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Mutli-Objective Optimisation of Process Parameters in Statistical Relations Support ACO seed MFSA Method of Milling Operations Process on AL 6063-T6

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ABSTRACT

Milling process is one of the well accepted applications process in manufacturing as 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. With the objective of achieving the desired surface finish and minimum tool wear the optimization while milling Al 6063 – T6 material through accepted set of optimisation algorithms application in MATLAB programming this attempt is chosen. On identifying the best converged algorithm, subsequently the regression equations are incorporated in the programme as the initiation to predict the combination of optimised parameters in line with the defined objective and the simulation continued. The optimised parameter combinations were identified for each output parameter (Surface roughness and Tool flank wear).

Key words- Milling, Al6063-T6, Regression, Ant Colony Algorithm, Cuckoo Search, Genetic Algorithm, Modified Fish Swarm Algorithm, Particle Swarm Optimization Algorithm, Scatter Search Algorithm, Optimization, Minitab, MATLAB.

I. INTRODUCTION

Metal cutting through milling process is one of the very common operations in the manufacturing industries in fabricating the parts towards the final assembly purpose of the final product. In this context, achieving the desired surface quality is the challenging task. As the cutting tool wear also causative towards the surface quality as well as to the cost of production it is important in selection of the process parameters concern. The material Al 6063- T6 which is in the common usage of Architectural applications, Window frames, Doors, Shop fittings, Irrigation tubing, Extrusions, balustrade the rails and posts formed elbows etc. During this milling process the usual issues being faced are like the offset in dimensional accuracy and precision, required surface quality. Even then such primary issues have to be overcome. In this regard the main contributing attributes are 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.

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Inconsistency in the end surface quality of the produced parts also influenced through tool cutting edges stability which is the indication of tool flank wear. In turn the tools wear leads for the increase in cost of production and down time. As the selection of optimal cutting conditions and cutting parameters and machining environment is a prime call for any machining operations, this effort is taken with the aim on the multi-objective optimisation of process parameters cutting speed, depth of cut, feed, and cutting fluid flow rate in milling process of Al6063-T6 material.

Abbreviations Used

DOC	Depth of cut	R-sq (adj)	R - square adjusted statistical value
Exp	Experiment	R-sq (pred)	R - square predicted statistical value
F	Feed rate	S	Cutting speed
FF	Fluid Flow rate	GA	Genetic Algorithm
FW	Tool Flank Wear	SSA	Scatter Search Algorithm
MMC	Metal matrix composite	CSA	Cuckoo Search algorithm
Ra	Surface roughness	MFSA	Modified Fish Swarm Algorithm
Reg	Regression	PSO	Particle Swarm Optimization
R-sq	R - square statistical value	ACO	Ant Colony Algorithm

II. LITERATURE SURVEY

With the nonstop efforts put in by many researchers in making attempts through quite a lot of methods and skill to address the issues related and suggesting varieties in approaches to achieve the expected level of results in various machining processes on various materials like metals, alloys, composites. In addition, to identify and resolve the effects of input machining parameters on the output parameters almost all many of the researchers used optimization techniques. Tsao, C C [1] through the experimental investigation has proved the adaptability of Grey - Taguchi method in optimization of the parameters in milling operations on the aluminium alloy and predicted that the grey-Taguchi method is suitable for solving the surface finish quality and tool flank wear. Raviraj Shetty et al. [2] demonstrated by an exclusive study with the Taguchi optimization method for optimizing the process parameters in the turning operation on the age hardened AlSiC - MMC with CBN cutting tool. Paulo Davim, J [3] indicated that the higher cutting speed results in a smoother surface, through the application of Taguchi method in the experimental investigation conducted. Wang et al. [4] executed an experiment and optimized the machining variables involved for estimating and confirming the economic machining conditions in turning process by a deterministic approach.

David et al. [5] have predicted that the surface quality in high speed end-milling process by ANN approach and statistical tools towards different surface roughness predictor's combinations. In addition, Kirby, D.E, and Joseph, C.C. [6] have addressed and mapped the incidence of the quality issues in the resulting parameters in the operations performed on turning and milling machines which includes the machine tool condition, job clamping, tool and workpiece geometry, and cutting parameters used for machining. Finally, they developed a Fuzzy based prediction approach to optimize the surface roughness. Praveen Raj et al. [7] proved in their experimental investigation that the surface roughness, precision and damage factor in use of Ti-Namite carbide K10 end mill, Solid carbide K10 end mill and Tipped Carbide K10 end mill on GFRP composite material. Their analysis shows that, Ti-Namite coated carbide end mill and tipped carbide end mill produces causing little injure

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on GFRP composite material than the solid carbide end mill. Godfrey et al. [8] devised a novel model for correlating the relationships of drilling parameters and the effects on axial force and torque acting on the cutting tool by means of RSM approach. They have concluded that the torque varies non-linearly with reference to the chief cutting parameters like speed, feed rate, and diameter. Singh et al [9] have attempted in correlating the drilling-induced damage with the drilling parameters on UD-GFRP laminates.

III. EXECUTED EXPERIMENT AND OBSERVED DATA

K. Sundara Murthy and I. Rajendran, [10] executed an end milling operations experiment on the AL6063-T6 material specimen with the dimensions of 300 x 200 x 50 mm in the 3 HP powered universal geared type milling machine. The mechanical properties of the experimented material is with of Hardness (Brinell) - 73; Ultimate Tensile Strength - 241MPa; Tensile Yield Strength- 214 Mpa; Elongation – 12 %; Modulus of rigidity 68.9 - GPa; Fatigue strength – 68.9 GPa; Shear modulus – 25.8 GPa; Shear Strength – 152 MPa and Poisson’s ration- 0.33. LT740WWL category end mill cutting tool of 20 mm diameter with coated inserts APGT 1003 PDER-Alu LT05 are chosen to perform the operations. Vegetable oil coolube 2210 was applied as the cutting fluid in the process with MQL setup. The input machining variables chosen for the process in three states as noted in the Table 3.1. 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 3.1 Machining parameters and levels

Parameters	State 1	State 2	State 3
S, Cutting speed, m / min	35	56	88
F, Feed velocity, mm / min	180	250	355
DOC, Depth of cut, mm / min	1	1.2	1.4
FF, Fluid flow rate, ml / hr	300	600	900

Table 3.2 Experimental observed

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

Principal Component Analysis (PCA) and Grey Relational Analysis (GRA) were combined by K. Sundara Murthy and I. Rajendran, [10] to optimize the cutting parameters; genetic algorithm based artificial neural network hybrid prediction model is also proposed to estimate surface roughness and tool wear. Through this the

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conclusion projected is that the optimal parameters combination - cutting speed of 88 m / min, feed velocity of 180 mm / min, depth of cut of 1.4 mm and coolant flow rate of 600 ml / hr.

IV. MATHEMATICAL MODELING

To access the influence of the input variables (Cutting speed, Tool Feed, Depth of cut and Cutting fluid flow rate) on the output variables (Surface roughness and Tool flank wear) through the regression analysis Minitab17 software is used. Since the R - sq values are better in second order equations than the first order which indicates that the predictors explain about 99.91% of the variance in the output variables, also the adjusted R - sq values are close to the R - sq values which accounts for the number of predictors in the regression model and reveals the model fits significantly. In the way, such 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 x S) – (0.010475 x F) – (0.945 x DOC) – (0.000085 x FF) + (0.000010 x S x F) – (0.01042 x S x DOC) + (0.007964 x F x DOC)

(4.1)

“FW = -(0.363) + (0.01709 x S) + (0.001596 x F) + (0.171 x DOC) – (0.000224 x FF) – (0.000025 x S x F) – (0.00700 x S x DOC)+ (0.000182 x F x DOC)

(4.2)

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 outcome.

V. OPTIMIZATION METHODOLOGIES ADOPTED

The objective functions taken for the optimization to obtain minimum surface roughness and minimum tool flank wear. Analysis to optimise and predict the outcome are executed by applying Ant Colony Algorithm, Cuckoo Search, Genetic Algorithm, Modified Fish Swarm Algorithm, Particle Swarm Optimization Algorithm, Scatter Search Algorithm in the MATLAB programming with Elman Back Propagation. The experimental data set are given initially to train the programme with random selection of parameter values and compiled with 5000 iterations. The performance of the simulation referring with MSE values of each algorithm is evaluated. It has been noted that Modified Fish Swarm Algorithm converges as the best with minimum mean error in simulation followed by the ACO, PSO, SSA, CSA, GA respectively as listed in the Table 5.1. With an idea of feeding the simulated outcome of the second best fit algorithm (ACO) to the first best fit algorithm (MFSA) as the initial parameters set and the procedure of simulation carried out. Hybridization of regression relationship equations as the condition for simulation is also put in effect.

Table 5.1 Error level exhibit of Algorithms

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Algorithms	Error level	Position
Modified Fish swarm algorithm	0.000058735	1
Ant Colony Algorithm	0.000063761	2
Particle Swarm Optimization Algorithm	0.000066925	3
Scatter Search Algorithm	0.000072214	4
Cuckoo Search	0.000075116	5
Genetic Algorithm	0.000090946	6

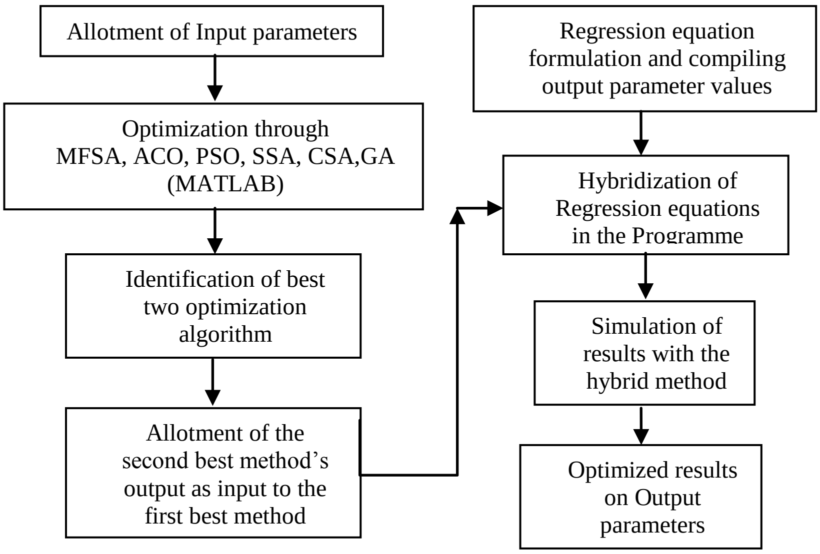

Figure 5.1 Block diagram of hybridization

As this effort yields improved state of results, for projecting the results with smooth curve fittings the input parameters level are subdivided into equal parts into steps as given in the Table 5.2.

Table 5.2 Step values allotment of input variables

Sl No	Parameter	Initial Value	Step value	Final value
1	Cutting speed (m / min)	35	3.533333	88
2	Feed velocity (mm / min)	180	11.666667	355
3	Depth of cut (mm)	1.0	0.026666	1.4
4	Fluid flow rate (ml / hr)	300	40	900

Table 5.3 Simulated results of v = 35; f = 180 (DOC 1.00, 1.03, 1.05)

fluid flow	DOC = 1.00		DOC = 1.03		DOC = 1.05	
	Ra	Tool Wear	Ra	Tool Wear	Ra	Tool Wear
300	0.799	0.256	0.803	0.252	0.804	0.252
340	0.687	0.256	0.798	0.274	0.803	0.278
380	0.882	0.238	0.796	0.236	0.796	0.232

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420	0.789	0.247	0.793	0.227	0.794	0.224
460	0.784	0.220	0.788	0.216	0.790	0.215
500	0.781	0.240	0.783	0.206	0.788	0.208
540	0.775	0.201	0.782	0.200	0.784	0.200
580	0.774	0.194	0.776	0.189	0.783	0.191
620	0.773	0.184	0.774	0.180	0.780	0.181
660	0.767	0.174	0.770	0.172	0.776	0.171
700	0.763	0.166	0.767	0.163	0.773	0.164
740	0.761	0.156	0.765	0.153	0.769	0.154
780	0.758	0.146	0.759	0.148	0.764	0.142
820	0.752	0.138	0.756	0.134	0.762	0.133
860	0.750	0.127	0.753	0.126	0.652	0.128
900	0.745	0.118	0.751	0.116	0.656	0.116

Table 5.4 Simulated results of v = 35; f = 180 (DOC 1.08, 1.11, 1.13)

fluid flow	DOC = 1.08		DOC = 1.11		DOC = 1.13	
	Ra	Tool Wear	Ra	Tool Wear	Ra	Tool Wear
300	0.806	0.253	0.692	0.249	0.711	0.248
340	0.806	0.274	0.808	0.266	0.810	0.256
380	0.801	0.232	0.690	0.233	0.706	0.228
420	0.798	0.222	0.801	0.222	0.803	0.253
460	0.794	0.215	0.798	0.214	0.800	0.214
500	0.791	0.205	0.794	0.206	0.685	0.205
540	0.789	0.199	0.793	0.198	0.678	0.196
580	0.786	0.188	0.788	0.185	0.676	0.183
620	0.779	0.180	0.782	0.178	0.685	0.179
660	0.778	0.169	0.670	0.170	0.687	0.165
700	0.774	0.159	0.673	0.160	0.691	0.158
740	0.659	0.153	0.677	0.149	0.696	0.151
780	0.663	0.142	0.681	0.142	0.700	0.139
820	0.667	0.132	0.686	0.132	0.705	0.135
860	0.671	0.123	0.691	0.122	0.710	0.125
900	0.676	0.119	0.695	0.118	0.715	0.114

Out of 57600 set of simulated results through the method adopted in the earlier steps with 50000 iterations, in the Table 5.3 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 1.05 mm / min are listed. Subsequent Table 5.4

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depicts the results for the DOC 1.08 mm / min to 1.13 mm / min. Fig. 5.2 to 5.7 represents the curve fit in for the simulated results.

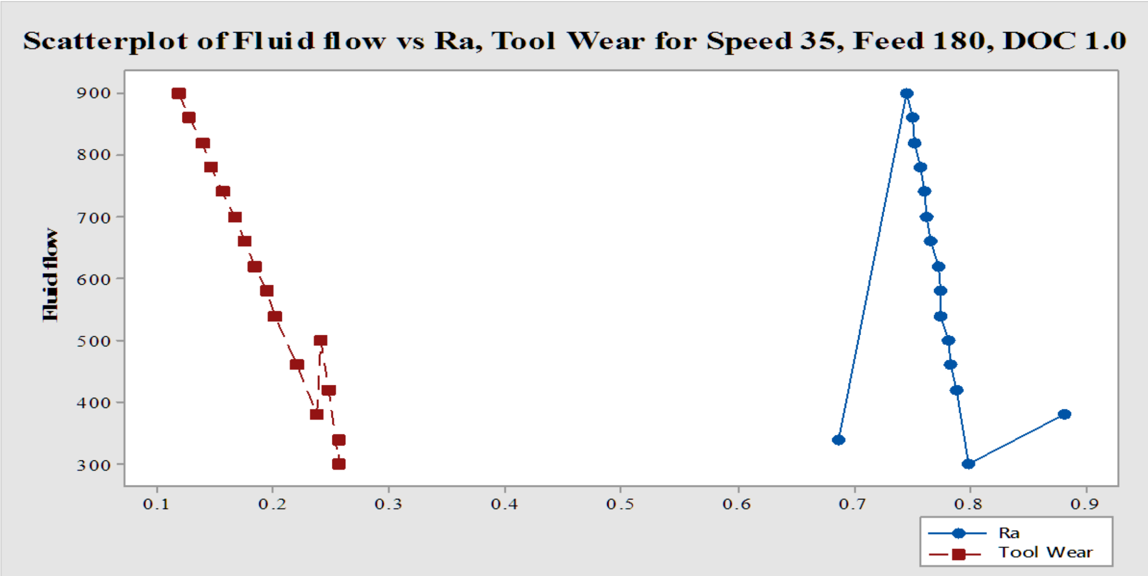

Figure 5.2 Fluid Flow Vs Ra, Tool wear for Speed 35, Feed 180, DOC 1.0

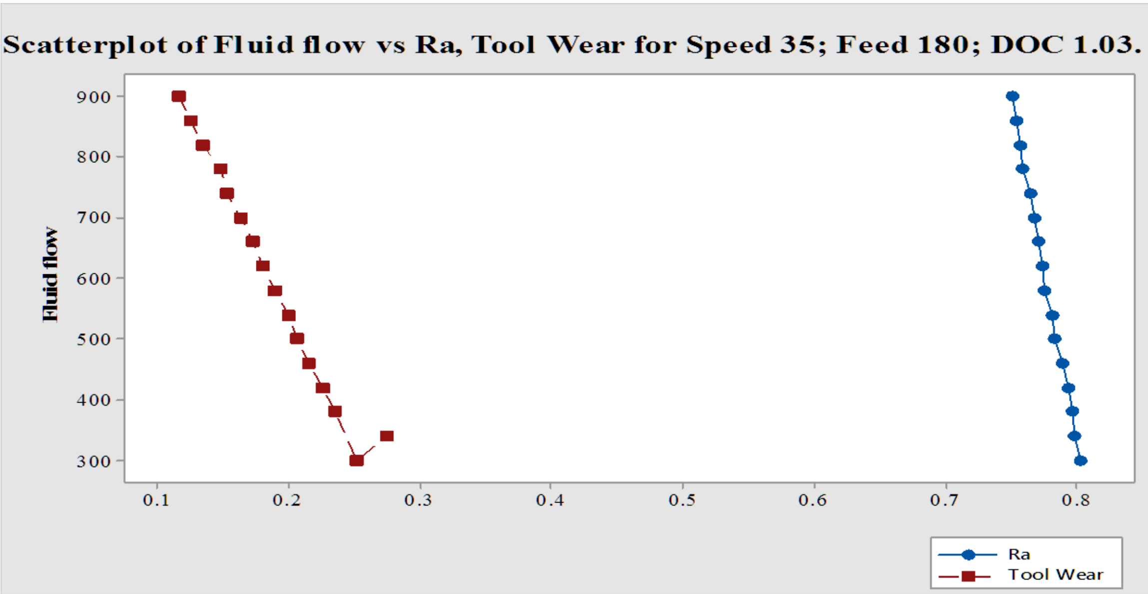

Figure 5.3 Fluid Flow Vs Ra, Tool wear for Speed 35, Feed 180, DOC 1.03

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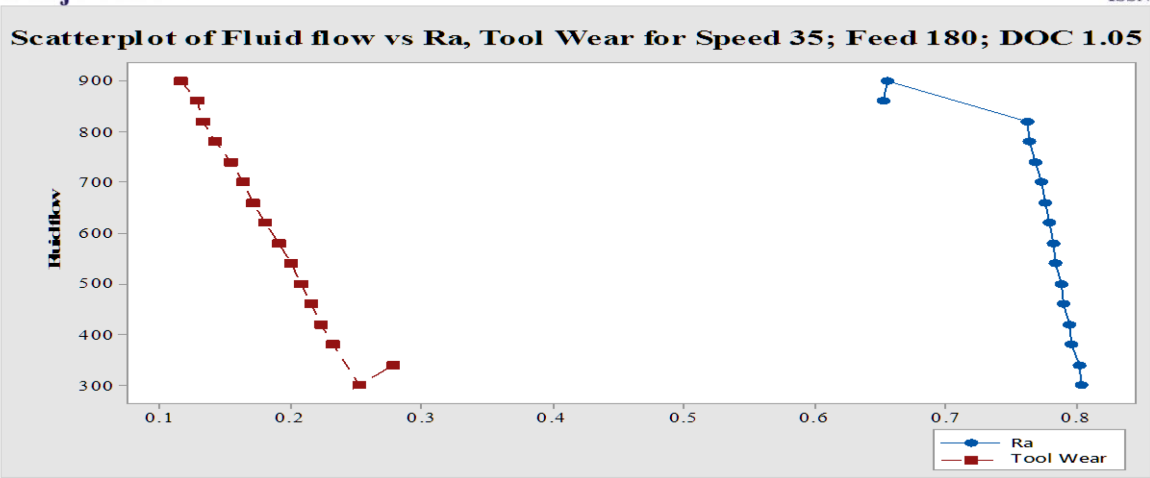

Figure 5.4 Fluid Flow Vs Ra, Tool wear for Speed 35, Feed 180, DOC 1.05

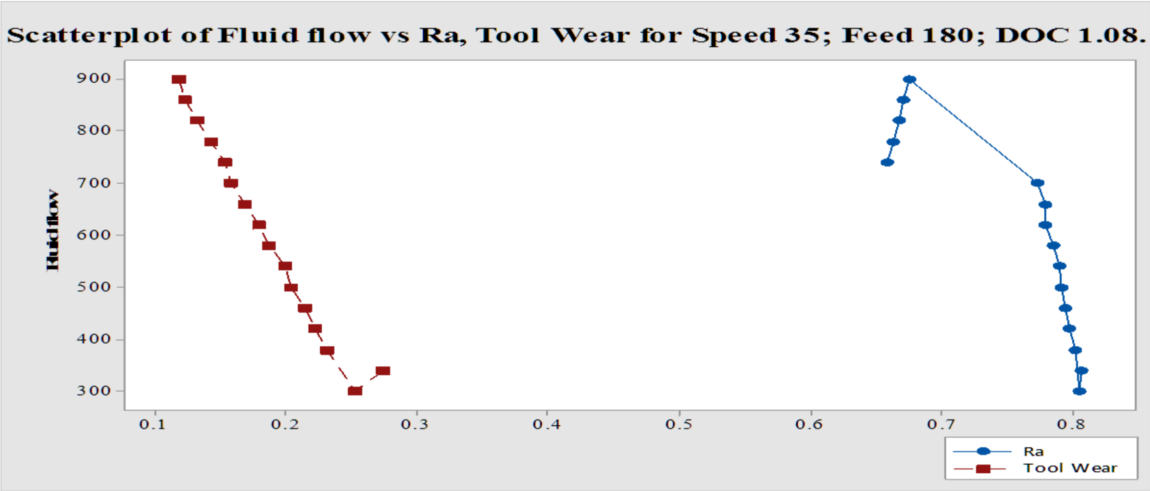

Figure 5.5 Fluid Flow Vs Ra, Tool wear for Speed 35, Feed 180, DOC 1.08

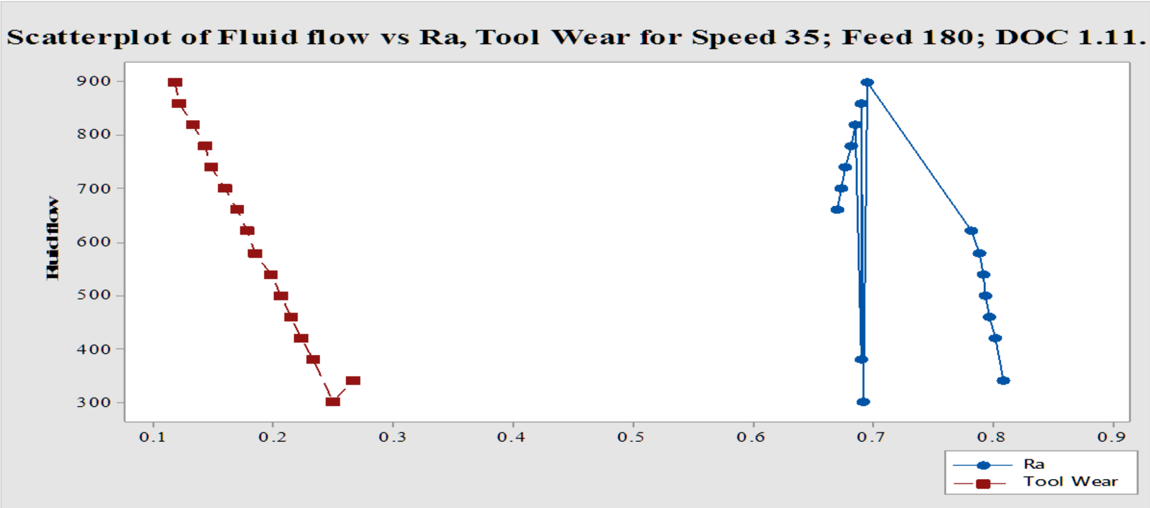

Figure 5.6 Fluid Flow Vs Ra, Tool wear for Speed 35, Feed 180, DOC 1.11

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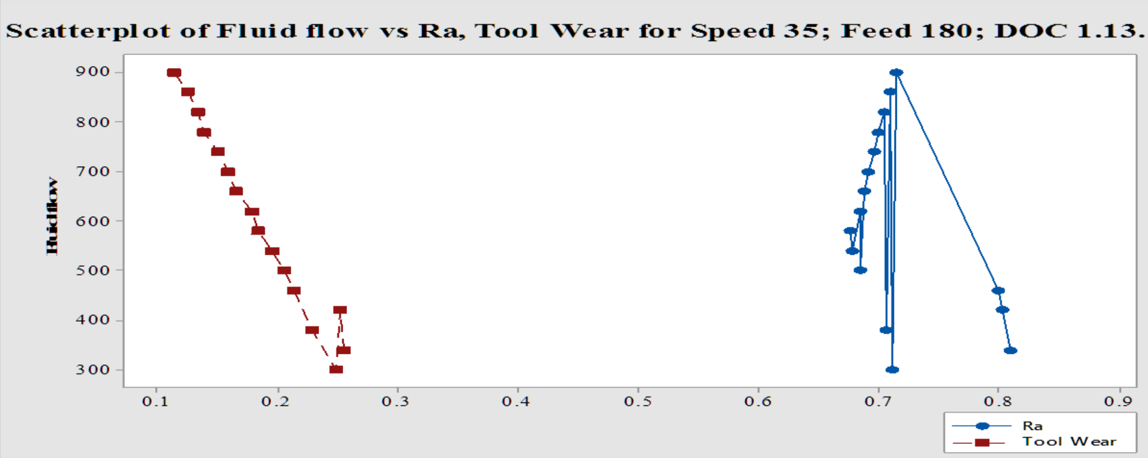

Figure 5.7 Fluid Flow Vs Ra, Tool wear for Speed 35, Feed 180, DOC 1.13

6 RESULTS AND CONCLUSIONS

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. Modified Fish Swarm Algorithm converges as the best with minimum mean error in simulation followed by the ACO, PSO, SSA, CSA, GA respectively.

Table 6.1 Optimized parameter combination for Surface roughness and Tool wear

Parameter	v	f	DOC	Fluid flow	Optimal Value
Ra	**35.00**	**343.33**	**1.03**	**740**	**0.389**
Tool Wear	**35.00**	**180.00**	**1.37**	**900**	**0.104**

The proposed regression relationship coupled ACO feed MFSA algorithm model has the conformity with investigational values, with mean value error of 0.00006 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. The fit in curves may be used as the reference to the manufacturers at time of processing. The regression relationship equations may be taken as the input phenomenon for simulation only after the confirmation of the statistical significance.

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