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Optimizing Machining Processes for Hybrid Glass Fiber-Reinforced Polymeric Nanocomposites: A Radial Basis Function Approach

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ABSTRACT

Hybrid glass fiber-reinforced polymeric nanocomposites (HGFRP) play a crucial role in various industries. However, optimizing drilling processes for these materials is essential. This research addresses this need by employing an artificial intelligence-based Radial Basis Function (RBF) model to efficiently optimize machining parameters, ensuring improved performance and cost-effectiveness across diverse industrial applications. The outcomes derived from the RBF model showcase an impressive Mean Squared Error (MSE) of 0.526. This superior performance surpasses that of both the Artificial Neural Network (ANN) and the Random Forest (RF) models in predicting response parameters such as delamination, thrust force, and torque within specified machining parameters, including spindle speed, feed rate, and drill diameter. The RBF attains an average MSE of 0.0021, 0.4145, and 0.13497 for the Delamination factor, Thrust force, and Torque, respectively, which outperforms comparative techniques. These outcomes contribute to the enhancement of manufacturing processes, elevate product quality, and ultimately bolster industrial competitiveness across various sectors. The knowledge and guidelines derived from this research pave the way for more efficient and precise machining of HGFRP, delivering tangible benefits to diverse industries.

Keywords: Hybrid glass fiber-reinforced polymeric nanocomposites, drilling, machining parameters, Artificial Neural Network, Radial Basis Function, Random Forest

1. Introduction

HGFRP composites have emerged as versatile materials with exceptional mechanical, thermal, and chemical properties, rendering them indispensable across a myriad of industrial applications [1, 2]. The combination of glass fibers and polymeric matrices imparts synergistic effects [3], enhancing the overall performance and functionality of these composite materials. Despite their widespread use, the need for drilling in HGFRP composites across diverse industrial applications [4] necessitates a comprehensive understanding of the machining processes involved.

The optimization of machining parameters, including spindle speed, feed rate, and drill diameter [5, 6], is crucial to achieving desirable outcomes in terms of minimizing delamination, controlling thrust force, and optimizing torque during the drilling process [7]. Delamination, which refers to the separation of layers within the composite material [8], is a critical concern as it can significantly compromise the structural integrity and overall performance of the material. Additionally, controlling thrust force and torque is vital for ensuring the efficiency and longevity of drilling tools [9], as well as preventing damage to the workpiece.

Conducting experiments to determine the optimal machining parameters is a conventional approach; however, this process comes with inherent drawbacks. Experimental processes are often time-consuming, expensive, and may not account for all possible variations in the material properties and environmental conditions [10]. Consequently, there is a pressing need for alternative methods that can expedite the optimization process while providing accurate and reliable results.

In response to these challenges, this research highlights the advantages of employing artificial intelligence-based predictive models for identifying machining parameters and their corresponding responses in HGFRP composites [11]. Artificial intelligence, with its ability to analyze vast datasets, recognizes intricate patterns and relationships that may elude traditional experimental approaches [12]. By utilizing machine learning algorithms, predictive models can effectively predict optimal machining parameters that mitigate delamination [13], minimize thrust force, and optimize torque, thereby streamlining the drilling process [14].

This research employs a RBF as an artificial intelligence-based predictive model [15] to identify the delamination, thrust force, and torque response in HGFRP composites under various machining parameters, including spindle speed, feed rate, and drill diameter [16]. The choice of the RBF is motivated by its capability to effectively capture complex relationships within the dataset [17], making it well-suited for modeling the intricate interactions between machining parameters and material responses.

The significance of this research lies in its potential to revolutionize the machining of HGFRP composites across diverse industrial applications. The utilization of RBF as an artificial intelligence-based predictive model introduces a novel and efficient approach [18] to optimize machining parameters such as spindle speed, feed rate, and drill diameter [19]. It contributes to the broader landscape of advanced manufacturing methodologies by introducing an approach that combines artificial intelligence with material science, promising more efficient, precise, and cost-effective solutions for diverse industrial applications.

Nomenclature

D_{max} = maximum diameter of the drilled hole including the delaminated zone

$\vec{x}$ is input vector

$\vec{C_i}$ is a centre vector

H is the number of receptive field units

σ_i is the variance of the Gaussian function

T_i is the desired output

Y_i is the actual output

n is the number of observations

Y_i is the actual value

$\hat{Y}_i$ is the predicted value

2. Literature review

In 2019 Prabhu et al investigated the impact of nanoclay addition to glass fiber-reinforced polyester composites. Pristine glass fiber-reinforced polyester composites. Glass fiber-reinforced polyester composites were prepared using the vacuum-assisted resin infusion technique. The paper also delved into optimizing cutting parameters (cutting speed and feed rate) to maximize mechanical properties during the drilling process of hybrid nanoclay glass fiber-reinforced polyester composites. Drilled samples underwent further mechanical testing, with tensile studies confirming superior mechanical properties for the optimal machining parameters of 0.045 mm/rev and 210 rpm for 3 wt% nanoclay in glass fiber-reinforced polyester nanocomposites. Overall, hybrid clay and glass fiber-reinforced nanocomposites exhibited better mechanical properties compared to pristine glass fiber-reinforced polyester composites.

In 2023, Raja et al [20] focused on delamination analysis in natural fiber–reinforced hybrid polymer composites made from neem, banyan fibers, and an epoxy matrix containing sawdust fillers during the drilling process, which is crucial for assembling composite components. The study employed the L27 factorial design orthogonal array to investigate three distinct spindle speeds, feed rates, and High-Speed Steel (HSS) drill bits used in drilling operations. Response Surface Methodology (RSM) was utilized to determine optimal responses for thrust force, torque, and delamination during drilling. The analysis of variance (ANOVA) results ($p < 0.04$) revealed that the optimal drilling parameters were a 6 mm drill bit diameter, 10 mm/rev feed rate, and a spindle speed of 1500 rpm. Overall, the study highlighted the crucial role of drilling parameters in ensuring an efficient drilling process for this specific natural fiber composite.

In 2021 Shanmugam et al [21] discussed the Filled hybrid composites are widely used in various structural applications where machining is critical. Hence, it is essential to understand the performance of the fibre composites' machining behaviour. As such, a new hybrid structural composite was fabricated with redmud as filler and sisal fibre as reinforcement in polyester matrix. The drilling experiment was conducted using Taguchi L27 orthogonal array. The effect of the drill tool point angle, the cutting speed, the feed rate on thrust force, delamination, and burr formation were analysed for producing quality holes. The significance of each parameter was analysed, and the experimental outcomes revealed some important findings in the context of the drilling behaviour of sisal fibre/polyester composites with redmud as a filler. Spindle speed contributed 39% in affecting the thrust force, while the feed rate had the maximum influence of ca. 38% in affecting delamination.

In 2022 Demirsöz et al [22] study the mechanical properties of the cutting elements and the effect of cutting parameters (spindle speed and feed rate) and reinforcement ratios on thrust force and surface roughness (Ra). The contribution of the cutting parameters to the investigated outcomes was determined using statistical analysis. Optical microscopy and scanning electron microscopy (SEM) was used to inspect the hole quality and damage mechanisms. The results revealed that the feed rate was the most contributing factor to thrust force (96.94%) and surface roughness (63.59%). Furthermore, in comparison to other hybrid composites, the lowest Ra value was obtained as 0.95 µm in samples containing 30% GB, while the Ra value was 1.04 µm in samples containing 10% GF + 20% GB. Polymer PA reinforced with 30% GF had the highest strength, modulus of elasticity, impact strength, and hardness.

In 2021 Yuan et al [23] proposed to optimize the cure process using the multi-field coupled model, surrogate model and genetic algorithm. A multi-field coupled FE model which takes the heat transfer, resin viscosity and resin flow-compaction process into consideration was developed to forecast the cure state of composite. A surrogate model was also built through RBF to reduce the computational cost and promote the optimization efficiency. After that, the non-dominated sorting genetic algorithm-II (NSGA-II) was combined with the surrogate model to search for global optimum solution. The results indicate that the proposed multi-objective approach proposed in this paper effectively reduce the cure time, maximum temperature overshoot and maximum gradient of DoC simultaneously, hence leading to good performances on thick composite laminate.

3. Proposed Methodology

The research methodology employed in this study follows a systematic approach to develop and evaluate RBF models for predicting response parameters in HGFRP composites. The dataset is divided into two subsets, with approximately 60% of the data allocated for training and the remaining portion designated for testing. This partitioning facilitates the training and subsequent evaluation of the predictive models [24]. The primary focus of this research is on the development of artificial intelligence models, specifically RBF, ANN, and RF models. These models aim to predict three crucial parameters in drilling processes: delamination, thrust force, and torque. The training process involves fine-tuning the model parameters using the training dataset, while the validation dataset plays a crucial role in optimizing the models' overall performance.

3.1. Drilling tests

The drilling operation is executed using a conventional vertical drilling machine, coupled with a Kistler dynamometer to measure cutting force and torque during the process. Delamination, a significant concern in drilling HGFRP composites, manifests at both the hole's inlet and exit. At the inlet, it occurs due to peeling action, while at the exit, it arises from the push-out action of the drill bit, as illustrated in Fig. 1. The anisotropic nature of the composite predominantly contributes to these occurrences. Various factors, including feed rate, spindle speed, drill diameter, drilling orientation, etc. [22], influence the hole's quality during the drilling process.

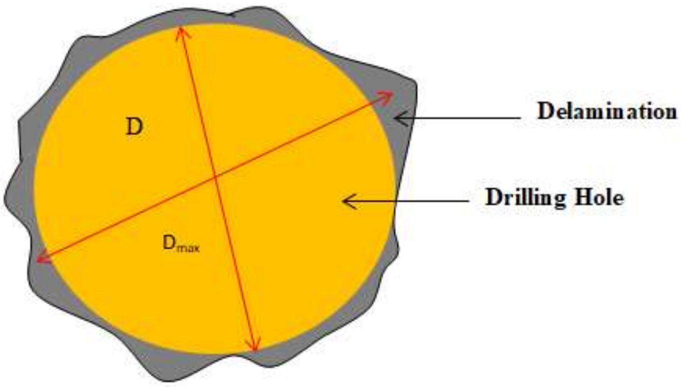

Fig. 1 - A schematic diagram of the measurement of the delamination factor.

Then the delamination factor (F_d) was calculated using Equation (1).

$$F_d = \frac{D_{\max}}{D_o} \quad (1)$$

Where, D_{max} = maximum diameter of the drilled hole including the delaminated zone, Do = base diameter of the drilled hole.

3.2. Radial basis function network (RBF)

The RBF is constructed with input, output and hidden layers of Gaussian activation functions. The network is capable of performing nonlinear mapping of the input features onto the output. The structure of RBF has only one hidden layer that applies a multidimensional nonlinear transformation from the input space to the hidden space. Gaussian function in the hidden layer is the most commonly used basis function for the RBF. It has been established that an RBF with sufficient number of Gaussian basis functions in the hidden layer can be used as a universal approximator. A schematic diagram of RBF is shown in Fig. 2.

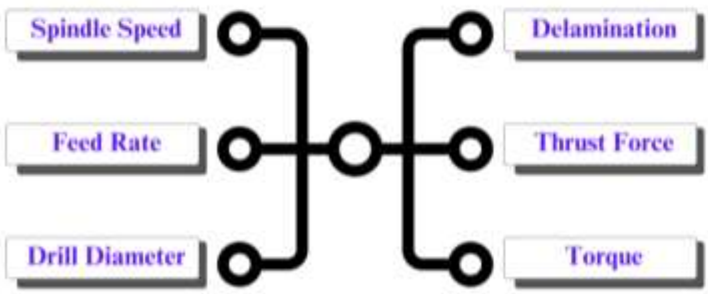

Fig. 2 - Schematic Diagram of Radial Basis Function Network.

The output of the ith receptive field unit (or hidden unit) is defines as Equation (2):

$$R_i(\vec{x}) = R_i\left(\frac{\left\|\vec{x} - \vec{C}_i\right\|}{\sigma_i}\right) \quad i = 1,2,\cdots,H \tag{2}$$

Where, $\vec{x}$ is input vector, $\vec{C}_i$ is a centre vector, H is the number of receptive field units, and σ_i is the variance of the Gaussian function. The output is the weighted sum of the function value associated with each receptive field is defines as Equation (3):

$$Y(\vec{x}) = \sum_{i=1}^{H} R_i W_i \tag{3}$$

Where, W_i is the connection weight of the output layer. The error function (E) is defined as (4):

$$E = \frac{1}{2}\sum_i (T_i - Y_i)^2 \tag{4}$$

Where, T_i is the desired output and Y_i is the actual output.

In this research, the criterion of convergent error MSE can be expressed as Equation (5)

$$MSE = \frac{1}{n}\sum_{i=1}^{n} Y_i - \hat{Y}_i^{\,2} \tag{5}$$

Where, n is the number of observations, Y_i is the actual value, and $\hat{Y}_i$ is the predicted value.

4. Result and discussion

The purpose of the research is to identify delamination, thrust force, and torque for given input spindle speed, feed rate, and drill diameter. This process employs RBF, ANN, and RF for prediction purposes and the performance of the employed techniques is evaluated through MSE. It is evident that the RBF model's predicted values are closer to the experimental results, i.e., lower MSE compared to ANN and RF in predicting delamination, thrust force, and torque. Details regarding these aspects are provided in the following investigations.

Fig. 3, 4, and 5 illustrate the performance of the RBF, ANN, and RF for delamination, thrust force, and torque. The results show that RBF predicted values are closer to the experimental values when compared to ANN and RF. The superior performance of the RBF model in predicting delamination, thrust force, and torque values, as compared to ANN and RF, can be attributed to the RBF model's inherent suitability for capturing intricate relationships in the data, effective training data representation, meticulous parameter tuning, and alignment of model simplicity with the complexity of the drilling process. These factors collectively contribute to the RBF model's closer proximity to experimental results in the specified parameters.

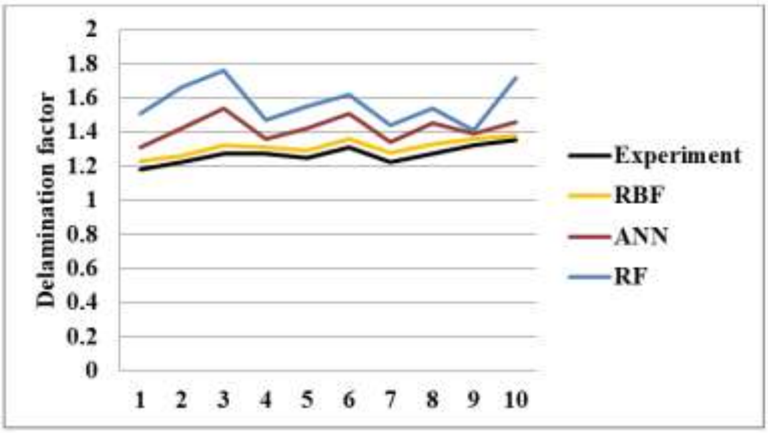

Fig. 3- Technique-wise delamination factor prediction results with respect to experimental values.

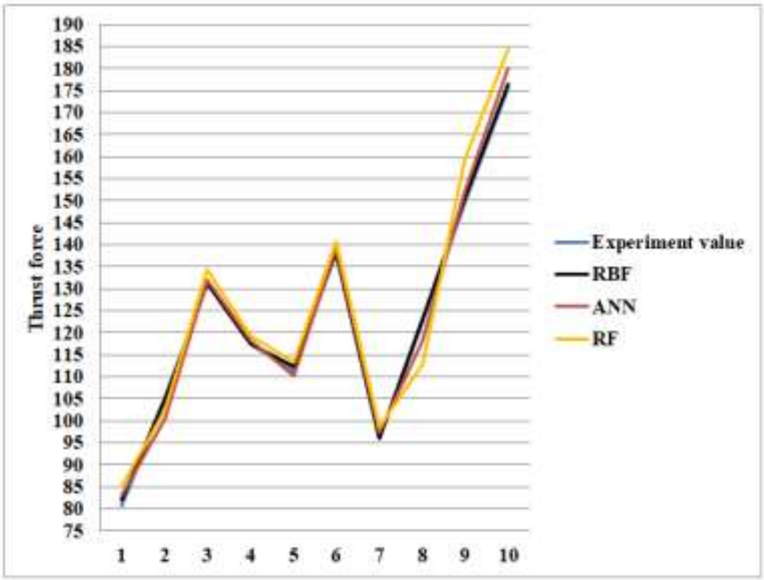

Fig. 4 - Technique-wise Thrust force prediction results with respect to experimental values.

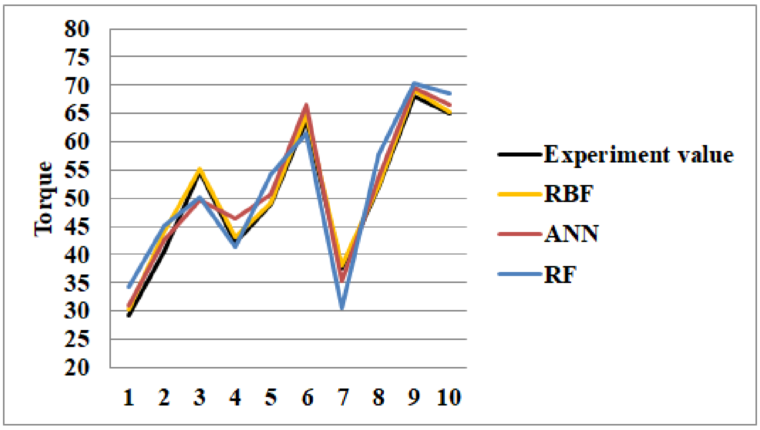

Fig. 5 - Technique-wise Torque prediction results with respect to experimental values.

4.1. Mean Square Error value

The MSE is a measure of the average squared difference between the predicted values (from models like RBF, ANN, and RF) and the actual or experimental values for Delamination factor, Thrust force, and Torque shown in table 1, table 2 and table 3. Specifically, it quantifies the average of the squared differences between each predicted value and its corresponding actual value. The formula for MSE is typically calculated as equation (5). The table illustrates MSE values for different machining parameters using RBF, ANN, and RF. For delamination factor, RBF exhibits the lowest MSE

(0.0022), implying superior accuracy, followed by ANN (0.02706) and RF (0.1035). In predicting thrust force, RBF again outperforms with the lowest MSE (0.5984), while ANN (7.4231) and RF (32.4188) show increasing prediction errors. Concerning torque, RBF maintains the lowest MSE (1.71019), followed by ANN (7.41709) and RF (20.4906). Generally, RBF consistently demonstrates strong predictive performance across all parameters, while ANN and RF show varying degrees of accuracy, indicating that the choice of the best technique depends on the specific machining parameter and desired prediction accuracy.

Table 1 - MSE Values of Models for Delamination Factor in Testing Data.

RBF	ANN	RF
0.0025	0.0169	0.1089
0.0016	0.04	0.1936
0.0025	0.0729	0.2401
0.0016	0.0081	0.04
0.0016	0.0289	0.09
0.0025	0.04	0.0961
0.0036	0.0144	0.0484
0.0036	0.0324	0.0729
0.0016	0.0049	0.0081
0.0009	0.0121	0.1369
Average MSE		
0.0022	**0.02706**	**0.1035**

Table 2 - MSE Values of Models for Thrust force in Testing Data.

RBF	ANN	RF
2.0736	5.4756	19.8025
0.0961	19.36	5.76
0.1764	0.25	7.84
0.0049	0.49	2.89
1.3456	0.7056	4.6656
0.1849	0.3249	4.41
0.04	1.69	7.29
0.4225	18.6624	94.09
1	7.0225	100
0.64	20.25	77.44
Average MSE		
0.5984	**7.4231**	**32.4188**

Table 3 - MSE Values of Models for Torque in Testing Data.

RBF	ANN	RF
0.9604	3.8809	25.7049
12.25	3.24	20.25
0.25	27.04	20.7936

1.0201	16.81	0.5476
0.1089	3.24	29.2681
1.1664	8.41	5.0176
0.36	4.41	50.6944
0.04	2.89	34.3396
0.8836	1.69	4.4521
0.0625	2.56	13.8384
Average MSE		
1.71019	**7.41709**	**20.4906**

5. Conclusion

The research highlights the significance of the RBF model's outstanding performance in accurately predicting critical response parameters, including delamination, thrust force, and torque within specified geometric parameters. This noteworthy achievement surpasses the capabilities of both the ANN and RF models, emphasizing the RBF model's potential to forecast crucial outcomes in manufacturing processes with precision. Furthermore, this research contributes to the integration of RBF, promising more efficient, precise, and cost-effective solutions for diverse industrial applications, solidifying the study's significance within the realm of modern manufacturing. Moreover, the study provides invaluable insights, tools, and guidelines tailored to meet the evolving demands of industries working with hybrid polymer composites. By delving into this field, the research not only enhances our understanding but also furnishes stakeholders with practical solutions poised to revolutionize manufacturing processes. These advancements have the potential to elevate product quality standards and ultimately enhance industrial competitiveness on a global scale.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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