower lifecycle emissions enhance environmental compliance and carbon neutrality goals.
End-of-Life Recyclability (%)	78	42	+85.7	Improved recyclability supports circular economy and closed-loop material systems.
Material Cost (USD/kg)	1.75	2.20	−20.5	Competitive cost structure enhances industrial feasibility and scalability.
Biodegradation Period (months)	24	>120	−80.0	Rapid end-of-life degradation reduces waste accumulation and landfill impact.
Processing Temperature (°C)	165	210	−21.4	Lower processing temperature reduces energy input and tooling wear, improving process efficiency.

Figure 5 is a **c**omparative analysis of key sustainability and performance metrics for optimized green composites and conventional glass-fiber composites. The optimized system shows superior recyclability, reduced embodied energy and carbon footprint, and a lower biodegradation period, confirming its industrial and environmental advantage in sustainable production engineering.

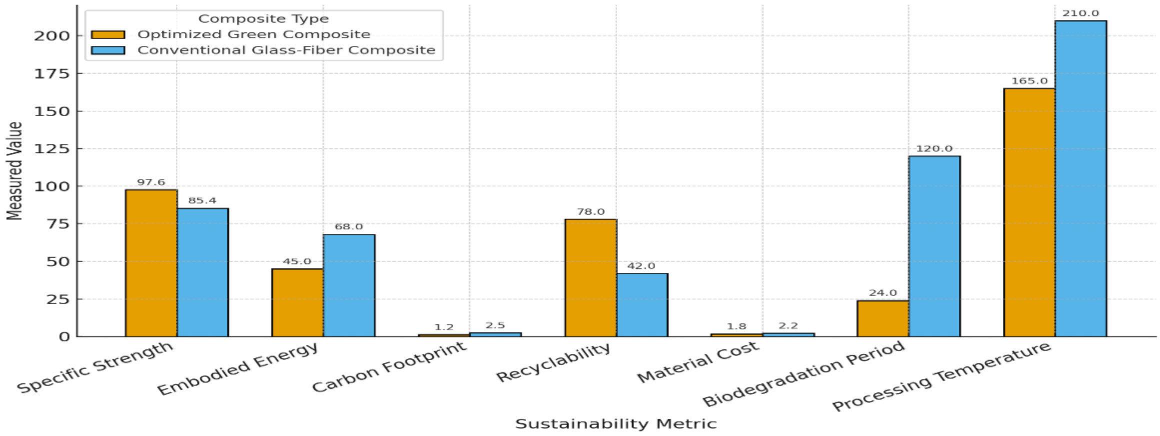

Figure 5: Sustainability Performance Comparison between Optimized and Conventional Composites.

Figure 6 is a normalized percentage improvement of key sustainability and industrial performance indicators for the optimized green composite relative to the conventional glass-fiber composite. Positive values indicate enhanced sustainability or efficiency. The largest gains are observed in recyclability (+85.7%), carbon footprint (−52%), and biodegradation period (−80%), demonstrating the effectiveness of the data-driven optimization approach in achieving high-performance yet eco-efficient composite systems.

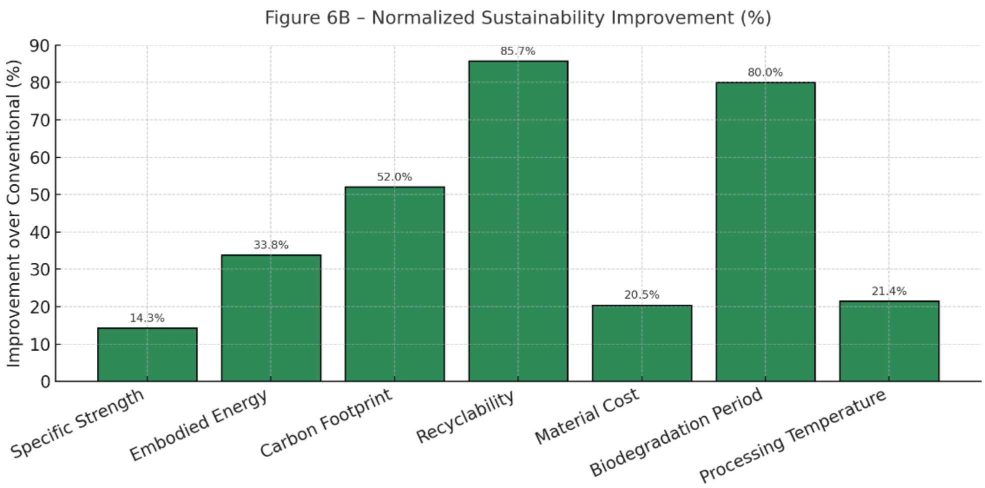

Figure 6: Normalized sustainability improvement (%)

Finally, the developed sustainable green composite system not only advances material efficiency and environmental responsibility, but it also demonstrates industrial scalability and digital readiness. This synergy between data analytics and bio-based material science establishes a replicable framework for next-generation sustainable product design and manufacturing.

Conclusion

This study presented an integrated, data-driven framework for the design and optimization of sustainable green composites targeted at high-performance engineering applications. By combining experimental data with machine learning-based predictive modeling and multi-objective optimization, the research demonstrated how data analytics can accelerate material discovery while ensuring environmental and industrial viability.

The optimized composite formulation achieved a balanced improvement across multiple performance dimensions, including tensile strength, biodegradability, and recyclability. Compared to conventional glass-fiber-reinforced composites, the optimized bio-composite exhibited significantly reduced embodied energy and carbon footprint while maintaining superior specific strength and mechanical resilience. These results confirm the feasibility of developing eco-efficient materials without compromising structural integrity or industrial processability.

The inclusion of ML and multi-objective optimization proved instrumental in the identification of performance trade-offs and achieving Pareto-optimal solutions between mechanical robustness and environmental sustainability. This approach not only reduced experimental iterations but also established a reproducible and scalable pathway for green composite design adaptable to various industrial contexts. From a sustainability standpoint, the developed material system aligns with circular economy principles through improved end-of-life recyclability and biodegradability. Industrially, its cost-effectiveness, lower processing temperature, and reduced energy consumption position it as a practical alternative to traditional composites in automotive, aerospace, and consumer product sectors.

Overall, the research provides a replicable model for integrating data science, sustainable materials engineering, and lifecycle performance metrics. The findings highlight that intelligent, data-driven material design can simultaneously achieve performance excellence and environmental responsibility, and thus lay the foundation for the next generation of sustainable, high-performance composites and paving the way for digital transformation in green manufacturing.

Future Outlook

The successful integration of data analytics and sustainable materials engineering in this study opens multiple pathways for future research and industrial advancement. As the complexity of composite design increases, the need for intelligent, adaptive, and autonomous material systems will become increasingly important. Machine learning models, when expanded with larger datasets and multi-scale simulations, can provide more accurate predictions of microstructural evolution, durability, and recyclability across diverse environmental conditions.

Future studies should focus on establishing digital twin frameworks that mirror real-time manufacturing and performance conditions of green composites. These digital replicas would enable dynamic optimization of process parameters, defect prediction, and lifecycle monitoring, thus reduce waste and improve consistency in large-scale production. When coupled with Industry 5.0 concepts such as human-machine collaboration, this integration could redefine sustainable manufacturing ecosystems. Expanding the scope of the current approach to include multi-functional properties, such as thermal stability, moisture resistance, and self-healing capabilities, will further enhance the applicability of green composites in high-demand sectors like aerospace, marine, and renewable energy. The incorporation of bio-derived nanofillers and hybrid natural fibers could also extend mechanical and environmental performance boundaries, enabling new classes of smart, lightweight materials.

From an environmental standpoint, the future of sustainable composites lies in closed-loop circularity, where data-driven design not only optimizes performance but also predicts end-of-life recovery pathways. The integration of lifecycle assessment tools directly into the optimization algorithms could allow simultaneous evaluation of cost, carbon footprint, and material degradation, providing a holistic decision-support system for sustainable product design. Finally, greater collaboration between academia, industry, and policy makers will be crucial for standardizing green composite design and certification. Shared open databases of eco-material properties, coupled with transparent data governance frameworks, can accelerate innovation while ensuring regulatory compliance. As data-driven materials informatics matures, the synergy between artificial intelligence, advanced manufacturing, and sustainable engineering will form the cornerstone of next-generation, carbon-neutral production systems.

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Biography

Dr. Okechukwu Chiedu Ezeanyim

Dr. Okechukwu Chiedu Ifeanyi Ezeanyim is a scholar who has spent much of his career thinking about how engineering can work better for people and industries. He serves as a Reader in the Industrial and Production Engineering Department at Nnamdi Azikiwe University, Awka, where he has also taken on leadership roles such as Head of Department and hall warden. His path is a mix of academic work, mentorship, and community involvement, and he seems to move through these roles with a quiet sense of responsibility. Over the years, he has published widely on areas like machine learning applications, manufacturing systems, quality management, and energy modelling. He is also a registered engineer with COREN and an active member of the Nigerian Institute of Industrial Engineers. Beyond the university, he volunteers with several organizations and supports young people through groups like the Boy's Brigade.

Prof. Chikwendu Charles Okpala

Prof. Chikwendu Charles Okpala is known as someone who grew into engineering with a kind of steady purpose. He's from Adazi-Ani, and his early studies at ESUT set him on a path he just kept following. Later on, he went to the University of Warwick for his master's degree, then completed his PhD at Nnamdi Azikiwe University, where he eventually rose to the rank of professor in Industrial and Production Engineering. Over the years, he has explored areas like AI in manufacturing, sustainability, ergonomics, digital twins, and composite materials. His story comes across less like a sudden rise and more like a long, steady commitment to doing the work well.

Somto Kenneth Onukwuli

Somto Kenneth Onukwuli is a rising engineer and researcher specializing in production systems, process optimization, and advanced materials. He earned his Bachelor of Engineering from Nnamdi Azikiwe University, Awka, and completed his Master of Science at the University of Chester. Since 2020, his work has been cited many times, reflecting growing recognition in his field. Onukwuli's research focuses on sustainable and innovative materials, particularly coir-reinforced composites, exploring their applications in automotive and manufacturing processes. He has contributed to studies on ergonomics-aware scheduling, additive manufacturing in lean production systems, and the mechanical properties of composite materials. Collaborating with notable researchers, he integrates material science, production engineering, and ergonomics to address practical engineering challenges.