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EVALUATION AND OPTIMISATION OF OPERATIONAL CONDITION THROUGH ACO SEED SCATTER SEARCH ALGORITHM FOR TURNING PROCESS ON AISI 316 L MATERIALS

Dr.D.Ramalingam[1], Dr.M.Saravanan[2], R.Rinu Kaarthikeyen[3]
M.Angel Shalini[4]

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

[2]Principal, SSM Institute of Engineering and Technology, Dindigul, (India)

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

[4]Research Scholar, Sri Ramakrishna College for Women, Coimbatore, (India)

ABSTRACT

Machining the materials and getting the required range of surface finish within the permissible range is one of the major setbacks in the manufacturing industries concern. Though there are many conventional metal cutting processes are there in practices, turning process is the most advantageous machining process and very commonly used by the manufacturing industries that too with automation and rigidity of the machine tool with high range of speed, feed improvement. Even then, the factors influencing this surface quality which are many in numbers, the main cutting condition variables like spindle speed, tool feed rate on the work material, depth of cut given on the material per travel are the major concerns. Henceforth right selection of such parameters and their suitable combinations are one of the top priority responsibilities by the operation engineers which are highly possible either through conventional or evolutionary optimisation techniques. Investigating and optimizing the combination of the input machining parameters to achieve the desired surface finish is considered as the objective of this presentation with the Ant Colony Optimisation seed Scatter Search algorithm technique in MATLAB programming. With the Reference to the convergence performance of the algorithms the hybridization of regression equations feed as input to the programming further simulation carried out. The outcomes of the results are found to be improved by each phase of the simulation. The optimum parameter combinations for improved surface finish are identified.

Keywords-*AISI 316L steel material, Turning, Regression, Ant Colony Algorithm, Genetic Algorithm, Scatter Search Algorithm, Particle Swarm Optimisation, Hybridization, Minitab, MATLAB.*

I. INTRODUCTION

AISI 316L steel material is preferred in the application in medical field as biomaterials, biomedical implants, biocompatible materials, chemical processing as it owes to the superior corrosion resistance to inter granular corrosion, to most chemicals, salts, acids and high creep strength even at elevated temperatures. Since material is being used for special applications, the surface finish quality calls to high degree of importance. Any material would have to undergo the machining processes before it attains its final shape and dimension. While such metal cutting operations are being carried out to the final stage, manufacturing to the required surface quality is the quite common issues, because of the variables involving in the machining are having its own impact on the outcome of the processing either individual or in combination. The important input cutting parameters among all are cutting speed, tool feed and the depth of cut in every pass. Henceforth right selection of such parameters and their suitable combinations are one of the top priority responsibilities by the operation engineers, to obtain desired surface quality and also to avoid rejection rate and rework. This investigation primarily aimed onto the analysis and optimisation of cutting variables like cutting speed, feed and depth of cut on the resultant parameter surface roughness.

Abbreviations Used

C_S	Cutting speed	GA	Genetic Algorithm
DOC	Depth of cut	R-sq	R - square statistical value
Exp	Experiment	R-sq (adj)	R - square adjusted statistical value
f	Feed rate	R-sq (pred)	R - square predicted statistical value
PSO	Particle Swarm Optimization	Reg	Regression
ACO	Ant Colony Optimisation Algorithm	Ra	Surface Roughness
SSA	Scatter Search Algorithm		

II. LITERATURE REVIEW

The importance of the surface quality is acknowledged by all researchers and manufacturers as this attribute has a distinct impact on the functional aspects of any product. Industrializing a product with reasonable surface quality, dimensional accuracy and precision is getting vital importance on the objectives of manufacturing. Researchers made attempts and confirmed that by make use of the optimization methodologies to achieve these objectives is possible. Maciej Grzenda et al [1] have experimented in face milling process and suggested with a roughness prediction model through a hybrid algorithm which was the combination of Genetic Algorithm and Neural Networks in high-torque. Azlan Mohd Zain et al [2] have investigated through the end milling operations by applying Genetic Algorithm (GA) to optimize the machining conditions in view of minimizing the surface roughness. With reference to the real machining data, the authors developed a best regression model to devise the fitness function of the GA. The outcome of the analysis was that the GA technique is capable of estimating the optimal machining conditions. Muthukrishnan et al. [3] experimented the application of ANN as well as ANOVA analysis for optimization of machining parameters in turning AlSiC composites and declared that both ANOVA and ANN modeling offer an organized and efficient method on optimization. Through their study Oezel T, Karpat Y [4] have announced that the surface roughness 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.). Tekiner and Yesilyurt [5] examined the suitable process parameters in the turning operations AISI 304 austenitic stainless steels. Hascalik et al [7] stated through their research the optimum selection of process condition is extremely important as this one determine surface quality and flank wear phenomena of the manufactured parts. In turning and facing operations an improper selection of cutting parameters will cause undesired surface roughness and high tooling cost. In order to decide the surface quality and tool wear the statistical design of experiments is used quite extensively. Suresh et al. [8] have developed a mathematical model for predicting value of surface roughness while machining mild steel using response surface methodology and optimized the developed model using genetic algorithm, in order to attain the required surface quality. Tzeng and Chen [9] used grey relational analysis to optimize the process parameters in turning of tool steels. The optimum turning parameters were determined based on grey relational grade, which maximizes the accuracy and minimizes the surface roughness and dimensional precision. The main aim of this investigation is to study the influence of the input machining parameters during turning operation on the average surface roughness of the machined surface. The examination and forecasting of optimized parametric combination is recognized through the application of ACO, PSO, GA and SSA algorithms through MATLAB programming. Also with a new approach as feeding the regression equation relationship as input fitness instead of random selection while simulation.

III. EXPERIMENTAL DATA

The properties of the work material AISI 316L steel taken for the experiment is material listed in the Table 3.1. In CNC lathe OKUMA Lb 10II model, a coated tool -DNMG 110402-M3 with TP 2000 coated grade which has rhombic shape with cutting edge angle 55° is used as the cutting tool to conduct the experiment by Nokolaos [12]. The coating on the tool is of four layers of Ti [C, N] + Al_2O_3 + Ti [C, N] + TiN with the cutting edge angle as 93°.

Table 3.1 Mechanical properties of AISI 316L material

Property	Quantity
Hardness, Rockwell B	79 HRB
Tensile strength, ultimate	560 MPa
Tensile strength, yield	290 MPa
Elongation of break	50%
Modulus of elasticity	193 GPa
Poisson's ratio	0.29

The main input cutting parameters identified and taken are the spindle speed, feed and depth of cut and the main resultant parameter is surface roughness of the product. The level of input parameter selected is listed through the Table 3.2. L_{27} Taguchi array is the plan of experiment and the experimental outcome observed is given through the Table 3.3

Table 3.2 Machining parameters and levels

Parameters	Units	Level 1	Level 2	Level 3
C_S, Cutting speed	m / min	265	356	440
f, Feed	mm / rev	0.06	0.08	0.12
DOC, Depth of cut	mm / min	0.10	0.15	0.20

Table 3.3 Experimental observed data

Exp No	S	F	DOC	Ra	Exp No	S	F	DOC	Ra
1	265	0.12	0.10	0.323	15	356	0.06	0.15	0.303
2	265	0.08	0.10	0.292	16	265	0.12	0.15	0.349
3	265	0.06	0.10	0.289	17	265	0.08	0.15	0.307
4	356	0.12	0.10	0.295	18	265	0.06	0.15	0.307
5	356	0.08	0.10	0.280	19	265	0.12	0.20	0.460
6	356	0.06	0.10	0.266	20	265	0.08	0.20	0.411
7	440	0.12	0.10	0.237	21	265	0.06	0.20	0.410
8	440	0.08	0.10	0.215	22	356	0.12	0.20	0.405

9	***440***	***0.06***	***0.10***	***0.176***	23	356	0.08	0.20	0.369
10	440	0.12	0.15	0.319	24	356	0.06	0.20	0.344
11	440	0.08	0.15	0.317	25	440	0.12	0.20	0.393
12	440	0.06	0.15	0.251	26	440	0.08	0.20	0.348
13	356	0.12	0.15	0.330	27	440	0.06	0.20	0.345
14	356	0.08	0.15	0.321	-	-	-	-	-

As per the experimental observed data the minimum surface roughness is recorded as 0.176 for the input cutting parameters combination speed 440 m / min, feed 0.06 mm / rev and depth of cut 0.10 mm.

IV. MATHEMATICL MODELLING

With the software Minitab 17 the statistical analysis is accrued out to estimate the affiliation of the inputs vs. output variables. Durbin Watson value in the second order equations are lies between 1to 2 which indicates that there is positive auto correlation between the predictors. Also the second order equation indicates that the predictors (input variables) explain 92.81% of the variance in the output variables. Regression models comparison for the statistical significance and the statistical values of the equations are tabulated in Table 4.1.

Table 4.1 Regression model

Regression	R-sq	R-sq	R-sq (pred)
First order	90.77%	89.56%	87.35%
Second order	92.81%	89.01%	81.38%

The adjusted R - sq values are close to the R - sq values which accounts for the number of predictors in the regression model. As both the values together reveal that the model fits the data significantly. With respect to the analysis outcome, the second order regression relationship equation is taken for further evaluation and optimizing the parameters. The residual plots outcome of the statistical modeling is shown in Fig. 4.1.

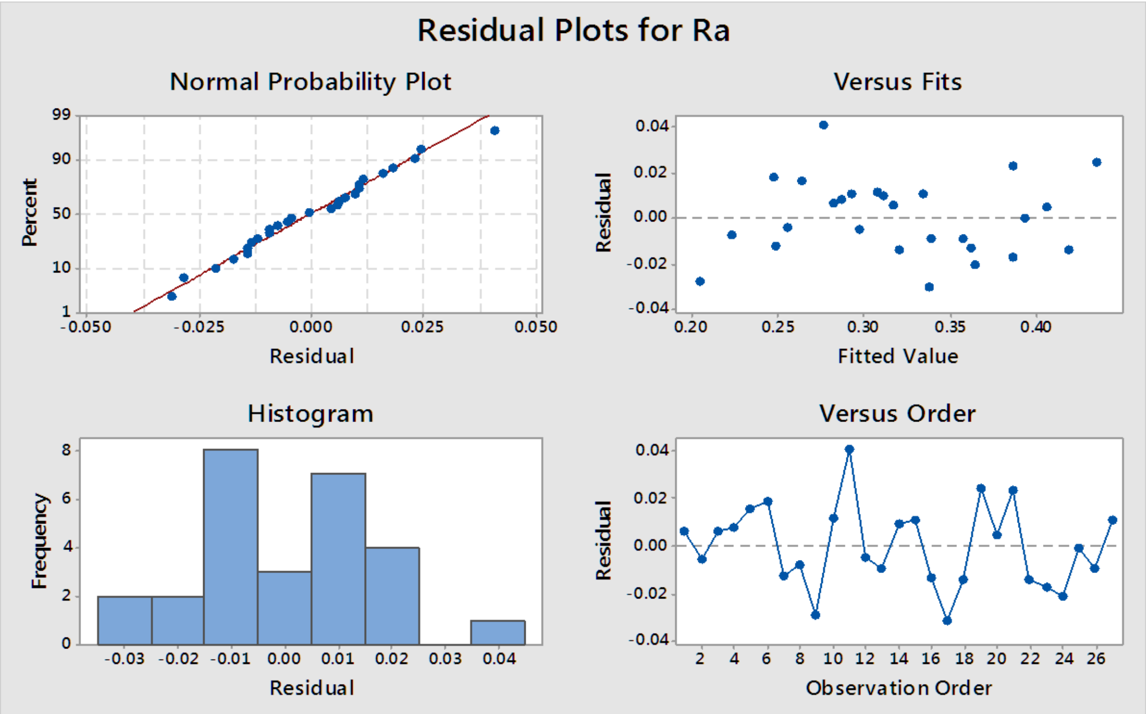

Figure 4.1 Residual plots of surface roughness

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Second order regression equations in terms of speed, feed and depth of cut combination is that,
Ra = (0.331) – (0.000148 x Cs) + (0.79 x f) – (1.16 x DOC) – (0.000001 x Cs^2) – (4.0 x f^2) + (5.56 x DOC^2) + (0.00100 x Cs x f) + (2.40 x f x DOC) + (0.00147 x Cs x DOC); where Cs represents the cutting speed, f denotes the feed and DOC represents the depth of cut. Through the best subset analysis result framed by Minitab software and also by analyzing the coefficients of each input parameters the feed is contributing more influence on the surface roughness comparing to the other two input variables.

Table 4.2 Regression computed values of the surface roughness.

Exp	Cs	f	DOC	Ra	Exp	Cs	f	DOC	Ra
1	265	0.12	0.10	0.298	15	356	0.06	0.15	0.257
2	265	0.08	0.10	0.278	16	265	0.12	0.15	0.343
3	265	0.06	0.10	0.263	17	265	0.08	0.15	0.319
4	356	0.12	0.10	0.252	18	265	0.06	0.15	0.302
5	356	0.08	0.10	0.229	19	265	0.12	0.20	0.416
6	356	0.06	0.10	0.212	20	265	0.08	0.20	0.387
7	440	0.12	0.10	0.195	21	265	0.06	0.20	0.368
8	440	0.08	0.10	0.169	22	356	0.12	0.20	0.384
9	***440***	***0.06***	***0.10***	***0.150***	23	356	0.08	0.20	0.351
10	440	0.12	0.15	0.254	24	356	0.06	0.20	0.330
11	440	0.08	0.15	0.222	25	440	0.12	0.20	0.340
12	440	0.06	0.15	0.201	26	440	0.08	0.20	0.303
13	356	0.12	0.15	0.304	27	440	0.06	0.20	0.280
14	356	0.08	0.15	0.276	-	-	-	-	-

The computed values for the same set of input parameters with the regression relationship is charted via Table 4.2 which reveals that the minimum surface roughness is recorded as 0.176 for the input cutting parameters combination speed 440 m / min, feed 0.06 mm / rev and depth of cut 0.10 mm.

V. OPTIMIZATION METHODOLOGIES

The aim of this attempt is to examine the force of the input cutting parameters on the resultant surface roughness and also to estimate the optimal combination of the variables to obtain the required level of output according to the final application. Optimisation techniques chosen are Ant Colony Algorithm, Genetic Algorithm, Scatter Search Algorithm, Particle Swarm Optimisation which are the popular algorithms applied by many researchers. Initially all the four algorithms are trained with the experimented data in MATLAB programming by random selection of the input for data training with the Gradient Descent with Momentum and Adaptive Learning. The indicator of the simulation performance is the mean squared error (MSE) in computation. The simulation programme was scheduled to take the regression equation relationship as input selection and allowed to compile. The performance order based on the MSE with the given set of parameters and the conditions of the regression relationship is given in the Table 5.1.

Table 5.1 MSE comparison of the algorithms

S No	Algorithm	MSE	Ranking
1	Scatter Search Algorithm	0.000342549	1
2	Ant Colony Algorithm	0.000361329	2
3	Particle Swarm Optimisation	0.000361396	3
4	Genetic Algorithm	0.000678061	4

Scatter search algorithm converged with the most minimum MSE and the ACO, PSO, GA are converged subsequently with small quantity difference of MSE. As ACO is in the second place of the performance the outcome of the ACO is taken as the seed values for the first best SSA and hybridization compiling is allowed. The MSE value of this ACO seed SSA approach is resulted with the further reduced quantity **0.000254275.** The convergence of the seed approach is found to be which confirms the enhanced results. The pictorial representation of the proposed method is shown in Fig. 5.1.

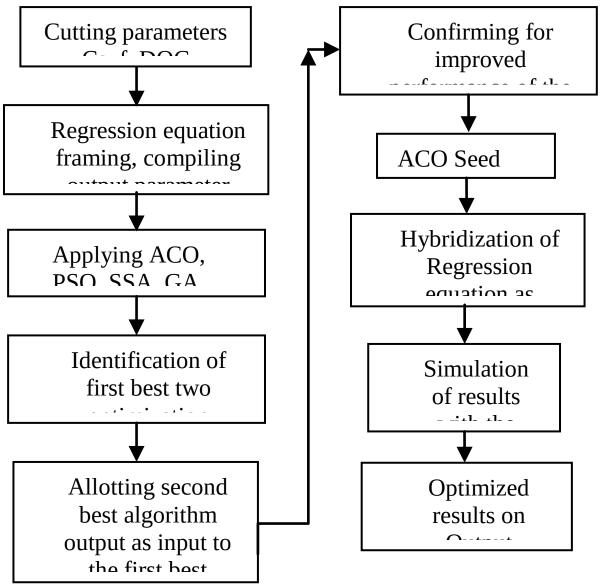

Figure 5.1 Block diagram of Hybridization of Regression in PSO Algorithm

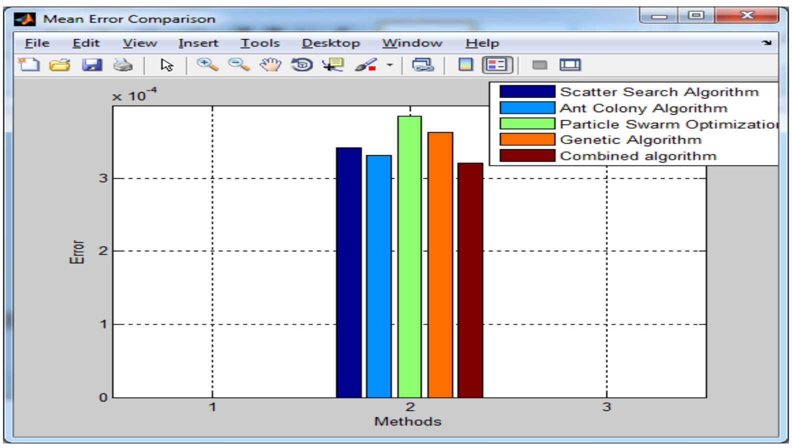

Figure 5.2 MSE comparison of Algorithms

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The step values given as input for simulation are as Speed = (265:17.5:440); Feed = (0.06:0.006:0.12); and Depth of cut = (0.10:0.01:0.20). The simulated results through the method adopted are marked in the Table 5.2, 5.3 and Table 5.4 for combination of speed, feed and depth of cut marked respectively.

Table 5.2 Iterated values of Ra for S 265 m / min, F 0.60 – 0.120 mm / rev and DOC 0.10 – 0.20 mm

Speed, 265 m /min											
f →	0.060	0.066	0.072	0.078	0.084	0.090	0.096	0.102	0.108	0.114	0.120
DOC	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra
0.10	0.310	0.311	0.311	0.312	0.313	0.278	0.285	0.292	0.298	0.303	0.308
0.11	0.305	0.306	0.277	0.289	0.297	0.304	0.309	0.313	0.317	0.320	0.322
0.12	0.308	0.299	0.305	0.309	0.312	0.314	0.317	0.319	0.322	0.324	0.327
0.13	0.283	0.300	0.303	0.306	0.310	0.314	0.318	0.321	0.324	0.327	0.330
0.14	0.304	0.293	0.301	0.307	0.312	0.317	0.320	0.323	0.326	0.329	0.332
0.15	0.329	0.300	0.306	0.311	0.315	0.319	0.323	0.326	0.329	0.332	0.335
0.16	0.339	0.301	0.307	0.312	0.317	0.321	0.325	0.328	0.331	0.334	0.337
0.17	0.359	0.357	0.309	0.314	0.319	0.323	0.327	0.330	0.334	0.337	0.397
0.18	0.377	0.374	0.373	0.378	0.378	0.383	0.389	0.394	0.400	0.413	0.422
0.19	0.400	0.400	0.398	0.398	0.401	0.403	0.410	0.417	0.425	0.436	0.446
0.20	0.423	0.421	0.425	0.423	0.427	0.433	0.436	0.446	0.455	0.463	0.477

Table 5.3 Iterated values of Ra for S 282.5 m / min, F 0.60 – 0.120 mm / rev and DOC 0.10 – 0.20 mm

Speed, 282.5 m /min											
f →	0.060	0.066	0.072	0.078	0.084	0.090	0.096	0.102	0.108	0.114	0.120
DOC	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra
0.10	0.310	0.312	0.315	0.317	0.319	0.322	0.328	0.285	0.292	0.298	0.304
0.11	0.268	0.311	0.314	0.277	0.289	0.298	0.305	0.310	0.314	0.317	0.320
0.12	0.268	0.287	0.299	0.305	0.309	0.312	0.315	0.318	0.321	0.323	0.326
0.13	0.277	0.294	0.300	0.303	0.307	0.311	0.315	0.319	0.323	0.326	0.329
0.14	0.285	0.283	0.293	0.301	0.307	0.313	0.317	0.321	0.325	0.328	0.331
0.15	0.333	0.288	0.297	0.304	0.310	0.315	0.320	0.324	0.328	0.331	0.335
0.16	0.343	0.344	0.300	0.307	0.313	0.318	0.323	0.327	0.330	0.334	0.337
0.17	0.356	0.359	0.357	0.309	0.315	0.320	0.325	0.329	0.333	0.337	0.341
0.18	0.372	0.371	0.372	0.374	0.377	0.382	0.383	0.393	0.399	0.405	0.417
0.19	0.391	0.394	0.394	0.392	0.399	0.399	0.407	0.411	0.417	0.429	0.437
0.20	0.414	0.414	0.415	0.414	0.420	0.422	0.429	0.436	0.442	0.456	0.464

Table 5.4 Iterated values of Ra for S 440 m / min, F 0.60 – 0.120 mm / rev and DOC 0.10 – 0.20 mm

Speed, 440 m /min											
f →	0.060	0.066	0.072	0.078	0.084	0.090	0.096	0.102	0.108	0.114	0.120
DOC	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra
0.10	0.235	0.253	0.265	0.278	0.285	0.293	0.297	0.296	0.296	0.293	0.292
0.11	0.223	0.241	0.256	0.257	0.305	0.308	0.313	0.315	0.317	0.313	0.312
0.12	0.243	0.254	0.304	0.311	0.322	0.327	0.331	0.336	0.333	0.332	0.328
0.13	0.294	0.270	0.288	0.288	0.339	0.341	0.346	0.352	0.351	0.350	0.345

0.14	0.297	0.327	0.338	0.345	0.354	0.361	0.365	0.366	0.365	0.367	0.361
0.15	0.327	0.331	0.330	0.327	0.326	0.324	0.378	0.380	0.383	0.380	0.378
0.16	0.327	0.355	0.365	0.372	0.379	0.386	0.393	0.396	0.396	0.396	0.393
0.17	0.326	0.343	0.334	0.335	0.395	0.401	0.404	0.406	0.408	0.409	0.407
0.18	0.328	0.340	0.350	0.348	0.403	0.412	0.415	0.418	0.422	0.420	0.421
0.19	0.375	0.357	0.360	0.365	0.366	0.365	0.424	0.430	0.429	0.432	0.434

The graphical representation of the surface roughness with respect to the speed 265 m / min for all combination of depth of cut and feed of 0.60 mm / rev, 0.090 mm/ rev are shown in the Fig. 5.3.

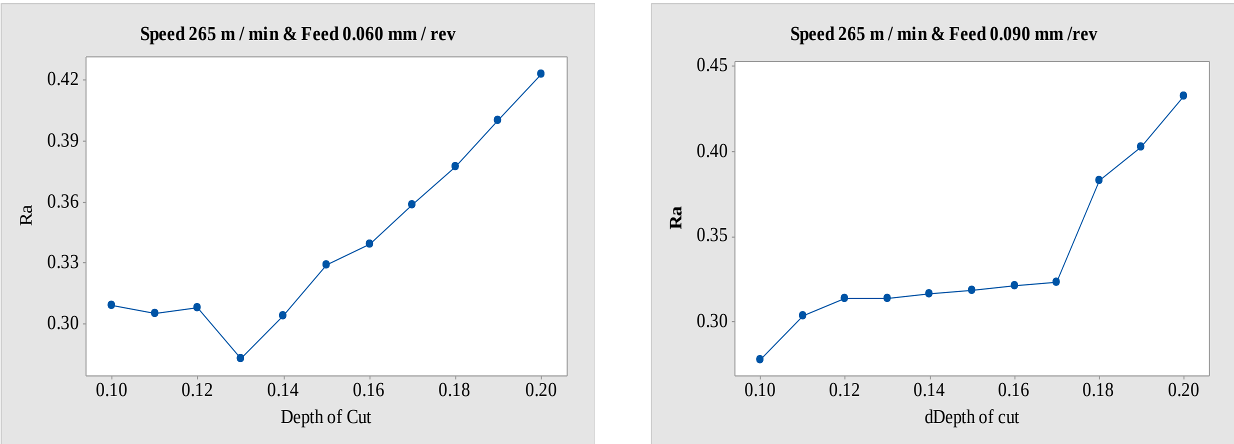


Fig. 5.3 Ra for the speed 265 m / min, feed 0.060, 0.090 mm / rev for all combination of depth of cut

The graphical representation of the surface roughness with respect to the speed 282.5 m / min for all combination of depth of cut and feed of 0.60 mm / rev, 0.090 mm/ rev are shown in the Fig. 5.4.

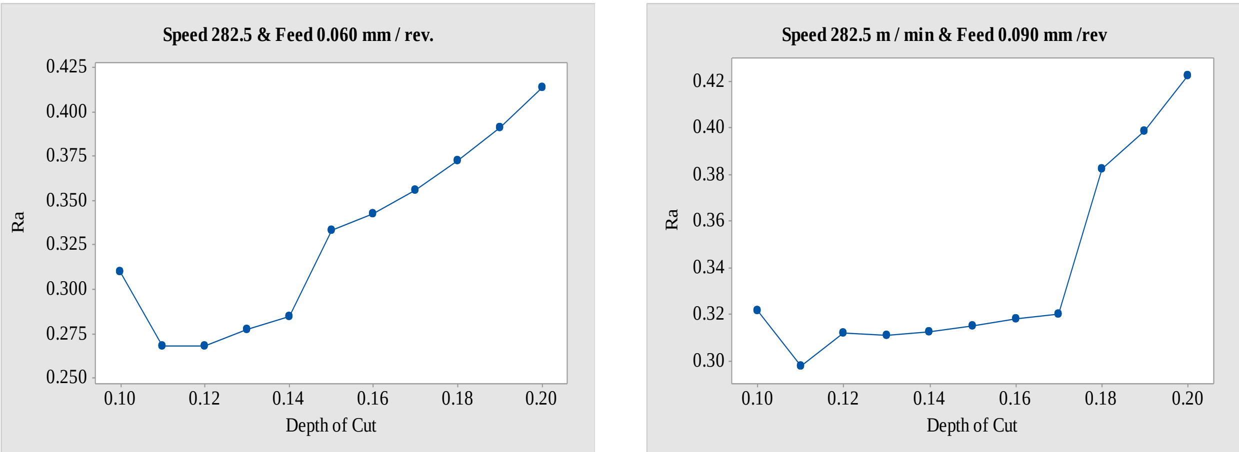
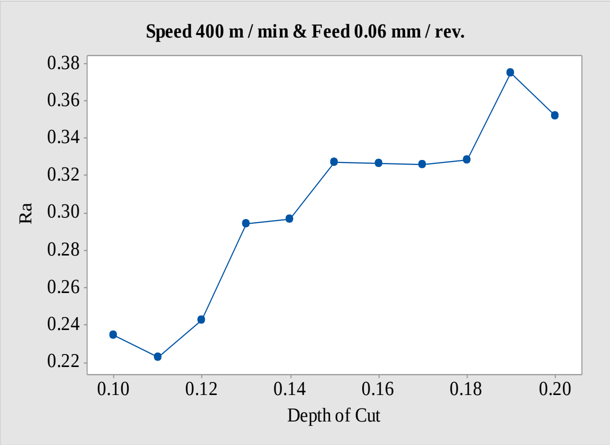


Fig. 5.4 Ra for the speed 282.5 m / min, feed 0.060, 0.090 mm / rev for all combination of depth of cut

The graphical representation of the surface roughness with respect to the speed 400 m / min for all combination of depth of cut and feed of 0.60 mm / rev, 0.120 mm/ rev are shown in the Fig. 5.5.



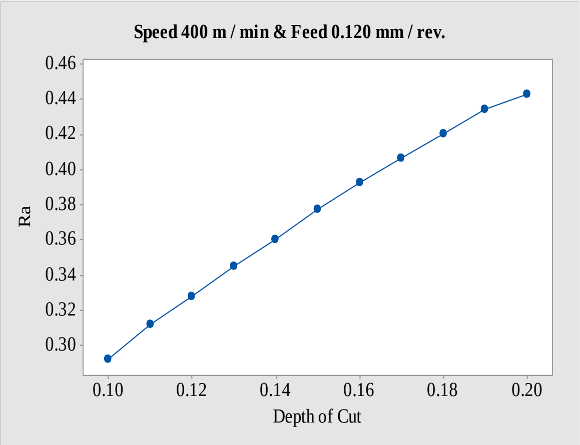


Fig. 5.5 Ra for the speed 400 m / min, feed 0.060, 0.120 mm / rev for all combination of depth of cut

VI. RESULTS AND CONCLUSIONS

Statistical significance is found to be fit for second order regression relationship between the input and output parameters. The best subset analysis and the coefficients of each input parameters reveals that the feed is contributing more influence on the surface roughness comparing to the other two input variables. Out of SSA, ACO, PSO, GA optimisation algorithms the SSA converges towards the accuracy level in computation. ACO seed SSA algorithm hybridization with regression relationship as input converges with further minimum mean error. The optimised result for this experiment is tabulated in Table 6.1.

Table 6.1 Optimised results

S	F	DOC	Optimised Ra
440	0.06	0.11	0.223

The proposed hybridization method may be considered for future references while compiling the optimisation of parameters in other process also. Manufacturers may use this as a referenceset for their processing in order to select the optimal parameter combination according to the required surface finish value to avoid the rework and part rejection. The analysis can be extended to find out the tool wear, material removal rate, machining time, power consumption etc. The computed values of the regression relationship equations need to be examined and ensured for statistical significance in all aspects while assigning as the input values for compiling. By selecting the steps value much closer leads to get smoother curve fittings for references. The presentation in graphs may be taken as a ready reckoner by the manufacturers for processing the parts. Attempts may be exercised with other familiar accepted optimisation algorithms.

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