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Optimizing to Minimize Thrust Force in Drilling Carbon Fiber Reinforced Plastic Composites with HSS Drill Bit Using Taguchi-Pareto Particle Swarm Optimization Method

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ABSTRACT

In this study, a robust method of Taguchi-Pareto (TP) coupled with particle swarm optimization (PSO) is proposed to minimize the thrust force in the drilling of carbon fiber reinforced plastic composites. Taguchi-Pareto is used against Taguchi (T) to emphasize the prioritization scheme essential for deploying the resources to parameters. Besides, and differently from earlier studies, particle swarm optimization is integrated with the Taguchi-Pareto to optimize the structure further. A further result is placed in the fitness function of the PSO to cultivate the velocity and position vectors. In the TP-PSO, the Pareto scheme is introduced to prioritize the factors based on the 80-20-rule. The Taguchi method yielded a feasible optimal parametric setting. The TPSO and TPPSO attained minimum thrust force in four and seven iterations, respectively. Furthermore, the PSO, TPPSO, and TPSO hold the first, second, and third positions, respectively. Results suggest that the proposed robust TPPSO offers an important indicator of optimization of the thrust force while drilling carbon fiber reinforced plastic composites using existing datasets. The usefulness of this effort is to help drilling operators and process engineers undertake energy-saving decisions.

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1. INTRODUCTION

Thrust force optimization in composite drilling is probably a largely essential and distinguished way of regulating the integrity of carbon fiber reinforced plastic (CFRP) composites (Mercy et al., 2020; Soepangkat et al., 2020). This force is a mechanical force summarizing the actions of velocity, mass changes, and the change in time of the particulates for the CFRP composites in the drilling process (Kulkarni and Ramachandran, 2018; Shokrani et al., 2019; Soepangkat et al., 2020; Tran et al., 2020a,b; Xu et al., 2021). The drilling bits work via the supply of electrical energy. As the acceleration of the bit is initiated to the near part of the holding position of the CFRP material, the particles are accelerated in the direction opposite to movements, and this triggers a force on the material (Mercy et al., 2020). The idea of thrust force is commonly applied by process engineers since their attention is focused on the timely delivery of drilled materials with the highest integrity levels (Gokulkumar et al., 2020; Mercy et al., 2020).

However, research has demonstrated that the traditional Taguchi method commonly deployed for thrust force optimization has shortcomings. Pinpointing what parameters of the multiple inputs for the drilling operation or its responses exhibit the highest influence on the thrust force is a challenging task to solve using the Taguchi method. Therefore, the drilling operation optimization has been handled more recently using the particle swarm optimization framework in the literature (Soepangkat et al., 2020). To the best of the authors' knowledge, past studies have fallen short in tackling the area where the reprocess engineer should direct attention and resources to attain the utmost drilling efficiency. But, ascertaining the areas to invest attention and resources is a significant milestone in ensuring unbiased centers and assures a healthy relationship among the operators who compete for the organizational resources. For instance, operators often have conflicts with accepting the number of resources distributed to them to persecute work. They complain of marginalization and partiality in treatment since the process engineer only uses intuition and experience to judge the distribution of resources to the operator; engineers in the process sparsely apply scientific methods.

Therefore, to overcome the weaknesses of previous studies regarding tackling the area to which the engineer should direct attention, this research proposes using a robust TP-PSO (Taguchi-Pareto-particle swarm optimization) method. It is a foundation to establish the optimum thrust force regarding parametric selection that develops efficient drilling parameters by eliminating variances. It also simultaneously establishes what parameter to focus efforts and resources on and concurrently improves the solution according to the drilling objective. Once the experimental trials are established, they are re-arranged in ascending order of the cumulative variances and the cut-off determined. To the best of the authors' knowledge, this method is applied within the ambit of the drilling problem for the first time. Taguchi-Pareto uses a two-phase method wherein the first phase, planning, conduct, and evaluation of the experimental matrix results, are established for the superior echelon of control factors. These results are then fed into the second phase of the method, where 80% of the outputs are asserted, and these yields 20% of all causes for the drilling parameters. Briefly, particle swarm optimization employs several particles that comprise a swarm traveling about, looking for space and the best solution to the problem.

In this research, the authors deployed Taguchi-Pareto and not another optimization tool because, distinct from other optimization tools, the decision-maker can easily establish problems with high-priority parameters and eliminate them or correct them instantly. Besides, an added advantage of the Taguchi Pareto is that Pareto charts, a tool to solve the problem, could easily be developed and allow beneficial decisions to be made easily while concurrently optimizing the parameters. Furthermore, some other advantages of Taguchi-Pareto include the ability to establish the root cause of problems in parameters. Briefly, the principal advantages of particle swarm optimization include its idea of simplicity and the easy implementation of the method. Furthermore, certain researchers have assumed that the study of drilling operations may be solved assuming an analytical solution framework. However, considering the complexity of integrating the nth order differential equation for the drilling problem formed with the 80-20 mile, the assumption is invalidated. This confirms that the solution to the problem may be judged by introducing the particle swarm optimization algorithm. Unfortunately, researchers in drilling studies are yet to acknowledge this crucial insight and add the viewpoint of particle swarm optimization with the existing research tradition on Taguchi and its improved variants. Omitting this fact from the literature on drilling may show serious erroneous assumptions that may be corrected. In this article, the authors seek the available evidence from the literature review that the omission of prioritization of parameters is associated with erroneous conclusions in drilling decision-making.

2. LITERATURE REVIEW

The current research on CFRP composites has amplified and positively directed research and practice to some important aspects (Odusoro and Oke, 2021). These are multi-objective optimization of CFRP drilling outcomes (Saravanan et al., 2012; Abhishek et al., 2016; Soepangkat et al., 2020, Wang and Jia, 2020), analysis of variance and regression models (Baraheni and Amini, 2019), grey fuzzy logic incorporating Taguchi method (Krishnamoorthy et al., 2012) and multicriteria studies (Priti et al., 2021). However, the Taguchi method is a principal tool adopted in the composite industry generally because of its simplicity (Gowda et al., 2015; Rajendran et al., 2021; Kilickap, 2010; Nasir et al., 2015; Prasad and Chaitanya, 2020). Besides being motivated by its simplicity, straightforward implementation, computational efficiency, and robustness in the control of parameters, researchers within the CFRP composite domain have adopted particle swarm optimization as a tool for drilling efficiency attainment (Soepangkat et al., 2020). But research is still needed regarding the amalgamation of the Taguchi method with the particle swarm optimization method; such an investigation is sparsely treated in the literature, and no study has been reported for the carbon fiber reinforced plastic composites. The results discussed in the literature by Krishnamoorthy et al. (2012) on the Taguchi method and Soepangkat et al. (2020) on particle swarm optimization to a large magnitude endorse the present research intention in this article, providing detailed information on the benefits derivable from drilling optimization through combined Taguchi and particle swarm optimization methods using experimental data. This is a novel aspect of the present study. An additional novelty is that the present study is implemented by introducing the Taguchi Pareto method to replace the Taguchi method, sot a new approach known as the Taguchi-Pareto-particle swarm optimization method is proposed.

Furthermore, Caggiano (2018) studied the machining behavior of CFRP composites in conventional and unconventional machining processes. Furthermore, Xu et al. (2021) proposed the wear characteristics of CFRP using the step and candlestick drill. Furthermore, Mercy et al. (2020) found speed as the most influential parameter in drilling pineapple fiber composites. Gokulkumar et al. (2020) applied TOPSIS and declared the most appropriate optimal drilling parameters for epoxy polymer composites. Besides, Agwa and Megahed (2019) concluded that feed and drill pre-wear are the most influential parameters, while speed has the least influence on the response variables of drilling.

Interestingly, the present authors made an effort to provide a selected literature review in a tabular form (Table 1).

Table 1. Literature summary of selected relevant studies in the drilling field

S/No.	Author(s) and year	Domain of study	Key input parametes used	Adopted method(s)	Output (responses)	Results
1	Soepangkat et al. (2020)	Multi-response optimization	Drill geometry, spindle speeds, feed	Back propagation neural network, particle swarm optimization	Thrust force, torque, hole entry delamination, and hole exit delamination	Integration of back propagation neural network, particle swarm optimization substantially predicted and enhanced the multi-performance characteristics accurately
2.	Wang and Jia (2020)	Multi-objective optimization	Spindle speed, feed rate, and point angle	Artificial neural network, non-dominated sorting genetic algorithm (NSGA-II), fuzzy C-means clustering	Thrust force and exit-delamination	The representative solutions yielded satisfactory performance with achieving a trade-off among thrust force, exit-delamination, and material removal rate.
3	Abhishek et al. (2016)	Multi-objective optimization	Drill speed, feed, and drill diameter	Fuzzy inference system, non-linear regression model, harmony search algorithm, genetic algorithm and Taguchi's robust optimization philosophy	Thrust force, torque, surface roughness, and delamination factor (both at entry and exit)	Harmony A search algorithm is efficient in searching optimal process parameters are less computational effort as compared to a genetic algorithm due to diversity in the search mechanism.
4	Krishnamoorthy et al. (2012)	Grey fuzzy logic	Hole drilling parameters	Taguchi's L27 orthogonal array, grey fuzzy optimization	Thrust force, torque, entry delamination, exit delamination, and eccentricity of the holes	Feed rate is the most influential factor in the drilling of CFRP composites
5	Saravanan et al. (2012)	Multi-objective optimization using genetic algorithm	Feed rate and the torque of the drilling tool	A genetic algorithm optimization technique	Hole eccentricity and material removal rate	The maximum and minimum eccentricity limits were calculated through finite element formation.
6	Baraheni and Amini (2019)	Rotary ultrasonic drilling	Cutting velocity, feed rate, thickness, and ultrasonic vibration	Analysis of variance, regression models	Thrust force and delamination	Thickness influence on delamination is more than other variables.

This is believed to provide updated research with important details domain of study work material, essential input parameters, the methods used in the study, the response, and the declared results. Arising from this tabulation, the following summaries are made:

1. Although various studies have discussed extensively aspects including metaheuristics, multi-response optimization, grey fuzzy logic, coupled non-linear regression, and multi-objective and Taguchi methods, none has considered the integration of the Taguchi method and the particle swarm optimization in the drilling of CFRPs according to the authors' best knowledge.
2. The multi-objective optimization methods have the largest share of applications in the drilling field, particularly the integration of the Taguchi method with other approaches that correct the weaknesses of the Taguchi method. However, the Taguchi particle swarm optimization method is missing in the literature.
3. Multi-criteria selection tools are expected to extend the knowledge frontier of the drilling process: analytic hierarchy process, best-worst method, DEMATEL, CRITIC, and fuzzy analytical hierarchy process are useful to expand the knowledge frontier in drilling.
4. The principal work materials studied are the carbon fiber reinforced polymer composites (Soepangkat et al., 2020; Wang and Jia, 2020, Abhishek et al., 2016; Krishnamoorthy et al., 2012, Saravanan et al., 2012; Baraheni and Amini, 2019), glass fiber reinforced composites (Agwa and Megahed, 2019; Kilickap, 2010; Bhat et al., 2020). However, very sparse investigations have been conducted on aluminum matrix-based composites (Gowda et al., 2015). Besides, extremely few studies have been

documented on jute fiber composites (Rajendran et al., 2021). Consequently, more extensive studies on the drilling operations of carbon fiber reinforced using the unique approach of the integrated Taguchi method and particle swarm optimization would be of significant interest to operators, process engineers, and engineering managers in the machine shop.

5. Metaheuristics are gradually being applied in drilling (Soepangkat et al., 2020).
6. In reports obtained from the literature, the thrust force surface roughness delamination has been the dominant response (Krishnamoorthy al., 2012; Soepangkat et al., 2020; Wang and Jia, 2020, Baraheni and Amini, 2019; Prasad and Chaitanya, 2020; Bhat et al., 2020. However, extremely little emphasis has been placed on the following responses in the literature: drill vibration velocity, hole diameter accuracy, residual tensile strength (Nasir et al., 2015), hole diameter accuracy, residual tensile strength (Nasir et al., 2015), torque (Agwa and Megahed, 2019) and hole eccentricity (Saravanan et al., 2012).
7. In optimization methods, economic parameters such as lubrication, material, and drilling costs have not been discussed (Shokrani et al., 2019; Lopes et al., 2020).
8. Investigations have completely ignored economic matters in drilling, yet the emphasis of decision-makers has been to minimize drilling costs.

Consequently, the present study adopted an innovative approach to solving the research gap concerning the optimization of thrust force while drilling the CFRP composites by addressing the research gap using the combined Taguchi and particle swarm optimization methods. Furthermore, to further discuss the research gap, which this paper is addressing, it is mentioned here that previous studies have tackled the particle swarm optimization through the use of computer coding that may be somehow difficult for the operator to revise due to changes in parameters; revisions are left in the hands of the program developers. However, a simplified approach using the Microsoft Excel spreadsheet is adopted to be more realistic. Extensive changes are permitted. Thus, the integrated Taguchi-particle swarm optimization method presented has not been previously discussed and eases the operator's implementation of the method in practice. Therefore, there is urgent to adopt this method for improved drilling operation efficiency.

3. METHODOLOGY

This section presents the methods utilized in the present study. The details of the particle swarm optimization method are first presented, followed by the method for the Taguchi-Pareto particle swarm optimization method.

3.1. Particle swarm optimization method (PSO)

In this article, the classical particle swarm optimization method was deployed to establish the least thrust force value in the machining of CFRP composite by exploiting the population-oriented stochastic procedure of the method and its social-psychological framework (Firmansyah et al., 2020). Firmansyah et al. (2020) asserted that this unique method of evaluating a non-linear function was initiated by the scientists named James Kennedy and Russell Eberhart in 1995 and shares the characteristics of being stimulated by random members to obtain a solution, a foundation that particle swarm optimization shares with the genetic algorithm (Firmansyah et al., 2020). Usually, the PSO works on mimicking the behaviors of social animals such as birds, and their relationship is such that they depend upon the success of one another (Firmansyah et al., 2020). For instance, in their search for food, they depend on the success of any of their members such that as a member of a subgroup of these animals finds food, other members follow the same path to achieve the same success (Firmansyah et al., 2020).

3.1.1 Procedure for PSO Implementation

This article adopts the steps for particle swarm optimization, PSO, elaborated in the classical study by Soepangkat et al. (2020). These are as follows:

Step 1: Create the starting position for the pre-defined number of particles to experiment with and define their initial velocities at random using digits obtained from the random table.

Step 2: Establish the particle's fitness value by considering its position. Usually, the fitness function is a formulated objective function, which may contain a variable that represents all other system attributes that are predefined.

Step 3: Establish the particles having the best fitness value, which is the outcome of substituting the obtained values of positions and velocities of the particles previously determined. The gbest is established. For each particle, the initial Pbest value is determined and made equal to the initial position.

Step 4: Use the values obtained for the Pbest and gbest to revise each particle's velocity. When a new velocity is calculated, each particle's position is also revised.

Step 5. Determine the fitness value for each particle.

Step 6. Establish the particle having the best fitness value and project it as the gbest. Establish the Pbest for each particle by weighing the present position with the Pbest from the earlier iteration.

Step 7: Crosscheck if the stopping criteria have been met or not. As the stopping criteria are attained, where the values of the Pbest and gbest in the new iteration are also the same as those in the previous iteration, stop the counting sequence. Otherwise, if the stopping criterion has not been met, continue the iterations until this has been achieved.

3.2. Signal-to-noise (S/N) ratio and Taguchi method

The mechanism of evaluating the proportion of the signals to the noise elements for the parameters to be evaluated in a process is the cornerstone of the Taguchi method. As commonly found in the literature, Mariajayaprakash (2013) and Mahapatra and Chaturvedi (2009) established the signal-to-noise ratio to comprise three distinct measures called the criteria of the S/N ratios: smaller-the-better, nominal-the-best, and the higher-the-better.

The various signal-to-noise criteria are therefore expressed as:

Smaller-the-better: $$\eta = -10\log_{10}\frac{1}{n}\sum_{i=1}^{n} y_i^2 \quad (1)$$

Nominal-the-best: $$\eta = -10\log_{10}\frac{1}{n}\sum_{i=1}^{n} \frac{\mu^2}{\sigma^2} \quad (2)$$

Higher-the-better: $$\eta = -10\log_{10}\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2} \quad (3)$$

where n is the total number of experimental trials conducted at the i^{th} setting, σ is the standard deviation, μ is the mean, y_i represents the value of the parameter of interest, η is the notation for the signal to noise.

Three levels were chosen for each of the parameters in the drilling process. Level means the scale of measurement.

3.3. The TPSO method interface and implementation

In the Taguchi-particle swarm optimization method interface, the point of amalgamation of the Taguchi method with the particle swarm optimization (PSO) method is at the Taguchi SN ratio table. This is the average of all the signal-to-noise ratios by considering the configuration of the orthogonal array by the distribution of the entries. Now, having obtained the optimal parametric setting by choice of $SP_3PA_1FR_3TF_1/TF_3$, the delta values are of interest to the researchers in obtaining the fitness function, *y = f(x)*. Assuming a third-order polynomial to mimic the drilling problem's reality, the values of 9.54 for speed, 1.35 for point angle, and 1.35 for feed rate need to be fitted into the model. Now the S/N ratio interior for the point angle and feed rate is the nominal the best, and therefore their values of 1.35 each are added to yield 2.70.

But the criterion for speed is smaller-the-better, and the value is 9.54 (delta value), which is considered in the fitness function. However, since there are two polynomial components of x^2 and x^3 considered, it is believed that the coefficient of x^3 should be the larger value of 9.54 since it will have the greatest impact on the fitness function. Similarly, the sum of 2.70 is believed to be more suitable as the coefficient of x^2 than for x^3 since it will have a lesser impact on the overall value of the fitness function. Thus, guided by this idea, the fitness function to be used for the particle swarm optimization problem is defined as

$$\text{Minimize} \quad y = f(x) = -2.70\, x^2 - 9.54x^3$$
$$\text{Where} \quad -26.10 \le x \le -14.19$$

The negative values of the coefficients of x^2 and x^3 in the objective (fitness) function were arrived at because the thrust force is a minimization problem, and the least values are desired. The limit of the function was decided based on the values for all the levels within the S/N response tale. Here, the lowest value in the table is -26.1, takings the lower bound of the fitness function. Also, -14.19 is the highest within the table and therefore given as the upper bound of the fitness function.

To implement the particle swarm optimization, it should be noted the technique was developed to mimic animals such as birds, for instance. In search of food, once a member locates the food source, others follow the path to achieve the same success. So for both the leader and followers, the idea of velocity at which the bee moves in search of food and the position it attains at each instance are important in the success of catching the food. This bears in mind that the food could be smaller insects, which also have a velocity of movement that changes their positions from time to time. Thus, two starting terminologies for the PSO implementation in the thrust force minimization problem are the velocity vector and the position vector. By starting with the velocity vector and considering the number of the flock as a particle, the movement of the particles is given by Equation (4):

Velocity:
$$v_{t+1} = w_t v_t + c_1 r_1 \left(P_t^g - x_t\right) + c_2 r_2 (P^g - x_t) \quad (4)$$

and the position vector is given by Equation (5):

Position: $$x_{t+1} = x_t + v_{t+1} \quad (5)$$

where,

t	: iteration number
r_1, r_2	: random member between 0 and 1
P_t^b	: personal best position at the t^{th} iteration
v_t, x_t	: velocity and position at the t^{th} iteration, respectively
w_t	: inertia weight
c_1, c_2	: correction factor
P^g	: global best position
PSO	: parameter setting for this problem

4. RESULTS AND DISCUSSIONS

4.1. The TPSO method

The following requirements are defined to implement this thrust force problem's particle swarm optimization algorithm. First, the population size is fixed at 5. This refers to the total number of birds in the group being examined. This means that at each instance of computing the velocity vector or position vector for the particles, only five members are considered to eliminate computational complexity. The second requirement is the dimension of the problem, which is given as one. This is easily noticeable from the constraint equation that follows the fitness function and the fitness function. Here the variable considered is x, which is one dimension. This is also reflected in the fitness function as the only one. However, in other problems, the population may be higher. Consider a case where x_1, x_2, x_3, and x_z are used in the fitness function; the dimension becomes four.

The value representing c_1 and c_2 is 1.5. The maximum number of iterations is 20, while the inertia weight (w) is 0.9. The values in the velocity vector, position vector, the fitness function, and P^{best} are put side by side for the easy assessment using the method, Table 2.

Table 2. Evaluation of the P^{best} values

Velocity (v)	**Position (x)**		**$f(x)$**	**P_t^b (pbest)**
0.83778 0.53204	-18.36	-20.09	58132.58	-18.36 -20.09
0.08747 0.51731	-23.30	-17.41	119208.90	-23.30 -17.41
0.90184 0.33978	-15.30	-16.89	33536.20	-15.30 -16.89
0.23701 0.80312	-19.14	-17.29	65902.88	-19.14 -17.29
0.16224 0.02743	-21.56	-17.96	94353.04	-21.56 -17.96

In the first matrix, velocity (v), two columns of five rows exist each. Each of these numbers was generated as a randomly chosen velocity between 0 and 1. These values are obtained from the random tables and may not be the same for two separate calculations by individuals from different random tables used. However, they should be the same values if the same random table is used by two individuals. The reason is that the principle of using the random table for the thrust force minimization problem should be followed. By taking a look at the random table, different authors have devised different random numbers. For certain authors, direct extraction of the needed numbers from the table is possible since the random numbers given are between 0 and 1. However, for other authors, direct extraction of the number between 0 and 1 is not possible. For instance, the first number of the first column for the random number table used for the solution of the problem is 83778, which is outside the 0 and 1 range desired. So in the random table, there may be several columns, with each column containing several numbers.

On reading the values, the researcher should start from the first value, i.e., 83778, accept or reject it and move to the next value within the same row (without jumping any value except on a rejection basis). This is done until all the values along the column are used, and the next value to use is the first on the second column. The procedure continues until the last value of the last column on the random table is exhausted. Then, the next value to read is the first one on the first column, and the process continues until the solution has been completed. To generate the random numbers for the first column of the velocity (v) vector, the first value is accepted, i.e., 83778. But values between 0 and 1 are desired. So the researcher needs to place a decimal before the first digit of the value so that the random number generated is 0.83778 and is accepted. The second value down the first column is 08747 and could be converted to the desired value as 0.08747 and therefore acceptable as the value of interest to the researcher. The procedure is conducted, and the other three values are obtained as 0.90184, 0.23701, and 0.16224, respectively. The second column is obtained by following the procedure for generating values for the second column. So the values from 0.53204 to 0.02743 are obtained.

Now, the random values for the position (x) vector are to be generated. The requirement is to randomly initialize positions between $-26.10 \leq x \leq -14.19$. This means that the random values generated must be between -26.10 and -14.19, inclusive. After using the last ten random values for the two columns of the velocity (v) vector, the eleventh element (value) is to be considered. Suppose it yields 37254; this value is rejected for consideration as the first two digits, “37,” are outside the range of “26” and “14” considered here. So the next value is considered. If, however, we have 18357, for instance, this is between “-26” and “-14” as it could be interpreted as -18.36, and this value is acceptable. So the five values for each of the two columns of the position (x) vector is generated in the same way. Here, the highest values for each column are searched for, and the values -15.30 and -16.89 are obtained for the first and second rows, respectively. The next step is to evaluate the value of the fitness function, f(x), given as Equation (6):

$$\text{Minimize } y = f(x) = -2.70\,x^2 - 9.54\,x^3 \qquad (6)$$

However, since this is the first iteration, the P^{best} is P^b, given as x. The next step is to calculate the global best, P^g. But by using the values of 0.90184 and 0.33978 as the v_1 and v_2, respectively, and x_1 and x_2 as -15.3 and -16.89, the fitness function $f(x)$ are obtained as 33536.2. Also, note that P_1^b and P_2^b are respectively -15.30 and -16.89 since there is no previous iteration. This computation terminates iteration 1. However, the result details of iterations 2 and 3 are excluded here, while that of iteration 4 is included for concise reporting. For iteration 4, for the first particle, the first component, fitness value is 26714.44 while the gbest (P^g) is (-14.19 -16.061). But by noting that the present $f(x)$ obtained and the previous one is the same, i.e., 26714.14, and their difference is zero, the optimal solution has been attained. Therefore, P^g (gbest) is (-14.19 – 16.061) (Table 3). This dictates x_1 as -14.19 and x_2 as -16.0612 and $f(x_1, x_2)$ is then 26714.44. By comparing these values with the one obtained from the Taguchi method alone, the optimal value of -14.19 was suggested at levels 1 and 3, which coincide with one of the minima of the P^g (gbest) of -14.19. However, the P^g (gbest) value of -16.061 was obtained, which is lower than -14.19 from the Taguchi method's response table. However, -16.061 is not shown directly on the factor/response level table from which results values are read. This, if proportions are to be followed and the value obtained, -16.061, should be interpreted concerning the lower value of 84.23N obtained by the experiment. The PSO is said to produce a value of 73.12N, which is lower than the experimental value of 84.23N. This value of 73.12N was obtained when the difference between -16.061 and -14.19 was first computed as 13.19%. Then the 13.19% of 84.23N is subtracted from 84.23N to obtain 73.12N. This result concludes that the

Table 3. Summarised values of pbest and gbest using velocity and position vectors for the thrust force minimization problem

Velocity (v)		**Position (x)**		**$f(x)$**	**pbest (p^b)**		**gbest (P^g)**	
v_1	v_2	x_1	x_2		p^b_1	p^b_2	p^g_1	P^g_2
Iteration 4								
1.453797	1.247493	-14.3784	-16.8174	27800.36	-14.3784	-16.8174	-14.19	-16.0613
2.556798	0.471697	-17.6558	-15.8893	51664.66	-17.6558	-15.8893		
1.043067	0.2477	-14.19	-16.0613	26714.44*	-14.19	-16.0613		
1.425093	0.557452	-15.8679	-15.2705	37435.76	-15.8679	-15.2705		
2.088582	0.423587	-16.8833	-17.0731	45142.03	-16.8833	-17.0731		

*Optimal in each iteration

Table 4. Re-arranged experimental trials based on the Pareto scheme

Initial order		**Descending order**				
Expl. trial	**Variance**	**Expl. trial**	**Variance**	**Cumulative**	**Percentage**	**80% cut-off**
1	1711.71	8	3037.32	3037.32	14.25	
2	2077.55	7	2845.60	5882.92	27.59	
3	2259.94	4	2682.78	8565.70	40.17	
4	2682.78	6	2483.72	11049.42	51.82	
5	2082.06	3	2259.94	13309.35	62.42	
6	2483.72	9	2141.20	15450.55	72.46	
7	2845.60	5	2082.06	17532.61	82.23	Cut-off point
8	3037.32	2	2077.55	19610.15	91.97	
9	2141.20	1	1711.71	21321.86	100	

Taguchi-particle swarm optimization method reduced the thrust force and its effects on tools from 84.23N (experimental) to 73.12N. Notice that in Table 3, the summary of each particle and each iteration are given only for the last iteration of the process for conciseness of presentation.

4.2. TP-PSO method to minimize thrust force determination

The Taguchi method was deployed in the previous section to evaluate the optimal parametric setting for the thrust force minimization problem while drilling the CFRP. However, it is assumed that the influence of the signal-to-noise ratio from each experimental trial on the optimal parametric setting for all the trials is the same. But the signal-to-noise ratio reveals the impact of noise on the system, and the experimental trial that experiences greater impact will influence the outcome of the drilling activity more than others without great impacts. Thus, it was decided to rate each experimental trial according to the degree of influence it impacts on the minimization of the thrust force. This prioritizes the experimental trials and brings about the Taguchi-Pareto method, which classifies certain experimental trials as extremely important and others as unimportant based on the 80-20 Pareto rule.

Since there are data on signal-to-noise ratios for the parameters and response (thrust force), an association is established by evaluating the variance using the analysis of variance (ANOVA) technique which indicates the degree to which the set of signal-to-noise ratios for the parameters is near or far away from that of the response (thrust force). Thus, the S/N ratio of all the parameters is added and matched against those of the thrust force in an ANOVA test. In Table 3, the variance values of the experimental trials have been shown, which are extracted from the ANOVA table run at 0.05 degrees of freedom. In Table 4, the first two columns show the variance results and the associated experimental trial numbers.

To apply the Pareto scheme, ordered variance values and the associated experimental trial numbers have been shown in the third and fourth columns, indicating that Experimental trial number 8 has the highest variance value of 3037.32. In contrast, the least variance is associated with experimental trial number 1 with a variance of 1711.71. The cumulative value is then obtained in the fifth column, while the percentages are shown in the sixth column of Table 3. The seventh column shows the cut-off for the Pareto principle application at the 8th experimental trial, precisely experimental trial 5. A cut-off of 82.23% was chosen since it is closer to the 80% cut-off value for the Pareto principle's application than the 72.46%, which is the value of the experimental trial 9 (Table 5). It then means that a revised S/N ratio table will be computed, and a revised response table from which the optimal parametric settings are determined will also be created.

Table 6, called the signal-to-noise response table, is extracted as the average value of the signal-to-noise ratio for the similar entries of the orthogonal array obtained from Table 5. There are twelve positions to fill the

Table 5. Taguchi-Pareto's Orthogonal arrays, factors, and signal-to-noise ratios for the drilling problem

									S/N ratio type				
Orthogonal array					Factors				LTB	STB	NB	STB	
Expt. No.	**S**	**PA**	**FR**	**TF**	**S**	**PA**	**FR**	**TF**	**S**	**PA**	**FR**	**TF**	**S/N ratios**
8	3	2	1	3	3000	118	100	310.47	69.54	-41.44	0	-49.84	-21.74
7	3	1	3	2	3000	100	500	197.35	69.54	-40.00	0	-45.90	-16.36
4	2	1	2	3	2000	135	300	310.47	66.02	-42.61	0	-49.84	-26.43
6	2	3	1	2	2000	118	100	197.35	66.02	-41.44	0	-45.90	-21.32
3	1	3	3	3	1000	135	500	310.47	60.00	-42.61	0	-49.84	-32.45
9	3	3	2	1	3000	135	300	84.23	69.54	-42.61	0	-38.51	-11.58
5	2	2	3	1	2000	100	500	84.23	66.02	-40.00	0	-38.51	-12.49

Key: Speed – S; point angle – PA; feed rate – FR; thrust force – TF; Smaller-the-better – STB; Larger-the-better – LTB; Nominal-the-best – NB

Table 6. Taguchi-Pareto SN ratio response table

Level	SP	PA	FR	TF
1	-32.45	-21.40	-21.53	-12.04*
2	-20.08	-17.12*	-19.01*	-18.84
3	-16.56*	-21.78	-20.43	-26.87
Delta	-49.01	-38.90	-40.54	-38.91
Rank	3	1	4	2

*Optimum value

average value, but eventually, one or more positions may not be filled because the responsible signal-to-noise ratio has been ignored since it is more than the 80% cut-off mark for the Pareto principle to be implemented for the Taguchi method. It could also be that all the twelve entries would be filled, but the averages of some positions will be less than what was conducted for the Taguchi response table earlier created for the work.

Meanwhile, the first computation will be for the speed parameter. To achieve this, Table 5 is revisited, and the column for the speed parameter is observed to establish all the entries with the code "1", which means level 1 for the speed parameter. The entire code "1" for the column "S" is only one, representing level 1. The corresponding S/N ratio for experimental trial three, which bears level 1, is -32.45, and since only an item is found, its average is -32.45. For the speed parameter, level 2, three experimental trials are attached to this, including experimental trials 4, 6, and 5. They have the corresponding S/N ratios of -26.43, -21.32, and -12.49, respectively, and an average of -20.08. For the third level of speed, by following the procedure, the average is -16.56, obtained from the S/N ratios corresponding to experimental trials 8, 7, and 9 as -21.74, -16.36, and -11.58, respectively.

For the first level of point angle, the average S/N ratio is -21.40, obtained from the S/N ratios corresponding to experimental trials 7 and 4 with the respective values of -16.36 and 26.43. Likewise, the averages of the second and third levels of point angle from the signal-to-noise ratio perspective are -17.12 and -21.78, respectively. For the feed rate, the averages of the S/N ratios for levels 1, 2, and 3 are -21.53, -19.01, and -20.43, respectively. For the thrust force, the S/N ratios for the first, second, and third levels are -12.04, -18.84, and -26.87, respectively. The data is obtained as the difference between the highest and lowest values for each parameter or response, ranging from -40.54 to -38.90, which is used to attach positions parameter and response. The point angle emerged as the first, thrust force as the second, speed as the third, and feed rate as the fourth position. The delta values were used to obtain the fitness function for the particle swarm optimization method to be combined with the Taguchi method. To obtain the fitness function, the signal-to-noise classification needs to be considered. The fitness function is according to three categories of signal-to-noise criteria for larger-the-better for the speed parameter, smaller-the-better for each of the point angle parameters, and thrust force response.

The third category, normal-is-the-best, has no values under the feed rate and is therefore ignored. Thus, the coefficients of -49.01 representing speed for larger-the-better will be used in one part of the equation. In the other part of the equation, -38.90 representing the smaller-than-better point angle, will be used. However, the data coefficient for thrust force is not considered since the fitness function was developed for the thrust force. Therefore, by fitting the coefficient into a polynomial of powers 2 and 3, the fitness function becomes $y = f(x) - 49.01\ x^2 - 38.90\ x^3$. The coefficient of x^2 is determined as -49.01 since the speed parameter is the weaker in ranks between itself and the points angle. It means that when the fitness function is computed, it will have less influence on increasing the fitness function values than the point angle parameter.

Now, commencing the problem evaluation using the Taguchi-Pareto method, the fitness function $y = f(x) - 49.01\ x^2 - 38.90\ x^3$ is used. The computation is commenced by the first iteration. Since this is the first iteration, the Pbest is Pb, given as x. The next step is to calculate the global best, Pg. But by using the values of 0.08747 and 0.51731 as the v1 and v2, respectively, and

Table 7.Summarised values of pbest and gbest using velocity and position vectors for the thrust force minimization problem (TP-PSO method)

Velocity (*v*)		Position (*x*)		*f*(*x*)	pbest (p^b)		Gbest (P^g)	
v_1	v_2	x_1	x_2		p^b_1	p^b_2	p^g_1	p^{g_2}
Iteration 1								
0.83778	0.53204	-23.3	-17.41	465452.2	-23.3	-17.41	-19.14	-27.93
0.08747	0.51731	-19.14	-27.93	254802.4*	-19.14	-27.93		
0.90184	0.33978	-21.56	-16.88	367067	-21.56	-16.88		
0.23701	0.80312	-20.09	-32.24	295639.3	-20.09	-32.24		
0.16224	0.02743	-30.77	-30.11	1086864	-30.77	-30.11		
Iteration 7								
1.251871	-1.74435	-16.56	-29.2312	163216.7*	-14.6982	-29.2312	-16.56	-24.2948
0.551808	0.6118	-17.8701	-24.51	206337.9	-17.7506	-24.51		
0.802803	-1.78551	-16.56	-29.7717	163216.7*	-15.3824	-29.7717		
0.703962	1.459848	-17.2072	-22.1181	183679	-17.0877	-22.1181		
3.239517	1.295646	-16.56	-24.2948	163216.7*	-12.3884	-24.2948		

*Optimal in each iteration

Table 8. Summarised values of pbest and gbest using velocity and position vectors for the thrust force minimization problem (PSO method)

Velocity (*v*)		Position (*x*)		*f*(*x*)	pbest (p^b)		Gbest (P^g)	
v_1	v_2	x_1	x_2		pb_1	pb_2	pg_1	Pg_2
Iteration 1								
0.83778	0.53204	0.04	0.848	0.001536	0.04	0.848	0.03	0.739
0.08747	0.51731	0.045	0.784	0.001934	0.045	0.784		
0.90184	0.33978	0.038	0.824	0.001389	0.038	0.824		
0.23701	0.80312	0.034	0.702	0.001117	0.034	0.702		
0.16224	0.02743	0.03	0.739	0.000873*	0.03	0.739		
Iteration 4								
-0.0701	-0.06234	0.649281	1.18364	0.147851	0.719386	1.245982	0.177142	0.763877
0.006187	-0.05455	0.135527	1.1312	0.015878	0.12934	1.18575		
-0.07646	-0.04031	0.692104	1.035291	0.147485	0.692104	1.035291		
-0.00804	-0.07575	0.231311	1.273976	0.041128	0.231311	1.273976		
8.55E-06	1.44E-06	0.177142	0.763877	0.025821*	0.177133	0.763876		

x1 and x2 as -19.14 and -27.93, the fitness function f(x) are obtained as 254802.4. Also, note that and are respectively -19.14 and -27.93 since there is no previous iteration. Thus, following the procedure for the implementation of TPSO here, the summarised table of iterations is obtained as follows (Table 7).

In Table 7, the result details of each particle at each iteration are summarized in a form, with only the first and last iterations shown for conciseness.

4.3. PSO method to minimize thrust force determination

The TPSO and TP-PSO methods were deployed in the previous sub-sections to evaluate the optimal thrust force. However, this sub-section attempts to evaluate the optimal thrust force without the influence of the Taguchi method as the PSO method. For the computation, the summary is presented as follows (Table 8). Table 8 is a summary of the result detail of each particle at each iteration. Here, for conciseness, the first and last iterations are shown.

4.4. Comparison of TPSO with literature and other results

At iteration 4, the P_1^g and P_2^g, which represent two values of the gbest (P^g) obtained, are -14.19 and -16.0613, respectively. These values are optimal because they slightly differ from their corresponding values of -14.19 (P_1^g) and -16.309 (P_2^g) in iteration 3, indicating that the optimal values have been obtained. At this point, the attention is directed to the value of the fitness function, *f*(*x*), which is 26714.44. This is the predicted value based on the computational experiments aided by particle swarm optimization. However, this needs to be compared with the value after the first iteration, which can be taken as the original experimental value of *f*(*x*), which is 33536.2. The difference in this assumed experimental value when optimization commenced, and the optimal value is 20.34%. It is, therefore, safe to assume that the experimental value of thrust force has been optimized by the combined Taguchi method and particle swarm optimization with a value reduction of 20.34%. It is interesting to compare this result with the work of Saravanan et al. (2012).

While the present work optimized the thrust force based on the combined action of the Taguchi method and the particle swarm optimization, the focus of Saravanan et al. (2012) was on the use of genetic algorithms alone. But genetic algorithm and particle swarm optimization are members of the evolutionary algorithms' family; hence, the two studies qualify for comparison. Interestingly, Saravanan et al. (2012) reported that when the genetic algorithm optimized the material removal rate and eccentricity, a gain of 10% was included, but the growth of 20.34% experienced in the present work is appreciable relative to the genetic algorithm methods results. This result validates the usefulness of the proposed TPSO method in accomplishing the optimization of thrust force. It should be noted that the computational experiments performed by Saravanan et al. (2012) are also on the drilling of CFRP composites, which makes the results obtained robust and reliable. Thus, the present study projects an idea about an accurate choice of speed, feed rate, and point angle to yield minimum thrust force in the drilling of CFRP composites.

To compare the results of the Taguchi method and TPSO, it was noticed that the experimental thrust force value was 310.47N, and this was optimized by the Taguchi method, reduced to 84.23N, which is a 72.78% reduction. But by implementing the TPSO, a further 20.34 % reduction is shown to mean that of the 84.23N obtained, 20.34% of it has been reduced, which brings the optimized thrust force by the TPSO method to (84.23 - (0.2034 x 84.23))N, which is 67.1N.

4.5. Advantages of Taguchi-Particle swarm optimization method and rationale for the method

In the pursuit of optimization using the combined Taguchi-particle swarm optimization (TPSO) method, the process engineer obtains unique benefits from its application to the drilling problem. Given that the thrust force is to be minimized while machining the CFRP composites, the TPSO method helps to lessen the influence of rising experimental costs as constantly quantitative information could be obtained from less experimental testing. Furthermore, the TPSO method is uniquely developed to optimize the six responses in drilling, namely the delamination at entry, delamination at exist, surface roughness, eccentricity, torque, and thrust force concurrently, which is a feature absent in many other competing models. Besides, the TPSO is robust in controlling the mentioned responses and exhibits a vigorous computational efficiency weighed against other mathematical procedures and heuristic approaches to problem-solving in the drilling domain. Thus, considering the mentioned advantages of this novel method, it was decided to implement the model using the experimental data of Krishnamoorthy (2011).

5. CONCLUSION

In this article, a new method named the Taguchi-particle swarm optimization method has been proposed for the first time in the CFRP composite literature to solve the thrust force problem responsible for load compression on the drill bits during the drilling process of the CFRP composites. Based on the literature data by Krishnamoorthy (2011), the method was tested, and the following conclusions were reached:

- The Taguchi method yielded a signal-to-noise ratio with the optimal parametric setting declared as $SP_3PA_1FR_3TF_1/TF_3$, which is -16.56 (SP_3), -20.43 (PA), -20.43 (FR_3), 14.19 (TF_1)/14.19 (TF_3). This is interpreted as 3000rpm (speed), 1000 (point angle), 500mm/min (feed rate) and 84.23N (thrust force).
- From the experiments conducted by Krishnamoorthy (2011), the minimum thrust force obtained was 84.23N. This is the least load compression experienced by the drill. However, the thrust force was further reduced to 73.12N by implementing the combined Taguchi-particle swarm optimization, which indicates an 11.11% reduction in the experimental values.
- The Taguchi-particle swarm optimization method is feasible to reduce the thrust force during CFRP composites' drilling exercise. A useful predictive method of thrust force has been developed and tested with experimental data.

Future studies may introduce control measures such as the variable control X bar and R bar charts as a step towards establishing possible outliers in the experimental results, and assignable causes of poor performance may be studied.

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