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Optimizing The Parameters of Carbon Fiber Reinforced Plastic Composite Drilling Process Using Signal-to-noise Ratio-based Grey Wolf Optimization Algorithm

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ABSTRACT

This study aims to develop an optimization scheme that contributes to the production of carbon fiber-reinforced plastics using the grey wolf optimization approach. Different from other optimization schemes such as the Taguchi method, which takes some time to compute and use, this grey wolf optimization approach introduced a fast convergence scheme to reduce computation time thereby making its implementation in the factory very interesting. Data used for the analysis was obtained from a doctoral thesis via an experimental approach. Four responses were considered in this work, namely the torque, delamination at entry and exit, eccentricity and thrust force. A spreadsheet was used to implement the computational procedure of the grey wolf optimization algorithm. In using the wolves, at the initial level, the starting point was a zero where hunting had not begun and the prey had just entered the park, which is within the territory of the grey wolves. With this in mind, real life is mimicked and such data gathered would aid precise decision-making. The results revealed the feasibility of the approach and convergence was obtained at the tenth iteration with the best fitness value at 9020785071. It is expected that the findings from this work will be useful as a method for planning in production planning and policy development for the carbon fiber-reinforced plastic industry. This study is a noteworthy contribution to the production development of CFRPs where the grey wolf algorithm is used to analyze the problem. In addition, evidence of the responses determining the quality of drilled products is provided.

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1. INTRODUCTION

Carbon fibre-reinforced plastics (CFRPs) are a special class of composites often reinforced with carbon fibre for high-strength attainment (Cetin et al., 2023; Xu et al., 2023). However, of great concern to CFRP manufacturers is the quality of the products. There have been serious challenges in obtaining high-quality products to confrontation issues such as high and unacceptable thrust force, and delaminating both at the entry and exit parts of the composites, among others (Kumar et al., 2020; Tamilarasan and Renugambal, 2023; Ahuja et al., 2023). It is understood that if acceptable quality CFRPs are to be delivered to the customers, models need to be built to achieve this for CFRP manufacturers. Then the quality of outputs needs to be measured for each production batch of the CFRP material. Unfortunately, the cost of conducting it is enormous and may negatively influence the profit made by the CFRP manufacturer. While this option is unattractive, a potentially useful option is the use of surrogates, the responses produced by the system, in terms of the measured thrust force, delamination at entry and exit, torque and eccentricity. In this context, a metaheuristic optimization procedure may be used to obtain the optimal responses which will maximize the quality of the manufactured CFRPs (Bhushi et al., 2020; Niranjan et al., 2022)

In the metaheuristic literature, several methods have been successfully applied to manufacturing problems. In some detail, authors have classified these methods into two district groups namely local searches, which describe metaheuristics as having sole solution. The second group is the random searches which depend on population. Notwithstanding, the group of previous literature applications common in the metaheuristic literature include genetic algorithms, krill herd algorithm, firefly algorithm, ant colony optimization, salp-swarm algorithm, parasitism-predation algorithm, harmony search algorithm, genetic algorithm, Taguchi-whale optimization algorithm, ant-lion optimization, ant colony algorithm, particle swarm optimization and grey wolf optimization (Eremin et al., 2015; Abhishek et al. 2017; Alcántar et al., 2017; Ravisankar and Umamaheswarrao, 2018; Gautam and Mishra, 2019; Boga and Koroglu, 2021; Yu et al., 2021; Balaji et al., 2021; Elsheikh et al., 2021; Kesarwani and Verma, 2022; Guru Mahesh and Kandasamy, 2023). From this list, grey wolf optimization (GWO) is one of the most promising and recent metaheuristic methods. It has its strength in obtaining the optimal solution as the superior solution falls under the domain of the optimal solution but it is fast to attain convergence. Moreover, the use of the grey wolf optimization procedure has been supported by several literature sources. These include fuel cell applications (Hao and Sobhani, 2021), air quality index (Li et al., 2022) image segmentation (Yu and Wu, 2022) and traffic flow (Sivakumar et al., 2022). Notwithstanding, their practical implementation in the context of optimizing drilling responses for the carbon fiber-reinforced plastic has not been readily achieved. Notice that the success and sustainability of the drilling process are hugely reliant on optimized thresholds usage of resources and the management of the drilling process without compromise for performance (Yarar and Karabay, 2020; Kumaran et al., 2018). Also, the continuous adoption of sub-optimal values of responses for decision-making indirectly leads to wastage and expensive maintenance of the drilling process. Optimal results guarantee the lowest cost of drilling and improved accuracy in drilling decision-making. Therefore, it is desirable to use the grey wolf optimization algorithm, which is agreeable with the present gap in the drilling literature and the requirement for faster optimization algorithms. Consequently, from the compatibility outlook, the use of the grey wolf optimization algorithm for drilling response optimization is promising. The grey wolf algorithm could be easily implemented in the drilling arena as it possesses fewer parameters. It could be implemented easily also. In this work, we use the grey wolf optimization and not another multicriteria approach because the GWO obtains a solution by applying the cooperative behavior of the grey wolves as they hunt those who fall into their territory. With this attribute in place, decision-makers can obtain solutions faster than many other methods and the quality of the solution is high and acceptable.

Furthermore, the orthogonal arrays, signal-to-noise ratios and delta values are important factors in enhancing optimization performance in Taguchi-motivated schemes (Okanminiwei and Oke, 2020; Francis et al., 2022; Taiwo and Oke, 2022). To further enhance optimization, aspect ratios of parameters and Pareto schemes have been introduced by earlier researchers. Based on Krishnamurthy's (2011), and Taguchi's factors and levels, a function was developed as the framework for the grey wolf algorithm. Several iterations based on the representative wolves of alpha, gamma and omega were simulated and the parameters, namely, speed, point angle and feed rate were optimized by exploiting the cooperative and social hierarchy attributes of the grey wolves. Also, by considering the gaps in knowledge within the area of CFRP development, this study proposes a grey wolf optimization method used to optimize the thrust force of the dulling process during the manufacture of the CFRP compared with the Taguchi-Pareto method already established in the literature, the innovation of the present study is reflected in the following issues (Taiwo and Oke, 2022): (1) Mathematical and empirical expressions are introduced to establish how the behavior of grey values can be used to optimize the thrust force While drilling the CFRP composite (2) An analysis of how each response parameters affect the quality of the CFRP composite produced (3) Based on analysis, the fusion of Taguchi-Pareto with the grey wolf optimization scheme is proposed to obtain superior optimal results. The attainment of this innovation was aided by the following definitions: (a) The lower and upper bounds of the fitness function are established from the Taguchi-Pareto table (Pratap Singh et al., 2022) (b) Position searches for the values using random numbers were introduced (c) Utilization of the optimal parametric setting from the Taguchi Pareto calculation to draw the fitness function was made (d) Determination of the delta for the optimal parametric setting. (e) Establishment of iteration to minimize the thrust force.

2. LITERATURE REVIEW

For the drilling process, responses in directing the thrust force, torque, declamation at entry and exit and eccentricity play a dominant role since they directly and substantially affect the quality of the drilled workpieces and products from the carbon fiber-reinforced plastic. Therefore, the accurate quality of drilled workpieces for the drilling process is essential. However, having demonstrated extraordinary strength, high fatigue resistance, good conduct of electricity, poor conduct of heat and high weight, carbon fiber-reinforced plastic has been widely used as a material in the drilling process for various applications. In a review, Lawal et al. (2023) established and evaluated diverse areas of nanofluid preparation and their applications in carbon fiber-reinforced plastics. The prominent conclusions of the work are (1) The overriding factors on surface finish are the cutting force and cutting temperature. (2) The focus of machining scientists is to control tool wear using adequate cutting fluids. (3) There is less attention given to uncertainties, but it is important in machining research. In another work, the deployment of carbon fibre-reinforced plastic for antibacterial activity against diseases in medical applications was established by Kim et al. (2023) proposed a vitrimer-based carbon fibre-reinforced plastics composite and tested its mechanical and impact strengths. It was concluded that the composite is potentially useful for medical devices. In an automobile application, Muflikhun and Yokozeki (2021) assessed the curing influence on a hybrid material consisting of carbon fibre-reinforced plastics. It was concluded that the energy release rate and fracture toughness of the laminate developed were influenced substantially by the curing circumstances while producing the laminate. Yet in another study, Severson et al. (2022) proposed a new choice chart aimed at establishing the number of plies, core density, stacking sequence and core thickness of a sandwich composite containing carbon fibre-reinforced plastics for surface mining applications. It was concluded that there is the feasibility of analyzing sandwich composite factsheets using standard 3D elements rather than using the support layer elements method. In Bhushi et al., (202) several metaheuristic methods were deployed to optimize the parameters of the drilling process. The methods include genetic algorithm, particle swarm optimization and simulated annealing while the parameters of interest are the helix angle of the drilling tool, feed rate and spindle speed. The most important result is that the helix angle of tools and feed rate are critical to influencing the drilling quality (delamination) of the carbon fibre-reinforced plastic studied. Montaginer and Hochard (2013) deployed a genetic algorithm to optimize the hybrid composite drive shaft for a carbon fibre-reinforced plastic. It relates to shear influences on flexural vibrations. The important outcome of the study is that some general rules concerning the design of shafts with optimal values were obtained. Ravisankar and Umamaheswarrao (2018) used the metaheuristic named ant colony optimization to optimize the carbon fibre-reinforced plastic during the drilling process. The most important result of the study is that useful result within an acceptable computational time was obtained in a near-optimal solution by the ant colony optimization. Abhishek et al. (2017) assessed the process accomplishment of the turning process for the carbon fibre reinforced plastic composite. To optimize responses, the fuzzy inference system was introduced and coupled with the multi-performance characteristics index as well as a non-linear regression method. Furthermore, the teaching-learning-based optimization and harmony search algorithm were also used in the modelling effort to solve the optimization problem. The algorithm presented showed robustness and was effective. Liu et al. (2003) assessed the degradation of the carbon fiber-reinforced plastic composite in mechanical characterization during drilling. The change in functional performance stimulated by the progressive damage was evaluated. The most important result is that the proposed 3-dimensional model was effective in optimizing the carbon fiber-reinforced plastic during the drilling process.

Jeyaprakash et al. (2022) evaluate the effect of drilling parameters on the responses of the system. The principal parameters are identified as the feed rate and cutting speed while the responses are entrance circularity, entrance diameter, entrance circularity, entrance diameter, taper angle, and exit diameter. The Taguchi method was used for the analysis. The principal result is that the feed rate outperforms the cutting speed. Mahdi et al. (2023) examined the drilling quality of carbon fiber-reinforced plastic from two perspectives: the use of tool geometric parameters and cutting parameters. An important result is that independent of the used tool, the feed rate value dictates the thrust force, entrance delamination and torque evolution. Qiu et al. (2022) established the optimal feed rate during the drilling pipe. The important result is that for a feed rate of 0.04mml/r, there exists a hole exit delamination during the phase of secondary drilling. Upputuri et al. (2020) conducted drilling experiments on carbon fibre-reinforced plastics and applied the Taguchi scheme to optimize responses including the delamination factor, thrust force and torque. The important result is that the medium speed of 2000rpm combined with a medium feed of 100mm/min yielded outputs of 138N, 1.027Nm and 1.015 as the thrust force, torque and delamination factor, respectively. Moreover, a summary of literature is presented in Table 1.

From the above review, it has been established that CFRPs are good applications in automobiles, medicine, surface mining and applications requiring nanofluids. Notwithstanding, the grey wolf algorithm is a novel scheme and a growingly acceptable method in engineering practice. However, it has not been proposed in any paper on the production or experimentation with carbon fibre-reinforced plastics: This ascertains that the application is novel. The population-oriented grey wolf optimisation scheme is founded on the social characteristics of grey wolves, where the members of the park work cooperatively by taking instructions from their superiors and each carries out its assigned responsibility in terms of guarding the park, chasing the prey, taking care of the elderly and more duties as may be assigned to them. This method's mechanism of operation follows the flow of three leaders.

Table 1. Literature summary on the drilling process

S/No.	Author(s) and year	Domain of study	Key input parameters used	Adopted method	Output (responses)	Results
1	Bhushi et al. (2020)	Optimization, metaheuristics	feed rate, spindle speed, and tool helix angle.	Response surface Methodology, regression equation, Particle Swarm Optimization, Genetic Algorithm, ANOVA and Simulated Annealing	Delamination at exit and entry	The tool helix angle and feed rate are the most important influencing factors having an impact on the CFRP composite drilling quality
2	Montagnier & Hochard (2013)	Optimization of Driveshaft material and operating speed	supercritical speeds, weight, vibration	Genetic algorithm	Shaft count and driveline weight in subcritical situations.	Under subcritical circumstances, the number of shafts and driveline weight substantially reduced
3	Ravisankar & Umamaheswarrao (2018)	Optimization(Multi-objective)	point angle, depth of cut, feed rate and cutting speed	Ant Colony Algorithm	surface roughness, thrust force, and delamination factor.	Cutting speed possesses the greatest impact on the output response
4	Abhishek et al. (2017)	machining process Optimization	feed rate, depth of cut and spindle speed	Fuzzy Inference System, Multi-Performance Characteristic Index and non-linear regression model, Teaching learning based Optimization and Harmony Search algorithm	Material Removal Rate, tool-tip temperature and surface roughness	Utilising the optimization model results in improved tool tip temperature, MRR and surface roughness
5	Liu et al. (2023)	Optimization	cutting forces, torques and delamination	3D numerical model	mechanical qualities of the hole surfaces deteriorate	The degree of damage that occurs in plies causes the rigidity of the hole surfaces to deteriorate.

Table 1. (cont')

S/No.	Author(s) and year	Domain of study	Key input parameters used	Adopted method	Output (responses)	Results
6	Mahdi et al. (2023)	Analysis and optimization	tools geometry feed rate and spindle speed	response surface methodology, artificial neural network and analysis of variance	thrust force, entrance delamination and torque evolution	The feed rate value is very important for thrust force, entry delamination and torque evolution. For optimum drilling performance, the study suggests spur drill will be suitable.
7	Qiu et al. (2022)	Validation of optimal value	feed rate, spindle speed, step ratio	Theoretical analysis	tear, delamination, hole exit damage	As the feeding rate increases, the delamination range narrows. The primary cutting phase is the step that causes tear once the feeding rate is above 0.06 mm/r.
8	Upputuri et al. (2020)	Optimization	feed rate, spindle speed, depth of cut	fuzzy logic, ANOVA analysis, Taguchi L_9 orthogonal array	de-lamination factor, thrust force, torque	The experimental values and the fuzzy findings show good agreement.
9	Jeyaprakash et al. (2020)	Analysis and optimization	feed rate and cutting speed	Taguchi array and Grey relational analysis	exit diameter, entry diameter, taper angle, entrance circularity	Feed rate showed more influence than cutting speed

They are known as the delta, beta and alpha wolves and while they produce the solution other wolves in each group follow. The alpha, for instance, is the strongest and is sometimes only two, which may be a female and a male. The beta group are next in strength, experience and responsibility to the alpha group. Then the delta group is the least in strength, experience and responsibility in the pack. Therefore, the grey wolf algorithm has been increasingly favored in the following applications: Yu et al. (2022) deployed the grey wolf optimization (GWO) to image segmentation within the computer vision and digital image processing domain. Here, using the simplest approach, the threshold method, it is possible to compare the pixel's intensity with a particular value. Li et al (2022) innovated the sustainable city and society drive by applying the optimization scheme of the grey wolf to predict the air quality in an urban area. Uniquely, Hao and Sobhani (2021) deployed the optimization scheme of the grey wolf in solid oxide fuel cells. This is a device that converts electrochemical substances to electricity through an oxidation process.

3. METHODOLOGY

3.1. An overview of Grey Wolf optimization

Grey wolf optimization, shortened as GWO, is a class of population-based and swarm optimization algorithms that emulate the social behavioral pattern in grey wolves. Swarm intelligence optimization was started by Beni and Wang in 1989 in the framework for global optimization as a set of algorithms for controlling robotic swarms. They are concerned with the setting up of intelligent multi-agent systems by adopting the social character of different animal societies (Abd El-Aziz, 2018). GWO has been confirmed by different research to have far-reaching applications in solving optimization problems. It is a technique proven to be appropriate for addressing meta-heuristic algorithm optimization problems recently introduced by Mirjalili et al. (2014) who was fascinated by how wolves hunt their prey. This inspiration led to a renowned algorithm that has now become a tool for many research works. It possesses excellent strength in research for unimodal problems and multimodal solutions and its useful varying applications avoid local minimal. Although the method has become popular in recent times, it has assisted researchers in accomplishing their goals of comparing different results and producing better outcomes. Several engineering challenges including mechanical design, time series forecasting, cluster analysis and structural design typically employ the GWO method, a high-performance swarm intelligent optimization technique to achieve better engineering solutions (Qin et al., 2022). GWO method leverages monitoring the hunting pattern of the wolf. The population size of the wolves plays a major role in the whole process of searching for and attacking the prey. It is evident that the more the number of wolves the faster they will be able to achieve a successful hunting activity. They move with an average population of 5 to 12, and they all follow unique social behaviour in an orderly pattern which makes it easy to identify the rulers and the followers. Alpha wolf, $X\alpha$ (highest fitness value of f(x)) leads the population and has the ultimate rank when compared with others, Beta wolf, $X\beta$, also called 2nd best fitness value, signals are sent to other wolves while supporting the leading wolf in the prey hunting. The delta, $X\delta$, is a wolf that functions as an assistant, playing a key role as a caretaker, pathfinder, killer, and elder. Omega is used to depict the other wolves (Kishor and Singh, 2016). Tracking, encircling, and eventually striking the steps in the hunting process for grey wolves. They are trained to act in this manner to survive. The social behavior of these animals is termed as hierarchical and it's a unique factor that made the patterns of their movement useful for research purposes. The primary fittest agents, Alpha, Beta, and Delta are selected using GWO as an evolutionary technique while the omega takes the others (Sivakumar et al., 2022). The prey is attacked by grey wolves to end the hunt when it halts moving. The wolves first begin to move randomly as they approach the prey, getting closer to it with time. The randomization then decreases, causing all other wolves to begin concentrating on Alpha, Beta, and Delta. We have the $X\alpha$ (highest fitness value of f(x)). This depends on the optimization problem, when minimizing the least value is chosen while maximizing selects the highest value. This pattern follows as it progresses from $X\beta$ (next to the highest value of f(x) 2nd best fitness value and (next to the $X\beta$ fitness value 3rd best fitness value) the other values are represented as other wolves which support in attacking the prey. (Hatamlou 2012).

3.2. Steps in Grey Wolf optimization implementation

The steps to be adopted in implementing the grey wolf algorithm are as follows:

1) Initialize population size: set as five wolves to ensure enough interactions with the parameters, given the three important wolves to carry out this optimization method.
2) Generate a Random number for the initial wolf table with the constraint of the factors. Using the X=L-Rand*(U-L) where X is the positions, L is the lower range value and U is the upper range value. Rand is represented as a random number from (0 to 1).
3) 3.Generate fitness function using the Taguchi signal-to-noise ratio table. The delta value in conjunction with the ranks is used to generate this fitness equation and also calculate the fitness values using the X positions.
4) Identity the X(t),$X\alpha$(highest value of f(x) best position), $X\beta$(next to the highest value of f(x) 2nd best position), $X\delta$(next to the $X\beta$ fitness value 3rd best).
5) 5.Compute the values to determine the space within hunted prey and grey wolf using the equation to start the iterations.

In this section, the working of the GWO regarding how the GWO can solve the optimization problem (optimization of parameters of carbon fibre reinforced plastic composite drilling process) is explained. The commencement step is to update the position of the grey wolf by using the equation for updating position, Equation (1). The term "t" in Equation (1) shows the possibility of iteration in the computation. The value of "t" is usually 3, where the components of the iteration are the values obtained from the alpha, beta and gamma involved. The iteration guarantees that successive values obtained from computations are closer approximations to the Xnew desired as the position of the grey wolves changes in the park during hunting and attacking prey.

Updating positioning equation is Equation (1):

$$X_{new} = X_t = \left(\frac{X_1 + X_2 + X_3}{3} \right) \tag{1}$$

Equation (1) contains X1, X2 and X3. But X1 is the best position of the group of involves, X2 is the second best position for the group of involves and X3 is the third best for the group of involves. However, to further explain the meaning of X1, X2 and X3 there is a need to work with an objective function. This objective function is a minimization function, which is also called the fitness function. Notice that the data used for the present analysis is the experimental data from Krishnamoorthy (2011), which produced Table 1. Having applied the signal-to-noise principle of lower the better in Table 1, there response table was obtained, which showed the optimal values for all the parameters. These details are not shown here for conciseness. Thus, the work goes ahead to apply the grey wolf to the optimal parametric settings produced by the signal-to-noise ratios. This qualifies the title of the present work as a merger of the Taguchi signal-to-noise ratios and the grey wolf optimization. Now, Minitab 18 (2020) version was used on the results of the optimal parameters to obtain Equation (2). Notice that in Equation (2), S is the speed, PA is the point angle and FR is the feed rate.

Fitness function development (minimization equation):

f(x) = 9.02078 S3+0.50339 PA2+0.367571 FR (2)

Now, to explain the best, second best and third best values from the data being considered, the values of S, PA and FR are each substituted in Equation (1) to obtain a set of values say with the values being 5000, 6500, 5250, 4920, 8460. So the question is from the set of five members stated, what is the best value, second best value and third best value? However, this should be defined according to the minimization of the response objective of the drilling process. From the set of numbers indicated, the best value, being the minimum is 4920. The second-best and third-best values are 5000 and 5250, respectively. According to the notations in the present work, the best value is the X alpha, the second best value is the X beta and the third best value is the X delta. Now, to compute the best position, Equations (4), (5), (6) and (7) are used to update the position of the involves indicated in Equation (1). In Equation (4) and (5), "rand" indicates the random numbers generated. The random numbers used in the present work, generated from the random number tables are 0.640729385, 0.005415743, 0.8582527, 0.196047495, 0.252475744 and 0.6960741. The random numbers picked always fall between 0 and 1. Also, to calculate the second best position Equations (8), (9), (10) and (11) are formed with Equation (8) resembling Equation (4) while pairs of other resembling equations are Equations (9) and (5), equation (10) and (6) as well as Equation (11) and (7). Furthermore, Equations (12), (13), (14) and (15) are formed with resemblances as Equations (12) and (14), Equations (13) and (5), Equations (14) and (6) as well as Equations (15) and (7).

To further explore the working steps of the grey wolf optimization algorithm, the next major step is to initialize the parameters. This entails the population size and the maximum iteration. Next, the researcher moves to obtaining the best, second and third-best positions. Afterwards, the calculations may be made using Equation (3). Then the researchers moved to evaluating the new position by using equation (1). It is essential to check if the new position lies between the bounds. Then the researchers finally perform the greedy selection.

a= 2(1- (iteration/maximum iteration)) (3)

A = 2a rand – a (4)

C_1 = 2 rand (5)

$$D_\alpha = | C_1 X_\alpha - X(t) | \tag{6}$$

$$X_1 = X_\alpha - A_1 D_\alpha \tag{7}$$

A_2 = 2a rand – a (8)

C_2 = 2 rand (9)

$$D_\beta = | C_2 X_\beta - X(t) | \tag{10}$$

$$X_2 = X_\beta - A_2 D_\beta \tag{11}$$

A_3 = 2a rand – a (12)

C_3 = 2 rand (13)

$$D_\delta = | C_3 X_\delta - X(t) | \tag{14}$$

$$X_1 = X_\alpha - A_1 D_\alpha \tag{15}$$

As indicated in the section on methodology, the objective (fitness) function developed in Equation (2) is a minimization problem. The limits of the variables S, PA and FR are set as Equations (16), (17), (18) and (19):

Speed: $1000 \le x \le 3000$ (16)

Point angle: $100 \le x \le 300$ (17)

Feed rate: $100 \le x \le 500$ (18)

Updating equation

$$X = L - R(U - L) \tag{19}$$

Where R is a random number between 0 to 1, L is the lower limit and U is the upper limit.

4. RESULTS AND DISCUSSIONS

To start the explanation of the results, one needs to consider the initialisation parameter. In this case, the swarm (population) is considered as 5. The number of iterations is set as 10 since it is to be manually driven. In this case, it is noticed that there are three parameters S, PA and FR. So the basic task is to compute the solution such that there are three columns in the spreadsheet. The first column is for the parameter S with five wolves under it. The second column, which contains the parameter PA also has five involves under it while the third column, which should contain the fitness function also has five involves under it. Thus the goal of the present researchers is to calculate and update the values in the three columns. However, it is possible to update by considering the initialized parametric values, which are the lower and upper bound values of the speed, point angle and feed rate, respectively.

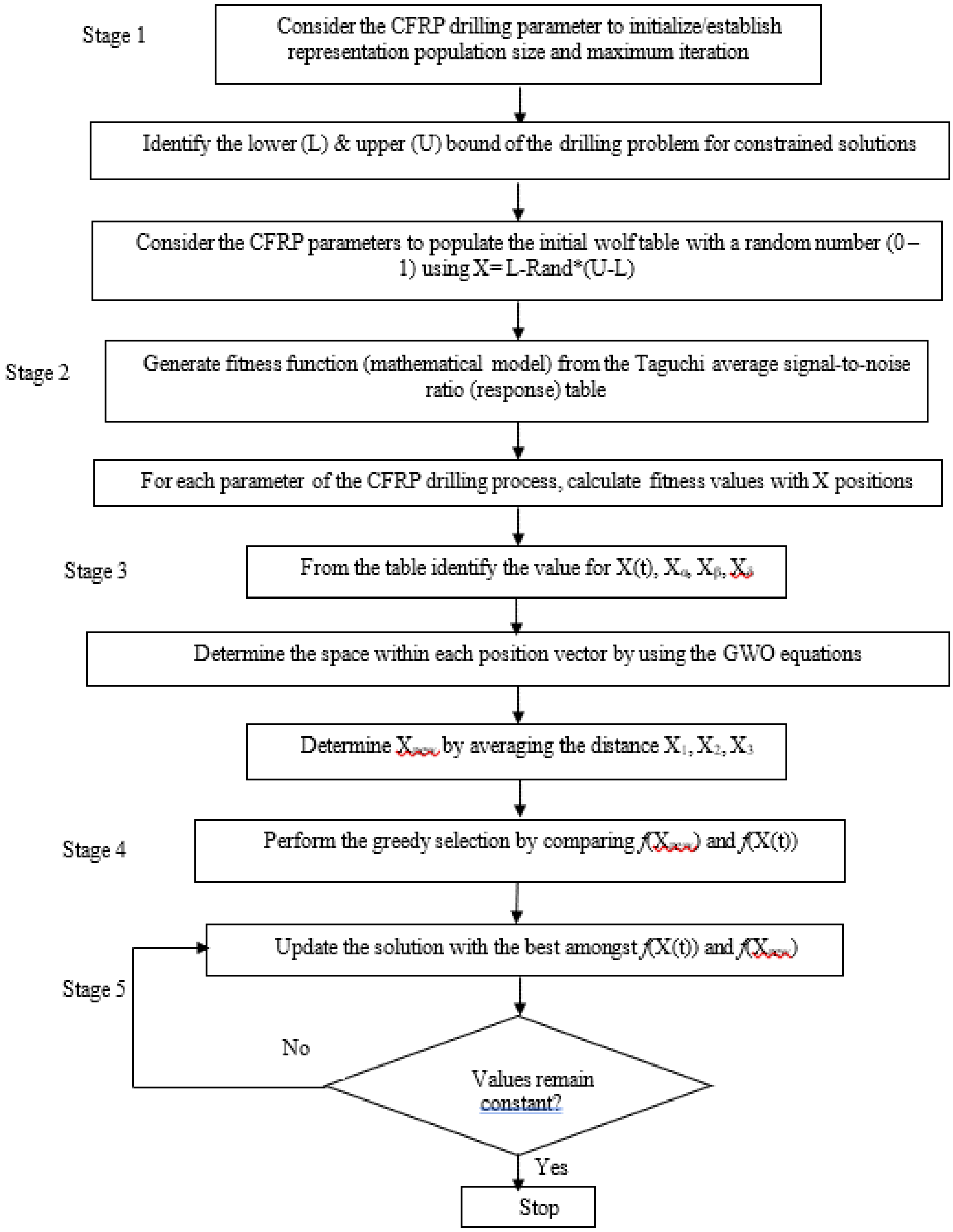

Figure 1 Schematic for the application of grey wolf optimization

To achieve this, the values of L, random numbers and upper values are substituted in Equation (19). Considering the speed parameters, S, there is a need to compute values for five different involves. The question is how do we compute for the first involvement? Notice that as one considers the constraint Equation (17), the lower and upper boundaries, L, and U are 1000 and 3000, respectively. Now, considering the first involve, L is 1000, U is 3,000 and a random number of 0.36518 is generated, when these values are substituted in Equation (19), a value of 1730.36 is obtained for the first involve. While keeping L, and U the same for involves 2,3,4 and 5, the random numbers are used as 0.46132, 0.31841, 0.8418 and 0.78435, respectively. The results of the predicted speed values for involves 2,3,4 and 5 are 1922.64, 1636.82, 2683.6 and 2568.7, respectively. This set of values is referred to as X alpha. To obtain values for Xbeta for involves 1,2,3,4 and 5, it is noticed that the lower and upper boundaries change to 100 and 300, respectively, for point angles. By following the same procedure as for X alpha, we obtained the values of X beta for involves 1, 2, 3, 4 and 5 as 267.436, 152.076, 429.792, 201.728 and 376.904, respectively. Similarly, for X delta, for the wolves 1 to 5, we obtained 151.674, 177.828, 109,414, 103.348 and 240.580, respectively. The calculations discussed so far are for the computation of the fitness function. Now, consider the first wolf and the various values of X1, X2 and X3, which correspond to X alpha, X beta and X delta. By substituting these values in Equation (2) for the fitness values, the value for f(x) is obtained. Let us consider the first involvement in all the parameters, S, PA and FR. Here, S is 1730.36, PA is 767.436 while FR is 151.674. when the coefficients of S, PA and FR, notably 9.02078, 0.50339 and 0.,367571 are substituted with the values of the variables S, PA and FR in Equation (2), the obtained result for wolf 1 is 46736246242. Accordingly, for wolves 2, 3, 4 and 5, the following respective values are obtained: 64111817815, 39559234719, 1.7434E+11 and 1.52892E+11.

Moreover, the computations are made for each row concerning S, PA and FA to obtain f(x), the task is to obtain the best value, second best value and third best value from the computations. To rate these values, the column for the fitness function f(x) is considered. Therefore, out of the rows of the f(x), containing the f(x) values, the minimum is chosen as the best: 39559234719. However, the corresponding values of S, PA and FR are identified as 1636.82, 429,792, and 109.4141, respectively. The last mentioned three values become the X alpha, indicating the best performing involves updating. They are the closest to the prey being hunted in the course of capturing the prey. Also, the second best value for the f(x) is 46736246242. Notice that the problem being solved is the minimization of the responses. Accordingly, the involves, represented as S, PA and FR for the second best value of f(x) have the following values of 1730.36, 267.436 and 151.674, respectively. The third best value is 64111817815 as f(x). The corresponding values of S, PA and FR are 1922.64, 152.076 and 177.828, respectively. Accordingly, these last three numbers obtained are X delta. Recall that some three values were obtained before these last set. Those values are the X beta values. Now, the focus is on computing the value of "a" from Equation (3). To use Equation (3), the maximum number of iterations is set as 20. Then Equation (3) is obtained as 2 (1-1/20) =1.9. After obtaining “a” as 1.9, the values of X1, X2 and X3 which are predictions of the alpha, beta and delta involved, may be obtained. It follows from the first wolf (row 1 of the computations under S, PA and FR) that X = [730.36 267.436 151.674]. Then X1 could be obtained by referring to Equation (4), (5), (6) and (7). Recall that the value of "a" has already been computed as 1.9 and a random number of 0.640729385 has been generated. By substituting these values into Equation (4), we have (2) (1.9) (0.640729385)-1.9], which gives 0.281459. Next is our interest in Equation (5) which simply multiplies 2 by a random number. The random number generated is 0.005415743, which gives C1 as 0.392095. Next, Equation (6) is used to calculate D alpha. Now, the X alpha to be used is X alpha = [1636.82 429.792 109.414]. Also, C1 has been computed for use as 0.392095. Here we compare the X alpha with the values of the first wolf. For X alpha, we have [1636.82 429.92 109.414] but for the first wolf, we have [1922.64 152.076 177.828]. By computing , we obtained -607.9050096. Then by substituting all the values, X1 is obtained as 1171.1. Similarly, the values of parameters for the second-best position may be contained as -495.0485125. Furthermore, for the third best position, D delta yields 392.148239 while X3 yields 719.024. Now by considering X1, X2 and X3, the average is obtained as 800.14581. This is the new updated value.

Having obtained the Xnew, there is needed to calculate the updated values. For this task, there is need to calculate X1 (i.e. S), X2 (i.e. PA) and X3 (i.e. FR). These values of X1, X2 and X3 will be compared with what was obtained earlier in the matrix for row 1 (wolf 1). The dilemma is to decide on which value to use between these calculated values of X1, X2 and X3 and the previous values of X1, X2 and X3. To successful progress, there is need to conduct a greedy selection. It means that we can calculate the function value at the new position, f(Xnew) and also at the previous value. To calculate f(Xnew) the values of X1, X2 and X3 at the new position can be substituted into the fitness function. These two values of f(Xnew) and f(X) are compared. Since minimization is sought, which ever is minimum out of the two values is used. The lower value of f(Xnew) and f(X) is accepted as the solution while the other function is discarded, what results from this action is a new matrix that will be created. So we have to update the wolves with the lower values of f(Xnew) and f(X). All what has been done is for the first wolf. Similarly, we could apply the steps to obtain values for the second, third, fourth and fifth wolf. Consider the calculation of X1. Notice that it is for the speed parameter. Speed falls between 1000 and 3000. If the value obtained is say 1500, it is within the boundary and the value of 1500 should be used. However, suppose a value of -1325 is obtained. This value is definitely outside this range. It is closer to 1000 than 3000. Therefore the value 1000 is used to replace the stated value of -1325. Now a comparison is made between the values under Xnew and those under the original framework. All the values can be computed repeatedly. The procedure will be followed for all others. The analysis of the result obtained from Table 2 is done using Microsoft Excel 2016.

The values generated for 5 wolves based on the random number from the Speed, Point angle, feed rate and the calculated fitness function by substitution are tabulated to begin the iteration as shown in Table 3. Table 4 is the initial calculated result for vectors and random numbers.

In Table 5, the summarized result of the best wolf among the top three wolves is shown. Table 5 starts with the input of data obtained from substitution into the equation.

Xnew is the average of the three-position vectors X1, X2, and X3, the greedy selection is performed to ensure the values of the parameters fall within the range. Table 6 shows the summary of the first iterations. Which are the bases for the next iteration. This process is repeated and results are generated.

The conclusion from this result is that the Taguchi-GWO method was able to reduce the thrust force and its effects on tools. This is shown in Table 7 and depicted in Figure 2.

Table 2. Drill parameters (Krishnamoorthy, 2011)

Level	S: Speed	P: Point angle	F: Feed rate
1	1000	100	100
2	2000	118	300
3	3000	300	500

Table 3. Estimation of fitness values

Speed: rev/mm (X_1)	Point angle (X_2)	Feed rate mm/min (X_3)	$f(x)$
1730.36	183.72	203.35	46736227248
1922.64	126.04	255.66	64111814198
1636.82	264.90	118.83	39559177058
2683.60	150.86	106.70	1.7434E+11
2568.70	238.45	381.18	1.52892E+11

Table 4. Initial calculated result for vectors and random numbers

A	A1	C1	A2	C2	A3	C3
1.9	0.5348	0.3921	-1.8794	0.5050	1.3614	1.3922

Table 5. Summarised values of the Best wolf, 2nd best wolf, 3rd best wolf and X_1, X_2, X_3 using parameters and position vectors for the thrust force minimisation problem (the first wolf iterations)

Category of wolf	Wolf's performance	Hierarchy	Hierarchy-multiplier	Repositioning Factor	New position	Average (B, S, T)
		X_α	C^*X_α	D_α	X_i	X (New)
Alpha wolf (X_1)	Best wolf	1636.82	641.79	-1088.57	2218.96	1560.60
	Second best wolf	264.89	103.86	-79.85	307.59	
	Third best wolf	118.83	46.59	-156.76	202.66	
Beta wolf (X_2)	Best wolf	1730.36	873.75	-856.61	120.43	227.12
	Second best wolf	183.72	92.77	-90.95	12.79	
	Third best wolf	203.35	102.68	-100.67	14.15	
Gamma wolf (X_3)	Best wolf	922.64	2676.6	946.24	634.47	137.08
	Second best wolf	126.04	175.46	-8.25	137.28	
	Third best wolf	255.66	355.91	152.56	47.96	

Table 6. Summarised values of iterations 1, 5 and 10 respectively are presented below for the thrust force minimisation problem (the first wolf iterations)

Iteration 1			
1560.60	227.12	137.08	34286403283
1922.64	126.04	255.66	64111814198
1492.54	141.77	173.58	29993245956
2513.97	253.47	100.00	1.43326E+11
2412.43	300.00	291.42	1.26651E+11
Iteration 5			
1000	100	100	9020785071
1000	100	122.32	9020785079
1427.871	147.5829	158.8281	26260984684
1191.949	119.783	136.4111	15276260918
1433.458	156.8058	155.9672	26570445408
Iteration 10			
1000	100	100	9020785071
1000	100	122.32	9020785079
1227.104	124.7442	133.2249	16668189924
1117.268	112.6445	120.8339	12581033482
1139.058	113.3738	117.9413	13331583864

Table 7. Best fitness value for the 10 iterations of T-GWO

Iteration	X_1	X_2	X_3	Best fitness value
1	1164.991	290.0394	127.6312	39559177058
2	1000	302.4744	100	29993245956
3	1000	235.9897	100	24592377849
4	1000	175.4229	100	24592377849
5	1000	171.9659	100	9020785071
6	1000	100	100	9020785071
7	1000	100	100	9020785071
8	1000	100	100	9020785071
9	1000	100	100	9020785071
10	1000	100	100	9020785071
11	1000	100	100	9020785071

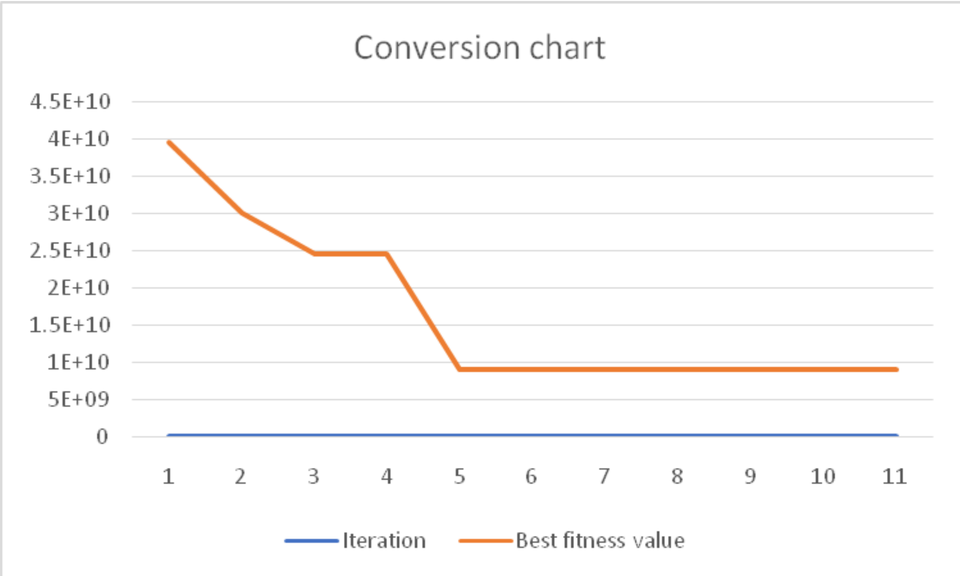

Figure 2. Convergence of best fitness value with iteration

It was noticed that at the end of the first iteration, the best f(x) was 14263085729, and it became 9020808071 at the end of iteration 3. At iteration 6, f(x) dropped to 9020785071. As we reached iteration 10, the minimum f(x) value was maintained as the same value at iterations 7, 8 and 9. An observation is that by comparing the fitness value with the number of iterations it starts to converge at iteration 6 and retains this value until iteration 10, which we used as a terminating criterion (Hatamlou, 2012). At this converging value, the corresponding values of S, PA and FR are 1000, 100 and 100 respectively. It means that the optimal spindle speed is 1000rpm, the point angle at the optimum points is 100° and the feed rate at the optimal level is 100mm/min. this concerns the results of Krishnamoorthy (2011) as indicated in Table 1. This study uncovers a new understanding of the optimization of drilling parameters of speed, point angle and feed rate as significant contributors to obtaining an optimized response. It challenges the present method of Taguchi method presented by Krishnamoorthy (2011), showcasing simplicity and robust results.

4.1. Validation

Research design validation is highly needed to produce the best practice in academic works. This helps to give credibility to an experimental approach and is defined as a process of using a novel approach to another problem or scenario to be sure the technique will produce similar results. It is important because design errors and experimental failures could be avoided and spotted before the approach is adopted. Failure to validate research methods has led to an increase in failure of structures during design simulations (Eisenmann, 2015). The research done by Kamal et al. (2015) worked on optimizing the performance of friction stir welding which involves joining metals with the internally produced heat within the workpiece and the non-consumable tool without melting processes. The cumulative impact of process variables including welding speed, tool rotation speed, tool shoulder diameter and tool pin profile have been examined for the percentage elongation and ultimate tensile strength of AA6082 alloy joined using the friction stir welded joints. Taguchi's design of experiments approach is being used in the study to obtain an optimal parametric setting from this welding process. We use the experimental data shown in Table 8, from Kamal et al., (2015), to conduct a validation of this novel Taguchi–grey wolf optimization method. After applying the Taguchi method to this experimental result, it produced a signal-to-noise ratio for the untreated and treated condition which is presented in Tables 9 and 10. The optimal parametric setting which is is presented in Table 11.

Table 8. Variables and their levels (Kamal et al., 2015)

Level	A: Tool Rotation Speed	B: Welding Speed	C: Tool pin profile	D: Tool shoulder dia
1	1200	20	1	14
2	1950	25	2	16
3	3000	30	3	18
4	4600	35	4	20

1 = cylindrical; 2 = threaded cylindrical; 3 = Square; 4 = trapezoidal

Table 9. Taguchi SN ratio Response table for untreated AA 6082-T6

Level	A	B	C	D
1	0.7490*	0.5092	0.5744	0.6371
2	0.6090	0.5762	0.6052*	0.6419*
3	0.5041	0.5907	0.5651	0.5483
4	0.4229	0.6088*	0.5402	0.4577
Delta	0.3261	0.0996	0.6050	0.1844
Rank	1	3	4	2

*Optimum value

Table 10. Taguchi SN ratio Response table for Cryogenic treated AA 6082-T6

Level	A	B	C	D
1	0.7152*	0.4907	0.5685*	0.6070*
2	0.5921	0.5572	0.5552	0.6068
3	0.4708	0.5563	0.5635	0.5226
4	0.4189	0.5928*	0.5099	0.4607
Delta	0.2963	0.1021	0.0587	0.1463
Rank	1	3	4	2

*Optimum value

Table 11. Experimental optimal parameters

Parameters	Untreated AA 6082-T6	Cryogenic Treated AA 6082-T6
Ultimate tensile strength UTS	341.273	335.491
Percentage elongation %EL	14.13	13.57
Parametric setting	$A_1B_4C_2D_2$	$A_1B_4C_1D_1$

. Using the delta values from the signal-to-noise response to generate a polynomial fitness functions Equations (20) and (21) for the untreated and treated alloy respectively. The fitness function of the untreated condition, Equation (20):

$$f(x) = 0.3261A^4 + 0.1844D^3 + 0.0996B^2 + 0.065C \quad (20)$$

The fitness function of the Cryogenic treated condition, Equation (21):

$$f(x) = 0.2963A^4 + 0.1463D^3 + 0.1021B^2 + 0.0587C \quad (21)$$

where

A is the tool rotation speed.

B is the welding speed.

C is the Tool pin profile (cylindrical, threaded cylindrical, square and trapezoidal.

D is the tool's shoulder diameter.

4.1.1. Results from validation

The best fitness value produces a similar trend as generated in the thrust force problem (Table 12).

4.1.2. Untreated AA 6082-T6

If proportions are followed and the value obtained, 8852490803784.80, is to be understood in terms of the lower value of 341.273, obtained by experiment, it is stated that the value produced by the T-GWO will generate a value of 253.06, which is lower than the UTS experimental value of 341.273 for the untreated condition. When the first calculation of the difference between 8852490803784.80 and 2248275044887.20 is 25.40%, the value of 253.06 is achieved. The remaining 25.40% of 341.273 is then subtracted from 341.273 to arrive at UTS of 253.06. Using the Taguchi-grey wolf optimisation technique, it can be inferred from this result that the UTS and its impacts on tools might be decreased from 341.273 (experimental) to 253.06. For the percentage of elongation, which had an experimental value of 14.13 for untreated AA 6082-T6, a value of 10.54 was produced. Figure 8852490803784.80 should be interpreted in terms of the lower value of 14.13, which was discovered through experimentation if proportions are to be followed and the value attained. When the first calculation of the difference between 8852490803784.80 and 2248275044887.20 is 25.40%, the value of 10.54 is achieved. The remaining 25.40% of 14.13 is then subtracted from 14.13 to obtain a % elongation of 10.54. Using the Taguchi-grey wolf optimisation technique, it can be inferred that the % elongation and its impacts on tools might be decreased from 14.13 (experimental) to 10.54.

4.1.3. Cryogenic treated AA 6082-T6

If proportions are to be followed and the value obtained, 20332767897759.50, is to be understood in terms of the lower value of 335.491, obtained by the experiment, the value produced by the T-GWO is stated to generate a value of 250.30, which is lower than the UTS

Table 12. Best fitness value for the 10 iterations on the Cryogenic treated and untreated condition

Iteration	Best fitness value (cryogenic treated condition)	Best fitness value (untreated condition)
1	20332767897759.50	8852490803784.80
2	13838988350228.70	6025225769656.09
3	10502999012197.40	4572801039091.15
4	8020216344814.19	3491845861679.67
5	7671592730720.83	3340061935644.25
6	6030164941105.22	2625416271770.92
7	6030164941105.22	2625416271770.92
8	5163931334813.98	2248275044887.20
9	5163931334813.98	2248275044887.20
10	5163931334813.98	2248275044887.20

experimental value of 335.491 for the cryogenic treated AA 6082-T6 condition. When the first calculation of the difference between 20332767897759.50 and 5163931334813.98 equals 25.39%, the value of 250.30 is achieved. After that, 25.39% of 335.491 is subtracted to arrive at a UTS of 250.30. Using the Taguchi-grey wolf optimisation technique, it can be inferred from this result that the UTS and its impacts on tools might be decreased from 335.491 (experimental) to 250.30. Cryogenic treated AA 6082-T6 yielded a value of 10.12 for the % elongation with an experimental value of 13.57. The figure of 20332767897759.50 should be interpreted in terms of the lower value of 13.57, which was derived by experimentation, assuming proportions are to be followed. The value of 10.12 is reached when the difference between 20332767897759.50 and 5163931334813.98 is originally estimated as 25.39%. The remaining 25.39% of 13.57 is then subtracted from 13.57 to obtain the percent elongation of 10.12. Using the Taguchi-grey wolf optimisation technique, it can be inferred that the % elongation and its impacts on tools might be decreased from 13.57 (experimental) to 10.12.

5. CONCLUSIONS

This study addresses how to integrate the Taguchi approach with the grey wolf optimization model to minimize thrust force. This work applied this dual technique to explore how thrust force could be minimized in drilling carbon fibre-reinforced plastic CFRP. Taguchi method was used to generate a polynomial fitness function combining all input parameters such as feed rate, point angle and spindle speed. The fitness equation is now utilized for grey wolf optimization to perform a minimization of the thrust force in the drilling process. By combining Taguchi and grey wolf optimization using data from Krishnamoody (2011), the parameters and outputs response when applying the Taguchi-grey wolf optimisation strategy the fitness value which is a combination of all inputs shows a drop in the values for each iteration until there were no changes after multiple iterations when this result is compared with other combined optimization methods, it is found have a corresponding outcome of minimization of the thrust force in the drilling process. The value produced from the T-GWO is stated to generate a value of 65.27N, which is lower than the thrust force experimental value of 84.23N (Krishnamoody, 2011) if proportions are to be followed and the value obtained 39559177058 (i.e the first value of the fitness in Table 4), is to be understood in terms of the lower value of 84.23N obtained by experiment. When the difference between 39559177058 and 9020785071 is initially calculated as 22.80%, the value of 65.27N is obtained. Then, to get 65.03N, the remaining 22.80% of 84.23N is deducted from 84.23N. This finding leads to the conclusion that the thrust force and its effects on tools might be reduced from 84.23N (experimental) to 65.03N using the Taguchi-grey wolf optimisation approach. This shows that the grey wolf optimization approach is a good option for predicting the optimal parameters of carbon fibre-reinforced plastic composite (CFRP). The results revealed that the developed function from the upper and lower bounded response table elements is reliable. The optimized parameters yielded a thrust force equivalent to 9020785071 units of simulation counts. The research supports practice in the drilling area. The study's innovative component is the use of a Taguchi-Grey Wolf optimizer for drilling process optimisation for this particular class of composite materials. Future research may include integrating the Taguchi Pareto with the grey wolf optimizer to achieve more stable results. In Summary, the optimization results of this work confirm the possibilities of selecting an optimum combination of feed rate, point angle and spindle speed to achieve minimum thrust force.

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