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Application of advanced algorithms for enhancement in machining performance of Inconel 718

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Inconel 718 is the most promising nickel-based alloy finding wide usage in engineering applications because of its good mechanical properties. However, this alloy is difficult to machine and results in poor surface quality after machining. Optimization of parameters is essential for improving machining performance of this costly and hard to cut material. The research discusses estimation of optimum parameters using teaching-learning based optimization (TLBO) and compares them to those obtained by genetic algorithm (GA) in turning of Inconel 718. The parameters cutting speed, feed rate and depth of cut are selected as independent variables. The experiments are designed using central composite design of response surface methodology for the modelling of turning process. Surface roughness, tool flank wear and cutting temperature are selected as response parameters for minimization. The adequacy of modified models developed by response surface methodology are tested and then utilized for formulation of multi-objective optimization function. The function is solved by GA and TLBO. After comparing optimization results, the best algorithm is used for confirmation test. Convergence of TLBO algorithm is much faster as compared to GA even though there is very little difference in the optimum values of parameters.

Keywords: Inconel 718, Response surface methodology, Teaching-learning based optimization, Genetic algorithm, Multi-objective optimization

Nickel based super alloys find significant applications in marine, petrochemical, aerospace, automotive and food processing industries because of its high strength and high corrosion resistance. 70% production of super alloy is consumed by the aerospace industry, mainly in the hot section of aircraft engines and turbines. Inconel 718 is the most promising nickel-based alloy finding wide usage in the last three decades[1-5]. In machining of Inconel 718, high cutting forces are encountered which result in high temperature (900-1300°C) at the tool chip interface. Inconel 718 has high hot hardness, poor thermal conductivity (11.2 W/m-K) and high work hardening tendency which makes machining more difficult[6-10]. The Inconel alloys also have a tendency to form built-up edge at temperatures generated during machining[11,12].

Surface roughness is an indicator of performance of machining process and it is functional requirement to achieve the desired fit. Surface roughness investigation, is essential for number of applications concerned with the control of friction, fatigue and wear of parts[13]. The ability of a manufacturing process to produce desired surface finish depends on machine tool, cutting process, cutting parameters, work material and cutting tool[14]. Inconsistency in the machining process affects the material removal rate and ultimately damages the work surface[15,16]. Whitehouse[17] proposed surface roughness model with feed and the nose radius of tool and models using cutting speed, feed and depth of cut by Fang and Safi-Jahanshahi[18], Wang and Li[19] do not include intricate interactions between parameters. Machining performance, surface integrity, dimensional accuracy and cost are affected by tool wear[20,21]. The flank wear is directly proportional to cutting speed and feed rate which results in increased temperature and controlling the level of tool wear is important to get desired surface finish[8,22,23]. The machinability can be improved along with tool life by employing suitable cooling methods[16,24-27]. The following works are concerned with optimizing the cutting parameters for improving surface roughness, tool wear, cutting forces and cutting temperature in machining of the nickel based super alloys using various cutting conditions.

Pusavec *et al.*[25,28] developed models for tool wear, cutting forces and surface roughness using response

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surface methodology (RSM) and optimised the machining performance using genetic algorithm (GA) for evaluating combined effect of cryogenic cooling and minimum quantity lubrication. Davoodi and Tazehkandi[16], Ezilarasan *et al*.[29] used RSM to determine the best suited cutting parameters to get optimal values for surface roughness and forces. Ezugwu *et al*.[30] established correlation between input and output parameters using artificial neural network (ANN). Homami *et al*.[22] established optimal input parameters for minimizing flank wear and surface roughness. Tamang and Chandrasekaran[31] combined ANN model with particle swarm optimization (PSO) for maximizing surface quality. Subhas *et al*.[32] established a model for the prediction for residual stresses, dimensional instability, surface roughness and tool life in machining. Senthilkumaar e*t al*.[33] combined GA with ANN for optimization of cutting parameters for flank wear and surface roughness. Pawade and Joshi[34] performed multi-objective optimization for cutting forces and surface roughness and found optimum cutting parameters using Taguchi grey relational analysis.

In published literature various advanced algorithms like- GA, PSO algorithm, etc are also reported. These algorithms are complex in nature and are inconvenient[35,36] to use. Venkata Rao and Kalyankar[36] applied a new algorithm known as Teaching-learning based optimization (TLBO) to optimize machining parameters which needs only common design (input) parameters. They reported better utility of TLBO over different nature-inspired optimization algorithms. Similar technique was adopted by Sahu and Andhare[37]. They used RSM model in GA with same rank of design parameters and confirmed their results with previous findings. Thus, the TLBO algorithm is found to be suitable for complex machining problems.

In order to achieve superior surface quality and maximum tool life by controlling cutting temperature, the modelling and optimization of cutting parameters using appropriate technique is needed. In this work, TLBO algorithm is applied for multiple response optimization of surface roughness, tool wear and cutting temperature in machining of Inconel 718 and the results are compared with those of GA.

Experimentation

Work piece and tool material

In the experimental study, hot rolled bars of diameter of 22 mm and length of 120 mm of Inconel 718 of hardness 46 HRC are selected. The chemical composition is 54.4% Ni, 17.5% Cr, 5.32% Nb, 3.02% Mo, 0.66% Al, 0.96% Ti, 0.25% Co and balance Fe (weight percent). PVD coated (Z_rCN) tungsten carbide inserts (Kennametal make, TNMG 160408UF) with double chip breaker geometry and nose radius of 0.8 mm are utilized for experiments. Each insert is mounted on tool holder with ISO designation MTJNL2525-M16 and new cutting edge was used for every experiment. The selection of the tools and cutting conditions was based on the tool manufacturer's manual and references from the literature[25,27,38]. The details pertaining to the cutting conditions are as follows: cutting speed = 9.5 to 110.45 m/min, feed rate = 0.06 to 0.23 mm/rev and depth of cut = 0.32 to 1.17 mm at constant cutting length of 50 mm.

Experiment setup

The experimental setup shown in Fig. 1 is used for the machining of Inconel 718. Turning was carried out on MTAB CNC lathe machine (Maxturn Plus+) of 5.5 kW equipped with Siemen's Sinumerik 828D control. After completion of turning, the surface roughness of machined parts is measured with

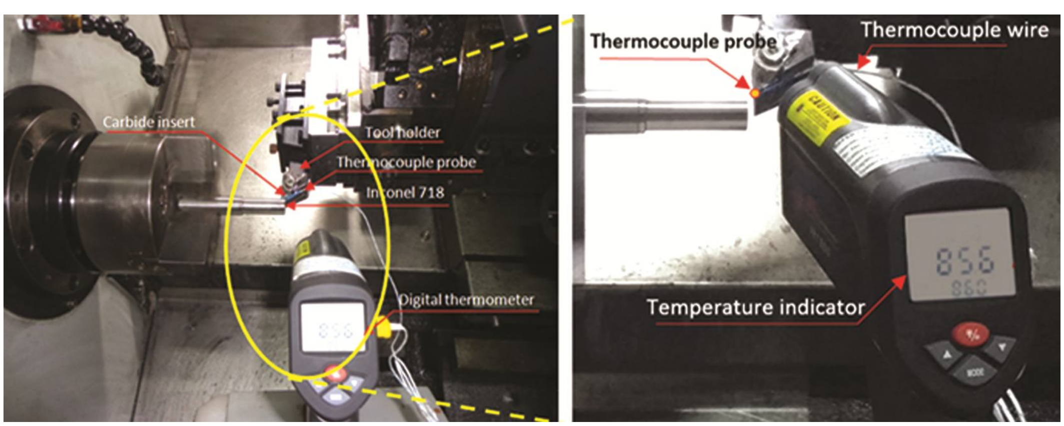

Fig. 1 — Experimental setup for the machining of Inconel (left) and temperature measuring device (right)

portable surface roughness tester (Make: Mitutoyo, SURFTEST SJ-410). The average of three measurements taken equally at 120º on the circumference of each finished part was noted. The tool flank wear was measured with the help of USB microscope (UM5 CAM). The average of wear band values was then used for further analysis. The temperature generated at tool chip interface was measured using a digital thermometer having range from 50°C to 1850°C (MEXTECH IR 1800 with thermocouple). For receiving exact temperature, K type thermocouple probe (50°C to 1370°C) is attached at a distance of 0.5 mm from the cutting edge[26]. The arrangement of temperature measuring device is shown in Fig. 1 (right).

Experimental design and result

RSM is one of the specific interests to produce an experimental design sequence which uses quadratic polynomial model for performing study. RSM is an arrangement of arithmetical and numerical techniques useful for improving and optimizing processes. Response surface designs are used for fitting the response surfaces using Box-Behnken design and central composite design (CCD). Box-Behnken design normally comprise of three factors which are limited to three levels. Central composite design (CCD) overcomes the drawbacks of Box-Behnken design by providing extreme factor combinations considering five levels of factor. The design consists of a factorial design or corner portion of cube, centre points and an axial or star point. Repetitive six experiments show an added center point to the CCD which confirm the repeatability of measuring process. The additional axial points increase the number of level. Hence, the design offers big spectrum of levels for the experimentation. As a result, a great deal of information is gathered for the effects of the factors and their interactions[39-43].

The aim of the experiments was to examine the effect of machining parameters on the surface roughness, tool flank wear and cutting temperature during turning of Inconel 718. Response surface methodology (RSM) is used for the modelling and optimization of the machining process. The RSM is a process to determine relationship among independent and dependent variables[39,40,42]. The experiments are designed using the central composite design (CCD) of RSM. CCD consists of a factorial design (corner portion 2^k) of cube, centre points and axial points. The corner portions of cube show eight experiments with 2^3 factorial design levels coded by -1 and +1, at the vertices of CCD. The additional axial points rise the number of levels and design with k factors where distance of the axial point from the design centre is $a = 2^{k/4}$. Design including axial points with the designed value α is called central composite design positioned on the coordinate axis of the factorial segment at a distance of α = 1.682 from the center[42]. Due to rotatable design of CCD, the run for every independent factor is at five levels and are denoted by -1.682, -1, 0, +1, +1.682 as shown in Table 1. In this experimentation, design uses variation of three input parameters - cutting speed (v), feed rate (f) and depth of cut (d) with five coded levels. The coded and normal levels of the input variables are presented in Table 1. The outcome of DOE shows 20 experiments according to the CCD, using RSM in MINITAB 16 software. The design matrix of input and measured values is presented in Table 2.

Table 1 — Level of cutting parameters for the turning of Inconel 718

Cutting parameters	Level 1	Level 2	Level 3	Level 4	Level 5
Coded values	-1.682	-1	0	1	1.682
Cutting speed, v (m/min)	9.5	30	60	90	110.45
Feed rate, f (mm/rev)	0.06	0.1	0.15	0.2	0.23
Depth of cut, d (mm)	0.32	0.5	0.75	1	1.17

Table 2 — Design matrix and experimental result

Run order	v (m/min)	f (mm/rev)	d (mm)	R_a (μm)	V_B (mm)	T (K)
1	90	0.2	1	0.66	0.832	995
2	9.5	0.15	0.75	1.13	0.49	810
3	30	0.2	0.5	0.89	0.487	852
4	60	0.06	0.75	0.61	0.503	890
5	60	0.15	0.75	0.65	0.751	920
6	60	0.15	1.17	0.76	0.8	940
7	110.45	0.15	0.75	0.49	0.82	1050
8	30	0.2	1	0.91	0.666	850
9	60	0.15	0.75	0.67	0.761	930
10	60	0.15	0.75	0.69	0.793	928
11	90	0.2	0.5	0.59	0.761	980
12	90	0.1	1	0.61	0.79	985
13	60	0.23	0.75	0.83	0.812	912
14	60	0.15	0.75	0.66	0.801	925
15	30	0.1	1	0.8	0.512	860
16	30	0.1	0.5	0.79	0.497	840
17	60	0.15	0.75	0.68	0.789	923
18	60	0.15	0.32	0.64	0.594	880
19	60	0.15	0.75	0.65	0.786	915
20	90	0.1	0.5	0.51	0.751	925

Results and Discussion

Modelling and validation of response surface equations

The response parameters of the process are surface roughness (R_a), tool flank wear (V_B) and cutting temperature (T) listed in Table 2. Using MINITAB16 software a relationship is established between response parameters (R_a, V_B and T) and cutting parameters (v, f, d). ANOVA is used to determine the significant and non-significant parameters on the basis of p (probability) values and F values.

Backward elimination method is used to find the best fit model and remove the insignificant variables. The ANOVA is used again to evaluate significance of modified regression model for p and F values as shown in Table 3. The p value less than 0.05 and high F values of the modified models indicate that the models are extremely significant[42]. After performing backward elimination method as discussed above, the refined models for turning of Inconel 718 are obtained. The modified models for estimating R_a, VB and T are presented in Eqs (1)-(3). The cutting speed, feed rate and depth of cut are found significant.

$$R_a = 0.9180 - 0.0107v + 1.0239f + 0.1170d + 4.7219\times10^{-5}v^2 \quad \text{... (1)}$$

$$VB = -0.5767 + 0.0097v + 6.2772f + 0.9059d - 5.0568\times10^{-5}v^2 - 17.6895f^2 - 0.4787d^2 \quad \text{... (2)}$$

$$T = 625.482 + 0.6637v + 1299.93f + 228.486d - 3248.76f^2 - 85.8349d^2 + 5.25vf + 0.95vd - 670fd \quad \text{... (3)}$$

The adequacy of regression models is examined by percentage of maximum errors, percentage of mean absolute error (MAE) and correlation coefficient (R^2). Estimated values obtained by modified RSM models were compared with the measured responses as presented in Table 4 by placing the same range of cutting parameters in regression Eqs (1)-(3). The percentages of maximum errors are 12.98%, 13.47% and 1.52% for R_a, V_B and T, respectively. Similarly, the percentages of mean absolute errors (MAE) are 4.03%, 4.69% and 0.6%, respectively. Also, the correlation coefficient (R^2) nearer to unity indicates best correlation between predicted data of model and experimental data as shown in Table 4. Thus, a strong relationship is established between estimated and experimental process responses.

Table 3 — Summarized ANOVA for Inconel 718 using backward elimination method

Source	Surface roughness (R_a)		Tool flank wear V_B		Temperature (K)	
Parameters	F ratio	p value	F ratio	p value	F ratio	p value
Regression model	57.40	<0.0001	25.57	<0.0001	105.05	<0.0001
v	186.19	<0.0001	87.08	<0.0001	722.21	<0.0001
f	20.91	<0.0001	22.98	<0.0001	13.55	0.004
d	6.82	0.020	16.29	0.001	40.61	<0.0001
v^2	15.34	0.001	15.21	0.002	-	-
f^2	-	-	14.98	0.002	13.18	0.004
d^2	-	-	6.80	0.022	5.70	0.036
vf	-	-	-	-	6.52	0.027
vd	-	-	-	-	5.34	0.041
fd	-	-	-	-	7.37	0.020

Effect of cutting parameters over R_a, V_B and T

Figures 2-4 show the effect of cutting parameters (v, f, d) and parametric interaction in dry turning of Inconel 718 using surface plots and main effects plots. Main effect plots were developed for every parameter by taking remaining parameters constant at center value as presented in Table 1. The dual effect of two parameters is expressed in the interaction plots by taking third parameter constant and at the center value.

The main effect plot in Fig. 2a clearly shows that minimum R_a occurs at a higher v, low f and d. However, it increases with increase in the f and d. It is observed that v is more dominating factor over R_a compared to f and d. In interaction plots, the interaction effect of v-f and v-d are strongly influencing the R_a compared to interaction of f-d as shown in Figs 2(b-d).

In Fig. 2 (b-d), 3D surface plots for surface roughness are shown Fig. 2 b shows the effect of speed and feed on surface roughness at mid value of depth of cut (0.75 mm). It is observed that least roughness is obtained at high speed and low feed. At constant feed, surface roughness decreases with increase in speed. Whereas, at constant speed, roughness increases and then decreases at feed of 0.16 mm/rev and increases with further increase in feed. Figure 2c shows the 3D response surface that corresponds to the effect of interaction of cutting speed and depth of cut on surface roughness, for feed rate equal to 0.15 mm/rev. Here also, for high value of cutting speed and for depth of cut equal to around 0.75 mm, drop in roughness value is observed. Similarly, for the combination of low feed rate and depth of cut, lower value of roughness is observed in Fig. 2d. It is observed from Table 3 that cutting speed

Table 4 – Design matrix and statistical validity of RSM predicted responses

Run order	V (m/min)	f (mm/rev)	d (mm)	R_a (µm)	Pred. R_a (µm)	% Error	V_B (mm)	Predicted V_B (mm)	% Error	T (K)	Predicted T (K)	% Error
1	90	0.2	1	0.66	0.66	0.11	0.83	0.87	-4.55	995	1003.90	-0.89
2	9.5	0.15	0.75	1.13	1.06	6.02	0.49	0.47	5.01	810	815.64	-0.70
3	30	0.2	0.5	0.89	0.90	-1.44	0.49	0.55	**-13.47**	852	846.96	0.59
4	60	0.06	0.75	0.61	0.60	2.42	0.50	0.55	-9.69	890	886.19	0.43
5	60	0.15	0.75	0.65	0.69	-5.75	0.75	0.78	-4.18	920	924.90	-0.53
6	60	0.15	1.17	0.76	0.74	3.09	0.80	0.78	2.90	940	933.38	0.70
7	110.45	0.15	0.75	0.49	0.55	**-12.98**	0.82	0.84	-2.61	1050	1034.06	**1.52**
8	30	0.2	1	0.91	0.96	-5.64	0.67	0.65	2.92	850	844.08	0.70
9	60	0.15	0.75	0.67	0.69	-2.59	0.76	0.78	-2.81	930	924.90	0.55
10	60	0.15	0.75	0.69	0.69	0.38	0.79	0.78	1.34	928	924.90	0.33
11	90	0.2	0.5	0.59	0.60	-1.83	0.76	0.78	-1.96	980	978.28	0.18
12	90	0.1	1	0.61	0.56	8.70	0.79	0.77	2.18	985	991.12	-0.62
13	60	0.23	0.75	0.83	0.77	7.32	0.81	0.75	8.03	912	915.14	-0.34
14	60	0.15	0.75	0.66	0.69	-4.15	0.80	0.78	2.33	925	924.90	0.01
15	30	0.1	1	0.8	0.86	-7.37	0.51	0.55	-7.33	860	862.80	-0.33
16	30	0.1	0.5	0.79	0.80	-1.32	0.50	0.46	8.33	840	832.18	0.93
17	60	0.15	0.75	0.68	0.69	-1.08	0.79	0.78	0.84	923	924.90	-0.21
18	60	0.15	0.32	0.64	0.64	0.46	0.59	0.61	-3.21	880	884.85	-0.55
19	60	0.15	0.75	0.65	0.69	-5.75	0.79	0.78	0.46	915	924.90	-1.08
20	90	0.1	0.5	0.51	0.50	2.27	0.75	0.68	9.60	925	932.00	-0.76
		MAE for R_a				4.03		MEA for V_B	4.69		MAE for T	0.60
		R^2				93.87		R^2	92.19		R^2	98.71
		R^2 (adjusted)				92.23		R^2 (adjusted)	88.58		R^2 (adjusted)	97.77

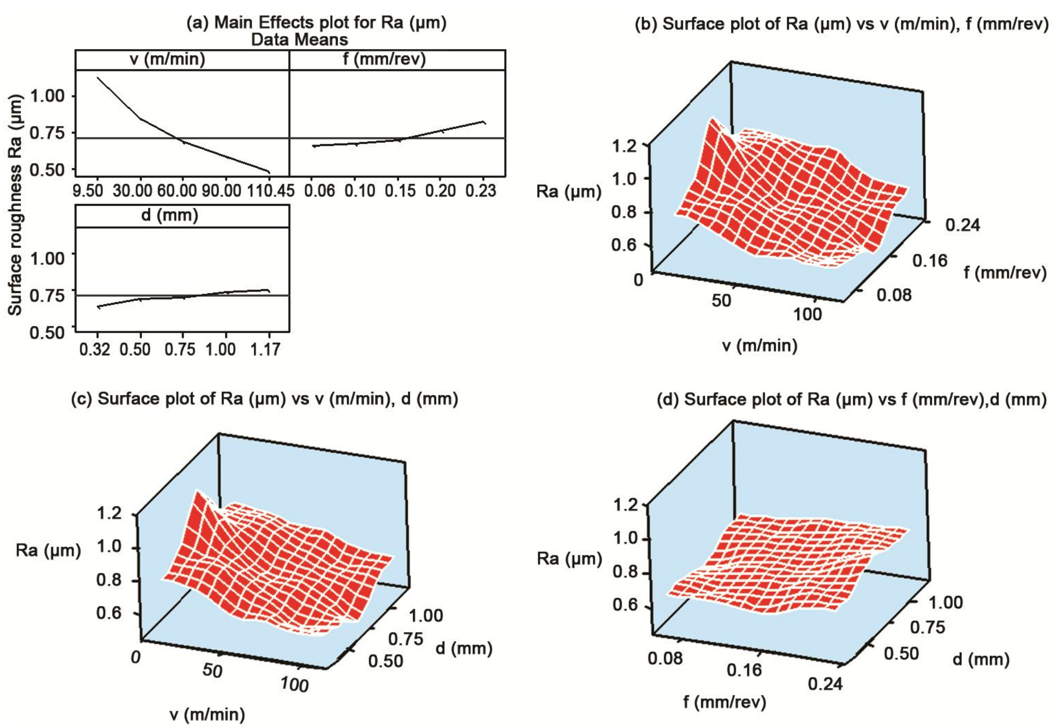

Fig. 2 — Effect of cutting speed, feed and depth of cut on surface roughness

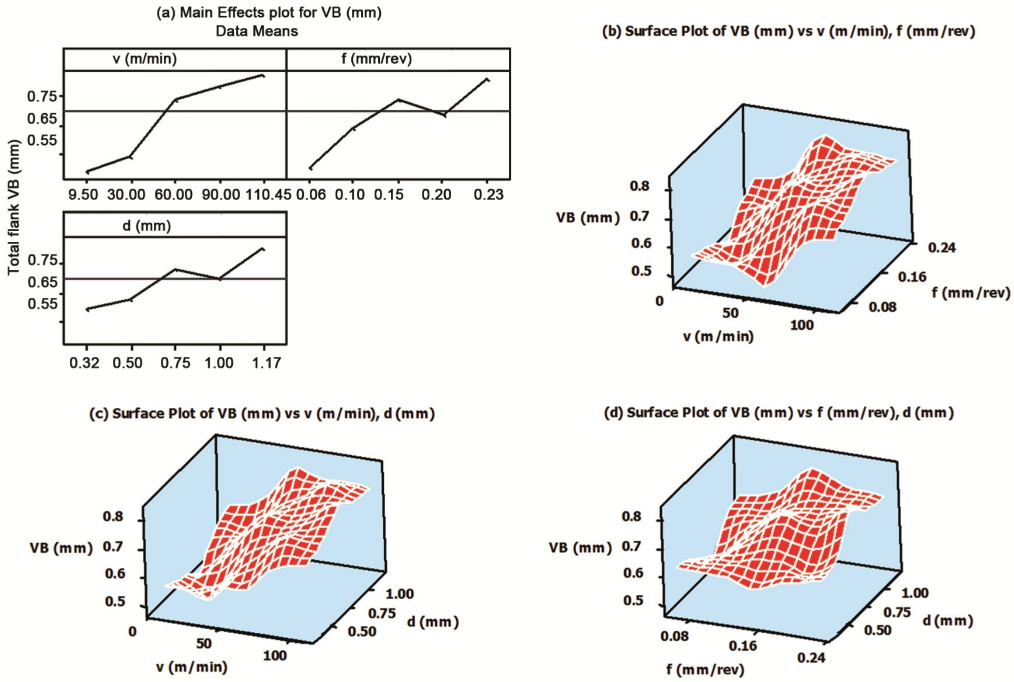

Fig. 3 — Effect of cutting speed, feed and depth of cut on tool flank wear

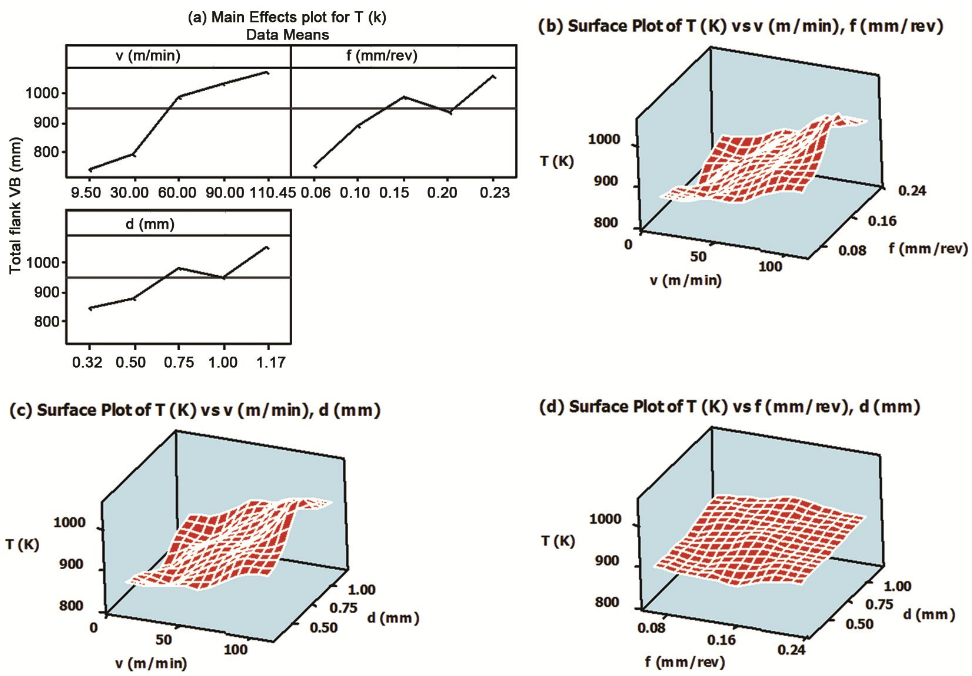

Fig. 4 — Effect of cutting speed, feed and depth of cut on cutting temperature

is more significant parameter for surface roughness, followed by feed rate and depth of cut. This is because, at high cutting speed, temperature increases at cutting zone, leading to softening of the surface of work material which results in reduction of roughness value[41].

The influence of *v*, *f* and *d* for monitoring of tool flank wear are presented in Figs 3 (a-d). Both surface and main effects plots clearly indicate a gradual increase of flank wear by increasing cutting parameters. Figure 3a shows that tool wear is influenced more by *v*. With the increase of cutting speed, the tool flank wear increases more as compared to effect of change of feed and depth of cut. However, value of tool wear first increases then decreases and again increases in case of feed rate and depth of cut. In interaction plots, Figs 3(b-d) show more interaction effect of *v-f*, *v-d* and *f-d* increasing flank wear gradually. Figure 3(b) signifies the interaction effect of cutting speed and feed rate for depth of cut of 0.75 mm. The significant drop of tool wear is seen at medium cutting speed and low feed rate. In Fig. 3c, the interaction effect of cutting speed and depth of cut on tool wear is shown for mid value of feed rate (0.15 mm/rev). By increasing cutting speed and depth of cut, the progress in wear of tool is observed. The lower value of tool flank wear is observed at low depth of cut and feed rate of 0.16 mm/rev, in Fig. 3d. Later on, increasing value of feed and depth of cut, increase in tool wear is seen. This is due to more friction between flank edge of tool and work surface at higher feed and depth of cut. In addition to high friction, more heat is generated because of low thermal conductivity of Inconel 718. Consequently, there is severe rise in temperature at tool chip interface. As reported in literature[15,16,42], increase of f and d result in breaking and chipping of cutting tool which drastically reduces the life of tool. It was observed that, sometimes breakage and chipping of tool affect continuity of machining process.

Figure 4a, indicates the dominance of cutting speed over temperature. The substantial linear increase of temperature is observed with cutting speed and slight non-linear increase with feed and depth of cut. The interaction effect of cutting speed and feed rate on temperature is presented for mid value of depth of cut (0.15 mm/rev) in Fig. 4b. By increasing cutting speed and feed rate, a rise in cutting temperature is seen. Similarly, Figs 4c and 4d signify the interaction effect of cutting speed and depth of cut and feed rate and depth of cut, respectively. The increasing trend of nature of surfaces is noticed in Fig. 4c. Slightly steady nature of surface plot is noticeable in Fig. 4d. It means that, in interaction plots, the interaction effect of *v-f* and *v-d* are strongly influencing the temperature shown in Figs 4b and 4c. Whereas, *f-d* has negligible effect on temperature as demonstrated by interaction plot in Fig. 4d. This is also confirmed by ANOVA examination in Table 3. In turning of Inconel 718 excessive heating of material is observed. This happens only due to high cutting temperature formed at high cutting speed resulting in excessive tool wear. Sometimes, at high feed and depth of cut, the built up edge formation takes place which could affect the surface finish[43]. The abrasive nature of Inconel 718 is definitely responsible for abrasive wear of the cutting tool on the flank face. Therefore, during machining of Inconel 718 the cutting temperature at 9.5 m/min was 810 K and at 110.45 m/min it was 1050 K at feed rate of 0.15 mm/rev and depth of cut 0.75 mm. Hence, these surface responses and main effects plots can be helpful in the prediction of the R_a, V_B and T at any region of the experiment.

Formulation of problem for multi-objective optimization function

This work deals with minimizing R_a, V_B and T for turning of Inconel 718 by formulating multi-objective optimization problem on the basis of weighted sum method. Primary objective is minimizing the R_a followed by V_B and then T in turning operation as stated in Eqs (1)-(3). These objectives are as follows,

Surface roughness (R_a) = Minimize R_a (v, f, d)

Tool flank wear (V_B) = Minimize V_B (v, f, d)

Cutting temperature (T) = Minimize T (v, f, d)

Where,

$$v_{\min} \le v \le v_{\max} \approx (9.5 \le v \le 110.45)$$
$$f_{\min} \le f \le f_{\max} \approx (0.06 \le f \le 0.23)$$
$$d_{\min} \le d \le d_{\max} \approx (0.32 \le d \le 1.17)$$

For getting multi-objective optimization function, the above mentioned single objective functions are combined as shown in Eq. (4). In this equation w_1, w_2, and w_3 are the weight factors. The weight factors w_1, w_2 and w_3 are judged and assigned values using assumption, functionality and importance of response parameters[44]. The normalized multi-objective function (Z) is formulated using different weight factors for all objectives and is given by Eq. (4).

$$Z = w_1\left(\frac{R_a}{R_{a\min}}\right) + w_2\left(\frac{VB}{VB_{\min}}\right) + w_3\left(\frac{T}{T_{\min}}\right) \quad \text{... (4)}$$

Equal weights were given to surface roughness and tool flank wear compared to cutting temperature as Inconel 718 alloys find application in places which demand excellent surface finish and higher reliability. Similarly, cutting tool plays more functional role in machining of this difficult to cut alloy. Hence, the corresponding weights were taken as w_1 = 0.4, w_2 = 0.4 and w_3 = 0.2. The R_a, V_B and T are used as Eqs (1)-(3). The minimum (best) values of the $R_{a\min}$, $V_{B\min}$ and $T_{\min}$ which calculated from Eqs (1)-(3) are used in normalized multi-objective function Eq. (4), which is modified as Eq. (5).

$$Z = 0.3367 + 9.3715\times10^{-4}v + 7.2674f + 1.0333d - 1.0773\times10^{-5}v^2 - 18.0262f^2 - 0.4872d^2 + 1.2589\times10^{-3}vf + 2.2781\times10^{-4}vd - 0.1606fd \quad \ldots (5)$$

Genetic algorithm

In present work, genetic algorithm is applied for optimizing the cutting parameters. The multi-objective optimization function as Eq. (5) is used to optimize the process. The fitness function is the combination of R_a, V_B and T for optimization. Constraints used in this process are the lower and upper bound values of cutting parameters presented in Table 1. The result investigated by GA is based on input population and output is generated using fitness function. The feedback given by fitness function, helps to confirm characteristic of input population and allow GA to reproduce more improved population using crossover and mutation based on optimization target[22,45,46].

Multi-objective function (Z) is solved by GA tool box in MATLAB R2015a. The population size of 50 is required and the best results obtained from 20 generations after the rigorous trials. The optimization plot of GA is shown in Fig. 5. According to the above constraints, the optimum results of cutting parameters (v = 108 m/min, f = 0.06 mm/rev and d = 0.33 mm), response parameters (R_a = 0.41 µm, V_B = 0.45 mm and T = 884.13 K) with corresponding function values of normalized multi-objective function are chosen and three sample strategies are presented in Table 5.

In case of GA, population size, mutation probability and number of generation are responsible to control the genetic search process. In this section, the purpose is to examine the sensitivity of the convergence speed. Figure 5 shows convergence of objective function (Z) versus number of generations for population size of 50. The objective function (Z) drops from 1.1 to 0.98 when generation size varies from 1 to 20. Once the generation size exceeds 20, a flat curve is observed. These convergence results show that minimum 20 generations are required for obtaining steady convergence curve while using GA.

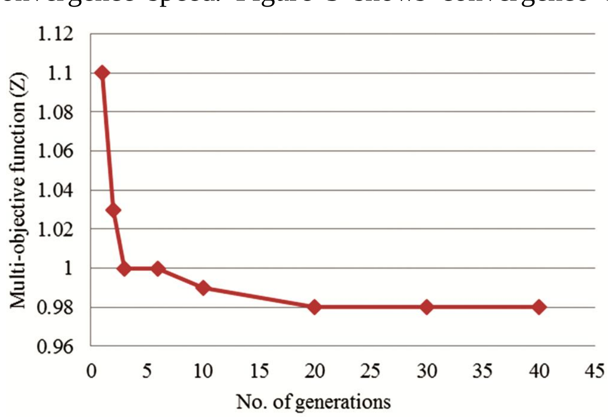

Fig. 5 — Optimization using GA

Teaching learning based optimization (TLBO)

TLBO is a teaching learning technique encouraged algorithm proposed by Rao *et al.*[35]. This algorithm presents equivalence effect of a teacher on the output of learners (scholars) in a class. Teacher and scholars are the two important components which explain teacher phase and learner phase. The scholar result is measured in terms of expertization of teacher as TLBO output. Hence, a teacher is highly expert person who educate scholars for achieving best result. In addition, scholars also upgrade their knowledge by communication among themselves which also assists in enhancing their results. The functioning of TLBO is separated into two parts, teacher phase and scholar phase.

Teacher phase

During this phase, a teacher desires to increase the mean result of the class (M_j) to his or her rank. For getting best result teacher attempts to improve existing mean (M_j) towards new mean as indicated (M_{new}) and the difference between the existing mean and new mean is given as Rao *et al.*[35].

$$\text{Difference of } mean_i = rad(M_{new} - M_j T_F) \quad \ldots (6)$$

Where, T_F is the teaching factor. It can be either 1 or 2 and and rad is a random number in the range of zero to 1.

Based on Eq. (6), the existing solution is revised pertaining to the expression

$$X_{newi} = X_{oldi} + \text{Difference of } mean_i \quad \ldots (7)$$

Scholar phase

This is a second phase of algorithm, where scholars improve their knowledge by communication among themselves. A scholar joins randomly to improve their

Table 5 — Performance of GA

Strategy	v	f	d	R_a	V_B	T	Z
1	108.5	0.06	0.33	0.41	0.45	884.77	0.984
2	108	0.06	0.33	0.41	0.45	884.13	0.984
3	108.3	0.06	0.33	0.41	0.45	884.59	0.983

knowledge if the other scholar has additional knowledge compared to his or her counterpart. The learning detail of this phase is presented in Eqs (8) and (9). At any iteration *i*, for two different scholars, X_i and X_j where $i \neq j$.

$$X_{new,i} = X_{old,i} + rad(X_i\text{-}X_j) \text{ if } f(X_i)<f(X_j) \quad \ldots (8)$$

$$X_{new,i} = X_{old,i} + rad(X_j\text{-}X_i) \text{ if } f(X_j)<f(X_i) \quad \ldots (9)$$

In this phase every variable (Scholar) compare randomly between any two value corresponding to their function values and modify using Eqs (8) and (9). The best solution is accepted by comparing with the result of teacher phase. The above two phases are repeated until the best solution is achieved.

After the analysis, X_{new} provides better function value which may be accepted. The functional steps to execute TLBO algorithm are summarized and presented by Rao and Patel[47] as:

(i) Initialize the scholars and number of subjects (design parameters).

(ii) Select the most excellent scholar as a teacher and estimate mean result of scholars in all subjects. Estimate the difference among present mean result and best mean result according to Eq. (6) using the teaching factor = 1 or 2.

(iii) Refresh the scholars' knowledge assisted by teacher's knowledge according to Eq. (7).

(iv) Update the scholars' knowledge using the knowledge of other scholars using Eqs (8) and (9).

(v) Repeat the process until the execution measure is met.

In present study, group of scholar is employed as range of cutting parameters. The subjects are offered to scholar, i.e., cutting parameters (*v*, *f* and *d*) and the teacher is allowing for best result in entire population. The main aim of this research is to find the optimum (best) cutting parameters for minimization of response parameters (R_a, V_B and *T*). Thus, turning of Inconel 718 is defined in a standard optimization problem format. The generated multi-objective function (5) is used to optimize the process parameters. Now, TLBO is utilized to solve the described problem. TLBO code given by Rao and Patel[47] is generated in MATLAB R2015a. Initially, population size and number of generation is used same as used for GA. The step by step procedure for use of TLBO is same as given by Rao and Kalyankar[36].

The optimum results of cutting parameters with corresponding function values of normalized multi-objective function (*Z*) are selected after some trials. It is noted that, in case of TLBO, the best results are obtained using only 3 generations with population size of 10. Whereas, in case of GA, minimum 20 generations are required with population size of 50, which indicated that, the less convergence time is required with TLBO algorithm compared to GA optimization.

Optimization plot of TLBO shown in Fig. 6, which proves the superiority of TLBO compared to GA (Fig. 5). Figure 6 shows the convergence of objective function (*Z*) obtained by TLBO for minimization of responses. The unsteady nature of convergence curve is observed at the beginning. However, quick stability in convergence curve is noticed once generation size crosses the value of 3 with the same value of 0.97 for objective function (*Z*) as was obtained while using GA (Fig. 5). It means the steady state of convergence of the objective function (*Z*) while using TLBO is reached in 3 generations as against 20 generations in case of GA. Thus, there is 85% improvement while using TLBO and proves the supremacy of TLBO over GA.

The results of three sample strategies using TLBO are obtained uniformity and presented in Table 6. The optimum values of cutting parameters and responses resulting from the optimization process are assessed by a confirmation test.

For multi-objective optimization for minimization of all responses, the optimization using TLBO analysis produced marginally better result than GA optimization shown in Table 7. Also, the optimum values of the *v*, *f* and *d* with TLBO are 107.7 m/min,

Table 6 — Performance of TLBO

Strategy	*v*	*f*	*d*	R_a	V_B	*T*	*Z*
1	107.7	0.06	0.32	0.41	0.44	881.39	0.977
2	109	0.06	0.32	0.41	0.44	883.06	0.976
3	108	0.06	0.32	0.41	0.44	881.78	0.977

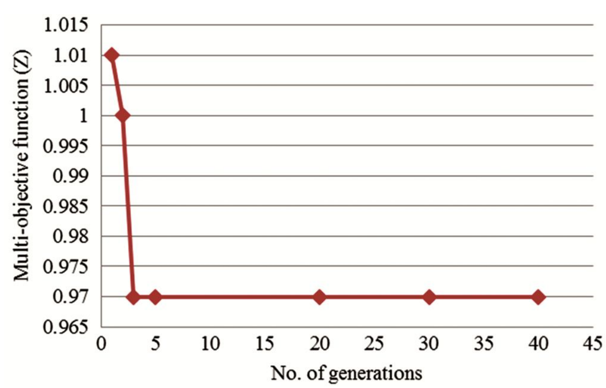

Fig. 6 — Optimization using TLBO

0.06 mm/rev and 0.32 mm respectively. Furthermore, the optimum values of R_a, V_B and T are 0.41 µm, 0.44 mm and 881.39 K, respectively. It is observed that, minimum values of tool wear and cutting temperature obtained by TLBO are lower than GA. Whereas same value of surface roughness is found in both algorithms.

The confirmation experiment was performed using optimum values of cutting parameters obtained by TLBO algorithm for response parameters. During experimentation, the responses R_a, V_B and T are measured as 0.45 µm, 0.49 mm and 897 K, respectively. The value of tool wear is measured using USB microscope and the flank wear of tool is shown in Fig. 7. The value of R_a, V_B and T are 9.75%, 10.20% and 1.74% higher than TLBO results which may be possibly because of the weights attached to each parameters and errors in machining and measurement methods.

TLBO algorithm provides slightly better results as compared to GA in terms of lower values of surface roughness, tool wear and cutting temperature as shown in Table 7. The main advantage of using TLBO algorithm is that it does not require any algorithm specific parameters like GA which requires mutation probability, cross over probability apart from population size and number of design variables. Also, TLBO algorithm converge to the solution faster than GA and requires lower population size and generations as shown in Figs 5 and 6. Thus, the TLBO algorithm can help machinist to obtain practical machining parameters for optimum machining response.

Table 7 — Comparison and confirmation of optimization result

Parameters	GA	TLBO	Confirmation test
v	108	107.7	107.7
f	0.06	0.06	0.06
d	0.33	0.32	0.32
Ra	0.41	0.41	0.45
VB	0.45	0.44	0.49
T	884.13	881.39	897

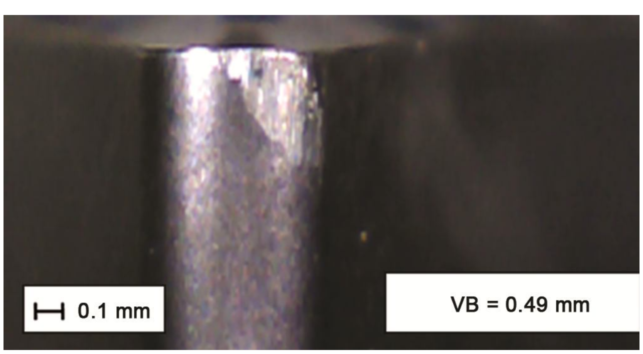

Fig. 7 — Tool flank wear at optimum cutting parameters

Conclusions

Following conclusion is drawn from this research. The experimentation was performed with CCD of RSM using three cutting parameters; *v*, *f*, *d* and the results are presented in terms of R_a, V_B and T.

Using RSM the capability of modified models is checked with the experimental data for R_a, V_B and T. The minimum values of the errors obtained enable us to conclude that a very strong relationship exists between estimated and experimental process responses. Hence, RSM is a capable tool for estimating process responses with desirable accuracy.

The modified response surface models can be applied to examine the interaction effects of the cutting parameters and their influence in affecting the process responses; such as surface roughness, flank wear and cutting temperature. The modified models were combined to form a single multi-objective function using weighted sum method. Also, optimum (minimum) values of responses were used from RSM optimization. The methodology used in the analysis has effectively developed a multi-objective function optimization problem. Further, the function is solved by genetic algorithm and teaching-learning based optimization. The optimum results of cutting parameters are; v = 108 m/min, f = 0.06 mm/rev, d = 0.33 mm and response parameters are; R_a = 0.41 µm, V_B = 0.45 mm, T = 884.13 K obtained by GA. In case of TLBO, the optimum values of the cutting velocity, feed rate, depth of cut are identified as 107.7 m/min, 0.06 mm/rev, and 0.32 mm, respectively. Furthermore, the optimum values of the surface roughness, flank wear and cutting temperature are 0.41 µm, 0.44 mm and 881.39 K, respectively.

The lower values of V_B and T are obtained by TLBO, whereas as same value of R_a is found in both algorithms. It is concluded that, for multi-objective optimization for minimization of all responses, the optimization using TLBO analysis produced marginally better result than GA optimization. It is promptly noted that, best results are obtained with population size of 10 using 3 generations only, which proves the superiority of TLBO over GA, which also indicated that, the less convergence time is required with TLBO algorithm compared to GA optimization. Thus, the success rate is improved by 85%.

The confirmation experiment was performed using optimum values of cutting parameters obtained by TLBO algorithm for process responses and it confirmed the results of TLBO algorithm. The confirmation test indicates that optimum values of surface roughness, flank wear and cutting temperature are slightly higher by 9.75%, 10.20% and 1.74% than TLBO result. Therefore, a novel advanced TLBO algorithm is the capable tool to achieve the optimum cutting condition. It can be helpful to increase surface quality and tool life by maintaining cutting temperature in turning of Inconel 718.

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