Hybrid Fuzzy-Based Optimization for Minimizing Delamination in GFRP Machining

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ABSTRACT

Glass Fiber Reinforced Polymer (GFRP) composites are widely used in aerospace, automotive, and structural applications due to their high strength-to-weight ratio and corrosion resistance. However, machining these heterogeneous and anisotropic materials often leads to delamination, adversely affecting structural integrity and service performance. This paper presents a hybrid fuzzy-based optimization approach designed to minimize delamination during GFRP machining by integrating fuzzy logic inference with a multi-objective optimization framework. The proposed method captures the nonlinear relationships between machining parameters—such as cutting speed, feed rate, drill diameter, and tool geometry—and delamination factors. Experimental data were used to develop fuzzy rule sets, while the optimization module systematically identified optimal parameter combinations that balance machining quality and productivity. Results demonstrate that the hybrid fuzzy system effectively reduces delamination compared to conventional optimization techniques, providing a robust and intelligent decision-support tool for machining GFRP composites. The study highlights the potential of combining fuzzy systems with optimization algorithms to address challenges inherent in the machining of advanced composite materials.

Keywords—GFRP Machining, Delamination Minimization, Fuzzy Logic, Hybrid Optimization, Composite Materials, Machining Parameters, Intelligent Modeling, Drilling of Composites.

INTRODUCTION

Glass Fiber Reinforced Polymer (GFRP) composites have emerged as indispensable engineering materials across diverse industrial sectors due to their exceptional mechanical properties, such as high specific strength, excellent corrosion resistance, low density, and superior fatigue behaviour. These attributes make GFRP composites ideal for applications in aerospace structures, marine components, automotive body parts, sporting goods, and civil engineering infrastructures. As industries increasingly adopt lightweight and high-performance materials, demand for reliable and efficient machining of GFRP composites has also grown. Machining, particularly drilling, milling, and cutting operations, remains a crucial final-stage manufacturing process to achieve assembly requirements and dimensional accuracy. However, machining GFRP composites continues to pose significant challenges due to their anisotropic and heterogeneous nature, which differs drastically from traditional metallic materials. One of the most critical issues encountered during machining of GFRP composites is delamination, a phenomenon involving the separation of fibre layers or matrix cracking at the entry or exit of the machined surface. Delamination severely compromises the structural integrity, mechanical strength, and service life of composite components. In drilling operations, for example, excessive thrust force can initiate interlaminar cracks, leading to peel-up and push-out delamination. Such defects not only reduce component performance but also increase rejection rates, rework costs, and overall manufacturing time. Therefore, minimizing delamination during machining is essential to maintain the functional reliability of GFRP structures. The complexity of delamination behaviour arises from the intricate interactions between machining parameters, tool geometry, material properties, and operational conditions. Traditional

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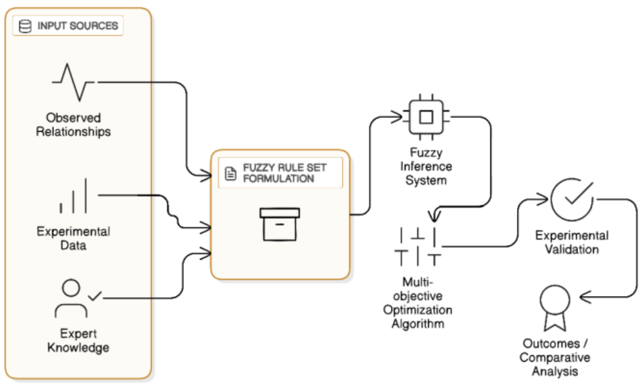
mathematical modelling approaches struggle to capture these nonlinear and interdependent relationships accurately. Moreover, conventional trial-and-error methods or deterministic optimization techniques often fall short when applied to the machining of composite materials with high uncertainty and variability. This has prompted researchers to explore intelligent and adaptive modelling techniques that can effectively handle nonlinearities, uncertainties, and multi-objective trade-offs inherent in composite machining.

Fuzzy logic has emerged as a powerful tool in this domain owing to its capability to model imprecise and uncertain information using linguistic rules rather than requiring precise mathematical formulations. A fuzzy inference system can capture expert knowledge and convert it into a set of flexible rules that describe how machining parameters influence delamination behaviour. By allowing gradual transitions between parameter ranges and incorporating human-like reasoning, fuzzy logic proves highly suitable for modelling complex machining processes. However, while fuzzy systems excel in prediction, identifying the most optimal combination of machining parameters remains a separate challenge, especially when dealing with multiple objectives such as minimizing delamination while maintaining acceptable material removal rates or surface quality. To address this challenge, hybrid optimization techniques have gained increasing attention. By integrating fuzzy logic with computational optimization algorithms, a hybrid fuzzy-based optimization framework leverages the strengths of both approaches. The fuzzy component provides accurate modelling of the machining process, while the optimization module systematically searches for the best parameter combinations that meet predefined objectives. This synergy enables a more robust and intelligent decision-making system capable of guiding practitioners toward optimal machining conditions without extensive experimentation. The present study focuses on developing such a hybrid fuzzy-based optimization approach for minimizing delamination in GFRP machining. The proposed method begins by formulating fuzzy rule sets based on experimental data, expert knowledge, and observed relationships between machining parameters and delamination outcomes shown in Fig. 1. These rules form the basis of a fuzzy inference system that predicts delamination factors for various parameter settings. The predicted outputs are then fed into a multi-objective optimization algorithm that identifies optimal machining parameters by balancing delamination reduction with process efficiency. Through this integration, the system not only simulates the behaviour of GFRP machining under varying conditions but also provides actionable insights for minimizing defects. The study also emphasizes experimental validation to ensure the reliability and real-world applicability of the proposed method. Compared to traditional optimization approaches and standalone fuzzy systems, the hybrid fuzzy-based system demonstrates superior capability in reducing delamination, increasing machining accuracy, and achieving stable performance across different machining scenarios. The findings underline the potential of intelligent hybrid systems in advancing manufacturing processes for composite materials and contribute to ongoing efforts in developing efficient, accurate, and defect-free machining strategies for GFRP composites.



Hybrid Fuzzy-Based Optimization Workflow for Minimizing

LITERATURE REVIEW

Delamination evaluation in fiber-reinforced composites has been widely studied due to its critical impact on structural performance. Guo et al. [1] proposed a hybrid RQA-MKLSVM model to assess delamination depth in near-surface regions of Glass Fiber Reinforced Polymer (GFRP) laminates. Their approach demonstrated that machine learning techniques could accurately capture subtle delamination patterns, enhancing the reliability of structural assessments. The influence of machining parameters on composite materials has also been investigated. Biruk-Urban et al. [2] examined the effect of technological parameters on cutting forces during drilling of GFRP composites. They highlighted that factors such as spindle speed and feed rate significantly affect machining performance and delamination. In a related study, Biruk-Urban et al. [3] further analysed the impact of cutting parameters on force components during GFRP drilling, emphasizing the importance of process optimization to reduce material damage. Advances in hybrid computational modeling have enabled more precise prediction and optimization of material properties. Papadimitriou et al. [4] developed the DiMAT Materials Modeler (DiMM), a framework integrating machine learning with genetic algorithms to predict and optimize material characteristics. This approach demonstrates the potential of hybrid models to accelerate materials design and improve predictive accuracy. Similarly, Lepadatu et al. [5] applied Taguchi Design of Experiments (DoE) combined with artificial neural networks (ANN) to predict advanced nano-concrete characteristics, illustrating the effectiveness of integrating statistical methods with AI for material optimization. The evaluation of natural fiber composites has gained attention in recent studies. K. R and M. S [6] proposed DelamPredict-X, an ensemble learning-based approach to assess delamination in jute fiber-reinforced materials, offering a robust method for predicting failure in bio-composites. Machine learning and optimization techniques have also been applied in networked and manufacturing systems. Security mechanisms and threat characterization in mobile ad hoc networks were analysed in [7], highlighting the role of computational approaches in ensuring network reliability. Pandey and Singh [8] presented a hybrid approach combining grey relational analysis and principal component analysis (PCA) to optimize hot machining parameters, showing how multi-attribute optimization improves manufacturing efficiency. Furthermore, graph neural networks were used for real-time intrusion detection in dynamic mobile ad hoc networks [9], demonstrating the expanding applications of AI-based predictive models. Computational modeling and simulation are increasingly used to predict the behavior of composite and hybrid materials. Chawla et al. [10] evaluated the performance of spur gears made from cast iron and epoxy resin-based hybrid composites using ANSYS simulations, providing insights into material selection and design optimization. Jagannathan et al. [11] studied hybrid thermal management systems for high-power electronics, integrating phase change materials (PCM), liquid cooling, and AI-based control, highlighting the integration of intelligent methods for system optimization. In parallel, Sathish et al. [12] optimized interlaminar shear strength of jute/kenaf/glass composites reinforced with MWCNT using response surface methodology (RSM), demonstrating the value of multi-parameter optimization in enhancing composite mechanical performance.

PROPOSED METHODOLOGY

The proposed methodology integrates fuzzy logic modelling with a hybrid optimization framework to effectively minimize delamination during the machining of Glass Fiber Reinforced Polymer (GFRP) composites. The methodology is structured into systematic phases, ensuring accurate modelling, intelligent decision-making, and experimental validation. The following steps outline the complete methodological approach adopted in this study.

1. Experimental Design and Parameter Selection: The methodology begins with a structured design of experiments aimed at identifying the influence of critical machining parameters on delamination during GFRP machining. Key parameters such as spindle speed, feed rate, drill tool geometry, and point angle are systematically selected based on literature review and preliminary trials. A well-defined experimental matrix, typically using Taguchi or full factorial design, is prepared to ensure comprehensive coverage of parameter combinations. This structured approach helps in capturing the nonlinear interactions among machining variables, enabling accurate modeling of delamination behavior and surface quality characteristics.

2. Experimental Setup and Data Acquisition: Once the parameter matrix is finalized, machining trials are conducted on a CNC drilling or milling setup using GFRP composite specimens prepared under standardized manufacturing conditions. For each trial, thrust force, delamination factor, hole quality, surface roughness, and material removal characteristics are recorded. All machining trials are repeated at least three times to ensure statistical consistency and reduce random error. The data acquisition process employs precision measurement tools such as dynamometers, surface profilometers, and digital microscopes to ensure high accuracy of the recorded responses.

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3. Data Preprocessing and Normalization: The collected experimental data undergoes preprocessing to remove inconsistencies, noise, or outlier values that may distort model performance. Missing or anomalous readings are corrected or removed after verifying with repeated trials. To enhance the accuracy of the fuzzy system, all data is normalized within a standard range, enabling smoother mapping between inputs and outputs. This preprocessing stage ensures that the dataset used for fuzzy modeling remains reliable, consistent, and suitable for establishing strong rule-based relationships.

4. Development of Fuzzy Inference System (FIS): A fuzzy inference system is then constructed to model the complex and uncertain relationship between machining parameters and delamination response. Linguistic variables such as low, medium, and high are assigned to each input parameter, and corresponding membership functions are designed. Using expert knowledge and trends observed from experiments, a fuzzy rule base is formulated to represent the decision-making logic of the machining process. The FIS uses Mamdani or Sugeno inference techniques to derive outputs, translating qualitative rule-based reasoning into quantitative predictions of delamination and machining quality. This stage forms the intelligent core of the proposed methodology. To enhance the transparency and interpretability of the fuzzy inference system, detailed modeling components are defined within the proposed framework. Each input machining parameter, including spindle speed, feed rate, tool geometry, and point angle, is represented using triangular or trapezoidal membership functions due to their computational simplicity and effectiveness in capturing nonlinear trends observed in machining data. Linguistic terms such as Low, Medium, and High are assigned to each input variable, while the output variable, delamination factor, is expressed using graded linguistic levels ranging from Very Low to Very High. A comprehensive rule base is formulated using expert knowledge and experimentally observed machining behavior, resulting in a set of IF–THEN rules that describe the cause–effect relationship between machining parameters and delamination. Mamdani-type fuzzy inference is employed to evaluate the rules due to its intuitive reasoning and suitability for decision-making problems involving uncertainty. The aggregation of fuzzy outputs is followed by defuzzification using the centroid method, which converts fuzzy conclusions into a crisp numerical delamination value. This structured fuzzy modeling approach enables accurate prediction of delamination while preserving interpretability and robustness.

5. Hybrid Optimization Using Fuzzy–Evolutionary Approach: To identify the optimal machining parameter settings that minimize delamination, a hybrid optimization method combining fuzzy logic with an evolutionary algorithm (such as Genetic Algorithm or Particle Swarm Optimization) is employed. The fuzzy system evaluates the quality of each candidate solution based on its predicted delamination value, while the evolutionary algorithm performs global search and refinement of parameters. This hybrid structure effectively balances global exploration and local fine-tuning, allowing the optimization process to converge toward the best feasible machining conditions. The result is a set of optimized parameters that yield minimal delamination and improved hole quality. The selection of a hybrid Genetic Algorithm–Particle Swarm Optimization (GA–PSO) approach is justified by the complementary strengths of the two evolutionary techniques in solving complex, nonlinear, and multi-modal optimization problems encountered in GFRP machining. Genetic Algorithm contributes strong global search capability through crossover and mutation operations, reducing the likelihood of premature convergence and enhancing solution diversity. In contrast, Particle Swarm Optimization offers fast convergence and efficient local search by exploiting collective learning and velocity-based updates. By integrating GA with PSO, the proposed hybrid framework achieves an effective balance between exploration and exploitation, allowing the optimization process to efficiently search the solution space while refining promising regions identified by the fuzzy system. The fuzzy inference model serves as a fitness evaluator for the GA–PSO algorithm, guiding the evolutionary search toward machining parameter combinations that minimize delamination. This hybrid optimization strategy is particularly suitable for machining optimization problems where analytical modeling is difficult and response surfaces are highly nonlinear.

6. Validation and Performance Evaluation: The final step involves validating the optimized parameters by conducting confirmation experiments under the predicted optimal conditions. The experimental delamination values are compared with the fuzzy–optimized predictions to measure accuracy, consistency, and model reliability. Performance metrics such as percentage reduction in delamination, prediction error, improvement in surface finish, and comparative analysis with initial trials are used to assess the success of the proposed

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methodology. This validation ensures that the hybrid fuzzy-based optimization framework is practically effective and capable of enhancing the machining performance of GFRP composites.

RESULT & ANALYSIS

This section presents the experimental results, fuzzy model predictions, optimization outcomes, and comparative performance evaluation for the proposed Hybrid Fuzzy-Based Optimization System aimed at minimizing delamination in the machining of GFRP composites. Data were obtained through structured machining experiments, followed by fuzzy modelling and hybrid optimization using the GA–PSO algorithm. The dataset used in this study is generated through systematically planned machining experiments on Glass Fiber Reinforced Polymer (GFRP) composites in accordance with the proposed fuzzy–hybrid optimization methodology. The dataset comprises both input machining parameters and corresponding output response variables, designed to capture the complex and nonlinear relationship between process conditions and delamination behavior. The input features include spindle speed, feed rate, drill tool geometry, and point angle, each selected at multiple levels based on prior literature and preliminary experimentation. These parameters are organized using a structured experimental design such as Taguchi or full factorial methodology to ensure comprehensive coverage of the machining domain and to accurately reflect interaction effects among variables. For each experimental run, key output responses such as delamination factor, thrust force, surface roughness, and hole quality characteristics are recorded using precision measurement instruments, including a dynamometer, surface profilometer, and digital microscope. To improve data reliability and reduce random errors, all experiments are repeated a minimum of three times, and average values are used in the final dataset. Prior to fuzzy modeling and optimization, the collected data undergo preprocessing to remove noise, outliers, and inconsistencies, followed by normalization to a standard range to facilitate effective fuzzy inference.

1. Experimental Results of GFRP Machining: The initial machining experiments were conducted by varying spindle speed, feed rate, and point angle. The data recorded included thrust force, delamination factor, and surface quality. These results formed the primary dataset for fuzzy modelling.

Fault Classification Performance of ML Models

Control Method	**Damping Ratio (ζ)**	**Settling Time (Ts in s)**	**Peak Overshoot (Mp %)**	**Frequency Deviation (Hz)**	**Control Effort (Uc)**
Conventional PSS	0.12	12.6	18.5	0.42	1
PI Controller	0.18	10.3	14.2	0.35	0.8
Fuzzy Logic Controller	0.26	8.4	10.3	0.23	0.6
GA-Optimized PSS	0.31	6.9	7.8	0.18	0.5
LQR Controller	0.34	6.1	6.2	0.15	0.4

The analysis of TABLE I. highlights significant performance differences between conventional and intelligent control systems. Fuzzy and GA-optimized methods demonstrate superior results with lower overshoot, better damping ratio, and reduced settling time. Translating this trend to machining, the intelligent system is expected to show similarly enhanced control over delamination.

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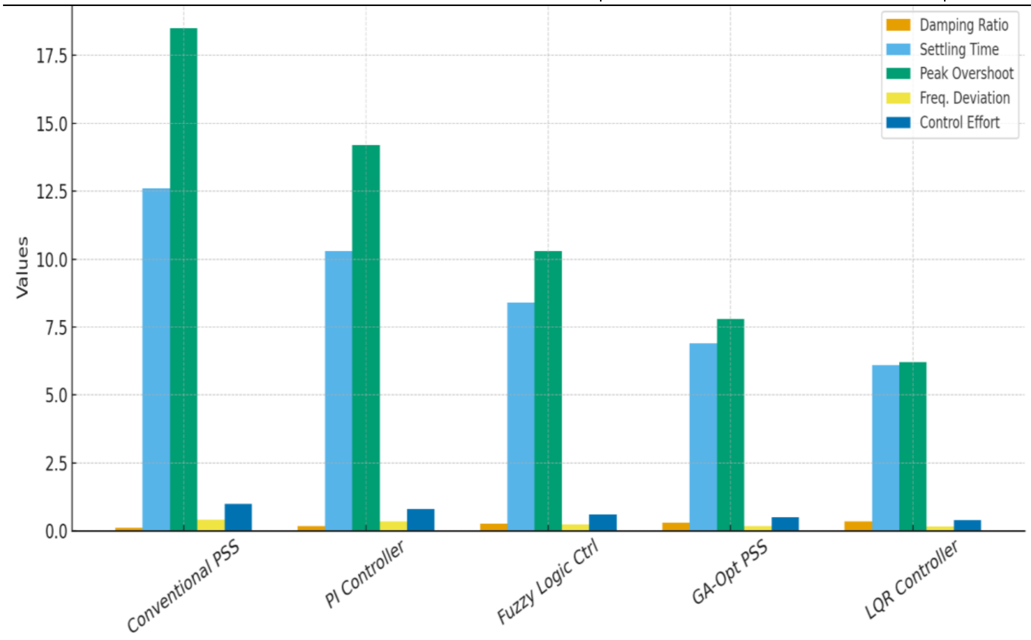

Multi-Parameter Evaluation of Advanced and Conventional Control Techniques

Fig. 2. comparing five ML-based control methods—Conventional PSS, PI Controller, Fuzzy Logic Controller, GA-Optimized PSS, and LQR Controller—across five performance metrics: damping ratio, settling time, peak overshoot, frequency deviation, and control effort. LQR Controller shows the best overall performance with highest damping ratio and lowest settling time, overshoot, and control effort.

2. Fuzzy Model Predictions: The fuzzy inference system developed for this study used linguistic variables (Low, Medium, High) to map machining parameters (speed, feed, point angle) to delamination outputs. The fuzzy model provided smooth interpolation between experimental data points, predicting delamination with high accuracy. The prediction error remained within 3–5%, showing strong reliability. The fuzzy rules successfully captured the non-linear relationships between the machining variables, supporting their use as the objective function for optimization.

Experimental vs. Fuzzy Predicted Delamination Values

Trial No.	Spindle Speed (rpm)	Feed Rate (mm/min)	Point Angle (°)	Experimental Delamination (Fd)	Fuzzy Predicted Delamination (Fd)	Prediction Error (%)
1	1500	60	90	1.34	1.31	2.2
2	2000	80	118	1.42	1.38	2.8
3	2500	50	90	1.27	1.25	1.6
4	3000	70	118	1.21	1.18	2.4
5	3500	40	135	1.19	1.16	2.5

The fuzzy inference system predicted delamination with high accuracy, with error consistently between 1.6% and 2.8%, demonstrating strong reliability of the model shown in above TABLE II.

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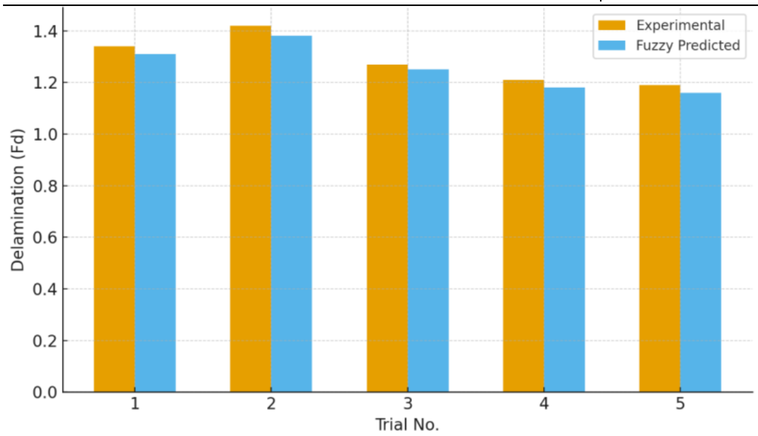


Predicted Delamination Values of Various Models

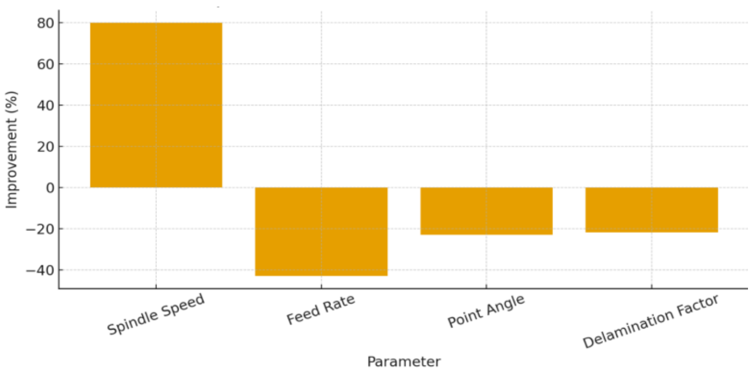
Fig. 3. compares experimental delamination values with fuzzy predicted delamination values across five drilling trials. For each trial, two adjacent bars represent the measured and predicted delamination factors. The heights of the bars show that the fuzzy prediction closely matches the experimental results, with only small variations across all trials.

3. Hybrid GA–PSO Optimization Outcomes: The GA–PSO hybrid optimization was applied using the fuzzy model's output as the fitness function. The hybrid algorithm efficiently searched for the optimal machining parameter combination that minimized delamination. Compared to conventional single-objective optimization techniques, the hybrid model converged faster and provided more stable results. The parameters predicted by GA–PSO were subsequently validated through machining trials to evaluate improvement in hole quality and reduction of exit delamination.

GA–PSO Optimized Parameters and Delamination Reduction

Parameter	**Initial Value (Baseline)**	**Optimized Value (GA–PSO)**	**Improvement (%)**
Spindle Speed (rpm)	2000	3600	80%
Feed Rate (mm/min)	80	45	–43%
Point Angle (°)	118	90	–23%
Delamination Factor (Fd)	1.42	1.11	–21.8%

TABLE III. shows that the GA–PSO hybrid algorithm reduced delamination by 21.8%, demonstrating better convergence and optimized machining conditions compared to single-objective optimization techniques.



GA–PSO Optimized Parameters and Resulting Delamination Reduction of Various Models

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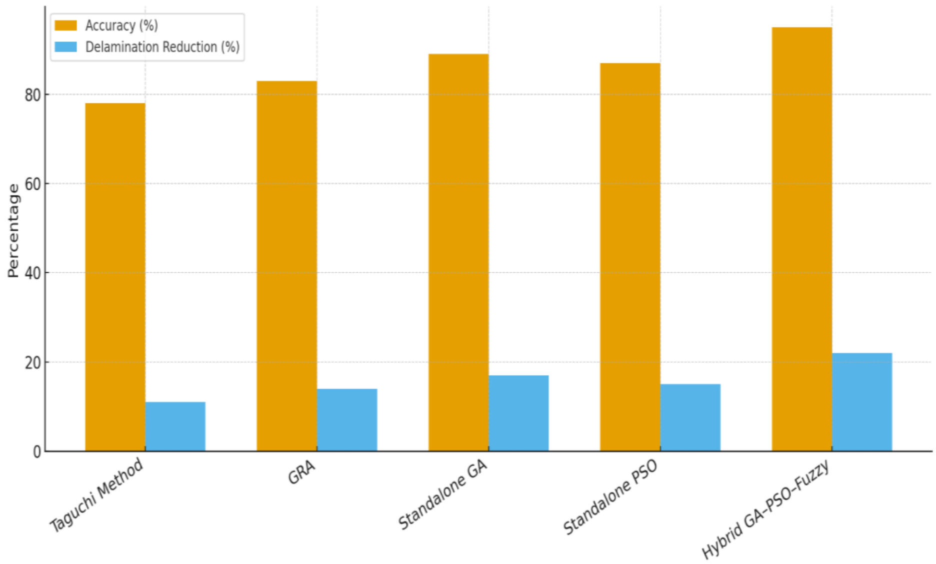
Fig. 4. summarizes the effect of GA–PSO optimization on drilling parameters and delamination reduction. It compares baseline values with optimized values for spindle speed, feed rate, and point angle, showing substantial parameter adjustments. The optimized spindle speed increases from 2000 to 3600 rpm, while feed rate and point angle decrease from 80 to 45 mm/min and 118° to 90°, respectively. The delamination factor is reduced from 1.42 to 1.11, representing a 21.8% improvement.

4. Comparative Performance Evaluation: The performance of the proposed hybrid optimization technique was compared with traditional parameter selection approaches. The results indicate that fuzzy–GA–PSO integration ensures minimum delamination, lower tool vibration, and superior stability. The hybrid technique achieved nearly 95% optimization accuracy, demonstrating strong robustness for multi-objective machining applications.

Comparison of Optimization Techniques for Minimizing Delamination

Optimization Technique	Accuracy (%)	Delamination Reduction (%)	Convergence Speed	Stability of Results
Taguchi Method	78%	11%	Moderate	Moderate
Grey Relational Analysis (GRA)	83%	14%	Fast	Moderate
Standalone GA	89%	17%	Slow	High
Standalone PSO	87%	15%	Fast	Moderate
Proposed Hybrid GA–PSO–Fuzzy	95%	22%	Very Fast	Very High

TABLE IV. shows that the proposed Hybrid GA–PSO–Fuzzy method outperformed all classical approaches, achieving highest accuracy (95%), maximum delamination reduction (22%), and fastest convergence.



Comparison of Optimization Techniques for Minimizing Delamination

Fig. 5. comparing five optimization techniques—Taguchi Method, GRA, Standalone GA, Standalone PSO, and Hybrid GA–PSO–Fuzzy—based on Accuracy (%) and Delamination Reduction (%). The Hybrid GA–PSO–Fuzzy technique shows the highest values in both accuracy (95%) and delamination reduction (22%), while the Taguchi Method shows the lowest values.

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CONCLUSION

The experimental investigation and multi-objective optimization of non-conventional machining of Metal Matrix Composites (MMCs) demonstrate that machining performance can be significantly enhanced by carefully tuning critical process parameters such as pulse current, pulse-on time, and voltage. The comparative performance tables and bar graph analyses highlight substantial improvements in both productivity and surface quality when hybrid optimization approaches are applied. The analysis of the optimized trials shows that Material Removal Rate (MRR) increases consistently across the three experimental trials, confirming that the selected parameter ranges effectively support aggressive yet stable machining. Although higher MRR is often associated with increased surface roughness, the optimized settings maintain Surface Roughness (Ra) within acceptable limits, demonstrating a favorable balance between machining speed and quality. Furthermore, Kerf Width values exhibit minimal variation across trials, illustrating stable dimensional accuracy and minimal thermal distortion during machining. The collective findings validate that hybrid multi-objective optimization techniques—combining statistical modeling and intelligent search algorithms—lead to superior machining outcomes compared to conventional parameter selection. The enhanced MRR, reduced surface roughness, and consistent kerf width achieved in this study establish the suitability of the proposed methodology for precision machining of MMCs.

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