**UNIVERSITY OF KASDI MERBAH OUARGLA**

**Faculty of Applied Sciences**

**Mechanical Engineering Department**


**A THESIS SUBMITTED TO OBTAIN THE DIPLOME OF**

Master of Science and Technology

In Mechanical Engineering

Field: Mechanical Manufacturing & Production

**By**


KORICHI Elhadj Mohamed & NECIB Mounir


**Title**

# Numerical study of the effect of EDM machining parameters on the quality of machined surfaces

Publicly discussed on 21/06/2022 by the jury

| | | | |
|---|---|---|---|
| ABDELKRIM Mourad | M.C.A | Kasdi Merbah University Ouargla | President |
| BELLOUFI Abderrahim | Professor | Kasdi Merbah University Ouargla | Rapporteur |
| GUEBAILIA Moussa | M.C.A | Kasdi Merbah University Ouargla | Examiner |

**Academic year: 2021 / 2022**

# *Dedication*

*We dedicate this modest work to those who have enlightened me the way of wisdom and give me all that is dear in life with a immense generosity and tender affection.*

*To you, my dear mother, and to you, my dear father.*

*To my family.*

*To all my friends and colleagues.*

*To all those who have helped me*

# *Appreciation*

*We thank God for giving us health, patience and courage throughout the work.*

*We want to thank warmly our thesis director, Professor. BELLOUFI Abderrahim. Thank you for your listening, your advice and your encouragement which have been invaluable to us in carrying out this work.*

*We would like to thank with greater gratitude Dr. ABDELKRIM Mourad For the interest in this work.*

*And for the honor he bestowed on us in presiding over the jury.*

*Our thanks also go to: Dr. GUEBAILIA Moussa For agreeing to evaluate this work and be part of the jury.*

*Finally, thank you to all the teachers of KASDI MERBAH OUARGLA University.*

*And all our colleagues.*

*KORICHI Elhadj Mohamed*

*NECIB Mounir*

# Table of contents

Chapter II
# Modelling methods



Chapter III
# Results & discussion

# Figures

Chapter I

## Background



Chapter II

## Modelling methods

Chapter III

# Results & Discussion

# Tables

Chapter II

## Modelling methods



Chapter III

## Results & Discussion

# Nomenclature

| Symbol | Unit | Appointment |
| --- | --- | --- |
| $Ra$ | $\mu$m | Roughness |
| $EDM$ | | Electrical Discharge Machining |
| $Ton$ | $\mu s$ | Time pulse on |
| $Toff$ | $\mu s$ | Time pulse off |
| $V$ | $volt$ | Voltage |
| $MRR$ | $mm^3$ / min | Material Removal Rate |
| $SR$ | $\mu$m | Surface Roughness |
| $DC$ | | Cycle of service |
| RSM | | Surface response method |
| Sumsq | | Sum of squares |
| $DF$ | | Degrees of Freedom |
| $SCT$ | | Sum of total squares |
| $SCE$ | | Sum of squares explained |
| $SCR$ | | Sum of residual squares |
| CCD | | Central Composite Design |
| $Y, Y_{pred}$ | | Predicted values |
| $ANOVA$ | | Analysis of variance |
| $X$ | | The model term matrix evaluated at the design points |
| $x$ | | Reduced (coded) centered prediction variables |
| $\bar{y}$ | | Average of the responses |
| ε | | Total error which is the difference between the observed values and the estimated values of the response |

# *General introduction*

# General introduction

The manufacture by removal of material is the subject of many studies because it I one of the most used processes in the mechanical industries. As a result, manufacturing technologies are constantly evolving to maintain their high levels of performance and their ability to meet new industrial demands in terms of quality and productivity.

With industrial and technological growth, the use of hard materials is increasing in various sectors, so the extraction of these materials becomes very difficult and expensive. Thus, it is necessary to replace traditional machines with modern ones [37].

Recently, the mechanical industries have placed a strong demand on unconventional manufacturing processes that can be used to produce high-strength and durable materials. Electro-erosion (EDM) is a non-traditional technology that removes materials from a part through a series of electrical sparks that form between the part and the cutting tool in the presence of a dielectric liquid.

EDM is one of the most important manufacturing processes for using solid materials that are difficult to use with traditional methods. Currently, EDM is the most appropriate method to treat these materials.

The formation of EDM sparks is a common treatment procedure, in which the spark between the electrode and the workpiece melts the material locally during the EDM process. The insulating fluid then expels the partially melted material [7]

The complex mechanisms of the EDM processing process make it difficult (experimentally) to determine the formula that links the process input parameters to the machining performance. It is possible to solve by modelling the process. This solves parameter selection problems and reduces the cost of the process.

The brief is divided into three chapters:

The first chapter is a bibliographical overview of the EDM process and the variables that influence it.

The second chapter presents the different modelling methods: multiple linear regression, simple linear regression and the method of response surfaces. These methods will then be used in the third chapter to model machining performance

The third chapter deals with the presentation, discussion and comparison of the different results obtained from the three modelling systems. The results found will be confirmed and validated by confirmation tests.

Chapter I

# *Generality in EDM machining*

## I.1 Introduction

Non-traditional machining processes are called advanced manufacturing processes since they are established in modern industries. These machining processes utilize various energies such as mechanical, thermal, electrical or chemical or combinations of these energies to remove extra material. In addition, non-traditional machining processes do not use sharp cutting tools.

Traditional machining processes such as turning, drilling, shaping and milling are not proper techniques to machine extremely hard and brittle materials. Traditional machining processes may have many difficulties in machining such materials. In machining extremely hard and brittle materials, conventional processes may not be feasible, satisfactory or economical due to the following characteristics:

- The tool is harder than work piece.
- There is a direct mechanical contact between the tool and the work piece.
- It is difficult to machine complicated shapes and obtain close tolerances.

Thus, non-conventional processes are applied instead of conventional methods for extremely hard and brittle materials [1].

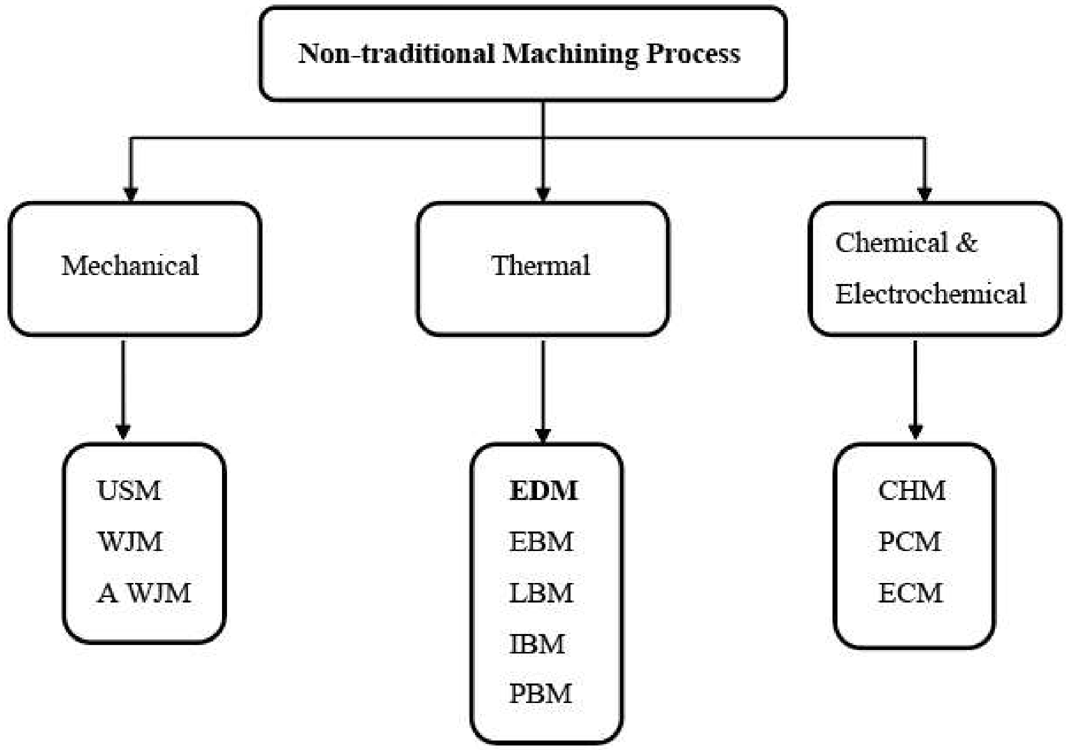



**Figure I.1** *Classification of Non-traditional Process Machining [1]*

In this chapter we will present a bibliographic synthesis. After some definitions and a brief historical introduction, we will present the physical phenomenon of basis of the machining process.

## I.2 Electrical discharge machining (EDM)

The history of EDM Machining Techniques goes as far back as the 1770s when it was discovered by an English Scientist. However, Electrical Discharge Machining was not fully taken advantage of until 1943 when Russian scientists learned how the erosive effects of the technique could be controlled and used for machining purposes [4].

While EDM is commonly thought as a slow manufacturing process, improvements in computer science and measuring and analyzing instruments, combined with constant research of the process, have made possible a better understanding of the material removal process. This has resulted in the enhancement of the machining process, improving machining times, surface quality and widening the application fields. This way, in recent years, EDM has become a competitive solution in a wide range of part jobs [5].

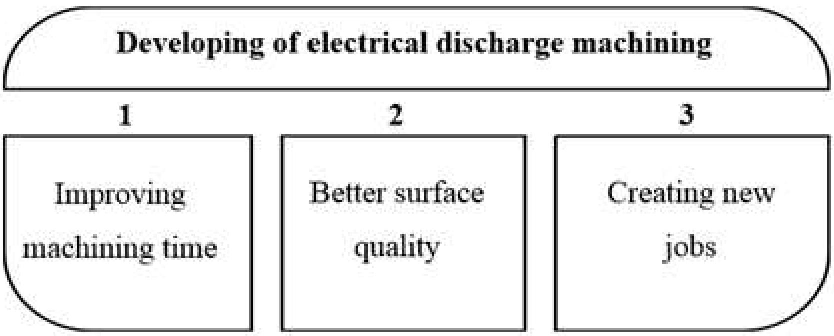



**Figure I.2** *EDM solutions*

Electric discharge machining (EDM) is defined as the removal of material by electric discharges between two electrodes (workpiece and tool) in a dielectric fluid. The material removal takes place by non-stationary electric discharges (sparks) which are separated from each other both spatially and temporally [2].

The material removal mechanism is a very complex phenomenon which involves many physical processes. Figure I.3 shows a scheme of the removal mechanism. A detailed explanation of EDM process [5].

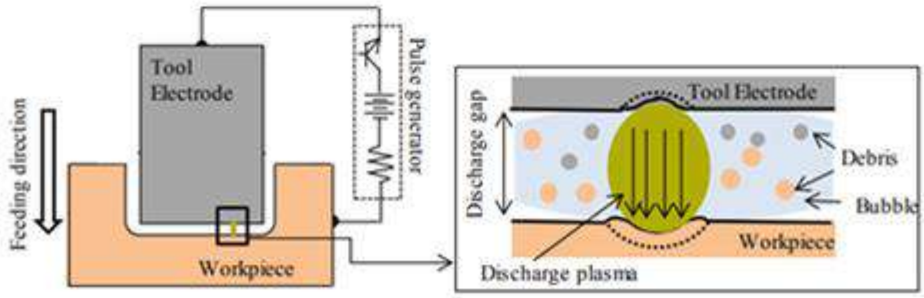



**Figure I.3** *Scheme of the material removal mechanism [5].*

## I.3 Principle of EDM

Electrical discharge machining is a process that uses electrical discharge from an electrode to erode an electrically conductive material, as a result, it is possible to erode or burn the shape of the electrode into the workpiece.

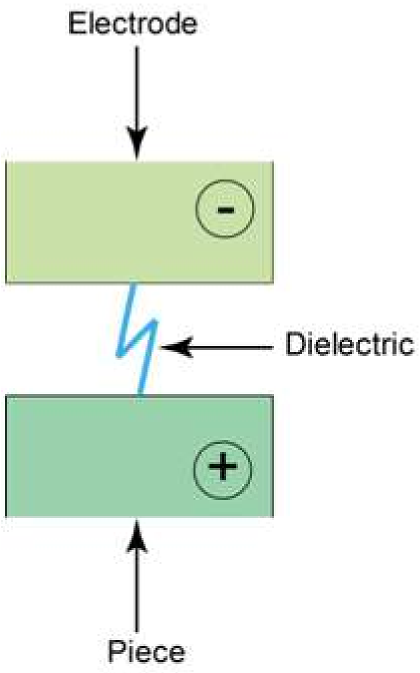



**Figure I.4** *Electrical discharge machining principle*

EDM spark erosion is the same as having an electrical short that burns a small hole in a piece of metal it contacts. With the EDM process both the workpiece material and the electrode material must be conductors of electricity. The EDM process can be used in two different ways:

a. A preshaped or formed electrode (tool),usually made from graphite or copper, is shaped to the form of the cavity it is to reproduce. The formed electrode is fed vertically down and the reverse shape of the electrode is eroded (burned) into the solid workpiece.

b. A continuous-travelling vertical-wire electrode, the diameter of a small needle or less, is controlled by the computer to follow a programmed path to erode or cut a narrow slot through the workpiece to produce the required shape [6].

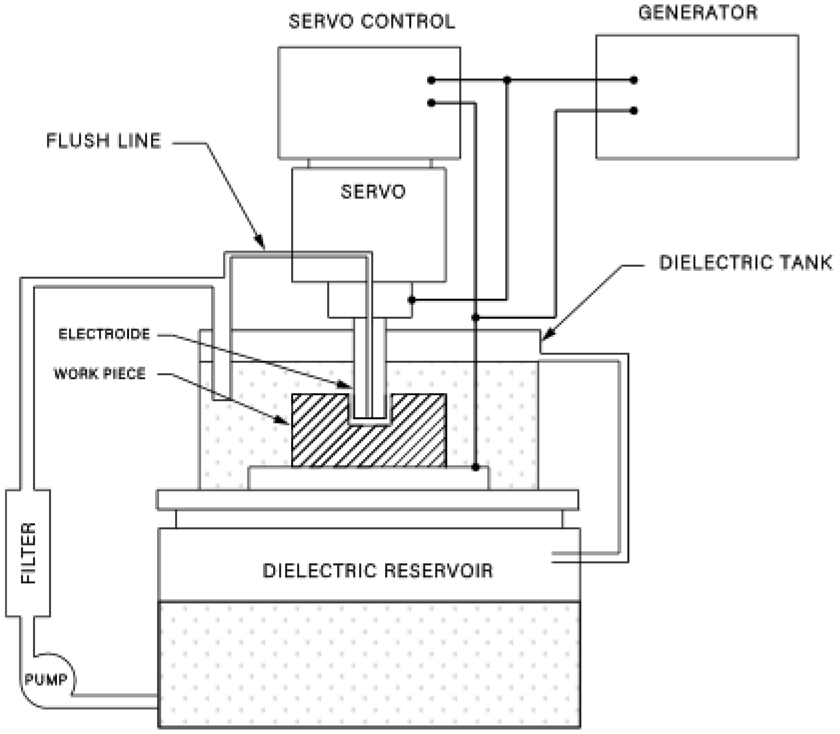



**Figure I.5** *Set up of Electric discharge machining*

The drawing is a schematic of a typical EDM system, an EDM system is comprised of a generator, also known as a power supply, a servo system (servo and servo control), a dielectric tank, and filtration system.

The workpiece is placed in the dielectric tank and affixed to a metal plate in the tank, the tank is filled with a hydrocarbon dielectric fluid (such as kerosene), which ionizes in the presence of an electrical field, the dielectric fluid breaks down electrically, after a short ionization period, assuming the electrical field intensity is high enough, the electrical field is created by applying a voltage between the electrode and the workpiece.

The servo system maintains the appropriate separation of the electrode and workpiece as determined by the the operator setting the desired gap voltageon the EDM generator.

The gap voltage feeds back to the servo control system so that the proper separation of the electrode and workpiece may be maintained [3].

## I.4 Electrical discharge machining mechanism

The material removal mechanism of the EDM process is the most is the conversion of electrical energy into thermal energy. During the machining process, sparks are produced between the part and the tool. The erosion being produced by electric shocks, the electrode and the part must be electrically conductors [7].

EDM machining is performed in a dielectric liquid between the electrodes a voltage which is greater than breakdown voltage, fixed by the insulating power of the dielectric and the distance of the electrodes, three phases are observed:

### I.4.1 Initiation of the discharge

Called the ionization phase under the action of the electric field, it is formed by ionization dielectric, a conductive channel between the two electrodes.

Ionization occurs where the electric field reaches an intensity maximum. This ionization phase corresponds to the dielectric rupture and lasts only a very short time (10 to 100 ns) compared to the discharge.

The conductor channel consists of a plasma, gas that undergoes very high temperature ionization (3,000 to 12,000 K). This plasma consists of metal atoms evaporated at the electrodes, M ions and electrons. These particles are created by violent shocks to atoms raised to high temperatures, this high temperature resulting from the heating itself of the medium caused by the shocks between particles and atoms [8].

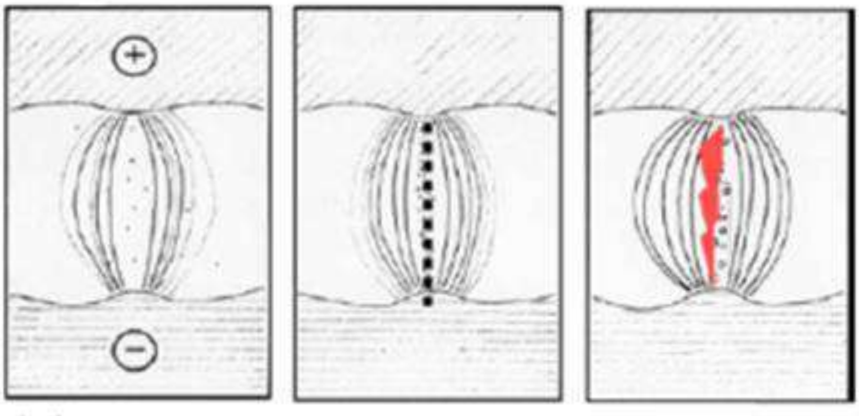


**Figure I.6** *Ionization [8]*

### I.4.2 Discharge phase

During the discharge phase (Figure I.7), a high current flow through the plasma channel and produces high temperature on the electrode surfaces. This creates very high pressure inside the plasma channel creating a shock wave distribution within the dielectric medium. The plasma channel keeps continuously expanding and with it the temperature and current density within the channel decreases. Plasma channel diameter stabilizes when a thermal equilibrium is established between the heat generated and the heat lost to evaporation, electrodes and the dielectric. This enlarged channel is still under high pressure due to evaporation of the liquid dielectric and material from the electrodes. The evaporated material forms a gas bubble surrounding the plasma channel. During this phase, high energy electrons strike the workpiece and the positively charged ions strike the tool (for negative tool polarity). Due to low response time of electrons, smaller pulses show higher material removal from the anode whereas, longer pulses show higher material removal from the cathode [8].

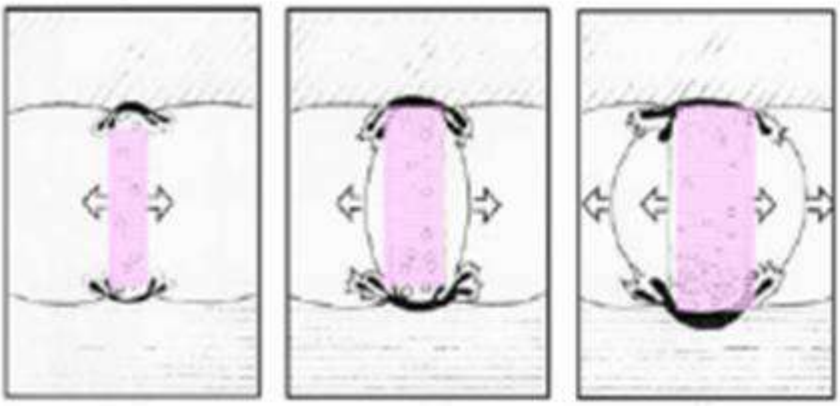


**Figure I.7** *Discharge phase [8].*

### I.4.3 Interval phase

The plasma channel de-ionizes when power to the electrodes is switched off. The gas bubble collapses and material is ejected out from the surface of the electrodes in the form of vapors and liquid globules.

The evaporated electrode material solidifies quickly when it comes in contact with the cold dielectric medium and forms solid debris particles which are flushed away from the discharge gap.

Some of the particles stay in the gap and help in forming the particle bridges for the next discharge cycle. Power is switched on again for the next cycle after sufficient de-ionization of dielectric has occurred. The steps in the phase are shown in Figure I.8

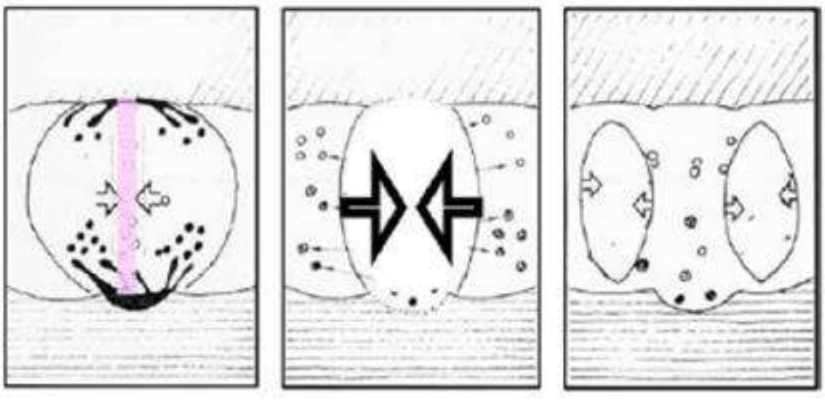


**Figure I.8** *Interval phase [8]*

## I.5 Electrical discharge machining types

Before getting to know EDM machine, start with understanding the type of EDM machine, EDM can be divided into three common types: wire EDM, sinker EDM, and hole drilling EDM.

### I.5.1 Wire Cutting Electrical Discharge Machining

The use of thin wires to cut objects can also be referred to as wire erosion, wire burning EDM. In this type, the wire is used as an electrode, and the wire is continuously fed from the automatic feed with the spool during processing. If you need to carry out the cutting process in the middle of the object, you can use the small hole to drill the EDM to punch the object, then pass the wire through the hole, further electric discharge machining, the wire can be fixed by the diamond guide, the liquid is used Ionized water, while wires are usually made of brass or copper [9].

Wire-cutting EDM is commonly used when low residual stresses are desired, because it does not require high cutting forces for removal of material. If the energy/power per pulse isrelatively low (as in finishing operations), little change in the mechanical properties of a material is expected due to these low residual stresses, although material that hasn't been stress relieved can distort in the machining process. Due to the inherent properties of the process, wire EDM can easily machine complex parts and precision components out of hard conductive materials [4].

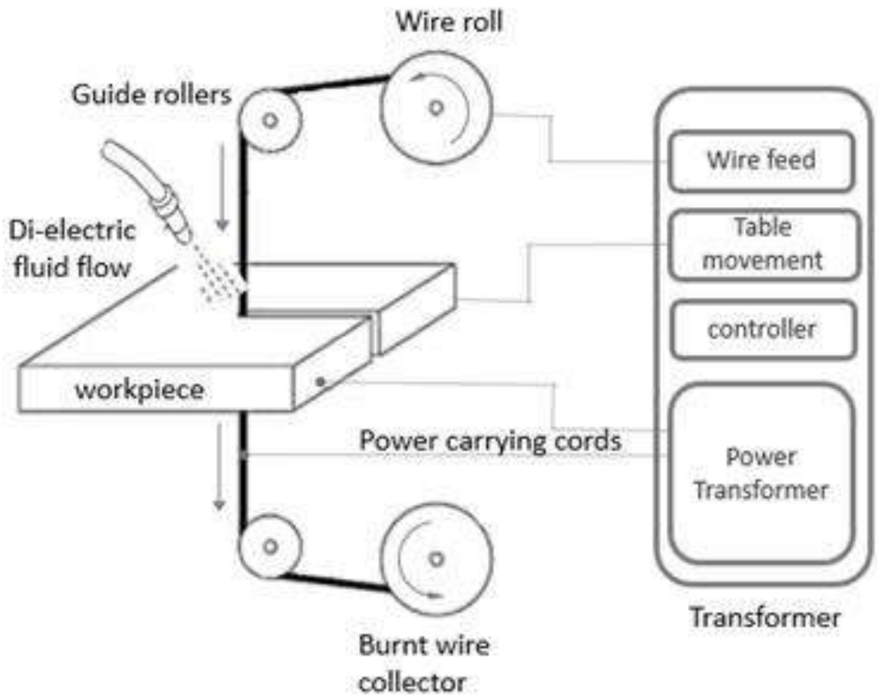



**Figure I.9** *line diagram of wire cut EDM process*

### I.5.2 Sinker Discharge Machining

The sinker EDM, also known as a die, traditional EDM or Ram EDM. The use of die EDM allows the user to produce complex shapes. This method requires the electrode (usually made of graphite or copper) to be pre-machined into the desired shape and then the electrode is sunk into the article to form a negative of its original shape [9].

In the Sinker EDM Machining process, two metal parts submerged in an insulating liquid are connected to a source of current which is switched on and off automatically depending on the parameters set on the controller. When the current is switched on, an electric tension is created between the two metal parts. If the two parts are brought together to within a fraction of an inch, the electrical tension is discharged and a spark jumps across. Where it strikes, the metal is heated up so much that it melts. Sinker EDM, also called cavity type EDM or volume EDM consists of an electrode and workpiece submerged in an insulating liquid such as, more typically, oil or, less frequently, other dielectric fluids. The electrode and workpiece are connected to a suitable power supply. The power supply generates an electrical potential between the two parts. As the electrode approaches the workpiece, dielectric breakdown occurs in the fluid, forming a plasma channel, and a small spark jump [9].

These sparks usually strike one at a time because it is very unlikely that different locations in the inter-electrode space have the identical local electrical characteristics which would enable a spark to occur simultaneously in all such locations. These sparks happen in huge numbers at seemingly random locations between the electrode and the workpiece. As the base metal is eroded, and the spark gap subsequently increased, the electrode is lowered automatically by the machine so that the process can continue uninterrupted. Several hundred thousand sparks occur per second, with the actual duty cycle carefully controlled by the setup parameters [9].

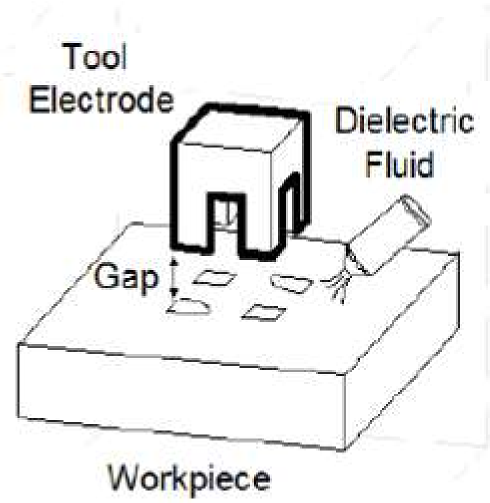



**Figure I.10** *Line diagram of sinker EDM machining*

### I.5.3 Hole Drilling Electric Discharge Machining

Drilling EDM, this process is used for drilling, and the EDM is capable of machining very small deep holes compared to conventional drilling methods. Besides, EDM drilling does not require any debarring. During this process, the electrodes are tubular and the dielectric fluid is fed through the electrodes themselves.

Usually, each conductive material can be processed by electrical discharge machining. Common materials include metals or metal alloys such as hardened steel, titanium, and composites. Typically, the electrodes for the electrospray EDM are made of copper or graphite. The main factors affecting the determination of the electrode material are the conductivity of the electrode and its corrosion resistance. The advantage of graphite is that it is easier to process than copper. However, copper has high electrical conductivity and strength. Brass is a copper and zinc alloy commonly used for wire EDM or small tubular electrodes. In contrast to the electrodes used for sinking, the wires used for EDM do not have to have good electrical resistance properties because new wires are continuously fed during the cutting process [9].

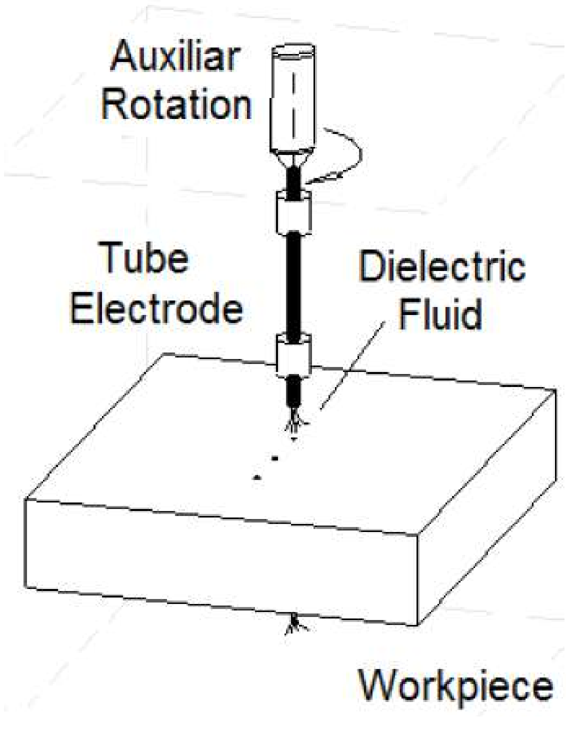



**Figure I.11** *Hole drilling electric discharge machining*

## I.6 EDM applications

The applications of electro-discharge machining (EDM) reside mainly in the mould and die industry, mainly when they are too hard to machine (with conventional techniques such as milling or turning).

This section presents some of the EDM applications commonly found in the industry. It includes also other experimental interests offering a possible expansion of applications EDM.

### 1.6.1 Injection Molding

Achieving the right dimension, depth, and shape of a mold is usually dependent on EDM. It is the major injection molding process used by mold manufacturers. Wire EDM is the main type used in this case.

Since injection molding requires various delicate and complex workpieces, this is usually the best method to use. Moreover, it often produces high precision and fine EDM surface finish [11].

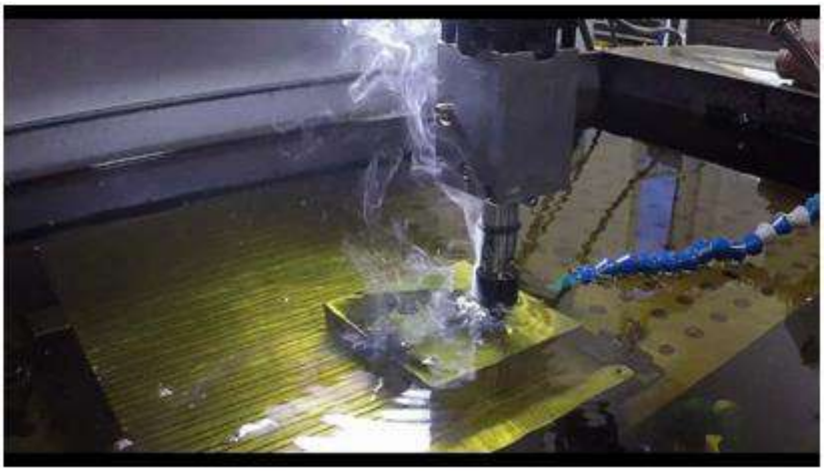


**Figure I.12** *Injection molding by EDM procedure [11]*

### I.6.2 Small hole drilling

Electrical discharge machining is a quick and unique way to create accurate deep small holes drilling in materials, regardless of their hardness.

The hole drilling process involves using a brass electrode tube to channel the electrical discharges onto the material. This helps to create holes of various small dimensions. The exciting thing is that it can make holes on inclined faces and other challenging positions [11].

***Figure I.13*** Small hole drilling [11]

### I.6.3 Die casting

EDM is also very suitable for die-making applications. Manufacturing highly tailored dies require extreme accuracy. These dies feature sharp internal corners, deep ribs, and other intricate features.

Also, dies are often made from very hard steel alloys. These alloys are usually harder to machine with traditional methods. The hard steel alloys may require finishing prior to heat treatment, which may reduce the accuracy of details. Therefore, employing the EDM process is more appropriate [11].

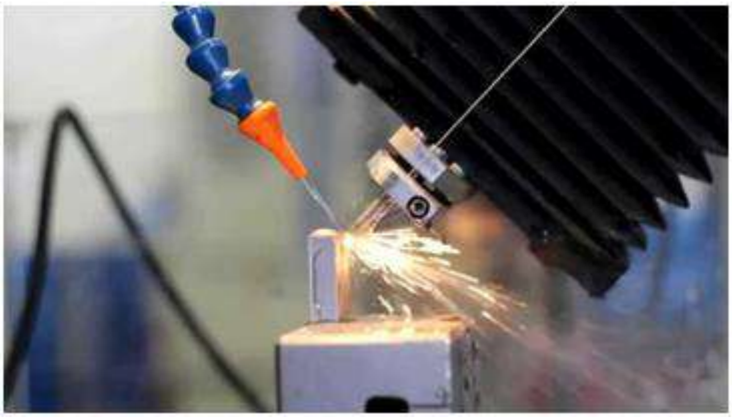


**Figure I.14** *Die casting application [11]*

## I.7 Parameters affecting electro erosion machining

Many attempts have been made by researchers to optimize these process parameters such as discharge current (Ip), activation time of pulses (Tone), pulse downtime (Toff) and open circuit voltage (V) for minimize SR and EWR and simultaneously improve the MRR. In general, the machining parameters are selected based on the experience of the operator or data provided by EDM machine manufacturers. When such information is used in electric discharge machining, machining performance is not consistent. The data provided by manufacturers regarding parameter settings does not are useful only for the most commonly used steels. The optimization of the parameters of EDM process becomes difficult due to the greater number of machining variables and slight changes in a single parameter significantly affect the process. The important parameters affecting the machining process can be divided into two categories, the electrical and non-electric parameters they are classified in the figure I.15 [7].

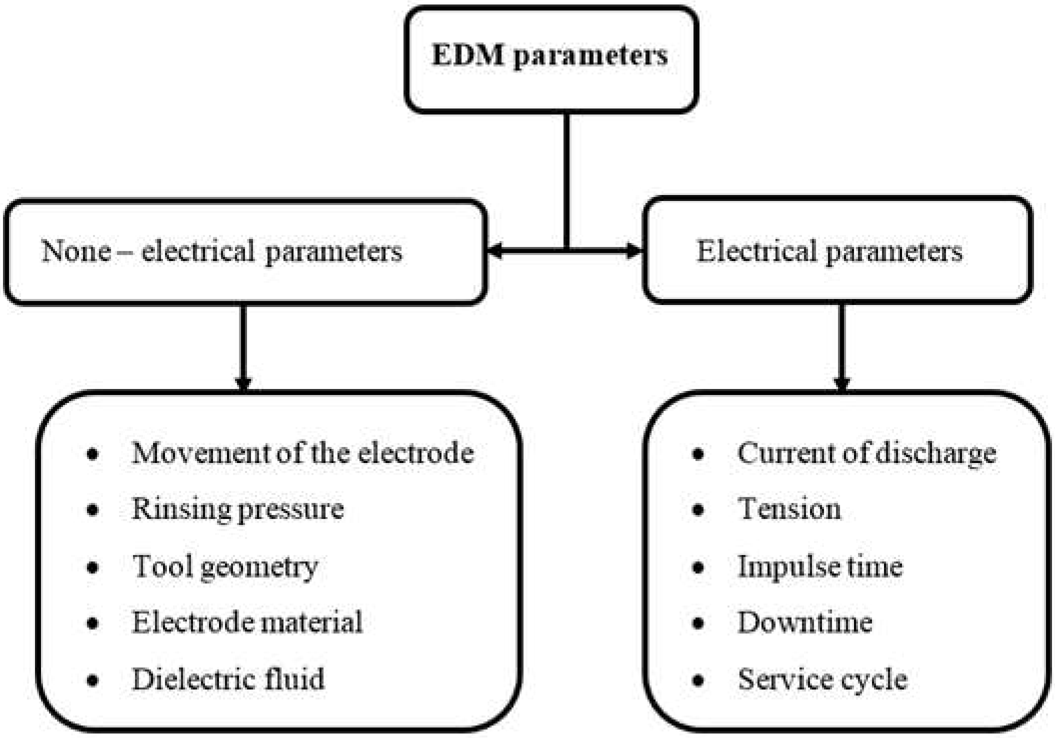



**Figure I.15** *EDM parameters [7]*

### I.7.1 Electrical parameters

The main electrical parameters are the discharge voltage, the discharge, pulse duration and interval, polarity, The discharge voltage is related to a spark gap and the breaking force of the dielectric fluid. The voltage at vacuum before increase of electric shock [7].

#### a) Spark On-time (pulse time or Ton)

The duration of time (μs) the current is allowed to flow per cycle. Material removal is directly proportional to the amount of energy applied during this on-time. This energy is really controlled by the peak current and the length of the on-time.

#### b) Spark Off-time (pause time or Toff)

The duration of time (μs) between the sparks (that is to say, on-time). This time allows the molten material to solidify and to be wash out of the arc gap. This parameter is to affect the speed and the stability of the cut. Thus, if the off-time is too short, it will cause sparks to be unstable.

#### c) Arc gap (or gap)

The Arc gap is distance between the electrode and workpiece during the process of EDM. It may be called as spark gap. Spark gap can be maintained by servo system.

**d) Discharge current (current Ip)**

Current is measured in amp Allowed to per cycle.Discharge current is directly proportional to the Material removal rate.

**e) Duty cycle (τ)**

It is a percentage of the on-time relative to the total cycle time. This parameter is calculated by dividing the on-time by the total cycle time (on-time pulse off-time).

$$\tau = \frac{Ton}{Ton + Toff} \tag{I.1}$$

**f) Voltage (V)**

It is a potential that can be measure by volt it is also affect to the material removal rate and allowed to per cycle. Voltage is given by in this experiment is 50 V. [4].

### I.7.2 Non – Electrical parameters

**a) Electrode rotation**

This is the speed of rotation of cylindrical or tool electrodes disk, measured in rpm. Generally, the rotation axis of the tool electrode is normal on the surface of the part and depends on the shape of the tool electrode. The increase in the tool’s electrode speed generates a higher centrifugal force which results in a faster removal of debris from the machining space, improving stability and machining performance

**b) Rinsing pressure**

Rinsing the dielectric during the sparking process has a negative effect on the EDM performance measures. Lonardo and Bruzzone revealed that the rinsing during the draft operation affected the MRR and TWR, while in the finish, it influenced the SR. The rinsing rate also influences the density of cracks and the recast layer, which can be minimized by obtaining an optimal rinsing rate.

**c) Tool geometry**

La géométrie de l'outil est liée à la forme des électrodes de l'outil, à savoir carré, rectangle, cylindrique, circulaire, etc. Le rapport longueur / diamètre de tout matériau façonné. En cas d'électrode à disque rotatif, le rapport devient épaisseur / diamètre. L'outil ayant moins de rapport d'aspect a donné une valeur plus élevée d’EWR.

**d) Tool material (electrode)**

Engineering materials with thermal conductivity and a melting point more can be used as a tool material for the EDM process. Copper, the graphite, copper-tungsten, silver tungsten, graphite and brass are some tool electrode materials (electrode) used in the EDM. [7].

## I.8 Literature review

An in-depth study of the literature was carried out for the various works on the improvement of the quality of the surfaces machined by EDM

**T. R. Ablyaz and D. A. Borisov (2017)** [12] Evaluate the influence of the surface roughness of the electrode tool on the productivity in electric discharge machining of 38Х2Н2МА steel by means of laboratory experiments, they used electrode tools with different roughness of the working surface, The machining time is determined on the basis of monitoring of the machine time of the Smart CNC. The machining depth is measured by means of a Carl Zeiss Contura G2 instrument. Each experiment is repeated three times, as a result, Ablyaz & Borisov reach a conclusion that In the finishing of 38Х2Н2МА steel by electric discharge machining (code E13), there is no need to use electrode tools with surface microprojections shorter than 1.1 μm in order to ensure that the roughness of the machined surface corresponds to microprojections of height 1.1‑1.6 μm, also the manufacture of electrode tools with microprojections shorter than 1.1 μm on the working surface is uneconomical.

**Y.S. Liao & al. (2004)** [23] designed a pulse generator circuit by removing the high voltage discharge of the original circuit. They found that a generator circuit DC pulse of positive polarity can provide a better surface roughness. They have done an experiment by varying different parameters such as voltage, current, capacity, appropriate values were chosen and a roughness of area of 0.22 μm is obtained.

**Rebelo & al. (2000)** [24] submitted an experimental study on the effect of EDM on material removal rate (MRR) and surface quality during machining high-strength copper/beryllium alloys. The processing parameters for rough, finishing and micro-finishing or polishing regimes were analyzed.

**J.C. Rebelo et al. (1998)** [25] conducted an experiment on the ROBOFORM 200 - «Charmilles» using martensitic steel as a workpiece. They varied the time and current. Many experimental techniques have been used to assess surface integrity. They found that the penetration and depth of cracks in the recast layer increase with the current, a white layer of cementation formed at the white layer and various heat-affected areas have been observed, as a function of the machining energy. The residual stress of a tensile nature is equally determined.

**Boujelbene et al. (2009)** [26] conducted experiments on two landfill machines to obtain a high surface condition and other aspects of machining. By making experiments, they discovered that when the discharge energy increased, the pulse increased, the surface became rougher and the thickness of the white layer increased. This happens because of the melting and re-melting of the material.

**Payal (2008)** [27] studied the effect of material removal parameters on the roughness of surface (Ra) for structural analysis of affected surfaces. Work on tools in copper, brass and dielectric fluid with kerosene as graphite electrode were made on a tool steel N-31. A detailed analysis of the structural features with machined surface scanning electron microscope (SEM) and optical microscope was performed using the Electroerosion Machining (EDM) mode by surface micrography, understanding that the mass surface samples melted have been removed from different electrode mist.

**Lin & al. (2008)** [28] studied the effect of discharge energy on the machining of cemented carbide using an electrolytic copper electrode. The EDM machining parameters have been varied in order to explore the effects of the electric discharge on machining characteristics, such as MRR, EWR and roughness of the surface. In addition, the effects of electric discharge energy on the affected layers thermically, surface cracks and machining debris have also been determined.

The experimental results show that MRR increases with the energy density of electric discharge.

**K.M. Patel & al. (2007)** [29] studied the machining characteristics, integrity of the surface and material removal mechanism of Al2O3-SiCw-Tic with EDM. They have concluded that the surface roughness and reclining layer increased with the current and time the pulse. The material is removed due to melting and evaporation by dissociation and, to some extent, current oxidation and decomposition reduced and higher current thermal spelling.

**Hwa -Teng Lee et al. (2004)** [30] experimented and found that the value of MRR and surface roughness increased with increasing current values pulsed, but after certain values, MRR and Ra decreased due to dilation electric plasma. The pulse current affects the surface crack density while the pulse duration influences the degree of crack opening. The residual stress induced by the drilling of holes increases with the increasing values of the pulsed current and the pulsed time.

**Avinash Sarode & al. (2016)** [31] evaluated the effect of the material and geometry of electrode in EDM performance for OHNS steel dies. In this experiment the EDM machine and the copper and brass electrodes were used for the machining of 48 x 48 x 8 mm OHNS steel parts. Input current, time pulse and duty cycle are considered as input parameter and MRR, EWR and surface roughness are considered output parameters. They have concluded that copper is the best electrode material because it gives a better state of surface area, high MRR and less wear of the electrodes, while the brass is close to Statistical Analysis of Variance (ANOVA) is conducted to identify the significant process parameters.

**Muthuramalingam & al. (2015)** [32] presented modelling of the process and the influence of the parameters of the electrical process: the shape of the impulses and discharge energy on performance measures such as material removal rate, surface roughness and electrode wear rate. Based on the results of examination, it was observed that the efficiency of the machining process can be improved by the parameters of the electrical process, and only less attention has been paid to the improvement of these parameters.

**Subramanian Gopalakannan & al. (2012)** [33] evaluated the effect of materials in electrodes: copper, copper-tungsten and graphite on 316 electric discharge machining L and stainless steel 17-4 PH. The input parameter was peak current (Ip). They have observed that the copper electrode gives the best MRR than the graphite, while the copper tungsten gives the lowest MRR value. Copper-tungsten offers electrode wear relatively low. Graphite and copper electrodes produce surface roughness comparatively high.

**Harpuneet Singh (2012)** [34] evaluated the effect of copper, chromium and on the machining of an EN-31 steel on an electric discharge machine using positive polarity. Kerosene is used as a dielectric. Input parameters considered are: current and pulse time and output parameters are: MRR, TWR, the hardness and roughness of the surface. The results indicate that the electrodes surface roughness and better hardness, while the copper-chromium electrodes offer a better MRR with less tool wear. The material removal rate is best for chromed copper at all values of pulsed current. The surface roughness increases with increasing current for aluminum electrode.

**Janmanee & al (2010)** [35] evaluated the effect of different electrode materials in electric discharge machining. The materials used for the electrode were graphite, the copper-graphite and copper-tungsten. The machine used in this study is the machine CNC FORM-2-LC and input parameters are: discharge current, downtime pulse, open circuit time, electrode polarity and output parameters were MRR, EWR, Ra. Graphite electrode gives the best MRR and the best Ra but with a high EWR.

**Zhang et al. (1997)** [36] proposed an empirical model, using both the tip and pulse time, for ceramic machining. They realized that the discharge current had a greater effect on the MRR; while time Impulse has more influence on Ra and the white layer.

## I.9 Conclusion

In this chapter we have presented the principle of the machining process by EDM and we have focused on the different parameters of this process. We presented also a bibliographical synthesis on the work dealing with the problem of selection of EDM machining parameters.

Chapter II

# *Modelling methods*

## II.1 Introduction

As an important subject in the statistical design of experiments, the Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response (Montgomery 2005). For example, the growth of a plant is affected by a certain amount of water x1 and sunshine x2. The plant can grow under any combination of treatment x1 and x2. Therefore, water and sunshine can vary continuously. When treatments are from a continuous range of values, then a Response Surface Methodology is useful for developing, improving, and optimizing the response variable. In this case, the plant growth y is the response variable, and it is a function of water and sunshine. It can be expressed as [15]:

$$y = f(x1, x2) + e \qquad \text{(II.1)}$$

## II.2 Surface response method

Response Surface Methodology, RSM (also known as Response Surface Modeling) is a technique to optimize the response(s) when two or more quantitative factors are involved. The dependent variables are known as responses, and the independent variables or factors are primarily known as the predictor variables in response surface methodology [13].

The objective of Response Surface Methods (RSM) is optimization, finding the best set of factor levels to achieve some goal. This lesson aims to cover the following goals.

The text has a graphic depicting a response surface method in three dimensions, though actually it is four-dimensional space that is being represented since the three factors are in 3-dimensional space the the response is the 4th dimension [14].

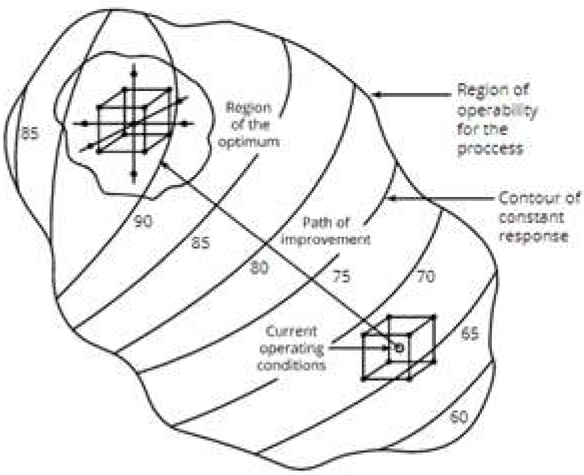



**Figure I1. 1** *The sequential nature of RMS [14]*

### II.2.1 Principal of surface response method

In the general case, the response surface is called the geometric representation of the response from a random spatial-temporal physical process to stimuli variables. The property studied, or answer Y, then results from the transfer by an explicit response function, or function of system input variables, changing the values of these variables resulting in a change in the value of the response function.

Experimental models of surfaces of response take into account the choice of stimuli variables, the definition of periods observation and error calculation. Input variables, stimuli representative of the phenomenon, are noted Xi (i = 1, . . ., n), and are also called basic variables of the phenomenon.

They are characterized by a set of statistical information noted θj (j = 1, . . , p) (functions independent or correlated distribution, normalized moments, ...). In the general case, the Xi variables are spatio-temporal processes, called stochastic reduced to vectors random when determining time and space indices

This transfer of stimuli variables can be represented by the diagram in figure II.2.

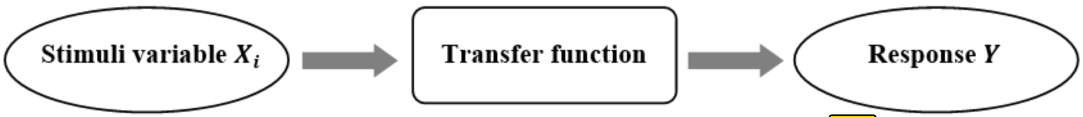



**Figure II. 2** *Diagram of a transfer function*

In general, the explicit form of this transfer function as a function of the base is unknown, and the search for an approximation, called the response function,becomes necessary. Most often, it belongs to a family of linear or non-linear usual functions, characterised by parameters

$$y_k (k = 1....,1) \qquad (II.2)$$

The response function can therefore be formally written as shown in Figure II.3

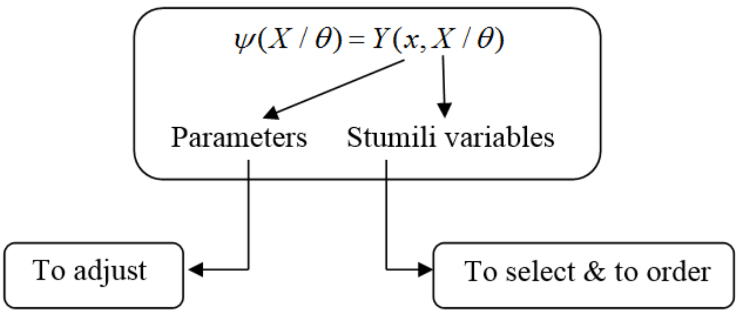



**Figure II. 3** *Formal expression of the response function*

### II.2.2 Surface response methodology steps

1) To determine the factor levels that will simultaneously satisfy a set of desired specifications,
2) To determine the optimum combination of factors that yields a desired response and describes the response near the optimum.
3) To determine how a specific response is affected by changes in the level of the factors over the Specified levels of interest.
4) To achieve a quantitative understanding of the system behavior over the region tested.
5) To predict product properties throughout the region, even for a factor combinations not actually run.
6) To find the conditions necessary for process stability (insensitive spot).

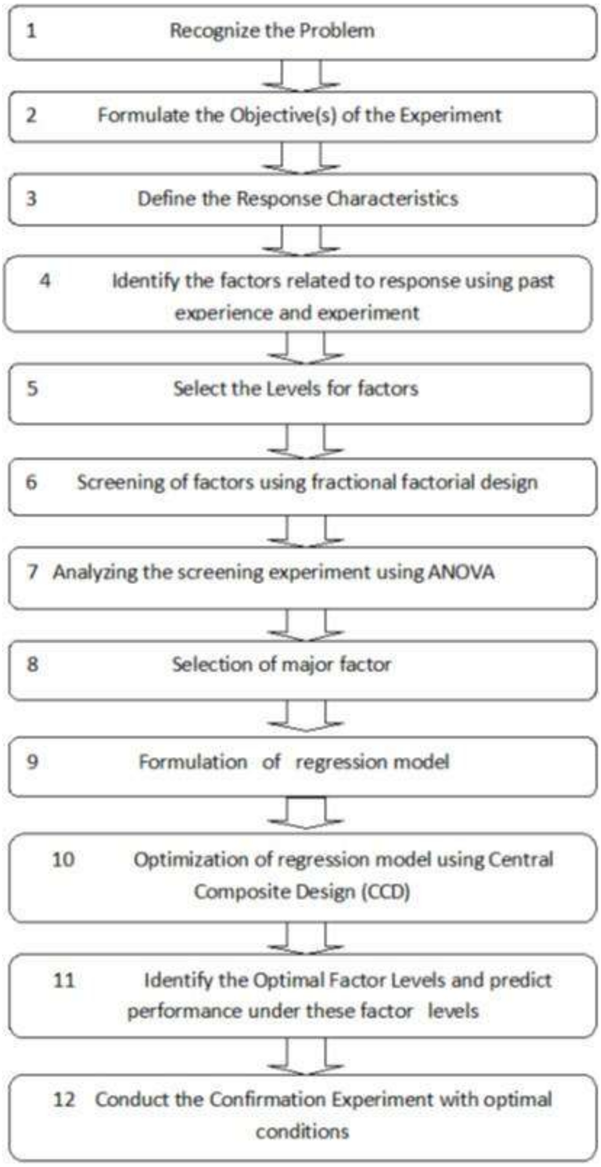



**Figure II. 4** Steps in Response Surface Methodology (RSM)

### II.2.3 First order model

- **Analysis of a First-Order Response Surface**

The relationship between the response variable y and independent variables is unknown. In general, the low-order polynomial model is used to describe the response surface f. The polynomial models are usually a sufficient approximation in a small region of response surface. Therefore, depending on the approximation of unknown function f, either first-order or second-order models are employed [16].

Furthermore, the approximating function f is a first-order model when the response is a linear function of independent variables. The first-order model with N experimental runs is carrying out on q design variables and a single response y as follows:

$$y = \beta_0 + \sum_{i=1}^{q} \beta_i x_i + \sum_{i=1}^{q} \beta_{ii} x_i^2 + x_{ij} x_{ij} + \varepsilon \qquad \text{(II.3)}$$

The response y is a function, f, of the design variables x1, x2,…,xq, plus the experimental error. The first-order model is a multiple-regression model and β i ’s are regression coefficients.

First-order model is used to describe flat surfaces with or without tilted surfaces. This model is not suitable for analyzing maximum, minimum, and ridge lines. Using first-order model approximation of f is reasonable when f is not too curved in that region and the region is not too big. First-order model is assumed to be an adequate approximation of the true surface in a small region of the x’s (Montgomery 2005). Moreover, first-order model indicates which way is up and down in the response. The method of steepest ascent is a procedure in which the algorithm follows the direction to move to increase response the most, which is used to identify a maximum. The method of steepest descent consists in taking the direction of the most quickly decrease in the response, which is used to identify the minimum [16].

- **Designs for Fitting the First-Order Mode**

The design of response surface models starts with the estimation of parameters, pure error, and lack of fit. Also, the experimenter needs to design a model that is efficient. Therefore, estimation of variances has to be taken into consideration. The **orthogonal first-order designs** minimize the variance of the regression coefficients β k . A first-order design is orthogonal if the off-diagonal elements of the (X´X) matrix are all zero (Montgomery 2005). The orthogonal first-order designs includes 2q factorial with center points and 2q-k fraction with resolution III or greater [16].

### II.2.4 Second-Order Model

#### a) Analysis of a Second-Order Response Surface

When there is a curvature in the response surface the first-order model is insufficient. Therefore, second-order model is useful in approximating a portion of the true response surface with curvature. The second-order model includes all the terms in the first-order model, and quadratic and cross product terms. It is usually represented as :

$$y_i = ax_i + b + \varepsilon_i \qquad \text{(II.3)}$$

The second-order models illustrate quadratic surfaces such as minimum, maximum, ridge, and saddle. If there exits an optimum then this point is called stationary point. The stationary point is the combination of design variables where the surface is at either a maximum or a minimum in all directions. If the stationary point is a maximum in some direction and minimum in another direction, then the stationary point is a saddle point (Oehlert 2000). The graphical visualization is very helpful in understanding the second-order response surface as it shown in Figure 3.2. Specifically, contour plots can help characterize the shape of the surface and locate the optimum response roughly [16].

#### b) Designs for Fitting the Second-Order Model

The most popular design for fitting the second-order model is Central Composite Design (CCD). It consists of factorial point (from a 2q design and 2q-k fraction with resolution V or greater), central point, and axial points. CCD often develops through a sequential experimentation. When the first-order model shows an evidence of lack of fit,then axial points can be added to quadratic terms and with more center points to develop CCD. The number of center points m at the origin and the distance α of the axial runs from the design center are two parameters in the CCD design [16].

There are a couple of ways of choosing α and m. First, CCD can run in incomplete blocks. A block is a set of relatively homogeneous experimental conditions so that an experimenter divides the observations into groups that are run in each block. An incomplete block design can be conducted when all treatment combinations cannot be run in each block. In order to protect the shape of the response surface, block effects need to be orthogonal to treatment effects. This can be done by choosing the correct α and m in factorial and axial blocks [16].

Also, α and m can be chosen so that the CCD is not blocked. If the precision of the estimated response surface at some point x depends only on the distance from x to the origin, not on the direction, then the design is said to be rotatable (Oehlert 2000). The rotatable design provides equal precision of estimation of the surface in all directions. The choice of α will make the CCD design rotatable by using eitherα = 2q/4 for the full factorial or α = 2(q−k)/4 for a fractional factorial [16].

In addition to CCD, Box-Behnken design can also be used for designing response surfaces. This model is a combination of 3q factorials with incomplete block designs [17].

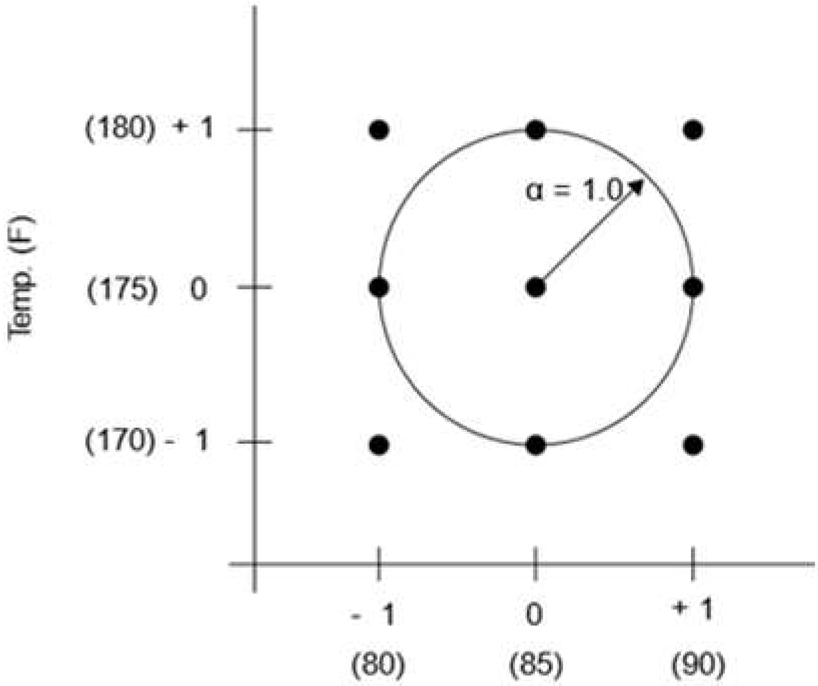



**Figure II. 5** *Two Variables CCF Design [17]*

### II.3 Linear regression

Regression is one of the most well-known and applied statistical methods for the analysis of quantitative data. It is used to link a quantitative variable to one or more other quantitative variables in the form of a model. If we are interested in the relationship between two variables, we will speak of simple regression by expressing one variable as a function of the other. If the relationship is between one variable and several other variables, it is called multiple regression. The implementation of a regression imposes the existence of a cause-effect relationship between the variables taken into account in the model.

The term regression is due to Galton (1886) who then observed the influence of the size of individuals (persons) on their weight. Linear regression is probably the most used statistical method by practitioners of all disciplines: the search for a link between two or more characters is a very common approach in medicine. in psychology. in physics, in economics ...etc.

Linear regression (or linear models) is a statistical tool used to study the presence of a relationship between a dependent variable y (quantitative and conti- nu) and one or more independent variables x1, x2, ..., xp (qualitative and/or quantitative) [18].

### II.3.1 Simple linear regression

Simple linear regression is a statistical technique used to explain and explain and express a random variable y according to a variable x and is used to predict future y values based on x .To describe a linear relationship between two quantitative variables or to predict y for a given value of x, we use a regression line:

$$y_i = ax_i + b + \varepsilon_i \tag{II.5}$$

Since any statistical model is only an approximation (we hope the best possible!!), there is always an error, noted in the model, because the linear link is not never perfect. If there were a perfect linear relationship between y and x, the error term would still be equal to 0, and all the variability of y would be explained by the independent variable x [18].

- ***The hypotheses relating to this model:***

H1: $E(\xi i) = 0, \forall I$ (II.6)

H2: $Var(\xi i) = \sigma^2 i, Cov(\xi i, \xi j) = 0, \forall i$ (II.7)

- ***Parameter Estimation:***

The estimation of the regression parameters is written:

$$y_i = \widehat{b} + \widehat{a}x_i \tag{II.8}$$

We look for $\hat{b}$ and $\hat{a}$ in this equiation which minimalizes the Mean square error $\sum_{i=1}^{n} \varepsilon_i^2$ this method is called Moinder ordinary square we write:

$$(\widehat{a}.b) = \min \sum_{i=1}^{n} \varepsilon_i^2 \tag{II.9}$$

$\widehat{a}.\widehat{b}$ are estimated by:

$$\widehat{a} = \frac{\sum_{i=1}^{n} x_i y_i - n\overline{x}\,\overline{y}}{\sum_{i=1}^{n} x_i^2 - n\overline{x^2}} \quad , \quad \widehat{b} = \overline{y} - \widehat{a}\overline{x} \tag{II.10}$$

- ***The confidence interval:***

Except the assumption that the residues are Gaussian (normal) which means $\varepsilon_i \sim N(0,\sigma^2)$ we have:

$$\frac{(n-2)S_\varepsilon^2}{\sigma_\varepsilon^2} \sim \psi_n^2 - 2 \tag{II.11}$$

$$\frac{\widehat{a}-a}{\sqrt{\mathrm{var}(\widehat{a})}} \sim T_n - 1 \tag{II.12}$$

This one allows to test the hypotheses of millity of a parameter dexes as well as of build confidence intervals of a and b at the confionce level $(1-\alpha)$.

So, the confionce interval of a is $]\widehat{a}-t_{n-2}^{\alpha/2}\sqrt{\mathrm{var}(\widehat{a})};\widehat{a}+t_{n-2}^{\alpha/2}\sqrt{\mathrm{var}(\widehat{a})}[$ , with $t_{n-2}^{\alpha/2}$ :

is order fractile $(1-\alpha/2)$ for the law of student.

The same thing with the interval of $\widehat{b}$ we have:

$$(n-2)\frac{S_\varepsilon^2}{\sigma_\varepsilon^2} \sim \psi_n^2 - 2 \tag{II.13}$$

- ***Model Significance Test:***

Analysis of the quality of the model to evaluate the quality of fit of the model the coefficient of determination R2 is used to define the equation of analysis of variance following:

$$SCT = SCE + SCR \tag{II.14}$$

Where:

$$SCT = \sum_{i=1}^{n}(y_i - \overline{y})^2 \quad \text{(Sum of total squares)} \tag{II.15}$$

$$SCE = \sum_{i=1}^{n}(y_i - \overline{y})^2 \quad \text{(Sum of squares explained)} \tag{II.16}$$

$$SCR = \sum_{i=1}^{n}(y_i - y_i)^2 = \sum_{i=1}^{n}\varepsilon_i^2 \quad \text{(Sum of residual squares)} \tag{II.17}$$

Therefore, the quality of the model is measured by a quantity called coefficient of determination D where:

$$D = \frac{SCE}{SCT} = 1 - \frac{SCR}{SCT} \tag{II.18}$$

This quantity indicates the y percentages explained by x.

- ***Model Validation Test:***

This test measures the total contribution of x on the determination of y donations this cos we want tests the mortgage

$$\begin{cases} H_0 ; a = 1 \\ H_1 ; a \neq 1 \end{cases} \quad \text{(II.19)}$$

The variability indicators are summarized in the variance analysis table below:

***Table 1*** *Validation Test of Variance Analysis Table [18]*

| **Source** | **Degrees of freedom** | **Sum of squares** | **Sum of average squares** | **Stat of Fisher** |
|---|---|---|---|---|
| Model | 1 | $SSM$ | $SSM$ | $F_{cal} = \frac{SSM}{S^2}$ |
| Error | $n-2$ | $SSR$ | $S^2 = \frac{SSR}{n-2}$ | / |
| Total | $n-1$ | $SST$ | $S^2 = \frac{SST}{n-1}$ | / |

We accept $H_0$ if:

$$F_{cal} < f_{(1,n-2)}^{1-\alpha}$$

Where:

$f_{(1,n-2)}^{1-\alpha}$ is the order fractile $(1-\alpha)$ the law of $(1, n-2)$ freedom of expression.

- **The forecast:**

One of the aims of the regression is to forecast, that is to say to predict the variable to explain y in the presence of a new value of the explanatory variable x. Therefore xn+1 a new value, for which we want to predict $y_{n+1}$. The model is always the same:

$$y_{n+1} = \theta_1 + \theta_2 x_{n+1} + \varepsilon_{n+1} \quad \text{(II.24)}$$

With: $E(\varepsilon_{n+1})$ and, $\text{var}(\varepsilon_{n+1}) = 0$, $Cov(\varepsilon_{n+1}, \varepsilon_i) = 0$ for $i = 1, ...., n$. It is natural to predict the corresponding value via the adjusted model:

$$y_{n+1} = \theta_1 + \theta_2 x_{n+1} + \varepsilon_{n+1} \quad \text{(II.25)}$$

Two types of errors will tarnish our prediction: the first is due to non-birth from "n+1, the second to the uncertainty on the estimators [18].

### II.3.2. Multiple linear regression

Multiple linear regression is a generalization of linear regression for its purpose is to study and model the relationship between an explained variable $(y)$ and several variables explanatory notes $(x_1, x_2, ...., x_n)$.

The model of the RLM is written in the form

$$y_i = b_0 + b_1 x_{i_1} + ... + b_p x_{i_p} + \varepsilon_i \tag{II.26}$$

So the matrix form as a result:

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \cdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & x_{12}.....x_{1n} \\ 1 & x_{21} & x_{22}.....x_{2n} \\ \cdots & .... & ............ \\ 1 & x_{n1} & x_{n2}.....x_{nn} \end{pmatrix} . \begin{pmatrix} b_0 \\ b_1 \\ \cdots \\ b_n \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdots \\ \varepsilon_n \end{pmatrix}$$

With: $Y = \begin{pmatrix} y_1 \\ y_2 \\ \cdots \\ y_n \end{pmatrix}$ and $X = \begin{pmatrix} 1 & x_{11} & x_{12}.....x_{1n} \\ 1 & x_{21} & x_{22}.....x_{2n} \\ \cdots & .... & ............ \\ 1 & x_{n1} & x_{n2}.....x_{nn} \end{pmatrix}$ and $\varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdots \\ \varepsilon_n \end{pmatrix}$

The X matrix is the matrix of explanatory variables; Y is observed: it is the vector of the data corresponding to the variable to be explained; but i is unknown (it is even to be estimated and test): it is the vector of the coeficients of the linear relation. On its side, the vector «residues are not observed [18]

- ***Estimation of parameters***: using the MCO method, calculate the statistic

$$\widehat{\theta} = (b_0, b_1, ....b_n)^t \tag{II.27}$$

For minimizing the amount $\varepsilon^t \varepsilon$ , so:

$$\widehat{\theta} = (X^t X)^{-1} X^t Y \tag{II.28}$$

- ***properties of the estimators:***

$$E(\widehat{\theta}) = 0 \text{ (unbiased estimator)} \tag{II.29}$$

$$\operatorname{var}(\widehat{\theta}) = \sigma^2 (X^t X)^{-1} \tag{II.30}$$

$$\operatorname{cov}(\widehat{\theta}, \varepsilon) = 0 \tag{II.31}$$

### II.3.3 Parameters of regression line

We start by recognizing that the response will vary even for constant values of the predictor, and model this fact by treating the responses yiyi as realizations of random variables

$$Y_i \sim N(\mu i, \sigma^2) \quad \text{(II.32)}$$

With means μi depending on the values of the predictor xixi and constant variance σ2

The simplest way to express the dependence of the expected response μiμi on the predictor xixi is to assume that it is a linear function, say

$$\mu_i = \alpha + \beta x_i \quad \text{(II.33)}$$

This equation defines a straight line. The parameter α is called the constant or intercept, and represents the expected response when $x_i = 0$. (This quantity may not be of direct interest if zero is not in the range of the data.) The parameter β is called the slope, and represents the expected increment in the response per unit change in xi [19].

You probably have seen the simple linear regression model written with an explicit error term as:

$$Y_i = \alpha + \beta x_i + \varepsilon_i \quad \text{(II.34)}$$

It may be of interest to note that in simple linear regression the estimates of the constant and slope are given by:

$$\hat{a} = \bar{y} - \beta x \ \text{ and } \ \beta = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sum (x-\bar{x})^2} \quad \text{(II.35)}$$

### II.3.4 Measuring the Goodness of Fit of a Linear Regression

A definite advantage of the least square's criterion is to provide an estimation of the fit quality of a regression model based on the decomposition of the variance of the dependent variable [20].

We can indeed consider that the information provided by a variable $Y$ on a set of individuals $1...i...N$ is proportional to the amount of deviation that exists between the different $Y_1$ values.... $Y_n$ If all the values were equal, the information would be null, whereas it would be higher the more the values differ. Applying the least squares criterion, we will therefore consider that the amount of total information contained in a variable $Y$ is proportional to its variance $(\sigma_Y)^2$ [20].

We can then break down this amount of total information ($Y$ variance) into two complementary quantities: the one that can be reconstituted from the knowledge of variable $X$ (variance of the estimated $Y$ values) and that which cannot be reconstructed from the knowledge of $X$ (variance of the regression residues). In total, the following relationship can be defined:

$$Var(Y) \quad = \quad Var(Y^* = aX + b) \quad + \quad Var(\varepsilon) \qquad \text{(II.36)}$$

***Total information*** = ***Modelled information*** + ***Residual information***

The quality of the adjustment therefore corresponds to the ratio between the total information on $Y$ and the information actually reconstituted from the knowledge provided by variable $X$. This quality of adjustment varies between $0\%$ ($X$ does not provide any forecast element on $100\%$) and $100\%$ (knowledge of the values of $X$ makes it possible to fully predict the values of $Y$) and depends on the intensity of the correlation between $X$ and $Y$ [20].

**Fit quality =** $Var(Y^*)/Var(Y) = [r(X,Y)]^2 =$ **determination coefficient** (II.37)

### II.3.5. Analysis of residues from linear regression

The *residual* for each observation is the difference between predicted values of $y$ (dependent variable) and observed values of $y$ [21].

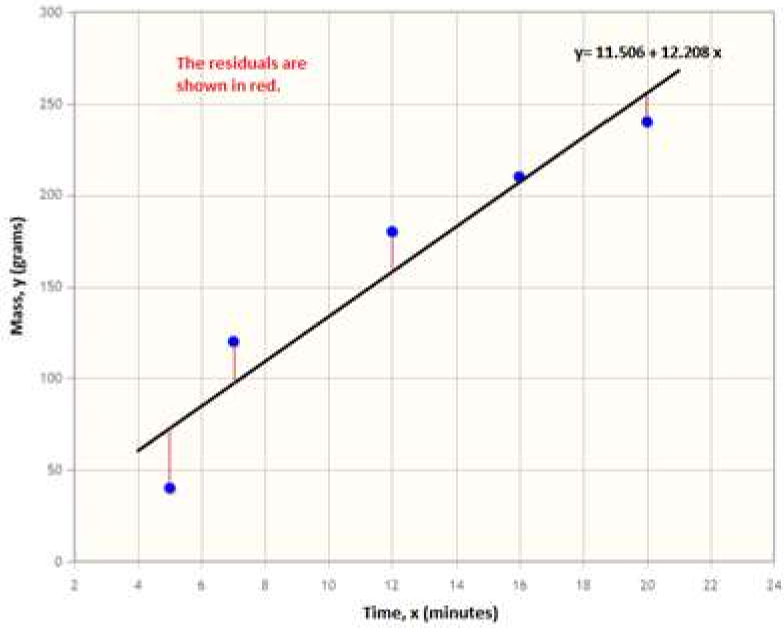



**Figure II.6** *Residuals*

**Residual = actual y value − predicted y value**

$$r_i = y_i - y_i \qquad \text{(II.38)}$$

Having a negative residual means that the predicted value is too high, similarly if you have a positive residual, it means that the predicted value was too low. The aim of a regression line is to minimise the sum of residuals [21].

Knowing that:

$$r_i = y_i - y_i \qquad \text{(II.39)}$$

and knowing that the regression line has the equation:

$$y_i = a + bx_i \tag{II.40}$$

We calculate the residual of an observation as follows:

$$r_i = y_i - y_i = y_i - (a + bx_i) \tag{II.41}$$

### II.3.6. Analysis of variance

Analysis of Variance (ANOVA) consists of calculations that provide information about levels of variability within a regression model and form a basis for tests of significance. The basic regression line concept, DATA = FIT + RESIDUAL, is rewritten as follows

$$(y_i - \overline{y}) = (y_i - \overline{y}) + (y_i - y_i) \tag{II.42}$$

The first term is the total variation in the response y, the second term is the variation in mean response, and the third term is the residual value. Squaring each of these terms and adding over all of the n observations gives the equation [22].

$$\sum (y_i - \overline{y})^2 = \sum (y_i - \overline{y})^2 + (y_i - y_i)^2 \tag{II.43}$$

This equation may also be written as SST = SSM + SSE, where SS is notation for sum of squares and T, M, and E are notation for total, model, and error, respectively [22].

The square of the sample correlation is equal to the ratio of the model sum of squares to the total sum of squares:

$$r^2 = SSM \,/\, SST \tag{II.44}$$

This formalizes the interpretation of $r^2$ as explaining the fraction of variability in the data explained by the regression model [22].

The sample variance $sy^2$ is equal to

$$\sum (y_i - \overline{y})^2 / (n-1) = SST \,/\, DFT \tag{II.45}$$

The total sum of squares divided by the total degrees of freedom (DFT)

For simple linear regression,

The MSM (mean square model) = $\sum (y_i - \overline{y})^2 / (1) = SSM \,/\, DFM$ (II.41)

since the simple linear regression model has one explanatory variable x [22].

The corresponding MSE (mean square error) = $\sum (y_i - y_i) / (n-2) = SSE \,/\, DFE$ (II.46)

The estimate of the variance about the population regression line $(\sigma)^2$

ANOVA calculations are displayed in an analysis of variance table, which has the following format for simple linear regression:

**Table II.2** *analysis of variance table [22]*.

| Source | Degrees of freedom | Sum of squares | Mean square | F |
|---|---|---|---|---|
| **Model** | 1 | $\sum(y_i - y)^2$ | $SSM / DFM$ | $MSM / MSE$ |
| **Error** | $n-2$ | $\sum(y_i - \overline{y_i})^2$ | $SSE / DFE$ | |
| **Total** | $n-1$ | $\sum(y_i - \overline{y})^2$ | $SST / DFT$ | |

**II.4 Conclusion**

At the end of this chapter, we identified three modelling systems, surface response method, simple linear regression and multiple linear regression. we also know how to model experimental data in empirical equations.

Chapter III

# *Results & discussion*

## III.1 Introduction

In this chapter. We will apply the two methods presented in the previous chapter (RSM surface response method, RLM multiple linear regression) to model EDM machining performance: material removal rate (MRR) and surface roughness (SR).

## III.2 Experimental data

Table III.1 summarizes the results of the EDM tests performed by Sahu & al [37]. This work is being done in order to study the influence of the parameters of the EDM machining process (pulse on time (Ton), pulse off time (Toff), servo voltage (SV) on Material Removal Rate (MRR) and Surface roughness (SR).

**Table III.1** Experimental results

| N° | Ton (µs) | Toff (µs) | SV (volt) | MRR ($mm^3$/min) | SR (µm) |
|---|---|---|---|---|---|
| 1 | 110 | 45 | 20 | 0.220637 | 1.405 |
| 2 | 120 | 45 | 20 | 0.448101 | 2.87 |
| 3 | 110 | 55 | 20 | 0.227062 | 1.391 |
| 4 | 120 | 55 | 20 | 0.407225 | 3.345 |
| 5 | 110 | 45 | 40 | 0.157805 | 1.39 |
| 6 | 120 | 45 | 40 | 0.371077 | 1.578 |
| 7 | 110 | 55 | 40 | 0.14984 | 1.401 |
| 8 | 120 | 55 | 40 | 0.306302 | 1.49 |
| 9 | 110 | 45 | 20 | 0.22588 | 1.341 |
| 10 | 120 | 45 | 20 | 0.45933 | 3.488 |
| 11 | 110 | 55 | 20 | 0.210858 | 1.296 |
| 12 | 120 | 55 | 20 | 0.427424 | 3.417 |
| 13 | 110 | 45 | 40 | 0.16485 | 1.368 |
| 14 | 120 | 45 | 40 | 0.331006 | 1.62 |
| 15 | 110 | 55 | 40 | 0.159317 | 1.433 |
| 16 | 120 | 55 | 40 | 0.31628 | 1.599 |
| 17 | 110 | 50 | 30 | 0.202971 | 1.404 |
| 18 | 120 | 50 | 30 | 0.38827 | 2.367 |
| 19 | 115 | 45 | 30 | 0.286261 | 1.494 |
| 20 | 115 | 55 | 30 | 0.283548 | 1.519 |
| 21 | 115 | 50 | 20 | 0.331577 | 2.276 |
| 22 | 115 | 50 | 40 | 0.215709 | 1.387 |
| 23 | 115 | 50 | 30 | 0.266409 | 1.469 |
| 24 | 115 | 50 | 30 | 0.266356 | 1.535 |
| 25 | 115 | 50 | 30 | 0.254277 | 1.516 |
| 26 | 115 | 50 | 30 | 0.245908 | 1.492 |
| 27 | 115 | 50 | 30 | 0.294183 | 1.564 |
| 28 | 115 | 50 | 30 | 0.285822 | 1.475 |

| | | | | | |
|---|---|---|---|---|---|
| 29 | 115 | 50 | 30 | 0.283582 | 1.555 |
| 30 | 115 | 50 | 30 | 0.279677 | 1.399 |

## III.3 Presentation of the prediction system

Two methods were used (multiple linear regression, and surface response method) to predict EDM machining performance based on the three and parameters entered (Figure III.1). In the Pulse on time (Ton) modelled system, Pulse off Time (Toff), Voltage (Volt) is considered input, while the material removal rate (MRR) and surface roughness (SR) are considered output.

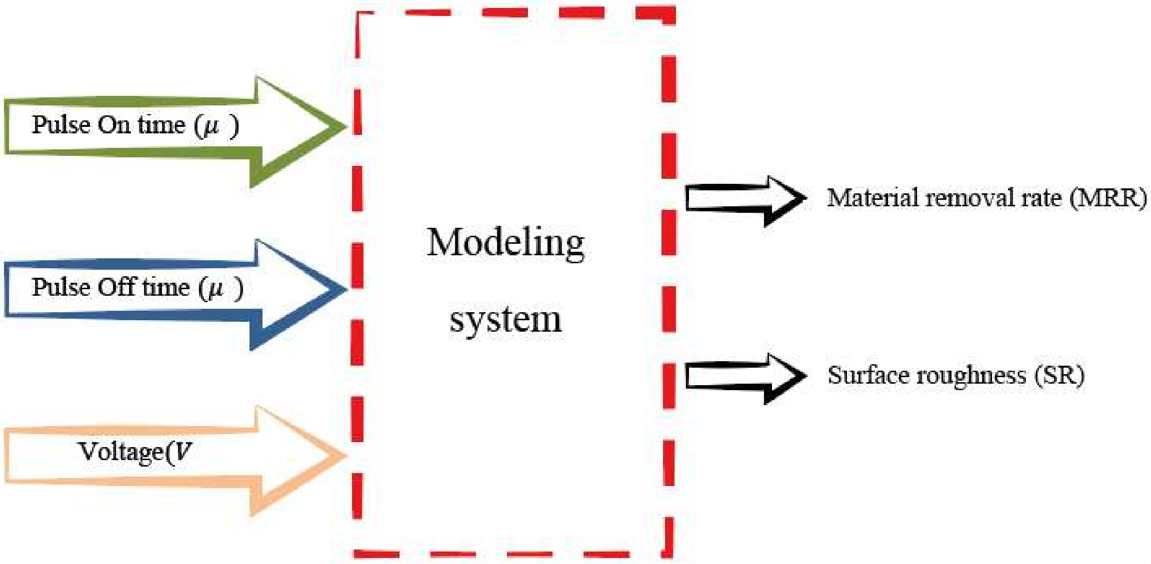



**Figure III.**1 Prediction system

### III.3.1 Limit values for parameters and machining performance

The table below groups the input and output parameter limit values for the modelling systems used.

**Table III.2** Limit values for inputs and outputs

| Variable | Nature | Min | Max |
|---|---|---|---|
| Ton (μs) | Input | 110 | 120 |
| Toff (μs) | Input | 45 | 55 |
| V (V) | Input | 20 | 40 |
| MRR ($mm^3/min$) | Output | 0.14984 | 0.448101 |
| SR (μm) | Output | 1.296 | 3.488 |

## III.4 Modelling by the Multiple Linear Regression Method

Linear regression is a method for making predictions or estimates based on existing values. From a supervised learning algorithm, a linear relationship is established between the inputs, which are pulse on time (Ton), pulse off time (Toff), and voltage (V) and the two outputs (which are the material removal rate (MRR) and the surface roughness (SR).

The multiple linear regression modelling algorithm is implemented by **"MATLAB"**.

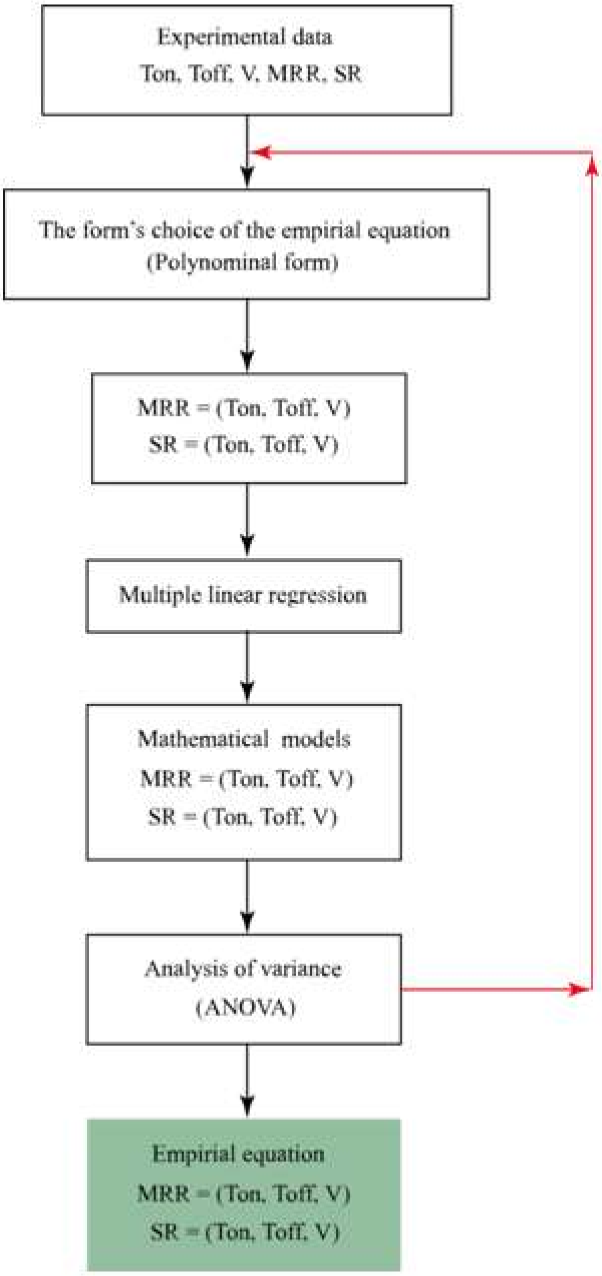



**Figure III.**2 Flowchart representing the multiple linear regression algorithm

The general form of the empirical equation used for modelling the two outputs (MRR and SR) is quadratic. It is given by :

$$Y = A_0 + A_1X_1 + A_2X_2 + A_3X_3 + A_4(X_1X_2) + A_5(X_1X_3) + A_6(X_2X_3) + A_7(X_1^2) + A_8(X_2^2) + A_9(X_3^2) \qquad \text{(III.1)}$$

The linear regression here aims to determine the values of the coefficients (A0, A1,…, A9) for the material removal rate equation and the values of the coefficients (B0, B1,…, B9) for the surface roughness equation. To define the two relationships.

The modelling is done in the MATLAB software on the basis of the linear regression functions used to find the values of the coefficients.

**Importante note :**

In order to value this model, we have to verify two main remarks, which are :

1. R-squared must be close to 1 (R-squared ≤ 1)
2. P-value must be close to 0 (P-value ≤ 0)

If these two remarks are realized, so the model is adequate.

After downloading the experimental data (see table IV.1), and executing the program we obtained the following results.

### III.4.1 Analysis of variation (ANOVA)

The analysis of variance ANOVA for both outputs (MRR and SR), is given in Tables III.3 and III.4.

#### a) ANOVA for material Removal Rate (MRR)

**Table III.3** Analysis of variance ANOVA for MRR

| | *SumSq* | *DF* | *MeanSq* | *F* | *Pvalue* |
|---|---|---|---|---|---|
| ***Total*** | *0.21177* | *29* | *0.0073023* | | |
| ***Model*** | *0.20767* | *09* | *0.023075* | *112.77* | *3.7358e-15* |
| ***Residual*** | *0.0040925* | *20* | *0.00020462* | | |

Number of observations : **30**, Error degrees of freedom: **20**

Root Mean Squared Error: 0.**0143**

R-squared: **0.981**,

Adjusted R-Squared **0.972**F-statistic vs.

Constant model : **113**,

p-value = **3.74e-15**

The pValue of the linear model is equal to 3.74e-15. That is, it is less than 0.05 (5%), so the model is significant.

#### b) ANOVA for surface roughness SR

**Table III.4** Analysis of variance ANOVA for SR.

| | *SumSq* | *DF* | *MeanSq* | *F* | *Pvalue* |
|---|---|---|---|---|---|
| ***Total*** | *12.395* | *29* | *0.4274* | | |
| ***Model*** | *11.369* | *09* | *1.2633* | *24.638* | *6.2539e-09* |
| ***Residual*** | *1.0255* | *20* | *0.051273* | | |

Number of observations: **30**, Error degrees of freedom: **20**

Root Mean Squared Error: **0.226**

R-squared: **0.917**, Adjusted R-Squared **0.88**

F-statistic vs. constant model: **24.6**,

p-value = **6.25e-09**.

The pValue of the linear model is equal to 6.25e-09. That is, it is less than 0.05 (5%), so the model is significant.

### III.4.2 Presentation of models

The execution of our algorithm leads us to find the empirical equations (III.2) and (III.3).

$$\begin{aligned} MRR(T_{on},T_{off},V) &= -7.8176 + 0.14712T_{on} - 0.06563T_{off} + 0.019438V \\ &-0.00046962(T_{on}.T_{off}) + 0.00095628(T_{on}.V) + 1.0179e\ \ 05(T_{off}.V) - 0.0002759T_{on}^{2} \\ &-0.0002T_{off}^{2} - 1.4525e\ \ 05V^{2} \end{aligned} \tag{III.2}$$

$$\begin{aligned} SR(T_{on},T_{off},V) &= 75.273T_{on} + 2.1637T_{off} + 0.59706V \\ &+0.012179(T_{on}.T_{off}) - 0.22519(T_{on}.V) + 0.0061666(T_{off}.V) + 0.000695T_{on}^{2} \\ &-0.00874T_{off}^{2} + 3.6674e\ \ 05V^{2} \end{aligned} \tag{III.3}$$

### III.4.3 Analysis results

The curves in Figures III.3 to III.4 show the analysis of linear regression results during modelling

#### a) Analysis results for material removal rate (MRR)

The analysis of the results of the modeling of the material removal rate by the multiple linear regression method is given by the figures below

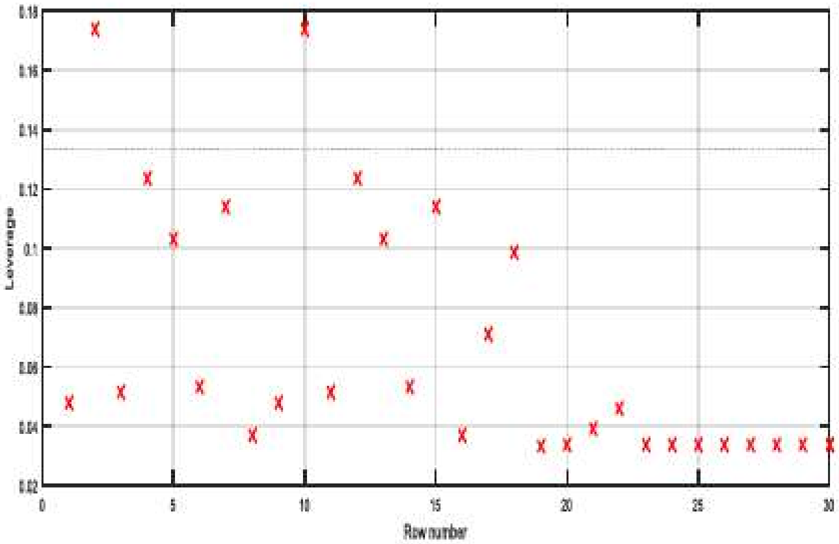



**Figure III.3** Leverage plot

**Comment**

From Figure III.3, we note that there is a high leverage point. But this graph does not reveal whether it is a point of an outlier. So you have to look for points with a great distance from Cook.

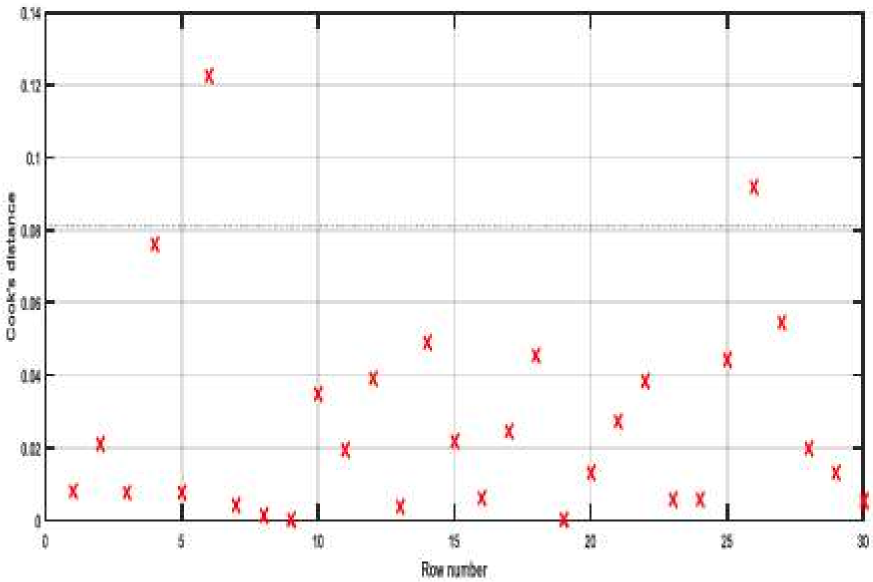



**Figure III.4**. Cook's distance plot

**Comment**

There are still two points with a great distance for Cook, but probably one there is only one very far point that probably doesn't affect our model.

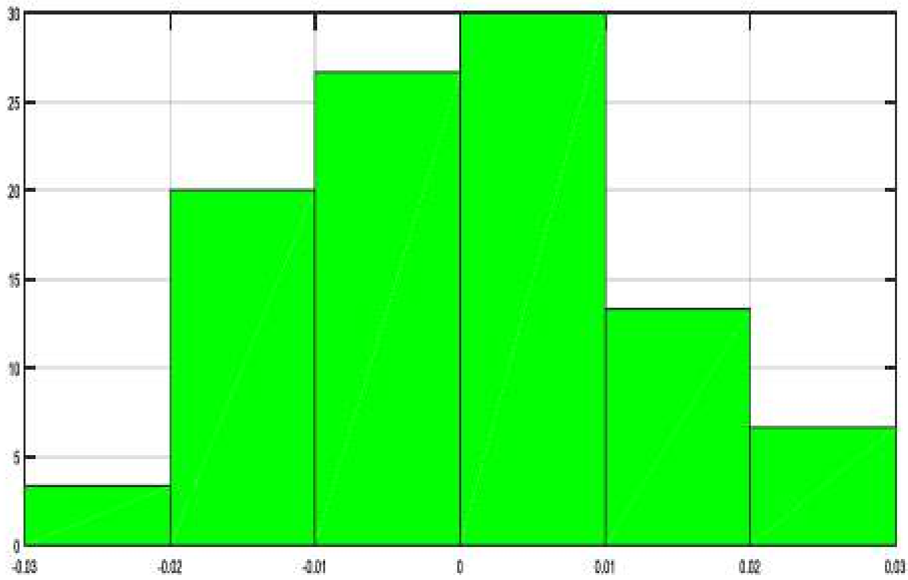



**Figure III.5** Histogram of residuals

**Comment**

We note that the data are well centered and seem to fit the normal law curve.

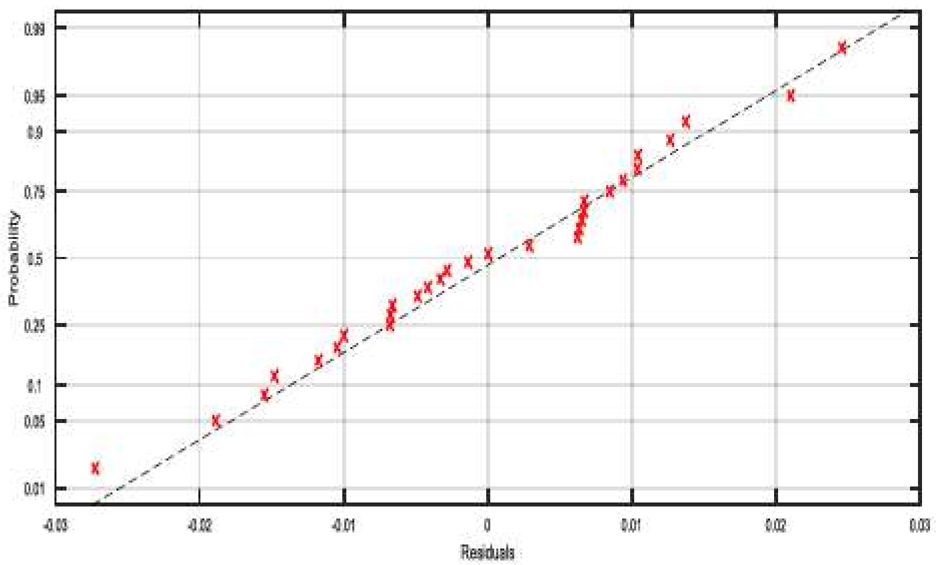



**Figure III.6** Normal probability plot of residuals

**Comment**

We note that the data are well centered and appear to fit the normal law curve,the relationship between the sample percentiles and theoretical percentiles is not linear; the condition that the error terms are normally distributed is not met.

**b) Analysis results for surface roughness (SR)**

The analysis of the tool surface roughness modelling results by the multiple linear regression method is given by the figures below.

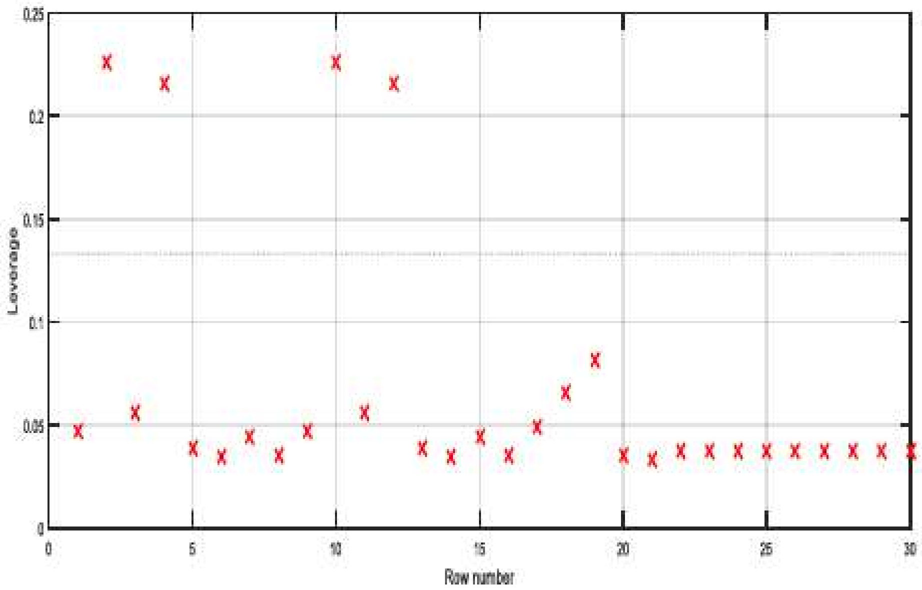
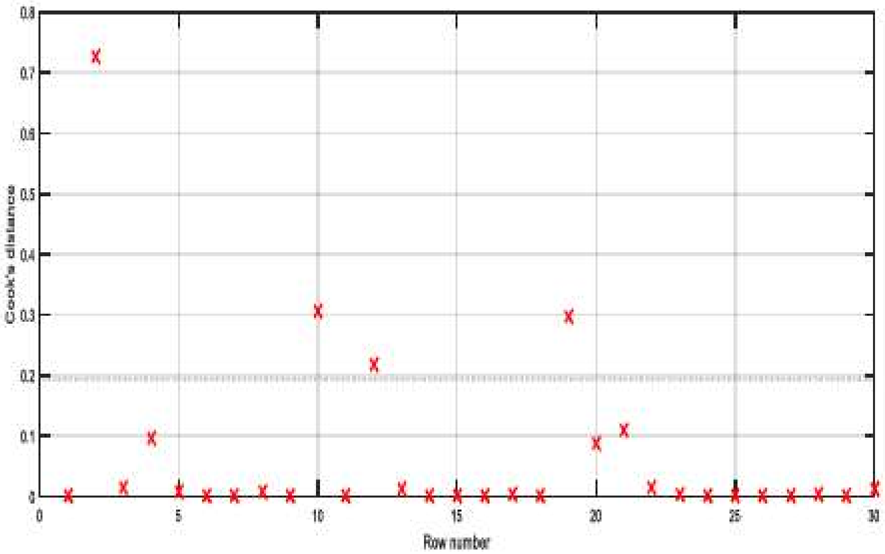



**Figure III.7** Leverage plot

**Comment**

Figure III.7 shows that there are high leverage points. However, this graph does not reveal whether the high leverage point is an abnormal value. Therefore, one must search for points with a great distance from Cook




**FigureIII.8** Cook’s distance plot

**Comment**

There are still four points (04) with a significant distance for Cook, but we can say that these points probably do not affect our model.

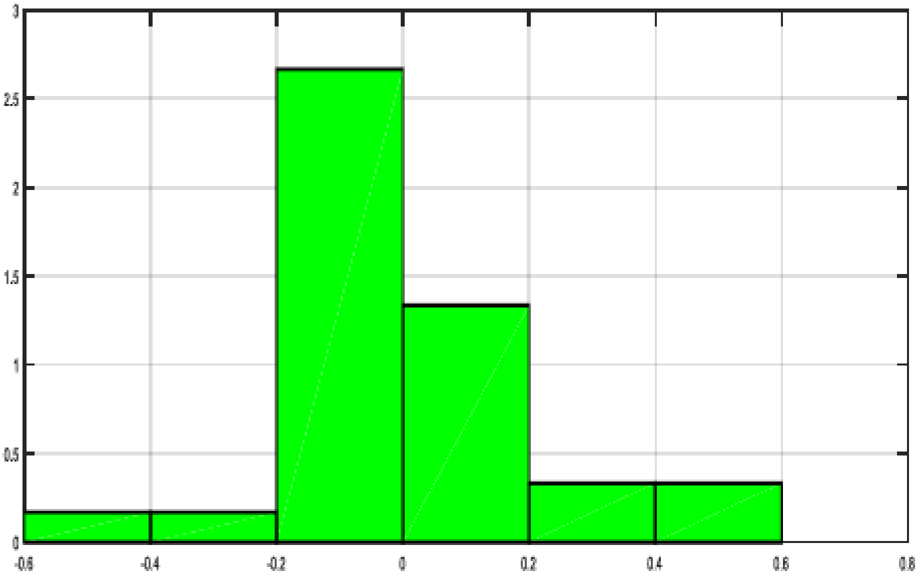



**Figure III.9** Histogram of residuals

**Comment**

The previous histogram of residuals suggests that the residuals are normally distributed. We can characterize this histogram as having a global maximum at (-0.2 to 0) and local maximum at (-0,6 to 0.2).

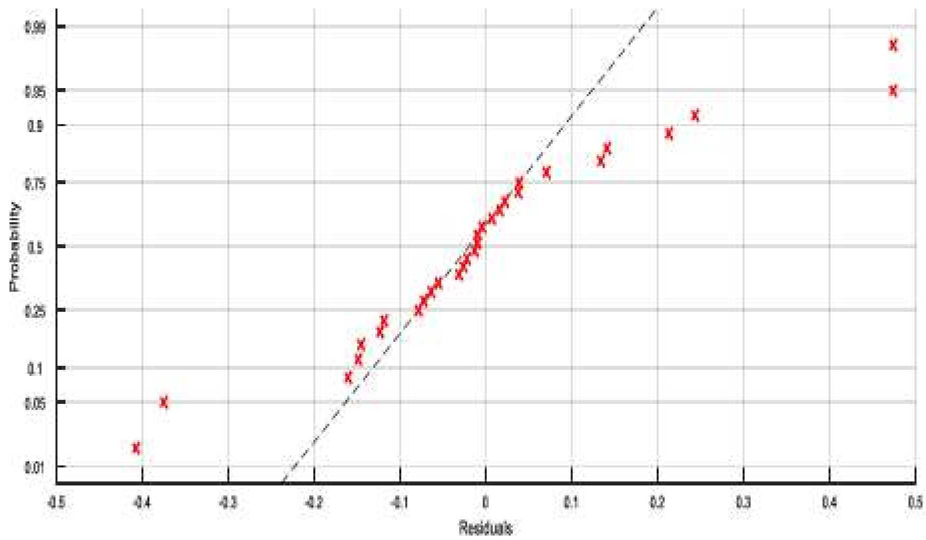



**Figure III.10** Normal probability plot of residuals

**Comment**

The normal probability graph above seems to be good, there are no points far from the straight line.

### III.4.4 Confirmation of material removal rate prediction model MRR

The calculation of model error and accuracy when predicting material removal rate is given in Table III.5

**Table III.5** Model errors and precisionbased on the multiple linearregressionmethod for the prediction of materialremoval rate (MRR).

| Trials | Ton | Toff | V | MRRexp | MRRpred | Error % | Accuracy % |
|---|---|---|---|---|---|---|---|
| 1 | 110 | 45 | 20 | 0.22064 | 0.22719 | 2.97054 | 97.0295 |
| 2 | 120 | 45 | 20 | 0.4481 | 0.45291 | 1.07366 | 98.9263 |
| 3 | 110 | 55 | 20 | 0.22706 | 0.22078 | 2.76836 | 97.2316 |
| 4 | 120 | 55 | 20 | 0.40723 | 0.41891 | 2.86871 | 97.1313 |
| 5 | 110 | 45 | 40 | 0.15781 | 0.16192 | 2.60473 | 97.3953 |
| 6 | 120 | 45 | 40 | 0.37108 | 0.34644 | 6.63975 | 93.3602 |
| 7 | 110 | 55 | 40 | 0.14984 | 0.1526 | 1.83889 | 98.1611 |
| 8 | 120 | 55 | 40 | 0.3063 | 0.30953 | 1.05334 | 98.9467 |
| 9 | 110 | 45 | 20 | 0.22588 | 0.22719 | 0.58044 | 99.4196 |
| 10 | 120 | 45 | 20 | 0.45933 | 0.45291 | 1.39723 | 98.6028 |
| 11 | 110 | 55 | 20 | 0.21086 | 0.22078 | 4.70369 | 95.2963 |
| 12 | 120 | 55 | 20 | 0.42742 | 0.41891 | 1.99261 | 98.0074 |
| 13 | 110 | 45 | 40 | 0.16485 | 0.16192 | 1.78016 | 98.2198 |
| 14 | 120 | 45 | 40 | 0.33101 | 0.34644 | 4.66227 | 95.3377 |
| 15 | 110 | 55 | 40 | 0.15932 | 0.1526 | 4.21901 | 95.781 |
| 16 | 120 | 55 | 40 | 0.31628 | 0.30953 | 2.13469 | 97.8653 |
| 17 | 110 | 45 | 30 | 0.20297 | 0.19354 | 4.64877 | 95.3512 |
| 18 | 120 | 45 | 30 | 0.38827 | 0.39866 | 2.67529 | 97.3247 |
| 19 | 115 | 55 | 30 | 0.28626 | 0.28617 | 0.03027 | 99.9697 |
| 20 | 115 | 50 | 30 | 0.28355 | 0.2731 | 3.68523 | 96.3148 |
| 21 | 115 | 50 | 20 | 0.33158 | 0.31778 | 4.16099 | 95.839 |
| 22 | 115 | 50 | 40 | 0.21571 | 0.23045 | 6.83509 | 93.1649 |
| 23 | 115 | 50 | 30 | 0.26641 | 0.2731 | 2.51103 | 97.489 |
| 24 | 115 | 50 | 30 | 0.26636 | 0.2731 | 2.53142 | 97.4686 |
| 25 | 115 | 50 | 30 | 0.25428 | 0.2731 | 7.40201 | 92.598 |
| 26 | 115 | 50 | 30 | 0.24591 | 0.2731 | 11.0572 | 88.9428 |
| 27 | 115 | 50 | 30 | 0.29418 | 0.2731 | 7.1671 | 92.8329 |
| 28 | 115 | 50 | 30 | 0.28582 | 0.2731 | 4.45151 | 95.5485 |
| 29 | 115 | 50 | 30 | 0.28358 | 0.2731 | 3.69678 | 96.3032 |
| 30 | 115 | 50 | 30 | 0.27968 | 0.2731 | 2.35214 | 97.6479 |
| | | | | | | **3.54977** | **96.4502** |

**Accuracy and error study of the multiple linear regression system**

In order to calculate the error of the N 30 tests, we use the next equation

$$e_i = \left[ \frac{\left| T_{\exp} - T_{pred} \right|}{T_{\exp}} \right] \times 100 \qquad \text{(III.4)}$$

$T_{\exp}$ : Experimental Temperature.

$T_{pre}$ : Predicted temperature.

$e_i$ : Error rate

In order to calculate the accuracy of the 30 tests, we use the next equation.

$$A = \frac{1}{N}\sum_{i=1}^{1}\left[\frac{\left|T_{\exp} - T_{pred}\right|}{T_{\exp}}\right] \times 100 \quad \text{(III.5)}$$

$N$ = 30 tests

$A$ : Accuracy

### III.4.5 Surface Roughness Prediction Model SR confirmed

Calculation of model error and accuracy when predicting wear rate of the tool is given in Table III.6

**Table III.6** Model errors and precision based on multiple linear regression method for surface roughness prediction SR

| Trials | Ton | Toff | V | SRexp | SRpred | Error % | Accuary % |
|---|---|---|---|---|---|---|---|
| 1 | 110 | 45 | 20 | 1.405 | 1.357522 | 3.379246 | 96.62075 |
| 2 | 120 | 45 | 20 | 2.87 | 3.233972 | 12.68194 | 87.31806 |
| 3 | 110 | 55 | 20 | 1.391 | 1.247356 | 10.32664 | 89.67336 |
| 4 | 120 | 55 | 20 | 3.345 | 3.193306 | 4.534936 | 95.46506 |
| 5 | 110 | 45 | 40 | 1.39 | 1.503648 | 8.176129 | 91.82387 |
| 6 | 120 | 45 | 40 | 1.578 | 1.632098 | 3.428276 | 96.57172 |
| 7 | 110 | 55 | 40 | 1.401 | 1.400818 | 0.013005 | 99.987 |
| 8 | 120 | 55 | 40 | 1.49 | 1.598768 | 7.299852 | 92.70015 |
| 9 | 110 | 45 | 20 | 1.341 | 1.357522 | 1.232036 | 98.76796 |
| 10 | 120 | 45 | 20 | 3.488 | 3.233972 | 7.282924 | 92.71708 |
| 11 | 110 | 55 | 20 | 1.296 | 1.247356 | 3.753364 | 96.24664 |
| 12 | 120 | 55 | 20 | 3.417 | 3.193306 | 6.546491 | 93.45351 |
| 13 | 110 | 45 | 40 | 1.368 | 1.503648 | 9.915804 | 90.0842 |
| 14 | 120 | 45 | 40 | 1.62 | 1.632098 | 0.746802 | 99.2532 |
| 15 | 110 | 55 | 40 | 1.433 | 1.400818 | 2.245792 | 97.75421 |
| 16 | 120 | 55 | 40 | 1.599 | 1.598768 | 0.014522 | 99.98548 |
| 17 | 110 | 50 | 30 | 1.404 | 1.323651 | 5.722863 | 94.27714 |
| 18 | 120 | 50 | 30 | 2.367 | 2.360851 | 0.25978 | 99.74022 |
| 19 | 115 | 45 | 30 | 1.494 | 1.010675 | 32.35108 | 67.64892 |
| 20 | 115 | 55 | 20 | 1.519 | 1.915856 | 26.12616 | 73.87384 |
| 21 | 115 | 50 | 40 | 2.276 | 1.792333 | 21.25075 | 78.74925 |
| 22 | 115 | 50 | 30 | 1.387 | 1.537776 | 10.87066 | 89.12934 |
| 23 | 115 | 50 | 30 | 1.469 | 1.537776 | 4.681824 | 95.31818 |
| 24 | 115 | 50 | 30 | 1.535 | 1.537776 | 0.180847 | 99.81915 |
| 25 | 115 | 50 | 30 | 1.516 | 1.537776 | 1.436412 | 98.56359 |
| 26 | 115 | 50 | 30 | 1.492 | 1.537776 | 3.068097 | 96.9319 |
| 27 | 115 | 50 | 30 | 1.564 | 1.537776 | 1.676726 | 98.32327 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 28 | 115 | 50 | 30 | 1.475 | 1.537776 | 4.256 | 95.744 |
| 29 | 115 | 50 | 30 | 1.555 | 1.537776 | 1.107653 | 98.89235 |
| 30 | 115 | 50 | 30 | 1.399 | 1.537776 | 9.919657 | 90.08034 |
| | | | | | | **6.816209** | **93.18379** |

### III.4.6 Validation of results

In order to prove the correct functioning of the prediction system of the comparison curves, the superimposed curves represent a comparison between the experimental values used for the model design and the values predicted by the model for the same machining parameters.

#### a) Validation of material removal (MRR) results

Figure III.11 represents a comparison between the experimental values of the material removal rate and those predicted by the model based on the multiple linear regression method.

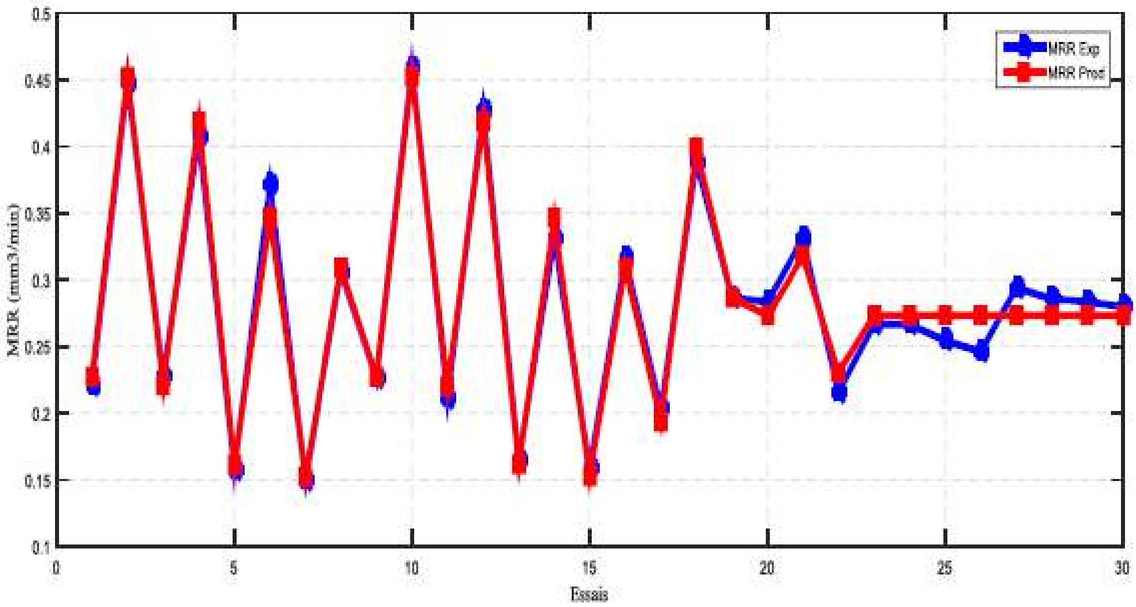



**Figure III.11** Validation of the expected material removal rate by multiple linear regression

The curves in Figure III.11 show agreement between the experimental data and the data predicted by the Response Surface Method, demonstrating the proper functioning of the prediction system.

#### b) Validation of results for surface roughness (SR)

Figure III. 12 represents a comparison between the experimental surface roughness values and those predicted by the model based on the multiple linear regression method.

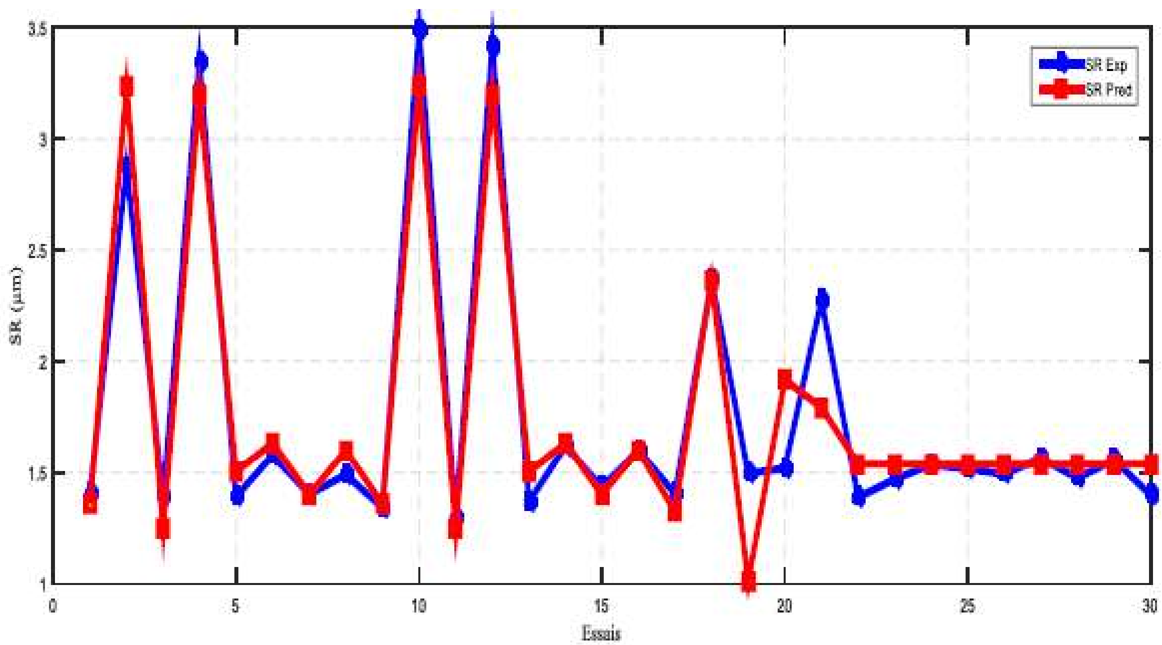



**Figure III.12** Validation of the surface roughness predicted by multiple linear regression

Figure III.22 shows that the two curves are similar, that is to say that the method of response surfaces can predict the wear rate of the tool correctly within a very specific range of machining parameters.

### III.5 Modelling by surface response Method RSM

Modelling with the Response Surface Method was performed with the software **"Design Expert".**

#### a) Suitable models for modelling the material removal rate MRR

Equation (III.6) was used to adjust the experimental rate data material removal (MRR). As indicated in Table III.7 the model suggested by the Response Surface Method is called 2FI (Two Factor Interaction).

$$Y = C_0 + C_1 X_1 + C_2 X_2 + C_3 X_3 + C_4 (X_1 X_2) + C_5 (X_1 X_3) + C_6 (X_2 X_3) \quad \text{(III.6)}$$

**Table III.7** Appropriate models for modelling material removal rates

| Source | Sequential p-value | Lack of Fit p-value | Adjusted $R^2$ | Predicted $R^2$ | |
|---|---|---|---|---|---|
| Linear | < 0.0001 | 0.0786 | 0.9578 | 0.9488 | |
| **2FI** | **0.0294** | **0.2706** | **0.9675** | **0.9591** | **Suggested** |
| Quadratic | 0.1154 | 0.5234 | 0.9720 | | |
| Cubic | 0.5234 | | 0.9710 | | Aliased |

### b) Appropriate models for surface roughness modelling SR

Equation (III.7) was used to model the surface roughness (SR) data, equation (III.7) is based on the quadratic model (modified quadratic model: removal of the last term $D_9(X_3^2)$ As shown in Table III.9 the suggested model is Model 2 FI, but its coefficients of determination are low in what influence prediction, the quadratic model has an acceptable coefficient of determination, but the model is not acceptable. To remedy this problem the last term of the complete quadratic model has been removed.

$$Y' = D_0 + D_1X_1 + D_2X_2 + D_3X_3 + D_4(X_1X_2) + D_5(X_1X_3) + D_6(X_2X_3) + D_7(X_1^2) + D_8(X_2^2) \qquad \text{(III.7)}$$

**Table III.8** Suitable models for modelling the surface roughness SR

| Source | Sequential p-value | Lack of Fit p-value | Adjusted $R^2$ | Predicted $R^2$ | |
|---|---|---|---|---|---|
| Linear | < 0.0001 | < 0.0001 | 0.6060 | 0.4784 | |
| **2FI** | **< 0.0001** | **< 0.0001** | **0.8680** | **0.8172** | **Suggested** |
| **Quadratic** | **< 0.0001** | **0.1323** | **0.9593** | | **Suggested** |
| Cubic | 0.1323 | | 0.9665 | | **Aliased** |

Where $X_1, X_2$ and $X_3$ are the independent variable values. $Y$ and $Y'$ are the response variables. $C_0$ and $D_0$ are constants. $C_1, C_2, C_3, D_1, D_2$ and $D_3$ are the linear coefficients, $C_4$, $C_5$, $C_6$, $D_4$, $D_5$, and $D_6$ are the interactive coefficients. $D_7, D_8$ are the quadratic coefficients.

## III.5.1 Analysis of variance (ANOVA)

ANOVA variance analysis for both outputs (MRR and SR) is given in Tables III.10, III.11 and III.12, III.13 respectively.

### a) ANOVA for MRR

**Table III.9** ANOVA for material removal rate MRR

| Source | Sum of Squares | df | Mean Square | F-value | p-value | |
|---|---|---|---|---|---|---|
| **Model** | 0.2063 | 6 | 0.0344 | 144.70 | < 0.0001 | significant |
| A-X1 | 0.1627 | 1 | 0.1627 | 684.74 | < 0.0001 | |
| B-X2 | 0.0020 | 1 | 0.0020 | 8.62 | 0.0074 | |
| C-X3 | 0.0343 | 1 | 0.0343 | 144.41 | < 0.0001 | |
| AB | 0.0008 | 1 | 0.0008 | 3.56 | 0.0719 | |
| AC | 0.0017 | 1 | 0.0017 | 7.14 | 0.0136 | |
| BC | 8.439E-06 | 1 | 8.439E-06 | 0.0355 | 0.8522 | |
| **Residual** | 0.0055 | 23 | 0.0002 | | | |
| Lack of Fit | 0.0021 | 7 | 0.0003 | 1.40 | 0.2706 | not significant |
| Pure Error | 0.0034 | 16 | 0.0002 | | | |
| **Cor Total** | 0.2118 | 29 | | | | |

**Table III.10** Fit statistics for MRR

| | | | | |
|---|---|---|---|---|
| **Std. Dev.** | 0.0154 | | **$R^2$** | 0.9742 |
| **Mean** | 0.2823 | | **Adjusted $R^2$** | 0.9675 |
| **C.V. %** | 5.46 | | **Predicted $R^2$** | 0.9591 |
| | | | **Adeq Precision** | 40.2149 |

According to the adjustment summary, the multiple linear model is significant for the analysis of the material removal rate. The R2 value is 96.75% and the adjusted R2 value is 97.42%. This clearly indicates that the regression model provides a good relationship between process factors and the response variable. Factors with a P-value less than 5% (i.e., 0.05)

Factors with a P value of less than 5% (i.e., 0.05) are the most significant. The factor A-discharge current and C- voltage and AC interaction have a significant effect. Of all the parameters the discharge current is the most significant for the MRR. Lack of Fit is also not significant this is desirable so MRR modeling is acceptable.

**b) ANOVA for SR**

As shown in the table below (III.11), and according to the adjustment summary, the multiple linear model is significant for the analysis of the surface roughness. The R2 value is 97.20% and the adjusted R2 value is 95.93%. This clearly indicates that the regression model provides a good relationship between process factors and the response variable.

**Table III.11** ANOVA for surface roughness SR

| Source | Sum of Squares | df | Mean Square | F-value | p-value | |
|---|---|---|---|---|---|---|
| **Model** | 12.04 | 9 | 1.34 | 77.03 | < 0.0001 | significant |
| A-X1 | 4.82 | 1 | 4.82 | 277.59 | < 0.0001 | |
| B-X2 | 0.0002 | 1 | 0.0002 | 0.0109 | 0.9180 | |
| C-X3 | 3.17 | 1 | 3.17 | 182.49 | < 0.0001 | |
| AB | 0.0066 | 1 | 0.0066 | 0.3793 | 0.5449 | |
| AC | 3.06 | 1 | 3.06 | 176.44 | < 0.0001 | |
| BC | 0.0085 | 1 | 0.0085 | 0.4874 | 0.4931 | |
| $A^2$ | 0.0486 | 1 | 0.0486 | 2.80 | 0.1100 | |
| $B^2$ | 0.0015 | 1 | 0.0015 | 0.0860 | 0.7723 | |
| $C^2$ | 0.0879 | 1 | 0.0879 | 5.06 | 0.0359 | |
| **Residual** | 0.3473 | 20 | 0.0174 | | | |
| Lack of Fit | 0.1185 | 4 | 0.0296 | 2.07 | 0.1323 | not significant |
| Pure Error | 0.2288 | 16 | 0.0143 | | | |
| **Cor Total** | 12.39 | 29 | | | | |

**Table III.12** Fit statistics for surface roughness SR

| | | | |
|---|---|---|---|
| **Std. Dev.** | 0.1318 | **$R^2$** | 0.9720 |
| **Mean** | 1.76 | **Adjusted $R^2$** | 0.9593 |
| **C.V. %** | 7.47 | **Predicted $R^2$** | NA[(1)] |
| | | **Adeq Precision** | 27.5111 |

Factors with a P value less than 5% (i.e., 0.05) are the most significant. The factor A-discharge current, B- pulse time A- discharge current and C- voltage, interaction AB and $B^2$ have a significant effect. Among all the parameters pulse time and AB interaction have the most significant for the SR. Lack of Fit is also not significant this is desirable so MRR modeling is acceptable.

### III.5.2 Presentation of models

$$MRR(T_{on},T_{off},V) = -4.00237 + 0.039108T_{on} + 0.030085T_{off} + 0.020049V$$
$$-0.000276(T_{on}.T_{off}) - 0.000206(T_{on}.V) - 0.000015(T_{off}.V) \quad \text{(III.8)}$$

$$SR(T_{on},T_{off},V) = +101.26054 - 2.10029T_{on} + 0.093285T_{off} + 0.888708V$$
$$+0.000770(T_{on}.T_{off}) - 0.008752(T_{on}.V) - 0.000460(T_{off}.V) + 0.000695T_{on}^2 \quad \text{(III.9)}$$
$$-0.001674T_{off}^2 + 0.001648V^2$$

### III.5.3 Analysis of results

The curves in Figures III.13 to III.14 show the analysis of multiple linear regression results during modelling.

#### a) Analysis of results for MRR

Figure III.13 shows that the normal probability graph for MRR clearly indicates that the residues are on a straight line, meaning that the error follows a normal distribution.

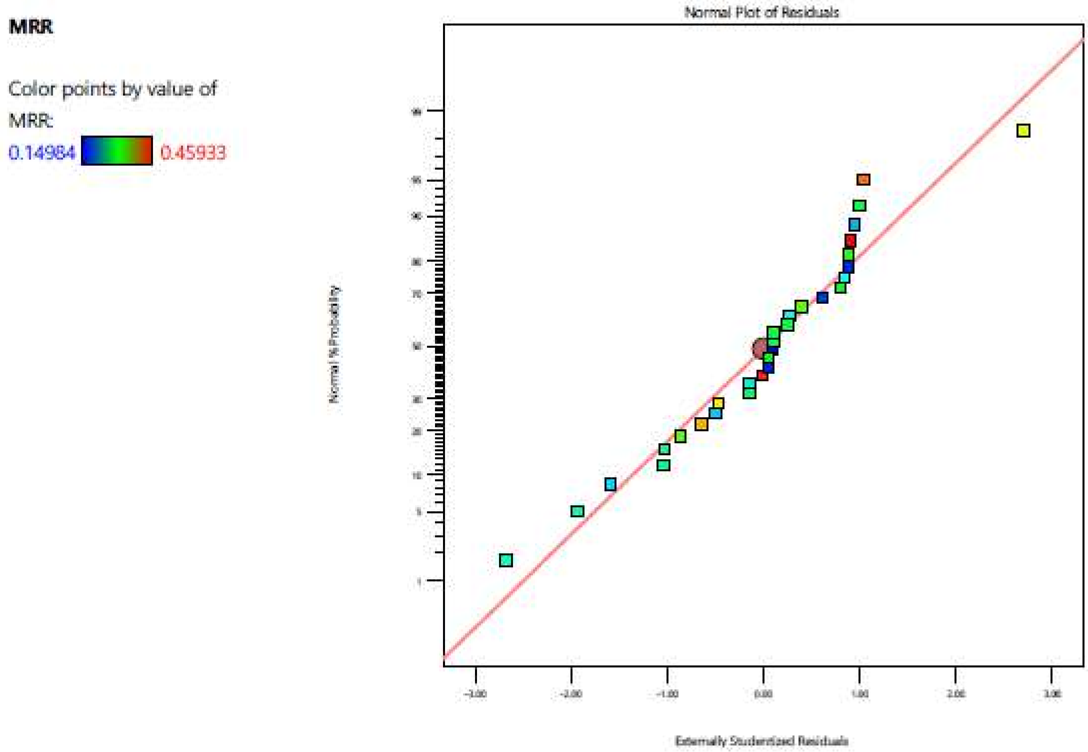



**Figure III.13** Normal probability diagram for MRR

Figure III.14 shows the graph of the predicted material removal rate values in relation to the experimental values, it shows that the model is well adjusted.

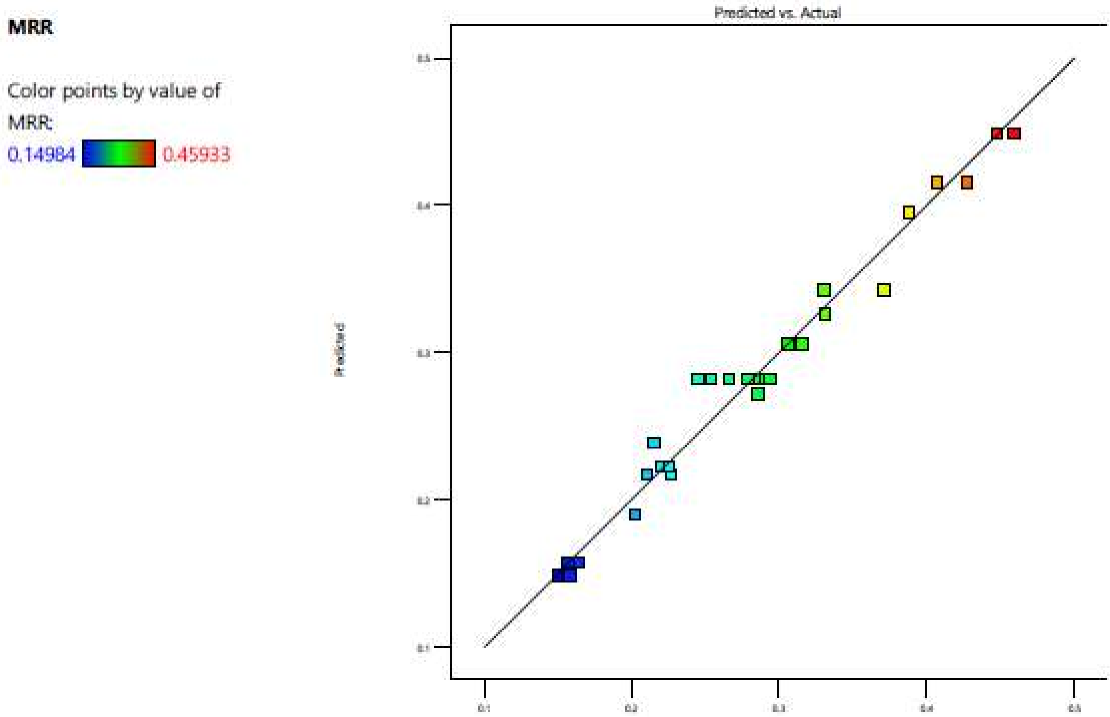



**Figure III.14** Predicted vs. actual for MRR

**b) Analysis of results for SR**

Figure III.15 shows that the normal probability graph for SR clearly indicates that the residues are on a straight line, meaning that the error follows a normal distribution

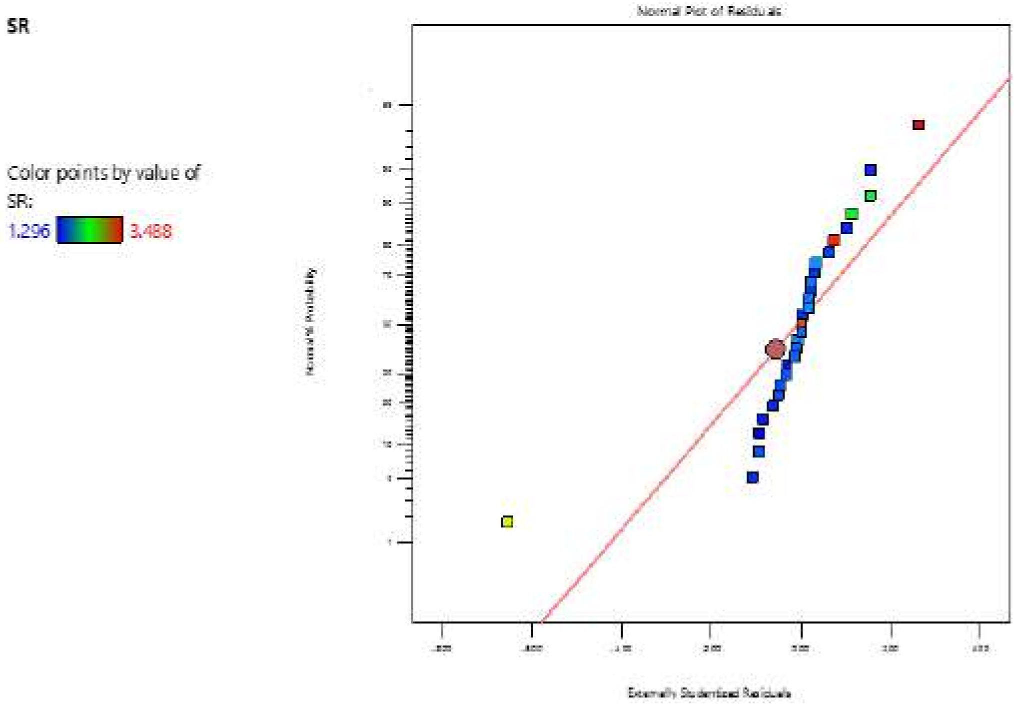



**Figure III.15** Normal probability diagram for SR

Figure III.16 shows the graph of the predicted surface roughness relative to the experimental values, it shows that the model is well adjusted.

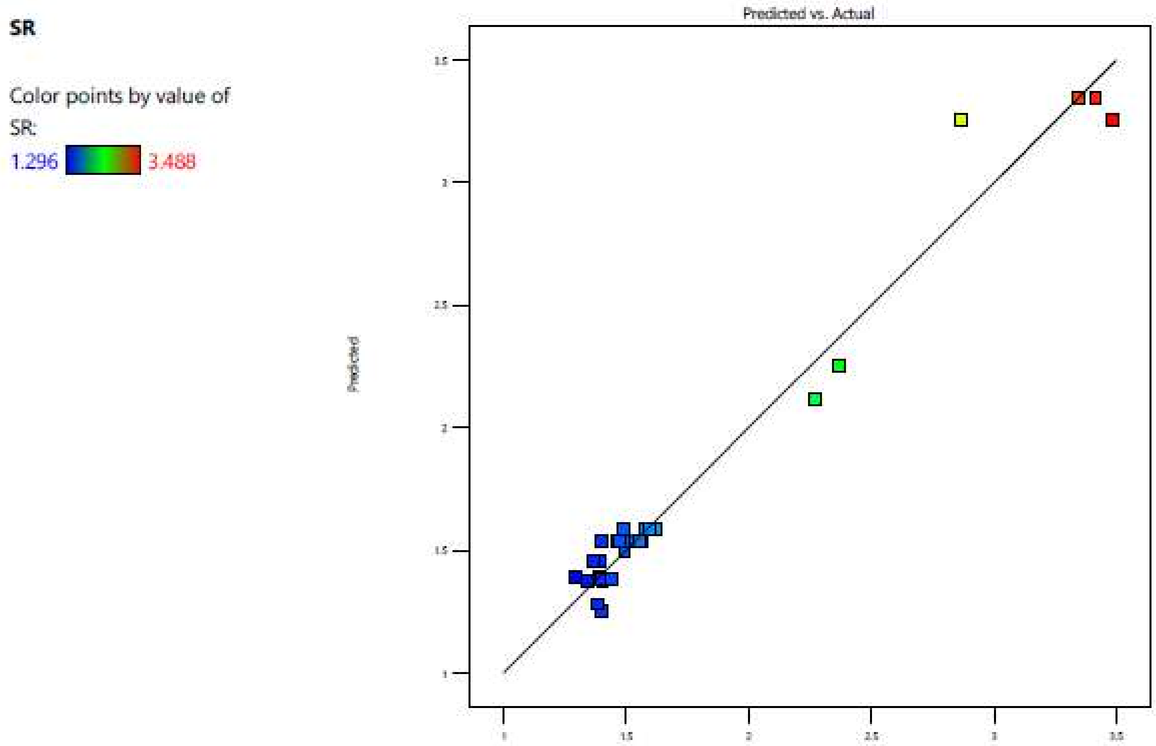



**Figure III.16** Predicted vs. actual for SR

## III.6 Comparative study between the two modelling methods

After the detailed study that took place, we were able to model each of the two outputs (material removal rate and surface roughness) by two methods. We will now conduct a comparative study between the models obtained in order to know the best method to model each output.

### III.6.1 Material removal rate MRR

In order to choose the best method of modelling the rate of material removal

The comparison was made by calculating the error and the the accuracy of the prediction of the material removal rate by each model as shown in Table III.14

**Table III.13** Errors and Accuracy of Material Removal Rate (MRR) Prediction by Both Methods

| | Output predicted by Linear regression | | Output predicted by Surface response | |
|---|---|---|---|---|
| **trials** | Error % | Accuracy % | Errors% | Accuracy% |
| **1** | 2,970535314 | 97,02946469 | 12,58991012 | 87,41008988 |
| **2** | 1,073664196 | 98,9263358 | 5,800924345 | 94,19907565 |
| **3** | 2,768362826 | 97,23163717 | 9,514141512 | 90,48585849 |
| **4** | 2,868708945 | 97,13129106 | 9,704708699 | 90,2952913 |
| **5** | 2,60473369 | 97,39526631 | 32,8823548 | 67,1176452 |
| **6** | 6,639754013 | 93,36024599 | 6,224584116 | 93,77541588 |
| **7** | 1,838894821 | 98,16110518 | 42,11492258 | 57,88507742 |
| **8** | 1,053339515 | 98,94666049 | 20,73868274 | 79,26131726 |
| **9** | 0,580440942 | 99,41955906 | 9,976536214 | 90,02346379 |
| **10** | 1,397230749 | 98,60276925 | 3,214464546 | 96,78553545 |
| **11** | 4,703686841 | 95,29631316 | 17,93007617 | 82,06992383 |
| **12** | 1,992611552 | 98,00738845 | 4,520335779 | 95,47966422 |
| **13** | 1,780163785 | 98,21983621 | 27,20351835 | 72,79648165 |
| **14** | 4,662271983 | 95,33772802 | 19,0839441 | 80,9160559 |
| **15** | 4,219009899 | 95,7809901 | 33,66119121 | 66,33880879 |
| **16** | 2,13469078 | 97,86530922 | 16,92961932 | 83,07038068 |
| **17** | 4,648767558 | 95,35123244 | 12,85109695 | 87,14890305 |
| **18** | 2,675290391 | 97,32470961 | 11,81265614 | 88,18734386 |
| **19** | 0,030269579 | 99,96973042 | 11,62715145 | 88,37284855 |
| **20** | 3,685231425 | 96,31476858 | 14,82006574 | 85,17993426 |
| **21** | 4,160994279 | 95,83900572 | 6,907294535 | 93,09270547 |
| **22** | 6,835088012 | 93,16491199 | 37,5278732 | 62,4721268 |
| **23** | 2,511026279 | 97,48897372 | 22,20683235 | 77,79316765 |
| **24** | 2,531424109 | 97,46857589 | 22,23114929 | 77,76885071 |
| **25** | 7,402006473 | 92,59799353 | 28,03753387 | 71,96246613 |
| **26** | 11,05722465 | 88,94277535 | 32,39504205 | 67,60495795 |
| **27** | 7,16710347 | 92,83289653 | 10,6692093 | 89,3307907 |
| **28** | 4,45151178 | 95,54848822 | 13,90655723 | 86,09344277 |
| **29** | 3,696779062 | 96,30322094 | 14,80629941 | 85,19370059 |
| **30** | 2,352141935 | 97,64785806 | 16,40928643 | 83,59071357 |
| **Model Errors and Accuracy (%)** | | | | |
| **Total** | 3,549765295 | 96,4502347 | 17,60993209 | 82,39006791 |

**Comment**

Table III.13 clearly shows the advantage of the multiple linear regression method for the prediction of material removal rate. So the method of multiple linear regression is recommended for the prediction of the removal rate of the material in EDM machining.

### III.6.2 Surface roughness SR

In order to choose the best method of modelling the surface roughness, we used the thirty confirmatory tests as a basis for the comparison that we will make, and so it will be a good form of comparison. The comparison was made by calculating the error and accuracy of the surface roughness prediction by each model as shown in Table III.15

**Table III.14** Surface Roughness (SR) prediction errors and accuracy by both methods.

| | **Output predicted by Linear regression** | | **Output predicted by Surface response** | |
|---|---|---|---|---|
| **Trials** | Error% | Accuracy% | Error% | Accuracy% |
| **1** | 3,379245552 | 96,62075445 | 0,019946619 | 99,98005338 |
| **2** | 12,68193728 | 87,31806272 | 0,13445122 | 99,86554878 |
| **3** | 10,3266427 | 89,6733573 | 0,000125809 | 99,99987419 |
| **4** | 4,534935725 | 95,46506428 | 0,000515695 | 99,9994843 |
| **5** | 8,176129496 | 91,8238705 | 0,050600719 | 99,94939928 |
| **6** | 3,428276299 | 96,5717237 | 0,006866286 | 99,99313371 |
| **7** | 0,013004996 | 99,986995 | 0,013429693 | 99,98657031 |
| **8** | 7,299852349 | 92,70014765 | 0,065560403 | 99,9344396 |
| **9** | 1,232035794 | 98,76796421 | 0,026826995 | 99,97317301 |
| **10** | 7,282924312 | 92,71707569 | 0,066549599 | 99,9334504 |
| **11** | 3,753364198 | 96,2466358 | 0,073167438 | 99,92683256 |
| **12** | 6,546491074 | 93,45350893 | 0,020566286 | 99,97943371 |
| **13** | 9,915804094 | 90,08419591 | 0,067496345 | 99,93250365 |
| **14** | 0,746802469 | 99,25319753 | 0,019237654 | 99,98076235 |
| **15** | 2,245792045 | 97,75420796 | 0,042144837 | 99,95785516 |
| **16** | 0,014521576 | 99,98547842 | 0,007076298 | 99,9929237 |
| **17** | 5,722863248 | 94,27713675 | 0,106940883 | 99,89305912 |
| **18** | 0,259780313 | 99,74021969 | 0,046237854 | 99,95376215 |
| **19** | 32,35107764 | 67,64892236 | 0,002730924 | 99,99726908 |
| **20** | 26,12616195 | 73,87383805 | 0,011688611 | 99,98831139 |
| **21** | 21,25074692 | 78,74925308 | 0,068332601 | 99,9316674 |
| **22** | 10,87065609 | 89,12934391 | 0,075245133 | 99,92475487 |
| **23** | 4,68182437 | 95,31817563 | 0,046123213 | 99,95387679 |
| **24** | 0,180846906 | 99,81915309 | 0,001143322 | 99,99885668 |
| **25** | 1,436411609 | 98,56358839 | 0,013690633 | 99,98630937 |
| **26** | 3,068096515 | 96,93190349 | 0,029996649 | 99,97000335 |
| **27** | 1,676726343 | 98,32327366 | 0,017420077 | 99,98257992 |
| **28** | 4,256 | 95,744 | 0,041867797 | 99,9581322 |
| **29** | 1,107652733 | 98,89234727 | 0,011733119 | 99,98826688 |
| **30** | 9,919656898 | 90,0803431 | 0,098466762 | 99,90153324 |
| | **Model Errors and Accuracy (%)** | | | |
| **Total** | 6,816208717 | 93,18379128 | 0,039539316 | 99,96046068 |

**Comment**

Table III.14 clearly shows the advantage of the Surface response method for the prediction of surface roughness. So the method of surface response is recommended for the prediction of the surface roughness (SR) in EDM machining.

## III.7 Interactive effects

### a) Interactive effect of discharge pulse off time and pulse time on MRR

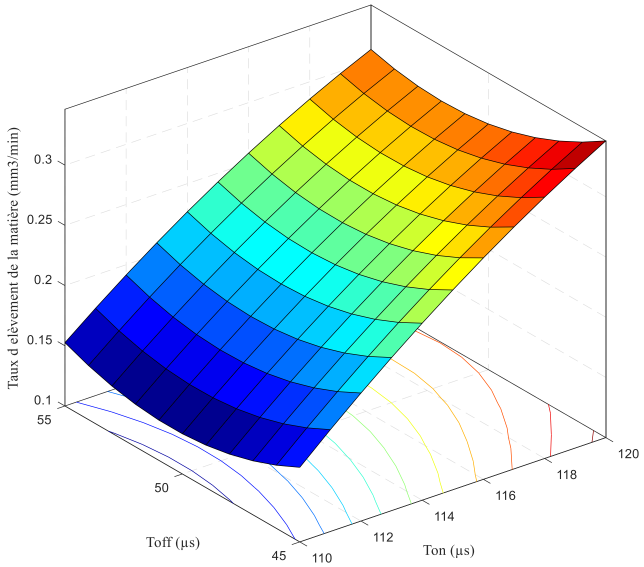



**Figure III.17** Expected surface roughness variation as a function of pulse on time discharge and pulse off time when V=20 (µs)

Figure (III.17) shows that the material removal rate takes these maximum values for large values of the pluse time whatever the values of the pulse off time.

Also from figure (III.17) it is also clear that the factor affecting the material removal rate is the pluse time. The pulse off time also plays a role in modifying the material removal rate but its influence is less important than the pluse time

### b) Interactive effect of pulse on time discharge and voltage on MRR

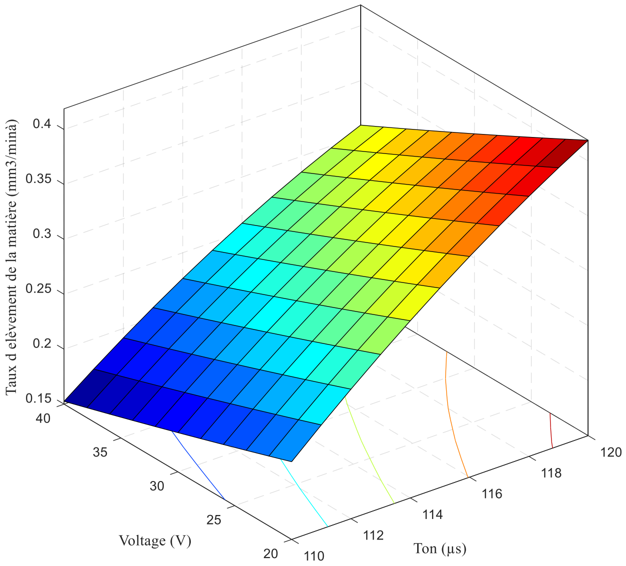



**Figure III.18** Change in expected material removal rate as a function of pulse on time discharge and voltage when Toff=45 µs

The figure (III.18) shows that the material removal rate takes these maximum values for large values of the pluse time and simultaneously with large values of the voltage.

It is also clear that both factors (pluse time and voltage) affect the material removal rate.

### c) Interactive effect of pulse time and voltage on MRR

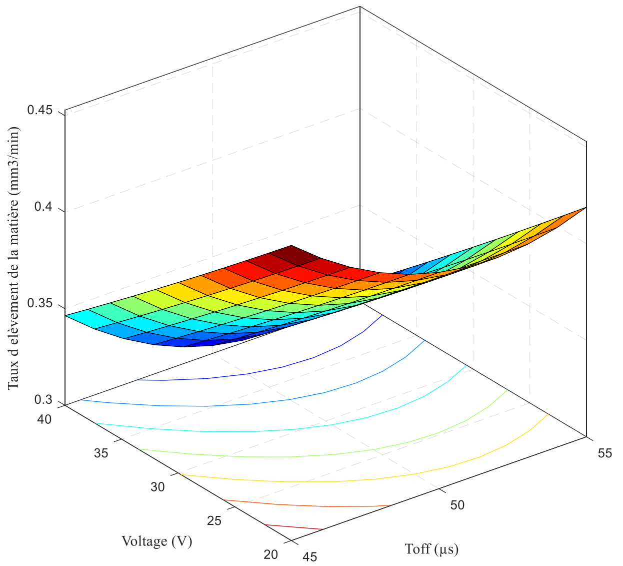



**Figure III.19** Change in expected material removal rate as a function of pulse time and voltage when Ton=110 µs

Figure (III.19) shows that the material removal rate takes these maximum values for small values of the voltage whatever the values of the pulse off time.

Also from figure (III.19) it is also clear that the factor affecting the material removal rate is the voltage. The pulse off time also plays a role in modifying the material removal rate but its influence is less important than the voltage.

**d) Interactive effect of pulse on time discharge and pulse time on SR**

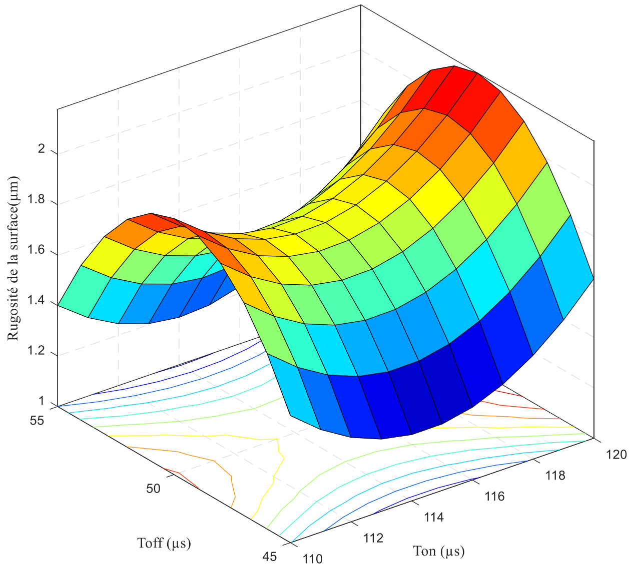



**Figure III.20** Variation of the expected surface roughness as a function of pulse on time discharge and pulse time when V=20 volt**.**

Figure (III.20) shows that the surface roughness reaches maximum values for the low and high value of the pulse off time and decreases for the average pulse off time values regardless of the pulse time values.

The most important factor the effect on surface roughness is a pulse off time.

**e) Interactive effect of pulse on time discharge and voltage on SR**

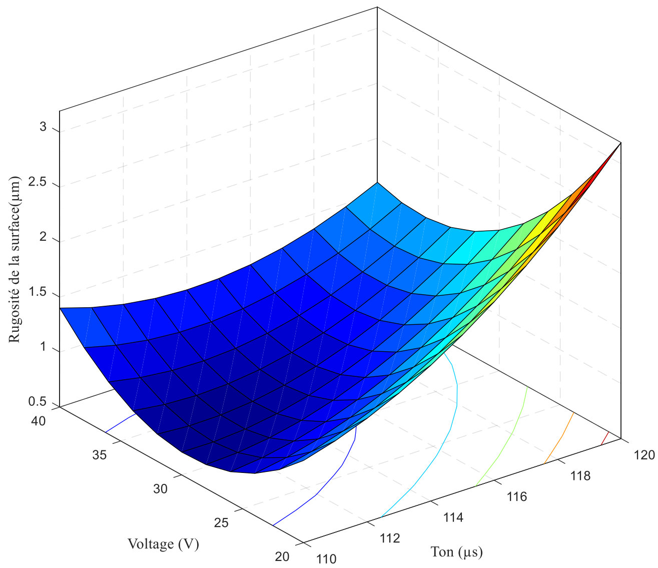


**Figure III.21** Variation of surface roughness as a function of pulse on time discharge and voltage when Toff=45 μs.

Figure (III.21) shows that the surface roughness takes extreme values of large values of the pluse time and at the same time with small values of voltage.

It is also evident that both factors (pluse time and voltage) affect the surface roughness.

### f) Interactive effect of pulse time and voltage on SR

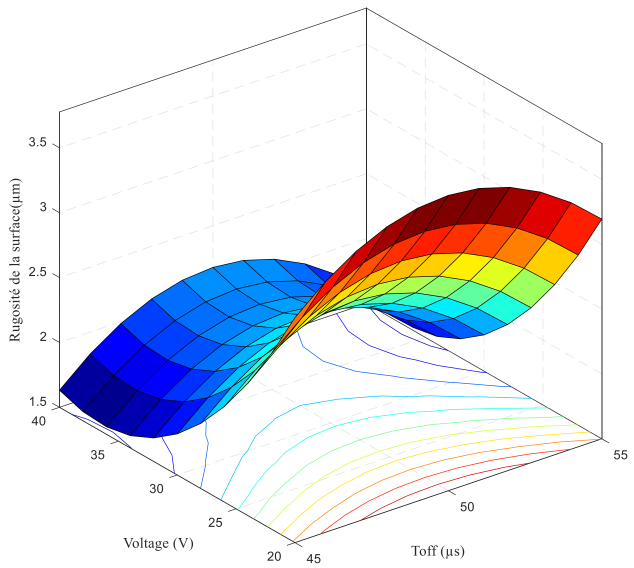



**Figure III.22** Expected surface roughness variation as a function of pulse time and voltage when Ton=110 μs

Figure (III.22) shows that the surface roughness reaches these extreme values for the lower voltage values and whatever the pulse off time values are. The most influential factor on surface roughness is the voltage. The change in surface roughness is also affected by the pulse off time, but is less significant than the voltage.

# *Conclusion*

# Conclusion

The work carried out as part of this brief has led to a better understanding of the effect of different input parameters on the performance of AISI 1095 steel EDM machining. pulse on time discharge, pulse time and voltage were considered input variables. The analysis of the effect of process parameters on machining performance was carried out by two methods: multiple linear regression, the response surface method. The study we undertook concluded that:

- The methods used in this work can be used to predict the rate of material removal and the surface roughness in practice. They are useful as an economical way to increase the material removal rate (MRR) and reduce the surface roughness (SR) for EDM machining of AISI 1095 steel.
- Comparison and validation of predicted results with experimental test results confirmed the accuracy of the models developed. The multiple linear regression technique and the surface response method were better and more accurate (96.45%, 82.39%, respectively) than the material removal method. Therefore, both methods can be made economical and efficient to predict the performance of EDM machines.

  With regard to surface roughness, the response surface modelling technique was better and more accurate than the other two prediction methods (96.45%, 99.96%).
- All machining parameters directly affect EDM machining performance but in varying proportions, depending on the nature of the desired performance. Where the discharge current is found to have the greatest effect on the rate of material removal. Although we find that pulse on time discharge and voltage have the greatest influence on the surface roughness.

# References


**[1].** **Nourbakhsh, Farnaz**, "Machining stability of wire edm of titanium" (2012). Industrial and Management Systems Engineering -- Dissertations and Student Research. 37.

**[2].** **Andreas Jørgensen and Michael Hauschild** Management Engineering, Technical University of Denmark, Lyngby, Denmark, The International Academy for Production Engineering (ed.), CIRP Encyclopedia of Production Engineering, DOI 10.1007/978-3-642- 20617-7, # CIRP 2014.

**[3].** **Benjamin Fleming**, 2005, The edm how-to book, United states of America, $4^{th}$ Printing, ISBN 0-9767596-0-8.

**[4].** **Shailesh kumar dewangan,** 2010**,** Experimental Investigation of Machining Parameters for EDM Using U-shaped Electrode of AISI P20 Tool Steel, Department of Mechanical Engineering, National Institute of Technology, Rourkela (India).

**[5].** **Olatz Flaño Alaña**, 2018, Approaches for improvement of edm performance and for the understanding of electrode wear phenomena, Bilbao.

**[6].** **Steve Krar,** Electrical discharge machining (Cutting Metal to Precise Shapes using Electricity).

**[7].** **Mezoudj Mourad,** 2020, Prédiction des Paramètres du Processus d'Usinage par Electroérosion, Departement Of mechanical engineering, Kasdi Merbah university, Algeria, Ouargla.

**[8].** **Sourabh Kumar Saha, 2008,** Experimental Investigation of the Dry Electric Discharge Machining (Dry EDM) Process, Kanpur 208016 (INDIA).

**[9].** https://www.market-prospects.com/articles/electrical-discharge-machining#:~:text=Wire%20Cutting%20Electrical%20Discharge%20Machining%3A,with%20the%20spool%20during%20processing

**[10].** **Kosaraju Satynarayana1, Kumkuma Rajkiran2, Pujari Anil kumar3, D Chakradhar4,** A Role of cryogenic in Wire cut EDM process, Mechanical Engineering Department, Bachupally 500090, Kerala, India.

**[11].** https://www.rapiddirect.com/blog/what-is-electrical-discharge-machining/

**[12].** **T. R. Ablyaz* and D. A. Borisov**, 2011, Influence of the Surface Roughness of the Electrode Tool on the Productivity in Electric Discharge Machining of Steel, Perm Polytechnic University, Perm, Russia.

**[13].** https://www.theopeneducator.com/doe/Response-Surface-Methodology/What-is-Response-Surface-Methodology

**[14].** https://online.stat.psu.edu/stat503/lesson/11

**[15].** https://www.researchgate.net/profile/Mohamed-Mourad-Lafifi/post/Can_I_optimise_a_set_of_responses_from_a_Taguchi_L9_array_using_RSM/attachment/59d64e2179197b80779a787f/AS%3A491401210273792%401494170586276/download/chapter3+Response+surface+Methodology.pdf

**[16].** **Nuran Bradle,** The surface response methodology, Department of Mathematical Sciences, Indiana University of South Bend.

**[17].** **Raja Rajeswari Ponnusamy**, 2019**,** The Performance of Response Surface Methodology Based on the OLS and MM-Estimators for Second-Order Regression Model, International Journal of Recent Technology and Engineering (IJRTE).

**[18].** **Hachmine Abdelkader, 2017,** Spécification des modèles linéaires et non-linéaires dans l'inférence statistique (régression linéaire et non-linéaire), Mathematics department, Kasdi Merbah university, Algeria, Ouargla.

**[19].** **Berkani Fatiha, 2016,** Application de la Régression Linéaire Multiples sur la Balance Commerciale Algériènne, Mathematics department, Kasdi Merbah university, Algeria, Ouargla.

**[20].** http://grasland.script.univ-paris-diderot.fr/STAT98/stat98_7/stat98_7.htm

**[21].** https://www.ncl.ac.uk/webtemplate/ask-assets/external/maths resources/statistics/regression-and-correlation/residuals.html#:~:text=Definition,yi%E2%88%92%5Eyi.

**[22].** http://www.stat.yale.edu/Courses/1997-98/101/anovareg.htm

**[23].** **J.C. Rebelo, A.M. Dias, R. Mesquita, M. Santos**, "An experimental study on electrodischarge machining and polishing of high strength copper-beryllium alloys" Journal of Materials Processing Technology, 108(5): (2000) 389-397. https://doi.org/10.1016/S0924-0136(99)00492-6

**[24].** **J.C. Rebelo, A.M. Dias, D. Krember, J.L. Lebrun**, Influence of EDM pulse energy on the surface of integrity of martensitic steel", Journal of material processing Technology 84, 1998, 90-96. https://doi.org/10.1016/S0924-0136(98)00082-X

**[25].** **M. Boujelbene, E. Bayraktar, W. Tebni, S. Ben Salem**, "Influence of machining parameters on the surface integrity in electrical discharge machining", Archives of Materials Science and Engineering, volume 37, issue 2, June 2009, 110-116.

**[26].** **H.S. Payal,** "Analysis of electro discharge machined surfaces of EN-31 tool steel Niscair Publications. Vol-67, pp 1072-1077, (2008). http://nopr.niscair.res.in/handle/123456789/2537

**[27].** **Y.C. Lin, B. H. Yan, C. C. Wang, H. M. Chow**, "Feasibility study of rotary electrical discharge machining with ball burnishing for Al2O3/6061Al composite", 23(5): 391–399. (2008). https://doi.org/10.1016/S0890-6955(00)00005-5

**[28].** **Y.C. Lin, B. H. Yan, C. C. Wang, H. M. Chow,** "Feasibility study of rotary electrical discharge machining with ball burnishing for Al2O3/6061Al composite", 23(5): 391–399. (2008). https://doi.org/10.1016/S0890-6955(00)00005-5

**[29]. K.M. Patel, P.M. Pandey, P.V. Rao, "**surface integrity and material removal mechanism associated with the EDM of Al2O3 ceramic composite, Int. Journal of refractory metals and hard materials 27, issue 5, 2007, 892-899.https://doi.org/10.1016/j.ijrmhm.2009.05.003

**[30]. H.T. Lee, F.C. Hsu, T.Y. Tai,"**Study of surface integrity using the small area EDM process with a Copper-Tungsten electrode, material science and engineering A364**,** 2004, 346-356. https://doi.org/10.1016/j.msea.2003.08.046

**[31]. Sarode, A.J. Parmar, U. Pandharkar, S. Junnarkar**, Effect of Electrode Material and geometry EDM Performance for OHNS dies steel" IJAEMS. 2016

**[32]. T. Muthuramalingam , B. Mohan**, A review on influence of .electrical process parameters in EDM process, archives of civil and mechanical engineering 15(2015) 87-94. https://doi.org/10.1016/j.acme.2014.02.009

**[33]. H. Singh** "Investigating the Effect of Copper Chromium and Aluminum Electrodes on EN-31 Die Steel on Electric Discharge Machine Using Positive Polarity" World Congress on Engineering. (2012).

**[34]. S. Gopalakannan, T. Senthilvelan** "Effect of Electrode Materials on Electric Discharge Machining of 316 L and 17-4 PH Stainless Steels" Journal of Minerals and Materials Characterization and Engineering. (2012).

**[35]. P. Janmanee** (2010) "Performance of Difference Electrode Materials in Electrical Discharge Machining of Tungsten Carbide" ERJ.

**[36]. J.H. Zhang, T.C. Lee, W.S. Lau,** , Study on the electro discharge machining of a hot pressed aluminum oxide based ceramic". Journal of Materials Processing Technology, 63(4): (1997) 908-912. https://doi.org/10.1016/S0924-0136(96)00012-X

**[37]. Shiba narayan sahu. (2012).** Optimization of EDM Process., Mémoire de Master National Institute of Technology, Rourkela, Oriss

## Abstract

This work aims to study the effect of EDM machining parameters on the removal rate of MRR material and the roughness of machined surfaces during machining. The machining parameters taken into account for this study are: pulse time, voltage and pulse downtime. In this work, two models are developed to study the effect of these parameters on the machining performance. The first model is based on the multiple linear regression technique, the second model is based on the response surface method. The results obtained during this study show that the developed models have a high prediction accuracy which exceeds 96% in all cases. The study concluded that the best model to predict the material removal rate is the model based on the multiple linear regression technique, with an accuracy of more than 96.45%. While the model based on the response surface method was the best in predicting roughness with an accuracy that exceeds 99.96%. The analysis of the results led to the fact that the two most influential factors on the machining performance are pulse time and voltage.



**Key words:** EDM, Machining Parameters, Multiple Linear Regression, Response Surfaces.



## Résumé

Ce travail vise à étudier l'effet des paramètres d'usinage par électroérosion sur le taux d’enlèvement de la matière MRR et la rugosité des surfaces usinées lors de l’usinage. Les paramètres d’usinage pris en compte pour cette étude sont : temps d’impulsion, le voltage et le temps d’arrêt d'impulsion. Dans ce travail, deux modèles sont développés pour étudier l'effet de ces paramètres sur les performances d’usinage. Le premier modèle est basé sur la technique de la régression linéaire multiple, le deuxième modèle est basé sur la méthode de surfaces de réponses. Les résultats obtenus, lors de cette étude, montrent que les modèles développés ont une grande précision de prédiction qui dépasse 96% dans tous les cas. L'étude a conclu que le meilleur modèle pour prédire le taux d'enlèvement de la matière est le modèle basé sur la technique de régression linéaire multiple, avec une précision de plus de 96,45%. Alors que le modèle basé sur la méthode de surfaces de réponses a été le meilleur pour prédire la rugosité avec une précision qui dépasse 99.96%. L'analyse des résultats a conduit au fait que les deux facteurs les plus influents sur les performances d’usinage sont temps d’impulsion et le voltage.



**Mots clefs:** EDM, Paramètres d’usinage, Régression linéaire multiple, Surfaces de réponses.



## ملخص

يهدف هذا العمل إلى دراسة تأثير عوامل التصنيع عن طريق التفريغ الكهربائي على معدل إزالة المادة و خشونة الأسطح المشغلة عقب التصنيع. عوامل التصنيع التي اعتمدت في هذه الدراسة هي: تيار التفريغ، زمن النبض، الجهد و زمن توقف النبض. في هذه الدراسة تم تطوير نموذجين لدراسة تأثير هذه العوامل على أداء التصنيع. تم تطوير النموذج الأول باستعمال تقنية الانحدار الخطي المتعدد، فيما تم تطوير النموذج الثاني باستعمال طريقة أسطح الاستجابة. أظهرت النتائج المتحصل عليها خلال هذه الدراسة أن النماذج المطورة لديها دقة تنبؤ عالية تجاوزت 96٪ في جميع الحالات. وخلصت الدراسة إلى أن أفضل نموذج للتنبؤ بمعدل إزالة المادة هو النموذج المطور باستعمال تقنية الانحدار الخطي المتعدد بدقة تزيد عن 96.45٪. بينما خلصت الدراسة أيضًا إلى أن النموذج المطور باستعمال طريقة أسطح الاستجابة هو الأفضل للتنبؤ بخشونة السطح المشغل حيث تجاوزت دقته 99.96 ٪. تحليل النتائج أظهر أن العاملين الأكثر تأثيرًا على أداء عملية التصنيع هما زمن النبض والجهد.



**الكلمات المفتاحية:** التصنيع عن طريق التفريغ الكهربائي، عوامل التصنيع، الانحدار الخطي المتعدد، طريقة أسطح الاستجابة.