International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Investigation and Optimisation for the Damage Free Drilled Hole on HEMP Based FRP Drilling Through Regression Integrated Fuzzy Inference Feed RSM

Dr.D.Ramalingam*[1], R.Rinu Kaarthikeyen[2], Dr.S.Muthu[3], Dr.V.Sankar[4]

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

**corresponding author*

[2]*Research Associate, Manager – Engineering, TCMPFL, Chennai, (India)*

[3]*Principal, Adithya Institute of Technology, Coimbatore, (India)*

[4]*Professor, Nehru Institute of Engineering and Technology, Coimbatore, (India)*

ABSTRACT

FRP composite with Hemp fibre base is facing complexity at time of machining especially during conventional drilling process and the damage of the fibres are caused for the quality challenged outcome. The dimensional accuracy is affected because of this delamination effect. This revision investigates the crash and authority of the input drilling parameters (speed and feed) on the resulted drill hole damage factor in the drilling operation on the hemp fibre based frp composite which made out of three different fiber volume fractions (10%, 20% and 30%). Fuzzy inference system, Artificial Neural Network and Response surface modelling are the techniques selected in MATLAB programming. Statistical Regression relationship has been framed and integrated in the programme such as hybridization and the first best two techniques are coupled through seeding method. The optimum input parameters are identified and revealed.

Keywords- Hemp fibre composite, Drilling, Regression, Fuzzy inference system, Artificial Neural Network and Response surface modelling, hybridization, Optimisation, Minitab, MATLAB.

I.INTRODUCTION

FRP composite materials are occupying more and more in a wide range of application fields like aerospace, aircraft, transportation, autos, and sporting goods. Handsome number of researchers is intensively involved in mounting such composite materials which are well-fit with the situation. In this context, the process natural fiber composites made up of Hemp fibres is one among them. Such produced composites need machining operations at the stage of assembly. Though the conventional drilling operations are the most economical and efficient among all such machining processes some prime challenges are afford to face in FRP machining. The damages during drilling are the fibre pull out and surface damages. Improving the situation warrants for careful selection of machining parameters as well as combination. Applying the optimisation techniques and identifying the right and optimal combination of cutting parameters along with the identification of the level of influence on the output variables needs to be done in the manufacturing sectors. This investigation deals on the application of such optimisation techniques which are known as Response Surface Modeling, Fuzzy inference system and Artificial Neural Network to locate the condition for less fibre damage during drilling. Regression model has

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

been initially framed with Minitab software and the scale of influences of the input cutting parameters is interpreted. Integration of mathematical (Statistical Regression) relationship in the programme and hybridization of Fuzzy inference with the RSM is effected by feeding method of the outcome of second best suited technique to the first best fit technique in the MATLAB and optimal condition is identified.

II. LITERATURE SURVEY

Al-Refaie et al. [2] employed the Taguchi method coupled grey analysis to estimate the optimal combination of control parameters in milling, the measures of machining performance being the MRR and SR. Kaladhar et al. [3] conducted experiments and investigated the effects of process parameters on surface finish and material removal rate in turning of AISI 304 using PVD coated cermet inserts, to obtain the optimal setting of these parameters. Prajapati et al. [4] revealed the optimisation on surface roughness using grey relational analysis in straight turning operation of SS 3160. Isik et al. [5] examined the effect of dry machining on the output parameters such as flank wear, cutting force and surface roughness. They found the conditions in dry cutting as satisfactory compared to the flooded type of cooling. Kaladhar et al. [6] devised a multi-characteristics response optimization model based on Taguchi and utility concept to optimize process parameters, such as speed, feed, depth of cut, and nose radius on multiple performance characteristics namely, surface roughness and material removal rate during turning of AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool. Sharma and Sharma [7] developed the best process environment which could simultaneously satisfy requirements of both quality as well as productivity with special emphasis on reduction of cutting tool flank wear.

Dogra et al. [8] proved through the investigation that the effect of variation in tool geometry i.e. tool nose radius, rake angle, groove on the rake face, variable edge geometry, wiper geometry and curvilinear edge tools and on tool wear, surface roughness and surface integrity of the machined surface. Selvaraj et al. [9] demonstrated the cutting characteristics of AISI 304 austenitic stainless steel bars using TiC and TiCN coated tungsten carbide cutting tool. Yadav et al. [10] utilized the Taguchi method to plan the experiments and EN 8 metal selected as a work piece and coated carbide tool as a tool material in this work and hardness after turning has been measured on Rockwell scale. The obtained experimental data has been analyzed using signal to noise and. The main effects have been calculated and percentage contribution of various process parameters affecting hardness also determined. Mahdavinejad and sharifi [11] examined through the experiment on the effect of precision of machine tools and the input setup parameters on output machining parameters such as stock removal, tool wear ratio and surface roughness.

III. EXPERIMENT

Three different fibre volume fraction of 10 %, 20 % and 30% Hemp based FRP composite laminates with the properties as mentioned in the Table 3.1 taken for experimental investigation by Naveen. Et al [1] to assess the hole diameter accuracy during drilling operations.

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Table 3.1 Properties of Hemp based frp

Property	Quantity
Density	1.48 (g / cm^3)
Modulus	70 (GPa)
Tensile Strength	550-900
Elongation of Failure	1.6

The composite material specimen prepared to the size of 100×50×3 mm by hand layup technique. The composite matrix was G.P resin with hardener catalyst and cobalt as the accelerator and the curing was allowed at atmospheric condition for 24 hours. Using the 6 mm diameter drill the experiment executed on the conventional drilling machine with the process variables as input cutting speed (3 levels), feed (4 levels) as mentioned in Table 3.2. L_{12} array was taken for the experiment conducted and the fibre damage factor was considered as outcome variables. The machining processes were carried out as dry machining process and subsequently the responses with reference to each observation experimental data [1] are mentioned in the Table 3.3.

Table 3.2 Input cutting parameters level selection

Process parameters	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Cutting Speed (m / min)	40	60	80	-
Feed (mm / min)	0.1	0.2	0.3	0.5

Table 3.3 Experimental observed data set

Exp No	Cutting Speed (m / min)	Feed (mm / min)	Fibre Volume Fraction		
			10%	20%	30%
			Damage factor (DF_1)	Damage factor(DF_2)	Damage factor(DF_3)
1	40	0.1	1.004	1.008	1.009
2	40	0.2	1.008	1.012	1.018
3	40	0.3	1.020	1.024	1.028
4	40	0.5	1.029	1.032	1.038
5	60	0.1	1.003	1.005	1.006
6	60	0.2	1.005	1.010	1.012
7	60	0.3	1.018	1.020	1.022
8	60	0.5	1.024	1.030	1.032
9	80	0.1	**1.001**	**1.002**	**1.002**
10	80	0.2	1.005	1.008	1.010
11	80	0.3	1.015	1.018	1.020
12	80	0.5	1.021	1.028	1.029

For the machining parameter combination of 80 m / min speed and 0.1 mm / min feed the minimum damage factor noticed in the experiment is as 1.001 for the 10 % fibre volume fraction composite, 1.002 for the 20 % fibre volume fraction composite, 1.002 for the 30 % fibre volume fraction.

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

IV. MATHEMATICAL MODELLING

The influences of the input machining parameters (speed and feed) on the output parameter (fibre damage factor) are analysed by statistical regression relationship with the commercial Minitab17 software. The second order regression relationship between the variables shows higher level significance than the first order regression through the values of the R – sq for all the fibre volume fraction composites. Both the first and second order statistical values of R-sq can be viewed from the Table 4.1. The second order regression equations through the Minitab17 for the material removal rate in terms of input parameter combination are

Regression Equation of Df1 = (0.99839) – (0.000026* t1(1)) + (0.0781 *t1(2)) – (0.000336 *t1(1)*t1(2)) (4.1)

Regression Equation of Df2 = (1.00760) – (0.000149 *t1(1)) + (0.0593 *t1(2)) + (0.000086* t1(1)*t1(2)) (4.2)

Regression Equation of Df3 = (1.01004) – (0.000169 *t1(1)) + (0.0756 *t1(2)) – (0.000114* t1(1)*t1(2)) (4.3)

Where t1(1) represents the machining speed and t1 (2) represents the tool feed. The co efficient of the feed and speed in all equations revealed that the feed is the registering the higher side influence than the speed.

Table 4.1 Regression model comparison for surface roughness

Fibre Volume	Regression	S	R-sq	R-sq(adj)	R-sq(pred)
10% fibre	First order	0.0027506	93.17%	91.65%	89.00%
	Second order	**0.0027428**	**93.96%**	**91.69%**	**89.80%**
0% fibre	First order	0.0019338	97.14%	96.50%	95.30%
	Second order	**0.0020354**	**97.18%**	**96.12%**	**94.20%**
30% fibre	First order	0.0021217	97.13%	96.49%	95.09%
	Second order	**0.0022249**	**97.19%**	**96.14%**	**94.09%**

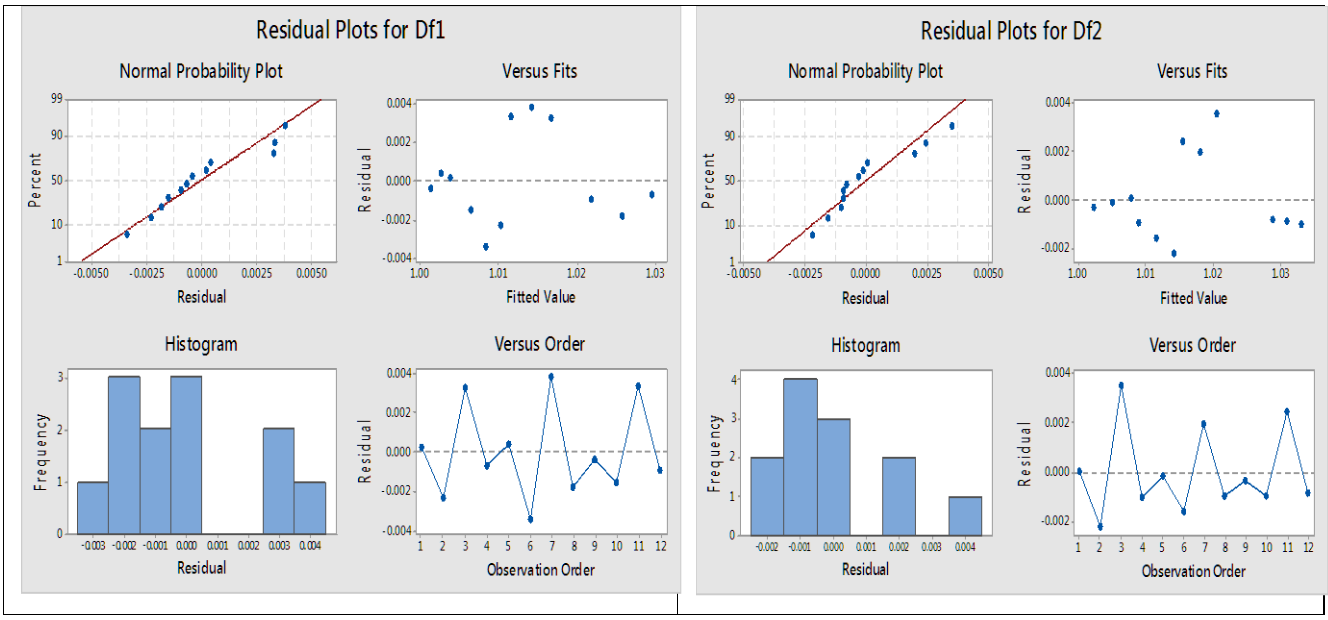

Figure 4.1 Residual plots of Fibre damage factor DF1 and DF2

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

The residual plots through Minitab analysis for the fibre damage factor DF_1 and DF_2 are depicted in Figure 4.1. while doing the statistical best subset regression analysis the results reveals that the feed is the major influencing factor which contributes around 83.2 % whereas the speed exhibits very little amount of influence on the Fibre damage factor..

V. OPTIMISATION METHOD IMPLEMENTATION

With the primary objective of minimizing the drill hole diameter damage factor, one of the main quantitative components in industrial decision making at time of processing the application of programming in the MATLAB R2017 software as an attempt is made in this assignment to forecast the outcome variable referring to the input process variables. With the optimization techniques namely Fuzzy inference system, Response surface modelling and Artificial neural network the objective functions were fixed. To analyze the influence of the cutting speed and the feed on the drill hole damage factors designated as DF_1, DF_2 and DF_3 through MATLAB R2017 platform with the Elman Back Propagation approach is applied. The number of iterations initiated for this simulation is 10000 and then revised to 50000 iterations. The compatibility of the employed optimisation techniques is assessed through the accuracy level in computation which is in the form mean squared error occurred rate as the indicator. Figure 5.1 shows the progress of the training data in MATLAB.

The accuracy level of the computation is recorded as 0.001069 error level deviation for the Response Surface modelling, 0.01658 error level deviation for the Fuzzy inference and 0.1689 for the Artificial neural network to the stimulated objective functions. These values demonstrate that the confidence level on the RSM as the best fit model and the Fuzzy as the second best fit model. The feeding of the second best fit model outcome as the input values to the first best fit model is programmed in the MATLAB and the Fuzzy feed RSM model is performed as the trial. The accuracy level with reference to the error in approximation is tuned with the improvement of 14.98 %.

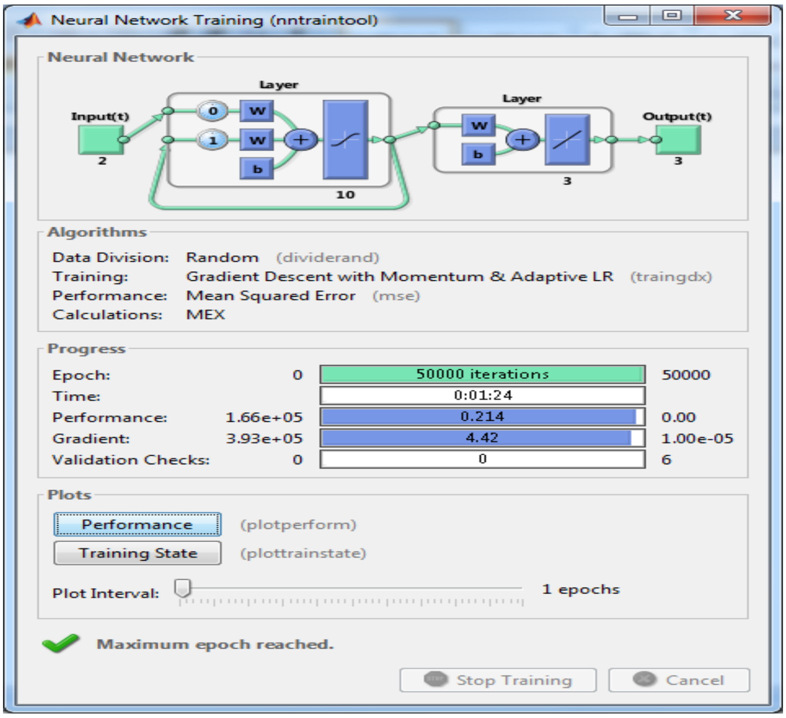

Figure 5.1 Data training progress of 50000 iterations

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

As the algorithm converges with the minimum value of mean squared error, as a novel attempt the regression relationship equation is fed in the programme. Initially the random selection of values for computation is performed and replaced with the condition of the regression relationship is programmed. This attempt realizes to the level of 12.63 % improved outcome. The new approach of hybridization with regression equations as condition for simulation and regression calculated values replacing the experimental values are shown as the flow chart through the Fig. 5.2.

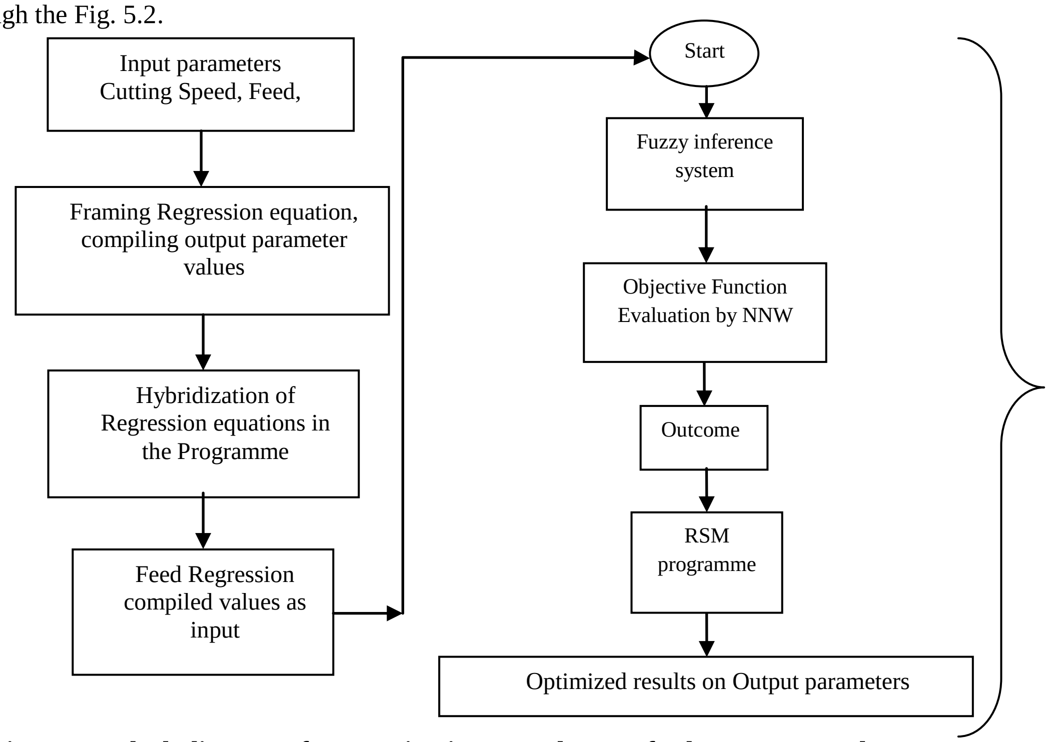

Figure 5.2 Block diagram of Regression integrated Fuzzy feed RSM approach

With the view of obtaining a smooth path curve with closer interval values of the process outcomes, the parameters selected was sub divided with 15 step values referring to the L1 and L3 level of the parameter selection. (i.e) 2.666667 mm / min in speed, 0.026667 step values in feed. The computed results of the DF_1, DF_2 and DF_3 through this Regression relationship integrated Fuzzy feed RSM approach for all combination of the parameter input given to the programme are listed in the Table 5.1 to Table 5.3.

Table 5.1 DF_1, DF_2, DF_3 Vs F for speed 40, and 45 and 50 m / min

Feed	Speed 40 m / min			Speed 45 m / min			Speed 50 m / min		
	DF1	DF2	DF3	DF1	DF2	DF3	DF1	DF2	DF3
0.10	1.002	1.007	1.008	1.005	1.015	1.002	1.005	1.013	1.003
0.12	1.005	1.011	1.015	1.003	1.014	0.999	1.004	1.010	1.001
0.14	1.011	1.022	1.021	1.008	1.013	0.998	1.009	1.013	1.000
0.16	1.013	1.018	1.018	1.012	1.017	0.997	1.011	1.015	0.999
0.18	1.008	1.018	1.014	1.011	1.016	0.998	1.011	1.013	1.001
0.20	1.009	1.018	1.011	1.011	1.019	1.003	1.011	1.017	1.005
0.22	1.013	1.020	1.010	1.012	1.018	1.008	1.012	1.017	1.009
0.24	1.014	1.020	1.010	1.014	1.019	1.013	1.013	1.016	1.013
0.26	1.015	1.023	1.011	1.015	1.020	1.015	1.014	1.019	1.014
0.28	1.015	1.023	1.013	1.015	1.021	1.016	1.015	1.020	1.015
0.30	1.017	1.023	1.015	1.016	1.021	1.016	1.016	1.019	1.016

Table 5.2 DF_1, DF_2, DF_3 Vs F for speed 55, and 60 and 65 m / min

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Feed	Speed 55 m / min			Speed 60 m / min			Speed 65 m / min		
	DF1	DF2	DF3	DF1	DF2	DF3	DF1	DF2	DF3
0.10	1.005	1.013	1.003	1.005	1.014	1.003	1.004	1.014	1.004
0.12	1.005	1.007	1.002	1.006	1.006	1.003	1.005	1.006	1.005
0.14	1.009	1.012	1.001	1.009	1.012	1.003	1.009	1.012	1.005
0.16	1.010	1.014	1.001	1.009	1.015	1.003	1.008	1.016	1.005
0.18	1.011	1.011	1.004	1.010	1.010	1.008	1.009	1.008	1.011
0.20	1.011	1.016	1.008	1.010	1.016	1.010	1.010	1.016	1.013
0.22	1.012	1.016	1.011	1.011	1.015	1.013	1.010	1.015	1.016
0.24	1.013	1.015	1.013	1.012	1.014	1.014	1.011	1.014	1.016
0.26	1.014	1.018	1.014	1.013	1.018	1.015	1.012	1.019	1.017
0.28	1.014	1.019	1.015	1.014	1.019	1.015	1.013	1.018	1.017
0.30	1.015	1.017	1.016	1.014	1.016	1.017	1.014	1.018	1.018

Table 5.3 DF_1, DF_2, DF_3 Vs F for speed 70, and 75 and 80 m / min

Feed	Speed 70 m / min			Speed 75 m / min			Speed 80 m / min		
	DF1	DF2	DF3	DF1	DF2	DF3	DF1	DF2	DF3
0.10	1.003	1.013	1.005	1.002	1.017	1.008	1.001	1.007	1.010
0.12	1.005	1.008	1.007	1.004	1.006	1.009	1.003	1.014	1.012
0.14	1.008	1.011	1.008	1.007	1.014	1.011	1.006	1.013	1.014
0.16	1.007	1.014	1.008	1.005	1.018	1.012	1.004	1.012	1.015
0.18	1.008	1.011	1.015	1.007	1.006	1.018	1.006	1.020	1.019
0.20	1.009	1.013	1.016	1.007	1.023	1.018	1.006	1.007	1.020
0.22	1.009	1.017	1.018	1.008	1.013	1.020	1.006	1.024	1.021
0.24	1.010	1.013	1.018	1.009	1.016	1.020	1.008	1.016	1.022
0.26	1.011	1.016	1.019	1.009	1.023	1.021	1.008	1.013	1.022
0.28	1.011	1.022	1.019	1.010	1.012	1.021	1.009	1.024	1.023
0.30	1.012	1.014	1.020	1.011	1.028	1.022	1.010	1.010	1.024

The resultant values through this integrated optimisation methods are graphically represented in the subsequent Figures 5.3 to 5.11.

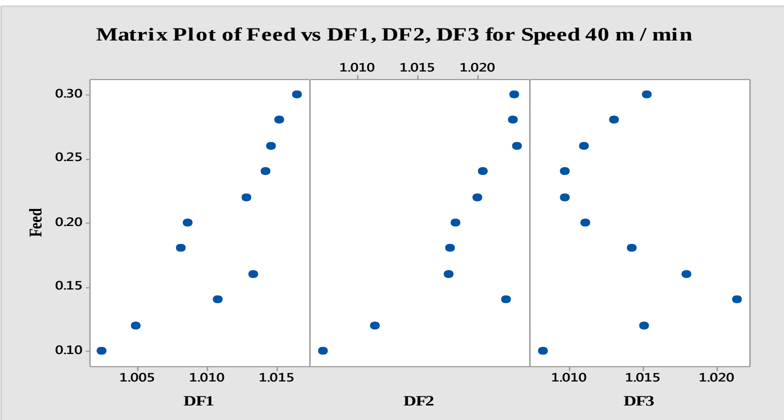

Figure 5.3 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 40 m / min

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

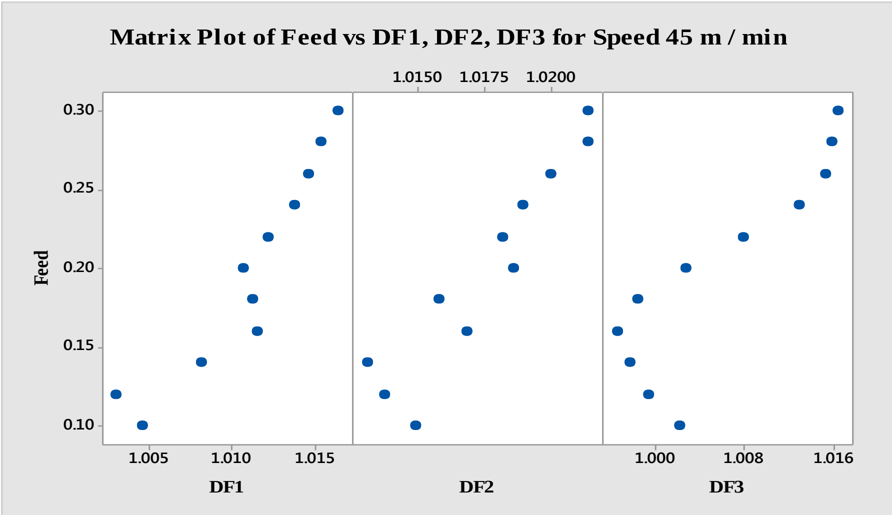

Figure 5.4 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 45 m / min

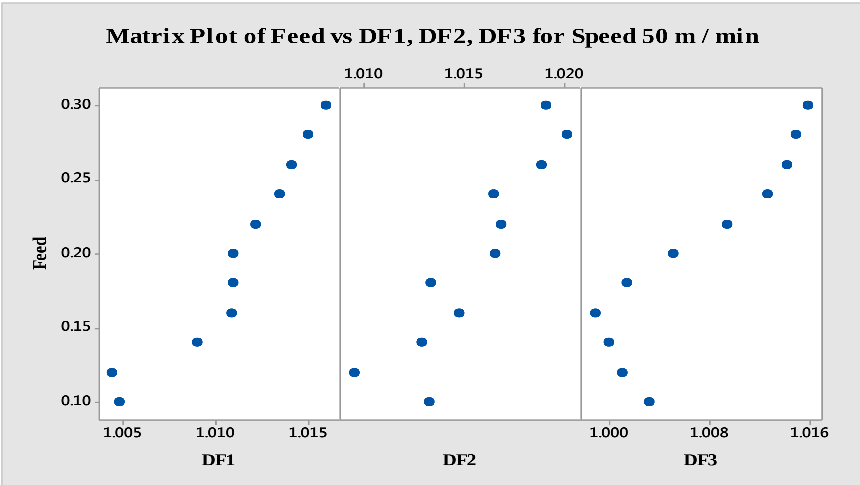

Figure 5.5 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 50 m / min

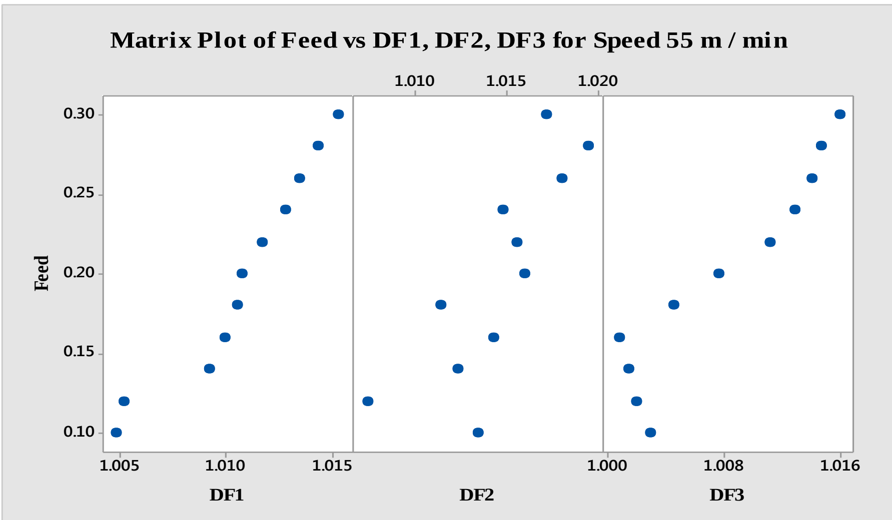

Figure 5.6 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 55 m / min

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

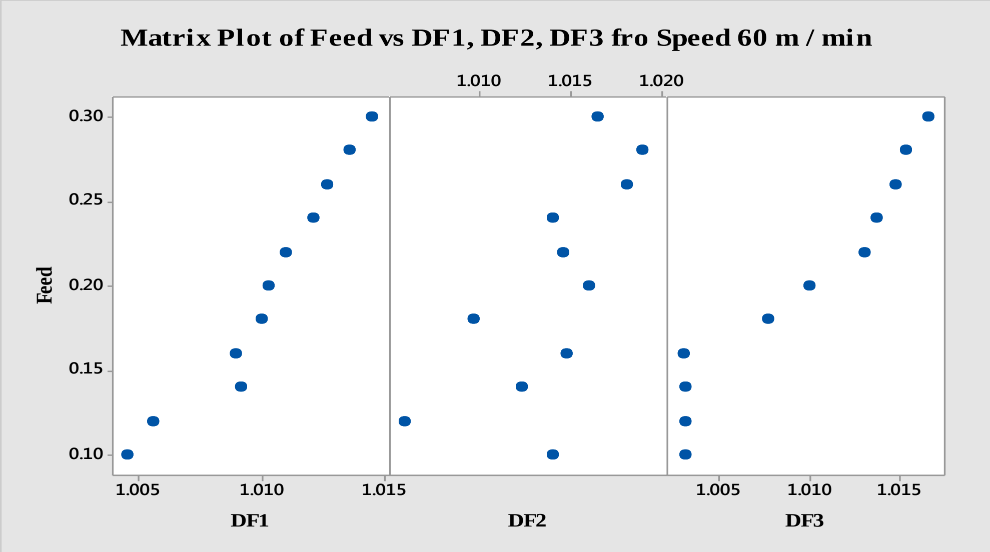

Figure 5.7 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 60 m / min

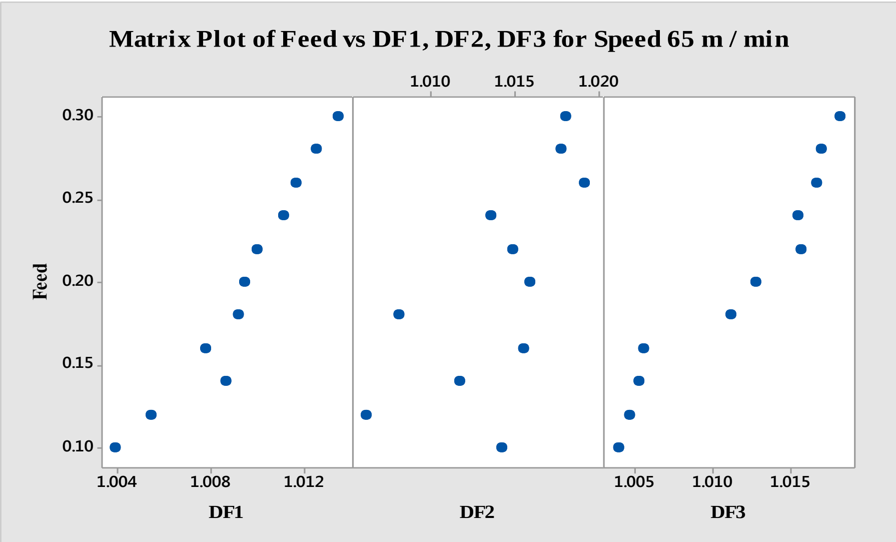

Figure 5.8 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 65 m / min

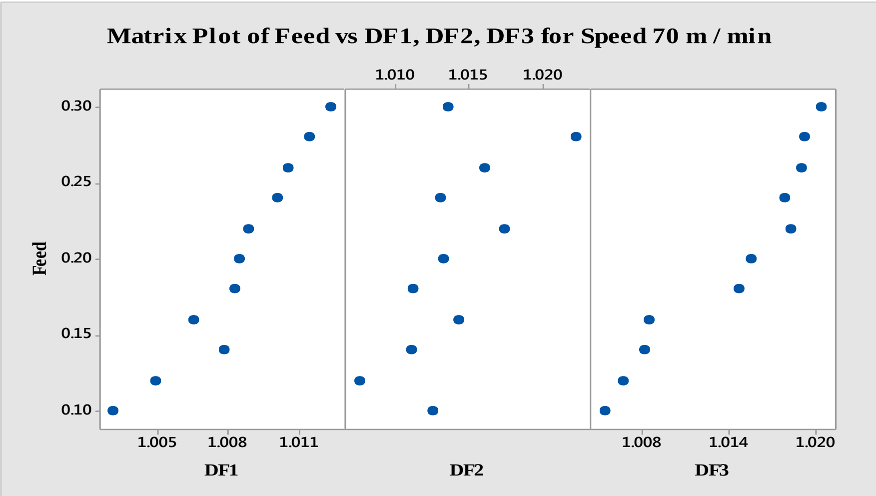

Figure 5.9 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 65 m / min

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

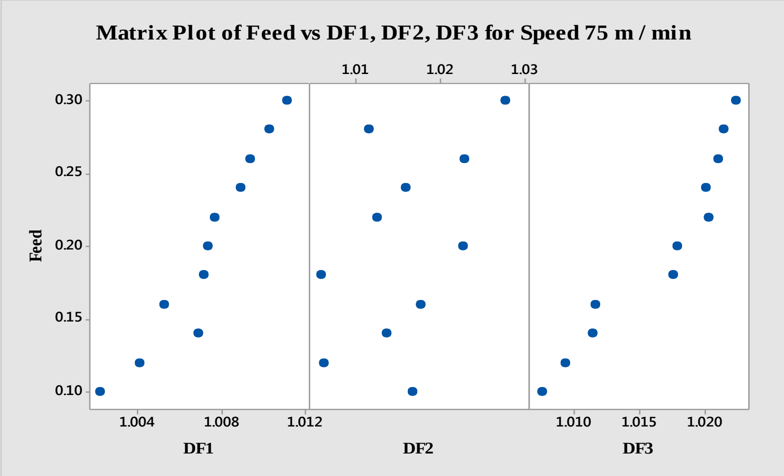

Figure 5.10 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 75 m / min

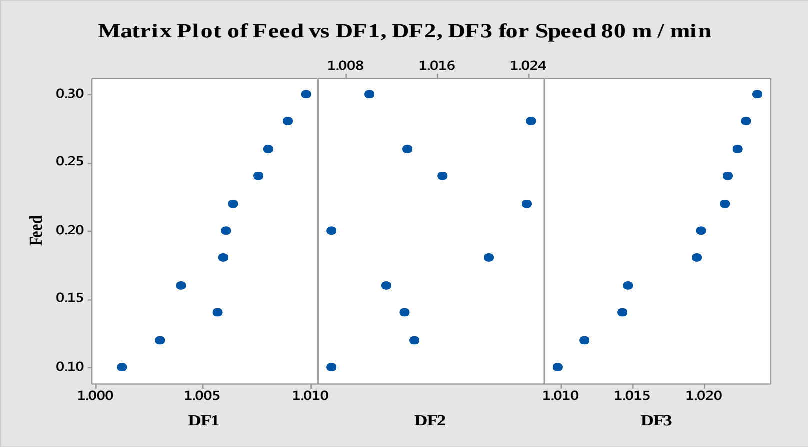

Figure 5.11 Matrix plot of tool feed Vs DF_1, DF_2, DF_3 to the speed 80 m / min

VI. RESULTS AND CONCLUSION

The hemp based FRP laminates taken for the drilling experiment with the objective of forecasting the drill hole accuracy and damage factor (delamination). In the initial regression modeling and analysis it has been observed that among the feed and speed, all equations revealed that the feed is the registering the higher side influence than the speed. Artificial Neural Network, Fuzzy Inference and Response Surface Modelling are the three optimsation techniques employed in this investigation and the RSM and Fuzzy inference occupies the first two places respectively in terms of minimum deviations in MSE computational error. Regression relationship also taken as the conditional input to the programme and regression integrated Fuzzy feed RSM model was programmed and results were found to be more tuned than the individual performance of the optimisation techniques employed. The optimal combination of the input machining variables for minimum deviation in the dimensional accuracy and damage factor for all the three fibre volume percentage frps are listed in the Table 6.1

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Table 6.1 Optimal combination of machining variables

Parameter	Speed	Feed	Optimised Value
DF_1	80	0.10	1.001
DF_2	75	0.18	1.006
DF_3	45	0.16	0.997

The graphs are plotted to the reference ready reckoner to the manufacturer concern dealing with sandwich Frps.

REFERENCES

[1] Naveen, P.N.E, Yasaswi, M,& Prasad.R.V, 2012, Experimental Investigation of Drilling Parameters on Composite Materials, IOSR Journal of Mechanical and Civil Engineering (IOSRJMCE), vol. 2, issue 3, pp 33-37.

[2] Al-Refaie, L. Al-Durgham, N. Bata, Optimal parameter design by regression technique and grey relational analysis, The World Congress of Engineering, 2010.

[3] M. Kaladhar, K. V. Subbaiah, C. S. Rao, K. N. Rao, Determination of optimum process parameters during turning of AISI 304 austenitic stainless steels using Taguchi method and ANOVA, International Journal of Lean Thinking, Vol. 3(1), 2012, pp.1-19.

[4] N. K. Prajapati, S.M. Patel, A Review on Optimization of Process Parameters for Surface Roughness and MRR for S.S.316.on CNC, International Journal of Advanced Engineering Research and Studies, Vol.2, 2012, pp.100-103.

[5] I. Yahya, An Experimental Investigation on effect of Cutting fluids in Turning with Coated Carbides Tool, Journal of Mechanical Engineering, Vol.56(3),2010, pp.1-7.

[6] M. Kaladhar, K. V. Subbaiah, C. S. Rao, K. N. Rao, Application of Taguchi approach and Utility Concept in solving the Multi-objective Problem when Turning AISI 202 Austenitic Stainless Steel, Journal of Engineering Science and Technology Review, Vol. 4 (1), 2011, pp. 55-61.

[7] N. Sharma, R. Sharma, Optimization of Process Parameters of Turning Parts: A Taguchi Approach, Journal of Engineering, Computers & Applied Sciences, Vol.1 (1), 2012, pp.1-5.

[8] M. Dogra, V. S. Sharmab, J. Durejac, Effect of tool geometry variation on finish turning, Journal of Engineering Science and Technology Review, Vol .4(1), 2011, pp. 1-13.

[9] P. D. Selvaraj, P. Chandramohan, Optimization of Surface Roughness of AISI 304 Austenitic Stainless Steel in dry Turning operation using Taguchi design method, Journal of Engineering Science and Technology, Vol. 5 (3), 2010, pp. 293- 301.

[10] A. Yadav, A. Bangar, R. Sharma, D. Pal, Optimization of Turning Process Parameters for Their Effect on En 8 Material Work piece Hardness by Using Taguchi Parametric Optimization Method, International Journal of Mechanical and Industrial Engineering, Vol.1(3), 2012, pp.36-40.

[11] R.A. Mahdavinejad, H.B. Sharifi, Journal of Achievements in Materials and Manufacturing Engineering, Vol. 37 (2), 2009, pp.571-577.