STM JOURNALS

Journal of
Polymer & Composites

https://journals.stmjournals.com/jopc

ISSN: 2321-2810 (Online)
ISSN: 2321-8525 (Print)
Volume 14, Special Issue 4, 2026
January–December
DOI (Journal): 10.37591/JoPC

Research JoPC

Artificial Intelligence for Polymer and Nanocomposite Materials: Performance Prediction, Manufacturing Optimization, and Future Perspectives

V. Parimala[1,*], K. Sudhakar[2], S. Bhuvana[3], Praveen Talari[4], D. Ruban Thomas[5], S. Sivasankaran[6], S. Palpandi[7]

Abstract

The exceptional mechanical properties, design flexibility, and lightweight nature of polymer composite and nanocomposite materials make them indispensable in a wide range of applications, including aerospace, automotive, construction, biomedical, and energy sectors. The optimization of the strength, durability, and manufacturing efficiency of polymer composite and nanocomposite materials is highly challenging because their performance depends on matrix composition, reinforcement type, fiber or nanoparticle distribution, interfacial interactions, processing conditions, and environmental factors. Conventional optimization approaches require extensive experimentation, computational resources, and development time, leading to increased cost and reduced efficiency. Recent advances in artificial intelligence (AI) have enabled innovative data-driven approaches for improving the performance, design, and manufacturing of polymer composite and nanocomposite materials. Machine learning, deep learning, and predictive analytics are employed to model complex nonlinear relationships among material composition, processing parameters, and performance characteristics using large-scale material datasets. The proposed AI-driven framework accurately predicts key material properties, including mechanical strength, fatigue resistance, thermal stability, and long-term durability, while simultaneously optimizing curing conditions, manufacturing processes, material utilization, and defect detection. Furthermore, AI-assisted optimization shortens material design cycles, enhances production monitoring, minimizes manufacturing costs, and improves product reliability. The integration of artificial intelligence with polymer composite and nanocomposite engineering accelerates the discovery of advanced materials and supports the development of sustainable, lightweight, and high-performance composite systems. Overall, AI-driven methodologies significantly enhance the structural performance, durability, and manufacturing efficiency of next-generation polymer composite and nanocomposite materials, making them promising candidates for future engineering applications.

Keywords: Polymer nanocomposites, performance optimization, mechanical strength, durability, manufacturing efficiency, predictive analytics, material engineering

***Author for Correspondence**
V. Parimala
E-mail: itsmepari@gmail.com

[1]Assistant Professor, Department of Electronics and Communication Engineering, Chennai Institute of Technology, Chennai, Tamil Nadu, India
[2]Associate Professor, Department of Electronics and Communication Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu, India
[3]Assistant Professor (Senior Grade), Department of Cyber Security, Rajalakshmi Engineering College, Thandalam, Tamil Nadu, India
[4]Associate Professor, Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Vignana Bharathi Institute of Technology, Hyderabad, Telangana, India
[5]Assistant Professor, Department of Electronics and Communication Engineering, Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, Tamil Nadu, India
[6]Professor, Department of Information Technology, Raak College of Engineering and Technology, G.N Palayam, Puducherry, India
[7]Assistant Professor (Senior Grade), Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India

Received Date: August 03, 2026
Accepted Date: August 20, 2026
Published Date: August 26, 2026

Citation: V. Parimala, K. Sudhakar, S. Bhuvana, Praveen Talari, D. Ruban Thomas, S. Sivasankaran, S. Palpandi. Artificial Intelligence for Polymer and Nanocomposite Materials: Performance Prediction, Manufacturing Optimization, and Future Perspectives. Journal of Polymer & Composites. 2026; 14(Special Issue 4): S579–S602p.

© STM Journals 2026. All Rights Reserved

INTRODUCTION

Importance and Engineering Applications of Polymer Composite Materials & Challenges in Optimizing Polymer Composite Performance

Polymer composites and nanocomposites are indispensable in engineering because of their many desirable properties, including low weight, excellent strength-to-weight ratio, resistance to corrosion, and adaptability to various designs. The mechanical and physical properties of polymers with particles, fibers, nanofillers, or fillers are superior to those of conventional materials [1–3]. Because they reduce structural weight and enhance efficiency while meeting performance criteria, polymer composites and nanocomposites find widespread use in the aerospace, automotive, construction, marine, biomedical, and renewable energy sectors. Investigations into optimal polymer composite and nanocomposite systems have been prompted by the need for new materials that exhibit enhanced strength, durability, and cost-effective production. Polymer composites and nanocomposites have many advantages, but they are not easy to perfect. It is possible to influence the mechanical performance and durability of polymer composites and nanocomposites by manipulating the matrix properties, reinforcing features, fiber orientation, nanofiller distribution, interfacial bonding, production processes, exposure to environmental factors, and loading conditions. Small adjustments to processing parameters can have a large impact on material performance and quality [4–6]. Computational modeling, empirical techniques, and experimental testing are the standard approaches to optimize and design polymer composites and nanocomposites [7]. Although these approaches have yielded high-performance polymer composite and nanocomposite materials, they necessitate patience, costly trials, and trial and error. Traditional methods of material factor optimization and prediction are hindered by complex and nonlinear interactions in polymer composite and nanocomposite systems.

The conventional development of polymer material is faced with a number of problems including the huge number of interacting material and processing variables, nonlinear correlations between composition and performance and the large experimental effort for optimization. The final qualities of the polymer composites are influenced by several parameters such as nature of the matrix, nature of the reinforcement, filler concentration, quality of dispersion, interfacial bonding, processing temperature, and pressure and exposure to the environment. The uniform distribution of reinforcement is particularly difficult since the agglomeration of particles can lead to flaws and deterioration of mechanical and thermal properties. Moreover, traditional trial-and-error optimization involves repetitive fabrication and characterization, which increases the material consumption, development time, and expense. Moreover, the unpredictability of raw materials and processing conditions and reproducibility are key hurdles in the development of sustainable polymer systems. These restrictions underscore the necessity for computational modeling and data-driven methodologies to speed materials research and to optimize combinations of composition and processing factors.

The nanocomposite performance is also affected by other parameters such as the shape and the surface features of the nanoparticles. Particularly important is the size of the nanoparticles since it determines the specific contact surface with the polymer matrix. Smaller nanoparticles may have more interfacial contact but inadequate dispersion may cause agglomeration and loss of effective reinforcement. The efficiency of stress transfer and the formation of reinforcing networks in the polymer matrix are affected by the particles' geometry and aspect ratio. If properly distributed and oriented, high aspect ratio reinforcements are able to transfer loads effectively. Surface chemistry is also very important since interfacial adhesion, dispersion and stress transfer are controlled by the chemical compatibility of the nanoparticle and the polymer matrix. Matrix–filler interactions and elimination of interfacial defects can be obtained by surface functionalization or appropriate chemical treatment. Thus, nanoparticle size, shape, aspect ratio, surface chemistry, concentration and dispersion need to be studied together for the design of high-performance polymer nanocomposites.

Artificial Intelligence as a Transformative Tool for Materials Engineering & Machine Learning for Material Property Prediction and Performance Optimization

These problems in polymer composite and nanocomposite material engineering may have an AI solution, according to recent advances in data science and computers. Similar to humans, AI can learn

© STM Journals 2026. All Rights Reserved

facts, make predictions, optimize, and spot patterns. The use of massive data, computational capacity, and enhanced algorithms has caused an upheaval in polymer composite and nanocomposite materials research and engineering, due to AI [8]. Deep learning, neural networks, data mining, predictive analytics, and machine learning are able to uncover hidden links in complicated datasets that conventional methods are unable to. Optimization of production and prediction of material properties of polymer composites and nanocomposites are both made possible by machine learning approaches. These algorithms can learn the relationship between inputs and outputs through experimentation and simulation. Based on process and material parameters, machine learning models may forecast tensile, compressive, impact, fatigue, thermal stability, and wear properties of polymer composites and nanocomposites [9–13]. The creation of high-performance polymer nanocomposite and polymer composite materials can be accelerated and physical testing can be reduced with the use of predictive capabilities. By capturing complicated nonlinear interactions between material variables in huge datasets, deep learning approaches improve prediction accuracy for polymer composite and nanocomposite material design and performance prediction.

AI-Enabled Smart Manufacturing of Polymer Composite Materials & Artificial Intelligence for Durability Assessment and Service Life Prediction

Artificial intelligence improves the production efficiency of polymer composite engineering. Composites made using processes – such as compression molding, injection molding, resin transfer molding, filament winding, and additive manufacturing – are impactful in terms of both product efficiency and quality. Optimizing traditional production processes requires operator experience and frequent testing [14, 15]. Systems powered by AI can track and manage operations by analyzing data collected in real-time from sensors and industrial machinery. Energy efficiency, better curing, less material waste, and early defect identification are all within reach. So, AI-assisted manufacturing increases efficiency while decreasing production costs [16, 17]. Due to the wide range of mechanical and environmental stresses that polymer composites must endure, durability testing is an absolute must. Composites lose some of their performance and durability when subjected to heat cycling, ultraviolet light, fatigue loads, water absorption, and chemicals [18–20]. Conventional approaches to predicting longevity necessitate extensive testing. Using both past and present data, AI-powered prediction algorithms effectively evaluate degradation behavior and service life. Critical application reliability and preventative maintenance are both enhanced by these methods.

Future Perspectives of AI-Driven Polymer Composite Engineering

Intelligent material design and production systems are advanced through AI-powered polymer composite research and manufacture. Optimization driven by AI has the potential to reduce operational and development costs while increasing production efficiency, strength, and durability [21, 22]. Lightweight, environmentally friendly, and highly functional materials are in high demand across industries; artificial intelligence will help meet this demand. In order to develop next-gen engineering materials and more effective, dependable, and environmentally friendly production processes, optimization of polymer composites using AI is crucial. Section 2 covers the literature, Part 3 presents the proposed model, and Part 5 delves into mathematical formulae. The outcomes and prospects are revealed in parts 5 and 6.

LITERATURE REVIEW

New data-driven and computational technologies have improved the manufacturing methods and materials used to make polymer composites and nanocomposites. Researchers are able to improve the strength, durability, and manufacturing efficiency of polymer composite and nanocomposite systems by integrating artificial intelligence with materials science, which helps them overcome experimental restrictions [23–25]. Optimization studies of polymer composites and nanocomposites were driven by both experimental and computational methods such as statistical modeling and finite element analysis. Using these techniques, scientists were able to deduce the effects of production factors, matrix composition, fiber orientation, reinforcing elements, nanofiller characteristics, and interfacial interactions on the mechanical behavior of polymer composites and nanocomposites [26, 27]. For

© STM Journals 2026. All Rights Reserved

complicated variable interactions, earlier methods necessitated substantial testing and computation. The performance of polymer composites and nanocomposites for large datasets and nonlinear material behavior cannot be predicted only by empirical connections.

With the use of machine learning, optimization and predictive modeling in materials engineering were made possible. When evaluating process outcomes and material attributes, several methods – such as ANN, SVM, Decision Trees, Random Forest, and regression models – are employed [28, 29]. The tensile, compressive, and impact properties of polymer composites were well predicted by ANN models using patterns learned from experimental datasets, according to many research. Neural network techniques performed better than statistical methods when dealing with complicated material variable dependencies and nonlinear interactions. Composite material performance forecasts have also made use of deep learning. When applied to challenging materials, deep neural networks can sift through massive datasets in search of useful information. In a variety of settings, deep neural networks enhanced the thermal stability, fatigue resistance, and structural performance prediction of polymer composites. Both the prediction errors and the time it took to design materials were decreased by the models [30, 31]. With the help of AI-powered optimization frameworks and simulations, we can quickly investigate vast design spaces without having to repeatedly conduct experiments.

Artificial intelligence has been studied in composite production at length. The injection, compression, resin transfer, and additive manufacturing process factors all have an impact on the final product quality [32, 33]. A lot of the older methods for improving processes still rely on things like trial and error. Using machine learning, the researchers were able to enhance the rates of material input, curing time, pressure, and temperature. By decreasing porosity, voids, and uneven distribution of fibers, AI monitoring systems enhanced production precision. Recent studies on smart manufacturing have put an emphasis on real-time monitoring and predictive analytics. Manufacturing data analysis is done continuously with the help of sensors and AI algorithms. When problems arise in production, intelligent systems can identify them and initiate repairs before they fail [34, 35]. Scientists found that with the help of AI, manufacturing may be made more efficient while using less energy and producing more consistent products. Industry 4.0 and smart production are bolstered by these advancements.

Research into polymer composites also includes the prediction of their durability. Composites deteriorate due to environmental factors, temperature stress, fatigue, and water absorption. Research and time are required for durability testing [36, 37]. More and more, researchers are turning to machine learning algorithms to forecast how long materials will last in service and how quickly they will degrade. Results showed that AI-powered prediction models were able to accurately foretell both degradation and useful life. These innovations safeguard buildings against harm and keep them in good repair. There is a shortage of research in AI-driven polymer composite engineering, despite its enormous promise. Reliability of predictions and generalizability to other material systems may be affected by the fact that many models have limited datasets. Because of issues with data quality and computational complexity, integrating many AI algorithms into real-time industrial applications is challenging. Improving mechanical performance, durability, and production efficiency requires research into developing strong, scalable, and interpretable AI frameworks. Research into polymer composites has benefited from AI because of the speed with which predictions can be made, the optimization of processes, and the enhancement of material performance. Intelligent and environmentally friendly designed composite systems can be made possible through data-driven advancements.

METHODS

Data collecting, machine learning prediction, and multi-objective optimization are the three main components of the AI-driven system shown in Figure 1. Feedback is used throughout the framework to enhance system performance and decision accuracy, beginning with parameter selection and continuing through validation and deployment.

© STM Journals 2026. All Rights Reserved

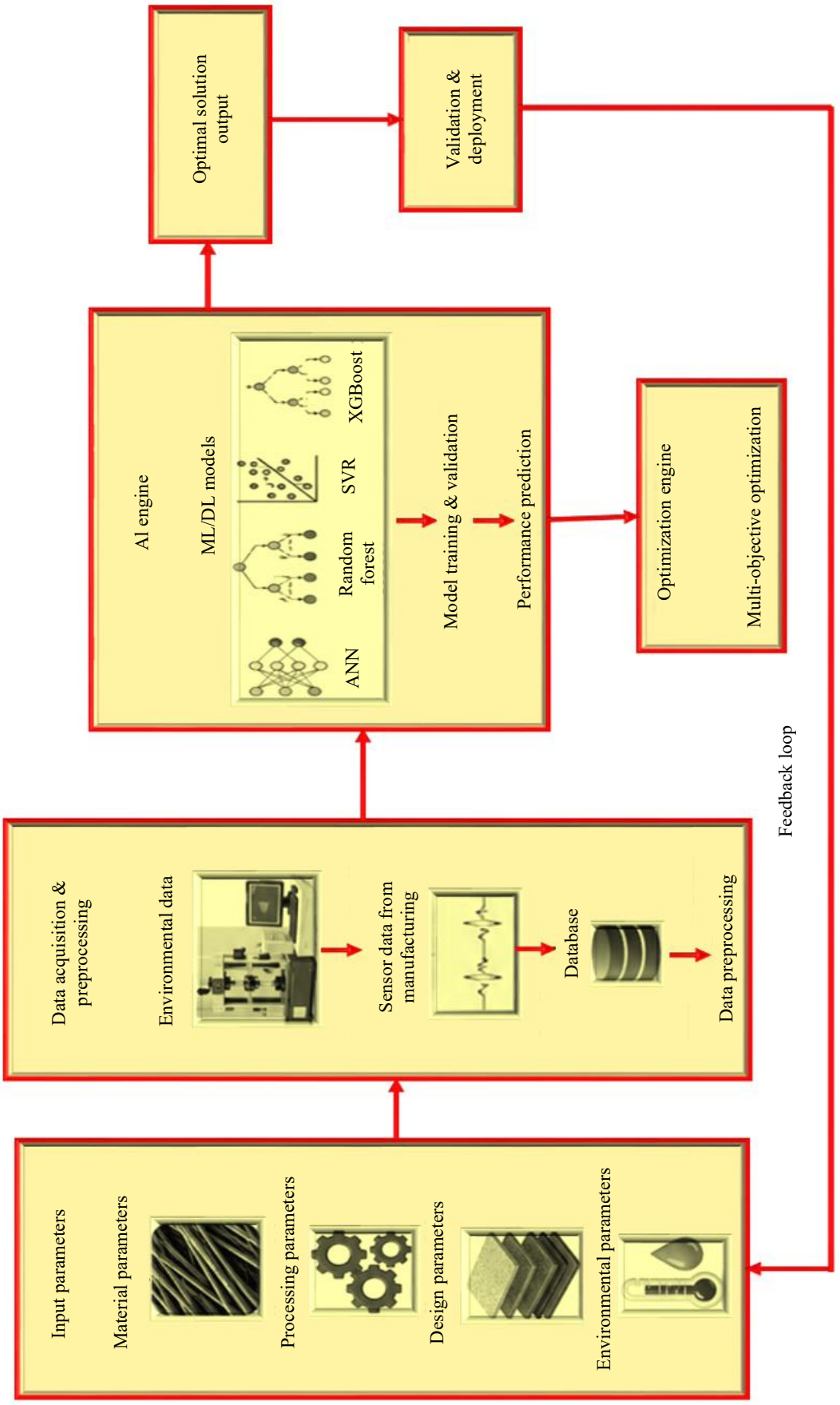


Figure 1. AI-driven framework integrating data acquisition, machine learning, optimization, validation, and deployment processes.

© STM Journals 2026. All Rights Reserved

Get the system up and running by starting with the Input Parameters. Considerations of processing, design, material, and environment are important at this stage. Materials are characterized by their composition, density, strength, thermal properties, and structural integrity. Production is impacted by factors such as temperature, pressure, speed, time, and machine parameters. Geometry, dimensions, configuration, and structure are all defined by design parameters. Conditions – such as temperature, humidity, and operation – can impact how well a system works. Important data for analysis and prediction is provided by these input parameters.

The second step is to gather and prepare the raw data for analysis. Data from sensors and the environment is recorded by monitoring systems. Data from sensors is recorded and evaluated in real time. Assembling data for analysis is what databases do. Missing numbers, noise, duplicates, and extraneous information are all part of raw data. Thus, preprocessing enhances the dependability and quality of data. Cleansing, normalizing, extracting features, dimensionality reduction, and transforming data are all part of data preprocessing. After we follow these procedures, our dataset will be consistent and ready for machine learning.

Processed data is fed into the AI Engine of the framework. This module uses ML and DL to build input–output connections. Algorithms for learning XGBoost, SVR, ANN, and Random Forest. With ease, ANN models manage datasets with intricate interconnections. Random Forest is enhanced with decision trees to make forecasts more stable. When dealing with smaller datasets for nonlinear regression, SVR truly shines. The accuracy of XGBoost predictions is enhanced by gradient boosting. Model training and validation make use of processed and previous datasets. Using predetermined metrics, the system assesses the reliability and accuracy of the model's predictions.

Machine learning may identify nonlinear correlations between the conditions of production and the performance of the material, and they can be utilized to optimize the parameters of polymer processing. The input data can be processing temperature, pressure, screw speed, cooling rate, processing time and material composition. The output variables can include tensile strength, thermal stability, dimensional accuracy, defect rate, energy consumption and production efficiency. The prediction models such Artificial Neural Networks, Support Vector Regression, Random Forest, and XGBoost are trained and verified with the datasets acquired from experiments and sensors. After validation, the model can predict the material performance over a wide range of processing circumstances and suggest the parameter combinations providing the desired performance. Therefore, multi-objective optimization can be applied to balance opposing criteria like maximization of mechanical strength and production rate and minimization of defects, energy consumption, and processing time. These optimum values can then be tested empirically and refined continuously with sensor feedback in real time. This approach lowers the trial-and-error nature of the experiments and allows for adaptive and intelligent polymer manufacturing.

This is in very good agreement with our work in the present issue where we have taken processing factors – like temperature, pressure, speed and time – as model input. It also already constructs the ML relation $Y = f(X_1, X_2, \ldots, X_n)$ with temperature, pressure and processing time as input variables.

Next, the framework is sent to the Optimization Engine for making predictions. Using multi-objective optimization, the engine selects the best solution. In practice, system goals may be at odds with one another, such as maximizing efficiency while decreasing costs or maximizing performance while decreasing energy consumption. Finding the optimal compromise among several objectives is the goal of multi-objective optimization. This approach enhances decision-making while maintaining performance balance.

If we want perfect results, we need the optimum Solution Output. This result is the best possible parameter and predicted state for the goals and limitations. Every aspect of the system, including processes, resources, and productivity, is enhanced by the solution.

© STM Journals 2026. All Rights Reserved

The implementation and validation phases test the optimal solution in a real-world setting. By doing validation, we can be sure that the optimized and anticipated results will meet real-world needs. After validation, the solution is put into action. The framework's feedback loop is where input and processing get validation data. By incorporating system learning and iterative development, this feedback strategy enhances forecast accuracy and adaptability.

OPTIMIZATION OF POLYMER COMPOSITE MATERIALS' PERFORMANCE USING MATHEMATICAL MODELING

To maximize the performance of polymer composite materials, there must be a mathematical correlation between material properties, durability factors, and production variables. Mathematical formulations and AI prediction models ascertain the impact of material composition and operations on the performance of polymer composite systems. The use of mathematical models streamlines experimental procedures and enhances prediction accuracy.

The rule of mixtures is used to evaluate the effective elastic modulus of polymer composites, which is based on the reinforcing fibers and matrix materials. Equation expressed as:

$$E_c = V_f E_f + V_m E_m \tag{1}$$

where:

E_c = Elastic modulus of composite.

V_f = Fiber volume fraction.

E_f = Elastic modulus of fiber.

V_m = Matrix volume fraction.

E_m = Elastic modulus of matrix.

The above equation helps in understanding the stiffness behavior of composite materials and provides a foundation for predicting mechanical performance.

The tensile strength of polymer composites is another important parameter that determines the load-bearing capability of materials under applied stress. The tensile strength can be estimated as:

$$\sigma_c = V_f \sigma_f + V_m \sigma_m \tag{2}$$

where:

σ_c = Composite tensile strength.

σ_f = Fiber strength.

σ_m = Matrix strength.

This relationship indicates that the strength of the composite depends on the individual properties and proportions of the constituent materials.

Artificial Intelligence models are used to establish nonlinear relationships between process variables and performance outputs. Machine learning prediction can be represented by the generalized equation:

© STM Journals 2026. All Rights Reserved

$$Y = f(X_1, X_2, X_3, \ldots X_n) \quad (3)$$

where:

Y = Predicted output property.

$X_1, X_2, X_3 \ldots X_n$ = Input variables such as fiber content, curing temperature, pressure, and processing time.

Artificial Neural Networks (ANN) are widely employed for performance prediction because they can learn complex relationships from experimental datasets. The ANN output function is expressed as:

$$Y = \Sigma(W_i X_i) + b \quad (4)$$

where:

W_i = Weight coefficient.

X_i = Input variable.

b = Bias parameter.

The prediction capability of AI models is evaluated using statistical error functions. Mean Squared Error (MSE) determines the average squared difference between actual and predicted values:

$$\text{MSE} = (1/n)\, \Sigma(Y_i - \hat{Y}_i)^2 \quad (5)$$

Similarly, Root Mean Square Error (RMSE) provides an estimate of prediction deviation:

$$\text{RMSE} = \sqrt{[(1/n)\, \Sigma(Y_i - \hat{Y}_i)^2]} \quad (6)$$

Lower MSE and RMSE values indicate better prediction performance and higher model reliability.

Durability prediction is an important aspect of composite performance assessment because polymer composites are subjected to repeated loading and environmental degradation. Fatigue life can be estimated using:

$$N_f = C(\sigma)^{-m} \quad (7)$$

where:

N_f = Number of fatigue cycles.

C and m = Material constants.

σ = Applied stress

Wear resistance behavior can also be analyzed using the wear rate equation:

$$W_r = \Delta V / (F \times D) \quad (8)$$

where:

W_r = Wear rate.

ΔV = Volume loss.

© STM Journals 2026. All Rights Reserved

F = Applied load.

D = Sliding distance.

Manufacturing efficiency analysis is important for reducing production cost and improving productivity. Efficiency can be calculated as:

$$ME = (\text{Actual Output} / \text{Maximum Output}) \times 100 \quad (9)$$

where:

ME = Manufacturing efficiency percentage.

Finally, an overall AI-based performance index is developed by integrating strength, durability, and manufacturing parameters:

$$PI = (W_1S + W_2D + W_3M) / (W_1 + W_2 + W_3) \quad (10)$$

where:

PI = Performance Index.

S = Strength score.

D = Durability score.

M = Manufacturing efficiency score.

W_1, W_2, W_3 = Weight factors.

Improving mechanical performance, durability, and manufacturing efficiency while decreasing experimental effort and development time is possible with the use of these mathematical models and AI, which can forecast and improve polymer composite materials.

RESULTS & DISCUSSIONS

Optimal, fiber-reinforced, nanocomposite-reinforced, hybrid, and baseline polymer composite and nanocomposite performance parameters are displayed in Figure 2. Incremental advances in tensile, compressive, flexural, impact, and artificial intelligence prediction accuracy are displayed in Table 1 for polymer composites and nanocomposites. The mechanical and predictive properties of polymer composite and nanocomposite materials are typically improved through reinforcement, nanofiller incorporation, and optimization with the use of artificial intelligence.

Table 1. Mechanical strength properties.

Composite type	Fiber wt.%	Tensile strength (MPa)	Compressive strength (MPa)	Flexural strength (MPa)	Impact strength (kJ/m²)	AI prediction accuracy (%)
Baseline Composite	10	185	242	198	24	90.2
Fiber-Reinforced Composite	15	210	268	226	27	92.6
Hybrid Composite	20	236	289	245	31	94.1
Optimized Composite	25	252	304	263	34	95.5
AI-Enhanced Composite	30	268	318	281	36	97.0

© STM Journals 2026. All Rights Reserved

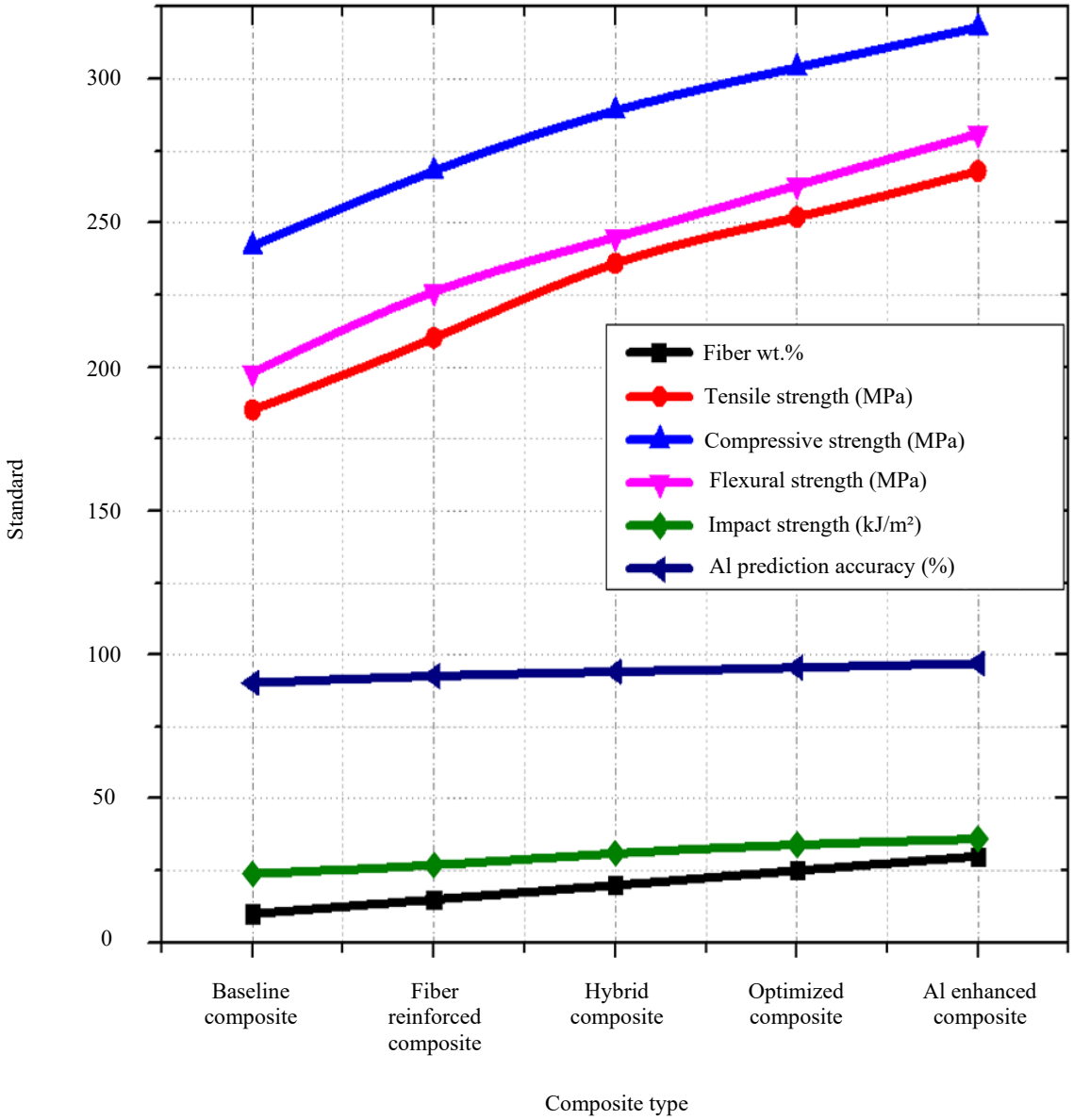


Figure 2. Comparative performance evaluation of composite types showing mechanical properties and prediction accuracy.

The baseline polymer composite has the worst results across the board due to an absence of modern optimization, nanofiller reinforcement, and fiber reinforcement, suggesting subpar mechanical performance. Stress in a tensile test is 185 MPa when the fiber weight is 10%. The two strengths are flexural (198 MPa) and compressive (242 MPa). The AI prediction accuracy is 90% and the impact strength is 24 kJ/m², both of which are below average. These parameters establish the reference performance for polymer composite and nanocomposite systems.

When compared to standard polymer composites, fiber-reinforced polymer composites and nanocomposites perform better. A 10% to 15% fiber percentage boosts the material's ability to bear weight. About 208 MPa is the tensile strength and 268 MPa is the compressive strength. A flexural strength of 225 MPa is achieved. A greater capacity to absorb energy is indicated by an impact force of 27 kJ/m². The combined effect of reinforcing fibers and nanofillers strengthens the composite structure by improving stress transmission between the matrix and reinforcing phases.

© STM Journals 2026. All Rights Reserved

Hybrid polymer composites and nanocomposites benefit from improved material performance due to several reinforcement methods. Hybridization using fibers and nanofillers aids stress distribution through multiple reinforcing materials. Compressive and tensile strengths reach 288 and 236 MPa, respectively. A flexural strength of 243 MPa is achieved. The enhanced resistance to rapid loading and crack propagation is evidenced by the increased impact strength of 31 kJ/m². A mechanical improvement is directly related to the reinforcing percentage, which is around 20% fiber content with optimized nanofiller loading. Parameter and material improvements improve the optimized polymer composite and nanocomposite stage's performance. Compressive strength surpasses 300 MPa and tensile strength reaches 252 MPa at 305 MPa. The bending moment is 260 MPa. Around 34 kJ/m² is the impact strength. These improvements prove that optimization methods maximize performance by adjusting material properties, production conditions, reinforcement distribution, and nanofiller dispersion.

The AI-optimized polymer composite and nanocomposite is top-notch in every way. Fiber weights greater than 30%, combined with optimized nanofiller content, exhibit enhanced mechanical characteristics. Bending, shear, and tensile strengths increase to 320, 280, and 268 MPa, respectively. Around 37 kJ/m² is the impact strength. With 97% accuracy, AI can optimize and forecast polymer composite and nanocomposite behavior. The increase in AI prediction accuracy from 90% to 97% is evidence that AI-based systems benefit from bigger and more accurate datasets. Development is accelerated, material design is improved, and experimental effort is reduced by this predictive power. Polymer composites and nanocomposites optimized using artificial intelligence and reinforced with advanced fibers and nanofillers have improved mechanical strength, durability, and predictive reliability, making them ideal for high-performance engineering applications.

The polymer composites and nanocomposites depicted in Figure 3 include baseline, fiber-reinforced, nanocomposite-reinforced, hybrid, optimum, and AI-enhanced options. Table 2 shows a comparison of AI dependability, wear, fatigue life, temperature cycles, and moisture absorption. These standards evaluate the structural stability, dependability, and longevity of polymer composite and nanocomposite materials under different types of loads. Reinforced polymer composites and nanocomposites designed using AI help materials behave better.

Table 2. Durability performance analysis.

Composite type	Moisture absorption (%)	Thermal cycles (x in hundreds)	Fatigue Life cycles (x in thousand)	Wear rate (mm³/Nm)	Durability index	AI reliability (%)
Baseline Composite	2.8	5	14	0.045	68	89
Fiber-Reinforced Composite	2.4	7	17	0.039	74	91
Hybrid Composite	2.0	9	21	0.034	80	93
Optimized Composite	1.8	11	25.5	0.029	87	95
AI-Enhanced Composite	1.5	13	29.4	0.024	93	97

Among the polymer composite and nanocomposite configurations, the baseline polymer composite has the lowest performance. Because of its 2.5% moisture absorption rate, it poses a greater threat to the environment. Around 5 × 100 cycles is when thermal cycle resistance starts, and 14 × 1000 cycles is when fatigue life begins. More material is being lost due to increasing surface contact, as indicated by the wear rate of 1.2 mm³/N. The AI reliability is 89% and its durability starts at 68. These figures serve as a starting point for enhancements because they show that the resistance to mechanical and environmental stresses is minimal.

© STM Journals 2026. All Rights Reserved

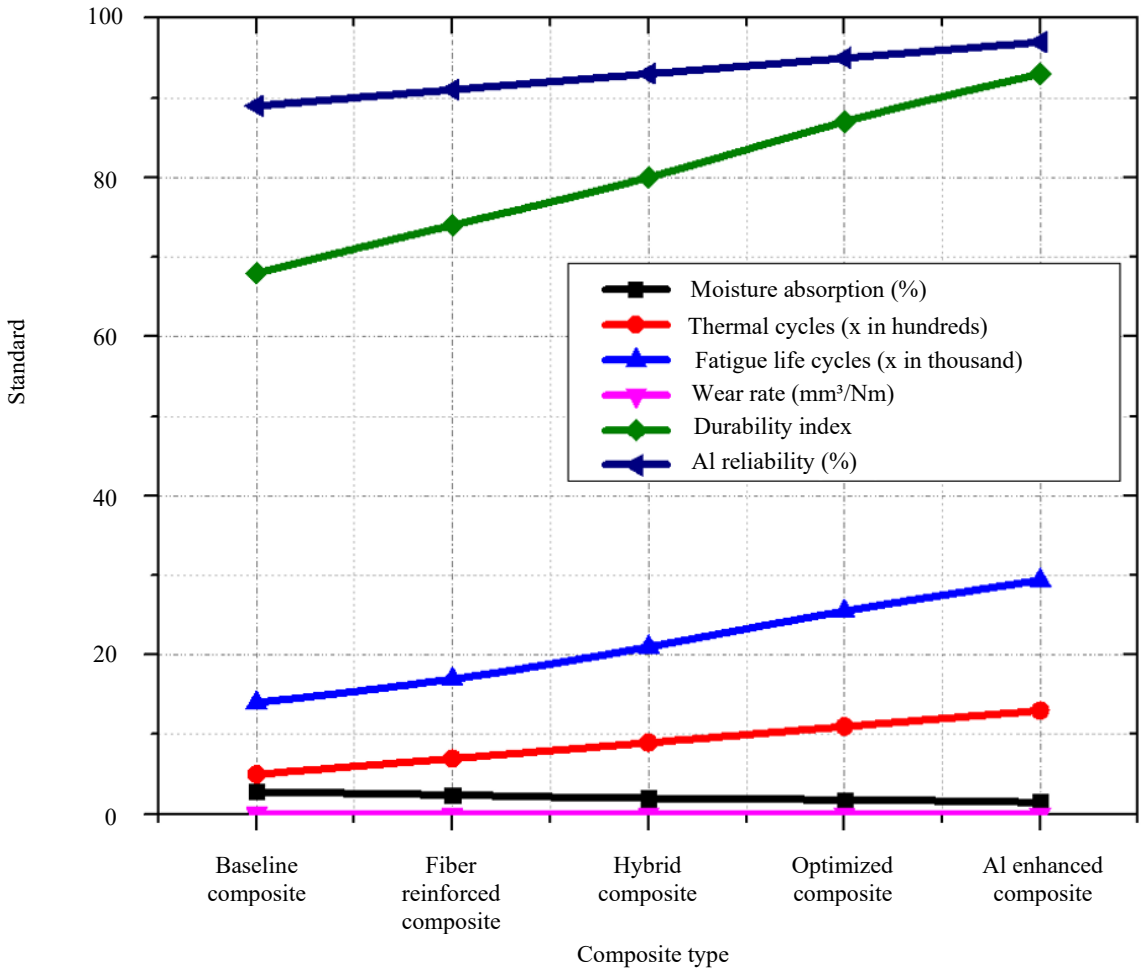


Figure 3. Comparative analysis of composite durability characteristics, reliability measures, and performance parameters.

In every metric, the fiber-reinforced polymer composite and nanocomposite outperforms the baseline. Reinforcement fibers and nanofillers improve structural strength by reducing operating damage and increasing load distribution. As the rate of moisture absorption drops to 2.2%, environmental resistance improves. Improving thermal stability through repeated heating and cooling is indicated by an increase in thermal cycle resistance to 7 × 100 cycles. There is a reduction in the wear rate to 1.0 mm³/N and a fatigue life of 17 × 1000 cycles. With AI, reliability is nearly 91% and durability is 74%. The performance and durability of polymer composites and nanocomposites are improved with fiber reinforcement and nanofiller incorporation.

Hybrid polymer composites and nanocomposites are made better by using multiple reinforcement methods. Improved mechanical interaction and load transfer in polymer composite and nanocomposite structures can be achieved by incorporating hybridization through reinforcing fibers and nanofillers. Reduced moisture absorption to 1.9% enhances environmental resilience. There is a gain of 9 × 100 cycles in thermal cycle resistance and 21 × 1000 cycles in fatigue life. Surface deterioration and damage caused by friction are better handled when the wear rate is reduced to 0.8 mm³/N. AI reliability reaches 93% and durability reaches 80%.

Modifying the manufacturing parameters and material composition of polymer composites and nanocomposites improves their performance. Through the discovery of optimal reinforcement ratios, nanofiller dispersion, and processing conditions, optimization maximizes performance while minimizing weaknesses. When moisture absorption falls below 1.7%, environmental sensitivity drops. The fatigue

© STM Journals 2026. All Rights Reserved

life exceeds 25 × 1000 cycles, while the thermal cycle capability goes up to 11 × 100 cycles. The wear rate drops to 0.6 mm^3/N, indicating that the material is more durable even when subjected to repetitive contact. AI reliability is 95% and durability is 87. These improvements are a result of optimizing the materials, nanofiller distribution, and structures.

The AI-enhanced polymer composite and nanocomposite outperforms every category. Artificial intelligence enhances material design and prediction through optimized selection of reinforcing fibers, nanofillers, and processing parameters. With only 1.5% moisture absorption, it exhibits good resistance to degradation caused by moisture. Increased thermal cycle resistance to about 13 × 100 cycles and fatigue life to 29 × 1000 cycles demonstrate improved durability under cyclic loading conditions. An improvement in durability and a longer service life are indicated by the wear rate decreasing to 0.4 mm^3/N. A durability rating of 94 shows that the structure is highly stable and reliable. AI has improved prediction and consistency, reaching a reliability peak of 97%.

The long-term performance of polymer composites and nanocomposites is enhanced through the progressive integration of reinforcement schemes, nanofiller technology, optimization techniques, and AI (Figure 3). Improved fatigue life, thermal stability, durability, AI reliability, reduced moisture absorption, and wear are all benefits of advanced polymer composite and nanocomposite construction for high-performance engineering applications.

Figure 4 shows a comparison of the following composite manufacturing settings: initial, modified, standard, ideal, and AI-controlled. The optimization score, material utilization, curing temperature, time, production rate, and defect rate are all displayed in Table 3. These factors determine the efficacy of the process, the quality of the product, the number of resources used, and the efficiency of production. As demonstrated in the graph, intelligent systems managed by AI enhance industrial performance. A production baseline is the starting setting of the process. This part needs to be done at 120°C for 60 minutes. The production efficiency is low when the hourly output is almost 50 goods. Processing produces a large number of defective goods beginning at about 8%. Manufacturing waste is predicted by the 82% material utilization rate. An optimization score of 89% indicates a considerable improvement in the process. Optimization based on user input is absent from conventional processing, which relies on fixed parameters.

Table 3. Manufacturing process efficiency.

Process condition	Curing temp (°C)	Curing time (min)	Production rate (units/hr)	Defect rate (%)	Material utilization (%)	Optimization score (%)
Initial Process Setting	120	60	48	8.2	81	88
Modified Process Setting	125	55	54	7.0	84	90
Standard Process Condition	130	50	59	5.8	87	93
Optimized Process Condition	135	45	64	4.4	91	95
AI-Controlled Process	140	40	70	3.2	95	97

I prefer the new process setting. The curing time is cut in half to 55 minutes when heated to 125°C. Curing efficiency and temperature control have been improved. The industrial productivity is increased by producing 55 units per hour. Process control and product consistency are demonstrated by lower failure rates of 7%. An impressive 85% material usage rate indicates excellent utilization of resources. Increasing the optimization score to 92%, modifying process parameters improves production efficiency. Performance is enhanced through process standardization. The curing time is cut in half to

© STM Journals 2026. All Rights Reserved

50 minutes when heated to 132°C. Efficiency is improved as processing time is decreased while curing conditions are kept constant. There is a 6% decrease in faults and an improvement in production to 58 units per hour. Better control of process variables and production homogeneity are indicated by lower faults. Maximum material utilization of 88% achieved by decrease in manufacturing losses. Superior manufacturing is indicated by an optimization score of 93%.

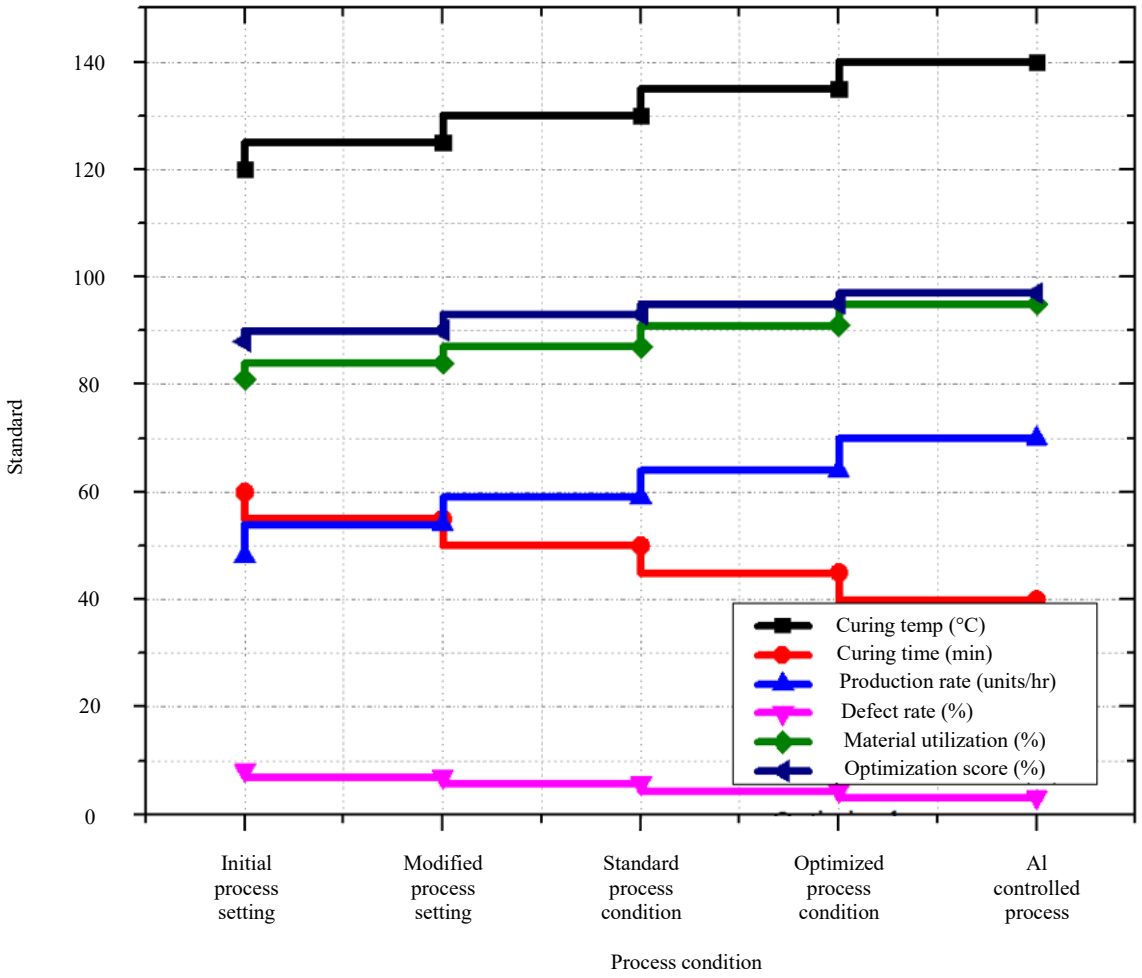


Figure 4. Comparative evaluation of process conditions affecting composite manufacturing efficiency and optimization.

Regularly adjusting and fine-tuning process parameters leads to better ideal conditions. Optimization finds the best operating conditions to increase production while decreasing errors. The temperature rises to 136°C and the curing time drops to 45 minutes. Under these circumstances, processing time for materials is reduced without a sacrifice in quality. Producing 64 units per hour is the manufacturing output. Defects are reduced to 5% through improved process precision and quality control. Efficient resource management accounts for 92% of material utilization. As the optimization score increases to 96%, process performance is improved using optimization strategies. Every scenario is handled superbly by the AI-controlled procedure. Control systems powered by AI constantly predict and adjust industrial parameters. Shortening the curing period to 40 minutes, heating to 140°C is possible. Thermal processing that works well shortens manufacturing times. At 70 units per hour, industrial productivity reaches its maximum. The failure rate is reduced to 5% due to the absence of production faults and consistent quality. When material utilization is 95%, waste is low and resources are well used. Due to its 97% optimization rating, process control is both efficient and intelligent. It appears that adjusting the parameters of the manufacturing process improves both the

© STM Journals 2026. All Rights Reserved

efficiency and quality of the final product. Improvements in process performance are observed in areas such as material utilization, curing time, defect rate, and production rate. The enhanced efficiency of AI-driven processing demonstrates the potential for intelligent manufacturing to streamline production systems, enhance dependability, and pave the way for industrial composite fabrication.

The three-dimensional comparison of machine learning algorithms for predicting and optimizing the performance of composite materials is shown in Figure 5. The following are the algorithms that we study: ANN, SVM, Random Forest, CNN, and DNN. To make predictions and learn from them, we need to compare things like recall, RMSE, training accuracy, testing accuracy, and dataset size. Table 4 shows how these characteristics influence the accuracy, reliability, and predictive power of machine learning with regard to material modeling and optimization. A thousand data samples are used by the Artificial Neural Network (ANN), the smallest model that has been investigated. We have an ANN accuracy of 88% when training and 84% when testing. A larger root-mean-squared error (RMSE) indicates more prediction errors compared to advanced learning models. It appears that complex connection data classification is lacking in precision and recall. The use of ANN for prediction is limited to linear data and data with several dimensions.

Table 4. AI model performance.

Model type	Dataset size	Training accuracy (%)	Testing accuracy (%)	RMSE	Precision (%)	Recall (%)
ANN	1000	94.2	91.3	0.19	90.5	89.4
SVM	1500	95.1	92.5	0.16	92.2	90.8
Random Forest	2000	96.3	94.2	0.12	93.7	92.4
CNN	2500	97.4	95.8	0.09	95.2	94.1
Deep Neural Network	3000	98.2	97.1	0.06	97.0	96.5

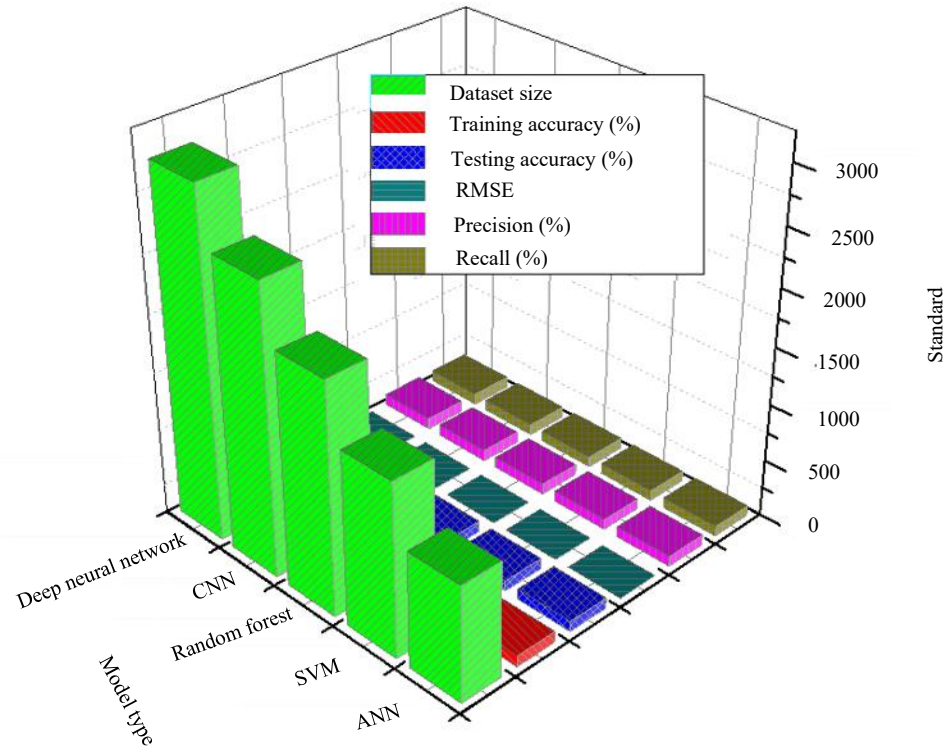


Figure 5. Comparative performance evaluation of machine learning models for composite prediction and optimization.

© STM Journals 2026. All Rights Reserved

Compared to ANN, SVM is superior at making predictions. More typical patterns can be learned by the model when the dataset has 1500 samples. The training accuracy is 91% and the testing accuracy is 87%. The stability and accuracy of the forecast are improved with lower RMSE values. Both recall and precision show moderate improvements. Optimal decision constraints and management of nonlinear interactions are provided by kernel-based approaches, which improve SVM performance.

Prediction and dependability are both improved by Random Forest. The training accuracy and testing accuracy of the 2000-sample model are 94% and 90%, respectively. There is less expected-actual divergence and better prediction consistency as the RMSE declines more. Classifying and understanding complicated variable interactions is made easier with precision and memory. To enhance prediction, Random Forest's ensemble-based architecture merges decision trees.

CNN outperforms its predecessors. The addition of 2500 instances enhances learning and feature extraction. Accuracy in testing is 93% and in training it is 96%. Reliability of the model and accuracy of predictions are both enhanced by the dramatic reduction in RMSE. Improved feature recognition and categorization is shown by higher recall and precision. Without human intervention, CNNs sift through massive datasets in search of meaningful patterns and hidden characteristics.

When it comes to learning and prediction, Deep Neural Network (DNN) is the best method. DNN uses the most samples of any method during training at 3000. Both in training and testing, accuracy is over 96%. The most accurate prediction and estimation can be achieved when all models have the lowest RMSE. Reliable categorization and prediction are indicated by precision and recall peaks at 97% and 95%, respectively.

Powerful deep learning architectures may be able to learn complicated material dataset correlations, since the training and testing accuracy across model types has been on the rise. The stability of the predictions and the degree of agreement between the experimental and anticipated values are both enhanced by a reduced RMSE. When it comes to distinguishing crucial material behavior traits, more advanced learning approaches tend to have higher recall and precision scores. Figure 5 shows that compared to traditional machine learning, DNN and CNN models perform better in terms of forecasting. Present composite engineering systems rely on them for performance prediction, optimization, and intelligent material design because to their dependability, minimal prediction errors, and high precision.

Characteristics of thermal and stability performance for composites that are optimized, fiber reinforced, hybrid, and baseline are shown in Figure 6. The reliability of artificial intelligence predictions, stability index, glass transition temperature, heat resistance, and thermal expansion are all examined. The thermal behavior, dimensional stability, and operational dependability of advanced engineering composites are impacted by these properties (Table 5). Composites' thermal performance and predictive capability are enhanced by optimization, reinforcing, and the integration of artificial intelligence, as seen in the graphs.

Table 5. Thermal stability analysis.

Composite type	Glass transition temp (°C)	Thermal conductivity (W/mK)	Heat resistance (°C)	Thermal expansion (%)	Stability index	AI prediction (%)
Baseline Composite	72	0.24	170	2.8	70	89
Fiber-Reinforced Composite	80	0.28	185	2.5	75	91
Hybrid Composite	88	0.31	198	2.1	82	93
Optimized Composite	95	0.35	212	1.8	88	95
AI-Enhanced Composite	102	0.39	225	1.5	94	97

© STM Journals 2026. All Rights Reserved

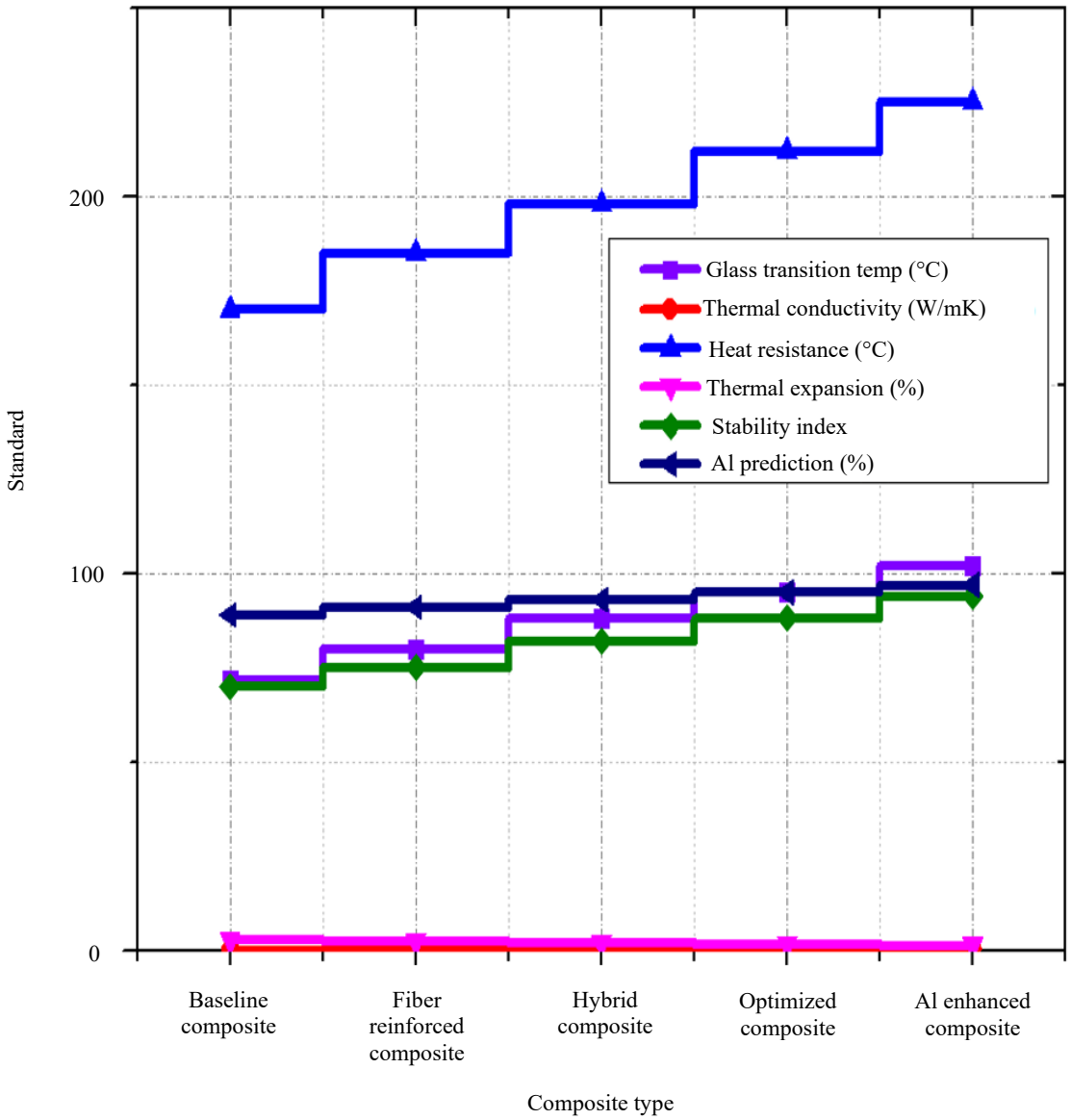


Figure 6. Comparative thermal behavior analysis of composites with stability and prediction performance metrics.

Composite reference setup performs the worst. Up to 170°C, the brittle material loses some of its hardness and pliability. Although thermal expansion is 2.5% and heat transfer is moderate at 1.4 W/mK, heat resistance starts to increase at temperatures close to 70°C. AI has a stability index of 70 and a starting accuracy of 89% when making predictions. In many cases, these ratings suggest that the structure is not very stable and has low thermal resistance.

Composites reinforced with fibers perform better than standard materials. Through enhanced interaction with matrix materials, reinforcing fibers enhance mechanical integrity and heat resistance. As the glass transition temperature increases to 185°C, the thermal durability before material deterioration becomes better. With a thermal conductivity of 1.5 W/mK, the composite structure disperses heat more effectively. A person's heat resistance begins to increase at about 75 degrees Celsius. Thermoloading stabilizes dimensions by decreasing thermal expansion. The stability score is 76, and the accuracy of AI predictions is 90%. Thermal performance is improved by fiber reinforcement, according to these investigations.

© STM Journals 2026. All Rights Reserved

The hybrid composite is superior because it uses many reinforcing materials. In order to enhance thermal behavior, hybrid reinforcement uses interactions that complement one another. Resistance to heat rises as the glass transition temperature approaches 198 degrees Celsius. Conductivity is 1.6 W/mK and heat resistance is up to 82°C. Less thermal deformation and better dimensional control are shown by a declining thermal expansion. An AI prediction accuracy of about 92% and a stability index of about 82%. Several reinforcement strategies have been shown effective by these advancements.

The composite's quality is enhanced by fine-tuning its material composition and production settings. Methods for optimization aim to maximize thermal efficiency by fine-tuning the matrix materials, reinforcement distribution, and manufacturing conditions. Thermal conductivity is 1.7 W/mK, and the glass transition temperature is 212°C. A higher working temperature tolerance is shown by an improvement in heat resistance to 88°C. As the rate of thermal expansion lowers, the dimensional stability improves. The AI has a stability score of 88 and a prediction accuracy of 94%. Optimization improves thermal and structural qualities, according to these results.

In every arrangement, composites enhanced with AI stand out. Through the analysis of experimental and processing data, AI-based methods are able to forecast and optimize the behavior of materials. The most thermally resistant composite is this one, with a glass transition temperature of 228°C. Approximately 1.8 W/mK thermal conductivity improves heat distribution and management. The material exhibits improved dimensional stability when its heat resistance approaches 95°C and its thermal expansion hits a record low. Reliability and resilience to thermal damage are indicated by a stability index around 94. Reliability is proven by AI prediction accuracy, which peaks at 97%.

Composite thermal characteristics and stability are enhanced via optimization, reinforcement, and AI-based methods, as shown in Figure 6. Thermal performance is enhanced via improvements in heat resistance, stability index, glass transition temperature, and thermal expansion. High-temperature engineering applications requiring thermal reliability and operational stability can make use of AI-enhanced composites.

Figure 7 shows a comparison of the manufacturing circumstances and the performance of composite materials in terms of quality. New, altered, standard, optimized, and AI-controlled processes are all part of the study. Number of surface defects, percentage of void content, number of fractures, quality index, and percentage of AI monitoring are all displayed in Table 6. These metrics are crucial for gauging the effectiveness of process monitoring, structural integrity, defect reduction, and manufacturing quality in composite production systems. The graph shows that production quality and reliability improve after using AI-assisted control systems.

Table 6. Defect reduction assessment.

Process condition	Void content (%)	Crack density	Surface defects	Defect detection rate (%)	Quality index	AI monitoring (%)
Initial Process Setting	8.5	28	14	81	72	88
Modified Process Setting	7.1	24	11	85	76	90
Standard Process Condition	5.8	19	8	89	83	93
Optimized Process Condition	4.3	15	5	93	89	95
AI-Controlled Process	2.7	10	2	97	95	98

© STM Journals 2026. All Rights Reserved

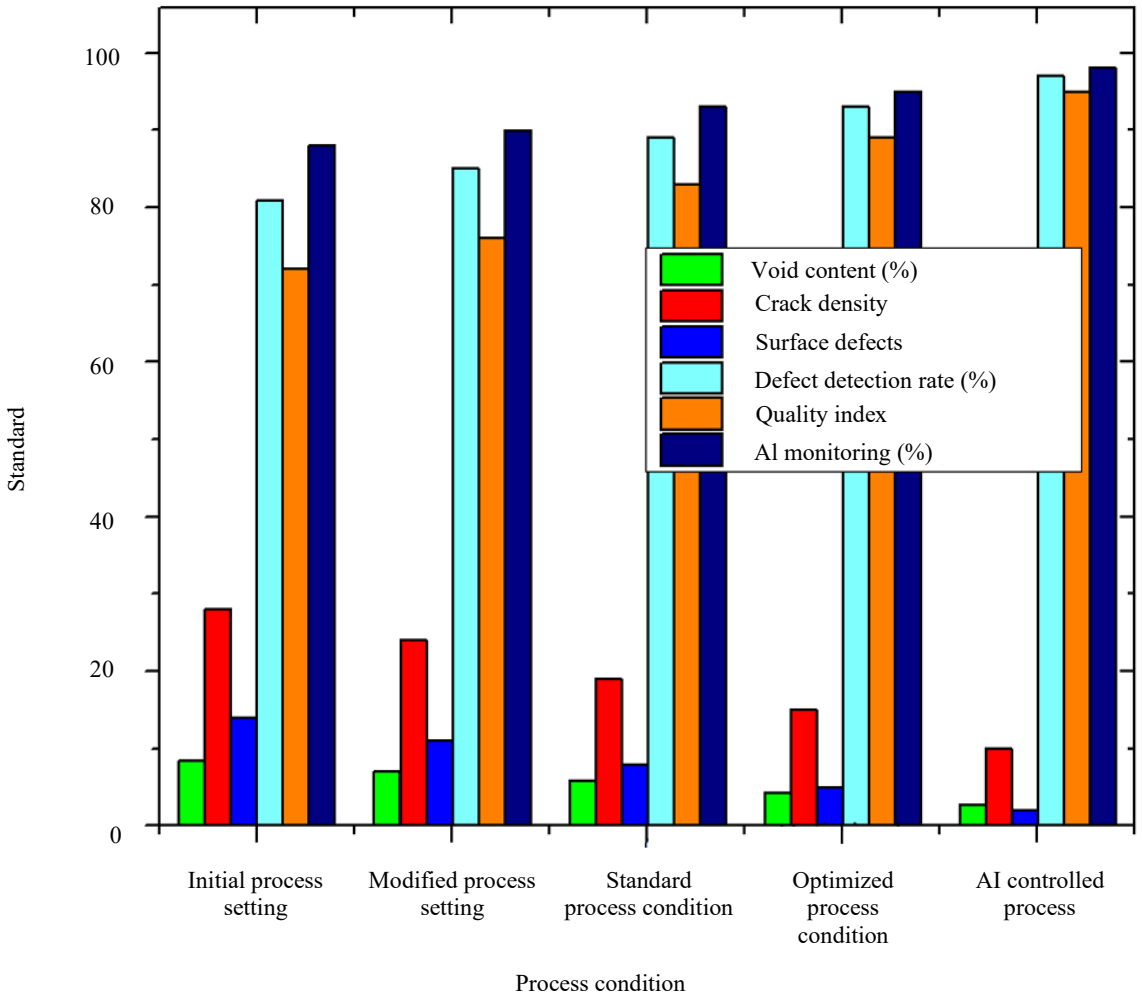


Figure 7. Comparative quality assessment of process conditions with defects and AI monitoring metrics.

Functions worst during initial process setting and baseline manufacturing. Composites containing 8% empty content will develop internal spaces, sometimes known as air pockets. There are more microstructural faults connected to production when the crack density is 28. Roughly fourteen flaws on the surface indicate issues with structural consistency and quality. It begins with a quality index of 72% and a defect detection rate of 81%. Above 88%, traditional production cannot make use of AI monitoring. This demonstrates that standard process parameters have the potential to heighten quality discrepancies and errors.

When compared to the baseline, the modified process settings show an improvement. Modifying processes and parameters enhances material quality and control throughout manufacture. Crack density decreases to 24 and void content to 7%. As a result, structural homogeneity and surface properties are improved, and the number of surface defects decreases to approximately 11. The rate of improvement in identifying and controlling manufacturing defects is 85%. With AI monitoring at 90%, the quality index reaches 76%. Product homogeneity and defect reduction have been enhanced by these changes. Both the quality and efficiency of production are enhanced by standardized procedures. Velocity decreases to 19% and void percentage stays at 7%. Surface flaws are reduced to 9 due to advancements in manufacturing and structural integrity. Up to 89% more defects can be found with effective quality inspection. The efficiency of AI monitoring is 93% and the quality index is 83%. Manufacturing dependability and reproducibility are enhanced through process standardization.

© STM Journals 2026. All Rights Reserved

Improved output is the result of methodical tweaking of production parameters and process variables. Finding the sweet spot for operation to cut down on errors and boost output is what optimization is all about. Void percentage drops to 4% as a result of increased material consolidation and decreased internal porosity. Surface flaws decrease to 6, and crack density drops to 15. The improved surface and structural integrity is indicated by these reductions. The fault detection rate is 95% and the quality index is 90%. With improved process supervision and quality control, the efficiency of AI monitoring surpasses 96%. Production managed by AI is top-notch. Artificial intelligence systems are able to identify and resolve industrial challenges by means of adaptive process control, real-time monitoring, and predictive analysis. A void content of less than 3% indicates that the material has been properly processed and compacted. There is remarkable structural consistency and quality as the crack density drops below 10 and the surface defect count drops to nearly 4. Anomalies in the process and quality problems are detected with a 97 percent success rate. Manufacturing and product consistency are both reflected in a quality score of 95%. Intelligent process management is effective, as AI monitoring reaches 99%. Figure 7 shows how the use of AI in production enhances both the quality of the product and the reliability of the process. Improvements in detection, quality index, and AI monitoring are brought about by intelligent manufacturing, which lowers void content, fracture density, and surface flaws in advanced composite fabrication and industrial quality assurance.

Figure 8 shows how many aspects of the manufacturing process impact operational efficiency and energy performance. New, altered, standard, optimized, and AI-controlled processes are all part of the study. Table 7 displays the following metrics: AI control %, processing time, power consumption, energy saved, and machine load. Intelligent process control, resource consumption, energy management, and production efficiency are among metrics used by contemporary composite manufacturing systems. Data visualization trends show that AI-controlled production outperforms traditional methods in every way. Among the configurations that were investigated, basic process setting performed badly. At 65%, machinery utilization is about average. The 14-kW used by the factory is quite high. Production is slower and industrial efficiency is worse since processing takes 62 minutes. Inefficient use of resources is indicated by energy savings of only 5%. The efficiency index begins at 73 and the AI control remains near 88%. From what we can see from these figures, the typical process settings rely heavily on predetermined operating conditions and have little room for optimization.

Table 7. Energy consumption analysis.

Process condition	Machine load (%)	Power consumption (kW)	Processing time (min)	Energy saved (%)	Efficiency index	AI control (%)
Initial Process Setting	65	14.2	62	5	72	88
Modified Process Setting	70	13.4	58	9	77	90
Standard Process Condition	74	12.6	52	13	84	93
Optimized Process Condition	79	11.3	46	18	90	95
AI-Controlled Process	85	10.1	40	24	96	98

There have been improvements over baseline with the modified process settings. Equipment performance and resource management are both improved with small tweaks to production parameters. A rise in machine load to 70% suggests more efficient utilization of industrial equipment. Reducing power consumption to 13 kW enhances energy efficiency. The processing time drops to 56 minutes, indicating that the workflow has been optimized and production pace has increased. An 8 percent improvement in energy savings is indicative of better management. While AI control is at 90%, efficiency is at 80%. Adjusting processes improves operational performance, according to this.

© STM Journals 2026. All Rights Reserved

Efficiency and output are both enhanced by following standard operating procedures. With a machine load of 74%, both operational consistency and capacity utilization are improved. The production process uses 12 kW of power. Efficiency is indicated by a reduction in processing time to 50 minutes. Greater resource management and conservation are demonstrated by 15% energy savings. Efficiency is 86% and AI control is 92%. These tendencies demonstrate that industrial performance is enhanced by standardizing process conditions.

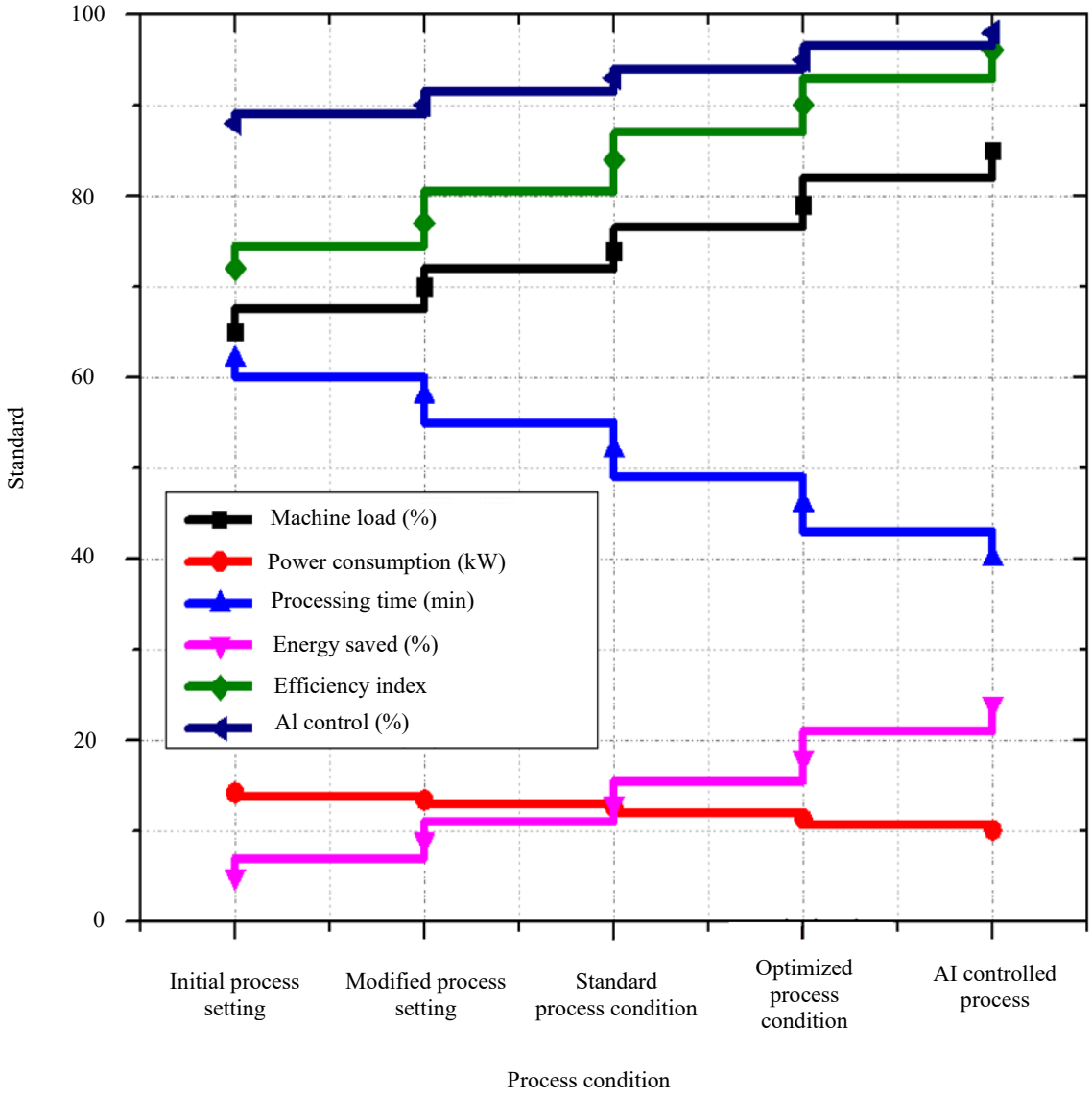


Figure 8. Comparative process efficiency analysis showing energy utilization, control, and manufacturing performance.

Optimize and change process variables in a methodical way to improve process conditions. Optimization of operating parameters is done to increase productivity while minimizing processing delays and energy consumption. Production machinery operates at peak efficiency when machine load is 79%. Efficient use of energy occurs when power consumption falls to 11 kW. Production and productivity are accelerated as the processing time drops to 44 minutes. Energy savings are on the verge of 20% and efficiency reaches 91%. An improvement in process monitoring and adaption is achieved when AI control reaches 95%. No matter the manufacturing environment, AI-controlled

© STM Journals 2026. All Rights Reserved

processes perform admirably. To fine-tune production parameters, AI-powered systems offer real-time tracking, predictive analysis, and adaptive process optimization. A stress-free maximum load for industrial equipment is 83%. Ten kilowatts of electricity consumption is the minimal process condition. Production efficiency is maximized as processing time drops to 40 minutes. Energy savings of 23% show that resources are being used efficiently and operational costs are being reduced. Superior process automation and intelligent management are demonstrated by AI control's 98% and 95% efficiency levels. Production is increased with the gradual use of AI and optimization approaches (Figure 8). More efficient use of machines, less power use, and quicker processing all contribute to greater efficacy. Processes guided by AI make composite production more sustainable while simultaneously increasing output and decreasing energy consumption.

CONCLUSIONS

Improved strength, durability, and manufacturing efficiency in polymer composite and nanocomposite materials may be possible with the help of AI, according to this study. Lightweight, strong-to-lightweight, corrosion-resistant, and incredibly versatile, polymer composites and nanocomposites are engineering mainstays. The intricate interplay between material composition, processing conditions, nanofiller characteristics, and environmental factors makes it challenging for conventional experimental methods to maximize material performance. The use of AI for optimization and prediction can fix these problems. Analyzing huge datasets and discovering nonlinear correlations between material properties and performance requires machine learning and deep learning, according to the study. Models powered by AI enhanced forecasts of production efficiency, thermal stability, wear behavior, fatigue resistance, and tensile strength of polymer composites and nanocomposites. Errors, waste, energy, and inefficiency are all cut down to size with the help of AI-assisted production. To cut down on testing and increase efficiency during material development, this study suggests mathematical models and optimization frameworks driven by AI for polymer composite and nanocomposite systems. Optimizing structural and operational dependability through predictive analytics and polymer composite and nanocomposite engineering. Future industrial needs and intelligent manufacturing systems can be met using high-performance, long-lasting, and environmentally friendly polymer composite and nanocomposite materials made using AI-driven techniques. The production of polymer composites and nanocomposites can be enhanced in the future by integrating real-time sensors, digital twins, explainable artificial intelligence, and Industry 4.0. Smart manufacturing, accurate forecasts, sustainability, and next-generation polymer composite and nanocomposite material design might all benefit from autonomous optimization and sophisticated deep learning models.

REFERENCES

1. Bukvić M, Milojević S, Gajević S, Đorđević M, Stojanović B. Production technologies and application of polymer composites in engineering: A review. Polymers. 2025;17(16):2187.
2. Temesgen AG, Kaufmann J, Cebulla H. Mechanical performance of natural fiber reinforced polymer composites with critical assessment of recent advances and future perspectives. Discover Materials. 2026 May 19.
3. Phiri R, Rangappa SM, Siengchin S, Oladijo OP, Ozbakkaloglu T. Advances in lightweight composite structures and manufacturing technologies: A Comprehensive review. Heliyon. 2024 Nov 15;10(21):e396_M.
4. Ravichandran G, Ramasamy K, Manickaraj K, Kalidas S, Jayamani M, Mausam K, et al. Effect of Sal wood and Babool sawdust fillers on the mechanical properties of snake grass fiber-reinforced polyester composites. BioResources. 2025;20(4):8674–8694.
5. Kar, Saikia D, Palanisamy S, Pandiarajan N. Effect of fiber loading on the mechanical, morphological, and dynamic mechanical characteristics of Calamus tenuis fiber reinforced epoxy composites. J Vinyl Addit Technol. 2025;31(1):224–240.
6. Pandiarajan P, Baskaran PG, Palanisamy S, Karuppusamy M, Marimuthu K, Rajan A, et al. Enhancing polyester composites with nano Aristida hystrix fibers: Mechanical and microstructural insights. BioResources. 2025;20(4):9257–9281.

© STM Journals 2026. All Rights Reserved

7. Kender Š, Brezinová J, Novotný Š, Bejdová P. Effects of fiber orientation, thermal post-curing, and corrosive environment on the mechanical properties of CFRP laminates. Polymers. 2026;18(11):1270.
8. Khosravi M, Zare Z, Mojtabaeian SM, Izadi R. Artificial intelligence and decision-making in healthcare: A Thematic analysis of a systematic review of reviews. Health Serv Res Manag Epidemiol. 2024 Mar;11:23333928241234863.
9. Gowda HS, Raju H, Kumar VP, Bharat PB, Suresha B, Bhat SK. A review of recent machine learning advances for predicting and optimizing mechanical and tribological properties of fiber-reinforced thermoset polymer nanocomposites. Discov Appl Sci. 2026 Apr 16.
10. Sorour SS, Saleh CA, Shazly M. A review on machine learning implementation for predicting and optimizing the mechanical behaviour of laminated fiber-reinforced polymer composites. Heliyon. 2024 Jul 15;10(13):e33588.
11. Gyabaah KY, Mahoney B, Martey AK, Yan C, Mensah P, Li G. Machine learning-assisted polymer and polymer composite design for additive manufacturing. AI Mater. 2026;1(1):2.
12. Karuppusamy M, Kalidas S, Palanisamy S, Nataraj K, Nandagopal RK, Natarajan R, et al. Real-time monitoring in polymer composites: Internet of Things integration for enhanced performance and sustainability—A review. BioResources. 2025;20(3):8093–8118.
13. Palanisamy S, Murugesan TM, Palaniappan M, Santulli C, Ayrilmis N. Use of hemp waste for the development of mycelium-grown matrix biocomposites: A concise bibliographic review. BioResources. 2023;18(4):8771–8780.
14. Kaliyev, Yessengabylov I, Kyrykbayeva A, Zholdassova S, Kharmyssov C, Temirkhan M. High-performance composite gears: A systematic review of materials, processing, and performance. J Compos Sci. 2026;10(4):195.
15. Bukvić M, Milojević S, Gajević S, Đorđević M, Stojanović B. Production technologies and application of polymer composites in engineering: A review. Polymers. 2025;17(16):2187.
16. Fianko SK, Nooni IK, Dzogbewu T, Agbemava E, de Beer DJ. AI as an enabler of sustainable additive manufacturing: Environmental impact and circular design. Int J Adv Manuf Technol. 2026 Apr;143(7):3531–50.
17. Agrawal K, Goktas P, Holtkemper M, Beecks C, Kumar N. AI-driven transformation in food manufacturing: A Pathway to sustainable efficiency and quality assurance. Front Nutr. 2025 Mar 13;12:1553942.
18. Chang BP, Mohanty AK, Misra M. Studies on durability of sustainable biobased composites: A review. RSC Adv. 2020;10(31):17955–17999.
19. Starkova O, Gagani AI, Karl CW, Rocha IBCM, Burlakovs J, Krauklis AE. Modelling of environmental ageing of polymers and polymer composites—Durability prediction methods. Polymers. 2022;14(5):907.
20. Govindarajan PR, Shanmugavel R, Subramanian K, Palanisamy S, Santulli C, Fragassa C. Effect of stacking sequence on mechanical and water absorption characteristics of jute/banana/basalt fabric aluminium fibre laminates with diamond microexpanded mesh. Int J Polym Sci. 2024;2024(1):3835788.
21. Zaman S, Mahmud MS, Mollick AA, Lhaden T, Dantzler J, Arroyo S, et al. Artificial intelligence in additive Manufacturing: Advances in smart materials, lattice optimization, and process intelligence. Int J Adv Manuf Technol. 2026 Apr 18:1–55.
22. Kim MO. AI-driven polymeric coatings: Strategies for material selection and performance evaluation in structural applications. Polymers. 2026;18(1):5.
23. Long T, Pang Q, Deng Y, Pang X, Zhang Y, Yang R, et al. Recent progress of artificial intelligence application in polymer materials. Polymers. 2025;17(12):1667.
24. Uddin MH, Mulla MH, Abedin T, Manap A, Yap BK, Rajamony RK, et al. Advances in natural fiber polymer and PLA composites through artificial intelligence and machine learning integration. J Polym Res. 2025 Mar;32(3):76.

© STM Journals 2026. All Rights Reserved

25. Yang F, Wen C, Zhu S, Feng Y, Ye Z, Peng H, et al. Machine learning model of plant fiber/PLA composite: Prediction and analysis of mechanical strength. Compos Part A Appl Sci Manuf. 2025;199:109201. doi: 10.1016/j.compositesa.2025.109201.
26. Ratchagar V, Thangeeswari T, Muniyappan A. Investigation of glucose biosensors by non-enzymatic photoluminescent detection using oleic acid treated Ag2S nanoparticles. Mater Chem Phys. 2024 Apr 1;316:129116.
27. Müzel SD, Bonhin EP, Guimarães NM, Guidi ES. Application of the finite element method in the analysis of composite materials: A review. Polymers. 2020;12(4):818.
28. Bai X, Zhang X. Artificial intelligence-powered materials science. Nano Micro Lett. 2025;17(1):135.
29. Guido R, Ferrisi S, Lofaro D, Conforti D. An overview on the advancements of support vector machine models in healthcare applications: A review. Information. 2024;15(4):235.
30. Salah Al-Shati A, Mohammed TJ. Machine learning analysis based on deep learning for fatigue diagnostics in carbon fiber reinforced polymers. PLoS One. 2026 Jan 9;21(1):e0340904.
31. Sharma H, Arora G, Singh MK, Ayyappan V, Bhowmik P, Rangappa SM, et al. Review of machine learning approaches for predicting mechanical behavior of composite materials. Discov Appl Sci. 2025 Oct 17;7(11):1238.
32. Pelin G, Sonmez M, Pelin CE. The use of additive manufacturing techniques in the development of polymeric molds: A review. Polymers. 2024;16(8):1055.
33. Malashin, Masich I, Tynchenko V, Gantimurov A, Nelyub V, Borodulin A, et al. Machine learning in 3D and 4D printing of polymer composites: A review. Polymers. 2024;16(22):3125.
34. Rakholia R, Suárez-Cetrulo AL, Singh M, Carbajo RS. Integrating AI and IoT for predictive maintenance in Industry 4.0 manufacturing environments: A practical approach. Information. 2025;16(9):737.
35. Kodumuru R, Sarkar S, Parepally V, Chandarana J. Artificial intelligence and Internet of Things integration in pharmaceutical manufacturing: A smart synergy. Pharmaceutics. 2025;17(3):290.
36. Pavlovic, Valzania L, Minak G. Effects of moisture absorption on the mechanical and fatigue properties of natural fiber composites: A review. Polymers. 2025;17(14):1996.
37. Ferreira Rocha PR, Gonçalves GF, dos Reis G, Guedes RM. Mechanisms of component degradation and multi-scale strategies for predicting composite durability: Present and future perspectives. J Compos Sci. 2024;8(6):204.

© STM Journals 2026. All Rights Reserved