# Optimization of the Shaft Machining Process Using 2k Factorial Design

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## Abstract

Optimizing a shaft machining process is critical to reaching the quality requirements specified by the customer. Thus, the study's objective is to define the appropriate parameters to optimize the axle machining process used in a didactic experiment in a laboratory of manufacturing processes in a public university. For this, an Experimental Project was carried out to reach the best fit to minimize the shaft shape error and improve the process quality. To develop this study, the experiment design is based on the 2K factorial design methodology and ANOVA analysis. The findings show that the shape error is related to the interaction between feed rate, depth of cut and tool tip radius.

## Keywords
Experimental Project, 2k Factorial Design, Machining, Learning process.

## 1. Introduction

Due to the complexity, high level of abstraction, and different mathematical techniques to be explained, teaching and learning in engineering courses are challenging tasks (Chowdhury et al., 2019). Given this context, it is important to integrate theory into practice through laboratory manufacturing experiments (Zhu, 2020). Didactic training using the machining process needs optimization because the resources are increasingly decreasing in education, making it difficult to teach engineering courses effectively (Chowdhury et al., 2019). Also, companies' resources are restricted, so students are prepared to optimize resources for the job market.

Following Ribeiro and Caten (2014), Experimental Project methodology is strongly supported by statistical concepts. It seeks to optimize the planning, execution, and analysis of an experiment that improves systems performance. Within this theme, a method to plan these experiments aiming at optimization are the 2K factorial design, whose objective is to perform tests with each of the possible combinations. Based on this, we could establish and analyze the main interaction effects of the parameters, so that we may point out the best experimental conditions of the manufacturing process (Galdámez, 2002).

Therefore, Experimental Project was carried out with the objective of defining the appropriate parameters of the axle machining process used in a didactic way by a laboratory of manufacturing processes. With this, we could plan our experimental project and conclude about the best process fit, so that the shaft shape error is minimized and, thus, the process quality is improved (Ribeiro and Caten, 2014).

Thus, the study was carried out at a Public University in southern Brazil, more specifically in Manufacturing Processes laboratory, which offers services that comprise the machining area, such as milling, turning, drilling, among others. We collected the sample according to the distribution of the Minitab Software. Considering the measurements of each combination of parameters, we could observe that this type of method was effective to determine the optimal adjustment to minimize the shaft shape error machined in the laboratory, which generated a rational use of the university resources and improved the teaching and learning process of engineering courses.

### 1.1 Objectives

The main objective of this study is to improve the quality of the machining process performed by the laboratory of manufacturing processes with the minimization of the shaft shape error. For this, some specific objectives were followed as shown in Figure 1.

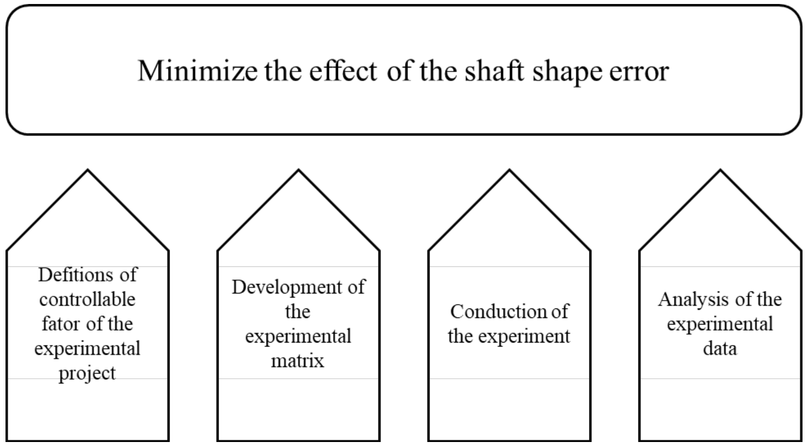


Figure 1. Objectives of the study

As shown in Figure 1, our first objective was to define the controllable factors of the experiment, which are those that can affect the quality requirements from the process if they are changed. Then, we constructed the experimental matrix to plan the experiment through the 2k factorial design that studies a *k* number of factors, each at two levels called low or high. Then, we conducted the experiment, considering the measurements of controllable factors according to the experimental matrix planning. Finally, the statistical analysis was performed using the ANOVA analysis, identifying the effects of the factors on the response variable (shape error of the machined shafts).

## 2. Literature Review

This chapter will address issues related to (i) the machining process and (ii) the fundamental of the 2K factorial design.

### 2.1 Machining processes

Manufacturing processes and their design are one of the main factors of quality and economic efficiency in industrial production (Klocke, 2013; Paslauski et al., 2016; Enrique et al., 2018). Within a multitude of manufacturing processes, machining consists of the manufacturing process performed through cutting tools removing unwanted parts of some object to transform it into the desired shape (Liang et al., 2004). Considering this type of process, the surface quality of a part and its roughness are important quality requirements, because they determine the functional behavior of a part (Lu, 2008). Therefore, the optimization of manufacturing conditions is important in these processes because they determine the products quality involved in the processes (Puertas and Luis,2003).

The machining process can be accomplished using various machines; however, the Computer Numerical Control (CNC) machine is spread in various industries and is also implemented in engineering schools for teaching and practical learning processes (Hung-Wei and Ching-Hung, 2017; Zhu, 2020). For example, Hidalgo et al. (2008) implemented a didactic training course/methodology using CNC in a virtual environment to teach their students. The students could access CNC parameters and simulate to apply their knowledge. Moreover, the use of this type of machine helps in improving the accuracy of machining and part quality that are considered as indicators of product quality. So, for instance, when the machining parameters are well established, the equipment could guarantee the part quality (Hung-Wei and Ching-Hung, 2017).

Therefore, to ensure the quality of a process and its optimization, it is important to verify how controllable parameters should be combined to generate the best results in terms of time, cost, and resources (Ribeiro and Caten, 2014). Thus, the combination of process parameters such as cutting speed, feed rate, rotation speed, tool tip radius can represent the conditions necessary to optimize machining operations, minimizing or maximizing required performance (Yusoff et al., 2011). To also ensure this quality and optimize process with the use of the right parameters, machining operations are becoming progressively complex, so a learning game was created to teach mechanical engineering students, improving their machining skills, and helping to develop their ability to reach the required performance (Pons-Lelardeux et al., 2015).

### 2.2 The 2K factorial design

Manufacturing processes involve many factors and levels that directly influence the operations quality. Thus, it is important to control experiment factors when we are planning our experiment, obtaining the answers through statistical methods and techniques (Galdámez, 2002). According to Ribeiro and Caten (2014), the experimental project design should consider:

i. Customer's voice: definition of the quality characteristics that are the process quality that the client perceives as important.
ii. Engineer's voice: definition of how quality characteristics should be analyzed to define an output variable or measurable response variable.
iii. Controllable factors: definition of parameters that may affect the quality characteristics if they change.
iv. Constant factors: definition of parameters kept constant because they do not have significant influence on the measurement.
v. Noise factors: factors that can influence process performance but cannot be controlled.

To plan the experiment, there are several methods that can be applied, one of which is the 2k factorial design, that studies a k number of factors, each at two levels called low or high (Galdámez, 2002). In situations where the number of factors is greater than two, it is interesting that the test levels are limited, otherwise the number of test combinations may make the experiment impossible (Carpinetti, 2010).

According to Neves et al. (2002), this type of planning is usually represented by bk, "b" being the number of levels chosen and "k" represents the number of factors. According to these authors, the most usual case of factorial planning is one in which each factor k is present at only two levels, this situation is called factorial design 2k. Through this procedure, tests are performed with each of the possible combinations, enabling the analysis of the main effects and interaction of the factors considered. The results may point out the best combination for the manufacturing process, for instance. In addition, it is important to randomize the experiments to balance the effects produced by the non-controllable factors in the analyzed responses and mitigate experimental bias (Galdámez, 2002). For example, Gao et al. (2016) showed some important machining parameters in experimental simulation, they compared simulated results and measured results to validate their simulated model based on some key parameters: cutting forces and surface roughness.

After the tests, data should be interpreted. So, we could understand and analyze how the system reacts to the parameters combinations and which factors cause statistically significant effects within the assessed levels. To do so, this difference is evaluated by means of statistical significance tests, by examining the p-value. If it is less than a specified significance level ($\alpha$), usually 0.05 (95% confidence interval), the difference can be declared statistically significant and reject the null hypothesis (Minitab ®, 2018).

## 3. Methods

Following the Experimental project design, the first phase consists of defining the quality characteristics which are the process characteristics that the client perceives as important to be attended. The next phase is the definition of input parameters, which is the translation of quality characteristics into a technical language (Ribeiro and Caten, 2014). Through a simulated research, we sought to find which characteristics of the assembly areas are important for the internal customers. Based on this, we also sought to evaluate the performance of the shaft machining process. So, the characteristic described by the customers was translated into a response variable, or better, the characteristic should be measured as the result of the experiment (Ribeiro and Caten, 2011).

Then, controllable factors and their minimum and maximum levels were defined to perform the experiment in the machining process. The parameters (feed rate, depth of cut and tool tip radius) were defined based on their quality characteristics resulting from the process if they are changed, these data are shown in Table 1. Then, the constant factors (the wear of the machining tools) of the experiment were also determined, that is, these factors do not have great capacity to influence the measurements of the process. We also determined the noise factors (oscillation of the raw material and machining equipment performance), which can influence the performance of the process, but that cannot be controlled.

Table 1. Intervalo de investigação dos fatores controláveis

| **Controllable factors** | **Levels** | | |
|---|---|---|---|
| | **Low** | **High** | **Units** |
| X1: Feed rate | 10 | 30 | mm/min |
| X2: Depth of cut | 30 | 50 | µm |
| X3: Tool tip radius | 1 | 3 | mm |

Finally, the experimental matrix was elaborated for a $2^3$ experiment, because the number of factors was equal to three (Table 1) and two levels of each factor (high and low) were investigated, resulting in $2^3 = 8$ test combinations. To be able to perform two repetitions, the experiment was divided into two blocks, each block referring to one day, due to the availability of the laboratory technician who operated the CNC Lathe.

Through this project, an experimental matrix was generated using the Software Minitab®, version 18. To perform this procedure, the coded matrix was generated and the matrix with the actual values of the levels of the factors that were controlled in the experiment. Then, a column with the response variable collected in the experiment was inserted. The response variable values were measured in $\mu m$ of the shaft shape error. For the generation of the experimental order, the option of randomizing assays was selected, so we could mitigate the interference of other possible sources of variability in the results of the experiment.

As the turning of the shafts is a critical process for quality management and optimization models, we have chosen it to this study. To perform the turning of the shafts, CNC LOGIC Gold 220VS Diplomat lathe was used. This machine is mainly used for didactic purposes in a manufacturing process laboratory of a public university, which one of the manufacturing objects is a steel shaft. The inserts used for turning the shafts of the experiment were of the brand Sandvik Coromant - Class GC4315, which consists of a hard metal with CVD cover (Chermical Vapor Deposition) and is recommended for both finishing and thinning in applications with continuous cuts to light burst.

For the study, specifically, 16 steel shafts were machined following the order established by the experimental matrix. After the production of each shaft, measurements were taken using a micrometer. For this, we took care to always measure the same location to avoid measurement bias in the results. To measure the shape of the machined shaft, an external micrometer with a capacity of 0 to 25 mm, resolution/graduation of 0.01 mm model 103-137 and accuracy of +/- 0.002 mm of the Mitutoyo brand was used. This instrument is recommended for more accurate measurements than a pachymeter, providing accurate, reliable, and agile measurements.

## 4. Data Collection

Data was collected in the morning shift on two consecutive days, so we blocked the experiment in two periods, since there was a restriction on the time available for the tests. All tests were performed on the same machine: in the CNC lathe, as aforementioned in the Methods section. In addition, the experiment did not have operator interference during machining because it is fully automated using the FANUC programming language. In the execution of the experiment, the shafts were machined according to the random order generated by the experiment worksheet, and we measured at the time of removal of the machine part. To illustrate how the process works, the machining process can be seen through the video presented in the QR Code in Figure 2 (please scan the QR Code).

Figure 2. Shaft machining process QR Code

The machine operator was the laboratory technician, and his function was to replace the part that would be machined, tighten the plate and the counterpoint advance. As the parts were supplied in the machine, according to the order stipulated by the experimental matrix, the cutting data (the controllable factors of the experiment) were changed before the operation began. At the end of the operation, the laboratory technician removed the part from the machine and passed it on so that the measurements could be performed.

## 5. Results and Discussion

In this section, we will present the results and discussions about the Experimental project carried out.

### 5.1 Numerical Results

The results were obtained from the tests performance with all the combinations defined by the experimental matrix. We wanted to determine and understand the main and interaction effects of the factors investigated. Then, we could determine the best experiment combinations (Galdámez, 2002). This methodology was chosen for the present study because we sought to know the effects of three factors in which each was investigated at two levels. It is important to highlight that experiments of this type are illustrated in several studies on techniques of planning and analysis of experiments (Devor et al., 1992; Montgomery, 1991). The complete results of the measurements taken are presented in Table 2

Table 2. Experimental matrix and output results

| **Standard order** | **Trial order** | **Central point** | **Blocks** | **Feed rate (mm/min)** | **Depth of cut (µm)** | **Radius (mm)** | **Shaft shape error (µm)** |
|---|---|---|---|---|---|---|---|
| 6 | 1 | 1 | 1 | 10 | 30 | 1 | **15** |
| 8 | 2 | 1 | 1 | 30 | 30 | 1 | **19** |
| 1 | 3 | 1 | 1 | 10 | 50 | 1 | **21** |
| 2 | 4 | 1 | 1 | 30 | 50 | 1 | **23** |
| 5 | 5 | 1 | 1 | 10 | 30 | 3 | **15** |
| 3 | 6 | 1 | 1 | 30 | 30 | 3 | **18** |
| 4 | 7 | 1 | 1 | 10 | 50 | 3 | **22** |
| 7 | 8 | 1 | 1 | 30 | 50 | 3 | **22** |
| 2 | 9 | 1 | 2 | 10 | 30 | 1 | **17** |
| 3 | 10 | 1 | 2 | 30 | 30 | 1 | **20** |
| 7 | 11 | 1 | 2 | 10 | 50 | 1 | **23** |
| 6 | 12 | 1 | 2 | 30 | 50 | 1 | **24** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 8 | 13 | 1 | 2 | 10 | 30 | 3 | **17** |
| 1 | 14 | 1 | 2 | 30 | 30 | 3 | **19** |
| 4 | 15 | 1 | 2 | 10 | 50 | 3 | **24** |
| 5 | 16 | 1 | 2 | 30 | 50 | 3 | **22** |

Using Minitab Software® version 18, a complete factorial experiment was planned with three factors, 16 trials and two replicates, as aforementioned. Through data collection, it was possible to perform variance analysis (ANOVA) to identify the effects of factors on the response variable. The results of the analysis are presented in Table 3.

Table 3. Experiment ANOVA

| Source | DF | SQ (Aj.) | QM (Aj.) | F value | P-value |
|---|---|---|---|---|---|
| Model | 8 | 135 | 16,875 | 60,970 | 0,000 |
| Blocks | 1 | 7,563 | 7,563 | 27,320 | 0,001 |
| Linear | 3 | 116,188 | 38,729 | 139,920 | 0,000 |
| **Feed rate (mm/min)** | **1** | **10,563** | **10,563** | **38,160** | **0,000** |
| **Depth of cut (µm)** | **1** | **105,063** | **105,063** | **379,580** | **0,000** |
| Radius (mm) | 1 | 0,562 | 0,562 | 2,030 | 0,197 |
| Interactions between 2 factors | 3 | 10,688 | 3,563 | 12,870 | 0,003 |
| **Feed rate (mm/min)*Depth of cut (µm)** | **1** | **7,562** | **7,562** | **27,320** | **0,001** |
| **Feed rate (mm/min)*Radius (mm)** | **1** | **3,063** | **3,063** | **11,060** | **0,013** |
| Depth of cut (µm)*Radius (mm) | 1 | 0,063 | 0,063 | 0,230 | 0,649 |
| Interactions between 3 factors | 1 | 0,563 | 0,563 | 2,030 | 0,197 |
| Feed rate (mm/min)*Depth of cut (µm)*Radius (mm) | 1 | 0,563 | 0,563 | 2,030 | 0,197 |
| Error | 7 | 1,938 | 0,277 | | |
| Total | 15 | 136,938 | | | |

According to the ANOVA results presented in Table 3, it is possible to verify that the main effects of feed rate and depth of cut are significant because its p-value is lower than the α considered to be 5% ($p<0.05$). In addition to the main effects, the significance of the interactions between feed rate and depth of cut and feed rate and tooltip radius was also detected by the analysis of variance, also considering an α of 5%.

## 5.2 Graphical Results

Based on the results of Table 3, we elaborated graphs for the identification of the optimal fit of the process, as shown in Figures 3 and 4.

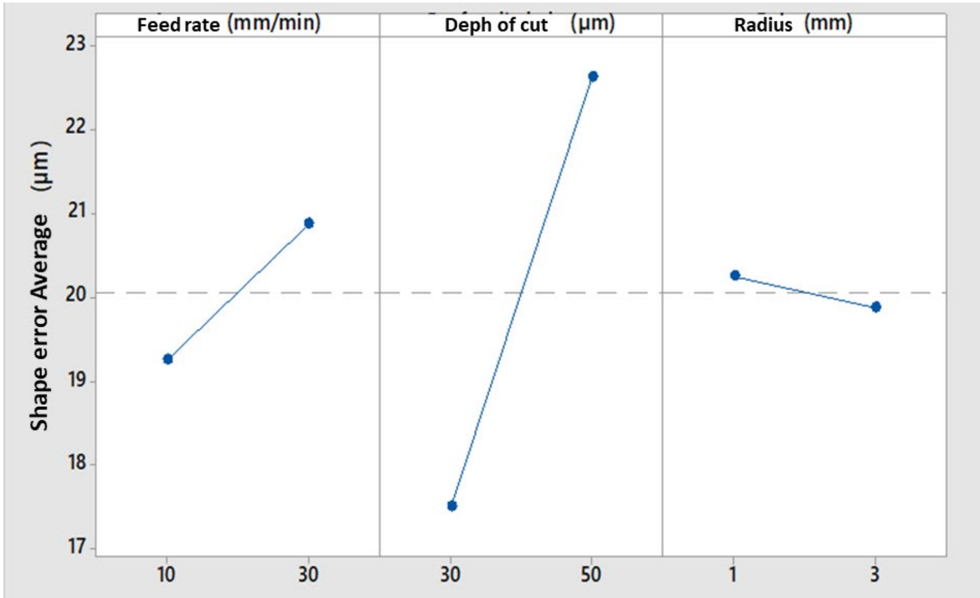


Figure 3. Graphics of the main effects for the shape error

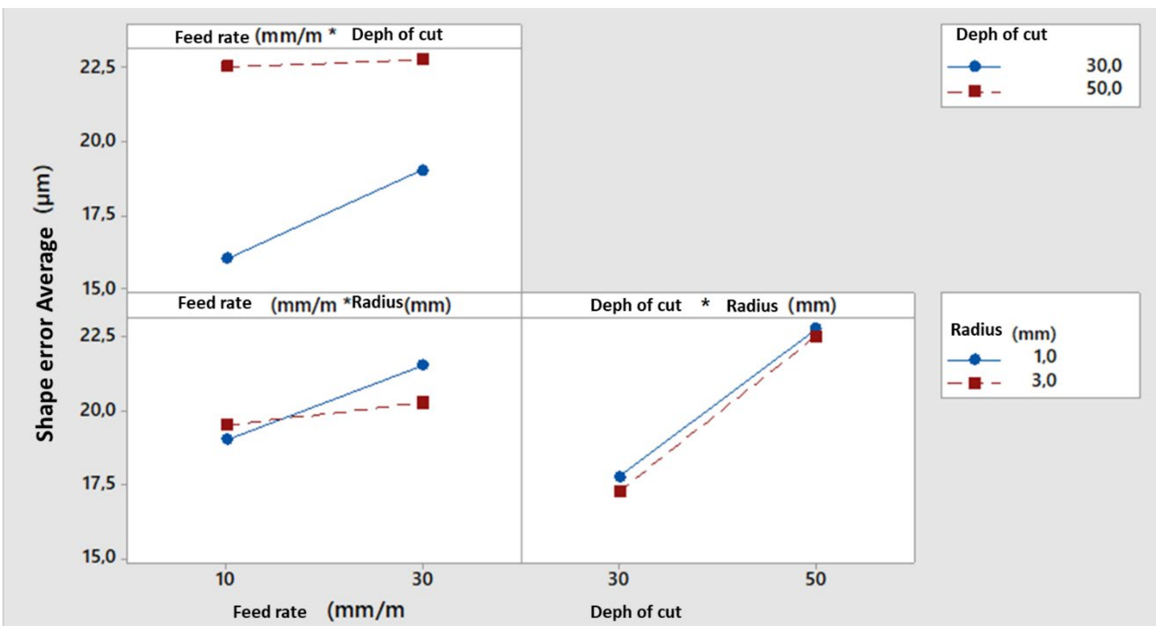


Figure 4. Interaction graphs for shape error

Based on the graphics, we could identify a strong interaction between feed rate and tooltip radius factors because the lines intersect. Moreover, there is a weak interaction between feed rate and depth of cut because there is a lack of parallelism with low inclination. Based on these analysis, we could generate an optimal solution to minimize the shaft shape error: the best combination of the studied factors. The optimal results are in figure 5.

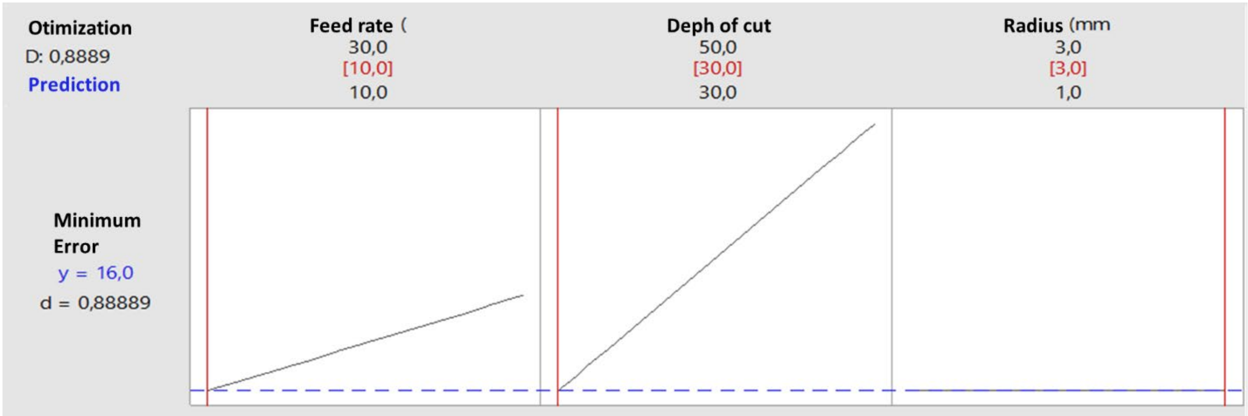


Figure 5. Optimization graph

### 5.3 Proposed Improvements

According to the graph presented in Figure 5, we verified that the optimal fit for the studied process is feed rate at the low level (10 mm/min), depth of cut at the low level (30 µm), and tooltip radius at the high level (3 mm). With this combination, the machined shaft shape error can be adjusted to 16 µm, thus minimizing the machining process's quality problem.

We suggest that other tests be performed with different values of parameters to establish a cycle of continuous improvement and to optimize the use of resources for this type of production. It is important to highlight that the analyzed context requires maximum resources optimization since it has little investment to produce the shafts, and the available resources are scarce. Therefore, this experiment can be considered quite relevant since it identified the best way to produce shafts aimed at teaching engineering undergraduates. Our study brought novelty regarding optimization parameters because other studies about didactic machining focus on developing a friendly framework and creating a module to facilitate the teaching and learning process (Bustamente et al., 2014). Also, other authors explored the importance of didactic puzzle games in the learning process of machining, and they have already patented this idea (Serrano, 1994). Thus, considering this context, if we join our findings with the previous literature about the theme, we observe that if we integrate optimal fit, simulation, new teaching frameworks, and puzzle games, for instance, the students could be beneficiated with a strong and wide learning experience. Furthermore, even though our study has been applied in a public university, our findings could also be used in industry because the industry is also seeking to reduce their costs and to improve the use of resources.

## 6. Conclusion

We sought to define the levels of shaft machining parameters that minimize the problem of shaft shape error. For this, we used a methodology of design of experiments, called factorial project 2k, specifically a factorial project $2^3$, and the ANOVA analysis. For this, we investigated three factors at two levels: feed rate (10 and 30 mm/min), depth of cut (30 and 50 µm), and tooltip radius (1 and 3 mm). We performed 16 trials (eight on each day), and we analyzed the combinations identified in the experimental matrix.

Based on our data collection and analysis, we could identify the optimal fit of each factor level to minimize the shaft shape error. The finding showed that feed rate [mm/min]: 10 mm/min; depth of cut [µm]: 30 µm; tooltip radius [mm]: 3 mm.

Therefore, by adopting the indicated levels, we could minimize the effect of the shaft shape error, ensuring better quality to the machining process performed by the manufacturing process laboratory of a public university. Also, it is interesting to emphasize that the use of Experimental projects facilitates the analysis process since the way information is collected mitigates possible bias that may arise in the practical day-to-day. Another relevant point is that through this optimization, the resources used for the teaching and learning process in engineering courses are improved, increasing the effectiveness of teaching.

For future studies, we suggest changing the process parameter values to establish a cycle of continuous improvement and rational use of resources. Also, it is interesting that the engineering students themselves replicate these experiments to propose better ways of using resources or even the study of other process parameters.

## Biographies

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