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SIMULATION AND PREDICTION OF PROCESS PARAMETERS IN CNC TURNING ON AISI 316L MATERIAL THROUGH REGRESSION HYBRID PSO ALGORITHM

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ABSTRACT

Turning process is the most advantageous machining process and very commonly used by the manufacturing industries. AISI 316L steel material have the application in medical field as biomaterials, biomedical implants, biocompatible materials it requires the most desired surface quality. Obtaining the required surface quality is one of the major challenge and the prime responsibility in the manufacturing operations. 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 Particle Swarm Optimisation technique in MATLAB programming. Referring to the convergence performance of the PSO the hybridization regression equations in the PSO and the regression computed values of parameters feed as input the further simulation carried out. The results are found to be more tuned in each phase of the simulation. The optimised parameter combinations for gorgeous surface finish are identified.

Key words: AISI 316L steel material, Turning, Regression, Particle Swarm Optimisation, Hybridization, Minitab, MATLAB.

I. INTRODUCTION

Because of the superior corrosion resistance to inter granular corrosion, to most chemicals, salts, acids and high creep strength at elevated temperatures AISI 316L steel material is preferred in the application in medical field as biomaterials, biomedical implants, biocompatible materials, chemical processing, food processing, photographic, pharmaceutical, textile finishing, marine exterior trim. As a special material, the surface finish quality warrants high degree of importance in these applications. During manufacturing bringing the required surface quality is the most common challenge 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 most common primary input machining parameters are machining speed, tool feed into the work material and the depth of cut in each pass. The optimal selection of such parameter combination is the main objective of the manufacturing engineers not only towards the desired outcome but also to avoid rework and rejection rate. This investigation primarily focused towards the analysis and optimisation of primary machining variables cutting speed, feed and depth of cut on the resultant parameter surface roughness and laying a smooth path in turning operations on AISI 316L material.

Abbreviations Used

S	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
PSO	Particle Swarm Optimization	Ra	Surface Roughness

II. RELATED LITERATURE

The significant importance of the surface roughness property is recognized by all researchers and manufacturers as this characteristic has a direct impact on the serviceable attributes of any product. So as to achieve reasonable surface quality with dimensional accuracy and precision, it is crucial to make use of the optimization methodologies to achieve the objectives. Suresh et al. [1] have applied the Response Surface Method and genetic algorithm in order to forecast the surface finish and optimized the progression parameters. Several researchers made attempts to predict the surface quality in turning operation through applying neural network techniques as well as statistical modeling. Mital and Mehta [2] have developed a modelling with statistical approach in their research towards the surface roughness. M.A. El-Baradie [3] has coined surface roughness modeling to predict the reasonable outcome while turning the grey cast iron material with the BHN value of 154. El-Sonbaty and Megahed [4] have applied the neural network technique in their investigation on turning operations. Hasegawa et al. [5], Sahin Y and Motorcu [6,7], G. Petropoulos et al. [8], Grzesik and Wanat [9] have made considerable amount of contributions through their investigations and devised surface modeling to establish the required and desirable surface quality. Lin et al. [10] applied the Response Surface Methodology to predict the surface roughness in their experiments. Gopal and Rao [11] also explained the application of Response Surface Methodology in the surface quality prediction modelling through experimental investigation in grinding operations. Singh and Kumar [13] employed the micro-genetic algorithm implementation to conduct the optimization process in turning operations on EN-24 steel. Nikolaos et al. [12] have investigated in detail about the surface roughness prediction in turning process on AISI 316L material. Agapiou [14] explained the suitability of regression analyses applications to find the optimal levels and to analyze the effect of the drilling parameters on surface finish. Oezel and Karpat [15] have reported that the surface roughness is primary results of process parameters such as tool geometry and cutting conditions (such as feed rate, cutting speed, depth of cut, etc.). Emad Ellbeltagi et al. [16] offered a paper on comparison among five evolutionary–based optimization algorithms (GA, MA, PSO, ASO, and SFL). They concluded that, the PSO method was generally found to perform better than other algorithms in terms of success rate and solution quality. Saravanan et al. [17] applied the non-traditional techniques for cutting parameters optimization (GA, SAA, TS, MA, ACO and the PSO) and compared the results. Denkena et al. [18] developed a MATLAB - simulink model and applied the

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simulation by varying cutting parameters with cutting tool geometry to optimize the deficiency of surface quality. Achala et al. [19] have investigated the turning process dynamics through the MATLAB software as a platform. The principal purpose 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 PSO algorithm through MATLAB programming. A narrative approach of feeding the regression equation relationship as input instead of random approach and the experimental output values are replaced with the regression values.

III. EXPERIMENTAL WORKS AND MATHEMATICAL MODELING

On the AISI 316L steel material which has the mechanical properties listed in the Table 3.1, turning experiment has been conducted in the CNC lathe OKUMA Lb 10II model by Nokolaos [12] as the 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 preferred because of the superior corrosion resistance to inter granular corrosion, to most chemicals, salts, and acids. Also have high creep strength at elevated temperatures.

Table 3.1 Mechanical properties of AISI 316L material

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

The cutting tool material used in the experiment is of a coated tool -DNMG 110402-M3 with TP 2000 coated grade which has rhombic shape with cutting edge angle 55°. 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°. Speed, feed and depth of cut were taken as the input parameters and the main outcome parameter is surface roughness of the product. The level of input parameter selected is depicted through the Table 3.2.

Table 3.2 Machining parameters and levels

Parameters	Units	Level 1	Level 2	Level 3
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

Taguchi L27 array was taken as the experimental plan. Atomic Force Microscope is utilized to measure the surface roughness. The observed experimental outcome is tabulated in the Table 3.3.

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Table 3.3 Experimental observed data of machining AL6063-T6

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	-	-	-	-	-

The relationship of the inputs vs. output variables are analysed with the Minitab17 software. First, second and third order regression models are framed and compared for the statistical significance and the statistical values of the equations are tabulated in Table 3.3.

Table 3.3 Regression model comparison for Surface roughness

Regression	S	R-sq	R-sq	R-sq (pred)	Durbin - Watson
First order	0.02051	90.77%	89.56%	87.35%	1.46435
Second order	0.02105	92.81%	89.01%	81.38%	1.63960
Third order	0.010991	98.85%	97.00%	90.57%	2.58458

Third order regression R - sq values are the best than the first and second order regressions. While interpreting the Durbin Watson values, of the third order regression is above 2 which indicate that the negative autocorrelation. 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. 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. Finally the second 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. 3.1.

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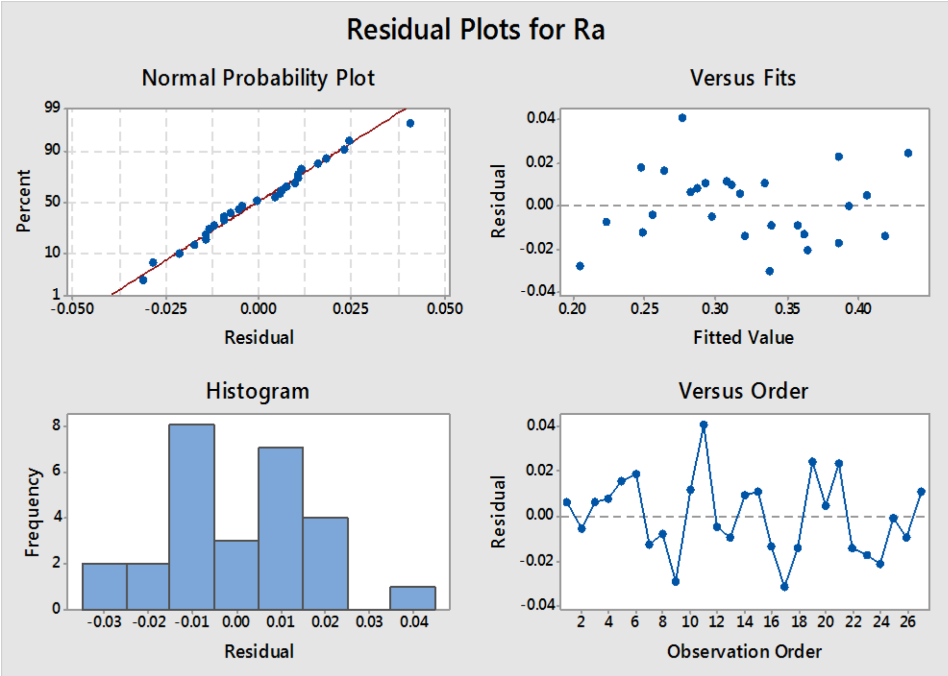

Figure 3.1 Residual plots of surface roughness

The framed second order regression equations through the Minitab17 for the surface roughness in terms of speed, feed and depth of cut combination are

Surface Roughness, "Ra = (0.331) – (0.000148*Speed) + (0.79*Feed) – (1.16*Depth of cut) – (0.000001*Speed^2) – (4.0*Feed^2) + (5.56*Depth of cut^2) + (0.00100*Speed*Feed) + (2.40*Feed*Depth of cut) + (0.00147*Speed*Depth of cut)"

(3.1)

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.

IV. OPTIMIZATION METHODOLOGIES ADOPTED

The primary objective of this attempt is to investigate the intensity of the impact of the input parameters on the surface roughness of the product and to forecast the optimal combination of the variables to attain the required level of output. For that the optimisation technique selected is Particle Swarm optimisation which is one among the popular algorithms being applied by many researchers. Initially the PSO algorithm is 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 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 0.002767 mean error value. While increasing the number of iterations step by step and evaluated, it is noticed that the employed PSO algorithm attains a steady rate of mean error as 0.000638 which shows 76.9 % improvement at 50000 turn's iterations. Instead of taking the values at random, the simulation programme was scheduled to take the regression equation relationship as input selection with the equated steps and allowed to compile. The net outcome was found to be improved further with convergence of mean error

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value is 0.000361 which projects the enhanced results. Further to advance the simulation, the input values of the surface roughness through experimented data are replaced with the values computed through regression equation. On performing the simulation with these changes the results are found to be further tuned to the mean error reduction (final mean error value is 0.00031). The pictorial representation of the newly proposed method is shown in Fig. 4.1. The mean error comparison between each pahase of the method is focuesd through the Table 4.1.

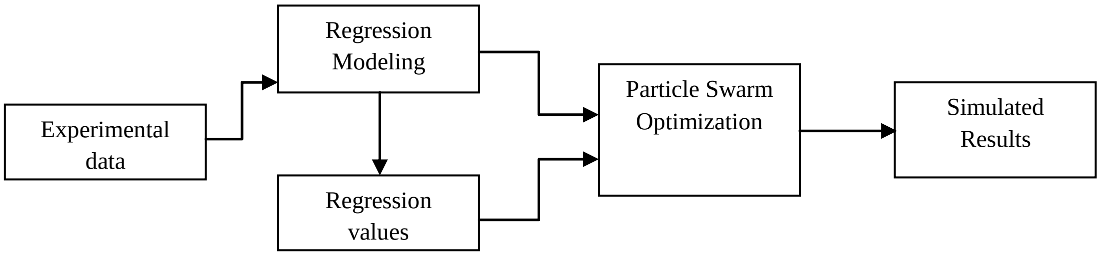

Figure 4.1 Block diagram of Hybridization of Regression in PSO Algorithm

Table 4.1 Mean error comparison

Description	**PSO with Experimental data**		**PSO with Regression Formula**	**PSO with Regression values as input**
Iterations	5000	50000	50000	50000
Mean error value	0.0027671	0.0006388	0.000361	0.00031

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 4.2 and Table 4.3 for combination of speed, feed and depth of cut marked respectively.

Table 4.2 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 →	0.60	0.66	0.72	0.78	0.84	0.90	0.96	0.102	0.108	0.114	0.120
DOC	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra
0.10	0.310	0.310	0.311	0.313	0.313	0.318	0.319	0.325	0.328	0.333	0.337
0.11	0.304	0.306	0.309	0.309	0.313	0.315	0.361	0.351	0.341	0.336	0.341
0.12	0.322	0.306	0.349	0.330	0.306	0.276	0.318	0.320	0.327	0.332	0.340
0.13	0.298	0.312	0.309	0.313	0.315	0.364	0.364	0.364	0.358	0.344	0.321
0.14	0.341	0.319	0.315	0.316	0.320	0.322	0.326	0.334	0.338	0.346	0.354
0.15	0.328	0.327	0.329	0.329	0.331	0.332	0.338	0.343	0.348	0.355	0.363
0.16	0.343	0.341	0.340	0.342	0.340	0.344	0.350	0.355	0.360	0.370	0.381
0.17	0.358	0.354	0.355	0.354	0.358	0.364	0.368	0.375	0.383	0.438	0.435
0.18	0.434	0.375	0.376	0.376	0.380	0.382	0.385	0.452	0.447	0.438	0.425
0.19	0.431	0.436	0.441	0.446	0.450	0.454	0.458	0.461	0.463	0.465	0.460
0.20	0.429	0.435	0.441	0.446	0.451	0.455	0.460	0.465	0.471	0.475	0.476

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Table 4.3 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 →	0.60	0.66	0.72	0.78	0.84	0.90	0.96	0.102	0.108	0.114	0.120
DOC	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra	Ra
0.10	0.311	0.313	0.318	0.316	0.320	0.323	0.325	0.332	0.332	0.338	0.341
0.11	0.309	0.314	0.314	0.317	0.367	0.356	0.346	0.336	0.330	0.338	0.361
0.12	0.311	0.351	0.333	0.312	0.285	0.319	0.325	0.328	0.332	0.334	0.341
0.13	0.353	0.315	0.315	0.361	0.353	0.348	0.347	0.346	0.340	0.320	0.348
0.14	0.338	0.324	0.323	0.326	0.324	0.331	0.331	0.337	0.342	0.390	0.318
0.15	0.333	0.329	0.331	0.334	0.333	0.339	0.343	0.344	0.350	0.356	0.364
0.16	0.341	0.344	0.345	0.341	0.345	0.349	0.351	0.356	0.363	0.371	0.378
0.17	0.358	0.358	0.357	0.356	0.358	0.364	0.369	0.374	0.429	0.427	0.457
0.18	0.428	0.432	0.372	0.373	0.375	0.382	0.443	0.437	0.422	0.401	0.411
0.19	0.427	0.432	0.437	0.441	0.445	0.448	0.450	0.451	0.452	0.448	0.433
0.20	0.427	0.432	0.437	0.441	0.445	0.449	0.453	0.458	0.460	0.459	0.454

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 to 0.78 mm/ rev are shown in the Fig. 4.2.

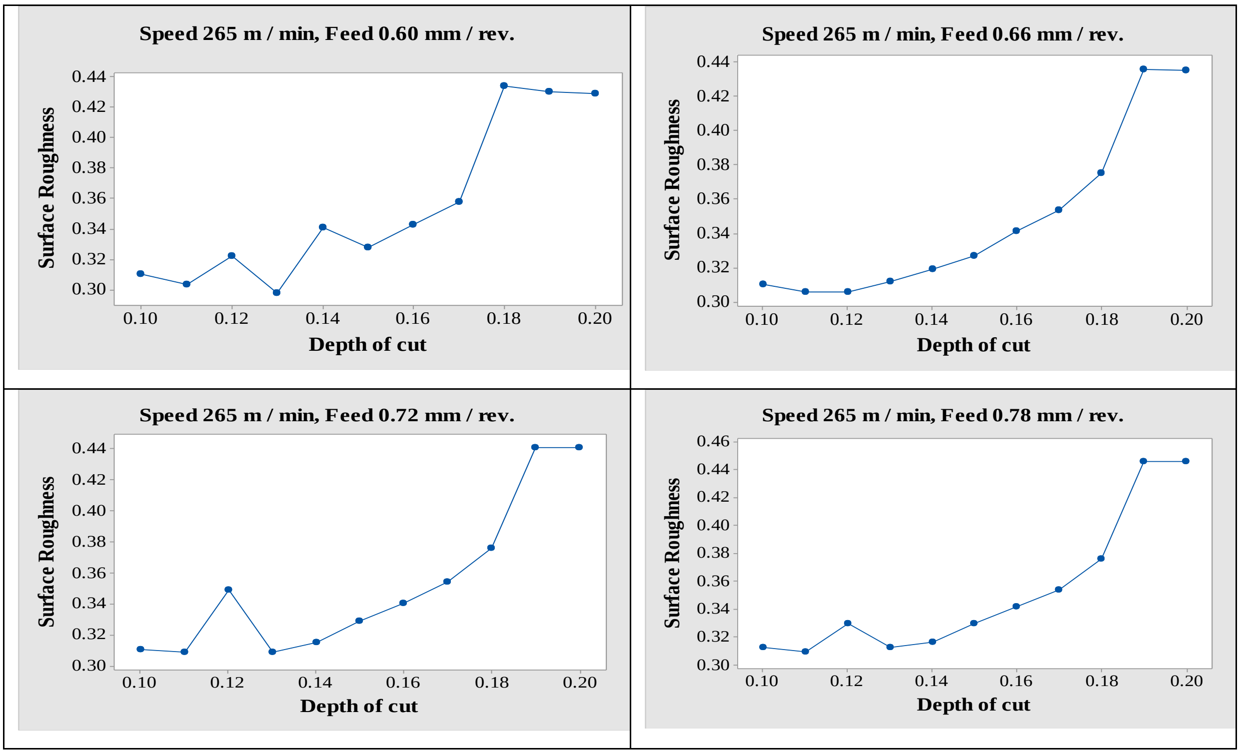

Fig. 4.2 Surface roughness for the speed 265 m .min, feed 0.60 – 0.78 mm / rev for all combination of depth of cut

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V. RESULTS AND CONCLUSIONS

Second order regression relationship is found to be fit with statistical significance. Feed is most contributing input parameter which influences the surface roughness values highly comparing to the other two input variables. PSO algorithm hybridization with regression relationship and regression computed values as input converges with minimum mean error. The optimised result for both the cases in individual simulation is tabulated in the following Table 5.1.

Table 5.1 Optimised results

Case No	S	F	DOC	Optimised Ra
Case1	440	0.066	0.10	0.255
Case 2	440	0.066	0.10	0.251

Case 1 represents the regression relationship hybridization while case 2 represents the regression compute value taken as input in the hybridization. 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.

VI. RECOMMENDATIONS

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 present graphical values 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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