Journal of Advanced Engineering Research
ISSN: 2393-8447
Volume 1, Issue 1, 2014, pp.16-31

An Hybrid Taguchi-Grey Relational Technique and Cuckoo Search Algorithm for Multi-Criteria Optimization in Hard Turning of AISI D3 Steel

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ABSTRACT

In this work, under varying machining conditions the performance of multilayered coated carbide inserts are experimentally investigated using a hybrid Taguchi-Grey relational analysis. Two multi-layered coated inserts TiN/TiCN/Al_2O_3 and TiN/TiCN/Al_2O_3/TiN are used for turning AISI D3 Die steel. Taguchi's mixed level of Design of Experiments (DoE) are used, for machining parameters varied through four levels and coated cutting inserts varied through two levels, an L_{16} Orthogonal Array (OA) is selected. Experiments were conducted on a CNC turning centre and output responses flank wear, surface roughness and Material Removal Rate (MRR) are determined. For multi-response optimization, initially Signal-to-Noise (S/N) ratio is calculated and then Grey Relational Analysis (GRA) is applied to simultaneously optimize the output responses. Significance of input parameters on the overall grey relational grade is evaluated using Analysis of Variance (ANOVA). Empirical models are developed for the grey relational grade to predict the output responses using multiple linear regression models. Confirmation experiment performed with the optimum conditions shows a reduction in flank wear and surface roughness with an increase in MRR.

Keywords - Multilayered coated inserts, Taguchi's Technique, Grey Relational Analysis, Regression models.

1. INTRODUCTION

Turning is a process of removing unwanted material from a rotating workpiece to obtain a desired shape and size of component. Hard turning deals with turning materials with a hardness of above 45 HRC, typically in the hardness range of 58 to 68 HRC [1]. Hard turning operation is performed with coated carbide, cermet, ceramic, PcBN and PCD tools. In recent years, application of single-layer coated and multi-layered coated cutting tools are used for machining hardened materials to improve the tribological conditions at the tool-workpiece interface and at the tool-chip interface. Today 85% of carbide cutting inserts used in industry are coated, to obtain better results and great number of coating materials and methods are also available. By practical approach the type of tool wear mechanism should be identified and a suitable coating on cutting insert has to be selected by correlating the coating materials and their performance before choosing a cutting insert [2].

Coating does change the dimensions of the cutting tool. Coatings are often applied in multiple alternating layers since the hardness increases as its grain size decreases, and the grain size decreases simultaneously with the decrease in coating thickness. The effectiveness of various coatings depends on the type of machining operation and machining regime. The best results are achieved when multi-layer coatings are used to reduce the strength of adhesion bonds at the tool–chip interface and thus reduce the severity of the friction at this interface; improves tool life; increases machining superficial and in-depth residual stresses [3].

2. LITERATURE REVIEW AND PROBLEM IDENTIFICATION

With competition prevailing in the global market, manufacturing industries are more concerned about producing high quality products at lower cost. The factors that affect the quality of the machined component is surface roughness and dimensional tolerance, which are mostly influenced by the flank wear, the wear occurring at the flank face of the cutting tool insert when machining a hardened material. A combination of producing good quality components and high production rate are achieved through optimization of cutting parameters and cutting tool condition through various techniques.

Zou et al. [4] used Al_2O_3/TiN-coated tungsten carbide tools for finish-turning of NiCr20TiAl nickel-based alloy under various cutting conditions and the cutting forces, surface integrity, and tool wear are investigated and the inter-diffusing and transferring of elements between Al_2O_3/TiN-coated tungsten carbide tool and NiCr20TiAl nickel-based alloy are studied. Fahad et al. [5] investigated the cutting performance of tungsten carbide tools with restricted contact length and multilayer chemical vapor deposition deposited coatings, TiCN/Al_2O_3/TiN and TiCN/Al_2O_3–TiN in dry turning of AISI 4140 and the results show that coating layouts and cutting tool edge geometry can significantly affect heat distribution into the cutting tool. Hamdan et al. [6] presented an optimization method of the machining parameters in high-speed machining of stainless steel using coated carbide tool to achieve minimum cutting forces and better surface roughness using Taguchi's technique and pareto ANOVA and found that the feed rate is found to be more significant followed by the cutting speed and the depth of cut.

Suhail et al. [7] developed a method to identify surface roughness based on measurement of workpiece surface temperature and root mean square for feed vibration of the cutting tool during turning mild steel using grey relational analysis. Gopalsamy et al. [8] studied the machinability of hardened steel using grey relational approach and ANOVA to obtain optimum process parameters considering MRR, surface finish, tool wear and tool life for both rough and finish machining. Ahilan et al. [9] performed multi-response optimization of turning parameters and nose radius over surface roughness and power consumed using Taguchi based grey relational approach and found that the main influencing parameter is cutting speed followed by feed rate and depth of cut. In turning operations, for multi-response optimization Taguchi based grey relational approach is used [10,11] to identify the optimum conditions to obtain better results. Prediction of flank wear and surface roughness during hard turning is performed using uncoated carbide inserts of various tool geometries [12].

From the literature review performed, it is concluded that the output quality characteristics are mainly decided by the chosen machining conditions along with the cutting tool inserts which may be of different materials, grades, coated or uncoated [13-21]. In this work, machining parameters viz. cutting speed, feed rate and depth of cut are considered along with two different multilayered coated cutting tool inserts for turning hardened tool-die steel AISI D3 steel. A hybrid Taguchi-Grey relational analysis is applied for optimizing all the responses simultaneously to determine the optimal conditions for multi-objective conditions. Influence of the chosen input parameters on the output grey relational grade is evaluated using the statistical technique, ANOVA. Prediction of grey relational grade is carried out by developing empirical models by multiple linear and non-linear regression models.

The chosen machining conditions have a greater impact on the output responses. Higher cutting speed increases tool temperature and softens the tool material thereby aiding abrasive, adhesive and diffusional wear. With larger feed rate, the greater is the cutting force per unit area of chip-tool contact on the rake face and work-tool contact on the flank face and therefore cutting temperature and different types of wear are increased. An increase in the depth of cut increases tool wear to some extent by accelerating the abrasive adhesive and diffusional types of tool wear. When the material hardness is more, higher flank wear occurs; which has an impact on the surface roughness. The main objective of this work is to optimize the machining conditions by applying the hybrid Taguchi-Grey relational analysis by determining the grey relational grade to study the performance of multi-layered coated cutting tool inserts. The significance of this work is; two multilayered coated cutting inserts TiN/TiCN/Al_2O_3 and TiN/TiCN/Al_2O_3/TiN are chosen for analysis considering the mixed-level design of Orthogonal Array (OA) designed using Taguchi's DoE.

3. MATERIAL SELECTION

The work piece material D3 steel used in this work is high carbon-high chromium, oil-hardened steel used in applications which requires high resistance to wear or to abrasion and for resistance to heavy pressure rather than to sudden shock. Industrial applications include blanking, stamping and cold forming dies and punches for long runs and lamination dies. The chemical composition of AISI D3 steel is shown in Table 1.

The cutting tool inserts used for turning is multi-layered coated carbide inserts viz. TiN/TiCN/Al_2O_3 and TiN/TiCN/Al_2O_3/TiN. The primary function of the hard material layer applied on the cutting insert is to inhibit contact between the material, thereby reducing tool wear that are caused by the phenomenon of adhesion, abrasion, diffusion and oxidation. Multilayer coatings are provided on cutting tool inserts to improve the shear strength of the coating and to avoid crack propagation between different layer materials.

Table 1 Chemical composition of AISI D3 Steel

Sl. No	Elements	% Composition
1	Carbon	2.179
2	Silicon	0.511
3	Manganese	0.511
4	Chromium	12.634
5	Phosphorous	0.027
6	Sulphur	0.021
7	Nickel	0.080
8	Molybdenum	0.178
9	Aluminium	0.042
10	Boron	0.012
11	Copper	0.065
12	Vanadium	0.201
13	Tungsten	0.277
14	Lead	0.012
15	Iron	83.25

4. EXPERIMENTAL SETUP AND METHODOLOGY

The experiments are conducted on a 2 axis CNC Turning centre, Lokesh make TL-20, swing diameter 350 mm, between centre 600 mm, spindle speed 4500 rpm, main motor power of 11 kW. After performing the machining process, the flank wear is measured using a Mitutoyo digital tool makers microscope of specifications, eyepiece 15X, view field diameter 13 mm, objective 2X, working distance 67 mm, total magnification 30X. Surface roughness values of the machined surfaces are recorded by using a Kosaka Laboratory Ltd make Surfcorder SE1200; with a vertical measuring range of 520 µm, horizontal measuring range of 25 mm, vertical resolution of 0.008 µm, cut-off value of 0.8 mm with Gaussian filter. MRR is determined by noting the time and the weight of material removed. The purpose of this work, methodologies considered and procedures followed are given in detail in Figure 1.

4.1 Taguchi's Design of Experiment

Taguchi's DoE is a statistical technique, used to study many factors simultaneously and most economically. By studying the effects of individual factors on the results, the best factor combination can be determined [22,23]. Taguchi's technique is a powerful tool in quality optimization, which makes use of a special design of OA to examine the quality characteristics through a minimal number of experiments [24]. Taguchi's mixed level DoE is used to design the orthogonal array for three parameters varied through four levels and a single parameter varied through two levels. The control parameters and their levels chosen [25] are shown in Table 2.

For various combinations of control parameters and its levels, a L_{16} orthogonal array is formulated which is shown in Table 3.

For analysis, there are three categories of performance characteristics, (i.e.) Smaller-the-better, Larger-the-better and Nominal-the-better to determine the S/N ratio in Taguchi's technique. The impact of noise factors on performance is measured by means of S/N ratio. If the S/N ratio is larger, the product will be more robust against noise. For Smaller-the-better category, the quality characteristics are usually an undesired output, the objective is to reduce the value of the quality characteristics to the smallest possible value zero, which is the ideal or target value e.g. flank wear, surface roughness, cutting forces, etc. For Larger-the-better category, the quality characteristics are usually a desired output when to increase the values of quality characteristics as much as possible for responses such as MRR, tool life, productivity, etc. and for Nominal-the-better category, the quality characteristics are usually a nominal output when an ideal or target value is specified to quality characteristics such as dimensional tolerances, clearance, etc.

Smaller-the-better (Minimize):

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (1)$$

Larger-the-better (Maximize):

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \quad (2)$$

Nominal-the-better:

$$S/N = 10\log\left(\frac{\bar{y}}{s_y^2}\right) \quad (3)$$

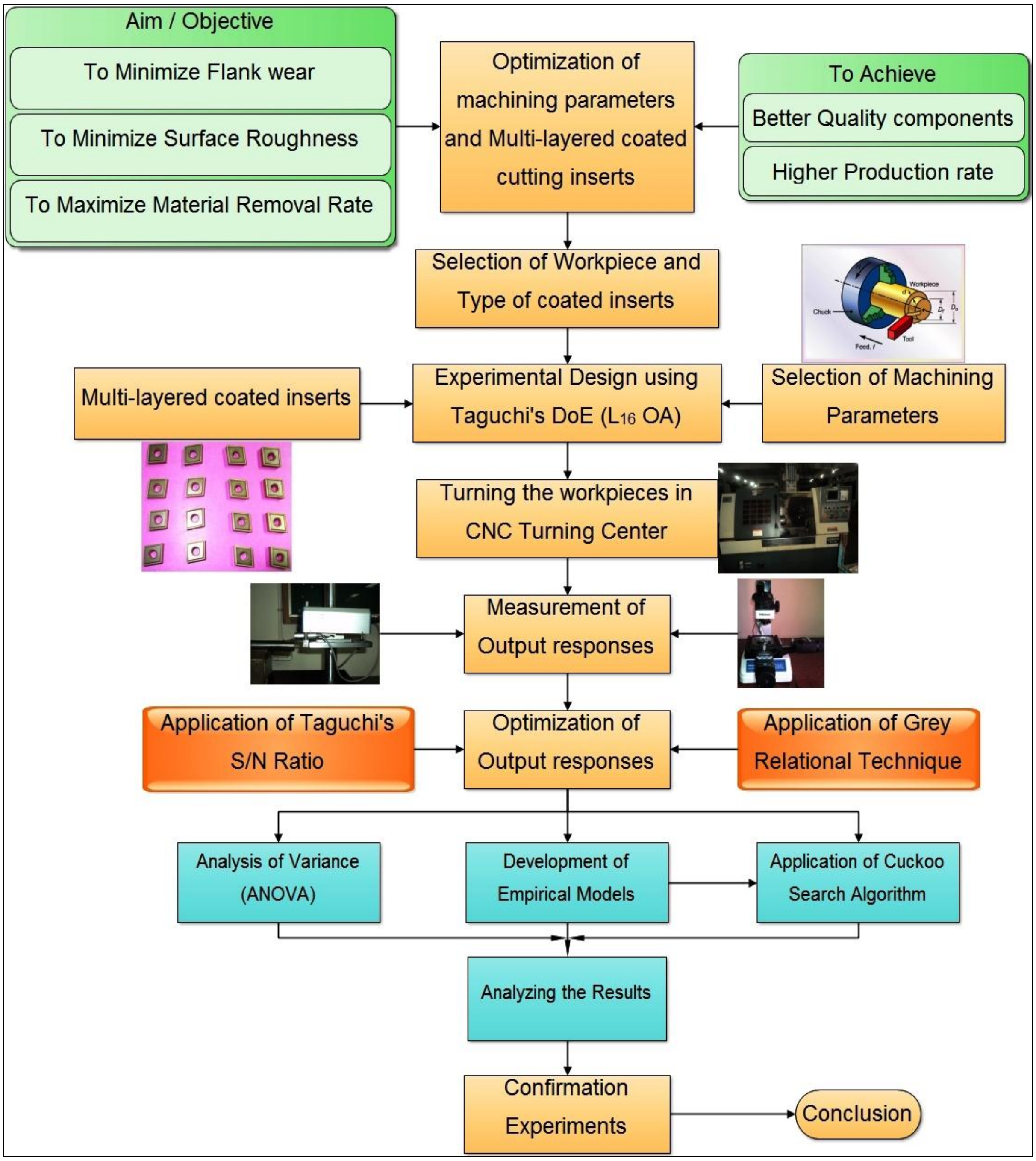

Figure 1 Flow chart showing the procedure and techniques used

Table 2 Control parameters and its levels

Parameter / Level	Level 1	Level 2	Level 3	Level 4
Cutting Speed (m/min)	253	281	309	338
Feed Rate (mm/rev)	0.203	0.279	0.356	0.432
Depth of Cut (mm)	0.30	0.40	0.50	0.60
Multilayered Coated Inserts	$TiN/TiCN/Al_2O_3$	$TiN/TiCN/Al_2O_3/TiN$	-	-

Table 3 L_{16} Orthogonal array for experiment

Exp. No	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)	Coating Material for Inserts
1	253	0.203	0.3	$TiN/TiCN/Al_2O_3$
2	253	0.279	0.4	$TiN/TiCN/Al_2O_3$
3	253	0.356	0.5	$TiN/TiCN/Al_2O_3/TiN$
4	253	0.432	0.6	$TiN/TiCN/Al_2O_3/TiN$
5	281	0.203	0.4	$TiN/TiCN/Al_2O_3/TiN$
6	281	0.279	0.3	$TiN/TiCN/Al_2O_3/TiN$
7	281	0.356	0.6	$TiN/TiCN/Al_2O_3$
8	281	0.432	0.5	$TiN/TiCN/Al_2O_3$
9	309	0.203	0.5	$TiN/TiCN/Al_2O_3$
10	309	0.279	0.6	$TiN/TiCN/Al_2O_3$
11	309	0.356	0.3	$TiN/TiCN/Al_2O_3/TiN$
12	309	0.432	0.4	$TiN/TiCN/Al_2O_3/TiN$
13	338	0.203	0.6	$TiN/TiCN/Al_2O_3/TiN$
14	338	0.279	0.5	$TiN/TiCN/Al_2O_3/TiN$
15	338	0.356	0.4	$TiN/TiCN/Al_2O_3$
16	338	0.432	0.3	$TiN/TiCN/Al_2O_3$

4.2 Grey Relational Analysis

GRA is used to determine the optimum condition of various input parameters to obtain the best quality characteristics [7,8,26,27]. GRA has been broadly applied in evaluating or judging the performance of a complex project with meagre information. However, data to be used in grey analysis must be pre-processed into quantitative indices for normalizing raw data for another analysis. Pre-processing raw data is a process of converting an original sequence into a decimal sequence between 0.00 and 1.00 for comparison. If the expected data sequence is of the form "Higher-the-better", then the original sequence can be normalized as,

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad (4)$$

where x^o_i (k) is the original sequence, x^*_i (k) the sequence after the data pre-processing, max x^o_i (k) the largest value of x^o_i (k), and min x^o_i (k) implies the smallest value of x^o_i (k).When the form "Smaller-the-better" becomes the expected value of the data sequence, the original sequence can be normalized as,

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad (5)$$

Following data pre-processing, a grey relational coefficient is calculated to express the relationship between the ideal and actual normalized experimental results. The deviation sequence is determined by finding the maximum of the normalized values regardless of response variables, trials and replications. Let this maximum value be R, which is known as reference value which is given as,

$$R = Max(X_{ijk}) \tag{6}$$

Find the absolute difference between each normalized value and the reference value (R), regardless of the response variables, trials and replications. Let it be Δ_{ijk}, where, i = 1,2,3, …,p and j = 1, 2, 3, …., q and k =1,2,3,…, r.

$$\Delta_{ijk} = X_{ijk} - R \tag{7}$$

Then the grey relational coefficient can be expressed as,

$$\zeta_i(k) = \frac{\Delta_{\min} + \zeta.\Delta_{\max}}{\Delta_{0i}(k) + \zeta.\Delta_{\max}} \tag{8}$$

where $\Delta_{oi}(k)$ is the deviation sequence of the reference sequence which is given by,

$$\Delta_{0i}(k) = \left\| x_0^*(k) - x_i^*(k) \right\| \tag{9}$$

$$\Delta_{\max} = \max_{\forall j \varepsilon i} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|,$$
$$\Delta_{\min} = \min_{\forall j \varepsilon i} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\| \tag{10}$$

ζ is distinguishing or identification coefficient: $\zeta \in [0, 1]$. $\zeta = 0.5$ is generally used. After obtaining the grey relational coefficient, we normally take the average of the grey relational coefficient as the grey relational grade. The grey relational grade is defined as,

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} {}_i\zeta_i(k) \tag{11}$$

In this analysis, the flank wear and surface roughness are to be minimized. Hence, Smaller-the-better formula for normalizing is selected.

4.3 Analysis of Variance

ANOVA is an important technique for analyzing the effect of categorical factors on a response. An ANOVA decomposes the variability in the response variable amongst the different factors. Depending upon the type of analysis, it may be important to determine which factors have a significant effect on the response, and how much of the variability in the response variable is attributable to each factor. For determining the significant factor which contributes more towards the output response ANOVA is done [28, 29].

4.4 Multiple Linear Regression models

Regression is a technique for investigating functional relationship between output and input decision variables of a process and may be useful for manufacturing process data description, parameter estimation and control [30]. The criteria for fitting the best line through the data in simple linear regression is to minimize the sum of squares of residuals (S_r) between the measured values of response and the values of response calculated with the regression model. The linear fit is expressed as,

$$y = a_0 + a_1 x \tag{12}$$

where '*y*' is the value of response and '*x*' is the value of variable. Multiple linear regressions are the extension of the linear regression when the response is a linear function of two or more independent variables. In general, the response variable *y* may be related to *k* regressor variables. The model in Equation (2) is called a multiple linear regression model with *k* regressor variables.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{13}$$

The parameters β_j, *j* = 0, 1,. , *k* are called the regression coefficients. These regression models are useful in predicting the response parameters with respect to the input control parameters.

4.5 Cuckoo search algorithm

Cuckoos are fascinating birds, because of the beautiful sounds and due to their aggressive reproduction strategy. Some species of cuckoos lay their eggs in communal nests, though they may remove others eggs to increase the hatching probability of their own eggs.

In Tapera type cuckoo species the female parasitic cuckoos are often very specialized in the mimicry in color and pattern of the eggs of a few chosen host species. This reduces the probability of their eggs being abandoned and thus increases their reproductivity. In addition, the timing of egg-laying of some species is also amazing. Parasitic cuckoos often choose a nest where the host bird just laid its own eggs. In general, the cuckoo eggs hatch slightly earlier than their host eggs. Once the first cuckoo chick is hatched, the first instinct action it will take is to evict the host eggs by blindly propelling the eggs out of the nest, which increases the cuckoo chick's share of food provided by its host bird. Cuckoo search algorithm uses the following three idealized rules:

- Each cuckoo lays one egg at a time, and dumps its egg in a randomly chosen nest;
- The best nests with high-quality eggs will be carried over to the next generations;
- The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability $p_a \in [0; 1]$. In this case, the host bird can either get rid of the egg, or simply abandon the nest and build a completely new nest.

In this algorithm, each egg in a nest represents a solution, and each cuckoo can lay only one egg (thus representing one solution), the aim is to use the new and potentially better solutions (cuckoos) to replace a not-so-good solution in the nests. When generating new solutions $x^{(t+1)}$ for a cuckoo i, a Levy flight is performed.

$$x_i^{(t+1)} = x_i^t + \alpha \oplus Levy(\lambda) \quad (14)$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interests. In most cases, we can use $\alpha = O(L/10)$ where L is the characteristic scale of the problem of interest.

The Levy flight essentially provides a random walk whose random step length is drawn from a Levy distribution

$$Levy \sim u = t^{-\lambda}, \qquad (1 < \lambda < 3) \quad (15)$$

which has an infinite variance with an infinite mean. Cuckoo search is a population-based algorithm, in a way similar to genetic algorithm and particle swarm optimization algorithm, but it uses some sort of elitism and/or selection similar to that used in harmony search. Secondly, the randomization in Cuckoo search is more efficient as the step length is heavy-tailed, and any large step is possible. Thirdly, the number of parameters in Cuckoo search to be tuned is fewer than genetic algorithm and particle swarm optimization algorithm, and thus it is potentially more generic to adapt to a wider class of optimization problems. In cuckoo search, each nest can represent a set of solutions; thus it can be extended to the type of meta-population algorithms.

5. RESULTS AND DISCUSSION

With the designed OA, experiments are conducted and the measured output responses viz. flank wear, surface roughness and MRR are determined, which are provided in Table 4. From the experimental results, it is observed that when the cutting speed is changed from 253 m/min to 281 m/min, a decrease in flank wear by 15.5%, surface roughness by 15.8% and MRR by 5.12% is noticed. An increase in flank wear by 37.62% and MRR by 13.62% and decrease in surface roughness by 24.84% is observed when cutting speed is changed from 281 to 309 m/min. With further increase in cutting speed from 309 to 338 m/min, a decrease in flank wear by 30.36%, surface roughness by 27.26% and MRR by 2.25% is obtained. When the feed rate is changed from 0.203 mm/rev to 0.279 mm/rev, flank wear and MRR increases by 52.2% and 24.12% with decrease in surface roughness by 3.82%. With further increase in feed rate from 0.279 to 0.356 mm/rev, an increase in surface roughness by 55.20% and MRR by 11.41% with decrease in flank wear by 26.63% is noticed. An increase in flank wear by 20.09% and MRR by 12.43% and decrease in surface roughness by 41.67% is observed when feed rate is changed from 0.356 to 0.432 mm/rev.

A decrease in flank wear and surface roughness by 19.17% and 47.82% with increase in MRR by 18.71% is obtained when the depth of cut is changed from 0.3 mm to 0.4 mm. By increasing the depth of cut from 0.4 to 0.5 mm, flank wear, surface roughness and MRR increases by 47.16%, 35.64% and 24.39%. An increase in flank wear by 36.05% and MRR by 14% and decrease in surface roughness by 14.08% is observed when the depth of cut is changed from 0.5 to 0.6 mm. When the multilayered coated cutting inserts is changed from TiN/TiCN/Al_2O_3 to TiN/TiCN/Al_2O_3/TiN, flank wear and surface roughness increases by 37.68% and 22% along with a decrease in MRR by 5.89%.

In this analysis, initially the S/N ratio for flank wear and surface roughness are determined using the formulae given in Equation (1) and S/N ratio for MRR is determined using Equation (2). For normalizing the calculated S/N ratio, Equation (5) is used for flank wear and surface roughness since the condition is Smaller-the-better and alternatively Equation (4) is used for MRR since the condition is Higher-the-better. Table 5 shows the calculated individual S/N ratio using Taguchi's technique and the normalizing sequence of the determined individual S/N ratio using grey relational technique.

Table 4 Measured output quality characteristics

Exp. No	Flank Wear (mm)	Surface Roughness (µm)	MRR (gm./min)
1	0.594	0.0405	134.062
2	0.638	0.0201	216.821
3	1.161	0.0407	256.450
4	1.845	0.0297	379.341
5	0.554	0.0206	135.386
6	1.300	0.0375	156.685
7	0.942	0.0320	306.717
8	0.785	0.0202	337.408
9	0.989	0.0175	248.012
10	1.773	0.0104	321.469
11	1.025	0.0425	232.24
12	1.141	0.0125	261.954
13	1.112	0.0103	260.009
14	1.234	0.0175	270.018
15	0.500	0.0175	279.707
16	0.586	0.0150	230.017

Following the normalizing procedure of data pre-processing, the grey relational coefficient has to be calculated for the individual output quality characteristics, for which the deviation sequence is determined. After determining the grey relational coefficient of each individual response, a grey relational grade is calculated by determining the average of all the grey relational coefficients, as given in Table 6.

The best levels of various chosen input parameters are identified by calculating the average values of grey relational grade corresponding to each level of parameters as shown in Table 7. It is observed from the response table, that the most critical parameter is depth of cut, which have a higher difference between the maximum and minimum level values of grey relational grade.

From the response table of grey relational grade, the optimal parameter levels are identified as, cutting speed of 253 m/min, feed rate of 0.356 mm/rev, depth of cut of 0.6 mm and multilayered coated cutting insert of TiN/TiCN/Al_2O_3/TiN. The main effects plot of grey relational grade is drawn from the response table as shown in Figure 2.

The interaction or interdependence plot between the chosen input control parameters over the determined grey relational grade is shown in Figure 3. A higher level of interaction is observed between cutting speed and feed rate for lower and higher level values of cutting speed, 253 m/min and 338 m/min. A moderate interaction exists between cutting speed and depth of cut for all cutting speed values. When the cutting speed is 253 m/min and 281 m/min, a higher interaction exists between cutting speed and multilayered coated tools. In between feed rate and depth of cut, for all level values of feed rate, a considerable interaction exists between the parameters. For lower feed rate level values of 0.203 mm/rev and 0.279 mm/rev a considerable interaction exists between feed rate and multilayered coated tools. Only for a lower depth of cut value of 0.3 mm, interaction effect is noticed between depth of cut and multilayered coated tool. The general observation is, for lower values of cutting speed, feed rate and depth of cut, a considerable interaction exists with multilayered coated tool and no interaction exists between them at higher level values.

Table 5 Signal-to-Noise ratios and its normalization for output responses

Exp. No	S/N Ratio			Normalized S/N Ratio		
	Flank Wear	Surface Roughness	MRR	Flank Wear	Surface Roughness	MRR
1	4.5243	27.8509	42.5461	0.1319	0.9660	0.0000
2	3.9036	33.9361	46.7220	0.1867	0.4717	0.4571
3	-1.2966	27.8081	48.1801	0.6452	0.9695	0.6200

4	-5.3199	30.5449	51.5806	1.0000	0.7472	1.0000
5	5.1298	33.7227	42.6315	0.0810	0.4890	0.0000
6	-2.2789	28.5194	43.9005	0.7549	0.9117	0.0000
7	0.5190	29.8970	49.7348	0.5004	0.7998	0.7511
8	2.1026	33.8930	50.5631	0.3564	0.4752	1.0000
9	0.0961	35.1392	47.8895	0.5224	0.3740	0.5914
10	-4.9742	39.6593	50.1428	0.9695	0.0068	0.8409
11	-0.2145	27.4322	47.3187	0.5498	1.0000	0.5283
12	-1.1457	38.0618	48.3645	0.6319	0.1366	0.6440
13	-0.9221	39.7433	48.2998	0.6122	0.0000	0.6369
14	-1.8263	35.1392	48.6279	0.6919	0.3740	0.6732
15	6.0206	35.1392	48.9341	0.0000	0.3740	0.7071
16	4.6420	36.4782	47.2352	0.1216	0.2652	0.5190

Table 6 Grey relational grade of combined output responses

Exp. No	Deviation Sequence			Grey Relational Coefficient			Grey Relational Grade
	Flank Wear	Surface Roughness	MRR	Flank Wear	Surface Roughness	MRR	
1	0.8681	0.0340	1.0000	0.365	0.936	0.333	0.545
2	0.8133	0.5283	0.5429	0.381	0.486	0.482	0.450
3	0.3548	0.0305	0.3800	0.585	0.942	0.571	0.699
4	0.0000	0.2528	0.0000	1.000	0.664	1.000	0.888
5	0.9190	0.5110	1.0000	0.352	0.495	0.335	0.394
6	0.2451	0.0883	1.0000	0.651	0.850	0.370	0.624
7	0.4996	0.2002	0.2489	0.493	0.714	0.710	0.639
8	0.6436	0.5248	0.0000	0.433	0.488	0.816	0.579
9	0.4776	0.6260	0.4086	0.511	0.444	0.550	0.502
10	0.0305	0.9932	0.1591	0.943	0.335	0.759	0.679
11	0.4502	0.0000	0.4717	0.526	1.000	0.515	0.680
12	0.3681	0.8634	0.3560	0.576	0.367	0.584	0.509
13	0.3878	1.0000	0.3631	0.563	0.333	0.579	0.492
14	0.3081	0.6260	0.3268	0.619	0.444	0.605	0.556
15	1.0000	0.6260	0.2929	0.333	0.444	0.631	0.469
16	0.8784	0.7348	0.4810	0.363	0.405	0.510	0.426

Table 7 Response table of grey relational grade

Parameter / Level	Level 1	Level 2	Level 3	Level 4	Max – Min
Cutting Speed	**0.645**	0.570	0.592	0.486	0.159
Feed Rate	0.483	0.575	**0.619**	0.616	0.136
Depth of Cut	0.567	0.455	0.600	**0.671**	0.216
Multilayered Coated Tool	0.542	**0.604**	-	-	0.062

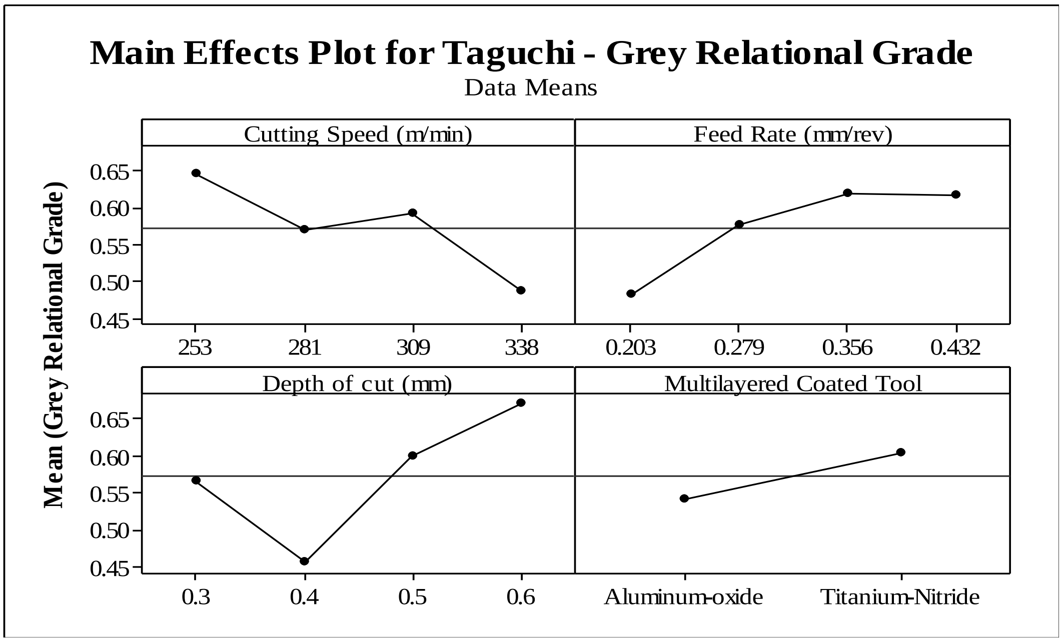

Figure 2 Main effects plot of grey relational grade

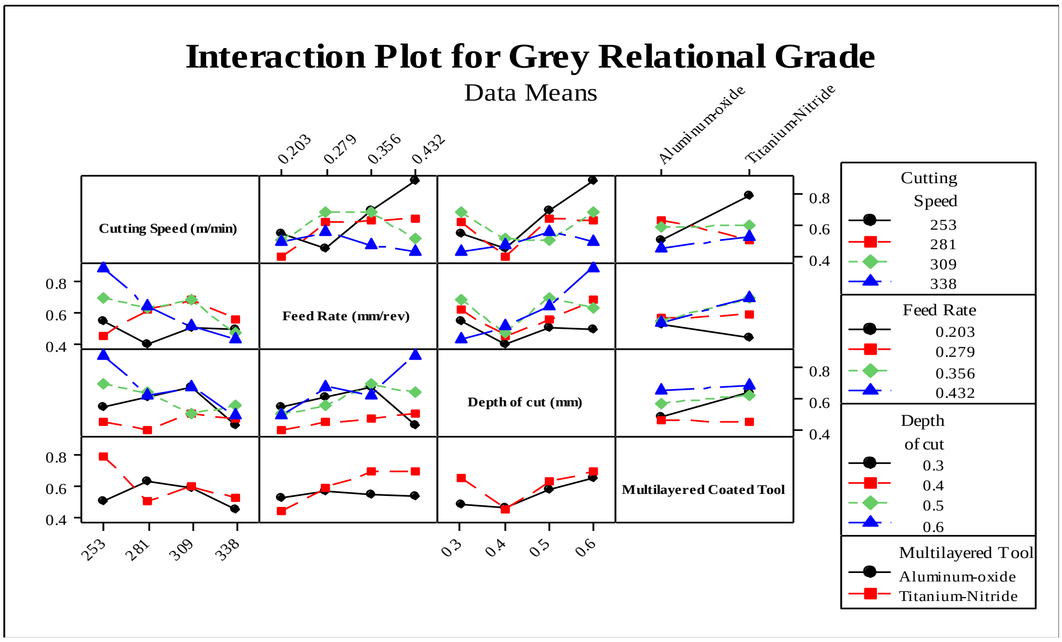

Figure 3 Interaction plot for grey relational grade

ANOVA is performed to determine the most significant parameter with respect to the calculated grey relational grade as shown in Table 8. The ANOVA result shows that, the most significant input parameter that contributes towards the grey relational grade is depth of cut by 39.84%, cutting speed by 21.62% and feed rate by 19.73%. The multilayered coated insert does not make a significant contribution towards the grey relational grade since both the chosen cutting inserts are multilayered.

Table 8 ANOVA table for grey relational grade

Source	DoF	Seq SS	Adj MS	F	P	% Contribution
Cutting speed	3	0.052813	0.017604	2.88	0.142	21.62
Feed rate	3	0.048204	0.016068	2.63	0.162	19.73
Depth of cut	3	0.097317	0.032439	5.31	0.052	39.84
Multilayered coated tool	1	0.015409	0.015409	2.52	0.173	6.31
Error	5	0.030533	0.006107			12.50
Total	15	0.244275				100.00

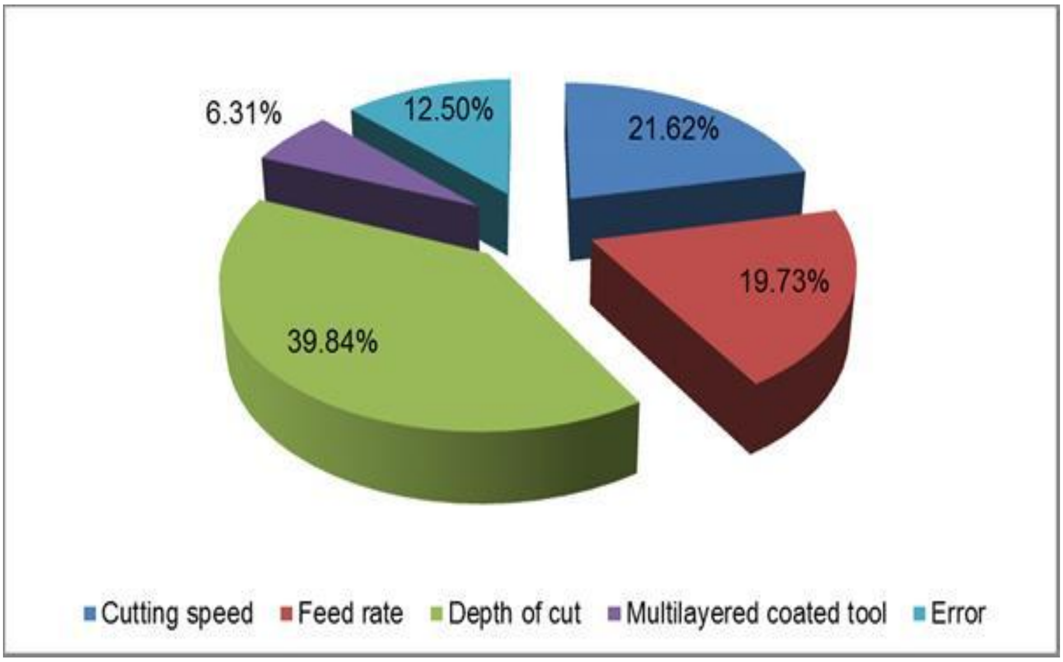

Figure 4 Percentile contributions of input parameters over grey relational grade

5.1 Confirmation Experiment for Taguchi-Grey analysis

With the identified optimal machining parameters of cutting speed of 253 m/min, feed rate of 0.356 mm/rev and depth of cut of 0.60 mm and the best multi-layered coated insert of TiN/TiCN/Al_2O_3/TiN, a confirmation experiment is conducted with the same experimental setup and the measured output responses are given in Table. 9.

Table 9 Measured responses of confirmation experiment

Flank wear (mm)	Surface roughness (µm)	MRR (gm./min)
0.982	0.0185	291.371

From the confirmation experiment, it is observed that the flank wear is reduced by 2.97 %, surface roughness is lowered by 29.90 % and MRR is increased by 13.63 % when compared with the average values of the experimental results.

5.2 Implementation of Cuckoo search algorithm

Empirical models are developed for the calculated grey relational grade in terms of the chosen input parameters to predict the output without any experimentation using Minitab 17, statistical software.

Non-linear regression models for $TiN/TiCN/Al_2O_3$ coated inserts:

$$\begin{aligned} Grey\ Relational\ Grade = {} & 4.53168 - 0.0150481 * speed - 4.14204 * feed \\ & - 7.00872 * depth + 0.0143996 * speed * feed \\ & + 0.0251433 * speed * depth + 1.51946 * feed * depth \end{aligned} \tag{16}$$

Non-linear regression models for $TiN/TiCN/Al_2O_3/TiN$ coated inserts:

$$\begin{aligned} Grey\ Relational\ Grade = {} & -6.98517 + 0.0274361 * speed + 20.2106 * feed \\ & + 2.08376 * depth - 0.0696428 * speed * feed \\ & - 0.0128201 * speed * depth + 2.03421 * feed * depth \end{aligned} \tag{17}$$

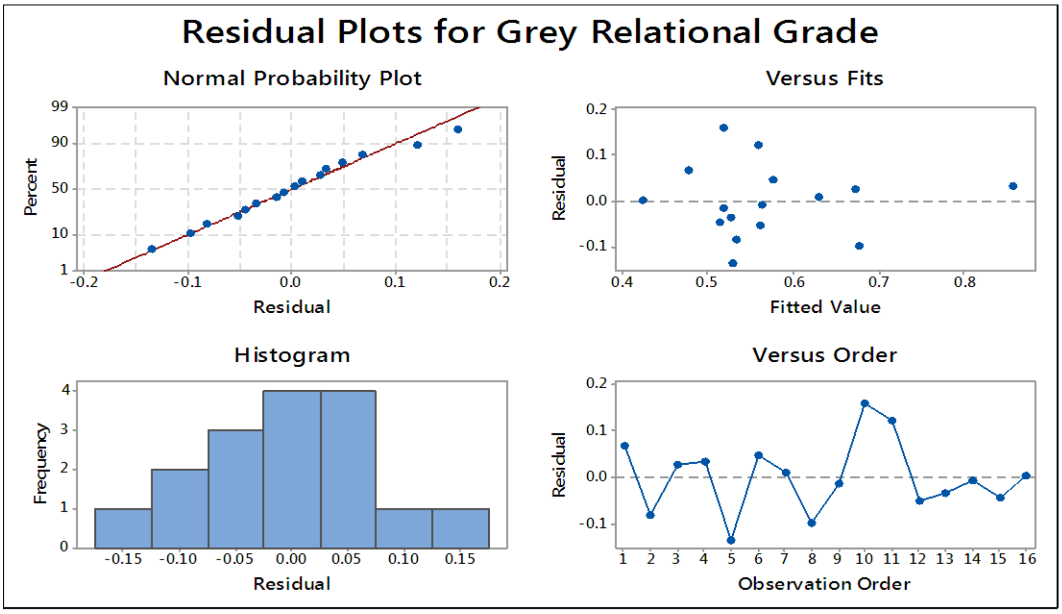

Figure 5 Residual plot of GRG during regression analysis

The residual plot of GRG obtained during regression analysis when geometrical parameters alone are considered is shown in Figure 5. The normal probability plot of the residuals follows a straight line with the residuals situated nearer to the straight line. In residual versus fits plot, the residuals appear to be randomly scattered around zero and most of the points are situated at the average fitted value and the residuals are minimum. The histogram of the residuals shows the distribution of the residuals for all observations which are skewed towards left and the bell shaped curve is formed. Residuals versus order graph plot can be particularly helpful in a designed experiment in which the runs are not randomized. The residuals in the plot are scattered around the center line.

The objective function is to minimize the GRG obtained for the tool coating material of $TiN/TiCN/Al_2O_3$ and $TiN/TiCN/Al_2O_3/TiN$ coated inserts, which is given as,

Lower and Upper limits of the parametric constraints are, 253 < cutting speed < 338, 0.203 < feed rate < 0.432, 0.3 < depth of cut < 0.6. The cuckoo search parameter values are, discover rate $p_a = 0.25$, number of nests n = 25, number of iterations = 100.

These parametric variable bounds and values are fed into the cuckoo search algorithm code written in Matlab

R13 and the output of the algorithm is analyzed. The best solution obtained is objective function value of 0.028 for a cutting speed of 253 m/min, feed rate of 0.203 mm/rev and depth of cut of 0.6 mm for lower flank wear and surface roughness and for maximum MRR. Fig. 6 shows the objective obtained during minimization of the GRG for all iterations. It is observed that initially the value of the objective function is at a higher value and as the iteration progresses, the objective function value converges quickly and it gets settled for the further iterations.

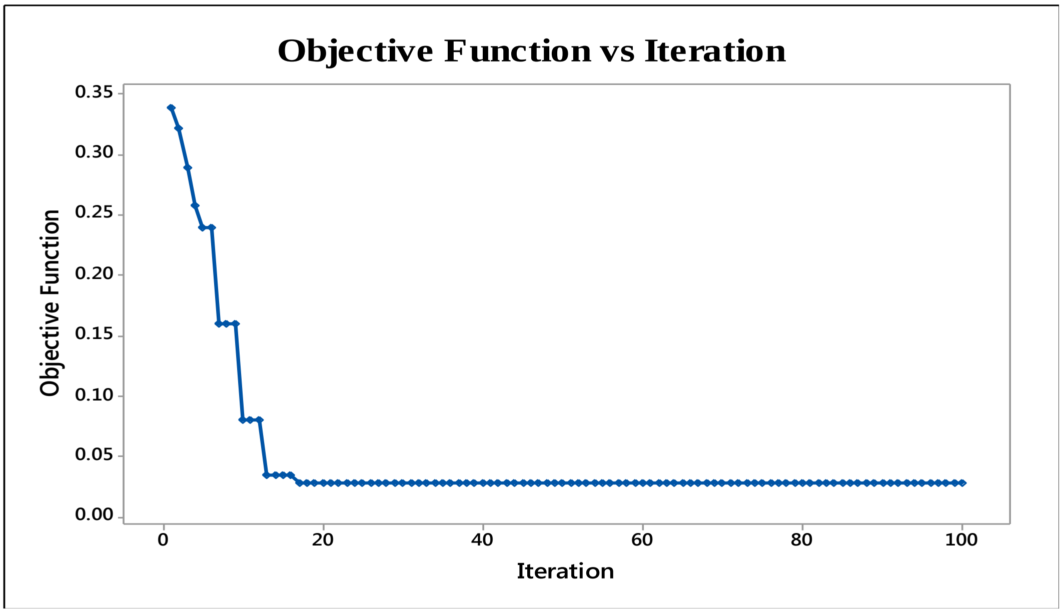

Figure 6 Variation of objective function with iterations

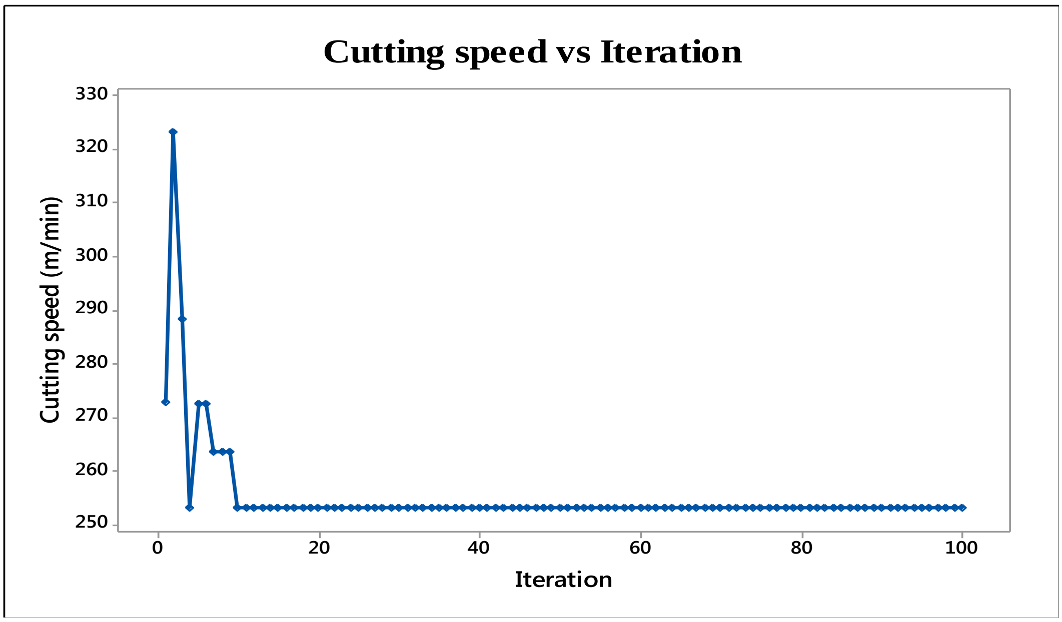

Figure 7 Variation of cutting speed with iterations

5.3 Confirmation experiment for Cuckoo search algorithm

With the identified optimal machining parameters of cutting speed of 253 m/min, feed rate of 0.203 mm/rev and depth of cut of 0.60 mm and the best multi-layered coated insert of TiN/TiCN/Al_2O_3/TiN, a confirmation experiment is conducted with the same experimental setup and the measured output responses obtained are given in Table 10.

From the confirmation experiment, it is observed that the flank wear is reduced by 36.10 % surface roughness is lowered by 93.80 % and MRR is increased by 11.23 % when compared with the average values of the experimental results.

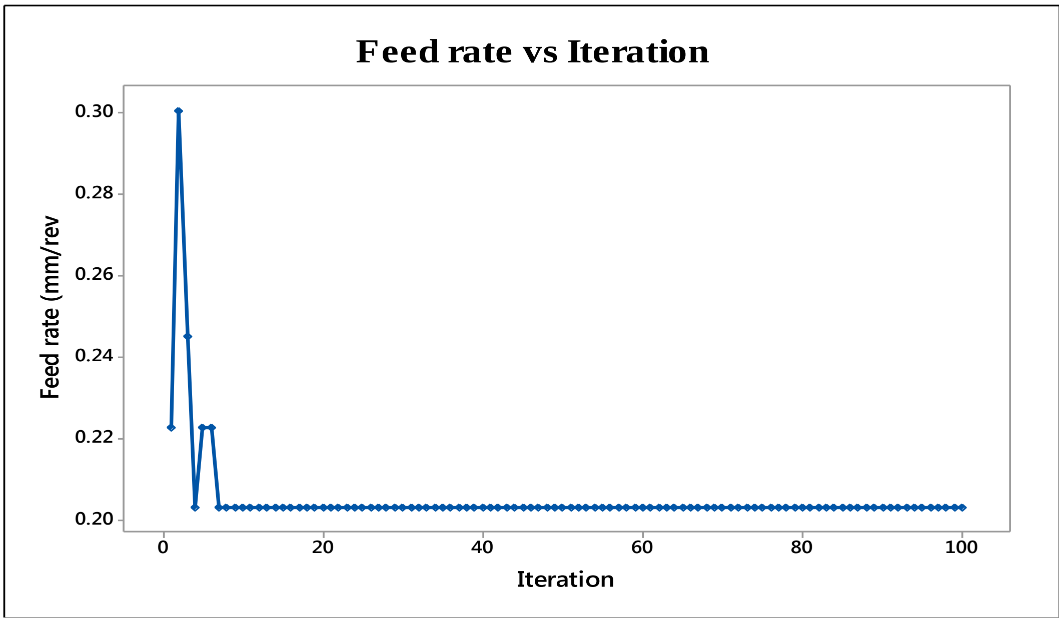

Figure 8 Variation of feed rate with iterations

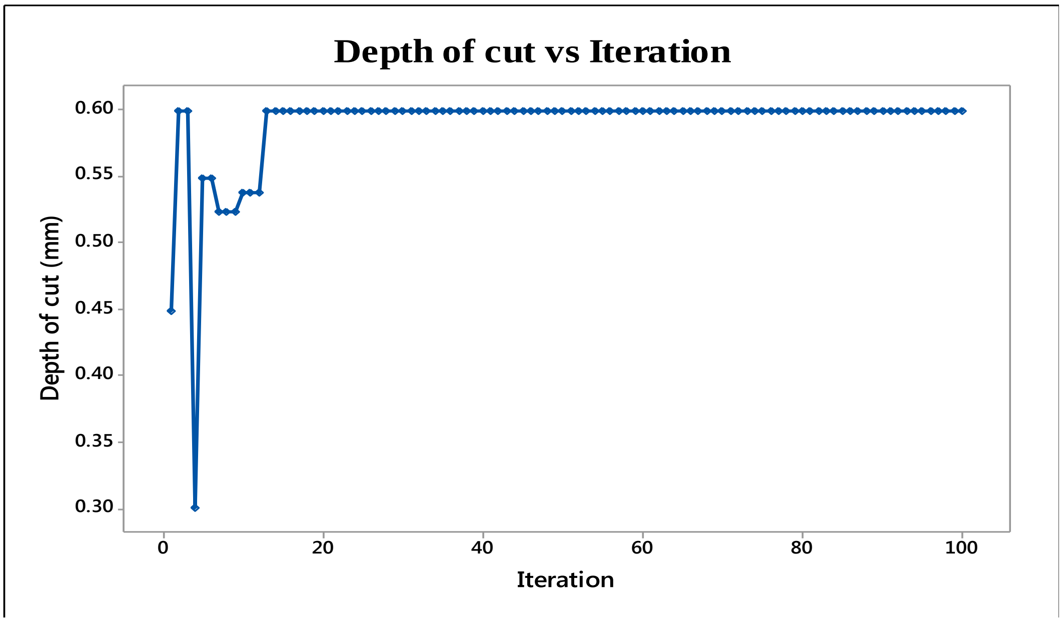

Figure 9 Variation of depth of cut with iterations

Table 11 Measured responses of confirmation experiment for cuckoo search

Flank wear (mm)	Surface roughness (μm)	MRR (gm./min)
0.743	0.0124	283.47

6 Conclusions

The conclusions derived during optimizing machining parameters by applying a hybrid Taguchi-GRA during turning hardened AISI D3 steel with different multilayered coated cutting inserts are as follows.

1. By applying Taguchi-GRA technique, the optimized condition obtained is cutting speed of 253 m/min, feed rate of 0.356 mm/rev, depth of cut of 0.6 mm and multilayered coated cutting insert of TiN/TiCN/Al_2O_3/TiN.

2. ANOVA result shows that depth of cut is the most significant input parameter that contributes towards the grey relational grade by 39.84%, cutting speed by 21.62% and feed rate by 19.73%. The contribution of multilayered coated tool is only 6.31%.

3. A considerable interaction effect is observed between feed rate and depth of cut, for all level values of feed rate. Multilayered coated tool has a significant interaction with lower level values of cutting speed, feed rate and depth of cut, whereas with higher values, no interaction exists.

4. Prediction of grey relational grade is carried out by developing linear and non-linear regression models, and the results show that non-linear regression models predicts grey relational grade more closely to experimental results.

5. Confirmation experiments performed with TiN/TiCN/Al_2O_3/TiN coated inserts with the obtained optimum condition shows a reduction in flank wear by 2.97%, surface roughness by 29.90% and an increase in MRR by 13.63 % when compared with the average values of the experimental results.

6. In general it is observed that an increase in tool life, surface quality and production rate can be achieved during turning hard materials with multilayered coated inserts.

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