International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

A Relative Assessment of Algorithms in Optimising the Influence of Process Parameters on Turning Process of Grey Cast Iron

Dr.D.Ramalingam*[1], R.RinuKaarthikeyen[2], Dr.S.Muthu[3], Dr.V.Sankar[4]

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

**corresponding author*

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

[3]*Principal, Adithya Institute of Technology, Coimbatore, (India)*

[4]*Professor, Nehru Institute of Engineering and Technology, Coimbatore, (India)*

ABSTRACT

Grey cast iron of the grade ASTM 48 is in the use for manufacturing 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 etc. The production volume rate is mainly lies with the material removal rate during machining process and this is essential towards fulfilling the demand. Henceforth the maximization of the MRR is indispensable in this regard. This attempt of investigation involves in optimising the MRR of turning operations on ASTM 48 Grey cast iron with the application of six optimization algorithms namely, Particle swarm Optimization, Scatter Search Algorithm, Simulated Annealing Algorithm, Artificial Bee Colony Algorithm, Ant Colony Algorithm and Firefly algorithm. By assessing the simulation performance of the algorithms in terms of MSE the best algorithm is chosen for further analysis and forecast with the hybridization approach of statistically significant relationship integrated in the programme. 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 identify the influences between the parameters and optimized.

Keywords- Turning, Grey cast iron of Grade ASTM 48, Regression, Particle swarm Optimization, Scatter Search Algorithm, Simulated Annealing Algorithm, Artificial Bee Colony Algorithm, Ant Colony Algorithm and Firefly algorithm, hybridization, Optimisation, Minitab, MATLAB.

I. INTRODUCTION

Nowadays, the manufacturers are keenly concentrating on improving productivity with reasonable cost with the time consciousness with no compromise in the product quality attributes. In addition, owing to the extensive use of highly automated machine tools in the industry, manufacturing domain requires dependable models, right ways and means to predict the resultant performance of machining processes. The necessity of selection, implementation on the optimal machining conditions and most appropriate cutting tool has been felt over in the

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

recent past and present. Obtaining the improved state of productivity is based on the rate of material being removed from the material stock during machining operations with minimum time which mainly depends on the exact assortment of process parameters. This phenomenon attracts the optimisation methodology is practice 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 attempt aims towards paying attention towards the maximization of MRR during machining operations. Six commonly used optimisation algorithms are chosen for evaluation and the convergence of each algorithm is observed with reference to the performance indicator MSE. The best performed algorithm is identified for this case and further evaluation is organized with hybridization between algorithm and statistical relationship. Machining speed, feed, depth of cut are the input parameters considered and material removal rate is chosen as the outcome process parameters.

III. RELATED WORKS

Srikanth and Kamala [1] have demonstrated the application of a unique real coded genetic algorithm (RCGA) to verdict 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). Aslan [2] declared through their research that the right and optimum selection of process condition is mainly important because that determine surface quality of the product and flank wear phenomena of the cutting tool. While performing the turning and facing operations an inappropriate choice of cutting parameters will cause undesired quality and high tooling cost. Thomas et al. [3] have realized that DOE which addresses the process of planning the experiment, so that the appropriate data could be identified and move to further intensive analysis by statistical methods, resulting in an applicable and the selective objective conclusion. Palanikumar et al. [4] have made with an attempt to assess the influence of machining parameters on surface roughness in processing composites and concluded that the feed rate has more authority on surface quality which followed by cutting speed. Suleyman et al. [5] have concluded through their research with the analysis based on the response surface methodology, that the tool nose radius is the dominant factor on the surface quality while doing turning process on the AISI steel. Nikolaos et al. [7] have investigated on the surface quality and predicted in turning process on AISI 316 L materials. Oezel and Karpat [8] have proved 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). An evolutionary approach was taken through applying the techniques of optimization for cutting parameters during continuous finished profile machining using non-traditional techniques by Saravanan et al [9]. In their attempt they have employed six non-traditional algorithms, the GA, SAA, TS, MA, ACO and the PSO to resolve the issues taken for their analysis. All the six, GA, SA, TS, ACO, MA and PSO were compared with different profiles. Moreover a user friendly software package had developed to input the profile interactively and to obtain the optimal parameters using all six algorithms. Agapiou [10] laid a path through their investigation on the suitability of regression analysis applications to find the optimal levels and to analyze the effect of the drilling parameters on surface finish. Emad Ellbeltagi et al. [11] mapped the suitability among five

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

evolutionary–based optimization algorithms (GA, MA, PSO, ASO, and SFL) and reported, PSO method was generally found to perform better than other algorithms in terms of success rate and solution quality.

III. EXPERIMENTAL OBSERVATION

Grey cast iron of the Grade ASTM 48 material taken for turning experiment by Md. Maksudul Islam et al. [6] with the intention of investigation of the material removal rate during processing in conventional lathe with the HSS cutting tool. The basic chemical composition of the specimen material is Carbon 3.2 to 3.5 %; Silicon 1.8 to 2.4 %; Magnesium 0.5 to 0.9 % and Fe as balance. Referring to the Mechanical properties the material exhibits 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. The process main input machining parameters are speed, feed and depth of cut. About three stages were chosen as listed in Table 3.1. For conducting the experiment L_{27} array was selected. The outcome parameter value with reference to the set of input parameter selection was observed [6] and given in the Table 3.2. Experiment executed in the environment as dry machining.

Table 3.1 Input machining parameters level selection

Machining parameters	Stage 1	Stage 2	Stage 3
Speed (rpm)	112	0.125	0.25
Tool Feed (mm/rev)	175	0.138	0.30
Depth of cut (mm)	280	0.153	0.35

Table 3.2 Experimental observed data set [6]

Ex. No.	Speed	Tool Feed	Depth of Cut	MRR	Ex. No.	Speed	Tool Feed	Depth of Cut	MRR
1	112	0.125	0.25	3.38	15	175	0.153	0.35	6.28
2	112	0.138	0.30	4.01	16	175	0.125	0.25	4.78
3	112	0.153	0.35	4.55	17	175	0.138	0.30	5.69
4	112	0.125	0.25	3.31	18	175	0.153	0.35	6.36
5	112	0.138	0.30	3.93	19	280	0.125	0.25	5.3
6	112	0.153	0.35	4.45	20	280	0.138	0.30	6.31
7	112	0.125	0.25	3.23	21	280	0.153	0.35	7.02
8	112	0.138	0.30	3.82	22	280	0.125	0.25	5.32
9	112	0.153	0.35	4.32	23	280	0.138	0.30	6.31
10	175	0.125	0.25	4.59	24	280	0.153	0.35	7.03
11	175	0.138	0.30	5.48	25	280	0.125	0.25	5.46
12	175	0.153	0.35	6.14	26	280	0.138	0.30	6.45
13	175	0.125	0.25	4.72	27	280	0.153	0.35	7.09
14	175	0.138	0.30	5.59	-	-	-	-	-

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

IV. MATHEMATICAL RELATIONSHIP

The level of impact of the input machining parameters (speed, feed and depth of cut) on the output parameter (material removal rate) are analysed by statistical regression relationship through the commercial Minitab17 software. Higher level of significance is registered by the second order regression relationship between the variables than the first order regression which is evident 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 4.1 Statistical relationship between the process variables

Parameter	Regression	S	R-sq	R-sq(adj)	R-sq(pred)
MRR	First order	0.39688	90.06%	88.76%	86.76%
	Second order without self power	0.402806	90.65%	88.42%	86.15%

The second order regression equation of the material removal rate in terms of input parameter combination is

MRR = - (0.7) + (0.038 x speed) + (13 x feed) + (5 x doc) – (0.61x speed x feed) + (0.203 x speed x doc) (4.1)

The statistical residual plots through Minitab analysis for the material removal rate are displayed in the Figure 4.1. The best subset regression analysis reveals that the speed is the major influencing factor which contributes 57.8 % ; the parameter depth of cut registered next level influence with 32.6 % whereas the feed rate exhibits very little amount of influence on the MRR.

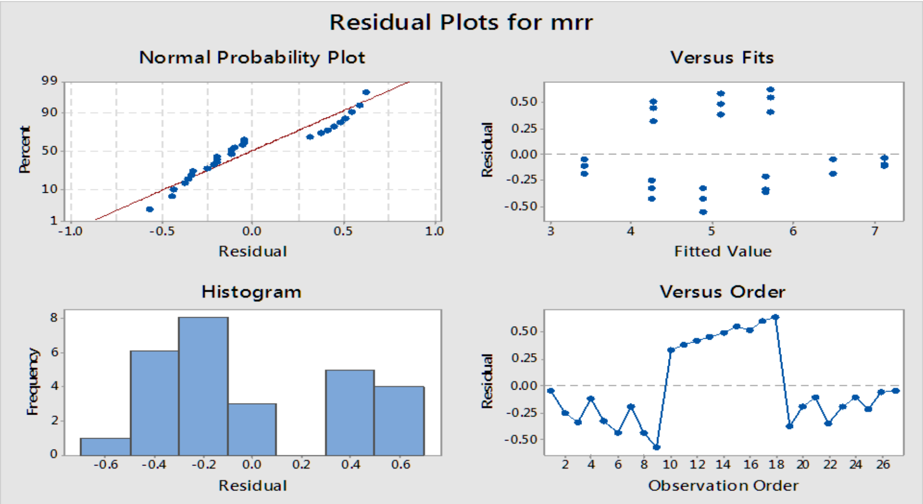


Figure 4.1 Residual plots of material removal rate

V. OPTIMISATION TECHINQUES

Process optimization is the arrangement order to get the adjustment in the process so as to optimize a set of parameters without violating the inbuilt restrictions. The accepted objectives through this exercise are either to minimize the cost of the process or to maximize the outcome with effectiveness. In the MATLAB R2017 software, an effort is taken in this paper to evaluate the effectiveness of the optimisation algorithms and also to forecast of the output variable referring to the input process variables with the optimization algorithms namely, Particle swarm Optimization, Scatter Search Algorithm, Simulated Annealing Algorithm, Artificial Bee Colony

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Algorithm, Ant Colony Algorithm and Firefly algorithm. Estimating of the optimized material removal rate in the turning process on the ASTM 48 grey cast iron specimen was performed with the main objective as maximizing. To analyze the authority of the machining speed, feed and depth of cut over the material removal tempo through MATLAB R2017 platform, the Elman Back Propagation process is functionalized. 50000 iterations have been initiated in this simulation process. The suitability of all the six algorithms are compared through the level of in computation which is in the form MSE (mean squared error) occurred rate as the performance indicator. Figure 5.1 shows the simulation progress of the data training in MATLAB. The accuracy level of the computation is mentioned in the Table 5.1.

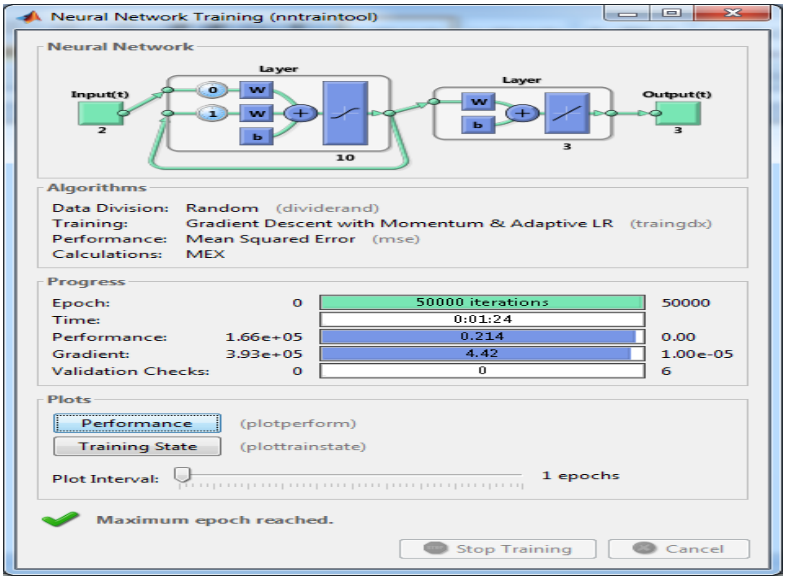
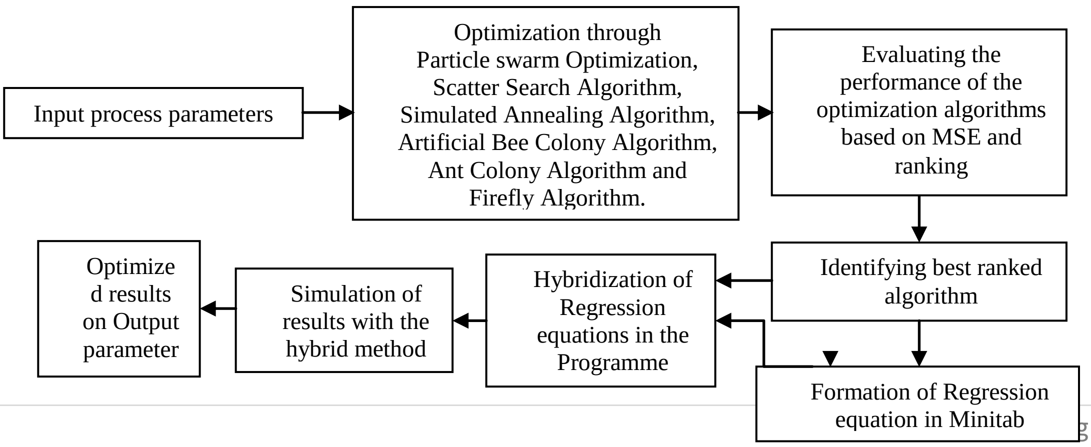


Figure 5.1 Data training progress of 50000 iterations

Table 5.1 Mean squared error value comparison

Algorithm	Mean squared error	Ranking
Firefly algorithm	0.000051	1
Ant Colony Algorithm	0.000764	2
Simulated Annealing Algorithm	0.003212	3
Scatter Search Algorithm	0.005372	4
Particle Swarm Optimization Algorithm	0.008319	5
Artificial Bee Colony Algorithm	0.018459	6



International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Figure 5.2 Block diagram of Hybridization

Firefly algorithm converges with the minimum value of mean squared error (0.000051) than the other algorithms in this simulation. The ranking of the algorithms with reference to the performance also noted through the Table 5.1. The new approach of hybridization with regression equations as clause for simulation is shown in the Fig. 5.2. In addition to that to form a soft curve with closer interval values of the material removal rate, the parameters selected was further division with 0.01 mm step value for depth of cut, 16.8 rpm step in speed and 0.0112 mm / rev step in tool feed. So computed results of the Material Removal Rate through this Regression integrated Firefly Algorithm method for all combination of the parameter including the step values chosen to the programme are listed in the Table 5.2 to Table 5.6.

Table 5.2 MRR for the speed 112, 128.8 rpm Vs feed 0.125, 0.1362, 0.1474, all depth of cut

v = 112 rpm				v = 128.8 rpm			
DOC	f = 0.125	f = 0.1362	f = 0.1474	DOC	f = 0.125	f = 0.1362	f = 0.1474
	MRR 1	MRR 2	MRR 3		MRR 1	MRR 2	MRR 3
0.25	3.234	4.729	4.966	0.25	4.932	4.847	5.095
0.26	3.515	4.550	4.420	0.26	4.041	4.727	4.637
0.27	3.796	4.328	3.942	0.27	4.354	4.523	4.169
0.28	4.072	4.127	3.608	0.28	4.668	3.926	3.816
0.29	4.352	3.724	3.660	0.29	4.101	4.240	3.499
0.3	3.863	4.003	4.019	0.3	4.039	4.004	3.811
0.31	3.861	4.281	4.281	0.31	4.046	4.106	4.122
0.32	3.825	3.960	4.639	0.32	4.016	4.175	4.892
0.33	3.835	4.166	4.800	0.33	4.029	4.470	4.746
0.34	3.820	4.174	4.495	0.34	4.073	4.509	5.060
0.35	3.829	4.166	4.771	0.35	4.142	4.519	5.374

Table 5.3 MRR for the speed 145.6, 162.4 rpm Vs feed 0.125, 0.1362, 0.1474, all depth of cut

v = 145.6 rpm				v = 162.4 rpm			
DOC	f = 0.125	f = 0.1362	f = 0.1474	DOC	f = 0.125	f = 0.1362	f = 0.1474
	MRR 1	MRR 2	MRR 3		MRR 1	MRR 2	MRR 3
0.25	5.400	4.975	5.371	0.25	5.960	5.134	5.870
0.26	4.503	4.890	4.991	0.26	5.420	5.068	5.659
0.27	4.847	4.679	4.432	0.27	5.283	4.815	5.012
0.28	4.297	4.340	4.051	0.28	4.529	4.689	4.450
0.29	4.265	4.685	3.833	0.29	4.353	4.419	4.103
0.3	4.191	4.171	4.178	0.3	4.330	4.366	4.483
0.31	4.221	4.239	4.522	0.31	4.395	4.341	4.865
0.32	4.170	4.438	4.868	0.32	4.333	4.677	5.240
0.33	4.223	4.781	5.217	0.33	4.398	5.064	5.626
0.34	4.341	4.829	5.564	0.34	4.609	5.173	6.002
0.35	4.448	5.022	5.912	0.35	4.812	5.565	6.387

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Table 5.4 MRR for the speed 179.2, 196 rpm Vs feed 0.125, 0.1362, 0.1474, all depth of cut

v = 179.2 rpm				v = 196 rpm			
DOC	f = 0.125	f = 0.1362	f = 0.1474	DOC	f = 0.125	f = 0.1362	f = 0.1474
	MRR 1	MRR 2	MRR 3		MRR 1	MRR 2	MRR 3
0.25	6.195	5.395	6.320	0.25	6.302	5.834	6.527
0.26	5.810	5.350	6.201	0.26	6.070	5.883	6.353
0.27	5.653	5.030	5.744	0.27	5.959	5.526	5.965
0.28	4.739	4.981	4.951	0.28	4.919	5.203	5.128
0.29	4.461	4.577	4.835	0.29	4.597	4.731	5.128
0.3	4.472	4.534	4.721	0.3	4.611	4.641	4.902
0.31	4.543	4.433	5.137	0.31	4.676	4.533	5.348
0.32	4.468	4.873	5.551	0.32	4.606	5.059	5.797
0.33	4.628	5.317	5.965	0.33	4.907	5.572	6.245
0.34	4.903	5.564	6.381	0.34	5.227	5.931	6.696
0.35	5.184	5.983	6.794	0.35	5.554	6.193	6.317

Table 5.5 MRR for the speed 212.8, 229.6 rpm Vs feed 0.125, 0.1362, 0.1474, all depth of cut

v = 212.8 rpm				v = 229.6 rpm			
DOC	f = 0.125	f = 0.1362	f = 0.1474	DOC	f = 0.125	f = 0.1362	f = 0.1474
	MRR 1	MRR 2	MRR 3		MRR 1	MRR 2	MRR 3
0.25	6.341	6.265	6.615	0.25	6.323	6.499	6.659
0.26	5.719	6.398	6.379	0.26	5.866	6.620	6.380
0.27	6.202	6.206	5.970	0.27	6.381	6.554	5.925
0.28	5.069	5.364	5.113	0.28	5.172	5.464	5.073
0.29	4.755	4.980	5.234	0.29	4.921	5.267	5.315
0.3	4.759	4.852	5.013	0.3	4.924	5.174	5.067
0.31	4.797	4.726	5.496	0.31	4.917	5.120	5.585
0.32	4.793	5.341	5.982	0.32	5.014	5.845	6.101
0.33	5.206	5.862	6.462	0.33	5.506	6.173	6.615
0.34	5.581	6.176	**6.948**	0.34	5.913	6.325	6.328
0.35	5.867	6.293	6.288	0.35	6.069	6.352	6.258

Table 5.6 MRR for the speed 263.2, 280 rpm Vs feed 0.125, 0.1362, 0.1474, all depth of cut

v = 263.2 rpm				v = 280 rpm			
DOC	f = 0.125	f = 0.1362	f = 0.1474	DOC	f = 0.125	f = 0.1362	f = 0.1474
	MRR 1	MRR 2	MRR 3		MRR 1	MRR 2	MRR 3
0.25	6.301	6.611	6.675	0.25	6.295	6.724	6.685
0.26	5.945	6.703	6.391	0.26	5.925	6.720	6.441
0.27	6.497	6.692	5.879	0.27	6.543	6.674	5.868
0.28	5.244	5.498	5.086	0.28	5.376	5.381	5.237
0.29	5.096	6.049	5.420	0.29	5.542	6.001	5.588
0.3	5.111	5.475	5.656	0.3	5.627	5.779	5.793

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

0.31	5.051	5.608	5.603	0.31	5.472	6.082	6.099
0.32	5.264	6.246	6.154	0.32	5.953	6.497	6.079
0.33	5.798	6.355	6.707	0.33	6.282	6.538	6.696
0.34	6.158	6.414	6.284	0.34	6.395	6.496	6.216
0.35	6.192	6.394	6.240	0.35	6.356	6.436	6.240

The duration of Firefly integrated with Regression relations availed 621.64 pulses to compute. The scatter plots formation through for the above results are shown for user references in the following Figures 5.3 to Figure 5.10

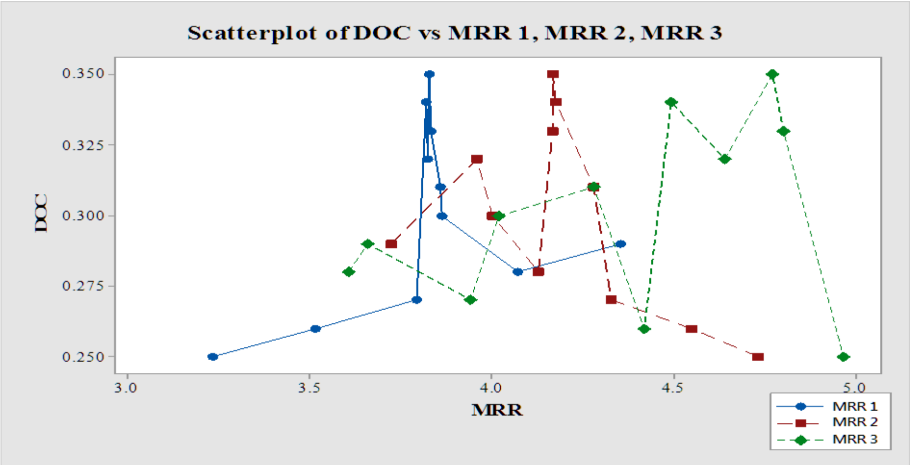


Figure 5.3 MRR plots of speed 112 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

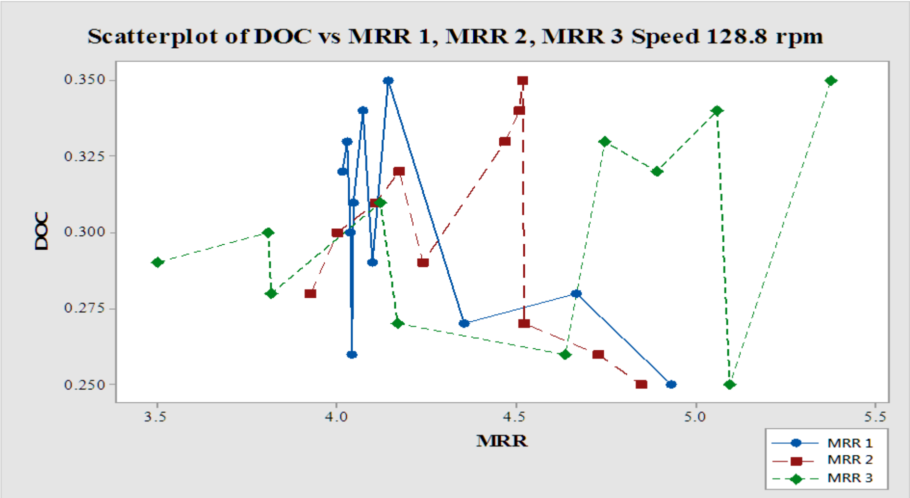


Figure 5.4 MRR plots of speed 128.8 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

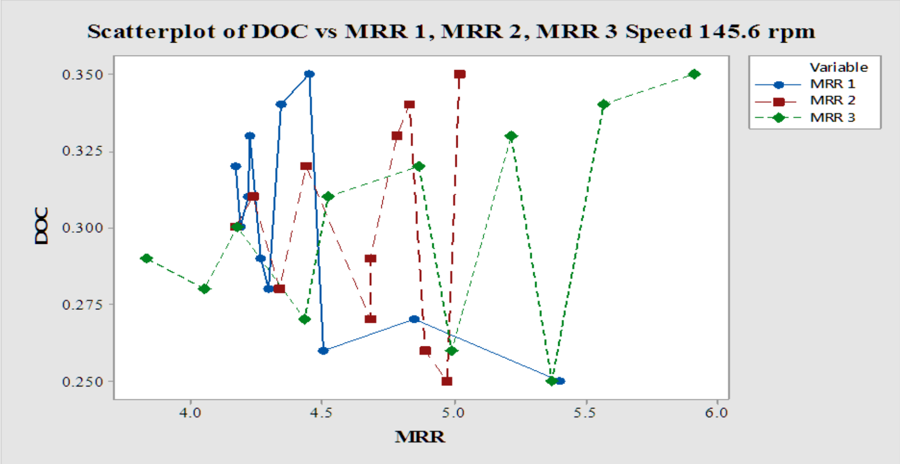


Figure 5.5 MRR plots of speed 145.6 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

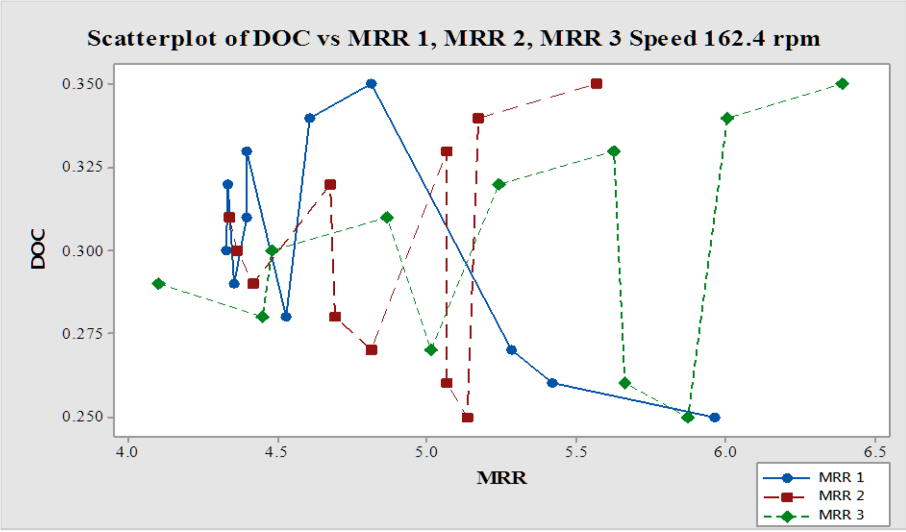


Figure 5.6 MRR plots of speed 162.4 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

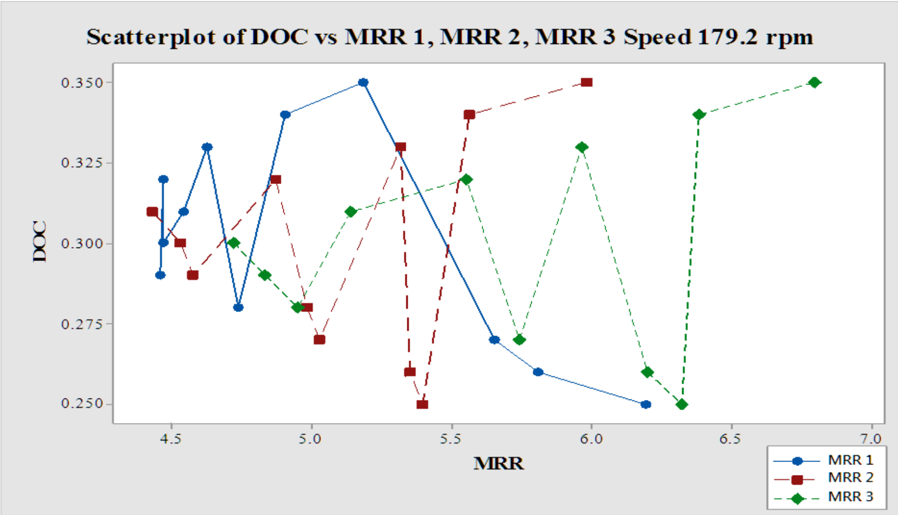


Figure 5.7 MRR plots of speed 179.2 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

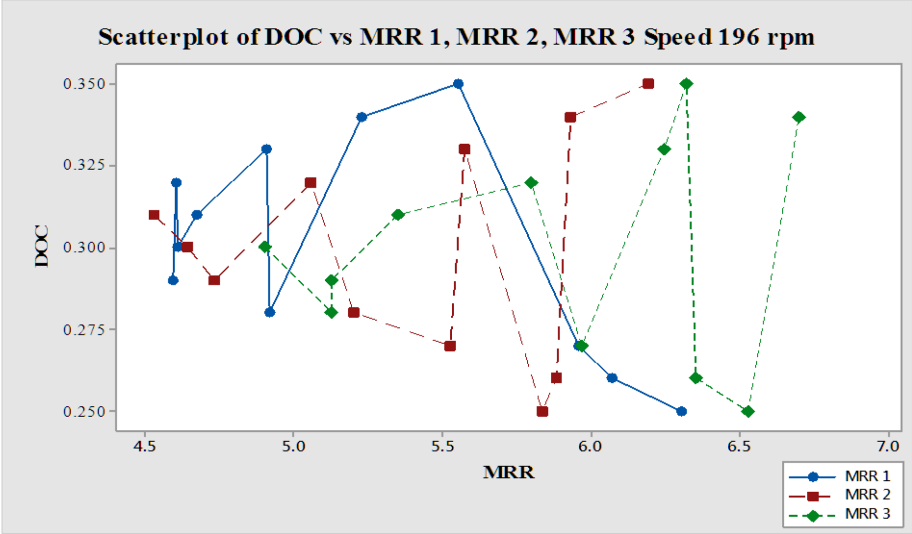


Figure 5.8 MRR plots of speed 196 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

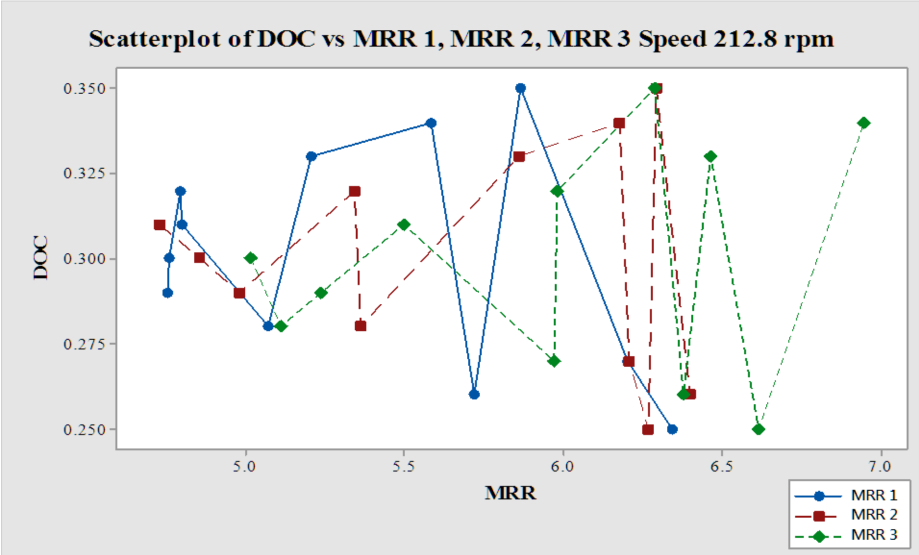


Figure 5.9 MRR plots of speed 212.8 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

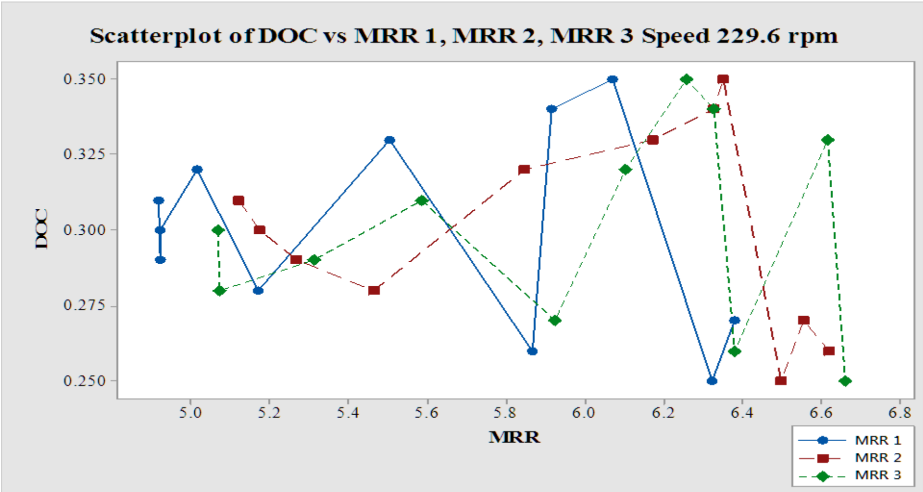


Figure 5.10 MRR plots of speed 229.6 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

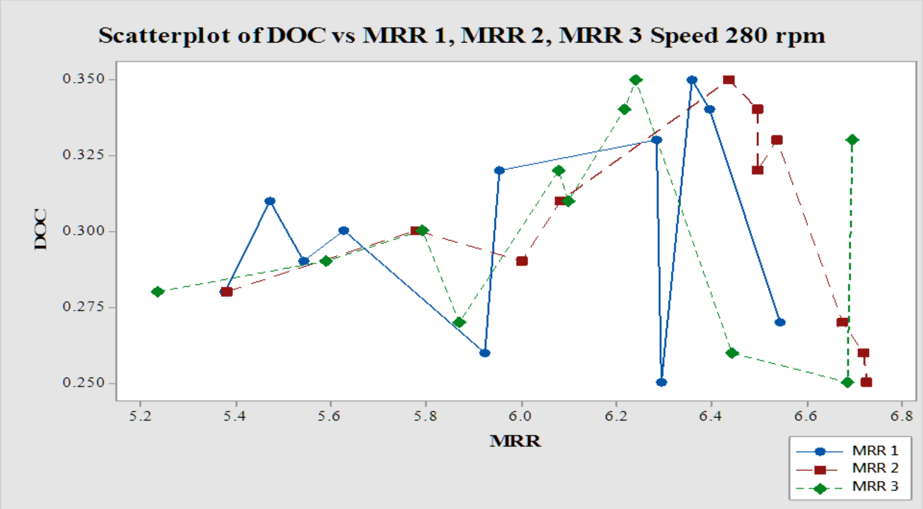


Figure 5.11 MRR plots of speed 280 rpm & feed 0.125, 0.1362, 0.1474 mm / rev

VI. RESULTS AND CONCLUSIONS

For chosen experimental parameters with the selected level, Second order without self power relationship between the input, output variables is statistically significant. Firefly Algorithm converges with minimum MSE towards optimising than the others (Particle swarm Optimization, Scatter Search Algorithm, Simulated Annealing Algorithm, Artificial Bee Colony Algorithm, Ant Colony Algorithm). Programming with the regression equation relationship as condition for the further simulation and estimating the outcome, the accuracy level in computation is improved and tuned to the finest level for the set of values. Speed is the major influencing factor which contributes 57.8 %; the parameter depth of cut registered next level influence with 32.6 % whereas the feed rate exhibits very little amount of influence on the MRR. The optimum value of MRR is 6.948 mm^3 / sec for the speed 212.8 rpm, 0.1474 mm / rev feed, 0.34 mm depth of cut combination.

REFERENCES

[1] 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.

[2] Aslan E., Camuscu N. & Birgoren B. (2007). Design of optimization of cutting parameters when turning hardened AISI 4140 steel (63 HRC) with Al2O3+TiCN mixed ceramic tool," Materials and Design, Vol.28, pp.1618-1622.

[3] Thomas, M.., Beauchamp, Y., Youssef, Y.A & Masounave, J (1997). An experimental design for surface roughness and built-up edge formation in lathe dry turning. Int. J. Qual. Sci. Vol.2 No.3, pp.167– 180.

[4] Palanikumar, K., Karunamoorthy, L., Karthikeyan, R. 2006. Assessment of factors influencing surface roughness on the machining of glass fibre-reinforced polymer composites. Material Design, Vol. 27, pp. 862–871.

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

[5] Suleyman Neseli, Suleyman Yaldizand, and Erol Turkes 2011. Optimisation of tool geometry parameters for turning operations based on the response surface methodology. Measurement, Vol. 44, pp. 580–587.

[6] 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.

[7] Nikolaos, Galanis, E. Dimitrios and Manolakos, Surface roughness prediction in turning of femoral head, Int J Adv Manuf Technol, 51, 2010, 79-86.

[8] T. Oezel and Y. Karpat, Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks, Int J Mach Tools Manuf, 45, 2005, 467-479.

[9] 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.

[10] J S. Agapiou, Design characteristics of new types of drill and evaluation of their performance drilling cast iron. I. Drill with four major cutting edges, Int J Mach Tools Manuf, 33, 1993, 321-341.

[11] Emad Ellbeltagi, Tarek Hegazy and Donald Grierson, Comparison among five evolutionary – based optimization algorithms, International Journal of Advanced Engineering Informatics, 19, 2005, 43-53.