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Procedia Technology 25 (2016) 955 – 962

Procedia Technology

Global Colloquium in Recent Advancement and Effectual Researches in Engineering, Science and Technology (RAEREST 2016)

Multi-response optimization in drilling of Carbon Fiber Reinforced Polymer using artificial neural network correlated to meta-heuristics algorithm

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Abstract

This paper aims to optimize the drilling process parameters using artificial neural network (ANN) linked with the most popular meta-heuristics technique such as Hybrid Particle Swarm Optimization Gravitational Search Algorithm (PSOGSA) and Genetic Algorithm (GA). An aerospace grade T300 Carbon Fiber-Epoxy composite laminate of 8 mm thick was made of T300 Polyacrylonitrile (PAN) based Carbon Fiber and two part Epoxy resin was use for this study. The Carbon Fiber used is Bi-directional (BD) with a ply thickness of 0.25mm and lay-up sequence of [60/90/0/90/90/60/0/60/60/60/60/45/90/90/0/45/60/90/60]. Drilling experiments were conducted on a composite laminate by varying the cutting speed (30, 40 and 50 m/min), feed rate (0.025, 0.05 and 0.1 mm/rev) and drill bit type (HSS, TiAlN and TiN). The experimental results in the form of thrust force, torque and surface roughness obtained are correlated with process parameters through artificial neural network (ANN) and optimized by PSOGSA and GA. The optimization results indicates that the proposed hybrid PSOGSA performances much better than the GA.

Peer-review under responsibility of the organizing committee of RAEREST 2016

Keywords: Drilling; Carbon Fiber Reinforced Polymer; Particle Swarm Optimization; Gravitational Search Algorithm; Artificial Neural Network

1. Introduction

Carbon-fiber-reinforced polymers are composite materials in which it consists of two parts: a matrix and reinforcement. The reinforcement within the CFRP is carbon fiber, that really provides the strength and also the matrix is two-part epoxy resin, to combine the reinforcements together. As the Carbon/Epoxy composite consists of

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Peer-review under responsibility of the organizing committee of RAEREST 2016
doi:10.1016/j.protcy.2016.08.187

two completely different components, the properties of the laminate rely upon these two components. The carbon fiber will offer the CFRP its strength and rigidity; measured by stress and modulus of elastic. In-contrast to the isotropic materials like steel and metallic elements, CFRP has directional strength properties.

Sangwan et al. [1] proposed an integrated approach of neural network and genetic algorithm to optimize the process parameter. Tsao and Hocheng [2] investigated the effects of varying the drill diameter and feed rate on drilling composite material using neural network. Garg et al. [3] proposed radial basis function network to predict the flank wear of drilling mild steel. Gill and singh [4] developed a Neuro-Fuzzy system of material removal rate for ultrasonic drilling. Mishra et al. [5] studied the residual tensile strength of drilled glass fiber reinforced polymer using neural network. Sanjay et al. [6] conducted drilling test on mild steel to monitor the tool wear using artificial neural network. Vrabel et al. [7] used neural network approach to predict the surface roughness of drilling of Udimet 720. Gowda et al. [8] conducted drilling test on MMC and predicted the responses using artificial neural network approach. Kannan et al. [9] conclude that the neural network approach can be effectively used to predict the thrust force, surface roughness and ovality in drilling copper. An integrated approach of artificial neural network and genetic algorithm was used by Sangwan et al. [10-11] for optimizing the process parameters. Kalantari et al. [12] used multi-objective optimization technique to forecast flexural properties of glass/carbon fibre epoxy composite. Abhishek et al. [13] have explored the use of harmony search algorithm coupled with the fuzzy logic to optimize the drilling process of CFRP. Phadnis et al. [14] conducted the drilling experiment on CFRP composite and verified the results with the finite element simulation using Abacus software. Sardinas et al. [15-16] evaluated the multi-performance characteristics of machining composite laminate using genetic algorithm. Ahmadi et al. [17] conducted production performance by linking the ANN to the PSO tool. Mallick et al. [18] resolved the static state problems using the meta-heuristics techniques (PSO and GSA).

2. Drilling Experiments

Nomenclature

x(1)	Cutting speed
x(2)	Feed rate
x(3)	Drill bit type

2.1. Material and methods

The composite material used for the drilling experiment was made of T300 Polyacrylonitrile (PAN) based Carbon Fiber and two part Epoxy resin. The Carbon Fiber used is Bi-directional (BD) with a ply thickness of 0.25mm and lay-up sequence of [60/90/0/90/90/60/0/60/60/60/60/45/90/90/0/45/60/90/60]. The composite was most widely used in aerospace application because of its superior mechanical properties. The epoxy used in the laminate is of two-parts, one is the hardener and the other is epoxy manufactured by Anabond Ltd. The drilling of CFRP was conducted on a CNC vertical drilling machine with 4.5 kW power and a maximum speed of 4000 rpm. Three drill bit namely HSS, TiAlN and TiN of diameter 6mm was used for the experimental trials.

2.2. Experimental Design

The Carbon/Epoxy laminate was drilled by varying the machining process parameters. The process parameters selected for the drilling test along with their levels are represented in Table 1. The thrust force and torque are measured by using the Kistler dynamometer for all the experimental trials. The surface roughness of the drilled holes is measured by Mitutoyo Surftest SJ-210 Surface Roughness Tester. The repeatability of the experimental results was carried out by conducting two repeated experimental trials.

2.3. PSOGSA

The PSO was popular for its efficiency to converge to the optimum value quickly and it works on the principle of altering its position velocity based on the new and its previous value. In GSA, the variables are considered as objects and these objects are evaluated by means of masses. The variables attract each other by means of the gravitational force, which in case move all the variables towards the heavier masses. The optimum/good solution for the problem corresponds to the heavier masses.

$$v_i^d(t+1)_{PSO} = w(t)v_i^d(t) + c_1 * r_1 * \left(pbest_i^d - x_i^d(t)\right) + c_2 * r_2 * \left(gbest_i^d - x_i^d(t)\right) \quad (1)$$

$$v_i^d(t+1)_{GSA} = rand_i * v_i^d(t) + a_i^d(t) \quad (2)$$

$$v_i^d(t+1)_{PSOGSA} = c_3 * r_3 * v_i^d(t+1)_{pso} + c_4 * (1 - r_3) * v_i^d(t+1)_{gsa} \quad (3)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)_{PSOGSA} \quad (4)$$

Where v is the velocity, x is the position, t is the iteration c_1, c_2, c_3 and c_4 are the acceleration coefficient, r_1 and r_2 are the random numbers. Equations (1-4) are used to get the velocity and position of the new particles.

Table 1 Design Parameters and Level

Drilling Parameter	Level 1	Level 2	Level 3
Cutting Speed (m/min)	30	40	50
Feed Rate (mm/rev)	0.025	0.05	0.1
Drill Bit Type	HSS	TiAlN	TiN

3. Results and discussion

3.1. Effect of process parameter on Experimental Results (Thrust Force, Torque and Surface Roughness)

From the Fig. 1 it is evident that the maximum thrust force was obtained when drilling at 30m/min of cutting speed, 0.1 mm/rev of feed rate and HSS drill bit. Also the minimum value of thrust force was obtained when drilling the laminate at 50 m/min of cutting speed, 0.025 mm/rev of feed rate and TiAlN drill bit.

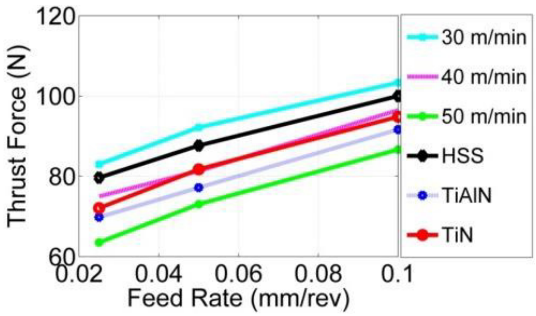


Fig. 1. Variation of Thrust Force with Cutting Speed, Feed Rate and Drill Tool

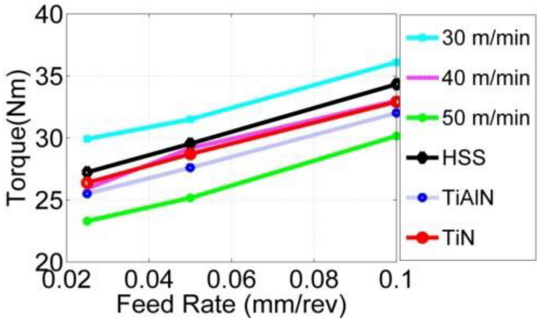


Fig. 2. Variation of Torque with Cutting Speed, Feed Rate and Drill Tool

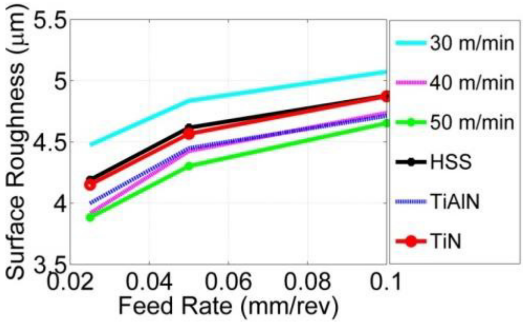


Fig. 3. Variation of Surface Roughness with Cutting Speed, Feed Rate and Drill Tool

The Fig. 1 clearly indicates that the value of thrust force decreases considerable by 15% and 35% when the cutting speed increases from 30 m/min to 40 m/min and 50 m/min. In contrast, the thrust force value increases significantly with the increase of feed rate by a magnitude of 40%. In the case drill bit the HSS and TiN produces maximum thrust force while the TiAlN produces minimum thrust force. The Fig. 2 clearly indicates that the magnitude of torque decreases considerable by 14% and 20% when the cutting speed increases from 30 m/min to 40 m/min and 50 m/min.

In difference, the torque value increases significantly to higher magnitude of 30% with the increase in feed rate. In the case drill bit the TiAlN produces minimum torque while the HSS and TiN produces maximum torque. The Fig. 3 shows the main effect plot for surface roughness, it indicates that the maximum value of surface roughness was obtained when drilling at 30 m/min of cutting speed, 0.1 mm/rev of feed rate and with HSS drill bit type. Also the minimum value was achieved when drilling at 50 m/min of cutting speed, 0.025 mm/rev of feed rate and with TiAlN drill bit type.

3.2. Prediction of Thrust Force, Torque and Surface Roughness using Artificial Neural Network (ANN)

Neural Networks (NN) are simplified models of the biological neuron system, that may be a parallel distributed processing system created of extremely interconnected neural computing components that have the flexibility to find out and thereby acquire information and build it offered to be used. NN architectures are classified into varied types on the basis of their supported learning mechanisms and alternative options. Some categories of NN ask this learning method as training and also the ability to resolve complicated problems using the information as abstract thought. The structural constituents of an individual's brain termed neurons are the entities, that perform computations like knowledge, logical abstract thought, pattern recognition and then on. Therefore the technology that has been engineered on a simplified imitation of computing by neurons of a brain has been termed Artificial Neural Networks (ANN).
The Fig. 4-6 shows the relationship between the experimental values and the ANN predicted value. From the results

it's obvious that the actual value coincidences very well with the predicted value of ANN model.

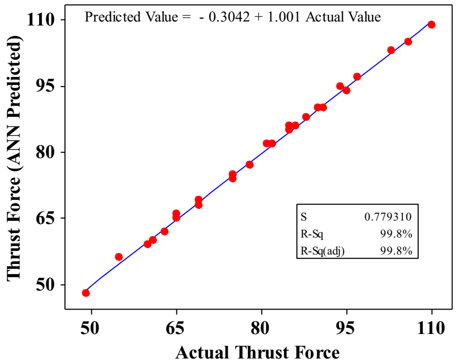


Fig. 4. Correlation graph of Thrust Force

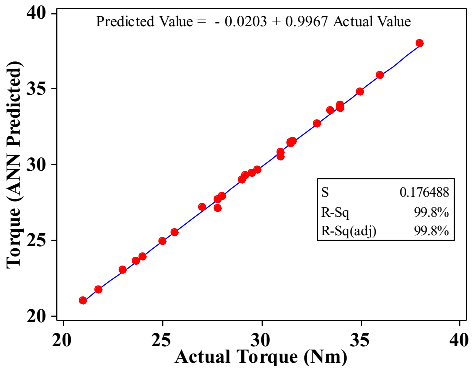


Fig. 5. Correlation graph of Torque

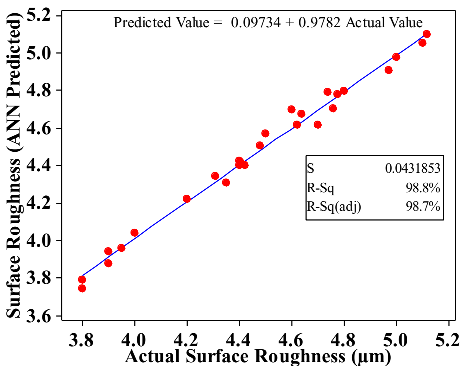


Fig. 6. Correlation graph of Surface Roughness

3.3. Mathematical Model of Thrust Force, Torque and Surface Roughness

Since the actual value of the experimental are in good agreement with the ANN predicted model, the mathematical model was created based on the ANN model. The quality of the drilled holes, machining time and productivity mainly depends on the selection of proper process parameters. In this work the process parameters namely the cutting speed, feed rate and drill bit type are selected based on the above concept. The mathematical model for all the responses are represented in Eq. (5) to (7).

$$Thrust\ Force = 100.554 - (0.0388889 * x(1)) + (454.698 * x(2)) - (21.6361 * x(3)) - (0.0113889 * x(1) * x(1)) - (1345.19 * x(2) * x(2)) + (5.94444 * x(3) * x(3)) \quad (5)$$

$$Torque = 48.9739 - (0.733972 * x(1)) + (104.089 * x(2)) - (5.83694 * x(3)) + (0.00576111 * x(1) * x(1)) + (94.5185 * x(2) * x(2)) + (1.50611 * x(3) * x(3)) \quad (6)$$

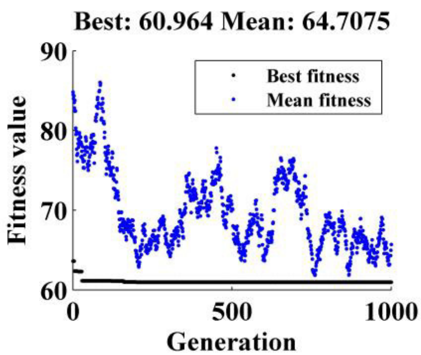
$$Surface\ Roughness = 8.51631 - (0.19399 * x(1)) + (21.8673 * x(2)) - (0.6058 * x(3)) + (0.002 * x(1) * x(1)) - (155.467 * x(2) * x(2)) + (0.158 * x(3) * x(3)) \quad (7)$$

3.4. Optimization of machining process parameters using GA and PSOGSA

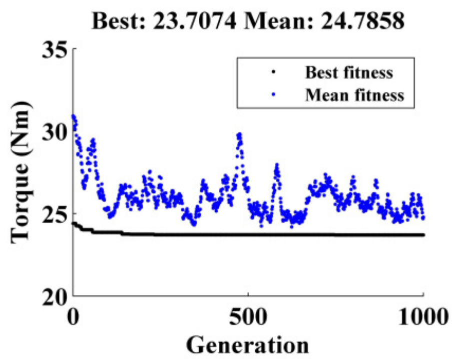
Though the drilling of Carbon fiber/Epoxy composite laminate has various combinations of process parameters, we consider only the cutting speed, feed rate and drill bit type. Hence selection of optimum process combination is very important to minimize the production cost.

3.5. Results of Genetic Algorithm (GA)

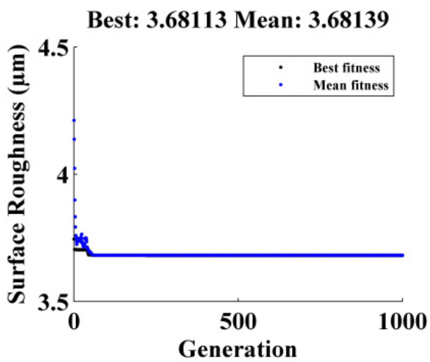
The input for the process parameter optimization was achieved by the ANN model. From the predicted values of the ANN model the regression equations were generated and given as the input to the objective function of the Genetic Algorithm (GA). The initial parameters setting for running the GA are given below: No of iteration – 1000, population size – 100, cross-over probability – 0.80, Roulette Wheel selection, mutation probability – 0.05. The Fig. 7 shows the minimum value of the response variable obtained by GA corresponding to the number of iteration.



(a)



(b)



(c)

Fig. 7. GA convergence characteristics of (a) Thrust Force; (b) Torque; and (c) Surface Roughnes

3.6. Results of Hybrid Particle Swarm Optimization Gravitational Search Algorithm (PSOGSA)

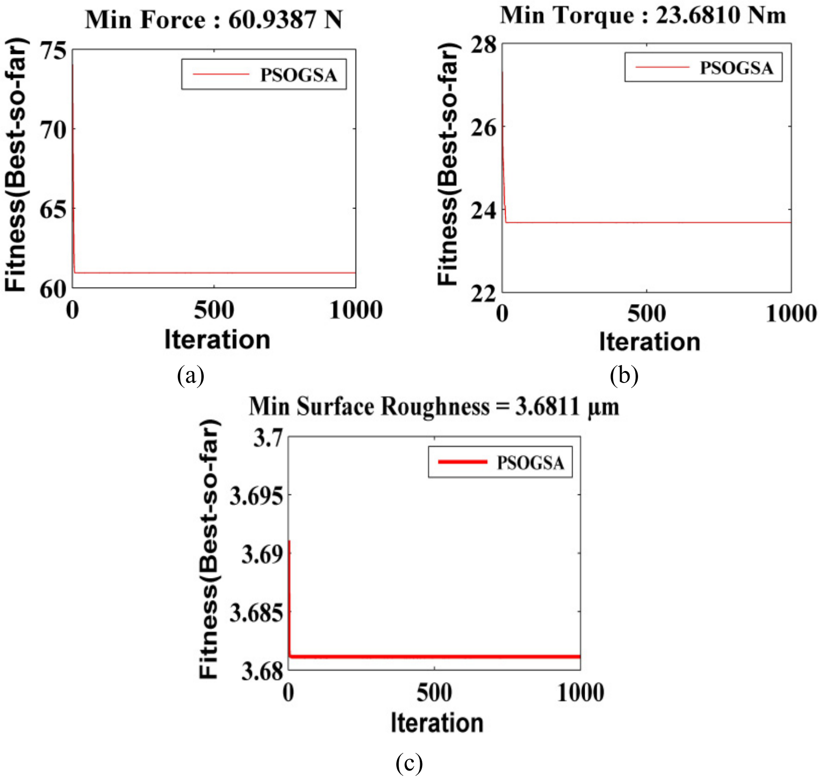


Fig. 8. PSOGSA convergence characteristics of (a) Thrust Force; (b) Torque; and (c) Surface Roughness

The input in the form regression equation to the PSOGSA was generated from the predicted value of the ANN model. The initial parameter setting for running the hybrid algorithm PSOGSA is given below: No of iteration – 1000, size of swarm – 100, learning factor, C_1 – 0.5 and C_2 – 1.5. The Fig. 8 shows the minimum value of the response variable obtained by GA corresponding to the number of iteration

3.7. Comparison of GA and PSOGSA results

Table 2 and 3 shows the single and multi-objective optimization responses values along with the optimum process parameters for drilling Carbon/Epoxy composite laminate obtained by using the two of the most powerful non-traditional technique, GA and PSOGSA. The results of the two algorithms clearly indicate that the PSOGSA is more powerful than the GA in terms of the number of iteration and process time.

Table 2. Results of single objective optimization using GA and PSOGSA

Algorithm	Response	Optimal Value	V (m/min)	F (mm/rev)	DB
GA	Thrust Force (N)	60.964	50	0.025	TiAlN
	Torque(Nm)	23.7074	50	0.025	TiAlN

	Surface Roughness (µm)	3.68139	48.498	0.0250	TiAlN
PSOGSA	Thrust Force (N)	60.9387	50	0.025	TiAlN
	Torque (Nm)	23.6810	50	0.025	TiAlN
	Surface Roughness (µm)	3.6811	48.4975	0.0250	TiAlN

Table 3. Comparative results of multi-objective optimization using GA and PSOGSA

Algorithm	Thrust Force (N)	Torque (Nm)	Surface Roughness (µm)	Optimum Values			No of Iterations
				V (m/min)	F (mm/rev)	DB	
GA	60.96	23.71	3.68	50	0.025	TiAlN	51
PSOGSA	60.93	23.68	3.68	50	0.025	TiAlN	4

4. Conclusions

In this paper the optimization of the process parameters with multiple characteristics in drilling of BD Carbon Fiber - Epoxy composite laminate was carried out by PSOGSA and GA. The conclusion drawn from the drilling experiments are given below:

1. Artificial Neural Network approach has found to be effective in predicting the minimum value of thrust force, torque and surface roughness compared to the experimental values.
2. The optimum process parameter combination for minimum thrust force, torque and surface roughness are higher cutting speed(50 m/min), lower feed rate(0.025 mm/rev) and TiAlN drill tool for the range selected.
3. The proposed hybrid algorithm (PSOGSA) converges to the optimal solution with lesser number of iteration compared to the Genetic Algorithm.

References

[1]. Sangwan K S, Saxena S, Kant G. Optimization of Machining Parameters to Minimize Surface Roughness using Integrated ANN-GA Approach. Procedia CIRP 2015; 29:305-10.

[2]. Tsao C C, Hocheng H. Evaluation of thrust force and surface roughness in drilling composite material using Taguchi analysis and neural network. J Mater Process Tech 2008; 203(1): 342-8.

[3]. Garg S, Patra K, Khetrapal V, Pal S K, Chakraborty D. Genetically evolved radial basis function network based prediction of drill flank wear. Eng Appl Artif Intel 2010; 23(7):1112-20.

[4]. Gill S S, Singh J. An Adaptive Neuro-Fuzzy Inference System modeling for material removal rate in stationary ultrasonic drilling of sillimanite ceramic. Expert Syst Appl 2010; 37(8):5590-8.

[5]. Mishra R, Malik J, Singh I, Davim J P. Neural network approach for estimating the residual tensile strength after drilling in uni-directional glass fiber reinforced plastic laminates. Mater Design 2010; 31(6): 2790-5.

[6]. Sanjay C, Neema M L, Chin C W. Modeling of tool wear in drilling by statistical analysis and artificial neural network. J Mater Process Tech 2005; 170(3): 494-500.

[7]. Vrabeľ M, Mankova I, Beno J, Tuharský J. Surface roughness prediction using artificial neural networks when drilling Udimet 720. Procedia Eng 2012; 48: 693-700.

[8]. Gowda B U, Ravindra H V, Ullas M, Prakash G N, Ugrasen G. Estimation of Circularity, Cylindricity and Surface Roughness in Drilling Al-Si 3 N 4 Metal Matrix Composites Using Artificial Neural Network. Procedia Mater Sci 2014; 6:1780-7.

[9]. Kannan T D B, Kumar B S, Baskar N. Application of Artificial Neural Network Modeling for Machining Parameters Optimization in Drilling Operation. Procedia Materials Science 2014; 5: 2242-9.

[10]. Sangwan K S, Saxena S, Kant G. Optimization of Machining Parameters to Minimize Surface Roughness using Integrated ANN-GA Approach. Procedia CIRP 2015; 29: 305-10.

[11]. Kant G, Sangwan K S. Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm. Procedia CIRP 2015; 31: 453-8.