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A Comprehensive Study on the Application of Regression Coupled Differential Search Algorithm in Forecasting the Influence of Turning Parameters on Machining AISI 316L Steel

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ABSTRACT

AISI 316L steel material have the application in medical field as biomaterials, biomedical implants, biocompatible materials it requires the most desired surface quality. During machining processes bringing the product to the required surface quality is one of the prime confront responsibility in the manufacturing operations. Among the metal removal processes turning is the most advantageous machining process and commonly used by the manufacturing industries. Analyzing and optimizing the combination of the input machining parameters to achieve the desired surface finish is taken as the objective of this attempt with the Differential Search Optimisation technique in MATLAB programming. Referring to the convergence performance of the DSA along with the hybridization of the statistical regression relations and simulation is performed. The optimised parameter combinations for the required surface finish are identified.

Keywords

Turning, AISI 316L steel material, Minitab, Regression, Hybridization, Differential Search Algorithm, MATLAB.

Abbreviations Used

v	Cutting speed	R-sq	R - square statistical value
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	Reg	Regression
DSA	Differential Search Algorithm	Ra	Surface Roughness

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I. INTRODUCTION

Conventionally, the selection of cutting conditions for metal cutting is the prerogative of the manufacturers. In such circumstances, the knowledge of the operator plays a most important role, nevertheless even for a well experienced operator it is cumbersome to locate the optimum values every time. The chief machining parameters in metal turning operations are cutting speed, feed rate and depth of cut etc. The setting of these parameters determines the quality characteristics of turned parts. Since turning is the primary operation in most of the production processes in the industry, surface finish of turned components has greater influence on the quality of the product. Surface finish in turning has been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built-up edge, cutting speed, depth of cut, cutting time, tool nose radius. Analyzing and optimizing the combination of the input machining parameters to achieve the desired surface finish while processing turning operation on the AISI 316L steel is taken as the objective of this attempt with the Differential Search Optimisation technique in MATLAB programming. Referring to the convergence performance of the DSA along with the hybridization of the statistical regression relations and simulation is performed.

II. RELATED LITERATURES

According to these parameters, a detailed literature survey is carried out as follows. K. Palanikumar, *et al*. [2] have demonstrated the application of the Taguchi method with fuzzy logic to optimize the machining parameters for machining of GFRP (Glass Fiber Reinforced Plastic) composites with multiple characteristics. A multi response performance index (MRPI) was used for optimization. The machining parameters like cutting speed, feed rate, depth of cut, and machining time were optimized with consideration of multiple performance characteristics like metal removal rate, tool wear, and surface roughness. T. Srikanth and V. kamala [3] indicated that a real coded Genetic Algorithm (RCGA) approach for optimization of cutting parameters in turning. This RCGA approach is quite advantageous in order to have the minimum surface roughness values, and their corresponding optimum cutting parameters, for certain constraints.

Adeel H. Suhail et al. [4] focused on an experimental study to optimize the cutting parameters using workpiece surface temperature and surface roughness by employing Taguchi techniques. T.G Ansalam Raj and V.N Narayanan Namboothiri [5] formed an improved genetic algorithm for the prediction of surface finish in dry turning of SS 420 materials. Taguchi offers a simple and systematic approach to optimize a performance, quality and cost. The quality of design can be improved by improving the quality and productivity in various company-wide activities. Al-Ahmari [6] developed empirical models for tool life, surface roughness, and cutting force for turning operations. Two important data mining techniques used were response surface methodology and neural networks. Taguchi's parameter design offers a simple and systematic approach which can reduce number of experiments to optimize design for performance, quality and cost. Signal to Noise(S/N) ratio and orthogonal array(OA) are two major tools used in robust design. S/N ratio measures quality with emphasis on variation, and OA accommodates many design factors simultaneously [7, 8, 9]. Azouzi et al. [10] proposed an on-line prediction of surface finish and dimensional deviation in turning using neural network-based sensor fusion. Avisekh Banerjee et al. [11] conducted a study of feasibility of on-line monitoring of surface roughness in turning operations using a developed opto-electrical transducer. Regression and neural network (NN) models

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were exploited to predict surface roughness and compared to actual and on-line measurements. Bajic et al. [12] focused on modeling of machined surface roughness and optimization of cutting parameters in face milling and examined the influence of cutting parameters on surface roughness in face milling. David et al. [13] described an approach to predict surface roughness in a high-speed end-milling process and used artificial neural networks and statistical tools to develop different surface roughness predictors. The activities concerned with quality include in quality of product planning, product design and process design. This attempt focuses on the optimisation of surface roughness parameter with reference to the inputs parameters using the Differential Search Algorithm linked by regression relationship.

III. EXPERIMENTAL WORKS AND MATHEMATICAL MODELING

Turning experiment has been conducted in the CNC lathe OKUMA Lb 10II model on the AISI 316L steel material which possesses the mechanical properties as listed in the Table 3.1 by Nokolaos [1] with the objective of analyzing the surface roughness on the machined product. This material is holding the application in medical field as biomaterials, biomedical implants, biocompatible materials, chemical processing, food processing, photographic, pharmaceutical, textile finishing, marine exterior trim. This material is holding good favorite, because of the superior corrosion resistance to inter granular corrosion, to most chemicals, salts, and acids and exhibits high creep strength at elevated temperatures.

Table 3.1 Mechanical characteristics of AISI 316L

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 coated tool -DNMG 110402-M3 with TP 2000 coated grade which has rhombic shape with cutting edge angle 55° is utilized as the cutting tool material for the conduction of experiment. The coating on the tool is four layers of Ti [C, N] + Al_2O_3 + Ti [C, N] + TiN with the cutting edge angle as 93°. The primary machining variables speed, feed and depth of cut were chosen as the input parameters and the surface roughness of the product is considered as the outcome parameter towards analysis. Three level of input parameter selected is listed in the Table 3.2. Experimental plan was followed with Taguchi L27 array. To measure the surface roughness, Atomic Force Microscope is utilized and the observed experimental data are tabulated in the Table 3.3

Table 3.2 Machining parameters and levels

Parameters	L 1	L 2	L 3
v, Cutting speed, m / min	265	356	440
f, Feed, mm / rev	0.06	0.08	0.12
d, Depth of cut, mm / min	0.10	0.15	0.20

.Table 3.3 Experimental observed data of machining AISI 316L

Exp No	v	f	d	Ra	Exp No	v	f	d	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

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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	-	-	-	-	-

VI.MATHEMATICAL REGRESSION MODELING

Commercial Minitab 17 software is engaged to derive the statistical relationship of the speed, feed and depth of cut vs. surface roughness. On comparison of the compiled first, second and third order regression models, the third order regression equations exhibits the statistical significance with 98.85 % R – Sq value which is given in the Table 4.1.

Table 4.1 Regression model comparison for Surface roughness

Regression	S	R-sq	R-sq	R-sq (pred)
First order	0.02051	90.77%	89.56%	87.35%
Second order	0.02105	92.81%	89.01%	81.38%
Third order	0.010991	98.85%	97.00%	90.57%

Third order regression R - sq values are the best than the first and second order regressions which indicates that the predictors (input variables) explain 98.85% of the variance in the output variables. 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. Henceforth the third order equation is preferred for the examination and optimizing the parameters. Some set of values are generated with this regression equation. The residual plots on the statistical analysis for the output parameter surface roughness are shown in Fig. 4.1.

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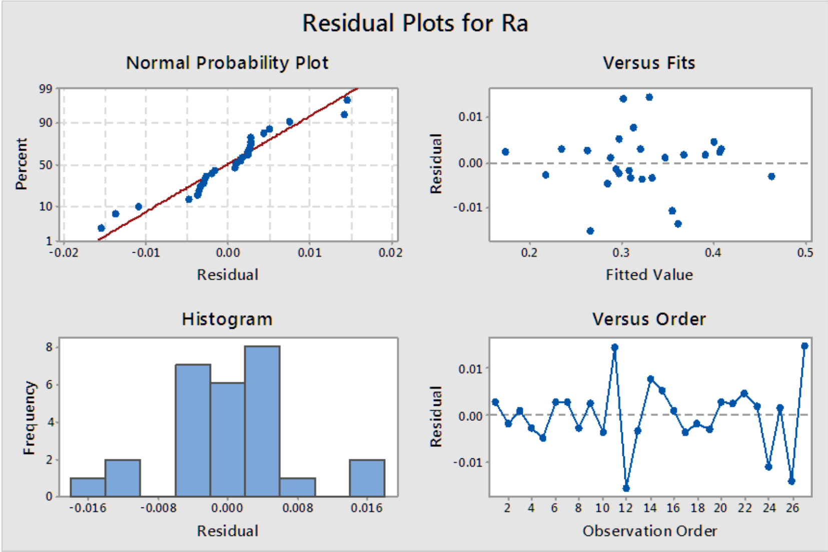

Figure 4.1 Residual plots of surface roughness

The finalized third order regression equation through the Minitab17 for the surface roughness in terms of speed, feed and depth of cut combination are

$$\text{Surface Roughness, Ra} = (0.269) + (0.00364*t1(1)) - (5.50*t1(2)) - (5.38*t1(3)) - (0.000012*t1(1)^2) + (45.3*t1(2)^2) + (46.0*t1(3)^2) + (0.0229*t1(1)*t1(2)) - (28.4*t1(2)*t1(3)) - (0.0037*t1(1)*t1(3)) - (0.2078*t1(1)*t1(2)^2) - (0.1220*t1(1)*t1(3)^2) + (0.000027*t1(2)*t1(1)^2) + (30.5*t1(2)*t1(3)^2) + (0.000062*t1(3)*t1(1)^2) + (161*t1(3)*t1(2)^2) - (0.0220*t1(1)*t1(2)*t1(3)) \quad (4.1)$$

Where t1(1) denotes the machining speed, t1(2) denotes the feed and t1(3) denotes the depth of cut during the machining operation. 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 speed and depth of cut.

V.OPTIMIZATION TECHNIQUES ADOPTED

The main purpose considered is to investigate the amount of influence of the speed. feed, depth of cut over the surface roughness and this attempt is made and also to estimate the optimal combination of the variables to attain the required level of output. For that the optimisation technique selected is Differential Search Optimisation technique which is one among the popular methods being applied by many researchers. DSA optimsation algorithm is trained initially 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 mean squared error (MSE) is the indicator of the simulation performance. The initial iteration was taken as 5000 turns and the outcome of the computation is converged with 0.0013627 mean error value. On stepping up the number of iterations stage by stage and evaluated, it has been observed that the employed DSA algorithm attains a steady rate of mean error as 0.0004592 which shows 66.3 % improvement at 50000 iterations. Then simulation of the programme was scheduled to take the statistical regression equation relationship as input selection instead observing the values at random, with the equated 11 steps and allowed to compile. The net outcome was found

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to be improved further with convergence of mean error value is 0.0002476 which projects the enhanced results. On performing the simulation with this modified approach the results are found to be further tuned. The mean error comparison between each pahase of the method is focuesd through the Table 5.1 to Table 5.6.

Table 5.1 Surface roughness value for the 11 steps of feed, depth of cut for the speed 265 rpm

Doc	0.06	0.066	0.072	0.078	0.084	0.09	0.096	0.102	0.108	0.114	0.12
	feed 1	feed 2	feed 3	feed 4	feed 5	feed 6	feed 7	feed 8	feed 9	feed 10	feed 11
0.1	0.307	0.307	0.310	0.337	0.360	0.316	0.334	0.341	0.317	0.374	0.309
0.11	0.288	0.342	0.306	0.307	0.311	0.314	0.291	0.277	0.348	0.300	0.376
0.12	0.310	0.305	0.306	0.305	0.298	0.311	0.324	0.321	0.316	0.381	0.313
0.13	0.316	0.311	0.307	0.340	0.323	0.337	0.331	0.318	0.367	0.316	0.382
0.14	0.320	0.317	0.306	0.322	0.303	0.347	0.322	0.372	0.325	0.386	0.323
0.15	0.371	0.321	0.310	0.290	0.327	0.313	0.352	0.326	0.380	0.327	0.391
0.16	0.331	0.298	0.347	0.374	0.348	0.380	0.348	0.389	0.338	0.398	0.334
0.17	0.401	0.325	0.371	0.360	0.369	0.349	0.377	0.342	0.400	0.339	0.406
0.18	0.336	0.379	0.397	0.411	0.371	0.405	0.369	0.410	0.352	0.415	0.421
0.19	0.371	0.352	0.405	0.363	0.421	0.363	0.421	0.358	0.424	0.437	0.425
0.2	0.411	0.385	0.437	0.452	0.417	0.441	0.398	0.434	0.452	0.435	0.477

The pictorial representation of the newly proposed method is shown in Fig. 5.1.

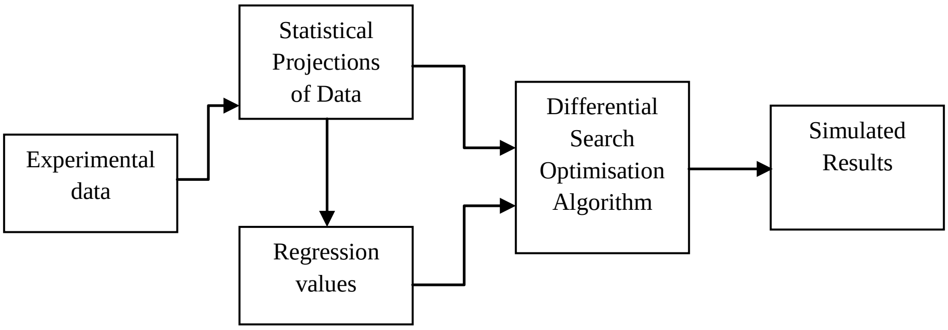

Figure 5.1 Block diagram of Hybridization of Regression in Differential Search Algorithm

Table 5.2 Surface roughness value for the 11 steps of feed, depth of cut for the speed 282.5 rpm

Doc	0.06	0.066	0.072	0.078	0.084	0.09	0.096	0.102	0.108	0.114	0.12
	feed 1	feed 2	feed 3	feed 4	feed 5	feed 6	feed 7	feed 8	feed 9	feed 10	feed 11
0.1	0.303	0.314	0.315	0.345	0.301	0.320	0.304	0.309	0.355	0.304	0.372
0.11	0.309	0.312	0.312	0.314	0.320	0.320	0.325	0.336	0.295	0.374	0.306
0.12	0.303	0.315	0.343	0.283	0.360	0.325	0.369	0.321	0.383	0.315	0.388
0.13	0.276	0.290	0.348	0.318	0.337	0.321	0.317	0.358	0.317	0.385	0.319
0.14	0.328	0.297	0.335	0.295	0.336	0.318	0.358	0.329	0.387	0.325	0.394
0.15	0.297	0.310	0.329	0.317	0.303	0.342	0.329	0.373	0.328	0.394	0.329
0.16	0.370	0.330	0.378	0.339	0.373	0.346	0.380	0.343	0.398	0.335	0.404
0.17	0.314	0.370	0.350	0.360	0.345	0.362	0.343	0.392	0.340	0.408	0.339
0.18	0.397	0.372	0.402	0.363	0.394	0.369	0.402	0.356	0.412	0.407	0.418
0.19	0.396	0.416	0.393	0.411	0.357	0.402	0.362	0.417	0.418	0.424	0.438
0.2	0.367	0.387	0.432	0.407	0.432	0.406	0.429	0.436	0.430	0.454	0.434

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Table 5.3 Surface roughness value for the 11 steps of feed, depth of cut for the speed 300 rpm

Doc	0.06	0.066	0.072	0.078	0.084	0.09	0.096	0.102	0.108	0.114	0.12
	feed 1	feed 2	feed 3	feed 4	feed 5	feed 6	feed 7	feed 8	feed 9	feed 10	feed 11
0.1	0.315	0.319	0.329	0.302	0.307	0.284	0.297	0.311	0.297	0.358	0.297
0.11	0.324	0.329	0.316	0.320	0.322	0.327	0.313	0.290	0.364	0.305	0.388
0.12	0.286	0.283	0.317	0.340	0.317	0.365	0.328	0.374	0.319	0.390	0.315
0.13	0.295	0.322	0.311	0.334	0.312	0.316	0.338	0.318	0.380	0.320	0.396
0.14	0.324	0.316	0.285	0.330	0.308	0.344	0.334	0.377	0.330	0.397	0.326
0.15	0.340	0.333	0.314	0.291	0.333	0.327	0.358	0.333	0.392	0.331	0.405
0.16	0.306	0.361	0.325	0.366	0.339	0.369	0.351	0.391	0.340	0.407	0.336
0.17	0.371	0.326	0.359	0.338	0.352	0.341	0.374	0.344	0.405	0.341	0.415
0.18	0.369	0.387	0.346	0.385	0.361	0.390	0.367	0.407	0.351	0.418	0.409
0.19	0.393	0.389	0.408	0.344	0.391	0.363	0.401	0.358	0.420	0.419	0.427
0.2	0.410	0.412	0.371	0.419	0.399	0.421	0.389	0.425	0.435	0.431	0.451

Table 5.4 Surface roughness value for the 11 steps of feed, depth of cut for the speed 317.5 rpm

Doc	0.06	0.066	0.072	0.078	0.084	0.09	0.096	0.102	0.108	0.114	0.12
	feed 1	feed 2	feed 3	feed 4	feed 5	feed 6	feed 7	feed 8	feed 9	feed 10	feed 11
0.1	0.299	0.316	0.294	0.292	0.330	0.330	0.333	0.333	0.326	0.290	0.355
0.11	0.313	0.318	0.286	0.324	0.330	0.285	0.286	0.340	0.307	0.381	0.315
0.12	0.284	0.317	0.309	0.299	0.354	0.331	0.358	0.328	0.383	0.318	0.392
0.13	0.321	0.306	0.318	0.303	0.314	0.318	0.316	0.361	0.323	0.395	0.326
0.14	0.310	0.330	0.322	0.294	0.330	0.331	0.360	0.340	0.393	0.330	0.403
0.15	0.334	0.317	0.337	0.324	0.318	0.344	0.339	0.378	0.336	0.405	0.336
0.16	0.342	0.306	0.356	0.329	0.360	0.351	0.377	0.352	0.404	0.340	0.413
0.17	0.354	0.359	0.327	0.346	0.335	0.358	0.351	0.393	0.346	0.415	0.345
0.18	0.372	0.323	0.376	0.350	0.380	0.371	0.395	0.363	0.415	0.350	0.423
0.19	0.386	0.392	0.384	0.385	0.358	0.381	0.366	0.411	0.357	0.426	0.423
0.2	0.388	0.402	0.404	0.385	0.411	0.398	0.417	0.376	0.428	0.435	0.434

Table 5.5 Surface roughness value for the 11 steps of feed, depth of cut for the speed 370 rpm

Doc	0.06	0.066	0.072	0.078	0.084	0.09	0.096	0.102	0.108	0.114	0.12
	feed 1	feed 2	feed 3	feed 4	feed 5	feed 6	feed 7	feed 8	feed 9	feed 10	feed 11
0.1	0.257	0.272	0.311	0.317	0.321	0.329	0.331	0.328	0.333	0.330	0.283
0.11	0.273	0.310	0.318	0.323	0.330	0.333	0.297	0.326	0.347	0.351	0.367
0.12	0.311	0.273	0.322	0.317	0.321	0.344	0.345	0.341	0.339	0.350	0.340
0.13	0.316	0.325	0.334	0.335	0.339	0.295	0.309	0.334	0.357	0.362	0.381
0.14	0.326	0.300	0.337	0.313	0.321	0.345	0.362	0.367	0.364	0.374	0.358
0.15	0.291	0.343	0.307	0.304	0.326	0.333	0.343	0.360	0.379	0.379	0.399
0.16	0.346	0.333	0.312	0.346	0.347	0.365	0.380	0.385	0.380	0.389	0.370
0.17	0.325	0.361	0.332	0.323	0.344	0.351	0.360	0.376	0.394	0.392	0.413
0.18	0.368	0.352	0.338	0.368	0.371	0.387	0.398	0.401	0.393	0.401	0.381
0.19	0.361	0.384	0.363	0.346	0.365	0.368	0.375	0.388	0.407	0.404	0.424
0.2	0.392	0.371	0.366	0.391	0.392	0.404	0.412	0.414	0.405	0.413	0.391

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Table 5.6 Surface roughness value for the 11 steps of feed, depth of cut for the speed 440 rpm

Doc	0.06	0.066	0.072	0.078	0.084	0.09	0.096	0.102	0.108	0.114	0.12
	feed 1	feed 2	feed 3	feed 4	feed 5	feed 6	feed 7	feed 8	feed 9	feed 10	feed 11
0.1	0.165	0.251	0.267	0.276	0.283	0.289	0.297	0.299	0.299	0.297	0.291
0.11	0.258	0.271	0.283	0.294	0.304	0.311	0.271	0.295	0.319	0.338	0.351
0.12	0.277	0.290	0.305	0.312	0.287	0.304	0.315	0.319	0.317	0.315	0.314
0.13	0.297	0.309	0.321	0.331	0.339	0.345	0.347	0.351	0.301	0.319	0.335
0.14	0.312	0.323	0.336	0.345	0.307	0.325	0.345	0.363	0.375	0.378	0.376
0.15	0.329	0.342	0.353	0.362	0.367	0.374	0.379	0.382	0.383	0.333	0.346
0.16	0.296	0.355	0.315	0.328	0.342	0.357	0.373	0.390	0.403	0.410	0.409
0.17	0.358	0.366	0.377	0.386	0.391	0.400	0.404	0.406	0.411	0.354	0.365
0.18	0.323	0.331	0.346	0.359	0.372	0.387	0.400	0.413	0.423	0.428	0.427
0.19	0.382	0.392	0.399	0.407	0.415	0.421	0.365	0.368	0.372	0.377	0.386
0.2	0.344	0.359	0.372	0.383	0.395	0.407	0.418	0.428	0.435	0.439	0.438

To view the results for future references and guideline as ready reckoner to the manufacturers the graphical representation of the results are exhibited in Figure 5.2 to Figure 5.7.

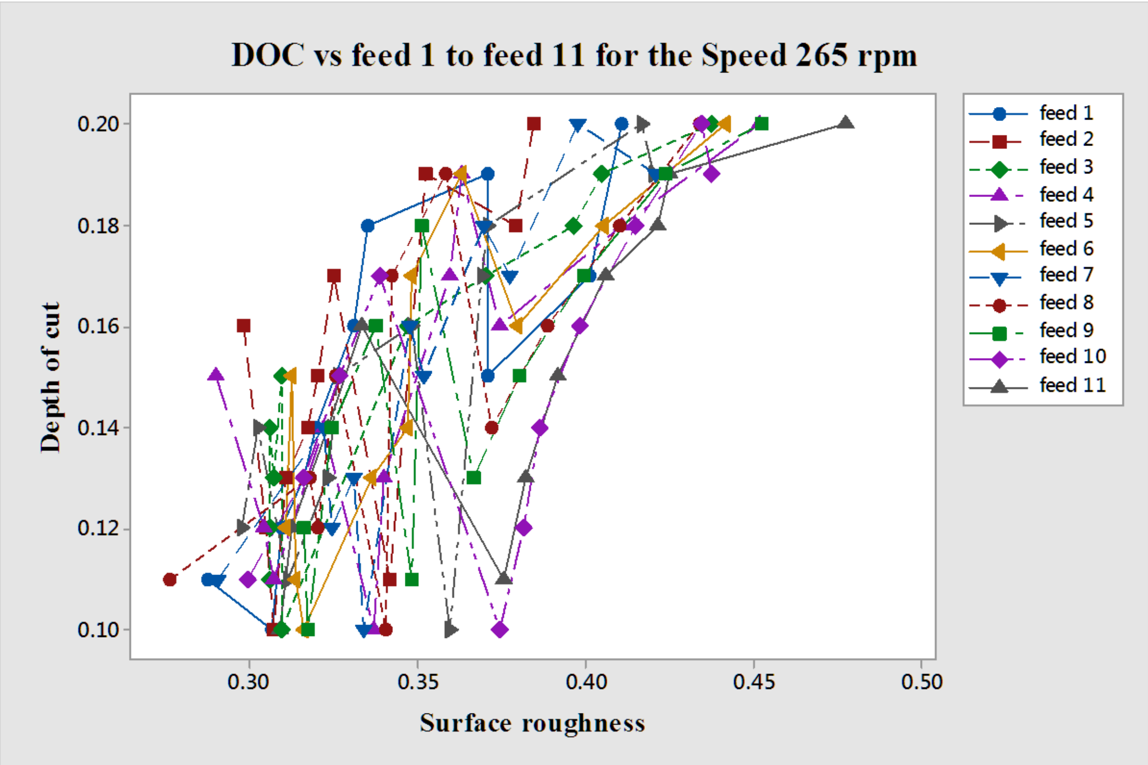

Figure 5.2 Surface roughness - DOC Vs all feed range for the speed of 265 rpm

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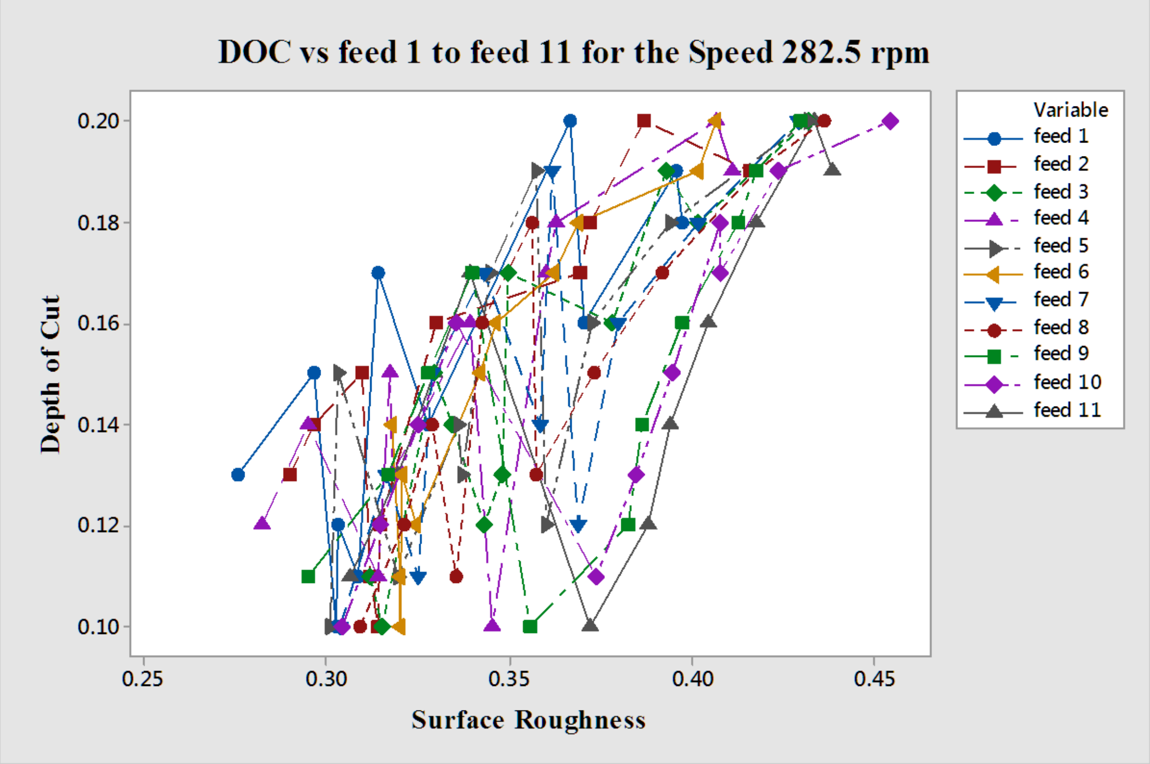

Figure 5.3 Surface roughness - DOC Vs all feed range for the speed of 282.5 rpm

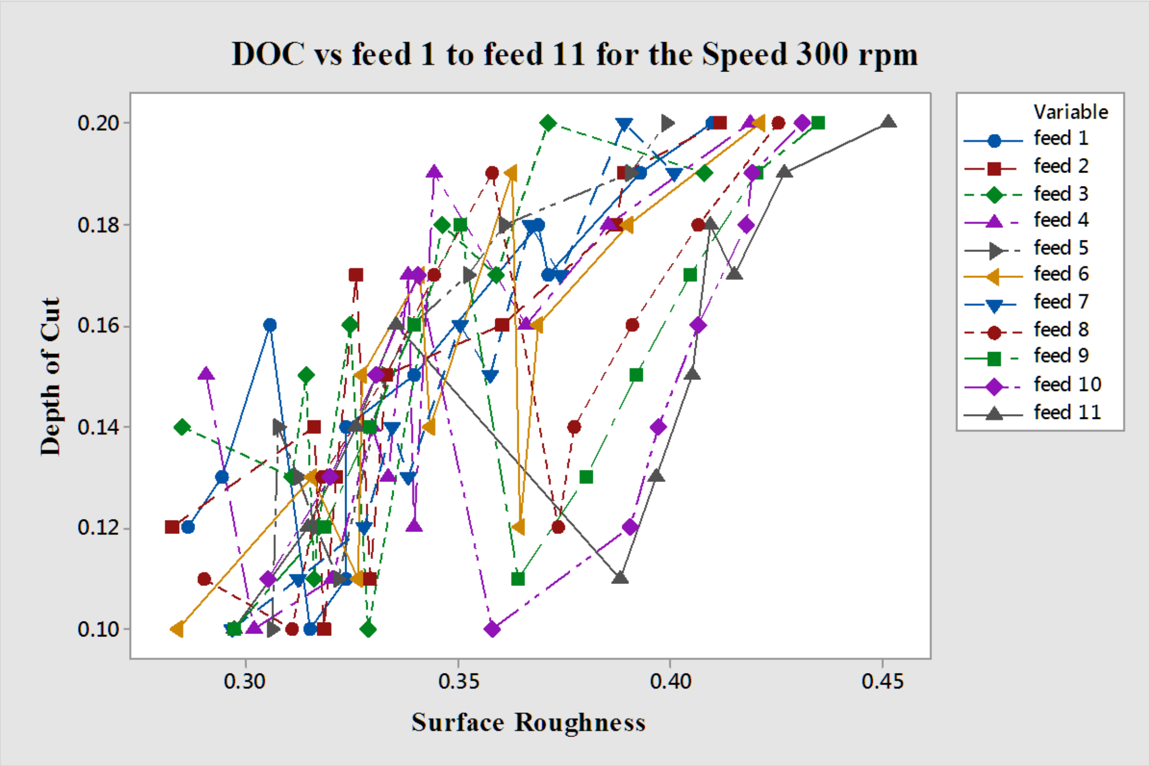

Figure 5.4 Surface roughness - DOC Vs all feed range for the speed of 300 rpm

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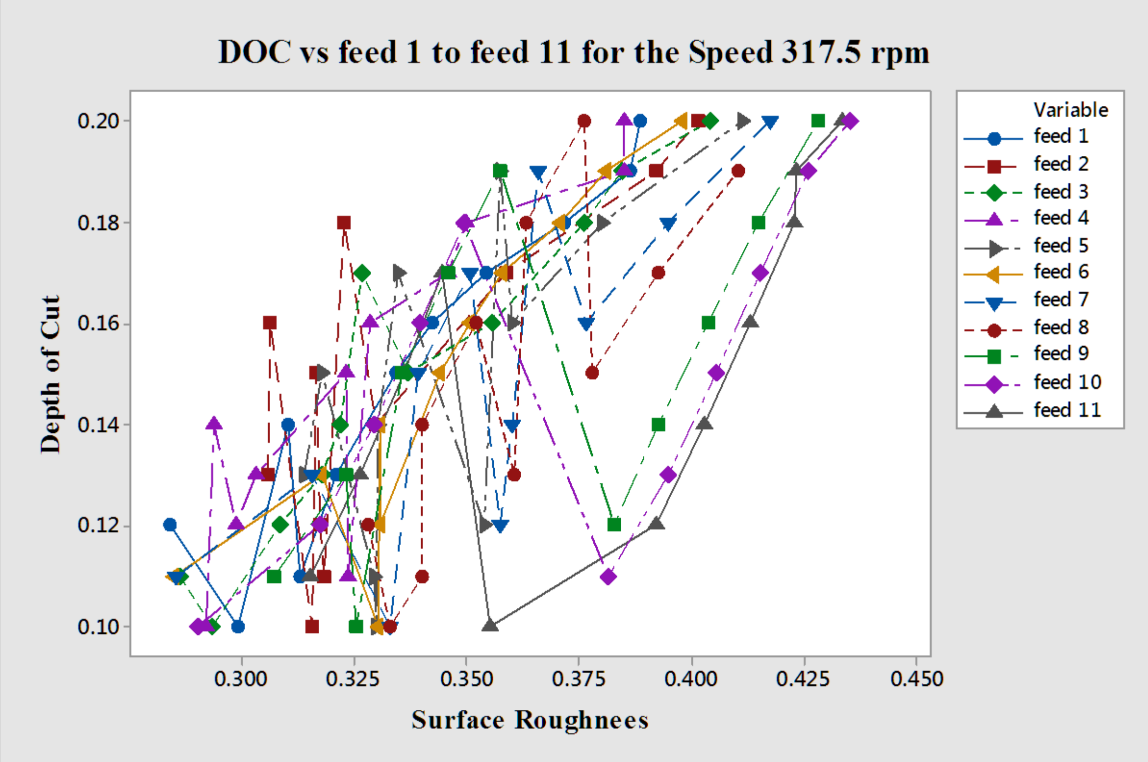

Figure 5.5 Surface roughness - DOC Vs all feed range for the speed of 317.5 rpm

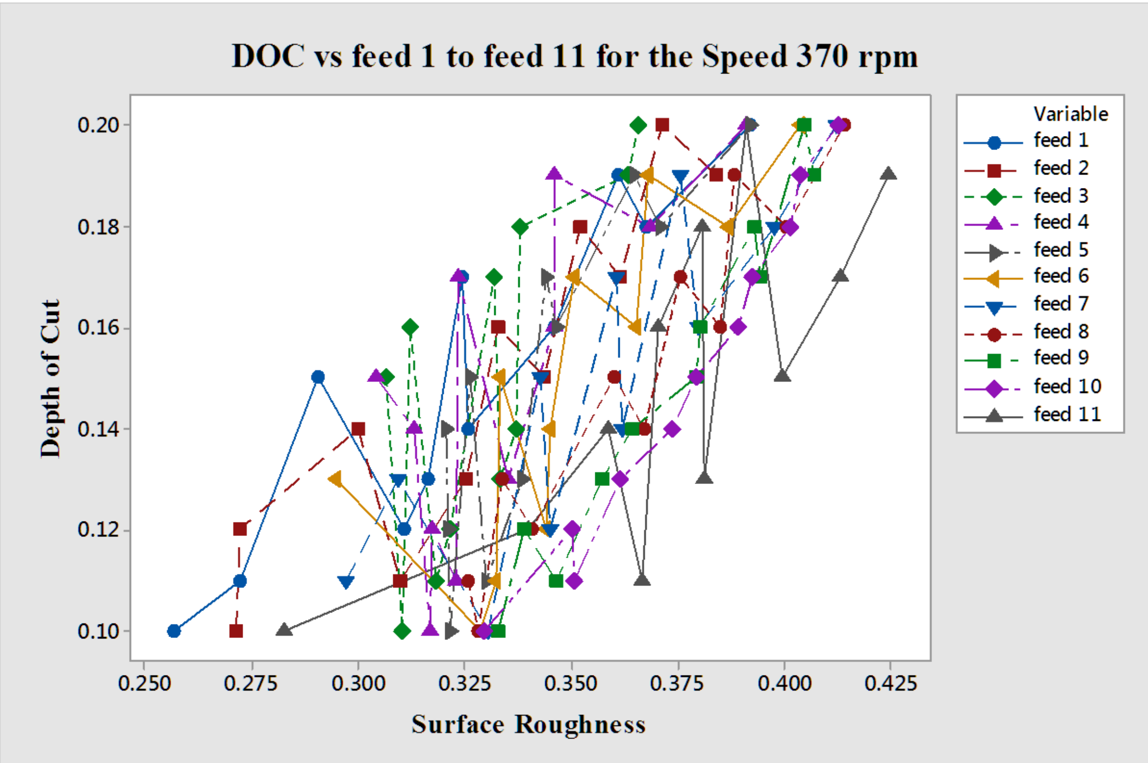

Figure 5.6 Surface roughness - DOC Vs all feed range for the speed of 370 rpm

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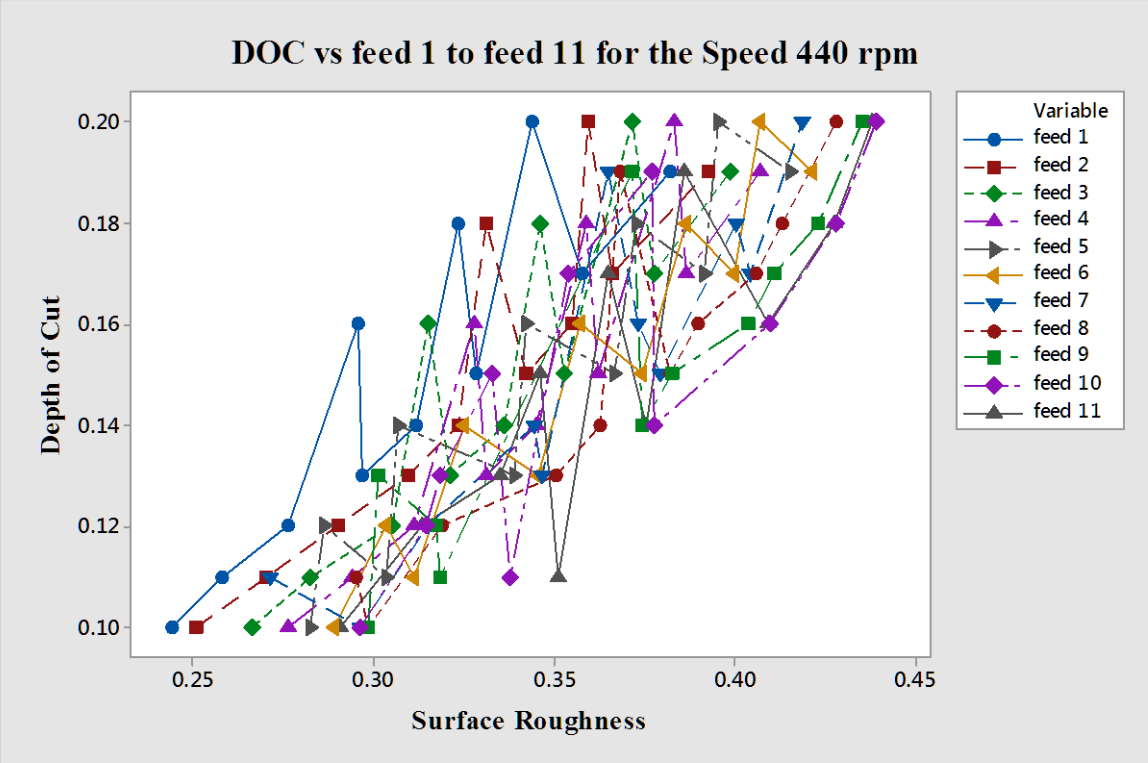

Figure 5.7 Surface roughness - DOC Vs all feed range for the speed of 440 rpm

The optimal combination of process parameters towards the minimum surface roughness 0.211µm is 440 rpm speed, 0.06 mm / rev feed and 0.10 mm / min depth of cut.

VI. CONCLUSIONS

Third order regression relationship between input variables (machining speed, feed, depth of cut) and output variable (surface roughness) is exhibiting the statistical significance and found to be fit. The best subset analysis between the individual and combination of the machining parameters and the coefficients of each input parameters reveals that the feed is influencing highly on the surface quality comparing to the other input variables. Regression relationship integrated DSA optimisation method converges with further minimum mean error with regards to this analysis. 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	0.10	0.211

The proposed hybridization method may be considered for future references while compiling the optimisation of parameters in furrther process. 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 various other output parameters like 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

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as the input values for compiling. By selecting the steps value much closer leads to get smoother curve fittings for references. Attempts may be exercised with other familiar accepted optimisation algorithms.

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