OPTIMIZATION OF CUTTING PROCESS PARAMETERS IN NICKEL-BASED ALLOY NIMONIC 80A USING MULTI-OBJECTIVE FUNCTION AND TAGUCHI ANALYSIS

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ABSTRACT

Nickel alloys are characterized by presenting a high cost in manufacturing of machined parts because of these material's characteristics makes it difficult to machine. Based on the complexity and in the widespread applications, the nickel-alloy machining needs to be judiciously investigated. The objective of this work is the study of the machining by external cylindrical turning on a CNC Machining, using a nickel-based alloy Nimonic 80A to optimize the variable response Roughness (Ra) and Length of Cutting (Lc). The proposed analysis to find the best values of Ra and Lc using multi objective functions optimized with Meta-Heuristic techniques (Simulated Annealing and Genetic Algorithm) and using two different methods of agglutination (Desirability and Average Percentage Distance). The design of the experiment was a Taguchi Orthogonal Array L8, operating in two levels. The machining experiments were accomplished considering the machining parameters: cutting speed (75 and 90 m.min^{-1}), cutting depth (0,8 and 1,6 mm), feed rate (0,12 and 0,18 mm.rev^{-1}), kind of tool (TNMG160404R-UX TP2500 and TNMG160404R-UX CP250) and environment (minimum quantity of fluid (MQF) and flood).

KEYWORDS: *Optimization, Desirability, Nickel-based alloy, machining*

I. INTRODUCTION

The nickel alloys have a chemical composition with high content of alloying elements which are responsible for their mechanical and thermal properties. Due to this, two intriguing characteristics appear. First, the little changes in chemical compositions could induce high modification in properties of material. Second, consequence for the first, the machining conditions could have high levels of change either. Therefore, the methods and procedures to analyze the efficiency of the machining nickel alloys should be evaluated and discussed.

The nickel alloys are typically used in the manufacture of components for aerospace applications [1]. Industries that manufacture components of nickel alloys are characterized by presenting a high cost in manufacturing of machined parts because of these material's characteristics makes it difficult to machine [2]. For this reason, it is interesting to perform scientific experiments to reduce the machining time parts and select the appropriate cutting tools and cutting conditions [3, 4].

Good results in machining operations are related to use of appropriate measurement systems, best cutting tools and cutting conditions, where these are essential elements in the planning process of the machining procedure. There are many techniques of experimental design to assist in the investigation of the best machining parameters [4, 5].

The appointment to the best parameter in machining evolves optimizations problems, more specifically multi-objective functions solved by optimization techniques. According to Lobato [6], real-world problems involve the simultaneous optimization with more than one features (often conflicting), named multi-objective optimization problem or optimization with multiple responses.

Many algorithms and techniques, such as meta-heuristics, have been introduced and proposed to optimize problems. Among them are genetic algorithms and simulated annealing. All these algorithms have shown a good mechanism to solve multiobjective optimization problems, since they are able to find a set of solutions [7].

D'Addona [8] used genetic algorithm for optimization of cutting parameters in a turning process to reduce production time, Durairaja [9] proposed the use of a parametric optimization for improved cutting responses such as tool life and surface finish in a process Micro CNC turning of an Inconel 600 alloy using Genetic Algorithm.

According to Habeeb [10] and Kamata [11], due to the very low thermal conductivity, cause an intensive wear rate of the cutting tools, decreasing its life. For this reason, the coolant fluid is widely used in machining processes, it has as its main objective the improvement of machining processes. Consequently, its improving surface finish and resulting in an increase of tool life.

According to Lee [12] and Xiao [13] to increase efficiency and productivity of the machining process, one must consider the type of cutting tool and machining parameters where the improvement of productivity and efficiency in the machining process can be obtained by process optimization.

The use of optimization techniques becomes economically feasible, only when it is guaranteed the effective employment of these tools during the machining processes [3]. However, to discover what are the best conditions to work it is necessary to investigate where it can be applied based on experimental procedures. For this way, there are some techniques described as Design of Experiments which help in this kind of investigation.

Project benefits include the possibility of experiments in improving performance in the process, avoiding trial and error to find solutions [14, 15]. To Antony [16] DOE emphasizes the development and use of regression models for predicting the process behavior under different process conditions.

The most widely used DOE method is named Taguchi method, which for Kishore [17] is a method that involves the orthogonal array to organize the parameters that affect the process and the levels that are diverse.

Taguchi developed the Robust Design that was introduced in the 1950s and 1960s. The application of his method has been an important factor in the rapid industrial growth of Japanese industries [18]. According to Taner and Antony [16], Taguchi methods can be used to reduce the time of experiment and produce sufficient information to reduce variability and ensure a better product quality or service. The benefits of this include the possibility of experiments in improving performance in the process, avoiding trial and error to find solutions, being considered as a powerful tool for process investigation and optimization [14, 19].

The use of optimization techniques, associated with design of experiments, is an usual and effective procedure to evaluate machine processes, especially when steel and alloy manufacturing are involved [20, 21, 22].

The aim of this work is focused on apply Taguchi method to obtain a multiple regression to optimize a cylindrical external turning process of the nickel based alloy (Nimonic 80A), using to investigate two different meta heuristics such as Genetic Algorithm and Simulated Annealing combined with two different ways to merge more than one multiple regression equation (average percentage distance (APD) and Desirability Function) to determine the optimal parameters of a turning process, evaluating the tool life and surface roughness as response variables.

Next, the article is organized into Materials and Equipment, Results and Discussion, Conclusions and finally, the list of References.

II. MATERIALS AND EQUIPMENT'S

The turning experiments involving the cutting length and roughness measurements were performed on a cylindrical Nimonic 80A Solubilized samples that are 69 mm in diameter and 180mm in length. The nickel alloys are typically used in components for aerospace applications to support high levels of temperature variance and the presence of austenitic matrix becoming difficult to machining [23]. The Nimonic 80A Solubilized chemical composition is shown in Table1.

Table 1 - Chemical composition of nickel-based alloy Nicomic 80A Solubilized

Composition	Ni	Cr	Cu	Fe	Ti	Al	Co	Nb	Mn	Si	S	Mo	B	P	C
NIMONIC 80 A	Balance	20.0	0.05	0.75	2.35	1.25	1.0	-	0.35	0.35	0.007	-	-	-	0.06

Source: Villares Metals Catalog

The lathe used for the tests is a CENTUR 30S, trademark ROMI 25 to 3500 rpm, with spindle power of 10 kW, and the ceramics inserts are coated and uncoated (TNMG160404R-UX TP2500 and TNMG160404R-UX CP250), removable, and square shaped. A Mitutoyo Surftest-301 roughness meter was adopted for the measurement of the roughness for each cutting condition. The roughness measurements were obtained after each 180mm of turning at nine different points of worked surface.

A Taguchi design L8 orthogonal array with two levels and five factors is applied to the experiment planning. Selected input factors and their levels are shown in Table 2. The ranges of the cutting parameters are chosen according to the recommendation of the manufacturer of the cutting tools.

Table 2 – Machining parameters and their respective Levels

	Level 1	**Level 2**
Cutting Speed (A)	75 m/min	90 m/min
Feed Rate (B)	0.12 mm/revol.	0.18 mm/revol.
Cutting Depth (C)	0.8 mm	1.6 mm
Tools (D)	TP2500	CP250
Environment (E)	MQF *	flood

*Minimal Quantity of Fluid

III. RESULTS AND DISCUSSION

The experimental procedure was conducted using two replicates for each experiment, considering that each replication represents the mean of a sample to Ra (µm), which was made using three measures in three different points of the workpiece.
To obtain the results Lc, Equation 1 was used.

$$L_c = \frac{L_f.\pi.D}{f.1000}\,(\text{meters}) \tag{1}$$

where L_f is given by the length of advancement, the diameter D of the cylindrical test body used and f feed rate.

Table 3 presents the cutting conditions represented by Cutting speed, Feed rate, Cutting depth, Tools and Environment along with the experimental results illustrated by Ra and Lc according to the L8 Taguchi design demonstrated before. In this Table 3, Ra varies between 1.39 and 4.52, while Lc varies between 151.6 m and 1215.4 m.

Table 3 – Results of Lc and Ra according to the cutting conditions.

Run	Speed (m/min)	Feed(mm/revol.)	Tool	Depth (mm)	Environ ment	Lc1	Lc2	Ra1	Ra2
1	75	0.12	TP2500	0.8	MQF	483.9	302.8	1.88	1.74
2	75	0.12	CP250	1.6	Flood	975.3	121.4	1.51	1.93
3	75	0.18	TP2500	0.8	Flood	241.3	166.5	3.32	3.73
4	75	0.18	CP250	1.6	MQF	392.9	283.1	2.40	3.08
5	90	0.12	TP2500	1.6	Flood	245.3	203.0	1.39	1.73
6	90	0.12	CP250	0.8	MQF	372.7	348.9	1.66	1.46
7	90	0.18	TP2500	1.6	MQF	151.6	159.0	3.85	4.52
8	90	0.18	CP250	0.8	Flood	326.9	392.7	2.25	2.51

3.1. Statistical analysis

3.1.1. Signal to Noise Function

According to Rosa [24] Taguchi's parameter design method normally selects an appropriate formulation of the S/N ratio and calculates the S/N ratio for each treatment. The S/N ratio is a logarithmic function used to optimize the process or product design, minimizing the variability.

There are three types of S/N ratios: nominal the best, larger the best, and the smaller the best, given by Equations 2, 3 and 4.

Nominal the best: $S/N = 10 \times \mathrm{Log}\left(\frac{\underline{y}^2}{\underline{S}^2}\right)$, (2)

Larger the best: $S/N = -10 \times \mathrm{Log}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$, (3)

Smaller the best: $S/N = -10 \times \mathrm{Log}\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right)$ (4)

where y_i is the response value of a specific treatment under *i* replications, *n* is the number of replications, $\underline{y}$ is the average of all *yi* values, and $\underline{S}$ is the standard deviation of all *yi* values.

3.1.2. Analysis of variance (ANOVA)

The analysis of variance (ANOVA) is a statistical method applied to analyze the experimental results obtained on the present work, it is used to quantify the significance of the factors when used alongside the Taguchi Method. Tables 4 and 5 respectively represent the results of the ANOVA analysis to Ra and Lc. The analysis is performed for a significance level x=0.05, where probability value higher than 0.05 indicates that the result may be considered statistically insignificant compared with the desirable.

Table 4 shows results of ANOVA for Ra. According to the analysis of variance, the factor feed rate, tool and interaction feed/tool are influent over the variable response roughness, considering 5% of significance.

Table 4: Analysis of variance for the variable Ra.

Factors	Seq SS	DF	Adj Ms	F	P-Value
Speed	0.0030	1	0.0030	0.0323	0.8618
Feed	9.5481	1	9.5481	101.9	0.0000
SpeedxFeed	0.1260	1	0.1260	1.345	0.2795
Tool	1.7956	1	1.7956	19.17	0.0023
Depth	0.2162	1	0.2162	2.309	0.1671
FeedxTool	1.5625	1	1.5625	16.68	0.0035
Environment	0.3080	1	0.3080	3.289	0.1073
Error	0.7493	8	0.0937		

The results of ANOVA for the Lc are presented in Table 5, such as the values adopted in the cutting regime. The results obtained show that all the factors and interaction cause influence over the response Lc, leading to conclude that all factors are responsible by variation of the tool life, considering 5% of significance.

Table 5: Analysis of variance for the variable Lc

Factors	Seq SS	DF	Adj Ms	F	P-Value
Speed	216491.0	1	216491.0	30.17	0.0006
Feed	258389.4	1	258389.4	36.01	0.0003
SpeedxFeed	192285.2	1	192285.2	26.79	0.0008
Tool	346498.0	1	346498.0	48.29	0.0001
Depth	61261.7	1	61261.7	8.538	0.0192
FeedxTool	62484.0	1	62484.0	8.708	0.0184
Environment	101041.5	1	101041.5	14.08	0.0056
Error	57405.6	8	7175.7		

Note: DF - Degrees of Freedom, Seq SS - Sequential Sum of Squares, Adj MS - Adjacent Mean Squares.

3.1.3. Graphical representation of main effects

The results obtained from the Taguchi experimental array L8 showed in Table 3 could be possible performed in a graphical representation of the factors effects over the response variable Ra (µm) and Lc(m), as shown in Figure 1 and 2.

In Figure 2, the factor B (feed rate) stands out clearly as the dominant parameter of the process. Other point could be observed because there is a drastic increase in the variable response roughness with the increasing of the feed rate, where can be seen that this factor is the only one to prove important in this process, overcoming the barrier of 2*σ, being σ given as the standard deviation.

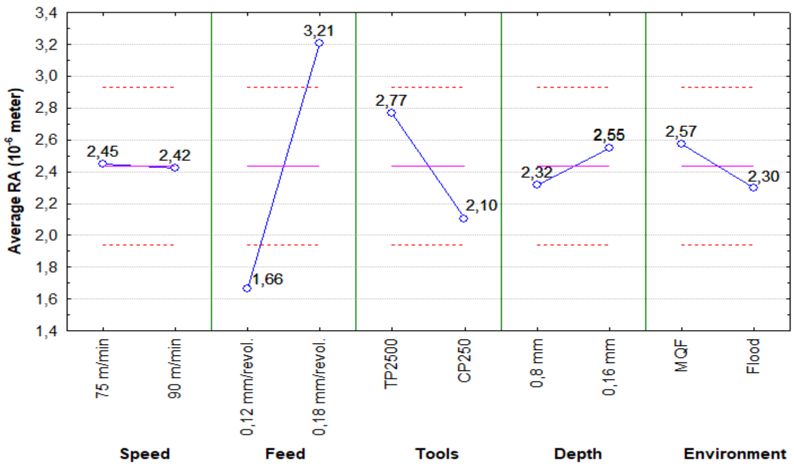

Figure 1: Effect of the factors over the variable response Lc

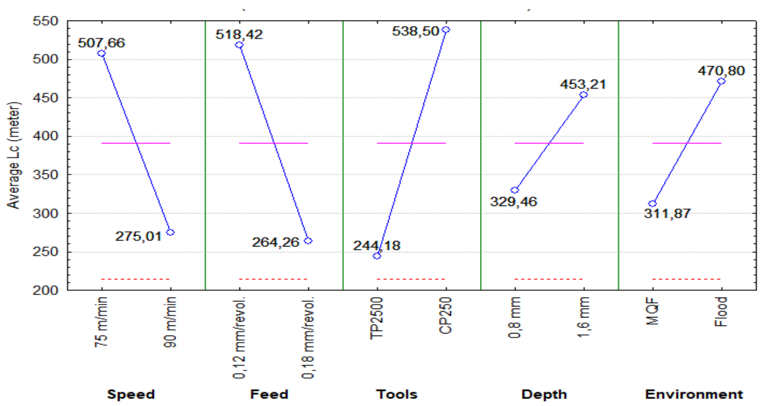

Figure 2: Effect of the factors over the variable response Ra.

To Bouacha [25], this result was expected, as is well known that the theory, the surface roughness can be predicted and assessed in of the feed rate and of the tool radius, as the angle of attack is not being tested and are the same for both tools, the feed showed to be the only one influential factor for this process.

3.2. Modeling of cutting parameters

3.2.1. Multiple linear regression

According to Kumar [26] multiple linear regression is the most common technique for statistical analysis that formulate a mathematical relationship between some independent variables and a dependent variable. The general mathematical expression for the MLR model is expressed by Equation 5.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \tag{5}$$

where, Y is the dependent variable, X_1, X_2, ….., X_n are the independent variables, β_0, β_1, …., β_n are the regression coefficients and ε is the error. To evaluate the quality of fit of the linear model, coefficient of determination R^2 can be used.

The model for roughness (Ra) and cutting length (Lc) was developed by using Statistica 8.0 software and given by the Equations 6 and 7.

$$Ra = 0.560 - 0.0275A + 1.545B + 0.2325C - 0.670D - 0.2775E - 0.1775AB + 0.625BD \tag{6}$$

Table 7: Analysis of significance for the coefficients of the model to Ra

	beta	st error beta	β	st error β	t(8)	p-level
intercept			0.5600	0.6121	0.9149	0,3870
Speed	-0.0145	0.0809	-0.0275	0.1530	-0.1797	0,8618
Feed	0.8169	0.0809	1.545	0.1530	10.097	0,0000
Speed x Feed	-0.0939	0.0809	-0.1775	0.1530	-1.1599	0,2795
Tool	-0.3542	0.0809	-0.6700	0.1530	-4.3785	0,0023
Cutting Depth	0.1229	0.0809	0.2325	0.1530	1.5194	0,1671
Tool x Feed	0.3304	0.0809	0.6250	0.1530	4.0844	0,0035
Environment	-0.1467	0.0809	-0.2775	0.1530	-1.8135	0,1073

Regression Summary for Dependent Variable: Ra
R= .97346475 R^2= .94763362 Adjusted R^2= .90181305
F(7,8)=20.681 p< 0.00016 Std.Error of estimate: .30604

In Table 7, the significance of the model is given by the coefficient of determination R^2= 0.9476, that means almost 95% of variation of the roughness can be explained by the variation of the factor. It means that the factors feed and tool showed be most important.
In the same way, Equation 7 is shown with Table 8 to explain the significance of the model.

$$Lc = 397.478 - 232.680A - 254.198B + 123.783C + 294.274D + 158.901E - 219.211AB + 125.023BD \tag{7}$$

Table 8: Analysis of significance for the coefficients of the model to Lc

	beta	st error beta	β	st error β	t(8)	p-level
intercept			397.478	169.457	2.3456	0.0470
Speed	-0.4088	0.0744	-232.680	42.3643	-5.4923	0.0006
Feed	-0.4466	0.0744	-254.198	42.3643	-6.0003	0.0003
Speed x feed	-0.3851	0.0744	-219.211	42.3643	-5.1744	0.0008
tool	0.5170	0.0744	294.274	42.3643	6.9463	0.0001
cutting lenght	0.2175	0.0744	123.783	42.3643	2.9219	0.0192
tool x feed	0.2196	0.0744	125.023	42.3643	2.9511	0.0184

Environment	0.2792	0.0744	158.901	42.3643	3.7508	0.0056

Regression Summary for Dependent Variable: Lc
R= .97758938 R^2= .95568100 Adjusted R^2= .91690188
F(7,8)=24.644 p<0.00008 Std.Error of estimate: 84.729

In Table 8, the coefficient of determination R^2= 0.9557, shows that the 95.57% of variation of the Lc can be explained by the variation of the factor Lc. P-values of all coefficients for this regression model were under 5%, thus, this empirical model could be considered to be statistically significant.

3.3. Optimization of cutting parameters

3.3.1. Objective function

The objective function was defined using the Response surface methodology model, described in section 4.1, shown in equations 11 and 12, and was optimized by Genetic Algorithm and Simulated Annealing optimization methods. The constraints conditions are showing in Table 9.

Table 9: Constraints used to simulate in GA and SA

	Target	L_i	T_i	L_s
Lc (m)	Maximize	300	1300	1300
Ra (µm)	Minimize	-	1	1.5
Factor D	Discrete	-1	or	1
Factor E	Discrete	-1	or	1

In optimization procedure was necessary the use of agglutination method because of the existence of two independent variables. The Average Distance Percentage and Desirability Function was used as agglutination method and the functions obtained by both methods was optimized by Genetic Algorithm and Simulated Annealing, allowing the comparison of the results.

3.3.2. Average Distance Percentage

The Average Percentage distance function (APD) is a function given by the distance value obtained from the prediction of each dependent variable of the multiple regression model with respect to a target value (T_i) divided by the same (T_i), all multiplied by 100. This target value varies with each response variable, in cases where multiple performance characteristics should make the sum of the distances divided by the number of response variables expressed by Equation 8.

$$APD = \frac{\sum_{i=1}^{p} \frac{|\hat{y}_i - T_i|}{T_i}}{p} . 100\% \quad (8)$$

Where p is the number of variable responses and $\hat{Y}_i$, the value predicted

3.3.3. Desirability Function

The Desirability function, initially proposed by Harrington [27], is a technique to analize experiments in which various responses may be optimized simultaneously [28]. According to Poroch-Seritan [29] the "Desirability" in a general approach is to translate the performance of products or processes di values that are within a range of $0 \leq 1 \leq d_i$, where *di* value increases when the *i*th response approaches the limits imposed.

Based on each of the individual desirability functions, it is usually calculated as a weighted geometric average of the individual entities. Thus, the multi-criteria problem is reduced to a single criterion D optimization problem [30].

Montgomery [28] modified this Desirability function which defined three classes of functions in three different response variables which are: Nominal the Best (NTB), smaller the best (STB) and Larger the Best (LTB). For type NTB, which has two restrictions: maximum and minimum to achieve a target value (Equation 9).

$$d_i = \begin{cases} \left[\frac{\hat{Y}_i - L_i}{T_i - L_i}\right]^s, & L_i \leq \hat{Y} \leq T_i \\ \left[\frac{\hat{Y}_i - L_s}{T_i - L_s}\right]^t, & T_i \leq \hat{Y} \leq L_s \\ 0, & \hat{Y} < L_i \text{ ou } \hat{Y} > L_s \end{cases} \quad (9)$$

Where *s* and *t* are predominant values of desirability function which in general are values between 0.01 and 10, L_i and L_s are lower and upper limits respectively specified for the ith response and T_i is the target value.

For the condition (Smaller the Best) STB which seeks to minimize the response variable, the desirability function is defined by Equation 10:

$$d_i = \begin{cases} 0, & \\ \left[\frac{\hat{Y}_i - L_s}{a - L_s}\right]^t, & a \leq \hat{Y}_i \leq L_s \\ 1, & \end{cases} \quad (10)$$

Where *a* is the lower value acceptable for the variable response $\hat{Y}_i$.
Finally, when you want to maximize the response variable (Larger the Best) LTB, the maid transformation formula is given by Equation 11:

$$d_i = \begin{cases} \left[\frac{\hat{Y}_i - L_i}{L_s - L_i}\right]^s, & L_i \leq \hat{Y} \leq L_s \\ 0, & \\ 1, & \hat{Y}_i > L_s \end{cases} \quad (11)$$

Pal and Gauri [31], since each response variable is converted to a value di, then the desirability function D can be calculated from the combination of the transformed responses through individual geometric mean, as described in (Equation 12).

$$D = \sum_{i=1}^{k} [d_i(Y_i)]^{\frac{1}{k}} \quad (12)$$

3.3.4. Results and analysis of the optimization procedures

In Table 10 shown the results obtained to Lc and Ra after GA and SA optimization procedure using each agglutination method described. The proposed process adjustment which minimizes Ra and maximizes Lc using APD and Desirability.

The results obtained using SA meta-heuristic indicates to adjust Speed to 90 m/min approximately, 0.13 mm/revolution for feed rate, depth to 0.9 mm when using CP250 as cutting tool and flood environment. In this case, the results for Lc found is nearly to 1,200m and Ra 1.00 µm, causing an average deviation of 3.5% compared with targets values. It is important to declare that the result values that were approximated, occurred due to the characteristics of the cutting machine.

Table 10: Level of the decoded predicted variable response with the mean distance to target (APD %)

	Factors	**Speed**	**Feed**	**Depth**	**Tool**	**Environment**	**Lc**	**Ra**	**APD %**
SA	**APD**	89.86	0.14	0.82	CP250	Flood	1.239.69	0.986	0.0301
		89.90	0.13	0.96	CP250	Flood	1.199.82	1.000	0.0387
	Desirability	89.53	0.13	1.07	CP250	Flood	1150.00	1.000	0.0578
		88.69	0.13	1.11	CP250	Flood	1098.00	0.999	0.0780
GA	**APD**	89.81	0.14	0.80	CP250	Flood	1.240.82	1.000	0.0228

	90.00	0.14	0.80	CP250	Flood	1.250.36	1.000	0.0193
Desirability	89.78	0.13	1.00	CP250	Flood	1183.24	0.999	0.0452
	88.69	0.13	0.97	CP250	Flood	1188.42	0.999	0.0431

The results obtained using GA meta-heuristic indicates to adjust Speed to 90 m/min approximately, 0.13 mm/revolution for feed rate. For the Depth the adjusts are 0.8 mm when using APD and 1.00 mm when using Desirability. The results described were obtained using CP250 as a cutting tool and flood environment. In this case, the results for Lc are 1250 meters and for Ra is 1.00 µm, causing an average deviation of 2.1% for APD and 4.4% for Desirability compared with targets values.

Figure 3 shows the interval for results obtained as a graphic representation to analyze the proposed results.

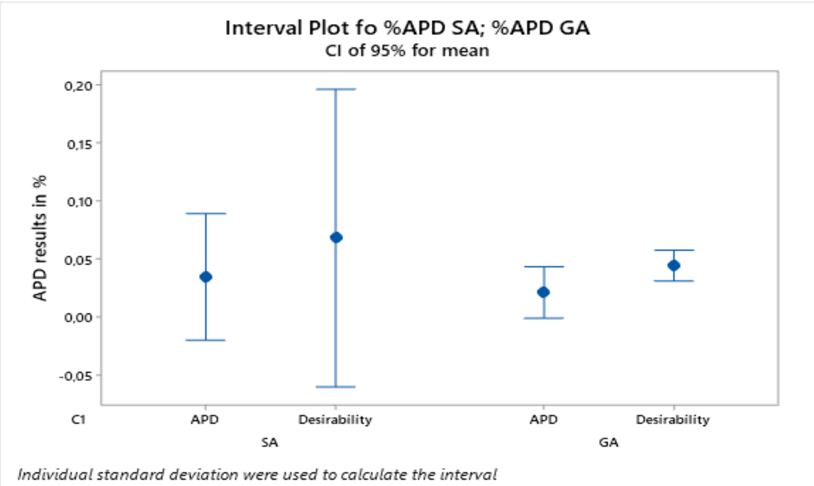

Figure 3: Interval Plot for SA and GA considering APD and Desirability

Figure 3 shows the variation for SA and GA considering the APD per centage (%APD) for both agglutination methods. It can be concluded that both agglutination method and both meta heuristics methods can be used for the multiple response optimization and there is no significant difference between them with 95% of confidence, in the case evaluated in this paper.

IV. Conclusion

The study presented the concept of cylindrical turning process of Nimonic 80A superalloy, considering as output process roughness and cutting length. The following conclusions are drawn from this investigation:

1. The main effects revealed that the factor B (feed rate) stands out as the dominant parameter of the process over the variable response roughness.
2. According to the analysis of variance to the roughness output, factors feed and tool are responsible for the main variation of the process, considering 5% of significance, in other words, the surface roughness is affected by the feed rate and tool.
3. The results of ANOVA for the Lc showed that all the factors and interaction cause influence over the response Lc, leading to conclude that all factors are responsible by variation of the tool life, considering 5% of significance.
4. Decreasing the magnitude of feed rate from 0.12 mm/revol. to 0.18 mm/revol., cutting length increase and roughness decreases.
5. Analyzing the responses about different Meta heuristics methods, the performance of the Simulated Annealing did not show significant difference compared with Genetic Algorithm, considering 5% of significance.

6. The desirability function, which is the most popular method to optimize processes with multiple responses, showed satisfactory results when compared with APD agglutination method.
7. Considering metaheuristic SA, the proposed adjustment to the variables is: variable Speed at 90 m/min, 0.13 mm/revol. for feed rate, 0.9 mm for depth approximately, using CP250 as cutting tool and flood environment.
8. Considering metaheuristic GA, the proposed adjustment to the variables is: speed 90 m/min, 0.13 mm/revol. for feed rate, 0.8 mm for depth using APD and 1.00 mm approximately for Desirability, using CP250 as cutting tool and flood environment.
9. The study will be beneficial for different industrial sectors once the optimization of cutting parameters were presented which results in the reduction of financial cost.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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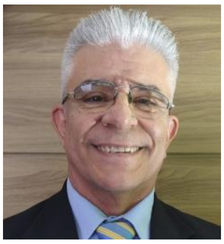

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