Modeling of Surface Integrity in Ball End Milling of Thin Cantilever Inconel 718 using Teaching Learning Based Optimization

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Abstract: This paper presents the application of Response Surface Methodology coupled with Teaching Learning Based Optimization Technique (TLBO) for optimizing surface integrity of ball end milling of thin Inconel 718 cantilever plate. The machining parameters spindle speed, feed, depth of cut, tool path and orientation are optimized with considerations of multiple response like surface roughness, micro hardness, and deflection of plate. Mathematical relationship between process parameter and surface roughness, microhardness and deflection are found out by using response surface methodology. It is observed after optimizing the process that at the spindle speed of 2000 rpm, feed 0.05 mm/tooth/rev, plate thickness of 4 mm and 15° workpiece inclination with horizontal tool path gives favorable surface integrity.

Keywords: Inconel 718, Ball end milling, RSM, Teaching learning based optimization, Deflection of workpiece

1 INTRODUCTION

Modeling of the manufacturing process is the replica of the actual process and its output. In order to generate valid mathematical model it is essential to have finite number of data collected from the experiments related to manufacturing process in use. There are few approaches that can be used to establish the mathematical model like statistical, numerical or analytical. In this study, the manufacturing process considered is the ball nose end milling of cantilever thin shaped Inconel 718. The machined surface quality generated in this process depends upon the input process parameters that include cutting speed, feed, cutter orientation and the workpiece thickness. These parameters independently or in combined influence the output variables i.e. deflection of machined workpiece, surface generation process and the micro deformation behavior of the machined surface and subsurface. Recently, Yildiz [1] presents a comparison of evolutionary based optimization technique to solve multi-pass turning optimization problems. The convergence speed of evolutionary algorithms to the optimal results is better than those of traditional optimization algorithms. Population-based algorithms such as cuckoo search algorithm, differential evolution algorithm (DE), particle swarm optimization algorithm (PSO), genetic algorithm (GA) and simulated annealing (SA) have been preferred in many applications instead of conventional techniques [2, 3]. The population-based algorithms may have premature convergence towards a local minimum. To find a remedy the mentioned weakness, they have been integrated with other techniques. The primary objective of a manufacturing operation is to efficiently produce parts with high quality. Milling is a widely used machining process in manufacturing, in which ball end milling produces complex surfaces. In order to improve the efficiency of the machining process and to reduce the total machining cost, optimum machining parameters have to be obtained. The setting up of machining parameters relies strongly on the operator's experience. Optimum machining parameters are of great concern in manufacturing environment. Surface integrity is major concern with performance of product in terms of fatigue life, creep resistance and stress corrosion cracking [4]. Response surface methodology (RSM) provides a powerful means to achieve breakthrough improvements in product quality and process efficiency. From the viewpoint of manufacturing, this can reduce the number of required experiments when taking into account the numerous factors affecting experimental results. RSM can show how to carry out the fewest experiments while maintaining the most important information [5]. Hou et. al. (2010) studied the influence of cutting speed, feed rate, and depth of cut on ignition of AM50A magnesium alloy during high-speed face milling and found that ignition could easily be caused under some cutting speed and feed rate when the depth of cut was fixed, and ignition was rarely observed when the depth of cut was 80 micron [6]. Bouzakis et al. (2003) modeled the workpiece and cutting edge to simulate the topography in the ball-end milling process [7]. Sonawane et. al. (2010) have developed mathematical model for the cutting forces observed during ball end milling operation of superalloy Inconel 718 [8]. In this research, a new hybrid approach based on teaching learning-based optimization (TLBO) algorithm and response surface methodology is presented.

2 RESPONSE SURFACE METHODOLOGY

Response surface modeling (RSM) is a collection of statistical and mathematical method which is useful for the modeling and optimization of the engineering science problems. RSM quantifies the relationship between the controllable input parameters and the obtained responses. An experiment is designed with 2^k (where, k = number of parameters, in this study k = 4) factorial with central composite-second order rotatable design is used. This consists of number of corner points = 16, number of axial points = 8, and a centre point at zero level = 6. The axial points are located in a coded test condition space through parameter ‘α’. For the design to remain rotatable, ‘α’ is determined as ($2^{4*1/4}$) = 2. Thus, the coded level for the axial points is at 2. The center point is repeated four times to estimate the pure error. Relation between the process parameter and output response given by quadratic non linear equation is as –

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{j>1}^{k} b_{ij} x_i x_j \quad (1)$$

where, all b’s are the regression coefficients, determined numerically by using least square fit method, x_i are the different control factors changing from i = 1 to n, n is the total number of control factors, y is the different responses [5]. In this study numbers of responses are three and control factors are four. Based on these levels, random run orders were generated for the experiments and machining were carried out for these 30 combinations of input parameters.

3. EXPERIMENTAL SETUP

The main objective of this study is to optimize the surface integrity of thin and low rigidity workpiece of Inconel 718 after machining.

Table 1 Factors with different level

	Parametric Level				
Input factor	-2	-1	0	1	2
Spindle speed (*S*) (rpm)	1500	2000	3000	4000	4500
Cutting feed (*f*) (mm/ tooth)	0.038	0.05	0.075	0.1	0.112
Plate thickness (*t*) (mm)	3.5	4	5	6	6.5
Workpiece angle and tool path orientation (*d*) (degree)	45 H	15 H	0 H	15 V	45 V
H = Horizontal and V = Vertical					

3.1 Workpiece and Tool Material

The work specimens are fabricated into thin rectangular plates (75 mm × 25 mm) of different thicknesses (3.5, 4, 5, 6 and 6.5 mm). All the work specimens are heat treated before machining. They are solutionized at 954°C to 982°C for 1 hour and air-cooled. Further, the solutionized samples are aged at 718°C for 8 hours and air-cooled. Chemical composition by % weight of workpiece are, Ni: 51.50, Cr: 20, Mg: 0.30, Si: 0.30, C: 0.08, Mo: 2.9, Ti: 0.3, P: 0.015, S: 0.015, Al: 0.95, B: 0.005, Co: 0.95, Nb: 5.10, Cu: 0.6, Fe: 17.00.

Solid carbide, Ti-Al-N coated ball-nose end mill cutter with 10 mm diameter, 10° rake angle and 30° helix angle possessing two flutes are used during the experiments.

3.2 Experiments and Measurements of response variable

The experiments were performed on a vertical machining centre (HARDINGE 600II) under dry (without coolant) conditions. The surface roughness of the machined specimens was measured using stylus-based surface roughness tester (Mitutoyo, SJ 301) with 0.8 mm cut-off length. A deflection sensor was attached at the free end of the cantilever work specimen. It was connected to a deflection measuring (acquisition) software through an amplifier. The dynamometer (Kistler make) was connected to the amplifier and further to the computer for cutting force data acquisition. Dynoware software was used for the evaluation of average load on the cantilever-type work specimens during the experiments.

Microhardness measured across machined surface at 20 µm, 40 µm, 60 µm, 100 µm and 200 µm beneath the machined surface by using Shimadzu Microhardness HMV – 2T tester.

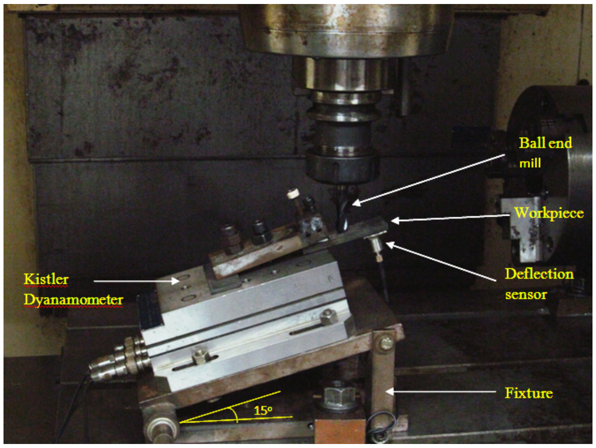

Fig. 1 A photograph of experimental set-up at 15° workpiece inclination

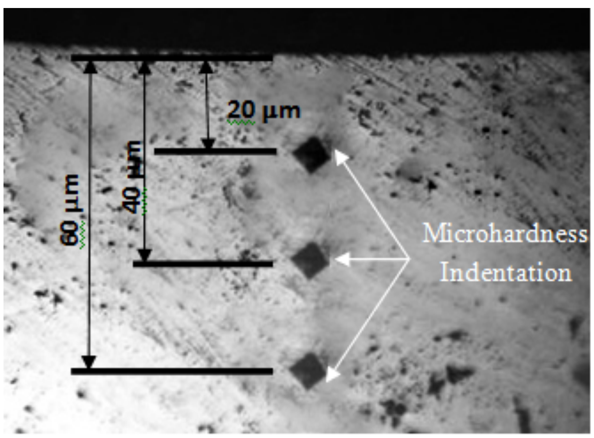

Fig. 2 Photographic view of microhardness indentation

4 RESULTS AND DISCUSSION

4.1 Development of Model

Surface roughness, microhardness and deflection are major concern with surface integrity point of view. Ball end milling of thin shaped workpiece causes deflection during milling. As a result, the tool contact with the workpiece changes. At a fixed side of cantilever, tool contact area is more as compared with the middle portion and free end portion of cantilever workpiece [see Fig. 3]. It is clearly noted from Fig. 3 that as the tool moves from fixed side of workpiece to free end side of the work piece, depth of cut varied because of bending of plate. This leads to reduction in width of the cut. However, from fixed side to free end width of the cut is reduced. Depending on deflection value, the width of cut changes. Let us say *a*, *b* and *c* *(mm)* are the value of width of cut at fixed side, middle portion and free end, then $a < b < c$. Hence, separate observations are recorded for surface roughness and microhardness in fixed, middle and end region.

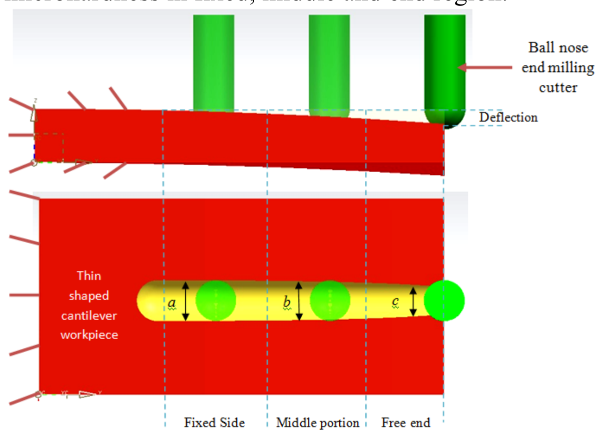

Fig. 3 Variation of cutting zone in different portion of cantilever with respect to deflection

Deflection values are recorded at the free end position. For the multiple pass operation, the strain hardening beneath the machined surface should be minimum, hence at 20 µm microhardness values were modeled. The developed second order regression model for surface roughness, microhardness and deflection are given as follows-

For fixed side of Inconel 718 thin plate surface roughness and microhardness are,

$$Ra(\,fixed) = 2.2366 + 0.1288*S + 0.2025*f - 0.00416*t + 0.1486*D - 0.2032*S*f - 0.06267*S*t + 0.033*S*D + 0.1358*f*t + 0.0206*f*D - 0.114*t*D + 0.1275*S^2 - 0.01045*f^2 + 0.111*t^2 - 0.0539*D^2 \quad (2)$$

$$MH\ (fix\ 20\ \mu m) = 534.16 + 32.22*S + 50.63*f - 1.041*t + 37.14*D - 50.81*S*f - 15.66*S*t + 8.27*S*D + 33.95*f*t + 5.15*f*D - 28.65*t*D + 31.88*S^2 - 2.61*f^2 + 27.76*t^2 - 13.48*D^2 \quad (3)$$

For middle side of Inconel 718 thin plate surface roughness and microhardness are,

$$Ra\ (middle) = 1.74 + 0.11048*S + 0.16631*f + 0.00597*t + 0.11415*D - 0.18228*S*f - 0.0105*S*t - 0.0189*S*D + 0.1444*f*t - 0.0339*f*D - 0.0750*t*D + 0.0994*S^2 - 0.00183*f^2 + 0.0969*t^2 - 0.038*D^2 \quad (4)$$

$$MH\ (mid\ 20\ \mu m) = 415.6 + 47.5*S + 76.6*f - 12.60*t + 34.3*D - 58.41*S*f - 2.25*S*t - 8.6*S*D + 31.2*f*t - 13.1*f*D - 24.4*t*D + 69.5*S^2 + 33.7*f^2 + 51.9*t^2 + 20.7*D^2 \quad (5)$$

For free end side of Inconel 718 thin plate surface roughness and microhardness are,

$Ra\ (End) = 2.60 + 0.1429 * S + 0.2663 * f + 0.0104 * t + 0.2034 * D - 0.328 * S * f - 0.04803 * S * t - 0.0714 * S * D + 0.2394 * f * t - 0.01142 * f * D - 0.0661 * t * D + 0.1524 * S^2 - 0.00955 * f^2 + 0.1486 * t^2 - 0.05384 * D^2$ (6)

$MH\ (end\ 20\ \mu m) = 370.1 + 43.5 * S + 52.8 * f - 12.6 * t + 34.9 * D - 45.6 * S * f - 20.8 * S * t - 0.08 * S * D + 35.2 * f * t - 9.4 * f * D - 27.2 * t * D + 51.5 * S^2 + 17.09 * f^2 + 29.3 * t^2 + 6.2 * D^2$ (7)

Deflection at free end,

$Deflection = 0.43 + 0.03 * S + 0.035 * f - 0.012 * t + 0.03 * D - 0.033 * S * f - 0.0279 * S * t + 0.010 * S * D + 0.031 * f * t + 0.0051 * f * D - 0.017 * t * D + 0.036 * S^2 + 0.012 * f^2 + 0.0141 * t^2 - 0.009 * D^2$ (8)

where, S = Spindle speed (rpm) , f = feed (mm/tooth/rev) , D = tool path and tool inclination and t = plate thickness (mm).

To test whether the data fit well or not, the R^2 and adjusted R^2 have been found out and is given in Table 2. It is observed that at mid and end R^2 values are marginally significant.

Table 2 R^2 and adjusted R^2 values

Response	R^2	Adjusted R^2
Ra at fixed	91.00	83.00
MH (fix 20 µm)	91.63	86.00
Ra at mid	92.20	84.23
MH (mid 20 µm)	89.64	78.24
Ra at end	92.07	90.23
MH (end 20 µm)	80.23	79.20
Deflection	91.00	84.76

It is noted from Table 2 at the mid and free end of plate, deflection values increases which is directly affecting the values of surface roughness and microhardness at that region.

4.2 Validation of models

Model validation is the next step after the model is established. In order to validate the model L8 orthogonal experiments are performed with the input factors shown in Table 3.

Table 3 Input factors for the confirmation test

Parameter	Level 1	Level 2
Spindle speed (rpm)	2000	4000
Feed (mm/ tooth)	0.05	0.1
Plate thickness (mm)	4	7
Workpiece path and cutter orientation (degree)	15° Horizontal	15° Vertical

From Table 4 and Table 5 it has been found that % error in the mathematical model are variying from 0% to 13 % which can be acceptable. Now, these model can be subjected to the optimization problem and subjected to constraints.

5 OPTIMIZATION OF PROCESS PARAMETERS BY TLBO

TLBO is a teaching–learning process inspired algorithm proposed by Rao et. al. (2012), which is based on the effect of influence of a teacher on the output of learners in a class. It has been used for optimization of mechanical elements [9], structural design [10] and manuafcturing problems [11, 12]. The algorithm mimics the teaching learning ability of teacher and learners in a class room. Teacher and learners are the two vital components of the algorithm and describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase) and interacting with the other learners (known as learner phase). The methodology of both phases is explained below.

(a) Teacher phase

It is the first part of the algorithm where learners learn through the teacher. During this phase, a teacher tries to increase the mean result of the class room from any value M1 to his or her level (i.e., TA). But practically, it is not possible and a teacher can move the mean of the class room M2 to any other value M2 which is better than M1 depending on his or her capability. Consider Mj be as the mean and Ti as the teacher at any iteration i. Now, Ti will try to improve existing mean Mj towards it so the new mean will be Ti designated as Mnew and the difference between the existing mean and new mean.

Difference $Mean_i = r_i\, M_{new} T_F M_j$ (9)

where teaching factor (TF) is the factor which decides the value of mean to be changed, and ri is the random number in the range [0, 1]. Value of TF can be either 1 or 2 which is a heuristic step and it is decided randomly with equal probability as-

T_F = round [1 + rand (0,2)] {2 -1} (10)

Based on this difference_ mean, the existing solution is updated according to the following expression –

$X_{new;i} = X_{old,i} + \text{Difference Mean}_i$ (10)

(b) Learner phase

It is the second part of the algorithm where learners increase their knowledge by interaction among themselves. A learner interacts randomly with other learners for enhancing his or her knowledge. As the

Table 4 Verification of model for surface roughness and deflection

Standard Run	Ra (fixed) Experiment	Ra (fixed) Model	% Error	Ra (middle) Experiment	Ra (middle) Model	% Error	Ra (end) Experiment	Ra at (end) Model	% Error	Deflection Experiment	Deflection Model	% Error
1	2.13	2.16	-1.55	1.8	1.81	-0.40	2.65	2.63	0.61	0.44	0.435	1.12
2	1.89	1.69	10.36	1.42	1.46	-2.48	1.9	2.03	-6.85	0.38	0.41	-8.38
3	2.57	2.82	-9.78	2.9	2.70	7.02	5.1	4.4	12.51	0.6	0.65	-8.35
4	2.28	2.24	1.64	1.76	1.80	-2.24	2.9	2.66	8.21	0.46	0.43	6.66
5	1.92	1.91	0.77	1.75	1.99	-13.9	3.1	2.94	4.99	0.445	0.415	6.48
6	2.73	2.47	9.63	1.92	1.97	-2.48	3.5	3.10	11.15	0.6	0.53	12.00
7	2.55	2.79	-9.28	2.1	1.99	5.35	3.16	2.90	8.11	0.65	0.59	9.28
8	2.71	2.54	6.19	2.68	2.65	1.11	3.9	3.77	3.08	0.55	0.53	4.02

Table 5 Verification of models for Microhardness

Standard Run No.	MH (fix 20 µm) Experimental	MH (fix 20 µm) Model	% Error	MH (mid 20 µm) Experimental	MH (mid 20 µm) Model	% Error	MH (End 20 µm) Experimental	MH (End 20 µm) Model	% Error
1	502	515	-2.73	540	530	1.69	450	430	4.25
2	530	522	1.46	490	474	3.20	420	376	10.43
3	789	804	-1.90	840	857	-2.06	680	674	0.74
4	534	535	-0.31	620	603	2.60	445	432	2.72
5	585	575	1.7	690	674	2.27	436	451	-3.44
6	580	591	-2.04	598	603	-0.92	520	507	2.37
7	680	671	1.21	674	677	-0.55	586	575	1.76
8	749	734	1.96	860	881	-2.52	650	645	0.71

Table 6 Condition for finding out optimum values

Optimization of surface roughness	
Objectives	Ra at fixed side of thin inconel 718 plate represented by eq. no. (2)
	Ra at middle side of thin inconel 718 plate represented by eq.no. (4)
	Ra at free end side of thin inconel 718 plate represented by eq. no. (6)
Subject to constraints	MH at fixed side at 20 µm < 500 eq. no. (3)
	MH at middle side at 20 µm < 500 eq. no. (5)
	MH at free end side at 20 µm < 500 eq. no. (7)
	0.1 < Deflection at free end < 0.5 eq. no. (8)
Optimization of Microhardness	
Objectives	Minimization of MH at fixed side at 20 µm eq. no. (3)
	Minimization of MH at middle side at 20 µm eq. no. (5)
	Minimization of MH at free end side at 20 µm 500 eq. no. (7)
Subject to constraints	Ra at fixed side eq. no. (2)
	Ra at middle side eq.no. (4)
	Ra at free end side eq. no. (6)
	0.1 < Deflection at free end < 0.5 eq. no. (8)

result of this work, firstly the regression model was developed with the help of experimental data more knowledge than him or her. Mathematically, the learning phenomenon of this phase is expressed below. At any iteration i, considering two different learners Xi and Xj where i≠j.

$$X_{new;i} = X_{old,i} + ri\ (Xi \_ Xj) \text{ If } f(X_i) < f(X_j) \qquad (12)$$

$$X_{new;i} = X_{old,i} + ri\ (Xj \_ Xi) \text{ If } f(X_j) < f(X_i) \qquad (13)$$

MATLAB program developed to run the algorithm and

5 CONCLUSIONS

response surface methodology. To check the validity of the mathematical model, experimentation was carried out with the help of orthogonal L8 array and error analysis is carried out. A MATLAB program was developed for TLBO to optimize the parameters. It is observed that for cantilever plate deflection is the process response which directly affect the other process response. In this study a hybrid optimization algorithm is presented for the optimization of machining parameters considering surface integrity. The TLBO is performed quite well on the optimization of machining parameters of milling operation problem finding better solutions compared to other approaches. From the above computational results and discussions, it is demonstrated that HRTLBO can be used as a powerful technique for optimization of machining problems. Spindle speed 2000 rpm and feed rate 0.05 mm/tooth are favorable conditions for inducing favorable surface integrity.

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Table 7 Optimized Input parameter and output response

Sr. No.	Cutting speed (rpm)	Feed (mm/tooth)	Workpiece thickness (mm)	Orientation (degree)	Surface Roughness (µm) Ra			Microhardness (HV)			Deflection
					Fix	Mid	End	Fix	Mid	End	
1	Minimum Surface Roughness Values, minimum deflection and minimum microhardness										
	2000	0.05	4.4	15 H	1.68	1.24	1.79	397	323	269	0.39
2	Minimum surface roughness with maximum microhardness										
	4000	0.1	4.05	15 H	2.15	1.71	2.53	512	613	469	0.46
3	Minimum plate deflection										
	2700	0.05	5.76	15 H	1.8	1.31	1.89	431	326	280	0.355
4	Maximum surface roughness with maximum deflection										
	4000	0.056	4	15 V	2.99	2.32	3.45	723	717	633	0.6

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