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Theme

**Empirical modeling and multicriteria
decision-making of surface texture and
tool wear in hard turning**

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Dedication

I dedicate this work to my beloved mother, for her endless love,
prayers, and support.

To my dear brothers, for their encouragement and presence.

To my dear uncle for his support.

May Allah protect them all.

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First and foremost, I would like to express my sincere gratitude to Allah Almighty for granting me the strength, patience, and guidance to complete this work.

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ملخص:

تعدّ الخراطة الصلبة الجافة (Dry Hard Turning, DHT) حلاً مبتكراً يهدف إلى استبدال عمليات التشغيل التقليدية التي تعتمد على سوائل القطع. ويؤدي غياب سائل التبريد الخارجي إلى تغيير آليات التلامس بين أداة القطع وقطعة، مما يؤثر في سلوك عملية التشغيل. تتناول هذه الدراسة تحليل قابلية تشغيل فولاذ الأدوات AISI D2 المعالج حرارياً إلى صلادة 55 ± 1 HRC. وتم تقييم أداء التشغيل بالاعتماد على ثلاثة مؤشرات رئيسية هي: خشونة السطح (Ra)، ودرجة حرارة القطع (T_c)، وتآكل وجه الخلوص (V_b). أما متغيرات القطع المدروسة فتشمل عمق القطع (ap)، والتغذية (f)، وسرعة القطع (V_c). وقد تم تحليل النتائج التجريبية باستخدام تحليل باريتو (Pareto Analysis) لتحديد أكثر العوامل تأثيراً، تلاه تطوير نماذج تنبؤية بالاعتماد على الشبكات العصبية الاصطناعية (ANN) وآلات متجهات الدعم (SVM). وأخيراً، أُجري تحسين متعدد المعايير باستخدام تقنية TOPSIS مع إسناد أوزان متساوية (33.33%) لكل معيار من معايير الأداء.

الكلمات المفتاحية : الخراطة الصلبة الجافة، سلامة السطح، تآكل وجه الخلوص، TOPSIS.

Abstract:

Dry hard turning (DHT) has emerged as an innovative alternative to conventional machining processes that rely on cutting fluids. The absence of external lubrication alters the contact mechanisms between the cutting tool and the workpiece, thereby affecting the machining behavior. This study investigates the machinability of AISI D2 tool steel heat-treated to a hardness of 55 ± 1 HRC. Machining performance is evaluated using three representative response variables: surface roughness (Ra), cutting temperature (T_c), and flank wear (V_b). The cutting parameters considered are depth of cut (ap), feed (f), and cutting speed (V_c). The experimental results are analyzed using Pareto analysis to identify the most influential machining parameters, followed by predictive modeling based on Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Finally, a multi-criteria optimization is performed using the TOPSIS method, assigning equal weights (33.33%) to each performance criterion.

Keywords: Dry hard turning, surface integrity, flank wear, TOPSIS.

Résumé :

Le recours au tournage dur (TD) à sec constitue une solution innovante visant à remplacer les procédés conventionnels utilisant des fluides de coupe. L'absence de lubrification externe entraîne une modification des mécanismes de contact entre l'outil de coupe et la pièce, influençant ainsi le comportement du procédé d'usinage. Cette étude porte sur l'analyse de l'usinabilité de l'acier AISI D2 traité à une dureté de 55 ± 1 HRC. Les performances sont appréciées à travers trois réponses représentatives : la rugosité de surface (Ra), la température de coupe (T_c) et l'usure en dépouille (V_b). Les paramètres de coupe investigués sont la profondeur de passe (ap), l'avance (f) et la vitesse de coupe (V_c). L'exploitation des résultats s'appuie sur une analyse de Pareto afin d'identifier les facteurs les plus influents, suivie d'une modélisation prédictive basée sur les méthodes ANN et SVM. Une optimisation multicritère est ensuite effectuée au moyen de la technique TOPSIS, en attribuant une importance équivalente (33,33 %) à chacun des critères de performance.

Mots-clés : Tournage dur à sec, intégrité de surface, usure en dépouille, TOPSIS.

Abstract

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NOMENCLATURE

Latin Symbols

V	Cutting speed	m/min
V_c	Cutting speed (alternate notation)	m/min
N	Spindle rotational speed	Rpm
f	Feed per revolution	mm/rev
fr	Feed rate	mm/min
d	Depth of cut	mm
ap	Depth of cut (alternate notation)	mm
R_a	Arithmetic mean surface roughness	μm
R_z	Average maximum height of the roughness profile	μm
R_t	Maximum height of the roughness profile	μm
R_q	Root mean square surface roughness	μm
T_c	Cutting temperature	$^{\circ}\text{C}$
T	Cutting temperature (alternate notation)	$^{\circ}\text{C}$
VB	Flank wear width	mm
V_b	Flank wear (alternate notation)	mm
VB_c	Flank wear – corner zone	mm
E	Young's modulus (elastic modulus)	GPa
R_m	Ultimate tensile strength	MPa
R_e	Yield strength	MPa
A	Elongation at break	%
T_m	Melting temperature	$^{\circ}\text{C}$
M	Margin (SVM hyperplane separation)	–
MSE	Mean Squared Error (ANN training criterion)	–
$MAPE$	Mean Absolute Percentage Error	%
$RASE$	Root Average Squared Error	varies
R^2	Coefficient of determination	–
$Si+$	Euclidean distance to the Positive Ideal Solution (TOPSIS)	–
$Si-$	Euclidean distance to the Negative Ideal Solution (TOPSIS)	–

C_i	Relative closeness coefficient (TOPSIS)	—
r_{ij}	Normalized element of the decision matrix	—
v_{ij}	Weighted normalized element of the decision matrix	—
w_j	Weighting coefficient for criterion j	—
x_{ij}	Original performance value (decision matrix)	—
W	Weight vector (SVM hyperplane normal)	—
b	Bias term (SVM / ANN)	—
x	Input feature vector (SVM)	—
x_i	Input variable (ANN)	—
w_{ij}	Connection weight between neuron i and neuron j	—
b_j	Bias parameter of neuron j	—
net_j	Weighted sum received by neuron j	—
y_j	Output of neuron j after activation function	—
y_i	Actual (experimental) target value	—
$\hat{y}_i$	Predicted value generated by the ANN model	—
Kn	RBF kernel function	—
$H1, H2, H3$	Hidden-layer neuron outputs (ANN models)	—
Greek Symbols		
ρ	Density	g/cm ³
λ	Thermal conductivity	W/m·K
ν	Poisson's ratio	—
γ	RBF kernel parameter (SVM)	—
α	Statistical significance threshold (Pareto)	—
π	Mathematical constant (≈ 3.14159)	—
Abbreviations		
<i>ANN</i>	Artificial Neural Network	—
<i>SVM</i>	Support Vector Machine	—
<i>RBF</i>	Radial Basis Function	—
<i>ReLU</i>	Rectified Linear Unit (activation function)	—
<i>TOPSIS</i>	Technique for Order Preference by Similarity to Ideal Solution	—

<i>MCDM</i>	Multi-Criteria Decision-Making	—
<i>PIS</i>	Positive Ideal Solution	—
<i>NIS</i>	Negative Ideal Solution	—
<i>OFAT</i>	One Factor At a Time (experimental approach)	—
<i>MRR</i>	Material Removal Rate	mm ³ /min
<i>HRC</i>	Hardness – Rockwell C scale	—
<i>HB</i>	Hardness – Brinell scale	—
<i>CVD</i>	Chemical Vapour Deposition	—
<i>PVD</i>	Physical Vapour Deposition	—
<i>PCBN</i>	Polycrystalline Cubic Boron Nitride	—
<i>PCD</i>	Polycrystalline Diamond	—
<i>cBN</i>	Cubic Boron Nitride	—
<i>ISO</i>	International Organisation for Standardisation	—
<i>AISI</i>	American Iron and Steel Institute	—
<i>ASTM</i>	American Society for Testing and Materials	—

General Introduction

Currently, hard turning is becoming one of the most significant machining processes for producing precision parts from hardened steels. Due to its high dimensional accuracy and surface finish characteristics, it is increasingly replacing traditional grinding in such industries as automotive, aerospace, and mold-making. Compared to grinding, hard turning provides many benefits such as increased productivity, decreased cost, flexibility, and reduced fluid consumption.

Cutting parameters, which include cutting speed, feed, and depth of cut, significantly impact the performance of the hard turning process through such machining responses as surface roughness, cutting temperature, and tool wear. Owing to the complicated interdependencies between the variables, prediction of machining performance and determination of optimal cutting conditions is not an easy task. Therefore, artificial intelligence approaches and multi-criteria optimization methods are increasingly used to enhance machining effectiveness and quality.

In such a case, the aim of this thesis work is to analyze the effect of cutting parameters on the hard turning process of hardened AISI D2 tool steel. The emphasis of this research is made on the effects of the three machined responses which are surface roughness (Ra), cutting temperature (T_c), and flank wear (V_b). The ANN and SVM modeling techniques have been used to predict the responses while TOPSIS multi criteria decision-making technique has been used to find the best cutting parameters.

The research objectives will be achieved through organization of the thesis as follows:

Chapter One will outline the theoretical framework of the research. Here the introduction of the concepts like manufacturing and material removal process, turning and hard turning operations, cutting parameters, surface roughness, cutting tool wear, cutting temperature and indexable cutting tool will be outlined. The chapter will end with a brief discussion on the concepts that are needed to understand the machining process and machining performance.

Chapter Two will describe the experimental approach used in the research. The work piece material (AISI D2 hardened steel), machine tool, cutting inserts, measurement tools and computational tool will be described. Then the experimental design which was carried out according to the Taguchi L16 orthogonal array design. Also, the modeling approach including Artificial Neural Networks (ANN) and Support Vector Machine (SVM) as well as multi-criteria optimization approach based on TOPSIS method will be described.

Chapter Three is about Results of the experiment are presented and analyzed. First, Pareto analysis is conducted to find out the statistically significant effects of the cutting parameters on the surface roughness, cutting temperature, and flank wear. The ANN and SVM-based predictive models are next assessed and compared in terms of their prediction accuracy. Lastly, the TOPSIS approach is employed to determine the optimal conditions for the machining process that will ensure the best machining process performance.

Lastly, the conclusions of the thesis are provided which summarize the outcomes of the research, pinpoint its contributions to knowledge, and suggest possible directions for future research in the area of intelligent machining process modeling and optimization.

Chapter 1:

Fundamentals of

Turning

1.1-Introduction

Manufacturing process is the heart of the industry because it is the basic step in the conversion of raw materials into products. Manufacturing process comprises various steps starting from designing to production. Some manufacturing processes include forming, cutting, assembling, and quality control.

Manufacturing processes need proper coordination between the different kinds of machines used in production, including lathes, milling machines, welding machines, among others, as well as the skills of people for producing highly efficient products in short period of time.

One of the most crucial manufacturing processes is turning process, characterized by producing accurate and complicated parts using the cutting process in which the workpiece rotates about its axis while the material is cut by the cutting tool. This chapter will elaborate on the turning process.

1.2- Definition of Manufacturing:

Manufacturing is the process of converting raw materials into final products using mechanical processes and techniques such as cutting, forming, and welding. This results in the creation of a new surface or the modification of an existing surface. Manufacturing can be a simple process, such as cutting a piece of wood into smaller pieces, or it can be a complex process, such as shaping a complex metal piece to produce a final product. Today, manufacturing is carried out by modern machines.

Fundamentally, manufacturing relies on a cutting tool moving through the material, causing the tool to break or remove the material, leading to the formation of chips. The characteristics of the resulting surface depend on several factors, including the type of tool used, cutting speed, feed, and depth of cut. Manufacturing machines differ in terms of tool and workpiece movement and the surfaces they produce, but they share the manufacturing principle [1]

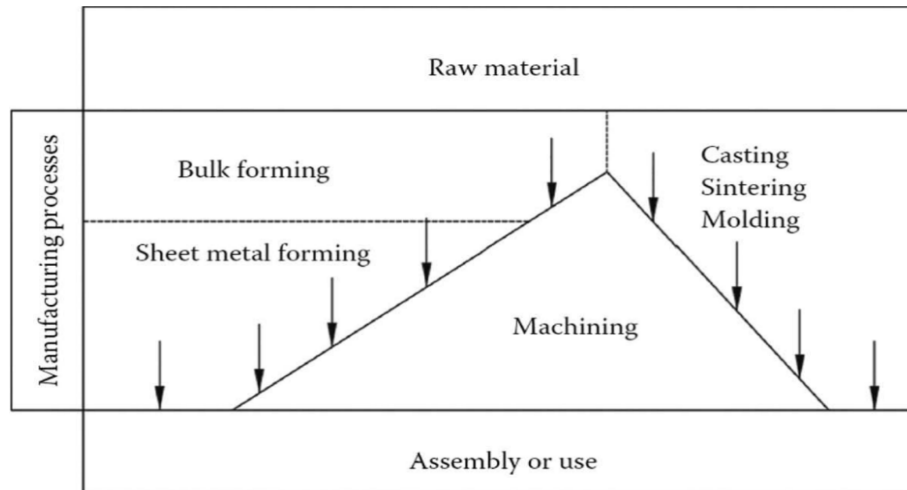


Figure 1-1- Manufacturing Processes [2]

1.2.1- Material Removal Processes in Manufacturing

Subtractive manufacturing, or material removal processing, entails the systematic reduction of a raw blank to achieve specified geometric profiles and dimensional tolerances. Conventional subtractive techniques namely turning, drilling, and milling utilize specialized cutting tools possessing superior hardness and wear resistance relative to the workpiece, with grinding operations deployed subsequently for surface texturing and smoothing. Conversely, advanced or non-conventional machining paradigms bypass mechanical tool contact entirely, exploiting concentrated thermal energy (such as laser beams) or chemical dissolution to erode material.

From a sustainability perspective, material removal inherently generates substantial scrap, contrasting sharply with formative processes like casting that maximize material utilization and minimize environmental footprints. Processes are further categorized by their manufacturing fidelity:

Net-shape processes: Operations that yield a component satisfying final geometric criteria directly, eliminating the need for secondary operations.

Near-net-shape processes: Operations where the initial shaping produces a geometry close to the final dimensions, requiring minimal post-processing or finish-machining. [3]

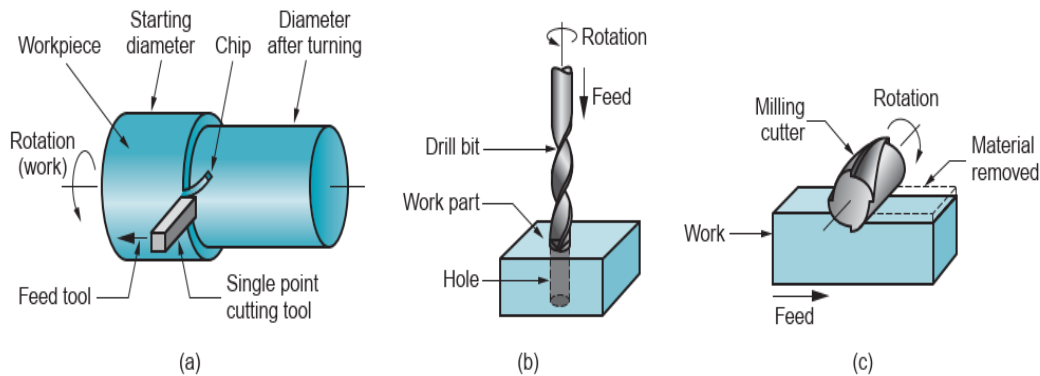


Figure 1.2- Common machining operations [3]

1.3- Turning principle

Turning process involves the machining of a circular or tapering part where a cylindrical or conical piece of stock is shaped to have a round or semi-round surface on its inside or outside. The cutter moves linearly or curvedly along the axis of the stock while the latter rotates. With these motions, the material can be cut away from the stock to form the desired profile. The chips are the parts removed by the tool. Motion of the tool feed relative to the workpiece. [4]

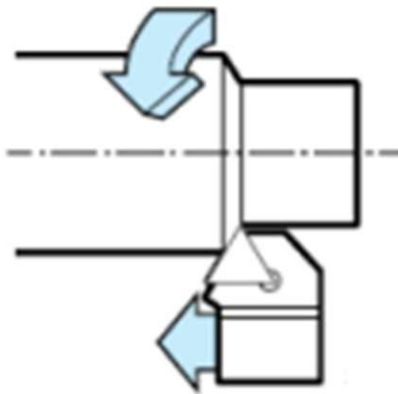


Figure 1.3- Turning principle [4]

1.4- Lathe Operations:

1.4.1- Straight Turning

The workpiece's diameter is decreased during this machining process because the feed motion, or tool movement, is a linear translation parallel to the workpiece's rotational axis. [5]

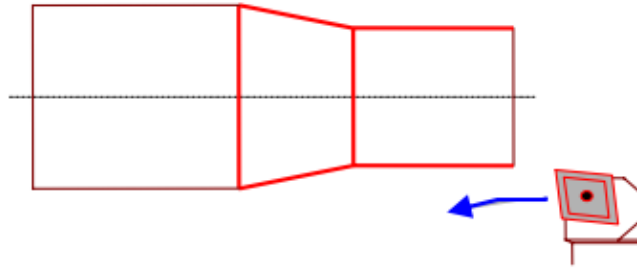


Figure 1.4- straight turning [5]

1.4.2- Facing

The workpiece's length is decreased by cutting a flat surface that is either internal or external to the spindle axis. [5]

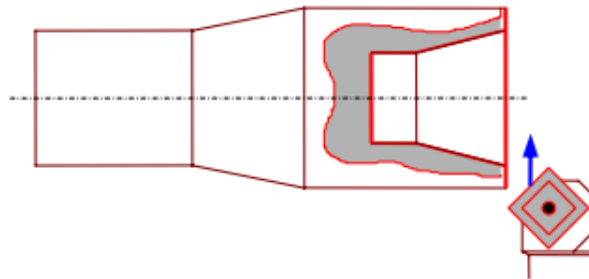


Figure 1.5- Facing [5]

1.4.3- Grooving

For example, this process involves cutting an internal or exterior groove to accommodate an O-ring or a circlip. [5]

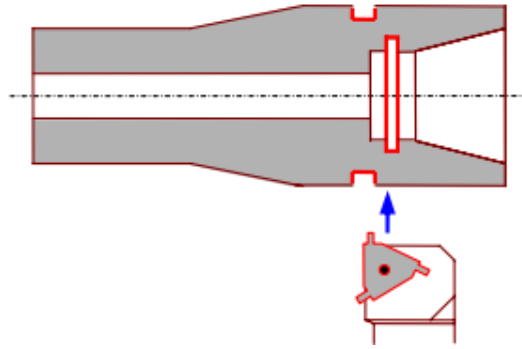


Figure 1.6- Grooving [5]

1.4.4- Threading

This process involves creating either internal or external threads. The cutting motion is mixed with the feed motion. [5]

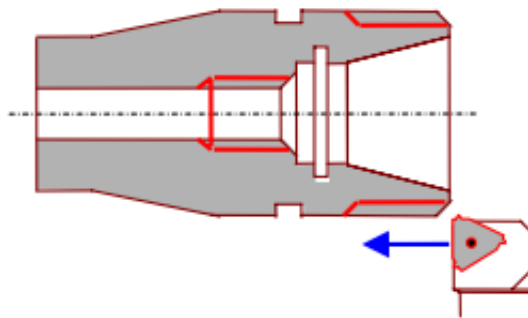


Figure 1.7- Threading [5]

1.4.5- Boring

In this process, an interior cylindrical or conical surface is machined. The feed action is comparable to straight turning. [5]

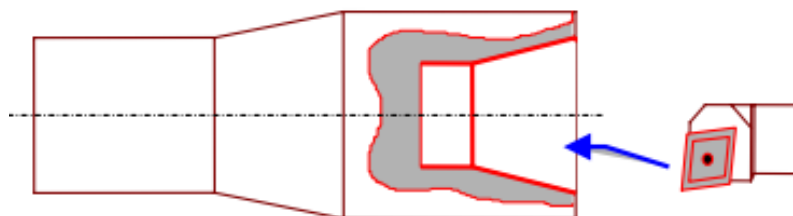


Figure 1.8- Boring [5]

1.5- Cutting parameters

1.5.1- Cutting Speed

Cutting speed of the tool is the distance travelled by the tool in a minute on the work piece. This speed is denoted by V and is an important parameter of machining process due to its relationship with characteristics of the process, the tool used, and mechanical and physical properties of the tool and material. Cutting speed is calculated with respect to rotational speed (N) of the spindle of the machine. The selection of the cutting speed V is dependent upon the practical machining conditions, such as the material of workpiece and material of the tool used. This is done by using the following equation:

$$V = \frac{\pi \times D \times N}{1000} \quad (1.1)$$

Where:

- V : cutting speed (m/min)
- D : workpiece diameter (mm)
- N : spindle speed (rev/min or tr/min)

Tool life is significantly impacted by cutting speed. Cutting circumstances, tool material, the kind of machined material (finishing or roughing), lubrication conditions, and the cutting tool's shape are the key factors that affect it.. [6]

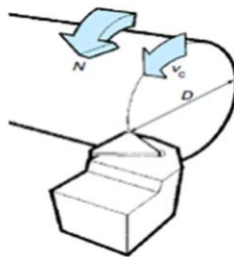


Figure 1.9- Cutting Speed [6]

1.5.2- Feed (f)

The feed (f) for a lathe process is the amount by which the cutting tool travels axially along the part per one revolution of the job, and is measured in mm/revolution. The feed rate (f_r), on the other hand, is the speed of travel of the cutting tool linearly along the longitudinal axis of the part, and is measured in mm/minute. Linear velocity can be related to feed/revolution through the spindle speed (N) as follows:

$$f_r = f \cdot N \quad (1.2)$$

Where:

- f : mm/rev
- f_r : feed speed (mm/min)
- N : spindle speed (rev/min)

Cutting conditions and speed may affect feed rate. As a result, it is chosen using the previously established criteria. [6]

1.5.3- Depth of Cut

Depth of cut (d) refers to the difference between the radii of the workpiece before and after machining in turning processes, while the length of the tool chip contact is referred to as the depth of cut in orthogonal machining. [7]

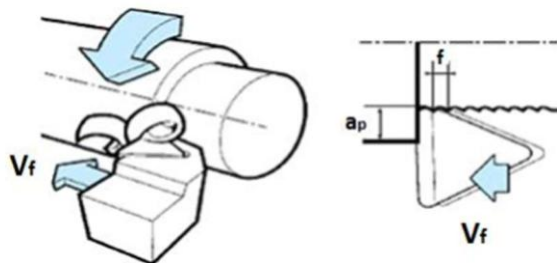


Figure 1.10- Feed and Depth of Cut [6]

1.6- Definition of Surface Roughness

Surface roughness is defined as the quantifiable irregularity on the surface of a material. Roughness may influence the properties of a material such as resistance, wear, and friction. roughness cannot be determined through touch or sight

1.6.1- Average Maximum Height of the Profile R_z

R_z is the average of the absolute values of the five greatest profile peaks' heights and the five deepest valleys' depths during the course of the assessment. [8]

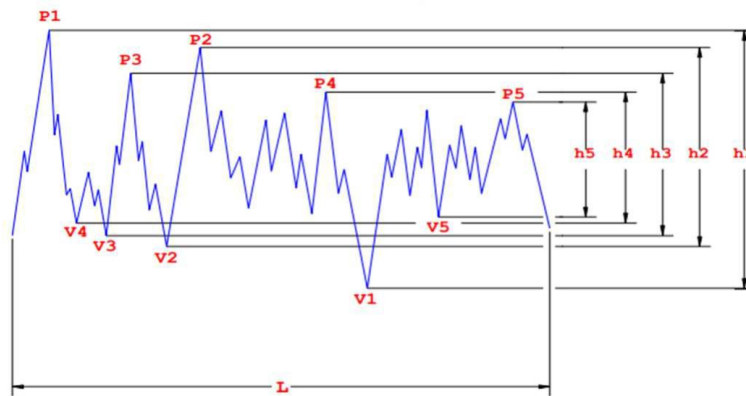


Figure 1.11 Average Maximum Height of the Profile R_z [8]

1.6.2- Roughness Average R_a

R_a is the arithmetic mean of the profile heights' absolute values during the course of the assessment. [8]

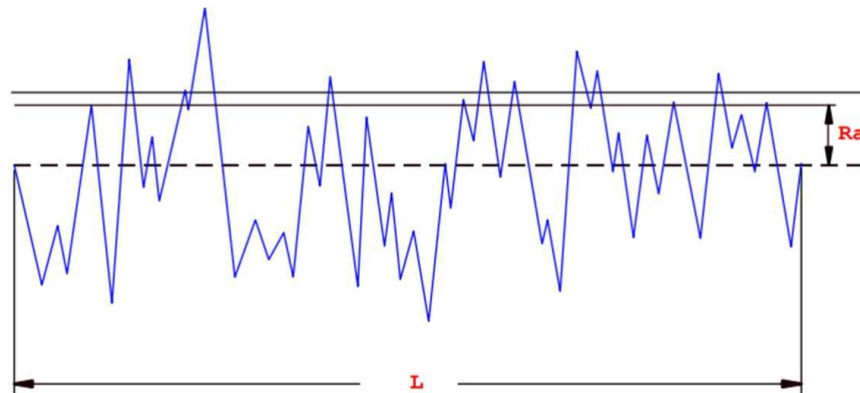


Figure 1.12 Roughness Average R_a [8]

1.6.3- Maximum Height of the Profile R_t

The evaluation's profile's vertical distance between its highest and lowest points is denoted by R_t . [8]

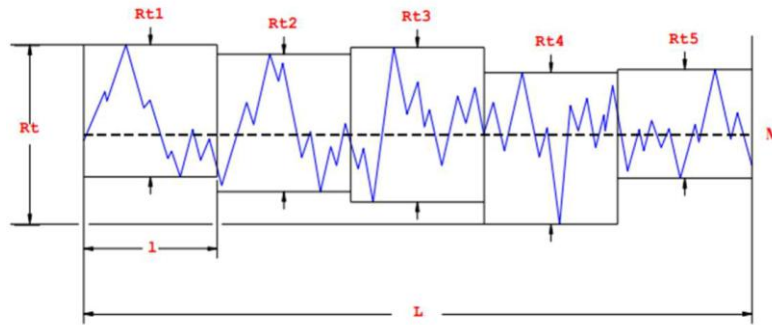


Figure 1.13 Maximum Height of the Profile R_t [8]

1.7- Hard Turning

Hard turning is used in preference to traditional methods for machining difficult metals which have a hardness of 45-65 on the scale. Because conventional cutting edges will shatter due to the hardness of the metals, bits of PCBN and ceramic take charge of the cuts. Factories now do this without the need of first machining the metal, placing it in hot conditions, and then smoothing it out. The process is best suited to pieces made of tough iron castings and steels. The technique, which was very precise, became the replacement for grinding in a lot of shops quietly. An advantage of hard turning is that it produces very smooth finishes, R_a sub $0.3 \mu\text{m}$, and achieves very precise tolerances, like $\pm 0.005 \text{ mm}$ or tighter. Fewer trips to different stages are needed, route. Many times, the material is in a better condition than grinding, mostly since there is less damage done by heat during the process. Normally, incisions are done at depths between 0.08 and 0.5 mm. Normally, speeds vary between 50 and 150 meters per minute. As the steps become smaller, the precision improves. Due to the heat resistance of both ceramics and CBN, these tools are often used in factories for production of items such as drive shafts, bearings, and gears. [9]

1.8- Tool life

Durability of the tool, also known as tool life, refers to the total time of operation that the cutting tool remains able to perform its operations within the required specifications for surface finish and dimensional tolerance. During the process of cutting, the cutting edge is subjected to wear due to the presence of unfavorable conditions such as cyclic load, frictional forces and high temperature gradients. The end of the operational life of the tool is determined by a defined value of tool wear that results into machining quality beyond the acceptable limits of engineering. The prediction of tool durability is very crucial for optimizing parameters and increasing efficiency of the manufacturing process. [10]

1.8.1- Tool wear

In the process of metalworking, the continuous rubbing between the flank face of the cutting tool and the surface of the machined piece causes a particular type of wear, called flank wear (VB). This form of tool wear results from the combined effect of micro-abrasive wear, adhesion, and high thermal stress created by chip formation. Failure to control the increase in this wear region will lead to poor surface finish, dimensional errors, and higher mechanical energy needed for the shearing process. Therefore, measurement of the VB wear value becomes an accepted way of diagnosing tool condition status and tool replacement scheduling. [11]

1.8.2- Wear zones

In material removing processes, progressive wear occurs in three essential regions of the cutting edge. Thus, tool wear can be classified into three basic types of failure: crater wear in the rake face region, flank wear in the clearance face region, and corner wear in the tool tip radius region. [12]

These specific wear zones are visually mapped and contrasted in Figure 1.14:

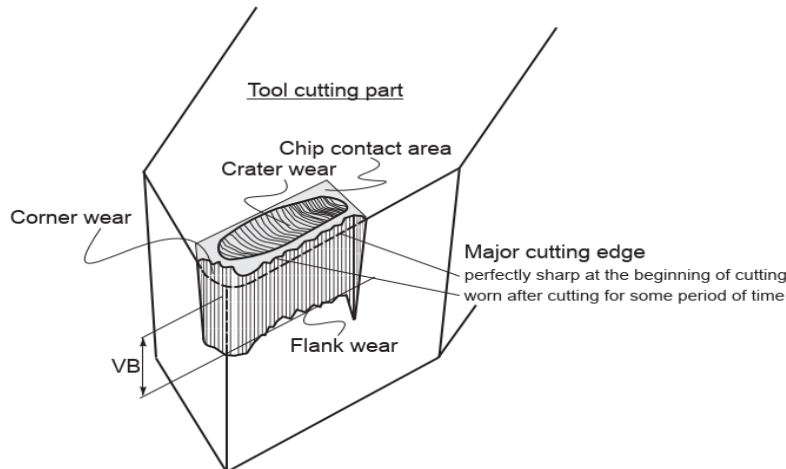


Figure 1.14 Types of wear observed in cutting tools [12]

1.8.2.1- Crater Wear

This wear process results in the formation of a concave area on the rake face of the tool as a result of the severe sliding effect of the chips along with their chemical diffusion during chip formation. Mechanically, cratering changes the cutting geometry through the increase in the rake angle that makes it easier for the chip to form owing to the reduction in the shearing resistance. Nevertheless, it results in the loss of the material from the tool and weakens the tool structure through its thinning that significantly increases the possibility of edge breaking. In contemporary manufacturing, cratering wear is usually seen as a second-rate issue compared with flank wear. [12]

1.8.2.2- Flank Wear

Occurring at the relief face of the insert, this kind of wear is caused by high levels of abrasive and adhesive friction on the newly created surface of the work piece. The damage caused by this process occurs in a flattened area referred to as the wear land, and its severity is evaluated through its width using a universal parameter called VB. Flank wear has a great impact on global machining processes since increased friction will lead to increased cutting forces. Exceeding the critical limit for this type of wear, which ranges between $VB = 0.5\text{mm}$ and 0.6mm , will definitely result in the destruction of the cutting tool. [12]

1.8.2.3- Corner Wear (Nose Wear)

Corner wear, which happens at the very radius of the tool tip, is continuous with the wear land of the clearance face, making it hard to distinguish a boundary between them. However, it is regarded

as a wear mechanism on its own because of its significant impact on the end-product and tolerances. The development of the nose wear results in the process called tool tip recession that makes the effective length of the cutting insert shorter, hence, reducing the amount of material being removed from the workpiece as compared to the actual programming. This causes the workpiece dimensions to be larger by about 0.03 to 0.05 mm. [12]

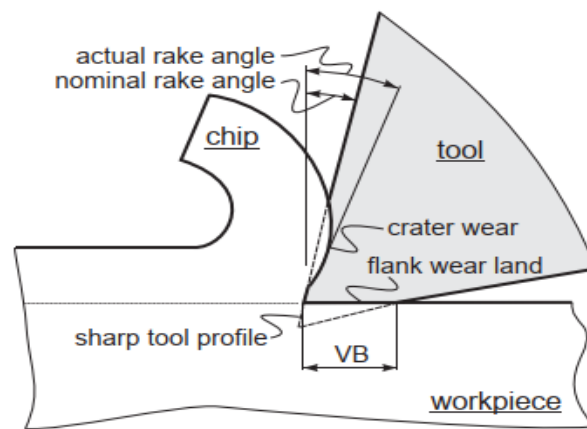


Figure 1.15 Cutting tool wear. [12]

1.9- Influence of Cutting Temperature on Process Stability

It cannot be overemphasized that thermal loads are bound to develop as a result of the transformation of the mechanical energy generated during shear and friction processes into heat. In fact, the cutting temperature is a fundamental aspect of the physics of the cutting process and determines its efficiency. Failure to regulate the accumulation of heat may lead to wear problems, distortion of geometry, and changes in the metallurgy of the surface of the product. In fact, the magnitude of the thermal load is dependent on the cutting parameters such as cutting speed, feed, depth of cut, micro-geometry of the cutting tool, workpiece properties, and cooling method used.[13]

1.10- Indexable Cutting Inserts: Classifications and Substrates

The indexable cutting inserts constitute modular, removable cutting edges mounted using mechanical fastening to the rigid tool holder, which forms the principal constituent of the lathe machines in applications like turning, facing, profiling, and cutoff operations. The elements consist

of the advanced tool materials with extraordinary hot hardness and wear resistance, namely, the cemented carbides, engineering ceramics, cBN, and PCD. The modular construction enables quick changing or indexing of worn-out cutting edges without any removal of the whole tool holder assembly, thereby substantially saving on tooling costs and eliminating machine down time. The efficiency of the cutting insert operation depends on the compatibility of its substrate material, micro geometry, coating technology, and cutting conditions used. The inserts are made in various polygonal forms of triangular, square, round, and rhombic shapes according to the ISO classification criteria depending on the part access and machining mode. In order to reduce the adverse tribological condition, modern inserts are coated with single or multiple layers (TiN, TiCN or Al_2O_3) using PVD and CVD processes, which result in reduced friction coefficient and improve thermal insulation. It is therefore imperative that there is a selection process for the insert properties.[14]

1.11- Conclusion

This chapter presented the fundamental concepts of hard turning, including turning operations, cutting parameters, surface roughness, cutting temperature, tool wear, and cutting inserts. These concepts provide the theoretical basis for the experimental work presented in the next chapter.

Chapter 2:

Materials and experimental methods

2.1- Introduction

In the machining process of AISI D2 tool steel, the output variables examined in this research work include surface roughness (Ra), cutting temperature (T_c) and flank wear (V_b). The surface roughness was measured through roughness testing, cutting temperature through thermal camera testing, and flank wear through optical microscope testing.

The tests were carried out by changing the cutting parameters; namely, cutting speed (V_c), feed (f), and depth of cut (ap). One at a time (OFAT) approach was used where only one cutting variable is varied while other variables are held constant.

This technique enabled individual contribution of each cutting variable to the machining behavior of AISI D2 steel to be evaluated.

2.2- Experimental Setup and Measurement Tools

In this experiment, cylindrical bars of AISI D2 tool steel with a hardness of (55 ± 1 HRC) were machined on an HMT NH22 lathe. CVD-coated carbide inserts ($\text{TiN-TiCN-Al}_2\text{O}_3$) mounted on ISO-standard tool holders were used for cutting.

Surface roughness was measured using a Taylor Hobson Surtronic 25 device, while cutting temperature was monitored with a FLUKE Ti32 thermal imaging camera. Tool wear analysis was carried out using an Olympus STM6 optical microscope equipped with a Olympus SC30 camera.

2.3- Machine Tool, Tool Holder and Insert

The hard turning trials were conducted using a high-speed medium duty HMT NH22 lathe with a power capacity of 11 kW and a high spindle speed. The machine's wide speed range, geared headstock, and stiff frame make it ideal for precision turning tasks in both traditional and challenging machining environments (figure 2.1).

K-grade CVD-coated carbide inserts ($\text{TiN-TiCN-Al}_2\text{O}_3$) were used for the cutting experiments. These inserts have good toughness, high wear resistance, and thermal stability, making it possible to machine hardened steels effectively while preserving acceptable tool life and surface quality.



Figure 2.1- the used lathe machine.

2.4- Workpiece Material

The materials that have been used for this study are the AISI D2 cold work tool steel that is known for its high carbon and high chromium content that makes it one of the most wear-resistant and hard steels, which is highly dimensionally stable after the heat treatment process. Due to its high chromium and carbon content, AISI D2 steel is very resistant to abrasion, as well as having a high compressive strength, making it an appropriate choice for dies, punches, shear blades, cutting tools, forming rolls, etc. The specimens used were made of AISI D2 steel that had a diameter of 48mm and length of 200mm.

The chemical composition of the steel used is given in Table 2.1.

Table 2.1 Chemical composition of AISI D2 steel [15]

Standard	Steel Grade	C (%)	Si (%)	Mn (%)
ASTM A681	AISI D2	1.40–1.60	≤ 0.60	≤ 0.60

P (%) max	S (%) max	Cr (%)	Ni (%) max	Mo (%)
0.03	0.03	11.00–13.00	0.30	0.70–1.20

2.4.1- Mechanical and Physical Properties

The following table presents the main mechanical and physical properties of AISI D2 steel, including tensile strength, Young's modulus, elongation at break, density, melting temperature, hardness, and yield strength.

Table 2.2 Mechanical and Physical Properties of 1 AISI D2 Steel [15]

Property	Symbol	Value
Density	ρ	7.70 g/cm ³
Young's Modulus	E	210 GPa
Tensile Strength	Rm	770–850 MPa (annealed condition)
Yield Strength	Re	450–650 MPa
Elongation at Break	A	1–5 %
Hardness (annealed)	HB	220–255 HB
Hardness (hardened)	HRC	58–62 HRC
Melting Temperature	Tm	1420–1450 °C
Thermal Conductivity	λ	≈ 20 W/m·K
Poisson's Ratio	ν	0.30

D2 steel falls under the category of high carbon and chromium cold work tool steel and stands out due to its excellent wear resistance, high compressive strength, and good dimensional stability when treated using heat. The huge number of carbides of chromium contained in its structure makes the steel highly resistant to abrasions. [15]

2.5- The equipment used in the experiment

2.5.1- Roughness Tester

The Taylor Hobson Surtronic 25 is a hand-held instrument for testing the texture features of the surface of the part through measuring surface roughness. It uses the skidless probe with the diamond tip moving along the part's surface for collecting detailed information about it. It provides fast and reliable measurements that can be performed both in laboratories and in industry. It can measure typical parameters such as Ra, Rz, Rq, and others. This instrument is often used for conducting experiments on surface integrity and machining because of its robust and small design, making in-situ measurements possible on the machined parts (Figure 2.2).[16]



Figure 2.2 The Taylor Hobson Surtronic 25 [16]

2.5.2- The thermal imager camera

The FLUKE Ti32 is a high-performance thermal imaging camera for non-contact temperature monitoring in industrial environments and experiments. Identifying infrared radiation emitted by the surface, it generates precise thermal maps enabling one to visualize temperature distribution when performing mechanical tests, electrical inspections, and machining. Hot spots and temperature gradients can be detected effectively due to high resolution of the detector and advanced image processing features of the camera. Due to robust design, it can be used in industrial settings and in research laboratories (Figure 2.3). [17]



Figure 2.3 FLUKE Ti32 thermal imaging camera 25 [17]

2.5.3- Tool wear measuring microscope

Olympus STM6 optical measuring microscope is an advanced inspection system, which finds application for dimensional measurements, surface analysis, and cutting tool wear assessment. The Olympus STM6 is capable of providing microscopic analysis and capturing images. In case it is equipped with a digital camera like Olympus SC30, it provides opportunities to process captured data with the help of special software. This device is highly used in tribology and machining because of high resolution and accuracy. (Figure 2.4). [18]



Figure 2.4 Olympus STM6 optical measuring microscope [18]

2.6- Computational Tools

The software packages used in this study are:

2.6.1- Minitab 22

(Figure 2.5), employed for statistical analysis, experimental design, regression modeling, and graphical representation of results.

2.6.2- JMP PRO 18

(Figure 2.6), used for data analysis, predictive modeling, visualization, and optimization of machining parameters.

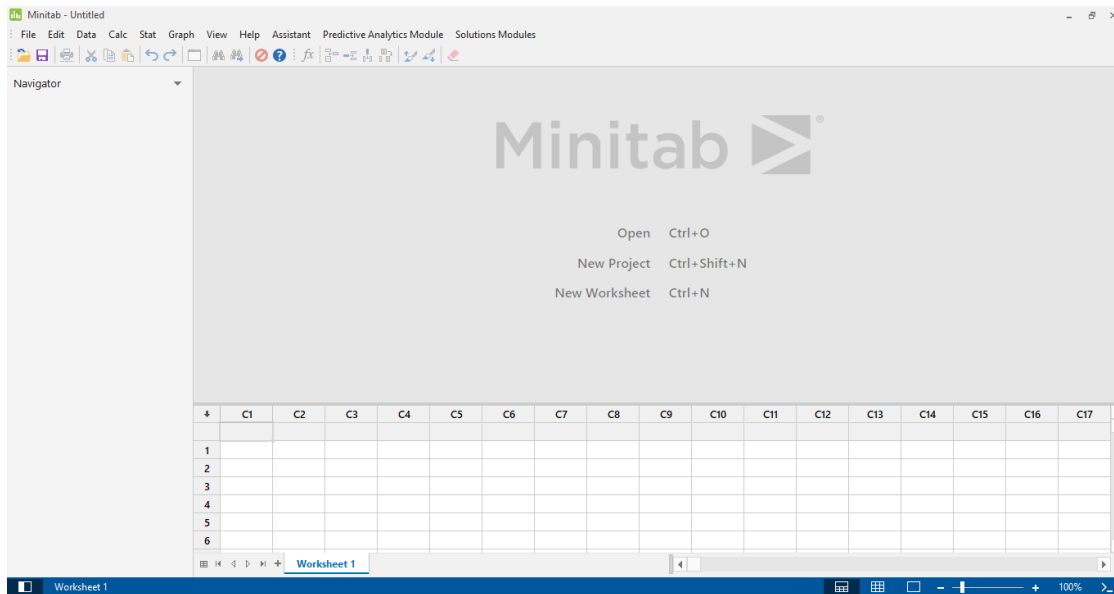


Figure 2.5 Minitab 22

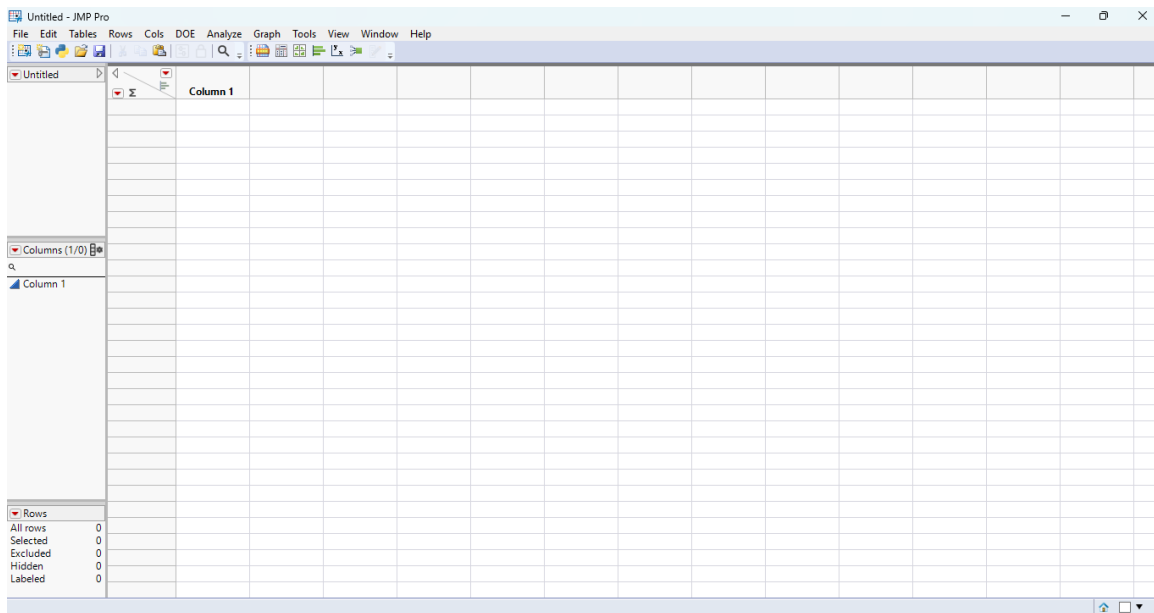


Figure 2.6 JMP PRO 18

2.7- Modeling and Optimization Methods

Optimization is a vital phase in machining as it aids in choosing proper machining conditions for the achievement of required values of responses. It is important since there is economic influence from the aspect of machining time, tool life, and production costs.

Optimization of machining processes is normally a complex problem requiring several basic components:

- Complete knowledge about the cutting process.
- The empirical models describing the relationship between the tool life, cutting force, power and other process responses and the cutting parameters.
- Redefining the machining limitations.
- Formulation of the right optimization criterion.
- Mathematical and numerical optimization methods.

Optimization in machining is often complex since the process itself is complicated. Even the smallest change in cutting parameters will have a considerable effect on other responses. Additionally, variables like the cutting force and tool wear have strong dependence on the cutting parameters. [19]

2.8- The used methods for modeling and optimization

2.8.2- Artificial Neural Networks (ANN)

A paradigm for connectionist-based artificial intelligence, the Artificial Neural Networks (ANN) is an example of bio-inspired computation techniques that attempt to replicate the parallel computing process of biological neural structures. The network is specifically designed for handling complex multi-variant connections between independent variables and dependent variable responses through data training algorithms.

The topology of the ANN includes interconnected processing units referred to as artificial neurons arranged in a hierarchical fashion into input, intermediate hidden layers and output layers. Each individual neuron is programmed to perform a series of arithmetic operations; these include capturing input signal vectors from previous neurons, multiplying the input by various synaptic weight values, adding the total weights and bias term, and passing the output through a mathematical transfer function.

The primary mathematical transformation executed within a hidden or output node j is formulated as follows:

$$net_j = \sum_{i=1}^n w_{ij} x_i + b_j \quad (2.1)$$

. Where:

- x_i denotes the input variables
- w_{ij} represents the connection weights between neurons
- b_j is the bias parameter
- net_j is the weighted sum received by neuron j .

To induce non-linearity into the network, this net integrated sum is projected through an activation function to generate the final nodal output y_j :

$$y_j = f(net_j) \quad (2.2)$$

The common types of transfer functions used in engineering modeling include the hyperbolic tangent, Rectified Linear Unit (ReLU), and the sigmoid function. Sigmoid function, which is an ideal transfer function in confining outputs in binary classifications and mapping, is given mathematically as:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (2.3)$$

In the iterative learning stage, the network adjusts the weight matrix and bias vectors through the process of supervised learning, particularly backpropagation, in order to minimize the variance between the actual output from the network and the experimental observation. The performance of the network is measured by the Minimum Squared Error (MSE):

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (2.4)$$

Where:

- y_i is the actual target value
- $\hat{y}_i$ is the predicted value generated by the network
- N is the total number of observations

With successive training epochs, the model is able to discern non-linear trends that lie hidden within the data array. In the field of high-end machining studies, ANNs act as excellent predictors of important tribological and physical values like flank wear (VB), tool life expectancy, thermal gradients during cutting, surface roughness values (Ra, Rz), and components of the cutting forces. Through this technique, it becomes possible for engineers to optimize machining processes without the necessity of undertaking expensive experiments. [20]

Figure 2.5 illustrates a simple neuron consisting of the input vector p , the weight vector W , the bias associated with the neuron b , the transfer function f , and finally the output a .

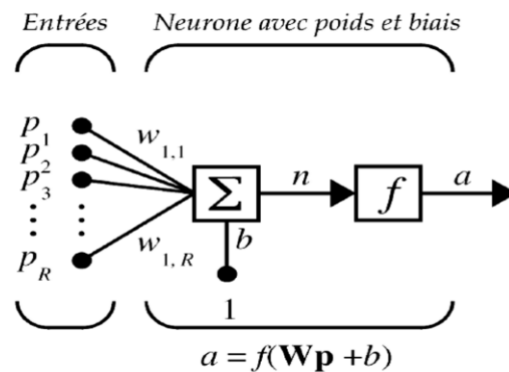


Figure 2.7 Diagram of a single neuron [21]

2.8.3- Pareto chart

is a combination chart of bars and a cumulative percentage line graph. The bars stand for the frequencies or values of various causes in descending order, and the cumulative graph indicates their contribution to the total effect as percentage values. Through identifying the "vital few" causes among the "trivial many," a Pareto chart enables engineers to select the right corrective actions and improve the performance of the processes.

In manufacturing and machining processes, Pareto analysis may be used to determine the key factors causing tool wear, surface finish, size errors, machinery breakdowns, and other production losses. Through concentrating on the few important factors, manufacturers can increase efficiency and save money. [22]

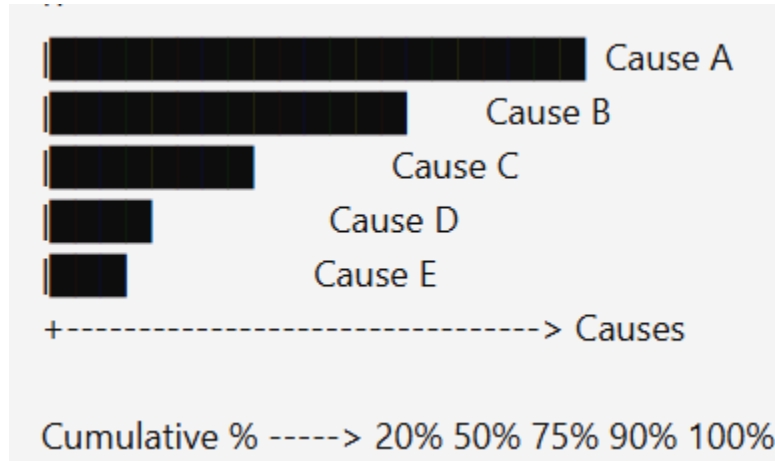


Figure 2.5 pareto chart example

2.8.4- Support Vector Machines (SVM)

With its theoretical foundation based on statistical learning theory, Support Vector Machines (SVM) are extremely useful supervised machine learning algorithms that have wide applications in classification, regression analysis, and pattern recognition. The core idea of SVM is to identify a hyperplane, which serves as a decision boundary between data points of different classes in such a way that the margin between them is maximized. Data points that lie nearest to the hyperplane are termed support vectors and help in determining the positioning of the decision boundary. The maximum separation margin helps SVM perform well when it comes to generalization and overfitting problems, especially in case of higher dimensional spaces and smaller datasets.

The optimal separating hyperplane for a binary classification problem may be represented as:

$$w^T x + b = 0 \quad (2.5)$$

where:

- w is the weight vector normal to the hyperplane,
- x is the input feature vector,
- b is the bias term.

The classification of a new sample is performed using the decision function:

$$f(x) = \text{sign}(w^T x + b) \quad (2.6)$$

where the sign function assigns the sample to one of the predefined classes according to its position relative to the hyperplane.

The objective of the optimization process is to maximize the margin M , which is inversely proportional to the norm of the weight vector:

$$M = \frac{2}{\|w\|} \quad (2.7)$$

subject to the constraint:

$$y_i(w^T x_i + b) \geq 1 \quad (2.8)$$

where x_i represents a training sample and y_i denotes its corresponding class label. Maximizing this margin improves the robustness of the classifier and enhances its ability to correctly classify unseen data.

Another significant benefit of the SVM is the ability of dealing with nonlinear classification problem by making use of kernels. Kernels allow mapping the input data into a high dimensional feature space where linear separability can be achieved. Without having to do any transformation, the SVM is capable of forming nonlinear boundaries. Some of the common kernels are the linear kernel, polynomial kernel, sigmoid kernel, and the radial basis function (RBF) kernel. Out of all these kernels, the RBF kernel is extensively used in engineering fields and is given by:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \quad (2.9)$$

where γ is a kernel parameter that controls the influence of individual training samples on the resulting decision boundary.

SVMs have widely been used in manufacturing and machining engineering for modeling processes, monitoring tool conditions, diagnosing faults, predicting surface roughness (R_a & R_z), estimating cutting forces, evaluating tool wear and cutting temperature predictions. Thanks to its high predictability and potential to create accurate models using relatively small data sets, SVM has proven useful for intelligent manufacturing systems. The use of SVM has facilitated the

optimization of processes, improvement of quality, cost reduction and decision making within the Industry 4.0 concept. [23]

2.8.5- The TOPSIS Multi-Criteria Optimization Methodology

Originally conceptualized by Hwang and Yoon in 1981, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) remains a foundational Multi-Criteria Decision-Making (MCDM) framework. It is explicitly engineered to rank competing alternatives when confronted with multiple, often antagonistic, objective functions. The algorithm operates on a geometric compromise principle: the optimal candidate must concurrently exhibit the minimal Euclidean distance to a hypothetical Positive Ideal Solution (PIS) and the maximum spatial divergence from the Negative Ideal Solution (NIS). The PIS embodies the absolute best performance across all criteria, whereas the NIS represents the theoretical worst-case scenario. Thanks to its robust computational logic and capacity to synthesize both "cost" (minimization) and "benefit" (maximization) metrics, TOPSIS is heavily relied upon in manufacturing process planning and supply chain optimization.

The mathematical execution of the TOPSIS algorithm follows a structured sequential procedure. First, to eliminate discrepancies caused by heterogeneous units of measurement, the raw decision matrix is vector-normalized into a dimensionless format. The normalized performance score r_{ij} for an alternative i under criterion j is computed as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (2.10)$$

where x_{ij} is the original empirical value. Subsequently, the normalized matrix is adjusted to reflect the relative priority of each criterion by multiplying it by a predetermined weight vector w_j , yielding the weighted normalized matrix v_{ij} :

$$v_{ij} = w_j r_{ij} \quad (2.11)$$

In the next phase, the algorithm extracts the theoretical ideal coordinates A^+ and anti-ideal coordinates A^- . This extraction is contingent on whether a specific criterion belongs to the benefit set J_b or the cost set J_c :

$$A^+ = \{\max(v_{ij}) \mid j \in J_b, \min(v_{ij}) \mid j \in J_c\} \quad (2.12)$$

$$A^- = \{\min(v_{ij}) \mid j \in J_b, \max(v_{ij}) \mid j \in J_c\} \quad (1.13)$$

The n-dimensional Euclidean separation distances of each specific candidate from these reference boundaries are then quantified using the following expressions:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - A_j^+)^2} \quad (2.14)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - A_j^-)^2} \quad (2.15)$$

Finally, a unified performance index, the relative closeness coefficient C_i , is calculated to establish the final ranking hierarchy:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (2.16)$$

where the coefficient spans a bounded range of $0 \leq C_i \leq 1$. An alternative approaching $C_i = 1$ is deemed superior, indicating strong proximity to the optimal condition. Within the domain of mechanical manufacturing, engineers frequently deploy TOPSIS to balance conflicting machining responses, such as maximizing the Material Removal Rate (MRR) while simultaneously minimizing cutting forces, flank wear, and surface roughness, thereby isolating the most economically and technically viable cutting parameters. [24]

2.9- Description of the Experimental Design

In this study, the influence of cutting parameters in longitudinal turning on machining performance was investigated. The input variables considered are depth of cut d (mm), feed f (mm/rev), and cutting speed v (m/min).

The output responses used to evaluate machining performance are surface roughness Ra (μm), cutting temperature T ($^{\circ}\text{C}$), and flank wear VBc (mm).

This experimental setup allows the analysis of the relationship between cutting conditions and machining quality in terms of surface finish, thermal behavior, and tool wear.

Table 2.3 Cutting parameters and their levels

Parameter	Level 1	Level 2	Level 3	Level 4	Output Responses
Depth of cut, d (mm)	0.1	0.2	0.3	0.4	Ra (μm), T ($^{\circ}\text{C}$), VBc (mm)
Feed, f (mm/rev)	0.04	0.08	0.12	0.16	
Cutting speed, v (m/min)	63	108	140	182	

2.10- Application of Taguchi Method

The Taguchi method is widely used as a quality engineering tool to improve experimental efficiency by reducing the number of required experiments while maintaining reliable results. It is employed to determine and optimize cutting conditions in order to achieve the desired surface roughness with minimal experimental effort.

In this study, an orthogonal array design was adopted using a Taguchi L16 (4^3) matrix, involving three factors each at four levels. This experimental design enables the investigation of the effects

of cutting parameters through only 16 systematically arranged experiments, instead of a full factorial design.

The Taguchi approach ensures a structured and efficient experimental plan, providing high-quality results without increasing the number of trials. The experimental layout based on the L16 orthogonal array is presented in Table 2.4

Table 2.4 final results with Taguchi L16 Experimental Design

Run	d (mm)	f (mm/rev)	v (m/min)	Ra (μm)	T ($^{\circ}\text{C}$)	VBc (mm)
1	0.1	0.04	63	0.62	164.4	0.05
2	0.1	0.08	108	0.712	180.3	0.061
3	0.1	0.12	140	0.916	209.2	0.075
4	0.1	0.16	182	1.28	254	0.095
5	0.2	0.04	108	0.552	202	0.045
6	0.2	0.08	63	0.836	186.9	0.07
7	0.2	0.12	182	1.012	257.6	0.113
8	0.2	0.16	140	1.212	218.9	0.082
9	0.3	0.04	140	0.544	259	0.068
10	0.3	0.08	182	0.88	288.2	0.126
11	0.3	0.12	63	1.024	202.9	0.075
12	0.3	0.16	108	1.316	218.9	0.071
13	0.4	0.04	182	0.72	309.8	0.135
14	0.4	0.08	140	0.872	277.9	0.086
15	0.4	0.12	108	1.036	249.2	0.062
16	0.4	0.16	63	1.376	226.9	0.064

2.11- Conclusion

This chapter described the materials, equipment, experimental procedure, and modeling methods used in this study. The experimental design and measurement techniques established the basis for the analysis, modeling, and optimization of the machining responses presented in the next chapter.

Chapter 3

Pareto chart, modeling
and multi-criteria
decision-making

3.1- Introduction

This chapter presents a statistical study of the machining performance parameters obtained during the hard turning of AISI D2 tool steel with a hardness of (55 ± 1) HRC. The investigated responses are surface roughness (Ra), cutting temperature (T_c), and tool flank wear (V_b), as functions of the cutting parameters: cutting speed (V_c), feed (f), and depth of cut (ap). The analysis is carried out using two modeling approaches, namely Support Vector Machine (SVM) and Artificial Neural Networks (ANN). The main objective is to identify the cutting parameters that have the greatest influence as well as their interactions on the responses under study. To this end, a Pareto chart is used to assess the statistical significance of the models developed.

A comparison between the predictive performances of the ANN and SVM models is conducted to determine the most accurate approach for responses modeling during the hard turning of AISI D2 steel. Finally, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was used to perform multi-criteria optimization of the relevant responses in question.

3.2- Experimental Results

The experimental data presented in Table 3.1 were taken from the study published by Kumar et al. [25], which investigated the hard turning of AISI D2 tool steel.

Table 3.1- Summary of the experimental results.

N°	Factors			Responses		
	ap (mm)	f (mm/rev)	V_c (m/min)	Ra (μ m)	T_c ($^{\circ}$ C)	V_b (mm)
1	0,1	0,04	63	0,62	164,4	0,05
2	0,1	0,08	108	0,712	180,3	0,061
3	0,1	0,12	140	0,916	209,2	0,075
4	0,1	0,16	182	1,28	254	0,095
5	0,2	0,04	108	0,552	202	0,045
6	0,2	0,08	63	0,836	186,9	0,07
7	0,2	0,12	182	1,012	257,6	0,113
8	0,2	0,16	140	1,212	218,9	0,082
9	0,3	0,04	140	0,544	259	0,068
10	0,3	0,08	182	0,88	288,2	0,126
11	0,3	0,12	63	1,024	202,9	0,075
12	0,3	0,16	108	1,316	218,9	0,071
13	0,4	0,04	182	0,72	309,8	0,135
14	0,4	0,08	140	0,872	277,9	0,086
15	0,4	0,12	108	1,036	249,2	0,062
16	0,4	0,16	63	1,376	226,9	0,064

3.3- Pareto analysis

The Pareto chart is an effective analytical tool for identifying the factors that exert a significant influence on the response variables. In the present study, a statistical significance threshold of $\alpha = 2,23$ was adopted as the reference criterion. Accordingly, only the effects represented by bars exceeding this threshold were considered statistically significant, indicating a meaningful contribution to the observed variations in the output responses [26].

3.3.1- Pareto analysis of surface roughness

According to the Pareto chart presented in figure 3.1, the surface roughness (Ra) is significantly influenced by two main effects f and ap , two quadratic effects (V_c^2) and (f^2), and one interaction term ($ap * V_c$). These effects exceed the reference line corresponding to the statistical significance threshold ($\alpha = 2,45$), confirming their substantial contribution to the variability of the response. Among the statistically significant factors, the factor f has the strongest influence on surface roughness. This dominant effect is attributed to the fact that increasing the feed enlarges the feed marks left by successive tool passes, thereby producing greater surface irregularities. Consequently, the Ra value increases with increasing feed, whereas lower feed reduce machining marks and improve the surface finish. This behavior is consistent with the theoretical principles of surface roughness generation in machining as well as the experimental findings reported by Mane et al. [27]. The Pareto chart further indicates that the remaining investigated factors do not have a statistically significant effect on the variability of surface roughness, as their standardized effects remain below the critical significance threshold.

3.3.2- Pareto analysis of cutting temperature

The Pareto chart analysis presented in figure 3.2 for cutting temperature (T_c) reveals five statistically significant effects influencing the thermal behavior in the machining zone, based on a significance threshold of $\alpha = 2,45$. Among these factors, the cutting speed (V_c) is identified as the dominant parameter. An increase in cutting speed intensifies the friction phenomena at the tool–workpiece interface, resulting in a substantial rise in the cutting temperature. The factor ap also exerts a significant influence on the thermal response, owing to the larger volume of

material removed, which promotes greater conversion of mechanical energy into heat within the primary shear zone.

The quadratic effects of V_c^2 and ap^2 are likewise statistically significant, although their contributions remain lower than those of the corresponding main effects. It is worth noting that the quadratic effect of the cutting speed is more pronounced than that of the depth of cut, indicating a stronger nonlinear influence of V_c on the cutting temperature. In contrast, the feed (f) exhibits a negligible effect, suggesting that the thermal mechanisms involved in the hard turning process are only weakly sensitive to variations in this parameter [26].

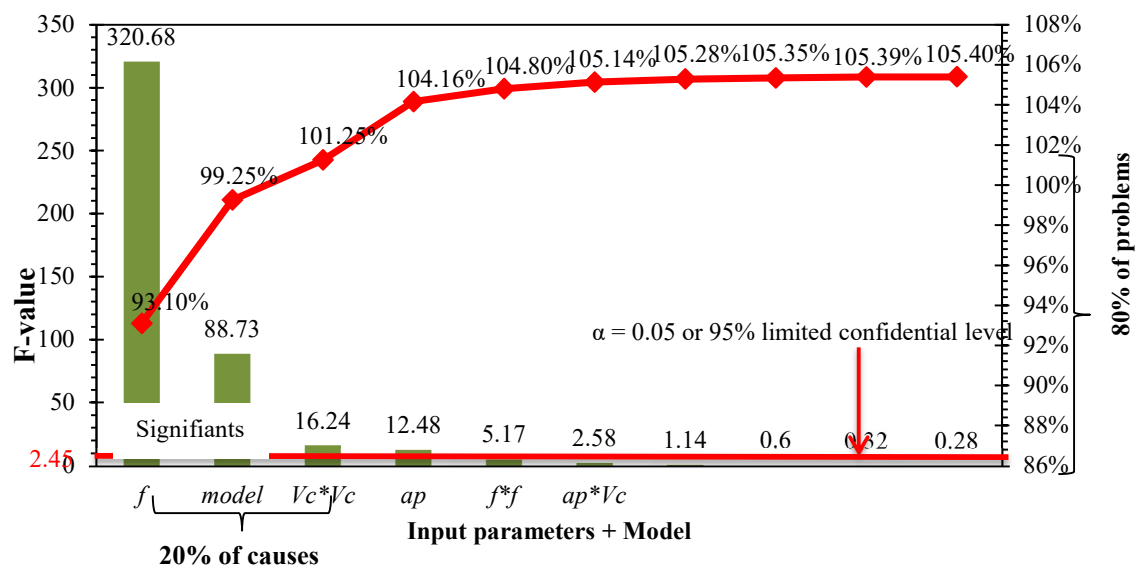


Figure 3.1– Pareto chart of surface roughness.

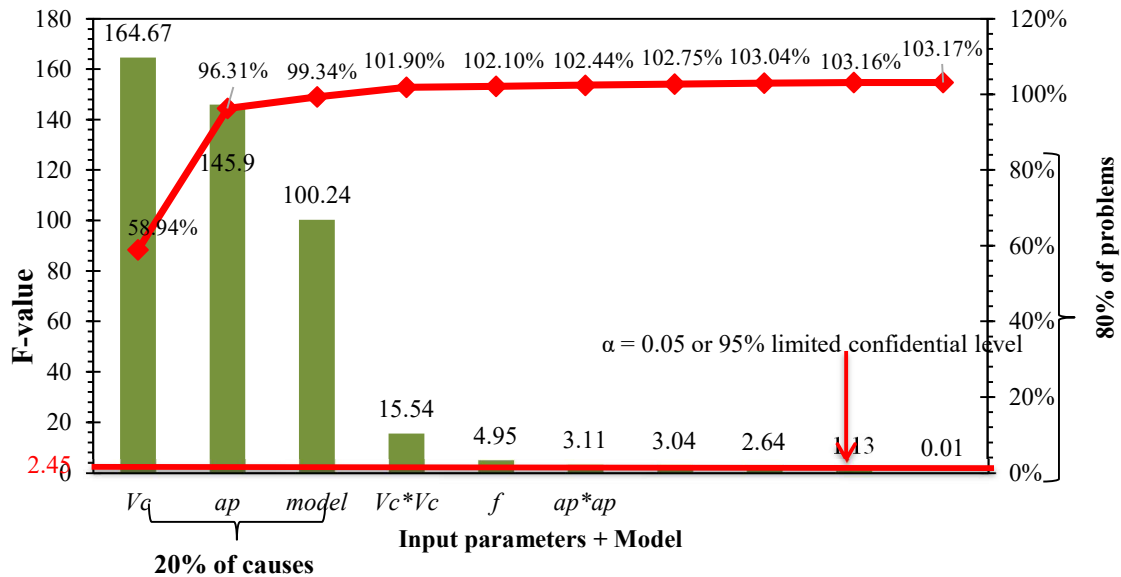


Figure 3.2– Pareto chart of cutting temperature.

3.3.3- Pareto analysis of flank wear

The Pareto chart analysis presented in figure 3.3 for tool flank wear (V_b) indicates that all the investigated factors, together with their quadratic effects and interaction terms, have a statistically significant influence on the response at a significance threshold of $\alpha = 2,23$. Among these factors, the cutting speed (V_c) and its quadratic term (V_c^2) are identified as the most influential. Increasing the cutting speed raises the temperature at the tool–workpiece interface, thereby accelerating the wear mechanisms and leading to a greater tool flank wear. In addition, the ($ap * V_c$) interaction exhibits a significant effect, which can be attributed to the increased tool–workpiece contact area. In contrast, the feed (f) has a negligible influence on the response under the investigated cutting conditions.

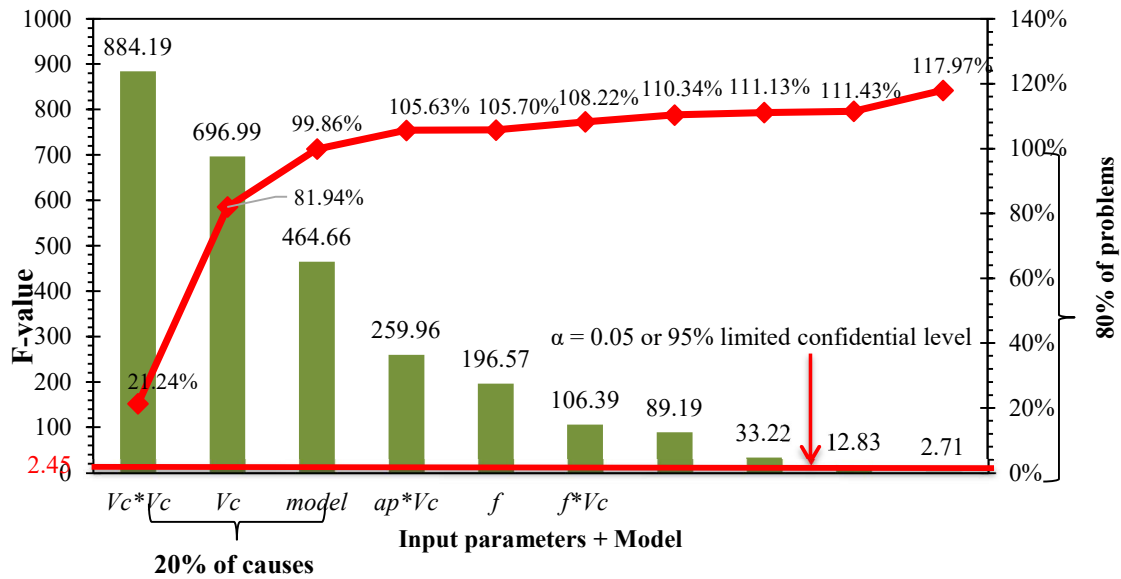


Figure 3.3– Pareto chart of flank wear.

3.4- Mathematical modeling

3.4.1- Artificial neural network (ANN) modeling

To model the machining performance, an artificial neural network (ANN) based on the backpropagation algorithm was developed. The model uses the depth of cut (ap), feed (f), and cutting speed (V_c) as input variables, while the output variables correspond to surface roughness (Ra), cutting temperature (T_c), and tool flank wear (V_b). The adopted network architecture consists of three input neurons, three hidden neurons, and one output neuron for each developed model. The hyperbolic tangent activation function was selected because of its effectiveness in nonlinear modeling applications. Network training was performed using the backpropagation algorithm with a learning rate of 0.1, aiming to minimize the mean squared error (MSE) computed from the normalized experimental data [28]. The training process continued until the convergence criterion of $\alpha = 0.05$ was reached [29]. During training, the network weights were iteratively updated using the gradient descent optimization method to improve the agreement between the predicted and experimental values. The final 3–3–1 architecture proved capable of accurately reproducing the behavior of the three investigated machining responses, as illustrated in figure 3.4.

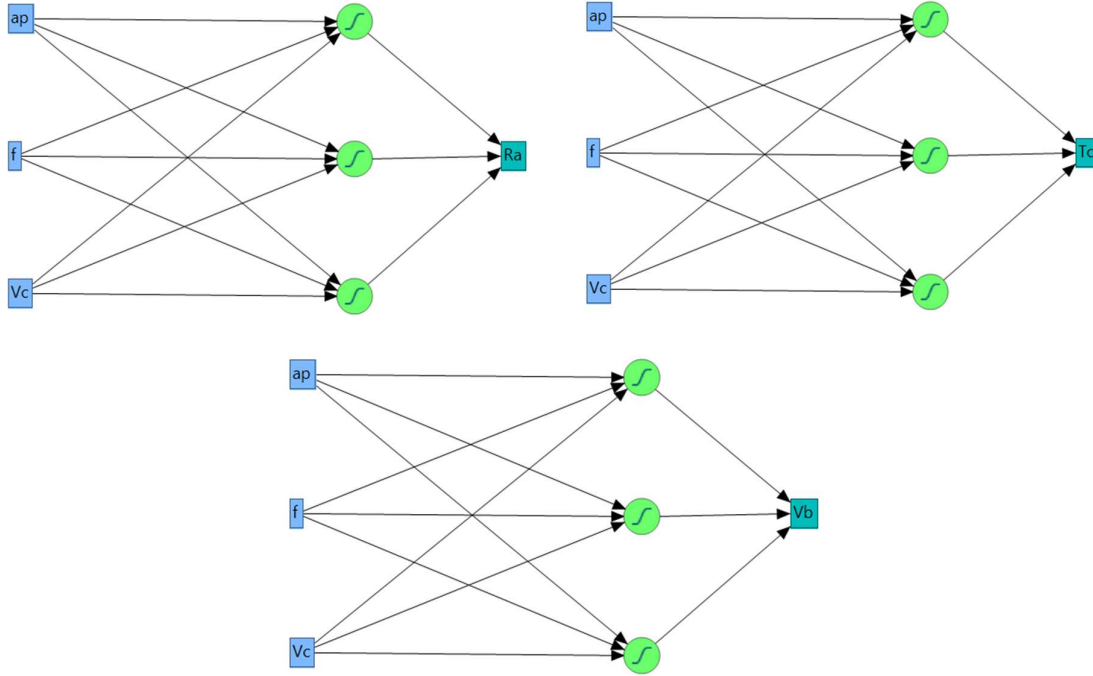


Figure 3.4- Artificial neural network with backpropagation algorithm (ANN) used.

The predictive models developed using artificial neural networks (ANNs) are presented in Equations (3.1)–(3.3). Equation (3.1) is dedicated to the prediction of surface roughness (Ra). The model achieved coefficients of determination R_{Ra}^2 of 0.9787 during the training phase and 0.9875 during the validation phase, demonstrating its excellent generalization capability. In addition, a Mean Absolute Percentage Error (MAPE) of 2.74% and a Root Average Squared Error (RASE) of 0.0323 μm indicate the high accuracy of the predicted surface roughness values.

$$Ra = 0.68690203 \times H_1 - 0.61414418 \times H_2 - 0.34266036 \times H_3 + 1.25094277 \quad (3.1)$$

$$R_{Ra}^2 = 0.9787 \text{ (Training)}, R_{Ra}^2 = 0.9875 \text{ (Validation)}, \text{MAPE} = 2.74\%, \text{RASE} = 0.0323 \mu\text{m}.$$

Where:

$$\begin{cases} H_1 = \tanh(0.5(2.569181 \times ap + 11.487207 \times f + 0.013858 \times V_c - 3.821021)) \\ H_2 = \tanh(0.5(0.634693 \times ap - 3.582858 \times f + 0.014892 \times V_c - 1.039718)) \\ H_3 = \tanh(0.5(1.028528 \times ap - 8.259888 \times f + 0.000965 \times V_c + 0.871441)) \end{cases}$$

Equation (3.2) represents the mathematical model developed to predict the cutting temperature (T_c). The obtained results demonstrate excellent agreement between the predicted and experimental values, with coefficients of determination ($R_{T_c}^2$) of 0.9996 during the training

phase and 0.9906 during the validation phase. Furthermore, the low values of the Mean Absolute Percentage Error (MAPE) (0.58%) and the Root Average Squared Error (RASE) (0.7637 °C) confirm the high predictive accuracy of the model and its ability to provide reliable estimates of the cutting temperature.

$$T_c = -166.680529 \times H_1 - 71.032821 \times H_2 - 96.875141 \times H_3 + 203.284781 \quad (3.2)$$

$$R_{T_c}^2 = 0.9996 \text{ (Training)}, R_{T_c}^2 = 0.9906 \text{ (Validation)}, \text{ MAPE} = 0.58\%, \text{ RASE} = 0.7637 \text{ }^\circ\text{C}.$$

Where:

$$\begin{cases} H_1 = \tanh(0.5(3.147533 \times ap - 3.604784 \times f + 0.000245 \times V_c - 1.207667)) \\ H_2 = \tanh(0.5(-1.613701 \times ap + 0.939264 \times f - 0.029905 \times V_c + 4.568819)) \\ H_3 = \tanh(0.5(-10.340311 \times ap + 7.575983 \times f + 0.003106 \times V_c + 1.900128)) \end{cases}$$

Equation (3.3) is dedicated to the prediction of tool flank wear (V_b). The developed ANN model exhibits excellent predictive performance, with coefficients of determination ($R_{V_b}^2$) of 0.9947 during the training phase and 0.9822 during the validation phase. Moreover, a Mean Absolute Percentage Error (MAPE) of only 0.96%, well below the 5% threshold, together with a Root Average Squared Error (RASE) of 0.0015 mm, confirms the high accuracy and reliability of the model for predicting the flank wear of the coated cutting tool.

$$V_b = 0.17455907 \times H_1 - 0.07461206 \times H_2 - 0.13732638 \times H_3 + 0.11426515 \quad (3.3)$$

$$R_{V_b}^2 = 0.9947 \text{ (Training)}, R_{V_b}^2 = 0.9822 \text{ (Validation)}, \text{ MAPE} = 0.96\%, \text{ RASE} = 0.0015 \text{ mm}.$$

Where:

$$\begin{cases} H_1 = \tanh(0.5(4.985958 \times ap - 5.544893 \times f + 0.028101 \times V_c - 5.950955)) \\ H_2 = \tanh(0.5(-0.140953 \times ap - 20.361146 \times f + 0.006641 \times V_c + 0.635276)) \\ H_3 = \tanh(0.5(3.736278 \times ap + 3.062181 \times f + 0.011751 \times V_c - 3.496867)) \end{cases}$$

Overall, the three developed ANN models exhibit excellent predictive performance, with coefficients of determination (R^2) exceeding 0.95 during the training phase and 0.98 during the validation phase. In addition, all MAPE values are below 5%, indicating a high level of prediction accuracy. These findings confirm the validity and robustness of the ANN models for the simultaneous prediction of the main performance indicators in hard turning. Among the three models, the cutting temperature (T_c) model achieved the highest predictive accuracy, followed by the tool flank wear (V_b) model, whereas the surface roughness (Ra) model showed slightly lower, yet still highly satisfactory, predictive performance.

3.4.2- Support vector machine (SVM) modeling

The mathematical models developed using the Support Vector Machine (SVM) approach are presented in Equations (3.4)–(3.6). Among them, Equation (3.4) describes the prediction of surface roughness (Ra). The model achieved coefficients of determination (R_{Ra}^2) of 0.9611 for the training dataset and 0.9438 for the validation dataset, indicating good generalization capability. The prediction error metrics, namely a Mean Absolute Percentage Error (MAPE) of 5.74% and a Root Average Squared Error (RASE) of 0.0476 μm , further confirm the suitability of the model for estimating surface roughness.

$$Ra = 0.93575163 + 0.04925221 \times T_{10} + 0.24546989 \times T_{11} + 0.01059361 \times T_{12} \quad (3.4)$$

$$R_{Ra}^2 = 0.9611 \text{ (Training)}, R_{Ra}^2 = 0.9438 \text{ (Validation)}, \text{MAPE} = 5.74\%, \text{RASE} = 0.0476 \mu\text{m}.$$

Where:

$$\begin{cases} T_{10} = (-2.1650635) + 8.66025403 \times ap \\ T_{11} = (-2.1650635) + 21.65063509 \times f \\ T_{12} = (-2.7387085) + 0.02222075 \times V_c \end{cases}$$

Equation (3.5) describes the model developed to predict the cutting temperature (T_c). The obtained results show coefficients of determination ($R_{T_c}^2$) of 0.9821 during the training phase and 0.9573 during the validation phase, demonstrating the model's good ability to reproduce the experimental data. In addition, a Mean Absolute Percentage Error (MAPE) of 2.91% and a Root Average Squared Error (RASE) of 0.6856 $^{\circ}\text{C}$ confirm the accuracy and reliability of the predicted values.

$$T_c = 229.24382017 + 27.42312578 \times T_{10} - 3.60977529 \times T_{11} + 28.633944 \times T_{12} \quad (3.5)$$

$$R_{T_c}^2 = 0.9821 \text{ (Training)}, R_{T_c}^2 = 0.9573 \text{ (Validation)}, \text{MAPE} = 2.91\%, \text{RASE} = 0.6856 ^{\circ}\text{C}.$$

Where:

$$\begin{cases} T_{10} = (-2.1650635) + 8.66025403 \times ap \\ T_{11} = (-2.1650635) + 21.65063509 \times f \\ T_{12} = (-2.7387085) + 0.02222075 \times V_c \end{cases}$$

Equation (3.6) describes the mathematical model developed to predict tool flank wear (V_b). The model achieved coefficients of determination ($R_{V_b}^2$) of 0.7112 during the training phase and 0.6823 during the validation phase, indicating a moderate predictive capability. In addition, a

Mean Absolute Percentage Error (MAPE) of 5.74% and a Root Average Squared Error (RASE) of 0.0144 mm indicate that the prediction errors remain acceptable, confirming that the model can be used to estimate tool flank wear with a satisfactory level of accuracy.

$$V_b = 0.07591543 + 0.00242736 \times T_{10} + 0.00010941 \times T_{11} + 0.02632556 \times T_{12} \quad (3.6)$$

$$R_{V_b}^2 = 0.7112 \text{ (Training)}, R_{V_b}^2 = 0.6823 \text{ (Validation)}, \text{MAPE} = 5.74\%, \text{RASE} = 0.0144 \text{ mm.}$$

Where:

$$\begin{cases} T_{10} = (-2.1650635) + 8.66025403 \times ap \\ T_{11} = (-2.1650635) + 21.65063509 \times f \\ T_{12} = (-2.7387085) + 0.02222075 \times V_c \end{cases}$$

Overall, the three SVM models exhibited different levels of predictive performance depending on the response considered. The cutting temperature (T_c) model achieved the highest accuracy, with coefficients of determination (R^2) of 0.9821 during the training phase and 0.9573 during the validation phase, together with a MAPE of 2.91% and a RASE of 0.6856 °C, indicating excellent predictive capability. The surface roughness (Ra) model also demonstrated good performance, with R^2 values of 0.9611 and 0.9438, a MAPE of 5.74%, and a RASE of 0.0476 μm , confirming its reliability. In contrast, the tool flank wear (V_b) model exhibited a more moderate predictive capability, with R^2 values of 0.7112 and 0.6823, although the prediction errors remained acceptable (MAPE = 5.74% and RASE = 0.0144 mm). Overall, the predictive performance of the SVM models can be ranked as follows: $T_c > Ra > V_b$.

3.4.3- Comparison between experimental and predicted results

Figure 3.5 compares the experimentally measured surface roughness (Ra) values with those predicted by the ANN and SVM models for the 16 experimental runs. Overall, both models successfully reproduce the experimental trend of surface roughness. The measured Ra values range from 0.544 μm (run 9) to 1.376 μm (run 16), indicating a substantial variation in surface quality under different machining conditions. The lowest roughness values were recorded for runs 5 (0.552 μm) and 9 (0.544 μm), whereas the highest values were observed for runs 12 (1.316 μm) and 16 (1.376 μm).

The ANN model provides predictions that are in excellent agreement with the experimental measurements, yielding values of 0.637 μm versus 0.620 μm for run 1, 1.219 μm versus 1.280 μm for run 4, and 1.346 μm versus 1.376 μm for run 16. Likewise, the SVM model adequately

reproduces the overall trend, predicting $0.539 \mu\text{m}$, $1.204 \mu\text{m}$, and $1.304 \mu\text{m}$ for the same runs, respectively. However, larger deviations are observed in some cases, particularly for run 9, where the SVM model predicts $0.642 \mu\text{m}$ compared with the experimental value of $0.544 \mu\text{m}$.

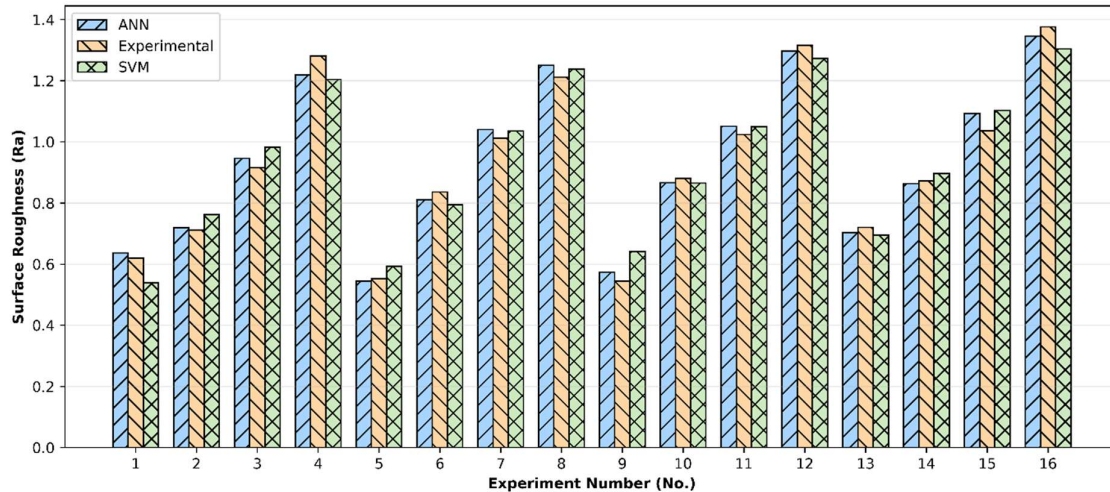


Figure 3.5- Comparison of the predictive performance of the ANN and SVM models with the experimental data for surface roughness (R_a).

Figure 3.6 compares the experimental cutting temperature (T_c) values with those predicted by the ANN and SVM models. The experimental temperatures range from 164.4°C (run 1) to 309.8°C (run 13), highlighting the strong influence of the cutting parameters on heat generation during the machining process. The highest temperatures were recorded for runs 13 (309.8°C), 10 (288.2°C), and 14 (277.9°C), whereas the lowest values were observed for Runs 1 (164.4°C), 2 (180.3°C), and 6 (186.9°C).

The ANN model demonstrates outstanding predictive accuracy, with deviations generally limited to only a few degrees. For example, for run 13, the predicted temperature is 309.57°C , compared with the experimental value of 309.8°C , corresponding to an error of less than 0.1%. Similarly, for runs 7 and 9, the ANN predictions (257.60°C and 258.40°C) are almost identical to the corresponding experimental values (257.6°C and 259.0°C , respectively).

The SVM model also captures the overall trend of the experimental data; however, larger deviations are observed in some cases. For instance, for run 4, the model predicts 226.31°C , whereas the experimental value is 254.0°C , resulting in an underestimation of approximately 27.7°C .

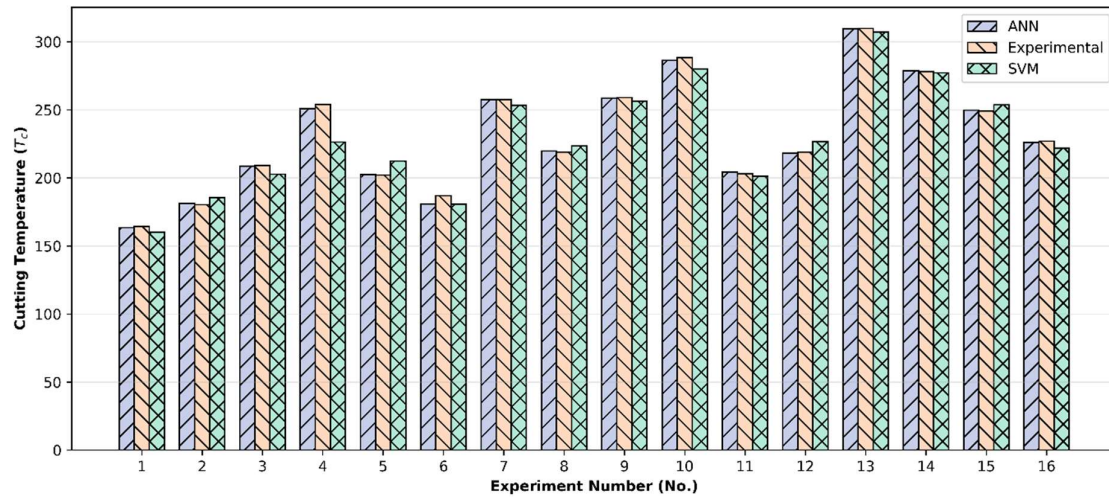


Figure 3.6- Comparison of the predictive performance of the ANN and SVM models with the experimental data for cutting temperature (T_c).

Figure 3.7 illustrates the comparison between the experimental and predicted tool flank wear (V_b) values obtained using the ANN and SVM models. The experimental flank wear values range from 0.045 mm (run 5) to 0.135 mm (run 13). The lowest wear values were recorded for runs 5 (0.045 mm), 1 (0.050 mm), and 2 (0.061 mm), whereas the highest values were observed for runs 10 (0.126 mm) and 13 (0.135 mm).

The ANN model reproduces the experimental results with remarkable accuracy. For example, for run 1, the predicted value is identical to the experimental measurement (0.050 mm). Likewise, for runs 13 and 14, the ANN predictions (0.135 mm and 0.086 mm, respectively) perfectly match the corresponding experimental values.

In contrast, the SVM model exhibits greater dispersion in its predictions. For instance, for Run 5, it predicts a flank wear of 0.066 mm, compared with the experimental value of 0.045 mm, corresponding to an overestimation of approximately 47%. Significant discrepancies are also observed for runs 6, 9, 11, and 16.

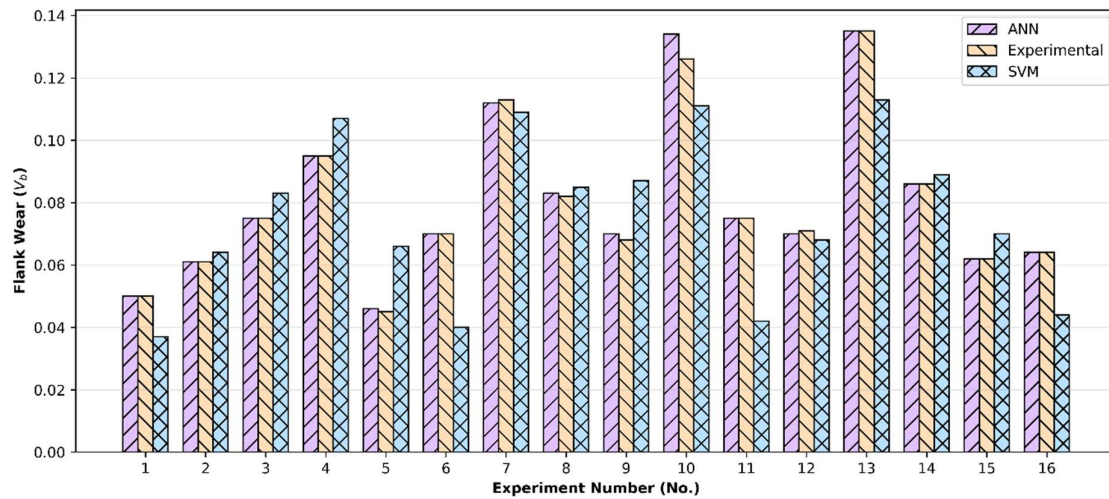


Figure 3.7. Comparison of the predictive performance of the ANN and SVM models with the experimental data for tool flank wear (V_b).

The combined analysis of figures 3.5–3.7 demonstrates that both artificial intelligence models are capable of accurately predicting the main machining responses investigated. However, the ANN model consistently outperforms the SVM model, providing predictions that are almost identical to the experimental values for surface roughness (Ra), cutting temperature (T_c), and tool flank wear (V_b). Although the SVM model successfully captures the overall experimental trends, it exhibits larger deviations for some experimental runs, particularly in the prediction of cutting temperature and tool flank wear. These findings confirm that artificial neural networks constitute a highly effective tool for modeling the complex nonlinear phenomena encountered in machining, enabling reliable prediction of surface quality, thermal behavior, and tool life. The excellent agreement between the experimental measurements and the ANN predictions further validates the robustness of the developed model and highlights its strong potential for the intelligent optimization of cutting parameters.

3.5- Multi-Criteria optimization

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is one of the most widely used multi-criteria decision-making (MCDM) methods for ranking and selecting

alternatives. Its fundamental principle is that the best alternative should be the one that is closest to the Positive Ideal Solution (PIS), which represents the best performance achieved for each criterion, and farthest from the Negative Ideal Solution (NIS), which corresponds to the least desirable performance for each criterion. Accordingly, the selection process is based on calculating the relative distances of each alternative from these two reference solutions, thereby identifying the cutting parameter combination that provides the best trade-off among the different performance criteria [30].

3.5.1- Construction of the decision matrix

In multi-criteria analysis, the construction of the decision matrix is a fundamental preliminary step. This matrix organizes the considered alternatives and the selected evaluation criteria into rows and columns. Each element of the matrix represents the performance of a given alternative with respect to a specific criterion. Such a structured representation enables a systematic comparison of the available alternatives and provides the basis for the calculations required by multi-criteria decision-making methods, particularly the TOPSIS approach [31].

Let the decision problem be defined as follows:

- ✧ $A_1, A_2, \dots, A_m$: the alternatives or experimental runs (rows of the decision matrix);
- ✧ $C_1, C_2, \dots, C_n$: the evaluation criteria or response variables (columns of the decision matrix).

The decision matrix, denoted by $X = [x_{ij}]$, contains the performance values of each alternative A_i with respect to each criterion C_j , where each element x_{ij} represents the performance of alternative A_i for criterion C_j .

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

In the present study, the decision matrix consists of $m = 16$ alternatives, corresponding to the 16 experimental runs, and $n = 3$ performance criteria (response variables).

3.5.2- Normalization of the decision matrix

Within the TOPSIS methodology, vector normalization is the most widely used approach for eliminating differences in scale among the evaluation criteria. Also referred to as Euclidean normalization, this technique transforms each criterion value into a dimensionless quantity by dividing it by the Euclidean norm of the corresponding column, which is calculated as the square root of the sum of the squared values of all observations for that criterion [32]. This transformation ensures the comparability of the evaluation criteria while preserving the relative proportions among the alternatives, as expressed in equation (3.7).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (3.7)$$

Where:

- r_{ij} : standardized element,
- $i = 1, \dots, m$, and $j = 1, \dots, n$.

Normalization converts the original data into dimensionless values on a common reference scale, generally ranging from 0 to 1. This process facilitates the comparative evaluation of the alternatives by highlighting their relative performance for each criterion, regardless of the original measurement units. The normalized values of the decision matrix (r_{ij}) are presented in Table 3.2.

Table 3.2- Normalized decision matrix (r_{ij}).

N°	r_{i1} (Ra)	r_{i2} (T _c)	r_{i3} (V _b)
1	0,160288013	0,174869748	0,149392906
2	0,184072685	0,191782333	0,182259345
3	0,236812612	0,222522818	0,224089358
4	0,330917187	0,270175888	0,283846521
5	0,142708037	0,214864289	0,134453615
6	0,216130288	0,198802652	0,209150068
7	0,261631401	0,274005153	0,337627967
8	0,313337212	0,232840559	0,245004365
9	0,140639805	0,275494311	0,203174352
10	0,227505566	0,306553902	0,376470122
11	0,26473375	0,215821605	0,224089358
12	0,340224233	0,232840559	0,212137926
13	0,186140918	0,329529489	0,403360845
14	0,225437334	0,29559795	0,256955798

15	0,267836098	0,265070202	0,185247203
16	0,355735976	0,241350036	0,191222919

3.5.3- Construction of the weighted decision matrix

Following the normalization step, the evaluation criteria are weighted to account for their relative importance in the decision-making process. This is achieved by assigning a weighting coefficient, w_j , to each criterion, with the sum of all weights equal to 1, thereby ensuring a consistent distribution of importance among the criteria. In the present study, the three performance responses surface roughness (Ra), cutting temperature (T_c), and tool flank wear (V_b) were considered to be of equal importance. Consequently, an equal weight of 0.3333 (33.33%) was assigned to each criterion. Applying these weighting coefficients to the normalized decision matrix, according to Equation (3.8), yields the weighted normalized decision matrix (v_{ij}), which serves as the basis for the subsequent steps of the TOPSIS method. The corresponding values are presented in Table 3.3.

$$v_{ij} = w_j \times r_{ij} \quad (3.8)$$

Table 3.3- Weighted normalized decision matrix (v_{ij}).

N°	$v_{i1} (Ra)$	$v_{i2} (T_c)$	$v_{i3} (V_b)$
1	0,053429284	0,058289858	0,049797585
2	0,0613575	0,063927381	0,060753054
3	0,078937458	0,074174199	0,074696378
4	0,110305619	0,090058539	0,094615412
5	0,047569298	0,071621358	0,044817827
6	0,072043357	0,066267484	0,06971662
7	0,08721038	0,09133496	0,112542543
8	0,104445633	0,077613442	0,08166804
9	0,046879888	0,091831345	0,067724716
10	0,075835113	0,102184532	0,125489915
11	0,088244495	0,071940463	0,074696378
12	0,113407964	0,077613442	0,070712571
13	0,062046911	0,109843053	0,134453481
14	0,075145703	0,098532552	0,085651847
15	0,08927861	0,088356646	0,061749006
16	0,11857854	0,080449931	0,063740909

3.5.4- Distance calculation

Once the weighted normalized decision matrix has been established, the next step in the TOPSIS procedure is to determine the relative position of each alternative with respect to the ideal reference solutions. To achieve this, two Euclidean distances are calculated: the distance to the Positive Ideal Solution (S_i^+), which represents the separation between an alternative and the ideal scenario combining the best performance for all criteria, and the distance to the Negative Ideal Solution (S_i^-), which measures the separation between the same alternative and the least desirable scenario [33]. The combined analysis of these two distance measures provides a comprehensive assessment of each alternative by simultaneously considering its closeness to the ideal solution and its remoteness from the anti-ideal solution. The mathematical expressions used to calculate these distances are given below.

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (3.9)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (3.10)$$

Where:

- v_{ij} : weighted normalized value of criterion j for alternative i ;
- v_j^+ : ideal (best) value of criterion j ;
- v_j^- : negative ideal (worst) value of criterion j .

The Positive Ideal Solution (PIS, (v_j^+)) and the Negative Ideal Solution (NIS, (v_j^-)) are determined from the extreme values of the weighted normalized decision matrix. Their identification depends on the optimization objective associated with each criterion, namely whether the criterion is to be maximized (benefit criterion) or minimized (cost criterion). The selection rules used to determine these reference values are presented as follows.

$$v_j^+ = \begin{cases} \max_i (v_{ij}) & \text{if criterion } j \text{ is to be maximized} \\ \min_i (v_{ij}) & \text{if criterion } j \text{ is to be minimized} \end{cases}$$

$$v_j^- = \begin{cases} \min_i (v_{ij}) & \text{if criterion } j \text{ is to be maximized} \\ \max_i (v_{ij}) & \text{if criterion } j \text{ is to be minimized} \end{cases}$$

The calculations performed using the weighted normalized decision matrix made it possible to determine, for each alternative, the distances to the Positive Ideal Solution (S_i^+) and the Negative Ideal Solution (S_i^-). The corresponding results are summarized in Table 3.4 and provide the basis for calculating the relative closeness coefficient, which is subsequently used to establish the final ranking of the alternatives.

Table 3.4- Distances to the S_i^+ , S_i^- solution.

N°	S_i^+	S_i^-
1	0,0082276	0,1186119
2	0,0222557	0,1039916
3	0,0466125	0,0800912
4	0,0866711	0,0452431
5	0,0133493	0,1205726
6	0,0362876	0,0908582
7	0,0854703	0,0425041
8	0,0710292	0,0634412
9	0,0406172	0,0995884
10	0,0962971	0,0443396
11	0,0528214	0,0769914
12	0,0739589	0,0716128
13	0,1045099	0,0565316
14	0,0639206	0,0663019
15	0,0546656	0,0812779
16	0,0773941	0,0765782

3.5.5- Calculation of the relative closeness coefficient

In the TOPSIS method, the relative closeness coefficient (C_i) is used to quantify the overall performance of each alternative with respect to the ideal reference solutions. It simultaneously reflects the ability of an alternative to approach the Positive Ideal Solution (PIS) while remaining distant from the Negative Ideal Solution (NIS). Consequently, a smaller value of (S_i^+) combined with a larger value of (S_i^-) indicates a more desirable alternative. The relative closeness coefficient is calculated according to Equation (3.11).

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (3.11)$$

The relative closeness coefficient (C_i) represents the final performance index of the TOPSIS method and serves as the basis for ranking the alternatives. Its value, ranging from 0 to 1, simultaneously reflects the degree of closeness of an alternative to the Positive Ideal Solution (PIS) and its distance from the Negative Ideal Solution (NIS). The higher the value of C_i , the better the overall performance of the corresponding alternative with respect to the selected evaluation criteria. Accordingly, the alternatives are ranked in descending order of their relative closeness coefficients, with the highest-ranked alternative representing the optimal configuration. The calculated C_i values and their corresponding rankings are summarized in Table 3.5, while figure 3.8 provides a graphical representation that facilitates the comparative analysis of the relative performance and the overall ranking of the different experimental configurations.

Table 3.5- Coefficient (C_i) and the corresponding ranking of the alternatives.

N°	C_i	Classification
1	0,9351341	1
2	0,8237137	3
3	0,6321139	6
4	0,3429739	14
5	0,9003202	2
6	0,7145983	4
7	0,3321299	15
8	0,4717856	12
9	0,7103026	5
10	0,3152775	16
11	0,5930956	8
12	0,4919415	11
13	0,3510376	13
14	0,5091429	9
15	0,5978799	7
16	0,4973505	10

Table 3.8 and figure 3.8 present the relative closeness coefficients (C_i) obtained for the 16 experimental runs. In the TOPSIS method, the relative closeness coefficient represents the degree of proximity of each alternative to the Positive Ideal Solution (PIS). Therefore, the higher the value of C_i , the better the overall performance of the corresponding alternative with respect to all the evaluation criteria considered.

The results reveal a substantial variation in the relative closeness coefficients, ranging from 0.3153 for experimental run n°. 10 to 0.9351 for experimental run n°. 1. This wide range of values indicates that the experimental conditions had a significant influence on the overall machining performance, highlighting the strong discriminative capability of the TOPSIS method in identifying the most suitable cutting parameter combination.

Experimental run n°. 1, with a relative closeness coefficient of 0.9351, ranks first among all the alternatives. This value, which is very close to 1, indicates an excellent proximity to the Positive Ideal Solution (PIS) and confirms that this experimental configuration provides the best trade-off among the different machining performance criteria considered. As illustrated in Figure 3.8, this run clearly stands out from the remaining alternatives and is therefore identified as the optimal cutting condition.

The second-best performance is achieved by experimental run n°. 5, with a relative closeness coefficient of 0.9003, followed by experimental run n°. 2, with a coefficient of 0.8237. These results indicate that both configurations also provide a high level of overall machining performance, although slightly inferior to that of experimental run n°. 1. The relatively small difference between runs n°. 1 and n°. 5 (0.0348) suggests that these two experimental conditions yield comparable overall performance.

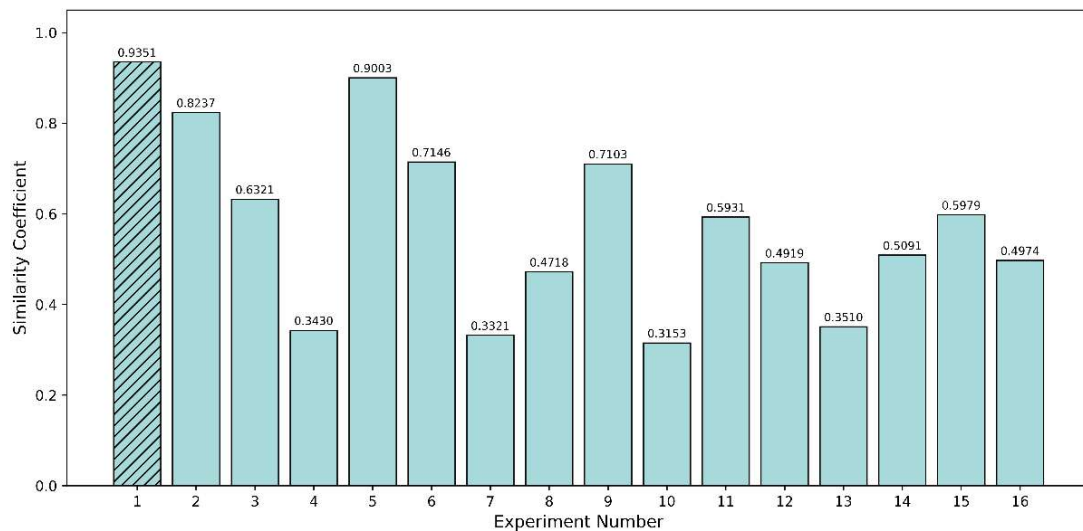


Figure 3.8- TOPSIS closeness coefficients (C_i) for the 16 experimental runs.

An intermediate group is formed by experimental runs n°. 6 (0.7146), n°. 9 (0.7103), n°. 3 (0.6321), n°. 15 (0.5979), and n°. 11 (0.5931). The relative closeness coefficients obtained for these experiments indicate a moderate proximity to the ideal solution. These alternatives can

therefore be considered acceptable configurations, although they remain less efficient than the best-performing solutions previously identified.

Experimental runs n°. 8 (0.4718), n°. 12 (0.4919), n°. 16 (0.4974), and n°. 14 (0.5091) exhibit relatively low intermediate relative closeness coefficients. Their greater distance from the ideal solution indicates a moderate overall performance, which is likely the result of a less favorable trade-off among the quality, cost, and environmental impact criteria.

The lowest relative closeness coefficients are observed for experimental runs n°. 10 (0.3153), n°. 7 (0.3321), n°. 4 (0.3430), and n°. 13 (0.3510). These values indicate that these alternatives are the furthest from the ideal solution and the closest to the anti-ideal solution. Consequently, they represent the least performing configurations among all the studied cases.

The examination of the bar chart visually confirms these observations. The bar corresponding to experimental run No. 1 clearly dominates all the other trials, while experimental runs n°. 4, n°. 7, n°. 10, and n°. 13 exhibit the lowest values. This graphical representation facilitates the rapid identification of the best and worst alternatives and highlights the ranking hierarchy obtained using the TOPSIS method.

Overall, the results demonstrate the effectiveness of the TOPSIS approach in discriminating among the different experimental conditions and identifying the best parameter combination. Experimental run n°. 1, with a relative closeness coefficient of 0.9351, is selected as the optimal configuration since it exhibits the highest proximity to the ideal solution and ensures the best trade-off among the conflicting objectives considered in this study. This outcome is further supported by the significant gap observed between this optimal case and the least performing alternatives, particularly experimental run n°. 10 (0.3153), thereby confirming the robustness of the selected optimal solution.

The multicriteria evaluation carried out using the TOPSIS method highlights its ability to effectively discriminate between the different experimental conditions and to identify the most efficient configuration. Among all the analyzed alternatives, experimental run n°. 1 stands out with the highest relative closeness coefficient (0.9351), indicating its strong proximity to the ideal solution and its capacity to provide the best compromise among the considered performance criteria. In contrast, experimental run n°. 10 exhibits the lowest coefficient (0.3153), reflecting a significant deviation from the ideal solution. The wide gap observed

between these extreme values emphasizes the sensitivity of the ranking results and confirms the robustness of the selected optimal solution.

Thus, the multicriteria optimization reveals that the best cutting parameter combination is obtained for $ap = 0.1$ mm, $f = 0.04$ mm/rev, and $V_c = 63$ m/min during the hard turning of AISI D2 steel (55 HRC). This optimal configuration is characterized by improved overall performance, including a reduced surface roughness ($0.62 \mu\text{m}$), a moderate cutting temperature (164.4°C), and low tool wear (0.05 mm).

3.6- Conclusion

The present study provides a comprehensive framework for analyzing, modeling, and optimizing the hard turning process of AISI D2 steel through the combined use of Pareto analysis, ANN and SVM modeling, and TOPSIS-based multicriteria optimization. The Pareto charts revealed that the cutting parameters influence the responses in a highly dependent manner: feed (f) is the dominant factor affecting surface roughness (Ra), cutting speed (V_c) primarily governs cutting temperature (T_c) and tool flank wear (V_b), while interaction and quadratic effects further explain the nonlinear nature of the process. In terms of predictive modeling, both ANN and SVM approaches demonstrated good predictive capability; however, ANN consistently outperformed SVM with higher coefficients of determination (up to 0.9996 for training and 0.9906 for validation) and lower prediction errors (MAPE between 0.58% and 2.74%), confirming its superior ability to capture the nonlinear relationships of the machining process. Finally, the TOPSIS optimization successfully identified the best compromise among conflicting objectives, with experimental run n°. 1 achieving the highest relative closeness coefficient (0.9351), corresponding to the optimal cutting conditions ($ap = 0.1$ mm, $f = 0.04$ mm/rev, $V_c = 63$ m/min), leading to improved machining performance in terms of low surface roughness, moderate cutting temperature, and reduced tool wear. Overall, the integrated methodology proves to be robust and effective for understanding, predicting, and optimizing hard turning performance.

General conclusion

The present study aimed to analyze, model, and optimize the cutting conditions employed in the hard turning of AISI D2 tool steel with a hardness of 55 HRC. The cutting parameters investigated were the depth of cut (ap), feed (f), and cutting speed (V_c). The machining performance was evaluated using three machinability indicators: surface roughness (Ra), cutting temperature (T_c), and tool flank wear (V_b). The main findings of this study are summarized as follows.

- ✧ The Pareto chart analysis revealed that the influence of the cutting parameters varies depending on the response under investigation. Surface roughness (Ra) is primarily governed by the feed (f), followed by the effects of the depth of cut (ap), selected quadratic terms, and the ($ap * V_c$) interaction. In contrast, both cutting temperature (T_c) and tool flank wear (V_b) are mainly controlled by the cutting speed (V_c), whose linear and quadratic effects are the most statistically significant. The depth of cut (ap) also has a considerable influence on the cutting temperature, whereas the ($ap * V_c$) interaction significantly affects tool wear. Conversely, the feed (f) has only a minor influence on the thermal and tribological responses.
- ✧ The evaluation of the artificial neural network (ANN) models confirms their excellent capability to predict the main responses of the hard turning process of AISI D2 steel. The coefficients of determination (R^2) range from 0.9787 to 0.9996 during the training phase and from 0.9822 to 0.9906 during the validation phase, demonstrating outstanding generalization performance. Prediction errors remain very low, with MAPE values ranging from 0.58% to 2.74%, while the corresponding RASE values are 0.0323 μm for surface roughness (Ra), 0.7637 $^{\circ}\text{C}$ for cutting temperature (T_c), and 0.0015 mm for tool flank wear (V_b). These results highlight the high accuracy and reliability of the ANN models for predicting the machining performance indicators.
- ✧ The three support vector machine (SVM) models exhibited different predictive performances depending on the response considered. The cutting temperature (T_c) model achieved the highest accuracy, with coefficients of determination (R^2) of 0.9821 (training) and 0.9573 (validation), together with a MAPE of 2.91% and a RASE of 0.6856 $^{\circ}\text{C}$. The surface roughness (Ra) model also demonstrated good predictive capability, with R^2 values of 0.9611 and 0.9438, a MAPE of 5.74%, and a RASE of

0.0476 μm . In contrast, the tool flank wear (V_b) model showed more moderate predictive performance, with R^2 values of 0.7112 and 0.6823, although the prediction errors remained acceptable (MAPE = 5.74%, RASE = 0.0144 mm). Overall, the predictive performance of the SVM models can be ranked as follows: $T_c > Ra > V_b$.

- ✧ The comparison between the ANN and SVM models demonstrates that artificial neural networks (ANNs) provide superior predictive performance for all three machining responses. The ANN models achieved high coefficients of determination ($R^2 = 0.9787\text{--}0.9996$) with low prediction errors (MAPE = 0.58–2.74%), whereas the SVM models exhibited more variable performance, particularly for tool flank wear (V_b), with a validation coefficient of determination of ($R^2 = 0.6823$). Both approaches identified cutting temperature (T_c) as the response that can be predicted with the highest accuracy. Overall, the ANN approach proved to be the most reliable technique for multi-response prediction in the hard turning process.
- ✧ The TOPSIS multi-objective optimization identified Experiment No. 1 as the optimal alternative, with the highest similarity coefficient of 0.9351, whereas Experiment No. 10 exhibited the lowest value (0.3153). The optimal cutting conditions were determined as a depth of cut (ap) of 0.1 mm, a feed (f) of 0.04 mm/rev, and a cutting speed (V_c) of 63 m/min. Under these conditions, a surface roughness of 0.62 μm , a cutting temperature of 164.4 $^{\circ}\text{C}$, and a tool flank wear of 0.05 mm were achieved, representing the best compromise among the machinability criteria considered.

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Perspectives

The results obtained in this study provide a solid basis for further research on the hard turning of AISI D2 tool steel. Future work could investigate the effect of other machining parameters, different cutting tool materials, and advanced cooling techniques such as minimum quantity lubrication (MQL) or cryogenic machining. In addition, the prediction models developed using ANN and SVM could be enhanced by using larger datasets or compared with other machine learning techniques. Such developments would contribute to improving machining performance and support the implementation of intelligent manufacturing systems in the context of Industry 4.0.