Optimization of process parameters in CNC turning of aluminium alloy using hybrid RSM cum TLBO approach

R R Rudrapati¹, P Sahoo² and A Bandyopadhyay³

¹Mechanical Engineering Department, G.H. Raisoni College of Engineering & Management, Pune, –412207, India
E-mail: rameshrudrapati@gmail.com

²Mechanical Engineering Department, IIT Patna -801103, India
E-mail: sahoopriyabatra89@gmail.com

³Mechanical Engineering Department, Jadavpur University, Kolkata - 700032, India
E-mail: asishbanerjee@gmail.com

Abstract. The main aim of the present work is to analyse the significance of turning parameters on surface roughness in computer numerically controlled (CNC) turning operation while machining of aluminium alloy material. Spindle speed, feed rate and depth of cut have been considered as machining parameters. Experimental runs have been conducted as per Box-Behnken design method. After experimentation, surface roughness is measured by using stylus profile meter. Factor effects have been studied through analysis of variance. Mathematical modelling has been done by response surface methodology, to made relationships between the input parameters and output response. Finally, process optimization has been made by teaching learning based optimization (TLBO) algorithm. Predicted turning condition has been validated through confirmatory experiment.

1. Introduction
Aluminum alloy are widely used for demanding various industrial applications [1] due to good combination of formability, light weight, strength, recyclability, durability, ductility, conductivity, corrosion resistances and mechanical properties [2, 3]. Because of these unique combinations of the excellent properties, the usage of various aluminum alloy materials in industries is increasing drastically. Aluminum alloys are generally made by near net manufacturing processes, so these materials required machining operation to get the required / desired shape, size, and dimension for its effective utilization in its operation. Machining parameters like depth of cut, spindle speed, feed, application of cutting fluid, generated vibration during machining etc., are expected to influence much on machined part(s). Improving the surface qualities of aluminum alloy is important area of research [4, 5].
The machining operation is used to bring the work piece at the required surface quality and geometry with the use the cutting tool with maximum performance during its lifetime [6]. The performance of the metal cutting operations may be affected from several parameters [4] like geometry of cutting tool, material properties, machine and cutting parameters, vibrations during operation, cutting forces, etc. Among the other parameters, cutting variables can play very important role for obtaining desired quality characteristics like surface roughness [7]. Minimizing surface roughness is of great importance for any metal cutting industries. Computer numerically controlled (CNC) turning is one of the fully automated operation that provides better improvement of productivity with constant good quality parts. Due to many advantages, CNC turning has been proved to be very versatile and useful machining operation in most of the modern manufacturing industries. In CNC turning process, surface roughness of the turned part is greatly influenced by process parameters. One has to control and optimize the process variables to obtain desired surface roughness value.

Surface roughness is universally accepted and most frequently used as indicator for the quality machined parts [8]. Surface roughness is a key factor in the machining process while considering machined part performance in its application and a factor that greatly influences manufacturing cost and quality [9]. It describes the geometry of the machined surface and combined with the surface texture. Surface finish influences the performance of a machine part like fatigue strength, wear resistance, strength of interference fit, corrosion resistance, heat transfer characteristics, coating characteristics etc. However, the mechanism behind the formation of micro irregularity is complicated, dynamic and process dependent, which is a crucial aspect directly linked to various parameters [10, 11] etc. Fishbone diagram with the various parameters those influence the surface roughness is shown in Figure 1. Among the other variables, process parameters can influence much on surface roughness as already mentioned earlier. Many machinists are using trial and error methods for setting cutting conditions in machines achieving the desired surface finish. This method is not efficient more over it is time consuming.

Investigators proposed and used various theoretical and experimental models to estimate the correct choice of input parameters to obtain desired surface roughness levels. Several researchers had reported articles on optimization of turning and CNC turning operation using various optimization techniques. Some of the reported articles have been discussed as follows.
Jayaraman and Kumar [5] had optimized machining parameters in turning of AA 6063 T6 aluminium alloy to predict desired responses: surface roughness, roundness and material removal rate. They stated from their study that feed rate, depth of cut are prominent factors which affect the quality characteristics of aluminium alloy turning. Abouluelatta and Madl [13] had developed mathematical model for surface roughness based on cutting parameters and machine tool vibrations. Upadhyay et al. [14] had been made an attempt to use vibration signals for in-process prediction of surface roughness during turning of Ti–6Al–4V alloy. Surface roughness was predicted by using acceleration amplitude of vibration in axial, radial and tangential direction.

Horvath and Agota [1] had done an experimental investigation for turning of two types of aluminium materials by using diamond tool to maximize productivity and minimize surface roughness. Tangjitsitcharoen and Moriwak [15] had developed a method to monitor and identify the states of cutting for CNC turning based on a pattern recognition technique. Dhabale et al. [16] developed an empirical model for predicting material removal rate and surface roughness in terms of spindle speed, feed rate and depth of cut using multiple regressions modelling method. Experiments were carried out on NC controlled machine tool by taking AlMg1SiCu as workpiece material and carbide inserted cutting tool. A non-dominated sorted genetic algorithm had been employed to find out the optimal setting of process parameters that simultaneously maximized material removal rate and minimized surface roughness.

The teaching-learning-based optimization (TLBO) algorithm is finding a large number of applications in different fields of engineering and science since its introduction in 2011 [17]. It proved its effectiveness in solving and providing global optimum conditions for machining processes [18]. Abhishek et al. [19] utilized TLBO to determine the most favorable parametric condition to predict desired responses: material removal rate, surface roughness and cutting

---

**Figure 1.** Fishbone diagram with the parameters that affect surface roughness [12]
force in turning of carbon fibre epoxy composite material. Yildiz [18] presented a TLBO cum Taguchi method based on hybrid approach to optimize multi-pass turning operation and found better results. Wenwen et al. [20] had minimized carbon emissions and operation time in turning operations by controlling cutting parameters with the use of multi objective teaching learning based optimization.

Present work is planned to study the significance of turning parameters on surface roughness of aluminium material in CNC turning operation. Response surface methodologies Box-Behnken design has been used to plan the experiments. Analysis, Modelling, and optimization of surface roughness have been done based on RSM combined with recently developed advanced optimization technique TLBO.

2. Response surface methodology and teaching learning based optimization

Response surface methodology (RSM) is a collection of mathematical and statistical procedures that are useful for modelling and analysis of problem, where output response is expected by various process variables and the objective is to optimize the response. RSM is very useful to find the operating conditions that produce the best response and identify new operating conditions that produce improved part qualities over the qualities achieved. In RSM, the mathematical model is developed to develop the relationships between the process variable and response. In the RSM, the quantitative form of relationship between the desired response and independent input variables can be presented as follows

\[ Y = f(A, B, C) \]  

where, A, B, C are input parameters and Y is the response variable,

The full quadratic model of the three factors is shown in Eq.2 [21].

\[ Y = \beta_0 + \beta_1 (A) + \beta_2 (B) + \beta_3 (C) + \beta_{11} (A^2) + \beta_{22} (B^2) + \beta_{33} (C^2) + \beta_{12} (AB) + \beta_{13} (AC) + \beta_{23} (BC) \]  

The betas are coefficients of linear, quadratic and interaction of input parameters A, B and C. The term \( \beta_0 \) is the intercept term, \( \beta_1, \beta_2 \) and \( \beta_3 \) are the liner terms, \( \beta_{11}, \beta_{22} \) and \( \beta_{33} \) are the squared terms, and \( \beta_{12}, \beta_{13} \) and \( \beta_{23} \) are the interactions between the independent / input variables. This empirical model is useful to determine the optimum parametric condition to obtain desired response variable.

Teaching-learning-based optimization algorithm (TLBO) is a teaching-learning process inspired algorithm proposed by Rao et al. [22], which is based on the effect of influence of a teacher on the output of learners in a class. 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).
The working of TLBO is divided into two parts, teacher phase and learner phase. Working of both the phase is explained below.

**Teacher phase:** It is first part of the algorithm where learners learn through the teacher. During this phase a teacher tries to increase the mean result of the classroom from any value $M_1$ to his or her level (i.e. $T_A$). But practically it is not possible and a teacher can move the mean of the classroom $M_1$ to any other value $M_2$ which is better than $M_1$ depending on his or her capability. Considering $M_j$ is the mean and $T_i$ be the teacher at any iteration $i$, now $T_i$ will try to improve existing mean $M_j$ towards it so the new mean will be $T_i$ designated as $M_{new}$ and the difference between the existing mean and new mean is given in Eq. 3 [23]

$$\text{Difference}_\text{Mean}_i = r_i (M_{new} - T_i M_j)$$

where $T_F$ is the teaching factor which decides the value of mean to be changed, and ‘$r_i$’ is the random number in the range [0, 1]. Value of $T_F$ can be either 1 or 2 which is a heuristic step and it is decided randomly with equal probability as:

$$T_r = \text{round } [1 + \text{rand}(0,1) \{2 -1\}]$$

The teaching factor is generated randomly during the algorithm in the range of 1-2, in which 1 corresponds to no change in the knowledge level, and 2 corresponds to complete transfer of knowledge. To simplify the algorithm the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria by neglecting in between values. However, one can take any value of $T_F$ in between 1-2.

Based on this Difference_Mean, the existing solution is updated by using Eq. 5.

$$X_{new,i} = X_{old,i} + \text{Difference}_\text{Mean}_i$$

where $X_{new,i}$ = new solution; $X_{Old,i}$ = existing solution / solution in the $i^{th}$ iteration

**Learner phase:** It is second part of the algorithm where learners increase their knowledge by interaction among themselves. A learner interacts randomly with other learners for improving his or her knowledge level. A learner learns new things if the other learner has more knowledge than him or her. Mathematically the learning phenomenon of this phase is expressed below.

At any iteration $i$, considering two different learners $X_i$ and $X_j$ where $i \neq j$

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

$$X_{new,j} = X_{old,j} + r_i (X_j - X_i) \quad \text{if } f(X_j) < f(X_i)$$

Accept $X_{new}$ if it gives better function value.

where $X_i$ and $X_j$ are two independent learners with different knowledge in the class, those have interact mutually to update their knowledge.
2.1 Scheme of investigation

Hybrid optimization approach used in the present work includes the following steps:
1. Identify the performance characteristics and turning parameters
2. Determine the number of levels for the turning parameters.
3. Select the appropriate number of experiments, and assign the input parameters to the Box-Behnken design.
4. Conduct the experimental runs based on the Box-Behnken design matrix
5. Measure the surface roughness ($R_a$)
6. Surface roughness modelling by using RSM
7. Study the effects of input parameters on surface roughness by analysis of variance technique
8. Predict the optimum turning condition to minimize surface roughness by teaching learning based optimization (TLBO)
9. Verify the optimal turning variables through the confirmation experiment.

3. Experimentation

Turning experiments are conducted on a CNC turning machine at G.C. Sen Memorial Machine Tool Research Laboratory, Mechanical Engineering Department, Jadavpur University, with the aim of studying the effects of turning variables on surface roughness. The selected process parameters and their ranges and Box-Behnken design matrix for experimentation are shown in Table 1 and Table 2 respectively. The experimental set up is shown in Fig. 2. After machining operation, surface roughness is measured by using Taylor Habson’s stylus type instrument. Surface roughness is selected as output responses, as it is universally accepted and used parameter for general quality control of the machined or turned part. Surface roughness has been measured in three different places of each work piece and the average value has been considered.

![Photographic view of CNC lathe used for experiment](image)

Figure 2. Photographic view of CNC lathe used for experiment
### Table 1. Process parameters and their levels

| Input parameters | Levels               |
|------------------|----------------------|
|                 | Level 1 | Level 2 | Level 3          |
| Spindle speed (A) | 600 rpm | 650 rpm | 700 rpm          |
| Feed rate (B)    | 25 mm/min | 37.5 mm/min | 50 mm/min          |
| Depth of cut (C)  | 0.2 mm | 0.3 mm | 0.4 mm          |

### 4. Results and analysis

Experimental runs have been conducted as per RSM’s Box-Behnken design matrix by considering three factor-three levels of input parameters and the corresponding output response i.e. surface roughness, is measured and shown in Table 2. The data shown in the Table 2 has been used to analyze and optimize the CNC turning process to minimize surface roughness value by using RSM along with teaching learning based optimization algorithm.

#### 4.1 Surface roughness modeling and optimization

RSM, which consists of collection of mathematical and statistical techniques for empirical model building, is used in the present study to postulate the mathematical relationships between the response variable (surface roughness) and input variables. General model of second order mathematical model is shown in Eq. 2. The values of all the constants $\beta_0$, $\beta_1$, $\beta_2$, $\beta_3$, $\beta_{11}$, $\beta_{22}$, $\beta_{33}$, $\beta_{12}$, $\beta_{13}$ and $\beta_{23}$ are determined by least square method using experimental data. The developed model is the following.

$$
Y_{Ra} = -17.220 + 0.053*A – 0.018*B + 5.241*C – 4.093E-005*A^2 + 5.530E-004*B^2 – 7.783*C^2 +1.20000E-06 *(A* B) -2.00000E-04 *(A* C) -0.00580000*( B*C)
$$

Where $R_a = $ response in micron, $A = $ Spindle speed in rpm, $B = $ feed rate in mm/min and $C = $ depth of cut in mm.

The adequacy of the developed model (Eq.8) is checked with analysis of variance.

#### 4.1.1. Analysis of variance

Analysis of variance (ANOVA) is a statistical technique used to check the adequacy of the model (Eq. 8) developed through response surface methodology. ANOVA from MINITAB 16.1 software, applied on experimental data and ANOVA table for surface roughness is shown in Table 4. ANOVA test is conducted at 95% confidence level i.e. 5% significant level. If probability value (i.e. P value) is less than 0.05 then the corresponding variables treated as significant. If P value is greater 0.05, those parameters considered to be insignificant at 95% confidence level.
Table 2. Box-Behnken design table and output response

| S.No. | Process parameters | Surface Roughness μm |
|-------|--------------------|----------------------|
|       | Spindle speed (A)  | Feed rate (B)        | Depth of cut (C) |
| 1     | 600                | 37.5                 | 0.4              | 0.749 |
| 2     | 650                | 37.5                 | 0.3              | 0.905 |
| 3     | 600                | 37.5                 | 0.2              | 0.704 |
| 4     | 600                | 50.0                 | 0.3              | 1.167 |
| 5     | 650                | 25.0                 | 0.4              | 0.653 |
| 6     | 700                | 50.0                 | 0.3              | 0.589 |
| 7     | 700                | 25.0                 | 0.3              | 1.163 |
| 8     | 650                | 50.0                 | 0.2              | 1.168 |
| 9     | 650                | 50.0                 | 0.4              | 1.200 |
| 10    | 600                | 25.0                 | 0.3              | 0.596 |
| 11    | 650                | 25.0                 | 0.2              | 0.592 |
| 12    | 650                | 37.5                 | 0.3              | 0.893 |
| 13    | 700                | 37.5                 | 0.2              | 0.682 |
| 14    | 700                | 37.5                 | 0.4              | 0.723 |
| 15    | 650                | 37.5                 | 0.3              | 0.886 |

The value of $R^2$ and adjusted $R^2$ of the developed model is (more than 99 %) shown in Table 4. The $R^2$ and adj $R^2$ in the table indicates that the regression model provides an excellent explanation of the relationship between the independent variables (factors) and the response (Surface Roughness).

From the ANOVA table for surface roughness as shown in Table 4, it is noted that individual effects of feed rate (B) and depth of cut (C), square combinations of all the factors: spindle speed (A), feed rate (B) and depth of cut (C) are most significant, as its P values are zero. Direct effect of spindle speed (A) is found to be insignificant as its P value more than 0.05. Response variable surface roughness is not influenced by process parameters, in case of interaction of the process parameters concerned, as their significant value of greater than 0.05.
### Table 3. ANOVA table for surface roughness

| Source   | DOF | Sum Square | Mean square | F-value | P-value |
|----------|-----|------------|-------------|---------|---------|
| Model    | 9   | 0.74       | 0.082       | 974.92  | 0.0001  |
| A        | 1   | 4.351E-004 | 4.351E-004 | 5.15    | 0.0725  |
| B        | 1   | 0.64       | 0.64        | 7610.71 | 0.0001  |
| C        | 1   | 4.005E-004 | 4.005E-004 | 47.41   | 0.0010  |
| A^2      | 1   | 0.039      | 0.039       | 457.68  | 0.0001  |
| B^2      | 1   | 0.028      | 0.028       | 326.38  | 0.0001  |
| C^2      | 1   | 0.022      | 0.022       | 264.76  | 0.0001  |
| A*B      | 1   | 2.250E-006 | 2.250E-006 | 0.027   | 0.8768  |
| A*C      | 1   | 4.000E-004 | 4.000E-004 | 0.047   | 0.8363  |
| B*C      | 1   | 2.102E-004 | 2.102E-004 | 2.49    | 0.1755  |
| Res.     | 5   | 4.224E-004 | 8.448E-005 | -       | -       |
| Lack     | 3   | 2.377E-004 | 7.925E-005 | 0.86    | 0.5778  |
| Pure     | 2   | 1.847E-004 | 9.233E-005 | -       | -       |
| Total    | 14  | 0.74       | R² = 0.9994; R² adj = 0.9984 |

#### 4.1.2 Main effect plots:  The main effect plots are drawn based on mean values of surface roughness with use of MINITAB 16.1 software and given in Figure 3.

![Main effect plots for surface roughness](image)

From the main effect plots (Figure 3), it is found that surface roughness of aluminium alloy is increasing and then decreasing with increase of spindle speed and depth of cut. Surface roughness is increasing with increase of feed rate as found from the Figure 3. Main effect
plots of aluminium alloy turning show that direct effects of turning variables are prominent on surface roughness.

The above mathematical model can be used to select the optimum conditions i.e. the input parameters for obtaining the desired surface roughness ($R_a$) within the limits of input parameters. Teaching learning based optimization algorithm has been used to solve the Eq. 8 to optimize the turning parameters to obtain minimum surface roughness ($R_a$) in CNC turning of aluminium alloy. Optimization of machining parameters helps machining economics in addition to achieving the desired results [24].

4.2 Optimization by TLBO

Basic details of the TLBO is explained earlier in section 2, the more details about TLBO is available in literature [22, 23, 25]. The execution steps for TLBO technique is given below.

Step 1: Initialization of population (i.e. learners’) and design variables of the optimization problem (i.e. number of subjects offered to the learner) with random generation and evaluate them.
Step 2: Selecting the best learner of each subject as a teacher for that subject and calculating the mean result of learners in each subject.
Step 3: Evaluating the difference between current mean result and best mean result according to Eq. 3 by utilizing the teaching factor (TF).
Step 4: Updating the learners’ knowledge with the help of teacher’s knowledge according to Eq. 5
Step 5: Updating the learners’ knowledge by utilizing the knowledge of some other learner according to Eqs. 6 and 7.
Step 6: Repeating the procedure from step 2 to step 5 till the termination criterion is met.

In each of the TLBO runs, optimal parametric condition and the corresponding output response value are produced. The obtained individual optimal parametric condition by TLBO for minimization of surface roughness is shown in Table 5.

5. Confirmatory test

Confirmatory test has been performed at predicted parametric setting obtained by TLBO as shown in Table 5, and found that predicted optimum turning condition is produced minimum roughness value as compared to initial experiments.

Table 5. Optimum parametric setting by TLBO and confirmatory test result
| S.No | Optimum input parameters | Predicted output response by TLBO | Obtained response by experimentation |
|------|--------------------------|-----------------------------------|--------------------------------------|
| 1    | Spindle speed (A)        | 700 rpm                           | Surface roughness = 0.42081 μm       |
|      |                          |                                   | Surface roughness = 0.442 μm         |
| 2    | Feed rate (B)            | 25 mm/min                          |                                      |
| 3    | Depth of cut (C)         | 0.2 mm                             |                                      |

6. Conclusions

Based on the scope and limitations of the present work, the following conclusions may be drawn from the results of the experiments and analysis of the experimental data in connection with CNC turning of aluminium alloy:

1. Second order mathematical model is developed for surface roughness by response surface methodology (RSM).
2. From ANOVA results, it is found that feed rate and depth of cut, and square combinations of all the parameters are significant on surface roughness.
3. Optimal parametric condition obtained teaching learning based optimization (TLBO) is: spindle speed = 700 rpm, feed rate = 25 mm/min and depth of cut = 0.2 mm and corresponding surface roughness is 0.42081 μm.
4. Confirmatory test results prove the predicted parametric condition.
5. From the present analysis it is found that hybrid RSM cum TLBO is very useful to optimize surface roughness in CNC turning of aluminium alloy.

References

1. Horváth R and Ágota D K 2015 Analysis of surface roughness of aluminum alloys fine turned: united phenomenological models and multi-performance optimization. *Measurement* 65 181–192
2. Prabakaran M P, Kannan G R, Thirupathi K and Hari prakash A 2014 Optimization turning process parameters of aluminum alloy 5083 using response surface methodology. *International Journal of Engineering Research & Technology* 3
3. Narayana B D and Chetana S B 2013 Optimization of cutting parameters for turning aluminium alloys using Taguchi method. *International Journal of Engineering Research & Technology* 2 1399-1407

4. Ali A and Rajamony B 2014 Optimization of cutting parameters for surface roughness in CNC turning machining with aluminum alloy 6061 material. *IOSR Journal of Engineering* 10 1-15

5. Jayaraman P and Kumar L M 2014 Multi-response optimization of machining parameters of turning AA6063 T6 aluminium alloy using grey relational analysis in Taguchi method. *Procedia Engineering* 97 197-204

6. Nalbant M, Hasan G, Ihsan and Go’khan S 2009 The experimental investigation of the effects of uncoated, PVD- and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks. *Robotics and Computer-Integrated Manufacturing* 25 211 – 223

7. Rudrapati R, Asish B and Pal P K 2011 Investigation on surface roughness in cylindrical grinding. American Institute of Physics (AIP) Conference Proceedings, USA 1315 1359-1364.

8. Garcia P E, Nunez P J, Salgado D R, Cambero I, Olivenza J M H and Sanz C J G 2013 Surface finish monitoring in taper turning CNC using artificial neural network and multiple regression methods. *The Manufacturing Engineering Society International Conference* 63 599-607

9. Wang Z, Meng H and Fu J 2010 Novel method for evaluating surface roughness by grey dynamic filtering. *Measurement* 43 (1) 78–82

10. Ahilan C, Somasundaram K, Sivakumaran N and Edwin R J D 2013 Modeling and prediction of machining quality in CNC turning process using intelligent hybrid decision making tools. *Applied Soft Computing* 13 1543–1551

11. Boothroyd G and Knight W A 1989 Fundamentals of Machining and Machine Tools, Marcel-Dekker, New York 1989

12. Benardos P G and Vosniakos G C 2002 Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments. *Robotics and Computer-Integrated Manufacturing* 18 343-354

13. Abouluelatta OB and Madl J 2001 Surface roughness prediction based on cutting parameters and tool vibrations in cutting operations. *Journal of Materials Processing Technology* 118 269-277

14. Upadhayay V, Jain P K and Mehta N K 2013 In-process prediction of surface roughness in turning of Ti–6Al–4V alloy using cutting parameters and vibration signals. *Measurement* 46 154-160
15. Tangjitsitcharoen S and Moriwak T 2008 Intelligent monitoring and identification of cutting states of chips and chatter on CNC turning machine. Journal of Manufacturing Processes 10 40-46

16. Dhabale R, Jatti V K S and Singh TP 2014 Multi-objective optimization of turning process during machining of AlMg1SiCu using non-dominated sorted genetic algorithm. Procedia Materials Science 6 961-966

17. Rao R V 2016 Review of applications of TLBO algorithm and a tutorial for beginners to solve the unconstrained and constrained optimization problems. Decision Science Letters 5(1) 1-30

18. Yildiz A R 2013 Optimization of multi-pass turning operations using hybrid teaching learning-based approach. International Journal of Advanced Manufacturing Technology 66 1319-1326

19. Abhishek K, Rakesh K V, Saurav D, Siba S M 2015 Parametric appraisal and optimization in machining of CFRP composites by using TLBO (teaching–learning based optimization algorithm). Journal of Intelligent Manufacturing

20. Wenwen L, Yu D Y, Wang S, Chaoyong Z, Sanqiang Z, Huiyu T, Min L and Shengqiang L 2015 Multi-objective teaching–learning-based optimization algorithm for reducing carbon emissions and operation time in turning operations. Engineering Optimization 47

21. Rudrapati R, Pal P K and Asish B 2012 Modeling of surface roughness in cylindrical grinding. International Journal of Machining and Machinability of Materials 12 28-36

22. Rao R V, Savsani V J, Vakharia DP 2011 Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. Computer Aided Design 43 303–315

23. Rao R V, Savsani VJ and Vakharia D P 2012 Teaching–learning-based optimization: an optimization method for continuous non-linear large scale problem. Information Sciences 183 1–15.

24. Rudrapati R, Pal P K and Asish B 2016 Modeling and optimization of machining parameters in cylindrical grinding process. International Journal of Advanced Manufacturing Technology 82 2167-2182

25. Rao R V and Kalyankar V D 2013 Parameter optimization of modern machining processes using teaching–learning-based optimization algorithm. Engineering Applications of Artificial Intelligence 26 524 –531