Performance Evaluation of Opposition Based Genetic Algorithm to Serve Multi Objective of CNC Turning Process

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Abstract

The machining is about outward look, the basic of contemporary manufacturing industry and is concerned either directly or indirectly in the manufacture of approximately every product of modern growth. A term that covers a hefty anthology of manufacturing processes planned to remove unwanted material, usually in the form of chips, from a work piece to give wanted geometry, size and to satisfy design requirements. This clears the research goal towards fusing soft computing methods to procure better outcome in short intervals. This paper incorporates the importance of predicting optimal tuning input parameters namely cutting speed, feed rate, depth of cut and nose radius for minimized surface roughness, maximized material removal rate and minimized tool wear. This goal is accomplished by developing a mathematical model, which joins optimization techniques. Genetic algorithm (GA) is the ultimate tool to use in this research work for its betterment; genetic algorithm has additionally developed as Adaptive Genetic Algorithm (AGA) and Opposition based Genetic Algorithm (OGA) amid opposition based genetic algorithm reveal better performance both in the mathematical model designing and tuning input parameter optimization. In this work three dissimilar super alloys have been subjected to turning on CNC lathes with a mix of uncoated and coated carbide turning inserts.

Keyword: Inconel718, Hastelloy276, Monel400, Turning inserts, genetic algorithm, adaptive genetic algorithm and opposition based genetic algorithm.

1 Introduction

Turning is a versatile and valuable machining operation. It is the most significant operation and is generally utilized as a part of the majority of the manufacturing industries because of its ability to produce complex geometric surfaces with reasonable accuracy and surface contour. In present industry, one of the patterns is to manufacture low cost, high quality products in short time. Increasing productivity, decreasing costs, and maintaining high product quality in the meantime are the fundamental difficulties manufacturing faces today [1]. Manufacturing technique that starts with corporate, business, and marketing procedures and after that expect an manufacturing system to shore up [2]. Manufacturers are underneath tremendous pressure to perk up productivity and quality while reducing the costs.

Machining in common and turning in specific, surface finish and accuracy of the machined surface has been recognized as quality traits then again, material removal rate (MRR), which shows processing time of the work piece, is another imperative factor that incredibly impacts production rate and cost and thus regarded as performance index specifically identified with profitability. The Tool wear and henceforth Tool life has been distinguished as an economic criterion, which is having a direct influence on quality and productivity. So an effort has been made to optimize quality and productivity in a way that these multi-criteria could be satisfied simultaneously up to the normal level.

The material removal rate (MRR) and Surface roughness (Ra) are a vital controlling factor of machining operation. MRR and Ra are estimation of productivity and quality of the machining component. In order to enhance the machining attributes, push to minimize the value of Ra and maximize the value of MRR by choosing optimal machining process parameters similar to cutting speed, feed rate, depth of cut and insert nose radius are required to be learn in details [3].

In order to develop a bridge among quality and productivity and to accomplish the same in an economic way, the current research work highlights optimization of CNC turning process parameters to give good surface finish , high material removal rate (MRR) and maximum Tool Life. The greater part of the above traits extraordinarily vary with the difference in cutting procedure parameters and tool geometry henceforth it warrants appropriate determination of cutting process parameters and tool

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geometry along with the capability to predict the different responses.

Surface roughness assumes an imperative part as far as good surface compete on the grounds that the good quality machined parts enhanced fatigue strength, creep life and corrosion resistance. It is a factor of extraordinary significance in the assessment of machining accuracy [4]. There are different machining parameters those affect the surface roughness, however those impacts have not been sufficiently evaluated yet especially while machining difficult to machine super alloys like Inconel 718, Hastelloy276 and Monel400.

Inconel 718 alloy has been utilized world-wide in aerospace, aircraft, oil, and chemical industries, and furthermore nuclear power plants due to its high strength, excellent ductility, good formability and weldability and so forth. Inconel 718, a superalloy based on iron-nickel hardened by precipitation, is a standout amongst the most generally utilized superalloy that displays adequate resistance to creep, ductility and fatigue resistance above 650°C [5]. The nickel-base alloy C276 was additionally one of austenitic stainless steels, which has a high strength corrosion-resistant and heat resistant alloy with high contents of Cr and Mo. It has been generally utilized as a pressure vessel material at elevated temperatures [6]. The authors recommended that Monel 400 can be utilized as a part of high corrosive environment and furthermore these joints perform pleasantly at high temperature environments [7]. In order for manufacturers to maximize their increases from machining, accurate predictive models for surface roughness, MRR and Tool wear must be built.

2. Literature review

Biswajit Das *et al.* [8] had suggested the experimental exploration on chip formation, surface roughness and cutting force measurement throughout the CNC milling operation of Al–4.5%Cu/TiC MMCs produced by the in situ practice and compared the results with those for Al–4.5%Cu/SiC MMCs produced by ex situ technique and with Al–4.5Cu master alloy. The cutting forces was measured during the milling operation with the aid of a dynamometer, surface roughness was measured by using a 3D profile meter, the chips formed were also characterized and compared from the viewpoint of mach inability. The potential of artificial neural network to predict the cutting force and surface roughness generated during machining in CNC milling machine.

Amir Malakizadi *et al.* [9] had proposed the material parameters by Oxley's machining theory, the optimum set of friction coefficients were determined through evaluation of the Finite Element (FE) simulation results. The final step involved direct integration of 2D FE models incorporating the optimum frictional boundary conditions with RSM to reassess the optimum set of material parameters. This approach was implemented to determine the constitutive parameters for wide range of materials including Inconel 718 in aged condition, AISI 1080 plain carbon steel and AA6082-T6 aluminum alloy. The calibration of material models using the presented inverse methodology led to a significant improvement in simulation results.

Şener Karabulut *et al.* [10] the milling tests were performed based on the Taguchi design of experiment method using L18 21 x 32 with a mixed orthogonal array. The effects of the cutting parameters on surface roughness and cutting force were determined by using Analysis of variance (ANOVA). The analysis results showed that material structure was the most effective factor on surface roughness and feed rate was the dominant factor affecting cutting force. Surface roughness values were significantly improved by between 196% and 312% in milling Al2O3 particle-reinforced aluminum alloy composite compared to AA7039 aluminum. Artificial neural networks (ANN) and regression analysis were used to predict surface roughness and cutting force. ANN was able to predict the surface roughness and cutting force with a mean squared error equal to 2.25% and 6.66% respectively.

Prasansub Saranya *et al.* [11] had proposed the considered to produce a multiproduct in line production by using Kanban System for improving Bottleneck Problem. We propose a Pull System and a Kanban System for quality developing and material replenishment. It was a part of JIT (Just-In-Time) through the process flow at manufacturing. Developed to smooth of flow of product at the Bottleneck point by using the withdrawal Kanban Card and Production Kanban Card and then reduce Work-In-Process (WIP).

Nilesh Pohokar *et al.* [12] had proposed the several techniques available to determine the optimum values of these parameters, in this paper machining parameters, cutting speed, feed, depth of cut, and one geometric parameter rake angle are considered for optimization. The neural networks were developed for predicting the results theoretically. To validate the results experimentally trials was then carried out a CNC milling using HSS tool by continuous running condition under dry run on the AISI 1040 MS plate of 140 X 120 X 10 mm workpiece. The predicted results match 90 % including the residuals. Thus proves the neural network is used for optimization of geometric and machining parameter.

3. Experimental Investigation

3.1 Work Material and Tool

Turning experiment was performed on CNC lathe with three different materials namely Hastelloy276, Inconel 718 and Monel400 rods of 25mm diameter and 100mm length using coated and uncoated carbide turning insert of Sandvik Coromant make with ISO specification numbers as given below.

3.1.1 Coated carbide Tool inserts

- CNMG12 04 04-SF1105
- CNMG12 04 08- SF1105
- 3 CNMG12 04 12- SF1105

3.1.2 Uncoated carbide Tool inserts

- CNMG12 04 04-QM H13A
- CNMG12 04 08-QM H13A
- 3 CNMG12 04 12-QM H13A

3.1.3 Work piece materials

- 1.Hastelloy276,
- 2.Inconel 718
- 3.Monel400

Table-1, Details of input parameters (control Factors) and responses

S.No	INPUT PARAMETERS (CONTROL FACTORS)	CODES	UNITS	LEVELS 1	LEVELS 2	LEVELS 3	RESPONSES
1	Cutting speed (µm)	A	m/min	25	30	35	Surface roughness(Ra)
2	Feed rate (mm^3/min)	B	mm/rev	0.08	0.11	0.14	Material Removal Rate(MRR)
3	Depth of cut (%)	C	mm	0.4	0.7	1.0	Tool wear
4	Nose radius (µm)	D	mm	0.4	0.8	1.2	

3.2 Experimental Setup

The turning of workpiece was performed on Jaguar CNC lathe manufactured by Pride machine tools Pvt, Ltd, Bangalore at Sri Venkata Sai CNC profiles, Hyderabad The photograph (Fig. 1) and specifications of the machine (Table 2) are given below. The machining variables are set according to the experimental design as Shown in table 1. The machining is done under wet condition using water soluble oil as cutting fluid. The material has been subjected to a rough cut initially to remove unevenness, if any.

Figure-1, Jaguar CNC Lathe

Table-2, Specifications of Jaguar CNC Lathe

SPECIFICATIONS	UNIT	JAGUAR
CAPACITY		
Swing Over bed	mm	500
Max. turning dia	mm	300
Max. turning length	mm	500
Standard chuck size	mm	200/250
SLIDES		
X Axis stroke	mm	160
Z Axis stroke	mm	500
Rapid rates	mm/min	20000
SPINDLE		
Spindle size		A2-6
Spindle bore	mm	63
Spindle front bearing dia	mm	100
Max bar capacity*	mm	42/51
Spindle speed range	RPM	50-3500
Spindle motor power	KW	7.5/11(11/15)
TURRET		
Size		BTP-80

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No. of stations		8
Max. boring dia	mm	40
Tool size	mm*mm	25*25
TAIL STOCK		
Quill stroke	mm	100
Quill bore taper	mm	MT-4
ACCURACY		
Positioning	mm	0.005
Repeatability	mm	0.003
Machine Weight(approx)	kg	3650
Machine dimension	mm	2300*2500*1690
CNC System**	Fanuc	

3.3 Measurement of Responses

3.3.1 Measurement of surface roughness

In this investigation, surface roughness (Ra) is measured by MITUTOYO SJ210 SURF TEST, a stylus type profilometer (Fig2) and its specifications are given in table 3. Each surface is characterized by the average surface roughness Ra value. The cut off length λc and the sampling number (N) are selected as 0.8mm and5 respectively, and travel length selected is 4mm. In total four different measurements in the scan direction are taken on the textured surface. The average of those four measurements is used to find out the ultimate Ra values.

Figure-2, Surftest SJ-210 Portable Surface Roughness Tester

Table-3; Specifications of Surftest SJ-210

Sl.No.	Details	Values
1	Measurement Range	360μm
2	Stylus	Diamond
3	Tip radius	5 μm
4	Measuring Force	4mN
5	Ditector range	21mm
6	Transverse speed	0.25mm/s (measurement) 1mm/s(return)

7	Resolution	0.0016 µm

3.3.2 Determination of MRR

The Material Removal Rate (MRR) is estimated by using following mathematical equation with time consideration.

$$MRR = \frac{\Pi}{4t}(D_o^2 - D_f^2) * L \qquad (1)$$

Here, D_o stands for initial diameter of the work piece in mm, D_f stands for final diameter of the work piece in mm, 't' is the machining time in minutes; L= Length machined in t seconds.

3.3.3 Measurement of Tool Wear

The Tool wear is measured after every set of experiments using Laser Scanning Microscope (Fig 3) at Central Manufacturing Technology Institute (CMTI), Precision Engineering Department, Bangalore.

Figure-3, LEXT OLS4100 Laser Scanning Microscope

The LEXT OLS4100 is a Laser Scanning Microscope to perform non-contact 3D observations and measurements of surface features at 10 nanometer resolutions. It also features a fast image acquisition and a high-resolution image over a wider area.

3.4 Proposed methodology

Turning is a type of machining, a material removal process, which is utilized to make rotational parts by cutting away unwanted material. Turning can be finished on the exterior surface of the component as well as within (boring). The preliminary material is ordinarily a work piece formed by erstwhile processes namely casting, forging, extrusion, or drawing. The turning procedure involves a turning machine or lathe, work piece, fixture, and cutting tool. This turning machine use input parameter as cutting speed, feed rate, depth of cut and nose radius to reveal the output as Surface Roughness (Ra), Material Removal Rate (MRR), Tool Wear (TW). Taken outputs performance measures considered are use to analyze the turning machine efficiency. To retrieve optimal performance from turning machine the input feed in this machine ought to regulate in optimal way, this regulation of input parameter done by fusing optimization procedures. To execute optimization methods for this model an objective function is required to finish this task effective. To achieve this task superior a mathematical model is intended for the use of objective function. Now, three kind of genetic algorithm optimization methods are connected for the retrieval of better performance in turning machine. The optimization method include in this procedure are Genetic algorithm (GA), Adaptive Genetic Algorithm (AGA) and Opposition Based Genetic Algorithm (OGA). Here, opposition based genetic algorithm is consider the proposed algorithm let us talk about that algorithm in detail.

3.4.1 Opposition based genetic algorithm

Case-1 (*Mathematical modelling*)

Initially, we design a mathematical model by incorporating soft computing techniques for the purpose of input attributes optimization, this designed model was utilized as an objective function in the input attribute optimization. Here, we are having a set of 6 experimental data sets for three different materials such as Hastelloy 276, Inconel718 and Monel400 turned with coated and uncoated carbide inserts of Sandvik make. Among these 80% of that data sets are utilized as a training parameter in developing this mathematical model and remaining 20% are utilized as testing parameter for validation. Once the model is trained, then it is utilized for predicting unknown values, this mathematical model will act as a real time experimental equipment to revel the output result as similar to that of experimental value. Here, three different mathematical models (objective function) are developed for surface roughness, material removal rate and tool wears. The optimization algorithms involved in this process are genetic algorithm, adaptive genetic algorithm and opposition based genetic algorithm.

Case-2 (*Input attributes optimization*)

In this optimization process input parameters cutting speed ranges from 25 to 35, feed speed ranges from 0.08 to 0.14, depth of cut ranges from 0.4 to 1 and nose radius ranges from 0.4 to 1.2; three objective constraint has to be solved in time those constrain are as follows surface roughness should be minimized, material removal rate should be maximized and tool were should be minimized. By satisfying the all the above constraint optimal input parameter should be anticipated. This case even includes all above mentioned case-1 optimization algorithms such as genetic algorithm, adaptive genetic algorithm and opposition based genetic algorithm

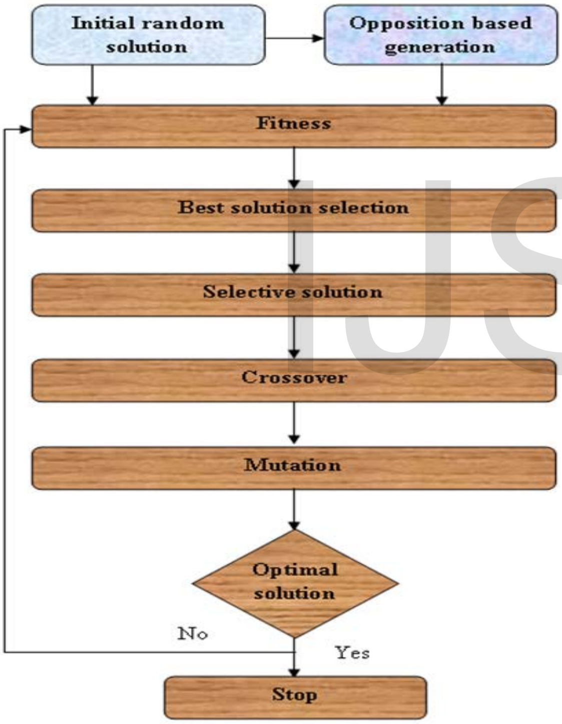

Figure-4, over all flow chart of proposed opposition based genetic algorithm

3.4.2 Initial solution generation

In this proposed opposition based genetic algorithm, there are two sorts of solution generation. Initially we generate random solution as that in an ordinary genetic algorithm within the specified minimum – maximum range. Here, four inputs are utilized to generate initial random solution those input parameters are cutting speed, feed rate, depth of cut and nose radius. Then, with this initial generation opposition based solution is generated, this opposition generation is done following method

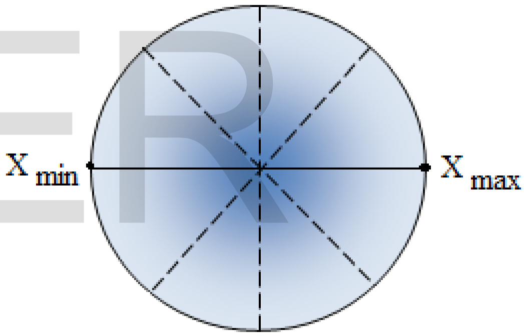

Figure-5, solution space

$$O_i = (X_{\max} + X_{\min}) - R_i \qquad (2)$$

Where, O_i indicate opposition based generation; $X_{\max}$ and $X_{\min}$ are the maximum and minimum range of solutions respectively and R_i indicate random solution.

3.4.3 Fitness computation

This process is otherwise said to be objective function; this process will reveal the fitness of each solution. The generated (random solution and opposition based generation) is fed to this objective function to identify their fitness value. The developed objective function is as follows.

$$f_i = \sum_{j=1}^{NH} \alpha_j \frac{1}{1+\exp(\sum_{i=1}^{NI} X_i \beta_{ij})} \qquad (3)$$

$$F_i = Actual(x_i) - predicted(f_i) \qquad (4)$$

Where, 'NH' is the number of hidden neuron and 'NI' number of attribute input; α and β are said to be weights.

3.4.4 Crossover

A crossover is a kind of genetic operator apply in this process for solution updating, the performance carries out in this process is shown below. Here, the type of crossover used is single point crossover and the crossover rate is 0.02; this is 2% in defining a solution. P1 and P2 are original solution these two solutions applied in the crossover process to attain two new updated solutions and those solutions are mentioned as C1 and C2.

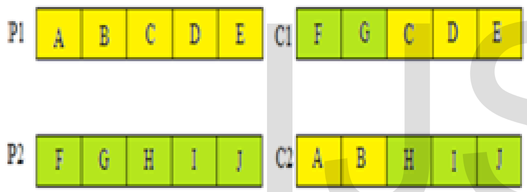

Figure-6, crossover

3.4.5 Mutation

Mutation is a kind of genetic operator apply in this process for solution updating, the performance carries out in this process is shown below. Here, the type of mutation used is a single point mutation and the mutation rate is 0.03; this is 3% in defining a solution. P1 and P2 are original solution these two solutions applied in the mutation process to attain two new updated solutions and those solutions are mentioned as M1 and M2.

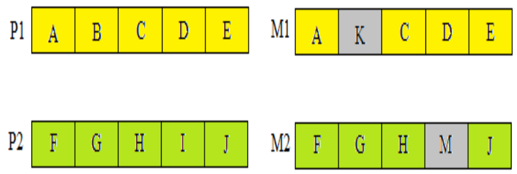

Figure- 7, mutation

4. Results and discussion

This work points in designing mathematical model and after that uses this mathematical model as an objective function to retrieve optimal turning input parameters. Different execution examinations have been completed to distinguish the appropriate optimization algorithm suits for this reason. Basically a mathematical model has been developed and its outcomes are plotted in the table for the comparison of three output values namely surface roughness, material removal rate and tool wear values accomplish from three dissimilar algorithms namely genetic algorithm, adaptive genetic algorithm and opposition based genetic algorithm with actual values acquire from experiment procedure. At that point, the error value for three different coated and uncoated materials are appeared, this error value carries the value of the outcomes reveal from mathematical models for individual algorithms contrast with the actual experimental value. At last, the mathematical model investigation ended up with convergence graph. The consequence objective analysis is the optimization, there we retrieve optimal values and error values from three dissimilar suggested optimization algorithms for three different two sorts of material.

4.1 Execution of mathematical model with different algorithms

This section comprised of table for three different two sorts of materials namely Hastelloy coated, Hastelloy uncoated, Inconel coated, Inconel uncoated, Monel coated, Monel uncoated. Every material based framed tables comprised of input parameters namely cutting speed (A), feed rate (B), depth of cut (C), nose radius (D) and output attributed such as surface roughness (Ra), material removal rate (MRR), tool wear (TW). For these input and output attributes three different optimization algorithms applied to evaluate the performance of mathematical model with actual values. The reveals results shows that the proposed optimization algorithm opposition based genetic algorithm shows better results compare with other algorithms (i.e) the revealed results are closely similar to actual experiment value.

Table-4, Work material: Hastelloy 276. Tool: Coated carbide inserts

Trial	A	B	C	D	Surface roughness (Ra)				Material removal rate (MRR)				Tool wear (TW)			
					Actual	GA	AGA	OGA	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA
1	25	0.08	0.4	0.4	1.003	1.265	1.251	0.912	452.94	445.95	446.82	452.42	145.7	146.17	144.75	144.914
2	25	0.11	1	0.8	1.262	1.114	1.112	1.262	1128.99	1129.16	1128.77	1128.89	191.4	191.42	191.67	191.325
3	25	0.14	0.4	0.8	0.585	0.554	0.549	0.585	519.33	517.99	519.40	519.17	511.4	511.39	511.17	511.340
4	30	0.08	0.7	0.4	0.928	1.256	1.252	0.764	845.4	844.89	844.92	845.52	159.98	161.97	158.17	159.899
5	30	0.08	0.4	1.2	0.59	0.764	0.754	0.591	284.33	283.06	284.36	284.41	165.7	165.54	165.44	165.748
6	30	0.11	0.7	1.2	0.726	0.876	0.862	0.564	784.57	783.99	784.45	783.85	125.7	126.02	125.92	126.056
7	30	0.14	1	1.2	0.452	0.872	0.879	0.454	567.9	567.94	567.98	568.05	217.14	217.15	217.58	217.426
8	35	0.11	0.7	0.8	0.581	1.258	1.252	0.606	940.23	942.93	941.83	940.11	271.4	272.11	271.85	271.998
9	35	0.14	0.7	0.4	1.944	1.261	1.252	1.997	1500.39	1501.73	1501.32	1501.19	97.14	80.86	95.37	97.060

Table-5, Work Material :Hastelloy276 , Tool: Uncoated Carbide

Trial	A	B	C	D	Surface roughness (Ra)				Material removal rate (MRR)				Tool wear (TW)			
					Actual	GA	AGA	OGA	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA
1	25	0.08	0.4	0.4	0.667	0.777	1.055	0.662467	469.45	469.06	468.99	469.5901	450	451.27	449.89	449.98
2	25	0.11	1	0.8	0.459	0.400	0.320	0.437585	1116.65	1114.90	1117.573	1116.85	182	181.64	181.36	182.42
3	25	0.14	0.4	0.8	0.458	0.497	1.163	0.443724	565.63	565.15	565.0887	565.58	422	422.02	419.45	422.22
4	30	0.08	0.7	0.4	0.499	0.565	0.977	0.499759	685.31	688.51	685.3499	686.24	280	279.82	280.38	279.62
5	30	0.08	0.4	1.2	0.418	0.451	1.274	0.416438	1119.33	1119.44	1119.397	1117.86	426	431.97	417.59	426.18
6	30	0.11	0.7	1.2	0.691	3.460	1.243	0.585373	958.06	953.60	953.6591	959.22	214	222.04	215.63	212.48
7	30	0.14	1	1.2	0.643	0.480	1.101	0.64213	1098.21	1105.54	1105.672	1098.10	212	211.57	212.22	210.75
8	35	0.11	0.7	0.8	0.596	2.271	1.157	0.576809	1090.99	1090.51	1090.602	1090.26	488	487.62	487.95	488.08
9	3	0.1	0.	0.	1.435	1.47	1.06	0.6078	1133.	1132.	1133.3	1133.4	438	434.	439.	439.

	5	4	7	4		2	9	65	41	93		4		71	34	03

Table-6, Work Material: Inconel718, Tool: coated Carbide

Trial	A	B	C	D	Surface roughness (Ra)				Material removal rate (MRR)				Tool wear (TW)			
					Actual	GA	AGA	OGA	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA
1	25	0.08	0.4	0.4	1.017	0.470	0.309	1.240	151.99	141.601	142.112	151.977	188	187.16	187.47	187.77
2	25	0.11	1	0.8	0.937	1.655	0.233	0.938	992.4	992.296	992.09	992.29	224	223.66	223.80	226.13
3	25	0.14	0.4	0.8	0.632	1.265	0.305	0.776	1552.95	1552.52	1552.76	1552.8	554	544.06	554.16	553.24
4	30	0.08	0.7	0.4	0.788	0.832	0.309	0.996	684.93	688.88	685.43	687.68	442	444.96	442.56	438.39
5	30	0.08	0.4	1.2	0.655	0.124	0.296	0.698	236.16	233.55	234.41	236.15	424	424.21	424.96	427.00
6	30	0.11	0.7	1.2	0.749	0.256	0.199	0.712	1015.98	1015.15	1015.36	1017.16	496	495.94	496.96	497.009
7	30	0.14	1	1.2	0.784	0.578	0.752	0.784	1175.87	1176.25	1176.26	1176.41	302	302.31	301.49	303.513
8	35	0.11	0.7	0.8	0.567	0.218	0.309	0.735	1084.82	1084.69	1084.89	1085.02	258	260.55	245.57	256.615
9	35	0.14	0.7	0.4	1.59	0.949	0.309	1.592	1206.75	1207.63	1206.60	1206.68	224	225.63	222.01	223.261

Table-7, Work Material: Inconel718, Tool: Uncoated Carbide

Trial	A	B	C	D	Surface roughness (Ra)				Material removal rate (MRR)				Tool wear (TW)			
					Actual	GA	AGA	OGA	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA
1	25	0.08	0.4	0.4	0.56	1.95	0.9047	0.769	359.41	357.99	359.58	359.24	308	306.42	306.59	308.80
2	25	0.11	1	0.8	0.95	0.52	1.0452	0.957	1049.83	1049.85	1046.69	1053.29	221	221.35	221.60	220.85
3	25	0.14	0.4	0.8	0.85	1.09	0.9048	0.760	730.62	730.16	730.51	730.58	371	368.68	369.27	371.50
4	30	0.08	0.7	0.4	0.71	0.89	0.9047	0.768	692.19	696.55	692.62	692.63	303	303.32	303.37	304.36
5	30	0.08	0.4	1.2	0.60	0.80	0.9045	0.754	338.51	337.58	337.29	338.49	414	411.86	412.65	413.81
6	30	0.11	0.7	1.2	0.69	1.37	0.9057	0.743	931.5	931.316	931.54	931.32	440	440.33	440.86	439.95
7	30	0.14	1	1.2	0.80	0.94	0.9199	0.805	1111.96	1119.67	1118.98	1112.51	392	392.85	392.49	392.08
8	3	0.1	0.	0.	0.86	1.3	0.904	0.76	703.9	703.8	703.0	703.8	400	406.2	406.3	400.1

	5	1	7	8		2	4	6	8	8	6	5		5	2	3
9	35	0.14	0.7	0.4	1.11	0.98	0.9044	0.766	1533.04	1537.65	1533.14	1533.07	298	296.29	296.31	298.60

Table-8, Work Material: Monel 400;, Tool: Coated Carbide

Trial	A	B	C	D	Surface roughness (Ra)				Material removal rate (MRR)				Tool wear (TW)			
					Actual	GA	AGA	OGA	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA
1	25	0.08	0.4	0.4	1.44	1.301	1.366	1.44	336.14	331.15	331.70	335.38	255	263.58	263.20	256.03
2	25	0.11	1	0.8	2.32	2.158	2.32	2.32	1152.69	1152.39	1152.7	1152.79	223	223.20	222.98	223.24
3	25	0.14	0.4	0.8	3.08	2.903	3.10	3.25	489.22	494.41	488.67	489.08	146	146.97	146.16	146.21
4	30	0.08	0.7	0.4	1.64	1.856	1.86	1.87	387.54	388.43	387.69	387.68	458	458.02	458.01	458.11
5	30	0.08	0.4	1.2	1.72	4.4101	2.11	1.65	718.87	719.02	718.91	718.56	274	273.80	273.80	274.22
6	30	0.11	0.7	1.2	2.22	1.581	1.16	2.42	172.6	172.81	172.61	172.16	174	173.37	173.42	173.83
7	30	0.14	1	1.2	2.17	2.003	2.19	2.15	1504.08	1503.95	1504.18	1503.94	139	138.86	138.99	139.29
8	35	0.11	0.7	0.8	1.36	1.248	1.25	1.25	1088.81	1091.50	1090.70	1089.7	174	177.86	177.85	174.24
9	35	0.14	0.7	0.4	2.91	3.186	3.19	2.90	1441.54	1441.19	1440.66	1441.62	434	432.49	432.39	433.46

Table-9, Work Material: Monel 400;, Tool: Uncoated Carbide

Trial	A	B	C	D	Surface roughness (Ra)				Material removal rate (MRR)				Tool wear (TW)			
					Actual	GA	AGA	OGA	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA
1	25	0.08	0.4	0.4	0.76	3.86	0.39	0.99	331.04	319.20	328.02	330.78	594	593.99	594.37	593.97
2	25	0.11	1	0.8	2.22	2.23	1.94	2.20	1235.99	1235.97	1236.00	1236.01	469	467.86	469.45	468.99
3	25	0.14	0.4	0.8	3.07	1.87	3.07	3.45	608.08	608.23	608.07	607.77	512	514.36	512.59	512.005
4	30	0.08	0.7	0.4	1.17	0.93	1.22	1.23	1083.75	1079.99	1084.11	1085.20	600	602.26	600.42	599.999
5	30	0.08	0.4	1.2	1.33	1.34	1.29	1.41	305.3	305.78	305.99	305.26	600	600.08	600.16	599.992
6	30	0.11	0.7	1.2	2.04	1.98	1.84	2.11	632.27	630.88	631.31	631.27	495	497.94	498.05	496.799
7	3	0.1	1	1.	1.80	1.71	1.84	1.82	982.9	982.9	982.9	983.1	217	214.	214.	217.0

	0	4		2					9	7	0	7		35	35	17
8	3 5	0.1 1	0. 7	0. 8	2.49	2.31	2.46	2.49	1171. 63	1171. 62	1170. 02	1170. 69	592	587. 22	592. 07	591.5 69
9	3 5	0.1 4	0. 7	0. 4	20.73	20.6 5	21.9 4	20.6 3	1595. 25	1595. 53	1592. 33	1594. 47	243	245. 76	245. 18	244.7 13

4.2 Performance evaluation of mathematical model with different algorithms

This section comprised of analysing the performance of mathematical models obtained from three different algorithms for three pair of different material-tool insert combinations such as Hastelloy- coated insert, Hastelloy-uncoated insert, Inconel- coated insert, Inconel- uncoated insert, Monel- coated insert and Monel –uncoated insert.. The different algorithms involved in these processes are Genetic Algorithm (GA), Adaptive Genetic Algorithm (AGA), Opposition based Genetic Algorithm (OGA).

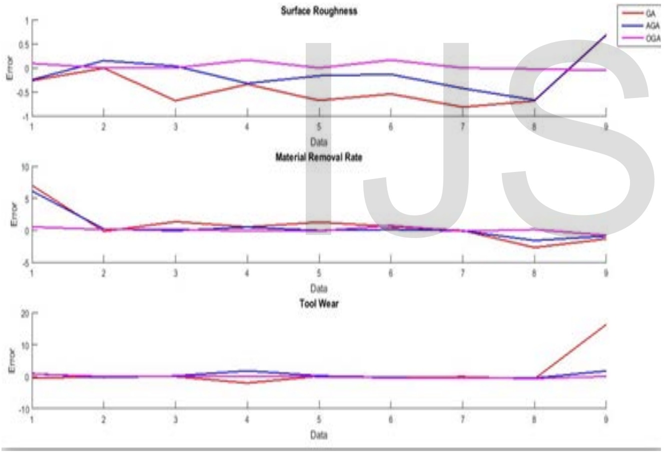

Figure-8, Error values obtained from three different algorithms for Hastelloy- coated insert workpiece - tool insert combination

In figure:8 error graph clearly shows the output attribute surface roughness, material removal rate and tool wear the proposed algorithm opposition based genetic algorithm reveals better results than other two algorithm genetic algorithm and adaptive genetic algorithm. Error values are nothing but the difference between actual value and predicted value; if the result of the error value is zero then the performance of the mathematical model is said to be superior. In all three attributes the proposed algorithm opposition based genetic algorithm reveals better results. Next to proposed algorithm adaptive genetic algorithm have a close call from the proposed opposition based genetic algorithm. Especially in tool wear all three algorithm behaves literally, in material removal rate apart from three validation others having close call for all three algorithms.

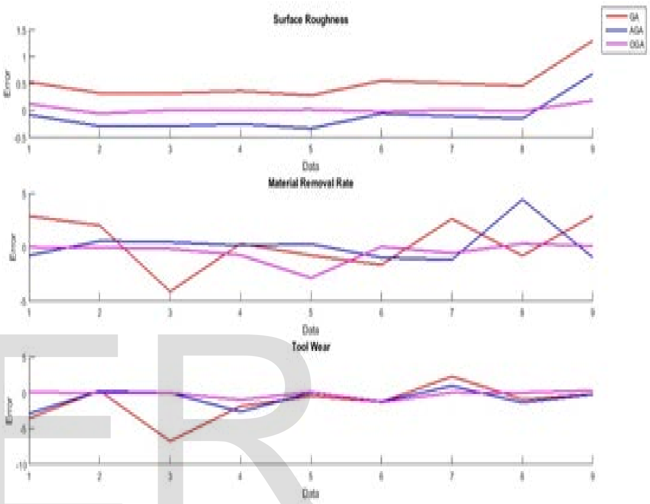

Figure-9, Error values attain from three different algorithms for Hastelloy- uncoated insert work piece - tool insert combination

In case of Hastelloy machined with uncoated insert, error graph(figure:9) evidently illustrates the output attribute surface roughness, material removal rate and tool wear the proposed opposition based genetic algorithm reveals better results than other two algorithm genetic algorithm and adaptive genetic algorithm. In all three attributes the proposed algorithm opposition based genetic algorithm reveals better results. Next to proposed algorithm adaptive genetic algorithm have a close call from the proposed opposition based genetic algorithm. Specially in surface roughness the performance of all three algorithm behaves linearly the adaptive genetic algorithm results are under rated in its performance, in tool wear other that three validation almost all other portions suggested three algorithms having its close call.

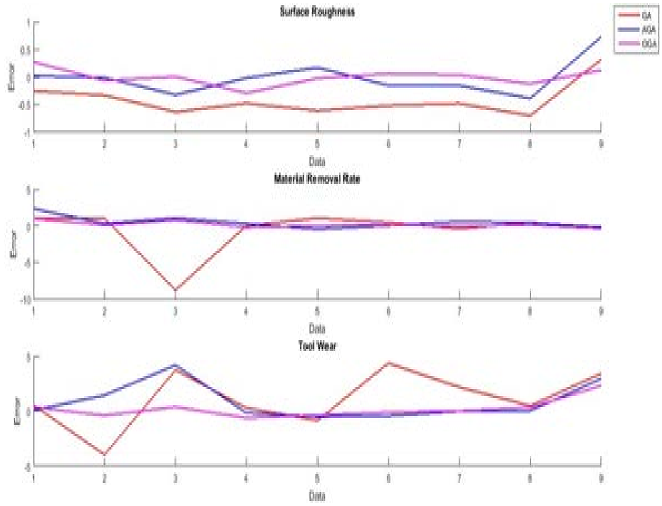

Figure-10, Error values attain from three different algorithms for Inconel- coated insert tool work combination

In Inconel- coated insert tool work combination, the error graphs depicted in figure: 10 palpably demonstrate in all three attributes the proposed algorithm opposition based genetic algorithm reveals better results. Next to proposed algorithm the adaptive genetic algorithm has a close call from the proposed opposition based genetic algorithm. Particularly in surface roughness and material removal rate the both opposition based genetic algorithm and adaptive genetic algorithm behave literally almost same in their performance.

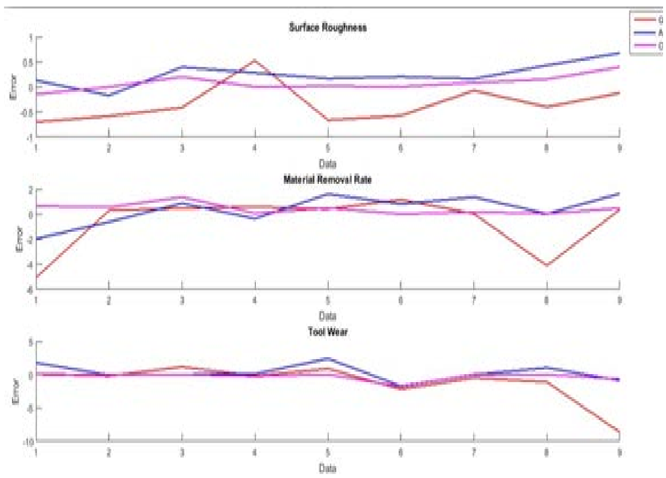

Figure-11, Error graph for Inconel- uncoated insert tool work combination

Figure: 11, shows Error values obtained from three different algorithms for Inconel- uncoated tool work combination. The graph deliberately reveal in all three attributes the proposed algorithm opposition based genetic algorithm reveals better results. Subsequently adaptive genetic algorithm has a close call from the proposed opposition based genetic algorithm. Particularly in tool wear all three algorithms genetic algorithm, adaptive genetic algorithm and the proposed opposition based genetic algorithm behave literally almost same in their performance.

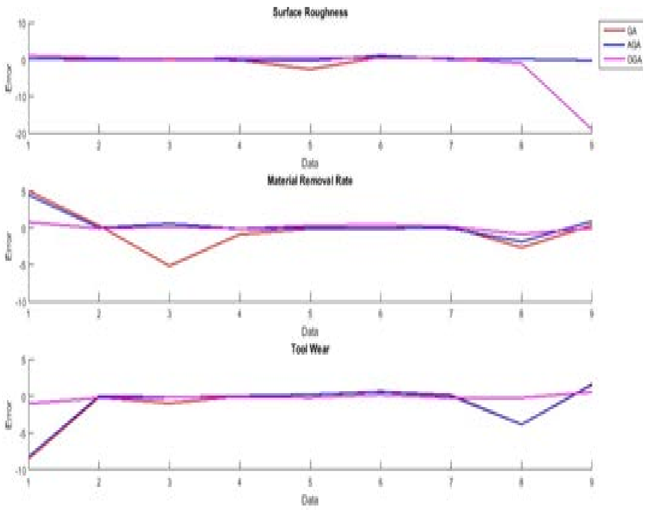

Figure-12, Error values attain from three different algorithms for Monel coated

In Monel coated, figure: 12 error graphs deliberately reveal in all three attributes the proposed algorithm opposition based genetic algorithm reveals extremely satisfactory results. Subsequently adaptive genetic algorithm has a close call from the proposed opposition based genetic algorithm. Especially in surface roughness and tool wear genetic algorithm and adaptive genetic algorithm having close call of nearly 80% of validation values almost similar to that of proposed algorithm

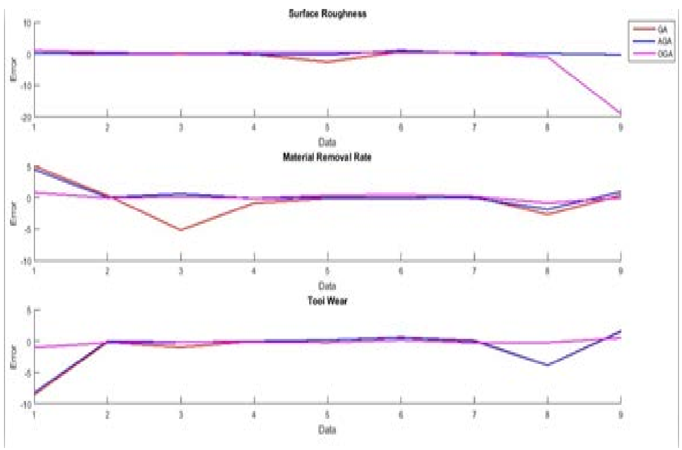

Figure-13, Error values obtained from three different algorithms for Monel- coated insert tool work combination

In Monel- coated insert tool work combination the error graph shown in figure:13, deliberately reveal in all three attributes the proposed algorithm opposition based genetic algorithm reveals extremely satisfactory results. Subsequently adaptive genetic algorithm has a close call from the proposed opposition based genetic algorithm. Especially in surface roughness and tool wear genetic algorithm and adaptive genetic algorithm having close call of nearly 80% of validation values almost similar to that of proposed algorithm.

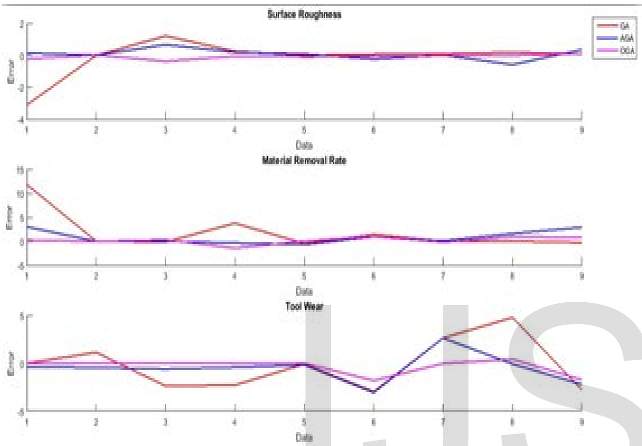

Figure-14, Error values obtained from three different algorithms for Monel –uncoated insert tool work combination

In Monel –uncoated insert tool work combination, figure: 14 error graph deliberately reveal in all three attributes the proposed algorithm opposition based genetic algorithm reveals extremely satisfactory results. Subsequently adaptive genetic algorithm has a close call from the proposed opposition based genetic algorithm. Especially in surface roughness and material removal rate having a close call other than two or three validation for adaptive genetic algorithm and opposition based genetic algorithm.

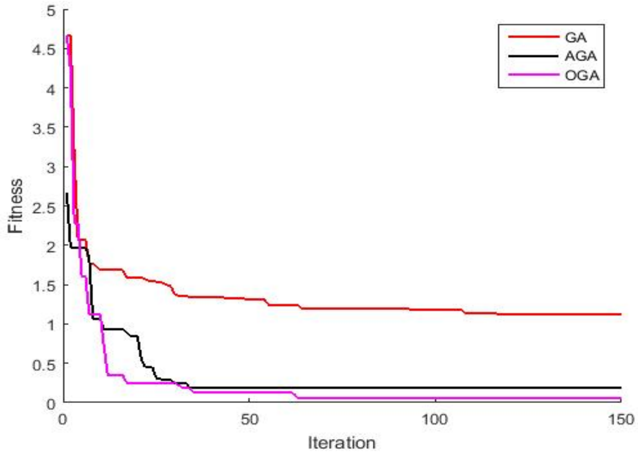

Figure-15, Convergence graph comparison for three different optimization algorithms

Convergence graph in drawn for iterations and fitness value attains from different optimization algorithms. Optimization algorithms involved in this process are genetic algorithm, adaptive genetic algorithm and opposition based genetic algorithm. From this performance analysis the proposed opposition based genetic algorithm converges early and attains its lowest convergence rate at 55th to 60th iteration. Adaptive genetic algorithm converge early nearly 40th iteration, in other hand the genetic algorithm cross 100th iteration to get converge and in proposed opposition based genetic algorithm get converge nearly 60th iteration. Initially our proposed algorithm exhibit slow performance up to 6th iteration at that time other two algorithm genetic algorithm and adaptive genetic algorithm performs literally after that the proposed algorithm take a lead and finally end with superior performance compare with other two algorithm.

Table-10, optimally obtained input and output attributes

Material	Algorithms	A	B	C	D	Ra	MRR	TW
Hastelloy-Coated tool	GA	33	0.080197	0.4878	1.128957	0.126979	2243.984	56.51829
	AGA	31	0.129581	0.746622	0.961788	0.123911	3933.092	49.50899
	OGA	30	0.138187	0.937485	1.121135	0.059276	6817.791	43.79881
Hastelloy-Uncoated tool	GA	30	0.122626	0.94944	0.400511	0.014209	2886.301	113.621
	AGA	31	0.102356	0.556889	0.470199	0.075845	1970.511	79.466
	OGA	27	0.129361	0.659032	0.427264	0.010645	4715.536	19.23348
Inconel-Coated	GA	31	0.138407	0.943236	0.671911	0.12745	4638.955	182.5058
	AGA	29	0.137194	0.627939	1.127318	0.092042	5280.448	98.82355

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tool	OGA	26	0.102185	0.731892	1.161157	0.073737	5378.572	88.43079
Inconel-Uncoated tool	GA	31	0.145937	0.527802	0.541853	0.127282	2356	161.8054
	AGA	26	0.115807	0.803864	1.088951	0.100827	6395.305	133.8542
	OGA	26	0.094474	0.930975	0.410885	0.072417	74599.64	128.2024
Monel-Coated tool	GA	31	0.133729	0.457366	0.447843	0.132649	3254.49	105.7995
	AGA	30	0.14892	0.565353	0.908011	0.118872	3009.483	54.10983
	OGA	30	0.114282	0.956782	0.537904	0.052095	5633.774	13.16142
Monel-Uncoated tool	GA	25	0.13666	0.538757	1.042162	0.507853	19054.53	66.87684
	AGA	33	0.124548	0.775202	0.421484	0.135869	21004.97	89.36025
	OGA	33	0.146589	0.873487	0.460067	0.064162	3850.879	64.52319

In table: 10; the input attributes are cutting speed (A), feed rate (B), depth of cut (C), nose radius (D) and output attributed such as surface roughness (Ra), material removal rate (MRR), tool wear (TW). Here, coated and uncoated values are differentiating with their colour coating in all material. All suggested optimization algorithms reveal better results than the actual experimental values amid; the opposition based genetic algorithm is optimally preferred superior results among other comparative optimization algorithms in all material.

4.4 Material wise actual comparison among actual and predicted values

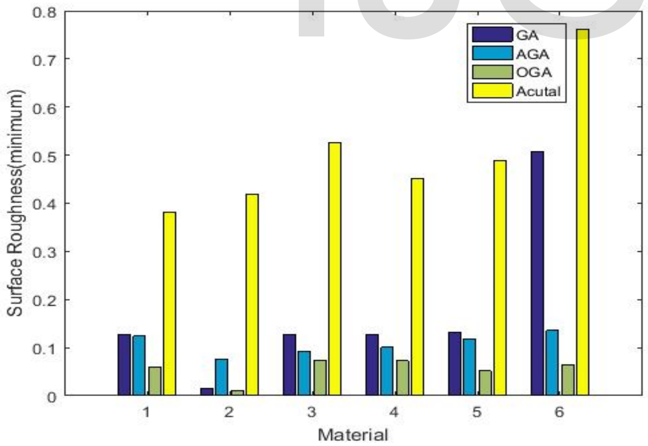

Figure-16, Material wise comparison for surface roughness

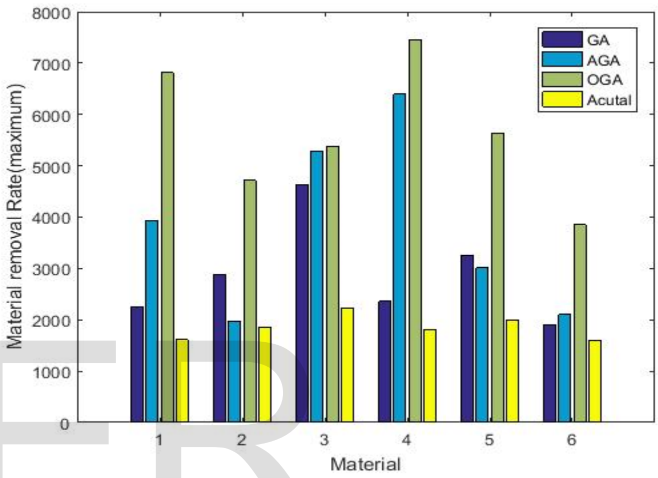

Figure-17, Material wise comparison for material removal rate

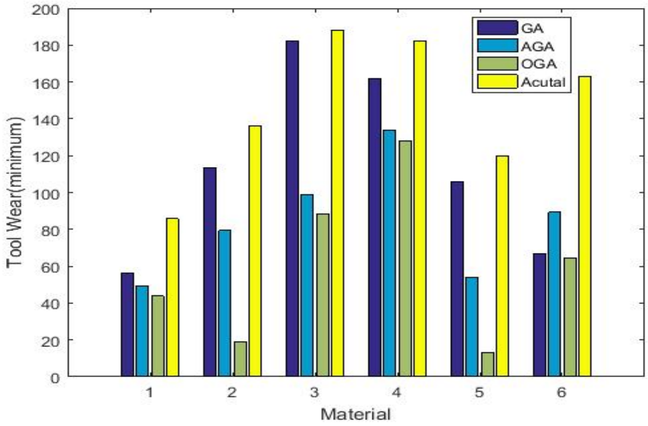

Figure-18, Material wise comparison for Tool wears

In this section for all three outputs such as surface roughness, material removal rate and tool wear predicted values are compared with actual values for all six different materials. These materials are numbered in x-axis and are namely Hastelloy coated insert (1) and Hastelloy uncoated -insert (2), Inconel –coated insert (3) and Inconel uncoated insert (4), Monel coated insert (5) and Monel uncoated insert (6). In figure: 16 discover that the proposed opposition based genetic algorithm behaves literally and reveals minimum values among its comparators in all six materials. In figure: 17 discover that the proposed opposition based genetic algorithm behaves literally and reveals maximum values among its comparators in all six materials. In figure: 18 discover that the proposed opposition based genetic algorithm behaves literally and reveals minimum values among its comparators in all six materials.

5. Conclusion

This paper manages designing mathematical modelling and afterward by using that mathematical model as an objective function to reveal optimal input and output attributes for machine turning process. This designing mathematical modelling and input and output attribute optimization process consolidate three distinctive optimization process specifically genetic algorithm, adaptive genetic algorithm and opposition based genetic algorithm. From the above outcomes analysis it is obviously express that the proposed optimization algorithm behave literally in all kind of investigation. In future, the upcoming researchers can apply their own developed optimization algorithms to enhance this work further.

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