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TECHNICAL PAPER

Multivariate mean square error for the multiobjective optimization of AISI 52100 hardened steel turning with wiper ceramic inserts tool: a comparative study

P. H. S. Campos[1,2] · G. Belinato[2] · T. I. Paula[2] · M. de Oliveira-Abans[2] · J. R. Ferreira[2] · A. P. Paiva[2] · P. P. Balestrassi[2]

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Abstract This work aims at comparing the optimization of an AISI-52100-steel turning process with a wiper tool attained through the use of the weighted multivariate mean square error (MMSE) method and that obtained through the use of the MMSE. Both of these methods combine principal component analysis and response surface methodology, with the difference that the weighted approach allows the assignment of different degrees of importance to each response. Three input factors were considered: cutting speed (V_c), feed rate (*f*) and depth of cut (*d*). Six highly correlated output characteristics (process responses) were considered: tool life (*T*), cutting time (C_t), total turning cycle time (T_t), processing cost per piece (K_p), arithmetic mean roughness (R_a) and maximum peak to valley roughness (R_t). It should be kept in mind that the material removal rate was a constraint of the problem and not a dependent factor, as a means to guarantee the existence of a minimum productivity. The multiobjective optimization results have been validated experimentally. All models developed in this study, both for turning outputs and for principal component scores, are then suitable for predicting and controlling turning processes similar to that studied here.

Keywords Multi-objective optimization · Hardened steel turning · Multivariate mean square error · Weighted multivariate mean square error · Response surface methodology

1 Introduction

During the past few years, there has been a significant industrial interest in using dry machining. Due to its many advantages, such as the reduced cycle times, improved flexibility, reduced machine tool costs and the fact that it is environmentally friendly, dry machining has become a very popular finishing process. Hard turning is defined as the process of single point cutting of pieces that have hardness values over 45 HRC, more typically ranging from 52 to 65 HRC [1, 2]. The selection of the most appropriate machining settings is crucial for the turning process since it can improve cutting efficiency, produce high-quality products and reduce process costs [3]. An increasing number of papers have been developing mathematical models to analyze the machinability of hard turning process.

Optimization of multiple responses is essential for producing precision parts with low costs in turning operations. Taguchi methods and Response surface methodology have been widely employed for this kind of optimization problem. However, when there are correlated responses being analyzed, those methods can be inadequate. If the variance–covariance structure among the responses is not considered, the optimization may lead to unsatisfactory results [4, 5]. The presence of such correlation, according to [6], can influence the optimization results, since it can create errors in the regression coefficients and unbalance the mathematical models. If the correlation (variance–covariance) is left out of the analysis, the regression equations cannot rightly represent

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✉ P. P. Balestrassi
ppbalestrassi@gmail.com

1 CAPES Foundation, Ministry of Education of Brazil, Brasília, DF 70040-020, Brazil

2 Institute of Industrial Engineering, Federal University of Itajubá, Itajubá, MG 37500-903, Brazil

the objective or constraint functions [7]. Still, there are few researches involving the optimization for multiple responses problem in turning process.

Concerned with these issues, Paiva et al. [8] presented the multivariate mean square error (MMSE) as an alternative hybrid approach for multivariate optimization. The MMSE method combines response surface methodology (RSM) with principal component analysis (PCA), for the optimization of the multiple correlated responses. This approach was first applied in a turning process, but it can be also applied to many other manufacturing processes presenting correlated responses. Although this approach is capable of suppressing the correlation's effect, such methodology is unable to attribute weights when the multiple responses present different degrees of importance, since the correlation matrix is unable to transfer to the components the weights assigned to the original responses [9].

To overcome the deficiency of the MMSE methodology, Gomes et al. [10] proposed the weighted multivariate mean square error (WMMSE), an adaptation of traditional MMSE that is capable of assigning different weights for responses with different degrees of importance in the optimization problem. The WMMSE was applied in the optimization of a flux-cored arc welding (FCAW) for stainless steel cladding process.

Addressing, therefore, these issues, the objective of this work was to obtain a process set for the optimization of six outputs in the AISI 52100 hardened steel turning using the designed technology for wiper mixed ceramic inserts. The considered responses included end of tool life, cutting time, total cycle time, total cost, arithmetic mean roughness and maximum peak to valley roughness. The hardened steel turning was configured in terms of cutting speed, feed rate and depth of cut and the optimization problem included a constraint for the material removal rate (MRR). All six responses were modeled by applying the surface response methodology, which is a collection of mathematical and statistical tools used to determine the mathematical relationships between the responses (objective functions) and selected input parameters [11, 12]. Furthermore, these six responses were simultaneously optimized by MMSE and WMMSE approaches, in order to compare the obtained results. The genetic algorithm was chosen for the optimization since it presents many advantages over traditional algorithms such as the fact that it is more efficient in solving complex problems [13].

2 Background

2.1 Response surface methodology

Response surface methodology is a combination of mathematical and statistical techniques used for modeling and analyzing problems in which the responses of interest are influenced by several variables [14]. Thus, when the mathematical relationships between input parameters and responses (objective functions) are unknown, the RSM enables such functions to be determined from experimental data, which are collected in a planned way [11].

The most employed experimental array in RSM is the central composite design (CCD). The CCD, built for k input variables, is a matrix composed of the following groups of experimental elements: a full factorial design (2^k) or fractional factorial design (2^{k-p}, p is the desired fraction), a set of center points (cp) and a set of extra levels called axial points ($2k$). The total number of required experiments is given by the sum $2^{k\ (\text{or}\ k-p)} + 2k + \text{cp}$. For each axial point, there exists an associated parameter α, defined as the coded distance of this point in relation to the center points. The default value for α is obtained by the expression $\alpha = (2^k)^{1/4}$ [15].

After defining the experiments, as from the CCD, these are performed and the responses of interest are measured. With these data, the response surface function that relates a given response y with the k input variables is then modeled through the Eq. (1) [14], where y is the response of interest, x_i are the input parameters, β_0, β_i, β_{ii}, β_{ij} are coefficients to be estimated and k is the number of input parameters considered [16].

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j}\sum \beta_{ij} x_i x_j \tag{1}$$

The coefficients in Eq. (1) are usually determined by the Ordinary Least Squares (OLS) algorithm [14]. After the response surface modeling, the ANOVA statistical procedure is applied in order to check the model's significance and adjustment. Finally, once the objective functions have been determined and statistically tested, mathematical programming techniques can be applied to these functions, so that the problem is optimized.

2.2 Multivariate mean square error

The MMSE, as presented by [17], is a method that combines the RSM [14] and the PCA [18], for the optimization of multiple correlated responses in multivariate processes. Given that the principal component (PC), through its scores, can be modeled by RSM, the eigenvalue λ represents the variance and taking ζ_{PC} as target for the principal component, the MMSE is defined in Eq. (2) [8]:

$$\text{MMSE} = (\text{PC} - \zeta_{\text{PC}})^2 + \lambda \tag{2}$$

In Eq. (2), PC is a second-order polynomial fitted in relation to the input variables. The target ζ_{PC} must keep a straightforward relation with the targets of the responses of interest, presenting a compatible value with the objectives of the original problem and it is established using Eq. (3) [8], where e is the eigenvector associated with the principal component, p is the number of responses of interest.

$$\zeta_{PC} = e^{T}[Z(Y_j|\zeta_{Y_j})] = \sum_{j=1}^{p} e_j \cdot [Z(Y_j|\zeta_{Y_j})] \tag{3}$$

The term $Z(Y_j|\zeta_{Y_j})$ in Eq. (3) is the standardization of the responses of interest in relation to their targets and it can be calculated as in Eq. (4), where ζ_{Y_j}, μ_{Y_j} and σ_{Y_j} are the target, mean and standard deviation for the jth response, respectively.

$$Z(Y_j|\zeta_{Y_j}) = \frac{\zeta_{Y_j} - \mu_{Y_j}}{\sigma_{Y_j}} \tag{4}$$

The MMSE must be minimized since it is expected the PC to achieve the established target with minimum variance. When more than one principal component is needed, the total multivariate mean square error (MMSE_T) can be optimized as in Eq. (5):

$$\text{Minimize} \quad \text{MMSE}_\text{T} = \left[\prod_{i=1}^{m} \text{MMSE}_i\right]^{\left(\frac{1}{m}\right)} = \left\{\prod_{i=1}^{m} [(\text{PC}_i - \zeta_{\text{PC}_i})^2 + \lambda_i]\right\}^{\left(\frac{1}{m}\right)}, \quad m \le p \tag{5}$$

$$\text{Subject to}: g_n(\mathbf{x}) \le 0 \tag{6}$$

$$\mathbf{x}^\text{T}\mathbf{x} \le \alpha^2 \tag{7}$$

In Eq. (5); MMSE_i is the multivariate mean square error for the ith principal component; m is the number of needed principal components; p is the number of responses of interest; PC_i is the response surface function for the ith principal component; ζ_{PC_i} is the target for the ith principal component; λ_i is the eigenvalue for the ith principal component. $g_n(\mathbf{x}) \le 0$ represents a constraint equation and $\boldsymbol{x}^\text{T}\boldsymbol{x} \le \alpha^2$ is the spherical constraint for the experimental region [10]. Since the principal components are linear combinations of the original responses, their optimization implies the optimization of the responses of interest.

2.3 Weighted multivariate mean square error

The MMSE formulation can only be applied when the responses of interest are treated with the same weights. In order to be able to optimize correlated responses with different degrees of importance, Gomes et al. [10] proposed the WMMSE. For applying the WMMSE, the following procedure must be followed [10]:

Step 1 The method starts with the standardization of the responses, which is important to unify the data set. The responses of interest collected in RSM may be standardized using the transformation: $Z(y) = [y - \mu_{Y_j}] \cdot (\sigma_{Y_j})^{-1}$

Step 2 Multiplied each standardized response by its respective weight, ω_j, such that $\sum \omega_j = 1$.

Step 3 Extract the principal component scores using the variance–covariance matrix (unlike the MMSE approach, in which the scores are extracted from correlation matrix).

Step 4 Define the number of principal components which must be retained in the analysis and produce pairs of weighted eigenvectors (e_i^*) and eigenvalues (λ_i^*).

Step 5 Establish RSM models for the significant principal components using the scores obtained in step 3.

Step 6 Calculate the respective targets for each principal component taking into account the weighted responses.

Step 7 Once the responses of interest have been weighted, the WMMSE optimization can be obtained as in Eq. (8), where WMMSE_T is the total weighted multivariate mean square error; WMMSE_i is the weighted multivariate mean square error for the ith principal component; υ_i is the degree of explanation for the ith principal component, such that $\sum \upsilon_i = \upsilon_\text{T}$; PC_i^* is the response surface function for the ith principal component obtained with the weighted responses; $\zeta_{\text{PC}_i}^*$ is the target for the ith principal component obtained with the weighted responses, calculated by: $\zeta_{\text{PC}_i}^* = e_{i1}^* \cdot Z(Y_1|\zeta_{Y_1}) + e_{i2}^* \cdot Z(Y_2|\zeta_{Y2}) + \cdots + e_{ip}^* \cdot Z(Y_p|\zeta_{Yp})$; λ_i^* is the eigenvalue for the ith principal component obtained with the weighted responses [10]

$$\text{Minimize} \quad \text{WMMSE}_\text{T} = \sum_{i=1}^{m}\left[\frac{\upsilon_i}{\upsilon_\text{T}} \cdot \text{WMMSE}_i\right] = \sum_{i=1}^{m}\left\{\frac{\upsilon_i}{\upsilon_\text{T}}[(\text{PC}_i^* - \zeta_{\text{PC}_i}^*)^2 + \lambda_i^*]\right\}, \quad m \le p \tag{8}$$

$$\text{Subject to}: g_n(\mathbf{x}) \le 0 \tag{9}$$

$$\mathbf{x}^\text{T}\mathbf{x} \le \alpha^2 \tag{10}$$

As it can be observed, the principal components are also weighted in the WMMSE function. However, these weights are attributed taking into account the degree of explanation of each component [10]. In both approaches presented, the optimal point can be identified by employing optimization algorithms on Eqs. (5)–(7) and Eqs. (8)–(10), respectively. For this study, the genetic algorithm was used in the optimization, since it has been characterized in the literature as an effective algorithm to global optimization [19, 20].

2.4 Genetic algorithm

The use of genetic algorithms (GA) is observed in several studies regarding manufacturing processes optimization, which also usually apply RSM as a mechanism for objective function building [21]. The GA procedure is grounded on the principles of natural selection. Assuming a population of solutions instead of a single one, this algorithm can be used for optimizing both constrained and unconstrained problems and also for single [22] or multiobjective problems [23, 24]. Most of GAs can also convert the constrained optimization problem into an unconstrained one, using a penalty function before the solution [22]. Every solution suggested by this iterative method is represented by a vector **x** of independent variables, where usually is used the binary coding for converting the independent variables of the problem into genes of a chromosome [19]. If the solution is not adequate for the objective function minimization, the problem is penalized. The GA mechanics is simple, involving the copy and swap of the binary strings.

Genetic algorithms usually work in three stages: (a) reproduction, (b) crossover and (c) mutation. The GA performance depends mainly on critical parameters as population size, crossover rate, mutation rate, number of iterations (generations) and their values [22]. Its advantage over traditional optimization methods is that it can simultaneously operate with a large set of search space points instead of a single point. On the other hand, a possible drawback is the fact that a large computational effort is required [25].

3 Experimental method

To accomplish the aims previously proposed, the optimization strategy was performed in three stages. Initially, the RSM was employed to the experiments planning, data collection, modeling of responses of interest and modeling of principal component scores. Then, the MMSE and the WMMSE methodologies were applied to the problem formulation, considering equal weights and different weights between the responses, respectively. Finally, the genetic algorithm was executed to identify the optimal point for both problems.

3.1 Experiments planning

Turning processes are commonly set by cutting speed (V_c), feed rate (f) and depth of cut (d). So, these variables were defined as input parameters. The experiments schedule was created as a CCD, for three parameters in two levels ($2^k = 2^3 = 8$), six axial points ($2k = 6$) and five center points (cp = 5), resulting in a total of 19 experiments. The coded distance from the center point to axial point (α) was 1.682. Table 1 presents the input parameters and their levels in the CCD array.

The set of responses included seven turning outputs, six of them to be optimized and one to be taken as a constraint. The characteristics to be optimized were end of tool life (T), cutting time (C_t), total cycle time (T_t), total cost (K_p), arithmetic mean roughness (R_a) and maximum peak to valley roughness (R_t). The MRR was taken as a constraint, to ensure the process optimization with good productivity.

3.2 Experimental procedure

For data collection, dry turning tests were conducted on a CNC lathe with a maximum rotational speed of 4000 rpm and power of 5.5 kW. The workpieces of AISI 52100 steel, with chemical composition 1.03% C, 0.23% Si, 0.35% Mn, 1.40% Cr, 0.04% Mo, 0.11% Ni, 0.001% S, 0.01% P, were prepared with dimensions of ϕ 49 mm × 50 mm and were quenched and tempered. After this heat treatment, their hardness was between 49 and 52 HRC, up to a depth of 3 mm below the surface. Figure 1 illustrates the AISI 52100 hardened steel turning process with wiper inserts considered in this work. Wiper mixed ceramic (Al_2O_3 + TiC) inserts (CNGA 120408 S01525WH), coated with a very thin layer of titanium nitride (TiN), were the employed tool (Fig. 2a). The tool holder had a negative geometry with ISO code DCLNL 1616H12 and entering angle $\chi_r = 95°$.

For the tool life measurement, the wiper inserts were worn until their flank wear (VB_C) indicator on the tool tip to reach 0.30 mm. This was the adopted criterion for the end of tool life and it was measured by an optical microscope.

Table 1 Parameters and their levels

Parameters	Unit	Notation	Levels				
			−1.682	−1	0	+1	+1.682
Cutting speed	m/min	V_c	186	200	220	240	254
Feed rate	mm/rev	f	0.13	0.20	0.30	0.40	0.47
Depth of cut	mm	d	0.10	0.15	0.22	0.30	0.35

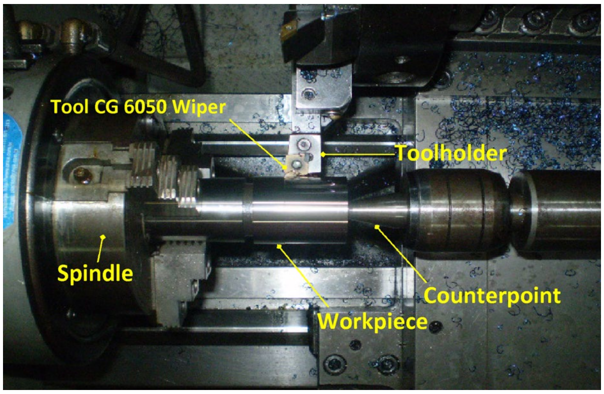
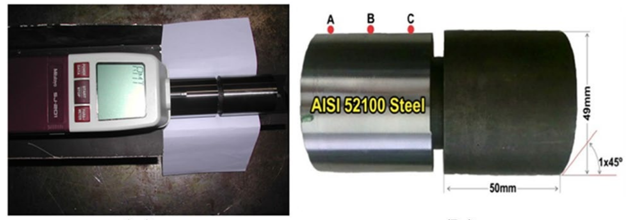


Fig. 1 AISI 52100 hardened steel turning process with wiper inserts

Once VB_C reached 0.30 mm (Fig. 2c), the number of steps executed until this condition was accounted.

The arithmetic mean roughness (R_a) and the maximum peak to valley roughness (R_t), both in µm, were measured for each wiper insert in its end of life. These responses were collected by a portable roughmeter (Fig. 3a), set to a cutoff length of 0.8 mm. The measurements were taken at three different points of the workpiece (Fig. 3b). Each point was measured four times (giving a total of twelve measures) and the mean value among them was considered.

A scanning electron microscopy (SEM) was applied for surface morphology examination. The workpieces' surfaces were analyzed in the SEM with the objective of verifying the deformation (lateral flow) of the peaks presented on the machined material. Figures 4, 5 and 6 show the analysis of the machining peaks for a feed rate $f = 0.25$ mm/rev. The distance between two peaks that obtained values close to 50 µm is presented in Fig. 4. In Figs. 5 and 6, a specific point of the material was analyzed, which presented a deformation width much greater than the other ones. The peak width and depth values for the workpieces machined with $f = 0.25$ mm/rev were larger than the ones machined with $f = 0.13$ mm/rev and $f = 0.20$ mm/rev. Larger feed rates are more aggressive to the material and require more cutting effort, which also results in greater material deformation.



(a) (b)

Fig. 3 **a** Roughness measurement; **b** surface roughness measurement positions

As for the MRR, such response was easily calculated by multiplying the cutting speed by feed rate by the depth of cut. It is expressed in cm^3/min. The end of tool life (T), in minutes, was then obtained multiplying the total number of passes by the cutting time (C_t) in each pass, this latter calculated as in Eq. (11), where l_f is the length of the workpiece (50 mm), d is the diameter of the workpiece (49 mm), f is the feed rate (mm/rev) and V_c is the cutting speed (m/min).

$$C_t = \frac{l_f \cdot \pi \cdot d}{1000 \cdot f \cdot V_c} \text{ (min)} \tag{11}$$

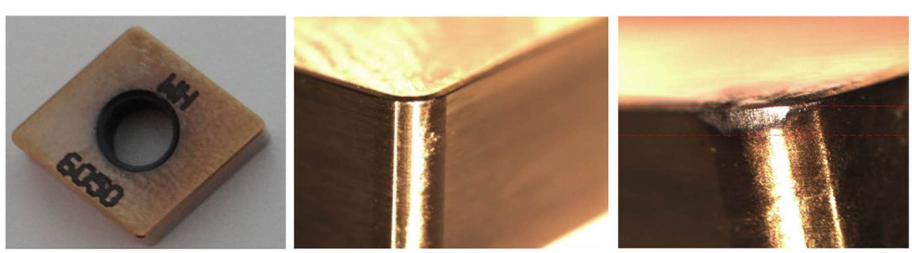
As from the end of tool life measurement, cutting time calculation and with the information in Table 2, the total cycle time (T_t) and the total cost (K_p) were calculated through Eqs. (12) and (13).

$$T_t = C_t + t_1 + t_2 \text{ (min)} \tag{12}$$

$$K_p = \left[\frac{t_1}{60} - \frac{1}{Z}\right] \cdot (S_h + S_m) + \frac{C_t}{60} \cdot (S_h + S_m) + \frac{C_t}{T} \cdot \left[\left(\frac{K_{th}}{N_{th}} + \frac{K_i}{N_i}\right) + \frac{t_i}{60} \cdot (S_h + S_m)\right] \text{ (U\$)} \tag{13}$$

In Eqs. (12) and (13), T is the tool life (min), C_t is the cutting time (min), t_1 is the unproductive time, calculated by $t_1 = t_s + t_a + \frac{t_p}{Z} - \frac{t_i}{Z}$ (min) and t_2 is the tool changing time, calculated by $t_2 = \frac{C_t}{T} \cdot t_i$ (min).

After all responses were collected, these were assembled to compound the experimental matrix (Table 3),



(a) (b) (c)

Fig. 2 Tool flank wear: **a** CG6050 wiper insert; **b** new tool edge; **c** worn tool edge (VB_C 0.30 mm)

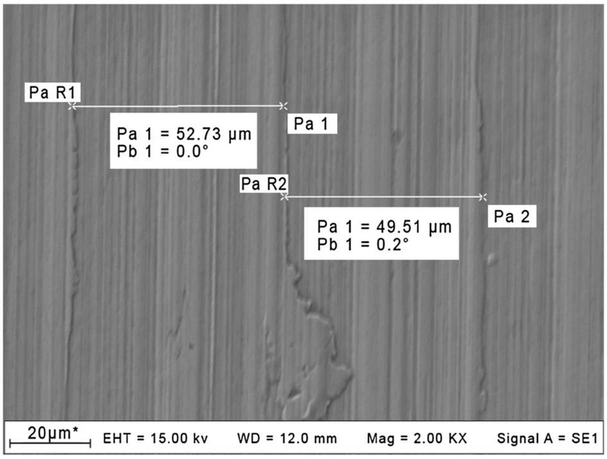


Fig. 4 Distance between peaks for workpiece ($f = 0.25$ mm/rev)

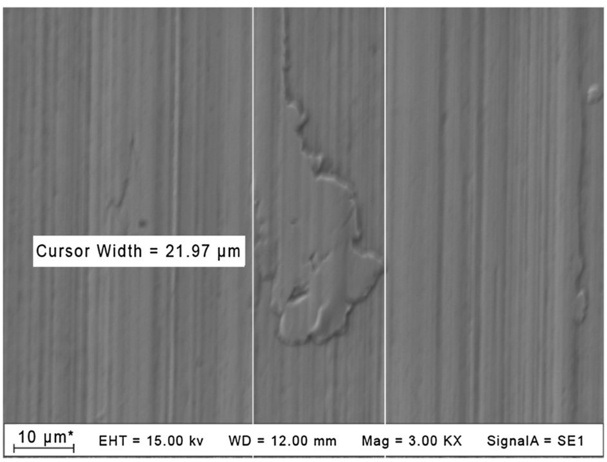


Fig. 5 Width of material deformation at a specific point ($f = 0.25$ mm/rev)

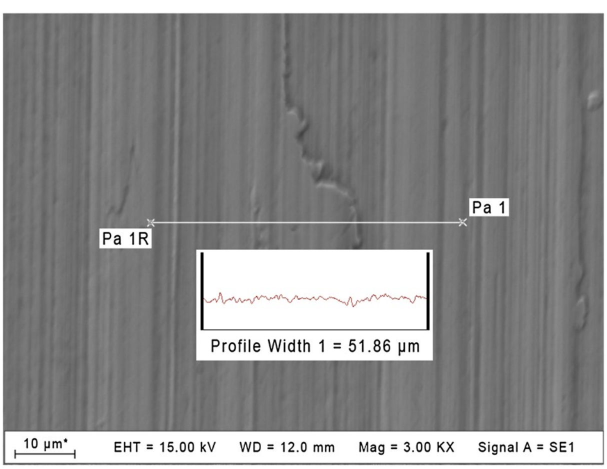


Fig. 6 Depth of specific material deformation peak ($f = 0.25$ mm/rev)

used as data source for the modeling and optimization of the process.

4 Results

4.1 Modeling of turning outputs

With the aim of verifying the behavior of AISI 52100 hardened steel turning outputs during the optimization process, all responses were modeled according to RSM. So, writing the generic model stated in Eq. (1) for the three input parameters considered in this work, the following expression is obtained:

$$y = \beta_0 + \beta_1 V_c + \beta_2 f + \beta_3 d + \beta_{11} V_c^2 + \beta_{22} f^2 + \beta_{33} d^2 + \beta_{12} V_c \cdot f + \beta_{13} V_c \cdot d + \beta_{23} f \cdot d \quad (14)$$

In Eq. (14), V_c, f and d are expressed in their coded form. The OLS algorithm, through software Minitab, was employed to determine the coefficients β_0, β_i, β_{ii}, β_{ij} of the models. Then, it was used the ANOVA procedure, also by Minitab, to check their statistical significance and to remove the no significant terms. Table 4 presents the developed coefficients for the final quadratic models.

The results of ANOVA are presented in Table 5, showing regression p values less than 5% of significance and adjustments above 90% for all responses. These results indicate that the models are statistically significant and, therefore, can be used in prediction and control of the turning outputs.

The response surface plots in Fig. 7 and the main effect plots in Fig. 8 illustrate how the machining parameters influence the responses that will be optimized. It is essential to realize that the feed rate (f) is the factor that most affect each response. For lower cutting speeds and feed rates, the maximum values of tool life (T) and minimum values of mean roughness (R_a) and maximum peak to valley roughness (R_t).can be found. Higher values of V_c and f ensure lower cutting time (C_t), total cycle time (T_t) and total cost (K_p).

4.2 MMSE optimization

The correlation structure between the responses to be optimized is shown in Table 6. As can be observed, these data are highly correlated, which makes of MMSE an appropriate approach to this problem.

Applying the PCA on the responses of Table 3, it was found the results presented in Table 7, which identified that 95.1% of the data are explained by three principal

Table 2 Data for total cycle time and total cost calculations

Description	Symbol	Unit	Value
Secondary time	t_s	Min	0.5
Tool approximation and retreat time	t_a	Min	0.1
Set-up time	t_p	Min	60
Insert changing time	t_i	Min	1
Batch size	Z	Units	1.000
Machine and labor costs	$S_m + S_h$	U$	50
Tool holder price	K_{th}	U$	125
Insert price	K_i	U$	31.25
Average tool holder life	N_{th}	Edges	1.000
Number of cutting edges on the insert	N_i	Edges	4

components. These new uncorrelated variables were then used to represent the original correlated responses during the optimization.

The next step consists in determining the quadratic models for the significant principal components. Thus, taking the scores calculated in the PCA and modeling these data according to RSM, Eqs. (15)–(17) were obtained. The results of ANOVA for these models identified p values less than 5% of significance for all of them. In relation to their adjustments, PC1 presented an adj. R^2 of 97.99%, with 95.15% for PC2 and 89.26% for PC3.

$$\begin{aligned} \text{PC1} = {} & 0.088 - 0.379V_c - 2.295f + 0.130d \\ & - 0.144V_c^2 + 0.349f^2 - 0.328d^2 \\ & + 0.299V_c \cdot f + 0.110V_c \cdot d \end{aligned} \tag{15}$$

$$\begin{aligned} \text{PC2} = {} & 0.982 + 0.075V_c + 0.050f + 0.599d - 0.565V_c^2 \\ & - 0.356f^2 - 0.444d^2 - 0.290V_c \cdot f \\ & - 0.321V_c \cdot d - 0.486f \cdot d \end{aligned} \tag{16}$$

$$\begin{aligned} \text{PC3} = {} & 0.449 + 0.322V_c - 0.073f - 0.074d \\ & + 0.086V_c^2 - 0.423f^2 - 0.288d^2 \\ & + 0.316V_c \cdot f + 0.307V_c \cdot d \end{aligned} \tag{17}$$

The targets for the principal components were established based on the targets of the original responses. These latter were established according to the distribution of experimental data (Table 8). For those responses whose optimization objective was chosen as maximization, the targets were defined near from the third quartile (Q3), while in those defined as minimization, the targets were fixed at values lesser than the first quartile (Q1). All the statistical metrics were calculated using the experimental data.

The data contained in Table 9, through Eqs. (3) and (4), were then used to calculate the targets for the principal components, resulting in targets of −0.816, −2.001 and 2.113 for PC1, PC2 and PC3, respectively.

Table 3 Experimental matrix

Test	Parameters			Responses						
	V_c (m/min)	f (mm/rev)	d (mm)	T (min)	C_t (min)	T_t (min)	K_p (U$)	R_a (µm)	R_t (µm)	MRR (cm³/min)
1	−1	−1	−1	17.21	0.19	0.86	0.76	0.25	1.41	6.00
2	+1	−1	−1	11.37	0.16	0.83	0.76	0.27	1.72	7.20
3	−1	+1	−1	5.96	0.10	0.77	0.72	0.31	2.12	12.00
4	+1	+1	−1	4.48	0.08	0.76	0.72	0.30	2.15	14.40
5	−1	−1	+1	9.42	0.19	0.87	0.84	0.25	1.45	12.00
6	+1	−1	+1	7.37	0.16	0.84	0.82	0.25	1.58	14.40
7	−1	+1	+1	4.03	0.10	0.78	0.79	0.34	2.01	24.00
8	+1	+1	+1	6.10	0.08	0.75	0.68	0.29	1.99	28.80
9	−1.682	0	0	9.51	0.14	0.81	0.74	0.29	1.69	12.28
10	+1.682	0	0	6.86	0.10	0.77	0.71	0.26	1.81	16.76
11	0	−1.682	0	14.18	0.27	0.95	0.89	0.21	1.54	6.29
12	0	+1.682	0	4.12	0.07	0.75	0.72	0.31	2.54	22.75
13	0	0	−1.628	9.42	0.12	0.79	0.70	0.31	1.94	6.60
14	0	0	+1.682	4.92	0.12	0.80	0.80	0.31	1.74	23.10
15	0	0	0	4.89	0.12	0.80	0.81	0.26	1.81	14.52
16	0	0	0	5.00	0.12	0.80	0.80	0.26	1.71	14.52
17	0	0	0	4.77	0.12	0.80	0.81	0.26	1.71	14.52
18	0	0	0	5.01	0.12	0.80	0.80	0.26	1.71	14.52
19	0	0	0	5.12	0.12	0.80	0.80	0.26	1.71	14.52

Table 4 Coefficients for the final quadratic models of turning outputs

Coef.	Responses						
	T	C_t	T_t	K_p	R_a	R_t	MRR
β_0	4.963	0.116	0.799	0.804	0.260	1.724	14.586
β_1	−0.861	−0.012	−0.012	−0.012	−0.007	0.048	1.343
β_2	−3.055	−0.050	−0.050	−0.040	0.028	0.278	4.926
β_3	−1.440	–	0.003	0.025	0.000	−0.052	4.932
β_{11}	1.115	–	−0.003	−0.027	0.005	–	–
β_{22}	1.456	0.019	0.017	–	–	0.094	–
β_{33}	0.756	–	−0.003	−0.017	0.018	0.023	0.151
β_{12}	1.060	0.004	–	−0.011	−0.010	−0.054	0.450
β_{13}	0.918	–	–	−0.015	−0.008	−0.029	0.450
β_{23}	1.435	–	–	−0.015	0.005	–	1.650

Table 5 ANOVA results

	Degrees of freedom		Sum of squares		Mean square		F	p value	Adj. R^2 (%)
	RG*	RS	RG	RS	RG	RS			
T	9	9	240.96	0.316	26.77	0.035	761.7	0.000	99.74
C_t	4	14	0.041	0.001	0.010	0.000	197.3	0.000	97.76
T_t	6	12	0.040	0.001	0.007	0.000	92.1	0.000	96.81
K_p	8	10	0.049	0.003	0.006	0.000	23.3	0.000	90.82
R_a	8	10	0.018	0.000	0.002	0.000	185.2	0.000	98.79
R_t	7	11	1.274	0.042	0.182	0.004	47.4	0.000	94.75
MRR	7	11	713.54	0.393	101.93	0.036	2853.7	0.000	99.91

Having developed the RSM models for the significant principal components and taking their calculated targets, the MMSE formulation was built, considering equal weights for all responses and equal weights for all principal components, which resulted in Eq. (18).

$$\begin{aligned} \text{Min} \quad \text{MMSE}_{\text{T}} = \{ & [(\text{PC1} + 0.816)^2 + 4.435] \\ & \cdot [(\text{PC2} + 2.0001)^2 + 0.872] \\ & \cdot [(\text{PC3} - 2.113)^2 + 0.397] \}^{\left(\frac{1}{3}\right)} \\ \text{St: } & \text{MRR} \geq 16.00 \\ & \mathbf{x}^{\text{T}}\mathbf{x} \leq 2.829 \end{aligned} \tag{18}$$

In Eq. (18), PC1, PC2 and PC3 are the RSM models described in Eqs. (15), (16) and (17), MRR is the constraint for MRR and $\mathbf{x}^{\text{T}}\mathbf{x}$ is the spherical constraint for the experimental region.

As previously presented, the MRR was treated in this problem as a constraint, looking for ensuring a minimum productivity of the turning process. The genetic algorithm was applied in the MMSE formulation after it was programmed in a Microsoft Excel worksheet. By employing the *Solver Evolutionary* supplement, considering the *GA* parameters in Table 10, the optimal point was identified (Table 11). The values of GA parameters were empirically chosen after preliminary tests.

Finally, applying this optimal combination of the input parameters in the developed models for the turning outputs (Table 4) and replacing their coded values by operational values (in uncoded form), it was found that the AISI 52100 hardened steel turning, with a reliability of 95%, is optimized with the following results presented in Table 12.

Good solutions were reached for practically all responses. The production times were better than their targets and the optimal values for total cost, average surface roughness and maximum peak to valley roughness established close to their desired values. However, the tool presented a relatively low life. This is mainly explained due to the multi-objective nature of the problem, in which one or more responses tend to be impaired in favor of the global optimization of all characteristics. Furthermore, the turning process was optimized considering the same weights between the responses. Therefore, with the aim of improving these results, it was employed the WMMSE, in order to perform a new optimization of the process, but now considering the responses with different degrees of importance.

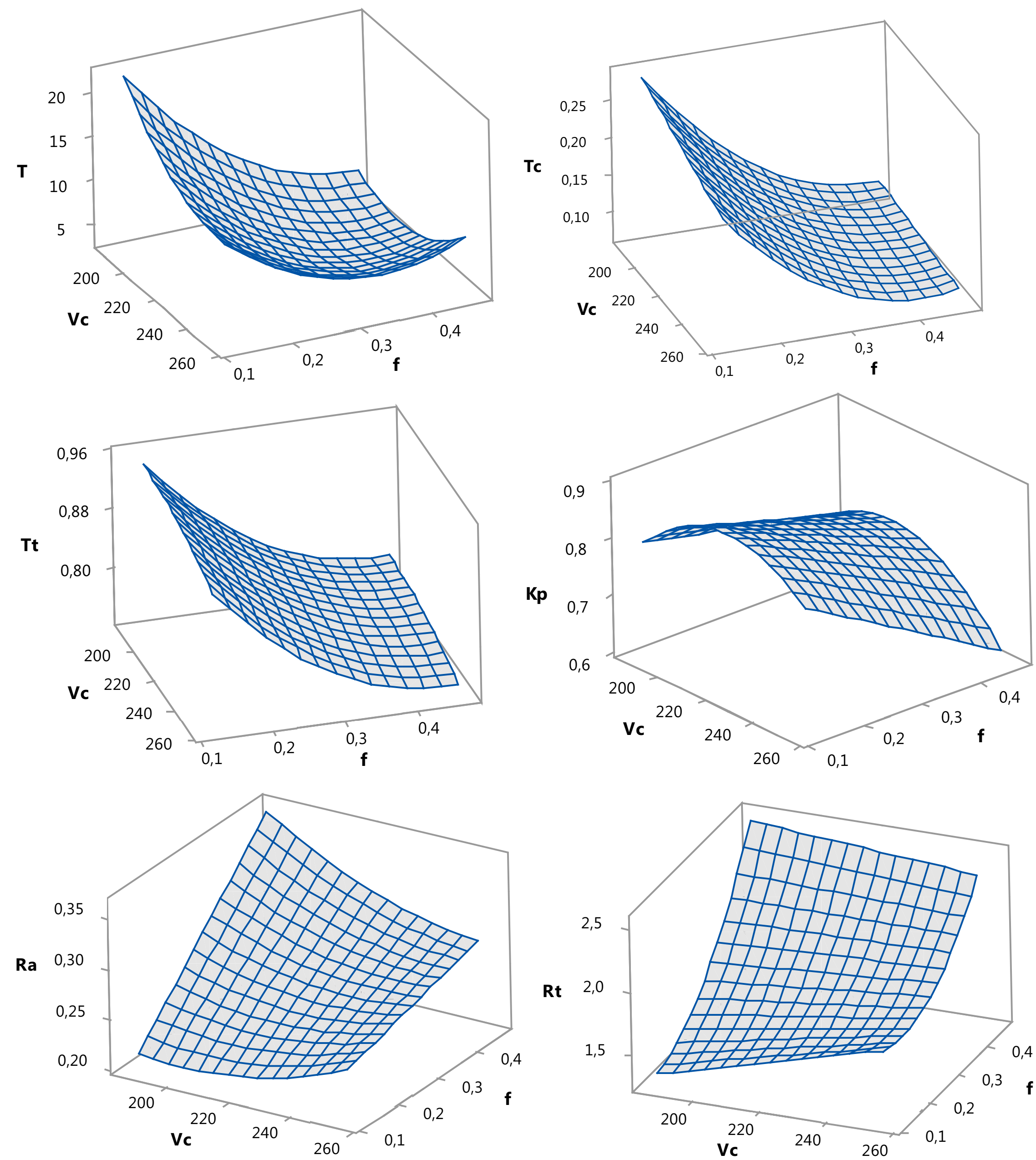


Fig. 7 Response surface plot for the responses. Hold value: $d = 0.225$

4.3 WMMSE optimization

Table 13 presents the calculated values after the standardization and weighting of the original responses (step 1 and step 2 described in Sect. 2.3). For this, the end of tool life, which is the characteristic to be improved, was judged three times more important than cutting time, total cycle time and total cost, and one and a half time more important than average surface roughness and maximum peak to valley roughness. The arithmetic mean roughness and maximum peak to valley roughness were considered twice more important than cutting time, total cycle time and total cost.

The PCA, applied on the data of Table 13 and using now the variance–covariance matrix (step 3), identified again that three principal components are needed to represent the

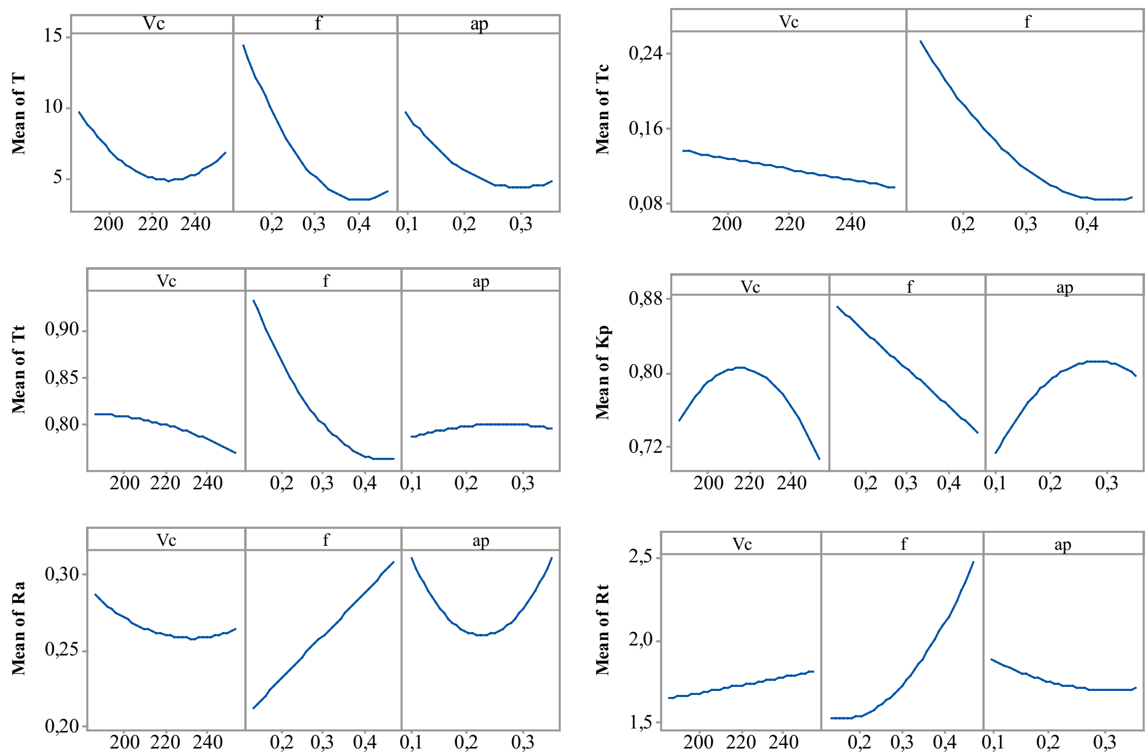


Fig. 8 Main effects plot for the six responses to be optimized

responses since they explain 96.4% of data (Table 14). Thus, these components were used in the optimization (step 4).

The RSM models for the principal components of the weighted responses (step 5) are presented in Eqs. (19)–(21). Such functions were determined as from the scores extracted in the PCA and using the same methodology of the previous developed models. Again, all models presented p values less than 5% of significance. The adj. R^2 values were 99.37% for PC1*, 96.92% for PC2* and 87.44% for PC3*.

$$\begin{aligned}\mathrm{PC1}^* = & -0.077 - 0.064V_c - 0.402f - 0.061d + 0.048V_c^2 \\ & + 0.074f^2 - 0.014d^2 + 0.106V_c \cdot f \\ & + 0.078V_c \cdot d + 0.074f \cdot d \end{aligned} \quad (19)$$

$$\begin{aligned}\mathrm{PC2}^* = & \; 0.222 + 0.043V_c - 0.056f + 0.109d - 0.092V_c^2 \\ & - 0.099f^2 - 0.118d^2 - 0.013V_c \cdot f \\ & - 0.025V_c \cdot d - 0.097f \cdot d \end{aligned} \quad (20)$$

$$\begin{aligned}\mathrm{PC3}^* = & -0.014 - 0.053V_c - 0.014f + 0.040d + 0.017V_c^2 \\ & - 0.056f^2 + 0.059d^2 - 0.024V_c \cdot f \\ & - 0.026V_c \cdot d + 0.023f \cdot d \end{aligned} \quad (21)$$

The targets for the principal components of the weighted responses (step 6) were calculated using Table 15 and Eqs. (3) and (4), similarly to the established targets in MMSE optimization. It was found 0.362 for PC1*, −0.874 for PC2* and −0.660 for PC3*. Then, the WMMSE formulation (step 7) was built following Eq. (22), where PC1*, PC2*, PC3*are the RSM models described in Eqs. (19), (20) and (21), respectively, MRR is the constraint for MRR and $\mathbf{x}^T\mathbf{x}$ is the spherical constraint for the experimental region.

Table 6 Correlation between the responses

	T	C_t	T_t	K_p	R_a
C_t	0.809				
	0.000				
T_t	0.754	0.996			
	0.000	0.000			
K_p	0.155	0.678	0.745		
	0.526	0.001	0.000		
R_a	−0.497	−0.730	−0.741	−0.604	
	0.031	0.000	0.000	0.006	
R_t	−0.585	−0.748	−0.760	−0.622	0.720
	0.009	0.000	0.000	0.005	0.001

Cells: Pearson correlation

p value

Table 7 Principal component analysis for the original responses

Eigenvalue	4.435	0.872	0.397	0.279	0.018	0.000
Proportion	0.739	0.145	0.066	0.046	0.003	0.000
Cumulative	0.739	0.884	**0.951**	0.997	1.000	1.000
Eigenvector	PC1	PC2	PC3	PC4	PC5	PC6
T	0.353	−0.708	−0.085	−0.016	−0.605	0.000
C_t	0.460	−0.134	−0.302	0.122	0.465	−0.669
T_t	0.463	−0.036	−0.323	0.104	0.355	0.737
K_p	0.351	0.669	−0.378	−0.050	−0.524	−0.095
R_a	−0.397	−0.162	−0.670	−0.602	0.068	0.000
R_t	−0.410	−0.071	−0.453	0.781	−0.113	0.000

Data extracted from correlation matrix

Table 8 Targets for the original responses

Objective	T (max)	C_t (min)	T_t (min)	K_p (min)	R_a (min)	R_t (min)	MRR (max)
Mean	7.355	0.129	0.807	0.772	0.276	1.807	14.694
Median	5.960	0.117	0.799	0.789	0.260	1.720	14.520
Q3	9.420	0.160	0.833	0.806	0.310	1.990	16.764
Q1	4.890	0.096	0.775	0.721	0.260	1.690	12.000
Target	10.000	0.100	0.770	0.630	0.250	1.700	16.000

Table 9 Data used in the establishment of targets for the principal components

	T	C_t	T_t	K_p	R_a	R_t
Mean	7.355	0.129	0.807	0.772	0.276	1.807
Standard deviation	3.661	0.048	0.048	0.054	0.031	0.270
Target	10.00	0.10	0.77	0.63	0.25	1.70
Standardization	0.723	−0.611	−0.778	−2.635	−0.841	−0.397
Eigenvector PC1	0.353	0.460	0.463	0.351	−0.397	−0.410
Eigenvector PC2	−0.708	−0.134	−0.036	0.669	−0.162	−0.071
Eigenvector PC3	−0.085	−0.302	−0.323	−0.378	−0.670	−0.453

Table 10 GA parameters used in the optimization

Parameters	Values
Iterations	1000
Convergence	0.0001
Population size	100
Mutation rate	0.10
Maximum time without improvement	100 s

$$\begin{aligned} \text{Min} \quad \text{WMMSE}_T = & \frac{0.724}{0.964}[(\text{PC1}^* - 0.362)^2 + 0.145] \\ & + \frac{0.185}{0.964}[(\text{PC2}^* + 0.874)^2 + 0.037] \\ & + \frac{0.055}{0.964}[(\text{PC3}^* + 0.660)^2 + 0.011] \\ \text{St} : & \ \text{MRR} \geq 16.00 \\ & \mathbf{x}^T\mathbf{x} \leq 2.829 \end{aligned} \tag{22}$$

Table 11 Optimal point identified in the MMSE approach

	Parameters			Responses			
	V_c	f	d	PC1	PC2	PC3	MMSE_T
Optimal point	1.600	0.345	0.385	−1.405	−0.629	1.402	2.282
Targets	–	–	–	−0.816	−2.001	2.113	–

Table 12 Optimal results for the AISI 52100 hardened steel turning obtained with the MMSE approach

	Parameters			Responses						
	V_c	f	d	T	C_t	T_t	K_p	R_a	R_t	MRR
Optimal point	252	0.33	0.25	6.46	0.08	0.76	0.69	0.27	1.84	21.11
Targets	–	–	–	10.00	0.10	0.77	0.63	0.25	1.70	≥16.00
Units	m/min	mm/rev	mm	min	min	min	U$	µm	µm	cm^3/min

Table 13 Standardization and weighting of the original responses

Test	0.3·Z(T)	0.1·Z(C_t)	0.1·Z(T_t)	0.1·Z(K_p)	0.2·Z(R_a)	0.2·Z(R_t)
1	0.808	0.131	0.116	−0.028	−0.168	−0.294
2	0.329	0.065	0.055	−0.030	−0.040	−0.065
3	−0.114	−0.069	−0.075	−0.095	0.215	0.231
4	−0.236	−0.102	−0.105	−0.092	0.151	0.253
5	0.169	0.131	0.135	0.123	−0.168	−0.264
6	0.001	0.065	0.071	0.095	−0.168	−0.168
7	−0.272	−0.069	−0.059	0.030	0.407	0.150
8	−0.103	−0.102	−0.115	−0.169	0.087	0.135
9	0.177	0.018	0.009	−0.058	0.087	−0.087
10	−0.041	−0.059	−0.068	−0.111	−0.104	0.002
11	0.559	0.291	0.292	0.217	−0.424	−0.198
12	−0.265	−0.114	−0.116	−0.098	0.215	0.542
13	0.169	−0.026	−0.040	−0.125	0.215	0.098
14	−0.200	−0.026	−0.016	0.059	0.215	−0.050
15	−0.202	−0.026	−0.016	0.061	−0.104	0.002
16	−0.193	−0.026	−0.017	0.053	−0.104	−0.072
17	−0.212	−0.026	−0.015	0.071	−0.104	−0.072
18	−0.192	−0.026	−0.017	0.052	−0.104	−0.072
19	−0.183	−0.026	−0.018	0.044	−0.104	−0.072

Table 14 Principal component analysis for the weighted responses

Eigenvalue	0.145	0.037	0.011	0.007	0.000	0.000
Proportion	0.724	0.185	0.055	0.035	0.001	0.000
Cumulative	0.724	0.909	**0.964**	0.999	1.000	1.000
Eigenvector	PC1*	PC2*	PC3*	PC4*	PC5*	PC6*
0.3·Z(T)	0.716	−0.652	−0.058	0.021	0.242	0.000
0.1·Z(C_t)	0.245	0.045	−0.015	−0.404	−0.572	0.669
0.1·Z(T_t)	0.239	0.086	0.003	−0.450	−0.436	−0.737
0.1·Z(K_p)	0.127	0.348	0.124	−0.648	0.647	0.095
0.2·Z(R_a)	−0.405	−0.531	0.691	−0.273	−0.040	0.000
0.2·Z(R_t)	−0.435	−0.403	−0.710	−0.374	0.064	0.000

Data extracted from variance–covariance matrix

In this formulation, it is convenient to highlight that, besides the responses, the principal components are also weighted, being these attributed weights based on the degree of explanation of each component.

The genetic algorithm was also applied in the WMMSE formulation, using the *Solver Evolutionary* supplement with the same parameters of Table 9. Table 16 presents the identified optimal point and Table 17 shows these results, with 95% of reliability, for the AISI 52100 hardened steel turning process.

4.4 Results and comparison

The results found with the MMSE and WMMSE optimizations are presented in Table 18. Basically, the difference between the identified optimal points in both approaches

Table 15 Data used to calculate the targets for the principal components of the weighted responses

	T	C_t	T_t	K_p	R_a	R_t
Mean	7.355	0.129	0.807	0.772	0.276	1.807
Standard deviation	3.661	0.048	0.048	0.054	0.031	0.270
Target	10.00	0.10	0.77	0.63	0.25	1.70
Standardization	0.723	−0.611	−0.778	−2.635	−0.841	−0.397
Eigenvector PC1*	0.716	0.245	0.239	0.127	−0.405	−0.435
Eigenvector PC2*	−0.652	0.045	0.086	0.348	−0.531	−0.403
Eigenvector PC3*	−0.058	−0.015	0.003	0.124	0.691	−0.710

Table 16 Optimal point identified in the WMMSE approach

	Parameters			Responses			
	V_c	f	d	PC1*	PC2*	PC3*	$WMMSE_T$
Optimal point	1.505	0.547	0.514	0.094	0.123	−0.035	0.384
Targets	–	–	–	0.362	−0.874	−0.660	–

Table 17 Optimal results for the AISI 52100 hardened steel turning obtained with the WMMSE approach

	Parameters			Responses						
	V_c	f	d	T	C_t	T_t	K_p	R_a	R_t	MRR
Optimal point	250	0.25	0.26	7.19	0.13	0.81	0.76	0.25	1.67	16.25
Targets	–	–	–	10.00	0.10	0.77	0.63	0.25	1.70	≥16.00
Units	m/min	mm/rev	mm	min	min	min	U$	µm	µm	cm^3/min

Table 18 Optimal results for AISI 52100 hardened steel turning

	Parameters			Responses						
	V_c	f	d	T	C_t	T_t	K_p	R_a	R_t	MRR
Targets	–	–	–	10.00	0.10	0.77	0.63	0.25	1.70	≥16.00
Optimal point, MMSE	252	0.33	0.25	6.46	0.08	0.76	0.69	0.27	1.84	21.11
Optimal point, WMMSE	250	0.25	0.26	7.19	0.13	0.81	0.76	0.25	1.67	16.25
Optimal point, GRA	254	0.47	0.15	6.89	0.08	0.73	0.62	0.30	2.51	18.09
Units	m/min	mm/rev	mm	min	min	min	U$	µm	µm	cm3/min

occurred in terms of the feed rate of the process. The WMMSE approach identified a low feed rate (0.25 mm/rev) in comparison to the value found in MMSE (0.33 mm/rev). As a consequence, an improvement of 11.3% was observed for the end of tool life, which increased from 6.46 to 7.19 min. Furthermore, the finishing of the machined piece was better in the second optimization, since the average surface roughness reached its target and the maximum peak to valley roughness was better than its target. Because they have received the lowest weights in the optimization, the cutting time, the total cycle time and the total cost increased in relation to the values obtained with the MMSE optimization. However, these responses were still close to their specified values and, therefore, were considered satisfactory. Figure 9 presents the overlaid contour plots for this process, highlighting how the optimal point changes when the multiple responses are optimized with different degrees of importance.

As it was said in the introduction of this study, traditional optimization methods that do not consider the correlation between the responses can lead to unsatisfactory results. For demonstration, we have also applied the gray relational analysis (GRA) for the optimization of the six responses, in order to compare the results found in the MMSE and WMMSE optimization. GRA optimization results are presented in Table 18, where it is possible to notice that both MMSE and WMMSE approaches present better optimal points for most of the responses.

5 Confirmation runs

The confirmation runs were conducted to check whether the responses at optimum highlighted by the optimization method employed are really attainable. The average results

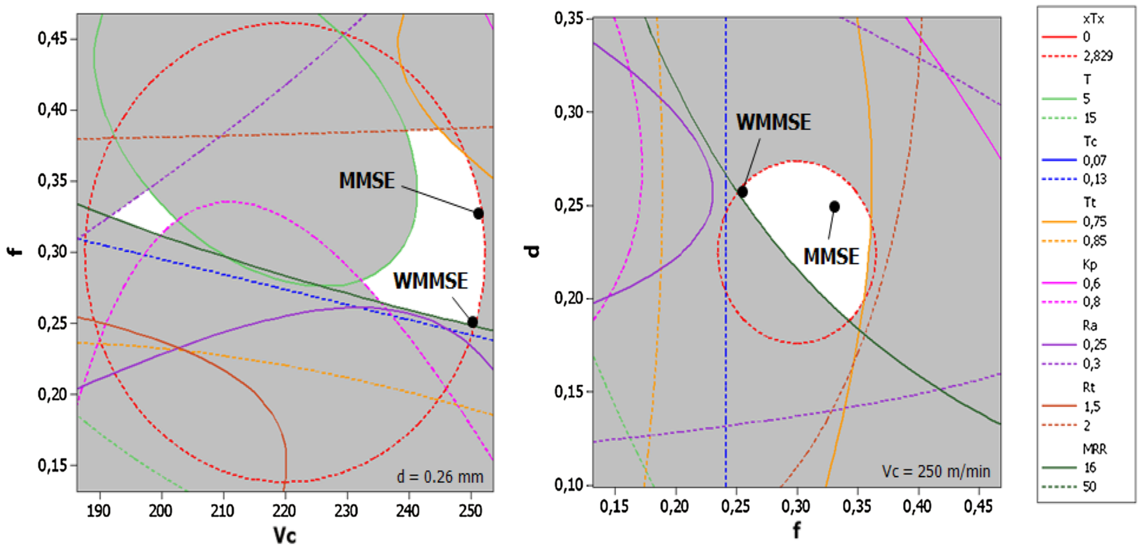


Fig. 9 Overlaid contour plots

Table 19 Optimal results for AISI 52100 hardened steel turning

	Parameters			Responses						
	V_c	f	d	T	C_t	T_t	K_p	R_a	R_t	MRR
Optimal point, WMMSE	250	0.25	0.26	7.19	0.13	0.81	0.76	0.25	1.67	16.25
Confirmation runs										
1	250	0.25	0.26	7.17	0.13	0.81	0.76	0.25	1.67	16.25
2	250	0.25	0.26	7.16	0.13	0.80	0.76	0.26	1.66	16.25
3	250	0.25	0.26	7.17	0.13	0.81	0.76	0.25	1.68	16.25
Means	250	0.25	0.26	7.17	0.13	0.81	0.76	0.25	1.67	16.25
Units	m/min	mm/rev	mm	min	min	min	U$	µm	µm	cm^3/min

of the confirmation experiment are the final step of the analysis of findings acquired. According to the results shown in Table 19, it can be concluded that the optimization method employed reached responses of exposed targets.

From the relations between flank wear and number of steps in the workpiece, it was obtained the end of life of the cutting tool, at the point at which the value of the flank wear reaches 0.3 mm. Figure 10 shows the tool wear VB_C function of the numbers steps in AISI 52100 steel with the parameter values: $V_c = 250$ m/min, $f = 0.25$ mm/rev, $d = 0.26$ mm.

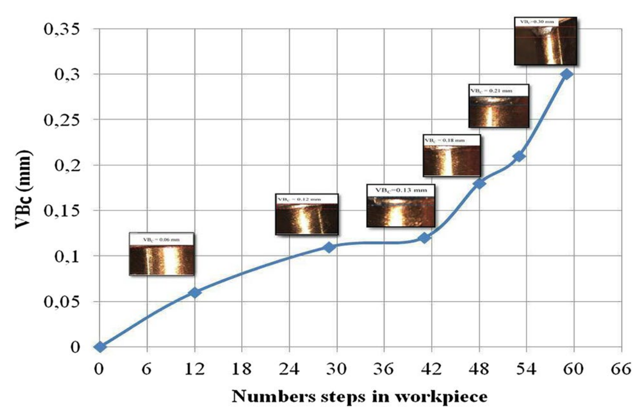


Fig. 10 VB_C × steps AISI 52100 steel: $V_c = 250$ m/min, $f = 0.25$ mm/rev, $d = 0.26$ mm

6 Conclusions

This work's aims are twofold: (a) to present the multi-objective optimization for highly correlated responses of the AISI 52100 hardened steel turning using wiper mixed ceramic inserts and (b) for such purpose, to employ both the MMSE and the WMMSE approaches so that a comparison may be made. The multiple responses were optimized with once with equal weights and once with different ones, taking into consideration the correlation structure between them. Based on this work's results, the following conclusions can be drawn:

- All developed models, both for turning outputs and for principal components, can be used in prediction and control of the process since they yielded p values less than 5% of significance and adjustments above 87%.
- The PCA reduced the problem dimensionality by 50%, once three principal components were enough to represent the six optimized responses.
- The MMSE optimization method provided good solutions for most of the responses. However, due to the multi-objective nature of the problem and the assumption of equal weights, a relatively short tool life was found.
- The weighting strategy employed by the WMMSE increased the length of the tool's life from 6.46 to 7.19 min (an 11.3% improvement). The resulting surface finishing was also better: the average surface roughness' target was reached and the maximum peak-to-valley roughness remained below its specified upper value.
- On the other hand and although having been considered satisfactory, the cutting time, total cycle time and total cost presented higher values if compared to the MMSE optimization.
- Considering that the WMMSE approach identified a better optimal condition for the process, it can be stated that the AISI 52100 hardened steel turning is optimized, with a reliability of 95%, through the following input parameters: $V_c = 250$ m/min, $f = 0.25$ mm/rev and $d = 0.26$ mm. It results in: $T = 7.19$ min; $C_t = 0.13$ min; $T_t = 0.81$ min; $K_p =$ U\$ 0.76; $R_a = 0.25$ µm; $R_t = 1.67$ µm; MRR $= 16.25$ cm^3/min.
- The confirmation tests yielded all responses inside their confidence intervals, allowing the experimental validation of this work.

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References

1. Grzesik W (2009) Wear development on wiper Al2O3-TiC mixed ceramic tools in hard machining of high strength steel. Wear 266:1021–1028. doi:10.1016/j.wear.2009.02.010
2. Ferreira R, Řehoř J, Lauro CH et al (2016) Analysis of the hard turning of AISI H13 steel with ceramic tools based on tool geometry: surface roughness, tool wear and their relation. J Braz Soc Mech Sci Eng. doi:10.1007/s40430-016-0504-z
3. Alaeddini A, Yang K, Mao H et al (2014) An adaptive sequential experimentation methodology for expensive response surface optimization—case study in traumatic brain injury modeling. Qual Reliab Eng Int 30:767–793. doi:10.1002/qre.1523
4. Huang MS, Lin TY (2008) Simulation of a regression-model and PCA based searching method developed for setting the robust injection molding parameters of multi-quality characteristics. Int J Heat Mass Transf 51:5828–5837. doi:10.1016/j.ijheatmasstransfer.2008.05.016
5. Costa DMD, Paula TI, Silva PAP, Paiva AP (2016) Normal boundary intersection method based on principal components and Taguchi's signal-to-noise ratio applied to the multiobjective optimization of 12L14 free machining steel turning process. Int J Adv Manuf Technol. doi:10.1007/s00170-016-8478-7
6. Box GEP, Hunter WG, MacGregor JF, Erjavec J (1973) Some problems associated with the analysis of multiresponse models. Technometrics 15:33–51
7. Chiao H, Hamada M (2001) Analyzing experiments with correlated multiple responses. J Qual Technol 33:451–465
8. Paiva AP, Paiva EJ, Ferreira JR et al (2009) A multivariate mean square error optimization of AISI 52100 hardened steel turning. Int J Adv Manuf Technol 43:631–643. doi:10.1007/s00170-008-1745-5
9. Costa DMD, Belinato G, Brito TG et al (2016) Weighted principal component analysis combined with taguchi's signal-to-noise ratio to the multiobjective optimization of dry end milling process: a comparative study. J Braz Soc Mech Sci Eng. doi:10.1007/s40430-016-0614-7
10. Gomes JHF, Paiva AP, Costa SC et al (2012) Weighted multivariate mean square error for processes optimization: a case study on flux-cored arc welding for stainless steel claddings. Eur J Oper Res. doi:10.1016/j.ejor.2012.11.042
11. Palani PK, Murugan N (2007) Optimization of weld bead geometry for stainless steel claddings deposited by FCAW. J Mater Process Technol 190:291–299. doi:10.1016/j.jmatprotec.2007.02.035
12. Naves FL, de Paula TI, Balestrassi PP et al (2017) Multivariate normal boundary intersection based on rotated factor scores: a multiobjective optimization method for methyl orange treatment. J Clean Prod 143:413–439. doi:10.1016/j.jclepro.2016.12.092
13. Caldas LG, Norford LK (2002) A design optimization tool based on a genetic algorithm. Autom Constr 11:173–184
14. Montgomery D (2009) Design and analysis of experiments, 7th edn. Wiley, New York
15. Box GEP, Draper NR (1987) Empirical model-building and response surfaces. Wiley, New York
16. Rocha LCS, Paiva AP, Paiva EJ, Balestrassi PP (2015) Comparing DEA and principal component analysis in the multiobjective optimization of P-GMAW process. J Braz Soc Mech Sci Eng. doi:10.1007/s40430-015-0355-z
17. Paiva AP, Ferreira JR, Balestrassi PP (2007) A multivariate hybrid approach applied to AISI 52100 hardened steel turning optimization. J Mater Process Technol 189:26–35. doi:10.1016/j.jmatprotec.2006.12.047
18. Johnson RA, Wichern DW (2007) Applied multivariate statistical analysis, 6th edn. Pearson Education Inc, Upper Saddle River
19. Busacca PG, Marseguerra M, Zio E (2001) Multiobjective optimization by genetic algorithms: application to safety systems. Reliab Eng Syst Saf 72:59–74. doi:10.1016/S0951-8320(00)00109-5
20. Zain AM, Haron H, Sharif S (2010) Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process. Expert Syst Appl 37:4650–4659. doi:10.1016/j.eswa.2009.12.043
21. Sivasakthivel PS, Sudhakaran R (2013) Optimization of machining parameters on temperature rise in end milling of Al 6063 using response surface methodology and genetic algorithm. Int J Adv Manuf Technol 67:2313–2323. doi:10.1007/s00170-012-4652-8

22. Öktem H, Erzurumlu T, Kurtaran H (2005) Application of response surface methodology in the optimization of cutting conditions for surface roughness. J Mater Process Technol 170:11–16. doi:10.1016/j.jmatprotec.2005.04.096
23. Christiansen M, Fagerholt K, Flatberg T et al (2011) Maritime inventory routing with multiple products: A case study from the cement industry. Eur J Oper Res 208:86–94. doi:10.1016/j.ejor.2010.08.023
24. Gomes JHF, Júnior ARS, Paiva AP et al (2012) Global Criterion Method based on principal components to the optimization of manufacturing processes with multiple responses. J Mech Eng 58:345–353. doi:10.5545/sv-jme.2011.136
25. Correia DS, Gonçalves CV, Da Cunha SS, Ferraresi VA (2005) Comparison between genetic algorithms and response surface methodology in GMAW welding optimization. J Mater Process Technol 160:70–76. doi:10.1016/j.jmatprotec.2004.04.243