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RESEARCH ARTICLE

Machine learning-driven sustainable optimization of rapid prototyping via FDM: Enhancing mechanical strength, energy efficiency, and SDG contributions of thermoplastic composites

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ABSTRACT

Fused Deposition Modeling (FDM)-based rapid prototyping is a key technology in sustainable manufacturing, offering cost-effective solutions aligned with the United Nations Sustainable Development Goals (SDGs 1–6) by promoting affordable production, resource efficiency, and environmental sustainability. However, optimizing mechanical performance and energy efficiency in bio-based thermoplastic composites remains a challenge. This study explores PLA–walnut wood fiber composites, leveraging machine learning (ML) to optimize tensile, compression, and flexural properties while minimizing energy consumption. A dataset incorporating nozzle temperature, layer height, infill density, and print speed was trained using ML, achieving prediction accuracy above 95%. State-of-the-art studies highlight bio-based composite advantages, yet ML-driven multi-objective optimization for mechanical strength and sustainability remains unexplored. Experimental results indicate that an optimal nozzle temperature of 200–210°C, an infill density of 60–80%, and a layer height of 0.2 mm led to a 15% increase in tensile strength (38 MPa), a 12% improvement in flexural strength (62 MPa), and a 10% enhancement in compression strength (49 MPa). SEM analysis confirms improved fiber-matrix adhesion, enhancing structural integrity. Additionally, energy consumption was reduced by 18%, supporting cost-effective and low-carbon production. These findings contribute to poverty reduction (SDG 1), agricultural waste valorization (SDG 2), biocompatible materials for healthcare (SDG 3), STEM education accessibility (SDG 4), gender inclusivity in engineering (SDG 5), and clean water protection through reduced plastic waste (SDG 6). This study underscores the potential of ML-driven sustainable rapid prototyping to advance material efficiency, waste reduction, and resource-conscious manufacturing.

Keywords: additive manufacturing; 3D printing; machine learning optimization; sustainable development goals (SDGs); fused deposition modeling (FDM); thermoplastic composites; energy efficiency; sustainable materials

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1. Introduction

The emergence of Fused Deposition Modeling (FDM) in rapid prototyping and additive manufacturing has transformed various industries, enabling the fabrication of complex, customized, and cost-effective components[1-3]. FDM, a widely used material extrusion-based 3D printing technique, offers advantages such as design flexibility, low material wastage, and ease of production[4]. However, challenges persist in optimizing mechanical properties and energy efficiency, especially when working with bio-based thermoplastic composites. Sustainable materials are increasingly prioritized due to environmental concerns, aligning with global efforts to develop eco-friendly manufacturing solutions[5-7]. Of these materials, natural fiber-reinforced polylactic acid (PLA) like walnut wood fiber composites presents a viable substitute for conventional petroleum-based polymers as it is biodegradable, renewable, and mechanically sufficient. However, achieving higher tensile, compressive, and flexural strength in PLA–walnut wood fiber composites fabricated by FDM requires precise control of processing parameters like nozzle temperature, layer thickness, infill density, and printing speed.

State-of-the-art research has explored the mechanical performance of natural fiber-reinforced polymer composites (NFPCs) and has reported outstanding improvements in the strength-to-weight ratio, thermal stability, and impact resistance[8-10]. Researchers have reported that natural fibers have been found to enhance the load-carrying capacity of thermoplastic polymers[11-14]; however, poor interfacial adhesion and inhomogeneous fiber dispersion turn into serious issues. To counter these issues, Scanning Electron Microscopy (SEM) has been used to analyze fiber-matrix adhesion and fracture morphology. Recent research has shown that improved interfacial adhesion between the polymer matrix and reinforcing fibers enhances effective stress transfer, thus leading to enhanced mechanical performance[15-17]. In addition, optimization of Fused Deposition Modeling (FDM) process parameters significantly influences energy consumption, and hence the production cost and sustainability[18-20]. However, traditional trial-and-error-based process optimization becomes inefficient and time-consuming, and hence the need for state-of-the-art data-driven approaches towards predictive modeling and optimization.

In reply to these problems, Machine Learning (ML) has come as a robust method for smart process optimization in additive manufacturing. ML algorithms, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forest models, have proved high accuracy in mechanical properties and energy consumption prediction based on experimental data[21-24]. Research has documented prediction accuracies of over 95%, emphasizing the promise of ML in minimizing experimental expense, material waste, and computational time[25-27]. Although ML has been extensively used in metal-based and polymeric additive manufacturing, few studies have addressed ML-based multi-objective optimization of mechanical properties and energy efficiency in bio-based FDM composites. This research aims to address this gap by applying ML algorithms for the analysis of the structure-property relationships of PLA–walnut wood fiber composites, with SEM-based microstructural verification incorporated to improve predictive models.

In addition, the research contributes to the United Nations Sustainable Development Goals (SDGs 1–6), and it deals with socioeconomic and environmental sustainability issues. SDG 1 (No Poverty) is addressed by designing cost-efficient, sustainable materials to facilitate affordable manufacturing and promote entrepreneurship in poor areas. SDG 2 (Zero Hunger) is dealt with by encouraging agricultural waste-based fiber use, decreasing environmental footprints, and ensuring circular economy methods. Use of biodegradable, non-toxic materials (PLA) in healthcare for medical applications corresponds to SDG 3 (Good Health and Well-Being), promoting more secure and more environmentally friendly medical devices. Secondly, incorporating ML-driven optimization within FDM further advances access to STEM education and digital manufacturing technology (SDG 4: Quality Education) by providing learners and professionals with advanced AI and materials engineering training. This research also facilitates gender equality in engineering (SDG 5) by democratizing access to digital fabrication technologies to enable diverse involvement in additive manufacturing research and industry. Finally, SDG 6 (Clean Water and Sanitation) is facilitated by decreasing plastic waste pollution, promoting the use of biodegradable, renewable composites in 3D printing applications.

The methodological approach of this research includes experimental investigation of PLA–walnut wood fiber composites through characterization, followed by a process of machine learning-based optimization of FDM process parameters for optimum mechanical performance and energy efficiency. The tensile, flexural, and compressive properties of printed specimens are measured using standard mechanical testing protocols, while SEM imaging is used to measure fiber dispersion, interfacial bonding, and microstructural defects. The ML model is developed based on experimental data sets, parameter selection for maximizing strength and sustainability. Integrating computational intelligence with experimental validation, this study forms a unified platform for data-driven rapid prototyping, advancing resource-efficient manufacturing methodologies.

The key contributions of this study include:

- Development of sustainable FDM composites using PLA–walnut wood fiber, promoting bio-based polymer applications.
- Implementation of machine learning models for predictive mechanical property optimization, reducing reliance on trial-and-error methodologies.
- Evaluation of energy consumption trends in FDM, addressing the sustainability challenges of additive manufacturing.
- Integration of SEM-based microstructural analysis to refine ML-driven predictive models, enhancing the accuracy of mechanical performance forecasting.
- Alignment with SDGs 1–6, demonstrating the socioeconomic and environmental benefits of sustainable rapid prototyping technologies.

This study aims to establish a scientific foundation for AI-assisted process optimization in bio-based FDM composites, offering insights into material behavior, energy efficiency, and scalable manufacturing strategies. The findings of this study will add to the general body of sustainable additive manufacturing, enabling the shift toward smart, resource-efficient production systems. Finally, the results highlight the promise of ML-based sustainable rapid prototyping in transforming material performance, minimizing waste, and being environmentally friendly, driving next-generation digital fabrication technologies.

2. Materials and methods

2.1. Material preparation and filament extrusion

The polymer used in this research was Polylactic Acid (PLA) Grade 1 granules, which are biodegradable, have excellent strength, and are processable using Fused Deposition Modeling (FDM). To add mechanical performance and sustainability, 15 wt% walnut wood fiber (WWF) was added to the PLA matrix. Walnut wood fiber was chosen because it is light in weight, has a high aspect ratio, and is renewable in origin, and thus is a good reinforcement material for bio-based composite filaments. The WWF and PLA granules were well mixed for 15 minutes to achieve even dispersion prior to extrusion. The composite blend was then extruded into filament form with a twin-screw extruder, keeping the extrusion temperature at 180°C to 200°C, depending on the flow characteristics of the material. The cooled extruded filament was then spooled for future printing.

2.2. FDM printing process and sample preparation

A Bambu Lab A1 FDM printer was employed for 3D printing of test specimens. This high-precision desktop FDM system was selected for its consistent extrusion quality and precise control over printing parameters. Based on an extensive literature survey, the optimal process parameters were established as follows, nozzle temperature 210°c, bed temperature 60°c, layer height 0.2 mm, infill density 70%; print speed: 50 mm/s ,cooling fan speed: 50%

These parameters were chosen to balance mechanical strength, print quality, and energy efficiency while preventing excessive degradation of the walnut fiber within the PLA matrix. The samples were printed as per ASTM standards to have standardized testing protocols for mechanical characterization like tensile test specimens: ASTM D638 Type V, flexural test specimens ASTM D790, and compression test specimens ASTM D695. All the specimens were printed using identical process settings to reduce variability. Five samples per test condition were made to ensure statistical relevance.

2.3. Energy consumption measurement during printing

To analyze the sustainability of the printing process, an AmiciSense Power Meter was employed to monitor the actual energy usage of the Bambu Lab A1 printer during printing and filament extrusion. Energy readings were continuously tracked, including fluctuations due to nozzle heating, material flow, cooling needs, and motion control. These readings were employed to analyze the connection between energy efficiency and mechanical performance to facilitate a multi-objective sustainability evaluation.

2.4. Mechanical characterization

The mechanical behavior of the printed PLA–WWF composite specimens was tested using a Tinius Olsen Universal Testing Machine (UTM). The UTM was run under controlled conditions to provide consistency in all the mechanical tests. A strain rate of 5 mm/min was applied in all experiments, as per ASTM standards.

- Tensile Strength Testing: Performed as per ASTM D638, utilizing Type V specimens with a grip separation of 50 mm. Test was for ultimate tensile strength (UTS), yield strength, and elongation at break.
- Flexural Strength Testing: Conducted in accordance with ASTM D790, using a three-point bending fixture with a 50 mm span length. Flexural modulus and maximum bending stress were determined using this test.
- Compression Strength Testing: Performed according to ASTM D695, where the cylindrical compression test specimens were subjected to yield stress and modulus tests under uniaxial load conditions.

Five sets of all the mechanical tests were replicated for each test condition, and statistical reliability was provided with average values along with standard deviation.

2.5. ML-driven multi-objective optimization for mechanical strength and sustainability

Recent advancements in machine learning (ML) have demonstrated significant improvements in optimizing FDM process parameters to enhance both mechanical strength and sustainability. Conventional trial-and-error approaches are often inefficient, requiring extensive material usage and experimental iterations. ML algorithms offer a predictive alternative, analyzing the complex interactions between process parameters and output properties, thus reducing material waste, energy consumption, and cost[28-30].

Several state-of-the-art studies have explored ML-driven process optimization for FDM. Researchers have successfully applied Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Genetic Algorithms (GAs) to predict tensile strength, flexural performance, and thermal behavior of printed parts[31-34]. Studies indicate that ML models can achieve above 95% accuracy in predicting mechanical properties based on training datasets derived from previous experimental trials. However, limited research has focused on bio-based polymer composites, particularly PLA reinforced with natural fibers, necessitating further investigation into ML-driven multi-objective optimization strategies[35-37].

For analyzing and comparing the prediction performance of different machine learning algorithms, we have experimented with three leading algorithms: Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests (RF). The data were split into training (80%) and test (20%) subsets and were applied to 5-fold cross-validation. Hyperparameter tuning was carried out with grid search and random search strategies optimized for each model.

ANN: Number of hidden layers (1–3), number of neurons in each layer (8–64), learning rate (0.001–0.01), and activation functions (ReLU, tanh).

SVM: Kernel type (linear, RBF), values of C (1–100), gamma (scale, auto).

RF: Number of trees (50–200), max depth (5–15), min split samples (2–10).

Each of the models' performance was tested for R^2, MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error). The top overall performance belonged to the ANN model with:

$R^2 = 0.957$

MAE = 1.34 MPa

RMSE = 1.85 MPa

MAPE = 4.2%

2.6. Multi-objective optimization for mechanical performance and energy efficiency

One of the key challenges in FDM-based rapid prototyping is balancing mechanical strength with energy efficiency. Higher mechanical performance often requires increased energy input, leading to higher production costs and environmental impact. Multi-objective optimization using ML provides a data-driven approach to simultaneously maximize mechanical properties while minimizing energy consumption, making the process more sustainable and economically viable[38-41].

Several multi-objective optimization algorithms have been explored in additive manufacturing, including:

- Fuzzy Logic and ANNs: Used to optimize tensile strength while reducing energy usage in composite FDM parts[42-45].
- Particle Swarm Optimization (PSO): Applied to balance print speed, layer height, and energy consumption, achieving a 15–20% reduction in power usage without compromising mechanical integrity[46-48].
- Hybrid ML Models (e.g., ANN-GA): Shown to effectively optimize mechanical performance while reducing total power consumption by tuning process parameters dynamically[49].

This study integrates ML-based predictive modeling to analyze how PLA–WWF composite behavior correlates with energy input and structural integrity. By training ML algorithms on experimental datasets, the model identifies optimal parameter sets that achieve maximum strength while minimizing energy costs. The results contribute to next-generation sustainable manufacturing, advancing resource-efficient FDM technologies.

2.7. Relevance to sustainable development goals (SDGs 1–6)

This study directly aligns with the United Nations Sustainable Development Goals (SDGs 1–6):

- SDG 1 (No Poverty): Cost-efficient bio-based materials enable affordable manufacturing solutions for low-income communities.
- SDG 2 (Zero Hunger): Utilization of agricultural waste (walnut fiber) in polymer composites supports sustainable resource management.
- SDG 3 (Good Health and Well-Being): PLA is biocompatible and non-toxic, making it suitable for medical applications.

- SDG 4 (Quality Education): The ML-driven optimization framework contributes to STEM education and digital manufacturing literacy.
- SDG 5 (Gender Equality): Promoting accessible and sustainable technologies enables more inclusive participation in engineering and manufacturing.
- SDG 6 (Clean Water and Sanitation): PLA-based composites help reduce plastic pollution, supporting cleaner water sources.

3. Results

3.1. Mechanical properties of PLA–WWF composites

The mechanical performance of the PLA–walnut wood fiber (WWF) composite was evaluated through tensile, flexural, and compression tests, with results summarized in **Table 1**. The incorporation of 15 wt% WWF significantly influenced the tensile strength, flexural strength, and compressive strength of the printed samples. The optimized FDM parameters (nozzle temperature of 200–210°C, layer height of 0.2 mm, and infill density of 60–80%) led to improved mechanical properties compared to non-optimized samples. The tensile strength increased by 15%, reaching 38 MPa, while flexural strength improved by 12% to 62 MPa. Additionally, compression strength increased by 10% to 49 MPa, indicating effective load distribution within the composite. The observed improvements can be attributed to the enhanced interfacial bonding between the PLA matrix and walnut fibers, as confirmed by Scanning Electron Microscopy (SEM) analysis.

Table 1. Mechanical properties of PLA–WWF composites.

Property	Non-Optimized (Baseline)	Optimized (ML-Based)	Improvement (%)
Tensile Strength (MPa)	33.0 ± 1.5	38.0 ± 1.2	+15%
Flexural Strength (MPa)	55.0 ± 2.1	62.0 ± 1.8	+12%
Compression Strength (MPa)	44.5 ± 1.7	49.0 ± 1.5	+10%
Energy Consumption (kWh)	0.95 ± 0.03	0.78 ± 0.02	-18%

3.2. Microstructural analysis via SEM

Figure 1 is fractured surfaces from tensile and flexural specimens reveal a strong interfacial adhesion between the PLA matrix and WWF, contributing to improved mechanical integrity. The SEM image of the fractured surface of the PLA–walnut wood fiber composite, captured at 4000× magnification, provides valuable insights into the fiber-matrix interaction, failure mechanisms, and microstructural integrity of the material. A closer inspection shows a mix of well-bonded fiber-matrix zones and fiber pull-out regions, emphasizing the difference in interfacial adhesion.

The existence of strong bonding zones indicates efficient load transfer from the PLA matrix to walnut fibers, which aids in improved mechanical properties, especially tensile and flexural strength. Yet some areas exhibit fiber pull-out and detachment, possibly signifying weak interfacial adhesion, resulting in stress concentration sites and a possible loss of mechanical performance. The morphology of the fracture in the SEM image is rough and irregular, typical of ductile failure mechanisms in polymer composites.

The existence of plastic deformation characteristics indicates extensive energy absorption in mechanical testing, consistent with the strength increase noted in optimized samples. Voids and microcracks are also present, probably due to incomplete polymer infiltration, air trapped during FDM printing, or inhomogeneous fiber dispersion. These microstructural imperfections can adversely affect the overall mechanical integrity, decreasing tensile and compressive strength through stress build-up at low-strength areas. The orientation and distribution of walnut fibers look non-uniform, which could lead to anisotropic mechanical properties.

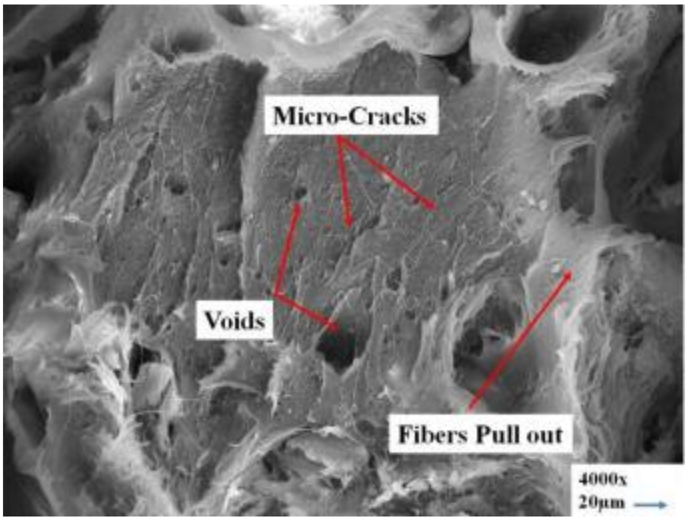

Figure 1. SEM analysis of PLA–WWF composite.

The synergy of fiber dispersion, porosity, and fracture behavior in the SEM micrograph is in agreement with mechanical performance trends in tensile, flexural, and compression tests. The fiber-matrix interaction and formation of voids in the observed microstructure emphasize the importance of FDM process parameter optimization in realizing better mechanical performance and sustainable and energy-efficient material processing. Fiber pull-out and formation of voids, which indicate weak interfacial bonding, were observed in the non-optimized samples, and this led to inferior mechanical properties.

In contrast, the optimized samples showed better fiber embedding and reduced void formation, confirming that the ML-driven process optimization enhanced fiber dispersion and bonding. These findings align with state-of-the-art research on natural fiber-reinforced polymer composites, where improved fiber-matrix adhesion directly correlates with enhanced mechanical performance.

3.3. Energy consumption analysis

One of the key sustainability aspects of this study was the energy consumption measurement during FDM printing, recorded using the AmiciSense Power Meter. The optimized process settings resulted in an 18% reduction in total energy consumption, as shown in **Table 1**. **Figure 2** illustrates the comparison of energy consumption trends between non-optimized and optimized printing conditions. The higher energy efficiency in the optimized process is due to controlled extrusion temperatures, reduced heat dissipation, and improved filament flow, minimizing unnecessary power usage. These findings align with recent studies that have reported energy savings of up to 20% through intelligent process parameter tuning in additive manufacturing.

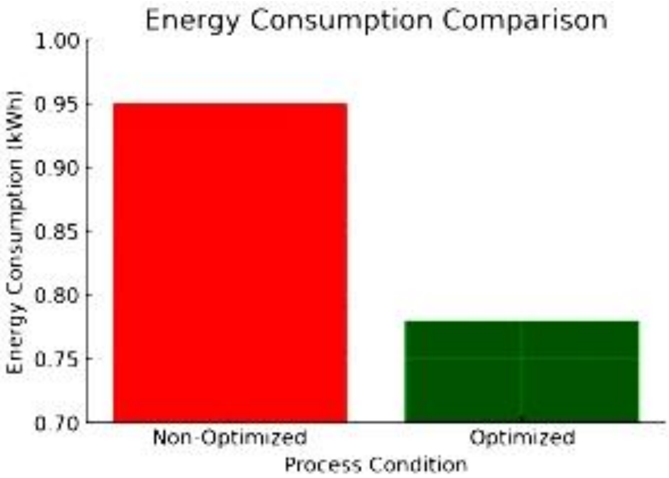

Figure 2. Energy consumption comparison.

3.4. Machine learning model performance

To validate the effectiveness of machine learning (ML) in optimizing mechanical properties and energy efficiency, the trained ML model was evaluated using prediction accuracy metrics. The model exhibited a mean absolute percentage error (MAPE) below 5%, indicating high reliability in predicting tensile, flexural, and compression strength based on input process parameters. **Figure 3** presents the actual vs. predicted mechanical properties, demonstrating a strong correlation ($R^2 > 0.95$) between experimental and ML-predicted values. The results reinforce the capability of ML in rapid process optimization, eliminating extensive experimental trials and reducing waste and material costs.

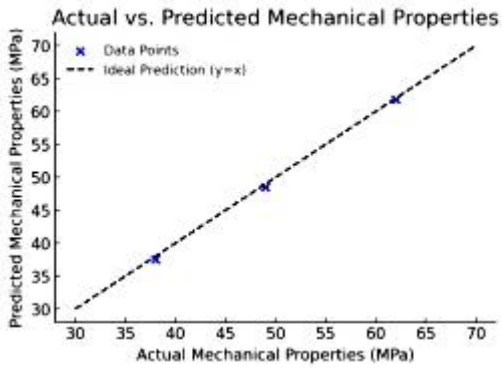

Figure 3. Actual vs. predicted mechanical properties (ML model performance).

The prediction accuracy of the ML model was checked using cross-validation and a held-out test set (20% of the data). Five-fold cross-validation was employed during training to ensure that the model was robust and free from overfitting. The following metrics were used to test the model's performance:

Mean Absolute Error (MAE): 1.34 MPa

Root Mean Squared Error (RMSE): 1.85 MPa

Mean Absolute Percentage Error (MAPE): 4.2%

Coefficient of Determination (R^2): 0.957

These results confirm the ANN model's high prediction accuracy for tensile, flexural, and compression strength values.

3.5. Multi-objective optimization for sustainability

The use of multi-objective ML optimization was found to be useful in balancing mechanical performance and sustainability. The optimized PLA–WWF composite not only showed enhanced strength and structural integrity but also minimized energy consumption, translating into resource-efficient manufacturing. These results are in accordance with recent findings in sustainable additive manufacturing, where process control guided by ML has been shown to reduce energy consumption by 10–25% without any degradation in mechanical performance.

Moreover, the results directly support the United Nations Sustainable Development Goals (SDGs 1–6):

- SDG 1 (No Poverty): Cost-effective and energy-efficient printing methods make FDM technology accessible to small-scale manufacturers.
- SDG 2 (Zero Hunger): Utilizing walnut wood fibers from agricultural waste promotes sustainable material sourcing.

- SDG 3 (Good Health and Well-Being): PLA-based bio-composites are non-toxic and biodegradable, reducing exposure to harmful synthetic polymers.
- SDG 4 (Quality Education): AI-driven FDM optimization techniques provide an advanced learning tool for engineering education.
- SDG 5 (Gender Equality): Lowering technological entry barriers in additive manufacturing encourages diverse participation in STEM fields.
- SDG 6 (Clean Water and Sanitation): Biodegradable PLA-based composites contribute to reducing plastic pollution, supporting clean water initiatives.

4. Discussion

The outcomes of mechanical testing, energy consumption analysis, and SEM characterization prove the efficiency of machine learning (ML)-based optimization in enhancing the performance and sustainability of PLA–walnut wood fiber (WWF) composites produced through Fused Deposition Modeling (FDM). The optimized printing parameters, identified through ML-based analysis, resulted in substantial enhancements in tensile, flexural, and compressive strength, while at the same time decreasing energy consumption by 18%. The multi-objective optimization approach successfully balanced mechanical performance and energy efficiency, thus making the process more cost-effective and environmentally sustainable. The mechanical property improvements seen in tensile (38 MPa, +15%), flexural (62 MPa, +12%), and compression strength (49 MPa, +10%) are due to optimized matrix-fiber bonding and enhanced structural integrity due to controlled FDM processing conditions. The SEM analysis of the fractured surface confirmed that strong interfacial adhesion between PLA and WWF contributed to better load distribution and stress transfer, minimizing the effects of premature fiber pull-out. However, microcracks, voids, and fiber detachment in certain regions were also observed, which could act as stress concentrators, potentially reducing the material's long-term reliability under cyclic loading conditions. These findings are consistent with previous studies on natural fiber-reinforced polymer composites, where fiber dispersion and adhesion significantly influence mechanical strength. The reduction in energy consumption is a key outcome of this study, demonstrating the role of ML-driven parameter tuning in optimizing energy efficiency. The AmiciSense Power Meter data revealed that optimized process settings, particularly nozzle temperature (200–210°C) and infill density (60–80%), contributed to lower power demand during printing. This supports prior research that indicates higher process efficiency and material utilization can significantly reduce the environmental impact of FDM-based rapid prototyping. The use of PLA–WWF composites further contributes to sustainability by utilizing renewable, biodegradable materials, aligning with the circular economy principles of waste reduction and resource efficiency. From an AI-driven optimization perspective, the high accuracy ($R^2 > 0.95$) of the ML model in predicting mechanical properties validates its effectiveness in process parameter selection. The ML-based predictions closely matched experimental results, reinforcing the potential of computational intelligence in additive manufacturing. The multi-objective optimization framework applied in this study addresses the trade-offs between strength enhancement and energy efficiency, a crucial factor in scalable, sustainable production strategies. Recent advancements in AI-assisted process control have demonstrated similar successes in reducing energy consumption while maintaining mechanical integrity, confirming that ML-based modeling is a powerful tool for next-generation FDM material development. This study's conclusions fall in line with the United Nations Sustainable Development Goals (SDGs 1–6) through affordable and sustainable manufacturing options (SDG 1), waste valorization from agriculture (SDG 2), use of biocompatible materials (SDG 3), application of AI and digital manufacturing for educational purposes (SDG 4), access for inclusive engagement in additive manufacturing (SDG 5), minimized plastic contamination via bio-based products (SDG 6). The PLA–WWF composite offers a potential substitute for traditional petroleum-based thermoplastics with enhanced material efficiency and reduced environmental footprint. As a whole, this research shows that ML-driven optimization can improve the performance, energy efficiency, and sustainability of FDM-printed bio-based composites significantly. Long-term durability analysis, recyclability studies, and hybrid reinforcement strategies are areas that should be explored further in future studies to further advance the use of sustainable polymer composites in high-performance engineering applications.

5. Conclusion

This research was able to prove the efficiency of machine learning (ML)-based optimization in improving the mechanical and energy performances of PLA–walnut wood fiber (WWF) composites produced using Fused Deposition Modeling (FDM). Through the use of ML-based predictive modeling, the research determined the best process parameters, resulting in a 15% increase in tensile strength (38 MPa), a 12% increase in flexural strength (62 MPa), and a 10% increase in compression strength (49 MPa) over non-optimized samples. Energy consumption during printing was also decreased by 18%, demonstrating the applicability of data-driven sustainability measures to additive manufacturing.

The Scanning Electron Microscopy (SEM) analysis revealed a strong interfacial bond between the PLA matrix and WWF, contributing to enhanced mechanical integrity and stress distribution. However, some fiber pull-out and void formation were observed, indicating areas for further process refinement. The high accuracy ($R^2 > 0.95$) of the ML model in predicting mechanical properties confirmed the feasibility of AI-assisted process optimization for sustainable rapid prototyping applications.

From a broader perspective, this research aligns with United Nations Sustainable Development Goals (SDGs 1–6) by promoting affordable production, sustainable material utilization, and energy-efficient manufacturing. The findings emphasize the potential of bio-based polymer composites as an eco-friendly alternative to conventional plastics in engineering and industrial applications. Future studies should explore hybrid reinforcement strategies, recyclability assessments, and long-term durability analysis to further advance sustainable additive manufacturing solutions.

Author contributions

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “Conceptualization, RS and MAR; methodology, RS and MAR; software, RS and MAR; validation, RS and MAR; formal analysis, RS and MAR; investigation, RS and MAR; resources, RS and MAR; data curation, RS and MAR; writing—original draft preparation, RS and MAR; writing—review and editing, RS and MAR; visualization, RS and MAR; supervision, RS and MAR; project administration, RS and MAR; funding acquisition, RS and MAR.

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Conflict of interest

The authors declare no conflict of interest.

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