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Optimization of Machining Parameters in Turning Operations for Surface Roughness and Materials Removal Rate on EN8 through Combined GA - SSA Algorithm

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ABSTRACT

For many industrial machining operations, the quality of surface finish is the prominent requirement. Nevertheless the selection of optimized cutting parameters is very essential for controlling the desired surface quality. Main aim of this attempt is to fix the set of cutting parameters combinations using optimization algorithms. Ant Colony algorithm, Scatter Search algorithm, Genetic algorithm and BAT algorithm were used for various parameters on the surface roughness to arrive a suitable combination of parameters which are optimal to meet the product quality requirement. The effectiveness of the algorithms is ordered based up on the error rate while computing and the best two algorithms are combined for more tuned outcome.

Keywords

EN8, Surface roughness, Ant Colony algorithm, Scatter Search algorithm, Genetic algorithm, BAT algorithm, Combined GA - SSA, MATLB, Minitab.

Academic Discipline And Sub-Disciplines

Machining of materials in Mechanical Engineering

SUBJECT CLASSIFICATION

Parameters Optimization

TYPE (METHOD/APPROACH)

Prediction, selection of process parameters towards quality outcome through optimization algorithms techniques.

1. INTRODUCTION

Turning operation is the most accepted machining course in the metal cutting process. As the economies of the operations depend on the input and output parameters, in order to obtain the reasonable product, one has to locate the set of input machining parameters with reference to the resultant parameters. This requires the optimization of cutting parameters as the key in component in preparation of machining processes. To optimize the machining operations the quantitative methods have been followed by considering a single objective only, such as minimizing the operational cost or maximizing the production towards profit etc. The single objective optimization intended for the process through quite a lot of diverse techniques have been applied, such as the regression analysis, differential calculus, linear programming, geometric and stochastic programming, computer simulation by many researchers. There have been a number of attempts by means of the multi-objective optimization even though in genuine applications it has been experienced difficulty on normal basis the trouble of concurrent optimization of more than a few objectives. Turning process is identified as a multiple-objective optimization problem with restriction of non-equating and mainly with the conflicting objectives production rate, operation cost and quality of machining where these objectives are influenced as a function of the cutting speed, feed rate and depth of cutting usually. Out of all the outcome parameters surface roughness and material removal rate are being considered as they have direct implication on product quality and production rate. Hence to achieve these objectives selection cutting parameters is getting most inevitable action.

Abbreviations Used

DOC	Depth of cut
SR	Surface Roughness
MRR	Materials removal rate
EXP	Experiment
ACO	Ant Colony Algorithm

SSA Scatter Search Algorithm

GA Genetic Algorithm

2. LITERATURE APPRAISAL

Machined surface finish is a feature of immense significance in the assessment of workshop manufacture, and significant concentration is at the present being paying attention on its dimension as a aspect of excellence organize [1]. Surface smoothness is also recognized to manipulate really such properties as wear confrontation of friction surfaces [2], get in touch with firmness of joints which is one among the most imperative parameters in touching mechanical properties. Quite a few researches were attempted to foresee the surface smoothness in turning operation by employing artificial neural network techniques and mathematical modeling. [3-5].Training of the neural networks is able to a degree acquire position and on the source of the consequences agreed by the accessible methodical and experimental models. Due to uncomplicated and very quick conceiving of the realistic models the neural networks approach is a common accepted tool. This technique has proved to be outstanding for obtaining the optimization results for every issue [6], And for the modeling of machining processes [7], designed for forecast the surface smoothness, cutting forces, vibrations [8], in addition to estimate the quantity of tool wear [10] also for adaptive managing of cutting process [11]. In the recent past, considerable amount of investigations have been conducted with surface roughness model to ascertain the surface smoothness [12-22]. Sahin and Motorcu [13,14] and Lin et al. [18] used the RSM for locating the surface roughness quality. Hasegawa et al. [12] and Gopal and Rao [17] also contributed through investigating the use of RSM in developing a surface roughness prediction model. Petropoulos et al. [15] found a pronounced effect of tool wear on the R_a and R_{max} values of surface roughness by statistical analysis. Antony [23] established the claim of multivariate numerical methods for formatting the most favorable situation in industrial experiments with multiple responses. Thurston and Carnahan [24] declared a technique based on application of fuzzy membership utility for decision-making in preface plan assessment of several attributes. Hsu[25] also experimented with an integrated optimization approach based on neural networks, exponential desirability functions and Tabu search to optimize a fused biconic taper process. A multi-objective optimization in the drilling progression of a laminate composite material was proposed by Sardinas et al.[26] . A micro-genetic algorithm was implemented to carry out the optimization process. A multi-response optimization of turning process on EN-24 steel by engaging TiC coated carbide inserts with the Taguchi's approach and utility concept was proposed by Singh and Kumar [27]. The primary objective of this paper is to study the effect of some machining parameters such as cutting speed, feed rate, and depth of cut during turning operation on the average surface roughness of the machined surface.

3. EXPERIMENTAL OUTCOME [9]

K.Adarsh Kumar et al.[9] conducted one experiment on face turning operation on the EN-8 work piece material by coated ceramic tool and the dimensional specification of the workpiece was of a length of 60 X 60 mm in diameter. The machining input variables cutting speed, feed and depth of cut in three levels were taken as a combination which is mentioned in the Table3.1

Table 3.1 Machining parameters

Variables / Levels	1	2	3
Cutting speed(rpm)	100	360	560
Feed (mm / rev)	0.14	0.15	0.16
Depth of Cut (mm)	0.5	1.0	1.5

The various alloying elements present in the experimental work piece and cutting insert are exposed in the Table 3.2.

Table 3.2 Chemical composition of EN-8 and Cemented Carbide cutting tool

<table>
<tr><td colspan="5">Composition of EN-8</td></tr>
<tr><td>C</td><td>Si</td><td>Mn</td><td>S</td><td>P</td></tr>
<tr><td>0.4%</td><td>0.25%</td><td>0.8%</td><td>0.015%</td><td>0.015%</td></tr>
<tr><td colspan="5">Composition of Cemented Carbide cutting tool</td></tr>
<tr><td>Co</td><td colspan="2">TiC</td><td colspan="2">WC</td></tr>
<tr><td>8%</td><td colspan="2">15%</td><td colspan="2">77%</td></tr>
</table>

With the Mitutoyo SJ-310 instrument the surface roughness after machining was measured. The outcome dependent parameters considered are the surface roughness and material removal rate. Altogether 27 exclusive observations were conducted and outcomes are collected in the Table 3.3. With Mini-Tab software, Regression analysis was made out in order to investigate and form the association among the response variables with reference to the input parameters and one or more predictors. A multiple regression examination was done on the observed facts. The coefficients of the analysis of variance results by the regression model well registered the linear relationships between the parameters and the regression equation framed [9] is

Surface Roughness Ra (μm) = 9.59 - 0.00476 Speed (rpm) - 31.6 Feed (mm/rev) + 0.559 DOC (mm)

The material removal rate also considered by standard formula for the combination of the input cutting parameters and included for computational analysis through algorithms.

Table 3.3 Experimental observation and outcome [9]

Exp No	Speed	Feed	Depth of Cut	SR	MRR
1	100	0.14	0.5	4.98	1319.47
2	100	0.14	1.0	5.3	2638.94
3	100	0.14	1.5	5.44	3958.41
4	100	0.15	0.5	4.49	1413.72
5	100	0.15	1.0	5.01	2827.43
6	100	0.15	1.5	5.34	4241.15
7	100	0.16	0.5	4.33	1507.96
8	100	0.16	1.0	4.59	3015.93
9	100	0.16	1.5	4.88	4523.89
10	360	0.14	0.5	3.81	4750.09
11	360	0.14	1.0	3.97	9500.18
12	360	0.14	1.5	4.28	14250.26
13	360	0.15	0.5	3.46	5089.38
14	360	0.15	1.0	3.69	10178.76
15	360	0.15	1.5	4.01	15268.14
16	360	0.16	0.5	3.15	5428.67
17	360	0.16	1.0	3.41	10857.34
18	360	0.16	1.5	3.66	16286.02
19	560	0.14	0.5	2.73	7389.03
20	560	0.14	1.0	3.11	14778.05
21	560	0.14	1.5	3.37	22167.08
22	560	0.15	0.5	2.42	7916.81
23	560	0.15	1.0	2.73	15833.63
24	560	0.15	1.5	2.98	23750.44
25	560	0.16	0.5	2.18	8444.60
26	560	0.16	1.0	2.49	16889.20
27	560	0.16	1.5	2.62	25333.80

4. PROPOSED OPTIMIZATION TECHNIQUES

In this paper, Ant Colony algorithm, Scatter Search algorithm, Genetic algorithm and BAT algorithm are trained to identify the various combinations of input parameters to determine the surface roughness and material removal rate and also to determine which combination of parameters are optimal for offering quality product according to the requirement in MATLAB (Elman Back Propagation). The computed outcomes of surface roughness and material removal rate through the algorithms are tabulated with reference to the experiment sequence in the Table 4.1 and 4.2

Table 4.1 Computed Surface Roughness – Algorithm wise

Exp No	ACO	GA	BAT	SSA
1	3.93	5.08	4.39	5.34
2	5.10	4.98	4.98	5.71
3	5.46	4.68	5.18	6.19
4	4.10	4.46	4.50	4.81
5	5.22	5.06	4.75	5.01
6	5.20	5.23	5.00	5.57
7	4.02	4.27	4.00	4.35
8	5.03	4.92	4.38	3.58
9	4.97	4.95	4.94	4.52
10	3.74	3.66	3.71	2.62
11	4.47	3.99	4.75	4.04
12	4.39	4.06	4.99	4.08
13	3.55	3.39	3.42	3.08
14	4.31	3.79	3.91	3.28
15	4.35	3.83	4.63	3.59
16	3.64	3.28	2.49	2.49
17	3.95	3.47	2.77	3.25
18	4.22	3.67	4.17	3.36
19	3.29	3.05	3.03	1.79
20	3.25	2.87	3.32	3.21
21	2.89	3.54	4.20	3.29
22	3.02	2.00	2.13	1.97
23	3.38	2.07	2.38	2.73
24	3.01	2.92	3.58	2.84
25	3.22	2.62	2.03	1.74
26	3.23	2.63	2.03	2.59
27	2.91	3.22	2.67	2.78

Table 4.2 Computed Material removal rate – Algorithm wise

Exp No	ACO	GA	BAT	SSA
1	1283.25	988.79	4410.83	1762.01
2	269.19	1319.91	13780.59	2964.67
3	5640.93	442.71	10698.91	1752.90
4	4881.36	194.46	16427.40	3660.74
5	11156.67	7701.63	8245.71	4261.22
6	8998.02	1220.25	11355.47	2514.71
7	6539.98	527.15	6241.81	1309.14
8	2179.27	6185.68	13171.84	2673.62
9	13276.41	1146.98	12031.09	1409.81

10	5314.39	6850.29	14888.38	3403.29
11	5943.74	7733.11	7769.42	12593.52
12	16018.14	349.08	8654.72	15375.59
13	843.06	5902.49	15834.69	8671.39
14	8236.40	14076.21	11041.29	14600.58
15	18096.24	5333.09	16279.29	11724.02
16	5384.52	5500.22	5160.05	4099.04
17	10862.37	15648.16	15399.81	15921.14
18	15763.32	3449.15	14826.38	13153.27
19	2847.14	9886.77	9585.06	7673.65
20	15838.36	9608.85	10751.28	18184.49
21	28910.38	287.11	12396.36	23714.28
22	5182.74	887.76	9932.42	9136.07
23	14540.64	7723.67	16237.13	16736.74
24	17845.11	13890.14	13476.31	19023.68
25	3562.87	12628.67	6401.03	10998.42
26	11570.89	23155.38	16849.66	18528.62
27	20828.51	9021.93	18938.64	17739.69

5. RESULTS AND DISCUSSIONS

On comparing the results of individual algorithm with the experimental observed values and the error rate on computation by the algorithms, which reveals that the Scatter Search algorithm is best suited to this set of parameters followed by the Genetic Algorithm comparing to the other two. In view of tuning the results furthermore an attempt is made by combining GA - SSA algorithms which is defined by considering the outcome values of Genetic Algorithm as input values to Scatter Search Algorithm and computed the fresh set of results. On examining the mean error between Combined GA - SSA computation and the all four algorithm's individual computation the error rate of Combined GA - SSA algorithm is much in minimum in all which is depicted in the figure 5.1 and 5.2. The time comparison of the computation time of all algorithms and Combined GA - SSA is shown in the figure 5.3 and tabulated in Table 5.1.

Table 5.1Rating of Algorithms on the basis of outcome accuracy

Algorithm	Error	Rating	Time	Rating
SSA	136.6607	1	6.8030	2
GA	276.4340	2	4.9549	1
ACO	281.4906	3	20.7122	3
BAT	496.1860	4	21.9499	4
Combined GA - SSA	53.2707	Least	17.3903	High

Though the computational time for Combined GA - SSA is on the higher value with reference to the Genetic and Scatter search algorithm the error rate is the lowest minimum which is evident in Table 5.1. Such computed outcome of the Surface roughness and Material removal rate through Combined GA - SSA are exposed in Table 5.2.

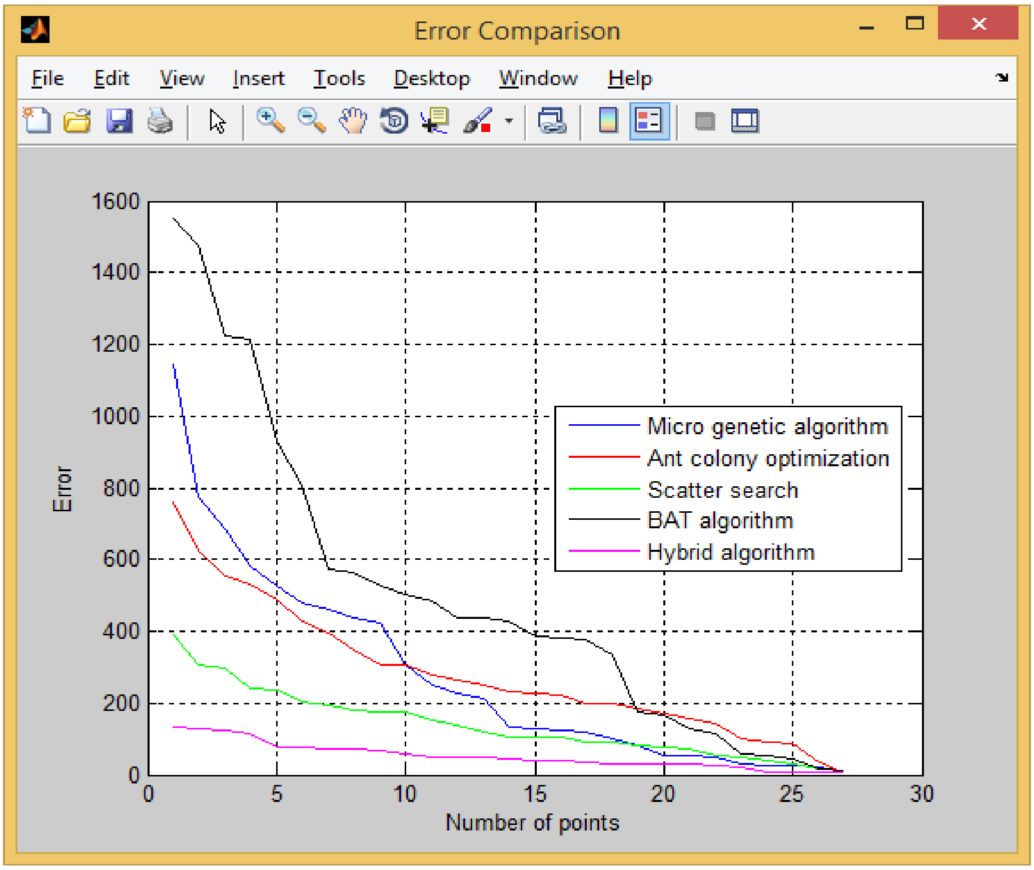

Figure 5.1 Error comparison of Combined GA - SSA algorithm with all four algorithms

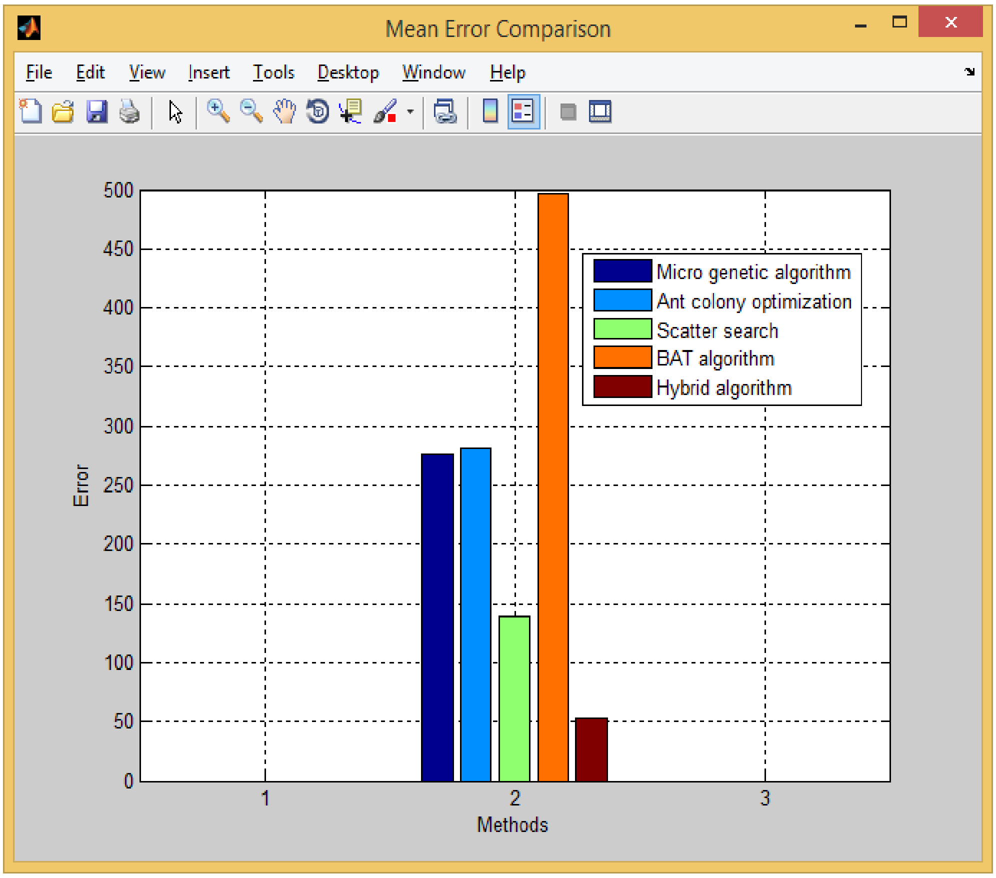

Figure 5.2 Mean Error comparison of Combined GA - SSA algorithm with all four algorithms

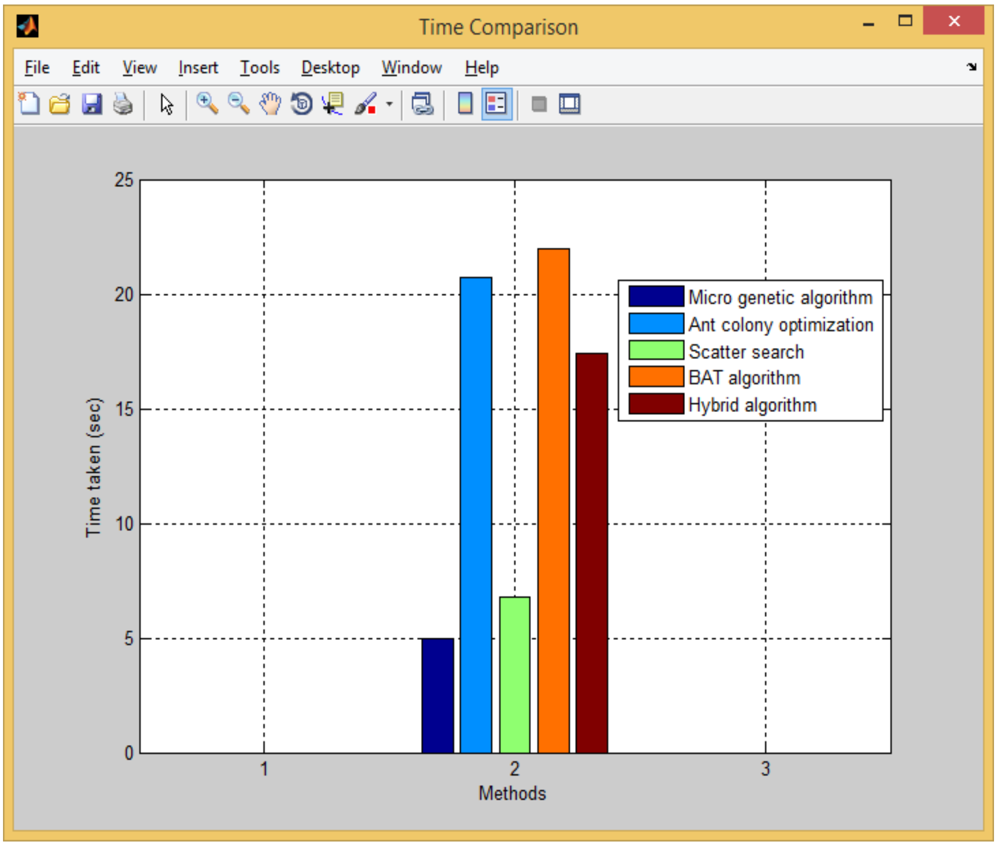

Figure 5.3 Computation time comparison of Combined GA - SSA algorithm with all four algorithms

Table 5.2 Combined GA - SSA algorithm outcome

Exp No	Surface roughness		Material Removal Rate	
	Exp	GA -SSA	Exp	GA - SSA
1	4.98	1.35	1319.47	1328.49
2	5.30	0.55	2638.94	2627.35
3	5.44	0.20	3958.41	3850.94
4	4.49	0.52	1413.72	1541.42
5	5.01	0.35	2827.43	2893.81
6	5.34	0.23	4241.15	4482.93
7	4.33	0.63	1507.96	1450.49
8	4.59	0.35	3015.93	2765.70
9	4.88	0.30	4523.89	4536.31
10	3.81	0.15	4750.09	4809.77
11	3.97	0.19	9500.18	9345.94
12	4.28	0.31	14250.26	14102.35
13	3.46	0.87	5089.38	5149.19
14	3.69	0.06	10178.76	10082.08
15	4.01	0.62	15268.14	15179.04
16	3.15	1.00	5428.67	5440.51
17	3.41	0.01	10857.34	11084.63
18	3.66	0.83	16286.02	16347.40

19	2.73	0.35	7389.03	7345.60
20	3.11	0.24	14778.05	14868.86
21	3.37	0.76	22167.08	22430.89
22	2.42	1.14	7916.81	7820.15
23	2.73	0.05	15833.63	15908.59
24	2.98	1.04	23750.44	23698.77
25	2.18	1.26	8444.60	8524.72
26	2.49	0.06	16889.20	16745.71
27	2.62	1.19	25333.80	25194.74

Through the regression analysis in Minitab to the material removal rate referring to the cutting variables combinations for the experimental values and the compiled values through GA - SSA combination the following results are arrived and shown below in the Table 5.3, 5.4 respectively. As the R – sq value is 90.04 % and 90.03 % respectively in the cases, the model is considered to be adoptable.

Table5.3 Regression Analysis: Model Summary, Experiment value of MRR versus Speed, Feed, DOC

S	R- sq	R- sq (adj)	R- sq (pred)
2390.82	90.04%	88.74%	84.95%

Regression equation framed for the experimental values through this model in Minitab is

MRR = -19227 + 28.27 Speed + 64088 Feed + 9613 DOC

Table5.4 Regression Analysis: Model Summary, GA - SSA computed value of MRR versus Speed, Feed, DOC

S	R- sq	R- sq (adj)	R- sq (pred)
2391.34	90.03%	88.73%	84.93%

Regression equation for the GA - SSA computation through the model is

MRR (GA - SSA) = -19085 + 28.27 Speed + 63222 Feed + 9601 DOC.

This validates the GA - SSA algorithm approach is very close and in line with the experimental outcome. With this validation the regression analysis is performed for the process outcome of surface roughness and framed the equation is

Surface roughness (GA - SSA) = -19085 + 28.27 Speed + 63222 Feed + 9601 DOC.

By executing the Best Subsets Regression through Minitab to access most influencing cutting parameter on the surface quality by speed, feed, and depth of cut is arrived. The following Table 5.5 confirms that the R-sq value (94) of the combination of feed rate with speed is greater than R-sq value (92.4) of the combination of speed and depth of cut which means the former is the most influencing combination on the surface quality. Table 5.6 reveals the depth of cut is most influencing the materials removal rate while combining with speed as the R-sq value is 88.6 than the feed rate combination with speed to which the R-sq value is 58.5.

Table 5.5Best Subsets Regression: SR versus Speed, Feed, DOC

R-sq	R-sq (adj)	R-sq (pre)	Speed	Feed	DOC
86.8	86.3	84.5	x		
7.2	3.5	0		x	
94	93.5	92.4	x	x	
92.4	91.8	90.3	x		x
99.6	99.6	99.5	x	x	x

Table 5.6 Best Subsets Regression: MRR versus Speed, Feed, DOC

R-sq	R-sq (adj)	R-sq (pre)	Speed	Feed	DOC
58	56.3	51	x		
31.5	28.8	19.5			x
89.5	88.6	85.6	x		x
58.5	55.1	47.3	x	x	
90	88.7	85	x	x	x

The surface roughness and the material removal rate for the various combinations of cutting parameters; feed rate and depth of cut computed through the combined *GA – SSA* algorithms are shown in the Figures 5.4 to 5.8 with reference to each spindle speed.

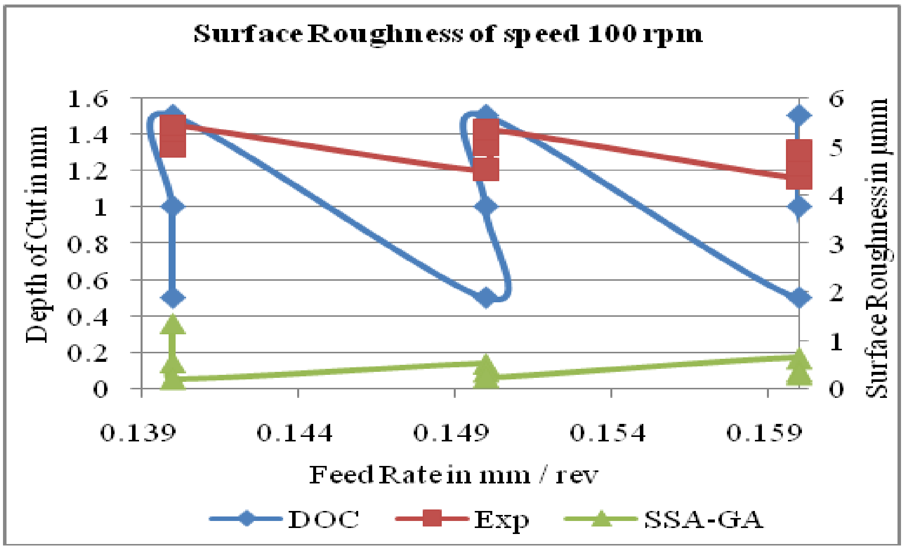

Figure 5.4 Surface Roughness of Combined GA – SSA for spindle speed 100 rpm

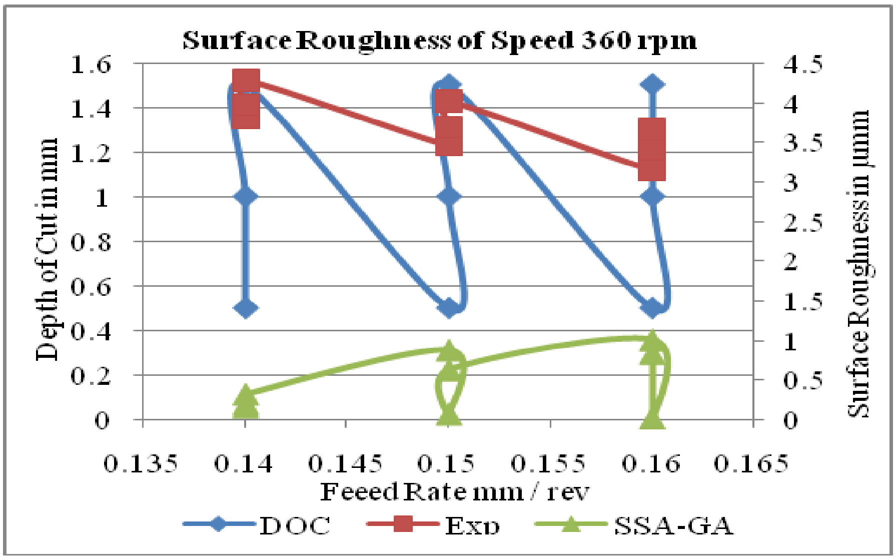

Figure 5.5 Surface Roughness of Combined GA – SSA for spindle speed 360 rpm

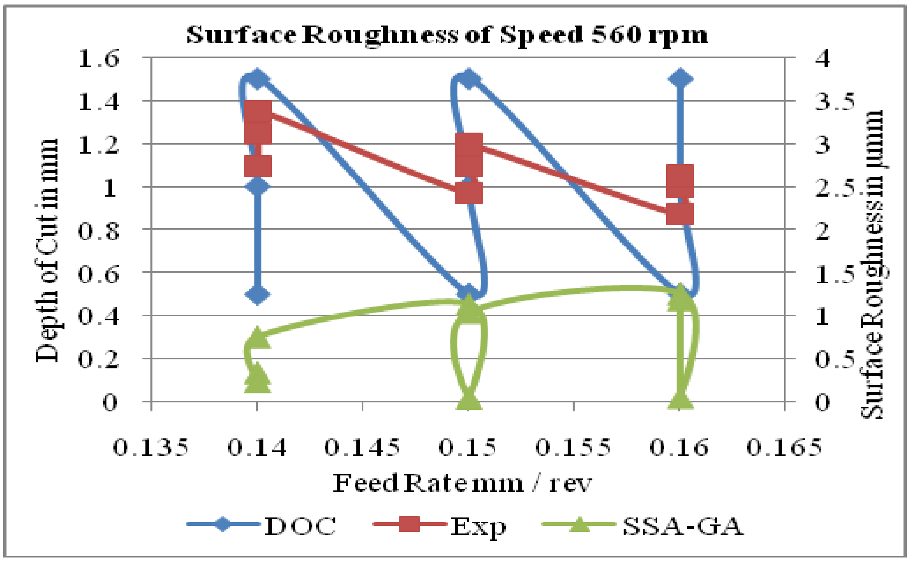

Figure 5.6 Surface Roughness of Combined GA – SSA for spindle speed 560 rpm

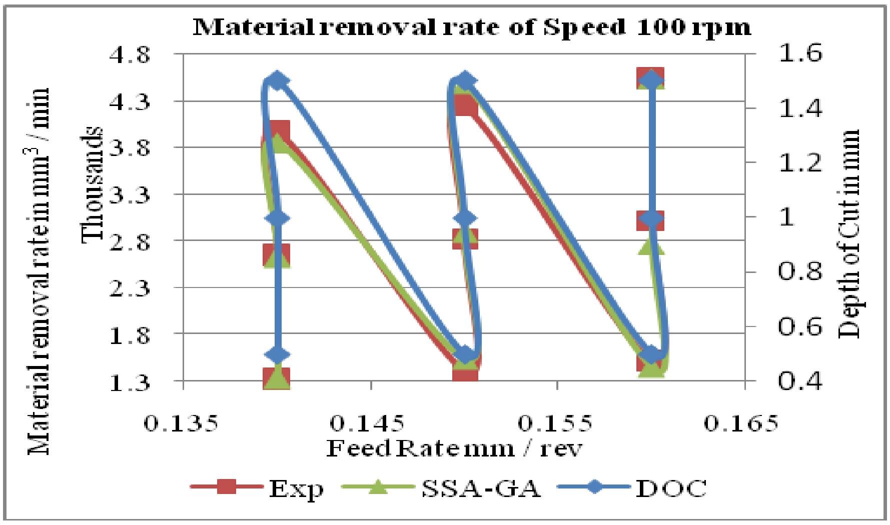

Figure 5.7 MRR Combined GA – SSA for spindle speed 100 rpm

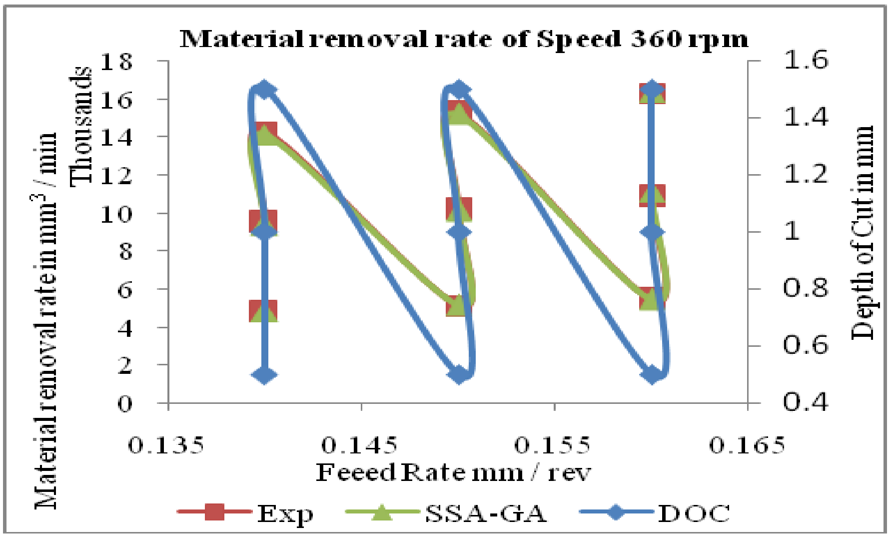

Figure 5.8 MRR Combined GA – SSA for spindle speed 360 rpm

6. CONCLUSION

In turning operations on EN-8 material for the given set of process conditions,

- While combining with speed, Feed rate confirms to be the prominent influence parameter on Surface roughness over depth of cut.
- In combination with speed, Depth of cut is the most influencing parameter than feed in determining the material removal rate.
- Scatter Search algorithm is yielding the best computation result in the optimization process among the employed four algorithms.
- Genetic Algorithm recorded the next best outcome comparing the Scatter search position for computation.Combined *GA – SSA* attempt concede added tuned outcome than the SSA and GA individual computation and the error rate further most low.
- The computation approach may be further extended to find the values of the surface roughness and material removal rate by assigning the intermittent values of input parameters and thereby smooth curve may be generated to pick the right set of cutting parameters for the desired output requirements while processing the given material.
- The present attempt may be extended with other heuristic algorithm and the outcomes may be tuned further.

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