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A COMPARATIVE EVALUATION OF GA AND PSO OPTIMISATION ALGORITHMS IN FORECASTING THE INFLUENCE OF TURNING PARAMETERS ON ASTM A48 GREY CAST IRON MACHINING

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ABSTRACT

ASTM 48 Grey cast iron is being used to produce casting parts with low or middle duty or load, such as various stove parts, gas burners, boiler parts, protective cover, hand wheel, brackets, base plate, crane balls, counter weight, handle, machine base, cases, bearing support, workbench, belt pulley, pump body, valve body, pipe fittings, flywheel etc. The material removal rates in the machining operations are one of the major deciding factors addressing to the volume production. To meet out the demand maximizing the MRR is essential. This investigation involves in optimising the MRR of turning operations on ASTM 48 Grey cast iron with the application of two optimization algorithms Genetic Algorithm and Particle Swarm optimisation. Based on the assessment of performance of the algorithms the outcome of the second best algorithm is taken as a input (feed) to the better performed algorithm as a hybridization approach. Machining speed, feed, depth of cut and material removal rate are chosen as the process parameters. Regression equation modeling, analysis and optimization algorithms are used to recognize the parametric influence and optimization.

***Key words*- ASTM 48 Grey cast iron, Turning, Regression, Genetic Algorithm, Particle swarm optimisation, hybridization, Optimisation, Minitab, MATLAB.**

I. INTRODUCTION

In the current state of affairs of manufacturing industries are starving towards improving productivity with reasonable cost in the right time without compromising the quality attributes. Attaining the higher productivity is based on the rate of material being removed from the material stock during machining operations with minimum time. For this turning process are the most commonly employed operations. Improved amount of material removal rate is highly depending on the right selection of process parameters for which the optimisation methodology is being used by all. Traditional and nontraditional optimisation techniques are available in plenty and the application part of optimisation techniques is carefully done in order to identify the algorithms which support to reach the optimum solutions to the issues by taking care of all related attributes. This study mainly focused towards the maximization of MRR during machining operations. Genetic algorithm and Particle swarm optimisation algorithms are chosen to apply in this aspect and the convergence of each algorithm is observed. Thereby hybridization of algorithms is effected to get the most tuned results. Machining speed, feed, depth of cut are the input parameters considered and material removal rate is chosen as the outcome process parameters.

Kaymakci et al [1] developed one unique cutting mechanics model to access and forecast the cutting forces in milling, boring, turning and drilling operations towards ensuring the product end quality. That particular operation models join all the material properties, tool geometry, cutting mechanics, process kinematics and structural dynamics together and are applied to envisage force, torque, power in metal cutting operations. Abou-El-Hossein et al [2] have industrialized about the impact of speed; feed rate; radial and axial depth of cut on the cutting force which in turn reflects on the quality by developing first and second order models to predict the cutting force created in the end milling operation of the material AISI P20 tool steel. Srikanth and Kamala [3] have suggested and applied a unique real coded genetic algorithm (RCGA) to sentence the optimal machining parameters through the explanations about the various issues of RCGA along with its advantages over the existing model of binary coded genetic algorithm (BCGA). Maciej Grzenda et al [4] have conducted experiment and finally suggested a roughness prediction model through a hybrid algorithm which was the combination of Genetic Algorithm and Neural Networks in high-torque face milling operations. Azlan Mohd Zain et al [5] have applied the Genetic Algorithm (GA) to optimize the machining conditions in view of minimizing the surface roughness in end milling operation. The optimal consequence of the tool radial rake angle in combination with speed and feed rate cutting conditions over the influence on the surface roughness was the main objective of the study. 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 that converges with the minimum surface roughness value.

Babu [6] had applied the Adaptive Genetic Algorithm and Simulated Annealing Algorithm for optimization of grinding parameters. The outcome of the attempt was that, AGA, SAA, PSO and MA were applied to solve the bench marked problems found in the literature and these were found outperforming some other algorithms in terms of minimization of multi objective in the selected grinding operation. The results obtained were compared and the best optimization technique for the particular machining operation was identified. Saravanan et al [7] have done a revolutionary approach by applying the techniques of optimization for cutting parameters during continuous finished profile machining using non-traditional techniques. About six non-traditional algorithms, the GA, SAA, TS, MA, ACO and the PSO had been employed to resolve this problem. The results obtained from GA, SA, TS, ACO, MA and PSO were compared for various profiles. Also, a comprehensive user friendly software package had been developed to input the profile interactively and to obtain the optimal parameters using all six algorithms. Noorul Haq et al [8] used particle swarm optimization algorithm (PSO) for optimal machining allocation. The objective was to obtain optimum tolerances of the individual components for the minimum cost of manufacturing. The result obtained by PSO was compared with geometric programming (GP) and genetic algorithm and the performance of the result were analyzed.

In this study the analysis and forecasting on the optimized parametric combination is carried out through the designated Genetic Algorithm and particle swarm optimization coded in MATLAB programming. Referring to the performance in computation as a new move feeding the outcome value of the second ranked algorithm as the input values to the first ranked algorithm by direct hybridization and the optimised parameters combinations are identified with the tuned results through the simulation.

II. EXPERIMENTAL PLAN AND OBSERVED DATA

For the investigation of the material removal rate on the material ASTM 48 Grey cast iron while machining in a conventional lathe machine with the high speed steel as the cutting tool material the experiments was performed by [9] Md. Maksudul Islam et al. The basic chemical composition of the specimen material is specified in Table 2.1 followed by the important mechanical properties

Table 2.1 Basic chemical composition of ASTM 48 Grey cast iron

Component	Quantity
Carbon	3.2 to 3.5 %
Silicon	1.8 to 2.4 %
Magnesium	0.5 to 0.9 %
Fe	Balanced

The tensile strength of class 20 is Min. 150 Mpa; the hardness range is 150 to 200 HB which has good casting property, shock absorption, wear-resisting property and machining performance. The machining input cutting variables are cutting speed, feed rate and depth of cut with three levels as mentioned in Table 2.2. L_{27} array was taken for the experiment conducted and the Material removal rate was considered as outcome variables. The machining processes were carried out as dry machining process and subsequently the responses with reference to each observation were arranged in Table 2.2. Then arrived observed experimental data [9] are mentioned in the Table 2.3

Table 2.2 Input machining parameters level selection

Turning parameters	Units	Level 1	Level 2	Level 3
Cutting Speed	(rpm)	112	0.125	0.25
Feed	(mm / rev)	175	0.138	0.30
Depth of cut	(mm)	280	0.153	0.35

Table 2.3 Experimental observed data set

Ex. No.	Cutting Speed (rpm)	Feed Rate (mm/ rev)	Depth of Cut (mm)	Material removal rate (mm^3 / sec)
1	112	0.125	0.25	3.38
2	112	0.138	0.30	4.01
3	112	0.153	0.35	4.55
4	112	0.125	0.25	3.31
5	112	0.138	0.30	3.93

6	112	0.153	0.35	4.45
7	112	0.125	0.25	3.23
8	112	0.138	0.30	3.82
9	112	0.153	0.35	4.32
10	175	0.125	0.25	4.59
11	175	0.138	0.30	5.48
12	175	0.153	0.35	6.14
13	175	0.125	0.25	4.72
14	175	0.138	0.30	5.59
15	175	0.153	0.35	6.28
16	175	0.125	0.25	4.78
17	175	0.138	0.30	5.69
18	175	0.153	0.35	6.36
19	280	0.125	0.25	5.3
20	280	0.138	0.30	6.31
21	280	0.153	0.35	7.02
22	280	0.125	0.25	5.32
23	280	0.138	0.30	6.31
24	280	0.153	0.35	7.03
25	280	0.125	0.25	5.46
26	280	0.138	0.30	6.45
27	280	0.153	0.35	7.09

IV. MATHEMATICAL MODELLING

With the Minitab17 software, the influences of the input machining parameters (speed, feed and depth of cut) on the output parameter (material removal rate) are analysed by statistical regression relationship. The second order regression relationship between the variables shows higher level significance than the first order regression through the values of the R – sq. Both the first and second order statistical values of R-sq can be viewed from the Table 4.1.

Table 3.1 Regression model comparison for surface roughness

Parameter	Regression	S	R-sq	R-sq(adj)	R-sq(pred)	Durbin - Watson
MRR	First order	0.39688	90.06%	88.76%	86.76%	0.62616
	Second order	0.100509	99.45%	99.28%	99.03%	0.66992

The second order regression equations through the Minitab17 for the material removal rate in terms of input parameter combination are

MRR = - (4.55) + (0.0822*Speed) + (13*feed) + (5.1*Doc) – (0.000112*Speed^2) – (0.614*Speed*feed) + (0.203*Speed*Doc)

(3.1)

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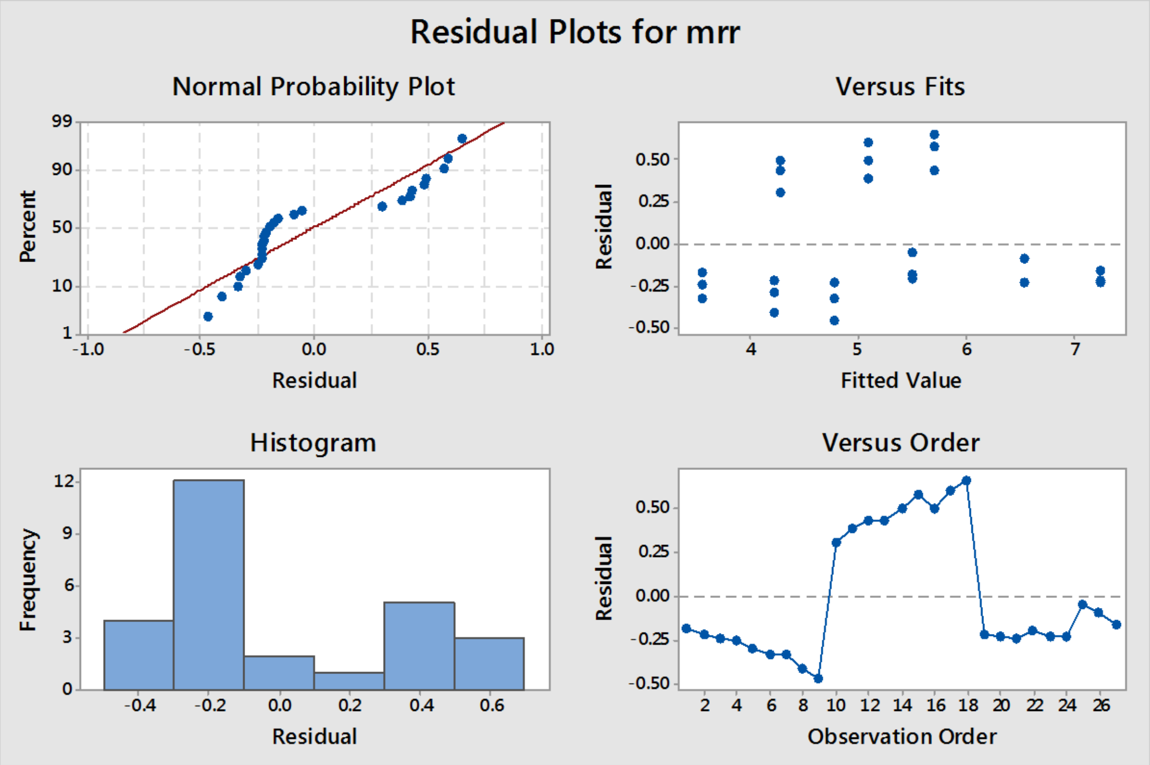

Figure 3.1 Residual plots of material removal rate

The residual plots through Minitab analysis for the surface roughness are depicted in Figure 3.1. The best subset regression analysis reveals that the speed is the major influencing factor which contributes 63.5 % ; the parameter depth of cut registered next level influence with 26.4 % whereas the feed rate exhibits very little amount of influence on the MRR.

IV. PARAMETRIC OPTIMISATION

Sentencing a choice with a good number of cost effective or uppermost attainable presentations under the given constraints is by maximizing preferred factors and minimizing undesired ones. Process optimization is the order of adjusting a process so as to optimize a number of particular groups of parameters devoid of violating some constraint. The most common goals are minimizing cost and maximizing throughput and effectiveness. This is one of the major quantitative gears in industrial decision making.

With the support of programming in the MATLAB R2017 software, an attempt is made in this paper for forecasting of the outcome variable referring to the input process variables with the optimization algorithms namely, Genetic Algorithm and Particle swarm Optimization. Forecasting of the optimized material removal rate in the turning process on the ASTM 48 grey cast iron specimen was performed on the primary objective as maximizing the outcome. To analyze the influence of the cutting speed and the feed on the MRR through MATLAB R2017 platform with the Elman Back Propagation approach is applied. The number of iterations initiated for this simulation is 50000 turns. The suitability of the both the employed algorithms are assessed through the accuracy level in computation which is in the form mean squared error occurred rate as the indicator. Figure 4.1 shows the progress of the training data in MATLAB. The accuracy level of the computation is mentioned in the Table 4.1.

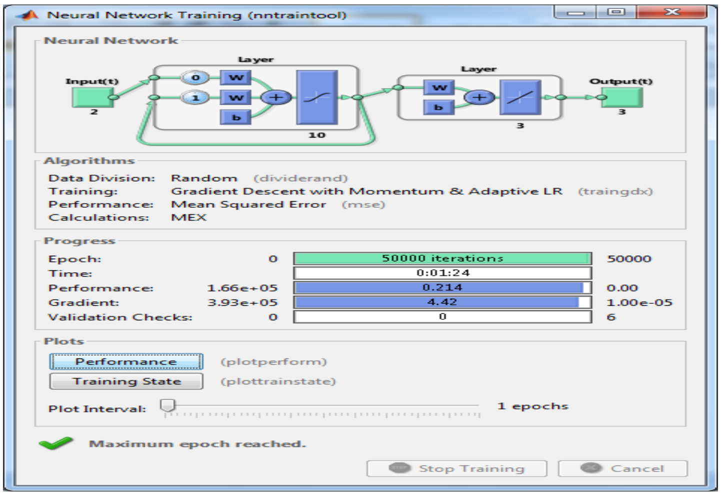

Figure 4.1 Data training progress of 50000 iterations

Table 4.1 Mean squared error value comparison

Algorithm	Mean squared error	Ranking
GA	0.01138	1
PSO	0.02635	2

Genetic algorithm converges with the minimum value of mean squared error than the PSO algorithm in this case. As the novel attempt is made by feeding the values off the PSO outcome as the input reference values to GA and the performance of the simulation is evaluated. The value of the mean squared error was noticed as 0.00849, i.e. around 23.4 % improvement is noticed. The new approach of hybridization with regression equations as condition for simulation and regression calculated values replacing the experimental values are shown in the Fig. 4.2

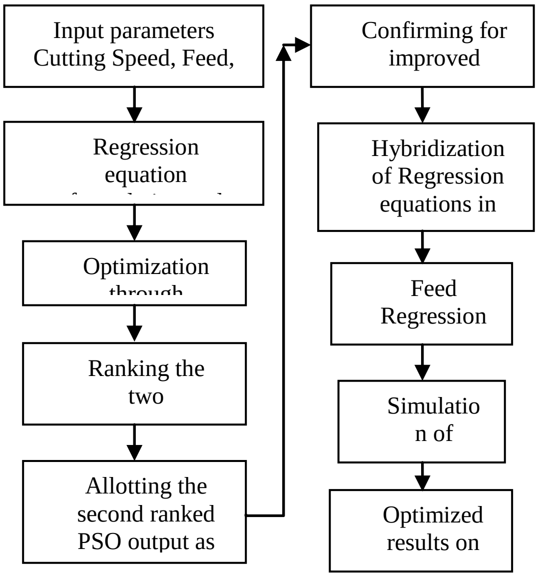

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Figure 4.2 Block diagram of Hybridization

In order to pave a smooth curve with closer interval values of the process outcomes, the parameters selected was sub divided with the step value 16.8 rpm in speed, 0.0112 step value in feed and 0.01 mm step value in depth of cut. The computed results of the MRR through this PSO feed GA approach for all combination of the parameter input given to the programme are listed in the **Table 4.2 to Table 4.4.**

Table 4.2 MRR for the speed 112, 128.8 rpm Vs all combination of feed and depth of cut

Speed 112 rpm				Speed 128.8 rpm			
DOC	Feed 0.125,	0.1362,	0.1474,	DOC	Feed 0.125,	0.1362,	0.1474,
0.25	3.239	3.468	3.960	0.25	3.729	3.972	4.485
0.26	3.885	4.087	5.128	0.26	4.040	4.560	5.428
0.27	3.792	3.703	4.470	0.27	3.655	4.334	5.084
0.28	3.202	3.447	4.729	0.28	3.662	4.328	5.282
0.29	3.092	3.726	4.524	0.29	3.586	4.238	5.174
0.30	3.100	3.491	4.349	0.30	3.603	4.082	5.047
0.31	3.106	3.410	4.262	0.31	3.572	3.955	4.936
0.32	3.117	3.348	3.934	0.32	3.551	3.836	4.434
0.33	3.109	3.290	4.217	0.33	3.512	3.730	4.748
0.34	3.096	3.242	3.800	0.34	3.472	3.636	4.335
0.35	3.077	3.202	3.703	0.35	3.429	3.557	4.157

Table 4.3 MRR for the speed 145.6, 162.4 rpm Vs all combination of feed and depth of cut

Speed 145.6 rpm				Speed 162.4 rpm			
DOC	Feed 0.125,	0.1362,	0.1474,	DOC	Feed 0.125,	0.1362,	0.1474,
0.25	4.154	4.440	4.979	0.25	4.519	4.851	5.415
0.26	4.500	4.900	5.634	0.26	4.900	5.127	5.772
0.27	4.127	4.831	5.522	0.27	4.463	5.166	5.800
0.28	4.188	4.863	5.717	0.28	4.603	5.247	6.008
0.29	4.111	4.686	5.688	0.29	4.557	5.070	6.027
0.30	4.118	5.033	5.652	0.30	4.581	5.455	6.058
0.31	4.053	4.542	5.567	0.31	4.505	5.086	6.018
0.32	4.010	4.384	5.417	0.32	4.453	4.929	5.948
0.33	3.942	4.232	5.216	0.33	4.368	4.757	5.623
0.34	3.880	4.096	5.565	0.34	4.293	4.591	6.002
0.35	3.816	3.979	4.825	0.35	4.214	4.441	5.546

Table 4.4 MRR for the speed 112, 128.8 rpm Vs all combination of feed and depth of cut

Speed 179.2 rpm				Speed 196 rpm			
DOC	Feed 0.125,	0.1362,	0.1474,	DOC	Feed 0.125,	0.1362,	0.1474,
0.25	4.820	5.196	5.778	0.25	5.061	5.468	6.055
0.26	5.239	5.279	5.864	0.26	5.511	5.387	5.925
0.27	4.710	5.387	5.980	0.27	4.926	5.543	6.105

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0.28	4.894	5.493	6.187	0.28	5.102	5.206	6.296
0.29	4.874	5.394	6.230	0.29	5.086	5.654	6.351
0.30	4.934	5.807	6.296	0.30	5.169	6.101	6.433
0.31	4.872	5.494	6.288	0.31	5.124	5.756	6.443
0.32	4.833	5.377	6.268	0.32	5.112	5.680	6.451
0.33	4.747	5.230	5.965	0.33	5.041	5.583	6.247
0.34	4.672	5.065	6.383	0.34	4.980	5.450	6.694
0.35	4.588	4.902	6.049	0.35	4.905	5.305	6.333

The scatter plots generated through the Minitab for the above results are shown in the following Figures **4.3 to 4.**

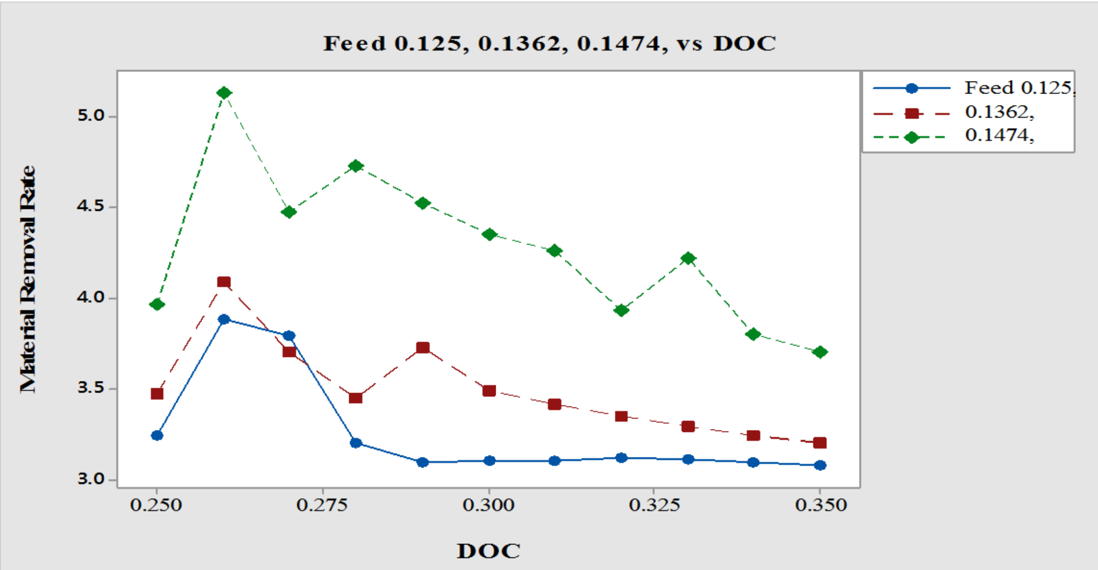

Figure 4.3 MRR plots of speed 112 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

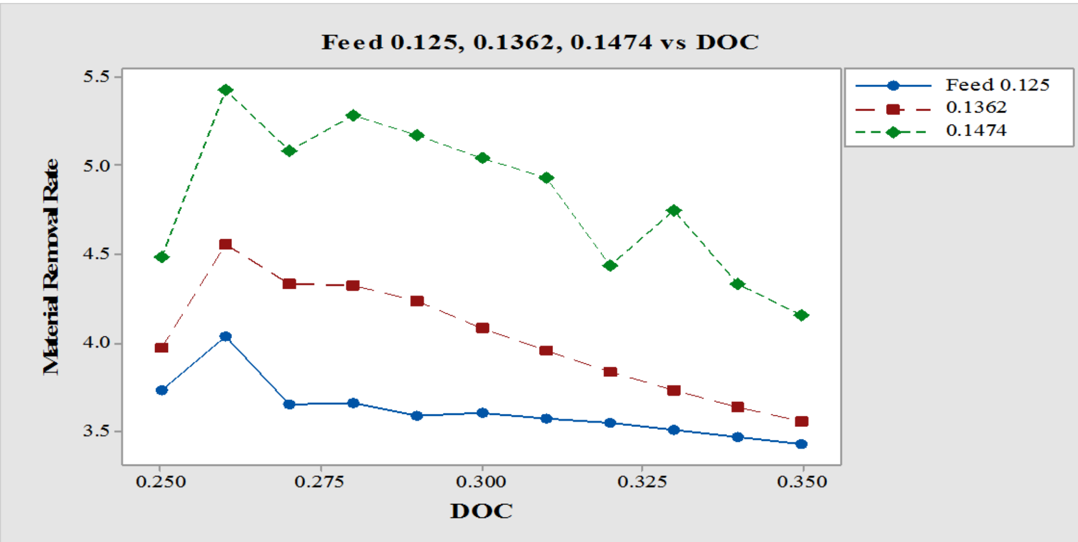

Figure 4.4 MRR plots of speed 128.8 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

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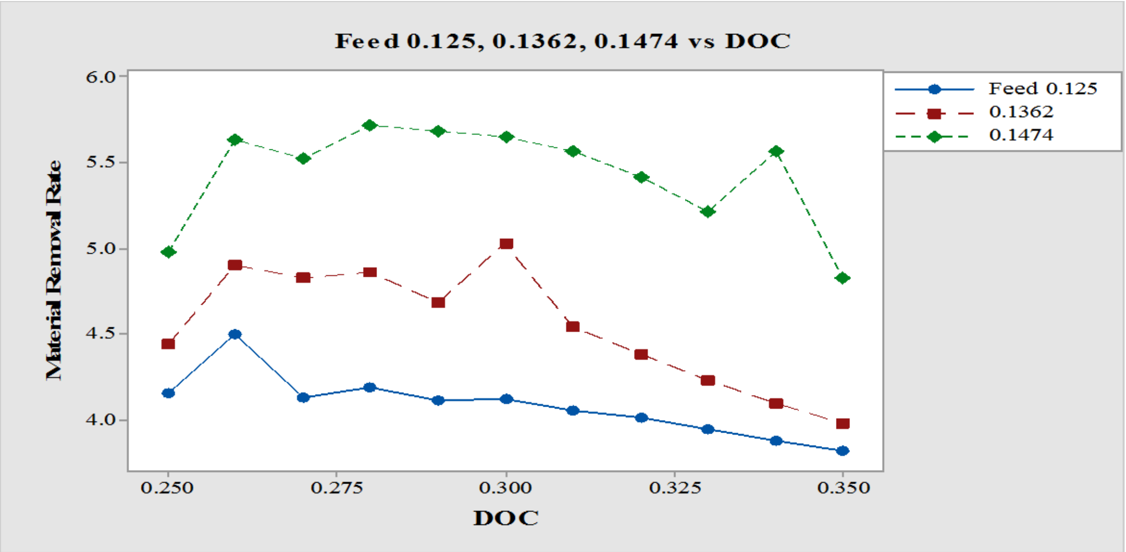

Figure 4.5 MRR plots of speed 145.6 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

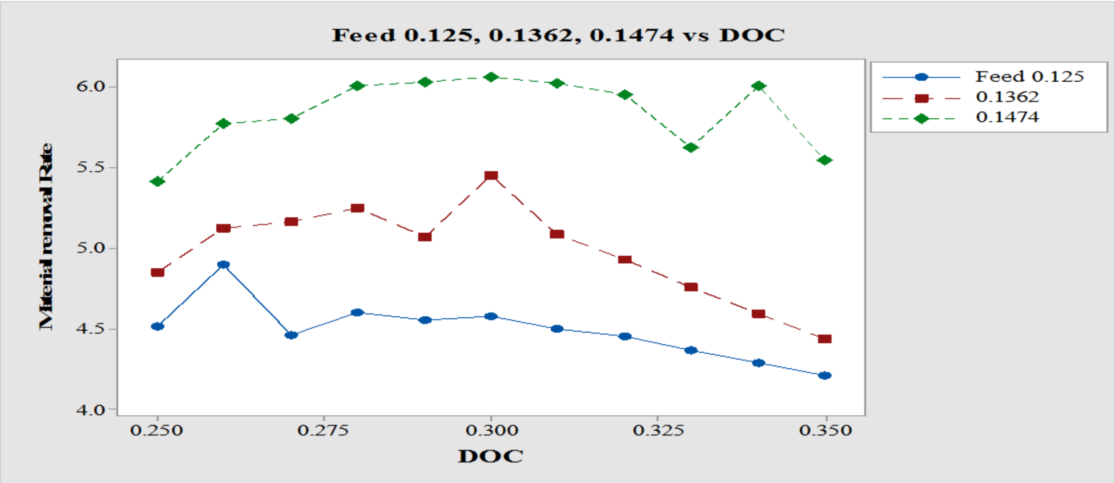

Figure 4.6 MRR plots of speed 162.4 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

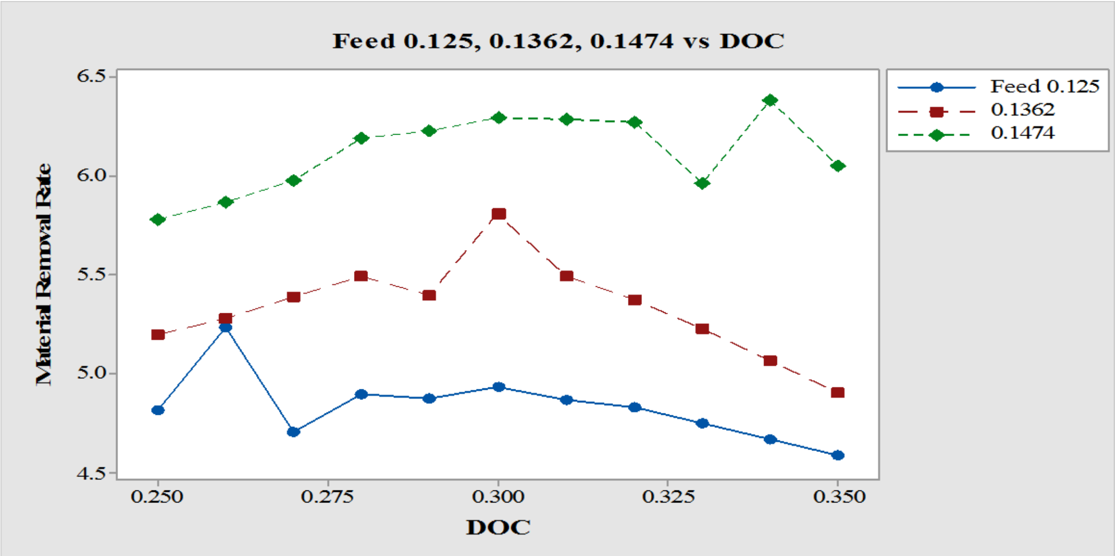

Figure 4.7 MRR plots of speed 179.2 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

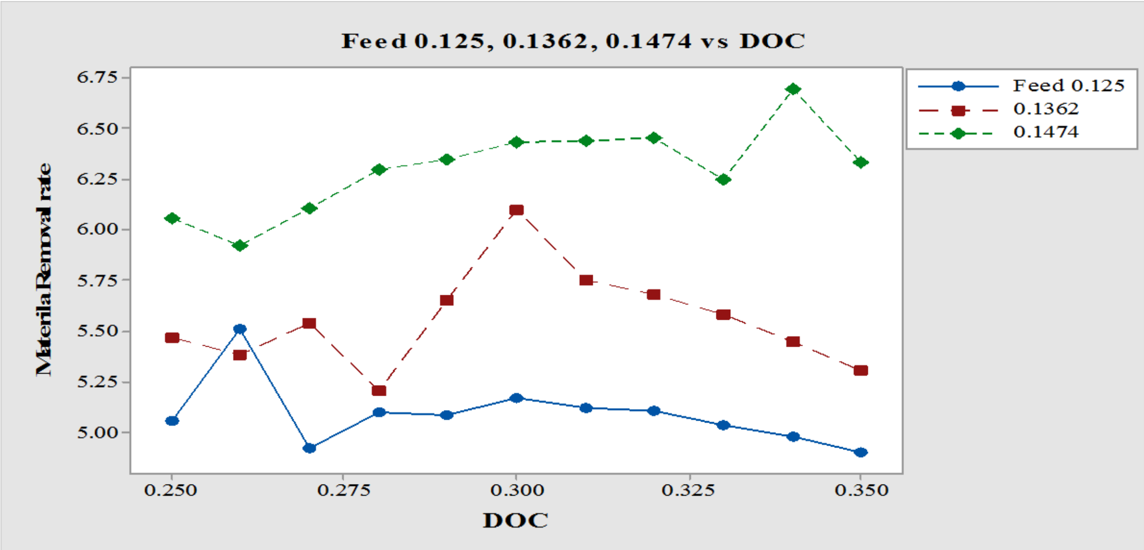

Figure 4.8 MRR plots of speed 196 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

V. RESULTS AND CONCLUSIONS

For the set of experimental parameters with the selected level, 2^{nd} order regression relationship between the input, output variables is significant statistically.

Genetic Algorithm converges with minimum mean squared error value towards optimising than the Particle Swarm Optimisation.

On replacing with the random process with regression relationship, feeding the regression computed values as input the accuracy level in computation is tuned to the finest level for the set of values.

Speed is the major influencing factor which contributes 63.5 %; the parameter depth of cut registered next level influence with 26.4 % whereas the feed rate exhibits very little amount of influence on the MRR.

The optimum value of MRR is 7.319 mm^3 / sec for the speed 263.2 rpm, 0.1474 mm / rev feed, 0.34 mm depth of cut combination.

Manufacturers may use the derived method of optimisation technique for simulating the outcome values and reference can be done at time of manufacturing products with the ASTM 48 Grey cast iron material.

REFERENCES

[1] Kaymakci M, Kilic ZM & Altintas Y, 2012, “Unified cutting force model for turning, boring, drilling and milling operations”, International Journal of Machine Tools and Manufacture, vol. 54-55, pp. 34-45.

[2] Abou-El-Hossein, KA, Kadirgama, K, Hamdi, M & Benyounis, KY, 2007, “Prediction of cutting force in end-milling operation of modified AISI P20 tool steel”, Journal of Materials Processing Technology, vol. 182, pp. 241-247.

[3] Srikanth T & Kamala V, 2008, “A Real Coded Genetic Algorithm for Optimization of Cutting Parameters in Turning”, IJCSNS, Int. J. Comput. Sci. Netw. Secur. vol. 8, no. 6, pp. 189-193.

[4] Maciej Grzenda & Andres Bustillo, 2013, “The evolutionary development of roughness prediction models”, Applied Soft Computing, vol. 13, no. 5, pp. 2913-2922.

[5] Azlan Mohd Zain , Habibollah Haron & Safian Sharif, 2010, “Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process”, Expert Systems with Applications, vol. 37, pp. 4650-4659.

[6] Babu K. (2004), ‘Optimization of grinding parameters using Adaptive Genetic Algorithm and Simulated Annealing Algorithm’, M.Tech. Thesis, SASTRA Deemed University, Thanjavur, Tamilnadu, India, 1-7.

[7] Saravanan R., Sivasankar R., Asokan P., Vijayakumar K. and Prabhaharan G. (2005), ‘Optimization of cutting conditions during continuous finished profile machining using non-traditional techniques’, International Journal of Advanced Manufacturing Technology, Vol. 26, No. 9, pp. 1123-1128.

[8] Noorul Haq A., Sivakumar K., Saravanan R. and Karthikeyan K. (2006), ‘Particle Swarm Optimization (PSO) algorithm for optimal machining allocation of clutch assembly’, International Journal of Advanced Manufacturing Technology, Vol. 27, pp. 865-869.

[9] Md. Maksudul Islam, Sayed Shafayat Hossain, Md.Sajibul Alam Bhuyan, 2015. Optimization of Metal Removal Rate for ASTM A48 Grey Cast Iron in Turning Operation Using Taguchi Method. *International Journal of Materials Science and Engineering.* Volume 3, Number 2, pp 134-146.