

Optimization and Predicting the Influence of Cutting Parameters over Surface Roughness and Delamination of Viapal VUP 9731 GFRP on Milling Operations through GA seed Scatter Search Algorithm

Dr.D.Ramalingam*¹, R.RinuKaarthikeyen², Dr.S.Muthu³, Dr.V.Sankar⁴

**¹Associate Professor, Nehru Institute of Technology, Coimbatore,(India)*

**corresponding author*

¹Research Associate, Manager – Engineering, TCM PFL, Chennai,(India)

²Principal, Adithya Institute of Technology, Coimbatore, (India)

³Professor, Nehru Institute of Engineering and Technology, Coimbatore, (India)

ABSTRACT

Milling operation is one of the common unconventional machining processes to achieve the size, shape and required surface quality. During milling operations on composite materials, delamination is one of the inevitable challenges which are commonly connected with the input machining parameters. In this attempt during milling on Viapal VUP 9731 GFRP composite material, the optimization of machining parameters referring to the surface roughness and delamination is analyzed through eleven optimization algorithms and forecasting of the combinations of such parameters is arrived in order to draw a path for reference according to the requirement of the product end quality. Initially algorithms are executed to iterate the values and the error rate is analyzed individually. Out of all the algorithms two best algorithms are chosen as best and second best based on the error rate occurred while computing the output. Two algorithms are combined by seeding the outcome values of the second best algorithm as the input values to the best algorithm to compute further. On confirming the outcome found to be tuned with the earlier results further forecasting of delamination factor, surface roughness for various combination of machining parameters is executed with step up number of iterations.

Keywords

Viapal VUP 9731; Milling; Delamination; SSA, SAA, ABC, ACO, PSO, HSA, GA, TSA, IWDA, FFA and BAT Algorithm; MATLAB. Minitab.

I. INTRODUCTION

In general the applications of Glass fiber reinforced plastics are increased in number of fields in order to make use of the combination of their physical and mechanical properties such as high specific strength, high specific stiffness and a light weight. At time of shaping the product concerned with these materials machining operations are being performed to reach the required dimension. Milling operations is one such process and the outcome is



associated with the input cutting parameters. During the machining operations on GFRP composite materials as they are extremely abrasive the choice of the cutting tool and the cutting parameters is extremely significant. Machining forces significantly influence the major impact on the surface quality such as delamination and surface roughness.

ABBREVIATIONS USED

GFRP	Glass Fiber Reinforced Plastic	v	Cutting speed, m/min
f	Feed, mm/rev	F _w	Machining force
F _d	Delamination factor	R _a	Surface Roughness, μm
EXP	Experiment	SSA	Scatter Search Algorithm
SAA	Simulated Annealing Algorithm	ABC	Artificial Bee Colony Algorithm
ACO	Ant Colony Algorithm	PSO	Particle Swarm Optimization Algorithm
HSA	Harmony Search Algorithm	GA	Genetic Algorithm
TSA	Tabu Search Algorithm	IWDA	Intelligent Water Drop Optimization Algorithm
FFA	Fruit Fly Algorithm	BAT	BAT Algorithm

II.RELATED LITERATURE REVIEW

Surface roughness is largely influenced by various cutting parameters which could be setup in progress, that are as spindle speed, feed rate and cut depth. However, the other uncontrolled variables like the physical, mechanical properties of materials in operation, cutting tool material and dimension, vibrations and heat generated during machining also contribute the impact on the outcome. [2–7]. Applying higher cutting speed and lower feed rate produced a improved surface finish.[7,8]. The material structural properties create greater impact on the finish of the machining process which leads to difficulties in the control of quality. The end surface roughness parameter is the major factor which could control the dimensional accuracy, the performance of the product concerned and also the manufacturing costs. Owing to this purpose there has been research and development with the objective of optimizing cutting conditions, to gain the determined surface roughness [9,10]. The findings of various authors reveals that [11–12], while milling operations carried out on composite materials, the surface roughness and delamination factor is strongly dependent on cutting parameters, tool geometry and machining forces. Santhanakrishnan et al. [12] and Ramulu et al. [13] performed an experiment on the machining of polymeric composites and accomplished that the increase in the cutting speed leads to obtain a better surface finish. Hocheng et al. [14] analyzed on the machining forces, tool wear and the surface quality owing to the fiber orientation. Hence it can be understood that many investigations that have been performed out with the objective of relating the surface quality, tool wear to the machining parameters. To execute this, many researchers have made attempts in Geometric programming [15], dynamic programming [16-18], integer programming [19], deterministic techniques [21-23] have been used for optimization of machining parameters. The genetic algorithm optimization has been commonly used in engineering applications [24-26]. In order to optimize machining parameters, the evolutionary methods have been modified or hybridized with other optimization techniques. Wang et al [27] have modified the genetic simulated annealing [28] approaches and



presented a new hybrid approach, named parallel genetic simulated annealing (PGSA) to find the optimal machining parameters for multi-pass milling operations. In this paper investigations is performed regarding the output parameters like machining force (F_w), delamination factor (F_d), surface roughness (R_a) influenced by the cutting parameters (cutting velocity and feed rate) on GFRP composite materials.

III. EXPERIMENT DATA

J Paulo Davim et al [1] has performed milling operation experiment on the reinforced with 65% of glass fiber unsaturated polyester hand lay-up material Viapal VUP 9731 which posses the mechanical and thermal properties as mentioned in the Table 3.1.

Table 3.1 Properties of Viapal VUP 9731 composite

Flexural strength (DIN EN 63)	480 N/mm ²
Tensile modulus (DIN 53457)	26,470 N/mm ²
Tensile strength (DIN EN 61)	480 N/mm ²
Compressive strength (DIN 53454)	196 N/mm ²
Tensile elongation (DIN EN 61)	1.7 %
Impact resistance (DIN 53453)	150 190 kJ/m ²
Martens temperature (DIN 53458)	200 °C
Thermal conductivity (DIN 52612)	0.15 0.22 W/m ⁰ C

The conducted experiments were on the hand lay-up discs made up of 22 mm thickness with a 5 mm diameter cemented carbide end mill (R12419680). During machining the depth of the cut was fixed as 2 mm. Experiment was performed on the ‘‘VCE500 MIKRON’’ machining center with 11 kW spindle power and a maximum spindle speed of 7500 rpm. Through the plan of experiments 9 tests were carried out by assigning cutting velocity (v); feed rate (f) as machining parameters to study the outputs variables machining force on the workpiece (F_w), delamination factor (F_d), surface roughness (R_a). The three levels of machining variables selected are mentioned in Table 3.2.

Table 3.2 Machining input cutting variables

Milling parameters	L1	L2	L3
Cutting speed, (v); m/min	47	79	110
Feed, (f); mm/rev	0.04	0.08	0.12

Table 3.3 Experimental data [1]

Exp	v	f	F_w	F_d	R_a
1	47	0.04	21.67	1.030	1.42
2	47	0.08	38.96	1.041	1.69
3	47	0.12	54.19	1.064	1.86
4	79	0.04	19.85	1.045	1.24
5	79	0.08	33.40	1.057	1.43
6	79	0.12	47.35	1.086	1.75
7	110	0.04	15.54	1.057	1.02
8	110	0.08	23.32	1.069	1.28
9	110	0.12	32.89	1.097	1.48



With the Kistler piezoelectric dynamometer 9257B the machining forces were measured and Hommel tester T1000 profilometer was used to evaluate the surface roughness. Of 30x magnification, 1 μm resolution Mitutoyo TM 500 microscope used to measure the damage caused on the specimen composite material. The obtained observation outcome of the experiments was arranged in the Table 3.3.

IV. MATHEMATICAL MODELLING

On performing Best Subsets Regression analysis in Minitab the point noted through Table 3.1, Table 3.2 and Table3.3 is the contribution of tool feed presents the greater impact on Fw, Fd and Ra over the cutting speed.

Table 3.1 Best Subsets Regression: Fw Vs v, f

R-Sq	R-Sq (adj)	R-Sq (pred)	v	f
72.3	68.4	52.8	-	x
22.3	11.2	0	x	-
91.6	92.8	83.9	x	x

Table3.2 Best Subsets Regression: Fd Vs v, f

R-Sq	R-Sq (adj)	R-Sq (pred)	v	f
60.5	54.9	32.7	-	x
35.5	26.3	0	x	-
96.0	94.7	92.0	x	x

Table3.3 Best Subset Regression: Ra Vs v, f

R-Sq	R-Sq (adj)	R-Sq (pred)	v	f
57.5	51.7	28.7	-	x
41.1	32.6	2.2	x	-
98.8	98.4	97.3	x	x

In the regression analysis of Fw versus v, f the p value is less than 0.01 which shows the statistically significant relationship between the variables at the 95% confidence level and the model summary in Table 3.4 reveals the R-sq value as 94.94% which is significant.

Table3.4 Regression Analysis: Fw versus v, f

S	R-Sq	R-Sq (adj)	R-Sq (pred)
3.51237	94.64%	92.85%	83.93%

Regression Equation of Machining force is, $F_w = 24.01 - 0.2275 v + 322.4 f$; and the Durbin-Watson test the statistic value is 0.894468 which is greater than 0.05, shows that there is no indication of serial autocorrelation. In the Fd versus v, f regression analysis the p value is less 0.01 (statistically significant at the 95% confidence level) and the R-sq value is 94.64% which is shown in Table 3.5

Table3.5 Regression Analysis: Fd versus v, f

S	R-Sq	R-Sq (adj)	R-Sq (pred)
0.004907	96.03%	94.71%	91.96%

The Regression Equation of Delamination factor is, $F_d = 0.98567 + 0.000466 v + 0.4792 f$ in which the Durbin-Watson Statistic is 2.79985. Of the Regression Analysis: Ra versus v, f statistical significance relationship between the variables at the 95% confidence level exists as the $p < 0.01$ and the model summary analysis of Table 3.6 gives the R-sq value as 98.77 % which confirms the significance.

Table 3.6 Regression Analysis: Ra versus v, f

S	R-Sq	R-Sq (adj)	R-Sq (pred)
0.0342588	98.77%	98.36%	97.28%

The Regression Equation of Surface roughness is , $R_a = 1.4884 - 0.006293 v + 5.875 f$ with the Durbin-Watson Statistic = 3.32343.

V. PROPOSED OPTIMIZATION TECHNIQUES

Forecasting of the Delamination factor and Surface roughness in the experimented composite materials was done with the objective of analyzing the influence of the cutting velocity, and the feed rate through the optimization algorithms Scatter Search Algorithm, Simulated Annealing Algorithm, Artificial Bee Colony Algorithm, Ant Colony Algorithm, Particle Swarm Optimization Algorithm, Harmony Search Algorithm, Genetic Algorithm, Tabu Search Algorithm, Intelligent Water Drop Optimization Algorithm, Fruit Fly Algorithm and BAT Algorithm in MATLAB (Elman Back Propagation) The computed values of the output parameters arrived through these algorithms with initial iterations (500 iterations) are compared with the experimental observations individually and the error rate with respect to each algorithm is verified. Figure 5.1 indicates the menu list in MATLAB, Figure 5.2 shows the training data in progress.

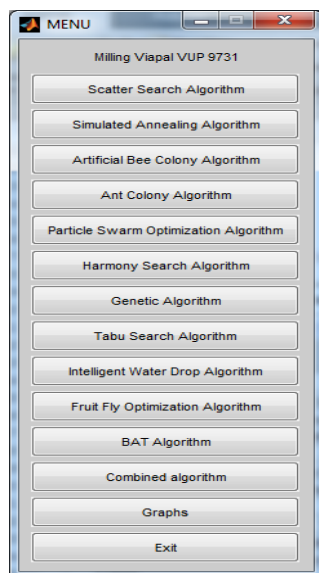


Figure 5.1 MATLAB menu list

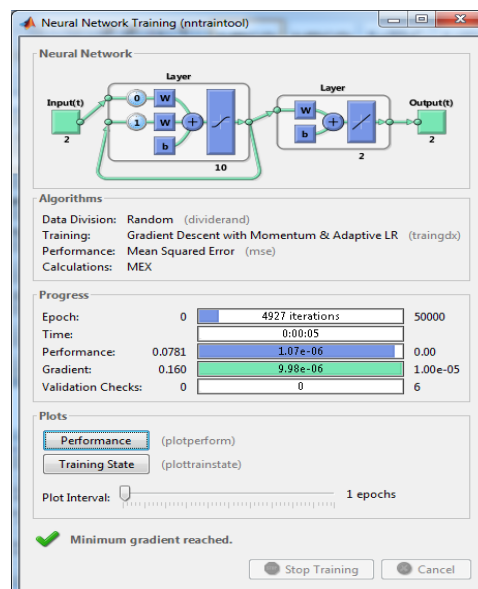


Figure 5.2 Data training progress of 50000 iterations

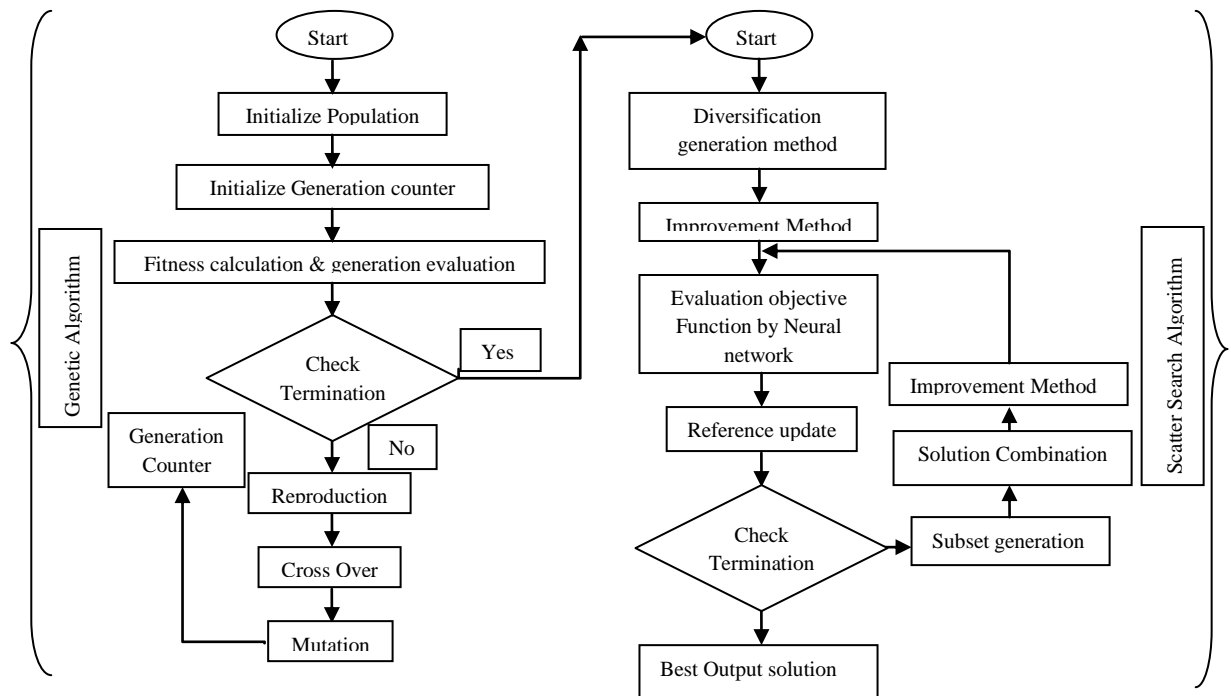


Figure 5.3 GA seed Scatter Search Algorithm

Upon the comparison, it is evident that the Scatter Search Algorithm is registered the most optimized values as the error rate registered is by the lowest value (0.124675) and next lowest error comparison value (0.154807) is obtained in Genetic Algorithm. In order to obtain tuned error rate, an attempt is made by seeding the output values of Genetic Algorithm as the input initialization values of the Scatter search and computed the combined GA Seed – Scatter Search Algorithm by shown in Figure 5.3. The output and the error rate value is recorded (0.012672) which is further less than the lowest error rate of the Scatter Search Algorithm and all the other algorithms are performed individually. Second set of computation with 1000 turns iterations also done and verified the results. As the same set of outcome registered as Scatter Search is the best and GA is the second best while the GA Seed – Scatter Search Algorithm output and the error rate value is recorded (0.010539) is found to be further tuned. Hence forth further computation of the above sequence is carried out with the iterations (stepwise as 2500, 5000, 10000, 25000 and 50000 iterations). The error rate of the individual algorithm on computing referring to each set of experimental combination are arranged in the Table 5.1 to 4 decimal points from 15 decimal computing values and the error rate comparison is revealed in Figure 5.4.

Table 5.1 Error Rate comparison with the experimental values of the incremental number of iterations

Number of Iterations	500	2500	5000	10000	25000	50000
SS	0.1247	0.1247	0.1247	0.1247	0.1247	0.1247
SA	0.1805	0.1805	0.1805	0.1805	0.1805	0.1805
ABC	0.1655	0.1655	0.1655	0.1655	0.1655	0.1655
ACA	0.2084	0.2084	0.2084	0.2084	0.2084	0.2084
PSO	0.2231	0.2231	0.2231	0.2231	0.2231	0.2231
HS	0.1987	0.1987	0.1987	0.1987	0.1987	0.1987

GA	0.1548	0.1548	0.1548	0.1548	0.1548	0.1548
TS	0.1900	0.1900	0.1900	0.1900	0.1900	0.1900
IWD	0.1974	0.1974	0.1974	0.1974	0.1974	0.1974
FFO	0.2177	0.2177	0.2177	0.2177	0.2177	0.2177
BAT	0.1841	0.1841	0.1841	0.1841	0.1841	0.1841
Best Algorithm	SS	SS	SS	SS	SS	SS
Second Best Algorithm	GA	GA	GA	GA	GA	GA

The error rate comparison of Scatter Search Algorithm, Genetic Algorithm and GA seed – Scatter Search algorithm is arranged iteration wise along with the percentage fall in each stage in the Table 5.2.

Table 5.2 Error rate comparison of SSA, GA and GA Seed SSA

No of Iterations	Scatter Search	Genetic Algorithm	GA Seed Scatter Search Algorithm	Error fall %
500	0.124675	0.154807	0.0126715133	-
2500	0.124675	0.154807	0.0065282484	15.10
5000	0.124675	0.154807	0.0039425539	7.86
10000	0.124675	0.154807	0.0022516798	42.89
25000	0.124675	0.154807	0.0012934700	42.56
50000	0.124675	0.154807	0.0008659841	33.05

As the error rate is steadily stepped down with the increased number of iterations and the value is 0.0008659841 for the combination GA seed – SS algorithm of 50000 iterations, the performance is considered for further evaluating the influence of input machining parameters on the output variables. Simultaneously the time for computing through each algorithm individually and combined algorithm referring to each set of experimental combination are arranged in the Table 5.3 to 2 decimal points. The comparison of time taken and mean error comparison between the algorithms can be witnessed through Figure 5.5 and Figure 5.6.

Table 5.3 Time values to compute referring to the incremental iterations (up to 2 decimal)

Number of Iterations	500	2500	5000	10000	25000	50000
SS	5.65	6.05	5.92	6.43	5.95	5.94
SA	3.01	3.21	3.43	3.67	3.25	3.26
ABC	17.72	17.32	17.36	17.86	17.24	17.62
ACA	3.86	4.30	4.49	4.50	4.29	4.38
PSO	4.12	4.34	4.52	4.90	4.46	4.40
HS	4.09	4.50	4.59	4.54	4.62	4.43
GA	1.91	2.02	2.05	2.52	2.21	2.10
TS	4.40	4.78	4.66	4.75	4.74	4.89

IWD	3.87	4.40	4.28	5.55	4.24	4.25
FFO	3.90	4.18	4.26	4.44	4.25	4.17
BAT	3.50	3.73	3.81	4.20	3.77	3.91
GA seed SSA	6.34	15.96	26.28	37.20	55.82	105.11

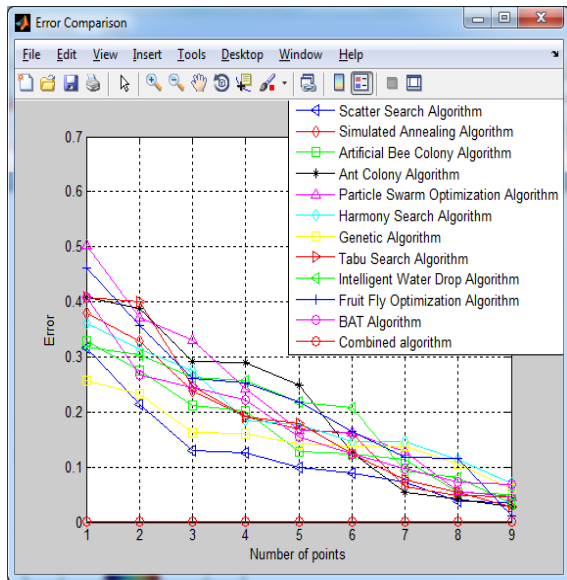


Figure 5.4 Comparison of Error on computing

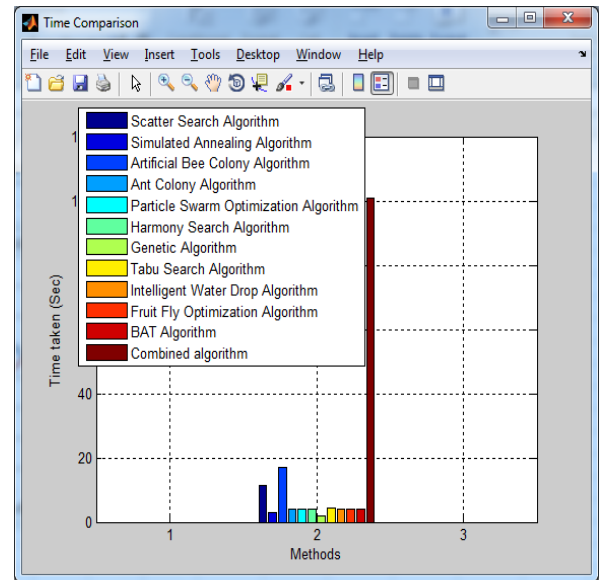


Figure 5.5 Comparison of time of computing

VI. RESULTS AND DISCUSSIONS

The computed values of delamination factor and surface roughness through the GA-SS combined algorithm with 50000 turns of iterations for the input machining parameters in line with the experimental combination are arranged in Table 6.1 and 6.2 respectively.

Table 6.1 Computed values of Delamination Factor through Algorithms

Exp No	Speed	Feed	Algorithms											
			SS	SA	ABC	ACA	PSO	HS	GA	TS	IWD	FFO	BAT	GA-SS
1	47	0.04	1.099	1.019	1.892	1.023	1.032	1.070	1.099	1.118	1.112	1.048	1.032	1.029
2	47	0.08	1.089	1.049	1.460	0.995	1.023	1.057	1.104	1.056	1.048	1.029	1.076	1.041
3	47	0.12	1.064	1.026	1.382	0.988	1.014	1.056	1.113	1.040	1.055	1.039	1.055	1.066
4	79	0.04	1.054	1.056	1.680	1.033	1.006	1.062	1.046	1.067	1.051	0.989	1.028	1.057
5	79	0.08	1.067	1.035	1.390	1.073	1.025	1.067	1.074	1.047	1.059	1.010	1.027	1.058
6	79	0.12	1.089	1.019	1.328	1.065	1.009	1.063	1.085	1.066	1.077	1.017	1.013	1.072
7	110	0.04	1.048	1.058	1.372	1.077	0.998	1.061	1.001	1.066	1.055	0.990	1.020	1.066
8	110	0.08	1.074	1.037	1.402	1.094	1.002	1.034	1.017	1.065	1.087	1.005	1.023	1.086
9	110	0.12	1.091	1.020	1.183	1.095	1.005	1.023	1.037	1.074	1.095	1.014	0.999	1.091

Table 6.2 Computed values of Surface Roughness through Algorithms



Exp No	Speed	Feed	Algorithms											
			SS	SA	ABC	ACA	PSO	HS	GA	TS	IWD	FFO	BAT	GA-SS
1	47.0	0.040	1.426	1.910	1.095	1.360	1.085	1.615	1.886	1.913	1.524	1.151	1.391	1.420
2	47.0	0.080	1.442	1.587	1.083	1.485	1.529	1.512	1.338	1.403	1.374	1.310	1.586	1.649
3	47.0	0.120	1.518	1.555	1.072	1.390	1.685	1.393	1.389	1.545	1.330	1.244	2.002	1.877
4	79.0	0.040	1.551	1.401	1.092	1.534	0.766	1.554	1.033	1.177	1.357	1.163	1.124	1.300
5	79.0	0.080	1.723	1.480	1.060	1.440	0.958	1.537	1.274	1.394	1.505	1.089	1.280	1.517
6	79.0	0.120	1.020	1.476	1.044	1.374	1.386	1.419	1.310	1.535	1.488	1.086	1.304	1.631
7	110.0	0.040	1.605	1.383	1.051	1.664	0.717	1.307	1.043	1.232	1.320	1.014	0.991	1.106
8	110.0	0.080	1.048	1.423	1.033	1.431	1.092	1.814	1.181	2.124	1.837	0.900	0.908	1.284
9	110.0	0.120	1.607	1.411	1.032	1.278	1.413	1.849	1.285	2.167	1.531	1.034	0.915	1.336

The optimized value of surface roughness is 1.106 μm is attained through the combination of speed as 110 m / min and feed rate 0.040 mm / rev. For the Delamination optimized value the combination is 47 m /min speed and 0.04 mm / rev feed rate. Further to obtain and examine the inclination of the respondent variables referring to the input variables combination and to form a smooth curve plotting, an attempt is made by fixing the interval between the input parameters cutting speed and feed (the first two levels considered in the experimental approach) are subdivided into ten steps L1 to L12 as noted in Table 6.3 and the combined algorithm is trained to compile.

Table 6.3 Subdivision of cutting parameters assigned for computation

Milling parameters	L1	L2	L3	L4	L5	L6
Cutting speed, (v); m/min.	47.0	50.2	53.4	56.6	59.8	63.0
Feed, (f); mm/rev.	0.04	0.044	0.048	0.052	0.056	0.06
Milling parameters	L7	L8	L9	L10	L11	L12
Cutting speed, (v); m/min.	66.2	69.4	72.6	75.8	79.0	110.0
Feed, (f); mm/rev.	0.064	0.068	0.072	0.076	0.08	0.12

Table 6.4a Computed values of Ra and Fd by GA – SSA

Feed	0.040		0.044		0.048		0.052		0.056		0.060	
Speed	Ra	Fd	Ra	Fd	Ra	Fd	Ra	Fd	Ra	Fd	Ra	Fd
47.0	1.420	1.0293	1.572	1.0332	1.577	1.0330	1.579	1.0329	1.588	1.0336	1.597	1.0344
50.2	1.503	1.0387	1.495	1.0329	1.603	1.0361	1.536	1.0326	1.592	1.0355	1.573	1.0348
53.4	1.484	1.0404	1.475	1.0344	1.598	1.0380	1.511	1.0333	1.584	1.0370	1.552	1.0356
56.6	1.463	1.0423	1.455	1.0363	1.595	1.0403	1.484	1.0343	1.579	1.0388	1.528	1.0364
59.8	1.442	1.0443	1.435	1.0384	1.593	1.0431	1.453	1.0354	1.576	1.0411	1.500	1.0373
63.0	1.419	1.0465	1.416	1.0409	1.593	1.0464	1.422	1.0369	1.577	1.0438	1.467	1.0381
66.2	1.394	1.0487	1.401	1.0438	1.592	1.0501	1.392	1.0389	1.579	1.0471	1.429	1.0392



69.4	1.367	1.0508	1.392	1.0472	1.589	1.0541	1.368	1.0417	1.580	1.0507	1.393	1.0406
72.6	1.339	1.0528	1.390	1.0510	1.580	1.0580	1.357	1.0455	1.575	1.0544	1.365	1.0429
75.8	1.314	1.0548	1.391	1.0550	1.565	1.0620	1.358	1.0503	1.563	1.0584	1.351	1.0465
79.0	1.300	1.0571	1.386	1.0586	1.553	1.0660	1.361	1.0555	1.548	1.0628	1.346	1.0511
110.0	1.106	1.0659	1.209	1.0668	1.432	1.0869	1.298	1.0804	1.371	1.0894	1.302	1.0872

Table 6.4 b Computed values of Ra and Fd by GA – SSA

Feed	0.064		0.068		0.072		0.076		0.08		0.12	
Speed	Ra	Fd	Ra	Fd	Ra	Fd	Ra	Fd	Ra	Fd	Ra	Fd
47.0	1.606	1.0353	1.616	1.0364	1.626	1.0377	1.638	1.0390	1.649	1.0405	1.877	1.0658
50.2	1.595	1.0365	1.600	1.0373	1.612	1.0385	1.624	1.0400	1.634	1.0414	1.865	1.0666
53.4	1.583	1.0377	1.583	1.0382	1.596	1.0396	1.608	1.0410	1.617	1.0423	1.852	1.0674
56.6	1.572	1.0391	1.564	1.0392	1.580	1.0407	1.592	1.0421	1.599	1.0434	1.837	1.0683
59.8	1.564	1.0410	1.541	1.0401	1.565	1.0421	1.573	1.0433	1.580	1.0445	1.822	1.0693
63.0	1.560	1.0432	1.513	1.0411	1.553	1.0439	1.552	1.0446	1.559	1.0458	1.805	1.0704
66.2	1.561	1.0461	1.478	1.0419	1.545	1.0461	1.526	1.0457	1.540	1.0473	1.785	1.0715
69.4	1.564	1.0493	1.439	1.0428	1.543	1.0489	1.492	1.0467	1.525	1.0492	1.759	1.0723
72.6	1.565	1.0528	1.400	1.0440	1.546	1.0521	1.453	1.0475	1.518	1.0518	1.724	1.0727
75.8	1.557	1.0562	1.370	1.0459	1.545	1.0555	1.413	1.0486	1.517	1.0549	1.680	1.0724
79.0	1.544	1.0600	1.350	1.0489	1.539	1.0589	1.378	1.0501	1.517	1.0582	1.631	1.0718
110.0	1.319	1.0887	1.299	1.0879	1.298	1.0876	1.291	1.0870	1.284	1.0859	1.336	1.0912

The outcome of the respondent parameters surface roughness and delamination factor through this computation are given in the Table 6.4a and 6.4b. The computed outcome values of surface roughness and delamination factor for the feed rate of 0.040 mm / rev for all the cutting speed combinations are presented in the Figure 6.1. From this plot the combination of cutting parameters can be located with respect to any required outcome.

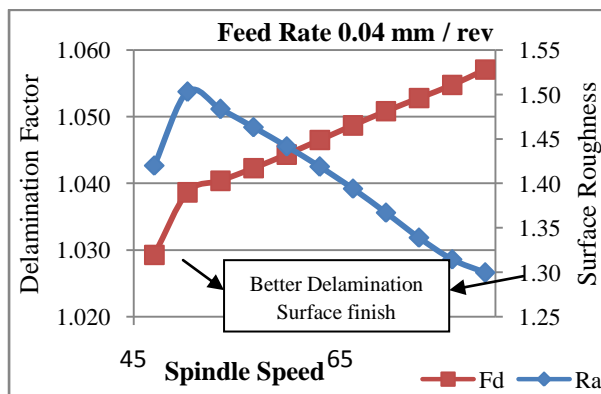


Figure 6.1 Fd, Ra of feed rate 0.04 mm / rev

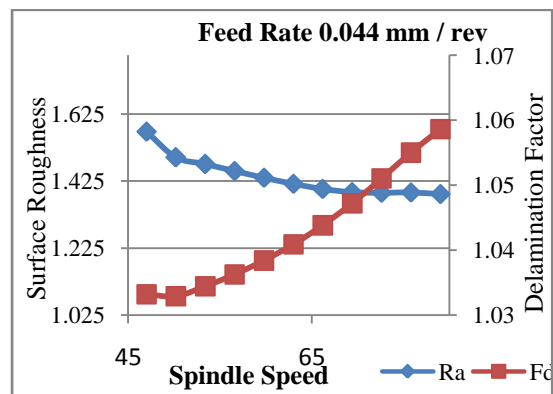


Figure 6.2 Fd, Ra of feed rate 0.044 mm / rev

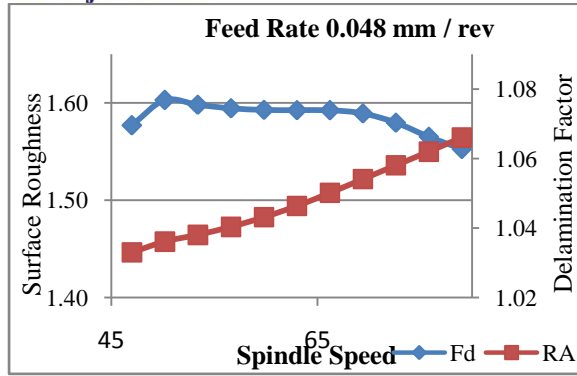


Figure 6.3 Fd, Ra of feed rate 0.048 mm / rev

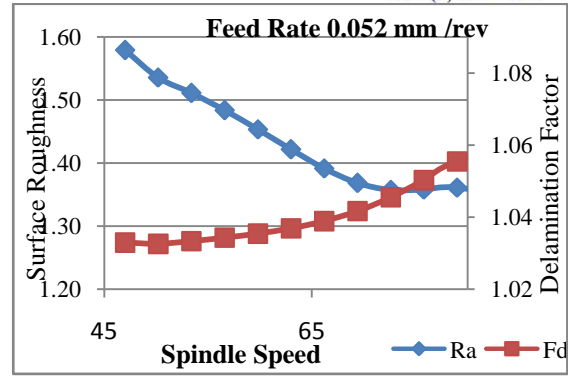


Figure 6.4 Fd, Ra of feed rate 0.052 mm / rev

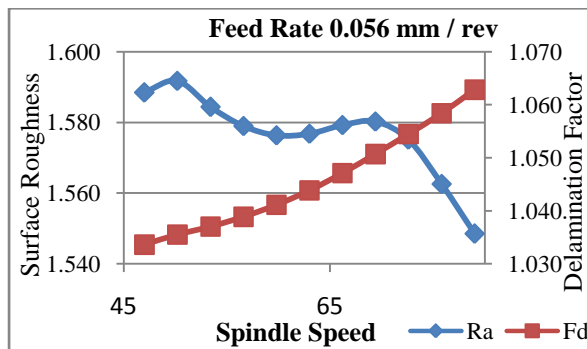


Figure 6.5 Fd, Ra of feed rate 0.056 mm / rev

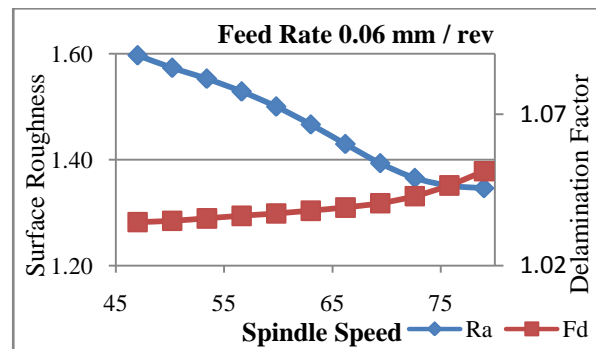


Figure 6.6 Fd, Ra of feed rate 0.06 mm / rev

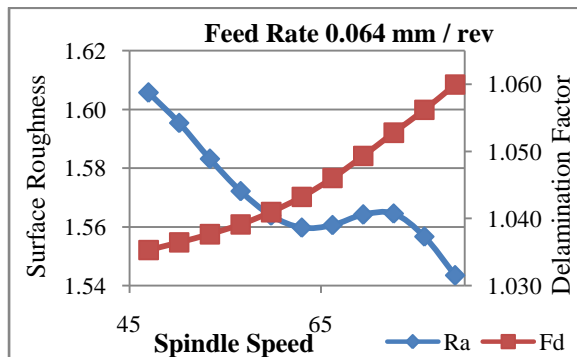


Figure 6.7 Fd, Ra of feed rate 0.064 mm / rev

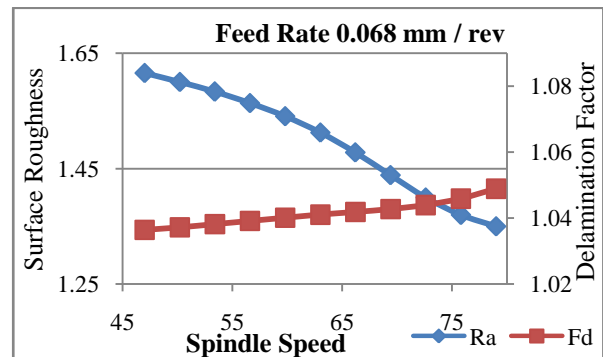


Figure 6.8 Fd, Ra of feed rate 0.068 mm / rev

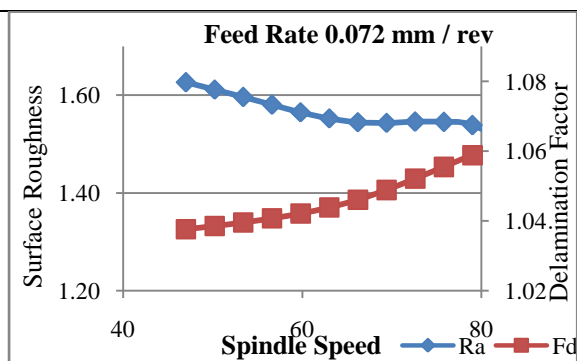


Figure 6.9 Fd, Ra of feed rate 0.072 mm / rev

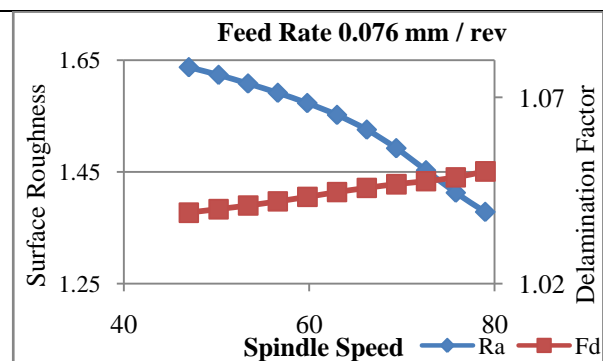


Figure 6.10 Fd, Ra of feed rate 0.076 mm / rev

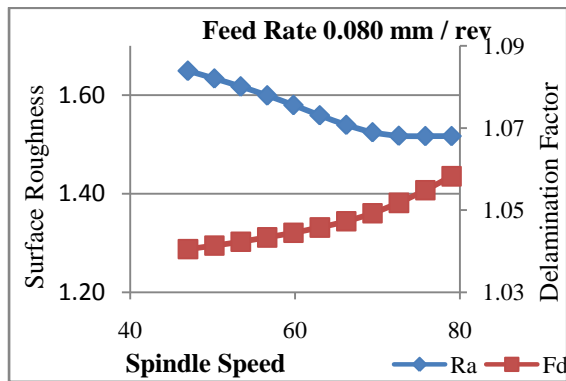


Figure 6.11 Fd, Ra of feed rate 0.08 mm /rev

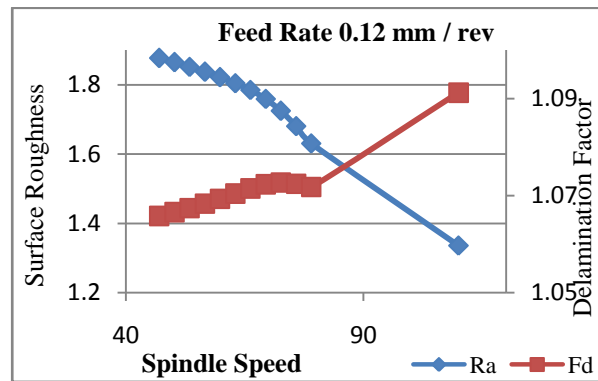


Figure 6.12 Fd, Ra of feed rate 0.12 mm /rev

By this way, Figures 6.2 to Figures 6.12 depicts the forecasting values of Fd and Ra for the feed rate of 0.044, 0.048, 0.052, 0.056, 0.060, 0.064, 0.068, 0.072, 0.078, 0.080 and 0.120 respectively. On verification the regression analysis of the computed outcome, the regression equation of delamination factor is, $Fd = 0.98181 + 0.000736 v + 0.2828 f$; with Durbin-Watson Statistic value 1.33841 and for the surface roughness is, $Ra = 1.6161 - 0.005116 v + 3.717 f$; with Durbin-Watson Statistic value 2.90319.

VII. CONCLUSION

- In this attempt SSA, SAA, ABC, ACO, PSO, HSA, GA, TSA, IWDA, FFA and BAT Algorithm are used to forecasting of the Delamination factor and Surface roughness in the experimented composite materials Viapal VUP 9731 with the objective of analyzing the influence of the cutting velocity, and the feed rate. The application of optimization algorithms are executed in MATLAB (Elman Back Propagation).
- Both the delamination and surface roughness is increased with the increase in feed rate.
- The optimized value of surface roughness is 1.106 μm is attained through the combination of speed as 110 m / min and feed rate 0.040 mm / rev.
- For the Delamination optimized value the combination is 47 m/min speed and 0.04 mm / rev feed rate.
- Upon the comparison, it is evident that the Scatter Search Algorithm registered the most optimized values with the lowest value (0.124675) error rate in computation.
- Next lowest error in computation is by Genetic Algorithm (0.154807).
- In order to tune the results, an attempt is made by allowing the output values of Genetic Algorithm as the input values to the Scatter search and computed the combined GA – Scatter output. The error rate in computing is recorded (0.012672) which is the lowest error rate of all the algorithms performed individually.
- The error rate is steadily in decreasing trend on the increased number of iterations and the value is 0.0009 for the combination GA – SS algorithm of 50000 iterations.
- Also to form a smooth curve plotting, an attempt is made by fixing ten divisions in the input parameters first two level interval in the experimental approach and the GA –SA combined algorithm is trained to compile. The results are plotted feed rate wise to locate the combination of machining parameters based on the expected product quality in future.

- Other algorithms are also may be tried to forecast the product quality in the machining parameters optimization in future.

REFERENCES

- [1] J. Paulo Davim, Pedro Reis, C. Conceicao Antonio, "A study on milling of glass fiber reinforced plastics manufactured by hand-lay up using statistical analysis (ANOVA)," *Composite Structures* 64: 493–500, 2004.
- [2] Anthony Xavier M, Adithan M "Determining the influence of cutting fluids on tool wear and surface roughness during turning of AISI 304 austenitic stainless steel," *J Mater Process Technol* 209:900–909, 2009.
- [3] Dhar NR, Kamruzzaman M, Ahmed M "Effect of minimum quantity lubrication (MQL) on tool wear and surface roughness in turning AISI-4340 steel," *J Mater Process Technol* 172:299–304, 2006.
- [4] Ezugwu EO, Bonney J, Fadare DA, Sales WF, "Machining of nickel-base, Inconel 718, alloy with ceramic tools under finishing conditions with various coolant supply pressures," *J Mater Process Technol* 162–163:609–614, 2005.
- [5] Isik Y, "Investigating the machinability of tool steels in turning operations," *Mater Des* 28:1417–1424, 2007.
- [6] Noordin MY, Venkatesh VC, Chan CL, Abdullah A, "Performance evaluation of cemented carbide tools in turning AISI 1010 steel," *J Mater Process Technol*, 116:16–21, 2001.
- [7] Zafer T, Sezgin Y, "Investigation of the cutting parameters depending on process sound during turning of AISI 304 austenitic stainless steel," *Mater Des*, 25:507–513, 2004.
- [8] Thepsonthi T, Hamdi M, Mitsui K, "Investigation into minimal-cutting-fluid application in high-speed milling of hardened steel using carbide mills," *Int J Mach Tools Manuf*, 49:156– 162, 2009.
- [9] Ramulu M, Wern CW, Garbini JL, "Effect of the direction on surface roughness measurements of machined graphite / epoxy composite," *Compos Manuf*, 4(1):39–51, 1993.
- [10] Erisken E, "Influence from production parameters on the surface roughness of a machine short fibre reinforced thermoplastic," *Int J Machine Tools Manuf*, 39:1611–18, 1999.
- [11] KoplevA, Lystrup A, Vorm T. "The cutting process, chips and cutting forces in machining CFRP," *Composites* 3;14(4):371– 6, 1983.
- [12] Santhanakrishnan G, Krishnamurthy R, Malhotra SK. "Machinability characteristics of fibre reinforced plastics composites," *J Mech Working Technol*, 17:195–204, 1998.
- [13] Ramulu M, Arola D, Colligan K. "Preliminary investigation of effects on the surface integrity of fiber reinforced plastics," In: *Engineering systems design and analysis* 2, PD, 64(2) ASME; 93–101, 1994.
- [14] Hocheng H, Puw HY, Huang Y. Preliminary study on milling of unidirectional carbon fiber-reinforced plastics. *Compos Manuf*, 4(2):103–8, 1993.
- [15] P.G. Petropoulos, "Optimal selection of machining rate variable by geometric programming," *International Journal of Production Research*, 11(4) 305-314, 1973.
- [16] Y.C. Shin, Y.S. Joo, "Optimization of machining conditions with practical constraints," *International Journal of Production Research*, 30(12) 2907-2919, 1992.



- [17] J.S. Agapiou, "The optimisation of machining operations based on a combined criterion Part 2: Multipass operations," *Journal of Engineering for Industry*, 114, 508-513, 1992.
- [18] E.J.A. Armarego, A.J.R. Simith, J. Wang, "Computer-aided constrained optimization analyses strategies for multipass helical tooth milling operation," *Annals of the CIRP*, 43(1) 437-442, 1994.
- [19] R. Gupta, J.L. Batra, J.K. Lal, "Determination of optimal subdivision of depth of cut in multipass turning with constraints," *International Journal of Production Research*, 33 115- 127, 1995.
- [20] S.E. Kilic, C. Cogun, D.T. Sen, "A computer-aided graphical technique for the optimization of machining conditions," *Computers in Industry*, 22(3) 319-326, 1993.
- [21] E.J.A. Armarego, A.J.R. Smith, J. Wang, "Constrained optimization strategies CAM software for single-pass peripheral milling," *International Journal of Production Research*, 31(9) 2139-2160, 1993.
- [22] M.T. Rad, I.M. Bidhendi, "On the optimization of machining parameters for milling operations," *International Journal of Machine Tools & Manufacture*, 37(1) 1-16, 1997.
- [23] J. Wang, "Computer-aided economic optimization of end-milling operations," *International Journal of Production Economics*, 54(3) 307-320, 1998.
- [24] Kunakote, T Bureerat, S "Multi-objective topology optimization using evolutionary algorithms," *Engineering Optimization*, 43(5) 541-557, 2011.
- [25] H. Md. Azamathulla, Wu, Fu-Chun, A Ab. Ghani, S. Narulkar, N. A. Zakaria, C. K. Chang, "Comparison between genetic algorithm and linear programming approach for real time Operation," *Journal of Hydro-Environment Research, Elsevier & KWRA.*,2(3)171-180, 2008.
- [26] A. Ab. Ghani, H. Md. Azamathulla, "Gene-Expression Programming for sediment transport sewer pipe systems," *ASCE Journal of Pipeline Systems Engineering & Practice*, 2(3) 102- 106, 2011.
- [27] Z.G. Wang, M. Rahman, Y.S. Wong, J.Sun, "Optimization of multi-pass milling using parallel genetic algorithm parallel genetic simulated annealing," *International Journal of Machine Tools & Manufacture*, 45(15) 1726-1734, 2005.
- [28] Z.G. Wang, Y.S. Wong, M. Rahman, "Optimization of multi-pass milling using genetic algorithm genetic simulated annealing," *International Journal of Advanced Manufacturing Technology*, 24 (9-10) 727-732, 2004.