Optimization of duplex stainless steel UNS S32205 end milling with noise factor analysisy

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Abstract

The metalworking industry faces challenges in maintaining process performance due to variables affecting product quality, particularly in processes requiring precise control over machined part finishes. Duplex stainless steels, known for their high strength, work hardening, and low thermal conductivity, pose specific machining challenges that can hinder producing high-quality components and equipment. This study aimed to determine optimal parameters for end milling of duplex stainless steel UNS S32205. Formulated as a combined objective function derived from minimizing the mean square error (MSE) for parameters R_a and R_t, subject to a common constraint. The optimization was conducted using generalized reduced gradient (GRG). A Pareto frontier was constructed, offering efficient results with R_a = 0.4534 µm and R_t = 3.2671 µm for varying weights assigned to R_a and R_t. Adjusting weights in the objective function allowed prioritization based on specific needs. Optimal input parameters were identified as cutting speed (v_c) = 60.79 m/min, feed per tooth (f_z) = 0.15 mm/tooth, axial depth of cut (a_p) = 0.90 mm, and radial depth of cut (a_e) = 16.31 mm, simultaneously optimizing both parameters. This approach reduced the mean square error (RMSE), determining roughness R_a and R_t mean and variance, thus improving the machining process. Confirmatory trials using an orthogonal Taguchi arrangement (L9) yielded results within the algorithm's confidence interval. This research offers a robust methodology for optimizing machining parameters, enhancing product quality in the metalworking industry.

Keywords: duplex stainless steel, end milling, roughness, mean, variance, optimization.

1. Introduction

Duplex stainless steel (DSS) has a microstructure that contains both austenite and ferrite. These alloys give DSS excellent mechanical properties, such as resistance to pitting and stress corrosion, which justifies its application in the oil and gas industry (Gamarra & Diniz, 2018; Policena *et al*., 2018; Selvaraj, 2018). The remarkable strength, poor thermal conductivity, and significant hardening properties of these materials pose challenges for machining processes, such as milling and turning. (Selvaraj, 2018).

End milling is an extremely relevant procedure in the manufacturing industry, playing a key role in the manufacturing of profiles, slots, contours, and mechanical components for the oil and gas industries (Kalidass & Palanisamy, 2018).

Due to the hardening capability of duplex stainless steels (DSS) and taking into account their thermomechanical properties, high temperatures arise in the regions due to the contact between the cutting tool and the chip, as well as between the cutting tool and the workpiece, resulting in a higher cutting force, tool wear, and reduced machined surface quality (Policena *et al*., 2018). The surface quality of the workpiece is an aspect related to tool life (Oliveira *et al*., 2020).

In the study by Vasconcelos *et al*. (2021), a full factorial design and the generalized reduced gradient method (GRG) were employed to identify the optimal points of the process variables that minimized the roughness on the machined part. The researchers concluded that statistical analysis proved to be a crucial tool in modeling the roughness response (R_t) and that optimization proved efficient in determining the optimal parameters.

In the study conducted by Paiva *et al*. (2009), multivariate optimization and the mean square error criterion were applied to the turning process of hardened steel AISI 52100. A combination of principal component analysis (PCA) and response surface methodology (RSM) was used.

Duarte Costa *et al*. (2016) proposed a novel hybrid multi-objective approach called NBI-MMSE, which integrates NBI (Normal Border Intersection) functions with multivariate mean square error (MMSE).

In this context, the aim of this study is to establish robust parameters to optimize the roughness R_a and the roughness R_t in the end milling process of duplex stainless steel UNS S32205, minimizing the EQM (Mean Square Error). The variables considered are cutting speed (v_c), radial depth of cut (a_e), feed per tooth (f_z) and axial depth of cut (a_p).

The selection of control variables in this study was carried out based on their direct influence on the milling process. The cutting speed (v_c) is a critical variable that affects the material removal rate and heat generation. The radial depth of cut (a_e) and axial depth of cut (a_p) are parameters that determine the amount of material removed in each pass of the tool. The feed per tooth (f_z) is a factor that influences surface roughness, as it determines the thickness of the chip cut by each cutting edge of the tool. These variables were chosen for their relevance in the milling process and the possibility of being adjusted and controlled to optimize surface roughness.

2. Robust parameter design

Robust Parameter Design (RPD) is a set of techniques for determining levels of control variables to achieve two goals: (a) ensuring that the mean value of responses is close to the desired target and (b) minimizing variability around that target (Montgomery, 2013).

According to Montgomery (2013), with respect to techniques employed for data modeling and analysis, Response Surface Methodology has been recognized as an effective approach for RPD (robust response planning). In this context, the analysis method is constructed from one of two experimental setups: cross or matched arrangements. For this particular study, a combined arrangement was chosen as the experimental strategy.

Combined arrangements are defined as sequences of experiments in which the noise variables are treated as control variables. In this way, control and noise variables are combined in a single experimental setup. Based on the data collected in the experiments, a response surface model can be built that relates the control variables, the noise, and their respective interactions. A second-order model is developed from a combined arrangement (Montgomery, 2013), according to Eq. 1.

$$y(x,z) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x^2_i + \sum_{i<j} \sum \beta_{ij} x_i x_j + \sum_{i=1}^{r} y_i z_i + \sum_{i-1}^{k} \sum_{j=1}^{r} \delta_{ij} x_i z_j + \varepsilon \qquad (1)$$

Where: y - Response of interest; z_i - Noise variables
k - Number of control variables
ε - Experimental error
β_0, β_i, β_{ii}, β_{ij}, γ_i, δ_{ij} - Coefficients to be estimated
x_i - Control Variables
r - Number of noise variables

The coefficients β_0, β_i, β_{ii}, β_{ij}, γ_i, δ_{ij} are estimated using the Ordinary Least Squares (OLS) Method. Once the response surface model has been established, the equation for the mean response y ($\mu(y)$) can be directly obtained from the combined model, according to Eq. 2:

$$\mu(y) = f(x) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x^2_i + \sum_{i<1} \sum \beta_{ij} x_i x_j \qquad (2)$$

The variance model is developed by employing the derivation, according to Eq. 3:

$$\sigma^2(y) = \sum_{i=1}^{r} \left[\frac{\partial_y(x,z)}{\partial_{z_1}} \right]^2 \cdot \sigma^2_{z_1} + \sigma^2 \qquad (3)$$

It is important to note that most studies related to Robust Parameter Design (RPD) use the combination of mean and variance in a single function to be minimized. This function is known as the Mean Squared Error (MSE), according to Brito (2013, 2014), being restricted to the space of experiments of the solution, so that $Min\ [\ \hat{y}\ (x) - T\ ]^2 + \sigma^2$ (Paiva *et al.*, 2012; Shi *et al.*, 2011).

Considering the existence of different degrees of importance between mean and variance, the objective function EQM can take the form $EQM_w = w_1 \times (\hat{y}(x) - T)^2 + w_2 \times \hat{\sigma}^2(x)$, where the weights w_1 and w_2 are defined as pre-specified positive constants (Kazemzadeh *et al.*, 2008). Such weights can also be chosen in different convex combinations, so that a set of solutions can be generated, where $w_1 + w_2 = 1$ with w_1 and $w_2 \geq 0$.

In this research, used was the concept of Mean Squared Error (MSE), developed by Köksoy & Yalcinoz (2006), which is defined as the sum of the variance with the squared difference between the mean of the response and the established target value. Thus, minimizing the EQM aims to ensure that the mean value of the response is as close as possible to the target value, reducing variability. The optimization of this process can be achieved according to Eq. 4.

$$EQM\ (y) = [\mu\ (y) - T_y\ ]^2 + \sigma^2\ (y) \qquad (4)$$
$$\text{Subject to: } x^T x \leq \alpha^2$$

Where: $MSE\ (y)$ - Mean square error of the response y
$\mu(y)$ - Model for the mean of the response y
T_y - Response target y
$\sigma^2(y)$ - Model for response variance y
$x^T x \leq \alpha^2$ - Spherical constraint for the experimental space.

It is noteworthy that the concept of the mean square error has been employed for robust optimization of different production processes (Priyanga & Muthadhi, 2023; Vedaiyan & Govindarajalu, 2023).

3. Experimental procedure

For data collection, the end milling experiments of duplex stainless steel UNS S32205 were planned by combined arrangement, using Minitab© statistical software, with four control variables and three noise variables, totaling 82 experiments. Tables 1 and 2 present the control and noise variables with their respective operating levels.

Table 1 - Control variables.

Variables	Levels				
	-2.83	-1	0	1	2.83
Cutting Speed (v_c) [m/min]	32.50	60.00	75.00	90.00	117.40
Feed per tooth (f_z) [mm/tooth]	0.04	0.10	0.13	0.16	0.21
Radial depth of cut (a_e) [mm]	12.26	15.00	16.50	18.00	20.74
Axial depth of cut (a_p) [mm]	0.43	0.80	1.00	1.20	1.57

Table 2 - Noise variables.

Variables	Levels		
	-1	0	1
Flank wear (v_b) [mm]	0	0.15	0.30
Fluid flow rate (Q) [l/min].	0	10	20
Fluid concentration (C) [%]	0	10	20

The workpiece was duplex stainless steel UNS S 32205. The specimen used had dimensions of 115 x 115 x 170 mm and an average hardness of 250 HB. The chemical composition is presented according to Table 3.

Table 3 - Chemical composition (% by Weight) of UNS S32205 duplex stainless steel (Imoa, 2014).

C	Si	Mn	P	S	N	Al	Cr	Mo	Ni	Cu	W	Co
0.01	0.47	1.22	0.019	0.01	0.19	0.00	22.2	3.14	5.62	0.19	0.02	0.05

The experiments were performed on a Eurostec CNC machining center, with a power of 15 kW and maximum speed of 10,000 rpm. The cutting fluid used was the synthetic oil Quimatic MEII. The tool used was an end mill code R390-025A25-11M, with a diameter of 25 mm, position angle χr of 90°, cylindrical shank and mechanical clamping, with 3 inserts. The inserts were ISO M30 carbide, code R390-11 T3 08M-MM 2040 (Sandvik-Coromant, 2023), coated with (Ti,Al)N + TiN through the Physical Vapor Deposition (PVD) process.

After the milling process of the duplex stainless steel UNS S 32205 specimen using the parameters determined by the experimental setup, the surface roughness R_a and the surface roughness R_t were evaluated on the machined area using a Mitutoyo Surftest SJ-210 M portable roughness meter. For the measurements, a *cut-off of* 0.8 mm was considered (Grouss, 2011).

The measurements were conducted at three distinct points (center and extremities) under ambient temperature conditions, enabling the consideration of the mean value of the readings for a precise analysis.

This study is experimental in nature to identify the optimum conditions for the surface roughness R_a and R_t during the end milling process of duplex stainless steel UNS S32205.

Design of Experiments (DOE) was employed, to collect the data analyzed by statistical methods, according to Montgomery (2013).

Robust parameter design (RPD) aims to minimize product and process variability, leading to improved quality and reliability (Souza *et al.*, 2018). This approach achieves process robustness by identifying optimal control parameter settings that minimize the impact of noise factors on response variables (Arkadani & Noorossana, 2008).

Data collection plays a crucial role in the conduct of the work, and an inadequate database can lead to questionable results. Therefore, it is of utmost importance to perform detailed planning of the experiment, followed by proper execution and accurate recording, according to the following steps:

Step 1 - Response Surface Methodology (RSM): used for planning the experiments, collecting data, mathematical modeling of the responses, and analyzing the influences of the parameters on R_a and R_t;

Step 2 - Mean Squared Error (MSE) Optimization: used to obtain the most appropriate combination of machining parameters that will allow maximizing the process results.

The set of runs was generated considering the controllable factors (cutting speed - v_c, feed per tooth - f_z, axial depth of cut - a_e, and radial depth of cut - a_e) and the noise variables (flank wear - v_b, cutting fluid flow - Q and cutting fluid concentration - C), according to Table 4.

Table 4 - Experimental matrix.

Experiments	Control Variables				Noise Variables			Answers	
	v_c	f_z	a_e	a_p	v_b	Q	C	R_a	R_t
1	-1	-1	-1	-1	-1	-1	1	0.520	4.210
2	1	-1	-1	-1	-1	-1	-1	0.347	2.760
3	-1	1	-1	-1	-1	-1	-1	0.630	3.667
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
80	0	0	0	0	0	0	0	0.380	2.837
81	0	0	0	0	0	0	0	0.340	2.640
82	0	0	0	0	0	0	0	0.397	3.136

4. Results and discussions

The modeling of the responses of the combined arrangement was written in terms of the control and noise variables considered in this study is presented as Eq. 5.

$$
\begin{aligned}
R_a, R_t\,(x,z) = {} & \beta_0 + \beta_1 f_z + \beta_2 a_p + \beta_3 v_c + \beta_4 a_e + \beta_{11} f_z^2 + \beta_{22} a_p^{\ 2} + \beta_{33} v_c^{\ 2} + \beta_{44} a_e^{\ 2} \\
& + \beta_{12} f_z a_p + \beta_{13} f_z v_c + \beta_{14} f_z a_e + \beta_{23} a_p v_c + \beta_{24} a_p a_e + \beta_{34} v_c a_e + \gamma_1 v_b \\
& + \gamma_2 C + \gamma_3 Q + \delta 11 f_z v_b + \delta_{12} f_z C + \delta_{13} f_z Q + \delta_{21} a_p v_b + \delta_{22} a_p + \delta_{23} a_p Q \\
& + \delta_{31} v_c v_b + \delta_{32} v_c C + \delta_{33} v_c Q + \delta_{41} a_e v_b + \delta_{42} a_e C + \delta_{43} a_e Q
\end{aligned} \qquad (5)
$$

Where: R_a and R_t - Answers of interest
β_0, β_i, β_{ii}, β_{ij}, γ_i, δ_{ij} - Coefficients to be estimated (i = 1, 2, 3, 4 i < j)
f_z - (Feed per tooth)
v_c - (Cutting speed)
v_b - (Flank Wear)
C - (Fluid concentration)
a_p - (Machining depth)
a_e - (Radial depth of cut)
Q - (Fluid Flow)

It was observed that the control variables cutting speed (v_c) and feed per tooth (f_z), exert significant influence on the surface roughness R_a. The variable's feed per tooth (f_z) and axial depth of cut (a_p) influence the roughness R_t. These relationships resulted in fits above 80% according to Montgomery (2013), Table 5.

Table 5 - Estimated coefficients.

R_a					R_t				
Term	Coef	EP of Coef	T-value	P-value	Term	Coef	EP of Coef	T-value	P-value
Constant	0.42560	0.01350	31.54	0.000	Constant	3.04570	0.0942	32.32	0.000
v_c	0.01597	0.00591	2.70	0.009	v_c	0.03850	0.0413	0.93	0.355
f_z	0.05574	0.00591	9.43	0.000	f_z	0.29390	0.0413	7.12	0.000
a_e	0.00198	0.00591	0.34	0.738	a_e	-0.02150	0.0413	-0.52	0.605
a_p	0.00826	0.00591	1.40	0.168	a_p	0.12340	0.0413	2.99	0.004
v_b	0.13823	0.00661	20.93	0.000	v_b	0.71500	0.0461	15.50	0.000
Q	-0.05342	0.00661	-8.09	0.000	Q	-0.10670	0.0461	-2.31	0.025
C	0.00452	0.00661	0.68	0.497	C	-0.08610	0.0461	-1.87	0.068
$v_c \times v_c$	0.04525	0.00511	8.86	0.000	$v_c \times v_c$	0.29020	0.0357	8.14	0.000
$f_z \times f_z$	0.06038	0.00511	11.82	0.000	$f_z \times f_z$	0.38380	0.0357	10.76	0.000
$a_e \times a_e$	0.06725	0.00511	13.17	0.000	$a_e \times a_e$	0.32590	0.0357	9.14	0.000
$a_p \times a_p$	0.04563	0.00511	8.93	0.000	$a_p \times a_p$	0.26140	0.0357	7.33	0.000
$v_c \times f_z$	0.08814	0.00661	13.34	0.000	$v_c \times f_z$	0.49540	0.0461	10.74	0.000
$v_c \times a_e$	-0.00517	0.00661	-0.78	0.437	$v_c \times a_e$	-0.06880	0.0461	-1.49	0.142
$v_c \times a_p$	-0.01127	0.00661	-1.71	0.094	$v_c \times a_p$	-0.02750	0.0461	-0.60	0.554
$v_c \times v_b$	**0.03502**	**0.00661**	**5.30**	**0.000**	**$v_c \times v_b$**	**0.27490**	**0.0461**	**5.96**	**0.000**
$v_c \times Q$	0.00005	0.00661	0.01	0.994	$v_c \times Q$	0.00090	0.0461	0.02	0.985
$v_c \times C$	0.00117	0.00661	0.18	0.860	$v_c \times C$	-0.05270	0.0461	-1.14	0.259
$f_z \times a_e$	0.00542	0.00661	0.82	0.415	$f_z \times a_e$	-0.02190	0.0461	-0.48	0.636
$f_z \times a_p$	0.01033	0.00661	1.56	0.124	$f_z \times a_p$	0.08670	0.0461	1.88	0.066
$f_z \times v_b$	**-0.07577**	**0.00661**	**-11.47**	**0.000**	**$f_z \times v_b$**	**-0.29080**	**0.0461**	**-6.30**	**0.000**
$f_z \times Q$	-0.00805	0.00661	-1.22	0.229	$f_z \times Q$	0.12220	0.0461	2.65	0.011
$f_z \times C$	0.00295	0.00661	0.45	0.657	$f_z \times C$	0.00690	0.0461	0.15	0.882
$a_e \times a_p$	-0.00548	0.00661	-0.83	0.410	$a_e \times a_p$	0.04770	0.0461	1.04	0.305
$a_e \times v_b$	0.00492	0.00661	0.75	0.460	**$a_e \times v_b$**	**0.11580**	**0.0461**	**2.51**	**0.015**
$a_e \times Q$	-0.00173	0.00661	-0.26	0.794	$a_e \times Q$	-0.00470	0.0461	-0.10	0.918
$a_e \times C$	-0.00555	0.00661	-0.84	0.405	$a_e \times C$	-0.02480	0.0461	-0.54	0.593
$a_p \times vb$	0.01014	0.00661	1.54	0.131	**$a_p \times v_b$**	**0.12050**	**0.0461**	**2.61**	**0.012**
$a_p \times Q$	0.00392	0.00661	0.59	0.555	$a_p \times Q$	0.00540	0.0461	0.12	0.908
$a_p \times C$	-0.00545	0.00661	-0.83	0.413	$a_p \times C$	-0.06470	0.0461	-1.40	0.167
S	R^2	R^2 (adj.)	R^2 (pred)		S	R^2	R^2 (adj.)	R^2 (pred)	
0.052841	96.09%	93.91%	89.93%		0.369048	93.51%	89.89%	83.30%	

The control variables v_c, f_z, a_e and a_p were transformed into their coded form. The coefficients were estimated using the Ordinary Least Squares (OLS) method using MINITAB 19® statistical software, by obtening the Eqs. 6 and 7:

$$\begin{aligned} R_a(x,z) = {} & 0.4256 + 0.01597v_c + 0.05574f_z - 0.00198a_e + 0.00826a_p + 0.13823v_b \\ & - 0.05342Q + 0.00452C + 0.04525v_c^2 + 0.06038f_z^2 + 0.06725a_e^2 \\ & + 0.04563a_p^2 + 0.08814v_c f_z - 0.00517v_c a_e - 0.01127v_c a_p \\ & + 0.03502v_c v_b + 0.00005v_c Q + 0.00117v_c C + 0.00542f_z a_e \\ & + 0.01033f_z a_p - 0.07577f_z v_b - 0.00805f_z Q + 0.00295f_z C \\ & - 0.00548a_e a_p + 0.00492a_e v_b - 0.00173a_e Q - 0.00555a_e C \\ & + 0.01014a_p v_b + 0.00392a_p Q - 0.00545a_p C \end{aligned} \tag{6}$$

$$\begin{aligned} R_t(x,z) = {} & 3.0457 + 0.0385v_c + 0.2939f_z - 0.0215a_e + 0.1234a_p + 0.715v_b \\ & - 0.1067Q - 0.0861C + 0.2902v_c^2 + 0.3838f_z^2 + 0.3259a_e^2 + 0.2614a_p^2 \\ & + 0.4954v_c f_z - 0.0688v_c a_e - 0.0275v_c a_p + 0.2749v_c v_b + 0.0009v_c Q \\ & - 0.0527v_c C - 0.0219f_z a_e + 0.0867f_z a_p - 0.2908f_z v_b + 0.1223f_z Q \\ & + 0.0069f_z C + 0.0477a_e a_p + 0.1158a_e v_b - 0.0047a_e Q - 0.0248a_e C \\ & + 0.1205a_p v_b + 0.0054a_p Q - 0.0647a_p C \end{aligned} \tag{7}$$

With the construction of the models $R_a, R_t\ (x,z)$, it was possible to establish the equations of mean and variance of the roughness R_a and R_t according to Eqs. 8 - 11:

$$\mu(R_a)(x,z) = 0.42560 + 0.01597v_c + 0.05574f_z + 0.00198a_e + 0.00826a_p + 0.04525v_c^2 + 0.06038f_z^2 + 0.06725a_e^2 + 0.0563a_p^2 + 0.08814v_cf_z - 0.00517v_ca_e - 0.01127v_ca_p + 0.00542f_za_e + 0.01033f_za_p - 0.00548a_ea_p \quad (8)$$

$$\sigma^2(R_a) = 0.02477 + 0.00969v_c - 0.02006f_z + 0.00149a_e + 0.00234a_p + 0.00123v_c^2 + 0.00581f_z^2 + 0.00006a_e^2 + 0.00015a_p^2 - 0.00530v_cf_z + 0.00033v_ca_e + 0.00070v_ca_p - 0.00075f_za_e - 0.00163f_za_p + 0.00015a_ea_p \quad (9)$$

$$\mu(R_t) = 3.0457 + 0.0385v_c + 0.2939f_z - 0.0215a_e + 0.1234a_p + 0.2902v_c^2 + 0.3838f_z^2 + 0.3259a_e^2 + 0.2614a_p^2 + 0.4954v_cf_z - 0.0688v_ca_e - 0.0275v_ca_p - 0.0219f_za_e + 0.0867f_za_p + 0.0477a_ea_p \quad (10)$$

$$\sigma^2(R_t) = 0.66622 + 0.40199v_c - 0.44313f_z + 0.17087a_e + 0.18230a_p + 0.07835v_c^2 + 0.09957f_z^2 + 0.01405a_e^2 + 0.01874a_p^2 - 0.16039v_cf_z + 0.06627v_ca_e + 0.07308v_ca_p - 0.06884f_za_e - 0.06965f_za_p + 0.03107a_ea_p \quad (11)$$

Using the MatLab® software, response surfaces were constructed that related the parameters under study to the roughnesses R_a and R_t. The analysis of the roughnesses R_a and R_t was carried out for several reasons, such as evaluating the surface quality, controlling the manufacturing process, predicting the product performance and optimizing the product design.

In the study in question, the choice of roughnesses R_a and R_t was due to their relevance to the objectives of the study, which aimed to evaluate the influence of process parameters on surface quality.

The analyses reveal that the interactions between the input variables played a significant role, since the combined effects of these parameters influence the results of the end milling process with respect to the roughness parameters R_a and R_t. Therefore, an analysis of the interactions was conducted, focusing on those that were deemed most significant.

The displayed graphs have curvature points where minimum values are identified for the mean and variance of R_a according to Figures 1 and 2.

The interaction between input variables is significant. When the cutting speed (v_c) is combined with the feed per tooth (f_z), the average roughness (R_a) increases considerably. Similar analysis is performed in Figure 2, where a relevant increase of the roughness variance R_a can be noticed when the values of cutting speed (vc) and feed per tooth (f_z) reach extreme values, considering the working parameters.

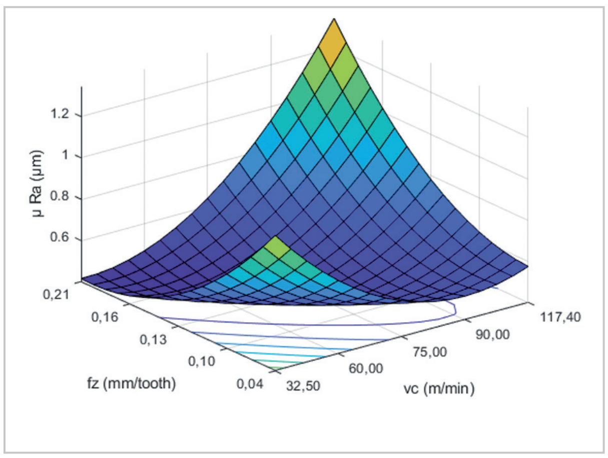

Figure 1 - Response surface for average R_a: Interaction between cutting speed (v_c) and feed per tooth (f_z).

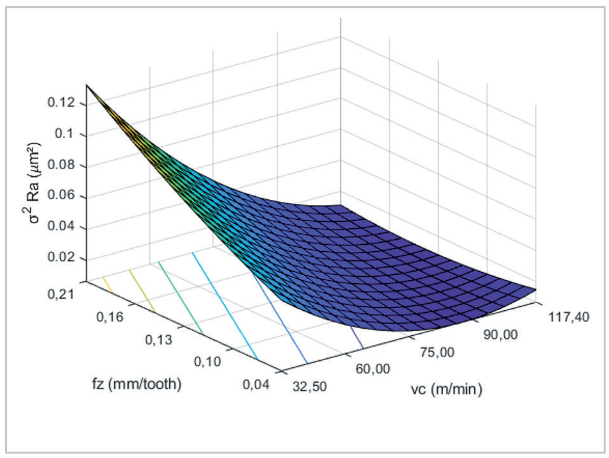

Figure 2 - Response surface for variance of R_a: Interaction between cutting speed (v_c) and feed per tooth (f_z).

It is also observed that there are significant interactions on end milling duplex stainless steel UNS S32205 according to Figures 3 and 4 on the roughness R_t.

For the roughness R_t, the interaction between feed per tooth (f_z) and axial depth of cut (a_p) is significant, as f_z increases along with a_p, there is a significant increase in the mean and variance.

The roughness R_t has behavior similar to R_a; a low value of R_a does not mean low R_t. While the roughness R_t is related to deep peaks and valleys, R_a are average values.

After formulating the mean and variance equations, it was possible to perform process optimization, minimizing the mean square error (RMSE). A target value for the roughness was established by individual optimization of the average value of the roughness R_a and R_t, using the minimization of Eq. 5. Thus, the target values of 0.4534 μm for R_a and 3.2643 μm for R_t were adopted, employing the GRG algorithm.

Eq. 14, which is the objective function, was developed from Eqs. 12 and 13. These latter equations represent the minimization of the mean squared error (MSE) for two responses, R_a and R_t, both subject to the same constraint.

The objective function (Eq. 14) is a combination of the two previous objective functions (Eqs. 12 and 13). In this combination, the results are weighted by two weights: w_1 and w_2. By adjusting these weights, we can give more importance to one objective over the other, depending on the specific needs of the problem we are solving.

Therefore, Eq. 14 is a weighted combination of the MSEs of R_a and R_t, allowing for the simultaneous optimization of the two responses. This results in a single objective function that, when minimized, leads us to the ideal solution for the problem.

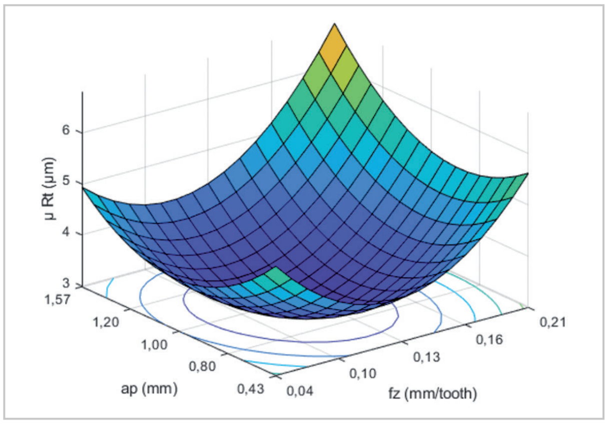

Figure 3 - Response surface for average R_t: Interaction between feed per tooth (f_z) and axial depth of cut (a_p).

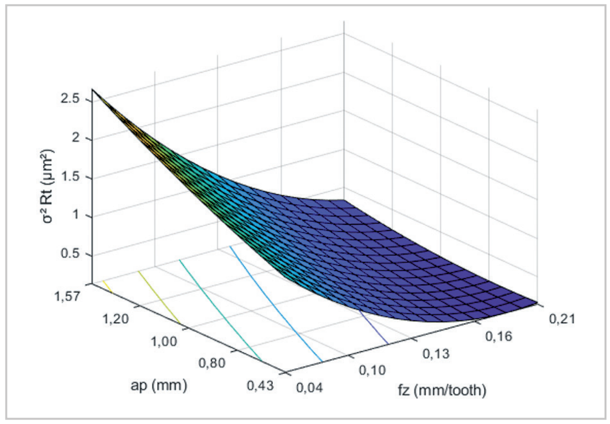

Figure 4 - Response surface for variance of R_t: Interaction between feed per tooth (f_z) and axial depth of cut (a_p).

$$\text{Minimize } EQM\,(R_a) = [\mu(R_a) - 0.4534] + \sigma^2\,(R_a) \quad (12)$$
$$\text{Subject to: } f_z^2 + a_p^{\,2} + v_c^{\,2} + a_e^{\,2} \leq 4$$

$$\text{Minimize } EQM\,(R_t) = [\mu(R_t) - 3.2643] + \sigma^2\,(R_t) \quad (13)$$
$$\text{Subject to: } f_z^2 + a_p^{\,2} + v_c^{\,2} + a_e^{\,2} \leq 4$$

$$EQM_{total} = w_1\,\{[\mu R_a - TR_a]^2 + \sigma^2 R_a\} + w_2\,\{[\mu R_t - TR_t]^2 + \sigma^2 R_t\} \quad (14)$$

Where: MSE (R_a, R_t) - root mean square error for the roughness R_a and R_t
w_1 and w_2 - weights assigned to the mean and variance of the roughness R_a and R_t
μ (R_a, R_t) - model for mean
σ^2 (y) (R_a, R_t) - model for variance

Using the Solver function, available in Microsoft Excel 2019® software, the robust parameters for the milling process of duplex stainless steel UNS S32205 were determined using the mean square error (MSE) method, according to Table 6.

Table 6 - Robust parameters determined using the EQM.

Weight w_1	Weight w_2	v_c (m/min)	f_z (mm/tooth)	a_e (mm)	a_p (mm)	$\mu(R_a)$ (µm)	$\mu(R_t)$ (µm)	EQM R_a	EQM R_t
0.00	1.00	61.27	0.15	16.30	0.90	0.4529273	3.2568946	0.0127131	0.2872047
0.05	0.95	61.27	0.15	16.30	0.90	0.4529343	3.2570000	0.0127102	0.2872048
0.10	0.90	61.26	0.15	16.30	0.90	0.4529421	3.2571168	0.0127069	0.2872051
0.15	0.85	61.26	0.15	16.30	0.90	0.4529508	3.2572470	0.0127032	0.2872056
0.20	0.80	61.25	0.15	16.30	0.90	0.4529606	3.2573932	0.0126992	0.2872065
0.25	0.75	61.24	0.15	16.30	0.90	0.4529717	3.2575584	0.0126946	0.2872078
0.30	0.70	61.23	0.15	16.30	0.90	0.4529844	3.2577465	0.0126894	0.2872098
0.35	0.65	61.22	0.15	16.30	0.90	0.4529990	3.2579628	0.0126835	0.2872126
0.40	0.60	61.21	0.15	16.30	0.90	0.4530161	3.2582140	0.0126766	0.2872168
0.45	0.55	61.20	0.15	16.30	0.90	0.4530362	3.2585092	0.0126687	0.2872227
0.50	0.50	61.18	0.15	16.30	0.90	0.4530603	3.2588614	0.0126592	0.2872312
0.55	0.45	61.16	0.15	16.30	0.90	0.4530897	3.2592885	0.0126480	0.2872437
0.60	0.40	61.13	0.15	16.30	0.90	0.4531263	3.2598175	0.0126342	0.2872625
0.65	0.35	61.10	0.15	16.30	0.90	0.4531733	3.2604895	0.0126170	0.2872913
0.70	0.30	61.06	0.15	16.30	0.90	0.4532355	3.2613718	0.0125950	0.2873374
0.75	0.25	61.00	0.15	16.30	0.90	0.4533220	3.2625809	0.0125657	0.2874153
0.80	0.20	60.92	0.15	16.30	0.90	0.4534499	3.2643394	0.0125250	0.2875578
0.85	**0.15**	**60.79**	**0.15**	**16.31**	**0.90**	**0.4536578**	**3.2671304**	**0.0124642**	**0.2878501**
0.90	0.10	60.57	0.15	16.31	0.90	0.4540517	3.2722345	0.0123644	0.2885748
0.95	0.05	60.05	0.15	16.31	0.91	0.4550575	3.2845232	0.0121720	0.2911673
1.00	0.00	57.36	0.15	16.30	0.93	0.4615971	3.3549912	0.0117800	0.3216968

After using the EQM, a Pareto frontier was constructed, where it can be observed that all the points presented are optimal, and the point related to the weights $w_1 = 0.85$ and $w_2 = 0.15$ was chosen for confirmation, according to Figure 5.

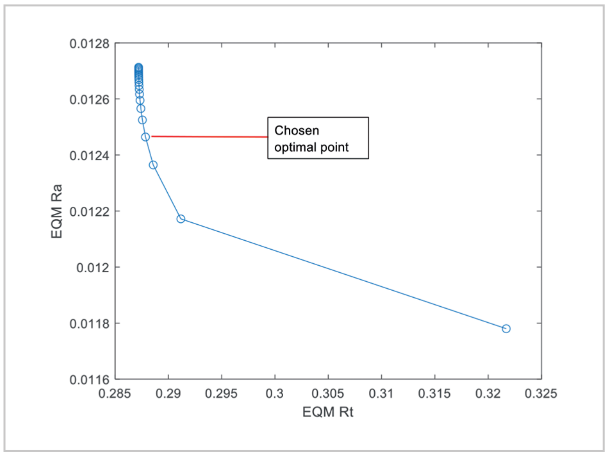

Figure 5 - Pareto frontier.

For the optimal setup were used the weights $w_1 = 0.85$ (average) and $w_2 = 0.15$ (variance) for the roughness R_a and R_t, respectively, according to Table 7.

Table 7 - Robust parameters determined by the Pareto frontier for EQM.

Control Variables					$\mu (R_a)$	$\mu (R_t)$	$\sigma^2 (R_a)$	$\sigma^2 (R_t)$
	v_c	f_z	a_e	a_p				
Optimum values	60.79	0.1881	16.31	0.90	0.4534	3.2671	0.0095	0.1821
Unit	m/min	mm/tooth	Mm	Mm	μm	μm	μm²	μm²

A Taguchi L9 design was built, and the optimal setup was inserted in the machine tool by varying the noise variables: tool flank wear (v_b), fluid flow (Q) and fluid concentration (C). After the execution of the confirmation tests, the following results were obtained for three conditions of new tools, worn with 0.15 mm and worn with 0.3 mm, according to Table 8.

Table 8 - Results of the confirmation experiments.

v_b	Q	C	R_a (Real)	R_t (Real)
0.00	0	0	0.431	3.544
0.00	10	10	0.427	3.386
0.00	20	20	0.474	3.281
0.15	0	10	0.456	3.238
0.15	10	20	0.441	3.470
0.15	20	0	0.482	3.577
0.30	0	20	0.451	3.310
0.30	10	0	0.470	3.518
0.30	20	10	0.513	3.265
	Average (real)		0.461	3.399
	Expected Value		0.454	3.267
	Error		1.51%	3.87%

The results of the confirmation experiments showed close proximity between the average (real) value and the predicted value of the roughness R_a, with an error of 1.51% and for the roughness R_t, an error of 3.87%.

They were analyzed using Analysis of Variance (ANOVA). It can be seen that the noise factors do not have a significant influence on the responses of the roughness R_a and R_t, since the P values are greater than 5%, according to Tables 9 and 10.

Table 9 - Analysis of variance for the μR_a confirmation experiment.

Source	GL	SQ (Aj.)	QM (Aj.)	F-Value	P-Value
v_b	2	0.001738	0.000869	6.38	0.13500
Q	2	0.003814	0.001907	14.01	0.06700
C	2	0.000151	0.000075	0.55	0.64300
Error	2	0.000272	0.000136		
Total	8	0.005974			

Table 10 - Analysis of variance for the μR_t confirmation experiment.

Source	GL	SQ (Aj.)	QM (Aj.)	F-Value	P-Value
v_b	2	0.006288	0.003144	0.50	0.66800
Q	2	0.015961	0.007980	1.26	0.44200
C	2	0.102976	0.051488	8.13	0.10900
Error	2	0.012659	0.006329		
Total	8	0.137883			

5. Conclusions

This study aimed to analyze, model, and optimize the end milling process of duplex stainless steel UNS S32205 by using interchangeable carbide tools. The responses evaluated in relation to the control and noise variables were R_a and R_t, and it was possible to conclude that:

- Using design experiments, the measured roughness's were in the range between 0.243 and 1.097 µm for R_a and 1.800 and 7.058 µm for R_t. Considering the values of R_a, they are within the range of values obtained in the milling process.
- It was possible to establish mathematical models for the characteristics of interest. The response model for the roughness R_a showed a high explanation rate of the variability of the data where R^2 was 93.91%. The model related to the roughness R_t, also showed a high value for R^2, it being 89.89%.
- The analysis of variance of the roughness response R_a showed that cutting speed (vc) and feed per tooth (f_z) were the variables that most influenced roughness. It was also observed that all quadratic terms were significant. The significant interactions for roughness were $v_c \times f_z$, $v_c \times v_b$ and $f_z \times v_b$.
- As for the analysis of variance of the roughness response R_t, the variables show that feed per tooth (f_z) and axial depth of cut (a_p) significantly influence roughness. All quadratic terms were significant. The significant interactions for roughness were $v_c \times f_z$, $v_c \times v_b$, $f_z \times v_b$, $f_z \times Q$, $a_e \times v_b$ and $a_p \times v_b$.
- From the interactions between the control and noise variables, it was possible to evaluate the robustness of the features of interest to the noise variables by establishing the mean and variance equations as the EQM equations for the features of interest.
- After minimizing the EQM, robust multi-objective optimization was performed. Thus, 21 Pareto-optimal solutions were obtained. These solutions allowed exploring different robust scenarios for the noise variables considered in this study, obtaining satisfactory results regarding the surface quality.

The confirmation experiments with the optimum levels of the control variables, v_c = 60.79 m/min, f_z = 0.15 mm/tooth, a_p = 0.90 mm and a_e = 16.31 mm, achieved responses of R_a = 0.4534 µm and R_t = 3.2671 µm. Thus, the robustness of the end milling process for duplex stainless steel UNS S32205 can be seen, mitigating the influence of the cutting fluid flow rate, tool wear, and fluid concentration on part roughness.

The ANOVA of the confirmation experiments showed that the noise variables do not significantly influence the roughness R_a and R_t as they have *P-values* above 5%.

EQM minimization, as an optimization method, has advantages and limitations that must be considered to ensure its adequate application.

On the one hand, the technique stands out for its simplicity, making it easier to implement and understand. Furthermore, its computational efficiency allows the optimization of large data sets in a timely manner. Finally, the EQM has a solid theoretical basis in statistics and econometrics, consolidating its reliability.

On the other hand, it is important to be aware of the limitations of the technique. Sensitivity to outliers can distort the model and the optimal solution, while emphasis on the mean can mask data variability and lead to unrealistic solutions. The difficulty in interpreting the optimal solution, especially in complex models, is also a point to be considered.

In short, EQM minimization is a valuable tool for process optimization, but its application must be done with caution and accompanied by a critical analysis of the results. The choice of the optimization methodology must consider the characteristics of the problem in question, the advantages and disadvantages of each method and the available resources.

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