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Master Thesis

Automated Experimental Design of Metal-Cutting Manufacturing Processes for AI Training

carried out for the purpose of obtaining the academic degree of Diplom-Ingenieurin (Dipl.-Ing. or DI) under the direction of

Ass.Prof. Dipl.-Ing. Dr.techn. Thomas Trautner

(Institute of Production Engineering and Photonic Technologies)

Univ.Ass.in Dipl.-Ing. Lea Tonejca

(Institute of Production Engineering and Photonic Technologies)

submitted to the Technical University Vienna

Faculty of Mechanical Engineering and Management Sciences

by

Natalia PESO GARCIA

Matr. Nr: 012126319

Vienna, June 2023

Natalia, Peso García

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Vienna, June 2023

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Kurzfassung

Diese Arbeit konzentriert sich darauf, eine Lösung für die Schaffung einer spezifischen Methodik zu finden, die es ermöglicht, reale Daten zu sammeln, um KI-Systeme zu trainieren, die darauf ausgerichtet sind, Fertigungsprozesse durch die Entwicklung von Vorhersagemodellen zu verbessern.

Dies geschieht durch standardisierte Experimentierprozesse, die die Methodik der Versuchsplanung (Design of Experiments, DOE) auf automatisierte Art und Weise nutzen, wodurch sichergestellt wird, dass die Durchführung dieser Experimente replizierbar und vollständig kontrolliert ist. Außerdem bietet es den Vorteil der Zeitoptimierung, sowohl für die nachfolgende Behandlung der Daten als auch für die Durchführung der Experimente selbst.

Darüber hinaus beinhaltet dieses Projekt ein Datenmanagement durch Fertigungsfunktionen, um eine kontinuierliche Identifizierung der Daten während der verschiedenen Phasen des Projekts zu gewährleisten und gleichzeitig eine geschlossene Feedbackschleife für die Korrelation von Daten und Anwendungen der entwickelten KI-Systeme zu schaffen.

Dieses Projekt hat gezeigt, dass die Anwendung der entwickelten Methodik zu strukturierten Daten führt, die für das Training von KI-Systemen verwendet werden können. Außerdem ermöglicht sie eine einfache Datenkorrelation und die Reproduzierbarkeit der Experimente.

Abstract

This thesis focuses on providing a solution for creating a specific methodology that allows the collection of real data to train AI systems focused on improving manufacturing processes by developing predictive models.

This is carried out through standardized experimentation processes using the design of experiments (DOE) methodology in an automated way, ensuring that the execution of these experiments is replicable and fully controlled. It also provides the advantage of time optimization, both for the subsequent treatment of the data and for the execution of the experiments themselves.

In addition, this work includes data management through manufacturing features to provide a continuous identification of data throughout the various stages of the project. This identification ensures control over the system while providing a feedback loop for the correlation of data and applications of the developed AI systems.

This thesis has shown that using the developed solution results in structured data that can be used to train AI systems. It also allows for easy data correlation and enables the experiments to be replicable.

List of Abbreviations

DOE	Desgin of experiments
AI	Artificial inteligent
ANOVA	Analysis of Variance
CAD	Computer-aided design
CAM	Computer-aided manufacturing
OFAT	One-factor-at-a-time
JSON	JavaScript Object Notation
CSV	Comma Separated Values
API	Application Programming Interface
ID	Identifier
FF	Feedrate
SS	Spindle Speed
CD	Cutting Depth
IFT	Institute of Production Engineering (Institut für Fertigungstechik)
CNC	Computerized Numerical Control
TXT	Text Document File

Table of Contents

1 Introduction

As presented by Țîțu et al. [1], companies are adopting a new approach to meet quality and optimization standards in the manufacturing industry, especially in machining processes. This involves digitalizing and automating processes by analyzing and using relevant data between the design and manufacturing phases.

Accordingly, data has become one of the most valuable resources, and obtaining data from actual processes has become essential. However, obtaining this data through structured means is crucial to ensure quality and reduce analysis time because, as it is known, Big Data analysis processes usually require considerable time and resources.

Smart Manufacturing is one of the current trends that focuses on achieving automation and digitization in the manufacturing sector. This new form of production is based on developing cyber-physical systems, such as the Internet of Things, predictive modeling, artificial intelligence, and data science [2].

As part of this new form of production, a new approach called feature-based management can be identified to improve the data analysis process. This approach is a new way of managing data based on specific attributes or characteristics.

The featured-based concept helps to control the system by identifying important elements and linking data to different stages of the process.

One of this work's objectives is to improve data extraction by developing an automated statistical experimentation methodology with feature-based management for metal-cutting processes.

The industry faces challenges when using statistical methods to analyze systems or problems. As a result, progress in digitalization in the sector is slowed down, which could be overcome by implementing structured processes that promote more efficient data collection [3]–[5]. Automated collection of real data can be used to analyze Big Data and its subsequent use in AI systems for process optimization.

This thesis presents a solution to address these problems by creating a structured methodology for varying experiments automatically using the statistical method of Design of Experiments (DOE). The solution also involves automating featured-based data management. With this new system, the intention is to offer a solution that allows the correlation of data from different sources of information in a more structured and straightforward way, a scenario easily found in the Big Data area.

That study is applied to a specific case study that analyzes the impact of different cutting parameters and machine accelerations during the milling processes on the part's surface roughness. For the measurement of the surface roughness, a novel system for the in-situ measurement in machine tools is studied.

Moreover, this method guarantees the quality and repeatability of the process, as well as an improvement in time efficiency, thanks to the automation of the experimentation and data management process.

This methodology, using DOE, provides an organized approach to statistically analyze systems and collect live data in a standardized way [6]. In addition, when this methodology is paired with feature data management, data analysis becomes more efficient. It also ensures that the data is standardized, replicable, identifiable, and comparable, allowing for the optimization of manufacturing processes using artificial intelligence solutions [7].

2 Motivation and State of the Art

In this section, the basic concepts underlying the thesis, as well as the theoretical bases of the methods used and the parameters studied, will be presented.

2.1 Manufacturing Industry

Globalization, increased consumer demand, and the trend towards customization of industrial solutions and commercial products lead to the demand for increasing productivity while reducing costs and maintaining product quality [8].

2.1.1 Standardization

Manufacturing systems can be very complicated due to the many variables involved. Without a framework for evaluation, controlling and analyzing these systems can be challenging. Process standardization is one of the possible solutions for enhancing process optimization through data analysis [9].

From the point of view of the manufacturing sector, where the internationalization of production has boosted collaborative work and consequently an intensification of communication, the creation of standards is essential [10]. This generation of standardized processes offers controlled tools that are accessible to all members of the system, offering greater control and the possibility of using the same methodology for different projects, thus optimizing the resources and knowledge needed to address them [10]–[13].

Concrete protocols for data generation and subsequent identification improve data processing and enhance digital solutions such as AI or machine learning in manufacturing [7].

Examples of standardized processes for systems analysis or innovation are the experimentation processes and statistical methods [7].

2.1.2 Data Correlation

Collecting and processing data from manufacturing processes is currently studied, which is extremely important for implementing digital solutions and their automation.

In order to implement AI solutions in the sector, what is needed is a large amount of data, and from them to achieve correlations that subsequently allow the application of methodologies such as the so-called data-driven decision [14].

2.1.3 Knowledge Feedback

For integrating AI solutions in the sector, the automation of data processing and correlation throughout the processes is important, given the abundant amount of data necessary.

According to Kusiak et al. [2], Smart Manufacturing is based on integrating physical and digital systems, that is, integrating the same system of the current manufacturing assets with sensors, simulation, intensive data modeling, and predictive engineering, called cyber-physical systems.

This thesis proposes a methodology for correlating real-time data from diverse sources through feature data identification and timestamps. That way, it facilitates the application of predictive systems in the design and production processes and ensures data traceability and identification at any project stage.

2.2 Problem Statement

The manufacturing sector uses both traditional technologies and new automated manufacturing technologies such as CNC machines, but the working methods with both are still, to some extent, manual. Machine operators often work based on their knowledge and experience in the sector, which means that this knowledge is not stored in a centralized or digitized environment that could be consulted and analyzed [5]. Techniques like trial and error make productions or projects but applying digital solutions to develop more efficient production can be challenging due to a lack of data continuity [5].

2.3 Design of Experiments (DOE)

Experimentation is one of the most widely used methods in multiple industries to foster innovation, problem-solving, and process optimization [7]. For example, creating knowledge-based systems or data-driven processes that improve productivity by using such data together with AI to predict results creates maintenance cycles or monitoring processes [15].

Studies such as the one conducted by Tanco et al. [16] show that about 76% of the observed companies need standardized and more knowledge about real applications or statistical methods within their work protocols methodology to evaluate their experiments correctly.

Tanco et al. [16] elaborate in their study on the industrial tendencies towards experimentation from the statistical point of view, the methods used, and the problems identified by the industries in this respect.

Some methods mentioned are Best Guess, One-factor-at-a-time (OFAT), and Design of Experiments (DOE). The first method is based on using previous knowledge to adjust the variables of the experiments in order to improve the results. The OFAT method is based on modifying one variable at a time to study its influence on a response variable. Finally, the DOE allows the analysis of a response through multiple variables, making it suitable for highly complex problems such as those found in the manufacturing sector [16], [17].

2.3.1 OFAT vs. DOE

When performing experiments, engineering often uses the One-factor-at-a-time (OFAT) methodology. However, it only allows the modification of one factor per experiment [18]. Therefore, it is not the most appropriate since, in manufacturing, multiple variables must be controlled simultaneously, such as cutting parameters, tools, materials, and coolants.

The OFAT selects a baseline as a reference for each studied factor and subsequently varies this factor individually over the rest of the factors to analyze the result [17]. This methodology configuration does not allow studying the interaction between factors, making this methodology less efficient than other statistical studies such as DOE [17].

In Figure 1, Montgomery et al. [17] show the graphs obtained from an experiment using OFAT, and it can be seen that for each factor, only the individual effect on the response variable of each of them can be analyzed.

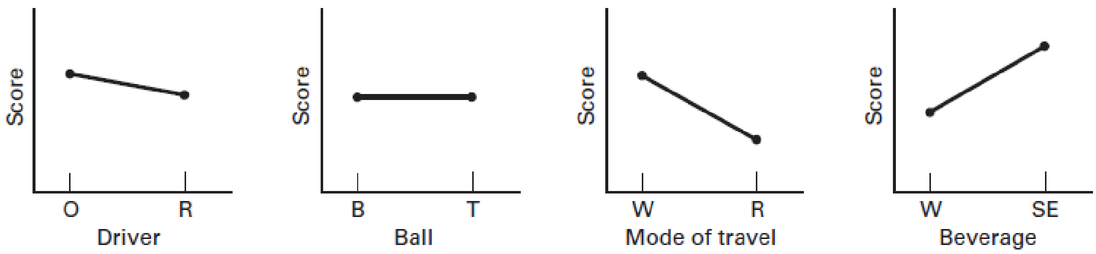


Figure 1: OFAT results for a golf experiment [17].

On the other hand, DOE methodology offers a tool that can be applied to complex experiments where the influence of multiple factors on a response variable levels can be analyzed at different [19]. During the experiments, various input variables (known as factors) are intentionally varied to observe their combined effect on a response. This allows for the identification of both the individual effect of each factor, and the effects of their interactions [16], [17]. Furthermore, allowing the variation of all factors simultaneously makes it more efficient than OFAT from the point of view of resources and time [9].

In summary, the following advantages could be gathered from a statistical and resource point of view of using and generating a standard methodology for experimentation using DOE rather than others [18]:

- Fewer resources are required, as fewer experiments need to be performed.
- More precise estimations.
- Allows a multifactorial study, including the interaction between them.
- Statistical systematization of the experimentation process allows the development of a standardized process and guarantees replicability.

2.3.2 DOE with AI

DOE allows structuring the data collection, making the learning stages of the AI algorithm more efficient [9] and increasing confidence in the data. In addition, conducting experiments according to strict methodology allows for better control over AI analysis and provides a theoretical foundation for the discovered solution [20].

With all this, what has been seen is that the combination of DOE and AI provides advantages such as "fewer training runs, better parameter selection, and a disciplined approach based on statistical theory" [19, p. 195].

It can be concluded that the DOE methodology is the appropriate methodology to apply in this work [17]. The advantages of DOE are:

- Improved performance of experiments given the high control over the overall process.
- Reduction of variability and greater conformity with the nominal or target requirements.
- Reduction of development time.
- Reduction of overall costs.

The next chapter will be about the theory behind DOE, the most commonly used methods in the industry, and the method selected for this project.

2.3.3 Method

For this section, the book "Design and Analysis of Experiments" by Montgomery [17] will be used as the theoretical basis.

The general definition of DOE, according to Montgomery et al. [15, p. 11], is that "statistical design of experiments refers to the process of planning the experiment so that appropriate data will be collected and analyzed by statistical methods, resulting in valid and objective conclusions".

DOE consists of two phases, the design of the experiment itself and the statistical analysis of the data, and both aspects are based on three basic principles: randomization, replication, and blocking [17], [22].

- Randomization: the concept of randomization applies to the order of execution of the experiments and the allocation of the material or sample. With this randomization, what is accomplished is to eliminate non-controlled factors [23], [17].
- Replication: For a good statistical analysis, it is necessary to repeat the experiment for each combination of factors [17].
- Blocking: arranging groups of similar experimental units into blocks. Improves the precision when comparing factors and is often used to reduce the variability of nuisance factors, i.e., those that can influence the response but are not of interest to the experimenter [17], [24].

Following the definitions in the work of Marin et al. [23], the terminology of the method can be defined as:

- Experimental unit: the object on which the experiment is conducted.
- Response variable: the variable to be studied.
- Factor: the independent variables considered as inputs that influence the variability of the response.
- Levels: the values chosen for the factors.
- Treatment: the specific combination of the factors to be studied.
- Experimental observation: each measurement of the response variable.

Finally, before explaining the different design methods, a general guide to the application of the method proposed by Montgomery et al. [17] is presented in the following table:

Table 1: Guideline for DOE [17]

1. Identification of the problem
2. Choice of the response variable
3. Selection of the factors, levels and ranges
4. Selection of the experimental design method
5. Execution of the experiment
6. Statistical analysis of the data
7. Conclusion and improvements

Some of the most common design methods used in the manufacturing industry when applying DOE are (1) Full Factorial Design, (2) Taguchi method, and (3) Central Composite Design (CCD).

1) Full Factorial Design.

This method is very efficient when used in experiments involving two or more factors by analyzing the global performance of every possible run or treatment in all possible combinations of the levels of each factor [17]. The factorial design studies the main effect of each factor and the interactions between factors on the response variable. As the number of levels and factors in the experiment increases, the responses tend to follow a less linear correlation [25].

For example, to analyze 2 or 3 factors with a maximum of 2 or 3 levels, more than 150 experiments would be needed. When analyzing more factors or levels, the experiment can be adapted straightforwardly to the fractional factorial, where only a specific fraction of the experiments is performed, maintaining the structure of the initial method.

- Fractional factorial. This method analyzes only a fraction of the experiments. It is used when there is a high volume of treatments, and it is not desirable to carry out many experiments. This methodology is used when it is assumed that the interactions between factors do not have much influence [25].

2) Taguchi.

This method is one of the most widely used in the industrial sector because it is a very fractionated methodology that still allows obtaining acceptable results depending on the required precision. This method implies reduced costs and time [26].

The disadvantage of this method is that being so fractionated assumes that the interaction has does not influence the response, making the results less accurate in complex engineering problems [25], [26].

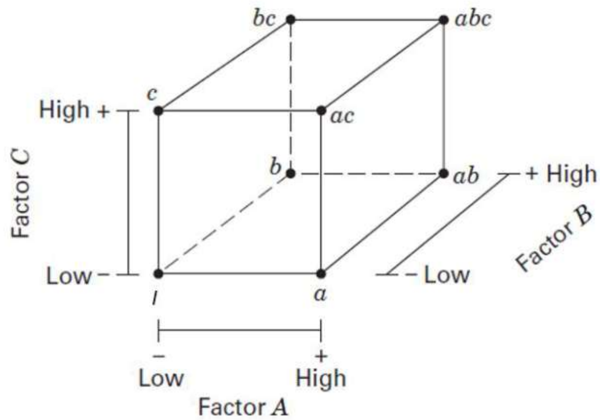
3) Central Composite Design (CCD)

This methodology is used when the desired result is a response surface. It is a fractional methodology with a specific structure since it starts from a central point and increases the study points axially, allowing the non-linear analysis of responses when more than three factors are involved [27].

For the case study of this project, the methodology selected is a specific approach of Full Factorial Design, called 2^k Factorial Design.

From Montgomery’s [17] explanation, 2^k Factorial Design is characterized by the number of analyzed levels. The name 2^k indicates that the experiments will have two levels, "+" and "-", with *k* factors, where these two levels often represent a maximum and a minimum value of the factor to be studied.

For this thesis, what is used is a 2^3 factorial design, which indicates that we will work with two levels and three factors, thus obtaining eight treatments to be studied. Graphically this situation can be represented using orthogonal coding [17]. From Figure 2, the design matrix is created (see Tables 5 and 6), indicating the combinations of treatments.



(*a*) Geometric view

Run	Factor A	Factor B	Factor C
1	−	−	−
2	+	−	−
3	−	+	−
4	+	+	−
5	−	−	+
6	+	−	+
7	−	+	+
8	+	+	+

(*b*) Design matrix

Figure 2: 2^3 Factorial Design. Geometry View and Design Matrix [17]

Once the outline of the experimental structure has been presented, the necessary formulas to calculate the effect of each factor, as well as their interactions and the statistical analysis used analysis of variance (ANOVA), are introduced.

Referring to the node nomenclature in Figure 2, the effects of the factors are calculated as follows [17]:

- Main effect: “the change in response produced by a change in the level of the factor” [17, p 180].
- Interaction: change in the response by the combined effect of two or more factors.

- Main effect factor A: $$A = \frac{1}{4n}[a - I + ab - b + ac - c + abc - bc] \qquad (1)$$

- Main effect factor B: $$B = \frac{1}{4n}[b + ab + bc + abc - I - a - c - ac] \tag{2}$$

- Main effect factor C: $$C = \frac{1}{4n}[c + ac + bc + abc - I - a - b - ab] \tag{3}$$

- AB Interaction: $$AB = \frac{1}{4n}[abc - bc + ab - b - ac + c - a + I] \tag{4}$$

- AC Interaction: $$AC = \frac{1}{4n}[I - a + b - ab - c + ac - bc + abc] \tag{5}$$

- BC Interaction: $$BC = \frac{1}{4n}[I + a - b - ab - c - ac + bc + abc] \tag{6}$$

- ABC Interaction: $$ABC = \frac{1}{4n}[abc - bc - ac + c - ab + b + a - I] \tag{7}$$

where:

$n =$ number of replicas.

$A, B, C =$ Each factor of the experiment.

$I, a, b, c =$ Sum of the two response variable replicates.

For the analysis of variance (ANOVA) used in these methodologies, the values of interest are [17]:

- Contrast: a linear combination of the parameters based on the geometric code. For example, from the formula (1), the contrast is $[a - I + ab - b + ac - c + abc - bc]$.
- Sums of square: represents a measure of variation or deviation from the mean [28].
- Mean square: is an estimator of the data variance [29].
- F_0 value: determine whether there is a significant difference in means between the group and the individual variability [30].

- Mean square: $$Mean = \frac{SS}{Degrees\, of\, freedom} \tag{8}$$

- Sums of squares, SS: $$SS = \frac{(Contrast)^2}{8n} \tag{9}$$

- F_o value: $$F_0 = \frac{Mean_i}{Mean_{error}} \quad (10)$$

Figure 3 shows the geometric representation of the effects and interactions of the factors for the 2^3 factorial design.

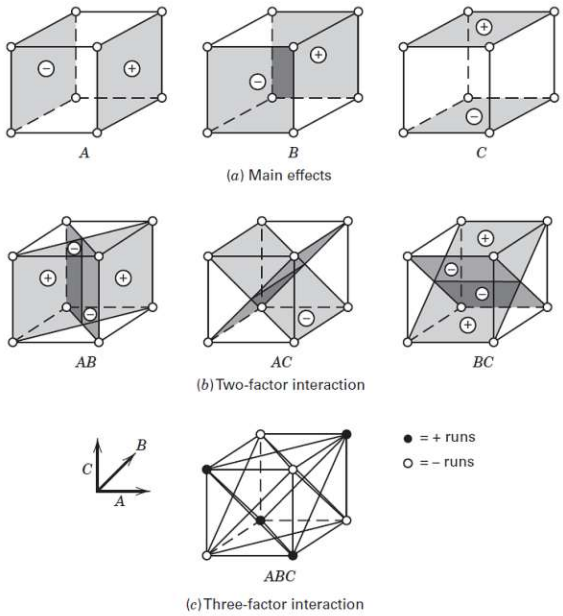


Figure 3: Representation of the effect and interactions for 2^3 designs [17].

3 Methodology

This thesis aims to develop a structured method for automatically generating experiments to guarantee reproducible conditions for AI training in a standardized way. Additionally, this automation aims to simplify the data analysis required for data-driven processes, as Big Data analysis involves complex processes that require high-quality data treatment and efficient use of time.

Along with the automation of the experimental process, this thesis includes the application of manufacturing features as key elements for data identification and the sensors measurement elements' activation and deactivation.

Automated design of experiments of metal-cutting manufacturing processes for AI training is developed to optimize the global process of the machining industry focused on surface roughness.

To obtain an experimental process development that guarantees typical industrial and replicable conditions, the method used in the thesis is the DOE, particularly the 2^3 Factorial Design method. This approach guarantees replicable conditions and aims to improve the process compared to traditional methods [17], [20]:

- Performance
- Estimation accuracy
- Cost reduction
- Explicit methodology
- Standardization/structuring in data collection

For this thesis, a specific case study will be carried out where the material to be treated is aluminum, and the surface roughness will be analyzed in three different machining operations, which are the industry's most relevant processes drilling, facemilling, and endmilling.

In addition, in order to promote the integration of information from all existing sources in the sector, this work considers the values of the cutting parameters from data found in the literature and manufacturer's data sheets, as well as the knowledge of machine operators to promote the exchange of knowledge, and the use of the most realistic data possible.

Each operation can be understood as an independent block of experiments, where the factors are cutting speed, feed per tooth, and cutting depth. The levels have been set at the maximum and minimum values based on manufacturer recommendations and input from experienced machine operators. By incorporating the industry knowledge of the operators, the design process considers their familiarity with the tools, machines, and materials.

In terms of the methodology followed throughout the project, the following phases can be identified:

1. Literature review and research:
    a. It consists of a study of the current state of the sector and the problem to be solved with the thesis. In this case, this research has focused on the DOE methodology and its alternatives, the trends in the use of DOE in the manufacturing industry, the current alternatives for collecting and structuring experimental data for AI, surface roughness, and the variables that influence it.
2. Selection of the DOE and design of the experiment method.
    a. Once the initial research has been carried out, the DOE theory has been applied to the specific case study of the project, seeking the most appropriate option for the entire project.
3. Development of the Plugin for NX for experiment automation.
    a. For this phase, the CAM software used is Siemens NX. Through the API NX Open, it is possible to program the plugin that automatically and randomly selects the experiments/treatments to be performed, thus following the DOE criteria. In addition, all the data generated will be stored in a MongoDB database to be able to use the data later.
    b. In this phase of the project, it is also conducted the identification of the relevant operations, i.e., the finished processes, which will become the features used for the data analysis.
4. Execution of first tests and final experiments with sensor data collection.
    a. During this phase, a series of tests are performed to make all the necessary checks on the automation of the experiments, adjust the values of the levels used during the experiments and finish defining the operation protocols. Once the tests have been conducted, the experiments will be executed according to the DOE methodology standards, from which live data of the machine accelerations and numeric control will be retrieved and then correlated.
5. Measurement of milled parts
    a. MiniProfiler MP15 tactile probe built into a tool holder as Surface Roughness Measuring System for in-situ measurement in machine tools. Study and application of the automated measurement system within the numerical control.
    b. Waveline W912RC instrumentation. Measurements of the surface roughness of the parts. Obtaining the profile of a complete line of each operation to later make comparisons with the rest of the data. From this

profile, the surface roughness data as Ra and the contour of the part can be extracted.

6. Automatization of data correlation and graphical and statistical data analysis.
   a. Finally, the processing of data obtained during machining is performed. Data identification through features and timestamps will be used to extract the relevant machining information at this stage. In addition, a data transformation is carried out for later visual comparison.
   b. For the graphical data comparison:
      i. From the NC data, timestamps, feature identification, and global X and Z positions will be used for correlating and transforming the acceleration data.
      ii. From the accelerations measured by the sensory tool holders, with the timestamp, and accelerations values, it will be possible to represent the acceleration as a dependence of tool position X after correlation with the NC data.
   c. ANOVA analysis following the DOE protocols. This will provide a theoretical base for how the factor influences the response variable.

Figure 4 summarizes and presents the thesis's overall concept [31].

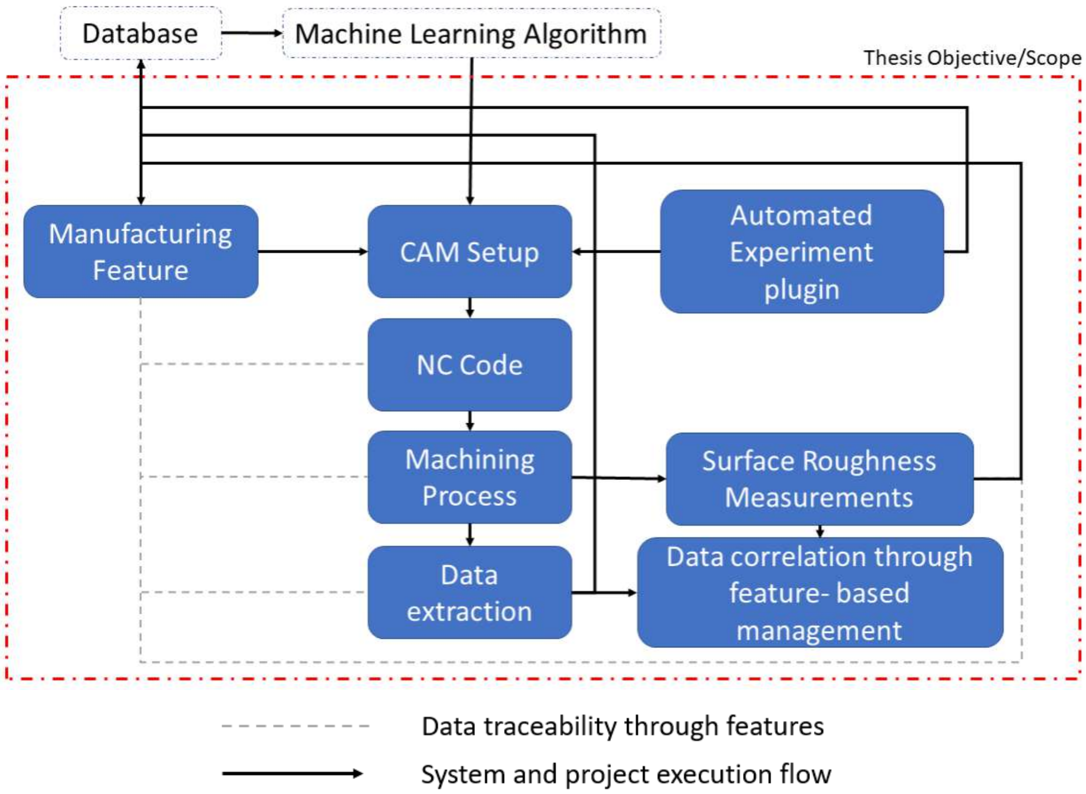


Figure 4: Project objective and scope

The blue boxes represent processes or elements that are used and obtained during the execution of the methodology:

- Manufacturing features: relevant CAM elements that will be studied and will identify the data.
- Automated DOE plugin: experiment generation software.
- CAM Setup: manufacturing configuration of the part to be machined.
- NC Code: manufacturing file with all the relevant project information.
- Machining process: manufacturing of the part and machined sample.
- Data extraction: data from numerical control and sensory tool holders.
- Surface Roughness Measurements: data of the roughness profiles of the samples and surfaces measured.
- Data correlation through features-based management: visual data correlation based on features.

On the other hand, the connections through black arrows represent the thesis workflow, and the dashed connections represent the traceability and identification of the data throughout the work.

4 Implementation

The following scope has been set for this work:

- Response variable: Surface roughness
- Operations to be analyzed:
  - Facemilling
  - Endmilling
  - Drilling
- Cutting parameters to be studied:
  - Cutting speed, v_c (m/min)
  - Feed per tooth, f_z (mm)
  - Cutting depth (mm)

However, since the software used in this project is Siemens NX, it allows us to control other variables, which are easily related, such as:

- Spindle speed (rpm)
- Feedrate (mmpm)

Therefore, it is necessary to use the formulas following equation to obtain the real values with which the program will work:

- Cutting speed, v_c (m/min):

$$v_c = \frac{\pi * \emptyset_{tool} * n}{1000} \quad (11)$$

- Feed per tooth, f_z (mm):

$$f_z = \frac{v_f}{n * n^{\underline{o}}\ of\ edges} \quad (12)$$

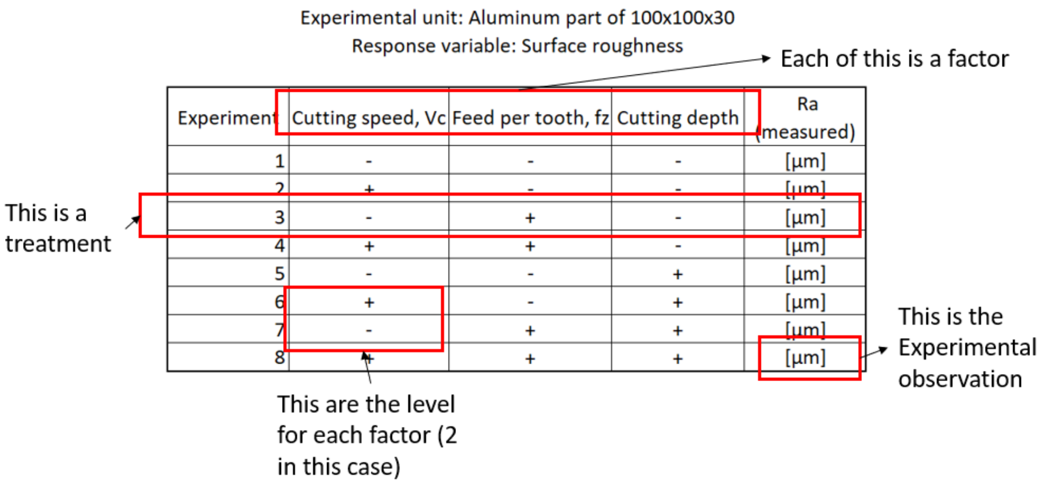
where:

n = spindle speed (rpm)

$\emptyset_{tool}$ = diameter of the tool used for machining (mm)

v_f = feedrate (mm/min)

Figure 5 shows graphically what each DOE term corresponds to in this project's case study.



Experiment	Cutting speed, Vc	Feed per tooth, fz	Cutting depth	Ra (measured)
1	-	-	-	[µm]
2	+	-	-	[µm]
3	-	+	-	[µm]
4	+	+	-	[µm]
5	-	-	+	[µm]
6	+	-	+	[µm]
7	-	+	+	[µm]
8	+	+	+	[µm]

Figure 5: Concepts of the DOE.

In addition, according to the DOE for this thesis, two material samples will be machined for each experiment, allowing an estimation of the experimental error.

4.1 Literature Review

Research platforms and databases focused on scientific journal articles, books, and scientific publications, such as Google Scholar[1], ScienceDirect[2], ResearchGate[3], IEEE Xplore[4], and others, were searched for:

- Most commonly used DOE methods, in which sectors, and the approaches of each.
- The average size of the experiments performed with this methodology.
- Most studied factors with effect on surface roughness.

The collected information has been used to establish the selection criteria for the DOE method used in this project. Once the essential parts of the DOE had been identified, a comparative evaluation of the different methods to perform the DOE was carried out to establish which would be the most appropriate for the project.

To this end, the following evaluation criteria were established:

- Considers the main effect of the factors.

---

1 Source: https://scholar.google.com/

2 Source: https://www.sciencedirect.com/

3 Source: https://www.researchgate.net/search

4 Source: https://ieeexplore.ieee.org/Xplore/home.jsp

  - Study of the individual impact of each factor on the response variable.
- Considers the interaction between factors.
  - Analysis of the interaction effect of the studied factors on the response.
- Experimentation cost.
  - Cost, number, and resources required to perform the experiment validation in the selected method.
- Effectiveness with two factors.
- Effectiveness with three factors.
- Effectiveness with four or more factors.
- Accuracy of predictions vs. the actual experiment.
  - The error between the predicted values of the mathematical model and the results of the actual experiments.
- Use for two levels.
- Use for three levels.
- Use for four or more levels.
- The number of case studies found in the first searches.
  - To study the manufacturing industry trend with the use of DOE.

A rating from 0 to 3 was established to evaluate these criteria, leading to an overall fitness value for each DOE.

Table 2: Rating for criteria evaluation for DOE

High	3
Medium	2
Low	1
Not applicable	0

Table 3: Evaluation of the selection of the DOE method.
References in Annex A

Wt.	Criteria	Full Factorial	Fractional Factorial	Taguchi	CCD
1	Considers the main effect of the factors	3	3	3	2
1	Considers the interaction between factors	3	2	1	2
-1	Experimentation cost	3	1	1	2
1	Effectiveness with 2 factors	3	2	2	2
1	Effectiveness with 3 factors	3	2	2	3
1	Effectiveness with 4 or more factors	2	3	2	3
1	Accuracy of predictions vs. the actual experiment	3	2	1	2
1	Use for 2 levels	3	3	3	2
1	Use for 3 levels	3	1	3	3
1	Use for 4 or more levels	3	1	3	3
0	Number of case studies found in the first searches	17	4	20	10
	Total evaluation:	23	18	19	20

From Table 3, the method recommended for the project is the Full Factorial method.

For this initial phase of the project, it has been decided to use two levels: the maximum and minimum values of the selected factors.

Table 4 shows the difference in the size of the experiments with full factorial and different levels, which becomes relevant if levels are added in the future.

Table 4: Ratio number of levels and experiments for three factor DOE.

$$N^{\underline{o}}\ experiments = (Levels)^3$$

Levels	Experiments
2	8
3	27
4	64
5	125

At this point of the project, the structure of the design of experiments can be found in Tables 5 and 6:

Table 5: Project DOE structure,

	Operation		
	Cutting Speed	Feed per Tooth	Cutting depth
Experiment	Vc (m/min)	fz (mm)	CD (mm)
1	-	-	-
2	+	-	-
3	-	+	-
4	+	+	-
5	-	-	+
6	+	-	+
7	-	+	+
8	+	+	+

Table 6: Siemens NX factors with the project DOE structure, 2^3 design.

		Operation				
		Cutting Speed	Spindle Speed	Feed per Tooth	Feed Rate	Cutting depth
Experiment	Combination	Vc (m/min) - DOE	SS (rpm) - NX	fz (mm) - DOE	FR (mmpm) - NX	CD (mm)
1	(-,-,-)	-	Vc (-) = SS(-)	-	FR = fz(-)*SS(-)*nºedges	-
2	(+,-,-)	+	Vc (+) = SS (+)	-	FR = fz(-)*SS(+)*nºedges	-
3	(-,+,-)	-	Vc (-) = SS(-)	+	FR = fz(+)*SS(-)*nºedges	-
4	(+,+,-)	+	Vc (+) = SS (+)	+	FR = fz(+)*SS(+)*nºedges	-
5	(-,-,+)	-	Vc (-) = SS(-)	-	FR = fz(-)*SS(-)*nºedges	+
6	(+,-,+)	+	Vc (+) = SS (+)	-	FR = fz(-)*SS(+)*nºedges	+
7	(-,+,+)	-	Vc (-) = SS(-)	+	FR = fz(+)*SS(-)*nºedges	+
8	(+,+,+)	+	Vc (+) = SS (+)	+	FR = fz(+)*SS(+)*nºedges	+
			We have 2 values for SS		We have 4 values for FR	

The steps followed during the execution of the design of experiments are summarized in Table 7. Its structure in Tanco et al. [9] as a guide for applying the DOE and has been adopted in this thesis.

Table 7: Guideline and summary of the DOE

	Activities	Content
DEFINE	Select Team	The project team "SurfAIce."
	Formulate problem	Development of an automated design of experiments for subtractive methodology manufacturing processes for AI training as part of the optimization of the global process of the machining industry regarding surface roughness by correlating the effects of several cutting parameters and the manufacturing acceleration with the final surface roughness of the milled parts through feature-based management
	State relevant background	Literature review of DOE methodology, similar case studies, interest from companies of the industry, and knowledge from machine operators
	Choose response	Surface Roughness
	State objective	Within 6-11 months, we aim to complete the experimental design and all the data collected and presented.
MEASURE	Identify Factors	Cutting speed, feed per tooth, spindle speed, feed rate, cutting depth, tool wear, sample material, tool material, coolant, etc.
	Classify Factors	Primary factors: Cutting speed, feed per tooth, and cutting depth.
	Validate measurements systems	Measuring equipment: • MiniProfiler MP15 tactile probe built into a tool holder [32] • Waveline W912RC from Jenoptik [33]
	Choose strategies for nuisance factors.	Use of randomization of experiment generation, as well as generation of replicates and blocking of experiments separated by operations.
	Choose ranges and levels.	The levels chosen will be a maximum and minimum value for each factor within the range of industrial usage in order to provide valuable and replicable data. (See Table 11, Section 5.2)
PRE-ANALYSE	Characterize the factors	The variables used by the NX Siemens software are characterized by the formulas (11) and (12) when representing the Vc and fz factors.
	Define characteristics needed for the design.	We need to know the selected factors' main and interaction effects with the response variable.
	Choose experimental design	2^3 Factorial Design
	Select Levels	See Table 11

EXPERIMENT	Outline experiment	A protocol for the execution of the experiments was made to guarantee the replicability of the methodology.
	Evaluate trial runs	Fourteen tests were performed to establish the levels of each parameter to provide a level of security and validity.
	Perform the experiment and recollect data.	Since we are working with a 2^3 design, eight experiments are conducted, and two samples of each are machined to comply with the replication principle.
ANALYSE	Determine factor effects	The results per operation of the ANOVA analysis and the DOE method can be found in Tables 24, 26, 28, and 30.
	Determine significant effects	The results per operation of the ANOVA analysis and the DOE method can be found in Tables 24, 26, 28, and 30.
	Model building	The data collected in the experiments will be used to develop predictive models through AI. The regression model is of theoretical relevance only.
	Optimization	Step to be performed after checking the validity of the results by the collaborators developing the machine learning algorithm.
	Evaluate new experiments	Step to be performed after checking the validity of the results by the collaborators developing the machine learning algorithm.
IMPROVE	Confirming testing	Analyze after experiments. It depends on the chosen method and scope of the thesis.
	Conclude and make recommendations.	The conclusion of the experiment can be found in Chapters 6 and 7.
	Implement new recommendations	Step to be performed after checking the validity of the results by the collaborators developing the machine learning algorithm.
CONTROL	Implement controls	Compilation of weekly/monthly progress reports depending on the thesis stage.
	Validate results	The validation of the experiments can be seen in Chapter 6, where a graphical validation of the data and an ANOVA analysis are included.
	Evaluate iteration	Step to consider after checking the validity of the data, in case it is necessary to analyze a more significant number of factor levels.

4.2 System Setup

Figure 6 shows a general diagram of the full implementation of the system developed for this work.

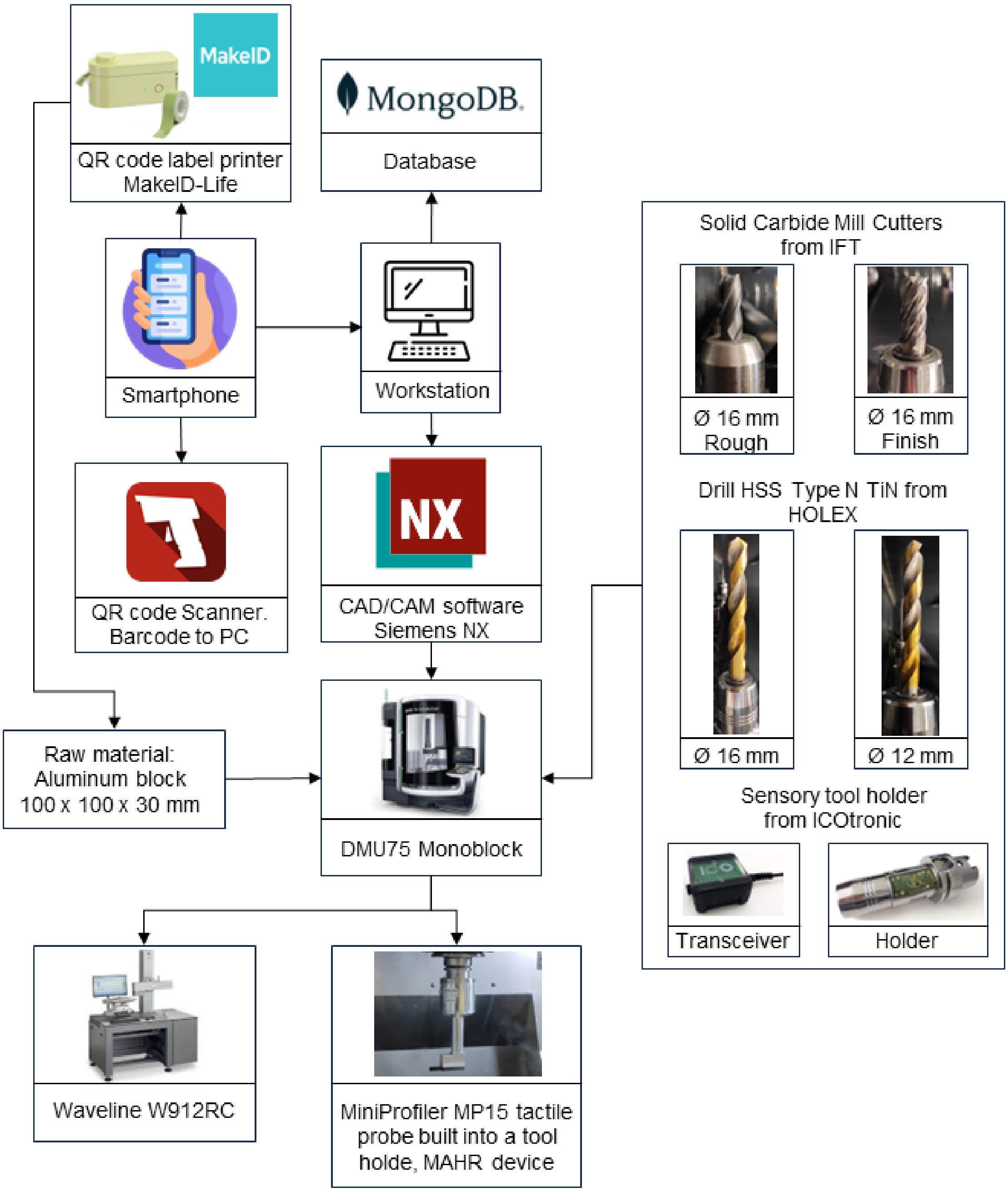


Figure 6: Hardware and software setup

The system developed in this work must automatically assign DOE values to a CAM project. Writing a custom code that can work just with CAD/CAM software under the needed conditions is necessary for this. That is why the software Siemens NX has been selected, as it has the API NX Open that allows programable codes to be created for use within the software, providing a complete solution.

This section introduces the resources used for this project and the execution of the experiments, see Figure 6.

- Workstation: A computer that will have all the necessary software installed for the execution of the system.
- Smartphone: Used to print the QR code labels and as a scanner communicating with the workstation.
- Barcode to PC [34]: Scanning app for the QR codes. It is installed on a mobile phone and a computer.
- MakeID-Life [35]: label printer from MakeID and the MakeID-Life mobile application.
- CAD/CAM software Siemens NX with the API NX Open: This will be used as the CAM setup for the whole project and to program the software for the automatization of the experiment, which will be explained in the next section.
- DMU 75 Monoblock [36]: Five-axis machining center that will be used for the execution of the experiments.
- Aluminum sample block: 100x100x30 mm aluminum samples will be used to machining the experiments.
- Facemilling and endmilling operations use the same tools: a solid carbide milling cutter of Ø16 mm, one for roughing operations and the second one for finishing operations. The cutter used for finishing operations is a cutter manufactured by the IFT (Institute of Production Engineering).
- Drill HSS Type N TiN Ø16mm from the manufacturer HOLEX.
- Drill HSS Type N TiN Ø12mm from the manufacturer HOLEX.
- Sensory tool holder from ICOtronic [37]: These holders have a built-in accelerometer and transmit data wirelessly to the signal, which streams the acceleration data over a CAN fieldbus.
- MongoDB: Database storing the experiment CAM setup data and the CNC code files.
- MiniProfiler MP15 tactile probe built into a tool holder [32]: Surface roughness measurement tool studied for the project.
- Waveline W912RC from Jenoptik [37]: Surface roughness measurement tool used for the project.

4.3 CAM Design

As previously mentioned in this document, the design software used in this project is SiemensNX-1953. As a CAD/CAM/CAE software, this program allows graphic design and manufacturing planning to be carried out in a single tool.

For this thesis and documentation, the “feature” will be used when referring to the machining operation or the obtained surface.

The CAD design used in the project consists of the following features:

- Two surfaces for FACEMILLING operations
- Two surfaces for ENDMILLING operations
- Two bores for two different diameters of DRILLING operations

The design of two units of each feature has been chosen to maintain one with constant values during all the experiments and the second being modified with the different DOE treatments.

Keeping one feature with constant values will provide a baseline between the experiments, and reference data for the study of factors that have not been considered in the DOE, such as tool wear or milling temperature. Figures 7 and 8 show the designed part, and its assembly and positioning in the CAD representation of the DMU 75 Monoblock machining center used to manufacture the parts.

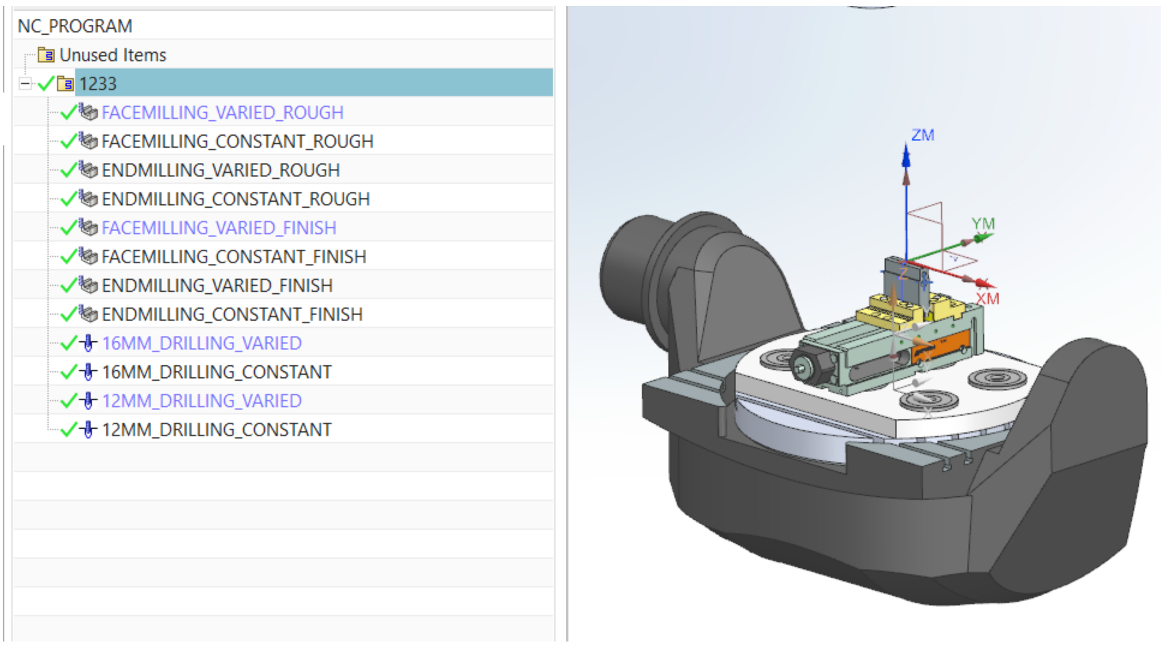


Figure 7: CAD Assembly of the project

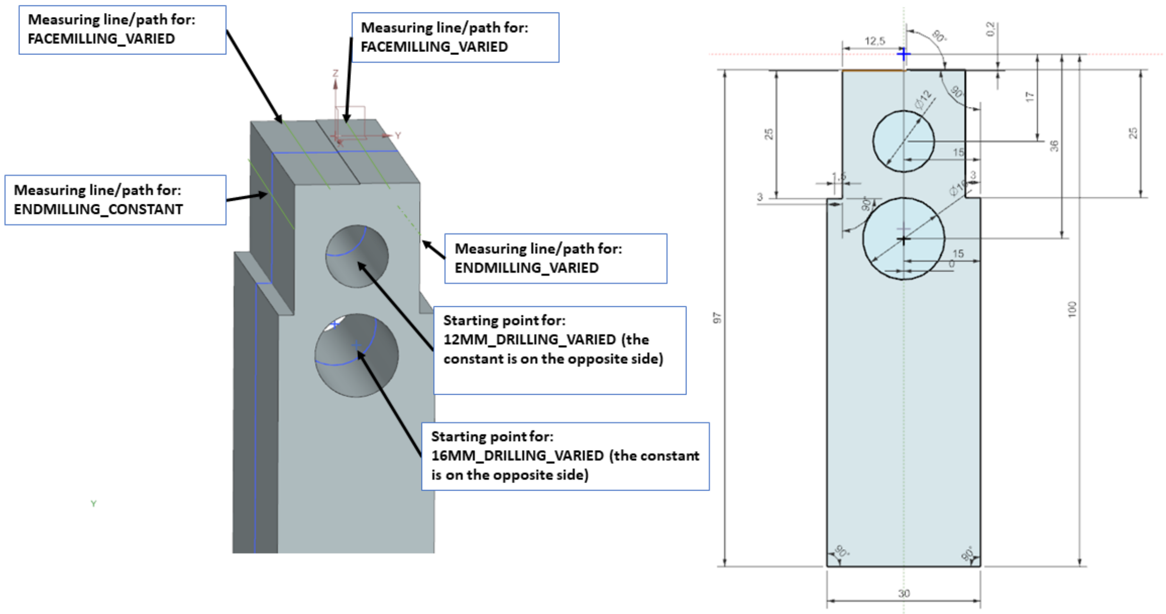


Figure 8: CAD design of the project part

The cutting strategy used in all the experiments is configured in this CAM design stage, and the definition of macro variables for identifying the operations (see Table 8).

Macro variables pass arguments from a subprogram to the main program. In this case from the NC code to the numeric control.

For this work, they are used to control the data collection of the finished milling and drilling operations to identify the operation and sort the specific lines of the operation from the exported files of NC-code and acceleration.

Table 8: Macro variable coding for the features

Feature Name #521	Nº
FACEMILLING VARIED	1
FACEMILLING CONSTANT	2
ENDMILLING VARIED	3
ENDMILLING CONSTANT	4
16MM Drilling	5
12MM Drilling	6

OPERATION NAME #522	Nº
FACEMILLING_VARIED_ROUGH	1
FACEMILLING_CONSTANT_ROUGH	2
ENDMILLING_VARIED_ROUGH	3
ENDMILLING_CONSTANT_ROUGH	4
FACEMILLING_VARIED_FINISH	5
FACEMILLING_CONSTANT_FINISH	6
ENDMILLING_VARIED_FINISH	7
ENDMILLING_CONSTANT_FINISH	8
16MM_DRILLING_VARIED	9
16MM_DRILLING_CONSTANT	10
12MM_DRILLING_VARIED	11
12MM_DRILLING_CONSTANT	12

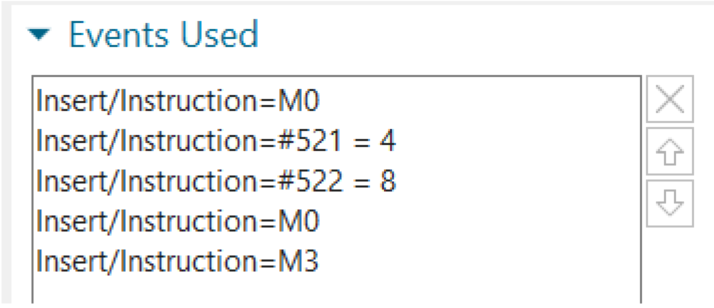


Figure 10: Macro variables inserted in CAM design

```
(FACEMILLING_CONSTANT_FINISH , TOOL : MILL_16MM_STH)

N462 M0
N464 #521 = 2
N466 #522 = 6
N468 M0
N470 M3
N472 M8
N474 G43 Z10. S1061 H1
N476 X62. Y2.25
N478 Z0.
N480 G1 Z-3. F250.
N482 G3 X58. Y6.25 I-4. J0.
N484 G1 X-58.
N486 M9
N488 G3 X-62. Y2.25 I0. J-4.
N490 G1 Z0.
N492 G0 Z10.
N494 #521 = 0
N496 #522 = 0
```

Figure 9: Extraction from NC Code with MACRO Variables

4.4 DOE Software with NX Open

For the development of the entire system, three different programs were developed:

- QRcode_generator: Generates de ID for the experiments.
- JSON_doc: Stores the information with the DOE values.
- DOE_Plugin: Main program of the systems to randomly assign DOE values to the CAM setup and generation of the NC code.

QRcode_generator

It is used to generate a QR of a timestamp to identify each experiment. The QR will be stored on the JSON document and in the NC-code and Mongo DB database, identifying the performed experiment.

The QR code is printed on the label adhered to the part for identification after machining.

JSON_doc

Provides a local JSON document where the eight DOE treatments are stored, a counter to know how many replicates of each one have been performed, and a variable that stores the QRs that were generated per experiment to identify each machined sample.

The JSON document has the following form:

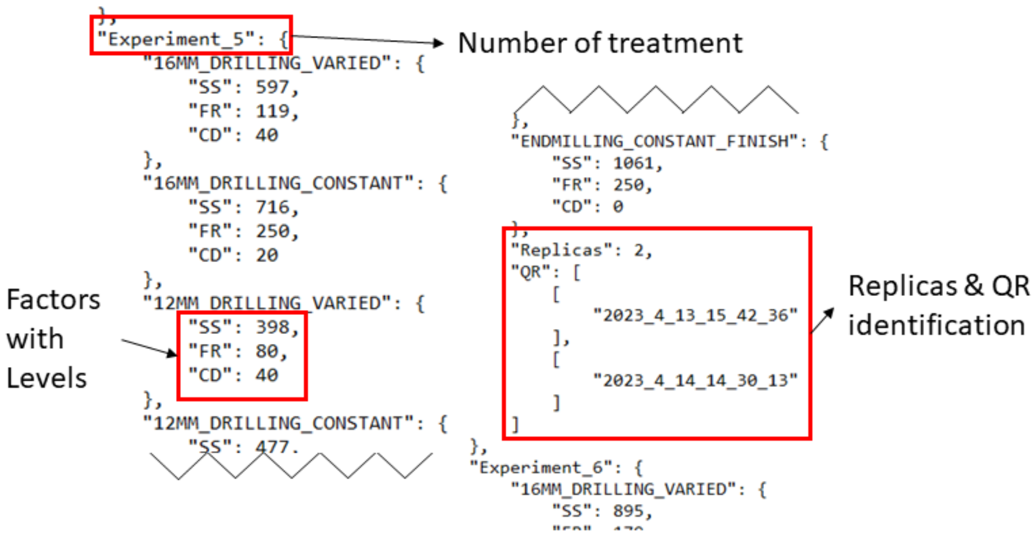


Figure 11: JSON document for the DOE Plugin

DOE_Plugin

This software aims to perform all the experiments in Table 6 of the DOE structure for NX. The plugin will follow the instructions provided below each point:

1. Execution of the plugin
2. Checking the tools used
3. Identification of each sample of the experiment
4. Random selection of the experiment
5. Assignment of the selected values with the experiment automatically to the CAM operations

6. Toolpath generation
7. Simulation of the process for collision control
8. Generation of the NC code
9. Update of files and databases used

To comply with the previous points, an executable code has been programmed with the API NX Open to develop the main plugin. In Figure 12, the general flowchart that the software follows is shown. A more detailed one can be consulted in Annex B.

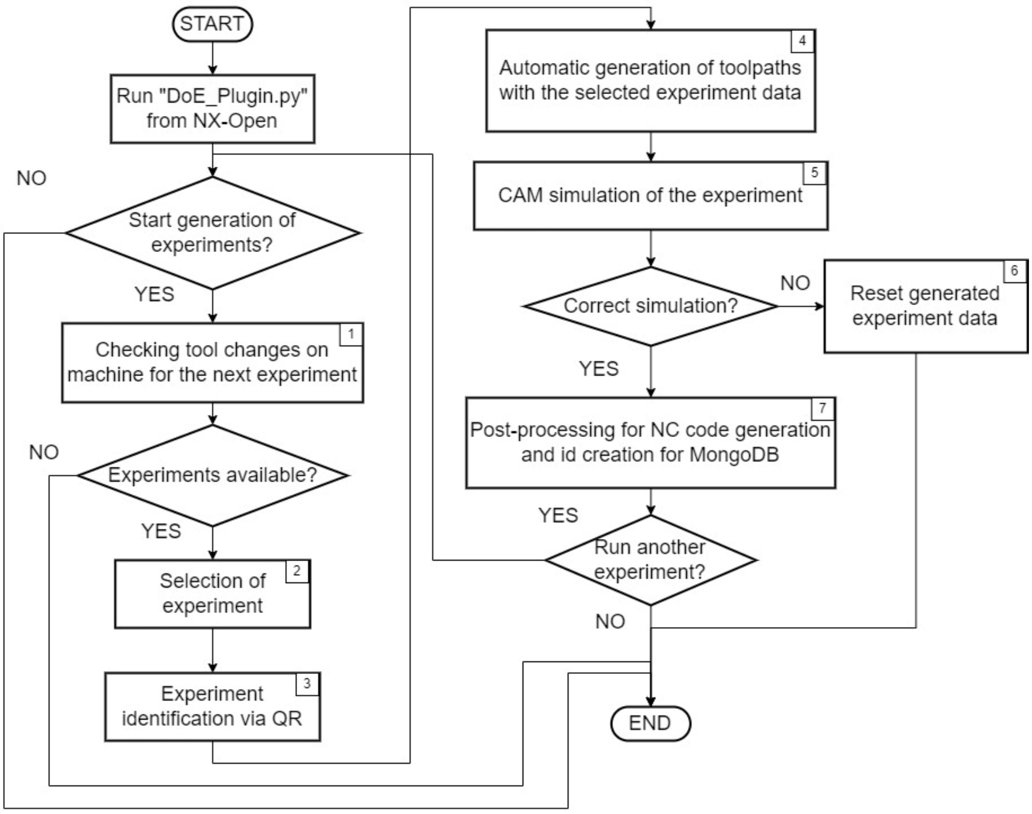


Figure 12: General flowchart for the automation of the DOE

According to Figure 12, below is the explanation, in the order of operation, of the blocks of the diagram, identified by numbers representing individual functions

1) Checking tool changes on the machine for the following experiment (Figure 13): This function checks whether one of the four tools used during machining is changed. This function has been included to track the resources used and may be helpful for tool wear analysis through comparisons of constant-value operations. This function asks the user if any tool has been changed. If not, the program goes to the next step. If yes, the program asks which of the four tools

has been modified. Finally, it updates a file that stores this information, to be later used to identify data to be uploaded to the MongoDB database.

Figure 13: Toolset identification and update for MongoDB

2) Selection of experiment: For the selection of experiments, two CSV files are used to store the number of experiments. One file stores the ones available to be executed, ongoing_experiment.csv, while the other stores the number of experiments already executed. This way, it is guaranteed that the eight DOE experiments are performed for each round of experiments and that their selection is made randomly, obeying one of the basic principles of DOE.
Once verified that experiments are still available, it reads the ongoing_experiment.csv file. Then, the program randomly selects the next experiment, updating the JSON document by increasing the number of replicates and updating both CSV files for the subsequent execution of the plugin.
3) Experiment identification via QR: This function is responsible for checking whether the QR of the sample has been scanned, and it is stored in the JSON document in the position reserved for the selected experiment.
To scan the QRs, a mobile application called Barcode to PC [34] sends the information from the QR scanned with the cell phone to a CSV file on the computer, from which the plugin subsequently extracts the information.
4) Automatic generation of toolpaths with the selected experiment data: Once the experiment is selected and the documents are updated with the number of replicates and QR identification. This function is responsible for automatically changing the values of the factors with those indicated in the DOE, which correspond to the machining parameters being performed in the selected experiment, maintaining the same machining strategy through all the experiments. After updating the data, the toolpath is generated, and the modified operations are confirmed on the screen.

5) CAM simulation of the experiment: A simulation is displayed for the user to check collisions and if the selected parameters give a correct result. After the simulation, the user is asked to verify whether to proceed. Depending on the user's answer, one of the following functions, 5 or 6, will be executed.
6) Reset generated experiment data: In case the user indicates that the simulation has been incorrect, the values of the files ongoing_experiment.csv and performed_experiment.csv are reset so that the experiment that was being studied is available again, and the values of the replicas registered in the JSON document are also updated, and the QR associated is eliminated.
7) Post-processing for NC code generation and id creation for MongoDB: In case the simulation is correct, the CAM project is post-processed, and therefore, the NC-Code file and the identifier (ID) for the MongoDB database are generated, where the QR of the sample, the experiment number, the replica, and the set of tools used in the experiment are stored.

   In addition to the generation of the NC-Code base file generated by Siemens NX, for this thesis, a modified NC-Code is generated that includes all the macro variables used to correlate the acceleration operation and the numeric control data received from the machining center.

In the following sections of the document, the most practical parts of the project, such as testing, experimentation, data collection, and data analysis, will be presented.

5 Validation

This chapter will be divided into three parts. The first will explain how the levels of variants for the DOE were selected; the second will refer to the final experiments and the last to the surface roughness measurement process.

In order to develop a method that can be replicated and standardized, a protocol for the execution of the experiment was made. The following describes the necessary steps for the execution of the tests and the final experiments.

1) Check the installation and operation of the software and programs needed for the experiments.
2) Checking of the NXOpen DOE_Software, and the files and programs used for its execution.
3) Check the machine, tools, sensory tool holders, and material.
4) Execution of experiments
    a. Generation, printing, and pasting of the QR identification label on the sample.
    b. Execute DOE_Software with NXOpen, and follow the steps displayed on the screen.
    c. Positioning of the part in the machining center and preparation for manufacturing.
    d. Extraction of NC code from DOE program and sending to the machine.
    e. Save/upload CAM settings to the MongoDB database.
    f. Machining part and live-data collection.
    g. Visual check of part and tooling conditions after manufacturing.
    h. Preparation for the next experiment.
5) Surface roughness measurements.

5.1 Relating Process Inputs to Surface Finish

For this work, the variable to be analyzed is the surface roughness of machined parts due to their relationship with several mechanical properties [3].

In order to make a satisfactory analysis of surface roughness, the industry's most widely used process is the experimentation and statistical analysis of the variables that affect the process. This approach allows for examining how several factors impact a process while optimizing resource use [5]. As a result, numerous studies have been conducted in the industry to determine the connection between cutting parameters and parts' surface roughness, aiming to gather adequate data on the process.

In particular, facemilling, endmilling, and drilling operations are studied in this work. In particular, there is a special interest in drilling operations, as seen in a survey carried out during the project by different companies in the sector.

This section will answer the following questions providing a theoretical background and present the measurement method chosen for the thesis.

- Why analyze Surface roughness?
- What is Surface roughness?

5.1.1 Industry Relevance

The surface roughness parameter is critical when talking about machined parts. It affects not only the aesthetic appearance but also directly affects the performance. This is due to its relationship with multiple mechanical properties, such as fatigue limit, friction coefficient, propensity to corrosion, tribology, and more [1], [6].

Due to these influences, the requirements for high-quality products, and the increase in demand with short product life cycles, it is crucial to control this variable during manufacturing [14]. Many of the mechanical failures in the parts originate on the surface: fatigue cracking, stress corrosion cracking, adhesive wear, excessive abrasive, and more [38]

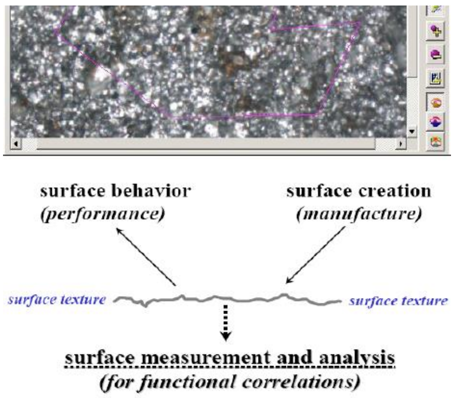


Figure 14: Surface caption: behavior and manufacture concepts [38]

The surface roughness quality is directly related to the cutting parameters, such as spindle speed, feed rate, and cutting depth [39]. Researchers have an interest in analyzing these parameters and their relationship.

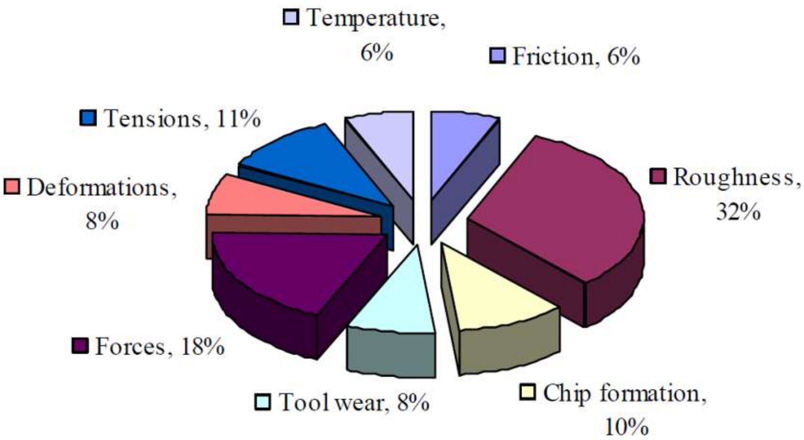


Figure 15: Research areas most studied in machining [1]

This work focuses on generating a standardized and automated process for the execution of experiments. The collected data will then be used to analyze the effects of the cutting parameters and accelerations on the part's surface roughness. That way, the data obtained follow a specific structure that allows the development of an AI to predict the surface roughness of the part from within the planning phase.

5.1.2 Definition

Surface roughness refers to one of the surface texture elements [40], which measures the final finish of the processed surfaces. Studied are the irregularities that occur on the surface since these are the ones that affect the mechanical properties of the parts [16]. However, before studying them, it is necessary to analyze surface characterization [41] as a synonym for texture.

Two types are differentiated: (1) the ideal surface or geometry is the desired surface, which is obtained from theoretical calculations, CAD design, theoretical tools, and kinematic movements from simulations, which results in a smooth linear surface called nominal surface. The second type (2) would be the real surface or surface texture that appears after operations [38], [39], [42]. From these types, the one of interest to industry and engineers is the real surface.

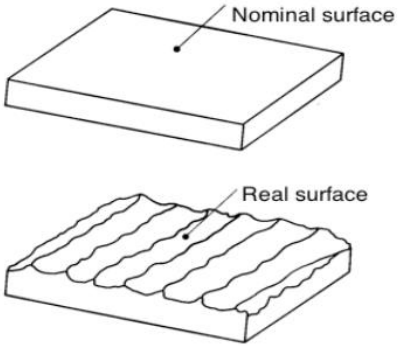


Figure 16: Surface characterization [39].

The irregularities are measured on this real surface to obtain the surface roughness values. These irregularities from the machining process can be caused by various factors, including the tool's vibration during manufacturing, the tool's geometry and wear, and the material's properties. These irregularities can create nucleation sites more likely to cause breakage and corrosion, negatively impacting the part's tribological properties and mechanical assemblies [41].

The surface texture, or real surface, is represented by the final surface's deviations from its ideal nominal surface value. These deviations are identified as follows [38], [43]:

- Roughness. This type of deviation is measured on the nano- or micro-scale.
- Waviness: These are irregularities measured on the surface with a wavelength in the macroscale.
- Lay: is the predominant direction of the surface pattern.
- Flaws: These are unintentional interruptions of the surface texture.
- Shape or form: deviations from the geometrical form of the nominal surface.

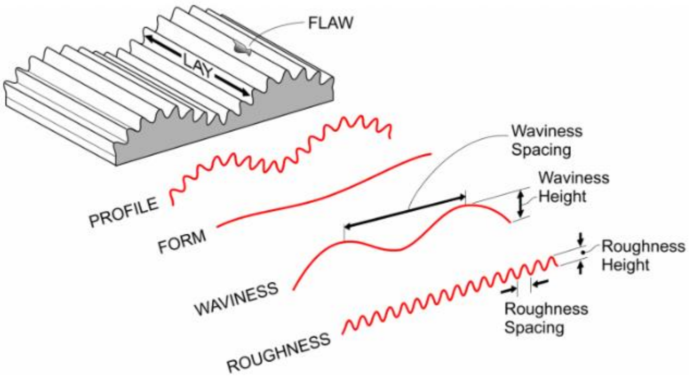


Figure 17: Surface texture - Forms of deviations [43]

Finally, as a compilation of the factors that affect surface roughness, a fishbone diagram from the work of Benardos et al. [14] has been included that summarizes most of them.

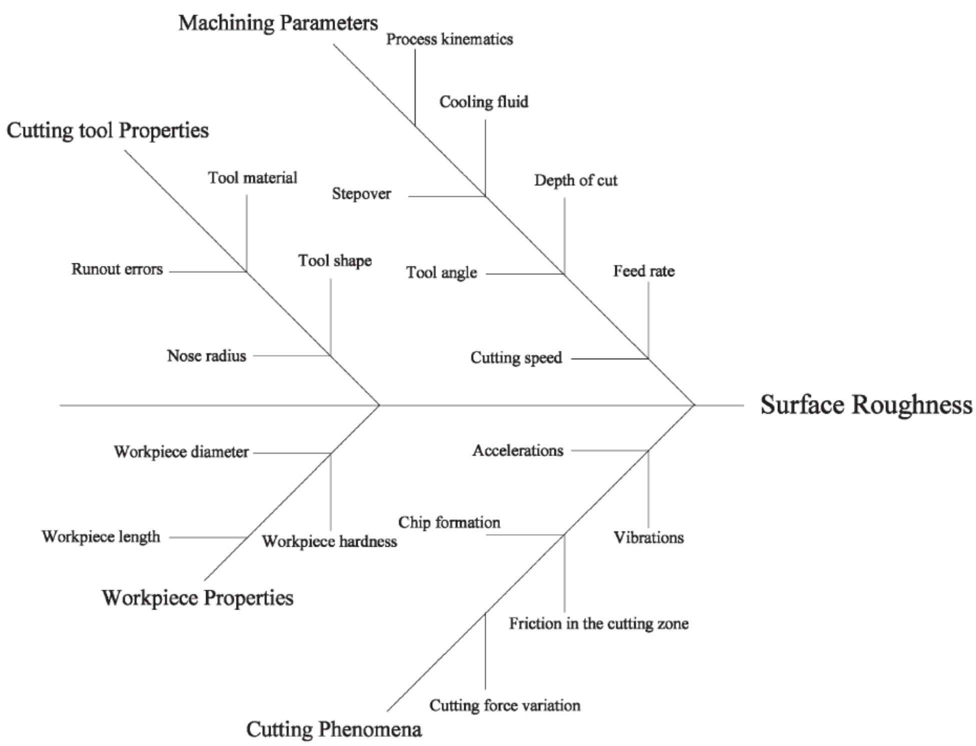


Figure 18: Parameters that affect surface roughness [14]

5.2 Selection of Variant Levels

Test runs were used to find the final values of the levels for the factors.

Fourteen tests were carried out, starting by adjusting and checking the values and conditions for the drilling operations and then adjusting the cutting parameters for the facemilling and endmilling operations. The starting values are shown in Table 9.

Table 9: Initial values for the DOE levels

OPERATION	TOOL Ø (mm)	Nº CUTTING EDGES (Z)	Cutting Speed, Vc(m/min) +	Cutting Speed, Vc(m/min) -	SPINDLE SPEED (rpm) +	SPINDLE SPEED (rpm) -	Feed per tooth, fz(mm) +	Feed per tooth, fz(mm) -	FEED RATE (mmpm) (+,+)	FEED RATE (mmpm) (-,+)	FEED RATE (mmpm) (-,-)	FEED RATE (mmpm) (+,-)	CUTTING DEPTH (mm) +	CUTTING DEPTH (mm) -
DRILLING	16	2	56	30	1114	597	0.125	0.05	279	149	60	111	40	5
	12	2	56	30	1485	796	0.10	0.05	297	159	80	149	40	5
FACEMILLING	16	4	140	60	2785	1194	0.10	0.08	1114	477	382	891	2.0	0.5
ENDMILLING	16	4	140	60	2785	1194	0.10	0.08	1114	477	382	891	1.0	0.5

For the execution of these tests, the selection of the DOE treatment was not made randomly, but the combinations to be tested were purposely selected.

In the first tests, it was observed that initial values used for the machining of the bores were not adequate since a remarkably high amount of chips accumulated in the tool, as can be seen in Figure 19, while in the operations with the default values from Siemens NX, the chip evacuation was ideal.

It was decided to perform the next series of experiments using those Siemens NX default values as mean values and selecting approximately equally spaced values for the DOE levels.

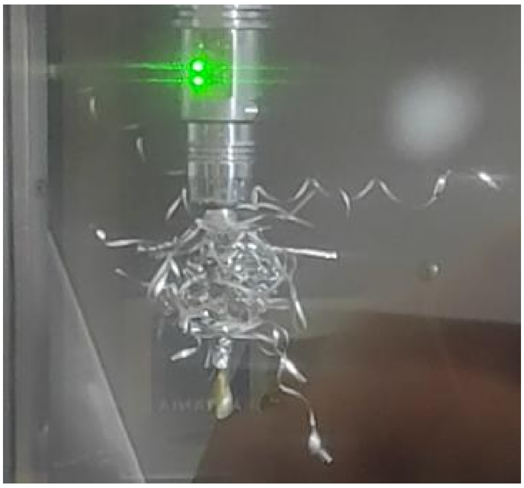


Figure 19: Drill tool after first test runs with initial values for the f_z and v_c.

These experiments showed that the results improved since the chips were evacuated entirely and, at the same time, maintained differences in surface roughness that could be detected by touching the machined part. These new values, Table 10, were set to be the final ones for the cutting speed and feed per tooth. After adjusting the speed, the cutting depth values were tested.

Table 10: New set of values for drilling compared to Siemens NX default

	Ø16 mm Drilling			Ø12 mm Drilling		
	MAX	NX default values	MIN	MAX	NX default values	MIN
Spindle speed (rpm)	895	716	597	796	477	398
Feed per tooth (mm)	0.25	0.175	0.1	0.32	0.26	0.2
Cutting speed (m/min)	45	36	30	30	36	15

For the setting of the depth of cut, the longest drilling depth without intermediate tool extraction studied was 60 mm. This was changed to 40 mm for better chip removal, followed by an intermediate tool extraction, before drilling the rest of the hole length

Accordingly, the milling operations were adjusted. Given that the initial tests showed that the milling conditions were very stable, it was decided to select more extreme values to evaluate better the impact of the accelerations on the final finish of the part. In this case, the default values of Siemens NX were used again as a midpoint. Machine operators and documentation of tool manufacturers were consulted to obtain well-differentiated values to produce a visible difference in surface roughness.

At the end of the testing phase, the final table of levels was obtained

Table 11: Final values for the DOE.

			Original DOE factors				NX Siemens DOE factors						Common factor	
			Cutting speed, Vc(m/min)		Feed per tooth, fz(mm)		SPINDLE SPEED (rpm)		FEED RATE (mmpm)				CUTTING DEPTH (mm)	
OPERATION	TOOL Ø (mm)	Nº CUTTING EDGES (Z)	+	-	+	-	+	-	(+,+)	(-,+)	(-,-)	(+,-)	+	-
DRILLING	16	2	45	30	0.25	0.10	895	597	448	298	119	179	40	10
	12	2	30	15	0.32	0.20	796	398	509	255	159	318	40	10
FACEMILLING	16	4	200	60	0.25	0.025	3979	1194	3979	1194	119	398	2.0	0.5
ENDMILLING	16	4	200	60	0.15	0.035	3979	1194	2387	716	167	557	1.5	0.5

Table 6 shows the combinations of the variables for the application in the DOE.

5.3 DOE Execution

After the execution of the fourteen tests, two batches of valid experiments were carried out following the protocol in the previous section.

In each batch, the eight experiments were performed randomly. For each experiment, photographs of the tools used before and after machining were taken to analyze whether a tool change was necessary. This could be helpful as some abnormalities could be related to the tools or the material adhered to it, especially with the drills.

These photographs showed minimal effect on the milling cutters (Figure 20). For the drills, it can be seen that there is a certain amount of aluminum adhered to them, especially the 12 mm, which was manually removed after every experiment (Figure 21).

Figure 20: Ø16 mm milling tool for finish passes sample 18

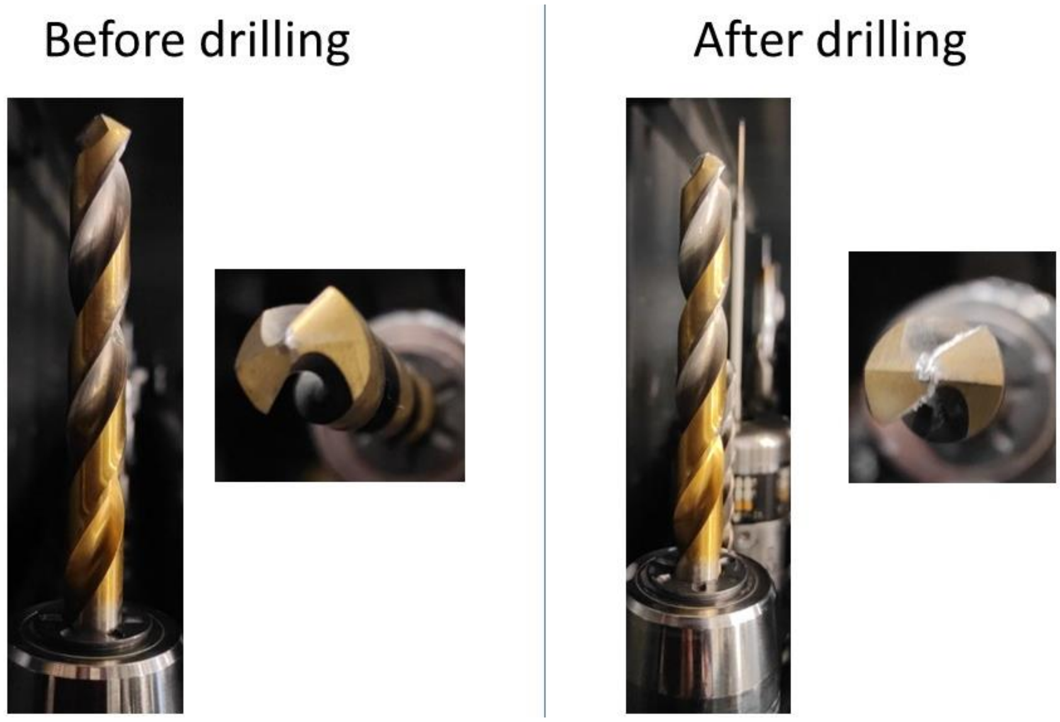


Figure 21: Ø12 mm drill before and after mechanized sample 22.

During the second round of experiments, a dent was observed on the tooltip of the Ø12 mm drill. Consequently, it was replaced with a new drill.

Later, when analyzing the surface roughness results, it was found that this change affects the surface quality, suggesting that the wear of the drills is very influential in the surface roughness of the final surface.

After the execution of the software, the data for each experiment is stored in the MongoDB server with the ID, as shown in Figure 13. The following information is available for each experiment.

- Parameters extracted from Siemens NX from the CAM setup and NC-Code files stored in the MongoDB server.
- Live data on accelerations and from the numeric control center. The data from the numeric control includes a timestamp, position, loads, macro variables, and speeds, and the acceleration data contains a timestamp and acceleration. These will be analyzed in Chapter 6.
- Photographs of the tools during the experiments, as well as videos.
- Final machined parts with their identification label.
- And then the surface roughness measurement data.

During the execution of the experiments, no anomalies occurred, except for one sample from the first round that had to be repeated because the live-data extraction software failed to communicate to a sensory tool holder.

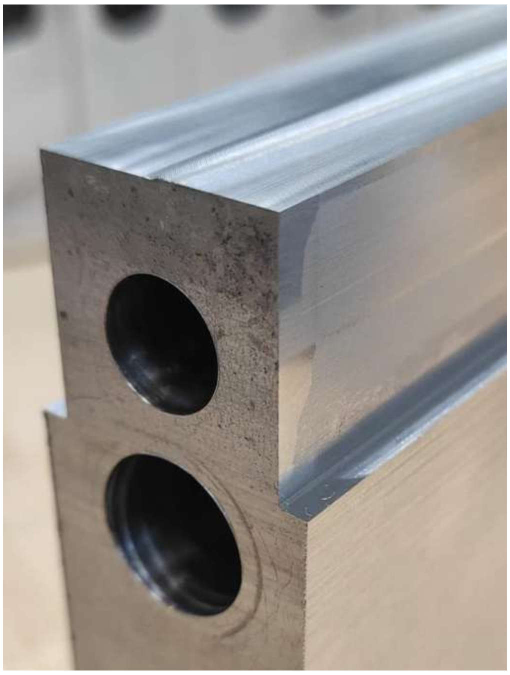


Figure 23: Sample 19;
Experiment 5 (-,-,+)

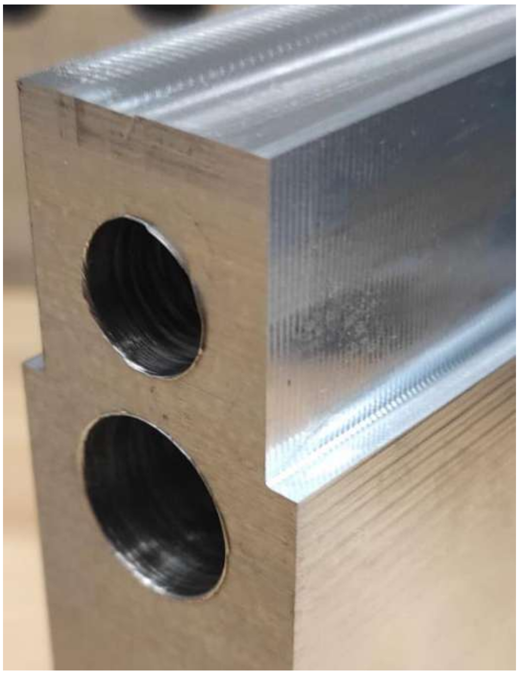


Figure 22: Sample 22;
Experiment 8 (+,+,+)

Figures 22 and 23 show two of the milled parts. It is possible to detect the differences in surface roughness.

Finally, Table 12 shows the sample number, the randomly selected experiment, and the associated QR code for the first batch. The data for the second batch can be found in Annex C.

Table 12: Summary of experiment and QR's

Sample	Experiment	Combiantion	QR	Sample	Experiment	Combiantion	QR
15	7	(-,+,+)		19	5	(-,-,+)	
16	3	(-,+,-)		20	2	(+,-,-)	
17	4	(+,+,-)		21	8	(+,+,+)	
18	6	(+,-,+)		22	1	(-,-,-)	

5.4 Surface Roughness Measurement

This section describes the measurement methods applied in this work, the parameters that reflect the surface roughness, and a brief description of the ISO standards.

There are different types of technology depending on the type of surface roughness measurement instrumentation available and the results to be obtained [44].

- Contact. Direct measurement methods.

- Stylus method.
- Non-contact methods.
  - Optical methods.

For this thesis, the stylus method was used [45]. This measurement method belongs to the contact measurement category and consists of a probe mechanically coupled to an arm of fixed length. The probe is positioned on the surface to be measured. With the activation of the instrument, the probe is lowered until it touches the surface, then is dragged at a constant speed to detect the difference in the height of the surface. (Figure 24, [46])

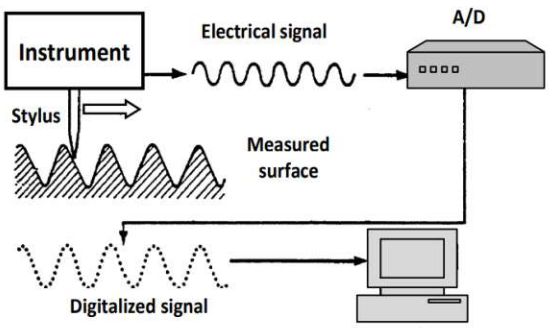


Figure 24: Surface measure with Stylus method [46].

The most relevant parameter used in manufacturing will be studied with the selected method. The parameters represent a deviation from the ideal surface and are usually by the height variations in the surface to a reference plane. The following is an explanation of the relevant parameter in the project as presented by Gadelmawla et al. [47]:

- Amplitude Parameters: essential parameters to characterize the surface topography. They measure the vertical deviations.
  - Arithmetic average height (Ra [µm]): This is the most common parameter to represent the quality of the surface. Furthermore, it is defined by the value of the absolute average of the measurements of the deviations above the mean line in the chosen sample length.

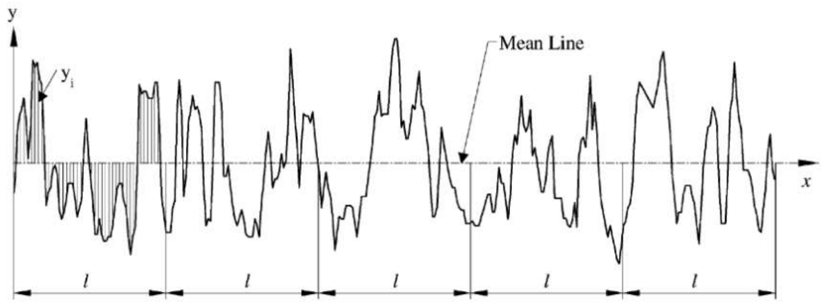


Figure 25: Graphical definition of Ra

The mathematical representation of this parameter is:

Continuous form $$Ra = \frac{1}{l}\int_0^l |y(x)|\,dx \quad (13)$$

Discrete form $$Ra = \frac{1}{n}\sum_{i=1}^{n} |y_i| \quad (14)$$

where the variables are:

$l =$ Length of the sample.

$y(x)\ or\ y_i =$ The value of the vertical deviation for each sample location or point.

$n =$ Number of points evaluated in the sample length.

There are more parameters related to surface roughness, waviness, and profile. However, for this thesis, only the one listed above is considered.

Lastly, this chapter briefly discusses the ISO standards that affect the project measurement process.

ISO 4287 relates to current use terms, definitions, and surface texture parameters. These parameters refer to different parts of the signal from the stylus instrument:

- P for Primary Profile.
- R for Roughness.
- W for Waviness.

The following table shows the rules for choosing the wavelength limit between roughness and waviness that apply when following measurements by the standard [48].

Table 13: ISO 4288 [48]

Measuring condition: *R*-parameter ISO4288: '96

Non-periodic profile				Periodic profile or *RSm*		Measuring Condition	
Ra,Rq,Rsk,Rku or *RΔq*		*Rz,Rv,Rp,Rc* or *Rt*				Sampling length: *lr* = λc (mm)	Evaluation length *ln* (mm) = 5 x *lr*
Ra (μm)		*Rz* (μm)		*RSm* (mm)			
Over>	Less	Over>	Less	Over>	Less		
0.006	0.02	0.025	0.1	0.013	0.04	0.08	0.4
0.02	0.1	0.1	0.5	0.04	0.13	0.25	1.25
0.1	2	0.5	10	0.13	0.4	0.8	4
2	10	10	50	0.4	1.3	2.5	12.5
10	80	50	200	1.3	4	8	40

Once all the experiments have been manufactured, the next step is to measure the surface roughness of all the surfaces. Eight surfaces will be measured for each part since both constant and DOE values operations will be measured.

Two different measurements devices were used for this work:

1. A novel prototype of a tactile surface roughness measurement device developed at IFT for in-situ measurements in machine tools [32].
2. Waveline W912RC from Jenoptik [40].

<u>**Surface Roughness Measuring System for in-situ measurement in machine tools**</u>

A surface roughness measurement device was developed at the IFT, which can be mounted into the CNC machine's spindle, similar to a tool holder. It can measure the surface finish with the precision of the numerical control using the machining center where the part was manufactured.

This novel project aims to create a G-code software to measure roughness using the machining center where the part was made. Additionally, a surface roughness measurement device is developed to work as a tool in the machine.

The measuring device is a MiniProfiler MP15 tactile probe [49] from the company Breitmeier built into a tool holder to be used in the DMU75monoblock, Figure 26.

The system is based on the execution of a main NC code which includes the points of the surface to be measured and the call to different subprograms already configured so that the roughness measurement is automatic. In this way, the only information to be provided to the system is the coordinates of the points to be measured.

Figure 26: MiniProfiler MP15 tactile probe built into a toolholder

Applying this system using a numerical control machine has the advantage of guaranteeing the repeatability of the mediations in different parts by always using the exact origin of coordinates and measuring points for each manufactured sample.

For this project, the measurement of the surfaces generated by the facemilling, endmilling, and drilling operations is studied, obtaining a total of eight surfaces to be measured.

The following is the procedure followed for the measurement of surfaces:

1) Machine coolant is used to clean surfaces, with no need for alcohol.
2) Surface measurement through the execution of the NC code. Two different machine centering's are needed.
    a. Part centering one for facemilling and drilling operations in Figure 28.
    b. Part centering two for endmilling, Figure 27.
3) Remove the part from the numerical control.

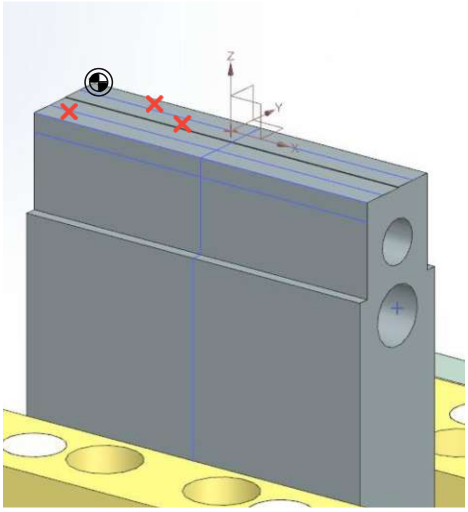


Figure 28: Part origin for facemilling and drilling measurements

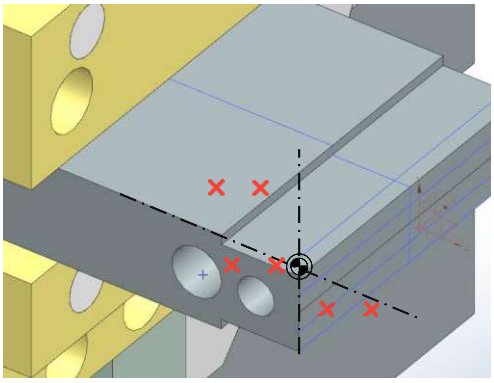


Figure 27: Part origin for endmilling measurements

Precise measurement points are necessary to generate the main code for the machining center. These points will then be transformed into G-code lines, as illustrated below.

```
G65P7X2.00Y-17.75Z-0.20S270.00;
G65P8M3.;
G65P7X6.00Y-17.75Z-0.20S270.00;
G65P8M3.;
```

Figure 30: NC code points for in-situ measurement of the facemilling operation

```
G65P10X0.0Y-12.0Z-33.0R8.0S90.0E25.0;
G65P12R8.0M2.;
G65P10X0.0Y-12.0Z-33.0R8.0S90.0E13.0;
G65P12R8.0M2.;
G65P13X0.Y-12.S90.;
```

Figure 29: NC code points for in-situ measurement of the drilling operation

From the code shown in the images above, for face and endmilling operations, P7 is used to position the tool in the indicated location for face and endmilling, and P8M is used to execute the measurement routine. In the case of bores, P10 positions, P12M2 executes the measurement, and P13 removes the device from inside the bore.

Table 14 below shows the meaning of the variables of the code presented above, as well as the measurement points for each operation.

Table 14: NC code variables for the in-situ measurement device

Variable	Meaning
G65	Command that calls a subprogram
P	Indicates the G-code program or subprogram to be executed
X	X-coordinate of tool positioning
Y	Y-coordinate of tool positioning
Z	Z-coordinate of tool positioning
S	Spindle rotational position for measurement
R	Bore radius to be measured
E	Depth positioning inside the bore to measure
M	Macro variables for executing specific programs

For the facemilling and endmilling operations, an entire segment of 94 mm is measured. Following the ISO standard, a sample length of 4 mm is measured. Table 15 shows the points used for the facemilling_varied operation, and Table 16 shows the endmilling_varied points.

Table 15: In-situ measurement points facemilling Varied

Operation	FACEMILLING_VARIED		
POINTS			
X	Y	Z	S
2.00	-17.75	-0.20	270.00
6.00	-17.75	-0.20	270.00
10.00	-17.75	-0.20	270.00
14.00	-17.75	-0.20	270.00
18.00	-17.75	-0.20	270.00
22.00	-17.75	-0.20	270.00
26.00	-17.75	-0.20	270.00
30.00	-17.75	-0.20	270.00
34.00	-17.75	-0.20	270.00
38.00	-17.75	-0.20	270.00
42.00	-17.75	-0.20	270.00
46.00	-17.75	-0.20	270.00
50.00	-17.75	-0.20	270.00
54.00	-17.75	-0.20	270.00
58.00	-17.75	-0.20	270.00
62.00	-17.75	-0.20	270.00
66.00	-17.75	-0.20	270.00
70.00	-17.75	-0.20	270.00
74.00	-17.75	-0.20	270.00
78.00	-17.75	-0.20	270.00
82.00	-17.75	-0.20	270.00
86.00	-17.75	-0.20	270.00
90.00	-17.75	-0.20	270.00

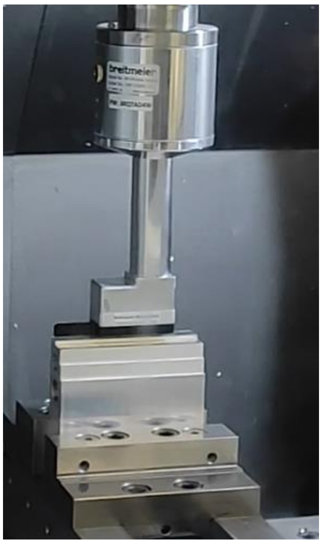


Figure 31: In-situ measurement device positioning for facemilling

Table 16: In-situ measurement points endmilling Varied

Operation	ENDMILLING_CONSTANT		
POINTS			
X	Y	Z	S
2.00	5.00	-3.00	270.00
6.00	5.00	-3.00	270.00
10.00	5.00	-3.00	270.00
14.00	5.00	-3.00	270.00
18.00	5.00	-3.00	270.00
22.00	5.00	-3.00	270.00
26.00	5.00	-3.00	270.00
30.00	5.00	-3.00	270.00
34.00	5.00	-3.00	270.00
38.00	5.00	-3.00	270.00
42.00	5.00	-3.00	270.00
46.00	5.00	-3.00	270.00
50.00	5.00	-3.00	270.00
54.00	5.00	-3.00	270.00
58.00	5.00	-3.00	270.00
62.00	5.00	-3.00	270.00
66.00	5.00	-3.00	270.00
70.00	5.00	-3.00	270.00
74.00	5.00	-3.00	270.00
78.00	5.00	-3.00	270.00
82.00	5.00	-3.00	270.00
86.00	5.00	-3.00	270.00
90.00	5.00	-3.00	270.00

Figure 32: In-situ measurement device positioning for endmilling

For the drilling, due to limitations with the length of the probe, an entire segment of 25 mm is measured. For this purpose, a sample length of 12 mm is measured following ISO standards. Table 17 shows the points used for the Ø16mm drilling.

Table 17: In-situ measurement points Ø16 mm drilling Varied

Operation	16MM_DRILLING_VARIED				
POINTS					
X	Y	Z	RADIUS	MEASURING ANGLE - S	MEASURED DEPTH -E
100.00	-13.00	-33.00	8.00	270.00	25.00
100.00	-13.00	-33.00	8.00	270.00	13.00

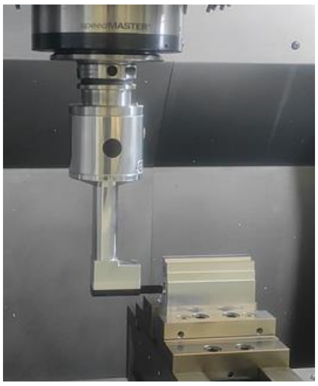


Figure 33: In-situ measurement device positioning for Ø16mm drilling

For each surface measured, several files are obtained with the collected data. A CSV file with the raw data of the measured X position and its vertical deviation Z. And a protocol showing the surface's roughness profile.

Table 18: Example of raw data from the in-situ measurement device

X (mm)	Z(µm)
0	-5.62381745
0.00048005	-5.52845001
0.0009601	-5.59806824
0.00144014	-5.56182862

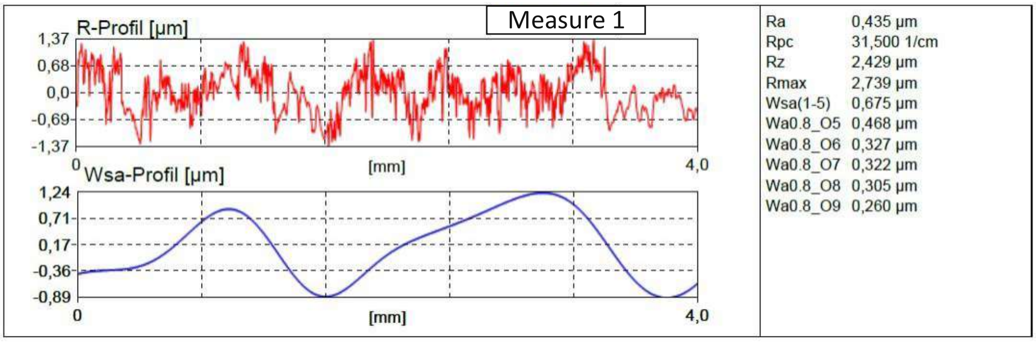


Figure 34: Roughness profiles from in-situ measurement device

With the configuration of the points presented in the table above, the procedure would be as follows:

- Machine centering as per Figure 28 to measure all surfaces of all samples milled for the facemilling and drilling operations with the above points.
- New machine centering with the base rotated. Rotate the A axis 90 degrees and set the C axis to 0 degrees for the varied operation and 180 degrees for the constant operation. Once the machine is centered, as shown in Figure 27, the main program of the NC code is executed with the selected points.

At this point, the measuring process is configured through the in-situ measurement device.

Due to the limited geometry of the MiniProfiler, with a probe length of 25 mm, it was impossible to measure the bores' entire length. Therefore, it was decided to use the second option presented in the paper to perform all measurements with the same device.

<u>**Waveline W912RC**</u>

Eight surfaces will be measured per part produced by the operation with constant, and DOE values.

The Waveline W912RC [37] machine is used for roughness measurement and two different probe systems are used since the probe used for facemilling and endmilling operations is too large for bore measurement.

Figure 35: Waveline W912RC, Jenoptik

The following procedure describes the required steps for the measurement of surfaces.

1) Clean all surfaces with a 99.6º alcohol solution and brush them to remove chips and grease. Then remove residues with compressed air.
2) Measurements were performed in order of the operations to take advantage of the positioning adjustment of the machine for all the samples. Three different positioning of the clamping base were required:
    a. For facemilling operations.
    b. For endmilling operations.
    c. For drilling operations, the same clamping system as with the facemilling, but different positioning of the measuring device.
3) A full one-line contour was recorded from each surface, and the profile was extracted.
4) From the obtained profile, it is necessary to filter the waviness from the data depending on the surface state to match the ISO 4287 standards (see Table 13) shown in Annex E [25]:

In order to correlate the positioning data of the surface roughness measurements with those of the accelerations, special care has been taken to position the parts in the clamping system of the measuring machine using the coordinates shown on the tool display.

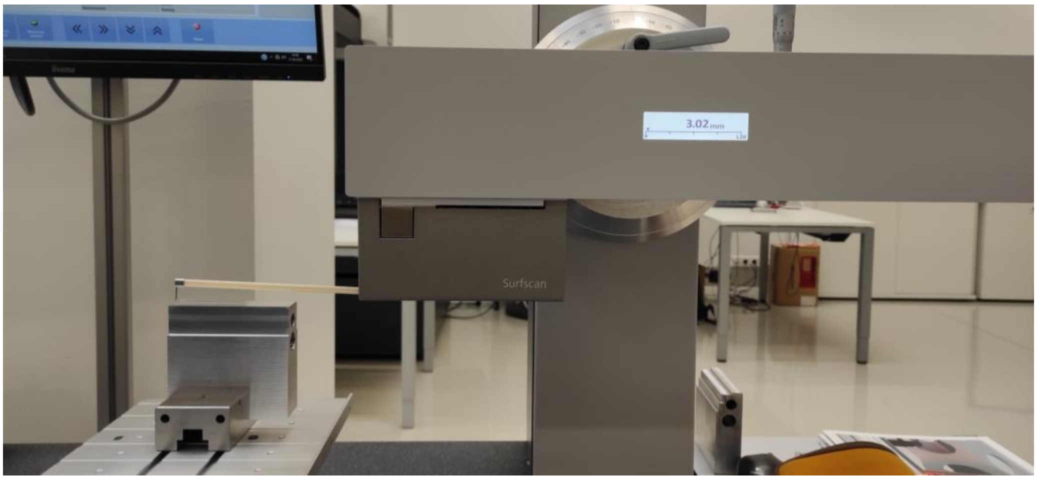


Figure 36: Surface roughness measurement process setting.

For the milling operations, a 93-millimeter-long profile is measured, starting at a point 2 to 3 millimeters away from the start of the part.

For drilling operations, a profile of 40 millimeters in length is measured, having an original of 50 mm, to safeguard the condition of the measuring probe since there is a slight discontinuity right in the center of the part and at the exit of the drill hole. Measurements are started 45 millimeters from the outer area of the bore. Figure 37 is included to understand the positioning and measurement segments.

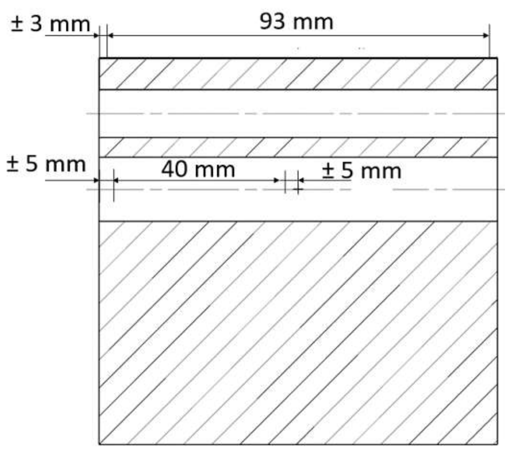


Figure 37: Measurement positioning sketch

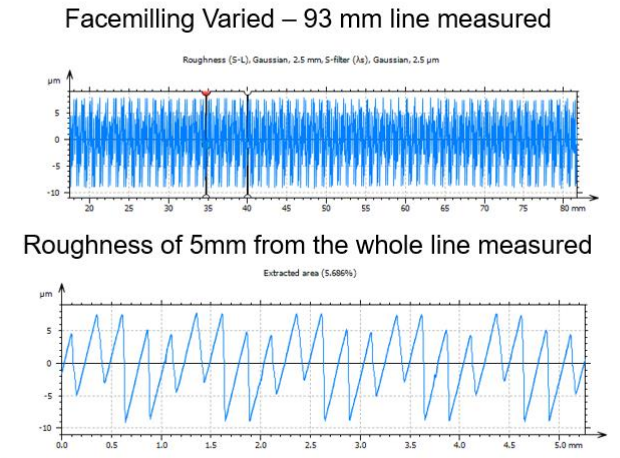
The contour measurement is carried out using the Evovis software of the Waveline W912RC machine, while MountainsMap® [50] has been used as a roughness data and profile tool.

This program allows the import of the profiles extracted from Evovis, and the extraction of the surface roughness data from the profiles, selecting which ISO standard to apply, as well as the filters applied to the data.

The following information is obtained from the software:

- Surface roughness profile graphs.
- Roughness parameter Ra(µm); others can be selected if necessary.
- Roughness profile file in text format with the points (x, z). This file allows visual validation.

Figure 38 shows examples of the graphics obtained from the extraction tool [50] and the parameter tables. In addition, eight tables with the surface roughness graphs for each operation are provided in Annex D.



ISO 4287 - Roughness (S-L)			
F: [Workflow] Leveled (LS-line)			
S-filter (λs): Gaussian, 2.5 µm			
L-filter (λc): Gaussian, 2.5 mm			
Evaluation length: All λc (37)			
Amplitude parameters			
Rp	7.551	µm	Maximum peak height of the roughness profile
Rv	8.919	µm	Maximum valley depth of the roughness profile
Rz	16.47	µm	Maximum height of roughness profile
Rt	17.40	µm	Total height of roughness profile
Ra	3.450	µm	Arithmetic mean deviation of the roughness profile
Rq	4.110	µm	Root-mean-square (RMS) deviation of the roughness profile

Figure 38: Surface roughness graphs and table of parameters – Sample 15, first batch of experiments

Table 19 shows an overview of all the surface roughness values measured per operation and experiment. Those with the lowest *Ra* are marked in green, and those with the highest *Ra* are marked in red. For the columns where the values of the constant operations are indicated, the parameters hardly vary for the milling operations. For the drilling operations, they are similar. Annex E includes the complete tables for the two rounds of experiments.

Table 19: Surface roughness per experiment from the first round

Temperature gradient per operation											
				Operations							
Experiment	Factors combination	Sample	Roughness Parameters	Facemilling_Varied	Facemilling_Constant	Endmilling_Varied	Endmilling_Constant	Ø16 drilling Varied	Ø16 drilling Constant	Ø12 drilling Varied	Ø12 drilling Constant
1	(-,-,-)	22	Ra(µm)	0.6262	1.8280	0.0853	0.2291	3.4540	5.5040	2.3820	6.5400
2	(+,-,-)	20	Ra(µm)	0.6951	1.8370	0.09294	0.2288	2.3140	4.2820	2.8720	5.2100
3	(-,+,-)	16	Ra(µm)	3.0430	1.7880	1.05100	0.2280	6.3240	4.7790	6.9050	4.2840
4	(+,+,-)	17	Ra(µm)	3.0440	1.8130	0.70230	0.2304	4.8610	3.9060	4.3610	5.5430
5	(-,-,+)	19	Ra(µm)	0.8883	1.8180	0.09464	0.2270	3.5240	5.2700	2.2580	4.6980
6	(+,-,+)	18	Ra(µm)	1.0220	1.8490	0.09036	0.2315	3.1830	4.7640	2.7080	6.0010
7	(-,+,+)	15	Ra(µm)	3.4500	1.8270	1.0390	0.2323	5.7160	4.5360	6.1390	5.9620
8	(+,+,+)	21	Ra(µm)	3.8230	1.8900	1.1170	0.2730	3.4420	4.5560	4.9930	5.7590

Temperature gradient per round of experiments											
				Operations							
Experiment	Factors combination	Sample	Roughness Parameters	Facemilling_Varied	Facemilling_Constant	Endmilling_Varied	Endmilling_Constant	Ø16 drilling Varied	Ø16 drilling Constant	Ø12 drilling Varied	Ø12 drilling Constant
1	(-,-,-)	22	Ra(µm)	0.6262	1.8280	0.0853	0.2291	3.4540	5.5040	2.3820	6.5400
2	(+,-,-)	20	Ra(µm)	0.6951	1.8370	0.09294	0.2288	2.3140	4.2820	2.8720	5.2100
3	(-,+,-)	16	Ra(µm)	3.0430	1.7880	1.05100	0.2280	6.3240	4.7790	6.9050	4.2840
4	(+,+,-)	17	Ra(µm)	3.0440	1.8130	0.70230	0.2304	4.8610	3.9060	4.3610	5.5430
5	(-,-,+)	19	Ra(µm)	0.8883	1.8180	0.09464	0.2270	3.5240	5.2700	2.2580	4.6980
6	(+,-,+)	18	Ra(µm)	1.0220	1.8490	0.09036	0.2315	3.1830	4.7640	2.7080	6.0010
7	(-,+,+)	15	Ra(µm)	3.4500	1.8270	1.0390	0.2323	5.7160	4.5360	6.1390	5.9620
8	(+,+,+)	21	Ra(µm)	3.8230	1.8900	1.1170	0.2730	3.4420	4.5560	4.9930	5.7590

5.5 Generalization of the System

The system proposed in this thesis consists of the following fundamental artifacts to be considered when generalizing it:

- CAM project in Siemens NX.
- QR-Generator: Program for generating QR codes to identify the parts (*QR_Generator.py*).
- Configurator: Program for generating QR codes to identify the parts (*doe_json.py*).
- DOE-Implementor: NX Open Plugin to apply the changing variant levels to the CAM project.
- Resources used by the different programs (*DOE_Plugin.py*).
    - DOE-parameters: JSON file containing DOE values, ID's, and the experiments counter (*db_doe_working.json*)
    - Variation list: CSV documents for the selection of the experiment (*ongoing_experiments.csv* and *performed_experiments.csv*)
    - ID files: To create the experiment ID for MongoDB (*id.txt*, *QR_scanned.csv*, and *set_tool_number.csv*)

The steps for applying the solution in other case studies are as follows.

<u>CAM project</u>

The DOE Plugin for the solution presented in the thesis uses the operations configured in the CAM project.

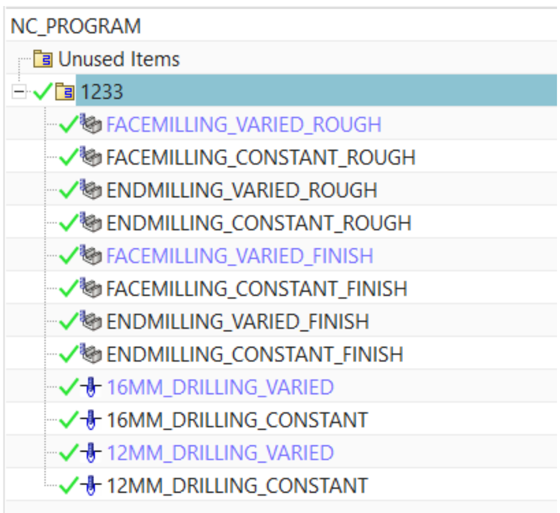


Figure 39: Operations in Siemens NX

To ensure correct variable calling, the operation names used in the CAM project, the JSON generation program, and in the main DOE execution program must remain consistent across all three files. See Annex G for code extractions (Figures 46 and 47).

The CAM project also defines the values of the macro variables used to identify the features (Table 8). Figure 40 shows how to configure them.

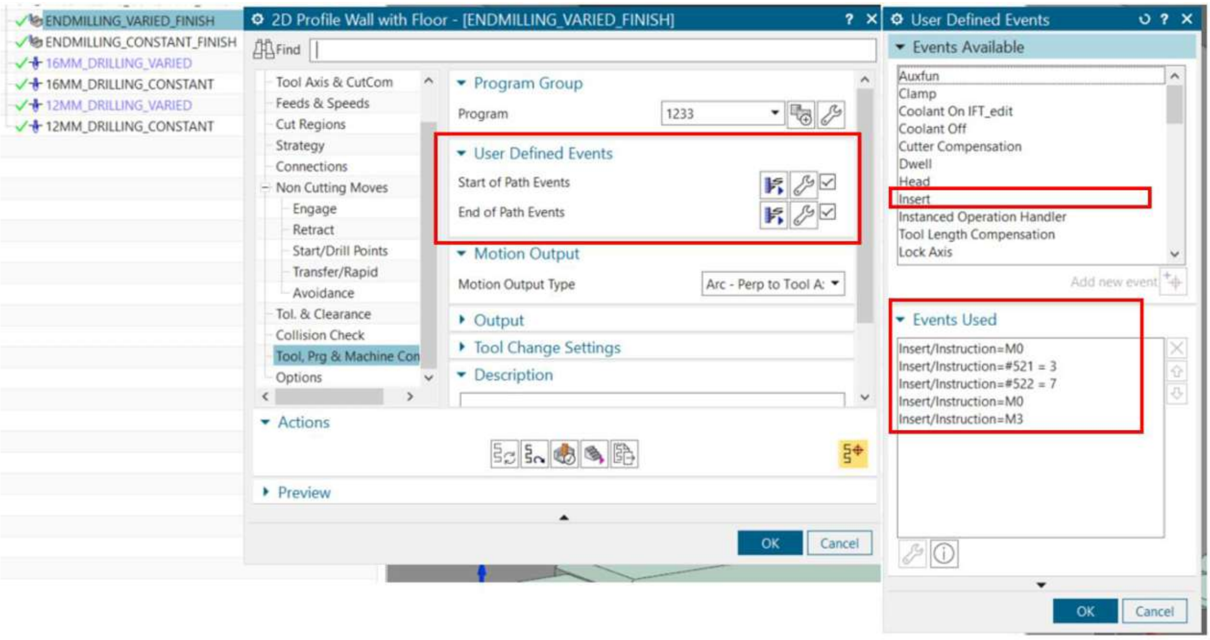


Figure 40: Configuration of MACRO variables on the CAM Project

JSON code

If the number of experiments is to be performed with a modify DOE, it is necessary to modify the program *doe_json.py* by adding new rows of data like the existing ones. (See Figure 40 for a reference of the program structure).

The newly added experiments must follow the same terminology:

- Experiment_X, to indicate the experiment number where X will be the experiment number.
- SS, FF, and CD to indicate the experiment-specific values for spindle speed, feedrate, and cutting depth.
- Setting the operation names according to those defined in the CAM Project is essential.
- Finally, the factors of SS, FF, and CD must be set accordingly to the custom levels of variants.

DOE_Plugin

The following steps must be followed to adapt the main code for the DOE (*DOE_Plugin.py*). The order presented in the flowchart in Figure 12 will be followed for the explanation.

Checking the used tool

For this function, the file *set_tool_number.csv* is used. It needs to be adapted if the tool number change.

Figure 41 shows an example.

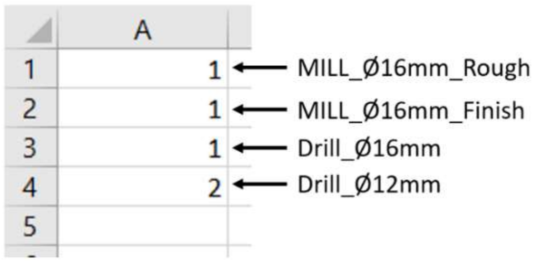


Figure 41: Example from case study for the *set_tool_number.csv*

Each row in the *set_tool_number.csv* (Figure 43) contains an integer that indicates how many tools have been used. If the experiments are executed for the first time with new tools, the column will have as many rows with "1" as tools.

In addition, the messages appearing in Siemens NX from the file *DOE_Plugin.py* must be modified to correspond to the tools used in the new application (lines 84, 94, 106, and 115). Lastly, lines 88, 97, 106, and 115 must be modified to the file's new location.

Selection of experiment:

If the DOE size is to be changed, the *ongoing_experiments.csv* file has to be modified. The new number of experiments must be written in the first column, in order, and one per row.

The *performed_experiments.csv* file will be created with the first execution of the DOE program and does not need to be modified.

Lines to modify in the *DOE_Plugin.py* for new file's locations:

- For *ongoing_experiments.csv*: 130, 145, 191 y 221
- For *performed_experiments.csv*: 155, 165, 205, 215, 227 y 228

<u>QR code scanning and storage</u>

The scanned QR (See Figure 6) is stored in the *QR_scanned.csv* file. To adapt the system, it is necessary to modify lines 247, 256, and 262 in the *DOE_Plugin.py* file to indicate the file's correct location.

<u>Actualization of JSON document after experiment selection</u>

Lines 285 and 308 from the *DOE_Plugin.py* file, referring to the location of the *db_doe_working.json* file, have to be modified.

<u>ID generation for MongoDB</u>

The files *set_tool_number.csv* and *id.txt* are used. For the adaptation, the file locations of lines 412, 424, 431, and 437 have to be changed on the *DOE_Plugin.py* file.

<u>Automated change of cutting parameters according to DOE</u>

Depends on the strategies used in the CAM Project.

Lines 630 – 671 from the file *DOE_Plugin.py* correspond to drilling operations. The changes to be made are the names of the operations and any cutting strategy adjustments different from those used in the case study of the thesis.

Lines 672 - 1140 from the file *DOE_Plugin.py* correspond to milling operations. The names have to be changed. The operations are broken down into different loops because different cutting strategies are used, so for their application to another case, the variables have to be adjusted according to the new strategies used.

<u>CAM Project simulation check</u>

This function updates the values used when the machining simulation is considered invalid. The simulation shall be invalidated when it can be observed that the displayed result is not the desired one.

The following lines of code from the file *DOE_Plugin.py* have to be changed to the correct locations: 348, 358, 376, 387, and 404.

6 Data Processing

The data analysis of this project is divided into three parts. The first one is an automated generation of the experiment validation of input data. The second part covers the correlation of the data obtained by different sources used in the project, such as the numerical control data, the acceleration sensors, and the roughness measurements. The third one is the statistical result of applying the ANOVA analysis on which the DOE methodology applied in the project is based.

6.1 Data Correlation

Automating data correlation is one of the objectives of the project. It consists of finding a solution to extract and relate the data from the various sources by identifying the manufacturing features and correlating the timestamps with the position data.

The different machining operations are used to sort the data, and they are identified by the macro variables introduced in Table 8.

The data sources used for this project are:

- Numerical control of the machining center: These files contain real-time information on the machining processes and include the information presented in Table 20.

Table 20: Content NC data file

Timestamp	#521	#522	xAbs	yAbs	zAbs	cAbs	aAbs	xLoad	yLoad	zLoad	Feedrate	Spindle Speed
1.68146E+15	1	5	50965	-7500	-3200	0	0	8	8	42	1194	1193
1.68146E+15	1	5	48418	-7500	-3200	0	0	6	9	42	1194	1193

- Sensory tool holder: This tool obtains live data of the accelerations in the radial direction of the tool. The following data is stored in the files (Table 21):

Table 21: Content Acceleration data file

Num	Timestamp	xAcc
191	1.68146E+15	-3.1967652
195	1.68146E+15	-3.2272832

- Surface roughness measurement device: The results of roughness measurements of each surface are collected (Table 22).

Table 22: Content surface roughness file

X(mm)	Z(µm)
45.509	-7.345199
45.519	-7.487306

For each experiment, three files are extracted from the numerical control (one for each tool), three from the sensory tool holders, and eight with the surface roughness values (one file for each surface).

From these files, the data correlation process will extract the relevant lines in order to be able to analyze the possible relationship between acceleration and roughness. In this extraction process, identifying the features using the macro variables #521 and #522 is most important (see Table 8), as well as using the timestamps of the NC and acceleration data.

The macro variables are used to separate the NC data and the acceleration values of the different operations into different files, and the timestamp is used to extract the relevant data from the machining of the part.

The following diagram (Figure 42) shows the structure of the project for the filtering and subsequent data correlation.

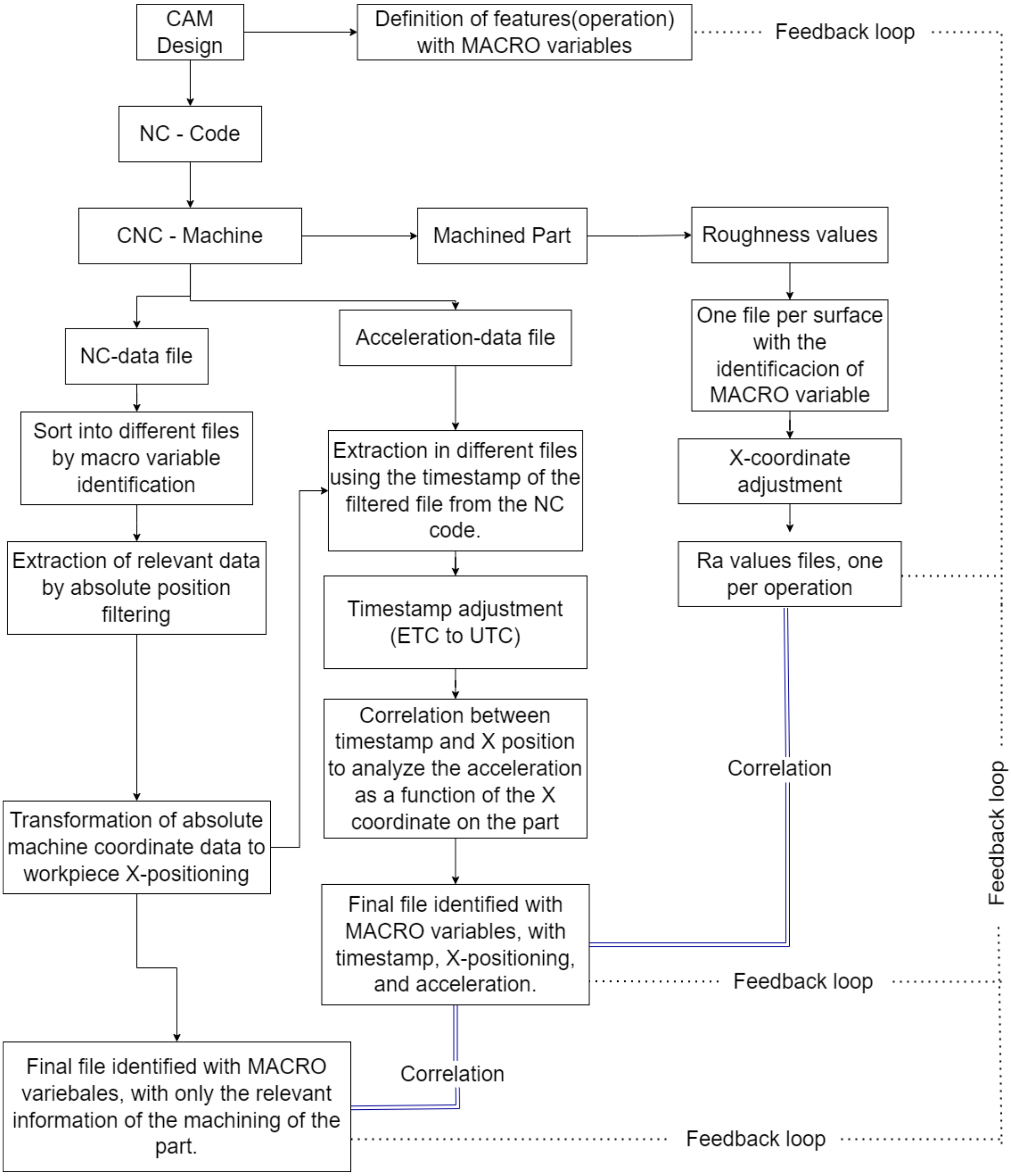


Figure 42: Diagram for the automatization of correlation of data

Next, it will be explained how the acceleration data has been obtained as a function of the X position using the data from the numerical control.

<u>Data correlation:</u> NC-data with Acc-data to make an axis transformation of the acceleration data (Figure 43).

To transform time to X position in the acceleration data, due to constant values observed on the final data, linear interpolation is used.

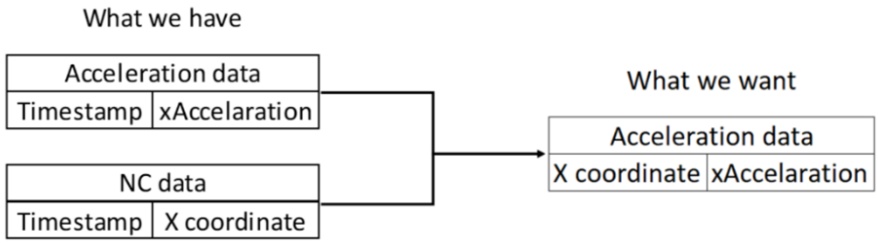


Figure 43: Diagram for data correlation

For the drilling operations, the process is done in multiple passes. The information collected during this process includes exit and entry movements for the chip breakage. Therefore, the acceleration data has been filtered only to show the moments of material removal.

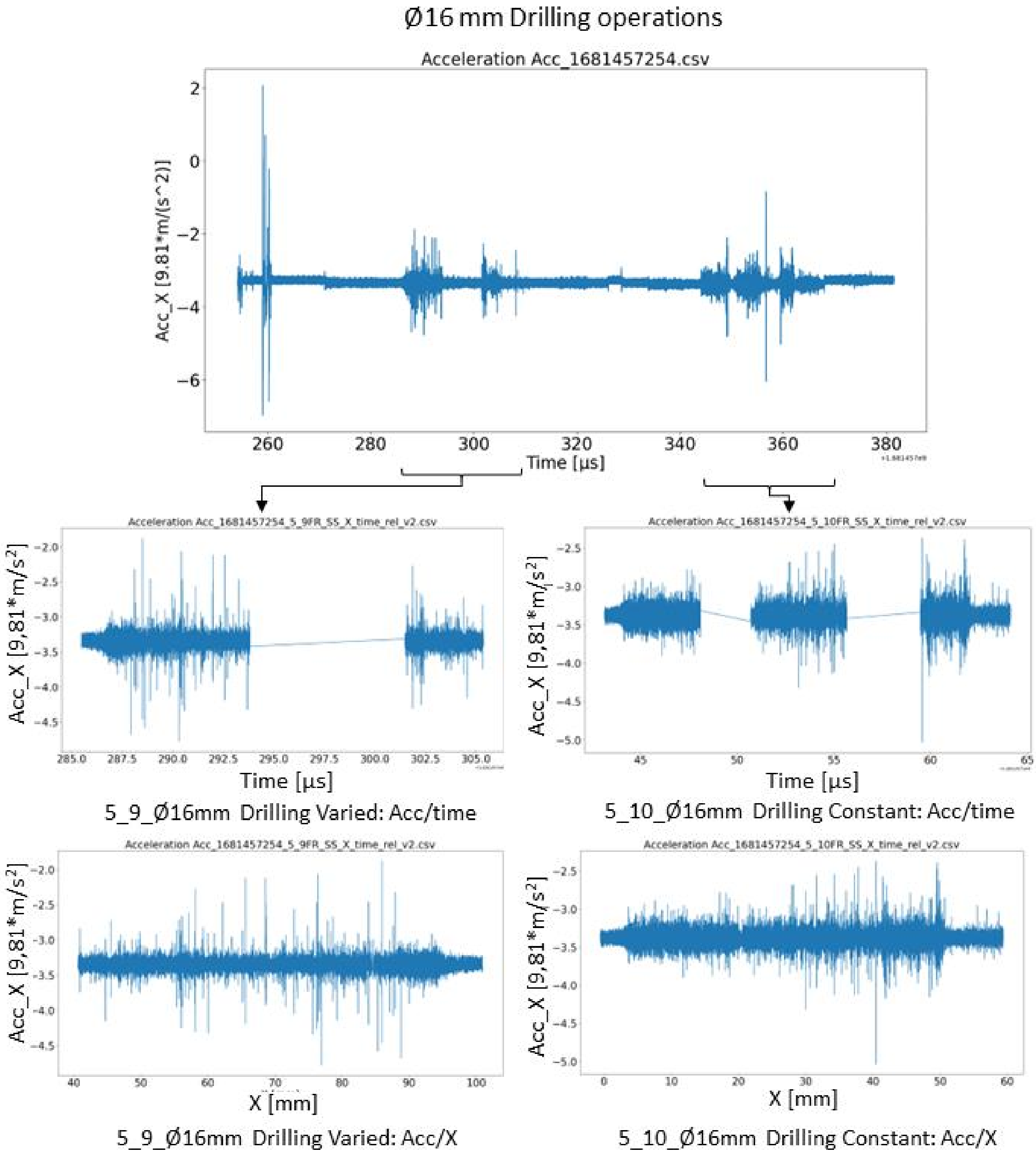


Figure 44: Acceleration data for drilling operations

6.2 ANOVA Analysis

The second analysis of the project is the ANOVA statistical analysis on which the DOE methodology used in the project is based.

The formulas (1 – 10) and Figure 2 for the nomenclature introduced in section 2.3.3 are used for this analysis.

Given the four different operations used in the DOE, an ANOVA analysis for each is done, obtaining an individual result for each operation.

For the four cases, the systems have seven degrees of freedom. Three are associated with the main effects, i.e., the alteration in the response resulting from a change in the level of the factor, three others with the two-by-two interactions, and the last one with the interaction between the three factors, where interaction means the change in the response by the combination effect those factors [17].

Tables 23 to 30 contain important DOE data, including factors and treatments, i.e., the combinations for the experiments, the roughness measurements for two replicates, and an ANOVA study evaluating the impact of each factor and their interactions.

Table 23: DOE results for the varied facemilling

Operation: Facemilling Varied, with Ø16 hard-metal mill							
Experiment	Factors			Surface Roughness, Ra (µm)		Label	Total
	Vc (m/min)	fz (mm)	CD (mm)	Replica 1	Replica 2		
1	60	0.025	0.5	0.62620	0.58440	*I*	1.21060
2	200	0.025	0.5	0.69510	0.66040	*a*	1.35550
3	60	0.25	0.5	3.04300	2.69700	*b*	5.74000
4	200	0.25	0.5	3.04400	2.70800	*ab*	5.75200
5	60	0.025	2	0.88830	0.88740	*c*	1.77570
6	200	0.025	2	1.02200	0.98040	*ac*	2.00240
7	60	0.25	5	3.45000	3.18500	*bc*	6.63500
8	200	0.25	2	3.27200	3.24200	*abc*	6.51400

Table 24: ANOVA results for varied facemilling

Factor	Contrast	Effect Estimate	Sum of Squares	Percent Contribution	Degrees of freedom	Mean Square	F0
Vc (A)	0.26260	0.032825	0.004309923	0.0199%	1	0.00431	0.2235874
fz (B)	18.29680	2.2871	20.92330564	96.7501%	1	20.9233	1085.44587
Cut Depth (C)	2.86900	0.358625	0.514447563	2.3788%	1	0.51445	26.6881817
AB	-0.48060	-0.060075	0.014436023	0.0668%	1	0.01444	0.74890275
AC	-0.05120	-0.0064	0.00016384	0.0008%	1	0.00016	0.00849959
BC	0.44500	0.055625	0.012376562	0.0572%	1	0.01238	0.6420634
ABC	-0.21480	-0.02685	0.00288369	0.0133%	1	0.00288	0.14959823
Error			0.15420985		8	0.01928	
Total			21.62613309		15		
		R2	0.992869282				

From this table, it can be seen that in the case of the facemilling operation, the factor with the most significant effect on surface roughness is the feed per tooth, with 96.7%, followed by the depth of cut.

In addition, the R2 coefficient of determination indicates how the regression model accurately fits the real data. Values close to 1, such as facemilling, indicate high accuracy.

Table 25: DOE results for varied endmilling

Operation: Endmilling Varied, with Ø16 hard-metal mill							
Experiment	Factors			Surface Roughness, Ra (µm)		Label	Total
	Vc (m/min)	fz (mm)	CD (mm)	Replica 1	Replica 2		
1	60	0.035	0.5	0.07218	0.07133	*l*	0.14351
2	200	0.035	0.5	0.07598	0.07187	*a*	0.14785
3	60	0.15	0.5	1.05100	0.86200	*b*	1.91300
4	200	0.15	0.5	0.70230	0.97680	*ab*	1.67910
5	60	0.035	1	0.07110	0.07210	*c*	0.14320
6	200	0.035	1	0.07155	0.07160	*ac*	0.14315
7	60	0.15	1	1.03900	1.05700	*bc*	2.09600
8	200	0.15	1	0.80820	0.78120	*abc*	1.58940

Table 26: ANOVA results for endmilling

Factor	Contrast	Effect Estimate	Sum of Squares	Percent Contribution	Degrees of freedom	Mean Square	F0
Vc (A)	-0.73621	-0.0920263	0.033875323	1.1520%	1	0.03388	4.83316664
fz (B)	6.69979	0.83747375	2.805449128	95.4087%	1	2.80545	400.267865
Cut Depth (C)	0.08829	0.01103625	0.000487195	0.0166%	1	0.00049	0.06951065
AB	-0.74479	-0.0930988	0.034669509	1.1791%	1	0.03467	4.94647728
AC	-0.27709	-0.0346363	0.004798679	0.1632%	1	0.0048	0.68465227
BC	0.09831	0.01228875	0.000604054	0.0205%	1	0.0006	0.08618342
ABC	-0.26831	-0.0335388	0.004499391	0.1530%	1	0.0045	0.64195127
Error			0.056071434		8	0.00701	
Total			2.940454712		15		
		R2	0.980931033				

In the case of the endmilling operation, the most significant effect on surface roughness is again the feed per tooth factor, with 95.41%, followed by the cutting speed with 1.15%, and the interaction between both (AB) with 1.179%. As for the R2, it indicates a particularly good fit for the real data.

Table 27: DOE results for Ø16 mm drilling

Operation: Drillinh Varied, with Ø16 drill							
Experiment	Factors			Surface Roughness, Ra (µm)		Label	Total
	Vc (m/min)	fz (mm)	CD (mm)	Replica 1	Replica 2		
1	30	0.1	10	3.45400	2.73300	*I*	6.18700
2	45	0.1	10	2.31400	2.73600	*a*	5.05000
3	30	0.25	10	6.32400	5.52900	*b*	11.85300
4	45	0.25	10	4.86100	3.42500	*ab*	8.28600
5	30	0.1	40	3.52400	3.41300	*c*	6.93700
6	45	0.1	40	3.18300	2.14600	*ac*	5.32900
7	30	0.25	40	5.71600	3.74600	*bc*	9.46200
8	45	0.25	40	3.81700	4.40700	*abc*	8.22400

Table 28: ANOVA results for Ø16 mm drilling

Factor	Contrast	Effect Estimate	Sum of Squares	Percent Contribution	Degrees of freedom	Mean Square	F0
Vc (A)	-7.55000	-0.94375	3.56265625	15.7692%	1	3.562656	6.54543897
fz (B)	14.32200	1.79025	12.81998025	56.7444%	1	12.81998	23.5533244
Cut Depth (C)	-1.42400	-0.178	0.126736	0.5610%	1	0.126736	0.23284389
AB	-2.06000	-0.2575	0.265225	1.1740%	1	0.265225	0.48728082
AC	1.85800	0.23225	0.21576025	0.9550%	1	0.21576	0.39640242
BC	-3.48200	-0.43525	0.75777025	3.3541%	1	0.75777	1.3922025
ABC	2.80000	0.35	0.49	2.1689%	1	0.49	0.90024545
Error			4.354368		8	0.544296	
Total			22.592496		15		
		R2	0.807264855				

For the Ø16mm drilling operation, the data are quite different from those obtained for the milling operations. In this case, according to the analysis, feed per tooth and cutting speed factors substantially affect the surface roughness and the interactions between the three. It can also be seen that the R2 value is lower for this one, implying that the linear regression model is no good fit for drilling operations.

Table 29: DOE results for Ø12 mm drilling

Operation: Drilling Varied, with Ø12 drill							
Experiment	Factors			Surface Roughness, Ra (µm)		Label	Total
	Vc (m/min)	fz (mm)	CD (mm)	Replica 1	Replica 2		
1	15	0.2	10	2.38200	1.42100	*I*	3.80300
2	30	0.2	10	2.87200	2.37300	*a*	5.24500
3	15	0.32	10	6.90500	2.62600	*b*	9.53100
4	30	0.32	10	4.36100	6.73300	*ab*	11.09400
5	15	0.2	40	2.25800	2.48600	*c*	4.74400
6	30	0.2	40	2.70800	1.96200	*ac*	4.67000
7	15	0.32	40	6.13900	5.02300	*bc*	11.16200
8	30	0.32	40	3.23200	6.63500	*abc*	9.86700

Table 30: ANOVA results for Ø12 mm drilling

Factor	Contrast	Effect Estimate	Sum of Squares	Percent Contribution	Degrees of freedom	Mean Square	F0
Vc (A)	1.63600	0.2045	0.167281	0.3071%	1	0.167281	0.06944162
fz (B)	23.19200	2.899	33.616804	61.7086%	1	33.6168	13.9549932
Cut Depth (C)	0.77000	0.09625	0.03705625	0.0680%	1	0.037056	0.01538277
AB	-1.10000	-0.1375	0.075625	0.1388%	1	0.075625	0.03139342
AC	-4.37400	-0.54675	1.19574225	2.1950%	1	1.195742	0.49637601
BC	0.03800	0.00475	9.025E-05	0.0002%	1	9.03E-05	3.7465E-05
ABC	-1.34200	-0.16775	0.11256025	0.2066%	1	0.11256	0.04672596
Error			19.271556		8	2.408944	
Total			54.476715		15		
		R2	0.646242326				

In the case of the Ø12 mm drilling operation, the factor with the most significant effect on surface roughness is again the feed per tooth with 61.7%, followed by the interaction between it and the depth of cut.

On the other hand, the value of R2 is relatively lower than the milling operations and even lower than the 16mm drilling operation. This situation could be because, during the execution of the second round of experiments, a tool change was done since it was observed that the drill tip had slightly deteriorated. In comparison to the previous round of experiments, this change has shown a significant improvement in the surface finish.

The results of the drilling operations with 12 mm of constant speeds are shown in Table 31, the rows marked in green correspond to the experiments where Ra corresponds to a new tool, and the differences can be observed.

Table 31: Roughness measurements for Ø12 mm constant drilling

Experiment	Factors combination	Ø12 drilling Constant	
		Ra1(µm)	Ra2(µm)
1	(-,-,-)	6.5400	6.3060
2	(+,-,-)	5.2100	3.3090
3	(-,+,-)	4.2840	3.0200
4	(+,+,-)	5.5430	5.6650
5	(-,-,+)	4.6980	6.5770
6	(+,-,+)	6.0010	3.2760
7	(-,+,+)	5.9620	3.5900
8	(+,+,+)	5.7590	5.7030

7 Conclusion

7.1 Summary

This thesis introduces an automated metal-cutting experimentation process that uses the design of experiments methodology for accurate data collection from real processes. Following a specific experiment protocol guarantees data quality and repeatability while enhancing efficiency and data accuracy.

This process will enable acquiring and analyze industry-relevant data through experimentation. Serving as a basis for optimizing CAM simulation processes and improving the final manufacturing results by developing a predictive model for surface roughness.

To achieve this, a system is developed that correlates data from various sources, such as the numerical control, acceleration sensors, and final surface roughness measurements, and relates them to the manufacturing operations on the part. This system improves correlation, data processing efficiency, and reproducibility.

Moreover, the thesis aims to provide genuine data for AI system training since statistical analysis provides a theoretical foundation that helps comprehend the system to improve design and manufacturing processes by creating a closed feedback loop to implement AI predictive models easily.

For the data correlation, the feature-based management implemented in the system allows for greater control over the data, assures the traceability of the data through the different stages of the process, and facilitates the interpretation and correlation of data in complex processes where different data sources are used.

To summarize, using an automated experimental process to gather high-quality industry data and a featured-based data management system for correlation leads to a replicable method. This method saves time and provides accurate results for Big Data analysis, making data correlation crucial [40].

The effects on surface roughness of various combinations of cutting parameters and cutting conditions on machined aluminum parts have been studied to demonstrate the developed solution.

Using the proposed DOE methodology allows reproducible experiment execution. Additionally, process data has been collected and analyzed using the correlation of different data sources, such as machine acceleration data and surface roughness results on parts.

7.2 Outlook

Finally, it remains to mention the possible future steps that can be developed based on this project.

- Analysis of other factors based on the results of the baseline experiments: In this project, the analysis has been focused on the three factors chosen, which have been cutting speed, feed per tooth, and depth of cut, but reference operations have also been carried out to see if external factors can have an impact on the surface roughness. In the specific case of the drills, tool wear could be an interesting factor to continue studying in future project stages.
- In-depth data correlation: On the other hand, given the validation and correlation of the data obtained in the thesis, this correlation has been done visually, pending a deeper analysis of the data to see if there is a clear relationship between acceleration and surface roughness.
- The data gathered with the experiments will serve as a database to improve the simulations before the manufacturing phases by relying on predictive models generated from a machine learning algorithm developed from the real data gathered with the experiments. Thus, achieving a reduction in process costs and better knowledge of the future process.
- In addition, validating this solution would show that it allows for a complete configuration using closed loops which consistently connect the initial design phases with the data and results of training AI systems to create predictive models that can be used in simulation tools for CAD/CAM programs.
- Finally, regarding the results obtained for the Ø12mm drilling operation. It has been observed that the wear of the drill bit considerably impacts the roughness of the part based on consistent operation measurements. Hence, exploring this area further in future work could be worthwhile.

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List of Figures

List of Tables

Appendix

Annex A: References for the Evaluation Criteria for DOE

In this appendix are the references used and categorized in Table 3:

Table 32: References for evaluation criteria for DOE

Criteria	Full Factorial	Fractional Factorial	Taguchi	CCD
Considers the main effect of the factors	[17], [25], [51]	[17], [25]	[25]	[27]
Considers the interaction btw. factors	[17], [25]	[17], [25]	[25]	[27]
Experimentation cost	[25], [26], [51], [52]	[51]	[26]	[1], [52]
Effectiveness with 2 factors	[17], [51]–[53]	[17], [25], [53]	[17], [25], [26], [53]	[1], [54]
Effectiveness with 3 factors	[17], [51]–[53]	[17], [25], [53]	[17], [25], [26], [53]	[1], [54]
Effectiveness with 4 or more factors	[17], [52], [53]	[17], [25], [51], [53]	[17], [25], [26], [53]	[1], [54]
Accuracy of predictions vs. the real experiment	[17], [26], [51]	[17], [26], [51]	[26]	[52]
Use for 2 levels	[17], [51]	[17], [51]	[17], [51], [55]	[1], [51]
Use for 3 levels	[17], [51]	[17], [51]	[17], [51], [55]	[1], [51]
Use for 4 or more levels	[51]	[51]	[17], [51], [55]	[1], [51]
Number of case studies found in the first searches	[51] (multiple internal references, up to 10), [22], [26], [55]–[60]	[51] (multiple internal references, up to 4)	[51] (multiple internal references, up to 10),[1], [56], [59], [61]–[68]	[51] (multiple internal references, up to 8), [1], [56], [69]

Annex B: Full Flowchart Diagram of the DOE Software

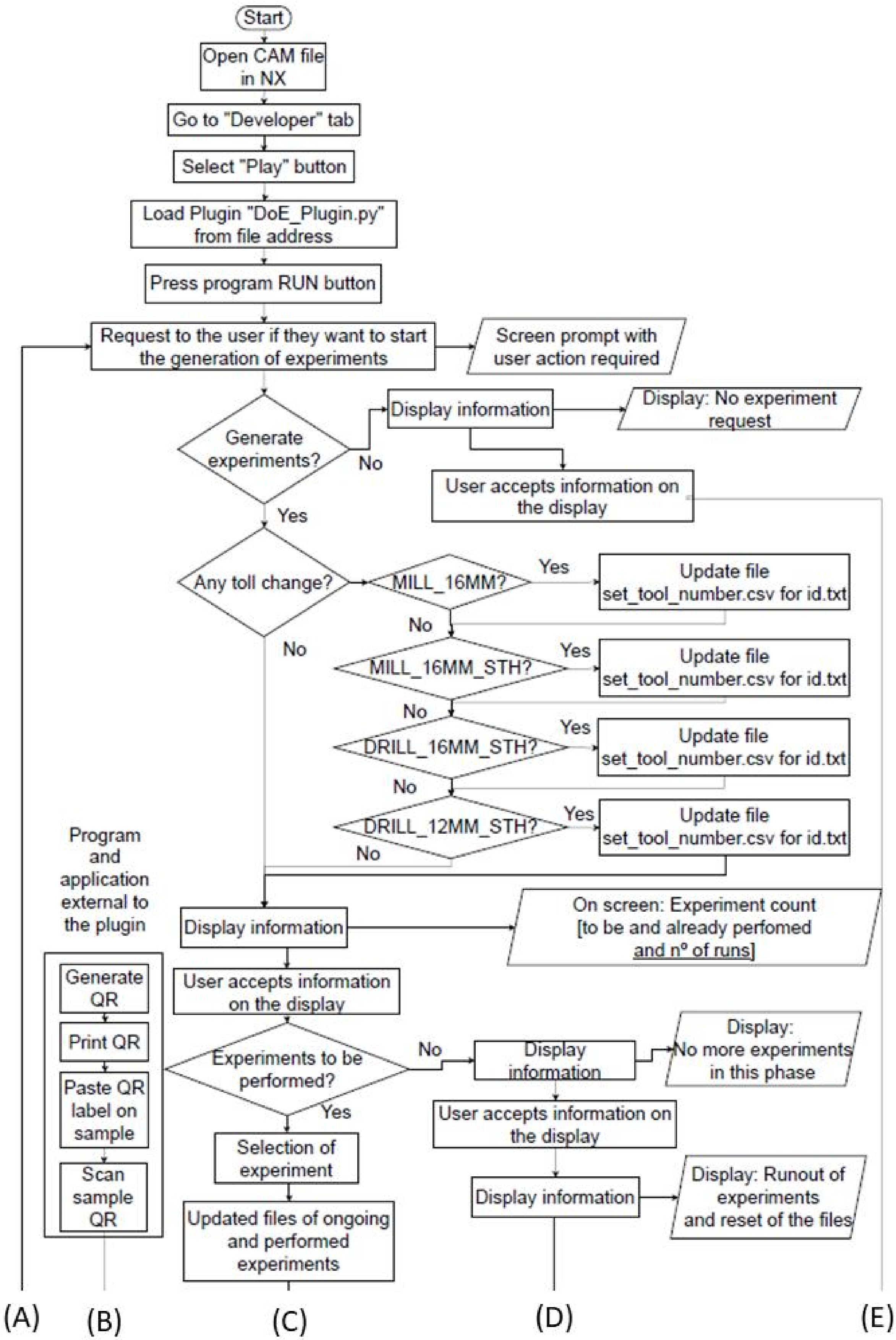
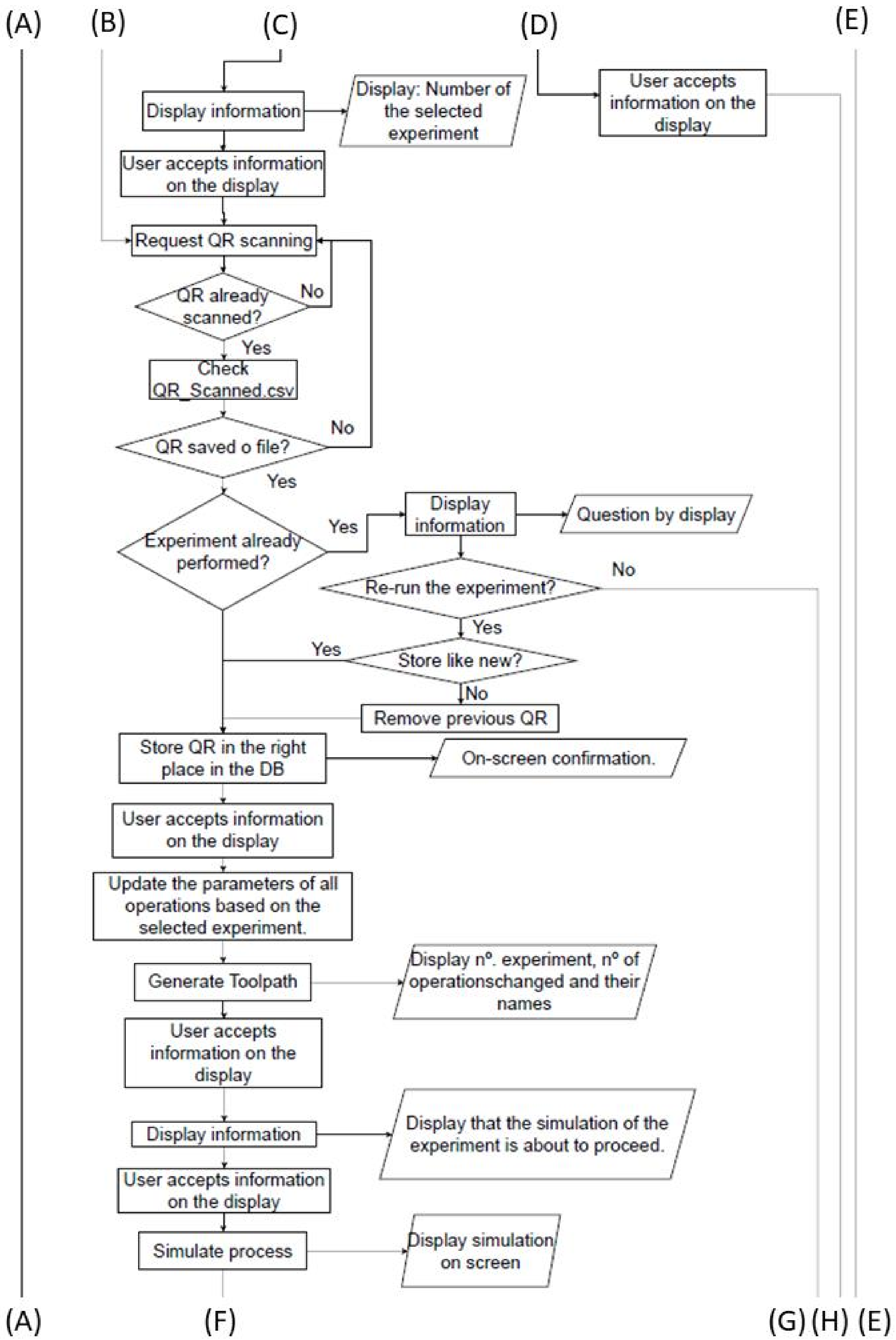
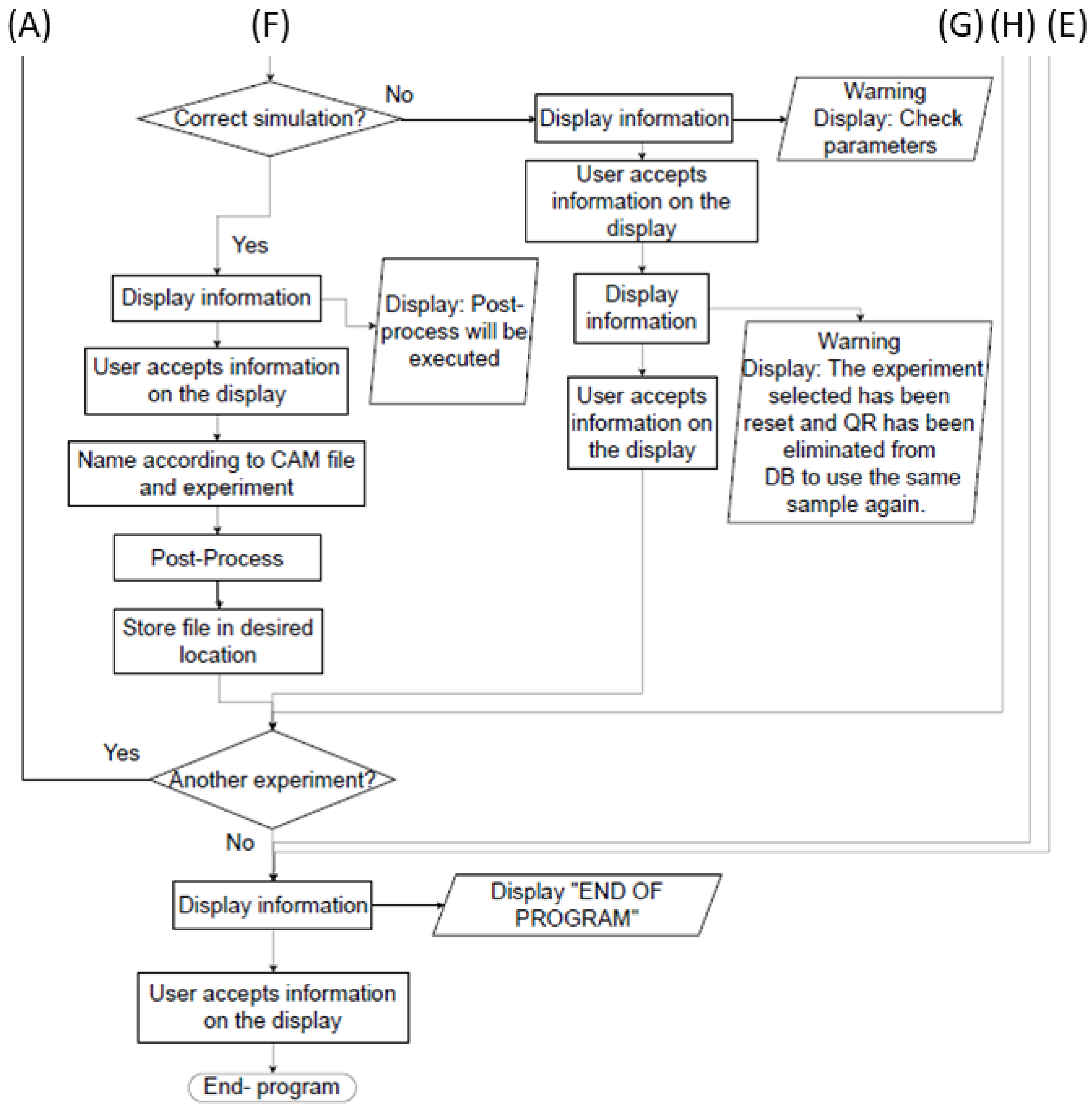


Figure 45: Complete Flowchart of the DOE Software



(A)
(B)
(C)
(D)
(E)
Display information
Display: Number of the selected experiment
User accepts information on the display
User accepts information on the display
Request QR scanning
QR already scanned?
No
Yes
Check QR_Scanned.csv
QR saved o file?
No
Yes
Experiment already performed?
Yes
Display information
Question by display
Re-run the experiment?
No
Yes
Store like new?
Yes
No
Remove previous QR
Store QR in the right place in the DB
On-screen confirmation.
User accepts information on the display
Update the parameters of all operations based on the selected experiment.
Generate Toolpath
Display nº. experiment, nº of operationschanged and their names
User accepts information on the display
Display information
Display that the simulation of the experiment is about to proceed.
User accepts information on the display
Simulate process
Display simulation on screen
(A)
(F)
(G) (H) (E)


(A)
(F)
(G) (H) (E)
Correct simulation?
No
Display information
Warning Display: Check parameters
User accepts information on the display
Yes
Display information
Display: Post-process will be executed
Display information
Warning Display: The experiment selected has been reset and QR has been eliminated from DB to use the same sample again.
User accepts information on the display
User accepts information on the display
Name according to CAM file and experiment
Post-Process
Store file in desired location
Yes
Another experiment?
No
Display information
Display "END OF PROGRAM"
User accepts information on the display
End- program

Annex C: Summary of Experiments and QR's for Second Batch.

Table 33: Summary of experiments and QR's for second batch

Sample 2nd Run	Experiment	Combiantion	QR
23	1	(-,-,-)	
24	4	(+,+,-)	
25	5	(-,-,+)	
26	8	(+,+,+)	

Sample 2nd Run	Experiment	Combiantion	QR
27	7	(-,+,+)	
28	2	(+,-,-)	
29	3	(-,+,-)	
30	6	(-,+,+)	

Annex D: ISO 4287 for Response Variable DOE.

Table 34: Type of filter λc(mm) per experiment and operation, ISO 4287

1st Run

Roughness Parameters, λs = 2,5 mm	Filter: λc (mm)	Number of the experiment per operation: Facemilling_Varied	Facemilling_Constant	Endmilling_Varied	Endmilling_Constant	Ø16 drilling Varied	Ø16 drilling Constant	Ø12 drilling Varied	Ø12 drilling Constant
0.02 < Ra(µm)< 0.1 0.1 < Rt(µm) or Rz(µm) < 0.5	0.25			1,2,5,6					
0.1 < Ra(µm)< 2 0.5 < Rt(µm) or Rz(µm) < 10	0.8	1,2,5,6	All	3,4,7,8	All				
2 < Ra(µm)< 10 10 < Rt(µm) or Rz(µm) < 50	2.5	3,4,7,8				All	All	All	All

2nd Run

Roughness Parameters, λs = 2,5 mm	Filter: λc (mm)	Number of the experiment per operation: Facemilling_Varied	Facemilling_Constant	Endmilling_Varied	Endmilling_Constant	Ø16 drilling Varied	Ø16 drilling Constant	Ø12 drilling Varied	Ø12 drilling Constant
0.02 < Ra(µm)< 0.1 0.1 < Rt(µm) or Rz(µm) < 0.5	0.25			1,2,5,6					
0.1 < Ra(µm)< 2 0.5 < Rt(µm) or Rz(µm) < 10	0.8	1,2,5,6	All	3,4,7,8	All			1,6	
2 < Ra(µm)< 10 10 < Rt(µm) or Rz(µm) < 50	2.5	3,4,7,8				All	All	2,3,4, 5,7,8	All

Annex E: Surface Roughness Values per Operation

Table 35: Surface roughness per experiment from both batches

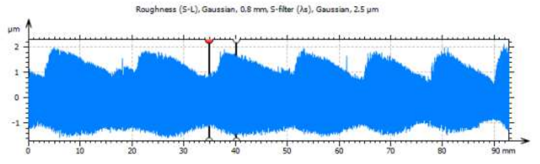
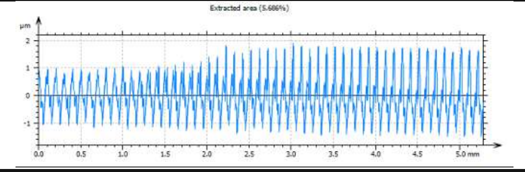
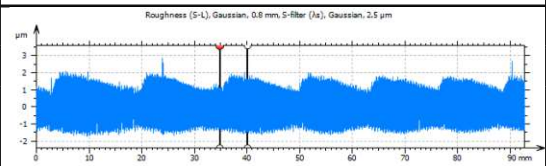
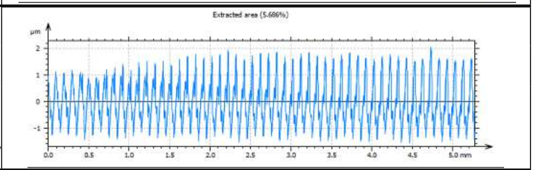
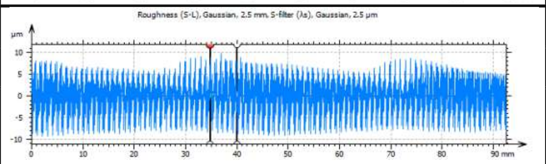
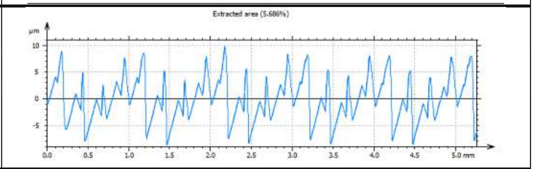
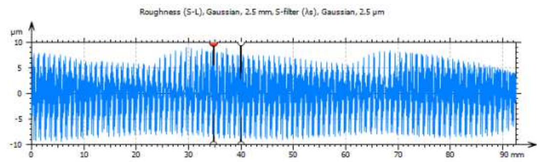
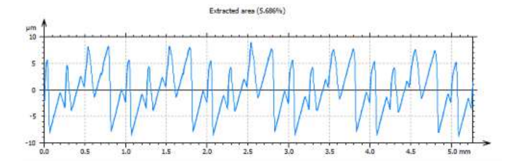
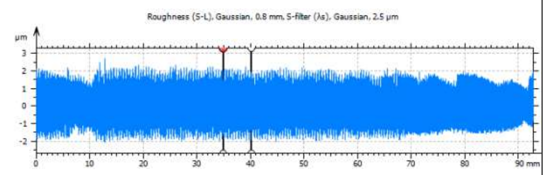
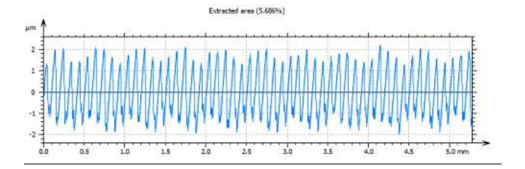
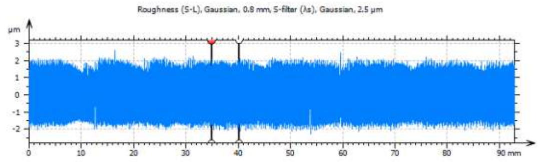
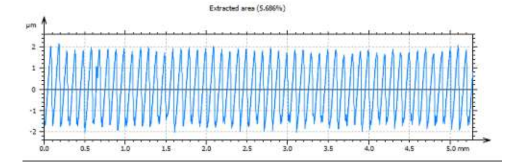
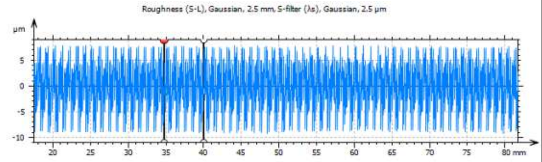
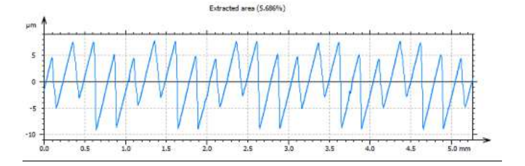
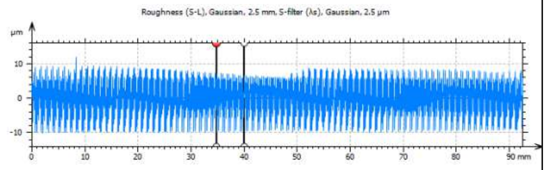
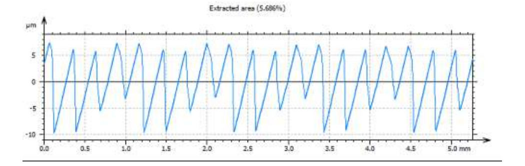
		Temperature gradient per operation																			
		Operations																			
Experiment	Factors combination	Facemilling_ Varied		Facemilling_ Constant		Endmilling_ Varied		Endmilling_ Constant		Ø16 drilling Varied		Ø16 drilling Constant		Ø12 drilling Varied		Ø12 drilling Constant	
		Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)
1	(-,-,-)	0.6262	0.5844	1.8280	1.7930	0.07218	0.07133	0.2291	0.2310	3.4540	2.7330	5.5040	4.3720	2.3820	1.4210	6.5400	6.3060
2	(+,-,-)	0.6951	0.6604	1.8370	1.8030	0.07598	0.07187	0.2288	0.2283	2.3140	2.7360	4.2820	4.3060	2.8720	2.3730	5.2100	3.3090
3	(-,+,-)	3.0430	2.6970	1.7880	1.8270	1.05100	0.86200	0.2280	0.2262	6.3240	5.5290	4.7790	4.1020	6.9050	2.6260	4.2840	3.0200
4	(+,+,-)	3.0440	2.7080	1.8130	1.8590	0.70230	0.97680	0.2304	0.2272	4.8610	3.4250	3.9060	3.5580	4.3610	6.7330	5.5430	5.6650
5	(-,-,+)	0.8883	0.8874	1.8180	1.8700	0.07110	0.07210	0.2270	0.2259	3.5240	3.4130	5.2700	3.7870	2.2580	2.4860	4.6980	6.5770
6	(+,-,+)	1.0220	0.9804	1.8490	1.8220	0.07155	0.07160	0.2315	0.2284	3.1830	2.1460	4.7640	4.2090	2.7080	1.9620	6.0010	3.2760
7	(-,+,+)	3.4500	3.1850	1.8270	1.8010	1.0390	1.0570	0.2323	0.2260	5.7160	3.7460	4.5360	3.6930	6.1390	5.0230	5.9620	3.5900
8	(+,+,+)	3.2720	3.2420	1.8700	1.8860	0.8082	0.7812	0.2260	0.2233	3.8170	4.4070	3.7590	3.0140	3.2320	6.6350	3.6060	5.7030

		Temperature gradient per operation																			
		Operations																			
Experiment	Factors combination	Facemilling Varied		Facemilling Constant		Endmilling Varied		Endmilling Constant		Ø16 drilling Varied		Ø16 drilling Constant		Ø12 drilling Varied		Ø12 drilling Constant	
		Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)	Ra1(µm)	Ra2(µm)
1	(-,-,-)	0.6262	0.5844	1.8280	1.7930	0.07218	0.07133	0.2291	0.2310	3.4540	2.7330	5.5040	4.3720	2.3820	1.4210	6.5400	6.3060
2	(+,-,-)	0.6951	0.6604	1.8370	1.8030	0.07598	0.07187	0.2288	0.2283	2.3140	2.7360	4.2820	4.3060	2.8720	2.3730	5.2100	3.3090
3	(-,+,-)	3.0430	2.6970	1.7880	1.8270	1.05100	0.86200	0.2280	0.2262	6.3240	5.5290	4.7790	4.1020	6.9050	2.6260	4.2840	3.0200
4	(+,+,-)	3.0440	2.7080	1.8130	1.8590	0.70230	0.97680	0.2304	0.2272	4.8610	3.4250	3.9060	3.5580	4.3610	6.7330	5.5430	5.6650
5	(-,-,+)	0.8883	0.8874	1.8180	1.8700	0.07110	0.07210	0.2270	0.2259	3.5240	3.4130	5.2700	3.7870	2.2580	2.4860	4.6980	6.5770
6	(+,-,+)	1.0220	0.9804	1.8490	1.8220	0.07155	0.07160	0.2315	0.2284	3.1830	2.1460	4.7640	4.2090	2.7080	1.9620	6.0010	3.2760
7	(-,+,+)	3.4500	3.1850	1.8270	1.8010	1.0390	1.0570	0.2323	0.2260	5.7160	3.7460	4.5360	3.6930	6.1390	5.0230	5.9620	3.5900
8	(+,+,+)	3.2720	3.2420	1.8700	1.8860	0.8082	0.7812	0.2260	0.2233	3.8170	4.4070	3.7590	3.0140	3.2320	6.6350	3.6060	5.7030

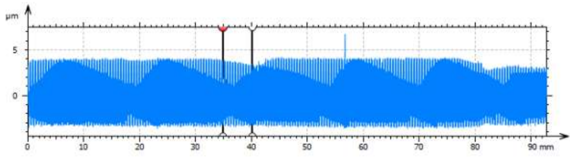
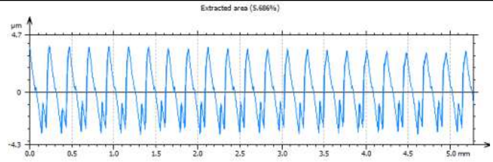
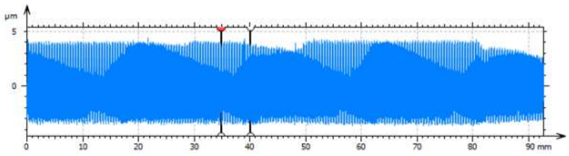
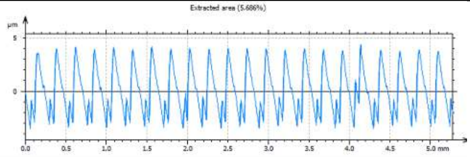
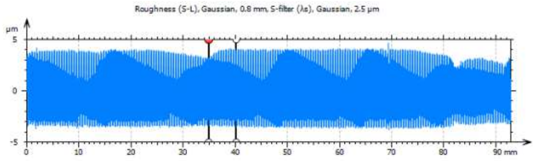
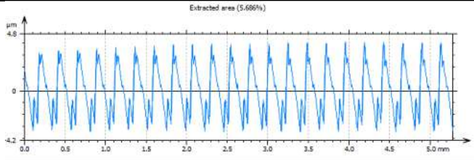
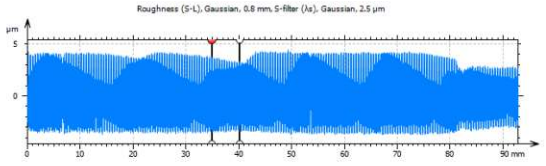
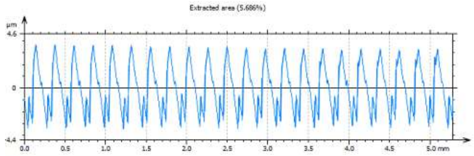
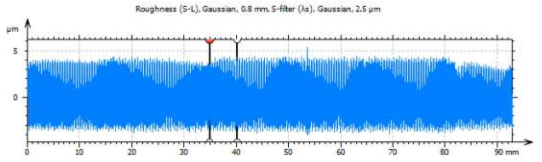
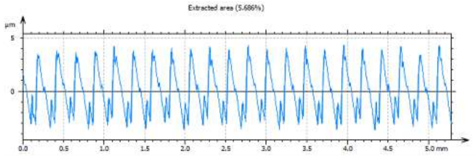
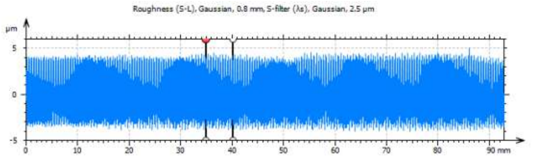
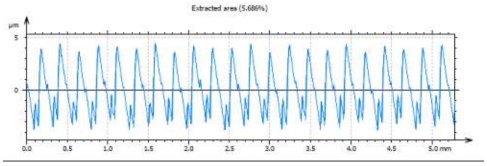
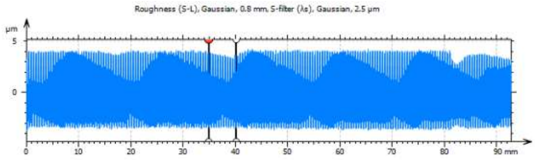
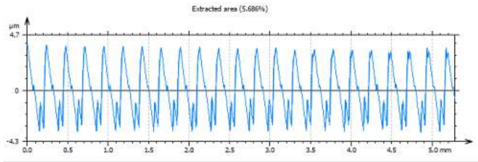
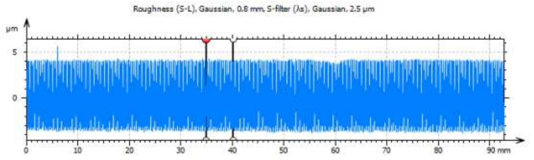
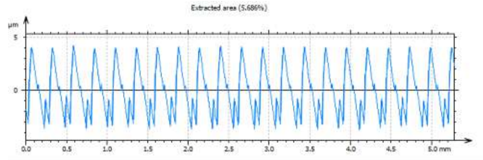
Annex F: Surface Roughness Profiles per Operation

In this annex, all surface roughness profiles per operation are included for quick visual comparison and data collection for the first run of experiments. For the second run, as they are replicas of the same experiments, and they are almost the same, it will not be shown here.

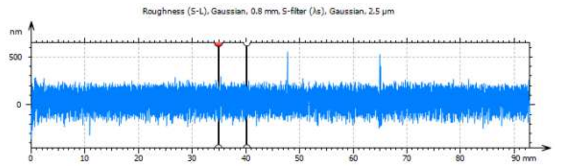
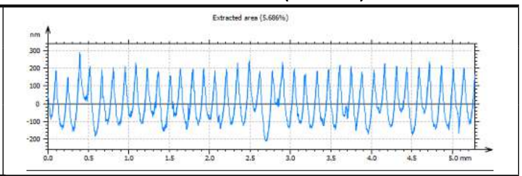
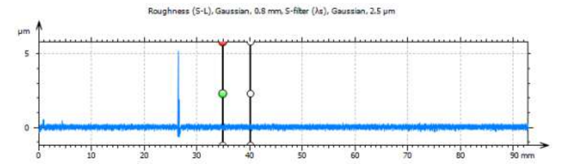
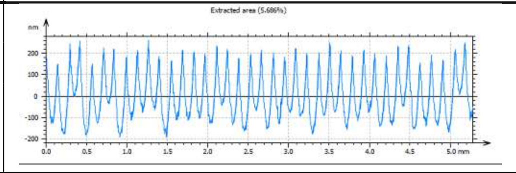
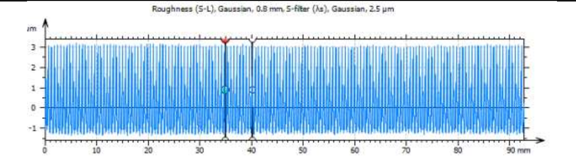
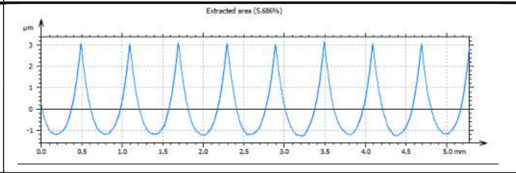
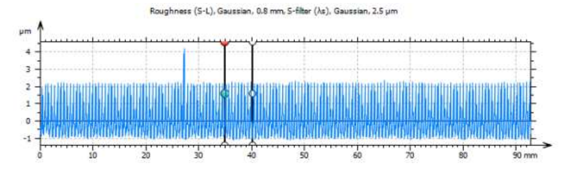
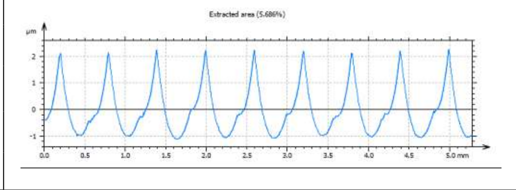
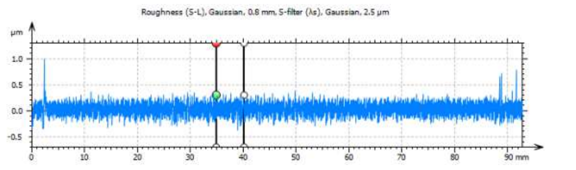
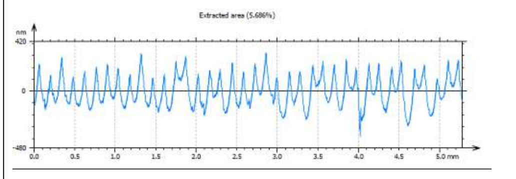
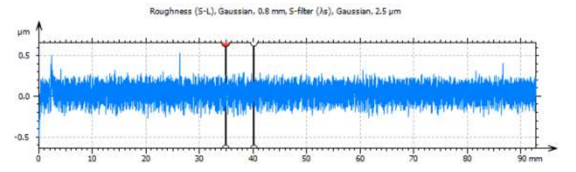
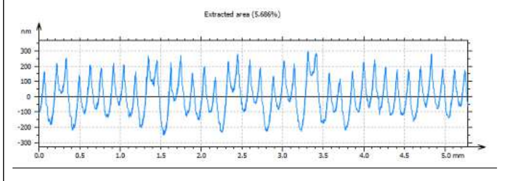
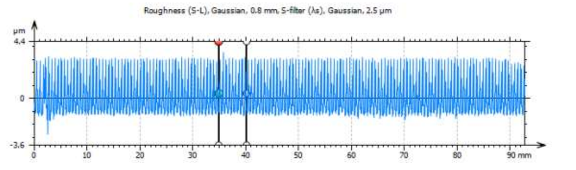
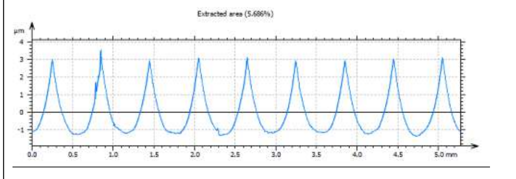
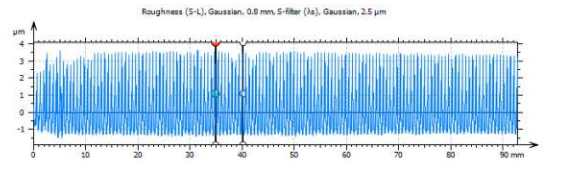
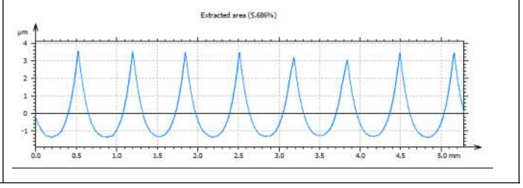
Facemilling Varied

Expt.	Complete Profile	Extraction (5 mm)
1 (-,-,-) Sample22		
2 (+,-,-) Sample20		
3 (-,+,-) Sample16		
4 (+,+,-) Sample17		
5 (-,-,+) Sample19		
6 (+,-,+) Sample18		
7 (-,+,+) Sample15		
8 (+,+,+) Sample21		

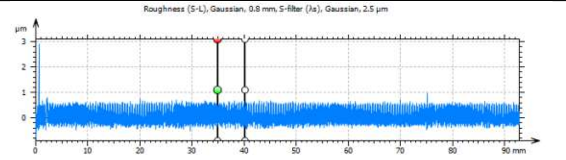
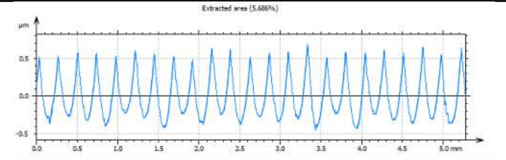
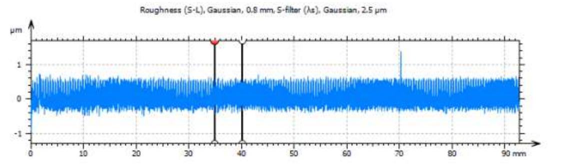
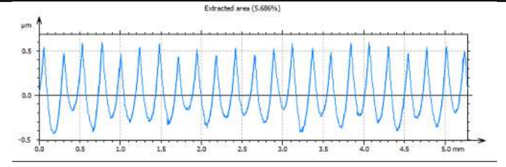
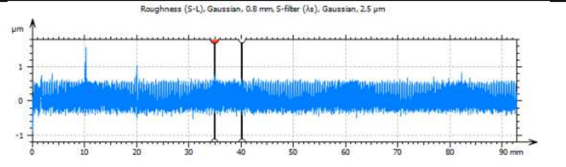
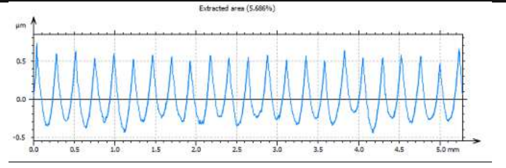
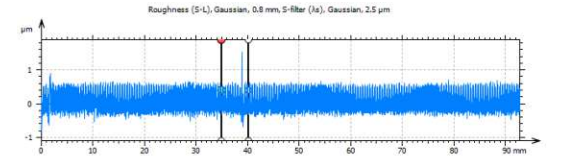
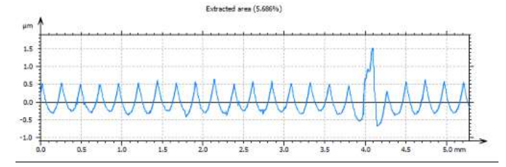
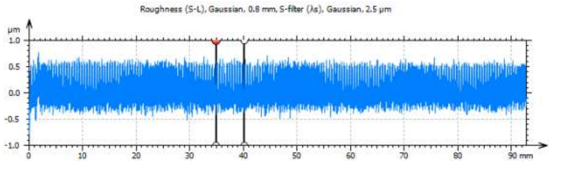
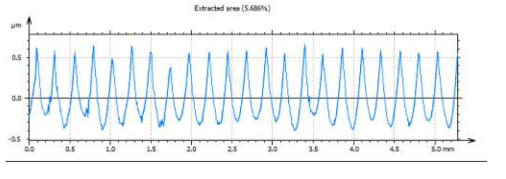
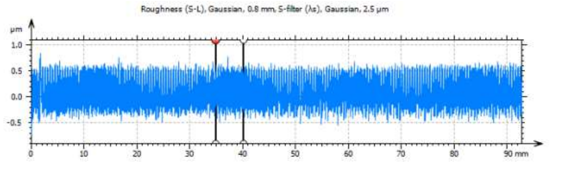
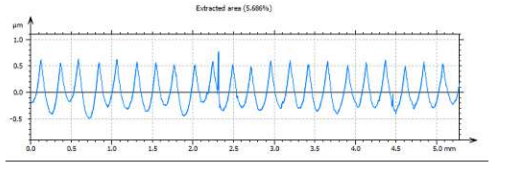
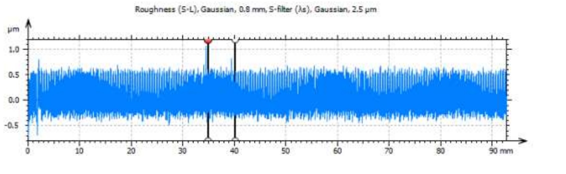
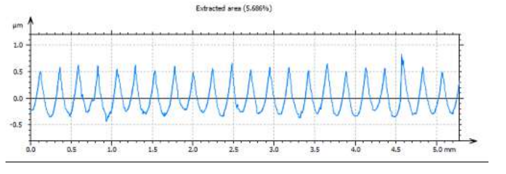
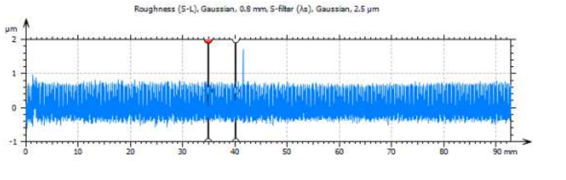
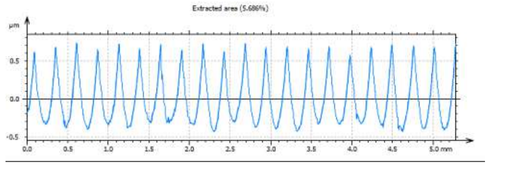
Facemilling Constant

Expt.	Complete Profile	Extraction (5 mm)
1 (-,-,-) Sample22		
2 (+,-,-) Sample20		
3 (-,+,-) Sample16		
4 (+,+,-) Sample17		
5 (-,-,+) Sample19		
6 (+,-,+) Sample18		
7 (-,+,+) Sample15		
8 (+,+,+) Sample21		

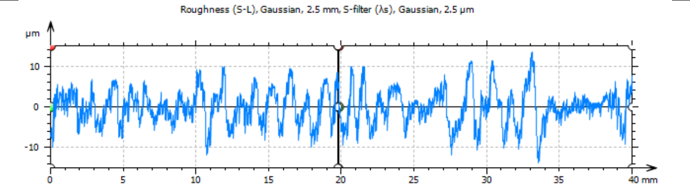
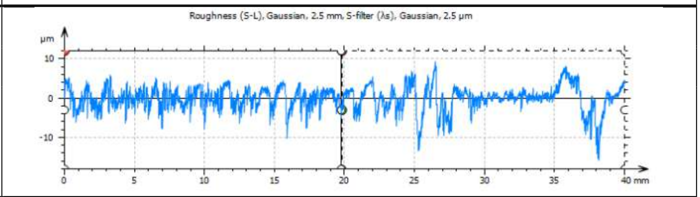
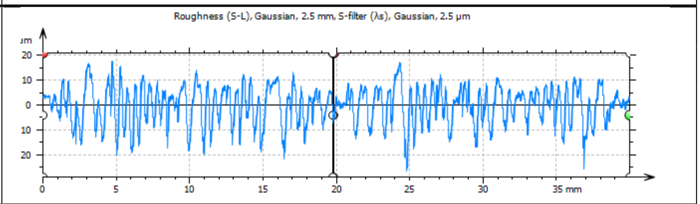
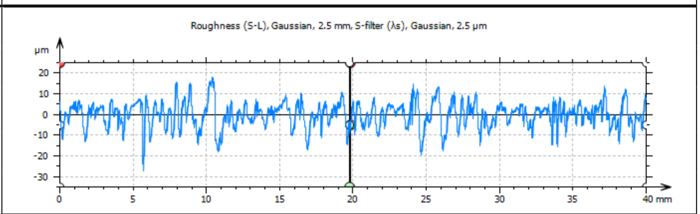
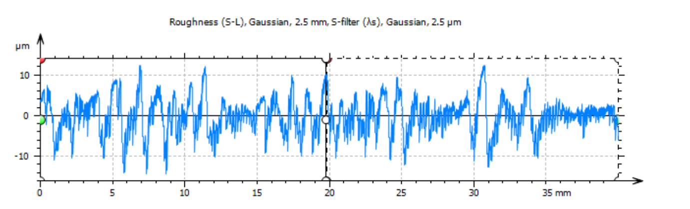
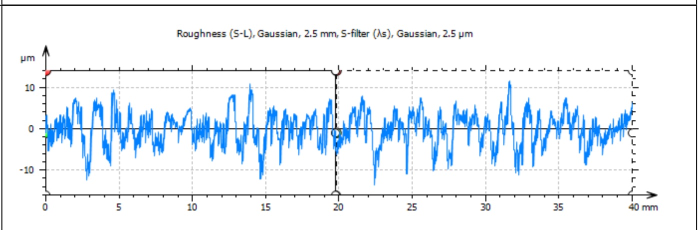
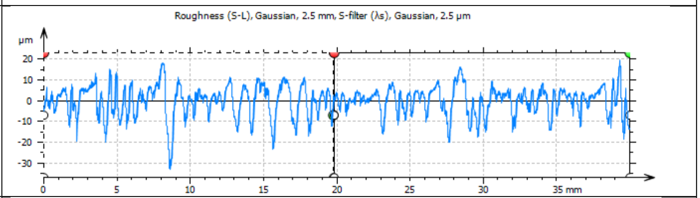
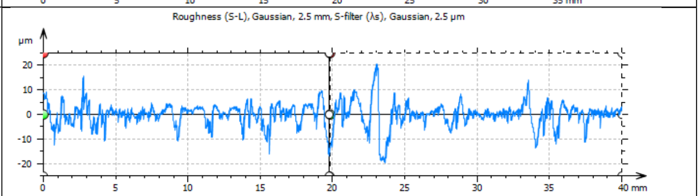
Endmilling Varied

Expt.	Complete Profile	Extraction (5 mm)
1 (-,-,-) Sample22		
2 (+,-,-) Sample20		
3 (-,+,-) Sample16		
4 (+,+,-) Sample17		
5 (-,-,+) Sample19		
6 (+,-,+) Sample18		
7 (-,+,+) Sample15		
8 (+,+,+) Sample21		

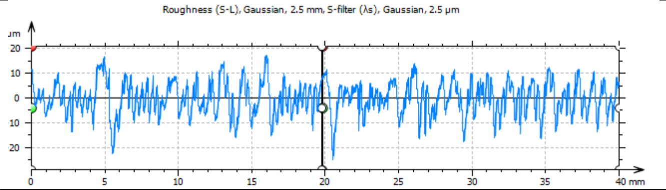
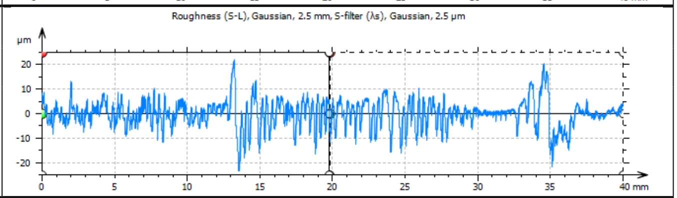
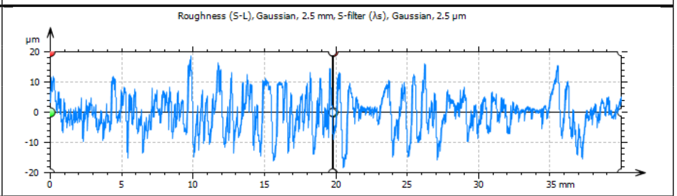
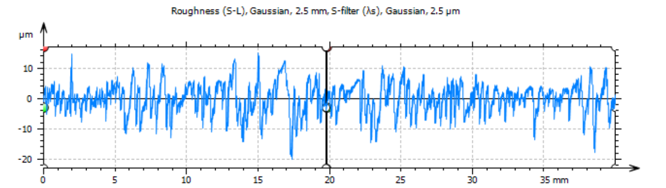
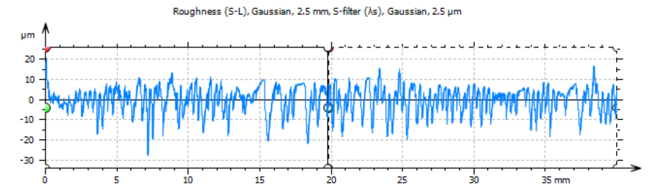
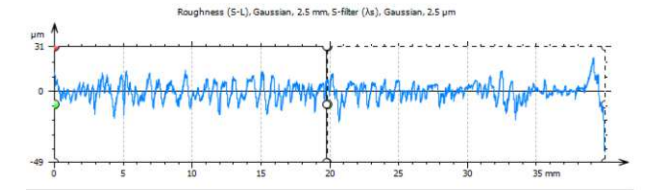
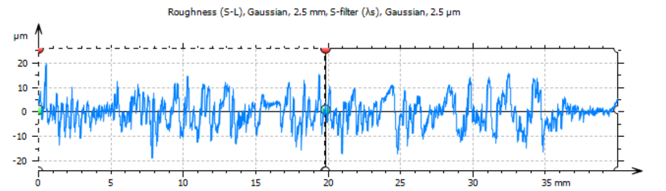
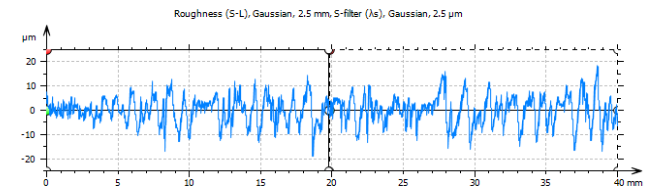
Endmilling Constant

Expt.	Complete Profile	Extraction (5 mm)
1 (-,-,-) Sample22		
2 (+,-,-) Sample20		
3 (-,+,-) Sample16		
4 (+,+,-) Sample17		
5 (-,-,+) Sample19		
6 (+,-,+) Sample18		
7 (-,+,+) Sample15		
8 (+,+,+) Sample21		

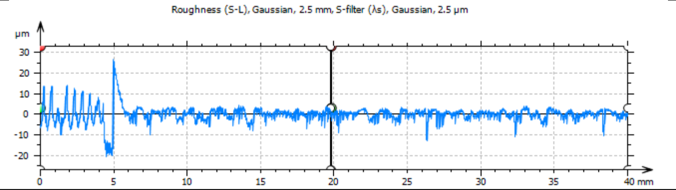
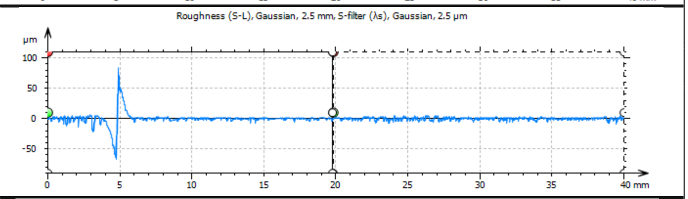
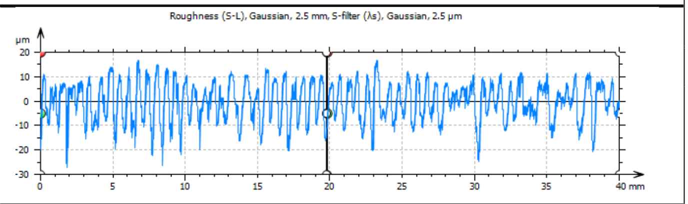
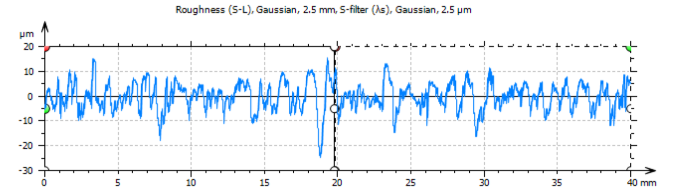
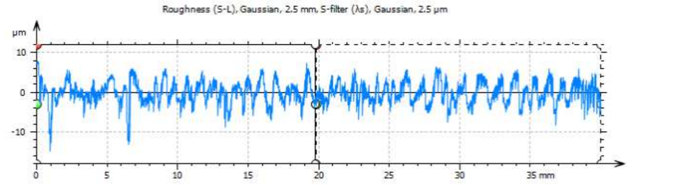
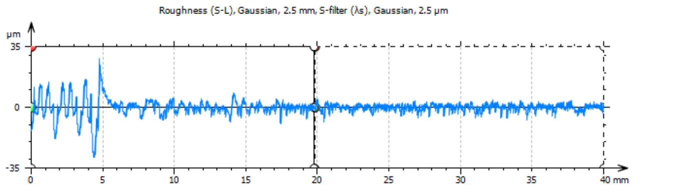
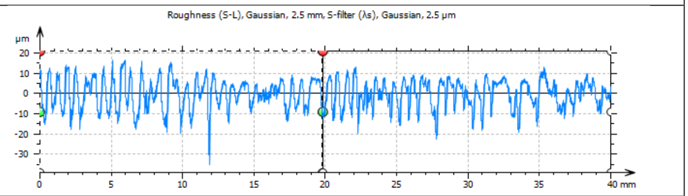
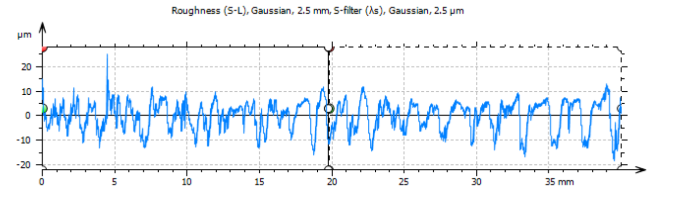
Ø16 Drilling Varied

Expt.	Complete Profile
1 (-,-,-) Sample22	
2 (+,-,-) Sample20	
3 (-,+,-) Sample16	
4 (+,+,-) Sample17	
5 (-,-,+) Sample19	
6 (+,-,+) Sample18	
7 (-,+,+) Sample15	
8 (+,+,+) Sample21	

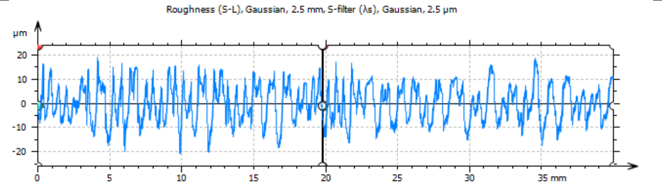
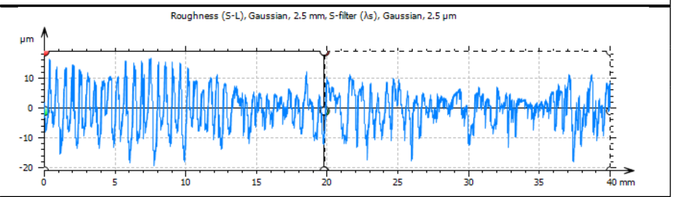
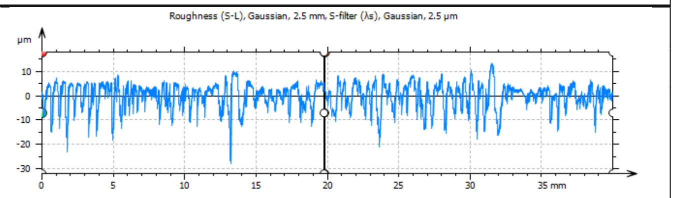
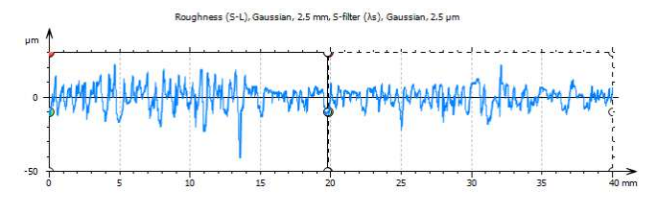
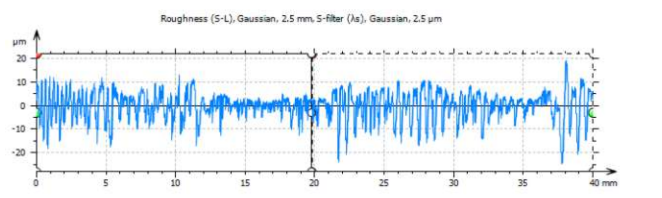
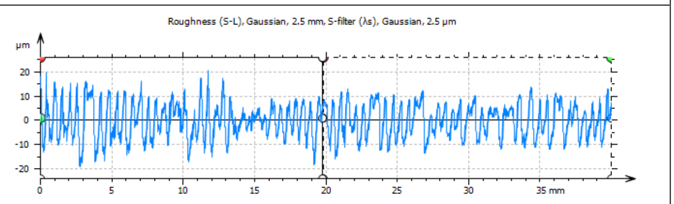
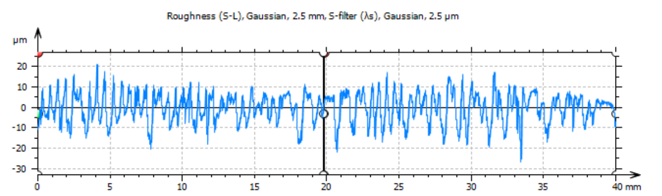
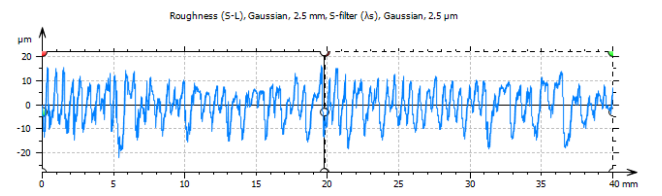
Ø16 Drilling Constant

Expt.	Complete Profile
1 (-,-,-) Sample22	
2 (+,-,-) Sample20	
3 (-,+,-) Sample16	
4 (+,+,-) Sample17	
5 (-,-,+) Smple19	
6 (+,-,+) Sample18	
7 (-,+,+) Sample15	
8 (+,+,+) Sample21	

Ø12 Drilling Varied

Expt.	Complete Profile
1 (-,-,-) Sample22	
2 (+,-,-) Sample20	
3 (-,+,-) Sample16	
4 (+,+,-) Sample17	
5 (-,-,+) Sample19	
6 (+,-,+) Sample18	
7 (-,+,+) Sample15	
8 (+,+,+) Sample21	

Ø12 Drilling Constant

Expt.	Complete Profile
1 (-,-,-) Sample22	
2 (+,-,-) Sample20	
3 (-,+,-) Sample16	
4 (+,+,-) Sample17	
5 (-,-,+) Sample19	
6 (+,-,+) Sample18	
7 (-,+,+) Sample15	
8 (+,+,+) Sample21	

Annex G: Code Extractions from the Proposed System

In the Figures 46 and 47 it can be seen the consistency in the use of the name of the operations.

```
##################################################################
### NEW PARAMETERs FOR THE EXPERIMENTs AND OPERATIONS SELECTED ###
### NOT VALID FOR CHANGE PARAMETER YET .....................   ###
##################################################################


for elem in data_json:
        if int(elem[-1]) == experiment:
            operations = list(data_json[elem])
            for op in operations[:12]:

                if op == "16MM_DRILLING_VARIED" or op =="12MM_DRILLING_VARIED" or

                    print_nx("\n Operation Type: holeDrilling")
```

Figure 46: Extraction from DOE_Plugin to change the operation parameters

```
import json


### Generator of the database for the DoE last CAM files###

doe_database = {'Experiment_1':{'16MM_DRILLING_VARIED':{'SS':597,'FR':119,
              'Experiment_2':{'16MM_DRILLING_VARIED':{'SS':895,'FR':179,'CD'
              'Experiment_3':{'16MM_DRILLING_VARIED':{'SS':597,'FR':298,'CD'
              'Experiment_4':{'16MM_DRILLING_VARIED':{'SS':895,'FR':448,'CD'
              'Experiment_5':{'16MM_DRILLING_VARIED':{'SS':597,'FR':119,'CD'
              'Experiment_6':{'16MM_DRILLING_VARIED':{'SS':895,'FR':179,'CD'
              'Experiment_7':{'16MM_DRILLING_VARIED':{'SS':597,'FR':298,'CD'
              'Experiment_8':{'16MM_DRILLING_VARIED':{'SS':895,'FR':448,'CD'
}
```

Figure 47: Extraction from JSON program with the DOE values per experiment and operation