Silicon (2019) 11:691–701
https://doi.org/10.1007/s12633-018-9953-6

ORIGINAL PAPER

A Novel Approach for Minimization of Tool Vibration and Surface Roughness in Orthogonal Turn Milling of Silicon Bronze Alloy

K Venkata Rao[1]

Received: 16 May 2018 / Accepted: 16 July 2018 / Published online: 24 July 2018

Abstract

The advanced manufacturing system is aimed to produce components at right quantity, quality and cost. Turnmilling is one of the advanced machining techniques that combines turning and milling processes for high metal removal rate. In orthogonal turn milling, bottom surface of the end mill cutter removes material from the surface of a rotating workpiece. Optimization of process parameters plays an important role in machining to improve quality and productivity and reduce production cost. In the present work, an advanced teaching learning based optimization (TLBO) technique was introduced to optimize process parameters in orthogonal turn milling of Silicon Bronze. Experiments were conducted at five levels of cutting speed, feed and depth of cuts. Experimental results of surface roughness and amplitude of cutter vibration were analysed using analysis of variance. The experimental results were also used to optimize process parameters through TLBO. Experiments were also conducted using TLBO optimized process parameters and the results were compared with TLBO results. The TLBO results were found to be in good agreement with target values of the responses. Artificial neural networks were developed for the surface roughness and amplitude of cutter vibration to verify optimization.

Keywords Turn milling · Silicon bronze · TLBO · ANN · Tool vibration · Optimization

1 Introduction

Silicon bronze is one of the copper-based alloys has excellent mechanical and physical properties. These properties make alloy suitable for many applications such as aircrafts, marine, industrial, chemical and mechanical. However, machining efficiency for such metals to be improved without compromising surface roughness and tool life. Turnmilling is a machining process developed by Sandvik Coromant to improve machining performance. The turnmilling is defined as "The milling of a curved surface, where the work piece is rotated around its centre point using a fourth machining axis" [1]. Turnmilling processes are divided into two types named as orthogonal turn milling and tangential turn milling. End mill cutters are used to perform both the turning and milling. In orthogonal turn milling, bottom teeth of vertical mill cutter remove material from the surface of the workpiece. Whereas in tangential turn milling, side teeth of end mill cutter remove material from the surface of work piece. In conventional turning of low machinability materials, surface roughness, low metal removal rate, tool vibration are considered to be difficulties. To overcome these difficulties, the concept of turn milling was developed in 1990s for machining of large crankshafts and landing gears which are made with low machinability materials [2].

Surface roughness and tool life are two important parameters in any machining process. In conventional turning process, cutting point of the tool has continuous contact with the workpiece to remove material in the form chip. Therefore, friction and temperature develop between workpiece and tool that results in tool wear and finally surface roughness on the machined surface increases. In the turn milling process, the end mill cutter has many cutting edge and their contact with work piece is not continuous and hence, the tool life increases [3]. Vedat and Cetin [4] have studied the effect of cutting parameters on surface roughness in turn milling using genetic algorithm. Experiments were conducted on SAE 1050 steel at different cutting speeds, depth of cuts and feeds. Surface roughness was found to be increased with increase of depth of

✉ K Venkata Rao
kvenkat_rama@rediffmail.com; kvenkatrama@gmail.com

[1] Department of Mechanical Engineering, Vignan's Foundation for Science, Technology and Research Deemed to be University, Vadlamudi, India

cut and feed rates. Junxue et al. [5] combined gray relation analysis (GRA) with Taguchi technique for multi response optimization of cutting parameters in the milling of Titanium alloy. They studied the effect of the milling cutter geometric parameters on surface roughness and residual stress and optimized the process parameters. Sivasakthivel et al. [6] investigated the effect of cutting parameters on the amplitude of mill cutter vibration. According to an orthogonal array of L25, milling experiments were conducted on aluminum alloy at different cutting speeds, axial depth of cuts, radial depth of cut, helix angles and feed rate. They used two channel accelerometer to measure the vibration of spindle and workpiece. Experimental data were analyzed and process parameters were optimized using Taguchi method based GRA for minimum vibration of the cutter. They stated that end mill cutters are subjected to wear and it results in a poor surface finish and tool life.

Compliance between tool and workpiece is considered as an important factor in evaluation of vibration of milling cutter as well as the workpiece. The tool-workpiece compliance is affected by direction of feed and cutting forces [7]. Amplitude of cutter vibration and relative friction between workpiece and tool were found to be less at starting of the operation and then they increase as the machining progresses. Ratnam et al. [8] studied machining characteristics such as surface roughness, surface hardness and amplitude of cutter vibration in orthogonal and tangential turn milling processes. As per orthogonal array of L16, experiments were conducted on extruded brass using high speed steels end mill cutter at different levels of spindle speed, feeds and depth of cuts. During the experimentation, they used Laser Doppler Vibrometer (LDV) to measure amplitude of cutter vibration. The experimental results were analyzed using Taguchi and analysis of variance (ANOVA) techniques and concluded that the tool vibration decreases as the spindle speed is increased. Resonance in the vibration makes the cutting tool oscillate with more amplitude and results in gradual tool wear and tooling cost. Mohammad et al. [9] developed a 3-D nonlinear dynamic model to study the effect of axial depth of cut, number of cutter teeth, cutting tool length and cutting tool diameter on the tool vibration in milling. They concluded that the steady state vibration response of the tool tip was found to be increased as the axial depth of cut was increased. In another study, Sadaf et al. [10] reported that the higher values of the feed rates cause higher amplitude of cutter vibration and results in excessive tool wear and surface roughness.

Vibration is one of the machining characteristics that is required to be controlled by changing process parameters. Otherwise, it causes low productivity because it directly affects the tool wear, surface roughness and dimensional accuracy [11]. Khalil and Danesh [11] used undecimated wavelet transform and gray-level co-occurrence matrix texture features to identify cutter vibration levels. They have used an accelerometer to measure the vibration of cutters and a vision based was used to capture surface image of machine component. Venkatarao et al. [12] have also used LDV to measure the vibration of work pieces in boring process and suggested for online tool condition monitoring in industrial applications. Zahia Hessainia et al. [13] established mathematical models for surface roughness in turning of hardened steels. Experiments were conducted at different levels of cutting speed, depth of cut, feed rate and vibrations. ANOVA was used to investigate effects of process parameters on tool vibration on surface roughness. Among the process parameters, feed rate was found to be a significant parameter on the surface roughness.

Multi response optimization techniques are widely used in manufacturing to optimize process parameters to improve overall efficiency of the process. Subramanian et al. [14] used response surface methodology (RSM) to optimize cutting parameters based on the amplitude of mill cutter vibration in the milling of Aluminum (AA 7075-T6). They used two channels piezoelectric accelerometers on spindle head to measure the vibration of cutter. A mathematical model was developed in terms of cutting speed, feed, radial rake angle and nose radius to predict the amplitude of cutter vibration. Cutting parameters were also optimized using RSM multi response optimization for minimum cutter vibration. Zhou et al. [15] have followed a hybrid multi response optimization technique to optimize process parameters for minimum surface roughness and maximum compressive residual stress in multi axis ball milling of Inconel 718 metal. Experiments were conducted at five levels of inclination angle, feed and cutting speed. The two responses were converted in single response using GRA and grey relation grade was calculated for all the responses. Radial basis function neural network was used to establish a relation between process parameters and grey relation grade and particle swarm optimization algorithm was used to optimize process parameters. It was concluded that the proposed technique can be generalized and implemented to other optimization problems. Optimization techniques like Taguchi, RSM, Grey relation analysis, particle swarm optimization, genetic algorithm, simulated annealing, and ant colony algorithm are used to optimize process parameters in machining process. Some researchers have failed in handling of the above optimization techniques and their outcomes were also not accurate [16]. The above techniques give equal weightage to the responses in multi response optimization. But the responses should be given weightage as per user preference for maximization of process performance [17, 18]. This method also has some limitations in optimization. To overcome those difficulties, Teaching and learning based

Table 1 Chemical composition, physical and Mechanical properties of ASTM B98

Chemical composition		Physical and mechanical properties	
Si	3.8	Density	8.53 g/cc
Mn	1.2	Hardness, Rockwell B	95
Fe	0.8	Tensile strength, Ultimate	745Mpa
Zn	1.25	Tensile strength, Yield	415 MPa
Pb	0.02	Modulus of Elasticity	105 GPa
Cu	Balance	Poisson's Ratio	0.346

optimization (TLBO) algorithm was developed by the concept of knowledge transfer from the teacher to students and from good student to slow learner in a class room. The TLBO is carried out in two phases such as teacher phase and learner phase. In teacher phase, knowledge transferred from the teacher to students and in the leaner phase knowledge is transferred from the good learner to slow learner through interaction to improve overall performance of the class room [19]. Rao et al. [16] stated that the TLBO is superior method that gives better results than the results obtained by other optimization techniques. Venkata rao and Murthy [20] have used the SVM, along with ANN and RSM to analyze the surface roughness and root mean square of work piece vibration velocity in the boring of AISI 316 stainless steel. They found that the ANN and SVM models have predicted the responses very close to the experimental values. Hybrid optimization approaches were also introduced by combining some of the techniques like TLBO, Taguchi technique, bee colony optimization approach, particle swarm optimization algorithm, ant colony algorithm, immune algorithm, genetic algorithm for multi response optimization of process parameters [21–23].

In the present work, TLBO technique was used to optimize process parameters for orthogonal turn milling of Silicon Bronze metal. The optimization was validated experimentally and also using artificial neural networks. ANN models were developed for the surface roughness and amplitude of cutter vibration to validate the optimization performed by the TLBO.

2 Materials and Experimentation

In this work, orthogonal turn milling experiments were conducted on ASTM B98 Silicon Bronze metal. ASTM B98 is a silicon bronze metal has excellent workability, high strength, low magnetic permeability and very good corrosion resistance [24]. The silicon bronze is used to make hydraulic pressure line in aircrafts, pole line hardware and rotor bars in electrical applications, screws, rivets, nuts, nails, shafts, heat exchangers, bearing plates, chemical equipments, pressure vessels in industrial applications and propeller shafts in marine applications. Chemical composition of Silicon Bronze is given in the Table 1.

In the present study, high speed steel (HSS) end mill cutters were used for the turn milling. The cutters are having cutting teeth at the bottom and sides also. Specifications of the end mill cutter were given in the Table 2.

In the present work, 25 experiments were carried out at five levels of cutter speeds, feeds and depth of cuts on the Silicon Bronze metal on using four axes CNC milling machine. Work piece with length of 90mm and diameter of 50 mm was held between two centers on the machine table. In machining, bottom teeth of end mill cutter removed the material from surface of the workpiece under dry condition. Each experiment was started with a new mill cutter and machining was stopped at the end of each pass. In each pass, amplitude of rotating mill cutter was measured using a Polytech PDV 100 portable type LDV as shown in the Fig. 1. During the machining, the vibration of cutter was measured after 45mm length of machining on the workpiece. At the end of each pass, the work piece was removed and its surface roughness was measured using SJ-210 model surftest. The surftest measures the surface roughness over the sampling length of 2.5mm. The surface roughness was measured at three places and an average value was taken for the analysis. Experimental results of surface roughness (Ra) and amplitude of cutter vibration (Y) were shown in the Table 3. The experimental data was analyzed with ANOVA to investigate the influence of process parameters on surface roughness and the amplitude of cutter vibration.

Table 2 Specifications of end mill cutter

Cutter Diameter (mm)	Clearance angle (°)	Rake angle (°)	Helix angle(°)	No. of flutes
20	15	12	35	2

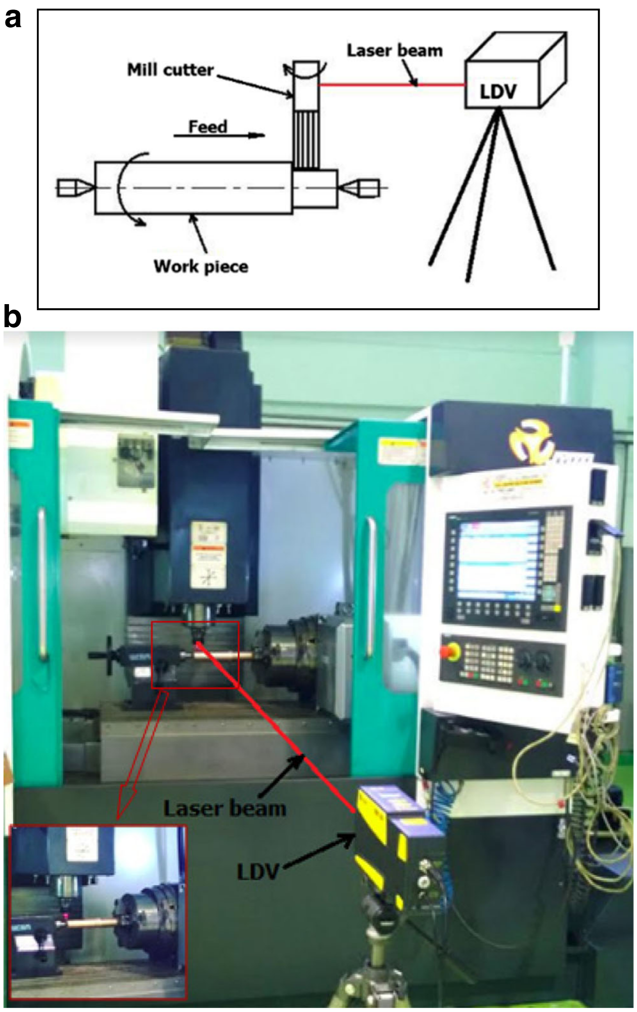

Fig. 1 **a** Orthogonal turn milling on cylindrical workpiece. **b** Experimental set up for orthogonal milling (PBR Visvodaya Institute of Science and Technology, Kavali-India)

3 Results and Discussion

In this work, LDV was used for online acquisition of cutter vibration data in the form of AOE signals. FFT analyzer was used for generating features from online AOE signals as shown in Fig. 2. The frequency domain spectrograph shows changes in the vibration along with frequency of vibration. In the present study, peak value was taken as the amplitude of cutter vibration. The peak value of amplitude was shown with a vertical red line at 1670Hz of frequency.

3.1 Analysis of Variance (ANOVA)

ANOVA is one of the widely used techniques in the analysis of machining characteristics to investigate the influence of the process parameters. The ANOVA separates the total variability of machining characteristic into contribution of each process parameters and error also. In the ANOVA analysis, SSis the total sum of squared deviation that represents the total deviation in the data [25, 26]. The total sum of squared deviation is used to estimate the contribution of the process parameters in percentage for each performance characteristic. In this ANOVA, variance ratio (F-value) represents significance of process parameters on the machining characteristics. It is calculated as by dividing the mean square with error mean square. The ANOVA was carried out at 95% of confidence level and the process parameters which are having p-value less than 0.05 are said to be significant. At the same time these process parameters should have the F value more than 4 [27, 28].

Table 4 is the ANOVA for the surface roughness that shows the effect of individual process parameters, square of process parameters and interaction of the parameters on the surface roughness. Based on the p-value and F-value, the $v, f, d, v^2, f^2, d^2$and interaction of v and f were found to be significant. The Silicon bronze metal has good machinability, that's why, the three parameters have a significant effect on the surface roughness. Table 4 is the ANOVA for the amplitude of cutter vibration that shows the effect of individual process parameters, square of process parameters and interaction of the amplitude of cutter vibration. Based on the p-value and F-value, the v, f, and interaction of $v$and $f$were found to be significant. Shengguan et al. [29] have studied the effect of process parameters on surface roughness and tool on wear high-strength wear-resisting bronze alloy with YW1 cemented carbide tool and YBC251 coated cemented carbide tool. They found that the feed rate was found to be a most significant parameter on surface roughness and too life than the cutting depth and cutting speed. Mohamed et al. [30] studied surface roughness and mechanical properties in machining of silicon based copper alloy. They found that the feed rate most significant parameter on the surface roughness

3.2 Teaching Learning Based Optimization

In the present study, TLBO was adopted for multi object optimization of process parameters. The TLBO was performed in two phases such as teacher phase and learner phase. In TLBO, the aim of the teacher is to improve average result of the class for a subject which was taught by him. In this method, number of subjects, number of students and their previous results are taken into account to improve mean results of the students. The teacher identifies good learners and allows them to transfer their knowledge to the slow learner to improve overall class result. The proposed method was suggested to solve real life industrial problems [19].

Table 3 Experimental results for five levels of process parameters

S. No.	Design of experiments			Ra(μm)	Y(μm)
	v (m/min)	f (mm/min)	d (mm)		
1	70	3	0.25	4.11	40.13
2	70	5	0.50	4.37	43.63
3	70	7	0.75	4.30	47.22
4	70	9	1.00	4.23	50.81
5	70	11	1.25	4.16	61.55
6	80	3	0.50	4.97	43.31
7	80	5	0.75	4.91	42.13
8	80	7	1.00	5.06	48.05
9	80	9	1.25	4.77	56.46
10	80	11	0.25	6.41	60.05
11	90	3	0.75	5.51	46.58
12	90	5	1.00	5.44	50.17
13	90	7	1.25	5.38	51.38
14	90	9	0.50	6.9	62.06
15	90	11	0.25	7.29	68.09
16	100	3	1.00	6.05	49.85
17	100	5	0.75	6.89	51.00
18	100	7	0.25	7.63	64.18
19	100	9	0.50	7.56	70.16
20	100	11	1.25	6.80	76.13
21	110	3	1.00	6.93	55.51
22	110	5	0.25	8.23	61.48
23	110	7	1.25	7.36	67.57
24	110	9	0.75	8.10	73.43
25	110	11	0.50	8.71	79.40

The process parameters, cutting speed, feed and depth of cut were assumed to be subjects and the experiments were considered to be a number of students. Objective functions were taken as surface roughness and the amplitude of cutter vibration. Twenty five experiments were conducted at five levels of process parameters within the given range. In each experiment, surface roughness and amplitude of cutter vibration are measured and given in the Table 3.

Parameter bounds:

$$\text{Cutting speed:}\quad 50 \leq v \leq 150 \tag{1}$$

$$\text{Feed:}\quad 1 \leq f \leq 12 \tag{2}$$

$$\text{Depth of cut:}\quad 0.25 \leq d \leq 2.0 \tag{3}$$

The objective functions for the surface roughness and amplitude of cutter vibration were derived from the data in the Table 3 using regression analysis. The aim of the

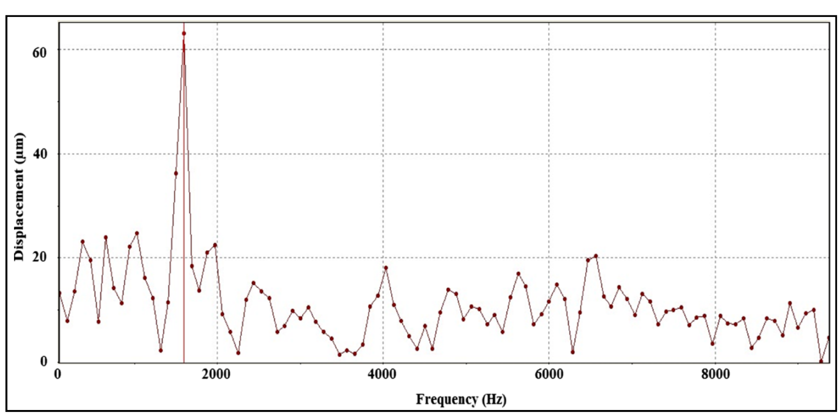

Fig. 2 Frequency domain spectrograph for the first experiment

Table 4 ANOVA for surface roughness and amplitude of cutter vibration

Source	Surface roughness				Amplitude of cutter vibration			
	df	F-Value	P-Value	Remark	df	F-Value	P-Value	Remark
Model	9	545.41	0.000	Significant	9	53.54	0.000	Significant
Linear	3	844.97	0.000	Significant	3	78.24	0.000	Significant
v	1	2358.2	0.000	Significant	1	82.50	0.000	Significant
f	1	250.40	0.000	Significant	1	76.29	0.000	Significant
d	1	212.62	0.000	Significant	1	0.12	0.738	Not significant
Square	3	6.07	0.013	Significant	3	3.40	0.062	Not significant
v*v	1	6.09	0.033	Significant	1	4.51	0.060	Not significant
f*f	1	5.24	0.045	Significant	1	8.82	0.014	Significant
d*d	1	11.25	0.007	Significant	1	0.08	0.781	Not significant
2FI	3	1.87	0.199	Not significant	3	4.11	0.038	Significant
v*f	1	5.18	0.046	Significant	1	4.32	0.042	Significant
v*d	1	1.99	0.189	Not significant	1	4.82	0.053	Not significant
f*d	1	3.60	0.087	Not significant	1	0.00	0.955	Not significant
Error	10				10			
Total	19				19			

present study is to minimize the objectives. There are two constraints considered in this work as the surface roughness and the amplitude of cutter vibration should not cross 3 µm and 60 µm respectively.

Objective functions:

$$\text{Minimize Ra} = -1.80v^{0.0881} f^{0.137} d^{-1.37} \tag{4}$$

$$\text{Minimize Y} = 10.575v^{0.327} f^{2.9867} d^{-9.5338} \tag{5}$$

Constraints:

Surface roughness constraint:

$$-1.80v^{0.0881} f^{0.137} d^{-1.37} \leq 3\mu\text{m} \tag{6}$$

Vibration constraint:

$$10.575v^{0.327} f^{2.9867} d^{-9.5338} \leq 60\mu\text{m} \tag{7}$$

Initial population (Table 5) was set with five experiments to reduce the time required for computation. The five experiments were selected randomly from the Table 3. The average value of the process variables was calculated. The constraints Z_{Ra}, Z_Y and overall constraint violation Z' values were calculated using the Eqs. 8-9 [19].

$$Z_{Ra} = Ra - 3\mu\text{m} \tag{8}$$

$$Z_Y = Y - 60\mu\text{m} \tag{9}$$

$$Z' = \frac{Z_{Ra}}{(Z_{Ra})\,max} + \frac{Z_Y}{(Z_Y)\,max} \tag{10}$$

$(Z_{Ra})max$ and $(Z_Y)max$ were taken as 4.36 and 7.57 respectively to calculate Z' value.

The difference_means for the cutting speed, feed rate and depth of cut were calculated using the process variables in the 1st rank experiment. Random numbers for v, f and d were selected as 0.91, 0.72 and 0.35 respectively, and T_f was taken as 1 to calculate difference_mean for the process variable as follows [19]:

$$\text{difference\_mean for } v = 0.91 * (70 - 90) = -18.2$$
$$\text{difference\_mean for } f = 0.72 * (3 - 5) = -1.44$$
$$\text{difference\_mean for } d = 0.35 * (0.25 - 0.75) = -0.175$$

New process variables (cutting speed, feed rate and depth of cut) and their corresponding surface roughness and

Table 5 Initial population (teacher phase)

S. No.	v	f	d	Ra	Y	Z_{Ra}	Z_Y	Z'	Rank
1	70	3	0.25	4.11	40.13	1.11	0	0.254	1
2	80	5	1.00	5.06	48.05	2.06	0	0.472	2
3	90	6	0.50	6.90	62.06	3.90	2.06	1.166	4
4	100	4	0.75	6.89	51.00	2.89	0	0.662	3
5	110	7	1.25	7.36	67.57	4.36	7.57	2	5
Mean	90	5	0.75						

Table 6 Updated process parameter, responses, constraints and violations (teacher phase)

S. No.	v	f	d	Ra	Y	Z_{Ra}	Z_Y	Z'	Rank
1	51.8	1.56	0.25[a]	2.634	29.78	0	0	0	1
2	61.8	3.56	0.825	3.602	33.54	0.602	0	0.138	2
3	71.8	4.56	0.325	4.705	44.57	1.705	0	0.391	3
4	81.8	2.56	0.575	4.969	39.48	1.969	0	0.451	4
5	91.8	5.56	1.075	5.576	46.94	2.576	0	0.590	5

[a] The values have crossed the limits, hence the bound value was taken

amplitude of cutter vibration values were calculated as follows:

$$v_1 = 70 + (-18.2) = 51.8$$
$$f_1 = 3 + (-1.44) = 1.56$$
$$d_1 = 0.25 + (-0.175) = -0.075$$

$$Ra = -1.80{*}51.8^{0.0881}1.56^{0.137}0.25^{-1.37} = 2.634$$

$$Y = 10.575 * 51.8^{0.327}1.56^{2.9867}0.25^{-9.5338} = 29.78$$

Similarly remain values were also calculated, the updated process parameters and the objective values were given in the Table 6. The values $Z_{Ra,}$, Z_Y and Z^{prime} were also calculated and presented in the Table 6. Based on the Z' value, ranking was given to the experiments.

$(Z_{Ra})max$ and $(Z_Y)max$ were taken as 4.36 and 7.57 respectively to calculate Z' value. The initial solution (Table 5) was combined with updated variables and responses shown in the Table 6 and ranking was assigned to them based on the Z' value. Five experiments were selected based on the non dominance rank and presented in the Table 7.

In the next step, the students can transfer the knowledge with others through interaction, which is called as learner phase. The good rank student/learner will select slow learner randomly and transfers knowledge to improve his/her result. In this section, the interaction was made between, 1 and 2, 2 and 3, 3 and 4, 4 and 5 and 5 and 1 students. New process variables and objective values after interaction were shown in the Table 8.

As it is the minimization function, knowledge was transferred from 1st rank student to the 2nd rank student. Random numbers for v, f and d were selected as 0.86, 0.72 and 0.45 respectively, and new process variables after interaction between 1 and 2 are obtained as follows:

New v = 51.8 + 0.86 × (51.8-61.8) = 43.2

New f = 1.56 + 0.72 × (1.56-3.56) = 0.12

New d = 0.25 + 0.45 × (0.25-0.825) = 0.0087

Similarly, knowledge was transferred between 2 and 3, 3 and 4, 4 and 5 and 5 and 1 students. Table 8 shows the new value of the process parameters after interaction and their corresponding responses. Again, ranking was given for all the experiments based on Z' value. $(Z_{Ra})max$ and (Z_Y) max were taken as 4.36 and 7.57 respectively to calculate Z' value.

Now the process variables and objective values obtained in teacher phase (Table 7) and leaner phase (Table 8) were again combined and presented in the Table 9. In Table 8, process parameters for S. No. 1 and 5 were found to be same, that's why, S. No. 1 was removed in the Table 9. Again, ranking was given based on Z′ value.

As shown in the Table 9, there were three combinations of process parameters given first rank based on Z' value. Now, it is required to calculate the crowding distance for the three combinations to select the best solution. Calculation of crowding distance for surface roughness, amplitude of cutter vibration and overall crowding distance was shown in the Tables 10 and 11. The objective values were arranged in ascending order and the crowding distance was calculated as follows [19]:

Crowding distances CD_6 and CD_1 were calculated as follows:

$$CD_6 = 0 + \frac{(Ra)_1 - (Ra)_7}{(Ra)_{max} - (Ra)_{min}} = 0 + \frac{2.639 - 2.077}{4.969 - 2.077} = 0.108$$

Table 7 Candidate solution based on the non dominance rank (teacher phase)

S. No.	v	f	d	Ra	Y	Z_{Ra}	Z_Y	Z'	Rank
1	51.8	1.56	0.25[a]	2.634	29.78	0	0	0	1
2	61.8	3.56	0.825	3.602	33.54	0.60	0	0.138	2
3	70	3	0.25	4.110	40.13	1.11	0	0.254	3
4	71.8	4.56	0.325	4.705	44.57	1.705	0	0.391	4
5	81.8	2.56	0.575	4.969	39.48	1.969	0	0.451	5

[a] The values have crossed the limits, hence the bound value was taken

Table 8 New process variables and objective values after interaction (learner phase)

S. No.	v	f	d	Ra	Y	Z_{Ra}	Z_Y	Z'	Interaction
1	50.00[a]	1.00[a]	0.25[a]	2.3995	27.52	0	0	0	1 and 2
2	54.74	3.90	1.08	2.0772	29.82	0	0	0	2 and 3
3	68.40	1.87	0.25[a]	4.1397	36.14	1.139	0	0.261	3 and 4
4	63.20	6.0	0.25[a]	4.2474	46.77	1.247	0	0.286	4 and 5
5	50.00[a]	1.00[a]	0.25[a]	2.3995	27.52	0	0	0	5 and 1

[a] The values have crossed the limits, hence the bound value was taken

Table 9 Combination of teaching and learning phases

S. No.	v	f	d	Ra	Y	Z_{Ra}	Z_Y	Z'	Rank	CD
1	51.8	1.56	0.25[a]	2.634	29.78	0	0	0	1	∞
2	61.8	3.56	0.825	3.602	33.54	0.60	0	0.138	2	-
3	70	3	0.25	4.110	40.13	1.11	0	0.254	3	-
4	71.8	4.56	0.325	4.705	44.57	1.705	0	0.391	6	-
5	81.8	2.56	0.575	4.969	39.48	1.969	0	0.451	7	-
6	50.0[a]	1.00[a]	0.25[a]	2.399	27.52	0	0	0	1	∞
7	54.7	3.90	1.08	2.077	29.82	0	0	0	1	∞
8	68.4	1.87	0.25[a]	4.139	36.14	1.139	0	0.261	4	-
9	63.2	6.0	0.25[a]	4.247	46.77	1.247	0	0.286	5	-

Table 10 Calculation of crowding distance for Ra and Y

Surface roughness			Cutter vibration		
S. No.	Ra	CD	S. No.	Y	CD
7	2.077	∞	6	27.52	∞
6	2.399	0.194	1	29.78	0.119
1	2.639	∞	7	29.82	∞

Table 11 Final solutions based on the ranks and crowding distances

S. No.	v	f	d	Ra	CD_{Ra}	Y	CD_Y	Overall CD
1	51.8	1.56	0.25[a]	2.634	∞	29.78	0.119	∞
6	50.0[a]	1.00[a]	0.25[a]	2.399	0.194	27.52	∞	∞
7	54.7	3.90	1.08	2.077	∞	29.82	∞	∞

Table 12 Combination of Initial population, teacher and learner phases

S. No.	v	f	d	Ra	Y
1	70	3	0.25	4.11	40.13
2	80	5	1.00	5.06	48.05
3	90	6	0.50	6.90	62.06
4	100	4	0.75	6.89	51.00
5	110	7	1.25	7.36	67.57
6	51.8	1.56	0.25[a]	2.634	29.78
7	61.8	3.56	0.825	3.602	33.54
8	71.8	4.56	0.325	4.705	44.57
9	81.8	2.56	0.575	4.969	39.48
10	91.8	5.56	1.075	5.576	46.94
11	68.40	1.87	0.25	4.1397	36.14
12	63.20	6.0	0.25	4.2474	46.77

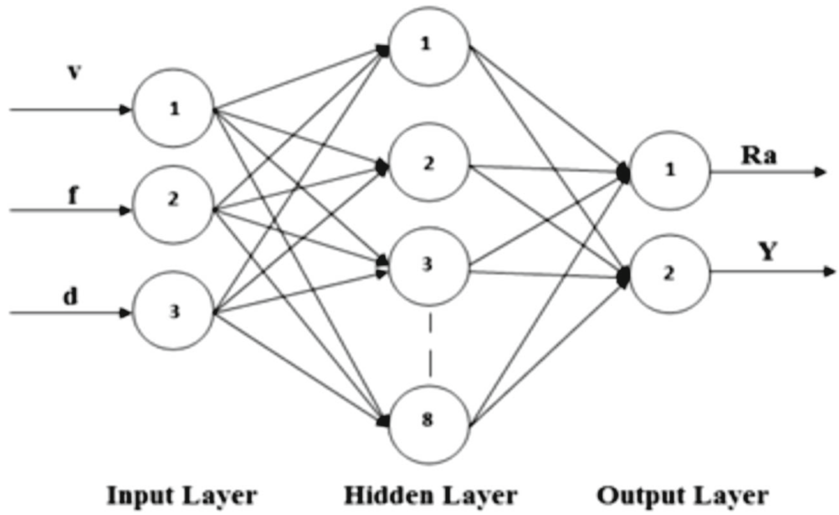

Fig. 3 Neural network architecture (3-8-2)

$$CD_1 = 0 + \frac{(Y)_7 - (Y)_6}{(Y)_{max} - (Y)_{min}} = 0 + \frac{29.82 - 27.52}{46.77 - 27.52} = 0.08$$

Based on the constraints given in the Eqs. 6 and 7, the surface roughness and the amplitude of the cutter vibration were found to be less than the target values of 3µm and 60 µm respectively. The process variables in the Table 11 were said to be better solutions for minimization of objectives.

3.3 Validation of Optimization

The TLBO optimization was validated with ANN technique and experimentally also. Best combinations (1st rank) of process parameters were selected from initial population, teacher and learner phases and presented in the Table 12 to train the ANN.

3.4 Artificial Neural Networks

The ANN is a technique used to predict more than one response simultaneously [31]. In this study, a multilayer perceptron ANN model was developed for surface roughness and amplitude of cutter vibration using Easy NN plus 8.0 software. As shown in the Fig. 3, the ANN model architecture constructed with three layers such as input

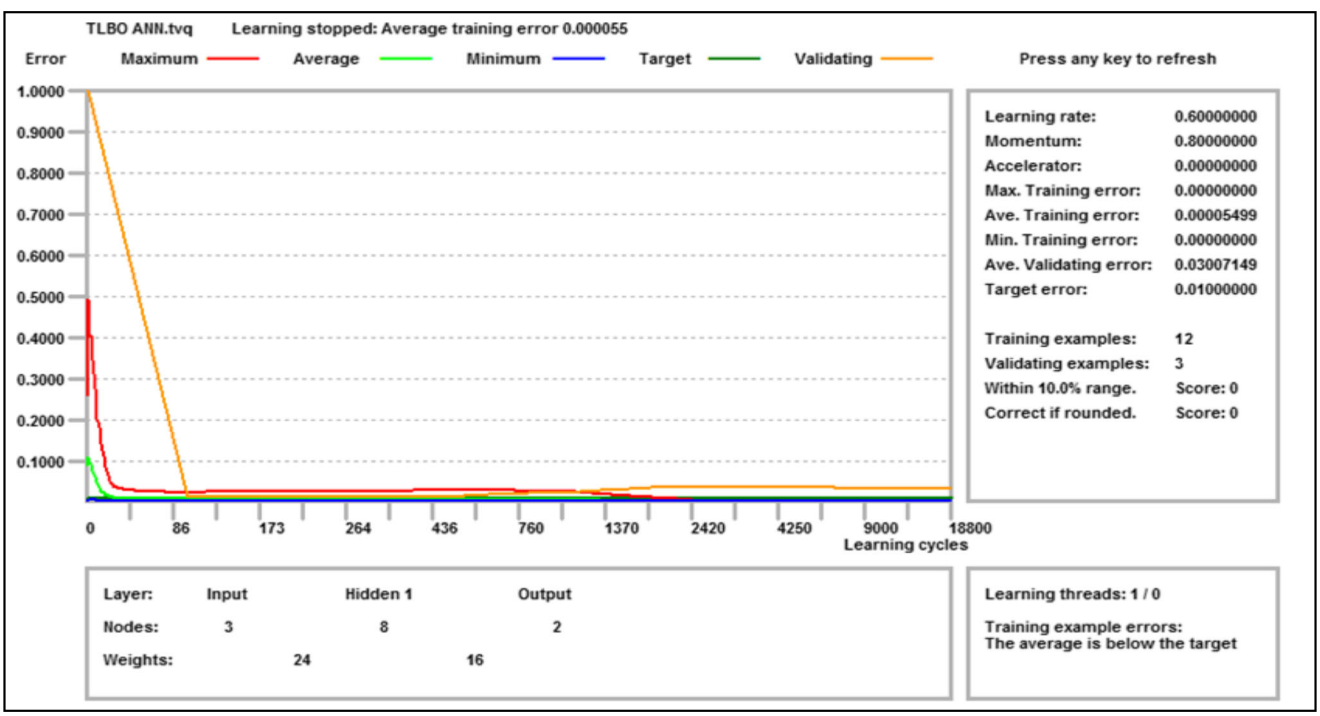

Fig. 4 Training of network with target and training errors

Table 13 Validation of optimization

Optimized process parameters			TLBO		ANN		Experimental	
v	f	d	Ra	Y	Ra	Y	Ra	Y
51.8	1.56	0.25	2.634	29.78	2.937	31.29	2.531	29.10
50.0	1.00	0.25	2.399	27.52	2.541	28.57	2.348	40.76
54.7	3.90	1.08	2.077	29.82	2.186	29.03	2.049	30.95

layer, hidden layer and output layer. The input layer consists of three neurons or nodes named as cutting speed, feed rate and depth of cut, the output layer consists of two neurons termed as surface roughness and amplitude of cutter vibration and the hidden layer consists of eight neurons. Number of neurons in the hidden layer was estimated by examining different neural networks on trial and error method.

The data in the Table 12 were used to train the neural network. A feed forward back propagation algorithm was used to train the proposed network. Information from the neurons of input layer was transmitted to the output layer through neurons of the hidden layer. As shown in the Fig. 4, the training graph was constructed with learning cycles on X axis and target error on Y axis. The red line, green line, blue line, dark green line and orange lines in the graph represent maximum training error, average training error, minimum training error, average validating error and target errors respectively. Training of the ANN was performed by adopting weights for the connections between the neurons. The network was trained at a learning rate of 0.6 and momentum by 0.8. The software itself selected weights for the connections between the input and hidden layers as 24 and 16 for the connections between hidden layer and output layer. Training error for the developed network was set at 0.01 and the training was stopped after 18,000 cycles when the average training error reached the 0.00005499. Surface roughness and amplitude of cutter vibration were predicted for the best three solutions and presented in the Table 13.

Table 13 shows the validation of TLBO of process parameters for minimum surface roughness and amplitude of cutter vibration. Average error between the TLBO optimized values and the ANN predicted values was found to be less than 5%. The ANN was successfully applied in different studies to predict and optimize machining characteristics with less error [20, 31, 32]. The TLBO optimization was validated with experimental results. Again, experiments were conducted with the three best combinations of process parameters. Each experiment was conducted two times, surface roughness and amplitude of cutter vibration were measured. Average values of the surface roughness and amplitude of cutter vibration were presented in the Table 13. Experimental values of surface roughness and amplitude of cutter vibration were found to be having good agreement with the optimized values. The experimental results have verified the results of the proposed approach and have improved the performance of turnmilling.

4 Conclusions

In the present work, process parameters were optimized for minimum surface roughness and amplitude of cutter vibration using an advanced optimization algorithm called as TLBO for orthogonal turn milling of Silicon Bronze metal. Results obtained by the TLBO were validated with the results of ANN. The following conclusions can be drawn from the work:

- The cutting speed, feed rate, depth of cut and interaction of cutting speed and feed rate were found to be significant on the surface roughness.
- The cutting speed, feed rate and interaction of cutting speed and feed rate were found to be significant on the amplitude of cutter vibration.
- Three best combinations of cutting speed, feed and depth of cut were obtained for minimum surface roughness and amplitude of cutter vibration by considering the amplitude of cutter vibration and surface roughness as 60μm (ISO 10816) and 3 μm respectively as constraints. But, the combination of cutting speed of 54.7m/min, feed rate of 3.9m/min and depth of cut of 1.08mm has a low surface roughness with tool vibration of 30.95μm. However remain two combinations were found to be next best optimal cutting conditions.
- The optimization was validated by experimental results. Experimental values of surface roughness and amplitude of cutter vibration were found to be having good agreement with the optimized values. The experimental results have verified the results of the proposed approach and have improved the performance of turnmilling.
- Based on the results and computational time, it can be concluded that the TLBO is an useful tool for multi response optimization of process parameter using less experimental data.

Acknowledgments This work (Major project) was funded by Science and Engineering Research Board, Department of Science and Technology, Government of India. Grant No.: SERB/F/1761/2015-16.

References

1. Milling Technical Guide. Sandvik Coromant, http://www.coromant. Sandvik.com. Accessed in May 2017
2. Yan R, Tang X, Peng FY, Wang Y, Qiu F (2016) The effect of variable cutting depth and thickness on milling stability for orthogonal turn-milling. Int J Adv Manuf Technol 82:765–777
3. Ramaswamy N (1968) Koeningsberger Experiments with Self propelled rotary cutting tools. In: Proceedings of 9th IMTDR conference, Part, vol 2, pp 945–959
4. Savas V, Ozay C (2008) The optimization of the surface roughness in the process of tangential turn-milling using genetic algorithm. Int J Adv Manuf Technol 37:335–340
5. Ren J, Zhou J, Zeng J (2015) Analysis and optimization of cutter geometric parameters for surface integrity in milling titanium alloy using a modified grey–Taguchi method. Proc Inst Mech Eng Part B: J Eng Manuf 230(11):2114–2128
6. Sivasakthivel PS, Sudhakaran R, Rajeswari S (2013) Optimization of machining parameters to minimize vibration amplitude while machining Al 6063 using gray-based Taguchi method. Proc Inst Mech Eng Part B: J Eng Manuf 227(12):1788–1799
7. Kono D, Moriya Y, Matsubara A (2017) Influence of rotary axis on tool-workpiece loop compliance for five-axis machine tools. Precision Eng 49:278–286
8. Ratnam Ch, Vikram KA, Ben BS, Murthy BSN (2016) Process monitoring and effects of process parameters on responses in turn-milling operations based on SN ratio and ANOVA. Measurement 94:221–232
9. Jalili MM, Hesabi J, Abootorabi MM (2017) Simulation of forced vibration in milling process considering gyroscopic moment and rotary inertia. Int J Adv Manuf Technol 89:2821–2836
10. Zahoor S, Mufti NA, Saleem MQ, Mughal MP, Qureshi MAM (2017) Effect of machine tool's spindle forced vibrations on surface roughness, dimensional accuracy, and tool wear in vertical milling of AISI p20. Int J Adv Manuf Technol 89:3671–3679
11. Khalili K, Danesh M (2015) Identification of vibration level in metal cutting using undecimated wavelet transform and gray-level co-occurrence matrix texture features. Proc Inst Mech Eng Part B: J Eng Manuf 229(2):205–213
12. Venkatarao K, Murthy BSN, Mohanrao N (2013) Cutting tool condition monitoring by analyzing surface roughness, work piece vibration and volume of metal removed for AISI 1040 steel in boring. Measurement 46:4075–4084
13. Hessainia Z, Belbah A, Yallese MA, Mabrouki T, Rigal J-F (2013) On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations. Measurement 46(5):1671–1681
14. Subramanian M, Sakthivel M, Sooryaprakash K, Sudhakaran R (2013) Optimization of end mill tool geometry parameters for Al7075-T6 machining operations based on vibration amplitude by response surface methodology. Measurement 46(10): 4005–4022
15. Zhou J, Ren J, Yao C (2017) Multi-objective optimization of multi-axis ball-end milling Inconel 718 via grey relational analysis coupled with RBF neural network and PSO algorithm. Measurement 102:271–285
16. Rao RV, Kalyankar VD (2013) Multi-pass turning process parameter optimization using teaching–learning-based optimization algorithm. Scientia Iranica E 20(3):967–974
17. Rao KV, Murthy PBGSN, Vidhu KP (2017) Assignment of weightage to machining characteristics to improve overall performance of machining using GTMA and utility concept CIRP. J Manuf Sci Technol. https://doi.org/10.1016/j.cirpj.2016.12.001
18. Cheema MS, Dvivedi A, Sharma AK (2013) A hybrid approach to multicriteria optimization based on user's preference rating. Proc I Mech E Part B: J Eng Manuf 227(11):1733–1742
19. Rao RV (2015) Teaching learning based optimization algorithm and its engineering application, Springer publishing company, 2nd chap, 1st edn. ISBN: 3319227319 9783319227313
20. Rao KV, Murthy PBGSN (2016) Modeling and optimization of tool vibration and surface roughness in boring of steel using RSM. ANN and SVM. J Intell Manuf. https://doi.org/10.1007/s10845-016-1197-y
21. Yildiz AR (2013) Hybrid Taguchi-differential evolution algorithm for optimization of multi-pass turning operations. Appl Soft Comput 13(3):1433–1439
22. Yildiz AR (2013) A new hybrid differential evolution algorithm for the selection of optimal machining parameters in milling operations. Appl Soft Comput 13(3):1561–1566
23. Yildiz AR (2013) Optimization of multi-pass turning operations using hybrid teaching learning-based approach. Int J Adv Manuf Technol 66(9–12):1319–1326
24. https://www.astm.org/Standards/B98.htm viewed on 10-03-2018
25. Rao PS, Gupta OP, Murty SSN, Rao ABK (2009) Effect of process parameters and mathematical model for the prediction of bead geometry in pulsed GMA welding. Int J Adv Manuf Technol 45:496–505
26. Sivaiah P, Chakradhar D (2018) Analysis and modeling of cryogenic turning operation using response surface methodology. Silicon. https://doi.org/10.1007/s12633-018-9816-1
27. Balaji M, Murthy BSN, Rao NM (2018) Multi response optimization of cutting parameters in drilling of AISI 304 stainless steels using response surface methodology. Proc I Mech E Part B: J Eng Manuf 232(1):151–161
28. Prasad Babu GHV, Murthy BSN, Rao KV, Ratnam Ch (2017) Multi response optimization in orthogonal mill turning by analysing tool vibration and surface roughness using response surface methodology. Proc Inst Mech Eng Part B: J Eng Manuf 231(12):2084–2093
29. Qu S, Sun F, Zhang L, Li X (2014) Effects of cutting parameters on dry cutting of aluminum bronze alloy. Int J Adv Manuf Technol 70(1–4):669–678
30. Taha MA, El-Mahallawy NA, Hammouda RM, Moussa TM, Gheith MH (2012) Machinability characteristics of lead free-silicon brass alloys as correlated with microstructure and mechanical properties. Ain Shams Eng J 3:383–392
31. Kianfar E, Shirshahi M, Kianfar F, Kianfar F (2018) Simultaneous prediction of the density, viscosity and electrical conductivity of pyridinium-based hydrophobic ionic liquids using artificial neural network. Silicon. https://doi.org/10.1007/s12633-018-9798-z
32. Khan A, Maity K (2018) A comprehensive GRNN model for the prediction of cutting force, surface roughness and tool wear during turning of CP-Ti grade 2. Silicon. https://doi.org/10.1007/s12633-017-9749-0