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Comparative Study to Optimize Surface Roughness of the Titanium Alloy Ti-6Al-4V by Applying Taguchi, RSM and TLBO Methods

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Abstract

Titanium alloys are used in aeronautics and the shipbuilding industry for their good intrinsic properties, namely low density (40% less than steel), very good mechanical properties and resistance to corrosion. The purpose of this study is to optimize the cutting conditions during the turning of Ti-6Al-4V titanium alloy with Minimum of Quantity of Lubrication (MQL) conditions leading to minimize the surface roughness (*Ra*). The tests were carried out according to a Taguchi L18 design plan by varying four input factors namely: the cutting speed, the feed rate, the depth of cut and the cutting tool material (coated carbide with (PVD) (GC1125) and uncoated carbide (H13A)). Analysis of variance (ANOVA) was used to found the contribution of each factor and to determine which parameters had a significant influence on the surface roughness. The treatment of the results made it possible to propose a mathematical model, which allows predicting *Ra*. In addition, Taguchi Signal/Noise (*S*/*N*) analysis was used in order to optimize the cutting conditions permitting to minimize *Ra*. The Desirability Function (DF) was also determined. In addition, the obtained results were compared to the one determined using Response Surface Methodology (RSM) and Teaching and Learning Based Optimization (TLBO). It is important to note that the TLBO method gave a very satisfactory result.

Keywords

titanium alloy, cutting parameters, roughness, modeling, optimization, TLBO, RSM, Taguchi

1 Introduction

Titanium alloys have many advantages such as low weight, high mechanical properties, corrosion resistance, and low thermal and electrical conductivity etc. Due to the mentioned advantages this type of materials have attracted many industries and found various applications in aerospace, turbine blades, automotive, biomechanical and medical. Many titanium alloys can be found and the most used one is Ti-6Al-4V, which contains 6% aluminum and 4% vanadium.

It has been reported by Revankar et al. [1] that the Titanium and its alloys are considered to be difficult to machine materials compared to aluminium and steel.

This is due to the fact of the increase in temperature in the cutting zone which does not dissipate due to the low conductivity of this type of material. Moreover, a strong adhesion can occur between the cutting tools and titanium workpiece [2]. Hence it has been recommended by Yang and Liu [3] the use of carbide tools (WC ± Co) for the machining of this type of material at cutting speeds below 60 m/min. For optimal performance other researchers [4–8] have proposed cemented carbides with 6% of Co content by weight and a WC particle size. To ensure product quality, reduce machining costs and increase productivity, in any machining process an optimal selection of cutting parameters is necessary.

As the quality of the machined surface is the most influential parameter on the performance of the finished parts and the production cost, many researchers have worked on optimizing the cutting parameters.

Due to the poor machinability of the titanium alloys its surface can be rapidly damaged during machining operations and the machined surface has undergone an alteration of its microstructure leading to an increase in its micro-hardness on its outer layer (≤10 μm) [9]. The cutting parameters on

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the surface roughness of different titanium alloys has been investigated using Response Surface Methodology (RSM) as tool for modeling and optimizing cutting conditions [10–16]. Several authors have reported via established models that the feed rate (*f*) was the main factor influencing surface roughness [12, 16]. In other words, *Ra* increased proportionally with feed rate and conversely increased with cutting speed and depth of cut, respectively. Additionally, to the effects of cutting parameters (cutting speed, feed rate and depth of cut) onto the surface roughness, many investigations were carried out in order to evaluate the influence of other parameters such as two coating layers namely Insert 1 coated with three layers TiCN, Al_2O_3 and TiN, the whole deposited by CVD; on the other hand, the insert 2 is coated with PVD with a thin layer of TiAlN [17], tool wear and cutting tool vibrations [18], wear [19], hard turning using Al_2O_3/TiC mixed ceramic as cutting tool [20] onto the surface roughness. In order to determine critical states of the cutting parameters variance analysis (ANOVA) was applied, while optimization of the parameters affecting the *Ra* was achieved with the RSM [21].

Several authors also suggested Artificial Neural Network (ANN) as an efficient technique on the investigations of the effects of cutting conditions on roughness predictions [22–27]. The genetic algorithms (GA) were also proposed for the determination of the cutting parameters in machining operations [28]. A combination of the GA and ANN techniques was proposed to determine the optimum machining parameters leading to minimum surface roughness [29].

The optimization of process parameters in turning of Titanium alloy (Ti-6Al-4V) under different machining conditions on *Ra* was investigated using Taguchi [30], under dry, flooded and Minimum of Quantity of Lubrication (MQL) [31] and also Taguchi with ANOVA [32].

A recently developed advanced optimization algorithm named as Teaching and Learning Based Optimization (TLBO) is used many researchers for the optimization parameters of the cutting tools processes [33–39].

In our work, we will make a comparative study concerning the minimization of the roughness (*Ra*) by different optimization methods namely the Taguchi signal/noise method, the Response Surface Methodology (RSM) and TLBO technique.

2 Material and methods

2.1 Used material

The workpiece used in this study was a Ti-6Al-4V bar with a diameter of 50 mm.

The chemical composition of the part is shown in Table 1, with the mechanical properties shown in Table 2.

2.2 Measurement of sized

Quantities Mitutoyo surftest 201 roughness tester has been used to measure the arithmetic roughness (*Ra*), of a length of 4 mm distance was analyzed.

The roughness was measured directly after each test three times on the surface of the workpiece with reference lines equal to 120°.

2.3 Experimental design

In this study the cutting experiments are conducted considering four parameters or input factors: two levels for the cutting material (*M*) and three levels for the depth of cut (*ap*), cutting speed (*Vc*) and feed rate (*f*).

A Taguchi L18 plan was adopted to achieve several combinations (Table 3). The 18 experiments were performed on a conventional lathe model SN40 having a 6.6 KW power motor. The experimental design adopted for machining Ti-6Al-4V with GC1125 (PVD) coated carbide tools and uncoated H13A carbide is performed with Minimum of Quantity of Lubrication (MQL). Fig. 1 shows all the equipment used.

2.4 Taguchi method

Taguchi method uses the orthogonal network specially designed to minimize the number of experiments without compromising the main effect and the interaction of the effect of the input parameters. The *S*/*N* ratio is used as a measurable value as an alternative to the standard deviation, because as the mean decreases, the standard deviation also decreases and vice versa. This method is based

Table 1 Chemical composition of Ti-6Al-4V

Element	AL	V	Fe	C	O	Ti
Content (%)	5.5–6.8	3.5–4.5	0.3	0.1	0.2	The balance

Table 2 Mechanical proprieties of Ti-6Al-4V

Titanium alloy	Ultimate tensile strength (MPa)	Hardness (HB)	Elongation (%)
Ti-6Al-4V	1000	241	14

Table 3 Input parameters and their levels

Factor	Symbol	Unit	Level		
			1	2	3
Cutting material	*M*	/	1	2	/
Depth of cut	*ap*	mm	0.2	0.4	0.6
Cutting speed	*Vc*	m/min	50	75	100
Feed rate	*f*	mm/rev	0.08	0.12	0.16

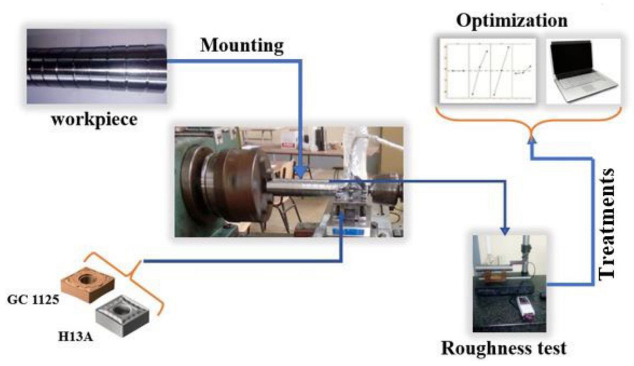

Fig. 1 Schematic representation of experimental details

on an analysis to determine the influence of the parameters on the performances in terms of mean and variance and which the most influencing factor is. In order to control the controllable and uncontrollable factors at the same time, this method converts the signal responses to noise to determine the performance of the system.

The aim of this study is to reduce the arithmetic surface roughness *Ra*, so we use the smallest characteristic is the best (smaller is better) calculated by Eq. (1):

$$\frac{S}{N} = -10\log_{10}\left[\frac{1}{n}\left(\sum_{i=1}^{n} y_i^2\right)\right], \tag{1}$$

where y_i is the observed data and n the number of observations.

2.5 Respon Surface Methodolgy (RSM)

The Response Surface Methodology (RSM) is a mathematical and more precisely statistical tool used for modeling and analyzing problems in which the output parameters depend on several input parameters in order to minimize them.

Thus, the first step of RSM consists in finding a useful and appropriate relation between the dependent parameter "y" and a set of independent parameters $\{x_1, x_2, \ldots, x_n\}$. If the output response is well demonstrated by a linear function of the independent variables, then the first order model which can be represented by

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \; . \tag{2}$$

A higher degree polynomial is used, such as the second order model which can be given by

$$y = \sum_{i=1}^{k} \beta_i x_i + \sum_{ij}^{k} \beta_{ij} \times x_i \times x_j + \sum \beta_{ij} x_i^2 + \varepsilon \; , \tag{3}$$

where:

- ε: represents the noise or the error observed in the response y,
- $(y–\varepsilon)$: expected response,
- β: regression coefficients.
- x_i: coded variables which correspond to the machining parameters studied.

After determining the optimization model and identifying the measures of the output variables and selecting the factors which influence considerably the understanding of the physical significance of the problem and some experience is essential. After that, the question is how to improve the fitting precision of response surface models that are based on planning experiments.

DOE techniques were used before, during and after the regression analysis to assess to the accuracy of the model. RSM also quantifies the relationships between one or more measured responses and can identify the essential input factors.

2.6 Teaching and Learning Based Optimization (TLBO)

The Teaching and Learning Based Optimization (TLBO) is a recent nature-based optimization algorithm who was adopted in various fields, notably in engineering due to its great ability to solve combinatorial optimization problems. TLBO lead to achieve the best solution among the different possible solutions by a process of inspiration of natural pedagogical learning of a classroom. In TLBO only common control parameters are needed for its operation and does not require any algorithm-specific parameters, hence its efficiency because the errors caused by incorrect setting of specific parameters are eliminated. The learners of a class are considered as the population in TLBO and the different subjects are analogous to the decision variables of the optimization problem. The best learner of the population is separated as a teacher. The educational performance of a learner is equivalent to the physical value of the individual in the population.

The TLBO algorithm consists of two phases:

1. the first "teacher phase" which is the simulation of the teacher's learning,
2. while the second "learning phase" is the imitation of interactive learning between learners [39].

This paper explains the TLBO algorithm based on [40, 41]:

- **Step 01**: Optimization function
  The optimization functions are defined by the mathematical model of surface roughness during turning obtained by the RSM method.

- **Step 02**: Initialization of the population
  The random population sample obtained is formed of the design variables, which are the cutting speed, the feed rate, the depth of cut and the values of the corresponding fitness functions which is the surface roughness.
- **Step 03**: Teacher phase
  During this phase, a teacher tries to increase the average result of the class by any value M_j at his level. The average population is calculated column by column, which will give the average for the particular parameter which can be expressed as

$$M_j = [m_1, m_2, \ldots, m_n]. \tag{4}$$

  The best solution will act as a teacher for this iteration:

$$X_j = [CM_{\text{mean}}, DOC_{\text{mean}}, CS_{\text{mean}}, f_{\text{mean}}]. \tag{5}$$

  The teacher will try to move the average from M_j to X_{teacher}, which will act as a new average for the iteration:

$$X_{\text{new}} = X_{\text{teacher}}. \tag{6}$$

  The difference between the two means is calculated using the Eq. (8) and the required learning factor (T_f) is taken equal to 1. The existing solution is then updated using Eq. (2):

$$\text{Difference\_mean}_i = \text{rand}\left(X_j - M_j T_f\right) \tag{7}$$

$$X_{\text{new},i} = X_{\text{old},i} + \text{Difference\_mean}_i. \tag{8}$$

  Accept X_{new} if it's better than X_{old}, otherwise keep X_{old}.
- **Step 04:** Learning phase
  In this phase the learners increase their knowledge by the interaction between them. A learner learns new things if the other learner has more knowledge than him. The learning phenomenon of this phase is expressed as follows. At any iteration *i*, considering two different learners X_i and X_j, where $i \neq j$:

$$X_{\text{new},i} = X_{\text{old},i} + r_i\left(X_i - X_j\right) \text{ if } f\left(X_i\right) < f\left(X_j\right), \tag{9}$$

$$X_{\text{new},i} = X_{\text{old},i} + r_i\left(X_j - X_i\right) \text{ if } f\left(X_i\right) > f\left(X_j\right). \tag{10}$$

  If the value of X_{new} gives a better function value, then it is accepted. In this case, each design variable compares and modifies randomly between any two values corresponding to their function values using Eq. (9) and Eq. (10).
- **Step 05:** Criteria for termination
  Repeating steps 3 and 4 until the best solution was obtained.

3 Results and discussions

3.1 Variance analysis and optimization with Taguchi method

The objective of this paper is to minimize the surface roughness (*Ra*) according to the input factors (cutting material, cutting speed, depth of cut and feed rate). The processing of the results is based on analysis of variance (ANOVA) in order to detect the parameters having a significant influence on the surface roughness *Ra*.

Table 4 shows the results of the surface roughness as a function of the variability of the input parameters according to the Taguchi L18 orthogonal network. The roughness values (*Ra*) are between [0.467–1.277] µm. To examine the effects of the control factors quantitatively, an ANOVA was performed by separating the total variability of the signal noise *S*/*N* ratio, which is determined by the sum of the squared deviations of the total *S*/*N* mean into the contributions of each of the factors and error.

In this study, the lower surface roughness on the one hand and the higher amount of chip removed on the other hand are desirable. The smallest characteristic (*S*/*N*) (Table 4) is the best (smaller-the-better) used for (*Ra*).

The optimum is a minimum value (smaller is better): Taguchi recommends the use of the function represented by Eq. (1).

Table 4 Experimental design and results obtained

N°	*M*	*ap* (mm)	*M* (m/min)	*f* (mm/rev)	*Ra* (µm)	*S*/*N*
1	1	0.2	50	0.08	0.589	4.5977
2	1	0.2	75	0.12	0.869	1.2196
3	1	0.2	100	0.16	1.249	−1.9312
4	1	0.4	50	0.08	0.673	3.4397
5	1	0.4	75	0.12	0.755	2.4411
6	1	0.4	100	0.16	1.25	−1.9382
7	1	0.6	50	0.12	0.845	1.4629
8	1	0.6	75	0.16	1.277	−2.1238
9	1	0.6	100	0.08	0.765	2.3268
10	2	0.2	50	0.16	1.191	−1.5182
11	2	0.2	75	0.08	0.468	6.5951
12	2	0.2	100	0.12	0.662	3.5828
13	2	0.4	50	0.12	0.652	3.7150
14	2	0.4	75	0.16	1.236	−1.8404
15	2	0.4	100	0.08	0.483	6.3211
16	2	0.6	50	0.16	1.066	−0.5551
17	2	0.6	75	0.08	0.467	6.6137
18	2	0.6	100	0.12	0.570	4.8825

ANOVA analysis showed in Table 5 presents the main factors effects as well as their interactions on *Ra*. It has been found that the feed rate (f) is the most influential factor on *Ra* followed by the cutting material (M) with contributions of 80.87% and 8.04% respectively. While the interactions f^2, $ap \times M$ and $f \times M$ have the contributions of 7.43%, 0.88% and 0.82% respectively.

F-value for each process parameter can be calculated as SSD/SSE. Larger the F-value indicate more effects on *Ra*. The estimate F-value of the model for *Ra* is 116.06, which shows the excellent significance of model because of higher magnitude of F-calculated value in comparison to F-table value (2.19) at 95% of confidence level (Table 5).

The best combinations of the control factors for minimizing *Ra* corresponding to optimal values are presented in Table 6. The main effects plot (Fig. 2) is generated using MINITAB statistical software [41] for exploring the effects of control factors on *Ra*.

Based on the *S*/*N* ratio and the ANOVA analysis, the optimal cutting parameters allowing to have a minimum roughness (Table 5) namely: cutting speed 100 m/min (level 3), feed rate 0.08 mm/rev (level 1) and depth of cut 0.6 mm (level 3) for a material from cutting tool GC1125 (level 2).

The plot confirms that the residues are distributed near to a straight line meaning that the errors are dispersed normally and indicating that the terms related to the model are significant. This confirms the appropriateness of the model due to the satisfactory of the null hypothesis (Fig. 3).

Table 5 Response table for Signal to Noise

Levels	*M*	*ap*	*Vc*	*f*
1	1.055	2.091	1.857	4.982
2	3.088	2.023	2.151	2.884
3		2.101	2.207	−1.651
Delta	2.034	0.078	0.350	6.633
Rank	2	4	3	1

Table 6 Response table for average

Source	DF	Som-Car-seq	Contribution%	Som-Car-adjust	*CM* adjust	*F*-Value	*P*-Value	Observation
Regression	7	1.48846	98.78	1.48846	0.21264	116.06	0.000	Significant
f	1	1.21858	80.87	1.21858	1.21858	665.09	0.000	Significant
M	1	0.12120	8.04	0.12120	0.12120	66.15	0.000	Significant
$Vc \times Vc$	1	0.00062	0.04	0.00538	0.00538	2.93	0.117	N. Significant
$f \times f$	1	0.11200	7.43	0.11200	0.11200	61.13	0.000	Significant
$ap \times f$	1	0.01044	0.69	0.01168	0.01168	6.37	0.030	Significant
$ap \times M$	1	0.01320	0.88	0.01320	0.01320	7.20	0.023	Significant
$f \times M$	1	0.01243	0.82	0.01243	0.01243	6.78	0.026	Significant
Error	10	0.01832	1.22	0.01832	0.00183			

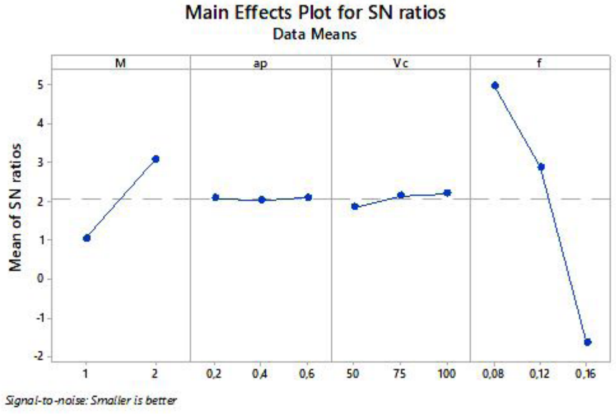

Fig. 2 *S*/*N* main effects plot of input parameters on *Ra*

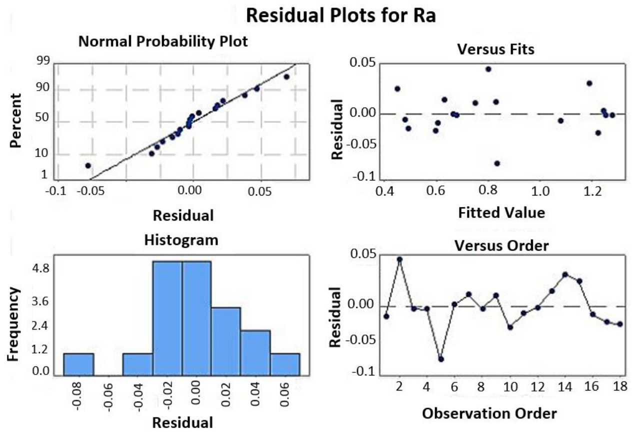

Fig. 3 Residual plots for *Ra*

3.2 Optimization with RSM

To model the surface roughness (*Ra*) the second-order quadratic model have been used in its general form shown in Eq. (3) [42–46]. Second order mathematical models of the surface roughness *Ra* have been developed whose controllable parameters are the material of the cutting tool (*M*), the cutting speed (*Vc*), the depth of cut (*ap*) and the feed rate (*f*) (Table 7).

Moreover, it can be seen that, the developed regression models are statistically significant as the *P*-value is under 0.05. The model developed for *Ra* is characterize by high values of R^2, adjusted R^2 and predicted one having the values 0.9878, 0.9793 and 0.9626 respectively (Table 8).

The RSM optimization results lead to have for *Ra* = 0.45056 µm for a cutting speed of 100 m/min, feed rate of 0.08 mm/rev, depth of cut of 0.6 mm and material cutting tools M_2.

The difference between the measured value of the dependent variable (y) and the predicted one ($\hat{y}$) called the residue (e) expressed as

$$e = y - \hat{y} \ . \tag{11}$$

The results of the roughness measured, and the values simulated by the models are presented on Table 9 where it can be notice that the error does not exceed 10% for a single experiment, which is acceptable.

Fig. 4 shows the superposition of the graphs of the measured roughness and the simulated ones where the two graphs are almost confused.

3.3 Optimization by the desirability function

The objective here is to minimize the surface roughness (*Ra*). It is based on the idea that the "surface finish" of a product or process which has multiple quality characteristics, one of which is outside certain "desired" limits, is completely unacceptable. The method automatically finds the operating conditions x that provide the "most desirable" response values [46].

For each response $Y_i(x)$, a desirability function $d_i(Y_i)$ assigns numbers between 0 and 1 to the possible values of Y_i, with $d_i(Y_i) = 0$ representing a completely undesirable value of Y_i and $d_i(Y_i) = 1$ representing a completely desirable or ideal response value. The individual desirability's are then combined using the geometric mean, which gives the overall desirability [46] expressed by

$$D = \left[\left(d_1(Y_1) \times d_2(Y_2) \times \cdots d_k(Y_k) \right)^{1/k} \right] . \tag{12}$$

If we want to minimize a response, we could use

$$d_i(\hat{Y}_i) = \begin{cases} 0 & \text{if } \hat{Y}_i(x) < L_i \\ \left(\dfrac{\hat{Y}_i(x) - L_i}{T_i - L_i} \right)^S & \text{if } L_i < \hat{Y}_i(x) < T_i \ , \\ 1 & \text{if } \hat{Y}_i(x) > T_i \end{cases} \tag{13}$$

where:

- Y_k denotes the number of responses.
- L_i, U_i and T_i are the lower, the upper, and the target values respectively, that are desired for the response with $L_i \le T_i \le U_i$.
- T_i denotes a small enough value for the response.
- Y_i is the found value of the i^{th} output during optimization processes.

The DF is a combined Desirability Function [46], and the objective is to choose an optimal setting that maximizes DF, in this study is to minimize *Ra*.

The influence of cutting parameters and their interaction effects can be analyzed by using 3-D response graphs. Fig. 5 shows the 3-D response graphs for surface roughness *Ra*, drawn by varying two parameters and keeping the other parameter at constant middle level. The decrease of feed rate led to minimize *Ra* (i.e., better surface finish).

Fig. 6 shows the response graph for two varying parameters cut depth and feed rate by keeping cutting speed at 75 m/min which indicates that the decrease of feed rate led to maximize the DF.

Table 7 Model of roughness

Material of cutting tools	Equations of *Ra*
M_1: Uncoated carbide H13A	$Ra = 1.371 + 0.16 \times ap - 17.784 \times f - 0.38 \times ap \times f + 2.799\text{E-}006 \times Vc^2 + 104.583 \times f^2$
M_2: Coated carbide GC1125 (PVD)	$Ra = 1.146 - 0.166 \times ap - 16.178 \times f - 0.38 \times ap \times f + 2.799\text{E-}6 \times Vc^2 + 104.583 \times f^2$

Table 8 Results of ANOVA for response model

R-Squared	Adj. *R*-Squared	Pred. *R*-Squared	*P*-value	*F* test
0.9878	0.9793	0.9626	0.000	116.06

Table 9 Comparison between predicted and measured value of roughness

N°	*M*	*ap*	*Vc*	*f*	Measured *Ra*	Simulated *Ra*	Error %
1	1	0.2	50	0.08	0.589	0.651	9.50
2	1	0.2	75	0.12	0.869	0.782	10.0
3	1	0.2	100	0.16	1.249	1.251	0.14
4	1	0.4	50	0.08	0.673	0.676	0.51
5	1	0.4	75	0.12	0.755	0.804	6.55
6	1	0.4	100	0.16	1.25	1.271	1.65
7	1	0.6	50	0.12	0.845	0.819	3.13
8	1	0.6	75	0.16	1.277	1.278	0.09
9	1	0.6	100	0.08	0.765	0.723	5.44
10	2	0.2	50	0.16	1.191	1.196	0.46
11	2	0.2	75	0.08	0.468	0.498	6.32
12	2	0.2	100	0.12	0.662	0.696	5.18
13	2	0.4	50	0.12	0.652	0.633	2.92
14	2	0.4	75	0.16	1.236	1.160	6.16
15	2	0.4	100	0.08	0.483	0.471	2.58
16	2	0.6	50	0.16	1.066	1.106	3.73
17	2	0.6	75	0.08	0.467	0.419	10.2
18	2	0.6	100	0.12	0.570	0.612	7.3

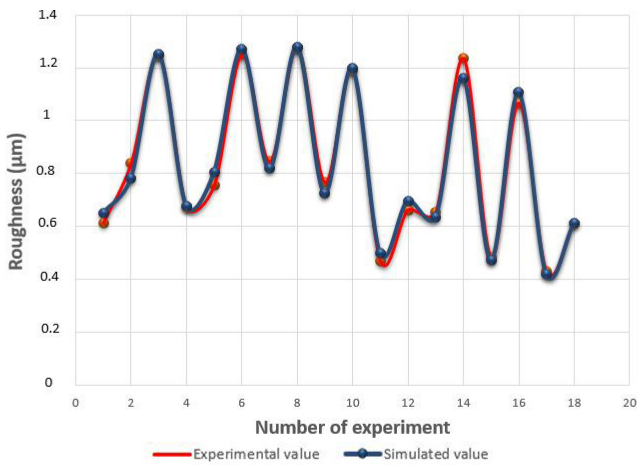

Fig. 4 Comparison between predicted and measured values of roughness

Figs. 7 and 8 show the optimization results, which presented the optimal factors to minimize *Ra*.

3.4 Optimization with TLBO

TLBO method implanted in Matlab has been applied for two cutting tool materials (M_1 and M_2) to optimize the roughness and the result obtained after 100 iterations are presented in Table 10. The obtained results show that best *Ra* of 0.41025 obtained with a cutting tool M_2 for the cutting parameters *ap*, *Vc* and *f* equal to 0.6, 50 and 0.08 respectively. It is important to note that the obtained *Ra* is smaller than the ones obtained previously by the other optimization methods and also with different cutting conditions. Numerical results show that the proposed evolutionary optimization algorithm is robust.

3.5 Pareto chart

The value of the Pareto Principle to a project manager is that it reminds you to focus on the 20% of the things that are critical for your project; however, they produce 80% of your results. Identify and focus on these things first, but do not ignore the remaining 80% of the cause entirely.

In this work Pareto diagram has been used to show the relative frequency of the influence of various parameters on *Ra* and to better view the results of the ANOVA (Fig. 9). It allows showing which 20% of the cases are at the origin of 80% of the problems where efforts should be concentrated to achieve the greatest improvement; we can see that the feed rate (80.87% of influence) should be the focus.

3.6 Confirmation tests

In order to verify the results obtained by various optimization methods and especially the TLBO this gave a minimum value of roughness. A confirmation test has to be carried

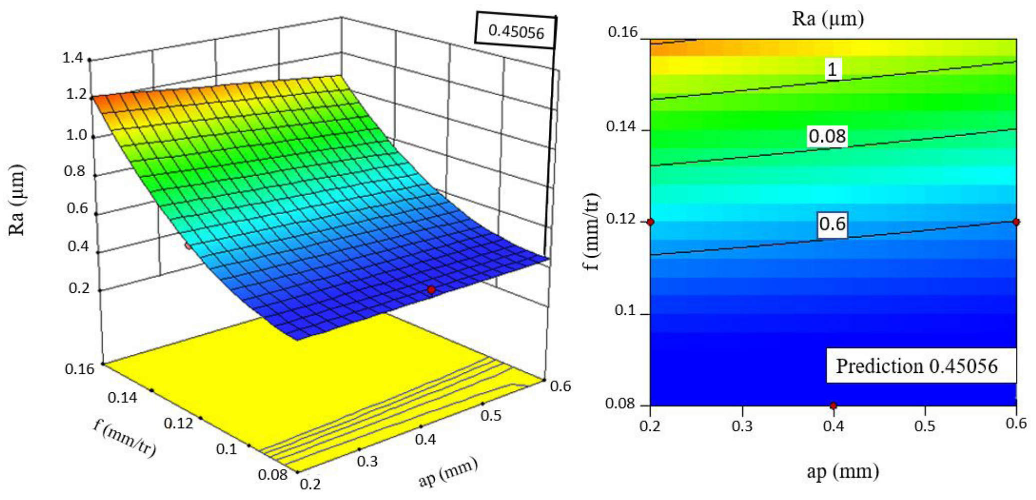

Fig. 5 Response surface plots of *Ra* considering feed rate and depth of cut

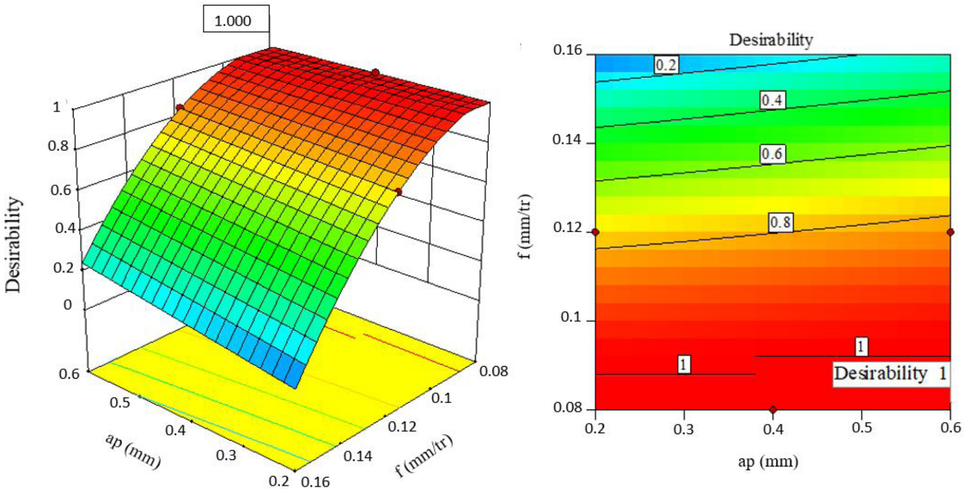

Fig. 6 Desirability plots of *Ra* considering speed and depth of cut

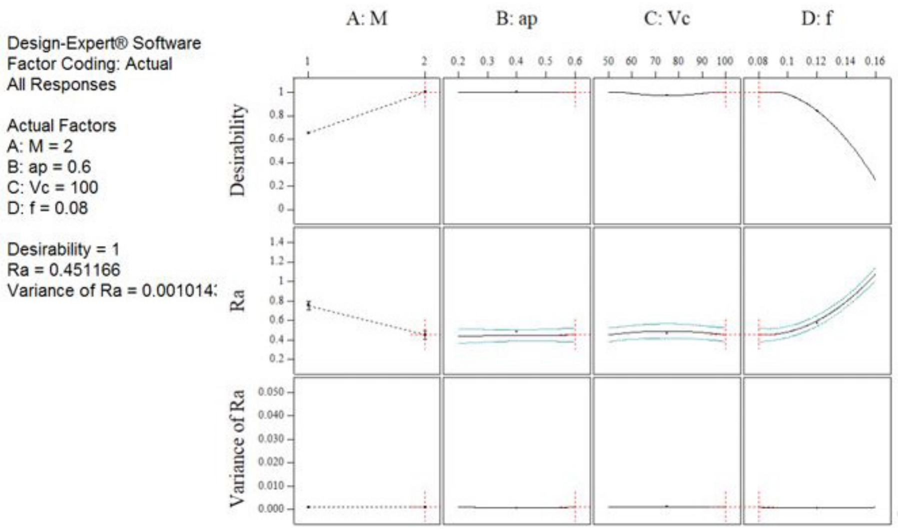

Fig. 7 Desirability plots of *Ra*

out with the cutting parameters: feed rate of 0.08 mm/rev, cutting speed 50 m/min and a depth of cut of 0.6 mm using coated carbide GC1125 (PVD) cutting tool material.

The obtained value of *Ra* is equal to 0.42 µm therefore a difference of 0.01 µm, which gives an error of 2.4%. Therefore, we can conclude that the TLBO method gives better results without forgetting to point out that the Taguchi plan saves us a lot of time and money because the material is very expensive so we reduced the number of experiments from 54 to 18.

4 Conclusion

Based on the experimental results, modeling and optimization of cutting tools conditions leading to minimize *Ra* using Taguchi, RSM and TLBO the main conclusions are:

- Taguchi L18 plan design was performed with quadratic models permitting to minimize the number of tests.
- The experimental results based on *S*/*N* ratio and ANOVA analysis provides a systematic and efficient methodology for the optimization of cutting parameters on *Ra*.
- The surface roughness *Ra* was mainly affected by the feed rate (80.87%) followed by the material of the cutting tool (8.04%) and then by the square of the feed rate (7.43%). While, the other parameter and their interaction do not exceed 1% for each of them.
- Using the TLBO algorithm, the minimum value of *Ra* was found equal 0.41 µm obtained with the cutting tool condition of: *Vc* = 50 m/min, *f* = 0.08 mm/rev and *ap* = 0.60 mm.
- TLBO performed better compared to those given by the other approaches namely RSM and Taguchi for the objective function used in this work.

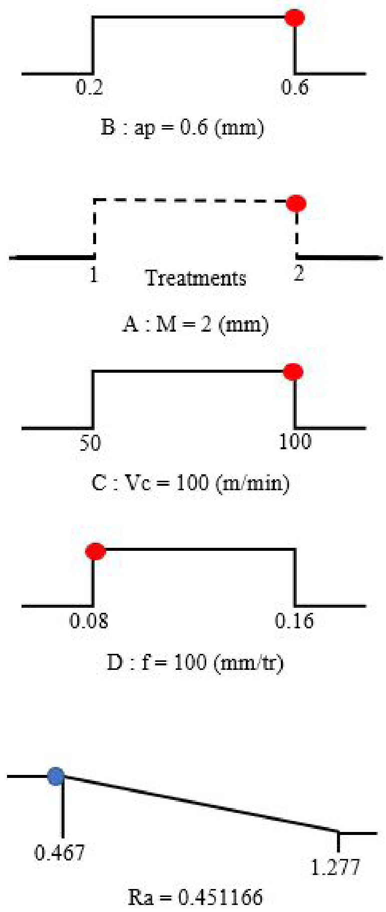

Fig. 8 Optimum values of cutting parameters (Desirability = 1.00)

Table 10 Results of TLBO

Cutting tools	M_1	M_2
Ra (μm)	0.64749	0.41025
ap (mm)	0.2	0.6
Vc (m/min)	50	50
f (mm/rev)	0.08539	0.08

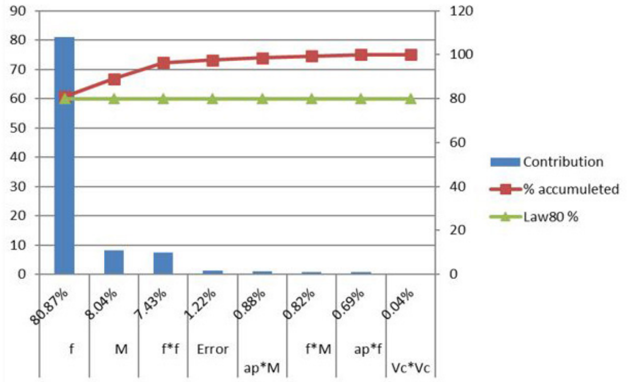

Fig. 9 Pareto chart of the standardized effects on surface roughness ($\alpha = 0.05$)

- A maximum error of 10% for the surface roughness was obtained between the TLBO results and the values of the confirmatory tests. This difference could be due to the weights attributed to the *Ra* during the formulation of the mono objective function and minor variations in the measurement conditions.

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