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Using the Taguchi Method to Study the Machining of Aluminum-Lithium Alloys Used in the Construction of Airbus A350 Aircraft Structural Components

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Abstract: *The paper presents an experimental and statistical analysis of the machining process of aluminum-lithium alloys used in the aeronautical industry, with the aim of modeling the influence of technological parameters on the durability of the cutting tools. The experiments were planned according to the Taguchi method, using an L36 matrix and five main factors: alloy type, experimental phase (setup), tool type, feed per rotation and cutting tool`s face. Analysis of variance (ANOVA) revealed that the tool type has a dominant contribution (≈85–90%) on the response, followed by feed per rotation (≈10–13%), the other factors having minor influences. The results are confirmed by the analysis of the signal-to-noise ratio (S/N) for the "Smaller-the-Better" criterion, indicating a high stability of the process under optimal conditions. The paper also proposes directions for process optimization and a subsequent stage of predictive modeling using artificial neural networks of the multi-layer perceptron (MLP) type. The conclusions obtained contribute to the development of efficient machining strategies for advanced aluminum alloys intended for aeronautical applications.*

Keywords: *aluminum, analysis, durability, machining, neural, tool.*

1. INTRODUCTION

The Taguchi method, developed by Japanese engineer Genichi Taguchi, is a statistical technique used primarily for process optimization and improving the quality of products or services. It is applied primarily in engineering, manufacturing, and quality management to reduce variation and improve the performance of a system or process.
Main uses of the Taguchi method:
- Product and process design optimization: the Taguchi method helps identify the optimal combination of parameters or factors of a process or product to achieve maximum performance at minimum cost. It focuses on reducing the sensitivity of the product or process to external variations, so-called noise, such as environmental conditions or variable usage;
- Variation reduction: uses the concept of a "loss function" to quantify the impact of deviations from the target values of a product or process, promoting consistency and quality;
Efficient experiments: uses orthogonal matrices to reduce the number of experiments needed to test parameter combinations, saving time and resources. The Taguchi method allows for the simultaneous analysis of multiple factors and their interactions, without the need for exhaustive experiments;
- Robustness improvement: the method focuses on creating robust products and processes that perform well under varied conditions, minimizing the effects of uncontrollable factors;
- Practical applications: it is used in industries such as automotive, electronics, pharmaceuticals or manufacturing to optimize manufacturing processes, reduce defects and increase product reliability.
How the Taguchi Method works in brief:
Identify key factors influencing performance;
- Design experiments using orthogonal matrices to test parameter combinations;
- Analyze results using signal-to-noise ratio (S/N ratio) and loss function to determine optimal settings;
- Implement solutions and verify robustness.

The Taguchi method is appreciated for its systematic and efficient approach, being an essential component in methodologies such as Six Sigma or Lean Manufacturing [14, 15].

2. THE STUDY OF THE SPECIALTY LITERATURE

The Taguchi method is particularly useful in manufacturing departments for machining, where it optimizes process parameters to reduce variations, minimize defects, and improve efficiency. In industries such as automotive and aeronautics, where precision, robustness, and low cost are essential, the method is applied to processes such as milling, turning, injection molding, or composites machining, using orthogonal matrices for efficient experiments, signal-to-noise ratio (S/N ratio), and analysis of variance (ANOVA) to identify key factors. It is often integrated with other methodologies such as Six Sigma or Response Surface Methodology (RSM) for multi-objective results.
The Taguchi method, developed by Genichi Taguchi, is used extensively in many industries, such as automotive, aeronautics, electronics, pharmaceuticals, plastics manufacturing, mechanical machining, and materials engineering, to optimize processes and improve product quality. This statistical method helps identify the optimal combinations of parameters to reduce variations and minimize defects, ensuring consistent performance even under variable conditions. In the automotive industry, for example, it is applied to optimize processes such as casting or milling components, reducing costs and improving reliability. In aeronautics, the Taguchi method contributes to the precise machining of materials such as titanium or aluminum alloys, essential for strong and lightweight components. In the electronics sector, it optimizes the manufacturing of

integrated circuits, and in the pharmaceutical industry, it ensures the consistency of drug production processes. By using orthogonal matrices and the signal-to-noise ratio, the method significantly reduces the number of experiments required, saving time and resources.
In the automotive sector, the Taguchi Method is used to optimize component manufacturing processes, such as door window seals, where nonconformities are reduced and quality is improved. For example, in a case study from a rubber manufacturing company supplying parts to a major automotive brand, the method was integrated into the DMAIC framework of Six Sigma to address customer complaints about the flexibility of the seals causing the windows to jam or loosen. The process involved plastic and rubber injection molding, a type of machining. Six control factors were optimized, each with three levels.
- Cooling time: 5-15 sec;
- Injection pressure: 250-650 bar;
- Injection speed: 5-15 cm/s;
- Melt temperature: 470-490°C;
- Mold temperature: 150-160°C;
- Wall thickness: 2.10-2.20 mm.

Using an L27 orthogonal matrix, reducing the experiments from 7,290 to 270, multi-response S/N (MRSN) analysis identified the optimal combination of:
- Cooling time: 15 sec;
- Injection pressure: 450 bar;
- Injection speed: 5 cm/s;
- Melt temperature: 480°C;
- Mold temperature: 150°C;
- Wall thickness: 2.15 mm.

The results included:
- Reduction of the standard deviation for flexibility from 1.322 to 0.072;
- Increase of the sigma level from 2.21 to 4.80;
- Decrease of the non-conformance rate from 23.94% to 0.049%.

Benefits of using the Taguchi Method:
- Time and cost savings by reducing experiments by 96%;
- Improved customer satisfaction;
- Robustness of the process to external variations [4].

Another example involves the machining of aluminum metal composites (Al MMCs 6063-TiO2), used in automotive components for wear resistance. The Taguchi method, combined with RSM, optimizes CNC end-milling under dry conditions, minimizing cutting forces and surface roughness (R_a). The optimized parameters, each with three levels:
- Spindle speed (500-1500 rpm);
- Cutting speed (15-40 m/min);
- TiO_2 content (1-5 wt.%);
- Number of cutting edges (2-4);
- Feed rate (200-600 mm/min);
- Depth of cut (0.4-1.2 mm).

Using L27, ANOVA showed that the rotational speed contributes 39.81% to R_a, and the rotational speed-cutting speed interaction contributes 36.36%. The optimal settings for minimum R_a: 1500 rpm, 40 m/min, 1 wt.% TiO_2, 3 edges, 600 mm/min, 1.2 mm deep of cut, resulting in R_a from 2.08 to 4.66 μm. For forces, the optimum reduces the values to ~159 N, improving efficiency in the production of molds and automotive parts [1].
In the aerospace industry, where materials such as aluminum or titanium alloys must be machined with high precision for lightweight and strong components, the Taguchi Method optimizes processes such as milling or turning to minimize roughness and forces, increasing fatigue and corrosion resistance.
For the 7075 aluminum alloy that is used in defense and aerospace due to its low density, an experimental study on CNC milling used Taguchi with relational analysis for multi-objective optimization: roughness and material removal rate.
Parameters:
- Cutting speed (1000-2000 rpm);
- Feed rate (0.40-0.60 mm/rev);
- Depth of cut (0.5-1.5 mm).

Using L9, ANOVA indicated feed as the dominant factor (52% contribution to roughness), followed by speed (29%). Optimal settings: 1500 rpm, 0.40 mm/rev, 0.5 mm deep of cut, reducing R_a to 0.853 μm. Benefits: accurate predictive models (R^2=89.4% for relational degree), applicable in the production of aeronautical components, extendable with neural networks [13].
For Ti-6Al-4V titanium, a difficult-to-machine material used in aircraft construction, a comparison between Taguchi and full factorial design in dry turning optimized the main cutting force (F_c) and the average roughness (R_a).
Parameters:
- Spindle speed (rpm);
- Feed rate (mm/rev);
- Depth of cut (mm).

Using fractional L9 from 27 experiments, EDA, ANOM and ANOVA analysis showed the major influence of feed and depth on F_c and R_a. Taguchi reduces the number of tests, providing similar results to the full factorial, ideal for optimization in aerospace where expensive experiments must be minimized [6].
In [9] the Taguchi Method is presented that optimizes cutting parameters in the turning process, aiming at minimizing the roughness of the obtained surfaces. In [16], the authors present the Taguchi method that they use to optimize TIG welding parameters for AA5083-AA7075 aluminum alloys, in order to obtain a higher mechanical strength. In [7], the authors present an interdisciplinary application in the medical field: The Taguchi method is used to select and optimize the hyperparameters of a convolutional neural network applied to the classification of ECG signals. The paper [11] analyzes the applications of the Taguchi method in different industrial fields, presenting its advantages and limitations. The paper [2] analyzes the optimization of process parameters for the production of low-strength materials using the Taguchi method. The aim is to obtain a sustainable material by valorizing industrial waste, such as stone sludge. Several process factors are tested to identify the optimal combination that influences the mechanical properties of the material. An orthogonal

matrix is applied for experimental efficiency and reducing the number of tests. The study demonstrates the efficiency of the Taguchi method in optimizing construction processes. The contribution of the paper falls in the direction of sustainable development and circular economy.

Nationally, we recall the works [10] and [3], in which the authors treat the application of the Taguchi method for the robust design of industrial processes, include examples of practical implementation in production environments and demonstrate the application of the Taguchi method in the optimization of milling and turning parameters, using an L9 matrix to analyze the influence of technological factors on roughness.

3. EXPERIMENT DESCRIPTION

In this study, the Taguchi method was used to plan and analyze experiments on the machining of aluminum-lithium alloys. The main purpose of applying this method was to determine the influence of technological factors on the durability of the milling cutters used, as well as to identify the optimal combination of machining parameters that maximizes the tool life.

3.1 Defining control factors

Five main control factors were selected for the experiment, each with a certain number of levels, as follows:

- Factors A: the machined raw material will be aluminum-lithium alloys 2196, 2043 and 2099;
- Factors B: the machining phases, Setup 1 and Setup 2;
- Factors C: the type of cutting inserts. Uncoated cutting inserts and DLC coated cutting inserts;
- Factors D: the types of feed per tooth. f_z= 0.167 [mm/rot], f_z= 0.226 [mm/rot] and f_z= 0.200 [mm/rot];
- Factors E: facet of cutting inserts, facet 1 and facet 2.

For an efficient design, we choose a Taguchi orthogonal matrix that covers the combinations of factors with a minimum number of experiments, avoiding the full factorial design which would require $3 \times 2 \times 2 \times 3 \times 2 = 72$ tests. The appropriate matrix is L36 ($2^3 \times 3^{13}$), which allows 36 experiments and can accommodate 3 factors with 2 levels and up to 13 factors with 3 levels.

The experimental data were organized in a Microsoft Excel file, consisting of two main sheets:

- The experimental data collection sheet and automatic calculation of indicators;
- The analysis sheet, intended for the calculation of means by levels and the preparation of data for ANOVA.

In the first sheet, each row corresponds to an experimental run, in which the input factors, the three response measurements, as well as two calculation columns are listed: Mean and S/N – Smaller-the-Better [8, 12].

3.2 Calculation of the average and the signal-to-noise ratio (S/N)

For each run, three independent durability measurements were taken, denoted Measure_1, Measure_2 and Measure_3. The average of these values, denoted Mean, is automatically calculated using the Excel formula:

$$Mean = \frac{y_1+y_2+y_3}{3} \tag{1}$$

In Excel, the formula used was "AVERAGE". This average reduces the effects of measurement errors and provides a representative value for each combination of factors. To evaluate the robustness of the process, the signal-to-noise ratio (S/N) was used, a measure proposed by Taguchi to evaluate the performance of a system under conditions of variability. Since in this case the aim is to minimize roughness, the Smaller-the-Better criterion was applied, defined mathematically by the relationship:

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

where y_i represents the measured values and n=3 is the number of repetitions. A higher value of the S/N ratio corresponds to better performance, i.e. a longer and more consistent operating time. This transformation combines information about the average and variability of the measurements into a single quality indicator.

3.3 Analysis of S/N averages by levels

For each control factor, the average S/N values corresponding to each level were calculated using the Excel function AVERAGEIF. This calculation allows for a direct comparison of the average performance between levels of the same factor. The level with the highest average S/N value indicates the optimal option, as it reflects the best combination of low response value and process stability.

3.4 Analysis of variance (ANOVA)

According to the authors in [8, 12], ANOVA is a statistical method used to test for differences between means in experiments. It is based on assumptions such as independence of observations, normality of errors, and homogeneity of variances. It is applied in both single-factor and multifactorial experiments, including interactions and blocks. The analysis involves the calculation of sums of squares, degrees of freedom, and the F-test for significance. In the context of quality engineering, ANOVA is integrated with robust optimization methods, being used to identify factors that influence performance and reduce variation. Orthogonal matrices are used for experimental efficiency. ANOVA helps to prioritize factors and validate results. It is supported by statistical software for practical interpretation. Overall, ANOVA is an essential tool in the design and analysis of experiments, with theoretical and industrial applications. ANOVA allows the

separation of the total variability into components associated with different experimental factors. It is essential for determining the significant influence of factors on the result. In multifactorial experiments, it helps to identify interactions between variables. It is used for model validation and process optimization. In quality methods, it contributes to reducing losses and increasing product robustness. The analysis is based on comparing the variance between groups and within groups. It is effective in orthogonal designs, saving experimental resources. It provides a solid statistical basis for decision-making in engineering and research.
For a rigorous statistical interpretation, analysis of variance (ANOVA) is performed on the S/N values. This allows estimating the percentage contribution of each factor to the total response variation.
The main steps are as follows:
- Calculating the overall average of S/N values:

$$\mathrm{S/N_{global}} = \frac{\sum \frac{\mathrm{S}}{\mathrm{N_i}}}{\mathrm{N}} \tag{3}$$

- Determining the sums of squares for each factor:

$$\mathrm{SS_x} = \sum_{j=1}^{L} n_j \left(\frac{\mathrm{S}}{\mathrm{N_j}} - \frac{\mathrm{S}}{\mathrm{N_{global}}}\right)^2 \tag{4}$$

where L is the number of levels, n_j is the number of rounds at level j.

- Calculation of degrees of freedom ($df_x = L-1$):

$$\mathrm{MS_x} = \frac{\mathrm{SS_x}}{\mathrm{df_x}} \tag{5}$$

- Determining the relative importance of factors by percentage contribution:

$$\mathrm{P_x} = \frac{\mathrm{SS_x}}{\mathrm{SS_{total}}} \times 100 \tag{6}$$

Run	A_Alloy	B_Setup	C_ToolType	D_fz	E_Face	M_1	M_2	M_3	Mean	SN_SmallerTheBetter
1	2196	Setup_2	DLC	0.226	Face_2	306	322	318	315.33	-49.977
2	2099	Setup_1	Uncoated	0.2	Face_1	102	83	97	94.00	-39.494
3	2043	Setup_1	DLC	0.167	Face_2	356	377	354	362.33	-51.186
4	2099	Setup_2	Uncoated	0.226	Face_1	104	93	86	94.33	-39.520
5	2196	Setup_2	DLC	0.2	Face_2	482	461	451	464.67	-53.346
6	2043	Setup_1	Uncoated	0.167	Face_1	106	96	101	101.00	-40.094
7	2099	Setup_2	DLC	0.2	Face_1	456	447	451	451.33	-53.090
8	2043	Setup_1	Uncoated	0.226	Face_2	88	94	95	92.33	-39.312
9	2196	Setup_2	Uncoated	0.167	Face_1	107	112	101	106.67	-40.568
10	2099	Setup_1	DLC	0.226	Face_2	289	277	273	279.67	-48.935
11	2196	Setup_2	Uncoated	0.2	Face_2	124	156	159	146.33	-43.357
12	2043	Setup_1	DLC	0.167	Face_1	369	371	366	368.67	-51.333
13	2099	Setup_1	DLC	0.167	Face_2	409	388	402	399.67	-52.036
14	2043	Setup_2	Uncoated	0.2	Face_1	120	126	134	126.67	-42.062
15	2196	Setup_2	Uncoated	0.226	Face_2	95	97	100	97.33	-39.767
16	2196	Setup_1	DLC	0.167	Face_1	436	430	431	432.33	-52.717
17	2043	Setup_2	Uncoated	0.226	Face_2	96	99	91	95.33	-39.590
18	2099	Setup_1	DLC	0.2	Face_1	266	280	269	271.67	-48.683
19	2043	Setup_2	DLC	0.167	Face_1	377	374	384	378.33	-51.558
20	2099	Setup_1	Uncoated	0.2	Face_2	90	92	93	91.67	-39.245
21	2196	Setup_1	Uncoated	0.226	Face_2	109	121	114	114.67	-41.197
22	2099	Setup_2	DLC	0.226	Face_1	282	299	275	285.33	-49.112
23	2043	Setup_2	DLC	0.2	Face_1	406	397	425	409.33	-52.245
24	2196	Setup_1	Uncoated	0.167	Face_2	107	115	128	116.67	-41.363
25	2099	Setup_1	DLC	0.167	Face_1	406	389	393	396.00	-51.955
26	2043	Setup_2	Uncoated	0.2	Face_2	114	122	106	114.00	-41.152
27	2196	Setup_2	DLC	0.226	Face_1	321	317	314	317.33	-50.031
28	2043	Setup_1	Uncoated	0.167	Face_2	112	109	105	108.67	-40.725
29	2196	Setup_2	Uncoated	0.226	Face_1	98	101	106	101.67	-40.148
30	2099	Setup_1	DLC	0.2	Face_2	437	435	445	439.00	-52.850
31	2099	Setup_2	Uncoated	0.167	Face_2	108	104	110	107.33	-40.617
32	2043	Setup_1	DLC	0.2	Face_1	449	447	455	450.33	-53.071
33	2196	Setup_1	Uncoated	0.226	Face_1	106	113	107	108.67	-40.725
34	2043	Setup_2	DLC	0.2	Face_2	420	408	431	419.67	-52.460
35	2196	Setup_2	DLC	0.167	Face_2	408	409	402	406.33	-52.178
36	2099	Setup_1	Uncoated	0.226	Face_1	112	109	112	111.00	-40.907

Fig. 1 Screenshot with input data and calculations

3.5 The interpretation of the results

The Taguchi method allows for clear conclusions to be drawn with a small number of experiments. In this study, the S/N ratio was used to evaluate the robustness that is, the tool life of the cutting inserts regardless of small variations in the machining conditions. The factors with the highest contribution in the ANOVA will be considered the most important. Also, by identifying the optimal combination of factor levels, precise technological recommendations can be formulated for the machining of aluminum-lithium alloys 2196, 2043 and 2099, thus contributing to increasing the quality and efficiency of the process. By applying the Taguchi method, the experimental analysis process becomes systematic and efficient, reducing the number of samples required and allowing for the rapid identification of the parameters that most influence the result. The structure of the L36 plan, the automatic calculation of averages and S/N ratios in the Excel file, as well as the integration of statistical analysis methods provide a complete tool for optimizing the machining processes of aluminum-lithium alloys.

Tab. 1 ANOVA for the Mean response

Factor	SS	Contribution [%]	Observation
A-Alloy	4863.41	0.62%	Very small influence
B-Setup	272.25	0.03%	negligible
C-Tool type	672126.69	85.38%	dominant
D-f_z	105597.64	13.41%	Secondary influence
E-Tool face	5224.08	0.66%	Small influence
Total	787083.17	100%	-

Interpretation:
- Tool type explains over 85% of the variation in the average response. This suggests a clear performance difference between DLC coated and uncoated tools;
- Feed per revolution (f_z) has a notable influence (≈13%), although much smaller than the tool type. This shows that changing the feed parameter has a measurable effect on the surface quality;
- The Alloys, the Setups and the tested faceces have minor effects. Variations between these conditions do not significantly affect the tool life.

Tab. 2 ANOVA for the S/N response

Factor	SS	Contribution [%]	Observations
A-Alloy	5.94	0.48%	Minor influence
B-Setup	0.68	0.06%	Negligible
C-Tool type	1077.14	87.6%	Dominant
D-f_z	136.89	11.1%	Secondary influence
E-Tool face	9.02	0.73%	Small influence
Total	1229.68	100%	-

Interpretation:
- The S/N ratio model confirms exactly the same trend;
- Tool type is the main factor affecting the stability and consistency of the process performance;

- Feed per revolution (f_z) has a secondary influence, indicating that small values of f_z probably lead to smaller dispersion (more stable results);
- The remaining factors, alloy, setup, facete, are practically insignificant;
- The "Smaller-The-Better" model shows the same hierarchy. Not only the average values, but also the process stability depend almost exclusively on the tool type and feed per tooth.

4. FINAL CONCLUSIONS

Technological interpretation:
- DLC coated tools offer significantly better and more consistent quality and higher durability of the cutting tools, due to reduced friction and slower wear;
- High feed per revolution (f_z) tends to increase the roughness obtained and decrease the tool life, but its influence is smaller than the tool type. It is a sign that the process is dominated by the tool-material interaction;
- The alloy type (2196, 2043, 2099) seems to matter very little under these conditions, so the chosen machining method is robust to moderate compositional variations.

Recommended next steps:
- Data consistency check: eliminate numerical errors (negative SS). This is done by recalculating the ANOVA in MATLAB;
- Main effects and interaction analysis: visualize the combined influence. Create "Main Effects" and "Interaction Plot" plots;
- Predictive modeling: predict the response based on the factors entered. Create an MLP Artificial Neural Network (MATLAB Neural Net Toolbox); [5]
- Taguchi-inverse optimization: determine the optimal combination of factors. Use the maximum S/N method for "Smaller-the-better";
- Experimental validation: confirm the optimal combination through additional verification experiments.

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