

Forecasting Optimised Tool wear, Surface Roughness, Material Removal Rate and Hole Diameter Error on OHNS in Drilling process through Scatter Search Integrated Micro GA Algorithm

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ABSTRACT

The main aim of this work is to use Taguchi method and Analysis of Variance to uncover the impact of cutting parameters such as spindle speed, feed and drill tool diameter on tool wear, surface roughness, material removal rate and hole diameter error for their optimization. The effect of drilling parameters on outcome parameters is analyzed in this scenario. The parameters effectiveness is calculated using optimization algorithms such as Micro Genetic algorithm, Scatter search algorithm and Modified fish swarm algorithm and Artificial Immune System Optimization. From the experimental result, the most appropriate algorithm was located and framed hybrid approach to tune further regulation to locate the Tool wear, MRR, Hole diameter error and Surface smoothness which is used for selecting the most suitable combination of parameters based on the minimum and maximum errors.

Key words- Material Removal Rate, Surface Roughness, Hole diameter Error, Tool Wear, Micro Genetic algorithm, Scatter search algorithm, Modified fish swarm algorithm and Artificial Immune System Optimization algorithm, Hybrid Algorithm, MATLAB.

I. INTRODUCTION

Oil Hardening Non Shrinking Die Steel (OHNS) is widely used in Blanking and stamping dies, Punches, Rotary shear blades, Thread cutting tools, Milling cutters, Reamers, Measuring tools, Gauging tools, Wood working tools, Broaches, Chasers. At the same time ideal type oil-hardened steel which is economical and dependable for gauging, cutting and blanking tools as well as can be relied for hardness and good cutting performance. In this presentation the response of OHNS is chosen while undergoing drilling process. By a large amount widespread technique of assembling formation is by make use of perfunctory fasteners, which requires drilling to make possible bolting to other structural workings. Even though a numeral of approaches have been available for

creation holes in any component, conservative drilling cultivate time is the most widely suitable and commonly accomplished machining process for hole making.

NOMENCLATURE: v , Cutting Speed (m / min) f_r , Feed (mm / rev) d , Drill diameter (mm) R_a , Surface roughness μm T_w , Tool wear (g) V , Material Removal Rate (mm³/min) DE_h , Hole Diameter error (mm)**II. RELATED LITERATURE**

During drilling, defects like undesired hole surface roughness associated to tool wear is an another crisis recurrently occur [1]. Drilling effected injure is a significant explore confront while this injure not only reflects in the exactness of the hole other than in addition now and then fallout in service presentation decline. This had been concluded that drilling- effected injure could be condensed by tuning the drill point geometry and optimizing the course parameters [2 3 4]. This drilling effected injure concern highly related by the contributing parameters like cutting speed and feed rate for dissimilar drill point configuration (four-facet, eight-facet, and Jo drill), and the injure area around the drilled hole at the entry as well as exit of drill at time of processing enhances with an increase in the ratio of cutting speed / feed rate. In case of applying Jo drill the injure rate may be in lowest amount was the conclusion registered by Mathew et al.[5] who checked the persuade of twist and trepanning tool on the process parameters thrust force and torque during drilling in glass fibre-rein-forced plastic (GFRP) composites. The inquiry has furnished that the concert by the trepanning tool was better to the twist drill. Mohan et al. [7] chosen Taguchi technique to optimize the input variables cutting speed, feed, drill size, and specimen thickness in drilling of GFRP composite and established that speed and drill dimension were the mainly considerable variables on machining trust force and sample depth and drill dimension were the influencing variables on the torque. Davim et al [8] also engaged Taguchi methods in their investigation of the drill rotation speed, feed, and thrust force, injure, and surface roughness in GFRP and projected the outcome as feed had greater authority on exact machining pressure and trust force. Kishore et al. [9] offered an analysis on the possessions of the machining speed, the feed and drill point configuration on the lingering tensile strength of the drilled unidirectional GFRP composite using Taguchi method and they had instituted the optimum levels of the process environment. DeFu Liu et al [10] reported that it has to boost drilling competence of composite laminates by the slightest squander and reparation; it is indispensable to appreciate the drilling actions by conducting a outsized amount of drilling experiments and via establishing of drilling models. C. Dhavamani et al [11] has attempted to appraise the texts in drilling processes towards optimizing the parameters involved in operations. A mixture of conformist techniques engaged in order to optimize the processing input output parameters which consist of Non-Linear Programming, geometric programming, linear programming, sequential unconstrained minimization technique, dynamic programming, goal programming, and etc. The newest techniques for optimization take account of scatter search technique, fuzzy logic, ant colony technique, genetic algorithm, response surface methodology and Taguchi technique for being functional productively in manufacturing applications for best possible assortment of progression variables in the area of operation. The

objective of their research focused to revise the consequence of cutting speed, feed, cutting tool dimension, processing time on the most significant outcome of metal removal rate, surface roughness, specific energy, tool material wear and the volume fraction. Also quoted the Taylor registration with the intention of a most favorable or fiscal cutting speed exists which might make best use of material removal rate. Substantial hard works are motionless in advancement on the approach conventional cutting state of affairs and cutting tool range at the process preparation stage. The necessity for the selection combined implementation over the processing parameters combination and largest appropriate tool material and its dimension being recognized in the recent past. Jyotiprakash Bhol et al [12] in their reporting commented that drilling is one of the straight material removal techniques which more or less envelop 40% amongst of all metal removal processes. During the process the cutting tool show off is listed the same as wear at flank, crater, corner and chisel wear. Out of which the flank wear is identified as the significant wear of all. Tool damage wear has an unconstructive result on the smoothness of finished surface along with the precision in the machined dimension of the work. Result of vibrations generation during machining in owe of the developed thrust force and torque while in operations which try to disassociate the work from the holding devices. Because of the flank wear upend, for the same combination input cutting variables, the processing forces end up with significant raise which will reflect in the quality product. Identifying the right combination of machining parameters which leads to the least flank wear with lowest amount thrust force and torque development are determined by skill and the optimum parameters could not be definite and taken for establishment. Many investigations have been done with Taguchi orthogonal array setup in drilling process on behalf of identifying the favorable optimal setting in machining.

III. EXPERIMENT PROCEDURE

J.Pradeep Kumar et al [6] conducted drilling process experiment on OHNS material with size 300 x 100 x 10 mm considered the participation machining parameters in three levels as marked in Table 3.1. The design of experiment was performed by Taguchi orthogonal array L2.

Table 3.1 Participation machining parameters

Variables / Levels	1	2	3
Cutting speed in m / min	5	6.5	8
Feed in mm / rev	0.15	0.20	0.25
Drill diameter in mm	10	12	15

Taguchi plan of experiments and investigation of variance were put in to ascertain the most advantageous cutting parameters and to examine the effects over the tool wear and noticed that the feed associated with the drill point angle were instituted as significant factors whilst cutting speed contribution ejects the slightest effectual parameter. Performed the drilling test were by means of HSS spiral type drill bits on DECKEL MAHODMC 835V (continues speed up to 14000rpm and 14kw spindle power) CNC machine. CNC part programs were formed by adopting Master Cam 10 CAD / CAM software on a delicate central processing unit. The concluding silhouette of the hole was resolute using a Renishaw cyclone CMM which has the three-axis mechanical arrangement, the probe head, control unit, and PC. The CMM employed was a vertical-arm CMM; using a Renishaw PH sensor mount with a touch-trigger probe and the surface roughness (Ra) is resulted with a

Mitutoyo Surftest SJ-201 Series 178-portable surface roughness tester instrument; tool wear was measured using the Shimadzu electronic balance machine. With the support of Minitab 13 software linear polynomial model was computed. Such Employed participation machining parameters and the responded upshot parameters are presented in Table 3.2

Table 3.2 Experimental observations

Exp No	v, (m/min)	f _r , (mm / rev)	d, (mm)	R _a , μm	T _w , (g)	MRR	DE _h , (mm)
1	5	0.15	10	2.84	0.035	1875	0.0290
2	5	0.20	12	1.39	1.536	3000	0.0294
3	5	0.25	15	2.60	0.854	4687.5	0.0266
4	6.5	0.15	10	1.13	0.958	2437.5	0.0250
5	6.5	0.20	12	1.55	0.963	3900	0.0248
6	6.5	0.25	15	1.77	0.296	6093.75	0.0658
7	8	0.15	12	1.69	0.025	3600	0.0217
8	8	0.20	15	2.23	0.372	6000	0.0258
9	8	0.25	10	5.52	0.018	5000	0.0262
10	5	0.15	15	2.08	0.105	2812.5	0.0286
11	5	0.20	10	1.49	1.451	2500	0.0282
12	5	0.25	12	4.91	0.032	3750	0.0268
13	6.5	0.15	12	1.20	0.106	2925	0.0317
14	6.5	0.20	15	1.24	0.598	4875	0.0224
15	6.5	0.25	10	4.52	0.120	4062.5	0.0212
16	8	0.15	15	1.36	0.024	4500	0.0248
17	8	0.20	10	1.17	1.566	4000	0.0208
18	8	0.25	12	4.39	0.111	6000	0.0289

V. METHODOLOGY PROPOSALS TOWARDS OPTIMIZATION

Parameters considered as participation and response variables are listed in Table 4.1. The mathematical relationship (correlation, regression) between each response variable – MRR, Surface roughness, Tool Wear and Hole diameter error with the participation variables individually with MiniTab17 in linear, quadratic, cubic, exponential, power, logarithmic functions and the values are represented through Figure 4.1 Correlation, Regression comparison of participation variables with MRR, Fig 4.2 Correlation, Regression comparison of participation variables with Surface roughness, Fig 4.3 Correlation, Regression comparison of participation variables with Tool wear and Fig 4.4 Correlation, Regression comparison of participation variables with Hole diameter Error respectively. While verifying all such computed relationship with the R² response the cubic relationship is found to be most significant.

The relationship equation of response variable with the participation variables is formulated as

$$Ra = -0.21 + 0.058 v + 22.35 f_r - 0.182 d$$

In this approach, Micro GA algorithm, Scatter Search algorithm, Modified Fish Swarm algorithm and Artificial Immune System Optimization is used to compute and optimize the Participation variables towards the response variables.

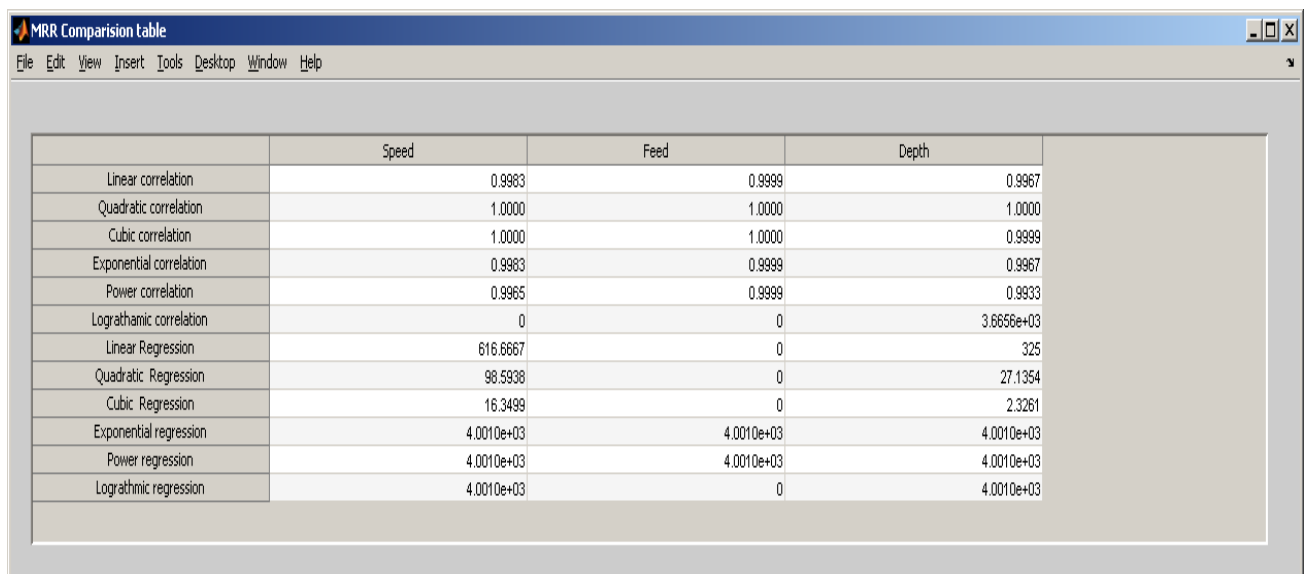
Micro GA algorithm: - The micro-Genetic Algorithm (μ GA) is an Evolutionary algorithm that in “small population” Genetic Algorithm (GA) which computes on the ideology of natural range or “continued existence of the fittest” to advance the finest probable resolution (i.e., design) over a numeral of generations to the most-fit, or best possible, solution.

Scatter Search algorithm:- Scatter search, a Stochastic algorithm orients its explorations scientifically relation to a set of reference points that classically consist of superior solutions obtained by preceding trouble solving efforts, where the criterion for “good” are not constrained to objective function values, and may apply to associate collections of solutions to a certain extent than to a single solution, as in the case of solutions that be at variance from each other according to certain specifications.

Modified Fish Swarm algorithm Swarm: - T.Bharathi et al. [13] presented that the Modified Artificial Fish Swarm Algorithm (MFSA) which has many benefits that includes higher convergence rate, flexibility, fault tolerance and high accuracy. General behaviors systems of standard AFSA are: Prey, Follow, and Swarm.

Artificial Immune System Optimization algorithm: - In artificial intelligence, artificial immune systems (AIS) are a class of computationally intellectual systems stimulated by the ideology and processes of the vertebrate immune system. The algorithms are classically modeled after the immune system's distinctiveness of learning and reminiscence for exercise in investigative.

The computed values of each response variables through the employed algorithms are tabulated in Table 4.1, 4.2 respectively and the graphical representations are projected in the Figures 4.5, 4.6, 4.7 and 4.8.



	Speed	Feed	Depth
Linear correlation	0.9983	0.9999	0.9967
Quadratic correlation	1.0000	1.0000	1.0000
Cubic correlation	1.0000	1.0000	0.9999
Exponential correlation	0.9983	0.9999	0.9967
Power correlation	0.9965	0.9999	0.9933
Logarithmic correlation	0	0	3.6656e+03
Linear Regression	616.6667	0	325
Quadratic Regression	98.5938	0	27.1354
Cubic Regression	16.3499	0	2.3261
Exponential regression	4.0010e+03	4.0010e+03	4.0010e+03
Power regression	4.0010e+03	4.0010e+03	4.0010e+03
Logarithmic regression	4.0010e+03	0	4.0010e+03

Fig 4.1 Correlation, Regression comparison of participation variables with MRR

RA Comparision table			
	Speed	Feed	Depth
Linear correlation	0	0.8969	0
Quadratic correlation	0.1396	0.9880	0.0525
Cubic correlation	0	0.9282	0
Exponential correlation	0.0866	0.9027	0.0257
Power correlation	0	0.8059	0
Lograthmic correlation	0	0	2.2378
Linear Regression	0.3812	0	0.2044
Quadratic Regression	0.0632	0	0.0179
Cubic Regression	0.0109	0	0.0016
Exponential regression	2.3933	2.3933	2.3933
Power regression	2.3933	2.3933	2.3933
Lograthmic regression	2.3933	0	2.3933

Fig 4.2 Correlation, Regression comparison of participation variables with Surface roughness

TW Comparision table			
	Speed	Feed	Depth
Linear correlation	0	0.3461	0
Quadratic correlation	0.0159	0.5112	0.0046
Cubic correlation	0	0.3148	0
Exponential correlation	0.0045	0.4169	1.7441e-04
Power correlation	0	0.2656	0
Lograthmic correlation	0	0	0.4794
Linear Regression	0.0853	0	0.0442
Quadratic Regression	0.0148	0	0.0039
Cubic Regression	0.0026	0	3.5662e-04
Exponential regression	0.5094	0.5094	0.5094
Power regression	0.5094	0.5094	0.5094
Lograthmic regression	0.5094	0	0.5094

Fig 4.3 Correlation, Regression comparison of participation variables with Tool wear

DE Comparision table			
	Speed	Feed	Depth
Linear correlation	0	0	0
Quadratic correlation	2.3655e-05	0.0223	5.7529e-06
Cubic correlation	0	0	0
Exponential correlation	6.9710e-45	0.0028	5.5135e-101
Power correlation	0	0	0
Lograthmic correlation	0	0	0.0259
Linear Regression	0.0045	0	0.0023
Quadratic Regression	7.5433e-04	0	1.9446e-04
Cubic Regression	1.2963e-04	0	1.6799e-05
Exponential regression	0.0282	0.0282	0.0282
Power regression	0.0282	0.0282	0.0282
Lograthmic regression	0.0282	0	0.0282

Fig 4.4 Correlation, Regression comparison of participation variables with Hole diameter Error

Table 4.1 Computed values of MRR and Hole Diameter Error – Experimental outcome Vs Algorithm wise

Ex No	MRR (mm ³ / min)					Hole Diameter error (mm)				
	Exp Value	AISA	MFSA	Micro	Scatter	Exp	AISA	MFSA	Micro	Scatter
1	1875.0	1874.9	1878.3	1875.2	1875.3	0.0290	0.0198	0.0658	0.0798	0.0893
2	3000.0	2932.3	2650.4	1617.4	3504.7	0.0294	0.0264	0.0478	0.0654	0.0834
3	4687.5	5470.5	4791.3	5026.2	5002.4	0.0266	0.0703	0.0532	0.0200	0.0213
4	2437.5	2832.4	1845.8	2369.8	2437.8	0.0250	0.0252	0.0458	0.0616	0.0520
5	3900.0	4238.9	3439.4	2311.3	3751.3	0.0248	0.0448	0.0215	0.0564	0.0700
6	6093.8	6435.2	6021.4	5568.9	6098.6	0.0658	0.0585	0.0231	0.0106	0.0446
7	3600.0	4176.5	3629.0	3382.8	3528.9	0.0217	0.0263	0.0215	0.0699	0.0933
8	6000.0	5759.7	5924.0	5905.4	5568.3	0.0258	0.0131	0.0187	0.0259	0.0547
9	5000.0	4869.1	4963.8	4688.7	5152.6	0.0262	0.0502	0.0051	0.0248	0.0493
10	2812.5	1438.2	3026.7	4342.3	3465.0	0.0286	0.0197	0.0769	0.0999	0.0718
11	2500.0	2763.5	1976.9	2304.0	3044.1	0.0282	0.0057	0.0391	0.0821	0.0784
12	3750.0	4444.0	3661.3	2892.1	3831.6	0.0268	0.0626	0.0306	0.0334	0.0569
13	2925.0	2908.4	2530.2	2212.1	3240.0	0.0317	0.0250	0.0582	0.0885	0.0999
14	4875.0	5053.9	4913.0	4917.8	5336.2	0.0224	0.0214	0.0598	0.0365	0.0619
15	4062.5	4126.9	3795.6	4321.9	4236.7	0.0212	0.0545	0.0009	0.0376	0.0555
16	4500.0	4612.2	4636.2	6929.5	4745.2	0.0248	0.0227	0.0334	0.0563	0.0671
17	4000.0	4201.4	3997.9	4239.9	4171.9	0.0208	0.0207	0.0014	0.0493	0.0676
18	6000.0	6031.1	6101.7	4840.3	5716.9	0.0289	0.0471	0.0018	0.0108	0.0490

Table 4.2 Computed values of Surface Roughness and Tool wear – Experimental outcome Vs Algorithm wise

Ex No	Surface roughness μm					Tool wear (g)				
	Exp Value	AISA	MFSA	Micro	Scatter	Exp	AISA	MFSA	Micro	Scatter
1	2.84	3.01	1.91	2.66	2.55	0.035	0.013	0.175	0.457	1.027
2	1.39	2.19	2.57	1.82	4.63	1.536	0.643	0.337	0.131	0.802
3	2.6	2.73	4.80	0.55	2.25	0.854	0.524	0.924	0.471	0.735
4	1.13	1.64	1.94	0.50	2.05	0.958	0.646	1.551	0.970	0.516
5	1.55	2.10	2.18	2.04	4.23	0.963	0.535	0.542	0.107	0.580
6	1.77	2.86	6.76	0.32	3.20	0.296	1.508	1.033	0.152	0.521
7	1.69	1.40	0.58	2.97	1.41	0.025	0.145	0.737	0.044	0.340
8	2.23	2.39	4.56	0.88	2.64	0.372	0.792	0.345	0.067	0.330
9	5.52	5.23	6.00	3.09	2.59	0.018	1.067	0.941	1.109	0.445
10	2.08	0.98	0.83	0.39	1.56	0.105	0.069	0.291	0.216	0.921
11	1.49	3.08	3.12	1.91	3.00	1.451	0.988	0.709	0.511	0.825
12	4.91	3.15	5.35	2.85	3.84	0.032	0.435	0.389	0.378	0.701
13	1.2	1.42	0.39	1.57	1.51	0.106	0.337	0.538	0.100	0.698
14	1.24	1.87	4.83	0.05	2.37	0.598	0.516	0.577	0.056	0.550
15	4.52	3.66	6.24	2.74	1.96	0.120	0.942	0.920	1.264	0.503
16	1.36	1.53	0.01	2.13	2.95	0.024	0.278	0.396	0.246	0.512
17	1.17	2.63	4.64	2.46	1.25	1.566	0.874	0.883	0.257	0.311
18	4.39	4.91	6.37	3.83	4.49	0.111	1.643	0.693	0.127	0.367

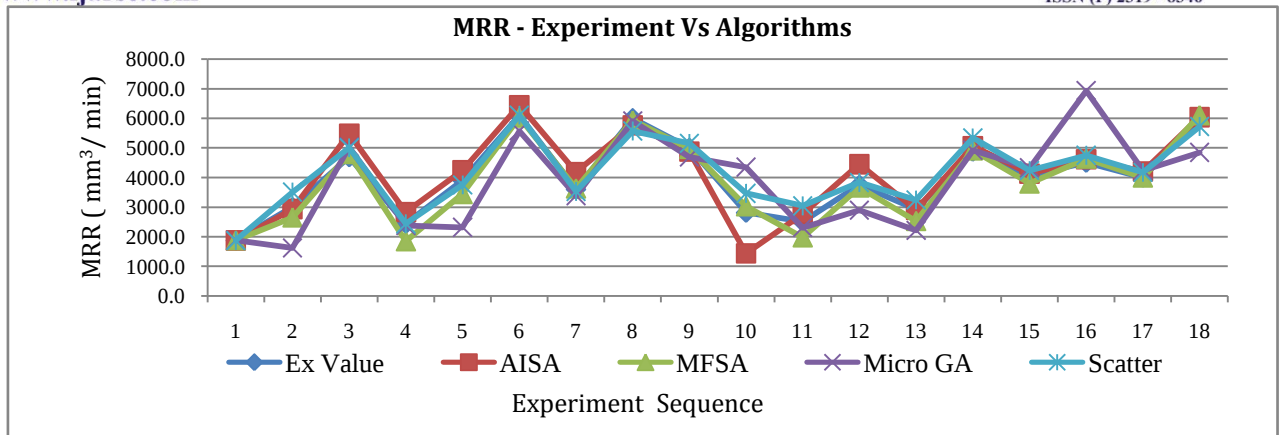


Fig 4.5 MRR comparison Experiment Vs Algorithms

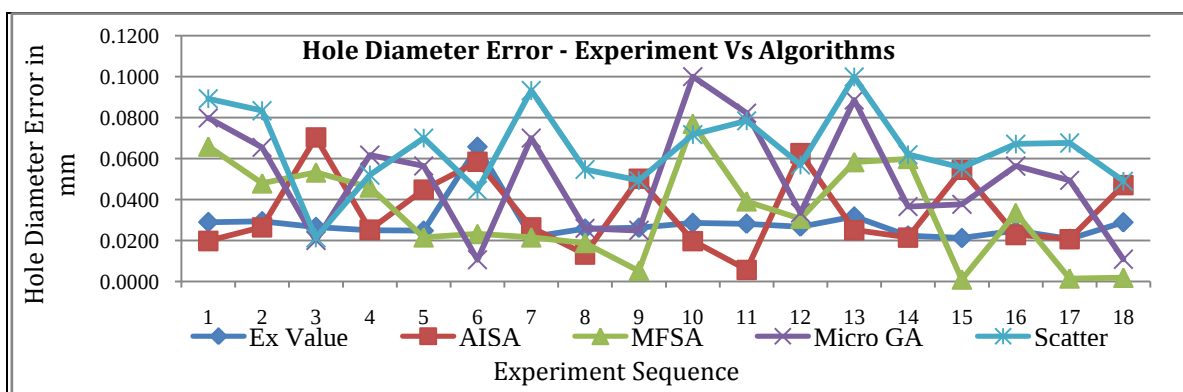


Fig 4.6 Hole diameter error comparison Experiment Vs Algorithms

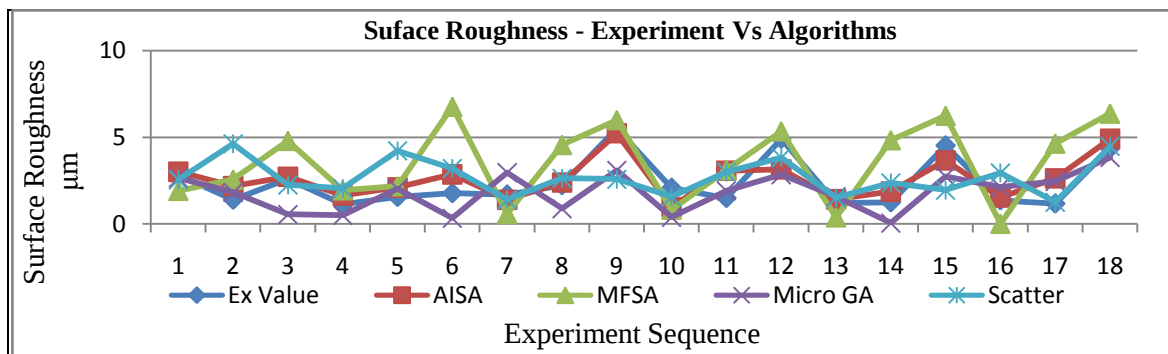


Fig4.7 Surface roughness comparison Experiment Vs Algorithms

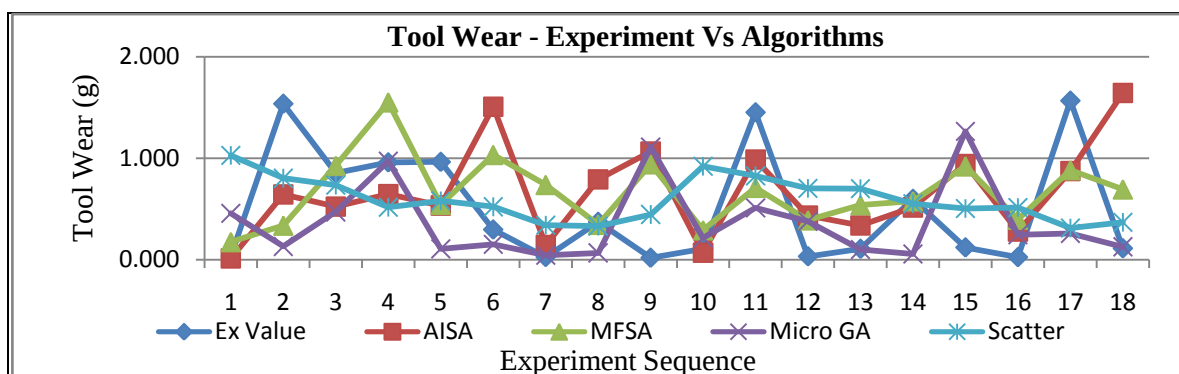


Fig4.8 Tool wear comparison Experiment Vs Algorithms

V. ANALYSIS OF COMPUTATIONAL RESULTS AND DISCUSSION

On comparing the outcome of Algorithms with the actual experimental observations individually on the parameters concerned, and identified the best outcome based on the minimal error rate the best and next best algorithms are taken out to frame hybrid algorithm. A hybrid algorithm is an algorithm that combines two or more other algorithms that solve the same problem, either choosing one (depending on the data), or switching between them over the course of the algorithm. This is generally done to combine desired features of each, so that the overall algorithm is better than the individual components. Scatter Search algorithm (second best) output is taken into the Micro Genetic Algorithm to form the hybrid outcome algorithm. Upon computing the mean error rate is brought down to the drastic level and the hybrid Scatter Search Integrated Micro GA Algorithm yields tuned result. The error as well as mean error comparison of this hybrid Scatter Search Integrated Micro GA Algorithm with other algorithms exposed in the Figure 4.5, Figure 4.6.

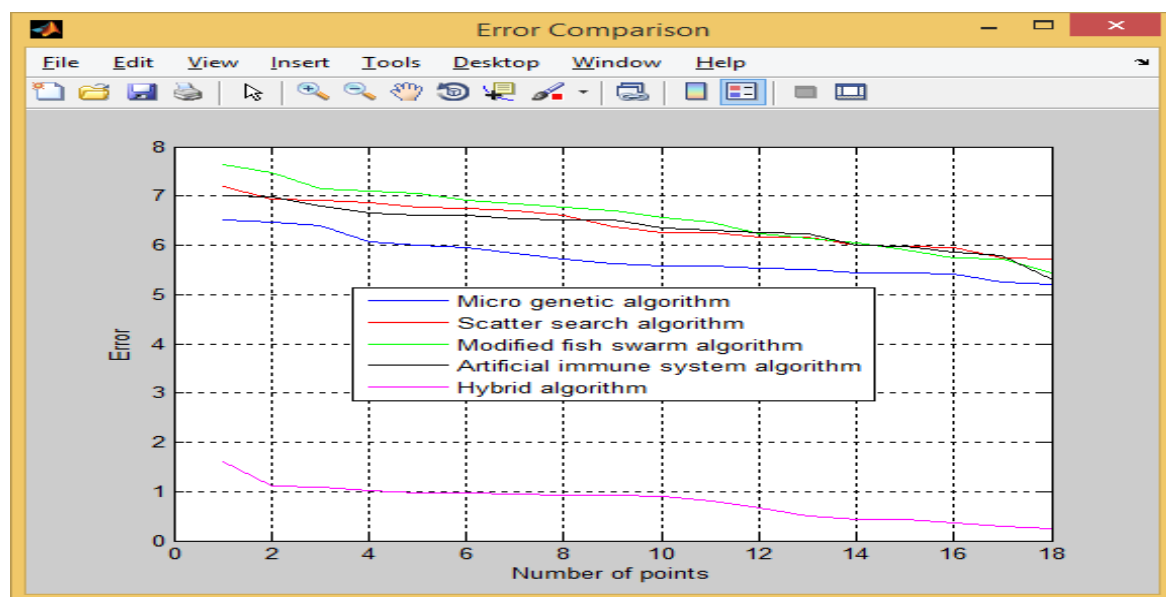


Fig 5.1 Error comparisons of Algorithms with Hybrid

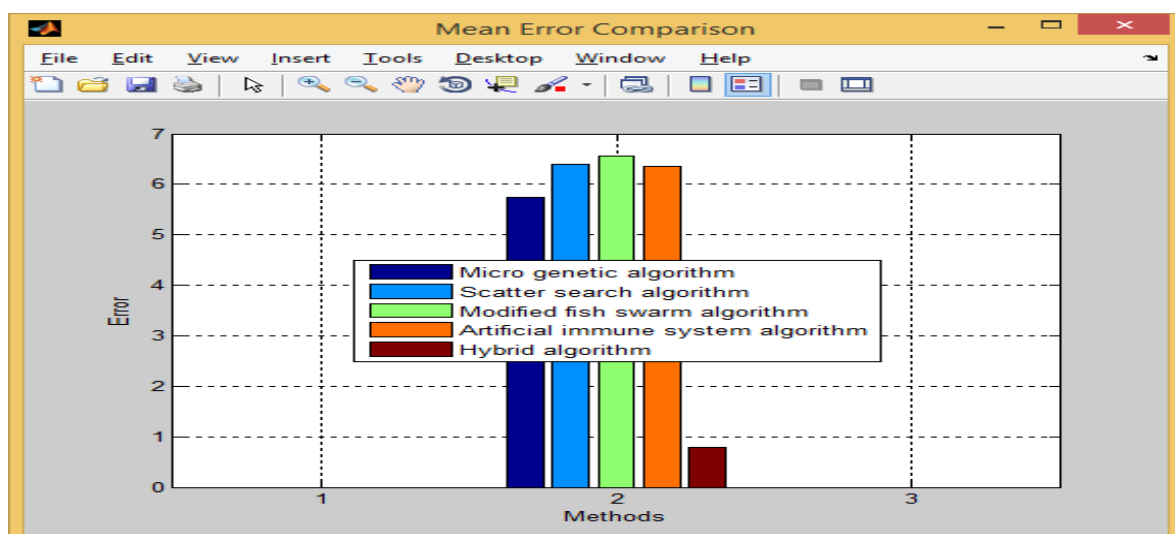


Fig 5.2 Mean Error comparisons of Algorithms with Hybrid

The time consumption to compute all algorithmic results also displayed in the Figure 5.3, in this computation the time taken for hybrid algorithm registers as the second largest, but resulted minimum error with reference to others. Both the error rate and time for computing is given in the Table 5.1. The values of the response variables with reference to the participation parameters computed through the Hybrid Scatter Search Integrated Micro GA are organized through Table 5.2.

Table 5.1 Error values and Time consumption of computation

Algorithm	Error	Time
Micro Genetic Algorithm	5.7508	10.2554
Scatter Search	6.4047	14.7069
Modified Fish Swarm Algorithm	6.5516	26.4458
Artificial Immune System Algorithm	6.3498	10.3848
Hybrid Scatter Search Integrated Micro GA	0.7912	17.6838

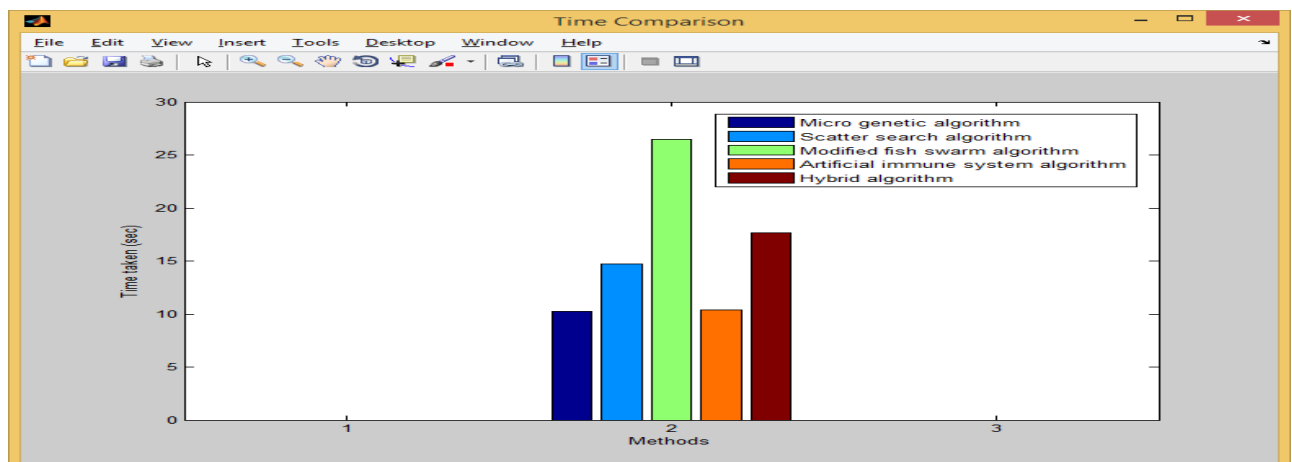


Fig 5.3 Time of computing by algorithms

Table 5.2 Outcome of Hybrid algorithm in output parameters

Hybrid Algorithm Outcomes													
v	d	f _r	R _a	T _w	V	DE _h	v	d	f _r	R _a	T _w	V	DE _h
5	10	0.15	0.7311	3.528	1874.99	0.0639	6.5	12	0.2	6.7013	2.714	3900.08	0.0262
6.5	10	0.15	0.6837	3.353	2437.51	0.0349	6.5	15	0.2	6.4607	3.334	4875.01	0.0275
6.5	12	0.15	4.4182	3.353	2925.05	0.0199	8	15	0.2	9.1175	2.735	6000.02	0.0460
8	12	0.15	2.0606	3.260	3600.02	0.0017	6.5	10	0.25	2.0198	3.305	4062.58	0.0105
5	15	0.15	7.6503	5.196	2812.53	0.0569	8	10	0.25	1.4038	5.087	5000.06	0.0089
8	15	0.15	7.6774	2.768	4500.06	0.0128	5	12	0.25	4.3611	3.517	3750.03	0.0313
5	10	0.2	2.1894	4.332	2500.00	0.0632	8	12	0.25	4.0481	1.702	6000.00	0.0426
8	10	0.2	1.2698	3.748	3999.99	0.0010	5	15	0.25	6.4426	3.788	4687.57	0.0006
5	12	0.2	7.5803	4.479	3000.01	0.0700	6.5	15	0.25	7.0961	4.132	6093.71	0.0488

VI. CONCLUSION

For the OHNS material with the given set of machining conditions, Feed rate registered the high level of influence on Surface roughness, Tool wear and hole diameter accuracy, over the other input parameters. Micro Genetic and Scatter search algorithms are registered the first and second best algorithm for computation to optimize the parameters. Hybrid of Scatter Search Integrated Micro GA capitulate further more tuned result. This hybrid algorithm may be used, for computing the results for various combinations of input parameters and selecting the most suitable combination of parameters based on the minimum and maximum errors while drilling operations in OHNS material.

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