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EVALUATING THE EFFECT OF DRILLING PARAMETERS ON ATLAC 382-05 COMPOSITE IN THE COURSE OF REGRESSION SEED ANN ADVANCE

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ABSTRACT

Drilling process is one of the inevitable machining operations in the field of manufacturing. In order to make the parts produced assembling operations need to be carried out. Hence to have the perfect matching in the assembly making holes with the dimensional accuracy as well as perfect surface finishes to the required level. Producing the parts into this desired dimensional accuracy, surface quality is the primary issues in the manufacturing operations. At the same time unlike the metals FRP composites are facing the delamination problems as an additional issue. With the intention of achieving the minimum delamination and desired surface finish which are influenced by the cutting forces generated at time of machining are considered for the analysis in this attempt through Artificial Neural Network in the MATLAB programming. Mathematical modelling is carried out and afterwards the regression equations are fed as input as a hybridization and the simulation is performed. The optimised output parameters are located with respect to the combinations of input cutting variables.

Key words. ATLAC 382-05 FRP, Drilling, Regression, ANN, Hybridization, Optimization, Minitab, MATLAB.

I. INTRODUCTION

Composite materials are becoming increasingly important in a wide range of fields and are replacing many traditional engineering materials. Composite materials such as fibre-reinforced plastics are broadly used in aerospace, automotive and civil applications due to their exceptional mechanical properties. Sanjay Rawat and Helmi Attia [1] have reported that about 30% of the external surface area of the Boeing 767 and 50% of the primary structure in Boeing 787 program consists of composites. These materials made by using FRPs for reinforcing plastic resin matrices, such as epoxy which are characterized by having higher specific strength (up to 4500MPa), higher fracture toughness, excellent corrosion resistance, higher specific stiffness coupled with favorable damping properties and zero thermal expansion coefficient. Drilling processes are widely used in the aerospace, aircraft, and automotive industries.

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Although modern metal-cutting methods have improved in the manufacturing industry, including electron beam machining, ultrasonic machining, electrolytic machining, and abrasive jet machining, conventional drilling still remains one of the most common machining processes. However, for the practical machining of FRP materials optimal machining parameters must be determined to achieve less tool wear, good surface finish, etc. Srinivas and Kalyamony [2] have discussed about the application of the Non-dominated Sorting Genetic Algorithm (NSGA-II) to optimize the machining parameters for machining GFRP composites with multiple characteristics. The principles of multiple performance optimizations differ from those of single performance optimization. In multi performance optimization, there is more than one objective function, each of which may have a different optimal solution. Most of the time these objectives found to be conflict with one another. In this investigation ATLAC 382-05 material drilling operation is taken for the analysis and prediction of optimum machining condition.

II. RELATED LITERATURE

Zhang et al. [4] investigated for the assessment of the exit defects in CFRP plates caused by drilling and concluded that delamination are the major mechanism in an exit defect caused by drilling. Caprino and Tagliaferri [5] have conducted experiments to compare the interaction mechanisms between drilling tool and material. The results obtained are useful describing the damage and pave path to design drill geometries specifically conceived for composite machining. They also confirmed that the amount of damage induced in a composite material at time of machining is sturdily dependent on the feed factor. Chen [6] has investigated on the variations of cutting forces with or without onset damage during the drilling operations and concluded that the damage-free drilling processes may be obtained by the proper selections of tool geometry and drilling parameters.

Lin and Chen [7] carried out a study on drilling composite material at high speed and concluded that an increase of the cutting velocity leads to an increasing drill wear. In this way the fact of increasing the wear of drill causes a rising of thrust force. Azlan Mohd Zain et al. [8] have attempted with the application of regression and ANN techniques to devise a model for machining performance estimation. Gaitonde and Karnik [9] devised a model for the estimation of the minimum burr size during machining operations with ANN and PSO optimization methods. Palanisamy et al. [10] have applied the tools ANN and regression to predict the tool wear in their investigation of end milling operations. In this paper the analysis and prediction of optimized parametric combination is identified with applying ANN hybrid with regression model through MATLAB programming.

III. EXPERIMENTAL DATA

Drilling experiments executed on the material ATLAC 382-05 FRP hand lay-up disc specimen with the dimensions of 22mm of thickness by Paulo Davim et al. [3] in the VCE500 MIKRON machining Center which has 11kW spindle power and a maximum spindle speed 7500 rpm. The properties of the selected ATLAC 382-05 FRP material is given in the Table 3.1

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Table 3.1 Properties of tested material ATLAC **382-05**

Properties	values	units
Flexural strength (DIN EN 63)	113	N/mm^2
Tensile Modulus (DIN 53457)	3380	N/mm^2
Tensile strength (DIN EN 61)	62	N/mm^2
Tensile Elongation (DIN EN 61)	2.1	%
Barcol hardness (934-1)(DIN EN 59)	40	
Charpy impact resistance	9	kJ/m^2
Temperature of deflection ISO 75 (HDT) (DIN 53461)	120	^0C
Thermal conductivity (DIN 52612)	0.22	W/m^0C

Brad & Spur cemented carbide (K10) drill with 5mm diameter was used as cutting tool in this experiment. The torque and thrust force produced at time of the machining was measured was made by a Kistler piezoelectric dynamometer 9272. The damage around the holes was measured with *Mitutoyo TM 500* shop microscope with 30× magnification and 1 µm resolution. The input cutting variables chosen for the process in three levels are as noted in the Table 3.2.

Table 3.2 Machining parameters and levels

Parameters	Units	Level 1	Level 2	Level 3
Cutting speed	rpm	3500	4500	5500
Feed velocity	mm / rev	0.05	0.10	0.20

The output variables fixed for investigation were the delamination, surface roughness and cutting Force. The observed experimental data by applying the Taguchi L9 array experimental plan are given in the Table 3.3, where CS denotes cutting speed in rpm; F is feed in mm /rev; CF is Cutting Force in N / mm^2 and ^{Ra} is surface roughness in µm.

Table 3.3 Experimental observed data of machining AL6063-T6

Exp No	CS	F	CF	DF	Ra
	rpm	mm/ rev	N / mm^2	mm /mm	µm
1	**3500**	**0.05**	943.81	**1.024**	5.88
2	3500	0.10	415.39	1.034	6.12
3	3500	0.20	229.80	1.060	6.52
4	4500	0.05	878.50	1.036	5.25
5	4500	0.10	420.78	1.047	5.44
6	**4500**	**0.20**	**195.04**	1.063	5.80
7	**5500**	**0.05**	980.10	1.048	**4.42**
8	5500	0.10	426.56	1.060	4.92
9	5500	0.20	215.94	1.080	5.27

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IV. MATHEMATICAL MODELING

The authority of the input variables (Cutting Speed and Tool Feed) on the output variables (Cutting Force, Delamination and the Surface roughness) are analysed through the regression analysis in Minitab17 software. Initially the first order regression and second order regression relationship between the variables are framed. The statistical values of the equations are tabulated in Table 4.1.

Table 4.1 Regression model comparison for Cutting Force, Delamination and Surface roughness

Variable	Regression	S	R-sq	R-sq	R-sq (pred)	Durbin - Watson
CF	First order	157.887	82.01%	76.02%	61.01%	2.94833
	Second order	28.4047	99.71%	99.22%	97.81%	2.49513
DF	First order	0.0026577	98.24%	97.65%	95.33%	2.23237
	Second order	0.0029068	98.95%	97.19%	84.93%	1.80971
Ra	First order	0.0907158	98.49%	97.99%	96.36%	2.07230
	Second order	0.0954002	99.17%	97.78%	91.14%	2.14547

The R - sq values referring to the second order regression relationships are better than the first order for all the three output variables which indicate that the predictors (input variables) explain around 99.6 % of the variance in the output variables. adjusted R - sq values are close to the R - sq values which accounts for the number of predictors in the regression model. Both the values jointly reveal that the model fits the data significantly. Hence forth second order equation is chosen for further investigation of optimizing the parameters. The Durbin Watson value in the second order equations are lies between 1to 2 which indicates that there is positive auto correlation between the predictors. Hence the framed second order regression equations through the Minitab17 for the individual output parameter in terms of input parameter combination are:

$$CF = (2338) - (0.310*\text{cutting speed}) - (17731*\text{feed}) + (0.000037*\text{cutting speed}^2) + (54609*\text{feed}^2) - (0.161*\text{cutting speed}*\text{feed}) \quad (4.1)$$

$$DF = (1.0095) - (0.000008*\text{cutting speed}) + (0.304*\text{feed}) - (0.089*\text{feed}^2) - (0.000016*\text{cutting speed}*\text{feed}) \quad (4.2)$$

$$Ra = (8.51) - (0.000942*\text{cutting speed}) + (6.16*\text{feed}) - (16.7*\text{feed}^2) + (0.000564*\text{cutting speed}*\text{feed}) \quad (4.3)$$

The residual plots through statistical formulation and analysis for the experimental output parameters surface roughness and tool flank wear are depicted through Fig. 4.1. The Parameter feed contributing to the highest level on the results which is followed by feed.

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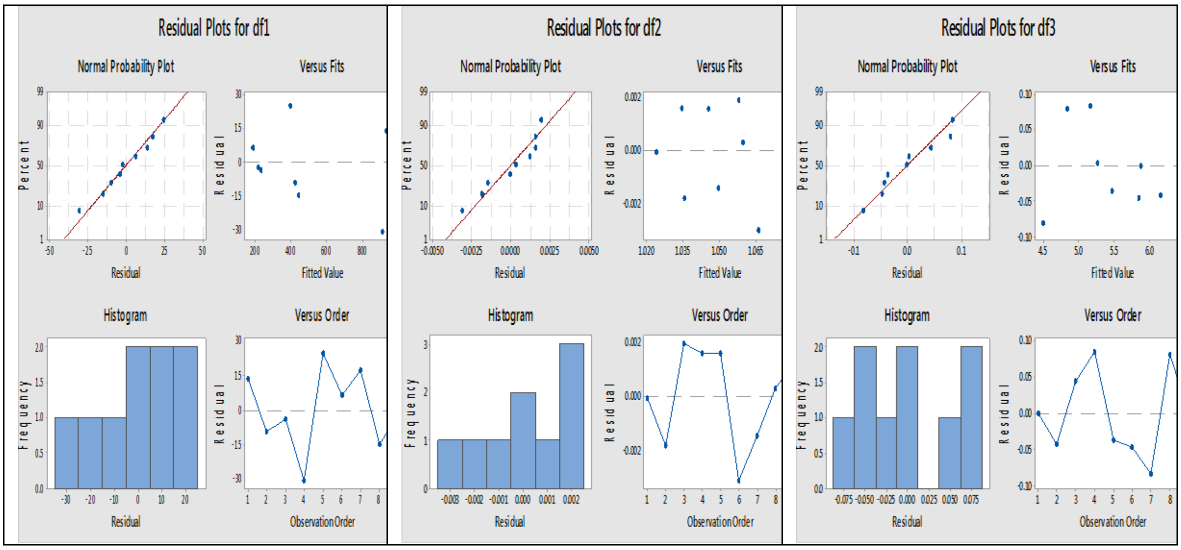

Figure 4.1 Residual plots of Cutting Force (df1), Delamination (df2), and Surface roughness (df3)

V. OPTIMISATION

Analysis towards optimizing and predicting the Cutting force, Delamination and Surface roughness on the tested AL6063 materials carried out with the main aim of investigating the influence of the speed and tool feed through Artificial Neural Network (ANN) in the MATLAB programming with Elman Back Propagation. The objective functions considered for the optimization to reach the minimized values of all the three output variables. The experimental outputs along with the input parameters are given as the initial values to train the programme with random selection of parameter values and compiled the outcome for 5000 iterations. The outcome of each method is evaluated with the amount of mean error in simulation. With the initial results it has been observed that ANN converges with mean error (0.652296) in simulation. In view of confirming the results, the same procedure has been adopted with 25000 and 50000 iterations and the mean error in computations in all the cases are found to be unique as 0.652296. With this confirmation of the same level of the mean error even in the increased number of iterations, one attempt has been made through providing the condition of the regression relationship formula in the programme simulation. By this attempt the outcome of the performance of the optimization methods evaluated and resulted in reduction of mean error value to 0.45822 in computation. In this case the number of iterations is maintained as 50000 turns. As the method of the simulation with regression relationship equations performing with improved level of performance (lower value of mean error) in compiling the results in order to project the results with smooth curve fittings the input parameters level are subdivided into further equal parts as the step division given in the Table 5.1.

Table 5.1 Step values allotment of input variables

Sl No	Parameter	Initial value	Step value	Final value
1	Cutting speed	3500	200	5500
2	Feed	0.050	0.015	0.200

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The simulated results through the method adopted in the earlier steps with 50000 iterations are given in the Table 5.2 for the Cutting force, Delamination and surface roughness referring to the combination of speed 3700 rpm to 4100 rpm with all the selected feed of 0.050 mm /rev to 0.200 mm / rev.

Table 5.2 CF, DF, Ra speed 3700 rpm to 4100 rpm with feed of 0.050 mm /rev to 0.200 mm / rev.

Feed	Speed 3700 rpm			Speed 3900 rpm			Speed 4100 rpm		
	CF	DF	Ra	CF	DF	Ra	CF	DF	Ra
0.050	882.04	1.039	5.030	904.31	1.032	4.899	931.14	1.037	4.775
0.065	633.03	1.029	5.628	620.71	1.034	5.563	724.27	1.031	5.502
0.080	580.89	1.037	5.453	572.55	1.034	5.329	567.18	1.042	5.224
0.095	449.34	1.035	5.486	440.52	1.041	5.404	434.66	1.038	5.330
0.110	342.36	1.053	5.546	333.06	1.048	5.441	326.71	1.056	5.337
0.125	259.95	1.032	5.590	250.17	1.039	5.519	243.35	1.039	5.444
0.140	202.13	1.058	5.636	191.86	1.052	5.540	184.55	1.057	5.437
0.155	168.87	1.033	5.713	158.12	1.042	5.641	150.33	1.044	5.562
0.170	160.19	1.059	5.751	148.96	1.052	5.660	140.68	1.053	5.553
0.185	176.08	1.036	5.809	164.36	1.048	5.731	155.61	1.053	5.639
0.200	216.55	1.063	5.808	204.35	1.054	5.703	195.11	1.053	5.573

The Cutting force, Delamination and surface roughness referring to the combination of speed 4300 rpm to 4700 rpm with all the selected feed of 0.050 mm /rev to 0.200 mm / rev are listed in the Table 5.3

Table 5.3 CF, DF, Ra speed 4300 rpm to 4700 rpm with feed of 0.050 mm /rev to 0.200 mm / rev.

Feed	Speed 4300 rpm			Speed 4500 rpm			Speed 4700 rpm		
	CF	DF	Ra	CF	DF	Ra	CF	DF	Ra
0.050	954.78	1.040	4.655	971.62	1.042	4.532	980.50	1.042	4.397
0.065	722.34	1.030	5.440	723.36	1.032	5.380	727.35	1.036	4.581
0.080	564.76	1.047	5.131	565.30	1.049	5.051	568.81	1.052	4.984
0.095	431.76	1.040	5.256	431.82	1.044	5.177	434.84	1.048	5.096
0.110	323.34	1.058	5.235	322.91	1.060	5.138	325.45	1.063	5.049
0.125	239.48	1.044	5.364	238.58	1.051	5.275	240.63	1.056	5.179
0.140	180.20	1.057	5.333	178.81	1.058	5.230	180.38	1.061	5.133
0.155	145.50	1.050	5.475	143.63	1.055	5.377	144.72	1.060	5.265
0.170	135.37	1.053	5.437	133.01	1.056	5.315	133.62	1.060	5.191
0.185	149.81	1.059	5.532	146.97	1.062	5.404	147.09	1.066	5.250
0.200	188.83	1.054	5.421	185.51	1.059	5.251	185.15	1.064	5.066

The Cutting force, Delamination and surface roughness referring to the combination of speed 4900 rpm to 5300 rpm with all the selected feed of 0.050 mm /rev to 0.200 mm / rev are listed in the Table 5.4

Table 5.4 CF, DF, Ra speed 4900 rpm to 5300 rpm with feed of 0.050 mm /rev to 0.200 mm / rev.

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Feed	Speed 4900 rpm			Speed 5100 rpm			Speed 5300 rpm		
	CF	DF	Ra	CF	DF	Ra	CF	DF	Ra
0.050	981.80	1.043	4.243	976.94	1.045	4.075	967.53	1.047	3.914
0.065	734.30	1.039	4.400	744.21	1.044	4.219	757.07	1.047	4.042
0.080	575.27	1.056	4.934	584.69	1.059	4.903	597.08	1.060	4.141
0.095	440.82	1.050	5.021	449.76	1.051	4.974	461.67	1.052	4.231
0.110	330.95	1.065	4.972	339.41	1.068	4.911	350.82	1.070	4.886
0.125	245.65	1.058	5.079	253.62	1.059	4.981	264.55	1.058	4.906
0.140	184.92	1.063	5.039	192.41	1.066	4.938	202.86	1.068	4.756
0.155	148.76	1.064	5.141	155.77	1.066	5.008	165.74	1.068	4.846
0.170	137.19	1.062	5.060	143.71	1.064	4.911	153.19	1.065	4.672
0.185	150.18	1.069	5.065	156.22	1.073	4.850	165.22	1.076	4.577
0.200	213.85	1.067	4.864	208.12	1.068	4.640	209.28	1.068	4.401

The pictorial representations of the above values are given in the following Fig. 5.1 and 5.2.

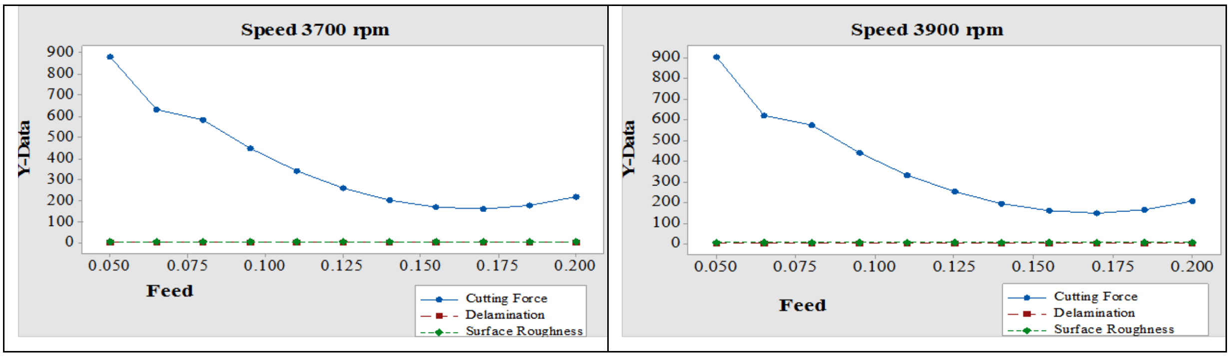

Figure 5.1 CF, DF, Ra speed 3700 rpm and 3900 rpm with feed of 0.050 mm /rev to 0.200 mm / rev.

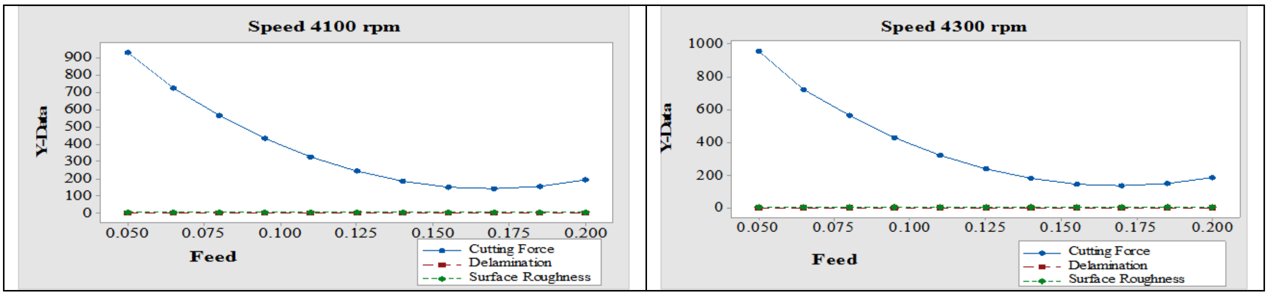

Figure 5.2 CF, DF, Ra speed 4100 rpm and 4300 rpm with feed of 0.050 mm /rev to 0.200 mm / rev.

IV. RESULTS AND CONCLUSIONS

With reference to the subset analysis in the regression model in Minitab, it is recorded as the highest influencing parameter is the feed 82 % contribution on the cutting force, 64 % contribution on the delamination and 77 % contribution on the Surface roughness followed by the parameter speed. This is substantiating with the co efficient values of the variables in the regression equation. In this attempt, simulation with regression relationship equations has been taken as the input to the MATLAB programme. The optimum combination of the input machining parameters for all the output parameters Cutting Force, Delamination and the surface quality is given in the Table 6.1 which confirms the adopted new approach (hybridization of Regression with ANN) yields good results.

Table 6.1 Optimized parameter combination

Parameter	Speed	Feed	Optimised value
CF	4500	0.170	133.01
DF	3500	0.050	1.024
Ra	5500	0.050	3.805

With this outcome it is suggested that the proposed hybridization of Regression with ANN prediction model may be effectively used for predicting the optimal input variables combination for better results in the end product.

REFERENCES

[1] Sanjay Rawat and Helmi Attia, Wear mechanisms and tool life management of WC–Co drills during dry high speed drilling of woven carbon fibre composites, Wear , 267, 2009, 1022-1030.

[2] N. Srinivas and D. Kalyanmoy, Muiltiobjective Optimization Using Non dominated Sorting in Genetic Algorithms J. Evol. Comput. 2, **1994,** 221.

[3] J. Paulo Davim, Pedro Reis and C. Conceicao Antonio, Drilling fiber reinforced Plastics manufactured by hand layup: Influence of matrix. Viapal VUP 9731 and ATLAC 382-05, Journal of Materials Processing Technology, 155-156, 2004, 1828-1833.

[4] H. Zhang, W. Chen.W, D. Chen and L. Zhang, Assessment of the exit defects in carbon fibre-reinforced plastic plates caused by drilling, Prec. Mach. Adv. Mater, 196, 2006, 43-52.

[5] G. Caprino and V. Tagliaferri, Damage development in drilling glass fibre reinforced plastics, Int. J. Mach. Tools Manuf, 35 (6), 1995, 817-829.

[6] W. Chen, Some experimental investigations in the drilling of carbon fibre-reinforced plastic (CFRP) composite laminates, Int. J. Mach.Tools Manuf, 37 (8), 1997, 1097-1108.

[7] S S Lin and I.K. Chen, Drilling of carbon fiber-reinforced composite material at high speed, Wear, 194 (1/2), 1996, 156-162.

[8] Azlan Mohd Zain, Habibollah Haron, Sultan Noman Qasem and Safian Sharif, Regression and ANN models for estimating minimum value of machining performance, Applied Mathematical Modelling, 36, 2012, 1477-1492.

[9] V N. Gaitonde and S R. Karnik, Minimizing burr size in drilling using Artificial Neural Network (ANN) - Particle Swarm Optimization (PSO) approach, J Intell Manuf, 23, 2012, 1783-1793.

[10] P. Palanisamy, I. Rajendran and S. Shanmugasundaram, Prediction of tool wear using regression and ANN models in end-milling operation, International Journal of Advanced Manufacturing Technology, 37, 2008, 29-41.