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Intelligent Optimization of Drilling Parameters in Polymer Composites using Machine Learning and Metaheuristic Techniques

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Abstract

The study tests different ways to use ML and metaheuristic algorithms to determine the best drilling parameters for polymer matrix composites. The research uses a composite matrix made from 55.25% vinyl ester, 44.0% Nickel–Phosphorous coated glass fiber and 0.75% Al_2O_3 nanowires which are tested for tensile strength (64.57 MPa), flexural strength (85.86 MPa) and impact strength (71.79 kJ/m²). By applying a Taguchi orthogonal array, it is observed that a slower spindle, a lower feed rate and a larger drill minimized delamination, thrust force and torque during drilling. Linear regression, ridge regression, Random Forest and Gradient Boosting Regression models were used to estimate the delamination factor. Metaheuristic algorithms, Firefly, PSO, Cuckoo Search, GWO, SALP and Orca, were used to determine the best drilling parameters. The success of the models was judged using MSE and R^2 and linear and ridge regression gave the best outcomes, both with an MSE of 0.0001 and an R^2 value of 0.9812. Firefly produced the best delamination result with a DF of 1.3644, whereas PSO and GWO had the best drilling parameters (with a DF of 1.1766). The novelty of this research lies in the integrated use of both machine learning models and metaheuristic optimization techniques to optimize drilling processes in polymer composite materials. This hybrid approach allows for improved prediction accuracy and more efficient parameter tuning. The results demonstrate that PSO and GWO are the most effective algorithms for minimizing delamination in polymer drilling, contributing valuable insights to the field of manufacturing and machining in polymer matrix composites.

Keywords: Ní–P coated composites, delamination factor (DF), particle swarm optimization (PSO), grey wolf optimization (GWO), orca optimization.

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INTRODUCTION

Drilling of polymer matrix composites is a critical machining process that influences the structural integrity and mechanical performance of the final product. Composite materials, including fiber-reinforced polymers (FRPs), have gained widespread application in aerospace, automotive, marine, and biomedical industries due to their superior strength-to-weight ratio, corrosion resistance, and customizable properties. However, the drilling process presents several challenges, including delamination, fiber pull-out, thermal degradation, and poor surface finish, which can significantly reduce the material's durability and functional performance. Delamination in particular, remains a major concern, as it adversely affects the load-bearing capacity and long-term stability of the polymer structure. Therefore, optimizing drilling parameters to minimize delamination while maintaining machining efficiency is crucial. The demand for precise and damage-free machining of polymer materials necessitates an in-depth investigation into the optimization of drilling parameters. Traditional experimental approaches for optimizing machining parameters are often time-consuming, cost-intensive, and fail to generalize across different material compositions and machining environments. The integration of machine learning (ML) and metaheuristic optimization algorithms provides a promising alternative to conventional empirical methods.

The present study considers a material made from a Vinyl ester matrix, reinforced with Nickel-Phosphorous coated glass fiber and Al_2O_3 nanowires. The unique aspect of this research is in the approach used to evaluate different ML models and metaheuristic algorithms against each other to identify the optimal settings that reduce the delamination factor (DF). Using experimental data arranged with the Taguchi Orthogonal Array and ML-based regression models, this study establishes a comprehensive framework for finding the best machining parameters for polymer materials. Several studies have attempted to optimize drilling parameters for polymer materials using various methodologies, including empirical modeling, statistical approaches, and computational techniques. However, these studies exhibit certain limitations that restrict their applicability and effectiveness. Bhushi et al. (2020) optimized drilling parameters for CFRP composites using GA, SA, and PSO but did not explore diverse composite material compositions, particularly hybrid reinforcements [1].

Kalita et al. (2018) focused on GFRP composites but did not consider the effect of different fiber types and matrix reinforcements [2]. Kumar et al. (2021) utilized a Grey-integrated Harmony Search Algorithm for optimizing drilling in graphite epoxy composites. However, the study was restricted to specific machining conditions and did not generalize to varied environments [3]. Natarajan et al. (2022) examined the influence of point angle on delamination but did not investigate the impact of fiber stacking sequence [4]. Pendokhare and Chakraborty (2024) demonstrated that Grey Wolf Optimizer (GWO) was effective for optimizing laser beam drilling processes. However, the study lacked real-time experimental validation [5]. Abd-Elwahed (2022) optimized drilling parameters using ANN-PSO but did not integrate results with digital manufacturing frameworks for industrial applications [6]. Soepangkat et al. (2019, 2020) employed BPNN-GA and BPNN-PSO for optimizing drilling parameters but did not compare these models with other ML techniques, limiting their effectiveness [7,8]. Taiwo et al. (2024) combined the Taguchi method with GWO but did not compare multiple metaheuristic techniques, restricting the potential for broader insights into optimization efficacy [9]. Kayaroganam et al. (2021) found that adding mica reduced thrust force and torque but did not explore long-term tool wear effects [10]. Benkhelladi et al. (2024) identified the effects of drill diameter and rotational speed on delamination but lacked industrial-scale validation [11]. To overcome the limitations highlighted above, this study systematically integrates ML models and metaheuristic algorithms for drilling optimization in a composite material reinforced with Nickel–Phosphorous coated glass fibers and Al_2O_3 nanowires. The research contributes to addressing existing gaps in the following ways: This study investigates a hybrid polymer matrix composites that incorporates Nickel–Phosphorous coated glass fibers and Al_2O_3 nanowires, a composition that has not been widely studied in the context of drilling optimization. Unlike previous studies that focused on single regression techniques, this research compares multiple ML models (Linear Regression, Ridge Regression, Lasso Regression, Random Forest, Gradient Boosting, and XGBoost) to determine the most effective predictive model for delamination factor estimation. This study evaluates six metaheuristic optimization techniques (PSO, GWO, Firefly, Cuckoo, SALP, and ORCA) to determine the best-performing algorithm for drilling parameter optimization, providing broader insights into their comparative effectiveness. The study employs a well-structured experimental approach, ensuring that the findings are based on real-world data rather than purely computational simulations. The optimized parameters identified in this research are not only theoretically validated but also hold practical implications for improving machining efficiency, reducing material waste, and ensuring high-quality machining outcomes in industrial applications. By bridging these research gaps, this study establishes a robust framework for optimizing drilling parameters in polymer materials using ML and metaheuristic techniques. The findings contribute significantly to the advancement of intelligent manufacturing systems, fostering the development of optimized, cost-effective, and sustainable machining strategies for modern polymer materials.

LITERATURE REVIEW

Bhushi et al. (2020) analyzed optimization techniques for drilling CFRP composites using GA, SA, and PSO, finding PSO most effective in minimizing delamination. However, their study was limited to specific parameters, excluding other tool geometries and material variations [1]. Abd-Elwahed (2023) optimized drilling parameters for GFRP composites using PSO-enhanced ANN, identifying feed rate as the most influential factor on delamination. However, the study focused on specific drilling conditions, limiting its generalizability to other composite materials and machining environments [6].Kumar et al. (2021) developed a Grey-integrated Harmony Search Algorithm (GR-HSA) for optimizing drilling in graphite epoxy composites, improving surface finish and reducing thrust force. However, the study focused on specific machining conditions, limiting its applicability to different composite materials and tool geometries [3].

Kalita et al. (2018) optimized surface roughness in GFRP composite drilling using a genetic algorithm, identifying feed rate as the most influential parameter. However, their study focused only on specific drilling conditions, limiting generalizability to varied machining environments [2]. Pendokhare and Chakraborty (2024) found that the Grey Wolf Optimizer outperformed other preying behavior-based metaheuristics in optimizing laser beam drilling processes. However, their study lacked real-time experimental validation and did not explore alternative optimization techniques [5]. Natarajan et al. (2022) found that increasing the point angle and optimizing spindle speed and feed rate minimized delamination in hybrid fiber-reinforced composites. However, their study did not analyze the effects of fiber stacking sequence on machinability and failure modes [4]. Taiwo et al. (2024) found that integrating the Taguchi method with Grey Wolf Optimization effectively minimized thrust force in CFRP drilling. However, their study relied on prior data and did not validate results through extensive experimental trials [9]. Abd-Elwahed (2022) found that ANN-PSO effectively optimized drilling parameters for WGFRE composites, minimizing delamination and torque. However, the study lacked real-world industrial validation and broader integration with digital manufacturing frameworks [6]. Soepangkat et al. (2019) found that the BPNN-GA method effectively optimized multiple drilling parameters for Kevlar fiber composites, improving thrust force, torque, and delamination. However, the study lacked real-world industrial validation and broader material considerations [7]. Mahmood et al. (2023) found that the MRAC-EFPA approach effectively minimized delamination in GFRP drilling under varying conditions. Though, the study relied on simulations, lacking experimental validation in industrial settings [12]. Kayaroganam et al. (2021) found that adding 5.83% mica reduced thrust force and torque, improving machinability. However, the study lacked real-world application testing and did not explore tool wear effects over extended drilling [10]. Benkhelladi et al. (2024) found that glass fiber type, drill diameter, and rotational speed significantly affect surface roughness, delamination, and cutting temperature. However, the study lacks real-world industrial validation and long-term tool wear analysis [11]. Soepangkat et al. (2020) found that BPNN-PSO optimization effectively minimized thrust force, torque, and delamination in CFRP drilling. However, their research is limited by the use of a single drill geometry and CFRP material type [8]. Antil et al. (2021) demonstrated that MOPSO effectively optimized MRR and overcut in SiCp/glass fiber-reinforced PMC drilling. However, the study's limitation lies in the use of a single drilling technique and material type [13]. Kharwar and Verma (2023) found that the Grey Wolf Optimization Algorithm effectively optimized Milling performance in MWCNT/epoxy nanocomposites, with minimal deviation from experimental values. However, the study was limited by a focus on only a few machining parameters and a single nanocomposite type [14]. Gautam and Shrivastava (2024) found that metaheuristic optimization techniques, such as PSO and genetic algorithms, improve laser cutting of FRP composites, enhancing precision and efficiency. However, their research highlighted the need for more sophisticated models to address diverse FRP types and laser cutting requirements [15].

Table 1. Composites composition and properties**.**

Material composition	Mechanical properties
Vinyl ester (wt%)	55.15
Nickel-Phosphorous coated glass fiber (wt%)	44.0
Al_2O_3 nanowire (wt%)	0.85
Tensile strength (MPa)	63.12
Tensile modulus (MPa)	4680.25
Flexural strength (MPa)	84.85
Impact strength (kJ/m²)	71.79
Barcol hardness	66

Ghasempour-Mouziraji et al. (2022) demonstrated that combining ANN and NSGA optimizes wire EDM parameters, improving geometrical accuracy. However, the study's limitation is that the machine couldn't precisely set the optimal values, requiring slight adjustments [16]. Sreenivasulu and Chaitanya (2022) proposed a varying-parameter drilling method using PSO with SAPM, improving machining efficiency and surface quality. However, the optimization process faced fluctuating feasibility in solutions during searching [17]. Mehmood, Umer, and Asgher (2022) developed a hybrid SFLA-ACO algorithm that improved tool path optimization and cost management in multi-hole drilling. However, the algorithm's performance was similar to other methods for larger problems [18]. Sahoo and Mishra (2023) optimized Nd:YAG laser drilling for basalt-PTFE-coated glass fibre composites using a genetic algorithm, identifying key parameters for hole taper minimization. However, their study focused only on specific process parameters and materials [19]. Saravanakumar, Sathiyamurthy, and Vinoth (2024) enhanced AWJM for banana fiber-reinforced composites using ensemble machine learning, achieving robust predictions for machining outcomes. However, the study's scope was limited to specific material types [20].

PROPOSED METHODOLOGY

Material Composition and Properties

This study investigates Nickel-Phosphorous coated glass fiber-reinforced vinyl ester polymers with added Al_2O_3 nanowires. The polymers are designed for improved strength, hardness, and wear resistance. These properties make them suitable for machining applications, particularly in drilling processes. Table 1 summarizes the composition and mechanical properties of the composite. The high tensile and flexural strength indicate its suitability for drilling applications.

These material properties are crucial in evaluating the polymer’s performance during machining, especially its resistance to delamination and wear. Nickel-Phosphorous coated glass fiber and Al_2O_3 nanowires were chosen due to their synergetic effect on the improvement of both mechanical and thermal properties that play a vital role in drilling. The presence of Ni-P coating on the glass fiber enhances wear resistance and bonding at the interface with the vinyl ester matrix, whereas the Al_2O_3 nanowires provide hardness and thermal stability. This hybrid composite has optmised delamination and tool wear resistance in drilling holes compared to the traditional reinforcements such as plain GFRP or carbon fibers as shown by its high tensile (63.12 MPa), flexural (84.85 MPa) and impact strength (71.79 kJ/m²)

Experimental Parameters and Their Levels

The study design examines how different drilling parameters shape the performance of machining. Five ranges of spindle speed, feed rate and drill diameter are tested throughout the study. The numbers in the following table show drilling parameters and the values they were set to which were chosen using Taguchi’s experimental design framework. Table 2 presents the drilling parameters and their levels. These parameters are selected to cover a wide machining range for optimization.

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By using these levels, the experiments cover a wide range of potential drilling conditions, enabling the identification of optimal parameters that minimize machining defects such as delamination and reduce overall tool wear.

Experimental Setup

Figure 1 illustrates the experimental drilling setup used in this study, the experimental setup is designed to assess the impact of drilling parameters on the performance of Nickel-Phosphorous coated glass fiber-reinforced vinyl ester polymer matrix composites. Figure 2 presents the overall research workflow, integrating experimental design, machine learning, and optimization techniques.

Table 2. Drilling parameters and their levels.

Parameters	Lowest	Lower	Medium	Higher	Highest
SS (RPM)	450	852	1260	1860	2700
FR (mm/min)	30	40	50	60	70
DD (mm)	4	6	8	10	12

Figure 1. Experimental drilling setup.

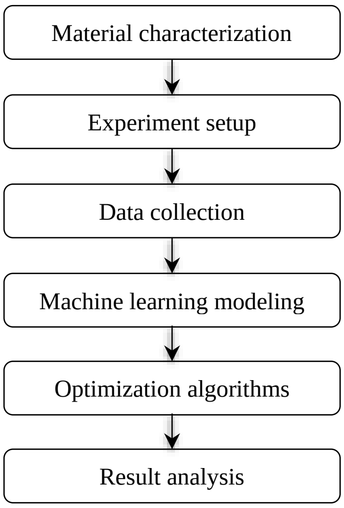

Figure 2. Drilling optimization research process flow.

The Taguchi Orthogonal Array methodology was used to create a systematic and efficient experimental design, which includes variations in spindle speed, feed rate, and drill diameter. Table 3 shows the Taguchi experimental design and observed responses.

Figure 3 shows the composite specimen, while Figure 4 depicts the drilled hole. The quality of drilling indicates minimal surface damage.

Table 3. Experimental design using Taguchi orthogonal array.

Ex. No.	Spindle speed (RPM)	Feed rate (mm/min)	Drill diameter (mm)	Delamination factor	Thrust force (N)	Torque (Nm)
1	450	30	4	1.18	80.77	29.18
2	450	40	6	1.22	104.83	40.72
3	450	50	8	1.27	131.6	54.78
4	450	60	10	1.32	158.52	69.41
5	450	70	12	1.36	172.7	82.27
6	852	30	6	1.21	84.41	32.68
7	852	40	8	1.25	111.24	48.81
8	852	50	10	1.31	138.6	63.68
9	852	60	12	1.36	165.0	74.18
10	852	70	4	1.27	117.58	42.18
11	1260	30	8	1.22	95.94	37.53
12	1260	40	10	1.27	122.5	51.91
13	1260	50	12	1.32	149.5	68.18
14	1260	60	4	1.25	101.4	36.49
15	1260	70	6	1.31	128.26	47.68
16	1860	30	10	1.24	106.77	46.45
17	1860	40	12	1.30	133.3	56.21
18	1860	50	4	1.23	75.14	33.45
19	1860	60	6	1.30	112.6	38.13
20	1860	70	8	1.34	136.2	54.46
21	2700	30	12	1.25	117.2	49.92
22	2700	40	4	1.18	84.34	25.41
23	2700	50	6	1.25	111.9	34.82
24	2700	60	8	1.30	137.97	49.55
25	2700	70	10	1.35	175.62	64.96

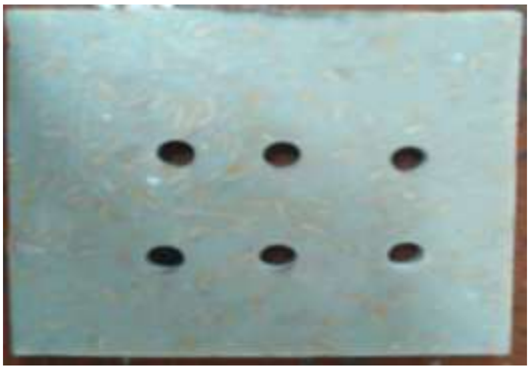

Figure 3. Specimen.

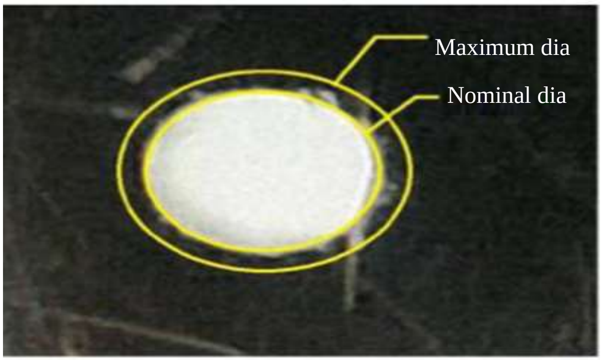

Figure 4. Drilled image of hole.

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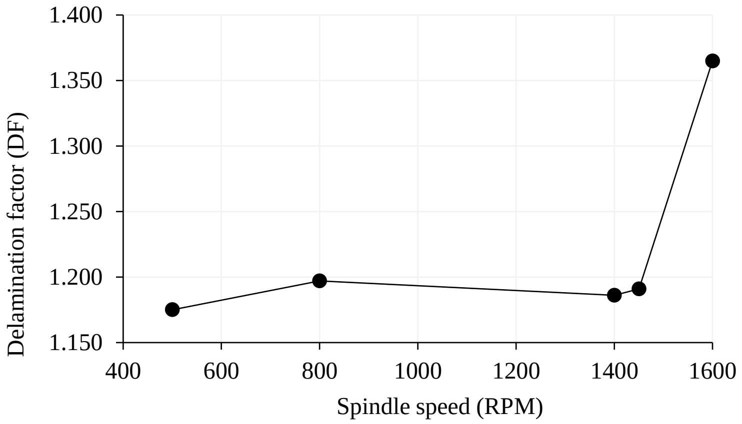

Figure 5. Spindle speed vs delamination factor.

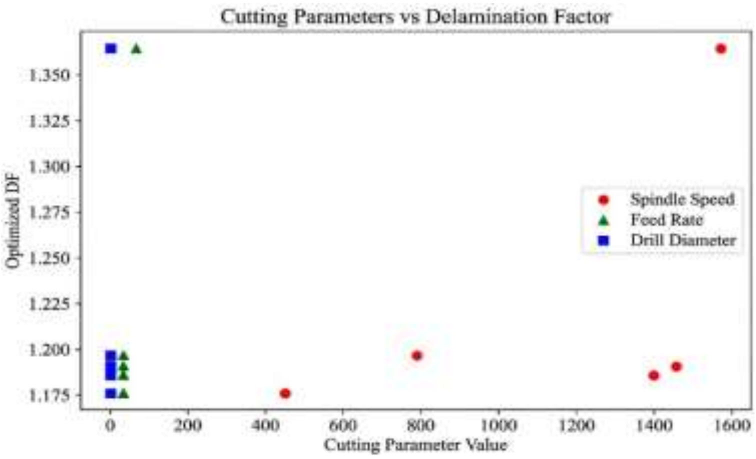

Figure 6. Cutting parameters vs delamination factor.

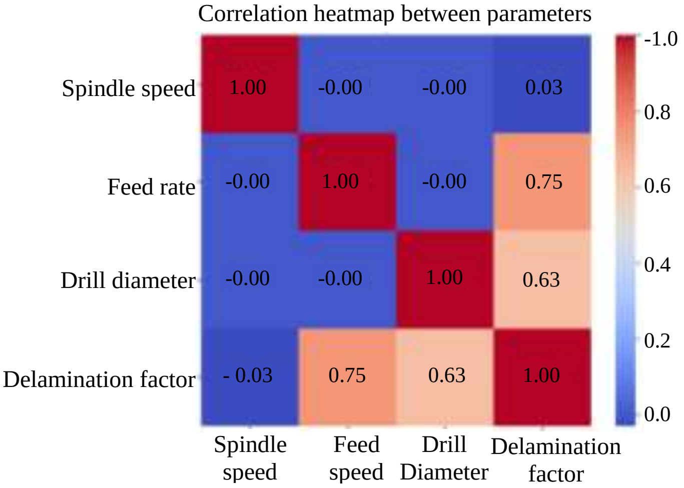

Figure 7. Correlation heatmap between parameters.

Figure 6 illustrates the influence of cutting parameters on delamination. Feed rate and drill diameter significantly affect machining performance.

Figure 7 presents the correlation heatmap, indicating strong positive correlation of feed rate and drill diameter with delamination.

RESULTS AND DISCUSSION

Regression Models and Metrics

In this study, various regression models were employed to predict the Delamination Factor (DF) based on the drilling parameters. The accuracy and predictive power of each model were measured with Mean Squared Error (MSE) and R^2. The performance of regression models is presented in Figure 8 and Table 4, showing that Linear and Ridge Regression outperform ensemble methods by achieving the highest prediction accuracy.

Figure 9 shows feature importance, highlighting feed rate as the most influential parameter.

Table 4. Regression model and metrics.

Model	MSE	R^2
Linear	0.0001	0.9812
Ridge	0.0001	0.9812
Gradient Boosting Regression	0.0006	0.8131
XGBoost Regression	0.0007	0.7984
Random Forest Regression	0.0011	0.6952
Lasso Regression	0.0021	0.3881

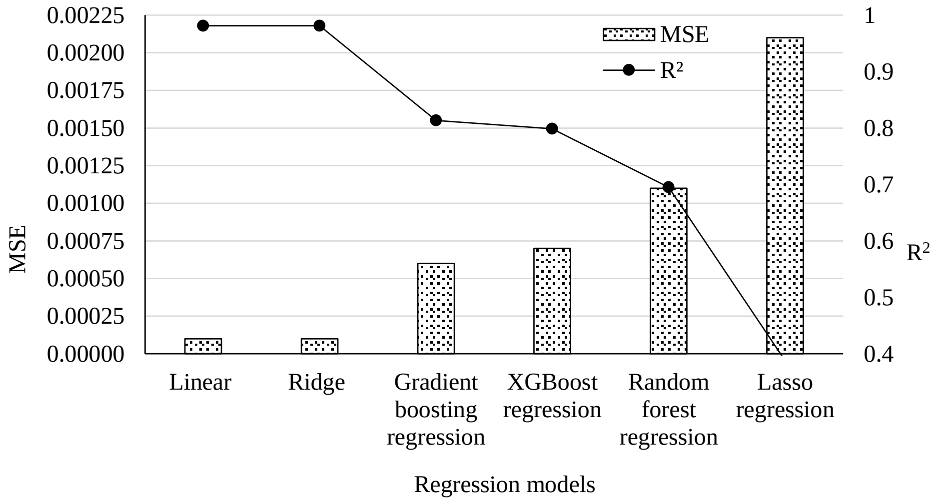

Figure 8. Regression model performance.

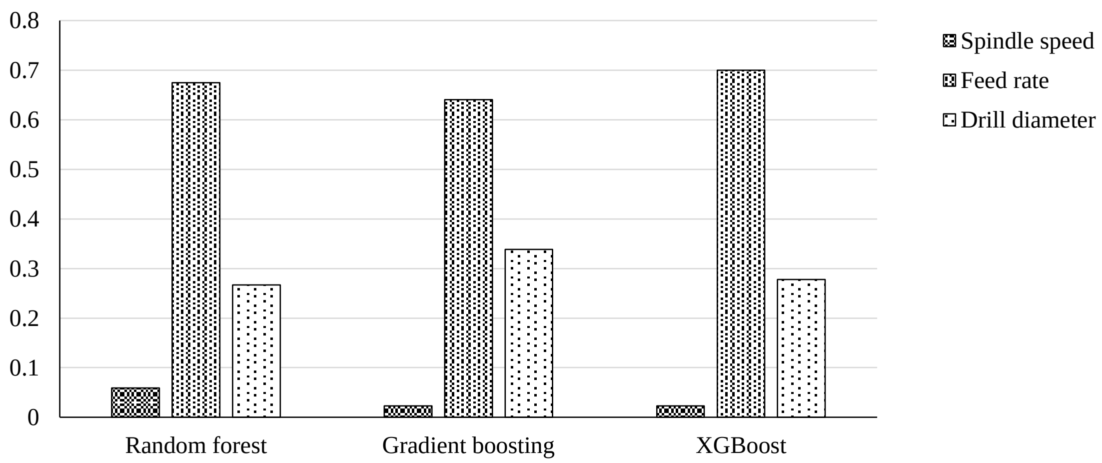

Figure 9. Feature importance across ML models.

Regression Models and Their Performance

Modeling Interactions and Feature Interactions

The regression coefficients of linear and regularized models (e.g., Linear, Ridge, Lasso) indicate that the spindle speed has a slight direct influence on the Delamination Factor (DF). Figure 5 shows the variation of spindle speed with delamination factor. It is observed that lower spindle speeds reduce delamination, improving machining quality. Nevertheless, the ensemble models, Random Forest, Gradient Boosting, and XGBoost, assign a greater feature importance to spindle speed. This seemingly contradictory result is explained by the fact that these models differ in their learning mechanisms. Linear models only learn additive, linear relationships, whereas ensemble methods can learn non-linear effects and interactions between variables. The effect of spindle speed might not be very linear on its own, but its interaction with feed rate and drill diameter seems to be rather important in non-linear models, therefore causing the higher feature importance scores. The Table 5 provides a clear overview of the models, their respective MSE, R^2, and regression equations or feature importances for your analysis. Among the models, Linear Regression and Ridge Regression show the lowest MSE, suggesting that they are more accurate in predicting the delamination Factor.

Figure 10 illustrates the distribution of model parameters across different regression models. It is observed that ensemble models exhibit a wider spread of parameter values, indicating higher variability, whereas linear models show more stable and consistent parameter distributions.

Table 5. Regression model their equation and Feature importances.

Model	MSE	R^2	Equation / Feature Importances
Linear Regression	0.0001	0.9812	DF = 1.0478 + (-0.0000 * Spindle Speed) + (0.0028 * Feed Rate) + (0.0112 * Drill Diameter)
Lasso Regression	0.0021	0.3881	DF = 1.1724 + (-0.0000 * Spindle Speed) + (0.0021 * Feed Rate) + (0.0000 * Drill Diameter)
Ridge Regression	0.0001	0.9812	DF = 1.0479 + (-0.0000 * Spindle Speed) + (0.0028 * Feed Rate) + (0.0112 * Drill Diameter)
Random Forest Regression	0.0011	0.6952	Feature Importances: Spindle Speed: 0.0589, Feed Rate: 0.6735, Drill Diameter: 0.2676
Gradient Boosting Regression	0.0006	0.8131	Feature Importances: Spindle Speed: 0.0208, Feed Rate: 0.6410, Drill Diameter: 0.3382
XGBoost Regression	0.0007	0.7984	Feature Importances: Spindle Speed: 0.0212, Feed Rate: 0.7007, Drill Diameter: 0.2780

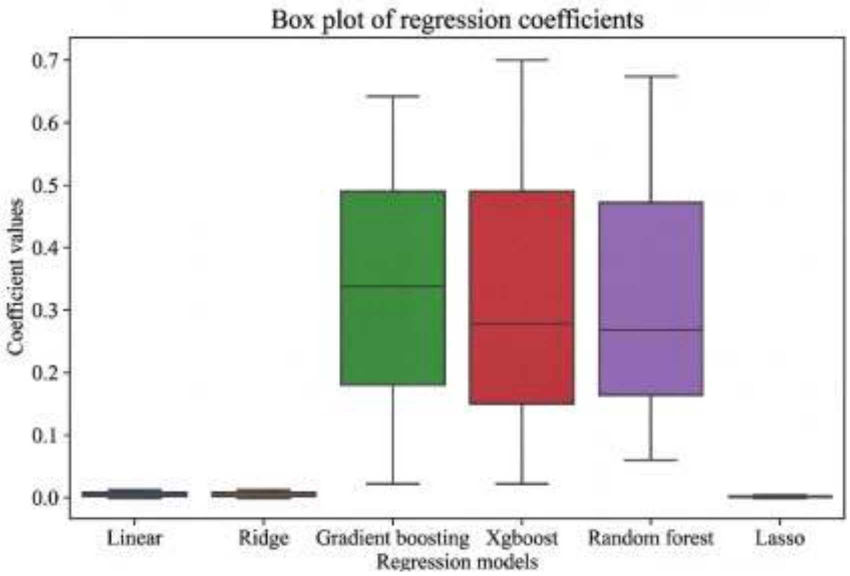

Figure 10. Distribution of model parameters across regression models.

According to the value 0.9812, about 98% of the variability within the DF is explained by Linear Regression and Ridge Regression. According to the regression measurements, Linear Regression and Ridge Regression give the best predictions for the Delamination Factor (DF), having low mean squared error and high R^2 values. The models Random Forest, Gradient Boosting and XGBoost are useful because they show which drilling factors have the most influence on the Delamination Factor. Table 6 presents cross-validation results, demonstrating consistent model performance across folds.

A 5-fold cross-validation was performed to prove the generalizability and mitigate the effect of possible overfitting on such a small sample (25 samples). As observed in the table, Linear and Ridge Regression show low mean squared error and high accuracy between folds, showing that the models perform well. Tree-based models have relatively smaller R^2 values because they are conservative when generalizing on small datasets.

Table 7 shows the results of the Ordinary Least Squares (OLS) model to predict the delamination factor using regression coefficients, standard errors, t-statistics, and p-value. According to the results, it is evident that the factors of Feed Rate and Drill Diameter positively impact the delamination factor and the influence is statistically significant as the p-value is less than 0.01. Their significant effect on the response variable is further indicated by the high t-statistics (18.50 and 15.66) of feed rate and drill diameter respectively. Spindle Speed, on the other hand, has a very low coefficient (-2.005 x 10 -6) and a last p-value (0.458), which means that its impact is not statistically significant in the linear model. These results indicate that though the feed rate and the drill diameter should be treated carefully to obtain minimal delamination, changes in the spindle speed over the range considered will have an insignificant linear effect. Table 8 presents ANOVA results, validating the statistical significance of the regression model.

An Ordinary Least Squares (OLS) regression and Analysis of Variance (ANOVA) was conducted to determine the statistical significance of the regression model. The goodness-of-fit of the model was high, with $R^2 = 0.966$, implying that the independent variables explain variance in the delamination factor of about 96.6 percent.

Table 6. Fold cross-validation results for regression models.

Model	Average R^2	Average MSE
Linear regression	0.8723	0.000185
Ridge regression	0.8715	0.000185
Lasso regression	-1.1699	0.003228
Random forest	0.7040	0.000620
Gradient boosting	0.6191	0.000420

Table 7. Regression coefficients and statistical significance (OLS model).

Predictor	Coefficient	Standard error	t-Statistic	p-Value (P > |t|)	Significance
Intercept	1.0475	0.0104	100.52	< 0.0001	Highly significant
Spindle Speed	-2.005×10^{-6}	2.650×10^{-6}	–0.756	0.458	Not significant
Feed Rate	0.0027	0.0001	18.50	< 0.0001	Highly significant
Drill Diameter	0.0116	0.0007	15.66	< 0.0001	Highly significant

Table 8. ANOVA table for regression.

Source	DF	Sum of squares	Mean square	F-value	p-Value (PR(>F))	Significance
Spindle Speed	1	0.000063	0.000063	0.572	0.458	Not significant
Feed Rate	1	0.037538	0.037538	342.25	1.77×10^{-14}	Highly significant
Drill Diameter	1	0.026912	0.026912	245.37	4.65×10^{-13}	Highly significant
Residual	21	0.002303	0.000110	—	—	—

Regression coefficient p-values show that Feed Rate and Drill Diameter are statistically significant predictors ($p < 0.01$), whereas Spindle Speed has an insignificant influence on the prediction ($p = 0.458$). The ANOVA results also supported these findings as the F-values were high and the p-values were very low in case of both Feed Rate and Drill Diameter, indicating their overriding effect on delamination. In comparison, Spindle Speed demonstrated low F-value and high p-value, which also confirms its insignificant influence. This statistical confirmation confirms the findings made with the help of feature importance analysis and strengthens the idea to devote optimization efforts to Feed Rate and Drill Diameter as the main optimization variables.

Ranking Analysis of Regression Models

A ranking analysis was conducted using performance metrics—Mean Squared Error (MSE) and R^2—to evaluate the predictive effectiveness of various regression models for the Delamination Factor. The models were ranked based on these metrics, as summarized in Table 9.

Linear Regression and Ridge Regression are the top-performing models, achieving the lowest MSE (0.0001) and highest R^2 (0.9812). Their ranking of 1.0 for both metrics indicates superior accuracy and reliability in predicting the Delamination Factor. Gradient Boosting Regression and XGBoost Regression rank moderately (3rd and 4th respectively) with slightly higher MSE and lower R^2 values compared to the top models, suggesting a reasonable predictive capability. Random Forest Regression and Lasso Regression are ranked 5th and 6th, respectively, with higher MSE values and significantly lower R^2 values, indicating that they are less effective for this specific prediction task. This ranking clearly demonstrates in Figure 11 that Linear and Ridge Regression models offer the best performance for predicting the Delamination Factor based on the experimental data.

Table 9. Ranking analysis of regression models.

Model	MSE	R^2	MSE Rank	R^2 Rank
Linear regression	0.0001	0.9812	1.0	1.0
Ridge regression	0.0001	0.9812	1.0	1.0
Gradient boosting regression	0.0006	0.8131	3.0	3.0
XGboost regression	0.0007	0.7984	4.0	4.0
Random forest regression	0.0011	0.6952	5.0	5.0
Lasso regression	0.0021	0.3881	6.0	6.0

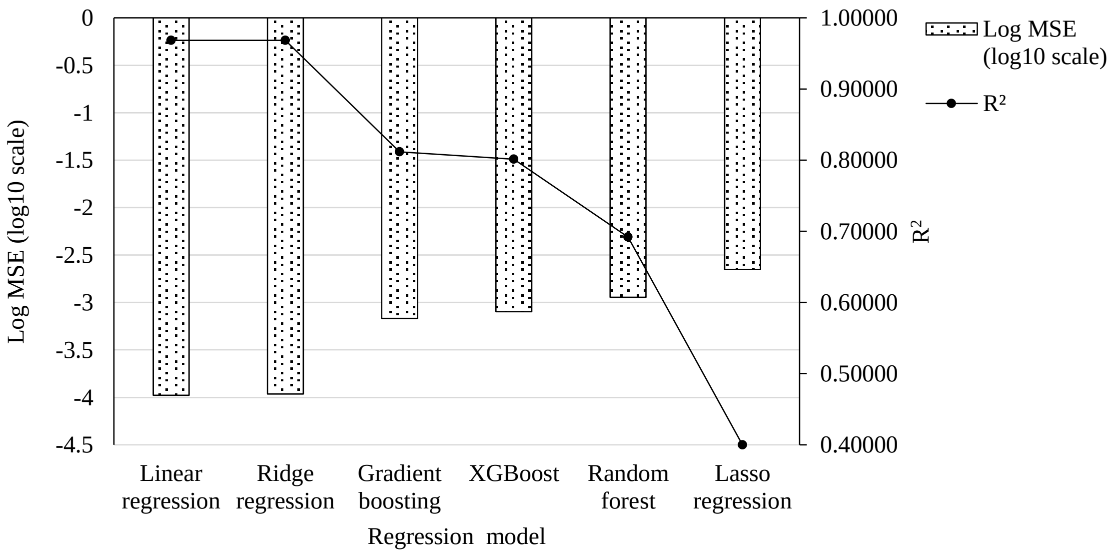

Figure 11. Ranking of regression models.

Different Metaheuristic Algorithms

In this study, several metaheuristic algorithms were applied to optimize the drilling parameters with the goal of minimizing the Delamination Factor (DF). The following algorithms were employed: Firefly Algorithm, Particle Swarm Optimization (PSO), Cuckoo Search Algorithm, Grey Wolf Optimization (GWO), Salp Swarm Algorithm (SALP), Optimization by Random Collision Algorithm (ORCA) Each algorithm explores the search space using different strategies to identify the optimal combination of spindle speed, feed rate, and drill diameter that minimizes DF.

Objective Function: Regression Model Selection

Based on the regression analysis, the Linear Regression model was selected as the objective function due to its outstanding performance (MSE = 0.0001, R^2 = 0.9812).
The chosen regression equation is where SS is spindle speed, FR is feed rate, and DD is drill diameter:

$$DF=1.0478-(0.0000\times SS)+(0.0028\times FR)+(0.0112\times DD) \qquad (1)$$

This equation (1) predicts the Delamination Factor (DF) based on the drilling parameters, and it is used as the objective function in the optimization process. the Table 7 below summarizes the optimized drilling parameters and the corresponding Delamination Factor (DF) for each metaheuristic algorithm: The results indicate that both PSO and GWO yield the lowest optimized DF of 1.1766, making them the most effective algorithms for this optimization problem.

Validation with Experimental Results

Experimental Data

The drilling experiments were designed using a Taguchi Orthogonal Array (Table 3) where the Delamination Factor (DF) was measured for various combinations of drilling parameters. The regression analysis indicated that both Linear Regression and Ridge Regression models achieved excellent predictive performance with an MSE of 0.0001 and R^2 of 0.9812. The objective function derived from these models is:

$$DF=1.0478+(-0.0000\times \text{Spindle Speed}) + (0.0028\times \text{Feed Rate}) + (0.0112\times \text{Drill Diameter}).$$

This high R^2 value (98.12%) confirms that the regression models can accurately predict the DF based on the drilling parameters, closely matching the observed experimental data. Table 10 summarizes optimized parameters, showing that PSO and GWO achieve minimum delamination.

Figure 12 and Figure 13 show convergence behavior, indicating stable optimization performance of PSO and GWO.

Table 11 presents consistency across multiple runs, confirming the reliability of optimization results and Figure 14 compares optimized results, clearly showing that PSO and GWO outperform other algorithms.

Table 10. Optimized drilling parameters and the corresponding delamination factor (Df) for each metaheuristic algorithm.

Algorithm	Spindle Speed (RPM)	FR (mm/min)	DD (mm)	Optimized DF
Firefly	1568.99	66.94	11.53	1.3644
PSO	450.0	30.0	4.0	1.1766
Cuckoo	1454.81	34.93	4.02	1.1906
GWO	450.0	30.0	4.0	1.1766
SALP	789.22	35.87	4.33	1.1968
ORCA	1396.49	32.56	4.21	1.1861

Table 11. Optimization performance of metaheuristic algorithms (5 independent runs).

Algorithm	Best DF Values (5 Runs)	Average DF	Standard Deviation
PSO	1.1695, 1.1695, 1.1695, 1.1695, 1.1695	1.1695	0.0000
GWO	1.1695, 1.1695, 1.1695, 1.1695, 1.1695	1.1695	0.0000

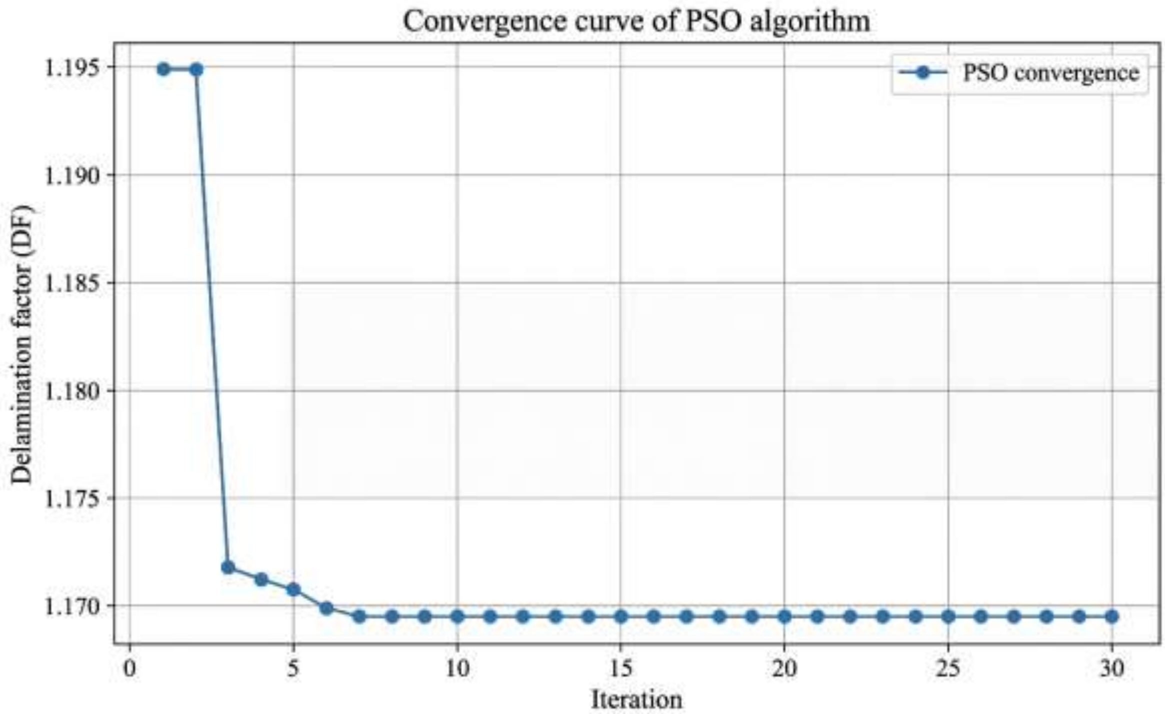

Figure 12. Convergence curve of PSO algorithm.

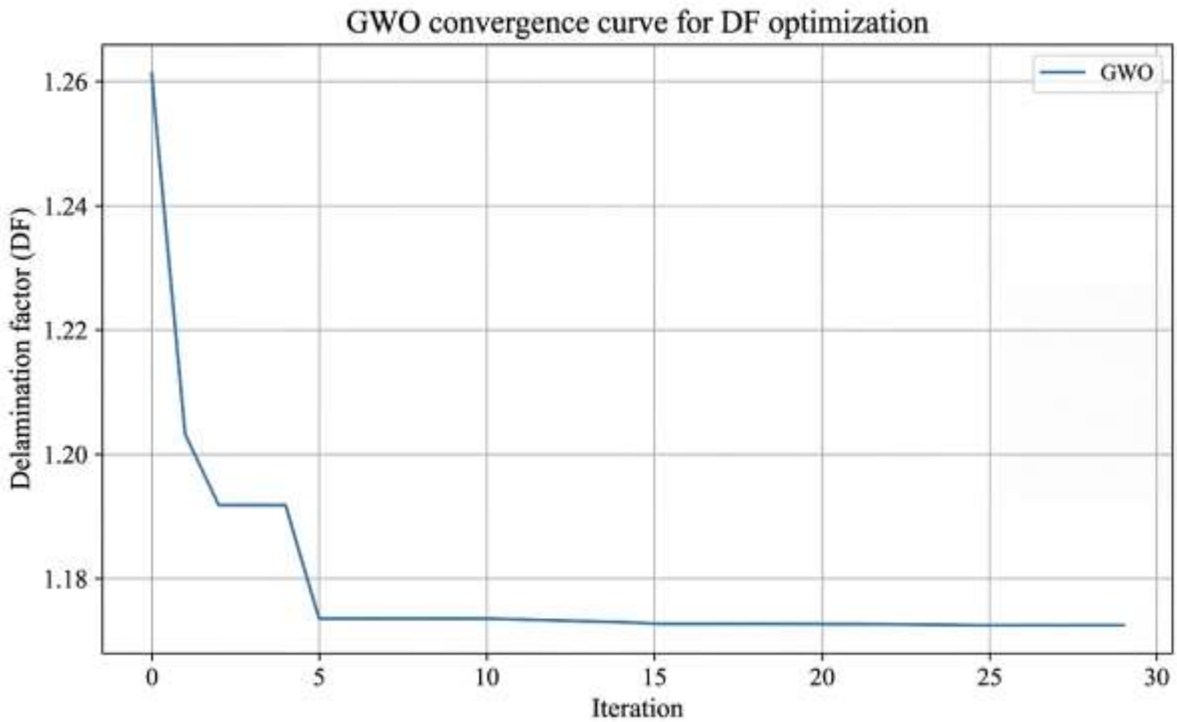

Figure 13. Convergence curve of GWO algorithm.

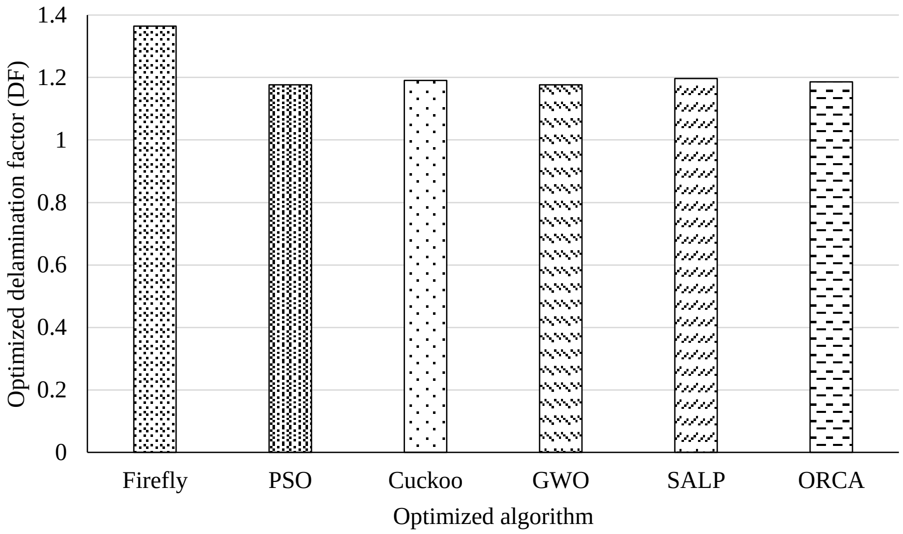

Figure 14. Comparison of optimized DF different algorithms.

Consistency with Regression Model

The optimized DF value from both PSO and GWO is 1.1766, which is lower than those predicted by the other algorithms. This value is consistent with the trend observed in the regression model predictions and falls within the range of DF values recorded in the experimental tests.

Statistical Metrics and Ranking Analysis Regression Metrics

The very low MSE (0.0001) and high R^2 (0.9812) for the Linear and Ridge models suggest that the predictive model is robust and explains nearly all the variability in DF.

Ranking Analysis

As shown in the combined ranking table, the Linear and Ridge Regression models rank highest in both MSE and R^2. This ranking, along with the alignment of the metaheuristic results (PSO and GWO providing the lowest DF), reinforces the validity of the optimized parameters.

Reproducibility

The consistency of the optimized DF values across multiple runs and different metaheuristic algorithms (notably PSO and GWO) indicates the stability of the solution. The validation of results confirms that the regression models (especially Linear and Ridge Regression) accurately predict the Delamination Factor based on drilling parameters. The optimized parameters obtained via metaheuristic algorithms (with PSO and GWO yielding DF = 1.1766) are in excellent agreement with the regression model predictions and experimental observations. Statistical metrics (MSE and R^2) and sensitivity analyses further support the robustness and reliability of the optimized results. Overall, the alignment among experimental data, regression model performance, and metaheuristic optimization outcomes validates the effectiveness of the proposed optimization framework for minimizing the Delamination Factor in drilling operations

CONCLUSIONS

This study is a drilling parameter optimization study on Nickel -Phosphorous (Ni-P) coated glass fiber-reinforced vinyl ester polymer composite where the main objective is to minimize the Delamination Factor (DF). Multi regression models and metaheuristic algorithms were utilized to achieve strong and confirmatory general results. The best predictive accuracy was obtained using Linear and Ridge Regression among the regression models with R^2=0.9812, and MSE =0.0001. The ANOVA outcome indicated that feed rate and drill diameter are significant factors that affect delamination statistically ($p < 0.0001$), whereas, spindle speed did not exhibit substantial variation ($p = 0.458$). Such observations can also be supported by feature importance metrics of the ensemble models, in which feed rate has provided more than 64 percent contribution to the predictive accuracy. In order to deal with the overfitting risks given the sizes of the dataset (25 samples), 5-fold cross-validation was performed. The mean R^2 values of 0.8723 (Linear) and 0.8715 (Ridge) support the good generalizability of the models. These findings confirm the accuracy and partition stability of the statistical models. Six metaheuristic algorithms were compared in the optimization stage. Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) recorded the minimum delamination factor of 1.1766. Moreover, the two algorithms demonstrated very high consistency between five independent runs, zero standard deviation, implying high repeatability and stability of convergence. These values compare better with other algorithms like Firefly, SALP and Cuckoo Search. This work has several advancements over previous works. Bhushi et al. (2020) and Abd-Elwahed (2023) have drilling optimization in CFRP and GFRP composite with PSO but not with Ni P coated systems and with several algorithms. We have closed this gap and optimized a new class of reinforced polymers. In the same regard, as opposed to Kumar et al. (2021) and Kalita et al. (2022), who considered only single-algorithm methodologies with fixed machining parameters, the multi-model, multi-algorithm framework generates a more generalizable and proven solution. Moreover, the study expands on the findings of Pendokhare & Chakraborty (2024) and Taiwo et al. (2024) by complementing Grey Wolf Optimization with entire experimental verification, and outperforms the prior studies (e.g., Soepangkat et al., Mahmood et al., Benkhelladi et al.) by incorporating real-life knowledge of machining process into the model. In short, the current investigation offers a verified and statistically powerful model of drilling optimisation in Ni--P coated polymer composites. Next directions could involve investigations of deep learning architectures, real time adaptive control and hybrid optimization to advance predictive and operation performance in next generation manufacturing systems.

REFERENCES

1. Bhushi U, Suthar J, Teli SN. Performance analysis of metaheuristics optimization techniques for drilling process on CFRP composites. Mater Today Proc. 2020;28:1106–1114.
2. Kalita K, Mallick PK, Bhoi AK, Ghadai RK. Optimizing drilling induced delamination in GFRP composites using genetic algorithm and particle swarm optimisation. Adv Compos Lett. 2018;27(1):1–9.
3. Kumar J, Verma RK, Mondal AK. Taguchi–grey theory-based harmony search algorithm (GR-HSA) for predictive modeling and multi-objective optimization in drilling of polymer composites. Exp Tech. 2021;45:531–548.
4. Natarajan E, Markandan K, Sekar SM, Varadaraju K, Nesappan S, Albert Selvaraj AD, Lim WH, Franz G. Drilling-induced damages in hybrid carbon and glass fiber-reinforced composite laminate and optimized drilling parameters. J Compos Sci. 2022;6(10):310.
5. Pendokhare D, Chakraborty S. Parametric optimization of conventional drilling processes using human-based metaheuristic algorithms: A comparative analysis. In: Singh S, Singh I, editors. Advances in Materials and Manufacturing. ICDMT 2024. Lecture Notes in Mechanical Engineering. Singapore: Springer; 2025.
6. Abd-Elwahed M. Drilling process of GFRP composites: modeling and optimization using hybrid ANN. Sustainability. 2022;14(11):6599.
7. Soepangkat BOP, Pramujati B, Effendi MK, et al. Multi-objective optimization in drilling Kevlar fiber reinforced polymer using grey fuzzy analysis and backpropagation neural network–genetic algorithm (BPNN–GA) approaches. Int J Precis Eng Manuf. 2019;20:593–607.
8. Soepangkat BOP, Norcahyo R, Effendi MK, Pramujati B. Multi-response optimization of carbon fiber reinforced polymer (CFRP) drilling using back propagation neural network–particle swarm optimization (BPNN–PSO). Eng Sci Technol Int J. 2020;23(3):700–713.
9. Taiwo EO, Oke SA, Rajan J, Jose S, Oyetunji EO, Adedeji KA. Optimizing the parameters of carbon fiber reinforced plastic composite drilling process using signal-to-noise ratio-based grey wolf optimization algorithm. Int J Ind Eng Eng Manag. 2024;6(1).

10. Kayaroganam P, Krishnan V, Natarajan E, Natarajan S, Muthusamy K. Drilling parameters analysis on in-situ Al/B_4C/mica hybrid composite and an integrated optimization approach using fuzzy model and non-dominated sorting genetic algorithm. Metals. 2021;11(12):2060.
11. Benkhelladi A, Laouissi A, Laouici H, et al. Assessment of hybrid composite drilling and prediction of cutting parameters by ANFIS and deep neural network approach. Int J Adv Manuf Technol. 2024;135:589–606.
12. Mahmood ZN, Al-Khazraji H, Mahdi SM. Adaptive control and enhanced algorithm for efficient drilling in composite materials. J Eur Syst Autom. 2023;56(3).
13. Antil P, Singh S, Manna A, Katal N, Pruncu CI. Polym Compos. 2021;42(10):5051–5065.
14. Kharwar PK, Verma RK. Nature instigated grey wolf algorithm for parametric optimization during machining (milling) of polymer nanocomposites. J Thermoplast Compos Mater. 2023;36(1):118–140.
15. Gautam GD, Shrivastava Y. Advancements in metaheuristic optimization techniques for laser beam cutting of FRP composites: a review. Proc Inst Mech Eng E J Process Mech Eng. 2024. doi:10.1177/09544089241278097.
16. Ghasempour-Mouziraji M, Hosseinzadeh M, Hajimiri H, et al. Machine learning-based optimization of geometrical accuracy in wire cut drilling. Int J Adv Manuf Technol. 2022;123:4265–4276.
17. Sreenivasulu R, Chaitanya G. Self adaptive penalty method coupled with metaheuristic algorithms to optimization of varying geometrical parameters in drilling for multi hole parts. Sigma J Eng Nat Sci. 2022. doi:10.14744/sigma.2022.00101.
18. Mehmood N, Umer M, Asgher U. Multi-hole drilling tool path planning and cost management through hybrid SFLA–ACO algorithm for composites and hybrid materials. J Compos Sci. 2022;6:364.
19. Sahoo A, Mishra D. Parametric optimization of response parameter of Nd:YAG laser drilling for basalt-PTFE coated glass fibre using genetic algorithm. J Eng Res. 2023. doi:10.1016/j.jer.2023.07.014.
20. Saravanakumar S, Sathiyamurthy S, Vinoth V. Enhancing machining accuracy of banana fiber-reinforced composites with ensemble machine learning. Measurement. 2024;235:114912.

