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MATERIAL SCIENCE AND NANOTECHNOLOGY

Investigations on the effects of nitrogen gas in CNC machining of SS304 using Taguchi and Firefly Algorithm

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Abstract. This work attempts to use nitrogen gas as a shielding gas at the cutting zone, as well as for cooling purposes while machining stainless steel 304 (SS304) grade by Computer Numerical Control (CNC) lathe. The major influencing parameters of speed, feed and depth of cut were selected for experimentation with three levels each. Totally 27 experiments were conducted for dry cutting and N_2 gaseous conditions. The major influencing parameters are optimized using Taguchi and Firefly Algorithm (FA). The improvement in obtaining better surface roughness and Material Removal Rate (MRR) is significant and the confirmation results revealed that the deviation of the experimental results from the empirical model is found to be within 5%. A significant improvement of reduction of the specific cutting energy by 2.57% on average was achieved due to the reduction of friction at the cutting zone by nitrogen gas in CNC turning of SS 304 alloy.

Key words: SS304 alloy; turning; Taguchi method; optimization; Firefly Algorithm.

1. Introduction

CNC machining processes are highly preferable in mass production with high accuracy and surface finish. Identification of optimum process parameters in machining processes plays a vital role in better finishing of components [1]. The SS 304 Grade is a potential material, which has many applications like Bio-Medical devices, MEMS, NEMS, and micro fabrication of miniaturized components in robotics, automotive and space applications, etc. [2].

Turning is one of the machining operations widely used for removing excess material with good surface finish [3]. In order to get good surface finish in CNC turning process, the study of cutting temperature [4], machining process parameters, and applying novel cutting fluids are highly essential for the performance characteristics. Recently, important developments have been achieved in turning of hard materials with respect to better surface finish by cryogenic cooling [5]. Cryogenic cooling, flood cooling, dry, high pressure coolant, compressed air/vapour as coolant, solid lubricant/cooling, and vegetable oil and their effect during CNC machining for sustainable development [6].

The evolutionary algorithms can be used for optimizing the process parameters to achieve precision results [7]. Moreover, scientific approaches like the design of experiments could be adapted to reduce the number of experiments, in the selection of process parameters, and ranges to obtain better performance in the process [8].

To reduce the surface roughness in the turning process of AISI 4142, the machining parameters fluid flow rate and frequency, position and angle of nozzle were optimized [9]. Natarajan et al. [10] employed nondominated sorting and modified teaching–learning-based optimization (NSMTLBO) to optimize CNC turning parameters. As a result, a variation of 3.7% was obtained between the experimental and simulation data. Response surface methodology and artificial neural network (RSM-ANN) model [11] was used to optimize the drilling parameters to improve the surface finish, which showed a deviation of 1.51% in the experimental and predicted data. The turning process parameters were optimized by the Taguchi method to improve the surface finish and to reduce flank wear [12]. The CNC turning process parameters for SKD11 tool steel were optimized by Taguchi-Grey Relation analysis. The surface roughness of AISI 5140 steel in turning process was optimized by the Taguchi method [13], and better surface roughness of 1.7 μm was achieved. Optimizing the turning parameter [14] for machining super alloy Inconel 718 by the Taguchi method improved the surface finish and minimized the tool wear. The Taguchi method was employed [15] to optimize the CNC milling process parameters which led to an improvement in tool life of 234% and 67% under wet and compressed air flow.

The process parameter of duplex turning process was optimized by Taguchi-Response Surface Methodology (RSM) and showed a rapid improvement in the surface roughness [16]. The Taguchi-based graph theory and matrix approach [17] were applied to identify the optimal process parameter while micro milling AISI 304 stainless steel. Medium carbon steel was turned by HSS and cryogenically treated HSS tool, and parameters like speed, depth of cut, feed rate were optimized using the Taguchi-Fuzzy logic method, which resulted in better surface finish [18].

The Firefly Algorithm is one of the most effective and efficient algorithms in the evolutionary algorithms [19–21] for optimizing the manufacturing problems. The stacking sequence of laminate composite plate was optimized by FA for increasing

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the critical buckling temperature [22]. Hybrid FA and Particle Swarm Optimization (PSO) were applied to identify the optimal turning process parameter of penalized support vector machine [23]. The Computer Aided Process Planning (CAPP) turning process parameters [24] were optimized by the FA method with good accuracy.

So far, the productivity of the components has been adversely affected by the poor surface characteristics as a consequence of the generation of high temperature in the cutting zone. The abundant use of conventional lubricants produces environmental pollution, is costly and causes health problems. To overcome these issues, this research work attempts at evaluating the impacts of nitrogen gas used as a coolant in the CNC machining of stainless steel 304 on the surface roughness and MRR. The Specific Cutting Energy was calculated with and without a coolant condition. The selected major influencing parameters are optimized using the Taguchi and Firefly Algorithm for obtaining a better quality. The optimization of multi performance CNC turning parameters by applying the FA method is a new attempt.

2. Methodology

SS 304 is the most common austenitic SS, which is less electrically and thermally conductive than carbon steel and nonmagnetic in nature. It has a higher corrosion resistance than regular steel and is widely used because of the ease in which it is formed into various shapes. However, it is very tedious to machine under conventional machining techniques due to the presence of chromium. The presence of chromium converts into chromate on the surface of SS 304 while machining by single/multi-point cutting tools. The presence of oxygen enhances the abovementioned conversions resulting in Built-up-Edge (BoE) chips. It affects the surface roughness and MRR and for this reason nitrogen gas is introduced at the cutting zone for preventing oxygen in the chemical reaction, which serves as a coolant to minimize the friction between the cutting tool and workpiece.

As a result, the effective heat transfer is done in the cutting zone by nitrogen gas and the entrapment of oxygen is prevented avoiding generation of chromates over the machined surface of SS 304. The complete chemical composition of the workpiece SS 304 is given in Table 1.

Table 1
Chemical composition of SS 304 grade

Material (wt. %)	Ni	Mn	C	Cr	Si	P	S	Fe
SS 304	9.25	2.0	0.08	19.0	1.0	0.045	0.03	Balance

2.1. Experimental design. The turning operation on SS 304 was performed using DESIGNERS LT 16 FANUC Oi-TA CNC lathe machine. The experimental study was carried out in accordance with L27 orthogonal array. Several trial experiments have been conducted to find out the ranges, finally parameters and the levels considered for the investigation are given in Table 2.

Table 2
Turning parameters and levels

Parameter	Symbol	Unit	Levels		
			–1	0	1
Spindle speed	S	rpm	500	1000	1500
Feed rate	F	mm/rev	0.05	0.1	0.15
Depth of cut	D	mm	0.25	0.5	0.75
Environment	–		Nitrogen gas		

The cutting insert used in the turning operation was uncoated carbide with nose radius of 0.4 mm. Generally, for good surface finish the nose radius could be maintained within the range of 0.6–0.8 mm [24]. The turning was done in the nitrogen gas cutting environment. For modifying the existing setup in a CNC machine, a hose was connected to the pressure regulator from a nitrogen gas cylinder to regulate the gas supply at the cutting zone. The delivery rate of nitrogen gas at the cutting zone is maintained as constant for all 27 experiments in order to evaluate the effect of nitrogen gas on CNC turning of SS 304.

Despite the fact that nitrogen gas is a reactive agent unlike argon gas, it is less expensive with more benefits, so this coolant was chosen for the turning process. The work piece having a diameter of 10 mm and length of 30 mm was used for the turning process. The output performance of the machining operation was measured in terms of surface finish and MRR. The material removal was measured using Sartorious weighing balance with 3-digit accuracy and surface roughness was measured by Mitutoyo SJ 210 [25]. Three readings were taken at different locations of the machined workpiece and its average was computed as surface roughness by Ra values. Table 3 shows the attained experimental results of the turning operation.

Table 3
Experimental result of turning operation

Exp. No	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	Surface roughness (µm)	MRR (g/min)
1	500	0.05	0.25	0.63	2.33
2	500	0.05	0.5	0.7	4.85
3	500	0.05	0.75	0.74	7.28
4	500	0.1	0.25	0.53	4.38
5	500	0.1	0.5	0.97	9.43
6	500	0.1	0.75	0.82	14.38
7	500	0.15	0.25	1.735	6.72
8	500	0.15	0.5	1.8	14.15
9	500	0.15	0.75	1.98	21.80
10	1000	0.05	0.25	0.6	4.63
11	1000	0.05	0.5	1.12	9.63
12	1000	0.05	0.75	0.82	14.02
13	1000	0.1	0.25	0.975	8.57
14	1000	0.1	0.5	0.8	18.27
15	1000	0.1	0.75	1.245	27.80

Exp. No	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	Surface roughness (µm)	MRR (g/min)
16	1000	0.15	0.25	1.82	12.25
17	1000	0.15	0.5	1.66	27.15
18	1000	0.15	0.75	1.87	41.15
19	1500	0.05	0.25	1.357	6.45
20	1500	0.05	0.5	1.454	14.00
21	1500	0.05	0.75	1.415	20.60
22	1500	0.1	0.25	1.075	12.55
23	1500	0.1	0.5	1.03	26.85
24	1500	0.1	0.75	1.675	41.40
25	1500	0.15	0.25	1.945	18.68
26	1500	0.15	0.5	2.045	39.75
27	1500	0.15	0.75	2.21	62.63

It is observed from the experimentation that a lower depth of cut with a medium feed rate and speed are parameters responsible for yielding lower surface roughness. In contrast, a higher depth of cut with higher feed rate and speed produced a higher MRR and surface roughness. Hence, the optimization of these parameters is inevitable, and Taguchi and FA have been used to obtain better surface roughness and MRR simultaneously.

2.2. Taguchi approach. The Taguchi method is applied for parameter optimization of the machining process [26]. In order to obtain better surface finish and higher MRR, an optimum parameter setting is essential. To determine the best outcome responses, the experimental values are converted into Signal-Noise-Ratio (SNR). In this investigation we assume 'the lower, the better' SNR for surface roughness and 'the higher, the better' SNR for MRR. Both have been determined by Eqs. (1, 2), respectively [27–29]. The SNR can be quantified to find out the controlled noise factors for the improvement of the performance characteristics [30, 31]. This method has been frequently employed for single performance optimization problem:

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ij}^2, \tag{1}$$

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} \frac{1}{y_{ij}^2}, \tag{2}$$

where L_{ij} is the loss function of the i^{th} performance characteristic in the j^{th} experiment; y_{ijk} the experimental value of the i^{th} performance characteristic in the j^{th} experiment at the k^{th} trial; n is the number of trials.

2.3. Mathematical modeling. The second order polynomial model [32] can clearly determine the correlation between the parameters and output responses. The appropriate experimental designs with accurate data could be used for the parameters predictions. It is assumed that for n runs of experiments, the second order Eq. (3) is formed as:

$$y_i = \beta_o + \sum_{j=1}^{f} \beta_j x_j + \sum_{j<k}^{f} \beta_{jk} x_j x_k + \sum_{j=1}^{f} \beta_{jj} x_j^2 + \varepsilon, \tag{3}$$

where y_i represents the performance of the i^{th} of n experimental runs; x_i is the parameter level for the j^{th} parameter; β_o represents the intercept; β_j is the linear effect of j^{th} factor; β_{jk} represents the interaction between j^{th} and k^{th} factor; β_{jj} stands for the quadratic of the j^{th} factor; ε is a normally distributed error.

2.4. Firefly Algorithm. FA is one of the best meta-heuristic algorithms developed from the flashing behavior of fireflies. The optimal solution achieved by this method is more efficient than the existing optimization tool [33]. This method is highly suitable for enhancing the feasible solution by minimizing the randomness. The significant role of this flashes is to stimulate a mating partner and to hunt for food. Normally, fireflies having higher intensity light attract the others to move towards them. FA is developed based on three rules [34, 35]:

- All artificial fireflies are unisex. They can be attracted to others not in terms of sex.
- The firefly with bright light attracts the flies having a lower light intensity.
- The firefly distance represents the optimal solution, and brightness of the flies represents the objective function.

The attractiveness β depends on the light intensity coefficient µ and distances between two fireflies which can be calculated by Eq. (4):

$$\beta = \beta_o e^{-\mu r^2}, \tag{4}$$

It is assumed that a firefly i located at x_i moves towards firefly j (brighter) located at x_j is derived by Eq. (5). This movement disturbs the attractiveness β, random parameter coefficient γ and random number ε. The (rand -1/2) is applied for ε, where rand represents the random number generator uniformly distributed in [0, 1]:

$$x_i = x_i + \beta_o e^{-\mu r_{ij}^2}(x_j - x_i) + \gamma\left(rand - \frac{1}{2}\right), \tag{5}$$

3. Results and discussion

3.1. Impact of nitrogen gas on specific cutting energy. Specific cutting energy is one of the vital parameters to assess the performance of the machining environment [36]. Generally, shear, frictional, surface and momentum energies are involved in a specific cutting energy. However, the tool nomenclature and material properties are the primary responsible factors for evaluating the role of shear force. This research identified the impact of nitrogen gas on the reduction of frictional forces at the cutting zone. Based on the experimental results, the regression Eqs. (6) and (7) for calculating the cutting forces without doing the experiments resulted in saving time and machining expenses. Subsequently, specific cutting energy was calculated by applying Eq. (8) for all 27 experiments shown in Table 4.

$$\text{Cutting force } F_c(\mathrm{N}) \text{ for dry cutting condition} = 219 + 1.2^* \text{ Speed (rpm)} + 148.63^* \text{ Tool feed rate (mm/rev)} + 43.31^* \text{ Depth of cut (mm)}, \tag{6}$$

$$\text{Cutting force } F_c(\mathrm{N}) \text{ for nitrogen gaseous condition environment} = 207.52 + 1.22^* \text{ Speed (rpm)} + 151.55^* \text{ Tool feed rate (mm/rev)} + 46.56^* \text{ Depth of cut (mm)}, \tag{7}$$

$$\text{Specific cutting energy `U'} \left(\mathrm{J/mm^3}\right) = \left(\text{Cutting force } F_c(\mathrm{N})^* \text{ Cutting velocity } V_c \text{ (m/min)}\right) / \text{ Material Removal Rate } \left(\mathrm{mm^3/min}\right). \tag{8}$$

Table 4
Calculated Specific Cutting Energy

Exp. No	Speed (rpm)	Feed (mm/rev)	Depth of Cut (mm)	Specific cutting energy under dry environment U (J/mm³)	Specific cutting energy under nitrogen gaseous environment U (J/mm³)	% difference
1	500	0.05	0.25	21.39	20.59	3.75
2	500	0.05	0.5	11.13	10.76	3.31
3	500	0.05	0.75	7.71	7.48	2.90
4	500	0.1	0.25	10.99	10.60	3.59
5	500	0.1	0.5	5.71	5.53	3.17
6	500	0.1	0.75	3.95	3.84	2.78
7	500	0.15	0.25	7.53	7.27	3.45
8	500	0.15	0.5	3.91	3.79	3.04
9	500	0.15	0.75	2.70	2.63	2.67
10	1000	0.05	0.25	23.80	23.04	3.20
11	1000	0.05	0.5	12.33	11.98	2.82
12	1000	0.05	0.75	8.51	8.30	2.47
13	1000	0.1	0.25	12.20	11.82	3.07
14	1000	0.1	0.5	6.32	6.14	2.71
15	1000	0.1	0.75	4.35	4.25	2.37
16	1000	0.15	0.25	8.33	8.08	2.95
17	1000	0.15	0.5	4.31	4.20	2.60
18	1000	0.15	0.75	2.97	2.90	2.28
19	1500	0.05	0.25	26.22	25.50	2.75
20	1500	0.05	0.5	13.54	13.21	2.42
21	1500	0.05	0.75	9.32	9.12	2.11
22	1500	0.1	0.25	13.41	13.05	2.65
23	1500	0.1	0.5	6.92	6.76	2.33
24	1500	0.1	0.75	4.76	4.66	2.03
25	1500	0.15	0.25	9.14	8.90	2.55
26	1500	0.15	0.5	4.71	4.61	2.24
27	1500	0.15	0.75	3.24	3.17	1.95

It is observed from the specific cutting energy values that a higher percentage of decrement of 3.48% is obtained at a lower speed of 500 rpm and a lower percentage of decrement of 2.47% is achieved at a higher speed of 1500 rpm. A significant improvement of the reduction of specific cutting energy by 2.57% on average was achieved under nitrogen gaseous cutting condition due the reduction in friction at the cutting zone. The penetration of nitrogen gas at the cutting zone reduces the friction between the tool and the workpiece, as well as between the tool and the chip. Nitrogen gas effectively evaluates the generated heat at the cutting zone resulting in a smooth and continuous chip.

The impact of nitrogen gas on specific cutting energy is presented in Fig. 1. The values of specific cutting energy under nitrogen gaseous cutting condition were lower than those in the dry cutting condition. The dry cutting condition develops the localized heat which influences the temporary welding of the chip with a tool and produces a chip with Built-up-Edge. Consequently, the specific cutting energy is higher for a dry cutting condition. In addition to that, the machining performance and power consumption have been improved when nitrogen gas used as a coolant gas prevents the oxidation on the machined surface. Most of the researchers revealed the impacts of liquid nitrogen on stainless steel by CNC turning. Meanwhile, the handling of cryogenic fluids, conversion from the ductile nature into the brittle nature, and the minimum heat required to form the shear zone are not still completely resolved. Also, the machining expenses should be considered while evaluating the machining environment.

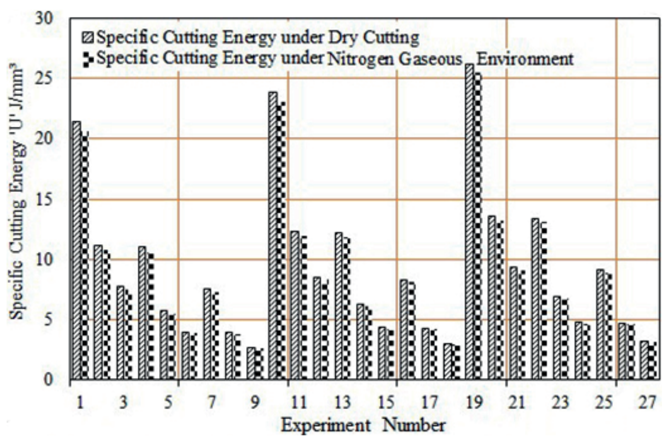

Fig. 1. Impact of nitrogen gas on specific cutting energy

3.2. Optimization.

3.2.1. Single Mode Optimization method. The SNR of Taguchi approach plays a significant role in improving the quality of the process. In this study, the lower the better SNR for surface roughness and the higher the better SNR for MRR were chosen.

Figure 2 depicts the effect of SNR on the surface roughness with different machining parameters such as speed, feed, and depth of cut. From the graph, it is understood that 500 rpm speed showed better surface finish. Moreover, the feed rate of 0.05 mm/rev and 0.25 mm depth of cut reduced the surface roughness rather than at other levels. In the environment of nitrogen gas coolant, good surface finishes were attained at

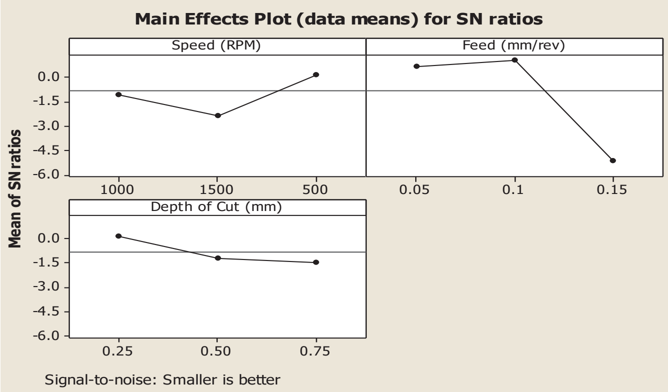

Fig. 2. SNR of surface roughness

a low speed, minimum feed rate and lower depth of cut. Amad et al. [37] noticed a similar enhancement in the surface finish with a nitrogen gas coolant. The optimal parameter condition for achieving higher surface finish was $S_1F_1D_1$. The effect of SNR for MRR at varying speed, feed and depth of cut are shown in Fig. 3.

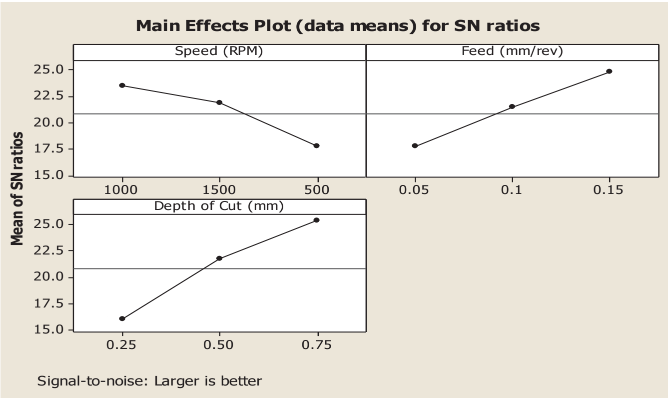

Fig. 3. SNR of MRR

The feed rate at 0.15 mm/rev, speed of 1500 rpm and 0.75 mm depth of cut brought higher MRR than other combinations. The optimal parameters level attained for surface roughness and MRR were different. The parameter speed influenced more achieving the minimum surface roughness and higher MRR. Hence, a multi response optimization method is essential to know the best parameters level combinations.

3.2.2. Mathematical models. The mathematical models were developed using MINITAB14 software package and given in Eqs. (9, 10).

$$\begin{aligned}\text{Surface roughness} &= 1.226 - 0.000143{*}S - \\ &- 20.575{*}F - 0.084{*}D + 0.0000005{*}S^2 + \\ &+ 170.244{*}F^2 + 0.252{*}D^2 - 0.0049{*}S{*}F + \\ &+ 0.000185{*}S{*}D + 1.146{*}F{*}D,\end{aligned} \tag{9}$$

$$\begin{aligned}\text{MRR} &= 19.822 - 0.019{*}S - 196.078{*}F - \\ &- 38.316{*}D + 0.00003{*}S^2 + 18{*}F^2 - 0.48{*}D^2 + \\ &+ 0.173{*}S{*}F + 0.038{*}S{*}D + 396.267{*}F{*}D.\end{aligned} \tag{10}$$

The statistical package MINITAB14 was employed to determine the coefficient of the second order polynomial model. The adequacy of the second order equation was performed through the Analysis of Variance (ANOVA) method. The R2 value for Eq. (9) of surface roughness was 0.93 and for Eq. (10) of MRR was 0.991, which is nearer to one. Further, from Tables 4 and 5, it is clear that the developed regression model was significant, and this model is adequate for predications. The parameter is significant with 95% confidence if F exceeds 3.52 [38]. It is noticed in Tables 5 and 6 that the parameter speed, feed, and depth of cut significantly influence the surface roughness and MRR by 95%.

Table 5
Analysis of variance for surface roughness

Source	DoF	Sum of squares	Mean square	F-Value	P-Value	Level (significant)
Model	9	6.4114	0.7124	24.99	0.001	Yes
S	1	0.03979	0.03979	6.002	0.023	Yes
F	1	0.04173	0.04173	11.489	0.010	Yes
D	1	0.03886	0.03886	6.943	0.021	Yes
S * S	1	0.05872	0.05872	1.847	0.0082	Yes
F * F	1	0.07296	0.07296	6.175	0.027	Yes
D * D	1	0.06892	0.06892	0.229	0.00892	Yes
S * F	1	0.04874	0.04874	2.515	0.0090	Yes
F * D	1	0.02957	0.02957	0.475	0.00641	Yes
D * S	1	0.05342	0.05342	0.294	0.00897	Yes
Residual Error	17	0.48455	0.02850			Yes

Table 6
Analysis of variance for MRR

Source	DoF	Sum of squares	Mean square	F-Value	P-Value	Level (significant)
Model	9	587.228	62.431	182.54	0.0001	Yes
S	1	0.006	0.006	3.062	0.007	Yes
F	1	63.05	63.05	3.11	0.006	Yes
D	1	12.61	12.61	3.039	0.007	Yes
S * S	1	0.000	0.000	0.103	0.0092	Yes
F * F	1	79.646	79.646	3.824	0.007	Yes
D * D	1	11.186	11.186	2.929	0.008	Yes
S * F	1	0.0256	0.0256	0.479	0.0090	Yes
F * D	1	0.0049	0.0049	0.0475	0.00641	Yes
D * S	1	0.0058	0.0058	0.0284	0.00897	Yes
Residual Error	17	4.946	0.2933			Yes

3.2.3. Multi-Mode Optimization method. FA is one best method to solve multi objective and nonlinear problems. Fig. 4 shows the flowchart for firefly algorithm. The objective function for the firefly optimization was defined as a combination of the minimum surface roughness and maximum MRR. Fig. 5 shows 2D plots for the new generation. The number of iterations preferred for the analysis was 100, the number of fireflies was 40, the light absorption coefficient μ was chosen as 1 and β as 0.2, which is the lowest value. This β value is changed with the absorption coefficient and source distance. Senthilkumar et al. [39] proposed an FA model to obtain a higher MRR and lower surface roughness in the turning of AISI 1045 steel.

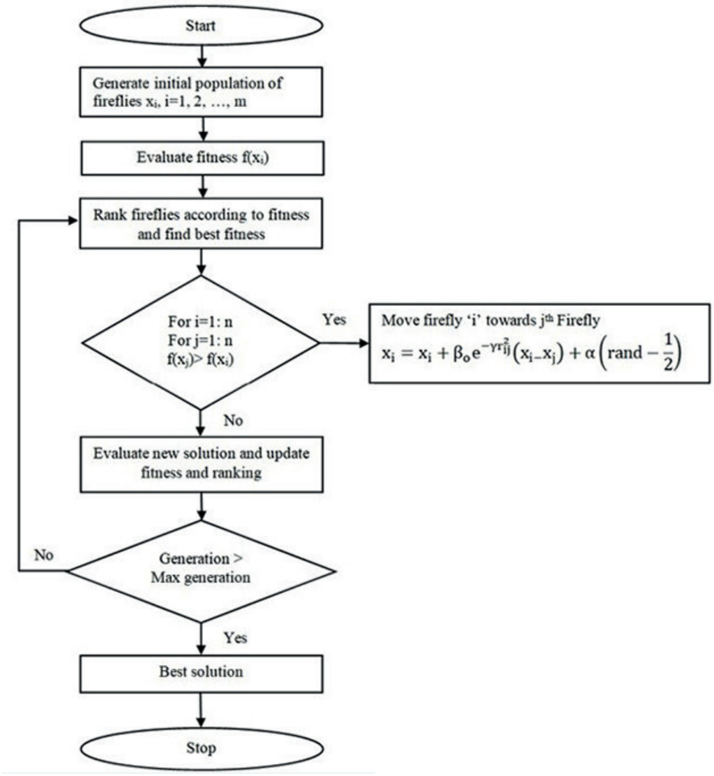

Fig. 4. Flowchart for Firefly Algorithm

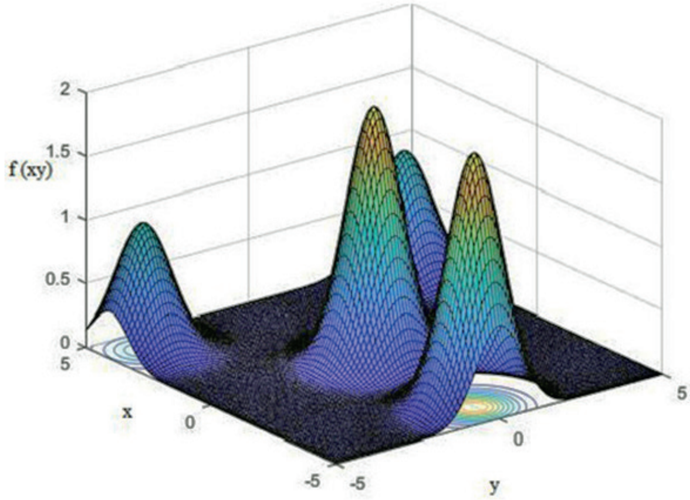

Fig. 5. Generations of new solutions

The lower and upper bound ranges of the input parameters, the lowest value of the surface roughness and the higher value of the MRR of the output responses were considered as the constraint for the firefly optimization MATLAB coding.

From Fig. 6, it is revealed at the start of the iteration that the deviation of the objection functions is higher and later it moves smoothly. The new generations are generated using random attraction of the fireflies and the appearances of the fireflies are up to the objective function. The attractiveness of the algorithm compares and locates the new firefly position with the old one. Otherwise, the firefly remains in the current position.

The termination criterion of FA is based on an arbitrary predefined number of iterations or a predefined fitness value. The minimum outcome of the objective function was 5.2921. Further, the feasible optimal level of the parameters obtained is 0.5 mm depth of cut, speed of 1000 rpm and feed rate of 0.883 mm/rev.

The confirmation test was conducted for the achieved optimal parameter condition, which resulted in a lower surface roughness of 0.61 μm, and a higher metal removal rate of 40.13 g/min. The deviation is found to be within 5%; hence, the optimal values significantly improve the surface roughness and MRR.

The scanning electron microscopic views of dry cutting and nitrogen gaseous conditions are presented in Fig. 7, which clearly indicates the impact of nitrogen gas on the machined surface of SS 304. The dry cutting generally generated the chip with some built-up edge resulting in poor surface roughness. However, nitrogen gas effectively protects the cutting zone by removal of heat, improves the tool life [37] and also prevents the formation of chromate layer due to the metal reaction with oxygen in the surroundings.

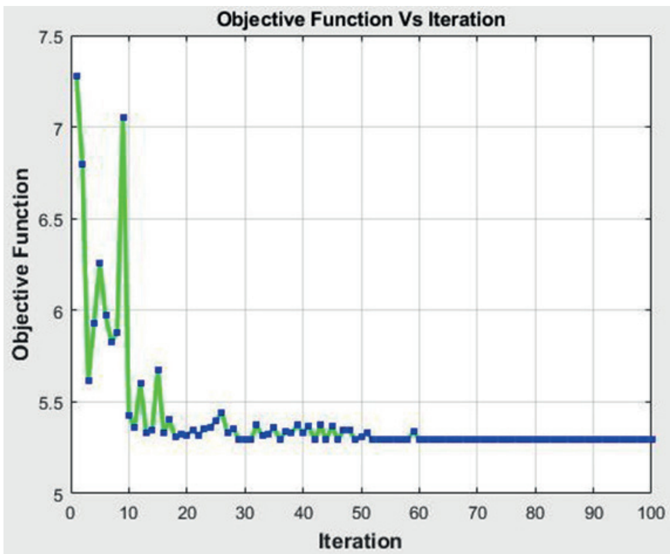

Fig. 6. Convergence of Firefly Algorithm

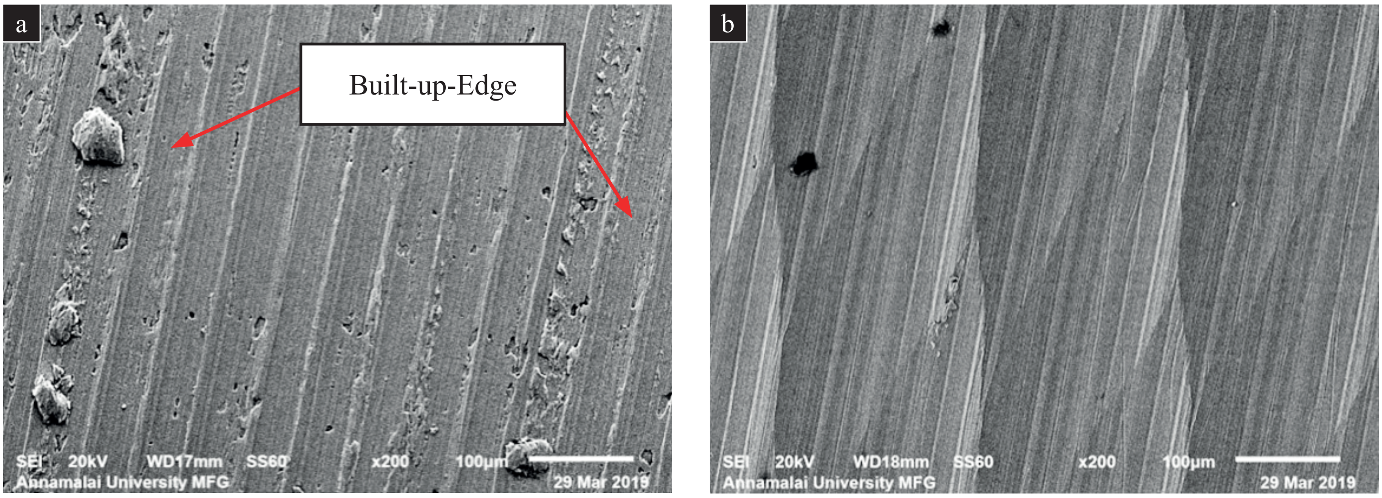

Fig. 7. SEM photographs for various cutting conditions: a) Dry cutting condition, b) Nitrogen gaseous condition

The chip formed in this condition was a little longer than that of plain condition even at small thickness of chip especially without built-up edge. These may have happened due to good heat transfer at the cutting inter-zone junction. Cooling purpose completely resulted in good surface finish, i.e. without generating built-up edge chips and smooth material removal which enhance the geometrical accuracy. Similar was observed by Tazehkandi et al. [40] in Inconel 740 alloy. Hence, the rejection rate is drastically reduced due to the use of nitrogen gas as a coolant medium of CNC machining of SS 304. Effective removal of heat at the cutting zone prevents the formation of chromate layer in the surface of the stainless steel. The confirmation experiments were conducted for the consistency of the developed mathematical models for the surface roughness and MRR and the results revealed that the deviation of experimental results from the mathematically found values are found to be within 5%. Hence, the developed mathematical models are significantly consistent in obtaining the optimum cutting conditions for machining of SS 304 using CNC turning machine.

4. Conclusions

This study elucidated the optimal machining process parameters for turning SS 304 steel in a CNC machine using nitrogen gas as a coolant, which improves the surface finish and MRR. The overall performance of the work can be concluded as:

- A significant improvement of reduction of 2.57% on average in Specific Cutting Energy was achieved under nitrogen gaseous cutting condition due to the reduction of the friction at the cutting zone. A higher reduction percentage of Specific Cutting Energy was observed at the lower range of speeds.
- Taguchi method SNR showed different parameter combination for surface finish and MRR. The parameter speed plays a significant role in obtaining feasible combinations. Hence, a multi-response method is essential in solving the problem.
- Firefly Algorithm is a sophisticated tool for getting a better optimal solution for a multi-response problem. Through the confirmation test it was validated that the firefly method produced a better output result at 0.5 mm depth of cut, speed of 1000 rpm and feed rate of 0.883 mm/rev. The nitrogen gas coolant resulted in good surface finish and smooth metal removal.
- The confirmation results revealed the consistency of the developed mathematical models and the deviations are found to be within 5%, which is a concrete evidence for the impact of nitrogen gas on machining of SS 304 using CNC turning machine.

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