MULTI-OBJECTIVE OPTIMISATION OF PROCESS PARAMETERS IN MILLING PROCESS ON AL 6063-T6 BY REGRESSION HYBRID FUZZY FEED RSM METHOD

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ABSTRACT

Milling operations is one of the imperative operation and very common in the manufacturing industries in order to fabricate the parts towards the structural assembly of the final product. Achieving the desired surface quality is the major challenge in the manufacturing operations. Same time tool wear also contributing towards the surface quality as well as to the cost of production. With the objective of achieving the desired surface finish and minimum tool wear the optimization through ANN, Fuzzy and RSM methods are applied in this attempt in MATLAB programming. Based on the performance of the optimization the feeding of the Fuzzy outcome to the RSM is implemented. Subsequently the regression equations and the regression computed values of parameters are fed as input as a hybridization and the simulation carried out. The optimised parameter combinations were identified for each output parameter (Surface roughness and Tool flank wear). Evaluated the hybridization method applied in this attempt through the comparison between the individual approaches.

Keywords: AL 6063- T6, Milling, Regression, ANN, Fuzzy, RSM, Hybridization, Optimization, Minitab, MATLAB.

I. INTRODUCTION

AL 6063is being used in Architectural applications, Window frames, Doors, Shop fittings, Irrigation tubing, Extrusions, balustrade the rails and posts formed elbows, bends and also finding applications in hydro formed tube for chassis. Milling process is one of the renowned applications in manufacturing domain to compose the parts for assembly thereby into the final product for application. It is one of the extensive and precision operations among all machining methods. During this operation the very common issues are being faced by every manufacturer like attaining the dimensional accuracy and precision, required surface finish. These primary challenges are highly linked with the process parameters like machining speed, tool feed rate, tool material and properties, tool geometry, cutting fluid properties and usage methods, machine tool rigidity etc over and above the work material properties. In addition, the surface quality of the produced parts mainly depends on the tool cutting edges stability to have the consistent surface finish which is the reflection of tool flank wear. Also tool wear causes for the increase in cost of production. Hence the selection of optimal cutting conditions and cutting parameters and machining environment is a prime call for any machining operations. This paper mainly focuses on the multi-objective optimisation of process parameters cutting speed, depth of cut, feed, and cutting fluid flow rate in milling.

Abbreviations Used

ANN	Artificial Neural Network	MMC	Metal matrix composite
CFRP	Carbon fibre reinforced composite	Ra	Surface roughness
DOC	Depth of cut	Reg	Regression
Exp	Experiment	RSM	Response Surface Method
F	Feed rate	R-sq	R - square statistical value
FF	Fluid Flow rate	R-sq (adj)	R - square adjusted statistical value
FW	Tool Flank Wear	R-sq (pred)	R - square predicted statistical value
GFRP	Glass fibre reinforced composite	S	Cutting speed

II. RELATED LITERATURE

Many researchers are continuously making attempts through several methods and technology to locate the issues related and suggesting various approaches to achieve the most desired results in various machining processes on various materials like metals, alloys, composites. Moreover in order to understand the effects of machining parameters in the various machining many of the researchers used optimization techniques. Wang et al. [1] conducted experiment and optimized the process parameters for locating and selecting the economic machining conditions in turning process through the deterministic approach. Oezel T and Karpat Y [2] have sentenced that the surface quality is one of the most specific requirements and is one of the main results of process parameters such as tool geometry (nose radius, edge geometry and rake angle) and cutting conditions (feed rate, cutting speed, depth of cut, etc.). Raviraj Shetty et al. [3] conducted an exclusive study with the Taguchi optimization method to optimize the machining parameters in the turning operation on the age hardened AlSiC - MMC with CBN cutting tool. Ozel, C and Kilickap, E [4] have confirmed that the process modeling and optimization are the primary issues in the process industries. Also they revealed that surface finish has been an important factor of any machining in assessing the performance of any machining operation. The influence of the process parameters on the dimensional accuracy of the produced holes on the work material for different coated drills has been investigated by Nouari et al [5]. Feng [6] has established with the findings of the research that the feed rate, the tool nose radius, the work material and speeds and the tool point angle have a significant impact on the surface quality by applying the fractional factorial experimentation method. Tsao, C C [7] has accomplished the usage of Grey - Taguchi method to the optimization of the parameters in milling operations on the aluminium alloy and concluded 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.

Haan et al. [8] experimented through the drilling operations to identify the effects of cutting fluids on hole quality and declared that the dry-drilled holes resulted in poorer surface finish than holes produced with cutting fluid application. Zeilmann, RP, Weingaertner WL [9] 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. David et al. [10] have demonstrated through an approach for predicting Surface roughness in a high speed end-milling process by ANN approach and statistical tools to predict the different surface roughness predictor's combinations. Rajasekaran et al. [11] used fuzzy logic for modeling and forecasting about the three machining input variables such as depth of cut, feed rate and cutting speed influence on the surface roughness of the CFRP composite.The outcome of the research was that the fuzzy logic modeling technique can be effectively used for the prediction of surface roughness in machining operations. Kirby, D.E, and Joseph, C.C. [12] have recognized the occurrence of the quality issues in the resultant parameters in cutting operations carried out on turning and milling machines which includes the machine tool condition, job clamping, tool and workpiece geometry, and cutting parameters used for machining. They developed a Fuzzy based prediction approach to optimize the surface roughness. Hussain et al. [13] proposed a surface roughness prediction model for the machining of GFRP pipes using Response Surface Methodology by using carbide tool (K20). Four parameters such as cutting speed, feed rate, depth of cut and work piece (fiber orientation) were selected as input variables. They conclude that the depth of cut influences with minimum effect on surface roughness comparing to other parameters. Mata et al. [14] developed a cutting forces prediction model for the machining of carbon reinforced PEEK CF30 using response surface methodology by using Tin-coated cutting tool. Three parameters such as cutting speed, feed rate and depth of cut were selected as input machining parameters for assessing the output parameter. They have concluded about aptness of the Multiple Regression models. Paulo Davim, J [15] confirmed that the higher cutting speed results in a smoother surface, by using the Taguchi method in his investigation.

In this paper the analysis and prediction of optimized parametric combination is identified with applying ANN, Fuzzy and RSM methods through MATLAB programming. A novel approach of feeding the regression equation relationship as input instead of random approach and the experimental output values are replaced with the regression values computed through the statistical relationship based on the fitness of the equation developed in Minitab.

III.EXPERIMENTAL DATA

The experiments on the end milling operations carried out on AL6063-T6 material specimen with the dimensions of 300 x 200 x 50 mm by Sundara Murthy et al. [16] in the 3 HP powered universal geared type milling machine which has the three dimensional travel capacity in X, Y Z directions as 725mm, 300 mm and 250mm respectively. The capacity range of the machine in speed and feed velocity configurations are 15-88 m / min and 75-355 mm / min. The mechanical properties of the selected material is given in the Table 3.1

Table 3.1 Mechanical properties of AL6063-T6

Properties	Values	Properties	Values
Hardness (Brinell)	73	Machinability	50%
Ultimate Tensile	241	Fatigue Strength	68.9 Gpa
Tensile Yield Strength	214	Shear Modulus	25.8 Gpa
Elongation	12%	Shear Strength	152 Mpa
Modulus of Elasticity	68.9	Poisson's Ratio	0.33

LT740WWL end mill cutting tool of 20 mm diameter with coated inserts APGT 1003 PDER-Alu LT05 are used for performing the machining. Vegetable oil coolube 2210 was used as the cutting fluid in the process with MQL setup for supplying oil in MQL condition. The input machining variables selected for the process in three levels as noted in the Table 3.2.

Table 3.2 Machining parameters and levels

Parameters	**Units**	**Level 1**	**Level 2**	**Level 3**
Cutting speed	m / min	35	56	88
Feed velocity	mm / min	180	250	355
Depth of cut	mm / min	1	1.2	1.4
Fluid flow rate	ml / hr	300	600	900

The output parameters taken for analysis were the surface roughness and flank wear of cutting tool which were measured through tool room microscope and surface roughness tester. The experimental observed data through Taguchi L9 array experimental plan are given in the Table 3.3, where S stands for cutting speed in m / min; F is feed in mm / min; DOC is depth of cut in mm / min; FF is fluid flow rate in ml / hr; Ra is surface roughness in µm and FW represents the tool flank wear in mm.

Table 3.3 Experimental observed data of machining AL6063-T6

Exp No	**S**	**F**	**DOC**	**FF**	**Ra**	**FW**
1	35	180	1.0	300	0.799	0.256
2	35	250	1.2	600	0.746	0.240
3	35	355	1.4	900	0.973	0.274
4	56	180	1.2	900	0.752	0.202
5	56	250	1.0	300	0.868	0.329
6	56	355	1.4	600	0.449	0.370
7	88	180	1.4	600	0.649	0.316
8	88	250	1.0	900	0.678	0.383
9	88	355	1.2	300	0.747	0.395

IV. MATHEMATICAL MODELING

Minitab17 software is used to access the influence of the input variables (Cutting speed, Tool Feed, Depth of cut and Cutting fluid flow rate) with the output variables (Surface roughness and Tool flank wear) through the regression analysis. 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 Surface roughness and Tool flank wear

Variable	**Regression**	**S**	**R-sq**	**R-sq**	**R-sq (pred)**	**Durbin - Watson**
Ra	First order	0.14987	47.52%	0.00%	0.00%	1.71486
	Second order	0.012393	99.91%	99.28%	57.91%	1.81616
FW	First order	0.0343946	87.30%	74.60%	30.62%	2.57887
	Second order	0.0062916	99.89%	99.15%	50.19%	1.81616

The R - sq values are better in second order equations than the first order for both the output variables which indicate that the predictors (input variables) explain 99.91% of the variance in the output variables. As the 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

"Ra = (2.187) + (0.00965*Speed) – (0.010475*Feed) – (0.945*DOC) – (0.000085*fluid flow) + (0.000010* Speed* Feed) – (0.01042*Speed*DOC) + (0.007964*Feed*DOC)"

(4.1)

"FW = -(0.363) + (0.01709*Speed) + (0.001596*Feed) + (0.171*DOC) – (0.000224*fluid flow) – (0.000025* Speed* Feed) – (0.00700*Speed*DOC)+ (0.000182*Feed*DOC)"

(4.2)

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 and 4.2.

Best subset regression analysis of the parameters are given below the Tables 4.2 and 4.3

Table 4.2 Best Subsets Regression: Ra versus Speed, Feed, Doc, Fluid flow

Variables	R-Sq	R-Sq (adj)	R-Sq (pred)	Mallows Cp	S	Speed	Feed	Doc	F F
1	31.0	21.1	0.0	0.3	0.12293			x	
1	16.3	4.4	0.0	1.4	0.14304	x			
2	**47.3**	**29.7**	**0.0**	**1.0**	**0.12261**	x		x	
2	31.2	8.2	0.0	2.2	0.14014		x	x	
3	**47.5**	**16.0**	**0.0**	**3.0**	**0.13406**	x	x	x	
3	47.3	15.7	0.0	3.0	0.13430	x		x	x
4	47.5	0.0	0.0	5.0	0.14987	x	x	x	x

Table 4.3 Best Subsets Regression: FW versus Speed, Feed, Doc, Fluid flow

Variables	R-Sq	R-Sq (adj)	R-Sq (pred)	Mallows Cp	S	Speed	Feed	Doc	F F
1	47.5	40.0	24.9	11.5	0.052847	x			
1	29.6	19.5	0.0	17.2	0.061214		x		
2	**77.1**	**69.5**	**51.2**	**4.2**	**0.037688**	x	x		
2	54.1	38.8	7.7	11.5	0.053400	x			x
3	**83.7**	**73.9**	**30.1**	**4.1**	**0.034874**	x	x		x
3	80.7	69.2	54.2	5.1	0.037874	x	x	x	
4	87.3	74.6	30.6	5.0	0.034395	x	x	x	x

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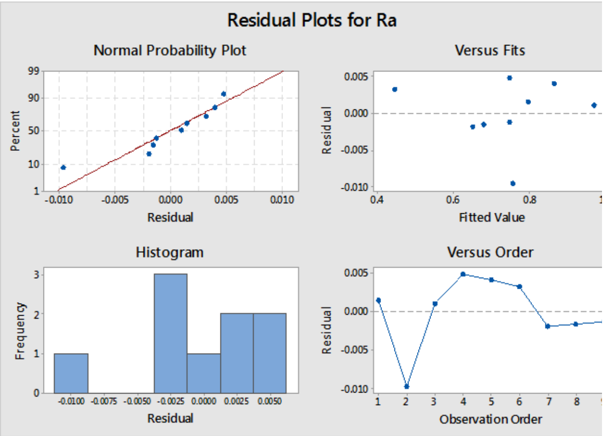

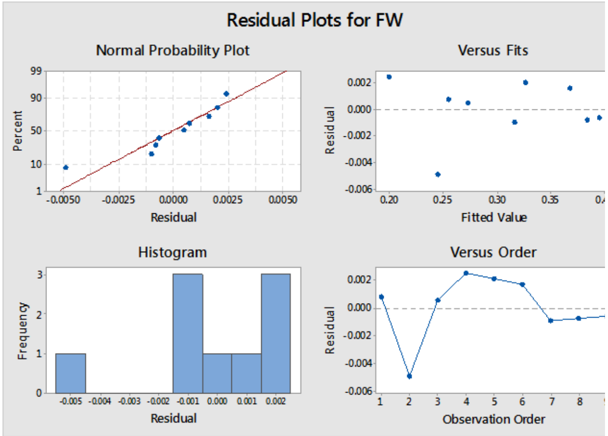

Figure 4.1 Residual plots of surface roughness **Figure 4.2 Residual plots of Tool Flank wear**

The Parameter speed is contributing the highest significance (47.5%) on the results which is followed by feed (29.6%) as an individual predictor. Two predictors model is concern with the lowest Cp value (4.2), highest adjusted R-sq value (69.5) and low S value (0.037688) is for the speed and feed combination. In the case of three predictors model the combination of Speed, feed and fluid flow records the significance contribution. The Doc is the least contributing predictor on the output variables.

V. METHODOLOGIES ADOPTED FOR OPTIMIZATION

Analysis towards optimizing and predicting the Surface roughness and the flank wear of the tool on the experimented AL6063 T6 materials carried out with the prime objective of investigating the influence of the cutting velocity, feed velocity of the tool, depth of cut and cutting fluid flow rate through Response Surface Method (RSM), Fuzzy system and Artificial Neural Network (ANN) in the MATLAB programming with Elman Back Propagation. The objective functions considered for the optimization to reach the minimum surface roughness and minimum tool flank wear. 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 the RSM converges as the best with minimum mean error in simulation followed by the Fuzzy method as the second best and subsequent place to ANN. With a new approach of feeding the outcome of the second best method (Fuzzy) to the first best method (RSM) and the procedure of simulation carried out. The simulation outcome was found to be further more tuned with reduction in the mean error of computation comparing to the individual method concerned. The new approach of hybridization with regression equations and regression values is shown in the Fig. 5.1

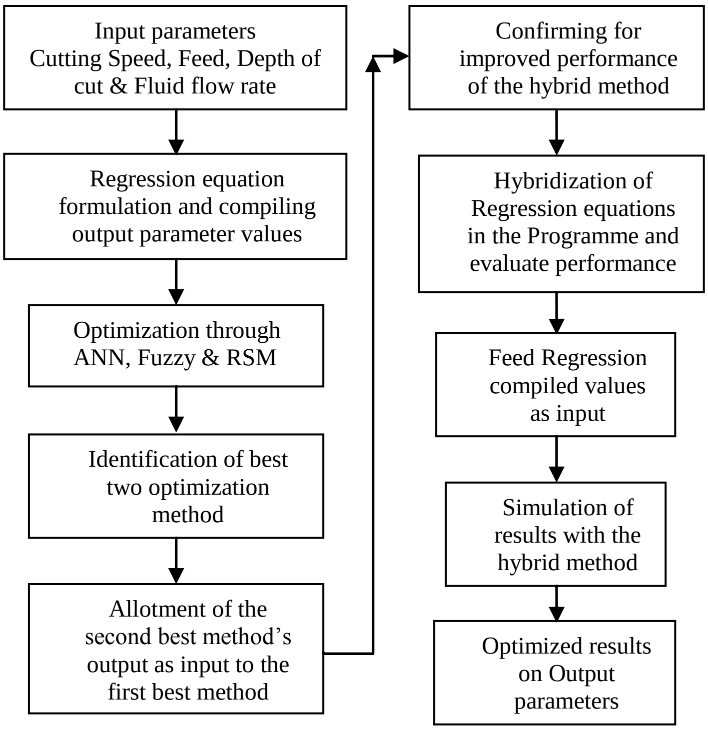

Figure 5.1 Block diagram of hybridization In view of confirming the results, the same procedure has been adopted with 25000 and 50000 iterations and the mean error in computations in all the cases are tabulated in the Table 5.1.

Table 5.1 Mean error comparison of Optimization methods

Method	Number of Iterations		
	5000	25000	50000
RSM	0.00030	0.00011	0.00011
Fuzzy	0.26789	0.26789	0.26789
ANN	0.27789	0.27789	0.27789
Fuzzy feed RSM	0.00011	0.00011	0.00011

With the 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 further reduction of (9.09%) mean error in computation. With this interpretation, instead of actual experimental output parameters value, the computed output parameters values through the regression relationship taken as the input into the above simulation procedures. In this approach slight improvement has been noticed in the Fuzzy as well as ANN method of computation. The final outcome of this try ended up, with the tuning of 9.91% improvement in the result. In both the cases the number of iterations is maintained as 50000 turns. The results are shown in the Table 5.2. As the method of the simulation with regression relationship equations and the regression computed values taken as the input performing with lowest level of

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mean error in compiling the results in order to project the results with smooth curve fittings the input parameters level are subdivided into equal parts as the step given in the Table 5.3.

Table 5.2 Comparison of regression formula, regression values as input

Method	Exp Value	Reg Formula	Reg Values
RSM	0.00011	0.00011	0.00011
Fuzzy	0.26789	0.26789	0.26661
ANN	0.27789	0.27789	0.27661
Fuzzy feed RSM	0.00011	0.00010	0.00009

Table 5.3 Step values allotment of input variables

Sl No	Parameter	Initial	Step value	Final value
1	Cutting speed (m / min)	35	10.6	88
2	Feed velocity (mm / min)	180	35	355
3	Depth of cut (mm)	1.0	0.08	1.4
4	Fluid flow rate (ml / hr)	300	100	900

The simulated results through the method adopted in the earlier steps with 50000 iterations are given in the Table 5.4 for the surface roughness, tool flank wear referring to the combination of speed 35 m/min, feed 180 mm/min with all the selected depth of cut 1.0 mm / min to 1.40 mm / min.

Table 5.4 Surface roughness and Flank wear of S = 35 m / min, F = 180 mm / min to DOC 1.0 to 1.40 mm min

	S = 35 m / min, F = 180 mm /min		S = 35 m / min, F = 180 mm /min		S = 35 m / min, F = 180 mm /min		S = 35 m / min, F = 180 mm /min		S = 35 m / min, F = 180 mm /min		S = 35 m / min, F = 180 mm /min	
	DOC = 1 mm /min		DOC = 1.08 mm /min		DOC = 1.16 mm /min		DOC = 1.24 mm /min		DOC = 1.32 mm /min		DOC = 1.40 mm /min	
FF	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**
300	0.801	0.256	0.810	0.249	0.820	0.247	0.752	0.243	0.778	0.242	0.815	0.238
400	0.754	0.222	0.802	0.231	0.811	0.215	0.817	0.223	0.827	0.207	0.840	0.205
500	0.732	0.209	0.793	0.208	0.802	0.202	0.811	0.185	0.822	0.197	0.752	0.191
600	0.771	0.185	0.781	0.182	0.790	0.181	0.803	0.176	0.812	0.174	0.823	0.170
700	0.765	0.165	0.772	0.160	0.784	0.156	0.793	0.157	0.803	0.153	0.752	0.149
800	0.754	0.143	0.767	0.138	0.778	0.137	0.787	0.135	0.795	0.129	0.742	0.127
900	0.748	0.118	0.756	0.117	0.765	0.113	0.776	0.110	0.784	0.107	0.763	0.101

The surface roughness and tool flank wear referring to the combination of Speed 35 m / min, feed 215 mm / min with all the selected depth of cut 1.0 mm / min to 1.40 mm / min are listed in the Table 5.5.

Table 5.5 Surface roughness and Flank wear of S = 35 m / min, F = 215 mm / min to DOC 1.0 to 1.40 mm min

	S = 35 m / min, F = 215 mm /min		S = 35 m / min, F = 215 mm /min		S = 35 m / min, F = 215 mm /min		S = 35 m / min, F = 215 mm /min		S = 35 m / min, F = 215 mm /min		S = 35 m / min, F = 215 mm /min	
	DOC = 1 mm /min		DOC = 1.08 mm /min		DOC = 1.16 mm /min		DOC = 1.24 mm /min		DOC = 1.32 mm /min		DOC = 1.40 mm /min	
FF	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**	**Ra**	**Fw**
300	0.783	0.285	0.754	0.285	0.786	0.280	0.821	0.277	0.851	0.277	0.885	0.270
400	0.714	0.258	0.744	0.273	0.779	0.242	0.813	0.240	0.842	0.254	0.877	0.250
500	0.707	0.261	0.738	0.230	0.772	0.220	0.800	0.231	0.832	0.228	0.866	0.228
600	0.698	0.218	0.730	0.216	0.762	0.212	0.791	0.209	0.824	0.207	0.860	0.203
700	0.687	0.195	0.720	0.193	0.751	0.189	0.784	0.186	0.820	0.186	0.849	0.201
800	0.681	0.175	0.712	0.169	0.742	0.169	0.774	0.168	0.808	0.160	0.842	0.160
900	0.670	0.149	0.703	0.149	0.737	0.146	0.768	0.145	0.799	0.140	0.833	0.138

The pictorial representations of the above values are given in the following Fig. 5.2 to 5.4.

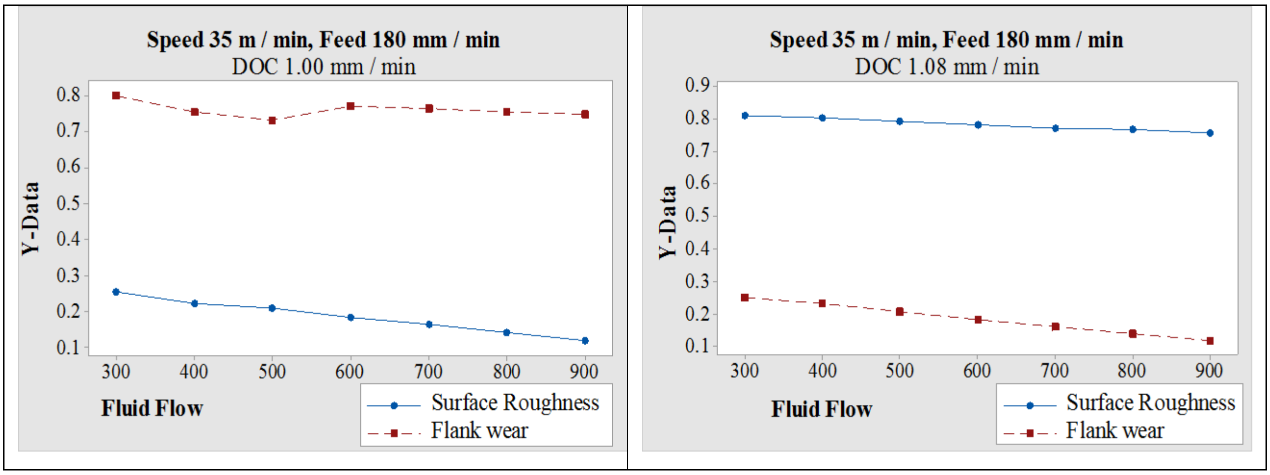

Figure 5.2 Surface roughness, Flank wear of speed 35 m /min, and feed 180 mm / min (DOC 1.0, 1.08 mm /min)

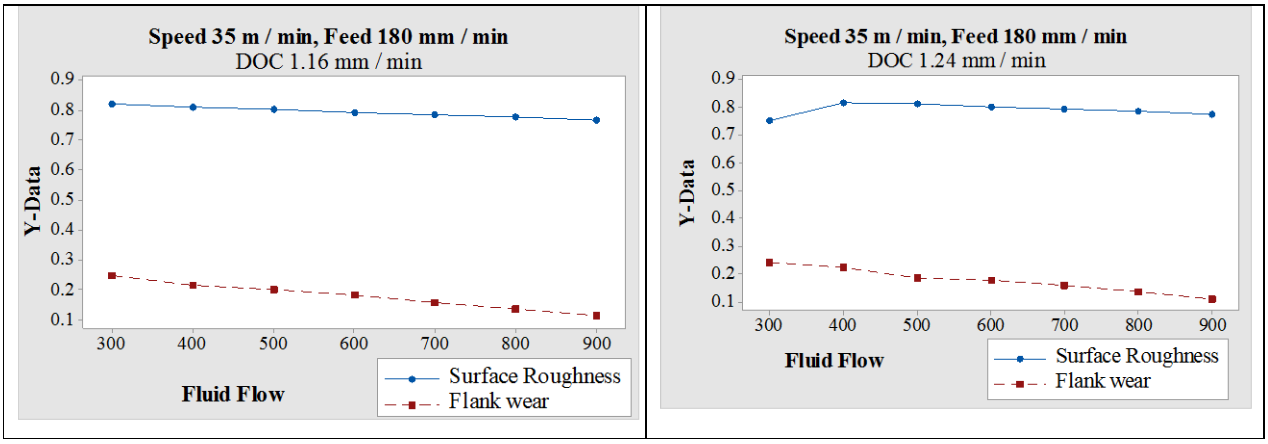

Figure 5.3 Surface roughness, Flank wear of speed 35 m /min, and feed 180 mm / min (DOC 1.16, 1.24 mm /min)

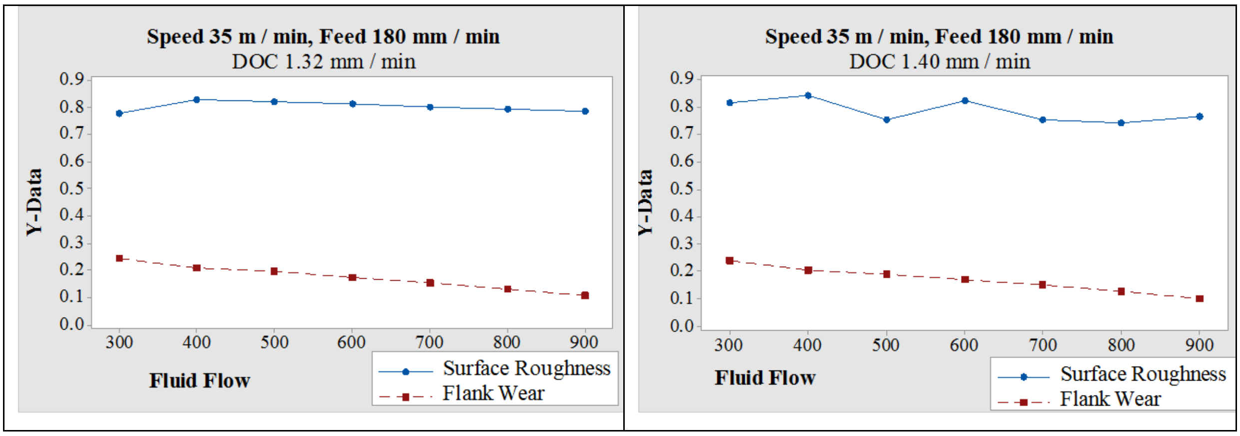

Figure 5.4 Surface roughness, Flank wear of speed 35 m /min, and feed 180 mm / min (DOC 1.30, 1.40 mm /min)

VI. RESULTS AND CONCLUSIONS

The highest influencing parameter is the cutting speed with 47.5% of contribution followed by the parameter feed velocity (29.6%) and subsequently queued lubricant fluid flow rate and depth of cut. In this attempt, simulation with regression relationship equations and the regression computed values taken as the input to the MATLAB programme.

The following conclusions are made:

The optimum combination of the input machining parameters for the surface quality is given in the Table 6.1 case wise (Experimental source, Computation through the regression equation and the simulation by Fuzzy output feed RSM method) which reveals the Fuzzy feed RSM simulation method yields good results.

Table 6.1 Optimized parameter combination for Surface roughness

Source	Speed	Feed	DOC	Fluid Flow	Ra
Experimental values	56	355	1.0	600	0.449
Regression equation values	56	355	1.0	600	0.455
Simulated values	35	355	1.0	900	**0.370**

Similarly the optimum combination of the input machining parameters for the minimum tool flank wear is given in the Table 6.2 case wise (Experimental source, Computation through the regression equation and the simulation by Fuzzy output feed RSM method) which reveals the Fuzzy feed RSM simulation method yields optimum results.

Table 6.1 Optimized parameter combination for Surface roughness

Source	Speed	Feed	DOC	Fluid Flow	Fw
Experimental values	56	180	1.2	900	0.202
Regression equation values	56	180	1.2	900	0.202
Simulated values	35	180	1.4	900	**0.101**

The proposed Fuzzy based feed RSM hybrid prediction model has exceptional conformity with investigational values, with mean value error of 0.00009 and this multi objective optimization approach is capable of predicting the optimum machining parameters combination in end milling operations of the tested Aluminium 6063 T6 material.

VII. RECOMMENDATIONS

The steps values between the input machining parameters may be taken in close range so as to simulated values much closer to form the further more smooth graphs. The outcome of the graph may be used as the reference guide by the manufacturers at time of processing the parts. Furthermore attempts may be initiated with the application of other familiar optimisation algorithms. The computed values of the regression relationship equations may be fed as the input values only after the confirmation of the statistical significance.

REFERENCES

[1] J.Wang, T.Kuriyagawa, X P. Wei and D M. Guo, Optimization of cutting condition for single pass turning operation using a deterministic approach, Int. J. Mach. Tools Manuf, 42, 2002, 1023-1033.

[2] T.Oezel and Y. Karpat, Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks, Int J Mach Tools Manuf, 45, 2005, 467-479.

[3] Raviraj shetty, Taguchi's techniques in machining of metal matrix composites. J. of the Braz .society of Mech.Sci. & Eng, 16 (1), 2009, 12-20.

[4] C. Ozel and E. Kilickap, Optimisation of surface roughness with GA approach in turning 15% SiCp reinforced AlSi7Mg2 MMC material, Int J Mach Machinability Mater, 1(4), 2006, 476-487.

[5] M. Nouari, G. List, F. Girot and D. Gehin, Effect of machining parameters and coating on wear mechanisms in dry drilling of aluminium alloys, Int J Mach Tools Manuf, 45, 2005, 1436-1442.

[6] C X. Feng, An experimental study of the impact of turning parameters on surface roughness, In: Proceedings of the Industrial Engineering Research Conference, 2001, Paper No. 2036. Dallas, TX.

[7] C C. Tsao, Grey - Taguchi method to optimize the milling parameters of aluminum alloy, Int. J. Adv. Mfg. Tech, 40, 2009, 41-48.

[8] D M. Haan, S A. Batzer, W W. Olson and J W. Sutherland, An experimental study of cutting fluid effects in drilling, J Mater Process Technol, 71, 1997, 305–313.

[9] R P. Zeilmann and W L. Weingaertner, Analysis of temperature during drilling of Ti6Al4V with minimal quantity of lubricant, J Mater Process Technol, 179, 2006, 124-127.

[10] V. David, M. Ruben, C. Menendez, J. Rodriguez and R. Alique, Neural networks and statistical based models for surface roughness prediction, International Association of Science and Technology for Development. Proceedings of the 25th IASTED international conference on Modeling, Identification and Control, 2006, 326-331.

[11] T. Rajasekaran, K. Palanikumar and B K. Vinayagam, Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool, Production Enineering Res. Deve, 5, 2011, 191-199.

ISBN: 978-93-86171-36-8

[12] D E. Kirby and C C. Joseph, Development of a Fuzzy-Nets-Based surface roughness prediction system in turning operations, Journal of Computers & Industrial Engineering. 53, 2007, 30-42.

[13] S A. Hussain, V. Pandurangadu and K. Palanikumar, Cutting power prediction model for turning of GFRP composites using response surface methodology, International Journal of Engineering Science and Technology, 3 (6), 2011, 161-171.

[14] F. Mata, E. Beamud, I. Hanafi, A. Khamlichi, A. Jabbouri and M. Bezzazi, Multiple regression prediction model for cutting forces in turning carbon-reinforced PEEK CF30, Advances in Materials Science and Engineering, 46, 2010, 1-7.

[15] J. Paulo Davim, A note on the determination of optimal cutting conditions for surface finish obtained in turning using design of experiments, J Mater Process Technol, 116, 2001, 305-308.

[16] K. Sundara Murthy and I. Rajendran, Optimization of end milling parameters under minimum quantity lubrication using principal component analysis and grey relational analysis, J. of Braz. Sco. Of Mech. Sci. & Eng, 34 (3), 2012, 253-257.