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Effective Utilization of Opposition Based Genetic Algorithm for Multi Objective Optimization of CNC Turning Process

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Abstract: The machining is about outward appearance, the fundamental of contemporary manufacturing industry and is concerned either directly or indirectly in the manufacture of almost every product of recent development. A term that covers a hefty anthology of manufacturing processes designed to remove unwanted material, habitually in the appearance of chips from a work piece to provide desired geometry, size and finish specified to fulfil design requirements. This paves the research intention towards incorporating soft computing techniques to acquire better result in short intervals. This study includes the significance of predicting optimal tuning input parameters such as cutting speed, feed rate, depth of cut and nose radius for minimized surface roughness, maximized material removal rate and minimized tool wear. This objective is achieved by developing a mathematical model which incorporates optimization techniques. Genetic Algorithm (GA) is the ultimate tool to utilize in this research for its bettermen, Genetic algorithm has further 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 research three different super alloys have been subjected to turning on CNC lathes with a combination of uncoated and coated carbide turning inserts.

Key words: Inconel 718, Hastelloy 276, Monel 400, turning inserts, Genetic algorithm, adaptive Genetic algorithm and opposition based Genetic algorithm

INTRODUCTION

Turning is a machining process in which a cutting tool, usually a non-rotary tool bit, generates a surface of revolution whilst the work piece turn around. Manufacturing strategy that begins with corporate, business and marketing strategies and then intend a manufacturing system to shore up (Elmoselhy, 2013). Manufacturers are beneath tremendous pressure to perk up productivity and quality while plummet costs.

Machining in general and turning in particular, surface finish and accuracy of the machined surface has been identified as quality attributes on the other hand, Material Removal Rate (MRR) which indicates processing time of the work piece is another important factor that greatly influences production rate and cost and hence treated as performance index directly related to productivity. The tool wear and hence, tool life has been identified as an economic criterion which is having a direct influence on quality and productivity. So, an attempt has been made to optimize quality and productivity in a manner that these multi-criteria could be fulfilled simultaneously up to the expected level.

So, as a whole, there is need for tools that will allow the prediction or estimation of the surface roughness, MRR and expected tool life before the machining of the part and which at the same time can be easily used in the production floor environment for contributing to the minimization of required time and cost and the manufacture of desired quality products.

In order to build up a bridge between quality and productivity and to achieve the same in an economic way, the present research highlights optimization of CNC turning process parameters to provide good surface finish, high Material Removal Rate (MRR) and maximum tool life. All of the above attributes greatly vary with the change of cutting process parameters and tool geometry hence, it warrants proper selection of cutting process parameters and tool geometry along with the ability to predict the various responses.

Surface roughness mainly depends on work piece hardness, tool geometry like nose radius, edge geometry, rake angle and various process parameters like feed rate, cutting speed, depth of cut, etc. There are various machining parameters those have an effect on the surface roughness but those effects have not been adequately

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quantified yet particularly when machining difficult to machine super alloys like Inconel 718, Hastelloy 276 and Monel 400. In order for manufacturers to maximize their gains from machining, accurate predictive models for surface roughness, MRR and Tool wear must be constructed.

Literature review: Das *et al*. (2016) have 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-4.5 Cu 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.

Optimization of geometry parameters for ceramic cutting tools in intermittent turning of hardened steel by Cui *et al*. (2016). The stress distribution of the tool body was obtained using finite element simulation. The initial damage of the cutting tool and the tool stress was integrated on the basis of the concept of damage equivalent stress. The evolutions of the maximum value of damage equivalent stress on the tool body were acquired for different cutting length ratios and different combinations of tool geometry parameters. Then, the cutting length ratios were 0.044 and 0.093, tool fracture was more likely to arise as the cutting tool cut into the work piece. AOM and ANOVA for tool lives demonstrated the correctness of the optimization method for tool geometry parameters.

Malakizadi *et al*.(2016) have 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.

Saenz *et al*. (2015) have proposed the a methodology for the selection and comparison of non-traditional sheet metal cutting processes as a new structure of selection by means of an expert system. The model was generated from a knowledge base acquired from diverse experts and the use of fuzzy logic techniques. With a simple input of the parameters of a piece, the system offers the most appropriate cutting options (based on the requirements of the piece) allowing a non-expert user selecting the most appropriate process with emphasis on a predefined priority: finish, cost or time. Results of experiments under three different approaches prove that the expert system here presented accurately prioritizes the most convenient cutting processes.

Karabulut *et al*. the milling tests were performed based on the Taguchi design of experiment method using L18 21×32 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 Al_2O_3 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.

Saranya and Fumio (2014) have 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).

Pohokar and Bhuyar (2014) have proposed the several techniques available to determine the optimum values of these parameters in this study 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 140×120×10 mm workpiece. The predicted results match 90% including the residuals. Thus, proves the neural network is used for optimization of geometric and machining parameter

Fig. 1: Jaguar CNC lathe

Fig. 2: Surftest SJ-210 portable surface roughness tester

Experimental investigation

Work material and tool: Turning experiment was performed on CNC lathe with three different materials namely Hastelloy 276, Inconel 718 and Monel 400 rods of 25 mm diameter and 100 mm length using coated and uncoated carbide turning insert of Sandvik Coromant make (Fig. 1) with ISO specification numbers as given:

Coated carbide tool inserts:

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

Uncoated carbide tool inserts:

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

Work piece materials:

- Hastelloy 276
- Inconel 718
- Monel 400

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 1) are given. The machining variables are set according to the experimental design as shown in Table 2. 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.

Measurement of responses

Measurement of surface roughness: In this investigation, surface Roughness (Ra) is measured by Mitutoyo SJ210 surf test, a stylus type profilometer (Fig. 2) 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 0.8 and 5 mm, respectively and travel length selected is 4 mm. 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.

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

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

Where:

D_o = The stands for initial diameter of the workpiece in mm
D_f = The stands for final diameter of the workpiece in mm
t = The machining time in minutes
L = The length machined in t seconds

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.

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.

Table 1: Specifications of surftest SJ-210

Details	Values
Measurement range	360 μm
Stylus	Diamond
Tip radius	5 μm
Measuring force	4 mN
Ditector range	21mm
Transverse speed	0.25 mm/sec (measurement) 1mm/sec(return)
Resolution	0.0016 μm

Table 2: Details of input parameters (control factors) and responses

Input parameters RS (control factors)	Codes units	Levels 1	2	3	Responses
Cutting speed (μm)	A (m/min)	25.00	30.00	35.00	Surface Roughness (Ra)
Feed rate (mm^3/min)	B (mm/rev)	0.08	0.11	0.14	Material Removal Rate (MRR)
Depth of cut (%)	C (mm)	0.40	0.70	1.00	Tool wear
Nose radius (μm)	D (mm)	0.40	0.80	1.20	

Table 3: Work material: Hastelloy 276. Tool: coated carbide inserts

					Surface Roughness (Ra)				Material Removal Rate (MRR)				Tool Wear (TW)			
Trial	A	B	C	D	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	145.70	146.17	144.75	144.914
2	25	0.11	1.0	0.8	1.262	1.114	1.112	1.262	1128.99	1129.16	1128.77	1128.89	191.40	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	511.40	511.39	511.17	511.340
4	30	0.08	0.7	0.4	0.928	1.256	1.252	0.764	845.40	844.89	844.92	845.52	159.98	161.97	158.17	159.899
5	30	0.08	0.4	1.2	0.590	0.764	0.754	0.591	284.33	283.06	284.36	284.41	165.70	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	125.70	126.02	125.92	126.056
7	30	0.14	1.0	1.2	0.452	0.872	0.879	0.454	567.90	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	271.40	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

Fig. 3: LEXT OLS4100 laser scanning microscope

MATERIALS AND METHODS

Turning is a form of machining, a material removal process which is used to create rotational parts by cutting away unwanted material. Turning can be complete on the exterior surface of the component as well as within (boring). The preliminary material is commonly a work piece produced by erstwhile processes such as casting forging, extrusion or drawing. The turning process entails a turning machine or lathe, work piece, fixture and cutting tool. This turning machine utilize 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 taken in to account are utilize for the purpose of analysing the turning machine efficiency. To retrieve optimal performance from turning machine the input feed in this machine should regulate in optimal way this regulation of input parameter done by incorporating optimization techniques. To perform optimization techniques for this concept an objective function is required to complete this task successful. To perform this task better a mathematical model is designed for the purpose of objective function. Here, three sort of Genetic algorithm optimization techniques are applied for the retrieval of better performance in turning machine. The optimization technique involve in this process 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’s discuss that algorithm in detail.

Opposition based Genetic algorithm

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 Inconel 718 and Monel 400 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 math ematical model will act as a real time experimental equipment to revel the output result as similar to that of exp erimental value. Here, three different mathematical models (objective function) are developed for surface roughness, material removal rate and tool wear. The optimization algorithms involved in this process are Genetic algorithm, adaptive Genetic algorithm and opposition based Genetic algorithm.

(Input attributes optimization): In this optimization process input parameters cutting speed ranges from 25-35, feed speed ranges from 0.08-0.14, depth of cut ranges from 0.4-1 and nose radius ranges from 0.4-1.2, 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 (Fig. 4).

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 in Fig. 5:

$$O_i = (X_{Max} + X_{min}) \tag{2}$$

Where:

O_i = Indicate opposition based generation

X_{max} and X_{min} = The maximum and minimum range of solutions, respectively

R_i = Random solution

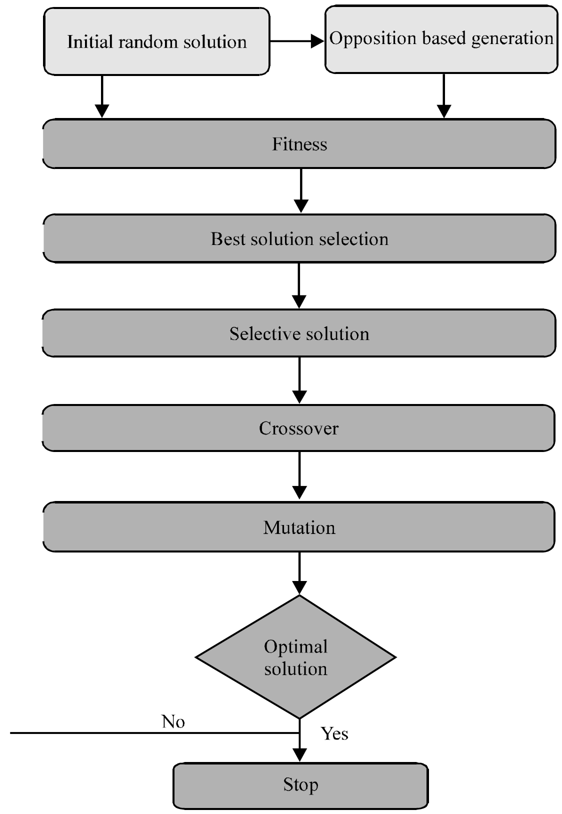

Fig. 4: Over all flow chart of proposed opposition based Genetic algorithm

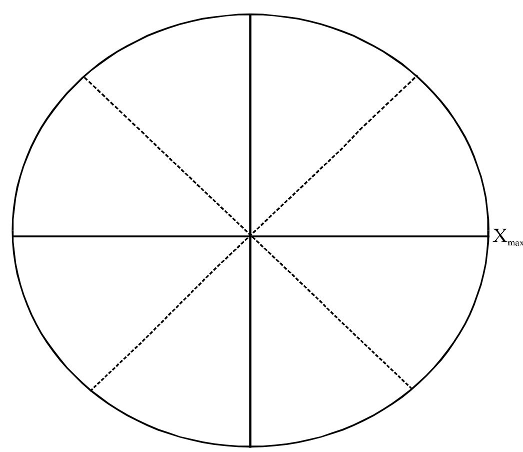

Fig. 5: Solution space

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:

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

$$F_i = \text{Actual}(x_i)\text{-Predicted}(f_i) \quad (4)$$

Where:

‘NH’ = The number of hidden neuron and
‘NI’ = Number of attribute input α and β are said to be weights

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 as. 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.

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.

RESULTS AND DISCUSSION

This research aims in designing mathematical model and then utilizes this mathematical model as an objective function to retrieve optimal turning input parameters. Various performance analyses have been carried out to identify the appropriate optimization algorithm suits for this purpose. Primarily a mathematical model has been developed and its results are plotted in the table for the comparison of three output values such as surface roughness, material removal rate and tool wear values attain from three different algorithms such as Genetic algorithm, adaptive Genetic algorithm and opposition based Genetic algorithm with actual values obtain from experiment process. Then the error value for three different coated and uncoated materials are shown, this error value carries the value of the results reveal from mathematical models for individual algorithms compare with the actual experimental value. Finally, the mathematical model analysis ended up with convergence graph. The significance objective analysis is the optimization, there we retrieve optimal values and error values from three different suggested optimization algorithms for three different two sorts of materials.

Execution of mathematical model with different algorithms: This study 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 4-8).

Performance evaluation of mathematical model with different algorithms: This study 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).

Error graph for Hastelloy-coated insert: Figure 6 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.

Table 4: Work materials: Hastelloy 276, tool: Uncoated Carbide

					Surface Roughness (Ra)				Material Removal Rate (MRR)				Tool Wear (TW)			
Trial	A	B	C	D	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	469.450	469.06	468.9900	469.5901	450	451.27	449.89	449.98
2	25	0.11	1.0	0.8	0.459	0.400	0.320	0.437585	1116.650	1114.90	1117.5730	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	565.630	565.15	565.0887	565.580	422	422.02	419.45	422.22
4	30	0.08	0.7	0.4	0.499	0.565	0.977	0.499759	685.310	688.51	685.3499	686.240	280	279.82	280.38	279.62
5	30	0.08	0.4	1.2	0.418	0.451	1.274	0.416438	1119.330	1119.44	1119.3970	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	958.060	953.60	953.6591	959.220	214	222.04	215.63	212.48
7	30	0.14	1.0	1.2	0.643	0.480	1.101	0.642130	1098.210	1105.54	1105.6720	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	1090.990	1090.51	1090.6020	1090.26	488	487.62	487.95	488.08
9	35	0.14	0.7	0.4	1.435	1.472	1.069	0.607865	1133.410	1132.93	1133.3000	1133.44	438	434.71	439.34	439.03

Table 5: Work materials: Hastelloy 276, tool: coated carbide

					Surface Roughness (Ra)				Material Removal Rate (MRR)				Tool Wear (TW)			
Trial	A	B	C	D	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	151.970	188	187.16	187.47	187.770
2	25	0.11	1.0	0.8	0.937	1.655	0.233	0.938	992.40	992.296	992.090	992.290	224	223.66	223.80	226.130
3	25	0.14	0.4	0.8	0.632	1.265	0.305	0.776	1552.95	1552.52	1552.760	1552.80	554	544.06	554.16	553.240
4	30	0.08	0.7	0.4	0.788	0.832	0.309	0.996	684.93	688.88	685.430	687.680	442	444.96	442.56	438.390
5	30	0.08	0.4	1.2	0.655	0.124	0.296	0.698	236.16	233.55	234.410	236.150	424	424.21	424.96	427.000
6	30	0.11	0.7	1.2	0.749	0.256	0.199	0.712	1015.98	1015.15	1015.360	1017.16	496	495.94	496.96	497.009
7	30	0.14	1.0	1.2	0.784	0.578	0.752	0.784	1175.87	1176.25	1176.260	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	1084.890	1085.02	258	260.55	245.57	256.615
9	35	0.14	0.7	0.4	1.590	0.949	0.309	1.592	1206.75	1207.63	1206.600	1206.68	224	225.63	222.01	223.261

Table 6: Work material: Inconel 718, tool: uncoated carbide

					Surface Roughness (Ra)				Material Removal Rate (MRR)				Tool Wear (TW)			
Trial	A	B	C	D	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	357.990	359.58	359.24	308	306.42	306.59	308.80
2	25	0.11	1.0	0.8	0.95	0.52	1.0452	0.957	1049.83	1049.850	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	730.160	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	696.550	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	337.580	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	1.0	1.2	0.80	0.94	0.9199	0.805	1111.96	1119.670	1118.98	1112.51	392	392.85	392.49	392.08
8	35	0.11	0.7	0.8	0.86	1.32	0.9044	0.766	703.98	703.880	703.06	703.85	400	406.25	406.32	400.13
9	35	0.14	0.7	0.4	1.11	0.98	0.9044	0.766	1533.04	1537.650	1533.14	1533.07	298	296.29	296.31	298.60

Table 7: Work material : Monel 400; tool: coated carbide

					Surface Roughness (Ra)				Material Removal Rate (MRR)				Tool Wear (TW)			
Trial	A	B	C	D	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA	Actual	GA	AGA	OGA
1	25	0.08	0.4	0.4	1.44	1.3010	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	0.8	2.32	2.1580	2.320	2.32	1152.69	1152.39	1152.70	1152.79	223	223.20	222.98	223.24
3	25	0.14	0.4	0.8	3.08	2.9030	3.100	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	1.8560	1.860	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	2.110	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	1.5810	1.160	2.42	172.60	172.81	172.61	172.16	174	173.37	173.42	173.83
7	30	0.14	1.0	1.2	2.17	2.0030	2.190	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	1.2480	1.250	1.25	1088.81	1091.50	1090.70	1089.70	174	177.86	177.85	174.24
9	35	0.14	0.7	0.4	2.91	3.1860	3.190	2.90	1441.54	1441.19	1440.66	1441.62	434	432.49	432.39	433.46

Table 8: Work material: Monel 400 tool: uncoated carbide

					Surface Roughness (Ra)				Material Removal Rate (MRR)				Tool Wear (TW)			
Trial	A	B	C	D	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	593.970
2	25	0.11	1.0	0.8	2.22	2.23	1.94	2.20	1235.99	1235.97	1236.00	1236.01	469	467.86	469.45	468.990
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	305.30	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	30	0.14	1.0	1.2	1.80	1.71	1.84	1.82	982.99	982.97	982.90	983.17	217	214.35	214.35	217.017
8	35	0.11	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	591.569
9	35	0.14	0.7	0.4	20.73	20.65	21.94	20.63	1595.25	1595.53	1592.33	1594.47	243	245.76	245.18	244.713

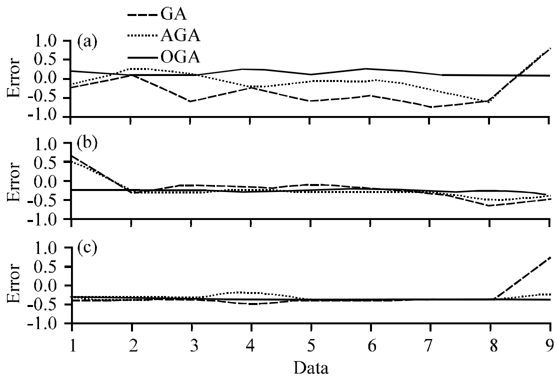

Fig. 6: Error values obtained from three different algorithms for Hastelloy-coated insert workpiece-tool insert combination: a) Surface roughness; b) Material removal rate and c) Tool wear

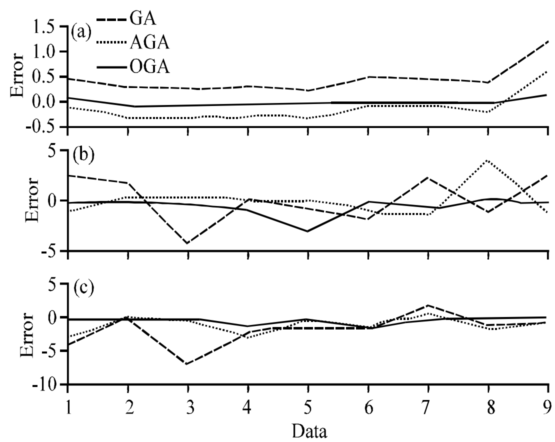

Fig. 7: Error values attain from three different algorithms for Hastelloy-uncoated insert workpiece-tool insert combination: a) Surface roughness; b) Material removal rate and c) Tool wear

Error graph for hastelloy- uncoated insert workpiece tool insert combination: In case of Hastelloy machined with uncoated insert, error graph (Fig. 7) 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.

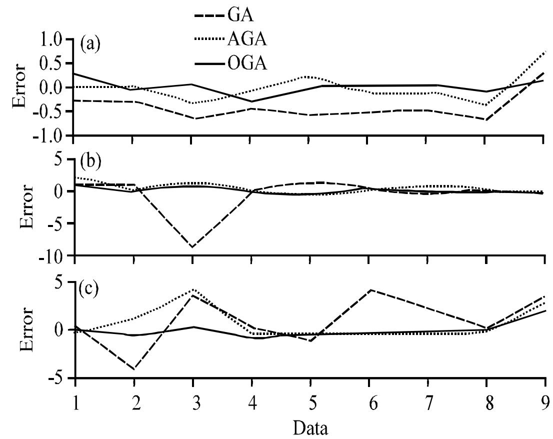

Fig. 8: Error values attain from three different algorithms for Inconel-coated insert tool work combination: a) Surface roughness; b) Material removal rate and c) Tool wear

Error graph for Inconel-coated insert tool work combination: In Inconel-coated insert tool work combination, the error graphs depicted in Fig. 8, 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.

Error graph for inconel-uncoated insert tool work combination: Figure 9 shows the 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.

Error graph for monel coated: In Monel coated, Fig. 10 error graphs deliberately reveal in all three attributes the proposed algorithm opposition based Genetic algorithm

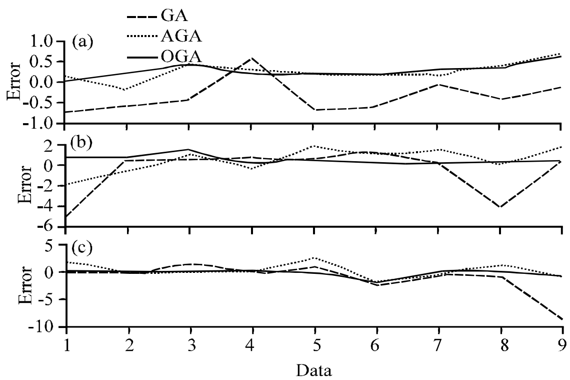

Fig. 9: Error graph for Inconel-uncoated insert tool work combination: a) Surface roughness; b) Material removal rate and c) Tool wear

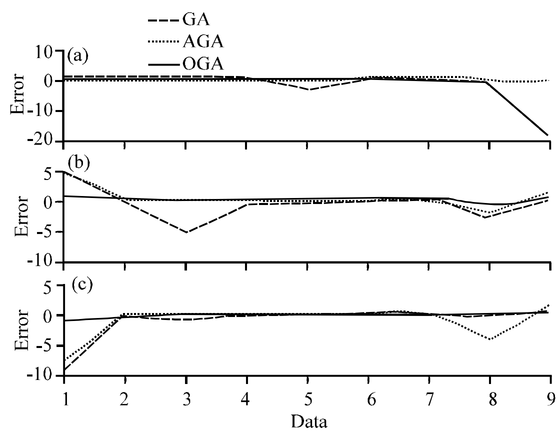

Fig. 10: Error values attain from three different algorithms for monel coated: a) Surface roughness; b) Material removal rate and c) Tool wear

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.

Error graph for monel-coated insert tool work combination: In Monel-coated insert tool work combination the error graph shown in Fig. 11, 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

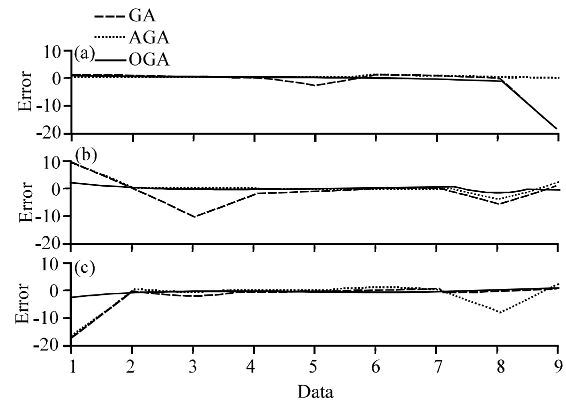

Fig. 11: Error values obtained from three different algorithms for Monel-coated insert tool work combination: a) Surface roughness; b) Material removal rate and c) Tool wear

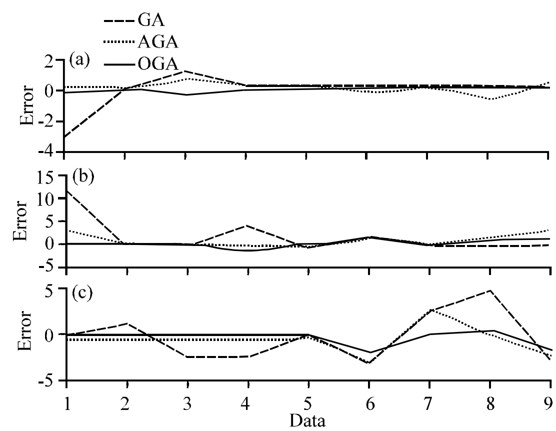

Fig. 12: Error values obtained from three different algorithms for Monel-uncoated insert tool work combination: a) Surface roughness; b) Material removal rate and c) Tool water

Genetic algorithm having close call of nearly 80% of validation values almost similar to that of proposed algorithm.

Error graph for Monel-uncoated insert tool work combination: In monel-uncoated insert tool work combination, Fig. 12 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.

Table 9: Optimally obtained input and output attributes

Material	Algorithms	A	B	C	D	Ra	MRR	TW
Hastelloy-coated tool	GA	33	0.080197	0.487800	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	0.949440	0.400511	0.014209	2886.301	113.62100
	AGA	31	0.102356	0.556889	0.470199	0.075845	1970.511	79.46600
	OGA	27	0.129361	0.659032	0.427264	0.010645	4715.536	19.23348
Inconel-coated tool	GA	31	0.138407	0.943236	0.671911	0.127450	4638.955	182.50580
	AGA	29	0.137194	0.627939	1.127318	0.092042	5280.448	98.82355
	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	2356.000	161.80540
	AGA	26	0.115807	0.803864	1.088951	0.100827	6395.305	133.85420
	OGA	26	0.094474	0.930975	0.410885	0.072417	74599.640	128.20240
Monel-coated tool	GA	31	0.133729	0.457366	0.447843	0.132649	3254.490	105.79950
	AGA	30	0.148920	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 toolGA		25	0.136660	0.538757	1.042162	0.507853	19054.530	66.87684
	AGA	33	0.124548	0.775202	0.421484	0.135869	21004.970	89.36025
	GA	33	0.146589	0.873487	0.460067	0.064162	3850.879	64.52319

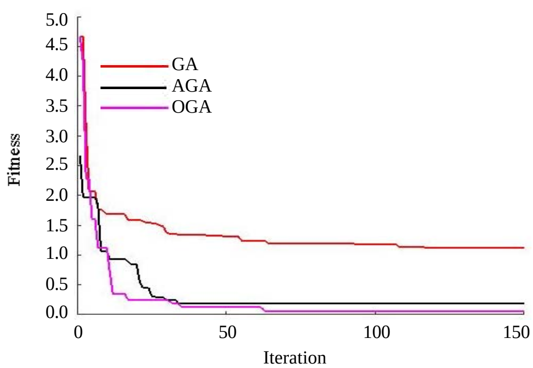

Fig. 13: Convergence graph comparison for three different optimization algorithms

Convergence graph in drawn in Fig. 13 for iterations and fitness value attains from different optimization algorithms. Optimization algorithm 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 55-60th 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.

In Table 9 shows 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),

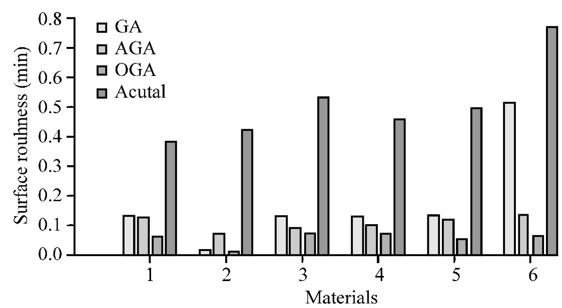

Fig. 14: Material wise comparison for surface roughness

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.

Material wise actual comparison among actual and predicted values: In this study 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 and Hastelloy uncoated insert inconel coated insert and Inconel uncoated insert Monel coated insert and Monel uncoated insert. Figure 14 discover that the proposed opposition based Genetic algorithm behaves literally and reveals minimum values among its comparators in all six materials. Figure 15 discover that the proposed opposition based Genetic algorithm behaves literally and reveals maximum values among its comparators in all six materials.

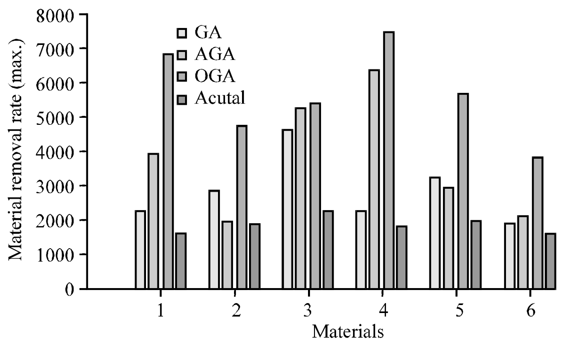

Fig. 15: Material wise comparison for material removal rate

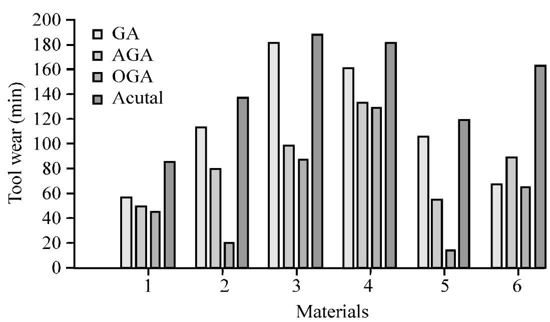

Fig. 16: Material wise comparison for tool wears

Figure 16 discover that the proposed opposition based Genetic algorithm behaves literally and reveals minimum values among its comparators in all six materials.

CONCLUSION

This study deals with designing mathematical modelling and then by utilizing 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 incorporate three different optimization process namely Genetic algorithm, adaptive Genetic algorithm and opposition based Genetic algorithm. From the above results and discussion analysis, it is clearly state that the proposed optimization algorithm behave literally in all sort of analysis.

SUGGESTIONS

In future the upcoming researcher can apply their own developed optimization algorithms to improve this research further.

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