Multi – objective Analysis and Parametric Estimation of Machining Force Delamination and Surface Quality in Milling Process on FRP composite through Statistical Linked DSA

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ABSTRACT

Milling process is one among the common traditional metal cutting operations mainly to trim down to the size, shape and required surface quality. At the same time during milling operations on composite materials, the commonly named damage delamination is one of the inevitable issue which are mainly depend on the input machining parameters. In this attempt the optimization of machining parameters referring to the surface roughness and delamination during milling on Viapal VUP 9731 GFRP composite material, is analyzed through Differential Search Algorithm and estimated the optimal combinations of such parameters. The objective is to lay down a path for reference according to the requirement of the product end quality. Initially algorithm is executed in MATLAB to iterate the values and the effectiveness of simulation is analyzed individually by means MSE. Subsequently the regression relationship is taken as the conditional approach for further simulation. 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 executedwith step up number of iterations.

KEYWORDS : *Milling, Viapal 9731 frp composite, Surface finish, Machining Force, Delamination, DSA, Hybrid, Optimisation, Minitab, MATLAB.*

1 INTRODUCTION

As the applications of FRPs are tremendously increased in every field of manufacturing wherever the weight density ratio plays a major role; also having the combination of their physical and mechanical properties such as high specific strength, high specific stiffness. 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 FRP composites the machining forces significantly influence and make the major impact on the surface quality such as delamination and surface roughness. In this study, the experiment conducted on Viapal VUP 9731 frp composites by [1] is taken and the optimsation method through DSA is applied to identify the improved combination of machining parameters.

ABBREVIATIONS AND SYMBOLS USED

FRP	Fiber Reinforced Plastic	N	Newton
v	Cutting speed, m/min	DSA	Differential Search Algorithm
f	Feed, mm/rev	Reg	Regression
F	Machining force, N	R-sq	R - square statistical value
D_f	Delamination factor	R-sq (adj)	R - square adjusted statistical value
R_a	Surface Roughness	R-sq (pred)	R - square predicted statistical value

II LITERATURE REVIEW

Milling is one of the most important machining processes in manufacturing parts made out of FRPs. Jamal [2] commented that high material removal rates rare possible in metals in milling operations but in milling of FRPs is conducted at much lower degree because of the reason that FRP components are largely commonly made close to the net shape and hence milling operations are subsequently limited largely to de-burring and trimming also to achieve contour shape accuracy. Tsao, C. C [3] has experimented and the declared the apt usage of Grey - Taguchi method in optimizing the parameters of milling operations on the aluminium alloy and declared that the grey-Taguchi method is suitable for solving the surface finish quality and tool flank wear problems in milling process of A6061P-T651 aluminum alloy. Machining forces, cutting force, feed force and depth force are the significant factors towards the damage namely delamination while milling composite materials and is the common tendency which is recognized through the experimentation and suitable analysis Sreejith et al. [4] and Ferreira et al. [5]. David et al. [6] have announced through their experiment and critical analysis of an approach to forecast the surface roughness in a high speed end-milling process by ANN approach and statistical tools to predict the different surface roughness predictor's combinations. Ozel C & Kilickap [7] revealed the truth that while the purpose of developing and optimizing a surface roughness model for machining processes, it is highly inevitable to recognize the present condition of exertion in these aspects. Zeilmann, RP, Weingaertner WL [8] have made an attempt to investigate the heat produced at time of machining along with the effect of application of lubricant while machining and studied the outcome on the surface quality. Radhakrishnan and Uday Nandan [9] came out to analyse the true association among machining parameters like cutting speed, feed rate and depth of cut to the machining force in the end milling process. They concluded, by using both multiple regressions and neural network modeling. Regression model was employed to fit the experimental data after filtering the abnormal data points, subsequently analysis carried out through using neural networks to capitulate a final model. Haan et al. [10] have addressed the effects of cutting fluids also on hole quality and declared that the dry-drilled holes resulted in poorer surface finish than holes produced with cutting fluid application along with main cutting parameters. Ramulu et al. [11] have stated that the surface roughness and delamination is the characteristic that could influence the dimensional precision, production costs and the performance of end product and because for these reasons there has been research and development with the objective of optimising cutting conditions, to obtain a desired machinability.

III EXPERIMENTAL OBSERVATION [1]

On the Viapal VUP 9731 reinforced with 65% of glass fiber unsaturated polyester hand lay-up material, which posses the material properties as listed in the Table 3.1milling process experiment has performed to analyse the machining force during machining and the milling induced damage namely delamination factor, surface quality after machining by J Paulo Davim et al [1] with the statistical tool analysis (ANOVA).

Table 3.1 Properties of Viapal VUP 9731 frp[1]

Property	Value
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 ^{0}C
Thermal conductivity (DIN 52612)	0.15 0.22 W/m^{0}C

The specimen wasmade up on the hand lay-up discs with 22 mm thickness and machining operations carried out with a 5 mm diameter cemented carbide end mill on the ‘‘VCE500 MIKRON’’ machining center with 11 kW spindle power and a maximum spindle speed of 7500 rpm. With L9 Taguchi array as the plan of DOE by assigning cutting velocity (v); feed rate (F) as machining input parameters to evaluate the outputs variables - machining force on the workpiece (F_m), delamination factor (D_f), surface roughness (R_a). The three states of machining variables chosen are listed in Table 3.2.

Table 3.2 Input cutting variables

Milling parameters	S1	S2	S3
Cutting speed, (v); m/min	47	79	110
Feed, (f); mm/rev	0.04	0.08	0.12

Kistler 9257B piezoelectric dynamometer was used to measure the machining forces 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.

Table 3.3 Experimental observation [1]

Exp	v	f	F	D_f	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

IV STATISTICAL PROJECTIONS

On evaluating the regression relationship between the parameters and Best Subsets Regression analysis in Minitab the point noted through Table 4.1 the second regression analysis of F versus v, f shows the statistically significant relationship between the variables at the 95% confidence level and the model summary reveals the R-sq value as 99.73% which is significant and model fit. Also the Durbin-Watson test the statistic value is greater than 0.05, shows that there is no indication of serial autocorrelation. In the D_f versus v, f analysis the R-sq value is 99.79% &Regression Analysis of Ra versus v, f statistical significance relationship between the variables at the 95% confidence level exists as the R-sq value as 97.13 % which confirms the significance.

Table 4.1 Regression Model summary

Parameter	Regression	S	R-sq	R-sq(adj)	R-sq(pred)	Durbin - Watson
F	Second order	1.10613	99.73%	99.29%	96.76%	1.70277
Df	Second order	0.0015853	99.79%	99.45%	97.60%	1.71057
Ra	Second order	0.0779463	97.13%	92.34%	77.69%	3.33973

Based on the model summary the regression equations framed for all the three output parameters are:

- Machining force = - (8.94) + (0.416 x machining speed) + (556.5 x feed) – (0.002573 x machining speed^2) + (14 x feed^2) – (3.004 x machining speed x feed)
- Delamination factor = (1.00291) + (0.000808 x machining speed) – (0.365 x feed) – (0.000003 x machining speed^2) + (4.688 x feed^2) + (0.001199 x machining speed x feed)

- Surface roughness = (0.543) + (0.01208 x machining speed) + (16.05 x feed) – (0.000119 x machining speed^2) – (65.6 x feed^2) + (0.0041 x machining speed x feed)

Table 4.2 Best Subsets Regression: F versus v, f, v x f

Variables	R-Sq	R-Sq (adj)	R-Sq (pred)	Cp	S	v	f	v x f
1	72.3	68.4	52.8	307.3	7.3878	-	x	-
2	98.8	98.4	96.7	10.8	1.6753	-	x	x
3	98.8	98.1	95.1	12.6	1.8275	x	x	x

The best subset analysis results posted through the Tables 4.2; 4.3; 4.4 confirms the contribution of tool feed as higher influence on F, D_f and R_a over the cutting speed.

Table 4.3 Best Subsets Regression: $D_f$versus v, f, v x f

Variables	R-Sq	R-Sq (adj)	R-Sq (pred)	Cp	S	v	f	f^2	v x f
1	92.5	91.4	87.8	103.9	0.0062532	-	-	-	x
2	98.7	98.3	97.0	15.4	0.0027794	x	-	x	-
3	99.1	98.6	97.1	11.7	0.0025290	x	x	x	-

Table 4.4 Best Subsets Regression: Ra versus v, f, v x f

Variables	R-Sq	R-Sq (adj)	R-Sq (pred)	Cp	S	v	f	v^2
1	52.2	45.4	22.7	44.8	0.20800	-	x	-
2	91.7	89.0	87.2	5.6	0.093566	-	x	x
2	89.2	85.6	82.6	8.2	0.10669	x	x	-
3	93.6	89.8	81.7	5.6	0.089870	x	x	x

Hence the second order regression relationship is considered for the application towards further evaluation.

V OPTIMIZATION TECHNIQUES

Differential Search Algorithm optimisation method is chosen and applied in this attempt in MATLAB to appraise the influence of the cutting velocity, tool feed on to the work material towards the resultant parameters Delamination factor and Surface roughness and to estimate the optimal parameters combination for the quality outcome through the optimization. Though Elman Back Propagation domain in MATLAB the DSA programme as follows.

function [direction,msg]=generate_direction(method,superorganism,size_of_superorganism,fit_superorganism);
switch method

```
   case 1,
      % BIJECTIVE DSA  (B-DSA) (i.e., go-to-rnd DSA);
      % philosophy: evolve the superorganism (i.e.,population) towards to "permuted-superorganism (i.e., random directions)"
      direction=superorganism(randperm(size_of_superorganism),:); msg=' B-DSA';
   case 2,
      % SURJECTIVE DSA (S-DSA) (i.e., go-to-good DSA)
      % philosophy: evolve the superorganism (i.e.,population) towards to "some of the random top-best" solutions
      ind=ones(size_of_superorganism,1);
      [null_,B]=sort(fit_superorganism);
      for i=1:size_of_superorganism, ind(i)=B(randi(ceil(rand*size_of_superorganism),1)); end;
      direction=superorganism(ind,:);  msg=' S-DSA';
   case 3,
      % ELITIST DSA #1 (E1-DSA) (i.e., go-to-best DSA)
      % philosophy: evolve the superorganism (i.e.,population) towards to "one of the random top-best" solution
      [null,jind]=sort(fit_superorganism); ibest=jind(ceil(rand*size_of_superorganism)); msg='E1-DSA';
      direction=repmat(superorganism(ibest,:),[size_of_superorganism 1]);
   case 4,
      % ELITIST DSA #2 (E2-DSA) (i.e., go-to-best DSA)
      % philosophy: evolve the superorganism (i.e.,population) towards to "the best" solution
      [null_,ibest]=min(fit_superorganism); msg='E2-DSA';
      direction=repmat(superorganism(ibest,:),[size_of_superorganism 1]);
end
```

Through the compiled DSA values of the output parameters are estimated with initial iterations (trained for 10000 iterations) are compared with the experimental observations individually and the offset rate is noted. Figure 5.1 shows the data training progress in MATLAB.

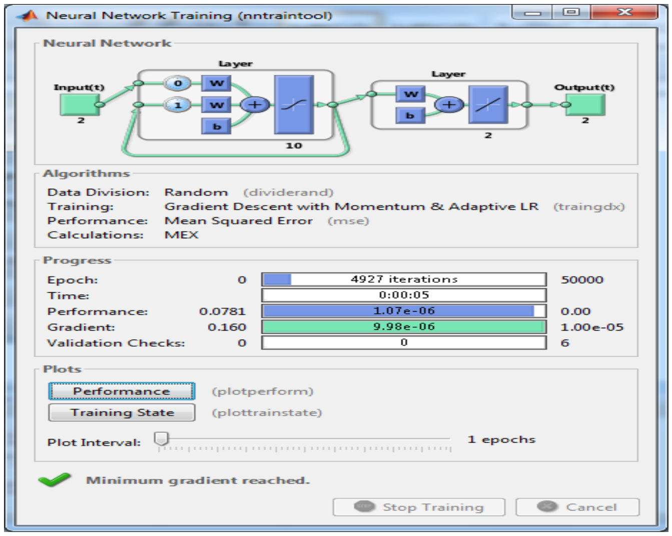

Figure 5.1 Data training progress of 50000 iterations

Upon the comparison, it is evident that the performance of the DSA is in the close tolerance the algorithm is coded to the execution in the Gradient Descent with Momentum & Adaptive Learning. The performance indicator is the mean square error. Based on the objectives, the coding was developed towards optimization, i.e. surface roughness to the minimum value as the objective functions. Initially the simulation is trained for 50000 iterations. Mean squared error in computation is found as 0.3640 with the compiling time 74.1137.

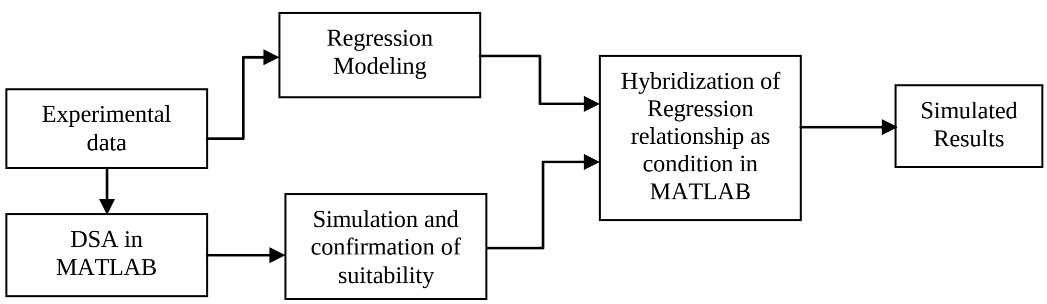

Figure 5.2 Flow chart of Regression hybridization with DSA

The regression relationship equations generated by the Minitab is fed into the programme for the closeness in resulting the simulation (MSE = 0.29382) and 19.28 % improvement in error reduction is noticed. The relevant flow of hybridization is shown through the Figure 5.2. With this the values for the step up periodical (15 intervals) between the parameter selection is chosen for subsequent simulation. The step up value for such computation is chosen as (47 : 4.2 : 110) for the speed parameter and (0.04 : 0.00533 : 0.12) for the feed parameters. The computed values through this hybrid approach are given in the Table 5.1.

Table 5.1 F, Df, Ra for v = 47, 51.2 and 55.4 m / min.

Feed	v = 47 m /min			v = 51.2 m /min			v = 55.4 m /min		
	F	Df	Ra	F	Df	Ra	F	Df	Ra
0.040	21.670	1.030	1.420	21.741	1.002	1.477	21.834	1.006	1.446
0.045	23.784	1.028	1.447	23.786	1.010	1.452	23.292	1.012	1.449
0.051	26.002	1.057	1.723	26.051	1.045	1.664	26.008	1.040	1.645
0.056	28.229	1.044	1.700	28.205	1.055	1.686	28.096	1.055	1.657
0.061	30.451	1.037	1.722	30.361	1.055	1.704	30.185	1.059	1.686
0.067	32.674	1.024	1.751	33.872	1.031	1.730	34.405	1.037	1.705
0.072	34.157	1.034	1.757	35.332	1.039	1.740	35.575	1.039	1.721
0.077	41.025	1.030	1.784	38.891	1.030	1.762	38.482	1.036	1.741
0.083	43.909	1.041	1.794	41.983	1.050	1.776	41.204	1.048	1.757
0.088	44.672	1.038	1.809	44.044	1.047	1.790	43.441	1.050	1.770
0.093	45.387	1.044	1.823	45.412	1.050	1.806	45.014	1.053	1.787
0.099	46.764	1.046	1.833	46.752	1.050	1.816	46.362	1.054	1.798
0.104	48.836	1.056	1.846	48.427	1.067	1.829	47.896	1.061	1.812
0.109	51.236	1.052	1.855	50.562	1.058	1.839	49.912	1.062	1.822
0.115	53.671	1.059	1.865	52.986	1.062	1.850	52.319	1.064	1.834
0.120	56.268	1.062	1.873	55.586	1.066	1.859	54.919	1.072	1.843

Table 5.2 F, Df, Ra for v = 63.8, 68 and 72.2 m / min.

Feed	v = 63.8 m /min			v = 68 m /min			v = 72.2 m /min		
	F	Df	Ra	F	Df	Ra	F	Df	Ra
0.040	21.743	1.017	1.389	21.557	1.021	1.362	21.287	1.024	1.336
0.045	22.850	1.025	1.639	22.832	1.031	1.608	22.958	1.036	1.573
0.051	25.645	1.045	1.605	25.331	1.047	1.584	24.924	1.047	1.562
0.056	27.602	1.058	1.595	27.219	1.059	1.561	26.743	1.060	1.524
0.061	29.554	1.061	1.648	29.105	1.063	1.628	28.560	1.064	1.608
0.067	34.668	1.047	1.649	34.511	1.053	1.619	34.178	1.059	1.585
0.072	35.784	1.044	1.680	35.814	1.049	1.658	35.782	1.054	1.636
0.077	37.796	1.048	1.694	37.513	1.054	1.668	37.247	1.060	1.640
0.083	39.586	1.048	1.716	38.756	1.049	1.694	37.948	1.050	1.671
0.088	42.073	1.059	1.727	41.265	1.064	1.704	40.362	1.068	1.679
0.093	44.156	1.054	1.748	43.698	1.055	1.726	43.210	1.055	1.703
0.099	45.609	1.064	1.758	45.255	1.070	1.736	44.902	1.075	1.712
0.104	46.879	1.058	1.774	46.401	1.058	1.753	45.923	1.059	1.731
0.109	48.561	1.072	1.785	47.873	1.076	1.764	47.188	1.081	1.742

0.115	50.806	1.067	1.797	49.954	1.068	1.777	49.063	1.068	1.755
0.120	53.363	1.083	1.808	52.442	1.087	1.788	51.409	1.090	1.766

Table 5.3 F, Df, Ra for v = 76.4, 80.6 and 84.8 m / min.

Feed	v = 76.4 m /min			v = 80.6m /min			v = 84.8 m /min		
	F	Df	Ra	F	Df	Ra	F	Df	Ra
0.040	20.923	1.025	1.311	20.472	1.026	1.287	19.923	1.027	1.263
0.045	23.248	1.039	1.534	23.727	1.043	1.490	24.393	1.046	1.441
0.051	24.423	1.046	1.540	23.836	1.045	1.516	23.155	1.045	1.489
0.056	26.177	1.061	1.485	25.519	1.062	1.441	24.774	1.063	1.392
0.061	27.927	1.065	1.586	27.207	1.065	1.563	26.391	1.065	1.537
0.067	33.705	1.064	1.549	33.136	1.068	1.509	28.012	1.072	1.464
0.072	35.680	1.058	1.612	30.577	1.062	1.587	29.632	1.065	1.559
0.077	36.986	1.066	1.610	36.718	1.071	1.577	31.252	1.076	1.540
0.083	37.187	1.054	1.646	36.483	1.057	1.619	35.839	1.061	1.589
0.088	39.387	1.073	1.652	38.390	1.077	1.623	37.429	1.082	1.592
0.093	42.678	1.056	1.678	42.104	1.058	1.651	41.495	1.061	1.621
0.099	44.531	1.080	1.688	44.119	1.084	1.661	37.740	1.088	1.632
0.104	45.411	1.060	1.707	44.817	1.062	1.680	44.099	1.064	1.651
0.109	46.514	1.085	1.718	45.832	1.089	1.692	45.110	1.093	1.664
0.115	48.189	1.068	1.732	47.411	1.068	1.706	46.792	1.069	1.678
0.120	50.289	1.093	1.743	49.149	1.095	1.718	48.082	1.098	1.691

Table 5.4 F, Df, Ra for v = 89, 93.2 and 97.4 m / min.

Feed	v = 89 m /min			v = 93.2 m /min			v = 97.4 m /min		
	F	Df	Ra	F	Df	Ra	F	Df	Ra
0.040	19.287	1.029	1.239	18.563	1.032	1.213	17.744	1.034	1.185
0.045	20.838	1.050	1.387	20.044	1.053	1.327	19.160	1.057	1.261
0.051	22.387	1.044	1.459	21.525	1.045	1.423	20.574	1.045	1.379
0.056	23.935	1.065	1.335	23.007	1.067	1.271	21.987	1.069	1.199
0.061	25.487	1.065	1.506	24.494	1.064	1.469	23.405	1.063	1.419
0.067	27.036	1.075	1.412	25.974	1.078	1.352	24.821	1.080	1.281
0.072	28.593	1.067	1.527	27.459	1.069	1.487	26.241	1.070	1.434
0.077	30.143	1.081	1.498	28.948	1.085	1.449	27.658	1.088	1.388
0.083	35.275	1.065	1.555	34.848	1.068	1.515	29.078	1.070	1.463
0.088	36.560	1.086	1.557	35.854	1.090	1.516	30.496	1.094	1.466
0.093	34.808	1.064	1.588	33.410	1.067	1.548	31.921	1.070	1.499

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0.099	36.366	1.091	1.600	34.898	1.095	1.563	33.341	1.098	1.519
0.104	43.250	1.066	1.619	36.387	1.069	1.581	34.763	1.071	1.536
0.109	44.320	1.096	1.633	43.482	1.099	1.598	36.189	1.101	1.556
0.115	46.342	1.071	1.646	39.369	1.073	1.610	37.609	1.075	1.568
0.120	47.149	1.100	1.660	46.347	1.102	1.625	39.034	1.104	1.583

Table 5.5 F, Df, Ra for v = 101.6, 105.8 and 110 m / min.

Feed	v = 101.6 m /min			v = 105.8 m /min			v = 110 m /min		
	F	Df	Ra	F	Df	Ra	F	Df	Ra
0.040	16.838	1.037	1.153	14.747	1.042	1.051	21.670	1.030	1.420
0.045	18.182	1.061	1.191	15.961	1.068	1.048	23.784	1.028	1.447
0.051	19.533	1.045	1.322	17.173	1.046	1.168	26.002	1.057	1.723
0.056	20.879	1.071	1.121	18.385	1.075	0.984	28.229	1.044	1.700
0.061	22.229	1.062	1.353	19.599	1.060	1.183	30.451	1.037	1.722
0.067	23.578	1.082	1.202	20.816	1.086	1.065	32.674	1.024	1.751
0.072	24.927	1.070	1.363	22.035	1.069	1.183	34.157	1.034	1.757
0.077	26.281	1.091	1.313	23.252	1.095	1.158	41.025	1.030	1.784
0.083	27.633	1.072	1.392	24.466	1.074	1.215	43.909	1.041	1.794
0.088	28.985	1.097	1.400	25.685	1.101	1.231	44.672	1.038	1.809
0.093	30.339	1.072	1.435	26.902	1.076	1.265	45.387	1.044	1.823
0.099	31.691	1.101	1.460	28.123	1.105	1.290	46.764	1.046	1.833
0.104	33.046	1.074	1.478	29.344	1.079	1.315	48.836	1.056	1.846
0.109	34.406	1.104	1.502	30.566	1.108	1.338	51.236	1.052	1.855
0.115	35.762	1.077	1.514	31.790	1.083	1.356	53.671	1.059	1.865
0.120	37.118	1.106	1.530	33.010	1.110	1.372	56.268	1.062	1.873

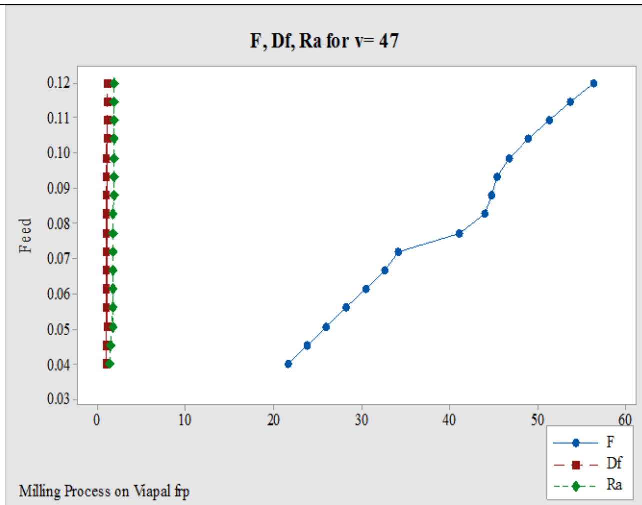

Figure 5.3 F, Df, Ra for v = 47 m / min.

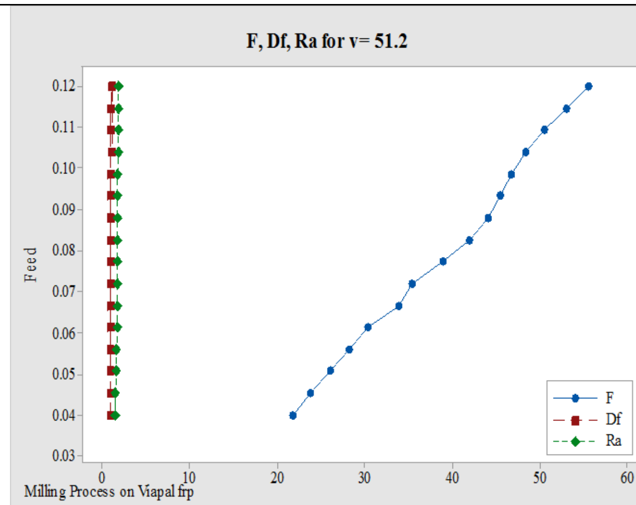

Figure 5.4 F, Df, Ra for v = 51.2 m / min.

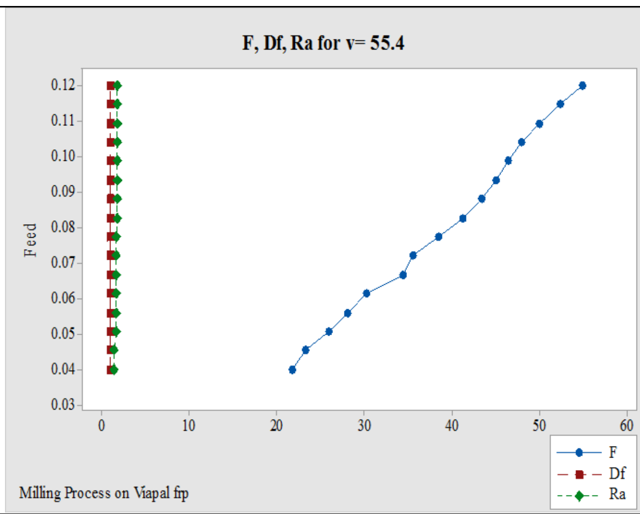

Figure 5.5 F, Df, Ra for v = 55.4 m / min.

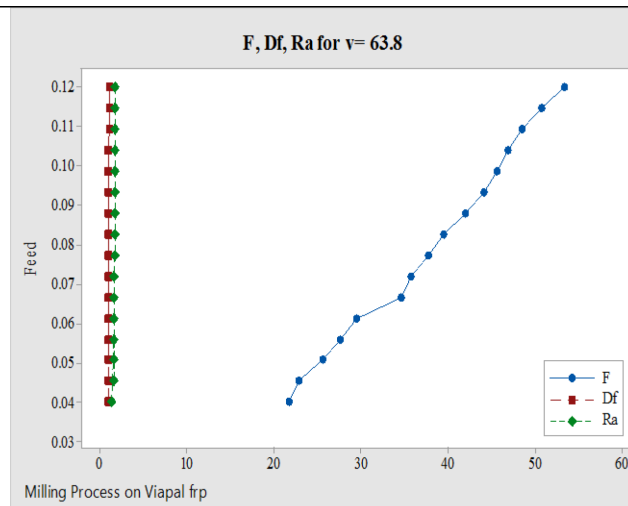

Figure 5.4 F, Df, Ra for v = 63.8 m / min.

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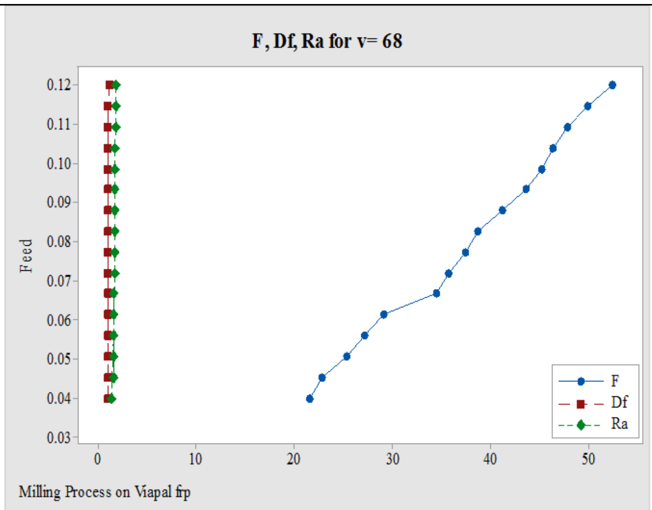

Figure 5.5 F, Df, Ra for v = 68 m / min.

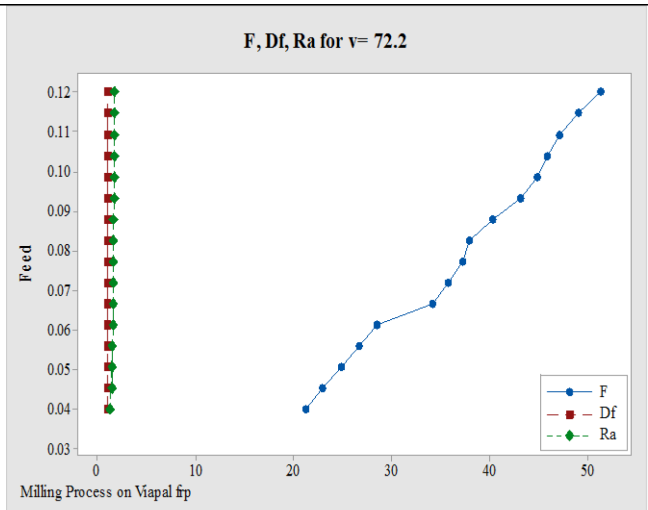

Figure 5.4 F, Df, Ra for v = 72.2 m / min.

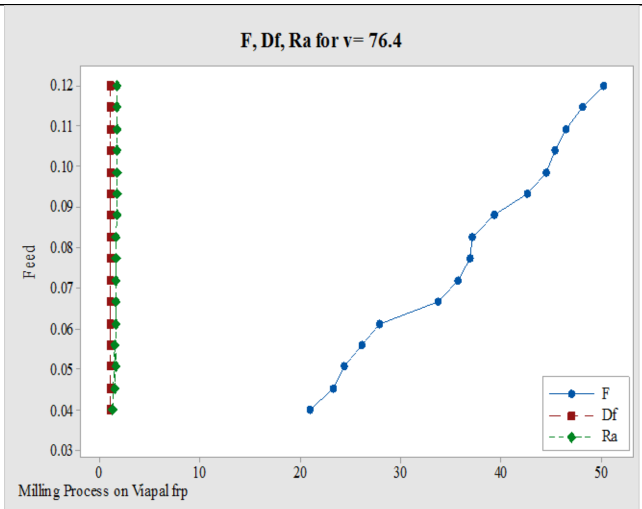

Figure 5.5 F, Df, Ra for v = 76.4 m / min.

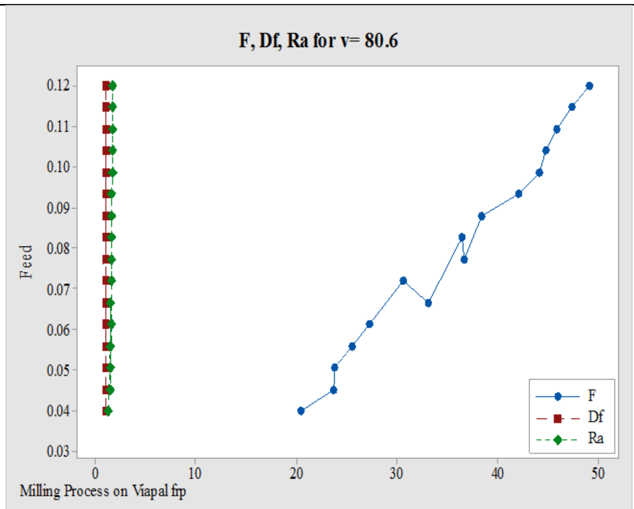

Figure 5.4 F, Df, Ra for v = 80.6 m / min.

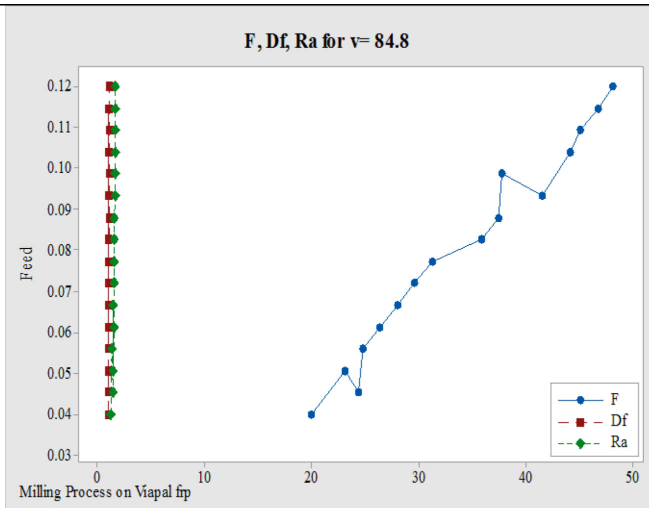

Figure 5.5 F, Df, Ra for v = 84.8 m / min.

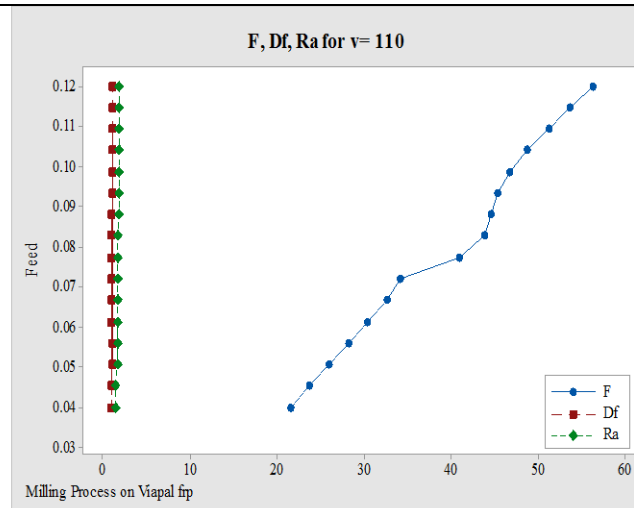

Figure 5.4 F, Df, Ra for v = 110 m / min.

VI RESULTS AND CONCLUSIONS

The experimental data set well fit in the second order statistical regression model. The regression relationship linked Differential Search Algorithm converges with minimal off set in simulation in terms of MSE. The contribution of tool feed registered to be higher in influencing the outcome parameters F, D_f and R_a over the cutting speed. The combination of machining parameters for optimum outcome through various approaches carried out in this attempt is listed in Table 6.1.

Table 6.1 Optimum values and combination of input parameters

Stages	Source	v	f	F	D_f	R_a
1	Experimental values	110	0.040	15.540	-	1.020
		47	0.040	-	1.030	-
2	Simulation through Regression Equation	110	0.040	14.752	-	0.987
		47	0.040		1.029	-
3	Simulation through Regression equation step values	110.0	0.040	14.752	-	-
		47.0	0.040	-	1.029	-
		93.2	0.040	-	-	0.995
4	DSA Hybridisation Regression simulation	110	0.040	14.747	-	-
		51.2	0.040	-	1.002	-
		110	0.056	-	-	0.984

The methodology of optimisation executed may also be refereed for further analysis as the results are in close proximity with the experiments. The exhibited GRAPHS may be utilized by the operator concern at time of performing the milling operations. Further smoothened curves may be produced by simulating with increase number of step values. Other algorithms are also may be tried to forecast the product quality through the machining parameters optimization in future.

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