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PROCESS PARAMETER OPTIMIZATION IN THE MACHINING OF FIBER-REINFORCED POLYMERS: A REVIEW OF METHODOLOGIES FROM TAGUCHI TO NEURAL NETWORKS

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Abstract. *The widespread adoption of Fiber Reinforced Polymers (FRPs), such as CFRP and GFRP, in weight-critical industries has necessitated highly precise secondary machining operations. However, the heterogeneous and anisotropic nature of these composites makes them susceptible to severe machining-induced defects, including delamination, matrix smearing, and rapid tool wear. To mitigate these issues, selecting and controlling optimal machining parameters (cutting speed, feed rate, and depth of cut) is critical. This paper comprehensively reviews the evolution of process optimization strategies in composite machining. It begins by examining established traditional statistical methods, including the Taguchi Method, Analysis of Variance (ANOVA), and Response Surface Methodology (RSM), which offer robust, data-efficient frameworks for linear process control. Subsequently, the paper explores the paradigm shift toward Artificial Intelligence (AI) and machine learning techniques, specifically Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Fuzzy Logic systems. These data-driven approaches successfully overcome the limitations of traditional models by capturing complex, non-linear thermo-mechanical dynamics and resolving multi-objective conflicts. Ultimately, this review highlights that the future of zero-defect composite manufacturing lies in integrating these methodologies into intelligent hybrid models that bridge the gap between experimental efficiency and advanced predictive accuracy.*

Keywords: *composite machining; process parameter optimization; artificial intelligence.*

1. Introduction

Composite materials, particularly Fiber Reinforced Polymers (FRPs) such as Carbon Fiber (CFRP) and Glass Fiber Reinforced Plastics (GFRP), have revolutionized modern engineering. Characterized by their exceptional strength-to-weight ratios, high stiffness, and excellent corrosion resistance, these materials have become indispensable in weight-critical sectors such as the aerospace, automotive, and marine industries. While composite components are typically molded to near-net shapes, secondary machining operations such as drilling for fastener assembly or milling for precise edge trimming are inevitably required to achieve final dimensional tolerances.

However, the machining of composite materials presents profound challenges compared to traditional homogeneous metals. Composites are inherently heterogeneous and anisotropic; their mechanical properties vary significantly depending on the fiber orientation. Furthermore, the highly abrasive nature of the reinforcing fibers leads to rapid tool wear. If the machining process parameters, primarily cutting speed, feed rate, and depth of cut, are not meticulously controlled, the resulting mechanical and thermal stresses can induce severe workpiece damage. These defects include matrix smearing, fiber pull-out, and most critically, delamination (the separation of adjacent composite layers), which drastically reduces the structural integrity and fatigue life of the final component.

Given the high material and manufacturing costs associated with aerospace- and automotive-grade composites, relying on trial-and-error to find the optimal machining parameters is economically unfeasible. Consequently, the manufacturing industry has historically relied on robust statistical optimization strategies. Techniques such as the Taguchi Method, Analysis of Variance (ANOVA), and Response Surface Methodology (RSM) have provided structured, highly data-efficient frameworks to minimize surface defects and maximize tool life.

As manufacturing demands stricter tolerances and composite structures become more complex, the limitations of linear, discrete statistical models have become apparent. This has prompted a paradigm shift toward data-driven Artificial Intelligence (AI) techniques, including Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Fuzzy Logic systems. These intelligent systems excel at recognizing the complex, non-linear thermo-mechanical behaviors inherent in composite cutting. This paper comprehensively reviews both the traditional and AI-driven methodologies used to optimize composite machining. Furthermore, it explores how the future of process optimization lies not in choosing between traditional and AI methods, but in integrating them into intelligent hybrid models that pave the way for zero-defect, highly efficient manufacturing.

2. Review Methodology

To ensure transparency and reproducibility, a systematic approach was adopted to select, screen, and categorize the literature reviewed in this manuscript. Relevant studies were identified through comprehensive searches across major academic databases, primarily relying on Scopus, Web of Science, ScienceDirect, and Google Scholar. The search strategy utilized targeted combinations of keywords including "Composite machining," "Process parameter optimization," "Taguchi method," "Response Surface Methodology," "Artificial Neural Networks," "Genetic Algorithms," and "Fuzzy Logic."

The screening process focused strictly on peer-reviewed journal articles and conference proceedings published within the last two decades. Studies were selected based on their explicit focus on optimizing secondary machining parameters (cutting speed, feed rate, depth of cut, tool geometry) for fiber-reinforced polymers (specifically CFRP and GFRP). Articles focusing purely on composite synthesis, primary forming processes, or non-machining applications were excluded to maintain focus. Once screened, the selected literature was logically categorized into two primary domains: traditional statistical optimization strategies (Section 3) and predictive modeling using artificial intelligence (Section 4), enabling a structured comparative discussion.

3. Traditional Optimization Strategies

In the machining of composite materials, selecting the correct process parameters, such as cutting speed, feed rate, and depth of cut, is critical. Unlike metals, composites are heterogeneous and anisotropic, meaning their properties vary with direction. This makes them prone to specific defects like delamination (separation of layers) and fiber pull-out. To address these challenges without wasting expensive materials on trial-and-error, researchers rely on statistical optimization strategies. The most established "traditional" methods are the Taguchi Method, Analysis of Variance (ANOVA), and Response Surface Methodology (RSM) [1].

3.1 The Taguchi Method

Developed by Dr. Genichi Taguchi, this method is widely regarded as a robust design strategy for quality engineering. Its primary goal is not just to maximize performance, but to make the manufacturing process insensitive to "noise," which represents uncontrollable variables such as machine vibrations or slight inconsistencies in the composite material. The methodology relies fundamentally on Orthogonal Arrays (OA), which are specialized standard tables that allow researchers to investigate a large number of variables with a minimum number of experiments. For instance, while a full study of three factors at three levels would typically require 27 separate experiments, a Taguchi L_9 array can derive statistically significant results in just 9 runs. This efficiency is particularly crucial in machining composites, where tool wear is rapid, and the workpieces are often prohibitively expensive to waste.

Another distinct feature of this approach is the use of the Signal-to-Noise (S/N) ratio to analyze data. Instead of simply evaluating the average result, the S/N ratio consolidates the mean and the variance into a single metric. The "Signal" represents the desirable value, such as a smooth surface finish, while the "Noise" represents the undesirable variability. In composite machining research, the "Smaller-the-Better" category is typically selected for minimizing defects like surface roughness (R_a) or delamination factor (F_d), where a higher S/N ratio indicates a more robust and stable process. Research by Palanikumar demonstrates the effectiveness of this method in turning Glass Fiber Reinforced Plastics (GFRP) [2]. Using an L_27 orthogonal array, the study optimized cutting parameters to minimize surface roughness. The analysis revealed that the Taguchi method successfully identified a robust operating window, highlighting that low feed rates and high cutting speeds are generally preferred to minimize the brittle fracture of fibers.

Similarly, Erkan et al. applied the Taguchi method to optimize the end milling process for Glass Fiber Reinforced Polymer (GFRP) composites [3]. By employing an L27 orthogonal array, they systematically evaluated the effects of cutting speed, feed rate, and depth of cut, along with tools with varying numbers of flutes, on the resulting surface roughness. Through the analysis of S/N ratios, the study corroborated that higher cutting speeds paired with low feed rates produced the optimal, smoothest surface finish, successfully minimizing surface roughness down to 1.626 µm.

3.2 Analysis of Variance (ANOVA)

While the Taguchi method is excellent for identifying the best levels for parameters (e.g., determining that Speed Level 2 is superior to Level 1), it does not explicitly quantify the magnitude of influence each parameter has on the final outcome. To bridge this gap, researchers employ Analysis of Variance (ANOVA). This statistical tool calculates the percentage contribution of each machining parameter to the total variation in the result, effectively separating the variation caused by control factors from that caused by experimental error. By establishing a hierarchy of influence, ANOVA allows engineers to prioritize which settings must be strictly controlled and which can be adjusted with less risk.

The utility of ANOVA is evident in studies such as those by Davim et al., which analyzed the milling of GFRP composites [4]. Their statistical analysis of machining forces and surface roughness provided a clear breakdown of parameter influence, revealing that the feed rate was the dominant factor, contributing over 70% to the variation in machining force, while cutting speed had a much smaller impact. Similarly, a simplified version of this technique, known as Pareto ANOVA, based on the Pareto principle (80/20 rule), is often utilized in industrial settings. This method allows engineers to quickly identify the "vital few" parameters, typically, feed rate in composite machining, that drive the majority of quality issues, ensuring that optimization efforts are focused where they will yield the most significant reduction in defects.

Further highlighting the necessity of ANOVA in varying contexts, Rao et al. applied this statistical method to a different machining operation: the drilling of GFRP composite laminates using High Speed Steel (HSS) twist drills. Using a Full Factorial Design, they measured the resulting surface roughness and applied ANOVA to evaluate the exact percentage contribution of drill diameter, feed rate, and spindle speed [5]. They found that the drill diameter was the most critical factor, contributing a massive 75.76% to the total variance in surface roughness, while feed rate and spindle speed had marginal impacts of 8.34% and 7.57%, respectively. This specific quantification allowed the researchers to confidently conclude that selecting a smaller drill size (such as the 6 mm diameter in their optimized setup) is the most decisive parameter for achieving high surface quality and dimensional accuracy in composite hole-making.

3.3 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) represents a more advanced statistical technique used for modeling and analyzing problems where a response of interest is influenced by several variables. Unlike the Taguchi method, which identifies the best point from discrete, pre-defined levels, RSM fits a mathematical equation (usually a second-order polynomial) to the experimental data. This creates a continuous "map" of the entire experimental region, allowing for the prediction of results at any point within the design space, even those that were not experimentally tested. The output is often visualized through 3D surface plots or 2D contour graphs, which are instrumental in visualizing the interaction between parameters—for instance, demonstrating how a high cutting speed might improve finish only if the depth of cut remains low.

The precision of RSM was demonstrated in a study by Nor Khairusshima et al., which utilized a Central Composite Design (CCD) to optimize the milling of Carbon Fiber Reinforced Plastics (CFRP) [6]. The developed mathematical model allowed the researchers to pinpoint a precise global optimum, specifically, a spindle speed of 3061 rpm and a depth of cut of 0.72 mm, rather than settling for a general level. The study confirmed that RSM is particularly superior when the interaction effects between variables are significant and need to be understood to prevent complex failure modes like delamination.

In another compelling application, Parida et al. utilized RSM to develop a second-order mathematical model for predicting surface roughness during the drilling of GFRP composites with High-Speed Steel (HSS) tools [7]. While many studies isolate the effects of individual parameters, the RSM approach successfully mapped the continuous, interacting relationships among spindle speed, feed rate, and drill bit diameter. The resulting response surface models and ANOVA validation (at a 95% confidence level) showed that spindle speed was the overwhelmingly dominant factor driving surface roughness, while feed rate had a statistically insignificant effect. By visualizing these mathematical relationships on a plotted response surface, the researchers were able to pinpoint a highly specific optimal operating window, using a low spindle speed, a medium feed rate, and a medium drill bit diameter that minimized surface defects, proving RSM's efficacy in generating highly reliable predictive equations for composite machining.

4. Artificial Intelligence and Predictive Modelling in Composite Machining

While traditional statistical methods like Taguchi and RSM are effective for defining linear relationships and robust operating windows, they often struggle to capture the complex, non-linear, and stochastic nature of composite machining. To overcome these limitations, researchers have increasingly adopted Artificial Intelligence (AI) techniques. These data-driven approaches require less domain-specific physical knowledge and can uncover intricate patterns within experimental data, enabling highly accurate predictions of process characteristics such as cutting force, temperature, and surface defects [8]. This section explores the application of Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Fuzzy Logic systems in the optimization of composite machining.

4.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are computational models inspired by the human brain, consisting of interconnected neurons arranged in layers. They are particularly powerful in machining research for their ability to model non-linear relationships between input parameters (such as speed and feed) and outputs (such as delamination or tool wear) without needing a pre-defined mathematical equation [8].

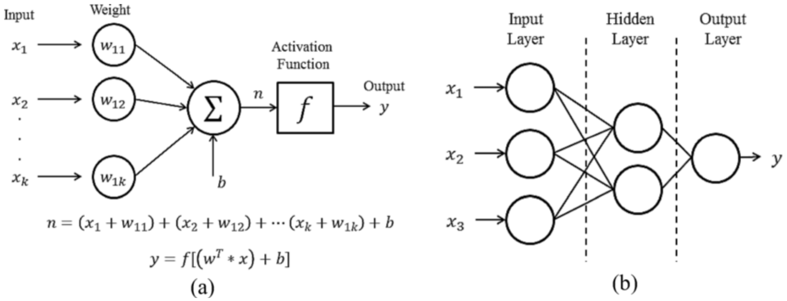

Figure 1 - a) ANN structure with one neuron. b) ANN scheme [9]

A significant application of ANN in composite machining is the prediction and prevention of delamination, a critical failure mode where layers separate. Research by Karnik et al. utilized ANN to model high-speed drilling of Carbon Fiber Reinforced Polymers (CFRP) [10]. Their study processed experimental data to predict the delamination factor based on spindle speed, feed rate, and point angle. A key finding from their ANN model was the counterintuitive benefit of high-speed machining; the model correctly predicted that higher spindle speeds generated frictional heat, which softened the polymer matrix (matrix softening), thereby reducing the thrust force and subsequent delamination damage.

Similarly, Popan et al. developed a feed-forward ANN model trained with backpropagation to optimize the piercing phase of Abrasive Water Jet (AWJ) machining of CFRP [11]. This phase is notorious for causing delamination due to the high initial impact pressure. The ANN analyzed inputs including water pressure (100–400 MPa), standoff distance (0.5–10 mm), and abrasive start synchronization (On/Off). The model predicted that reducing the water pressure to 100 MPa and maintaining a low standoff distance of 0.5 mm, combined with abrasive start synchronization ON, would eliminate delamination for the piercing process. Validation experiments confirmed the ANN's predictions, producing defect-free holes and preventing the rejection of expensive aerospace components.

Furthermore, researchers like Stone and Krishnamurthy implemented ANN for real-time process control [12]. They developed a neural network controller that monitored thrust force during drilling. The system could predict the onset of delamination and dynamically adjust the feed rate in real-time, effectively maintaining forces within a safe envelope and preventing damage at the hole exit.

4.2 Genetic Algorithms (GA)

Genetic Algorithms (GA) are optimization techniques based on the principles of natural selection and genetics. Unlike ANN, which is primarily a predictive tool, GA is an optimization search tool used to find the "global optimum" in a vast solution space. It operates by evolving a population of potential solutions through operations like selection, crossover, and mutation to find the best possible combination of machining parameters [8].

Kumar and Sait applied GA to optimize the turning parameters of composite pipes [14]. Their objective was to optimize the machining parameters to yield a minimum cutting force. The GA processed the experimental data and converged on a specific optimal set of parameters. From this analysis, the following conclusions are drawn: Force acting on the cutting tool is found to be minimum at a cutting speed of 75 m/min, a feed rate of 0.2 mm/rev, and a depth of cut of 0.5 mm.

To further enhance accuracy, researchers often combine GA with Neural Networks. Cao et al. utilized a hybrid GA-BPNN (Genetic Algorithm optimized Back-Propagation Neural Network) to model the high-speed milling of Carbon Fiber/Polyetheretherketone (CF/PEEK) laminates [15]. In this hybrid approach, the GA was used to optimize the initial weights and thresholds of the neural network, preventing it from getting stuck in local optima. This improved model was used to predict surface roughness (S_q) and fractal dimension (D_s). The results showed that the GA-BPNN model achieved a prediction accuracy exceeding 90%, significantly outperforming standard regression models in predicting the complex surface topography of machined thermoplastic composites.

These advanced optimization techniques are essential not only in the machining phase but also in the broader structural design of composites. Demonstrating this, Al-Hamzawi and Kovács developed a novel multi-objective optimization methodology to simultaneously minimize the weight and improve the structural responses of corrugated composite sandwich structures [16]. In their study, they utilized a hybrid framework that integrated Finite Element Analysis (FEA) for data generation with Artificial Neural Networks (ANN) to create highly accurate predictive models for structural behaviors such as deflection and stress. A Genetic Algorithm (GA) was then applied to these models to systematically identify optimal design variables, including ply orientations and core geometric dimensions. The approach successfully yielded a set of Pareto-optimal solutions that achieved significant weight reduction while maintaining and even improving the structural integrity of the composites. By leveraging these advanced algorithmic approaches, their research proves the effectiveness of navigating complex, multi-objective composite design problems, which share the same underlying mathematical complexities found in multi-objective machining parameter optimization.

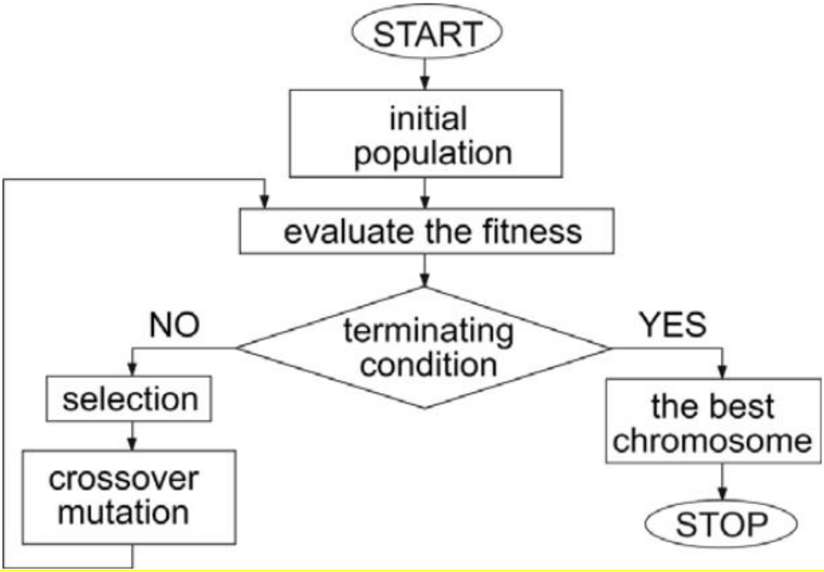

Figure 2 - Genetic algorithm scheme [13]

In the context of composite machining, GA is often used to find optimal parameters that lie between the discrete levels tested in standard experiments.

4.3 Fuzzy Logic and Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Fuzzy Logic is a computing approach based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic. It uses linguistic variables (e.g., "High," "Medium," "Low") and rule-based inference (IF-THEN rules) to model uncertainty. When combined with the learning capabilities of neural networks, it forms an Adaptive Neuro-Fuzzy Inference System (ANFIS), which is highly effective for modelling complex, ambiguous systems [8].

Fuzzy logic is particularly useful for multi-objective optimization, where manufacturers must balance conflicting goals, such as minimizing force while maximizing speed. Hari Babu et al. employed a Fuzzy Inference System (FIS) to optimize the drilling of hybrid Glass-Carbon Fiber Reinforced (GCFR) epoxy composites [17]. The study aimed to simultaneously minimize four distinct responses: Thrust Force, Torque, Delamination Factor, and Surface Roughness. The FIS combined these four values into a single metric called the Multi-Response Performance Index (MPI).

The experiments involved varying spindle speed (1000–3000 RPM), drill diameter (5–7 mm), and feed rate (50–150 mm/min). The FIS analysis identified that the optimal parameter combination for the best overall quality was a spindle speed of 3000 RPM, a drill diameter of 5 mm, and a feed rate of 50 mm/min. Furthermore, Analysis of Variance (ANOVA) on the MPI revealed that drill diameter was the most significant factor influencing the overall drilling quality of the hybrid composite, followed by feed rate.

In another application involving biocomposites, Tran et al. used ANFIS to predict surface roughness and thrust force [18]. Biocomposites often exhibit high material variability, which makes standard regression difficult. The ANFIS model, by adjusting its internal membership functions, was able to map the non-linear relationships between cutting parameters and surface quality more accurately than linear regression models, providing reliable predictions despite the "noise" inherent in natural fiber materials.

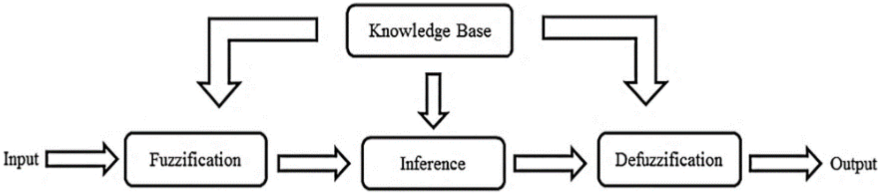

Figure 3 - Fuzzy logic scheme [9]

5. Comparative Discussion

The evolution of process optimization in composite machining, from statistical designs (Taguchi, RSM) to data-driven intelligence (ANN, GA, Fuzzy Logic), represents a shift from "robust design" to "intelligent manufacturing." While both approaches share the ultimate goal of improving quality and efficiency, their underlying mechanisms, capabilities, and applications differ significantly. This section compares these methodologies and highlights the emergence of hybrid models that leverage the strengths of both.

5.1 Linear Approximations vs Non-Linear Dynamics

Traditional methods, particularly RSM and Taguchi, are founded on the assumption that the relationship between machining inputs (e.g., speed, feed) and outputs (e.g., delamination, thrust force, surface roughness) can be approximated by smooth, continuous functions. Typically, linear or quadratic polynomials. This assumption holds well for homogeneous metals but often falls short for composites like CFRP and GFRP. As noted in the study by Karnik et al. [10], effects such as "matrix softening" introduce sharp non-linearities where an increase in speed suddenly reduces damage due to thermal softening. Traditional regression models might average this effect out, whereas AI models like ANN can capture the specific inflection point, providing a more accurate representation of the thermo-mechanical reality.

Furthermore, traditional methods generally require rigid experimental designs (e.g., Orthogonal Arrays) that test parameters at discrete levels (Level 1, 2, 3). If the true optimum lies between Level 2 and Level 3, the Taguchi method may miss it. In contrast, Genetic Algorithms (GA) operate as global search heuristics. As demonstrated by Kumar and Sait [14], GA can search the continuous space between discrete experimental levels, identifying a precise global optimum (e.g., 75 m/min) that was not explicitly tested in the initial design.

5.2 Multi-Objective Conflicts

A significant limitation of traditional methods is their struggle with multi-objective optimization. In composite machining, higher feed rates typically increase productivity (a positive outcome) but also increase thrust force and surface roughness (negative outcomes). Standard Taguchi analysis optimizes each response individually, often leading to conflicting optimal parameter sets. Researchers must then rely on engineering judgment to find a compromise.

AI methods, particularly Fuzzy Logic, offer a mathematical solution to this ambiguity. By converting disparate responses into linguistic variables and fusing them into a single index (such as the MPI used by Hari Babu et al. [17]), fuzzy systems provide a structured way to balance competing goals. This allows for the identification of a single "best compromise" setup that satisfies multiple quality criteria simultaneously, a capability that is less intuitive in standard ANOVA or Taguchi analysis.

Table 1 - Comparison of Traditional and AI Optimization Methods

Feature	**Traditional Methods (Taguchi, RSM, ANOVA)**	**AI Methods (ANN, GA, Fuzzy Logic/ANFIS)**
Primary Mechanism	Statistical inference, linear/quadratic regression, signal-to-noise ratios.	Pattern recognition, non-linear mapping, evolutionary search, linguistic reasoning.
Relationship Modelling	Best for linear or simple non-linear relationships. Assumes continuity.	Excellent for complex, highly non-linear, and discontinuous relationships.
Optimization Scope	Discrete (local). Limited to specific levels tested in the experiment.	Continuous (global). Can find optimal points between tested levels (GA).
Data Requirement	Low. Efficient designs (e.g., L9, L27) require fewer experiments.	High. Generally, requires larger training datasets to avoid overfitting.
Multi-Objective Capability	Limited. Optimizes responses individually; requires manual trade-offs.	High. Fuzzy logic and neural networks can fuse multiple outputs into a single index.
Interpretability	High. ANOVA explicitly quantifies the % contribution of each factor.	Low/Medium. ANNs are often "black boxes"; Fuzzy Logic provides interpretable rules.

5.3 Data Efficiency and Prediction Accuracy

The primary advantage of traditional methods remains their efficiency. A Taguchi L_9 array can yield statistically valid conclusions with only 9 experiments, making it highly cost-effective for industrial screening. In contrast, AI models, especially Deep Learning and complex ANNs, typically require large datasets to train effectively without overfitting. The "data scarcity" problem in composite machining—where experimental data is expensive to generate—is a key hurdle for AI. However, methods like ANFIS (used by Tran et al. [18]) and GPR (Gaussian Process Regression) are gaining popularity precisely because they can provide accurate non-linear predictions even with smaller datasets, bridging the gap between data hunger and experimental constraints.

6. Conclusions

The optimization of machining parameters for composite materials has undergone a significant evolution, transitioning from traditional statistical designs to advanced, data-driven artificial intelligence. The inherent heterogeneity and anisotropy of composites like GFRP and CFRP make machining a complex process, highly susceptible to defects such as delamination, fiber pull-out, and poor surface finish. As this review highlights, traditional methodologies (such as the Taguchi method, ANOVA, and RSM) have long provided robust, cost-effective frameworks for identifying critical parameters and establishing stable operating windows. They remain highly valuable for initial process screening and quantifying the linear impacts of factors like feed rate, cutting speed, and tool geometry.

However, the non-linear, stochastic nature of composite machining often exceeds the capabilities of standard regression models. AI techniques, including Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Fuzzy Logic systems, have emerged as powerful alternatives that require less domain-specific physical pre-definitions. These intelligent systems offer superior predictive accuracy by mapping complex thermo-mechanical behaviors, such as matrix softening, and by enabling continuous global optimization beyond discrete experimental levels. Furthermore, tools like Fuzzy Logic provide structured mathematical solutions to multi-objective conflicts, allowing manufacturers to simultaneously optimize competing goals like productivity and surface quality.

Ultimately, the future of composite machining optimization lies not in choosing between traditional and AI methods, but in integrating them. Hybrid approaches (e.g, using GA to optimize neural network weights (GA-BPNN) or combining fuzzy logic with adaptive learning (ANFIS)) demonstrate the highest potential.

Despite these advancements, several concrete research gaps remain to be addressed in future studies. First, the industrial implementation of AI-driven real-time adaptive control is heavily restricted by computational latency and a lack of robust, sensor-integrated edge computing solutions on the shop floor. Second, the training of highly accurate predictive models is frequently hampered by a scarcity of standardized, publicly available machining datasets. Finally, the inherent "black-box" nature of many deep learning algorithms limits their interpretability and hinders trust among manufacturing engineers. Future research must prioritize the development of Explainable AI (XAI) frameworks to clarify how these models reach their predictions. Furthermore, bridging these hybrid algorithms with Digital Twin technology could enable dynamic, real-time optimization and autonomous error correction, propelling the industry closer to the ultimate goal of zero-defect composite machining.

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ОПТИМІЗАЦІЯ ПАРАМЕТРІВ ПРОЦЕСУ ОБРОБКИ ВОЛОКОННО-АРМОВАНИХ ПОЛІМЕРІВ: ОГЛЯД МЕТОДОЛОГІЙ ВІД ТАГУЧІ ДО НЕЙРОННИХ МЕРЕЖ

Анотація. *Широке впровадження волокно-армованих полімерів (FRP), таких як CFRP та GFRP, у критично важливих галузях, вимагало високоточних вторинних операцій з обробки. Однак гетерогенний і анізотропний характер цих композитів робить їх вразливими до серйозних дефектів, спричинених обробкою, включно з розшаруванням, розмазуванням матриці та швидким зношенням інструментів. Для вирішення цих проблем критично важливо вибрати та контролювати оптимальні параметри обробки (швидкість різання, швидкість подачі та глибину різу). У цій статті ґрунтовно розглядається еволюція стратегій оптимізації процесів у композитній обробці. Він починається з вивчення усталених традиційних статистичних методів, зокрема методу Тагучі, аналізу дисперсії (ANOVA) та методології поверхні відгуку (RSM), які пропонують надійні, ефективні для даних рамки для лінійного керування процесами. Далі у статті розглядається зсув парадигми на користь штучного інтелекту (AI) та методів машинного навчання, зокрема штучних нейронних мереж (ANN), генетичних алгоритмів (GA) та систем нечіткої логіки. Ці підходи, засновані на даних, успішно долають обмеження традиційних моделей, фіксуючи складну, нелінійну термомеханічну динаміку та вирішуючи багатооб'єктні конфлікти. Незважаючи на ці досягнення, ще кілька конкретних дослідницьких прогалин залишаються для усунення в майбутніх дослідженнях. По-перше, промислове впровадження адаптивного керування в реальному часі на основі ШІ суттєво обмежене обчислювальною затримкою та відсутністю надійних рішень з інтеграцією сенсорів на периферії на виробництві. По-друге, навчання високоточних прогностичних моделей часто ускладнюється через нестачу стандартизованих, публічно доступних наборів даних для обробки. Нарешті, притаманна «чорна скринька» багатьох алгоритмів глибокого навчання обмежує їхню інтерпретацію та зменшує довіру серед інженерів-виробників. Зрештою, цей огляд підкреслює, що майбутнє виробництва композитів з нульовими дефектами полягає в інтеграції цих методологій у інтелектуальні гібридні моделі, які поєднують експериментальну ефективність і передову прогнозну точність.*

Ключові слова: *обробка композитів; оптимізація параметрів процесу; штучний інтелект.*