

**KARADENİZ TECHNICAL UNIVERSITY
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES**

MINING ENGINEERING DEPARTMENT

**AN INVESTIGATION INTO THE ABRASIVE WATERJET CUTTING OF NATURAL STONES:
IMPROVEMENT OF THE CUTTING PERFORMANCE AND LEVERAGING THE MACHINE
LEARNING ALGORITHMS FOR MODELLING AND OPTIMIZATION**

DOCTORATE THESIS

Imene ROGAİ

**JUNE 2025
TRABZON**



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**This thesis is accepted to give the degree of
DOCTOR OF PHILOSOPHY**

**By
The Graduate School of Natural and Applied Sciences at
Karadeniz Technical University**

The Date of Submission : 10 /06 /2025

The Date of Examination : 30 /06 /2025

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Trabzon 2025

PREFACE

This study was prepared as a Doctoral Thesis in Mining Engineering Department of Graduate School of Natural and Applied Science at Karadeniz Technical University. First of all, I am deeply grateful to the Scientific Research Projects Office of Karadeniz Technical University for the financial support (Project number: FDK-2022-10526). Additionally, special thanks go to the Çiftyıldız Marble Group, operated in Bursa, Türkiye for providing the raw natural stone samples. Moreover, I would like to express my gratitude to my supervisor Prof. Dr. İzzet KARAKURT, who provided endless help and shared his interests and knowledge with me during the preparation of this thesis. I would like to express my gratitude also to Prof. Dr. Gökhan AYDIN and Prof. Dr. İrfan TEMİZEL as the valuable members of the thesis monitoring committee, who provided me with references and assistance throughout my studies and whose information and support I frequently sought. In addition, Prof. Dr. Didem Eren SARICI from İnönü University in Malatya and Prof. Dr. Salih YILMAZ from Adana Alparslan Türkeş Science and Technology University in Adana deserve a special thank for their participation as the thesis defence examination jury. Furthermore, I would like to express my special thanks to the Department Head and his team who allowed me to benefit from the department laboratory facilities, Assistance Prof. Dr. Serkan KAYA for his guidance in laboratory scale measurements, Associate Prof. Dr. Yunus Emre KARABACAK who is from Mechanical Engineering Department at Karadeniz Technical University and Abdolsattar ROUDINI, a PhD. student in Mining Engineering Department at Karadeniz Technical University for their helps in modeling and optimization studies using machine learning algorithms respectively. Finally, I would like to express my deepest gratitude to my family and dear friends who have always been with me both materially and spiritually throughout my life.

Imene ROGAI
Trabzon, 2025

DECLARATION

I hereby declare that I have completed this study titled “*An Investigation into the Abrasive Waterjet Cutting of Natural Stones: Improvement of the Cutting Performance and Leveraging the Machine Learning Algorithms for Modelling and Optimization*”, which I submitted as a PhD Thesis, from beginning to end under the responsibility of my advisor Prof. Dr. İzzet KARAKURT. I declare also that I have collected the data myself, made the analyses, and completely cited references in the text and reference list to information I have received from other sources. Moreover, I declare that I have acted in accordance with scientific research and ethical rules during the work process, and that I accept all legal consequences in case the opposite occurs. 30/06/2025

Imene ROGAI

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Doktora Tezi

ÖZET

DOĞALTAŞLARIN AŞINDIRICI SUJETİ İLE KESİLMESİNE YÖNELİK BİR ARAŞTIRMA:
KESME PERFORMANSININ İYİLEŞTİRİLMESİ, MODELLEME VE OPTİMİZASYON İÇİN
MAKİNE ÖĞRENİMİ ALGORİTMALARINDAN YARARLANILMASI

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2025, 125 Sayfa, 4 Sayfa Ek

Bu tezde, mermer, traverten, bazalt, oniks ve tüf olmak üzere çeşitli kayalardan oluşan iş parçaları kullanılarak aşındırıcı su jeti (AWJ) çok geçişli kesme ve jetin ileri açılı hale getirme performansı deneysel olarak araştırılmıştır. Ayrıca; kesme performans göstergeleri, yapay sinir ağı, gradyan destekli karar ağaçları, Gauss süreci regresyonu, destek vektör makinesi ve parçacık sürüşü optimizasyonu gibi makine öğrenme algoritmaları (MLAs) ile modellenmiş ve optimize edilmiştir. Makine öğrenimi tabanlı modeller geliştirildikten sonra, ilgili modellerin istatistiksel doğruluğu, determinasyon katsayısı, ortalama karekök hatası ve ortalama mutlak yüzde hatası gibi göstergeler ile kapsamlı bir şekilde değerlendirilmiştir. Ek olarak, önerilen modelleri etkileyen tahmin edici değişkenlerin göreceli önemini belirlemek için rastgele orman regresyonundan yararlanılmıştır. Tekli kesme ile karşılaştırıldığında kesme performans göstergesine ve kaya türüne bağlı olarak, çoklu geçişli kesmenin kesme performansını önemli ölçüde iyileştirdiği belirlenmiştir. Çoklu geçişle elde edilen iyileştirmeler kadar olmasa da, jetin ileri açılı hale getirilerek gerçekleştirilen deneylerde de yine performans göstergesine ve kaya türüne bağlı olarak %42,94'e kadar iyileştirmeler elde edilmiştir. Bu iyileştirmelere ek olarak, kayaların AWJ çoklu geçişli kesimi sırasında aşındırıcı besleme miktarındaki ve su basıncındaki artışın önemli iyileştirmelere yol açtığı görülmüştür. Ayrıca, geliştirilen modellerin sıralaması kesme performans göstergelerine bağlı olarak değişse de, MLAs'nın AWJ çoklu geçişli ve ileri açılı jet kesme teknikleri ile elde edilen kesme performanslarının modellenmesi ve optimize edilmesi için başarılı bir şekilde kullanılabileceği sonucuna varılmıştır.

Anahtar Kelimeler: Aşındırıcı Sueti, Doğaltaş, Makine Öğrenmesi, Modelleme, Optimizasyon

PhD. Thesis

SUMMARY

AN INVESTIGATION INTO THE ABRASIVE WATERJET CUTTING OF NATURAL STONES: IMPROVEMENT OF THE CUTTING PERFORMANCE AND LEVERAGING THE MACHINE LEARNING ALGORITHMS FOR MODELLING AND OPTIMIZATION

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2025, 125 Pages, 4 Pages Appendix

In this thesis, the performance of abrasive waterjet (AWJ) multi – pass cutting and forward angling the jet was experimentally investigated using the workpieces of various rocks including marble, travertine, basalt, onyx and tuffs. Additionally, the cutting performance indicators were modelled and optimized using machine learning algorithms (MLAs) such as artificial neural network, gradient boosted decision trees, Gaussian process regression, support vector machine and the particle swarm optimization. Once the MLAs-based models were developed, the robustness of the models was comprehensively assessed through the statistical indices of determination coefficient, root mean square error and mean absolute percentage error. In addition, a random forest regressor (RFR) was leveraged to determine the feature importance of predictor variables influencing the proposed models. In comparison to the single cutting, it was determined that the multi-pass cutting significantly improves cutting performance, depending on the cutting performance indicator and rock type. In experiments where the forward angling the jet was used, improvements of up to 42.94% were achieved, depending on the performance indicator and rock type, although not as much as the improvements achieved with the multi – pass cutting. In addition to these improvements, it was found that the increase in abrasive flow rate and water pressure during AWJ multi – pass cutting of rock led to substantial improvements. Moreover, it was concluded that the MLAs can be successfully used to model and optimize the cutting performances obtained by AWJ multi – pass and forward angling the jet cutting techniques.

Key Words: Abrasive Waterjet, Natural Stone, Machine Learning, Modelling, Optimization

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LIST OF SYMBOLS AND ABBREVIATIONS

AAJ	: Abrasive airjet
ACO	: Ant colony optimization
AFR	: Abrasive flow rate
ANFIS	: Neuro fuzzy inference systems
ANNs	: Artificial neural networks
APS	: Abrasive particle size
AWJ	: Abrasive waterjet
AWSJ	: Abrasive water slurry jet
BA	: Bat algorithm
CAWJ	: Cryogenic abrasive waterjet
CNC	: Computer numerical control
CNN	: Convolutional neural network
CWZ	: Cutting wear zone
DA	: Declination angle
DT	: Decision trees
DWZ	: Deformation wear zone
FA	: Forward angling
GAs	: Genetic algorithms
GPR	: Gaussian process regression
GWO	: Grey wolf optimization
H_{CD}	: Total cutting depth
H_{CWZ}	: Cutting wear zone depth
H_D	: Jet lag or tailback
HMM	: Hidden Markov models
IAAWT	: Ice – assisted abrasive waterjet
IZ	: Initial zone
JIA	: Jet impact angle
KTU MERLAB	: Central Research Laboratory of Karadeniz Technical University
LN_2	: Liquid nitrogen
MAE	: Mean absolute error

MAPE	: Mean absolute percentage error
MAs	: Memetic algorithms
MAWJ	: Magnetorheological abrasive waterjet
Mg ₃ Al ₂ (SiO ₄) ₃	: Aluminum silicate
ML	: Machine learning
MLAs	: Machine learning algorithms
MPa	: Mega Pascal
N/A	: Non-applicable
NP	: Number of pass
PSB	: Printed circuit board
PSO	: Particle swarm optimization
R ²	: Determination coefficient
Ra	: Average surface roughness
RCZ	: Rough cutting zone
RFR	: Random forest regressor
RMSE	: Root mean square error
SA	: Simulated annealing
SAWJ	: Slurry abrasive waterjet
SD	: Standoff distance
SEM	: Scanning electron microscope
SVM	: Support vector machine
SZ	: Striation zone
TAAWJ	: Thermally – assisted abrasive waterjet
TS	: Traverse speed
UCAWJ	: Unsubmerged cavitating abrasive waterjet
UCS	: Uniaxial compressive strength
W _b	: Bottom kerf width
WJ	: Waterjet (pure)
WP	: Water pressure
W _t	: Top kerf width
α	: Kerf taper angle
β	: Declination angle

1. INTRODUCTION

As a widely utilized construction material worldwide, there is a growing demand for natural stones (e.g. marble and granite) both at homes and workplaces due to their distinctive properties such as hardness, resistance to environmental conditions and aesthetic appearance. This increasing demand has highlighted the need to improve and/or enhance traditional technologies, particularly in the final product stage of processing plants. In addition to these requirements, the traditional technologies often suffer from low efficiency, significant tool wear, high material loss, increased waste material and the environmental sensitivity (Lie et al., 2022a). Thus, there has been an increase in the search for new and/or alternative technologies in recent years. In this regards; AWJ technology has advanced rapidly and shown notable benefits in a variety of field since it was first introduced. As a unique cutting technique, it is distinguished by its capability of cutting a wide range of materials and complex shapes, low cutting force, high efficiency, cost-effectiveness, environmentally friendly and lack of thermal effects (Pawar et al., 2018). Although the technology can recently be classified using a variety of specifications such as pressure levels, jet processing techniques, jet medium, working environment, and abrasive mixing method, the fundamental classification is determined by the range of operational pressure and abrasive addition. In addition, the technology can be also classified as either pre-mixed or post-mixed abrasive waterjets based on the abrasive's mixing method. Moreover, there are two additional AWJ types as SAWJ and AWSJ to increase the homogeneity of the abrasive and water mixture as illustrated in Fig. 1.1. The abrasive particles are mixed with the water, which imparts high velocity to the particles within the mixing chamber. This acceleration is achieved through the small diameter of the nozzle, which converts the potential pressure energy of the water into the kinetic energy. A waterjet loaded with abrasive particles is then projected onto the workpiece and material removal occurs by means of abrasion and erosion regardless of the aforementioned classifications in this technology (Morisset et al., 2022).

Due to its remarkable advantages, the AWJ technology's capabilities in terms of process efficacy and efficiency have been investigated through theory, experimentation and process modeling methodologies. Despite these investigations, the cutting depth and surface irregularities such as striations and roughness are still the most significant problems limiting.

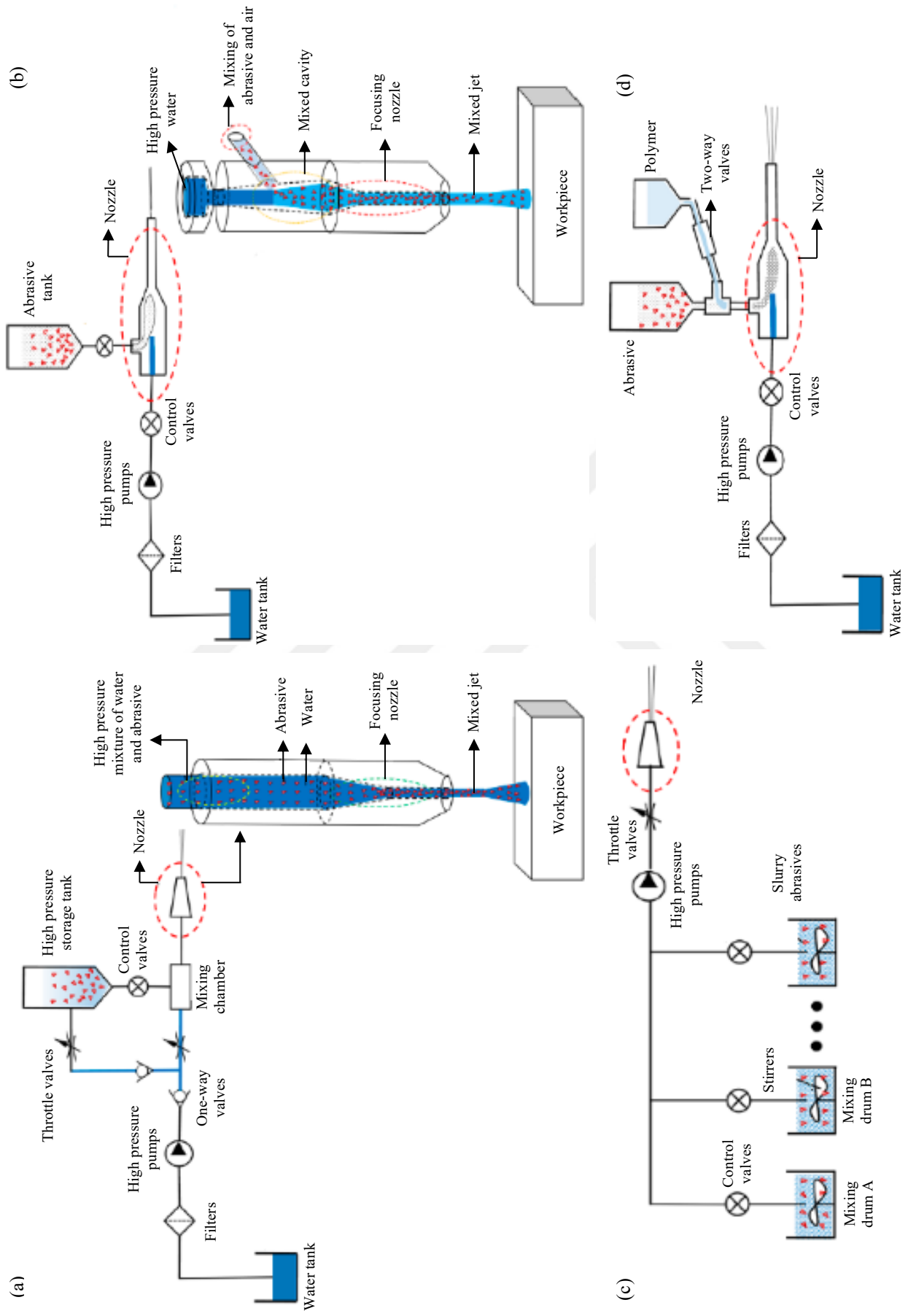


Figure 1.1. Principle diagram of AWJ; a) premixed AWJ, b) postmixed AWJ, c) SAWJ, d) AWSJ (Wang et al., 2023)

the wider applications of the technology as evidenced by the studies of Lemma et al. (2022), Wang and Guo (2003), Hashish (2004) and Wang and Zhong (2009). In this regards, recent years have seen substantial research and developments in order to enhance the technology's cutting capabilities in the form of cutting depth and surface irregularities. Among the newly developed techniques, the superiorities of the multi-pass cutting, controlled nozzle oscillation and delivering the jet to the cutting plane from various angles (forward angling the jet) have been demonstrated in various fields (Wang, 2007; Shanmugam et al., 2008; Wang, 2010; Dekster et al., 2023). In order to generalize the results, therefore, it is essential to study these techniques in more fields. In view of the limited number of studies that have focused only on the multi-pass and lack of studies for the forward angling the jet in rock cutting and/or processing applications, in this thesis, it is aimed to investigate experimentally performances of the multi-pass and forward angling the jet techniques in rock cutting applications by AWJ and leverage MLAs for modelling and optimizing the cutting performance.

1.1. Outline

Based on the aforementioned, this thesis is structured around eight chapters, first of which is introduction. Chapter 2 presents an overview on the state of the art in AWJ technology. Chapter 3 reports the recent studies, especially focusing on the rock cutting by AWJ in the relevant literature. The experimental study is delineated in Chapter 4, while Chapter 5 describes the modeling and optimization study. Chapter 6 details the results and discussion. Chapter 7 presents the core findings of thesis. The investigation is finalized by presenting the limitations of the thesis and recommendations for future works in Chapter 8.

2. STATE OF THE ART IN AWJ CUTTING/MACHINING

Today's modern AWJ technology were laid in the 1960s with the cutting/processing of wood and plastic materials. Towards the end of 1970s, the need for cutting/processing hard and durable materials such as rock, ceramics and steel emerged. Thus, abrasive waterjet technology has become more preferred in the field with the addition of abrasive particles to waterjet technology (Liu, 2004). With the addition of these particles, AWJ has made it technically and financially feasible to cut and/or machine materials that are hard to machine such as titanium alloys, ceramics, composites, rock, and rock-like (Wang, 2003).

2.1. Material Removal Mechanisms

A large number of investigations have been documented so far in order to explain the mechanism behind the phenomena that occur during AW cutting and/or machining. Based on these investigations, there is widespread consensus that two primary processes of material removal – macro and micro – are accepted. Kerf characteristics (generation) is referred to as a macro-sized material removal mechanism, whereas material removal by individual abrasive particles is described as a micro-sized mechanism.

2.1.1. Micro – sized Material Removal Mechanism

In the course of the procedure, the abrasive particles impact firstly the material's surface to be cut, and material removal occurs by these particles' micro-cutting actions. This indicates that the impact of a single abrasive particle plays a crucial role for the material removal in AWJ cutting applications. Therefore, figuring out the multi-particle impact requires an understanding of how a single particle affects the target, which can be either ductile or brittle. In this regards, several researches have attempted to explain the mechanism behind the micro-sized material removal in ductile materials, considering the particle's kinetic energy and the material's flow stress (Gudimetla et al., 2002; Kong et al., 2010; Anwar, 2013). They have utilized the high speed photographs and SEM pictures to define the micro-sized material removal mechanism. They have mainly reported that the entire process could be classified into two categories as cutting wear and deformation wear. They have also

declared that these wears have resulted from the low and high impact angles of the individual particle. In addition, the researchers have classified the impact angles in accordance with the particle rake angle, which is the angle formed by the particle's leading face and the target surface as illustrated in Fig.2.1(a). The cutting mode, which causes the target material to flow down the particle inclined face and form a piled up lip above the surface, dominates the deformation at rake angles larger than a critical rake angle that depends on the material Fig. 2.1(b). On the other hand, ploughing deformation pre-dominates if the rake angle increases negatively. In this situation, both sides and front of the generated crater exhibit lip development as is in Fig. 2.1(b). Similar to the ductile materials, a large amount of researchers have reported for the case in brittle materials in the relevant literature (Evans, 1978; Zheng and Kim, 1992, Camacho and Ortiz, 1996). They have emphasized that the erosion in brittle materials results from cracking process. Additionally, Zheng and Kim (1992) identified six categories in order to classify the erosion mechanisms for brittle materials described in the literature as conical, radial and lateral crack systems; intergranular cracking; ring fracture; micro-chipping; plastic deformation and melting; and finally the mixed damage. The scholars stated that the conical, radial, and lateral crack systems are the largest three impact damage mechanisms in these materials in addition to plastic deformation owing to the impact of both angular and spherical particles. Fig. 2.2(a) displays an overall look of brittle materials deformation, while Fig. 2.2(b) illustrates how tiny cracks combine to create a network, eventually resulting in the development of material removal.

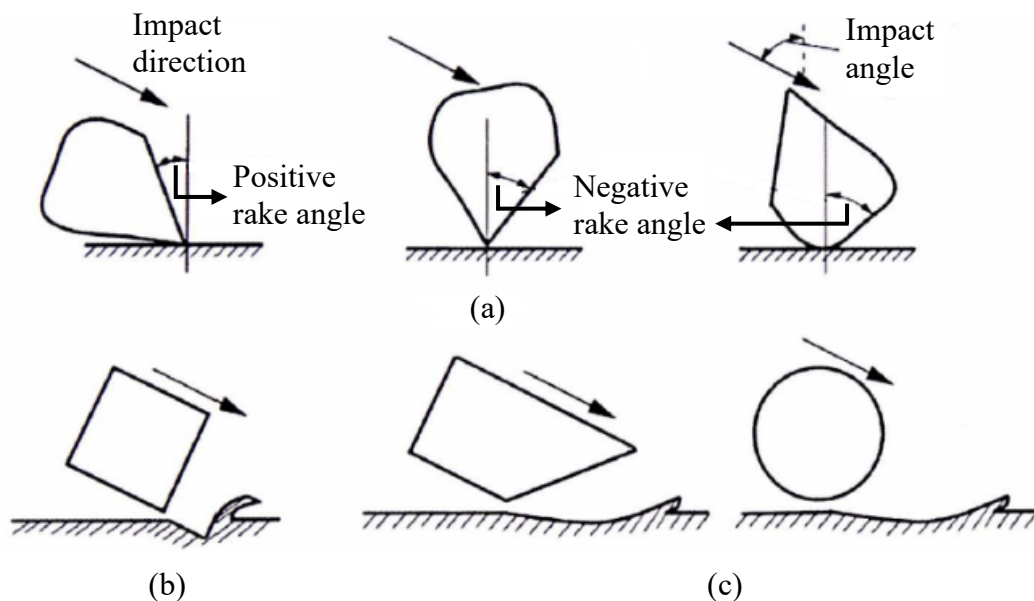


Figure 2.1. Target deformation as a function of particle rake angle (Anwar, 2013)

On the other hand, Evans (1978) described the lateral crack mechanism as the primary cause of material removal in brittle materials in conditions involving single or multiple particle impacts.

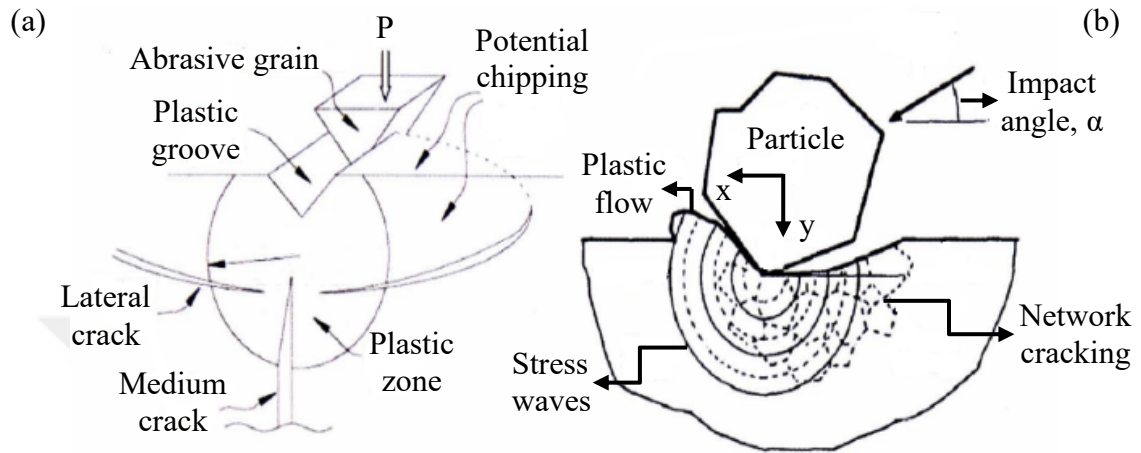


Figure 2.2. a) Radial, median and lateral cracks, b) scratching and network cracking (Evans, 1978; Zheng and Kim, 1992)

2.1.2. Macro – sized Material Removal Mechanism

Among top earliest studies in this field, Hashish (1984, 1988) noted that the cutting zone can be divided into two parts as the CWZ and DWZ. Later on, this definition has been further enhanced as three parts as the IZ, CWZ, and SZ as can be schematically depicted in Fig. 2.3 (1,2 and 3) respectively (Arola and Ramulu, 1996; Patel, 2004). Herein; the shallow, dark wear tracks produced by abrasive particles impinging on surfaces are known as the IZ, where particles impinging almost perpendicularly cause plastic deformation as the cutting mechanism for material removal. However, the IZ part can be usually ignored due to its extremely small magnitude (Wan et al., 2023a). A zone of small and randomly dispersed surface heights is defined by the CWZ. In other words, the CWZ displays the least amount of roughness throughout the whole surface since the kinetic energy of the AWJ particles is sufficiently high to penetrate and produce a smooth surface. The RCZ, or DWZ is striated and/or grooved and produced when the abrasive particles lack adequate kinetic energy. On the other hand, in the CWZ, the cutting wear mechanism governs the material removal because of the abrasive particles' shallow impact angle, whereas the DWZ is distinguished

by the deformation wear mechanism, resulting from the abrasive particles' high impact angle (Seo et al., 2003; Anwar, 2013).

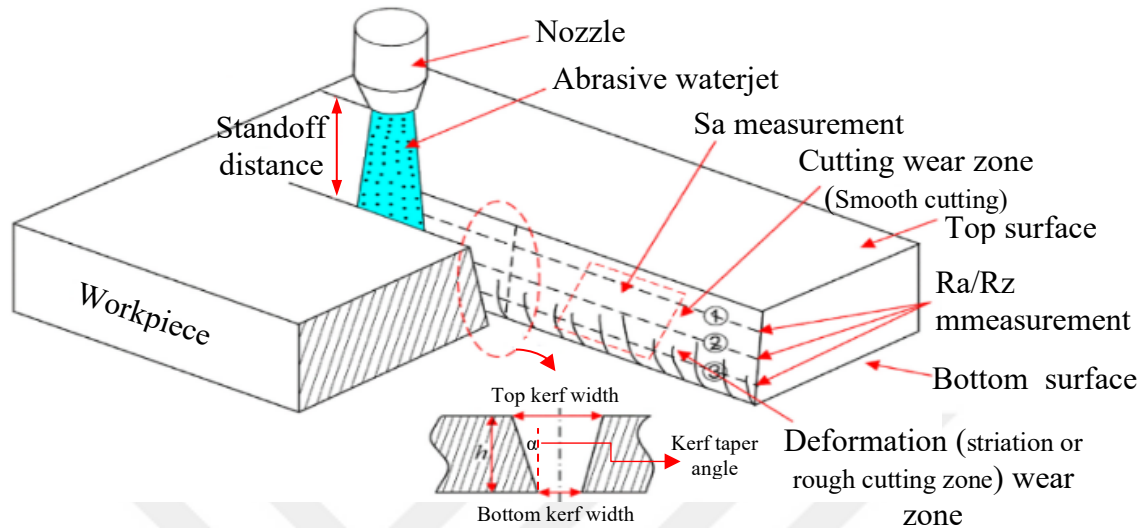


Figure 2.3. Schematic illustrations of the IZ (1), CWZ (2), DWZ (3) and other indicators in AWJ cutting application (Wan et al., 20223b)

2.2. Benefits and Drawbacks of the AWJ Technology

AWJ technology has various benefits over conventional and non-conventional cutting/machining technologies. Actually, its main strength lies in the materials versatility since it can cut/machine almost all hard to difficult materials such as metals, ceramics, composites, glass, rock and rock-like materials. Based on this main power, other benefits of the AWJ technology can be listed as below.

1. There is no remaining stress that are seen on the material's cut walls.
2. Burrs are drastically decreased apart from ductile materials in thin layers.
3. As a cold cutting process, it avoids heat-affected zones, preventing thermal distortion, and oxidation, which are common in thermal techniques.
4. Upon drying the workpiece following machining, there is minimal oxidation on the cutting edges.
5. It uses a high velocity water-abrasive jet, enabling precise cutting/machining with minimal force and no tool wear (Supriya et al., 2018; Liu et al., 2020; Saravanan et al., 2020). This makes AWJ especially suitable for machining heat-sensitive materials such as aerospace alloys and composites (Saravanan et al., 2020).

6. It is capable of producing complex geometries with high dimensional accuracy due to its CNC compatibility and absence of mechanical or thermal distortion (Natarajan et al., 2020).
7. The technology generates environmentally minimal waste mostly water and reusable abrasives, and eliminates the need for lubricants or coolants, making it a clean and sustainable option (Rajurkar et al., 2017).
8. It is cost-effective technology as the abrasives can be recycled, and the process consumes less energy, resulting in lower operational costs and reduced environmental impacts (Schramm et al., 2019).
9. No specialized auxiliary tools are needed.
10. It is a very reproducible technique.
11. It utilises widely available natural resources such as water and abrasive.
12. Since the system works automatically, there is no need for constant control by an operator.
13. Material loss is very low.
14. It has ease of installation and disassembly
15. Since the cutting process is done with water, flammable and hazardous materials can be cut more easily.

Despite the benefits listed above, the following drawbacks also restrict the technology's potential for broader use.

1. In the technology, there may be some localised deformation and burrs at the workpiece's bottom.
2. Not only does the electric motor and pump create mechanical noise during system operation, but the supersonic speed of the water at the primary nozzle output also makes the process extremely noisy.
3. It has comparatively high investment costs.
4. Abrasive disposal costs are not negligible.
5. The current kerf quality such as cutting depth and surface roughness remains still undesired.
6. The time spent for cutting is long, which increases the cutting cost.

2.3. Process Variables Affecting the Cutting Performance in AWJ Technology

Cutting performance and quality of the AWJ cutting are heavily influenced by a variety of process variables. These parameters include mainly the water pressure, the abrasive flow rate, the traverse speed, the stand-off distance, and the impact angle. Each of these variables plays a significant role in determining kerf geometry, surface finish, material removal rate, and cutting depth. Understanding the relationships between these parameters and cutting performance is essential for optimizing the AWJ cutting process. By systematically analyzing their effects, it becomes possible to enhance cutting performance, improve cutting quality, and expand the applicability of the AWJ technology.

2.3.1. Water Pressure

Water is pressurized to very high levels, ranging from 2000 to 4000 bar or from 200 to 400 MPa, prior to be forced through a small nozzle, which creates a high-velocity jet. With the addition of abrasive particles, this high velocity waterjet can effectively cut almost all materials including ceramics, metals, composites, rock and rock-like materials. That means, an increase in the water pressure may lead achieving effective penetration in especially hard materials. However, excessive pressure may lead to overcutting or surface damage as declared by Ma and Deam (2006) and Barabas and Florescu (2022). Thus, it can be stated that there is critical value for the water pressure depending on the material type.

2.3.2. Standoff Distance

Standoff distance is the distance between the nozzle and the material being cut. This variable significantly affects the cutting performance and quality, as it influences the abrasive jet's focus, energy dissipation, and ultimately the cutting depth. Miynarzuc et al. (2014) and Alsoufi et al. (2017) demonstrated that increasing the standoff distance results in wider kerfs, but reduces penetration depth and precision. Therefore, an optimal setting of standoff distance is highly recommended to minimize energy loss and maintain the cutting accuracies.

2.3.3. Abrasive Material and Abrasive Mass Flow Rate

In AWJ cutting, abrasives are the materials that provide mechanical force for material removal in the form of small chips. Thus, the selection or type of abrasive material significantly affects the cutting performance. In some investigations, the importance of abrasive materials' properties such as particle size, hardness, and purity in optimizing the cutting process has been emphasized (Aydin et al., 2017; Oh et al., 2019). While garnet is the most commonly used abrasive due to its efficiency and availability, alternative materials can be also utilized depending on the material being cut and the cutting requirements. In certain rock cutting applications, alternatives to garnet, such as fused alumina, silicon carbide and steel shot have demonstrated superiorities over the garnet in terms of the cutting efficiency (Kaya et al., 2023). On the other hand, abrasive mass flow rate that is the rate at which abrasive particles are injected into the waterjet stream, plays a crucial role in determining the material removal rate, cutting speed, surface finish, and overall process efficiency. It is typically measured in kilograms per minute (kg/min) or grams per second (g/s).

2.3.4. Traverse Speed

Traverse speed refers to the linear velocity at which the cutting head or nozzle moves over the surface of the material being cut/machined. Traverse speed governs the exposure time between the high-velocity abrasive waterjet and the workpiece. At lower traverse speeds, the abrasive waterjet spends more time on a specific area, enabling deeper penetration and smoother surface finishes. In contrast, higher traverse speeds reduce exposure time, which may lead to incomplete cuts, and rougher surfaces, though they are often favored for improving productivity and reducing cycle time. These have been supported by Karakurt et al. (2011) and Hlavac et al. (2017) since they noted that lower traverse speeds enhance cut quality, but reduce the productivity. Additionally, Alsoufi et al. (2017) identified the traverse speed as a dominant factor in surface quality.

2.3.5. Material Properties

It is known that the material properties play a significant role in any cutting and/or machining technologies such as AWJ cutting/machining. For instance, when evaluated specifically for rocks, the cutting performance is significantly affected by the rocks' intact properties such as hardness, grain size, mineral composition, porosity, and stratification. Liu et al. (2024) emphasized that rocks with coarse grains and heterogeneous mineral compositions, such as granite, tend to exhibit more unpredictable erosion patterns and rougher surfaces. Conversely, fine-grained homogeneous rocks (e.g. limestones) allow for more consistent cutting. Miranda and Quintino (2005) studied AWJ cutting of limestone and found that the mineralogical purity improves cut-ability and surface smoothness. Engin et al. (2013) worked with various rock types and determined that harder rocks require more specific energy to achieve a comparable cutting depths. Chomka et al. (2023) conducted a comparative study across granite, marble, basalt, and limestone and noted that marble required less energy and showed smoother kerfs, while granite required more energy and had greater taper angles.

2.4. Cutting Performance Indicators in AWJ Technology

Cutting performance indicators of the AWJ technology typically consist of three main variables as the kerf or geometrical characteristics, surface characteristics and energy consumption during the cutting/machining process. The geometrical characteristics are mostly assessed through kerf width, kerf taper angle and kerf depth (cutting depth), while those are the surface roughness, striation or waviness form and declination angle of the jet for the surface characteristics. Despite the separate classification for the kerf and surface characteristics, the surface roughness, striation or waviness form and declination angle of the jet can also be referred as the kerf or geometrical characteristics (Liu, 2004). The features of both kerf and surface characteristics produced by AWJ are described in detail below.

2.4.1. Kerf Width and Kerf Taper Angle

Kerfs, which are generated by the AWJ typically come in two varieties: through and non-through cuts as illustrated in Fig. 2.4. and Fig. 2.5 respectively. The former's entry is wider, and when the jet moves through the material thickness, its width gets smaller.

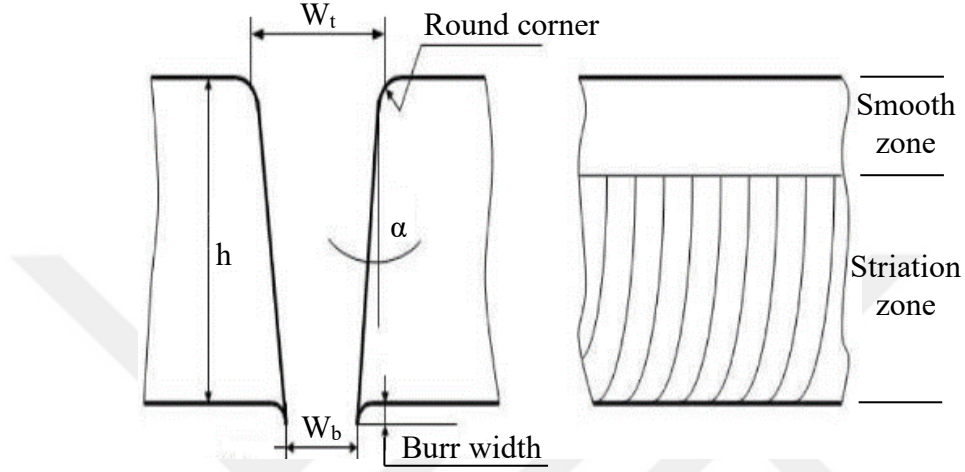


Figure 2.4. An illustration of the through cut in AWJ cutting

There are two distinctly different zones on the cross-sectional surface as the lower striated and the upper smooth zones. Kerf taper refers to an angle at which the cut walls deviate from vertical and it typically results in a V-shaped kerf (Wang & Guo, 2003). The kerf taper angle is mathematically expressed as in Eq.2.1.

$$\alpha = \tan^{-1} \left(\frac{W_t - W_b}{2h} \right) \quad (2.1)$$

Kerf taper angle is a key feature, directly affecting the dimensional accuracy of the final part. Among the various influencing factors, the traverse speed has been identified as the most critical parameter affecting kerf taper angle (Gupta, 2013; Karakurt, 2010). Thus, to minimize the kerf taper angle is essential for achieving precise and straight cuts in AWJ technology. On the other hand, the entry of the non-through cut is similar to that generated in the through cut. However, an irregular pocket is produced at the bottom of the cut due to the deflection of the jet, the rebound of the particles and the instability of the jet. As can be followed from Fig.2.5 that the produced kerf is divided into three zones, first two zones of

which resembles the zones of through cut. The last or third zone is called pocket zone that is generated at the bottom of the kerf (Chen et al., 1996).

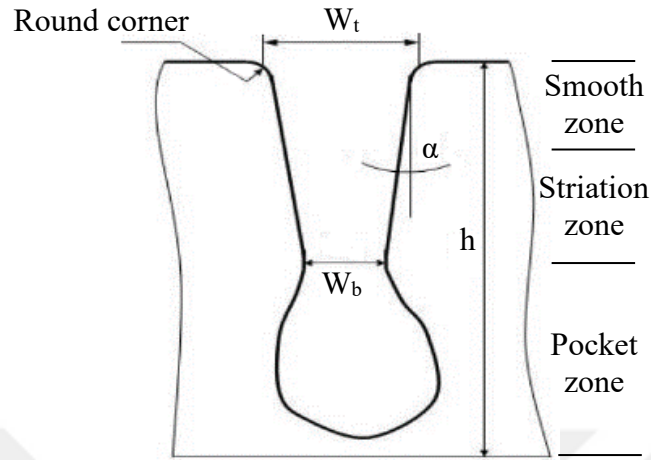


Figure 2.5. An illustration of the non through cut in AWJ cutting

As an another kerf characteristics, the kerf width is defined as the horizontal distance across a cut from one edge to the other. In other words, the kerf width is frequently used to represent the width of the cut achieved by the AWJ cutting. Thus, in terms of the material removal rate or material losses, it is among the most crucial cutting performance indicators (Karakurt et al., 2010).

2.4.2. Cutting and Cutting Wear Zone Depths

In AWJ cutting, the cutting depth is the maximum vertical penetration of the jet into the material and serves as a key indicator of process efficiency, especially for thick or hard materials. Achieving the largest and proper cutting depth is essential for the thoroughness of the cut, dimensional accuracy, and minimizing excessive abrasive use. It is influenced by the variables such as water pressure, abrasive flow rate, traverse speed, stand-off distance, and nozzle diameter. Higher water pressure and abrasive flow rate increase the penetration, while slower traverse speeds and smaller standoff distance allow greater energy concentration and deeper cuts. The cutting wear zone, typically in the upper part of the kerf, represents the region of highest erosion and also reflects the cutting efficiency. Its depth is similarly affected by jet energy, abrasive particle characteristics (size, shape, hardness), material brittleness, and standoff distance. Liu et al. (2024) emphasized that material hardness and abrasive concentration are particularly critical for both cutting depth and

cutting wear zone behavior, highlighting the importance of optimizing these variables for effective AWJ performance.

2.4.3. Surface Roughness

Surface roughness is a critical measure of cutting quality, expressed as the R_a , indicating deviations from an ideally smooth surface. It is influenced by the operating variables (e.g. water pressure, traverse speed, stand-off distance), material properties, and abrasive characteristics. It also varies along the cutting depth, with the cut cross-section typically divided into two zones (Hloch and Valícek, 2012; Zhao and Guo, 2014). The smooth cutting zone, found in the upper part, benefits from concentrated jet energy and exhibits the best surface quality. In contrast, the rough cutting zone, located near the bottom, forms as jet energy dissipates and abrasive particles scatter, producing streaks and higher roughness (Fig. 2.6). Minimizing these streaks or striations is essential for improving overall surface quality (Hloch and Valícek, 2012; Miao et al., 2018).

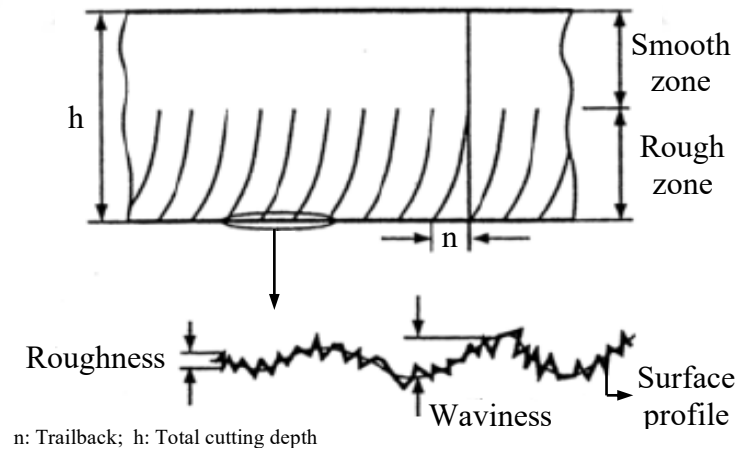


Figure 2.6 Zones and surface profile of the AWJ kerf for roughness (Pulikottil, 2016)

2.4.4. Declination Angle

As the cutting wear zone transitions into the deformation wear zone, the waviness or striation structures that are created on the cut surface, curve in the opposite direction to the direction of cutting. There are several parameters that define this curvature, one of which is the declination angle whose mathematical form is presented in Eq.2.2. It plays a significant

role in determining the quality, geometry, and accuracy of the cut. Adjusting this angle is essential for reducing kerf taper, improving surface finish, and addressing challenges such as jet lag or trailback (Fig. 2.7). That means, a better cutting capability is indicated by a smaller declination angle (Wang et al., 2021). This inference stems from the understanding that deviations occurring at elevated angles tend to exacerbate surface waviness and roughness. Consequently, the mitigation of such deviations becomes crucial, as it not only enhances the overall surface quality but also reduces the necessity for subsequent secondary operations.

$$\beta = \tan^{-1} \left[\frac{H_D}{(H_{CD} - H_{CWZ})} \right] \quad (2.2)$$

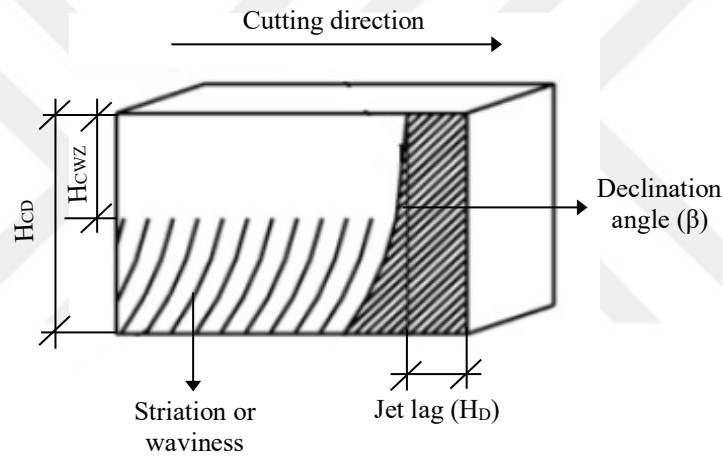


Figure 2.7. A schematic illustration for the cut surface and measurement of declination angle (Orbanic and Junkar, 2008)

2.5. Basic Application Fields of the AWJ Technology

A variety of industries use the technology, increasing production in terms of quality and speed, and thus reducing costs. Followings are summarized these fields.

- Food industry: The clean cutting method eliminates the possibility of food and food particles sticking to metal blades. Cutting all kinds of food items from chocolate to fish and frozen foods, has become possible with water jet cutting systems.

- Textile Industry: Textile products have a flexible and soft structure, which makes it difficult to move and cut materials. Thus, using the technology instead of a traditional knife makes cutting textiles easier.
- Electronic Industry: PSB is manufactured from any of the following materials: epoxy-glass, paper-based, polyamide, teflon and sheet, and these printed circuits, which are generally manufactured as a composite, are then cut using AWJ.
- Packaging Industry: Soft materials such as cardboard, paperboard, honeycomb materials, foam, rubber and polyurethane foams can be processed with water jet without using abrasive materials. The main application areas are tool cases, packaging of delicate and sensitive parts.
- Plastic Industry: Hard, dense and glass-like plastic materials cannot be cut efficiently along their sections, but other types of plastic materials can be cut very well. Polyurethane, ceramic, fiberglass, laminates, graphite, rubber, etc. are cut efficiently. Although some of these materials are cut with AWJ, most are cut with pure waterjets.
- Metal Industry: Waterjet cutting has found its most widespread use in cutting various metal materials since high heat is not generated during cutting and the crystal structure of the materials is not damaged. The application area covers a wide range from tin to tungsten carbide. All types of metals can be processed using water jet technology. Aluminum, mild steels, stainless steels, titanium and brass are the metals that can be commonly machined in this area. Large parts can be machined without warping or distortion. Materials working under pressure, alloys used in the space industry and medical parts can be processed in this way without weakening or contaminating them.
- Glass Industry: Glass pieces that need to be processed in a complex and smooth manner can be processed with waterjet technology in thicknesses between 0.8 mm and 100 mm. It is widely used in bulletproof glass and decorative pieces.
- Mining Industry: AWJ technology has the potential to be used in hole drilling, rock or coal excavation-cutting, hydraulic or hydromechanical excavation, tunneling, block extraction in natural stone quarrying and precision cutting in especially stone processing plants. In recent years, research has been also initiated to enable its use in comminution processes in the field of mineral processing.

2.6. Technological Developments for Improvement the Cutting Performance in AWJ Technology

Being a preferable technology in many sectors has led to numerous research, development and/or improvement studies on AWJ technology both in literature and in practice. Despite these efforts, the cutting/machining efficiency of the technology is still not at the desired level, especially on the basis of cut surface quality and total cutting depth. In addition, industrial demands for the production of parts with different geometric shapes have necessitated new technological searches for the diversification of AWJ technology. For this purpose, in recent years, new techniques developed to increase or improve the AWJ cutting performance such as forward angling the jet to the cutting plane, multi-pass cutting, controlled nozzle oscillation/vibration, abrasive air jet, magnetorheological abrasive waterjet, cryogenic abrasive waterjet, thermally assisted abrasive waterjet and ice assisted abrasive waterjet, have enabled AWJ technology to deliver cutting/machining processes to a further level. With some of these techniques, it is possible to achieve successful results without additional cost of cutting (Siores et al., 1996; Lemma et al., 2002; Wang, 2003; Patel, 2004; Wang, 2007; Shanmugam et al., 2008; Wang, 2010).

2.6.1. Abrasive Airjet

It is a type of AWJ where the cutting process is carried out with the help of compressed air. The technology is actually based on the principle of cutting/processing with an abrasive-compressed air mixture instead of the classical abrasive-water mixture. This method, which is especially effective in micron-sized processing applications, is preferred in surface processing and drilling operations of fragile materials such as ceramics, silicon and glass. This technology, which is high efficiency and low cost, is considered one of the best methods in the production of plasma screens (Fan et al., 2009). A schematic view of the AAJ is given in Fig. 2.8. Compressed air is cleaned with the help of a desiccator and filter in the system and transmitted to the cutting head. After being mixed with abrasive particles, it is focused on the material to be processed with the nozzle at the end of the cutting head. Small cracks and wears occur on the surface depending on the process parameters and material properties. While processing is taking place, the pieces broken from the material and the abrasive particles are held by a dust collector in the system.

2.6.2. Magnetorheological Abrasive Waterjet

Increase in diameter of the jet in the classical AWJ technology after exiting the nozzle prevents efficient cutting. This is undesirable, especially where precise surface cuts and/or

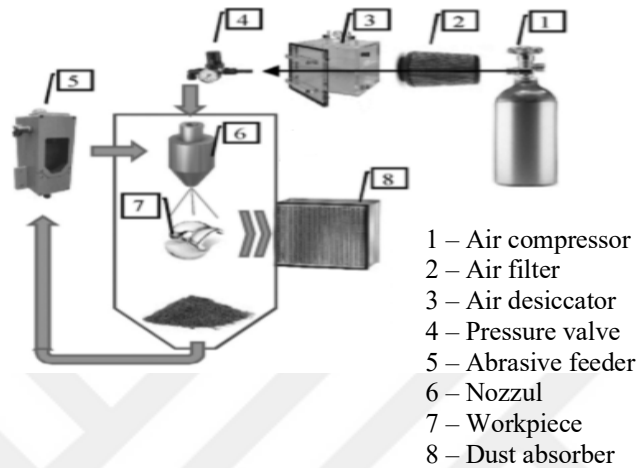


Figure 2.8. Schematic representation of abrasive air jet technology (Melentiev and Fang, 2018)

machining are required, as it requires a secondary operation. To improve this undesirable situation, which also limits the application of AWJ technology, some researchers have suggested that magnetorheological fluids can be used in AWJ technology. In fact, in their studies on this subject, they have also found significant improvements in AWJ cutting performance (Jha and Jain, 2004; Tricard et al., 2006; Kordonski and Sharey, 2007). The technology is described as a method obtained by adding some chemical additives and dispersed ferromagnetic particles to the classical abrasive-water mixture. The ferromagnetic particles in the mixture cause the abrasive particles to align in a structure with a high compressive force in the presence of a magnetic field. This means that a void-free and concentrated mixture/subject jet is obtained within the nozzle as it is seen in Fig. 2.9. Thus, the stability of the jet with increasing viscosity at the nozzle exit speed is maintained and the increase in the exit diameter depending on the material cutting depth is significantly prevented. Maintaining the jet exit diameter for a long time causes the abrasive grains in the jet to maintain their existing energy for a longer time, resulting in a more effective or efficient cut (Melentiev and Fang, 2018). Researches into the method have shown that while the jet exit diameter in the classical AWJ technology can only remain effective up to a few

nozzle diameters, in this method the jet exit diameter is effective up to 10 nozzle diameters (Kordonski ve Gorodkin, 2011). Despite its significant superiority, its high cost and complex technical structure limit the use of the technique.

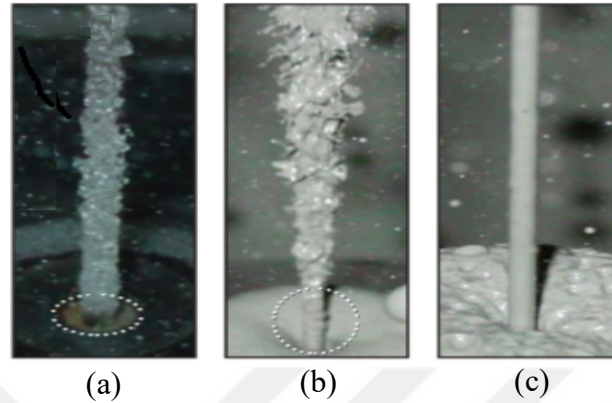


Figure 2.9. An illustration for the AWJ and MAWJ. a) classic AWJ, b) MAWJ without magnetic field c) MAWJ with magnetic field (Tricard et al., 2006)

2.6.3. Cryogenic Abrasive Waterjet

Some soft materials cannot be precisely cut/machined with classical AWJ technology due to loss of surface integrity. Cutting/machining such materials with AWJ technology using a coolant mixture can significantly change the material breakout mechanism. Cooling process causes some changes in the structure of the material being cut/machined in cutting/machined applications. This reduces the resistance of the material to an external mechanical effect. Therefore, the use of cooling in cutting/machining technologies can be considered as an alternative method for both performance enhancement and environmental protection (Yuvaraj and Kumar, 2016a; Melentiev and Fang, 2018). In this way, precise cutting/processing can be done while preserving the surface integrity of such materials. There are different coolant alternatives such as oxygen, hydrogen, nitrogen, helium, carbon dioxide that can be used as coolants in cutting/machining technologies. However, the LN_2 is the most preferred type due to its significant advantages such as not having any harmful effects, easy disposal after cutting/processing, and not being corrosive or flammable. On the other hand, in a study conducted with conventional AWJ and CAWJ, a smoother cutting surface was obtained with cryogenic AWJ (Yuvaraj and Kumar, 2016b). In the relevant research; it was determined that the number of abrasive particles embedded in the surface

during cutting/machining decreased significantly as a result of the coolant transmitted to the cut material under pressure hardening the material surface. Researchers have stated that this results in a higher quality surface after cutting. Despite the increase in cutting/machining performance provided by the method, the multiple increase in total energy consumption and the excessive microcracks that may occur due to high cooling temperatures are the factors that limit its use (Melentiev and Fang, 2018).

2.6.4. Thermally – Assisted Abrasive Waterjet

Main aim of the TAAWJ cutting/processing method is to heat the surface of materials that are difficult to cut/process, causing them to lose their hardness. In this way, hard surfaces are deformed and turned into materials that can be cut more easily. The heat required during cutting/machining is provided by oxy-acetylene welding equipment connected to an abrasive waterjet and acetylene is used as the primary fuel. A simple schematic representation of the method is given in Fig. 2.10. Acetylene is a hydrocarbon gas used as a fuel for welding applications in many industrial fields. It is used in welding and cutting of metals together with oxygen.

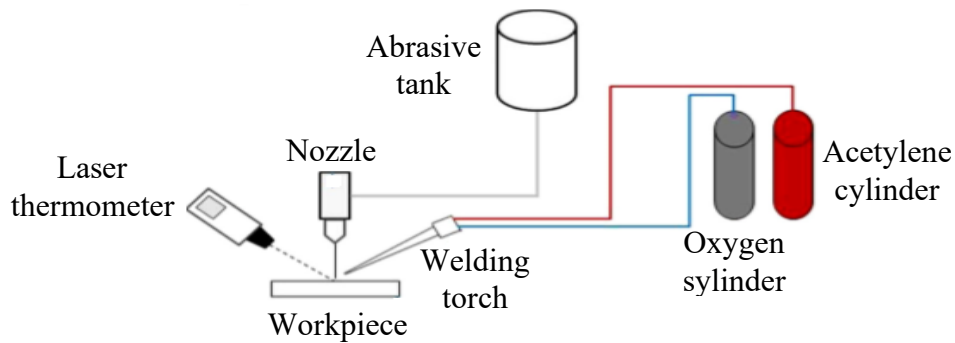


Figure 2.10. Schematic view of the TAAWJ (Patel and Tandon, 2015)

2.6.5. Ice – Assisted Abrasive Waterjet

As well-known, in classical AWJ technology, abrasive material is added to the system to increase the cutting power of the waterjet and to cut hard and durable materials such as rocks. Although there are various alternatives for this abrasive material, garnet is commonly used (Saraçyakupoğlu, 2012; Aydın et al., 2017). Adding these abrasive materials, including

garnet, to the system brings about some undesirable situations such as increased production and operating costs, environmental pollution and nozzle wear (Geren and Tatal, 2002). One of the R&D studies in recent years regarding AWJ technology is the use of abrasive materials in the relevant technology and the elimination of the disadvantages of using abrasive materials (Jerman et al., 2016). One of the materials that can be used as abrasive in AWJ technology is ice particles. These particles can be used as abrasives by integrating them into the waterjet through a standard method using a mixing tube. The hardness of ice particles is less than other materials used as abrasives in AWJ technology. Therefore, cutting/processing efficiency is low. However, it can be said that its low cost and environmental friendliness provide advantages in terms of total cutting/processing efficiency. When the method is compared with WJ and AWJ technology, it can be said that it is more environmentally friendly than AWJ technology and has higher cutting/processing efficiency than WJ technology. In other words; IAAWJ method is a method developed to fill the gap between WJ and AWJ technologies (Melentiev and Fang, 2018). AWJ technology, where ice particles are used as abrasives, can offer significant advantages in sectors where dirty surfaces are cleaned, sectors where pollution is not desired, such as the pharmaceutical or space industry, and in the food sector, as it offers significant advantages in terms of environmental aspects (Geren and Tatal, 2002; McGeough, 2016).

2.6.6. Controlled – Nozzle Oscillation/Vibration

Controlled – nozzle oscillation/vibration is one of the most effective technique among the developed techniques to improve AWJ cutting performance based on performance indicators such as total cutting depth and cutting wear zone depth (Wang, 2007; Wang and Zhong, 2009). The technique works on the principle of oscillating the nozzle in a pendulum-like motion in the angular direction parallel to the cutting direction at a certain angle and frequency (Fig. 2.11).

Oscillation angle and frequency are considered as two main factors affecting the cutting performance in the technique. In other words, in the normal cutting method with AWJ, the angle of impact of the jet coming out of the nozzle with the material is 90° and does not undergo any change during cutting. In the oscillation technique, the impact angle of the jet coming out of the nozzle can be changed in a controlled manner depending on the characteristics of the cut material.

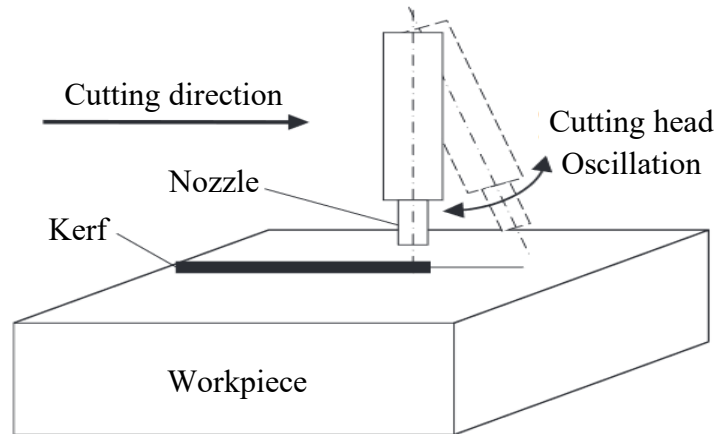


Figure 2.11. Controlled – nozzle oscillation in AWJ technology (Karakurt et al., 2019)

2.6.7. Multi – Pass Cutting

In cases, where the material thickness is beyond the jet cutting capacity, the desired performance cannot be achieved in AWJ technology. For this reason, some researchers have shown that multi – pass cutting along the same cutting line (kerf) with an appropriate combination of cutting parameters (Fig. 2.12) provides significant advantages over single – pass cutting (Momber and Kovacevic, 1998; Wang and Guo, 2003; Wang and Zhong, 2009; Wang, 2010; Azhari et al., 2016). Researchers have stated that multi – pass cutting has a very positive effects on the cutting and cutting wear depths. The same researchers emphasized that multi – pass cutting, both the cutting and cutting wear depths initially increase linearly, and when a critical level is reached, the decreases begin.

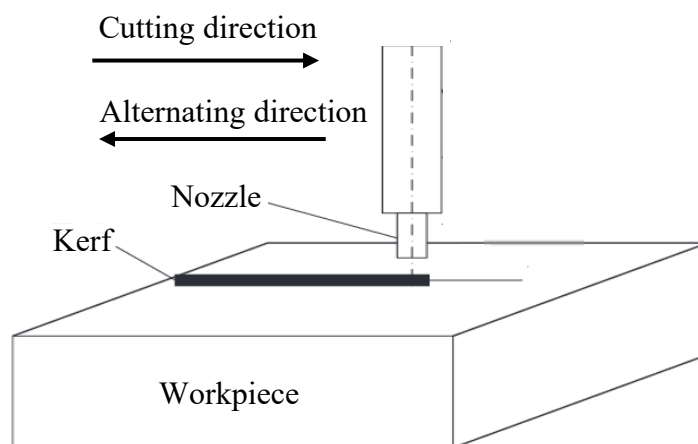


Figure 2.12. An illustration of the multi – pass cutting in AWJ technology

Most studies on the technique recommend that high traverse speeds to be preferred in multi – pass cutting and a good combination of other cutting parameters to be adjusted. Thus, it has been stated that quite good results can be obtained for AWJ cutting performance with multi – pass cutting compared to single pass and low traverse speeds in the same time interval.

2.6.8. Forward Angling the Jet

In cutting/machining applications with AWJ, two main zones are formed on the cut material surface: cutting wear zone and deformation wear zone (see Fig. 2.3). These zones are indicators of the material cutting quality, and these qualities are evaluated on the basis of parameters such as surface roughness and/or waviness/striations respectively. The formation of these regions is directly related to the angle at which the jet from the nozzle impacts the material surface. While there is no significant change in the exit angle when the jet from the nozzle first contacts the material, this angle increases as the cutting depth increases (along the material thickness). The jet that contacts the material at exit angles or close to this angle makes an effective cut, resulting in higher material cutting quality. As the contact angle widens, the cutting energy of the abrasive grains in the jet decreases and as a result of ineffective cutting, a more wavy/striated structure appears on the cut surface. Therefore, the material cutting surface quality can be increased and/or improved by a technique such as forward angling the jet impacting the material from different angles as shown in Fig. 2.13.

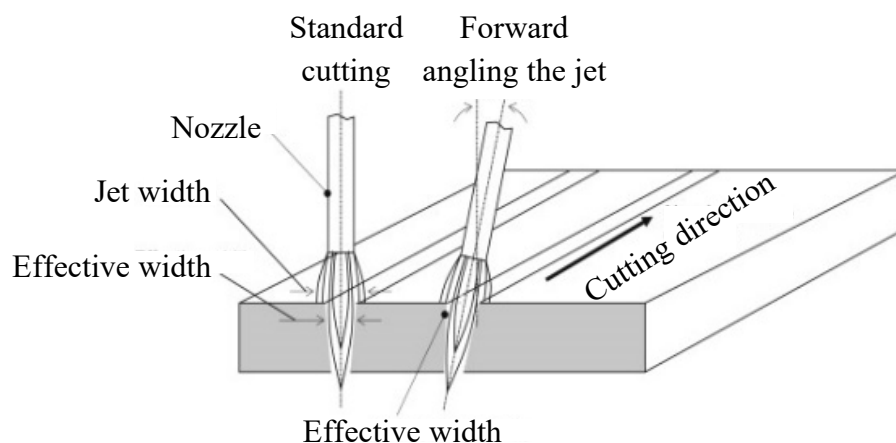


Figure 2.13. Forward angling the jet cutting in AWJ technology

Changes in the jet impact angle can cause a change in the erosion mode that is effective in material removal, thus reducing the wavy/striated structure formed on the cutting surface (Wang, 2003). In a study conducted by Chen and Siores (2001), it was determined that this technique had a positive effect on AWJ cutting performance. A similar finding was made by Wang (2003) and Shanmugam et al. (2008). It is also stated that the optimum impact angle to be selected in the technique is related to the properties of the material to be cut/processed (Wang, 2003).



3. LITERATURE REVIEW

Owing to its exceptional benefits, which include low material loss, dust-and-heat free operations, high efficiency, and the ability of cutting almost all geometric shapes, the AWJ technology has drawn the attractions of numerous researchers from various scientific and industries worldwide, and has been rapidly developing over the past decades. Some examples of recent work are as follows. Khanna et al. (2011) and Shah and Patel (2012) measured the material removal rate in their studies, where marble and granite samples were subjected to the AWJ cutting respectively. Utilizing the granitic rocks, the cutting performance of the AWJ were experimentally and statistically investigated on the basis of kerf width and cutting depth (Karakurt et al., 2012 and 2014). Mlynarczuk et al. (2014) worked with granites for describing the changes in surface quality in the AWJ technology, considering factors such as traverse speed and standoff distance. Abdullah et al. (2016) conducted a statistical analysis to explore the impact of cutting parameters and material type on cutting performance, specifically focusing on marble workpieces. Oh et al. (2016) developed a waterjet cutting depth model based on the effects of the maximum kinetic energy on the jet energy distribution in their study, using the granite and shale rocks. Oh and Cho (2016) derived a cutting depth prediction model that could be employed to the AWJ cutting process time estimation for granites. High traverse speed and low abrasive flow rate were found to be economically advantageous for cutting gemstones by AWJ (De Abreu et al., 2016). Alsoufi et al. (2017) found that the standoff distance and traverse rate are the most significant factors for the machined surface quality in their experimental trials concerning the Carrara marble. A practical approach for optimizing the particle waterjet variables was presented in rock breaking by Zhao et al. (2017). Aydin et al. (2017) demonstrated that the granite particles satisfy the specifications for use as an abrasive in the AWJ cutting of marble. Jiang et al. (2017) showed the superiorities of discontinuous waterjet over the continuous waterjet at fragmenting rock (granite). Oh et al. (2019) discovered that the abrasive (garnet) purity particle size distribution, specific gravity, and hardness are the most crucial factors influencing rock cutting performance. Arab and Celestino (2020) conducted experimental studies on AWJ cutting of four rock types, revealing that the efficiency of cutting and the mechanisms of rock disaggregation are significantly influenced by the specific properties and microstructures of each rock. In an another study, Tripathi et al. (2020) and Li et al.

(2022) tested the pulsating and non-pulsating waterjet performance for granites and marble respectively and revealed the superiorities of pulsating waterjet. Aydin et al. (2019) and Kaya et al. (2023) announced that the silicon carbide, steel shot and brown and white fused alumina produced higher cutting performances when compared to garnet as abrasive. Using the granite and marble as the target rocks, the AWJ multi-pass cutting is shown to be more efficient than single-pass cutting (Xiao et al., 2019; Cha et al., 2021a; Aydin et al., 2022; Ge et al., 2023; Cha et al., 2024). Cha et al. (2021b) determined that the close-sized particles are to be more likely to collide, which decrease cutting capability, depending on the abrasive particles' density and velocity in their granite cutting by the AWJ. Li et al. (2020), Liu et al (2021), Li et al. (2021) and Barabas and Florescu (2022) emphasized that an optimal perforation may be achieved by clarifying the effects of pressure, jet angle, target distance, and abrasive concentration. Perec et al. (2022) conducted experimental research specifically on the erosion of metamorphic rock (marble) by the AWJ. Chomka et al. (2023) achieved substantial results on the energy and time needed for effective natural stone (e.g. granite, limestone, basalt, marble) cutting with the AWJ. Using sandstone samples, Fan et al. (2023) conducted trials with the UCAWJ, an artificially created submerged environment and found that the UCAWJ performs higher rock-breaking performance based on the same operating conditions. Liu et al. (2024) determined that the grain size and mineral type of the rock have the most significant effects on the perforation depth and surface roughness respectively in AWJ granite cutting. In an investigation led by Wang et al. (2024), experiments were systematically carried out to examine the abrasive water jet cutting of hard rock across diverse cutting parameters. The study meticulously analyzed the influence of these cutting parameters on rock-breaking performance and delved into the underlying mechanisms governing the rock-breaking process.

3.1.1. Objective of the Current Thesis

As is evident from the literature review above, there are no relevant studies that have investigated AWJ forward angling the jet in rock cutting applications. Additionally, few scholars have looked at the AWJ multi-pass in rock cutting with the limited number of rock samples from different origin. Moreover, to the best of our knowledge, previous studies have not employed the MLAs for modelling and optimizing the cutting performance of the AWJ multi-pass and forward angling the jet in rock cutting applications. Thus, the current thesis's

aim is based on two folds. One is experimentally to investigate the cutting performance of the AWJ multi-pass and forward angling the jet techniques in rock cutting. The other is to leverage the MLAs for the modelling and optimizing the cutting performance of AWJ multi-pass and forward angling the jet techniques respectively. In this regards, rock workpieces were pre-dimensioned from various origins such as sedimentary and magmatic for the experimental study. By systematically analyzing and validating the AWJ multi-pass and forward angling the jet techniques, the current thesis provides data that could be used for scalable and useful improvements in the existing AWJ technology in rock cutting/machining. Additionally, this thesis not only attempts to test the newly developed techniques for improving the cutting qualities but also enables to predict the cutting performance and optimal process variables, offering a robust decision-making framework for the manufacturers. Moreover, this thesis presents a guide for the proper AWJ technological selection to achieve the best performance on the basis of rock types. Consequently, it can be stated that this thesis is unique in that it tests the AWJ forward angling the jet and multi-pass cutting techniques and models and optimizes the operating variables leveraging the MLAs in rock cutting applications.

4. EXPERIMENTAL STUDY

4.1. Target Material and Characterization

Operated in Türkiye, a commercial firm provided the workpieces from different samples of natural stone, known as white marble (R1), beige marble (R2), travertine (R3), onyx (R4), basalt (R5), Kayseri tuff (R6) and Bayburt tuff (R7) for the study. The workpieces have the dimensions of 100 mm*200 mm*400 mm and 5 mm*10 mm*20 mm for determining the rock properties (e.g. physico-mechanical) and the experimentation respectively. Figure 4.1 presents an illustration for the workpieces, including the processes for determination of rock properties. The relevant standards were followed for determining the rock samples' physico-mechanical properties (ISRM, 2007; EN 14157, 2017). In this regards, apart from the Schmidt Hammer hardness test, a core drilling equipment was used to extract core samples from the block samples to be utilized in the tests (Fig. 4.1: A-1). A barrel with a cold-drawn steel core (50 cm length, 54.7 mm (NX) diameter) was used to remove the samples from the blocks (Fig. 4.1: A-2). A core cutting saw was then used for the production of core and disc samples. Following that, the samples' surfaces were sanded and kept for two weeks at room temperature. Using caliper techniques, three disc samples of each type of rock were used to ascertain the physical properties (e.g. water content, porosity, density, absorption) of the rocks. The first step was to determine the dimensions of the samples using a digital caliper with an accuracy of 0.01 mm, and all samples were thereafter precisely weighed with 0.01 g precision using a digital scale. Eventually, the natural densities of each were established. The samples were subsequently dried in a 105°C oven for 24 hours, cooled in a desiccator and weighed. Following a 24-hour incubation period in water at 20 °C, the samples were weighed once again. Consequently, additional physical characteristics were determined by the computations outlined in the relevant standards (Fig. 4.1: A-8 and A-9). For the UCS test, five core samples of each rock type were prepared with a length to diameter ratio of between 2.5 and 3.0. A hydraulic press was used to shatter the samples at a steady stress rate of 0.5 MPa/s, and the breaking loads were noted. Values of the UCS were determined by applying the formulas outlined in the relevant standard (Fig. 4.1: A-6).

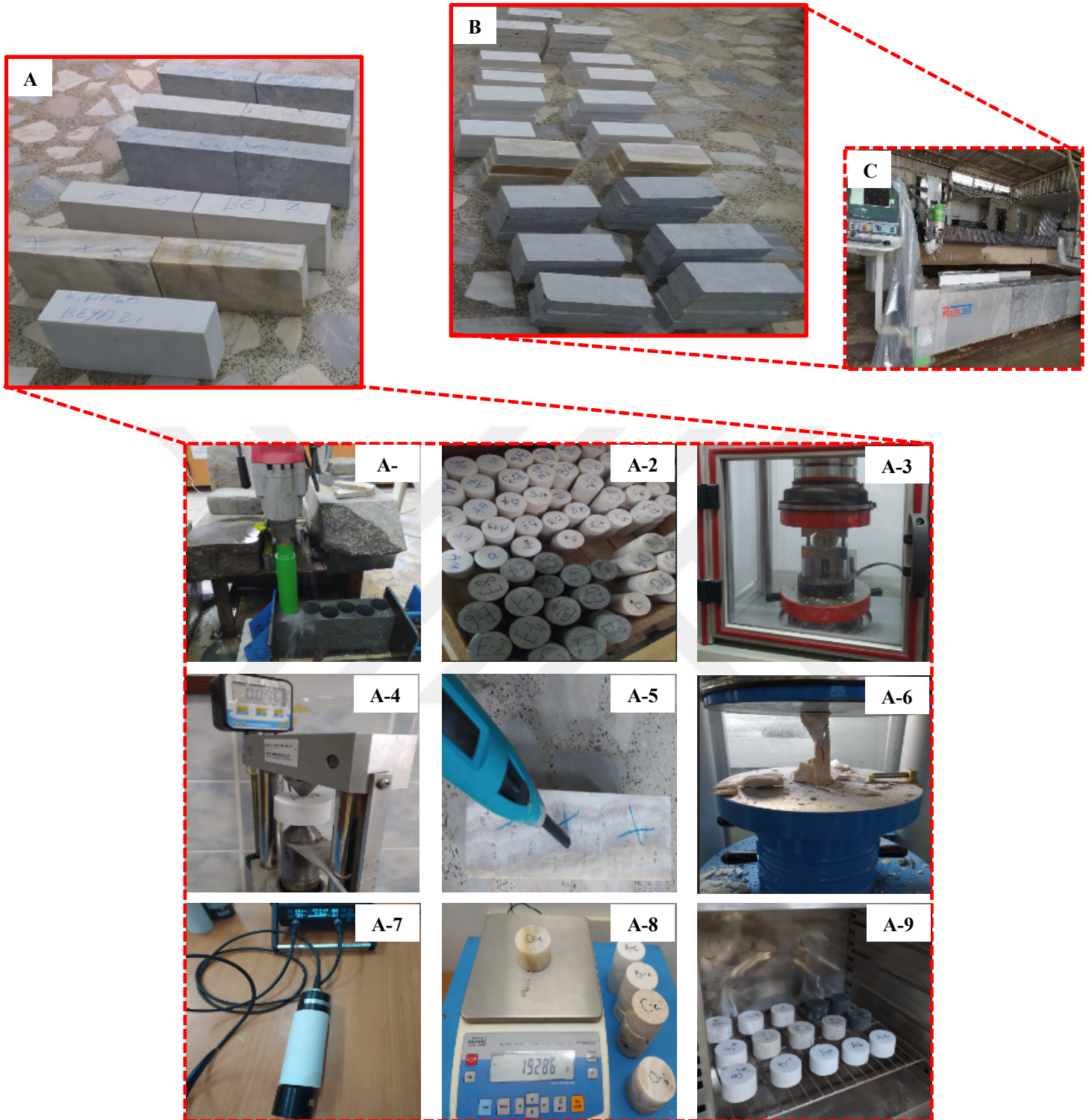


Figure 4.1. An illustration of the workpieces for the study. A: Block samples for determining the physico-mechanical properties, B: Plate samples for the experimentation, C: AWJ machine used for the experimentation, A-1: Coring process, A-2: Core samples, A-3: Brazilian tensile strength test, A-4: Point load strength test, A-5: Schmidt Hammer hardness test, A-6: Uniaxial compressive strength test, A-7: Ultrasonic velocity test, A-8 and A-9: Water content test

For determination of tensile strength and point load strength, ten disc samples with length to diameter ratios of 0.5 were prepared. NX (54.7 mm) was the diameter of the samples. Prior to being broken under the hydraulic press, the samples were put in the steel loading jaw for the tensile strength test. Following the guidelines outlined in the relevant standards, the samples were broken in the point load strength device for the test. Strength values were subsequently determined by applying the computations outlined in those guidelines (Fig. 4.1: A-3 and A-4). Additionally, three core samples from each type of rock was subjected to the ultrasonic velocity test in order to ascertain the p-wave transmission velocity. The test was carried out using an ultrasonic velocity tester and signal-receiving geophones (Fig. 4.1: A-7). Moreover, since Schmidt hardness ratings offer a scale of data for comparing the hardness of different materials, a digital L-type Schmidt hammer device was used for the rebound hardness test on the block samples with a 200 mm thickness, 400 mm length, and 100 mm width. Prior to the test, the upper surfaces of the blocks of natural stone were cleaned and smoothed with hand sandpaper. Blocks of natural stone were laid out on smooth, hard ground, and any necessary adjustments were made using a spirit level. A hardness value is yielded by the rebound of the device's steel tip, which weighs about 1 kg and is pressed on the surface. This value appears on the device's electronic panel. The 100*200 mm surfaces of the blocks were used for the test. After using the Schmidt hammer on 20 distinct surface spots, the rebound values were read to get the Schmidt hardness values (Fig. 4.1: A-5). Table 4.1 lists the physico-mechanical properties of the rocks in detail. Furthermore, almandine garnet, which comes from India and has a specific density of 3.8 and a mineralogical composition of $\text{Mg}_3\text{Al}_2(\text{SiO}_4)_3$, was utilized as an abrasive material in the study. A mesh size of 80, or a nominal particle size of 0.18 mm, is present over 90% of the abrasive particles.

The physico-mechanical properties of the studied rocks (R1–R7) reveal significant heterogeneity, reflecting their distinct lithological and textural properties. The carbonate rocks (R1–R4) exhibit relatively low water absorption capacities (0.059–0.120%) and high natural densities (2.645–2.689 g/cm³), indicating a compact and low-porosity structure. Their uniaxial compressive strengths (92.10–125.13 MPa) and ultrasonic velocities (5793–7001 m/s) further support their classification as dense and mechanically strength rocks. Notably, the Schmidt Hammer hardness (Q-values between 66.85 and 76.55) aligns with their observed strength properties. In contrast, the volcanic rocks (R5–R7) display markedly higher porosity and water absorption, particularly samples R6 and R7, which exhibit

effective porosities of 15.05% and 20.97%, respectively. These samples correspondingly have lower natural densities (1.73–1.99 g/cm³) and reduced ultrasonic velocities (2360–2677 m/s), indicating a more porous and less coherent matrix. Their uniaxial compressive strengths (41.85–56.24 MPa) and Schmidt rebound values (59.65–70.60) confirm their relatively weaker mechanical performance compared to the carbonate samples. R5 presents an intermediate behaviour: despite a higher porosity (4.64%) compared to the carbonates, it maintains a high uniaxial compressive strength (155.14 MPa) and the highest point load strength (12.274 MPa), suggesting a mechanically resistant structure likely due to its mineralogical composition and holocrystalline texture.

Tablo 4.1. Physico-mechanical properties of the rocks used in the study

Features	Rock type						
	R1	R2	R3	R4	R5	R6	R7
X1 (%)	0.102	0.120	1.339	0.059	1.766	7.61	12.71
X2 (%)	0.026	0.083	1.165	0.033	0.650	6.61	7.14
X3 (%)	0.076	0.036	0.155	0.025	1.102	0.50	4.67
X4 (%)	74.907	30.634	13.050	49.259	64.279	6.55	36.74
X5 (gr/cm ³)	2.675	2.645	2.419	2.689	2.661	1.99	1.73
X6 (gr/cm ³)	2.680	2.652	2.498	2.693	2.761	2.33	2.09
X7 (%)	0.274	0.319	3.201	0.158	4.644	15.05	20.97
X8 (%)	0.274	0.320	3.322	0.159	4.887	17.73	26.53
X9 (MPa)	6.533	8.686	6.055	6.617	10.429	3.85	4.58
X10 (MPa)	5.955	5.886	4.643	3.569	12.274	3.71	2.54
X11 (MPa)	92.098	125.125	54.247	95.602	155.140	56.24	41.85
X12 (m/s)	6621	6477	5793	7001	5885	2360	2677
X13, Q	73	76.55	66.85	69.8	77.8	70.60	59.65

X1: Water absorption capacity, **X2:** Effective water absorption, **X3:** Natural water content, **X4:** Saturation degree, **X5:** Natural density, **X6:** Mineral grain density, **X7:** Effective porosity, **X8:** Void ratio, **X9:** Brazilian tensile strength, **X10:** Point load strength, **X11:** Uniaxial compressive strength, **X12:** Ultrasonic velocity, **X13:** Schmidt Hammer hardness

In addition to the physico-mechanical properties, in order to determine the mineralogical composition of the rocks tested in this study, samples were also prepared and analysed in accordance with the relevant standards. The obtained results are summarized in Table 4.2.

Tablo 4.2. Mineralogical composition of the studied rocks in the study

	R1	R2	R3	R4	R5	R6	R7
Color	White	White	Yellowish Gray	Yellowish Gray	Dark Yellowish Green	Brownish Red	Yellowish Gray
Grain Size	Fine – grained	Fine – grained	Fine – grained	Coarse – grained	Fine – grained	Fine – medium grained	Fine – medium grained
Texture (Macro)	Massive	Massive	Porous	Macrocrystalline	Massive	Granular	Granular
Texture (Micro)	Granoblastic, Mosaic	Crumbly	Crypto-microcrystalline	Macrocrystalline	Holocrystalline	Crumbly	Crumbly
Main Components	Carbonate group minerals: fine to medium grained size, subhedral to euhedral	Carbonate group minerals: fine to medium grained, subhedral to anhedral	Carbonate group minerals: cryptomicrocrystalline, anhedral	Carbonate group minerals: coarse – grained, anhedral	Pyroxene group minerals: fine – medium grained, hypidiomorphic, Feldspar group minerals: fine – grained, hypidiomorphic	Dense volcanic glass splinters/shards: fine to medium grained.	Dense volcanic glass splinters/shards: fine to medium grained
Secondary Components	Mica group minerals: fine – grained, subhedral muscovite. Opaque oxides: fine to medium grained, anhedral	Fossil grains and shells: fine to medium grained, rounded, Intraclastic grains; Opaque minerals; Matrix mainly micritic and sparary	Opaque minerals: submicroscopic, homogeneous distribution.	N/A	Traces of altered minerals (zeolitization, less argillization, carbonation); Apatite; Opaque minerals: fine, hypidiomorphic	Mineral fragments (plagioclase, sanidine, pyroxene, opaque), very small amounts of vein rock fragments	Small amounts of pumice fragments; mineral fragments (plagioclase, sanidine, biotite); glassy matrix.
Explanation	Made entirely of carbonate minerals; granuloblastic and mosaic texture; pressure twinning; low density of secondary mica; some iron coatings.	Sedimentary rock with clastic texture; variable carbonate grain sizes; many fossils and intraclasts; micritic binder; carbonate-filled veins	Consists of calcite; irregular melting gaps; local grain growth; traces of microfossils and quartz; clay formation; opaque staining	Composed of calcite; elongated crystals; wavy quenching and grinding due to dynamic effects	Some minerals unidentified due to alteration; zeolite (natrolite) and analcime minerals detected	Opacification of pyroxene edges; reddish-brown stains; vein rock fragments with gabbroic composition; crystalline-vitric tuff with clear orientation	Reddish-brown opaque stains in matrix; clear orientation; crystalline-vitric tuff

R1: White marble; **R2:** Beige marble; **R3:** Travertine; **R4:** Onyx; **R5:** Basalt; **R6:** Kayseri tuff; **R7:** Bayburt tuff

It is evidently followed from the related Table that the petrographic characteristics of the studied rock samples (R1–R7) exhibit considerable diversity in terms of texture, grain size, and mineralogical composition, reflecting variations in their depositional and post-depositional histories. The carbonate-rich samples (R1–R4) predominantly display textures ranging from granoblastic to crypto-microcrystalline, with grain sizes varying from fine to coarse. These features suggest a spectrum of recrystallization intensities and diagenetic alterations, often accompanied by the presence of secondary components such as fossil fragments, intraclasts, and micritic matrices. The occurrence of pressure twinning and mosaic textures in carbonate minerals further supports evidence of post-depositional stress and recrystallization processes. In contrast, the volcanic-related samples (R5–R7) are characterized by holocrystalline and crystalline-vitric textures, with a matrix largely composed of volcanic glass and mineral fragments. The widespread presence of opaque minerals, pumice fragments, and signs of zeolitization and argillization indicate significant alteration subsequent to emplacement. The observed preferred orientation of volcanic shards and mineral fragments suggests deposition influenced by dynamic volcanic processes, likely pyroclastic in nature.

4.2. Experimental Set-up and Procedure

Following the characterization of and pre-dimensioned procedure, the workpieces were transported to a factory operating in Istanbul, where the cutting experiments were performed. Figure 4.2 provides an overview of the AWJ machine, utilized for the cutting tests. The AWJ machine has an intensifier-type high-pressure pump with a maximum pressure of 3800 bars. Cha et al. (2020) mentioned that an injection-type waterjet system is appropriate for rock-cutting and civil engineering applications that may be used in confined locations due to their simple equipment and systems. Thus, an injection-type waterjet system was used, which injects the abrasives into the high-velocity water flow to accelerate them in the thesis. Additionally, mounted on a five-axis linear stage, the waterjet cutting head permits cutting at various angles ranging from 0 to 90 degrees. Moreover, the AWJ focusing tube has dimensions of 1.1 mm in diameter and 75 mm in length, while the orifice has a diameter of 0.33 mm. Furthermore, the orifice and focusing tube are composed sapphire and tungsten carbide respectively. Preliminary trials for each rock, previous studies, and the AWJ machine's technical specifications were used to establish the levels for the operating

variables (Table 4.3). The rock samples were positioned vertically beneath the AWJ cutting head, with their 5 mm and 200 mm-sided surfaces facing upwards. In other words, the rock samples were allowed to be cut along their length (200 mm). The traverse speed, abrasive flow rate, water pressure, number of passes, and cutting direction during multi-pass cutting were among the variables that were investigated, while the forward angling the jet was the only operating variable for investigation. Firstly, every cutting parameter including water

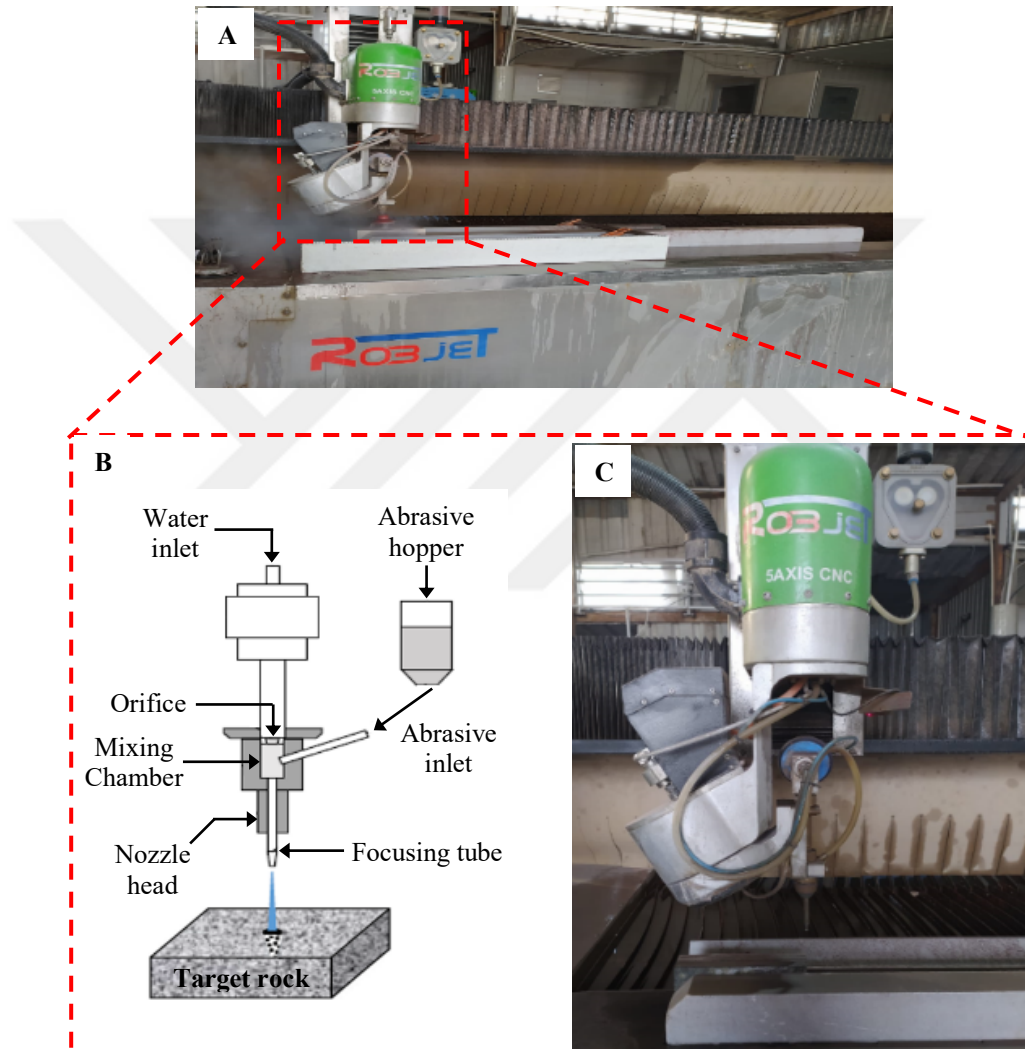


Figure 4.2. Experimental set-up. A: the AWJ machine, B: Schematic illustration of the cutting head, C: Cutting head

pressure, abrasive mass flow rate, and standoff distance was maintained constant with the exception of traverse speed. As part of this approach, cutting tests of single, double, triple, and quadruple passes were implemented for the multi-pass cutting, including 28 cutting tests. Secondly, to find out how these factors affected the cutting performance in multi-pass

cutting, the abrasive mass flow rate and water pressure were increased by one level while maintaining other parameters constant. Cutting tests were conducted for this experimental design in 28 and 15 cases, respectively. This resulted in a total of 71 cutting tests in seven different rock types for multi-pass cutting. To evaluate the impact of traverse speed on cutting depth during multi-cutting, a consistent exposure time was maintained for this part of the experimental program. On the other hand, in the experimental design for the forward angling the jet, four additional levels such as 88°, 85°, 80° and 75° were tested. Thus, 27 further tests (since R7 was broken during the test, the test at 75° could not be performed) were added to the study using this design. Consequently, there were 98 cutting tests performed within the scope of the thesis.

Tablo 4.3. Experimental cases

Variable	Level 1	Level 2	Level 3	Level 4	Level 5
TS (mm/min)	300	600	900	1200	
NP	1	2	3	4	
WP (MPa)	180	220 ^a			
AFR (g/min)	300	450 ^b			
SD (mm)	4				
APS (mesh)	80				
JIA (degree)	90 ^c	88	85	80	75
Cutting direction	Alternating ^d				

a: the WP was increased by one level to find out how this variable affects the cutting performance in multi-pass cutting, with other variables remaining the same

b: the AFR was increased by one level to find out how this variable affects the cutting performance in multi-pass cutting, with other variables remaining the same

c: The focusing tube was aligned with the workpiece (rock) at all times during the multi-pass cutting operations

d: Only for the multi-pass cutting

4.3. Cutting Performance Measurements

Upon completion of the cutting tests, the workpieces were meticulously packed to prevent any damage and subsequently transported to the laboratory in Mining Engineering Department at Karadeniz Technical University in Trabzon. Then, the workpieces brought to Mining Engineering Department laboratory, were kept at room temperature for 2 weeks to

reach the natural water content prior to cutting. In order to remove any loose abrasive particle and/or dust or rock fragments, air was then forced into the kerfs using a compressor. Later on, various cutting performance indicators, which are related to the kerf geometrical characteristics including the kerf width, kerf taper angle, surface roughness, declination angle, cutting depth and cutting wear zone depth, were accordingly measured respectively.

In practice, kerf width is measured with the goal of reaching the minimum width in order to limit the material loss and control the kerf taper. Hence, initially, the kerf widths of the workpieces on the cut surfaces were precisely measured at 2 cm intervals along the cutting line using a caliper. Nine (9) measurements were then taken for each rock sample, and the kerf widths were determined by calculating the arithmetic mean of these values. Figure 4.3 displays the kerf width measurements for the studied rocks.

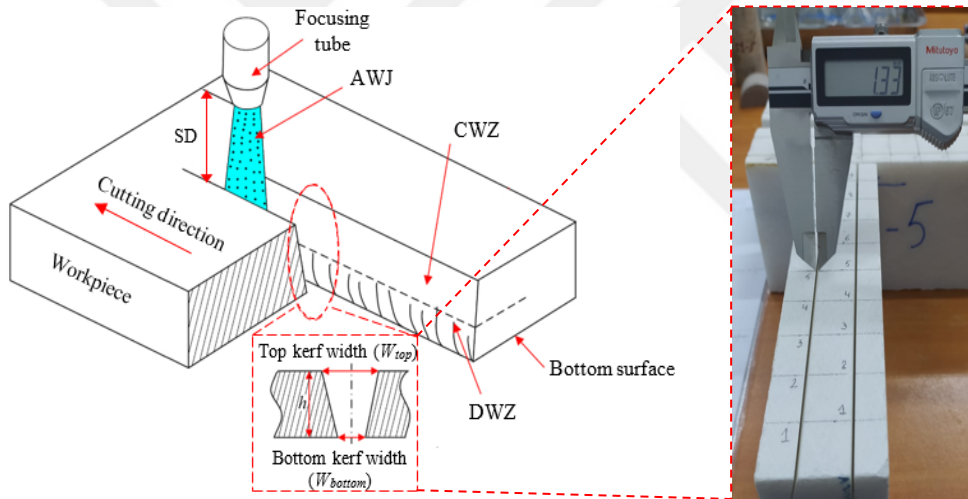


Figure 4.3. Kerf width measurements for the studied rock types

To calculate the kerf taper angles, the top width (W_t), which is the kerf width at the top of the kerf, the bottom width (W_b), which is the width where the deformation wear begins, and finally the vertical distance (h) from the top of the kerf to the end of the CWZ were measured with a caliper (see Fig. 2.5). Subsequently, the recorded data were put into the Eq. (2.1) and the kerf taper angles for all rock samples were calculated.

Following the measurements for the kerf widths and kerf taper angles, it was unable to determine other cutting performance indicators such as the surface roughness, declination angle, cutting depth and cutting wear zone depth within the kerfs due to the narrow kerfs. In order to measure these indicators on rock samples, the cutting line needs to be seen clearly.

The rock samples were, therefore, divided through the cutting kerf firstly. It is important to note here that soft cardboard pieces were inserted inside the kerfs prior to division in order to avoid friction between the kerf walls. Since many of the rock samples had already been cut, most of them were simple to divide. Those with shallower cuts were turned down and tried to cut with a laboratory scale circular saw in line with the AWJ cuts. Since the cutting lines do not overlap, special attention was paid to keeping a safe distance between the AWJ and circular saw cuts.

For surface roughness measurements on cut surfaces, a Mitutoyo Surftest SJ-301 roughness measuring device was used. This device scans a 1 cm long line on the surface at a speed of 1 mm/s with its a 2 μm radius needle tip probe of the apparatus connected to a body, and draws the micro roughness profile of the surface on the digital screen on the body, displaying the roughness values numerically. In addition, the surface profile graphic and other data can be physically printed from the device's roll paper tray (Fig. 4.4). Moreover, the device works with a sensitivity of 0.01 μm . It measures rough surfaces up to a maximum of 100 μm for Ra and Rq values, and 350 μm for Rz value. Surface roughness measurements were taken along a specific horizontal line at 2 cm intervals in the cutting-wear zone for all samples (each sample had nine roughness measurements). Then, the Ra and Rz values for each cutting surface were determined by calculating the arithmetic mean of the measured values.

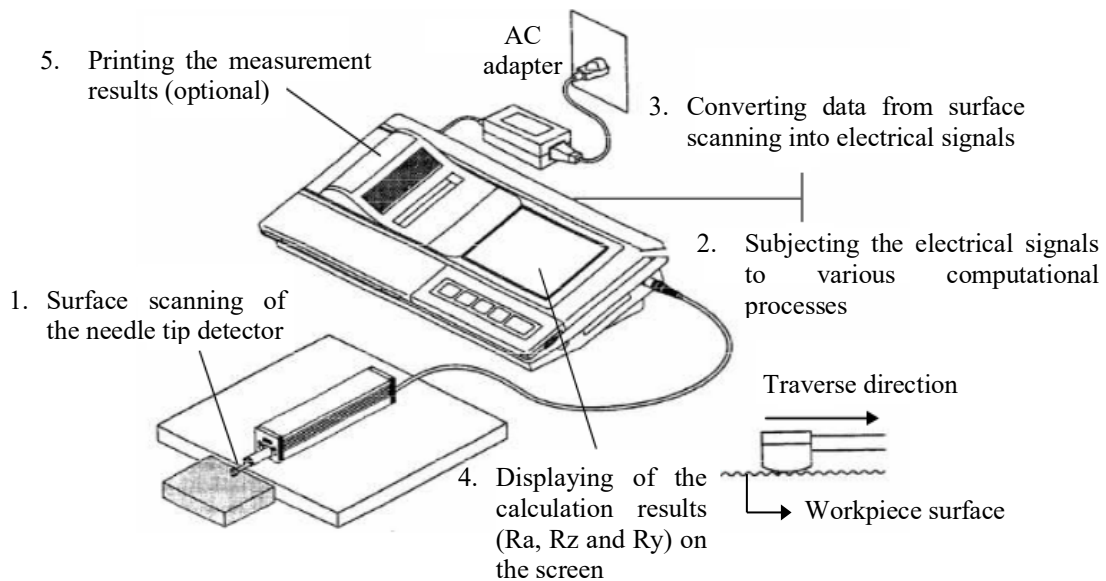


Figure 4.4. Schematic illustration of the Mitutoyo Surftest SJ-301 used for the surface roughness measurements in the study

As the CWZ transitions into the DWZ, the waviness or striation structures that are created on the cut surface curve in the opposite direction to the direction of cutting. There are several parameters, that define this curvature, one of which is the DA. A better cutting capability is indicated by a smaller DA (Wang et al., 2021). The DA for each rock was accurately calculated from the arithmetic mean of the data for 32 measurements (4 + 4 from two surfaces facing each other) using a digital caliper with the help of Eq. (2.2) as illustrated in Fig.4.5. That means, a total of almost 568 measurements were made for the multi-pass cutting, while those were 216 for the forward angling the jet cutting in the thesis.

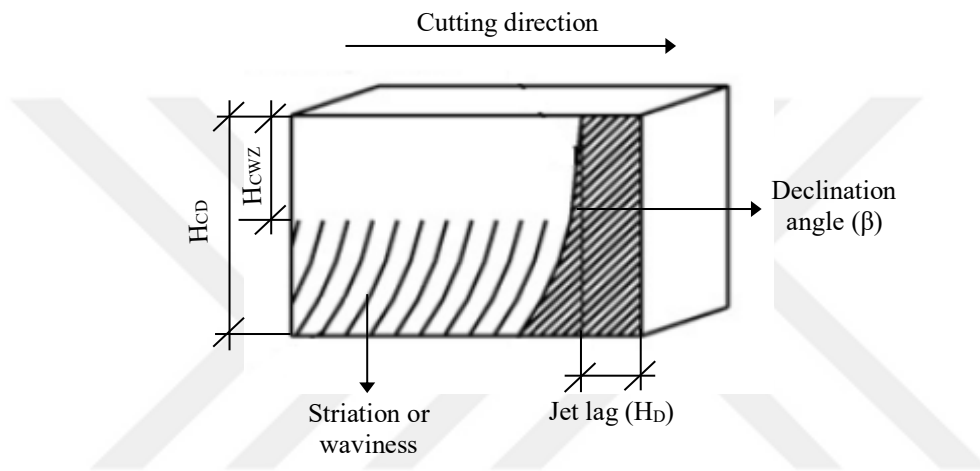


Figure 4.5. An illustration of the DA measured on the cut surfaces of the rocks (schematic illustration was adopted from Orbanic and Junkar, 2008)

Since the cutting depth is the major challenge limiting the widespread application of the AWJ technology, this thesis measured the cutting depth that indicates the distance measured vertically from the top surface to the cut's deepest point, as the performance output. The cutting depths were accurately measured using a digital caliper at intervals of 2 cm along the cutting line with an accuracy of 0.01 mm. For the cutting depths, nine measurements were made on each cut, meaning that a total of almost 900 measurements were made in the thesis. The cutting depths were calculated by taking the arithmetic mean of these values. On the same line as the cutting depth, the CWZ depth from the surface of the sample to the upper limit of the DWZ was also measured with a similar procedure (Fig. 4.6). Finally, the surface wear on the rock samples was examined using a SEM on a micro scale. Almost 1 cm³ sized specimens were cut from the cut surfaces using small circular saws in Mining Engineering Department. To ensure conductivity, non-conductive rock samples were coated with a thin layer of gold prior to SEM analysis. The coated specimens were then placed into the SEM

device for dehumidification under vacuum conditions. Later on, the samples were placed in the SEM device. Surface examinations were performed at various magnifications and microphotographs were taken for a comparative evaluation of the wear characteristics.

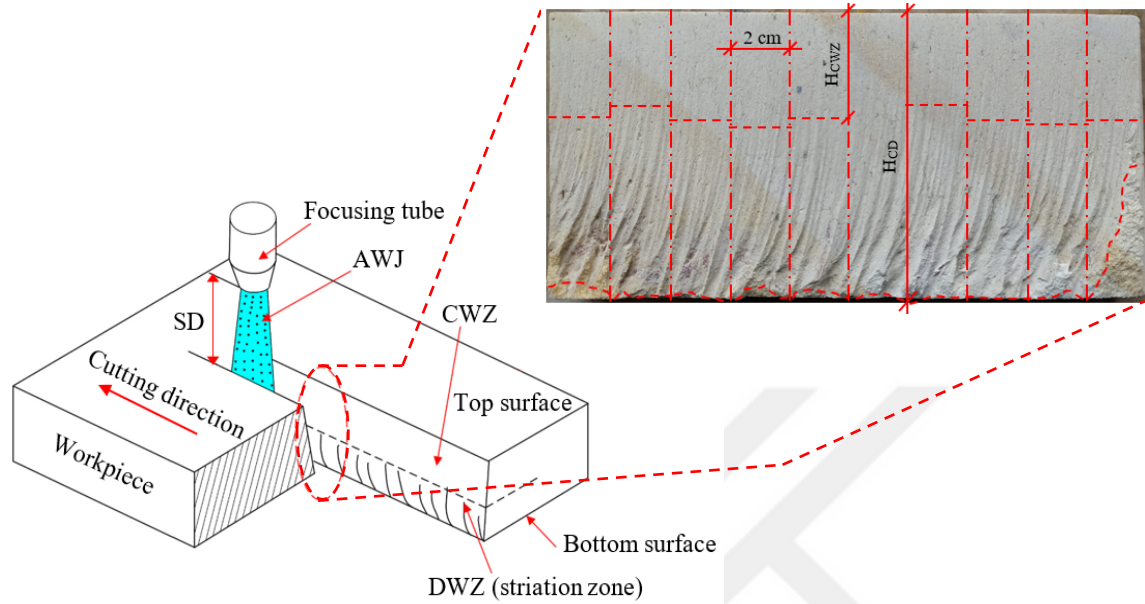


Figure 4.6. An illustration for the cutting depth and CWZ depth measurements in the study

5. MODELLING AND OPTIMIZATON STUDY

5.1. Data and Methodology

In the current thesis, the MLAs were leveraged in order to successfully model and optimize the cutting performance of the AWJ multi-pass and forward angling the jet techniques in rock cutting. The ML has recently been actively involved in the solution of numerous complex issues or the development of predictive models. Through process optimization, predictive model establishment, and enhanced problem-solving skills, it is a useful and helpful tool to support engineering practices across a wide range of industries (Aliramezani et al., 2022). A significant part of this innovative tool is the use of effective algorithms established with the help of computer science advancements. ANN, SVM, DT, GPR, CNN, ANFIS, HMM and PSO are among the most known MLAs, which are employed to establish the predictive models for a given input and output variables (Chen et al., 2024). Herein, it is important to note that the selection of the input and output variables is crucial to use these algorithms as models as stated by Bas and Karabacak (2023). Therefore, based on the rock properties, operating variables and experimental results, an input and output matrix was firstly created for the current thesis. Input parameters are the rock properties and operating variables varying levels, while the output parameter is the cutting performances including the cutting depth, CWZ depth, kerf taper angle, kerf width, surface roughness (both Ra and Rz) and DA from the experimentation. Based on these inputs and output, an array of 21x98 MATLAB matrix was designed for the data. Appendix I shows an example for the inputs and output matrix, which was utilized in modelling study. Additionally, the data was split into three subsets as 70% for training, 15% for validation, and 15% for testing in order to establish strong predictive models. Once the dataset was trained, validated and tested using the regression learner and test toolboxes of MATLAB software, three of abovementioned typical MLAs were chosen as the predictive models for the cutting performances since they have presented the largest performance on the basis of the performance metrics. On the other hand, a systematic three-stage methodology was followed as the data normalization, feature importance analysis, and parameter optimization using PSO through Python software for the case of optimization. Initially, data normalization was performed utilizing the MinMaxScaler technique to scale numerical features within the range

of (0,1), ensuring uniformity and mitigating potential biases in subsequent analyses. Eq. (2.3) presents the mathematical formula of the normalization (Yuan et al., 2025).

$$B' = \frac{|B - \bar{B}|}{\delta} \quad [2.3]$$

where; B' denotes the normalization result, B is the actual data, $\bar{B}$ indicates the mean of the data, and δ shows the standard deviation.

Following the data normalization, RFR was employed to determine the relative importance of predictor variables influencing the cutting performances as an output. The feature importance ranking has facilitated the identification of key parameters contributing to variations in the cutting performances. Subsequently, an optimization framework was developed using PSO to refine critical operational parameters, including NP, TS, AFR, FA, and WP for the tested rock types. The optimization process incorporated the mainly cost and time constraints to balance the operational efficiency with economic feasibility. Moreover, the basic principles of MLAs have recently been extensively used and documented in the relevant fields such as the existing literature. Therefore, their specifics are not detailed herein. Instead, the selected models are briefly explained below. Furthermore, Fig. 5.1 shows the flowchart of the thesis.

5.1.1. Gaussian Process Regression

An efficient technique for Bayesian non-linear and non-parametric regression and classification, the GPR includes the Gaussian-distributed random variables and finite elements (Xie et al., 2021). Herein, the Gaussian distribution describes the random variables, including scalars and vectors a mathematical function. Thus, the GPR is a useful tool for modeling intricate systems and solving probabilistic regression issues (Kong et al., 2018). A GPR model can be described as Eq.(2.4) for a set of input ($x_1, x_2, \dots, x_n$) and output variables (y), while an illustration of the GPR-based probabilistic regression is presented in Fig. 5.2 (Karabacak, 2024). As with SVM, various kernel functions can be employed to the GPR as the covariance functions to predict the output. Constant, linear, Gaussian noise, squared exponential, Ornstein-Uhlenbeck, Matern, periodic and rational quadratic are the common kernel functions to be applied in the GPR modelling (Fang et al., 2018).

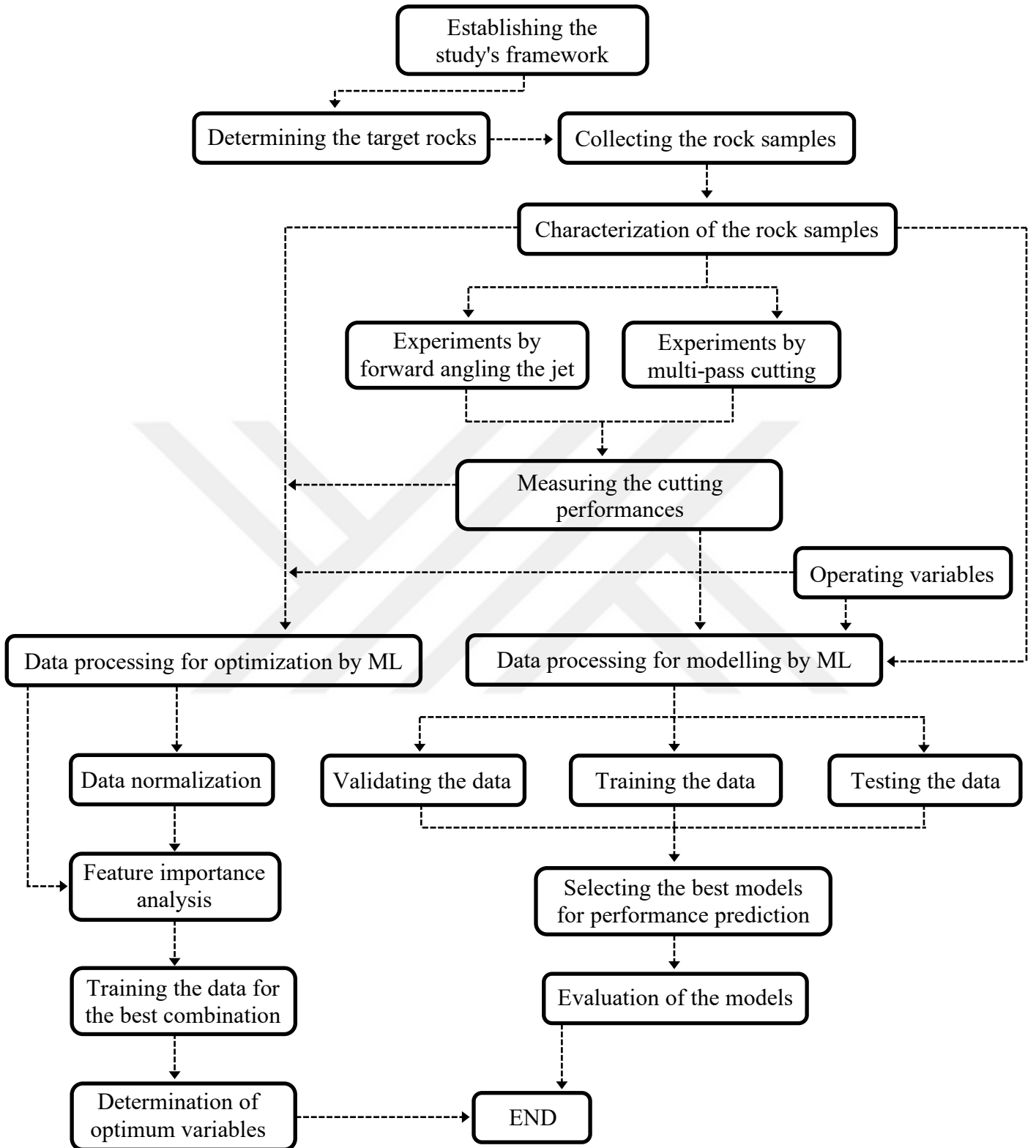


Figure 5.1. Flowchart of the study

$$y = f(x_i) + \varepsilon^{(i)}, i = 1, 2, \dots, n$$

[2.4]

where; $\varepsilon^{(i)}$ represents noise variable, with $\varepsilon^{(i)} \sim N(\mu, \sigma^2)$. In the GPR, the function $f(x)$ is expressed as GP and functionally illustrated in Eq.(2.5).

$$f(x) = GP[m(x), K(x, x')] \quad [2.5]$$

where; $m(x)$ and $K(x, x')$ denotes the mean and covariance functions respectively.

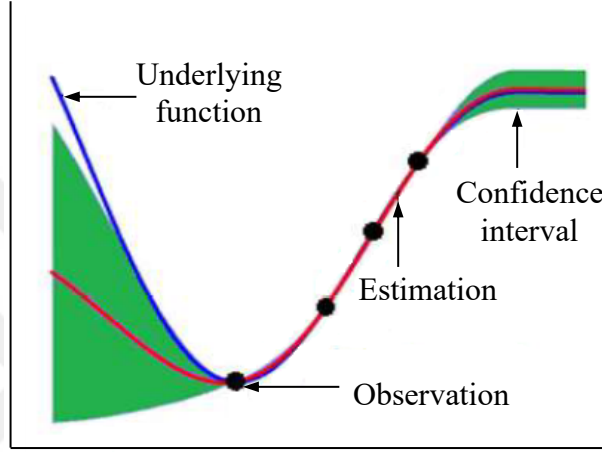


Figure 5.2. An illustration of a GPR

5.1.2. Artificial Neural Networks

ANNs are simplified representations of how the human brain processes information. In other words, the models created by simulating human brain neural network information processing are known as ANNs (Wu and Feng, 2018). Composed of directionally coupled neurons that are joined to form multiple layers known as input, hidden, or output layers, the ANNs are especially well-suited for complex tasks such as pattern recognition, classification, and nonlinear problem solving that are beyond the capabilities of traditional models. Following the input layer gets the input data's features, the hidden layer transmits the data via weighted connections, and the input values are compared to the threshold. Consequently, the activation function in the output layer can provide the final prediction result (Xu et al., 2023). A variety of activation functions exist. But, most often, the sigmoidal activation function is used (Caydas and Hascalik, 2008). Therefore, the sigmoidal activation function was utilized in the current study. Eq. (2.6) is the fundamental mathematical form of the ANN's output calculation, while a structure of the ANN is described in Fig. 5.3 (Xie

et al., 2021). As it is clearly seen from the structure that the ANN have also hidden neighboring layers coupled by varying weights in addition to the input and output layers. Moreover, the Eq. (2.6) means that an ANN model generates an output through a transfer function after multiplying the inputs with weights that are adjustable.

$$y = f(\sum_{i=1}^n [(x_i) \cdot (w_i)] + b) \quad [2.6]$$

where, y is the output, n is the number of inputs, w is the weight, x is the input, b is the bias, and f is the activation function.

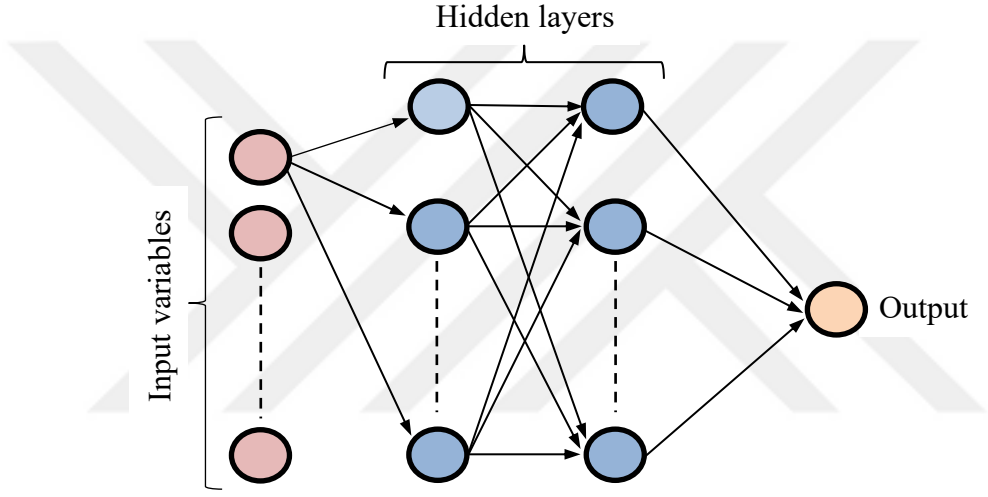


Figure 5.3. A structure of an ANN

5.1.3. Support Vector Machine

As one of the favored MLAs, SVM uses a hyperplane to split the dataset according to its linear form. In this case, the data on or close to the hyperplane are referred to as support vectors. The SVM's main objective is to use the specified support vectors for mapping the data points near the hyperplane. Errors are the distances between the data points and the hyperplane as shown in Fig. 5.4(a). Herein, the SVM aims to reduce the errors of the data points using the support vectors and hyperplane (Li et al., 2022b). In order to achieve this goal, the data is subjected to several kernel functions such as radial basis function, Gaussian kernel, sigmoid kernel, Laplace radial basis function, polynomial, hyperbolic tangent prior to the SVM-based model being trained and the nonlinear transformation being identified (Bas and Karabacak, 2023; Markal et al., 2024). Eq. (2.7) illustrates the SWM

mathematically, while Fig. 5.4(b) exhibits the general architecture network for SVM. Here; y describes the output, x means the input, b is the constant term, and w indicates the weight vector (Aliremazani et al., 2022).

$$y = (w^T) \cdot (x) + b \quad [2.7]$$

Regarding a kernel-based SVM, Eq. (2.7) will be as follows:

$$y = \sum_{i=1}^n [(w_i) \cdot K(x_i, x) + b] \quad [2.8]$$

where, $K(x_i, x)$ is a kernel function and often Gaussian kernel is used for SVM (Keerthi and Lin, 2003). Thus, the kernel function was chosen to be the Gaussian function in the current thesis.

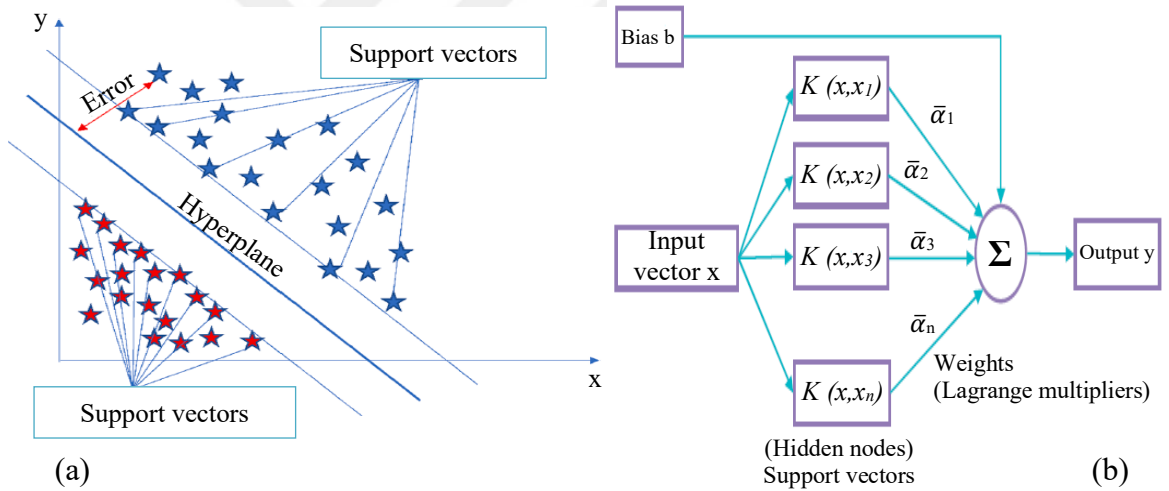


Figure.5.4. a) An illustration of the SVM algorithm with support vectors and hyperplane (Li et al., 2022b), b) network architecture of SVM (Chen and Yu, 2007)

5.1.4. Gradient Boosted Decision Trees

As a decision tree-based boosting ensemble learning technique, the GBDT algorithm is highly adaptable and can handle issues including overfitting, missing data, and multi-feature data combinations (Wang et al., 2025). The GBDT algorithm iterates and combines several decision trees, which are one of the base learners, for enhancing the model performance. In each iteration, the residual between the previous model's predicted and actual values is captured to train the subsequent tree. In the end, the prediction outcomes of

every fundamental regression tree are combined to create a potent learning model, which successfully addresses the issues of low accuracy and overfitting of individual regression trees. As well as being a traditional ensemble algorithm, the GBDT is also a boosting algorithm (Wu et al., 2024; Guangxing et al., 2024). Regarding a given input x_i of GBDT learners, the output y_i is mathematically expressed in Eqs.(2.9) and (2.10). Additionally, Fig.5.5 displays the GBDT model training procedure.

$$y_i = F_M(x_i) = \sum_{m=1}^M h_m(x_i) \quad [2.9]$$

$$F_M(x) = F_{m-1}(x) + h_m(x) \quad [2.10]$$

where; M is the number of the estimators, h_m are weak learners in the boosting. F_{m-1} is the previous ensemble, h_m presents the newly added tree.

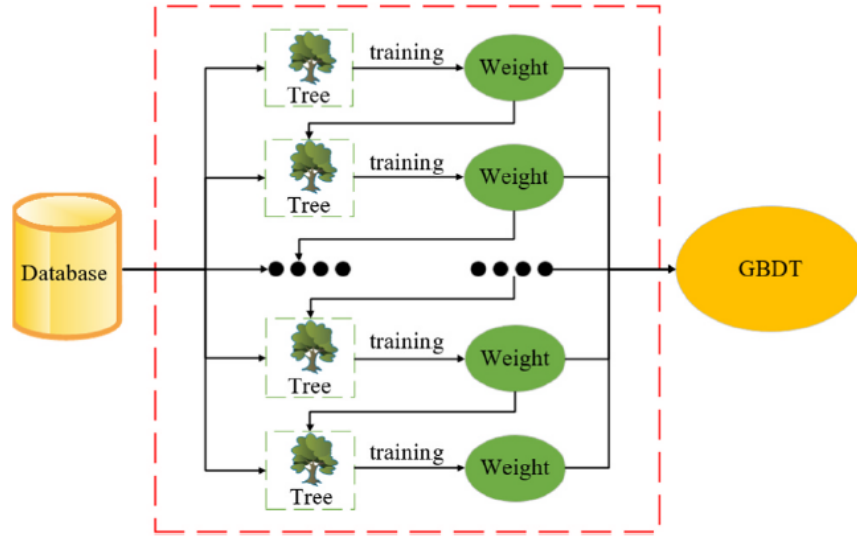


Figure 5.5. Diagram of the training structure for the GBDT model (Wu et al., 2024)

5.1.5. Particle Swarm Optimization

As a swarm-based stochastic optimization method, the PSO mimics the natural foraging behavior of animals such as fish schooling and bird flocking (Wang et al., 2018). For instance, birds interact with one another in the flock while foraging. They discover the ideal foraging spot after iteratively updating the position inside a constrained area and looking for the area nearest to food (Wu et al., 2024). The PSO algorithm assumes that the

area being searched for food is a D-dimensional target search space. In PSO, this search space is populated by a swarm of N_p particles, each of which represents a possible solution. Each particle's spatial position constitutes a solution for the final function. In other words, each particle looks for the best position and conveys its own information to other particles. This ensures that the group as a whole develops toward the best position (Fig. 5.6). On the other hand, at the iteration point t , the i th particle is assessed using its fitness function, which is impacted by the velocity vector, $V_i = [v_{i1}, v_{i2}, \dots, v_{iN}]$ and determined by its position vector, $X_i = [x_{i1}, x_{i2}, \dots, x_{iN}]$. The i th particle's V_i and X_i are updated on the basis of below equations [Eqs. (2.11) and (2.12)] (Luh and Lin, 2011).

$$V_i^{k+1} = (w) \cdot (V_i^k) + [(c_1) \cdot (r_1) \cdot (P_{best,i}^k - X_i^k)] + [(c_2) \cdot (r_2) \cdot (G_{best}^k - X_i^k)] \quad [2.11]$$

$$X_i^{k+1} = (X_i^k) + (V_i^{k+1}) \quad [2.12]$$

where; w represents the inertia weight within the range of [0-1], c_1 and c_2 are two constants for the acceleration or learning factors, while r_1 and r_2 identify two independent random numbers ranging from 0 to 1.

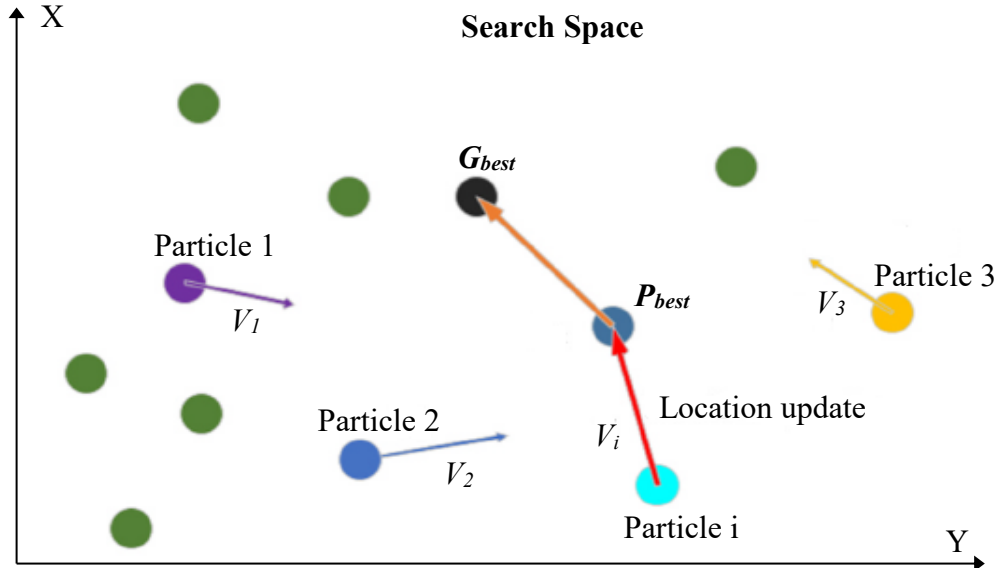


Figure 5.6. Particle updated in the PSO algorithm (Wu et al., 2024)

5.2. Performance Measurements for the ML – based Models

Robustness or prediction accuracy of the proposed ML – based models was comprehensively assessed through statistical metrics such as R^2 , RMSE and MAPE for both training and testing data. Among these metrics, the R^2 is a measure of the linear correlation between predicted and actual values. It has a range of 0 to 1, with 1 denoting a perfect model-data fit. Additionally, the RMSE is a measure of the square root of the total squared errors mean, while the MAPE represents the MAE, expressed as a percentage. Among the performance criteria, three of which were tested in the current study, the MAPE is the most useful tool when estimating relative error since raw data, preprocessed data, and input data used to estimate the model have distinct scales (Azadeh et al., 2011). Kim and Kim (2016) identify the MAPE as one of the most popular statistical metrics for assessing prediction accuracy owing to its benefits of interpretability and scale independence. The MAPE is well-liked by industry practitioners due to its scale independence and ease of interpretation as well (Byrne, 2012). Moreover, since it presents the error as a percentage, this performance indicator is simple to interpret. Furthermore, generally, the lower the MAPE and RMSE values, the more closely the fitted curve resembles the actual data. In other words, the proposed ML – based models' accuracy increases with decreasing values of the MAPE and RMSE (Paiva et al., 2021). The performance metrics that were used to assess the robustness of the proposed ML – based models are mathematically presented in Eqs. (2.13 – 15). Moreover, the reference range for the MAPE is given in Table 5.1.

Tablo 5.1. Reference table for the MAPE (Lewis, 1982)

(%)	Prediction accuracy
$MAPE \leq 10$	Excellent
$11 \leq MAPE \leq 20$	Good
$21 \leq MAPE \leq 51$	Reasonable
$MAPE > 51$	Poor

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (X_i - Y_i)^2} \quad [2.13]$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left(\frac{|X_i - Y_i|}{X_i} \right) \cdot 100 \quad [2.14]$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (X_i - Y_i)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad [2.15]$$

where; n is the total number of data, X_i is the actual value , and Y_i is the predicted value, and $\bar{X}$ is the mean of the actual value.

6. EXPERIMENTAL RESULTS AND DISCUSSION

An overview and quantitative analysis of the results from the experimentation are provided, comparing them with those in the relevant literature where necessary in this chapter.

6.1. Effect of the Multi – pass on the Cutting Performance Indicators

6.1.1. Kerf Width and Kerf Taper Angle

Kerf widths taken from multi-pass cutting of the machined rocks revealed that the kerf widths of the R3 and R5 showed an inconsistent trend, while those of the R1, R2, R4, R6, and R7 decreased with the multi-pass cutting (Fig. 6.1). Among the rock types whose kerf widths decreased, four pass produced the lowest kerf widths for the R1, R2, R4 and R6 whereas it was three pass for the R7, when compared to the standard or normal cutting. On the other hand, the kerf width of the R1 increased with two pass, but, decreased further with the increasing of the pass, while those for the R3 decreased with two pass, and then increased with three and four passes. The kerf width of the R5 was only the machined rock whose kerf width remained almost unaffected by the multi – pass cutting. Additionally, in comparison with single pass, R4 had the largest improvement (decrease rate) rate of 15.40%, whereas

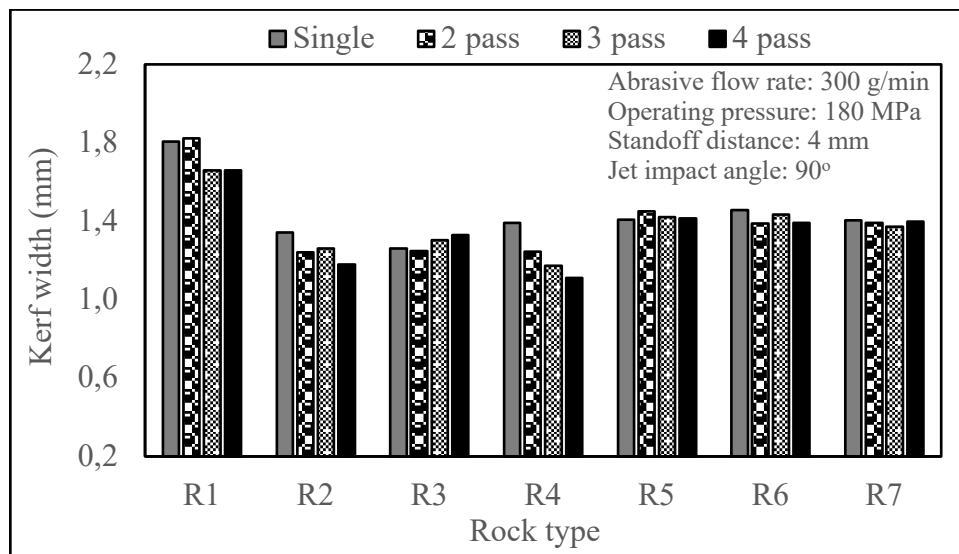


Figure 6.1. Kerf widths for the rock types in the multi – pass cutting

the lowest rate was achieved as 1.24% for the R7 (Fig. 6.2). On the other hand; Fig. 6.3 and 6.4 demonstrate the effects of the AFR and WP increases on the kerf widths in multi – pass cutting.

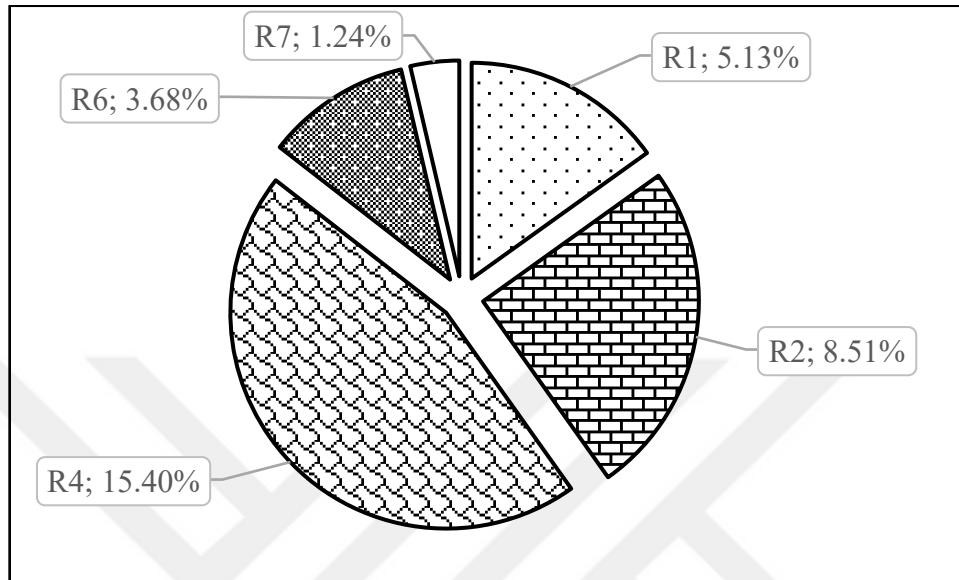


Figure 6.2. Average improvement (decreasing) rates for the kerf widths

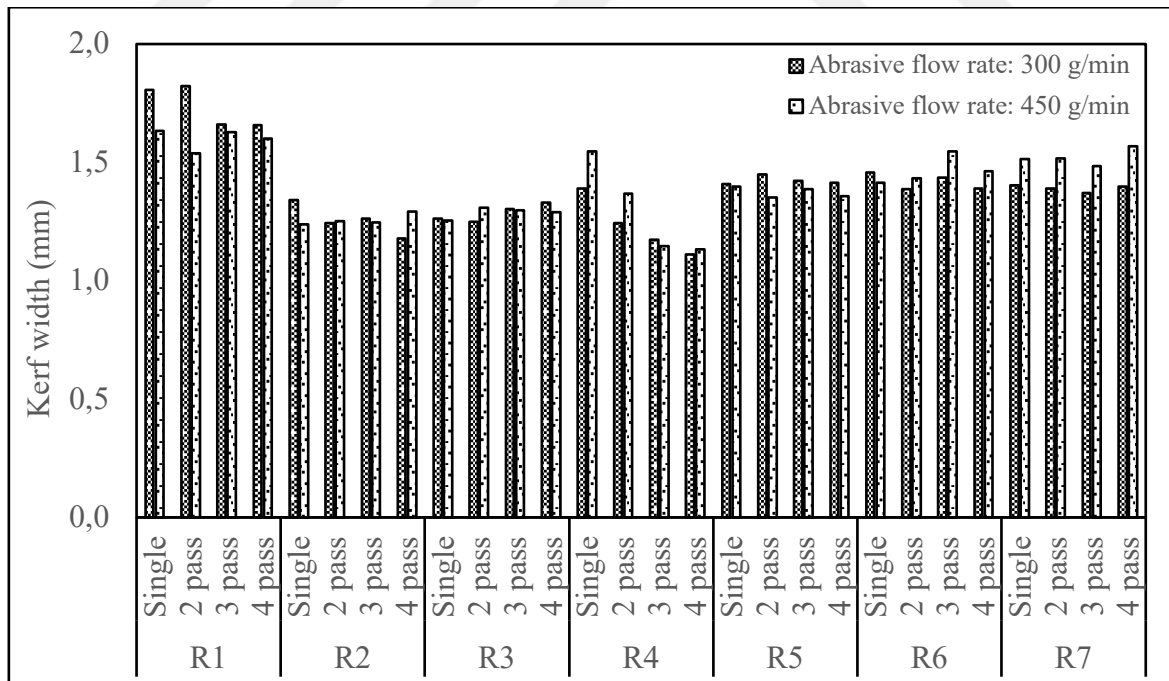


Figure 6.3. Effect of the AFR increase on the kerf widths in the multi – pass cutting

It can be inferred from Fig. 6.3 that an increase in AFR resulted in decreases in the kerf widths of the R1 and R5 for all passes, while those exhibited different behaviors based on the passes. For instance; two pass produced wider the kerf width, while single, three and four passes narrower widths for the rock type of R2. Similarly, three and four passes led to narrower kerf widths, but, single and two passes generated wider kerf widths for the R4. By the way, the rock type of R7 was only the rock type whose kerf width increased with an increase in AFR during multi – pass cutting. In addition to the effect of the AFR, one can understand that an increase in the WP affected kerf width of the R1 positively, whereas it affected negatively those of the R6 and R7 (Fig. 6.4). Moreover, it can be seen that single pass reduced the kerf widths of the R2 and R4 with an increase in the WP. Furthermore, two pass produced also lower kerf width for the rock type of R2 with an increase in the WP.

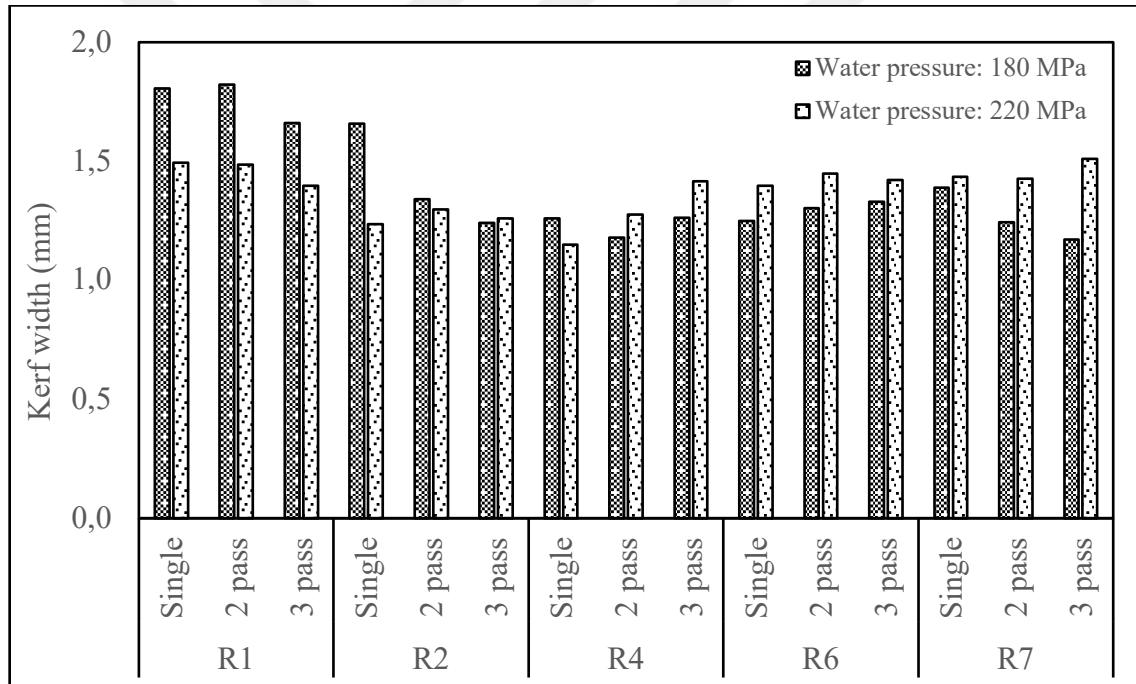


Figure 6.4. Effect of the WP increase on the kerf widths in the multi – pass cutting

In case of the kerf taper angle, it can be disclosed that the number of pass reduced the kerf taper angle of almost all rock types, with the exception of two pass for the R5 (Fig. 6.5). Among the rock types, the kerf taper angle for the R5 showed an increased trend when the multi – pass cutting was employed. In particular, the kerf taper angles for R1 and R2 were found to decrease significantly with the increase of NP. In other words, the average improvement rates in the kerf taper angles for the R1 and R2 were 57.30% and 50%

respectively. These rocks were followed by the R4, R7, R3 and R6 with almost 29%, 22%, 20.50% and 12% improvement rates correspondingly (Fig. 6.6).

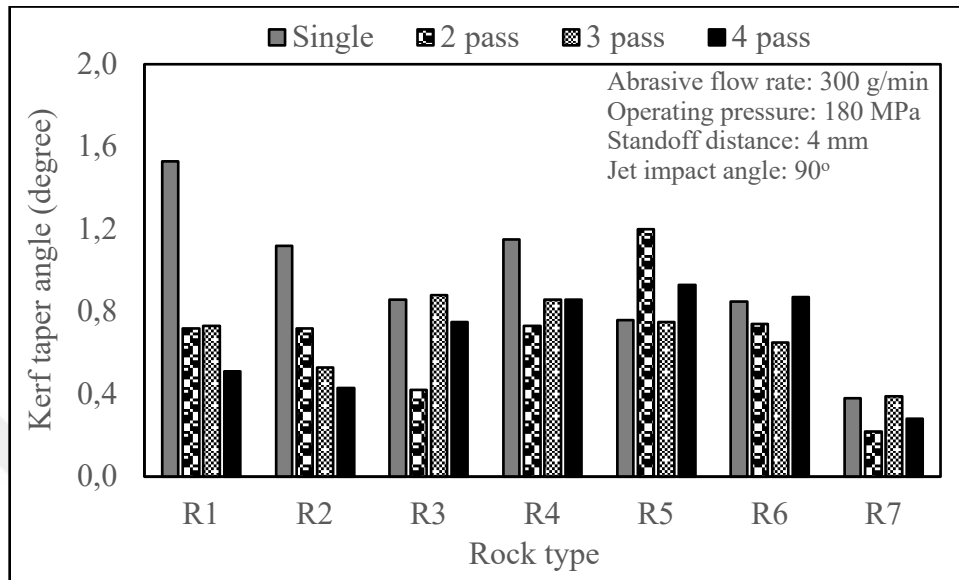


Figure 6.5. Kerf taper angles for the rock types in the multi – pass cutting

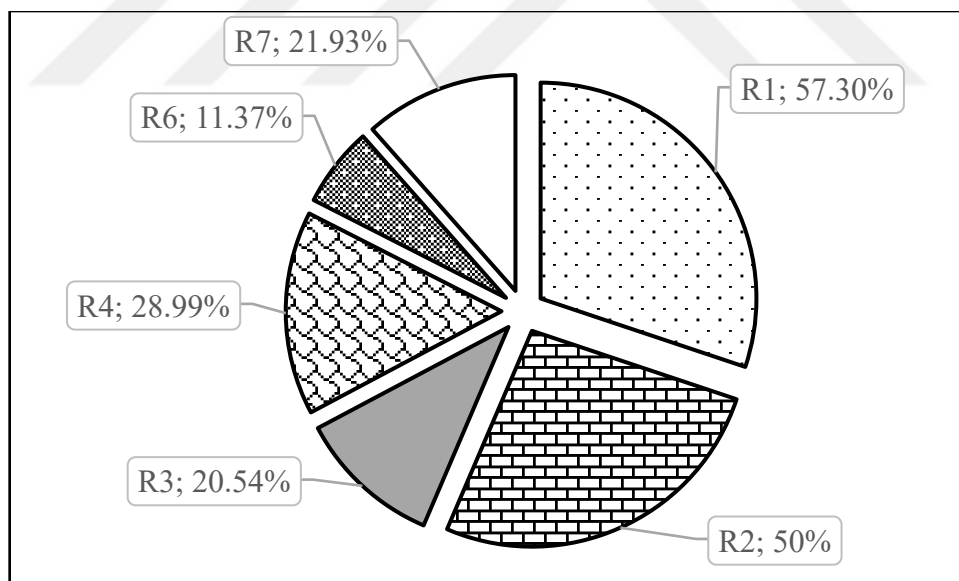


Figure 6.6. Average improvement (decreasing) rates for the kerf taper angles

As it can be evidently followed from Fig. 6.7 that an increase of the AFR resulted in decrease in the kerf taper angle of the R4 for all passes. However, the kerf taper angles of other rocks do not exhibit a constant trend to the increasing of the AFR. For example, the kerf taper angle of the R1 decreased only in single pass, while those of the R5 and R6 were in two and

four passes. Additionally, the kerf taper angles of the R2 showed a decreasing behaviour in two and three passes, whereas those were three and four passes for the R3. Moreover, single and three passes produced lower kerf taper angle for the rock type of R7.

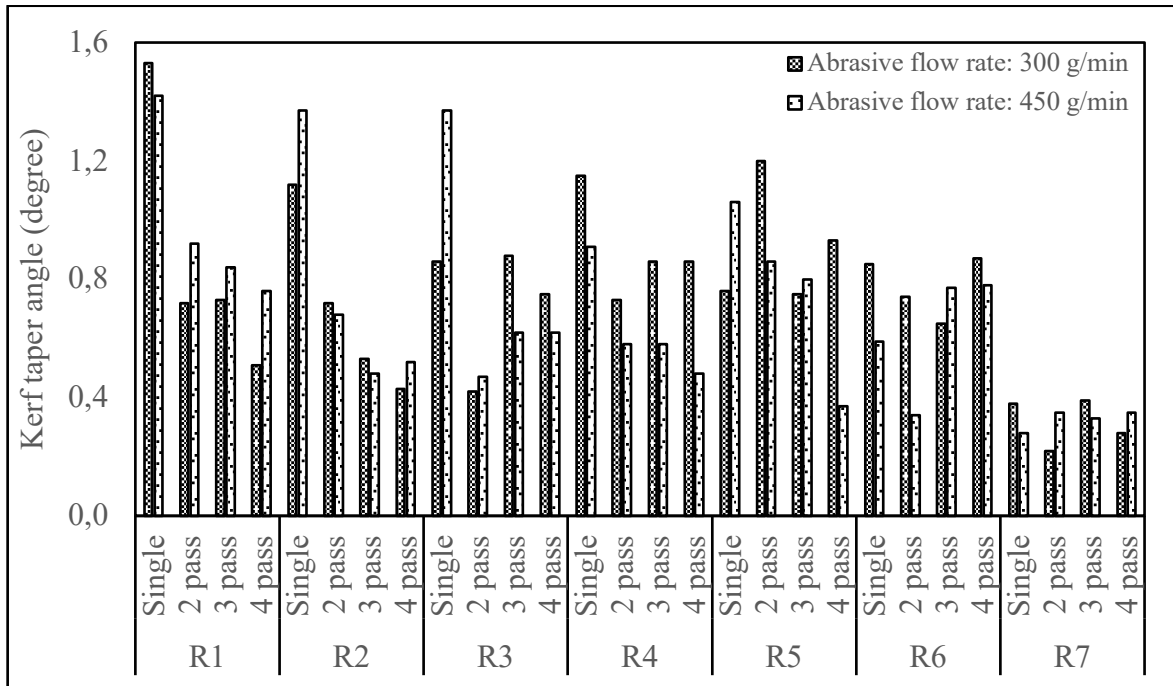


Figure 6.7. Effect of the AFR increase on the kerf taper angles in the multi – pass cutting

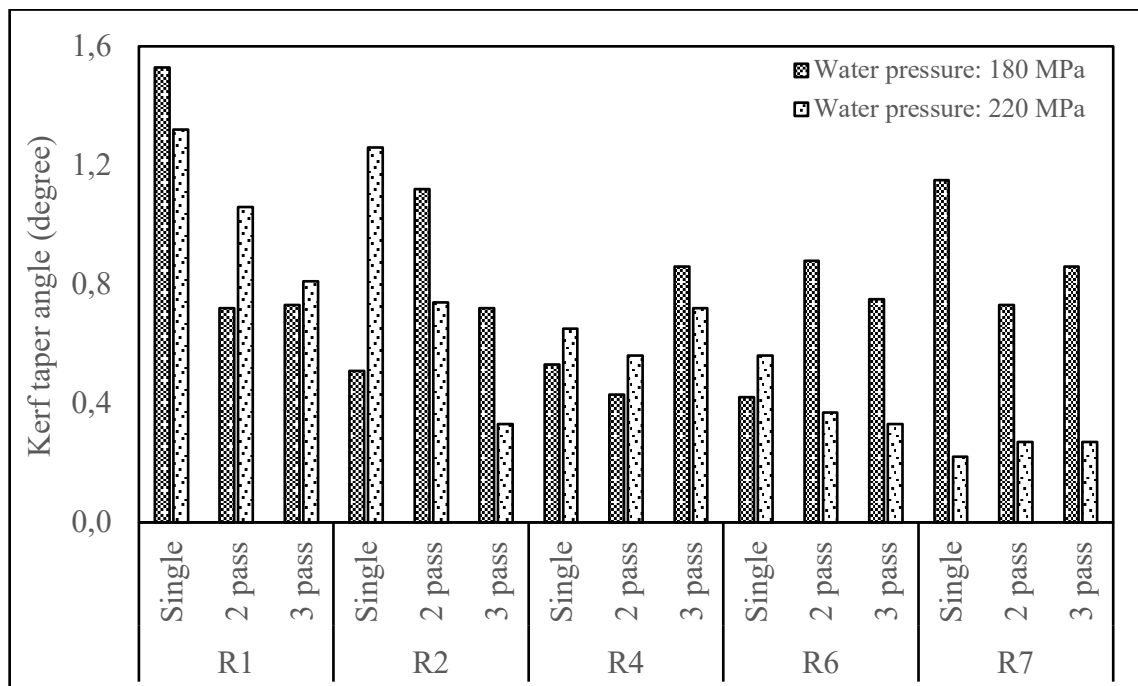


Figure 6.8. Effect of the WP increase on the kerf taper angles in the multi – pass cutting

Similar trend with the AFR increase was observed for the WP increase in the multi – pass cutting of the rocks (see Fig. 6.8). In other words, the WP increase led to achieve lower kerf taper angle for only one rock for all passes as was in the case of the AFR increase (this rock type was the R7, but it was the R4 in the case of AFR). Additionally, only single and three passes resulted in lower kerf angles for the R1 and R4 respectively.

6.1.2. Surface Roughness

As significant features for representing the cutting quality of the workpieces in AWJ technology, the surface roughness of the machined rocks as Ra and Rz were shown in Fig. 6.9 and Fig. 6.10. As it is evident from the related figures that the surface roughness of the R3, R5 and R6 decreased with all passes in terms of the Ra and Rz. That means, higher cutting qualities were recorded for these type of rocks. When compared to the single pass, their surface roughness in terms of the Ra decreased from 8.10 μm to 6.21 μm , a rate of 23.32% for the R3; from 7.07 μm to 5.75 μm , a rate of 18.57% for the R5; from 8.46 μm to 6.89 μm , a rate of 18.63% for the R6 respectively. Likewise, their surface roughness in terms of the Rz decreased from 42.58 μm to 32.94 μm , a rate of 22.63% for the R3; from 37.36 μm to 31.90 μm , a rate of 14.60% for the R5; from 40.03 μm to 36.28 μm , a rate of 9.37% for the R6 respectively. On the other hand, average improvement rates for the rock types of R4 and R7 were 8.37% and 5.43% in terms of the Ra, while those were 9.60% and 2.57% in terms

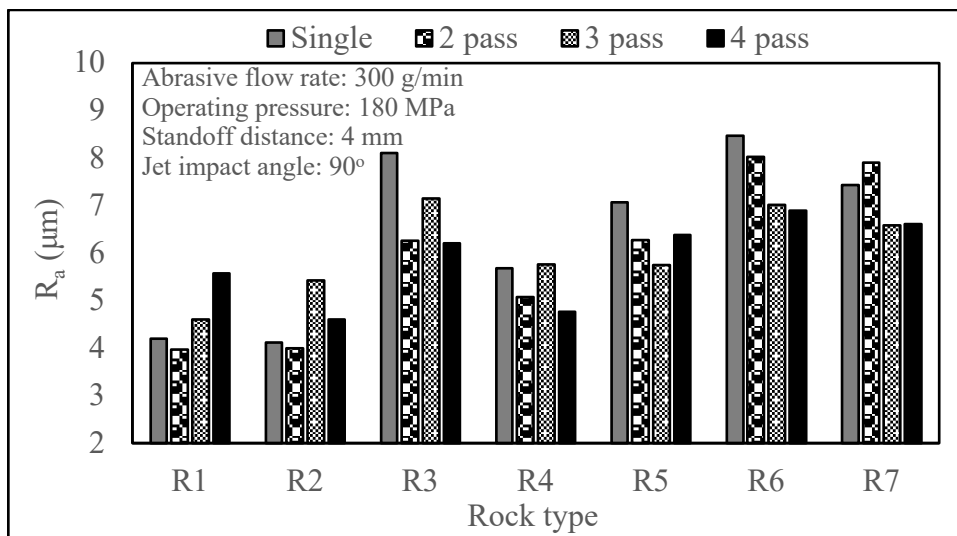


Figure 6.9. Surface roughness (Ra) for the rock types in the multi – pass cutting

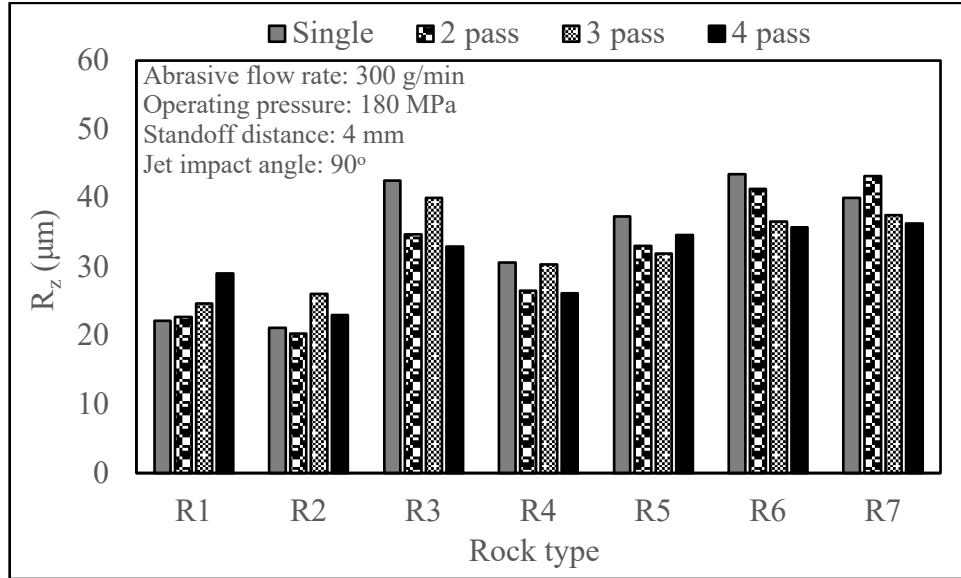


Figure 6.10. Surface roughness (R_z) for the rock types in the multi – pass cutting

of the R_z respectively (Fig. 6.11 and 6.12). Additionally, apart from the two pass, other passes did not produce higher cutting surface roughness for the rock type of R1 and R2.

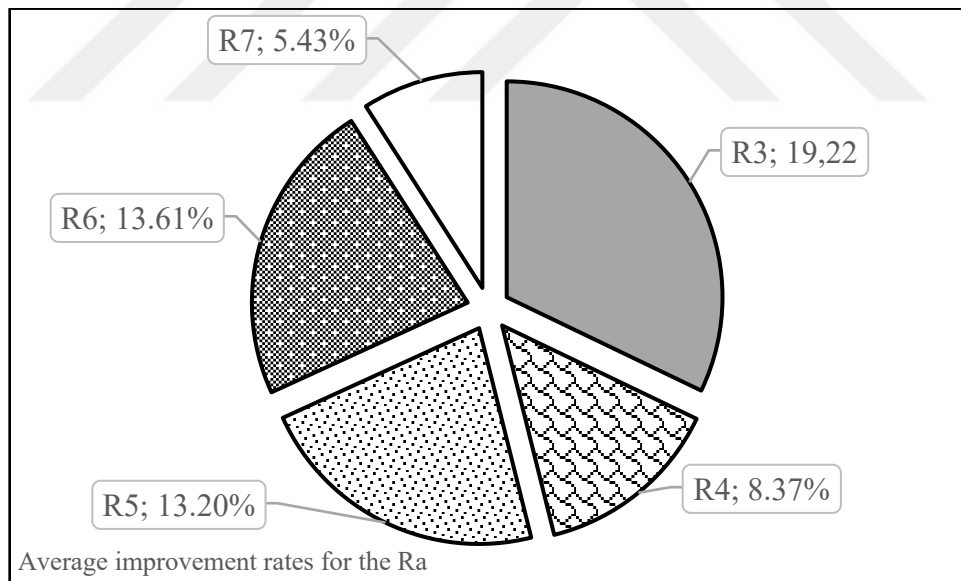


Figure 6.11. Average improvement (decreasing) rates for the surface roughness for the rock types in the multi – pass cutting

Given that the effects of the AFR and WP increase on the cutting surface qualities, it can be clearly disclosed that cutting surface qualities were improved with the increasing of the AFR in the multi – pass cutting for almost all rock types, apart from only two and four pass for the R5 and R7 respectively. In other words, the increasing of the AFR by one level affected

the cutting surface positively and the surface roughness in terms of the Ra were improved for the machined rock types. Additionally, almost similar trend was observed for the Rz. That is, the higher cutting surface qualities in terms of the Rz were achieved with the increasing of the AFR with the exception of two pass for the R4 and R5, and four pass for the R7. As a whole, it can be definitely deduced that increasing of the AFR improved generally the cutting qualities of the machined rocks (Fig. 6.13).

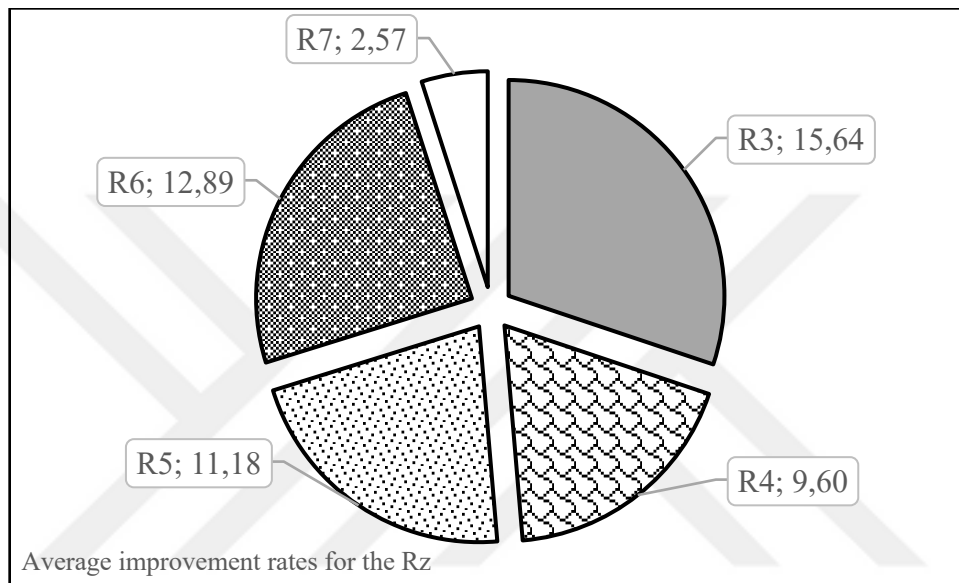


Figure 6.12. Average improvement (decreasing) rates for the surface roughness for the rock types in the multi – pass cutting

On the other hand, the increasing of the WP resulted in decreasing of the surface roughness of R1, R2, R4, R6 and R7 in terms of the Ra values, except for the opposite case in single pass for the R1. In case of the Rz, it can be seen that the surface roughness of the R2 and R4 decreased, while it was increased for the R7 totally. Moreover, the single pass produced worse cutting quality for the R1 and R6 together with three pass for the R6 (Fig. 6.14).

6.1.3. Declination Angle

Figure 6.15 displays the declination angles produced by AWJ multi-pass and forward angling cutting of the rock types tested. It appears evidently that the DA proportionally was reduced as the NP increased. Even, it is seen that that almost no DA (0.01 degree) formed with the four pass for the rock types of R5, R6 and R7. As it is also seen, the four pass

produced the lowest DAs for all rock types. Compared with the single pass, the largest average reductions were achieved with 79.29%, 77.64% and 75.07% in the rocks of R5, R7 and R6 whose DAs were almost zero degrees with four pass (Fig. 6.16).

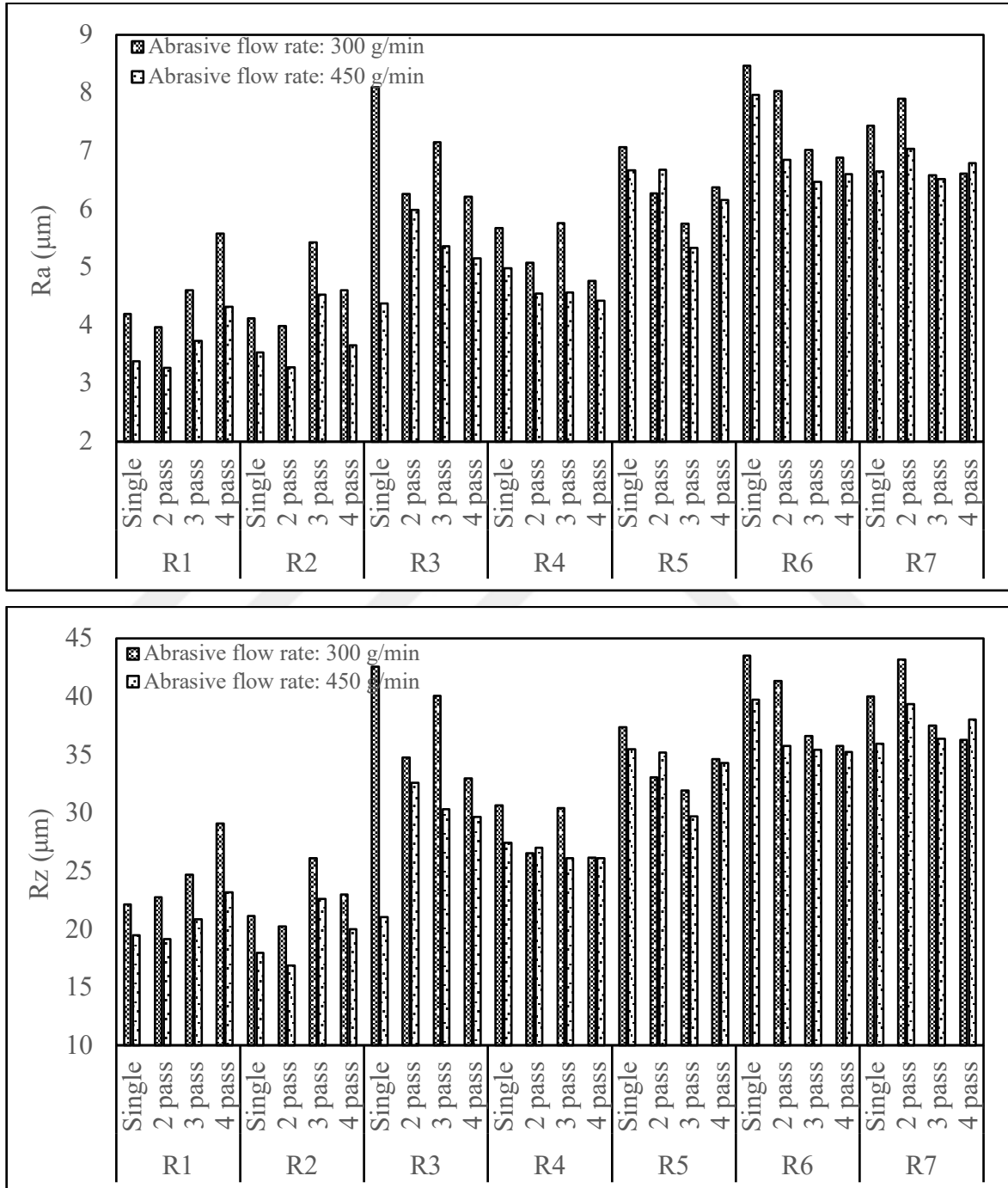


Figure 6.13. Effect of the AFR increase on the surface roughness (R_a and R_z) in the multi – pass cutting

On the other hand; Fig.6.17 and Fig.6.18 represent the effect of the AFR and WP increases on the DA in multi-pass cutting, showing the substantial reductions for all machined rocks.

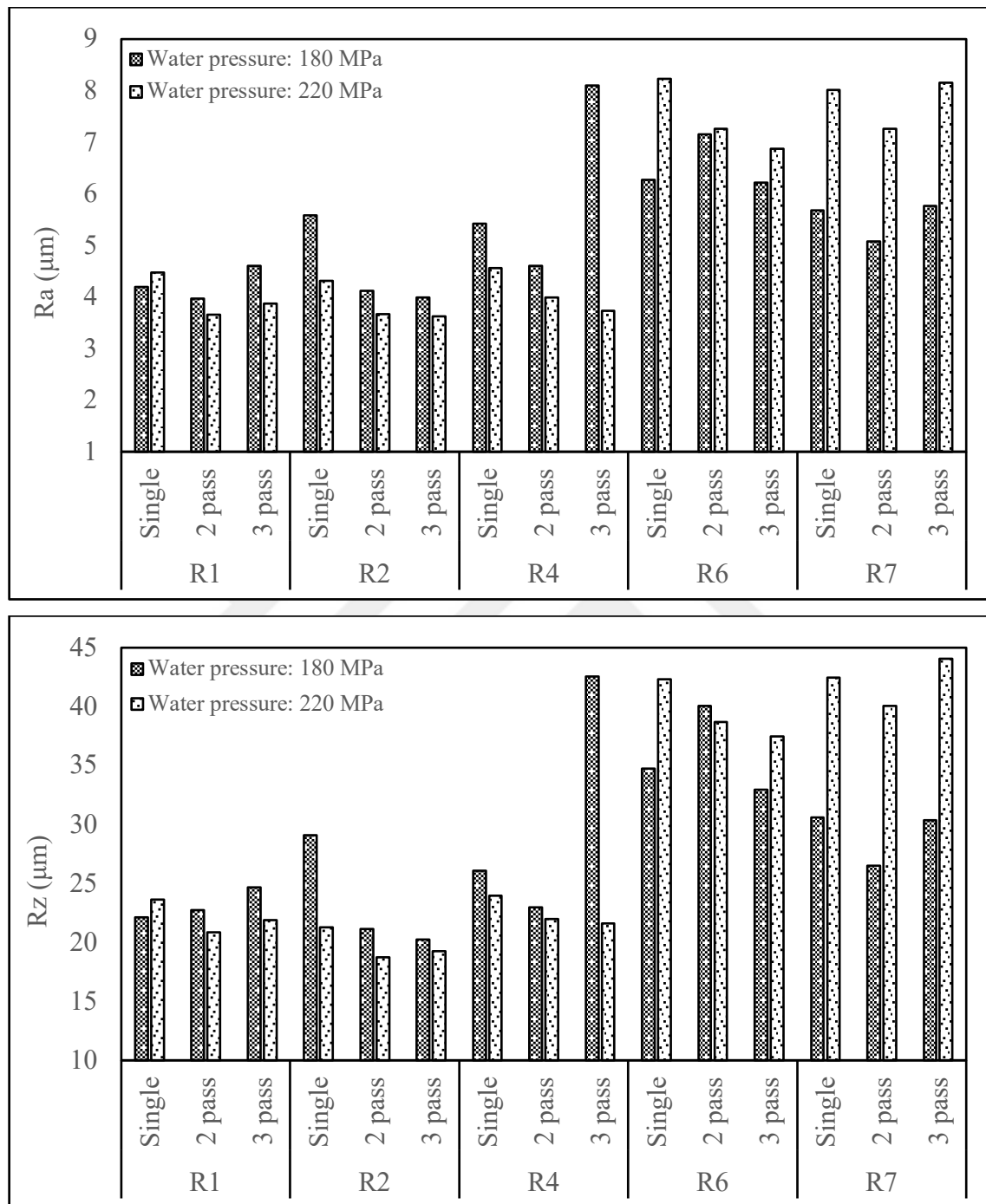


Figure 6.14. Effect of the WP increase on the surface roughness (R_a and R_z) in the multi – pass cutting

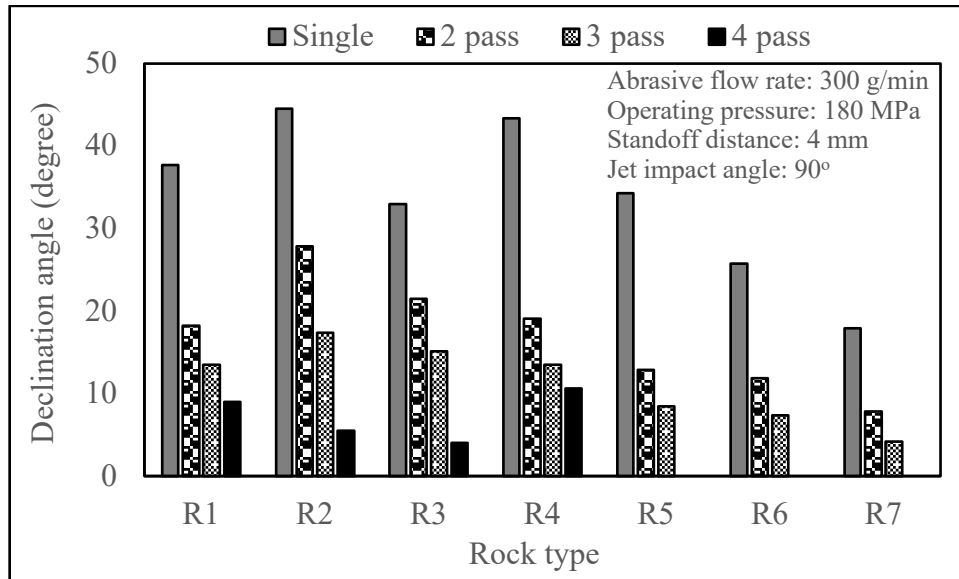


Figure 6.15. Declination angles for the rock types in the multi – pass cutting

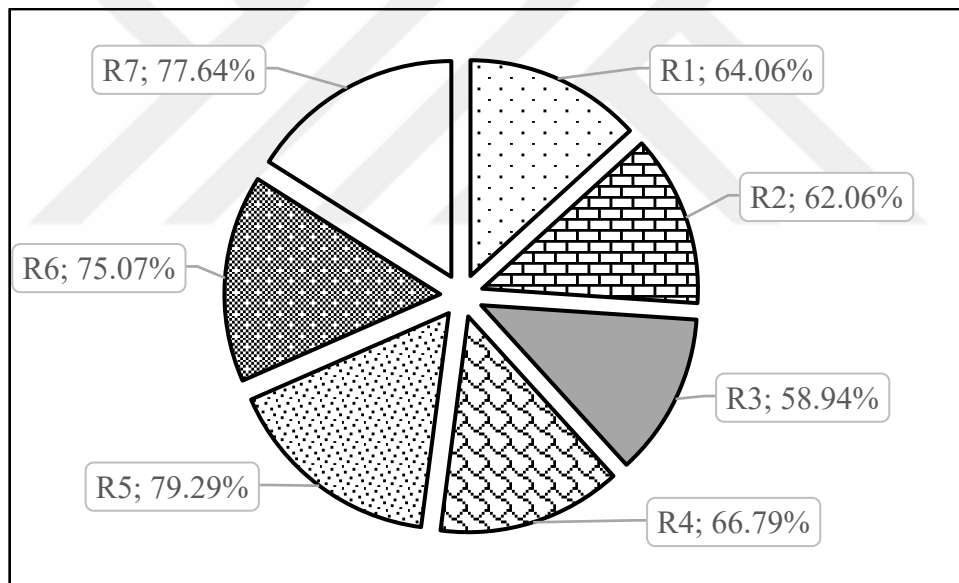


Figure 6.16. Average improvement (decreasing) rates for the declination angles for the rock types in the multi – pass cutting

6.1.4. Cutting and Cutting Wear Zone Depths

Figure 6.19 provides an overview on the cutting depths, obtained for the machined rocks. It is evident from Fig. 6.19 that the cutting depths gradually increased as the NP increased, varying from 18 to 76 mm. For the R1, R2, R6, and R7, four pass yielded the largest cutting depths of 27.23 mm, 21.02 mm, 39.45 mm, and 76.60 mm, respectively.

These were two pass for the R3 and R4, measuring 25.98 mm and 26.22 mm, while it was three pass for the R5 as 26.57 mm. In comparison with single pass, R7 had the highest improvement rate of 30.50%, whereas the lowest rate was achieved as 5.68% for the R2 (Fig. 6.20). On the other hand; Fig. 6.21 and 6.22 illustrate the effects of the AFR and WP increases on the cutting depths in multi – pass cutting. It can be generally concluded from Fig. 6.21 that substantial increases were achieved for the machined rock types. For better understanding, it can be stated that an increase of the AFR resulted in increases of the cutting depths for the R2, R4 and R5 in all passes. Those were three and four passes for the R1, two, three and four passes for the R3, only single pass for the R6, single and four passes for the R7 respectively.

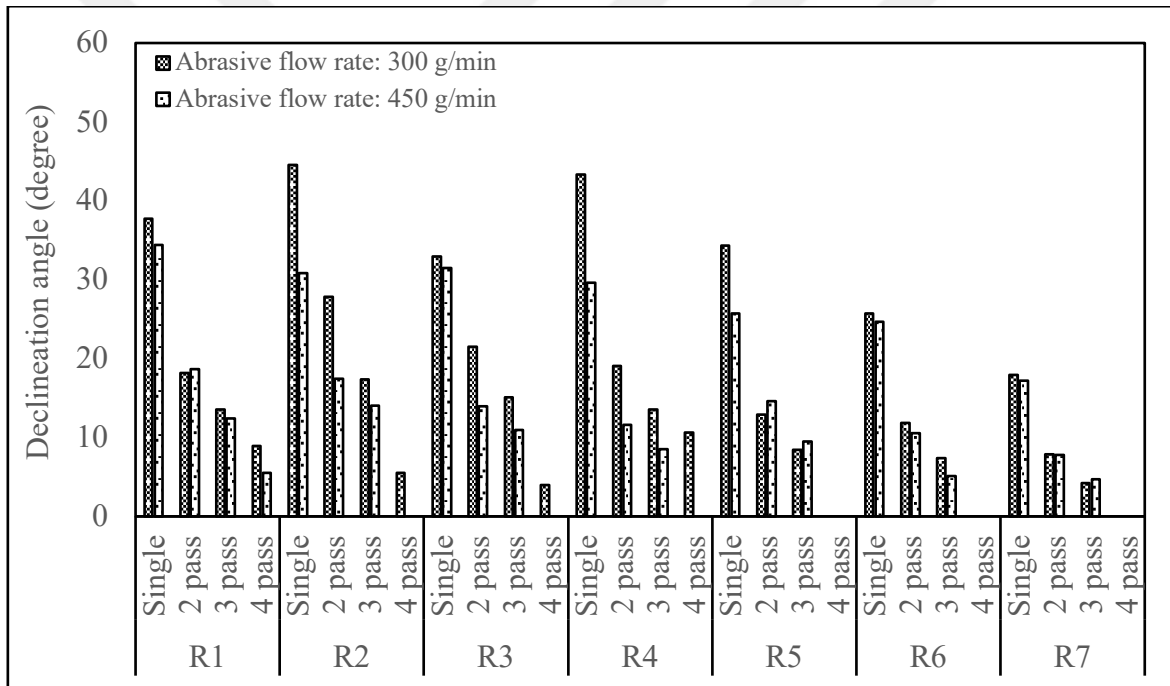


Figure 6.17. Effect of the AFR increase on the declination angle in the multi – pass cutting

On the other hand, the cutting depth of the R2, R3, R4 and R5 showed the largest increases with the increase of AFR. To put it more clearly, the cutting depths of the R4 and R5 were increased from 22.46 mm to 32.72 mm and 26.48 mm to 32.87 mm at the four pass, while those were from 24.10 mm to 29.72 mm and 18.26 mm to 21.58 mm for the R3 and R2 at four and two passes respectively. Besides the lower increase rates for other rock types, these results made the R2, R3, R4 and R5 as the rocks having the largest cutting depths with the increasing AFR. In contrast to the changes observed in cutting depths with the increasing

AFR, it is observed that the cutting depths of the tested rocks increase greatly with the increase in WP except the cutting depth in single pass for R2. In other words, the average increase in cutting depths was achieved as 21.92%, 32.57%, 23.72%, 17.02% and 28.10% for the R1, R2, R4, R6 and R7 respectively with the increasing WP (Fig. 6.22).

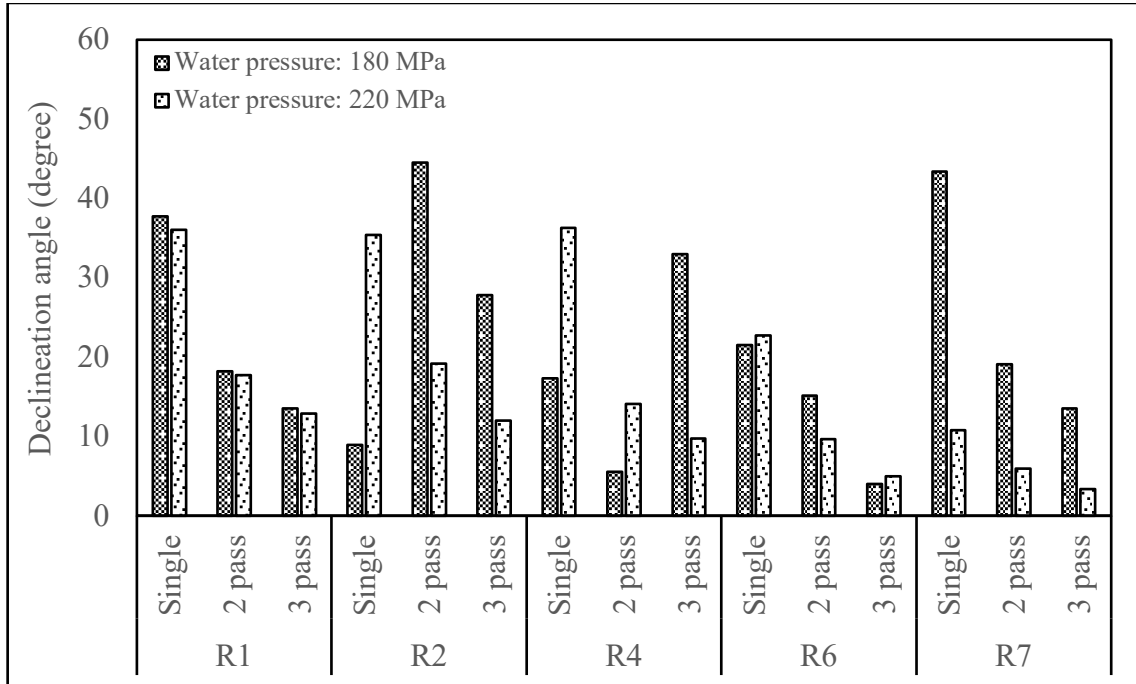


Figure 6.18. Effect of the WP increase on the declination angle in the multi – pass cutting

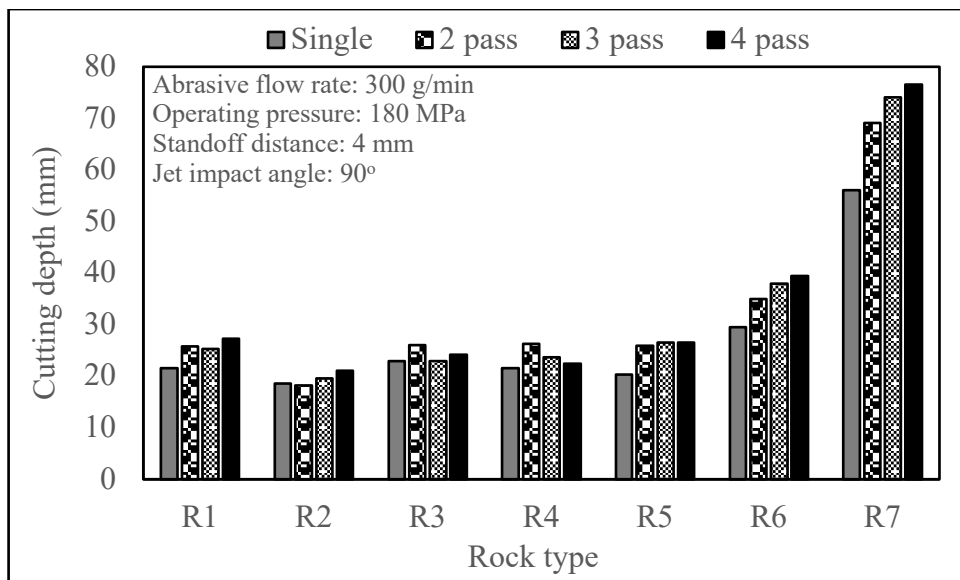


Figure 6.19. Cutting depths for the rock types in the multi-pass cutting

Regarding the cutting wear zone depths, it can be stated that the multi – pass cutting increased the CWZ depths of the R5, R6 and R7 for all passes in comparison to those recorded by single pass. In addition to these rocks, the CWZ depths of the R1, R2 and R4 were increased for the three and four passes, while the CWZ depth of the R3 was increased for the two and four passes respectively (Fig. 6.23). As it can be followed from Fig. 6.24 that the largest two average improvement rates in the CWZ depths for the machined rock types

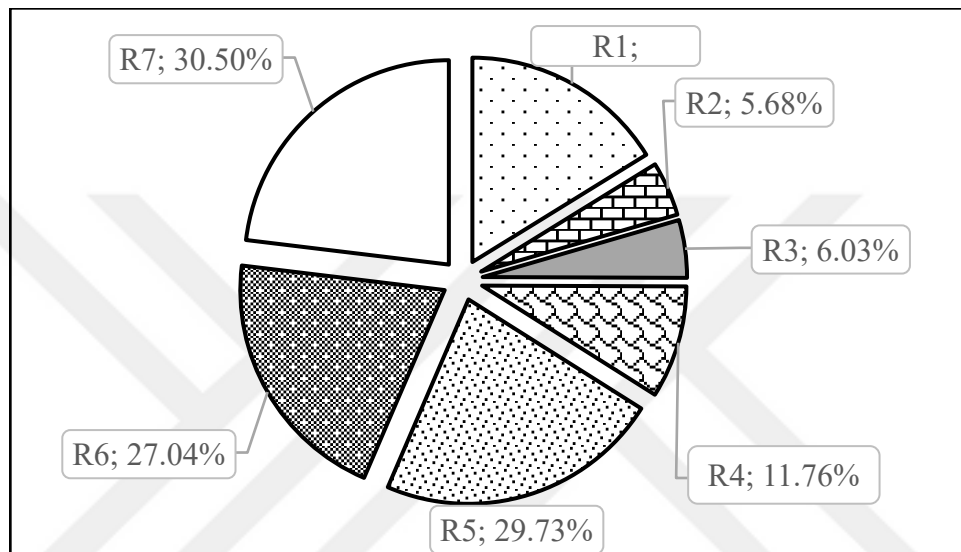


Figure 6.20. Average improvement rates for the cutting depths in the multi – pass cutting

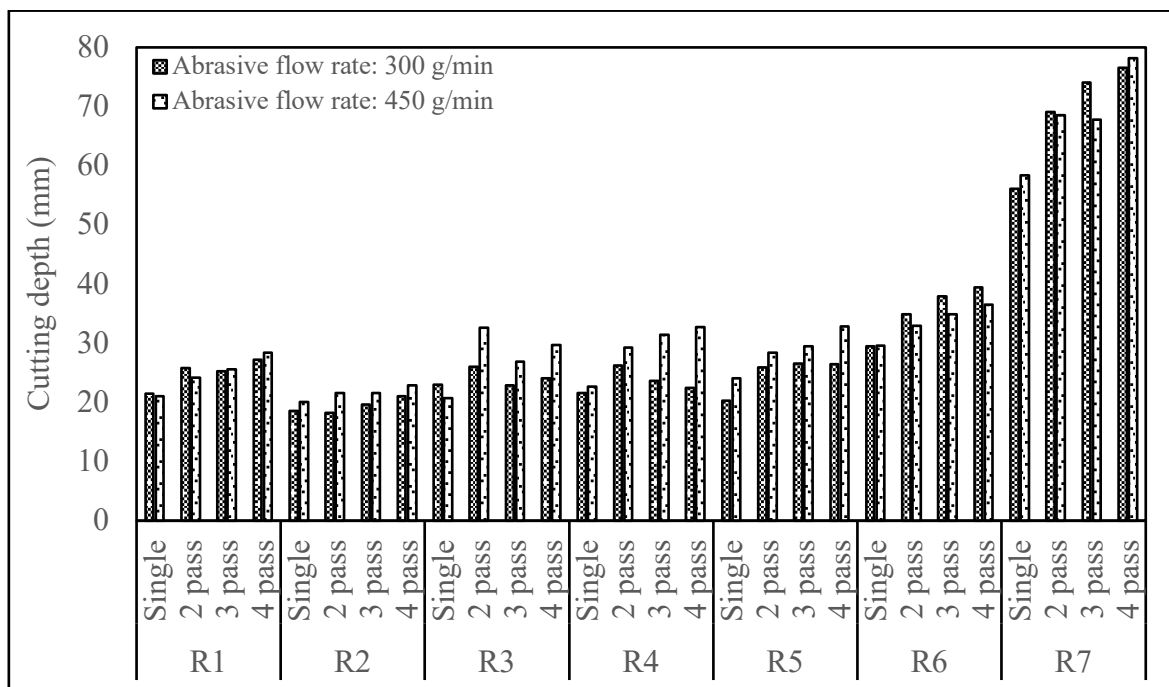


Figure 6.21. Effect of AFR increase on the cutting depths in the multi – pass cutting

were 29.04% and 25.04% for the R5 and R1 respectively. The R5 and R1 were followed by the others in terms of their average improvement rates. Moreover, Fig. 6.25 demonstrates the effect of the AFR increase on the CWZ depth in the multi – pass cutting. It is evidently seen that the CWZ depths of the R4, R5, R6 and R7 were positively effected by the increase of the AFR, while it was decreased for the R1. On the other hand, the CWZ depth of the R2

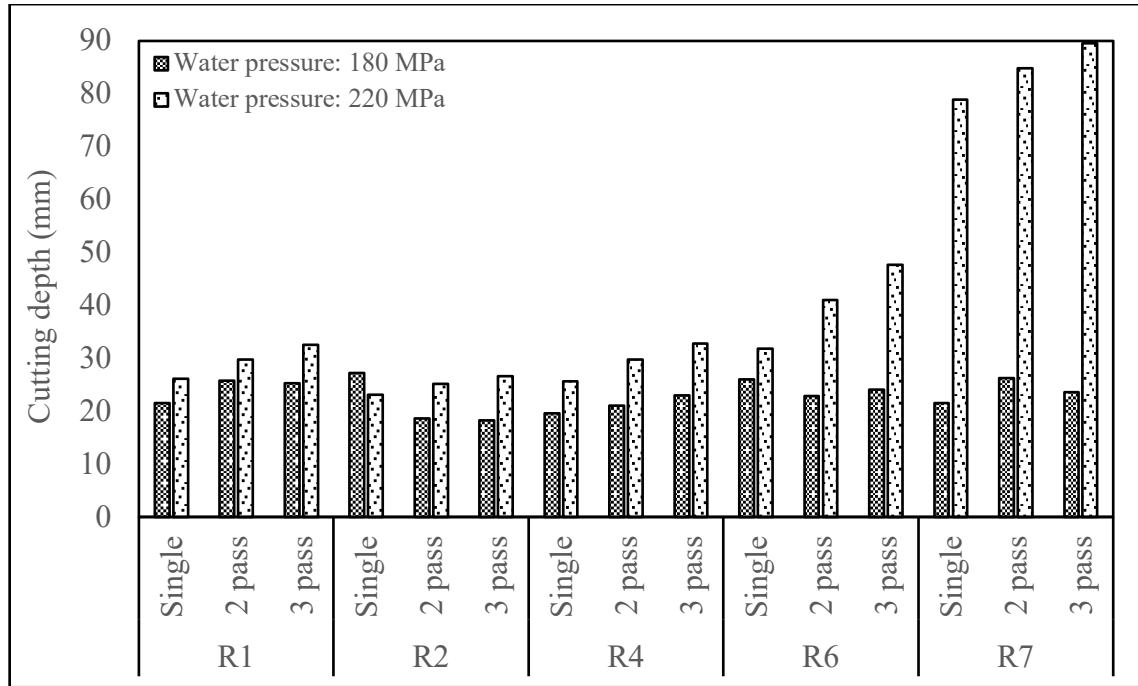


Figure 6.22. Effect of WP increase on the cutting depths in the multi – pass cutting

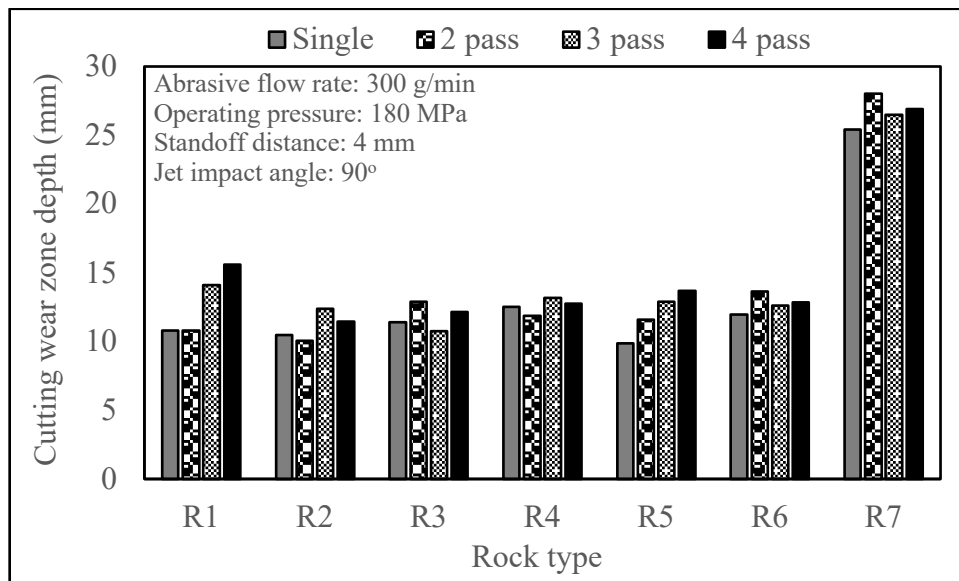


Figure 6.23. Cutting wear zone depths for the rock types in the multi – pass cutting

was only increased in two pass, while those were increased in two, three and four passes for the R3. Furthermore, one can see from Fig. 6.26 that the increasing WP increased the CWZ depths of the R1, R4 and R7 substantially. Despite the substantial increases for these rocks, the CWZ depth of the R2 was increased by two and three passes, whereas it was only three pass for the R6.

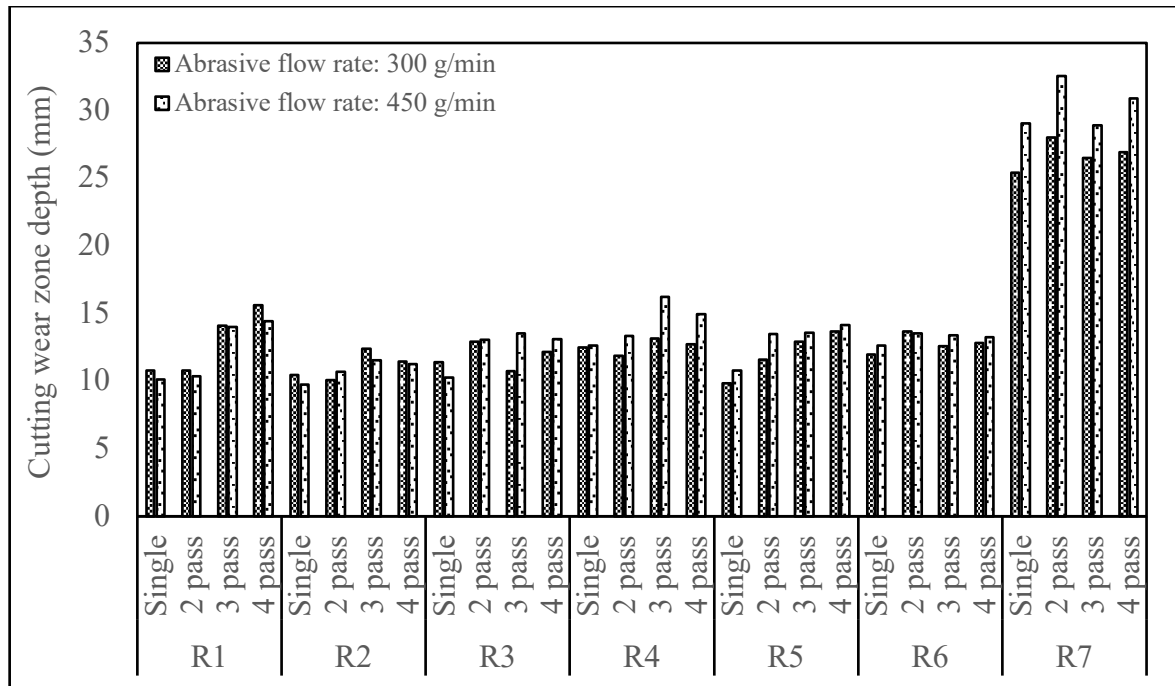


Figure 6.24. Effect of the AFR increase on the cutting wear zone depths in the multi – pass cutting

6.2. Effect of the Forward Angling the Jet on the Cuting Performance Indicators

6.2.1. Kerf Width and Kerf Taper Angle

Figure 6.27 exhibits the kerf widths of the machined rocks on the basis of AWJ forward angling the jet technique. It can be understood from the related Figure that the tested angles produced discernible results depending on rock types. For example, 75°, 88°, 85° and 80° produced the lowest kerf widths for the rock types of R1, R2, R4 and R6 respectively.

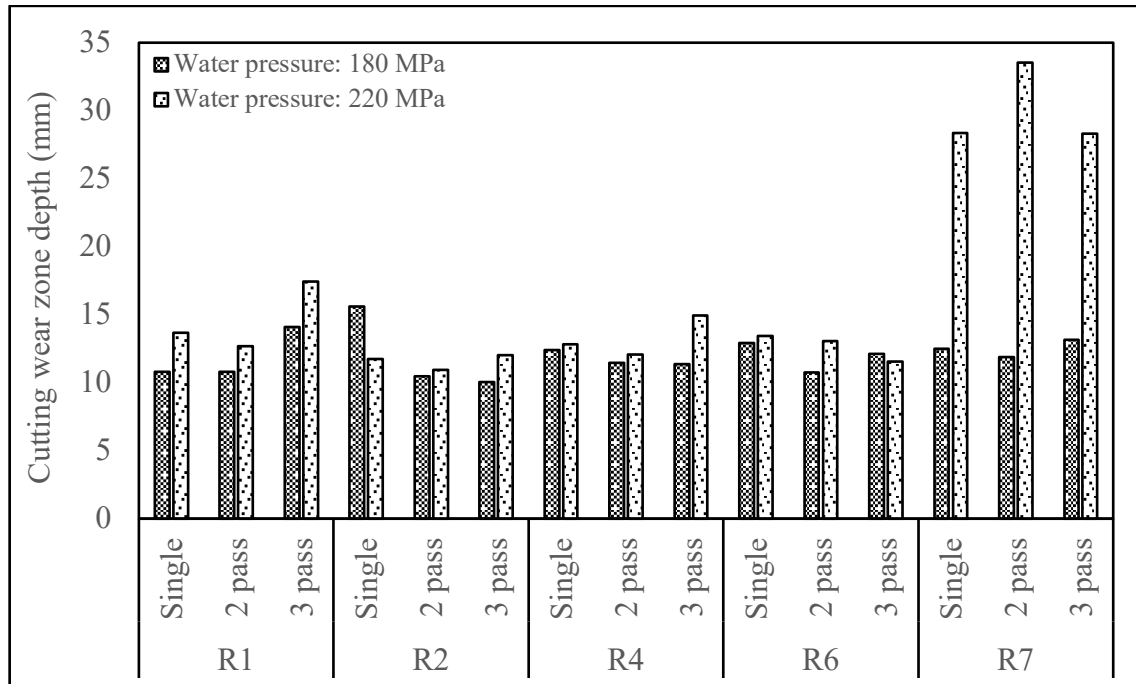


Figure 6.25. Effect of the WP increase on the cutting wear zone depths in the multi – pass cutting

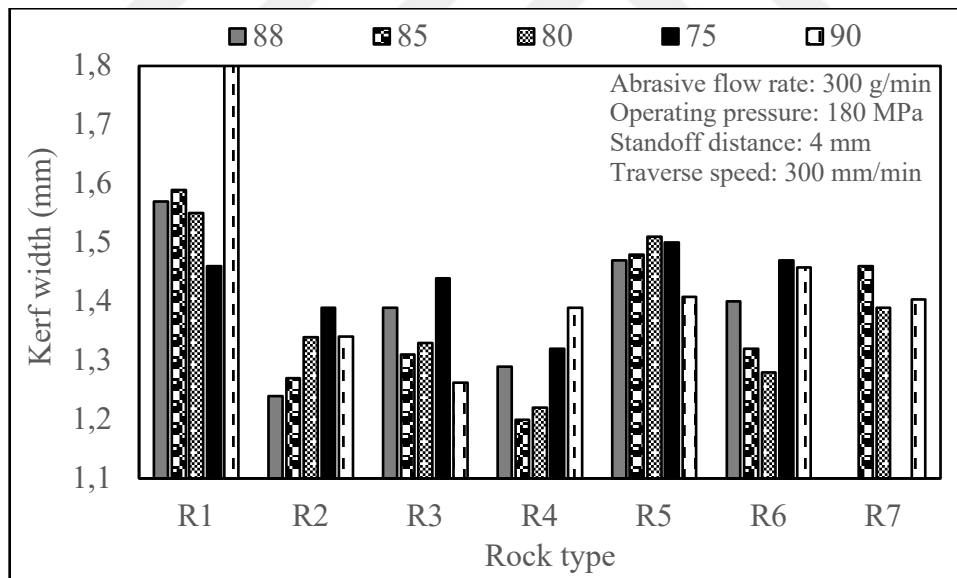


Figure 6.26. Kerf widths for the rock types in the forward angling the jet cutting

In contrast to these rocks, the standard cutting at 90° for the R3 and R5 generated the best results when compared to other impact angles. Additionally, jet impact angle of 80° produced almost the same kerf width with the impact angle of 90° for the R7. Regarding the kerf taper angles for the rock types as displayed in Fig. 6.28, jet impact angle of 80° result in the lowest kerf taper angles for the R1 and R5 respectively. Other tested jet impact angles such as 88°,

85° and 75° also produced lower kerf taper angles for the R1 when compared to the jet impact angle of 90° or jet impact angle of standard cutting in AWJ. In addition to the R1 and R5, the jet impact angle of 88° and 75° gave the lower kerf taper angles for the R3 and R4. On the other hand, jet impact angles of 85° and 88° generated the best kerf taper angle for the R6 and R7 respectively. Moreover, the kerf taper angles for the R6 were also reduced by the jet impact angles of 75°, 80° and 88° (Fig. 6.28).

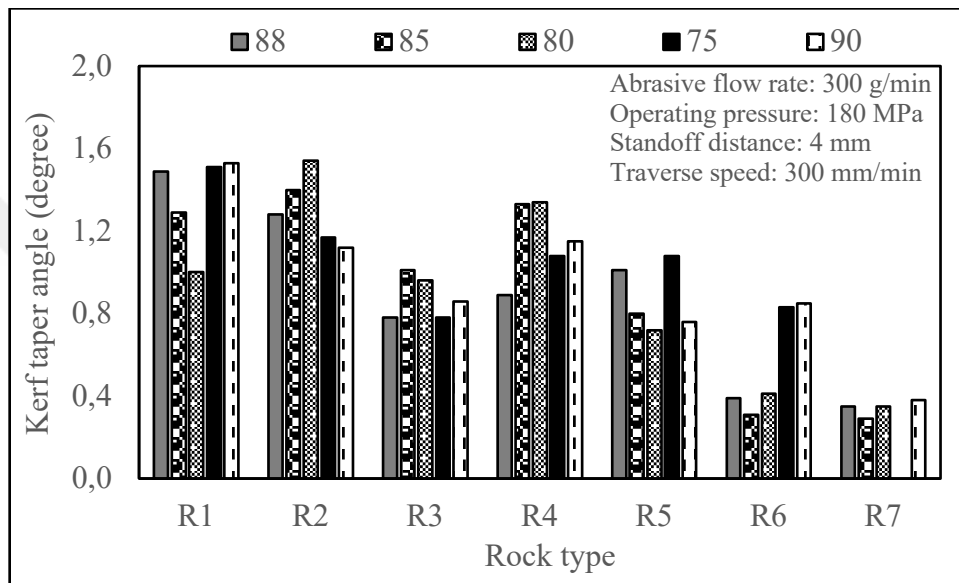


Figure 6.27. Kerf taper angles for the rock types in the forward angling the jet cutting

When the improvement rates for kerf widths and kerf cone angles of processed rock types are examined as a whole, it can be stated that significant improvements on average were achieved for the kerf widths of the R1, R4 and R6 with the rates of 14.57%, 9.53% and 6.19% respectively. For the case of the kerf taper angles, almost the same improvement rates (13.56% and 13.16%) were achieved for the R1 and R7. Herein, the kerf taper angle of the R6 had the largest improvement rate among the machined rock types (Fig. 6.29).

6.2.2. Surface Roughness

It can be concluded that the tested various jet impact angles improved the surface qualities of the machined rocks. To put it more clearly, Fig. 6.30 demonstrates that the jet impact angle of 75° result in the lowest roughness values in terms of the Ra for the R1, R5 and R6 respectively together with the lower values at 88° for the R2, 88°, 85° and 80° for

the R5 and R6. Additionally, 80° and 85° produced the lowest surface values for the R3, R4 and R7, while it was 88° and 75° for the R2. On the other hand, the surface roughness values in terms of the Rz were decreased on the basis of the forward angling the jet cutting. That is, almost all tested jet impact angles resulted in lower roughness values for the R3, R4 and R6 when compared to the jet impact angle of 90°. Besides, the jet impact angles of 88°, 85° and 75° presented the higher surface qualities for the R2 and R5, while those were 88° and 75° for the R1, 85° and 80° for the R7.

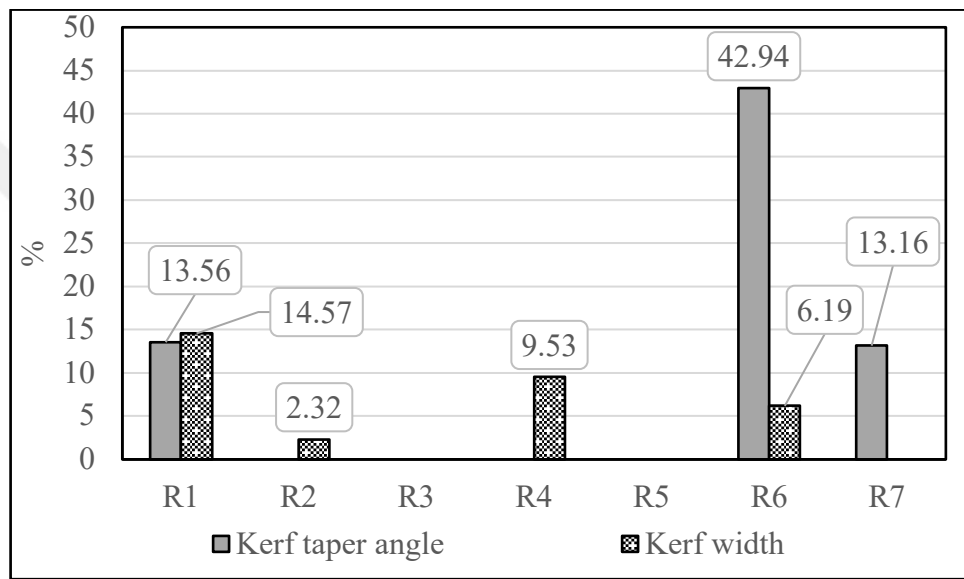


Figure 6.28. Average improvement rates for the kerf widths and kerf taper angles in the forward angling the jet cutting

On the other hand, the average improvement or reducing rates for the machined rock types based on the Ra and Rz are presented in Fig. 6.31. It can be inferred from related figure that each rock's surface roughness was improved by the forward angling the cutting. In other words, each rock type's surface roughness in terms of the Ra has the improvement rate, ranging from 2.24% to 33.31, while those were from 0.60% to 26.28% for the Rz.

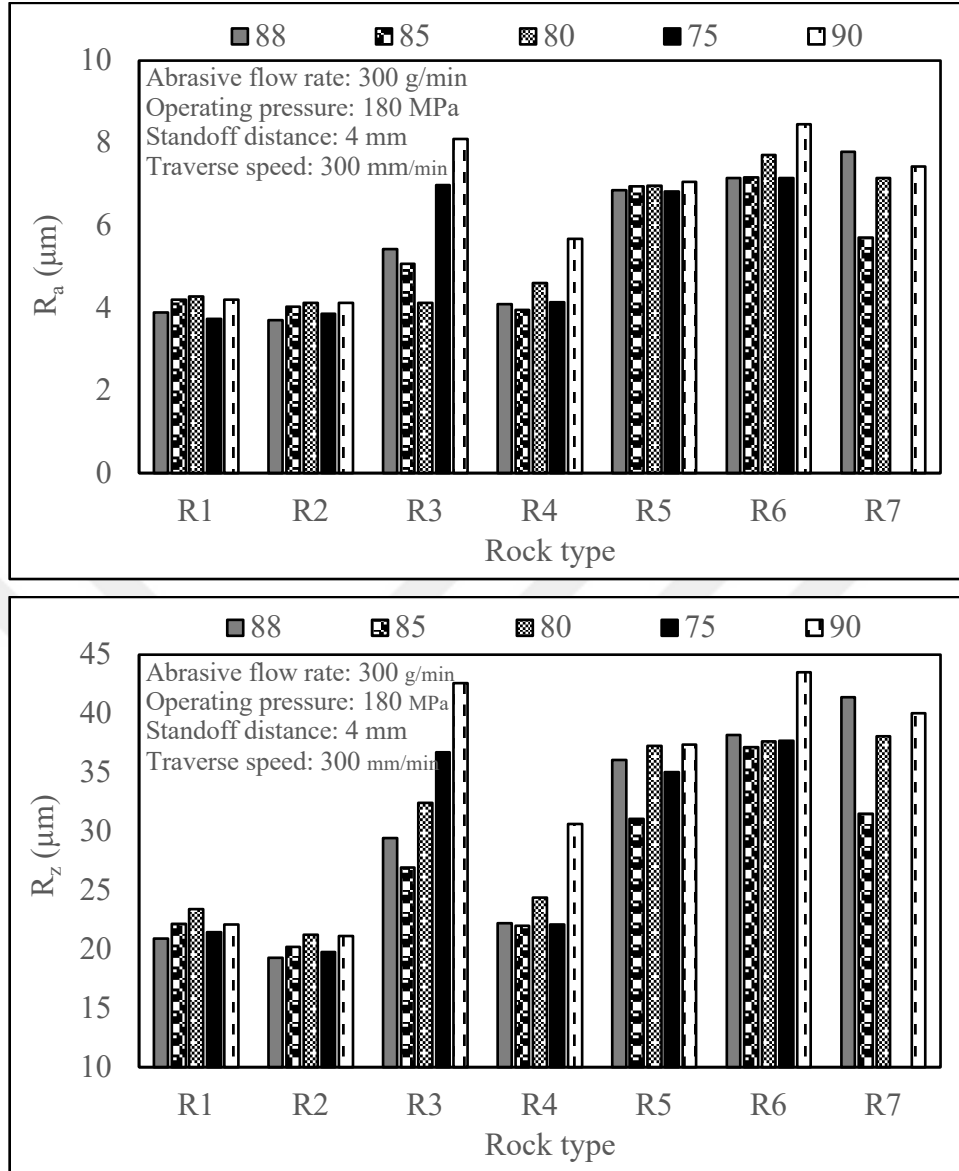


Figure 6.29. Surface roughness (R_a and R_z) for the rock types in the forward angling the jet cutting

6.2.3. Declination Angle

The AWJ forward angling the jet cutting yielded acceptable reductions in the DAs for the rock types (Fig. 6.32). It is clear from the figure that the lowest DAs were achieved at 88° for the R1 and R2; at 80° for the R3, R4 and R6; at 85° for the R5 and R7 respectively. Herein, the R7 has the largest average reduction rate of 25.40% in its DA, whereas the R6 has the lowest one of 2.11% in comparison to the DAs at 90°, which is the standard or normal cutting with AWJ technology (Fig. 6.33).

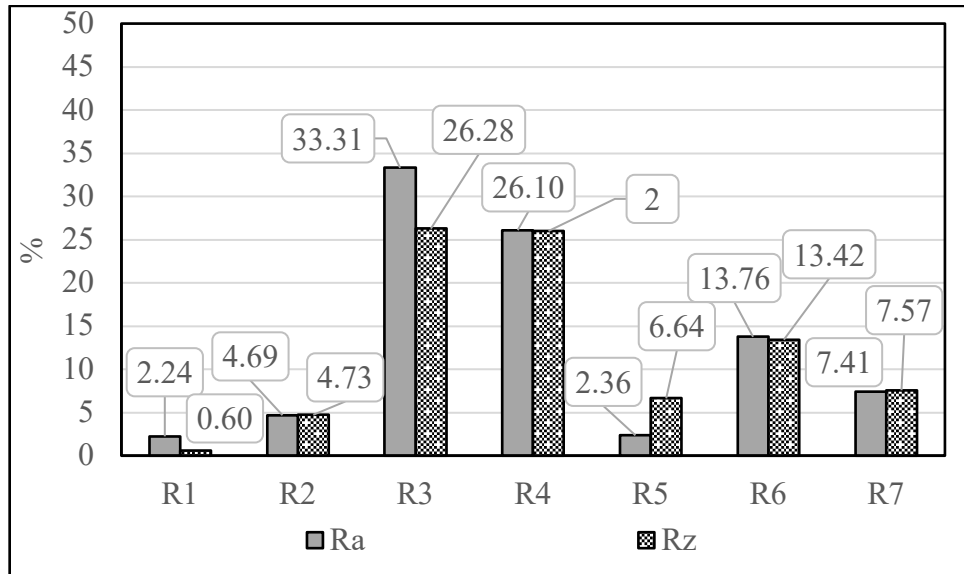


Figure 6.30. Average improvement or reducing rates for the surface roughness in terms of the Ra and Rz in the forward angling the jet cutting

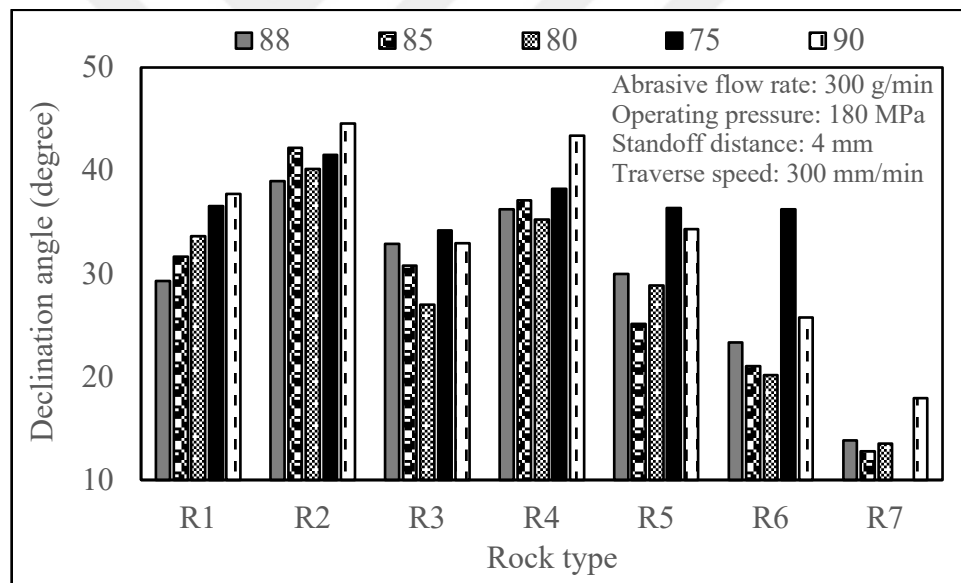


Figure 6.31. DAs for the rock types in the forward angling the jet cutting

6.2.4. Cutting and Cutting Wear Zone Depths

The AWJ forward angling cutting generated limited increases in both cutting and CWZ depths as can be followed in Fig. 6.34 and Fig. 6.35. In other words, the standard cutting where the jet impact angle is 90°, yielded the best results for the majority of the machined rocks such as R1, R2, R3 and R4 in terms of the cutting depths. However, the jet impact angle of 80° produced the largest cutting depth for the R5, while those were achieved in the

jet impact angle of 85° for the R6 and R7 respectively. The average improvement rates for these rocks were 2.97% for the R5, 8.26% for the R6 and 1.61% for the R7.

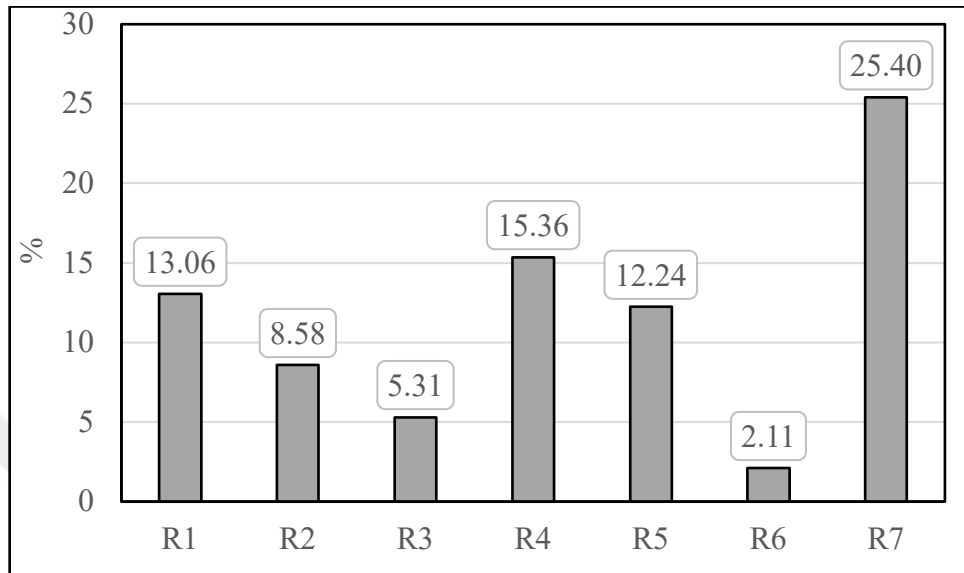


Figure 6.32. Average improvement rates for the DAs in the forward angling the jet cutting

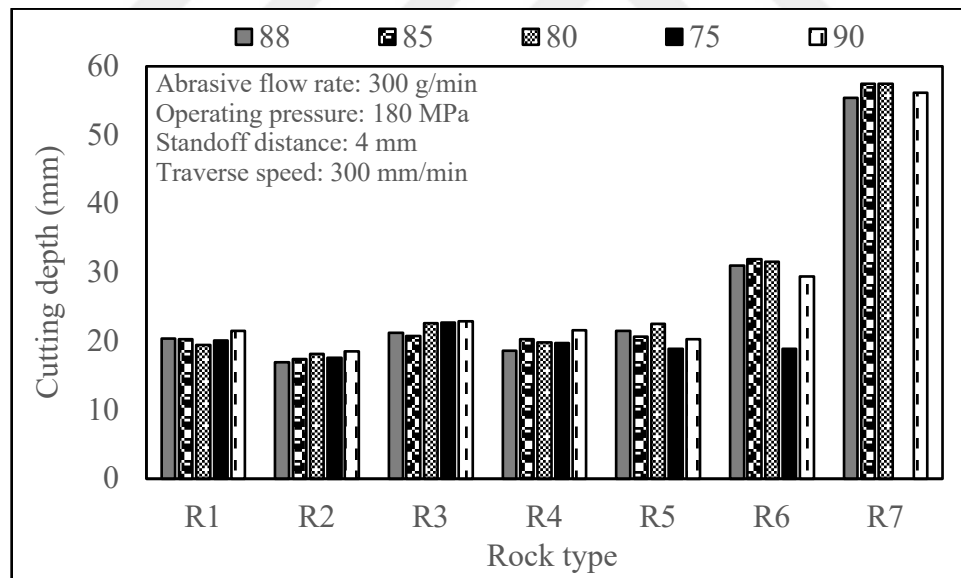


Figure 6.33. Cutting depths for the rock types in the forward angling the jet cutting

Similar to the results for the cutting depths, the changes for the CWZ depths were also remained limited. That is, the largest CWZ depths were achieved for three of the rock types including R2, R3 and R4 in the jet impact angle of 90° , while those were obtained in the jet impact angles of 75° for the R1, 85° for the R5 and 80° for the R6 and R7 respectively (Fig. 6.35). The average improvement rate for the rock types of having largest CWZ depths in

different angles were 6.96% for the R1, 5.12% for the R5, 17.08% for the R6 and 3.20% for the R7, when compared to the CWZ depths in the jet impact angle of 90 degree.

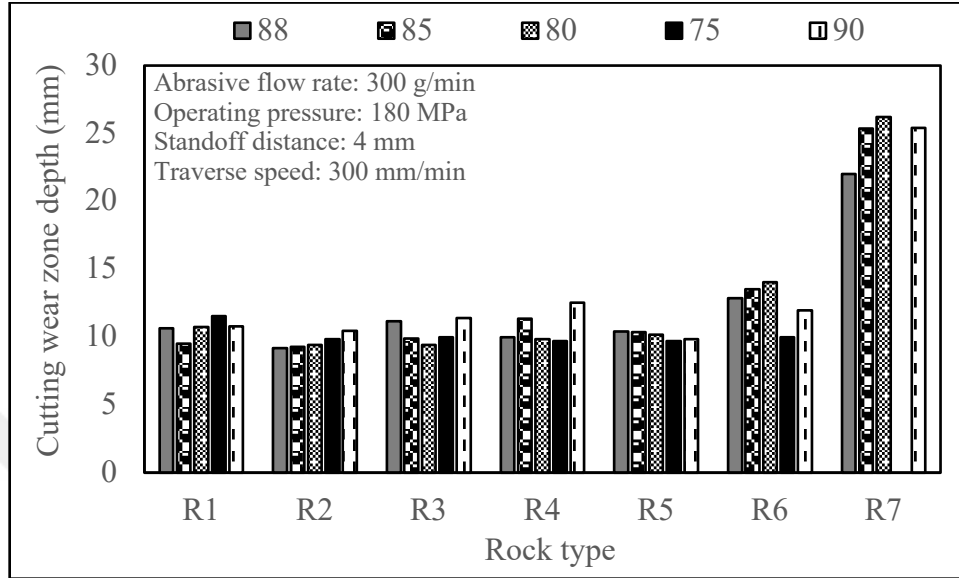


Figure 6.34. CWZ depths for the rock types in the forward angling the jet cutting

6.3. Overall Analysis of the Experimental Results

Overall experimental results demonstrated that the cutting performance of the AWJ technology is significantly influenced by both operational parameters and rock properties such as physico-mechanical and mineralogical. The AWJ multi – pass cutting consistently led to enhanced cutting quality, evident in reduced kerf width and taper angle, decreased the surface roughness, lower the DAs, and deeper cutting and CWZ depths. These effects were particularly noticeable in dense, low – porosity rocks such as the R1 and R2, which have higher UCSs, ultrasonic velocity, and fine – grained and massive textures. The progressive improvement in kerf geometry with additional passes in these rocks supports the conclusion that focused jet penetration and minimized abrasive scattering are achievable through repeated, stable cutting trajectories. This observed behavior is supported by Mahdevvari et al. (2025), who found that increases in jet velocity and abrasive concentration lead to better-defined kerfs and higher material removal rates, particularly in compact geomaterials. Likewise, Aydin et al. (2022) observed that two-pass cutting improves kerf quality, reduces taper, and enhances surface integrity by up to 47% in terms of surface striation reduction. In contrast, the rocks with higher porosity and greater water absorption capacity such as the

R5, R6, and R7, displayed more irregular kerf shapes and less consistent cutting behavior. Their heterogeneous internal structures disrupted jet coherence, increasing abrasive scattering and resulting in less predictable geometries. These rocks also showed deeper CWZ depth, likely due to abrasive infiltration into weak grain boundaries, which promotes subsurface cracking and spallation. Liu et al. (2015) demonstrated that in materials with lower UCS, jet impact angle and velocity significantly influence micro-damage formation and cutting performance, with intermediate angles (e.g., 10°) yielding optimal penetration while reducing surface-level deformation. These findings further support the notion that rock microstructure and jet dynamics interact strongly, particularly in porous lithologies. CWZ depths were particularly sensitive to both rock structure and process settings. The R5, R6, and R7 exhibited greater CWZ development across all passes, a consequence of their high porosity, lower UCS and PLS values, and higher water absorption rates. These features facilitate deeper abrasive penetration and promote matrix degradation, especially under higher energy input conditions. This observation corresponds well with Mahdevari et al. (2025)'s numerical results, which identified water absorption and porosity as key factors in subsurface wear formation. Moreover, Li et al. (2024), using a WOA-optimized support vector machine (SVM), emphasized that both stand-off distance and WP significantly influence CWZ extent. In contrast, denser rocks such as R1 and R2 exhibited relatively shallow CWZ depths. Their compact, crystalline matrices resist particle intrusion and absorb less water, which helps limit abrasive-induced fatigue. Although the CWZ depth increased with AFR and WP even in these rocks, the magnitude of the increase remained modest compared to weaker, more porous materials. This demonstrates that while higher energy enhances cutting efficiency, it can also lead to increased material wear—especially in rocks lacking structural cohesion. In another study using granite samples (Cha et al., 2021a), researchers discovered that multiple cutting outperformed single cutting. And, they claimed that the increased impact efficiency of abrasives in multi-pass cutting could explain the mechanism behind the phenomenon. In other words, the abrasive particles lose their energy when they collide with one another both before and after impacting the target. Thus, the energy loss can be minimized by making the abrasives less compact at a high traverse speed. In addition, for the abrasives to interfere with one another, their density and degree of dispersion are essential (Huang et al., 2018). Employing higher traverse speeds, which have a significant impact on the energy exposure duration and impact efficiency of the abrasive particles can reduce the interference of the abrasives. That means, faster traverse speeds

improve the energy efficiency by decreasing abrasive compactness and collision probability, which are directly correlated with abrasive density and dispersion degree. In conclusion, deeper cuts may arise from overlapping cutting as was the case in the current investigation. It is also discovered that the abrasive flow rate and waterjet pressure have discernible effects on the cutting depths in multi-pass cutting. This result is particularly consistent with the comparative study conducted by Agus et al. (2002) since they concluded that abrasive mass flow rate is one of the key variables for the optimum setting of cutting variables in multi-pass cutting processes. This finding was, further, supported by Cha et al. (2024), who indicated that an increase in the abrasive flow rate, which raises the quantity of abrasive particles impacting the rock per unit of time, is one of the key factors that improves cutting ability and deepens the cut. Additionally, one could argue that the abrasive particles' higher energy, which allow them to remove more material and produce deeper cuts, may be the reason why cutting depths tend to grow as water pressure rises. As stated by Cha et al. (2024), abrasive flow and kinetic energy increase in response to an increase in water pressure. This can result in a high energy abrasive waterjet being produced. Consequently, when this high energy abrasive waterjet beam impacts the rock, it helps to create a deeper cutting depth as in the current study. Mentioning the existence of an optimum jet impact angle, Wang et al. (2003) indicated the significance of the compensation in cutting operations where a jet impact angle from 80 to 90 degrees is applied. They claimed that the jet drag angle in the lower cutting zone is the key to reaching high cutting depths with a jet impact angle of 80 to 90 degrees. Thus, they emphasized that this would increase the particle energy component in the cutting direction, enhancing jet penetration depth. The relevant scholars stated also that cutting at angles lower than 80° would result in over compensation reducing the cutting efficiency, which may cause smaller cutting depths. Upon looking at the cutting depths achieved in the current study, it may be concluded that the results are in line with those of the relevant researchers since the cutting depths at 88°, 85° and 80° are higher for some rock types, lower for those at 75° for all rocks. Surface quality, represented by Ra and Rz values, improved across most rock types with increasing the NPs, especially in the R3, R5, and R6. Despite differences in the UCS, these rocks share fine – grained and homogeneous textures, ranging from crypto to microcrystalline matrices, which reduce erratic abrasive embedment and facilitate smoother finishes. Similarly, the R1 and R2 benefited from increased WP, likely due to enhanced energy transfer at the jet–rock interface and minimized abrasive rebound. However, rocks with more granular structures and higher void ratios, such as the

R6 and R7, demonstrated less pronounced improvements in the surface roughness. Their internal heterogeneities likely prevented the jet from maintaining consistent cutting action across the surface, which is essential for optimal finish. Declination angle, an indicator of jet path stability, also decreased notably with increased the NPs, especially in rocks with moderate porosity such as the R5 to R7. The DA values approached near-zero levels in four-pass operations, indicating a more stable and consistent abrasive path. These findings align with Cha et al. (2024), who reported that multi – pass strategies smooth out initial surface irregularities, enabling more controlled abrasive trajectories in subsequent passes. Enhanced jet stability was also supported by increased the AFR and WP, particularly when paired with precise stand-off distance adjustments. Such parameter optimization is consistent with hybrid machining research, where jet coherence has been shown to significantly influence dimensional accuracy and cut stability.

Collectively, these outcomes underline the importance of tailoring AWJ parameters to the mechanical and textural properties of the rocks. High – strength, low-porosity rocks are best processed using the AWJ multi-pass strategies with increased the WP and AFR to achieve cleaner, deeper cuts while preserving surface integrity. Meanwhile, more porous and weaker rocks require moderated energy input and optimized SDs to control the CWZ depths and minimize surface degradation. These results align with the study of Jiang et al. (2020), who emphasized that optimal penetration occurs at jet impact angles between 80° and 90° , where the jet's energy vector is best aligned with the cutting direction. This behavior was partially validated in the current study, especially for rocks with intermediate properties, which benefited from carefully selected impact angles during angled cutting operations.

7. MODELLING RESULTS AND DISCUSSION

7.1. Modelling Results of the Cutting Performance Indicators

Once the ML-based models developed for predicting the cutting performances such as the kerf width, kerf taper angle, surface roughness, declination angle, cutting depth and cutting wear zone depth using the experimental data, rock properties and operating variables, their performances were calculated using the Eqs. [2.13], [2.14] and [2.15] to provide a comprehensive evaluation and selection the best models. In the following sub-sections, the results are presented for each cutting performance indicator on the basis of three best models in detail, with the exception of kerf width and kerf taper angle.

7.1.1. Kerf Width and Kerf Taper Angle

Among the MLAs, it was determined that the ANN presents the best results for modelling both the kerf width and kerf taper angle of the machined rocks. In other words, the ANN's prediction trend almost coincided with the actual data when considering the response plots, shown in Fig .7.1. Additionally, the ANN models' reliability was confirmed by their R^2 values as 0.95 and 0.90 for the kerf width, 0.96 and 0.88 for the kerf taper angle in terms of the training and testing data respectively. On the other hand, while the R^2 is useful for assessing a model performance, it may be insufficient by itself to offer thorough evaluation. Thus, other evaluation criteria including the RMSE, MAPE, plots of the actual versus predicted values and residuals for both training and testing data set should be considered in order to confirm the generality and plausibility of the proposed models. Thus, these evaluation criteria were also tested in the modelling approach. Table 7.1 gives the the calculated results for RMSE and MAPE together with the R^2 values for both training and testing data respectively. Figures in Table 7.1 tell us that the developed ANN models have

Table 7.1. Errors of the ANN model for predicting the kerf width

Performance Indicator	Model	Training data			Testing data		
		RMSE	R^2	MAPE	RMSE	R^2	MAPE
Kerf width	ANN	0.0387	0.95	3.6	0.0938	0.90	4.2
Kerf taper angle		0.0905	0.96	4.5	0.2547	0.88	4.9

the RMSE of 0.0387 and 0.0938, the MAPE of 3.6 and 4.2 for the kerf width, the RMSE of 0.0905 and 0.2547, the MAPE of 4.5 and 4.9 for the kerf taper angle in terms of both training and testing respectively. The MAPE values for both kerf width and kerf taper angle in terms of the training and testing also indicate that the developed ANN models fall excellent capability category in predicting the kerf width and kerf taper angle according to classification for the MAPE in Table 5.1.

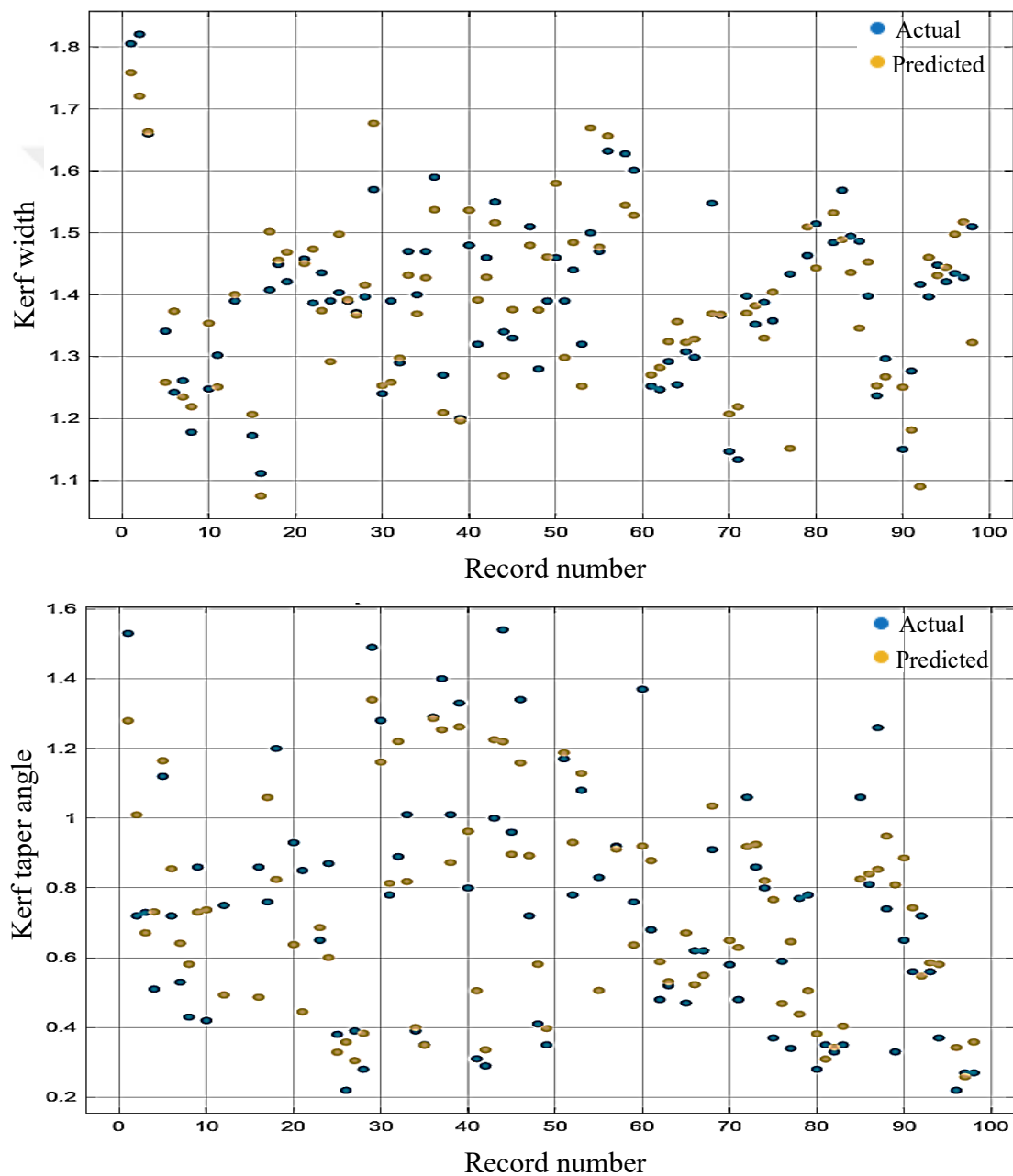


Figure 7.1. Response plots given by the developed ANN models for the kerf width and kerf taper angle

From the perspective of the predicted vs actual values and fits as shown in Fig. 7.2, it can be deduced that there is a strong correlation between the predicted and actual values for both kerf width and kerf taper angle. These results support the validity of the developed ANN models and suggest that the kerf width and kerf taper angle can be modelled in this manner. As an additional validation technique for examining the developed models, residue analysis is a superior test, offering a highly efficient way to identify anomalous behaviors of the data in the form of residuals (Aydin et al., 2013). Therefore, plots of the residuals are depicted in

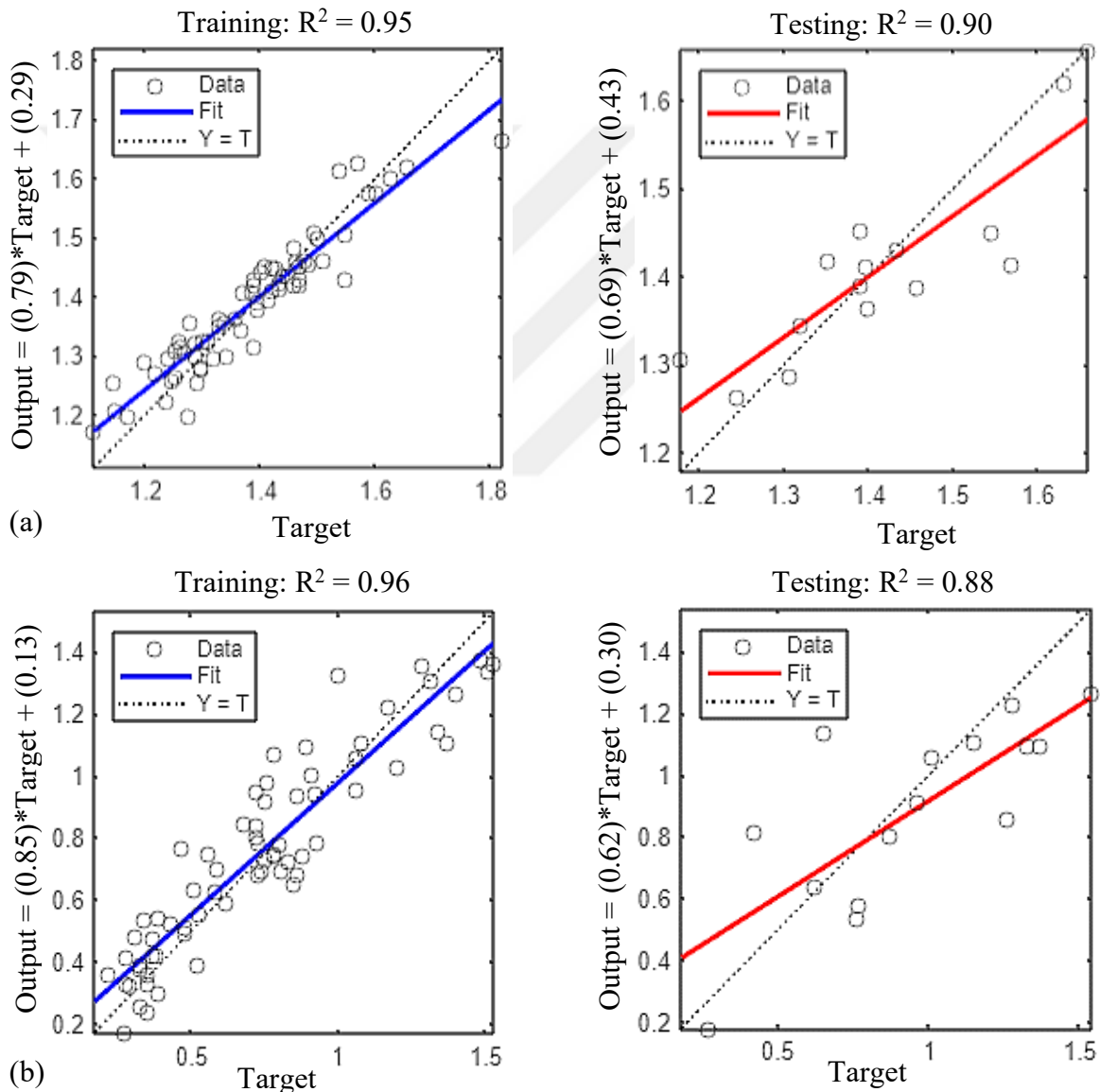


Figure 7.2. Actual vs predicted data and fits for the kerf width (a) and kerf taper angle (b)

Fig. 7.3 for both training and testing data set. It is generally evident that the residuals appear to be dispersed randomly throughout the line. This discloses that the validation of the

developed ML-based models was approved. Overall, the modelling results shows that the developed ANN models are capable of providing sufficient kerf width and kerf taper angle predictions for the conditions taken into account in this investigation.

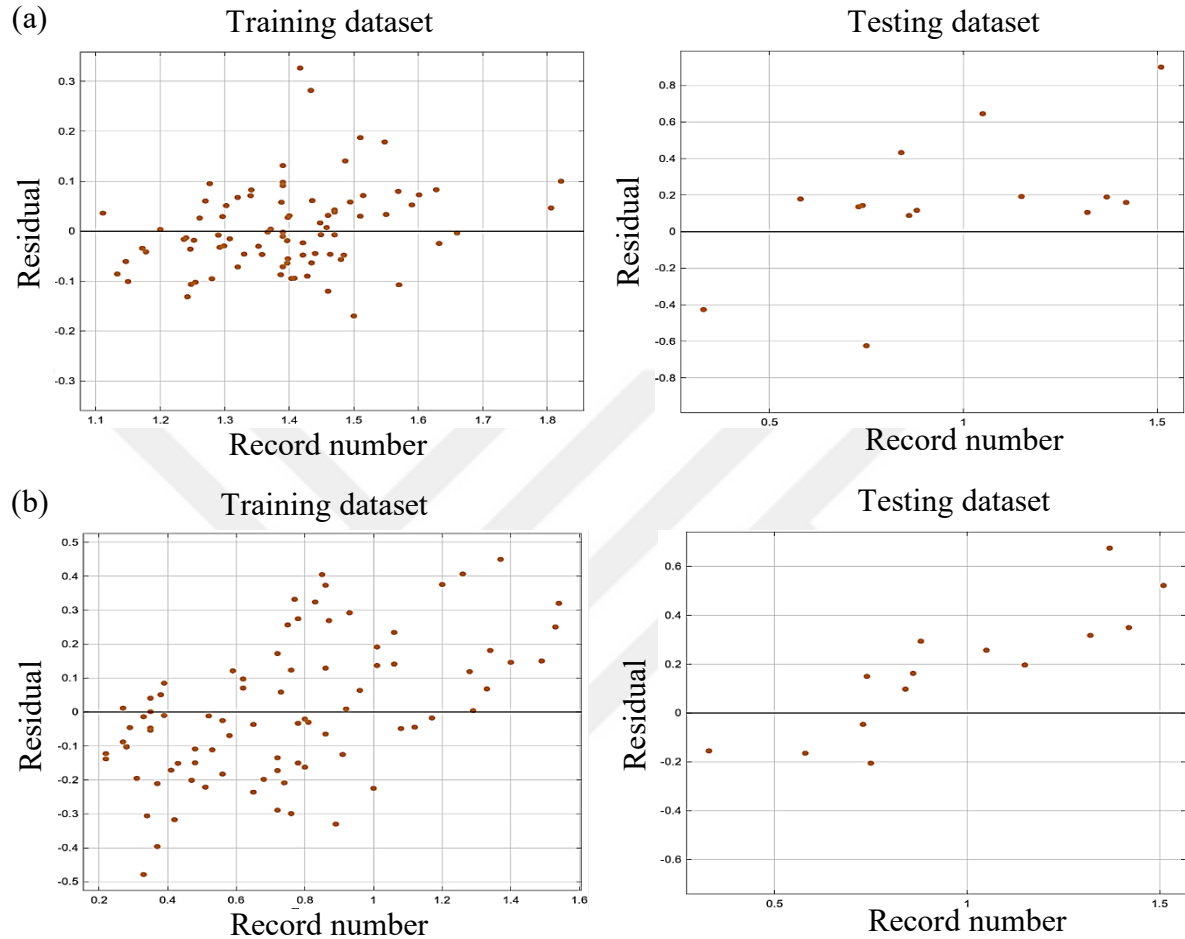


Figure 7.3. Residue plots of training and testing data sets for the kerf width (a) and kerf taper angle (b)

7.1.2. Surface Roughness

Three best ML – based models for surface roughness are the ANN, SVM and GBT for the Ra and ANN, SVM and GPR for the Rz. Additionally, the response plots obtained by these models are exhibited in Fig. 7.4 for the Ra and Fig. 7.5 for the Rz respectively. As it is clearly seen from the related figures that each model's prediction trend almost match with the actual data.

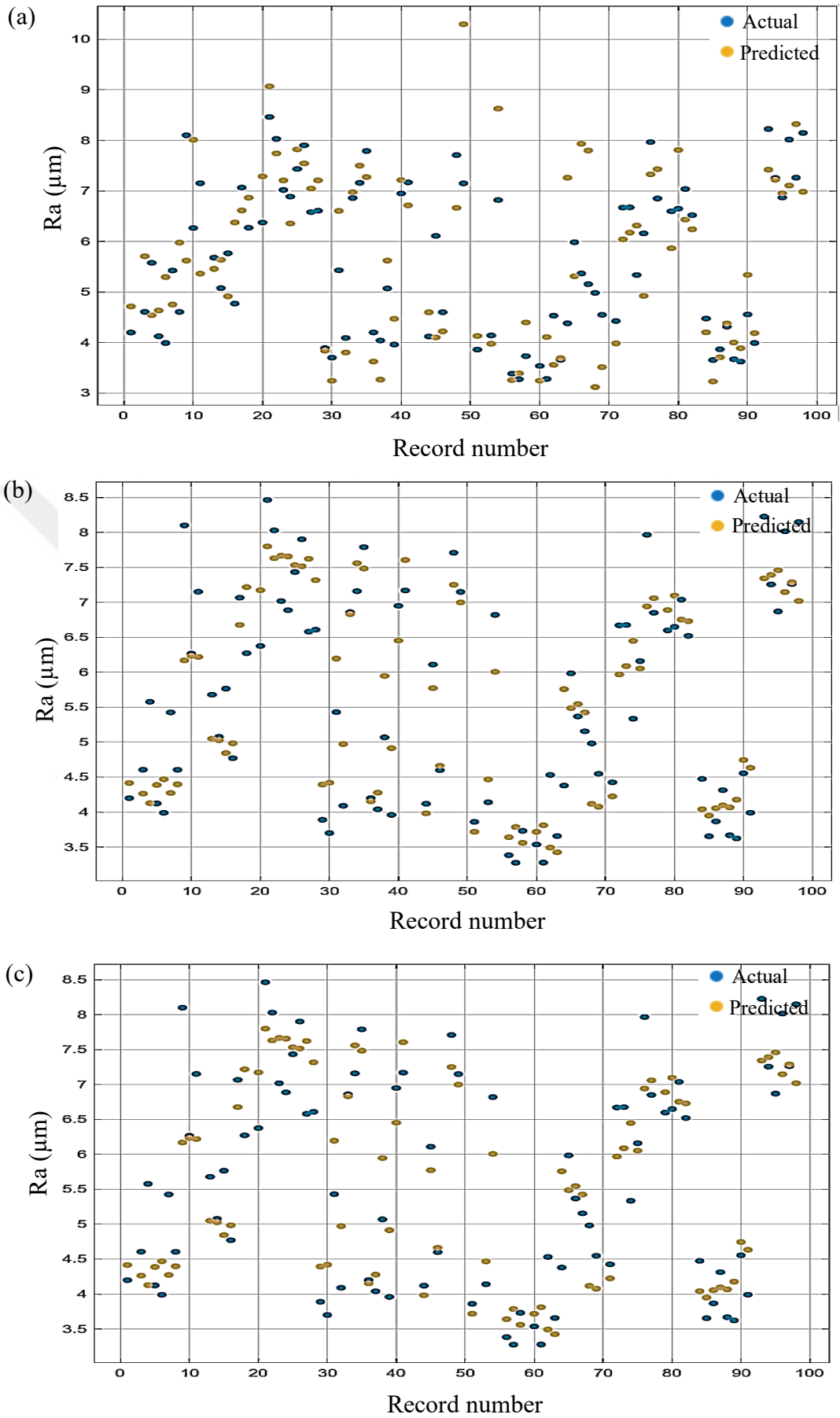


Figure 7.4. Response plots given by the developed ANN (a), SVM (b) and GBT models (c)

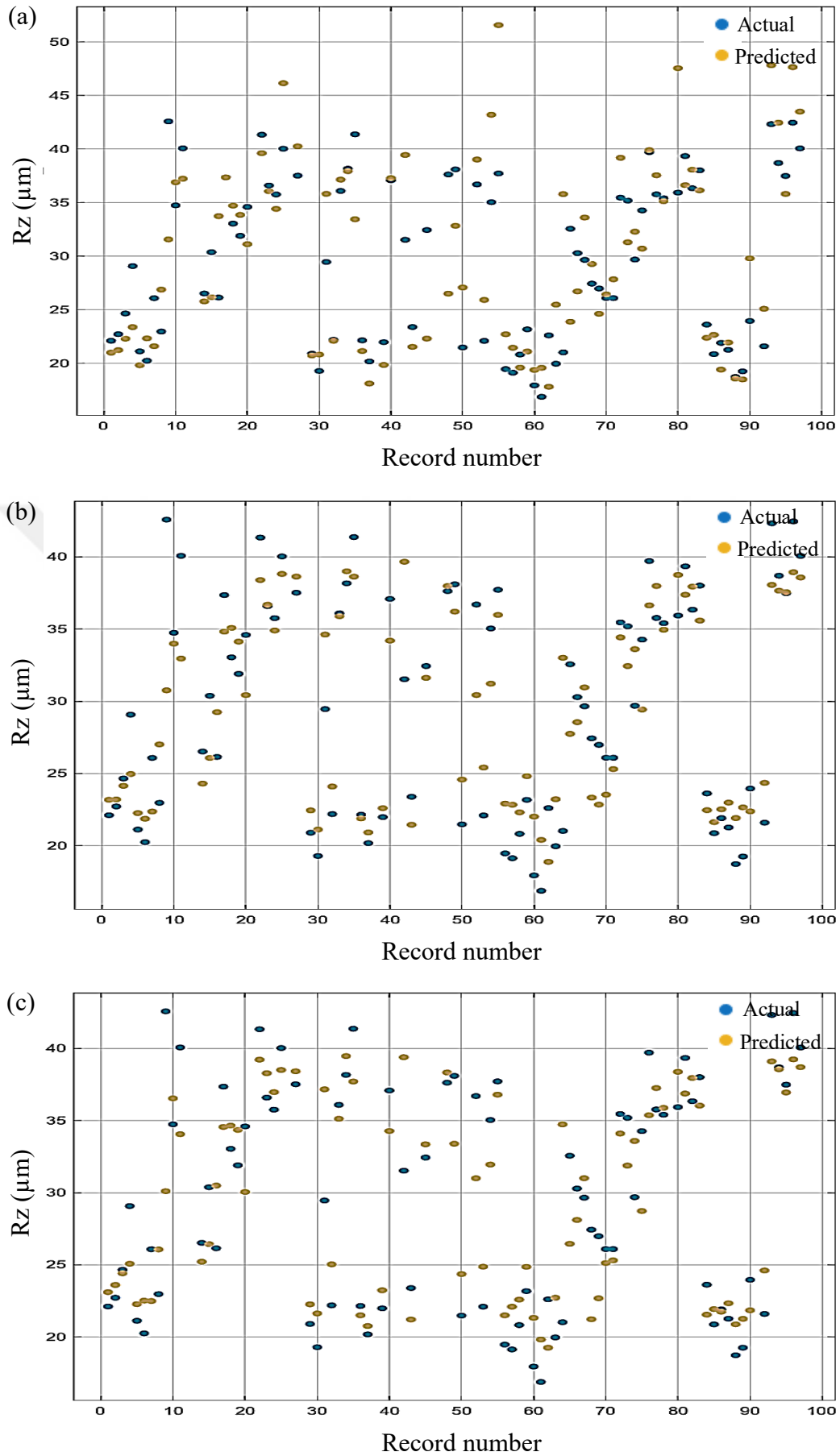


Figure 7.5. Response plots given by the developed ANN (a), SVM (b) and GBR models (c)

Moreover, the models' reliabilities were confirmed by their R^2 values as the ANN, SVM and GBT of 0.96, 0.83 and 0.82 for the Ra, the ANN, SVM and GPR of 0.90, 0.81 and 0.79 for the Rz in terms of the training dataset, while those were 0.87, 0.78 and 0.76 for the Ra and 0.88, 0.84 and 0.82 for the Rz in terms of the testing dataset respectively.

Other evaluation criteria including the RMSE, MAPE, plots of the actual versus predicted values and residuals for both training and testing data set were also considered in order to confirm the generality and plausibility of the proposed models. Table 7.2 gives the the calculated results for RMSE and MAPE together with the R^2 values for both training and testing data respectively. As can be followed, almost all developed models have excellent capabilities for predicting the surface roughness according to classification of the MAPE in Table 5.1.

Table 7.2. Errors of the developed models for the surface roughness (Ra and Rz)

Performance indicators	Model	Training data			Testing data		
		RMSE	R^2	MAPE	RMSE	R^2	MAPE
Ra	ANN	1.3435	0.96	7.1	0.8574	0.87	7.6
	SVM	0.6334	0.83	9.4	0.7595	0.78	10.9
	GBT	0.6491	0.82	8.7	0.6240	0.76	8.9
Rz	ANN	4.7181	0.90	9.8	3.5236	0.88	8.6
	SVM	3.4095	0.81	9.5	3.3100	0.84	8.5
	GPR	3.5777	0.79	9.7	3.4522	0.82	9.1

As shown in Fig. 7.6 and 7.7, the results indicate a significant relationship between the actual and predicted values for both Ra and Rz. These results support the validity of the developed models and suggest that the Ra and Rz can be modelled in this manner. Depicted in Fig. 7.8 and 7.9, the residuals for both training and testing data set evidently exhibit to be dispersed randomly throughout the line, approving the validation of the developed ML-based models. Consequently, the modelling results show that the developed models are capable of providing sufficient Ra and Rz predictions for the conditions taken into account in this study.

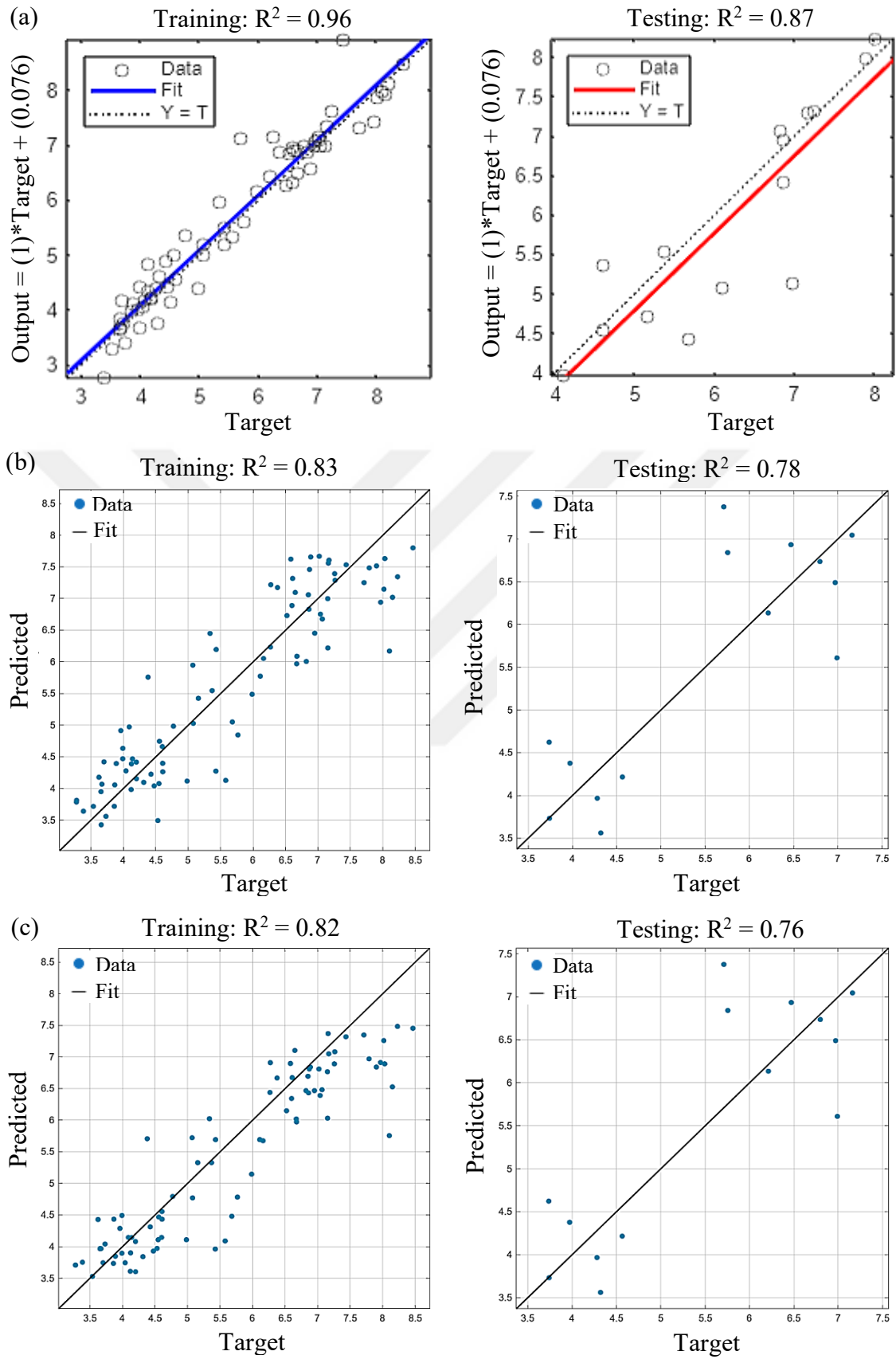


Figure 7.6. Actual vs predicted data and fits for the Ra by the ANN model (a), the SVM model (b) and the GBT model (c)

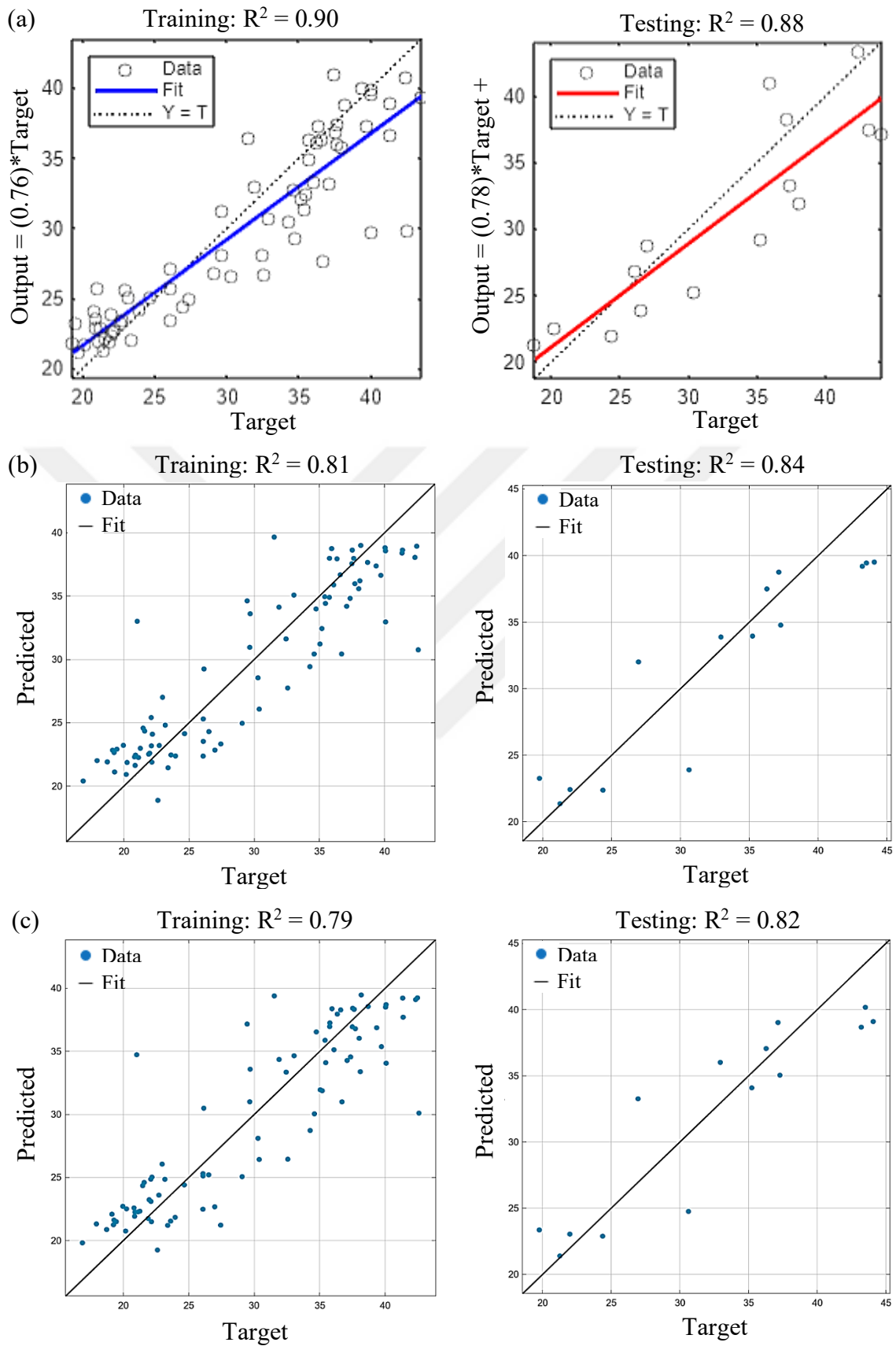


Figure 7.7. Actual vs predicted data and fits for the Rz by the ANN model (a), the SVM model (b) and the GBR model (c)

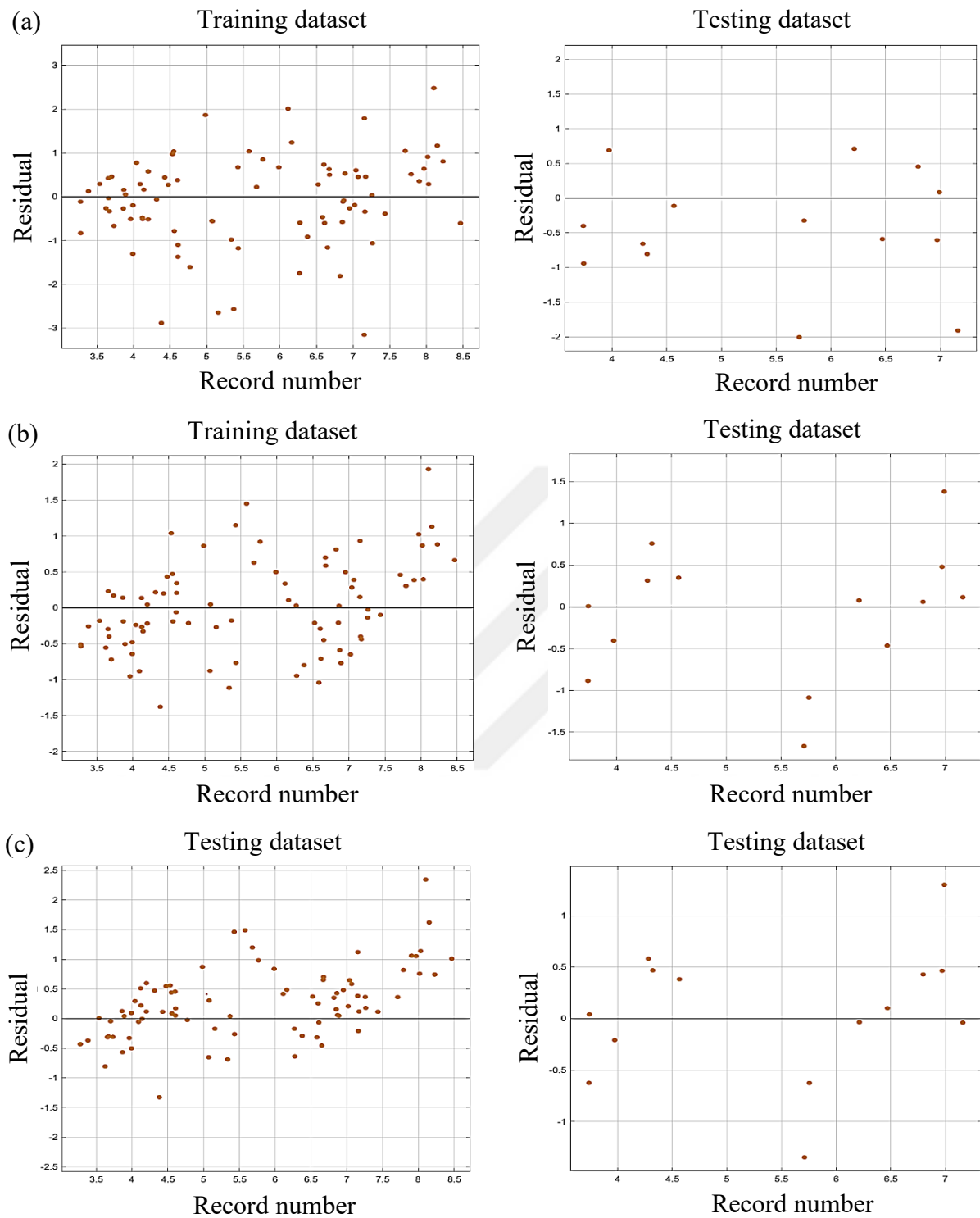


Figure 7.8. Residue plots for the Ra by the ANN model (a), the SVM model (b) and the GBT model (c)

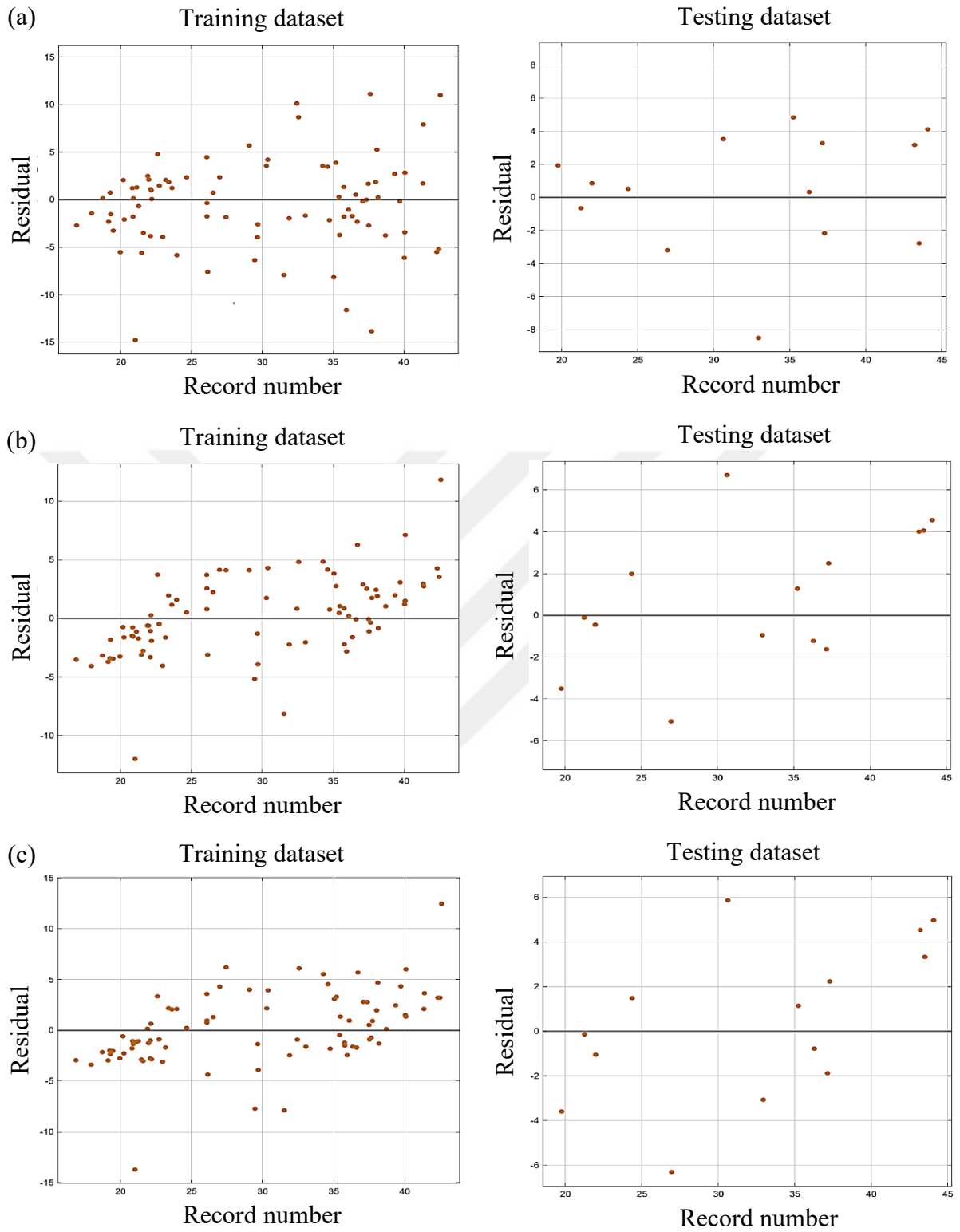


Figure 7.9. Residue plots for the Rz by the ANN model (a), the SVM model (b) and the GBR model (c)

7.1.3. Declination Angle

The response plots of proposed ML-based models for the DA are shown in Fig.7.10. One can understand from Fig. 7.10 that the prediction trends of all proposed models are in good agreement with the experimental data. On the basis of this, it can be concluded that the proposed models are reliable in predicting the DAs of the machined rocks. On the other hands, in order to confirm the generality and plausibility of the proposed models other error indicators such as RMSE and MAPE were also calculated and presented in Table 7.3. It is evidently seen that that the MAPEs' of the proposed models for both training and testing data sets are in the category of excellent accuracy since their values are less than the limit value of 10 as specified in Table 5.1. In addition, the proposed models' RMSE values are also close to the zero, indicating the reliability of the models in prediction of the declination angle. Moreover, considering the regression results displayed in Fig. 7.11, it can be deduced that there is a strong relationship between the predicted and actual DAs. As a further method of validation for the proposed models, the plots of the residuals are depicted and illustrated in Fig. 7.12. It is evidently seen from the figure that the residuals appear to be dispersed randomly throughout the line, approving the validation of the proposed ML-based models. Overall analysis of the modeling results indicates that the proposed ML-based models are quite good at predicting the DAs.

Table 7.3. Errors of the ML-based models for the DAs

Model	Training data			Testing data		
	RMSE	R ²	MAPE	RMSE	R ²	MAPE
ANN	4.3449	0.98	7.7	3.1347	0.94	8.3
GBDT	3.6979	0.92	6.3	2.9195	0.93	6.4
GPR	3.6191	0.92	8.6	3.3488	0.91	2.3

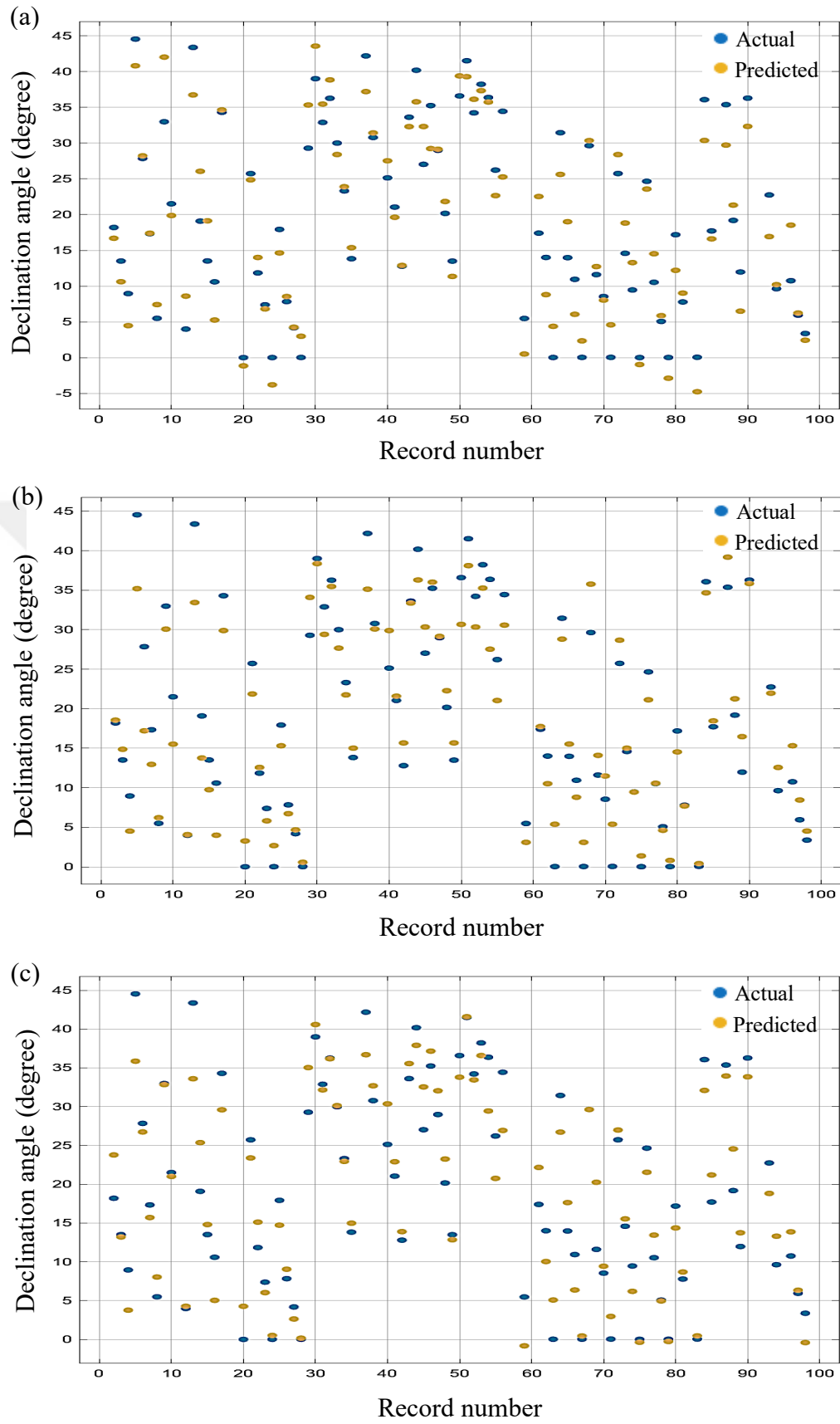


Figure 7.10. Response plots given by the developed ANN model (a), GBDT model (b) and GPR model (c)

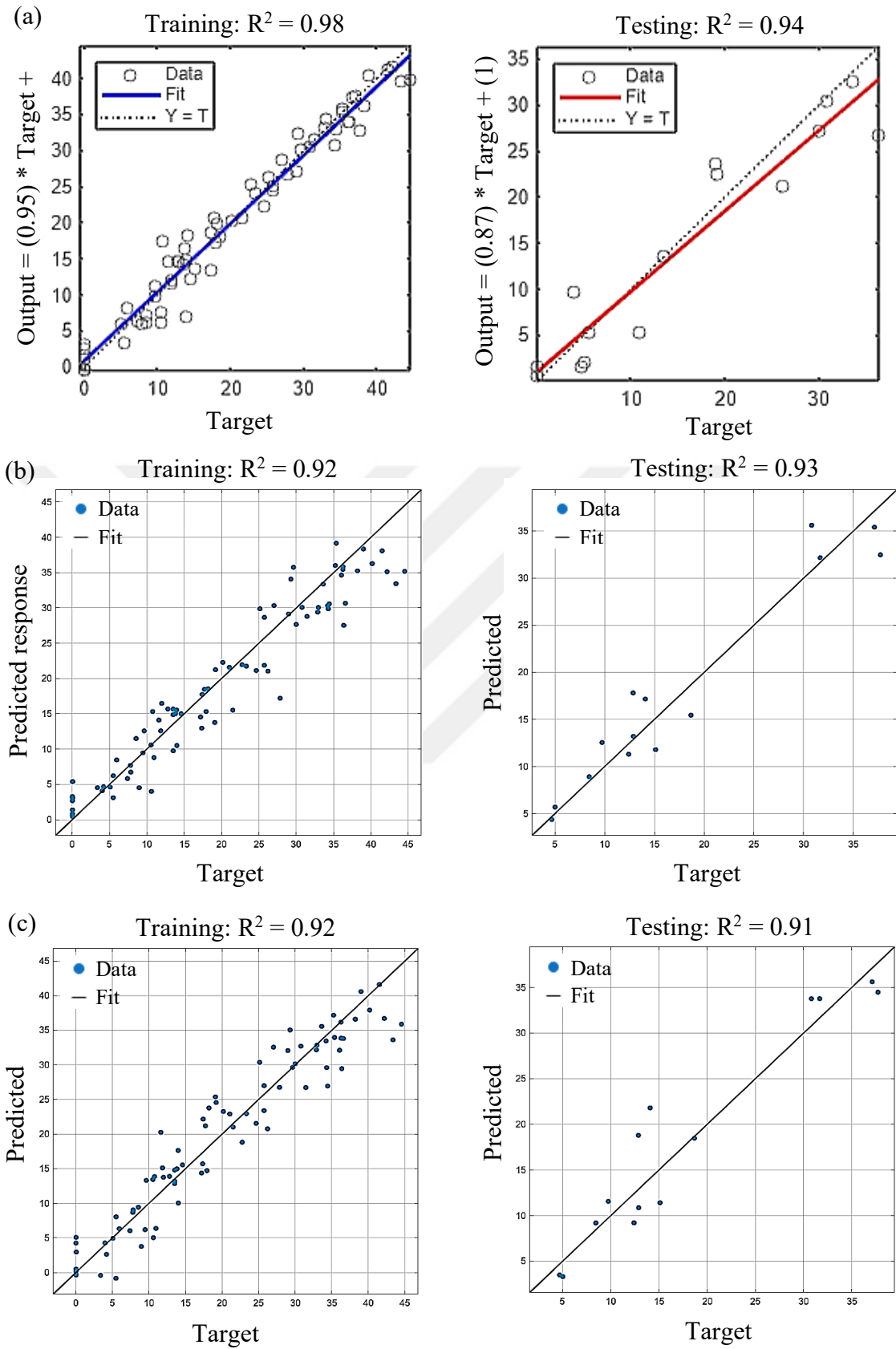


Figure 7.11. Actual vs predicted data and fits for the DAs by the ANN model (a), the GBDT model (b) and the GBR model (c)

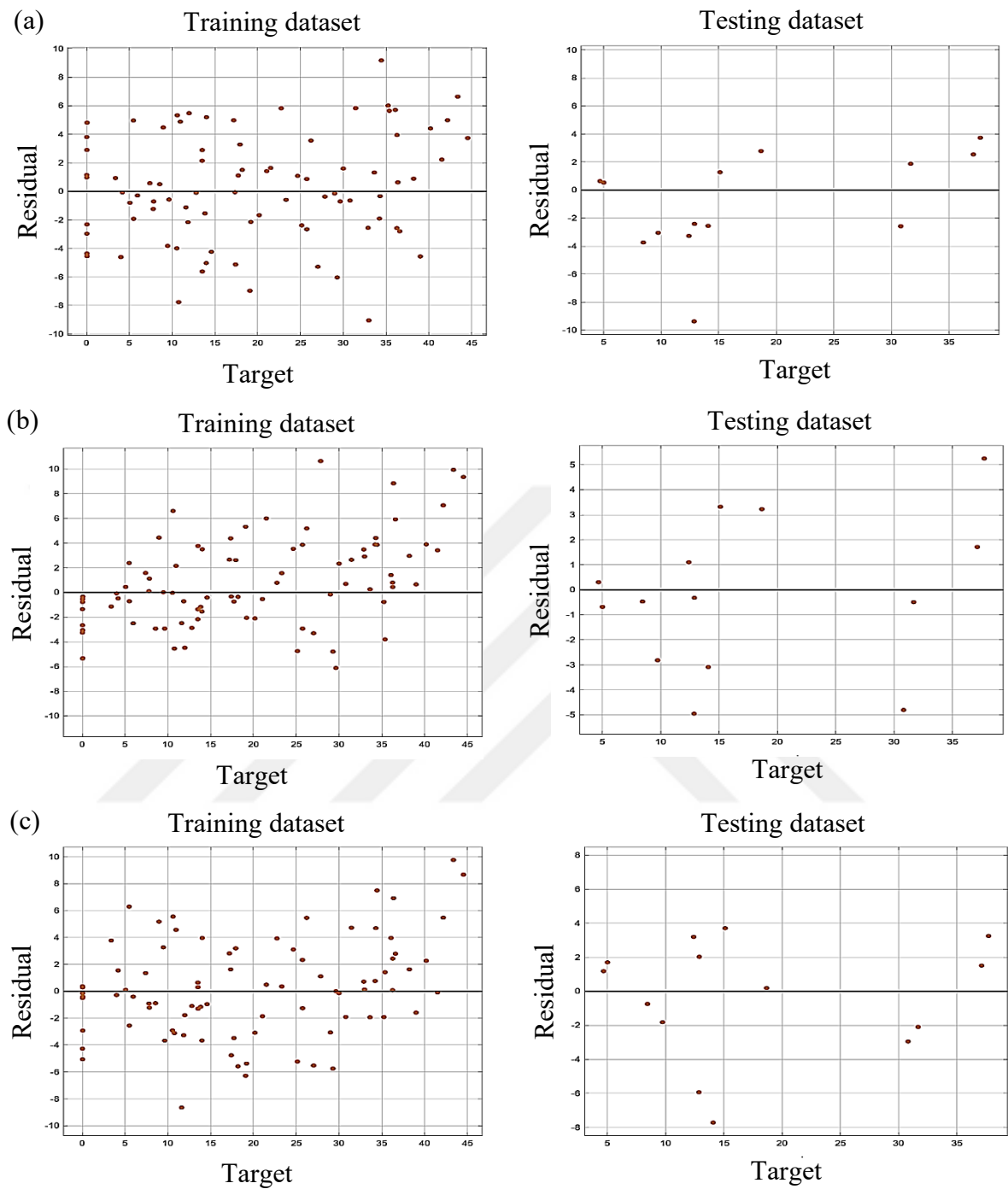


Figure 7.12. Residue plots for the DAs by the ANN model (a), GBDT model (b) and the GBR model (c)

7.1.4. Cutting and Cutting Wear Zone Depths

The response plots of three ML-based models for the cutting and CWZ depths are displayed in Fig. 7.13 and 7.14. Undoubtedly, it can be concluded that the developed ML-

based models are excellent tools for predicting the cutting and CWZ depths when considering the calculated results in Table 7.4 since they have largest R^2 values, ranging from 0.93 to 0.98 for training and from 0.83 to 0.87 for testing in terms of the cutting depth, while those were ranged from 0.92 to 0.99 for training and from 0.91 to 0.96 for testing in terms of the CWZ depth. In other words, all models' prediction trends almost coincide with the experimental data, indicating the reliability of the developed models in predicting the cutting nad CWZ depths.

Table 7.4. Errors of the ML-based models for the cutting and CWZ depths

Performance indicators	Model	Training data			Testing data		
		RMSE	R^2	MAPE	RMSE	R^2	MAPE
Cutting depth	GPR	2.655	0.98	6.4	1.880	0.87	5.9
	ANN	3.649	0.96	9.0	1.991	0.86	6.9
	SVM	4.569	0.93	9.3	2.149	0.83	7.7
CWZ depth	ANN	1.9000	0.99	10	1.6256	0.91	8.2
	GPR	1.3824	0.94	7.3	1.5951	0.95	5.6
	SVM	1.5877	0.92	8.0	1.4365	0.96	6.0

Additionally, as it can be followed, the GPR model provides the best accuracy with an RMSE of 2.655 and 1.880, MAPE of 6.4 and 5.9 for training and testing respectively. Other models as the ANN and SVM follow the GPR based on the RMSE and MAPE values in terms of the cutting depth. In terms of the CWZ depth, the ANN model gives the best accuracy with an RMSE of 1.9000 and 1.6256, MAPE of 10 and 8.2 for training and testing respectively. Other models such as the GPR and SVM follow the ANN based on the RMSE and MAPE values. From the perspective of the predicted and actual cutting depths as shown in Fig. 7.15 and 7.16, it can be reported that there is a strong correlation between the predicted and actual values including the cutting and CWZ depths. Moreover, the plots of the residuals are depicted in Fig. 7.17 and 7.18, as an additional validation technique for examining the developed models. It is generally evident from the related figures that the residuals appear to be dispersed randomly throughout the line. This discloses that the validation of the developed ML-based models was approved.

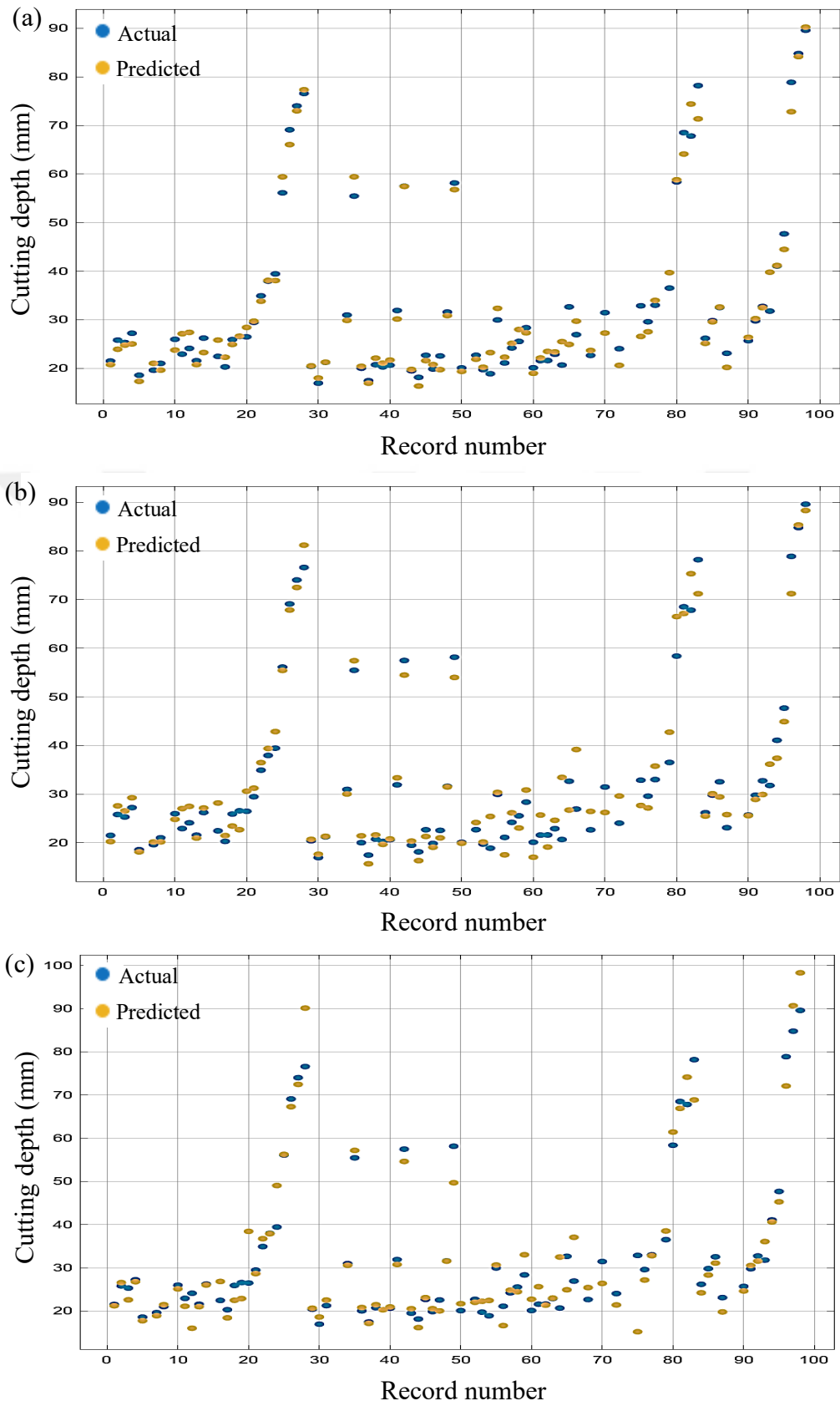


Figure 7.13. Response plots given by the developed GPR model (a), ANN model (b) and SVM model (c) for the cutting depth

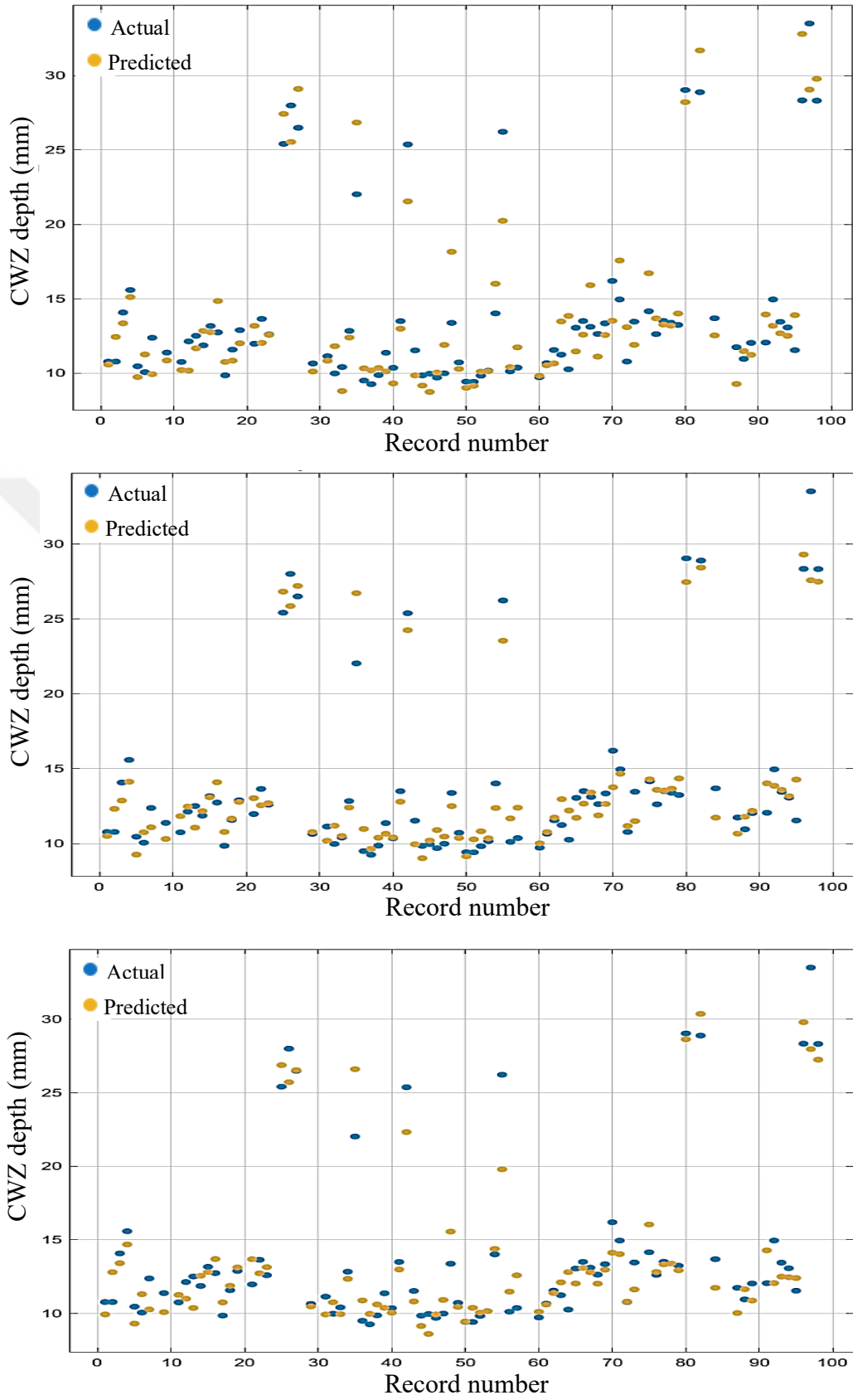


Figure 7.14. Response plots given by the developed ANN model (a), GPR model (b) and SVM model (c) for the CWZ depth

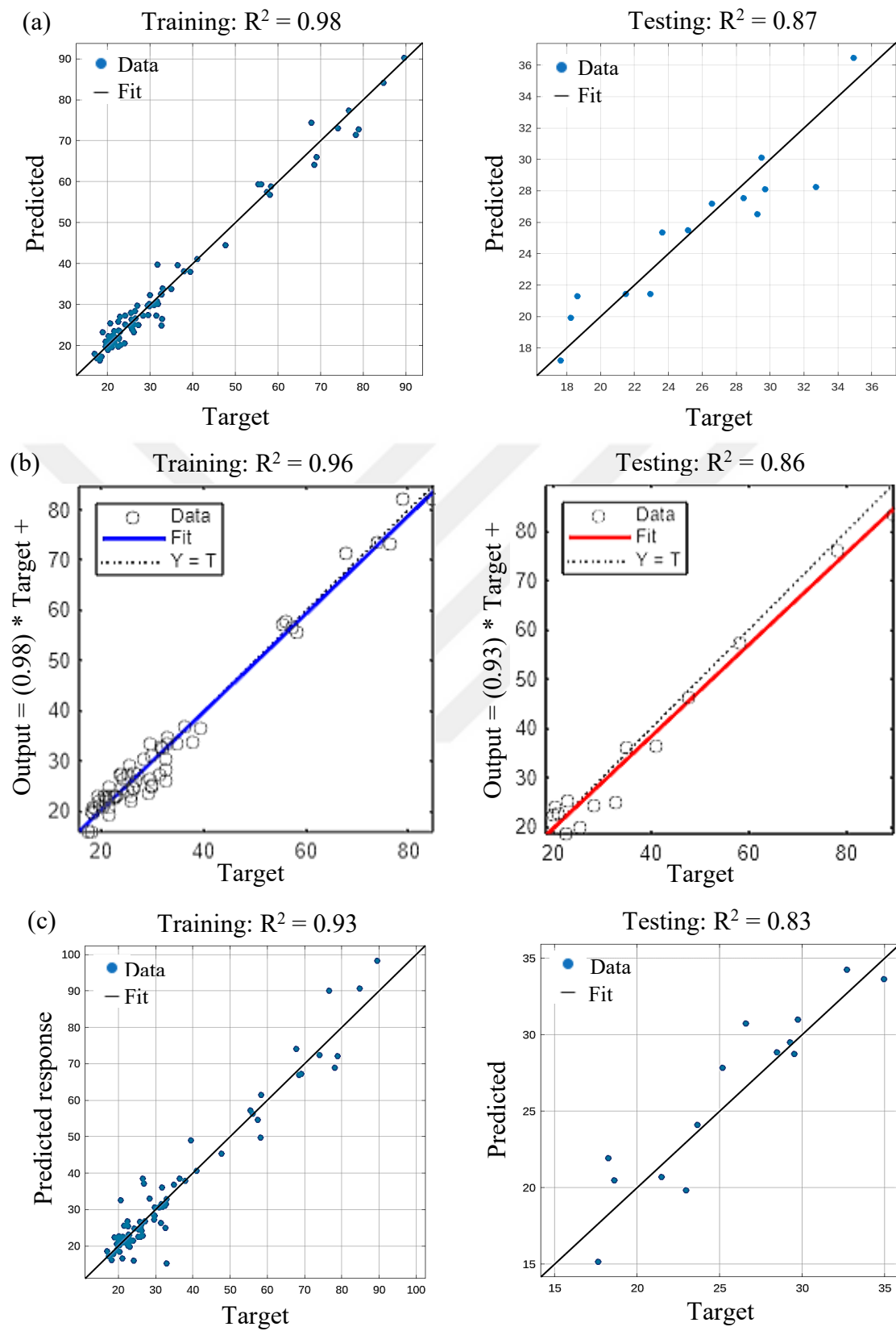


Figure 7.15. Actual vs predicted data and fits for the cutting depth by the GPR model (a), the ANN model (b) and the SVM model (c)

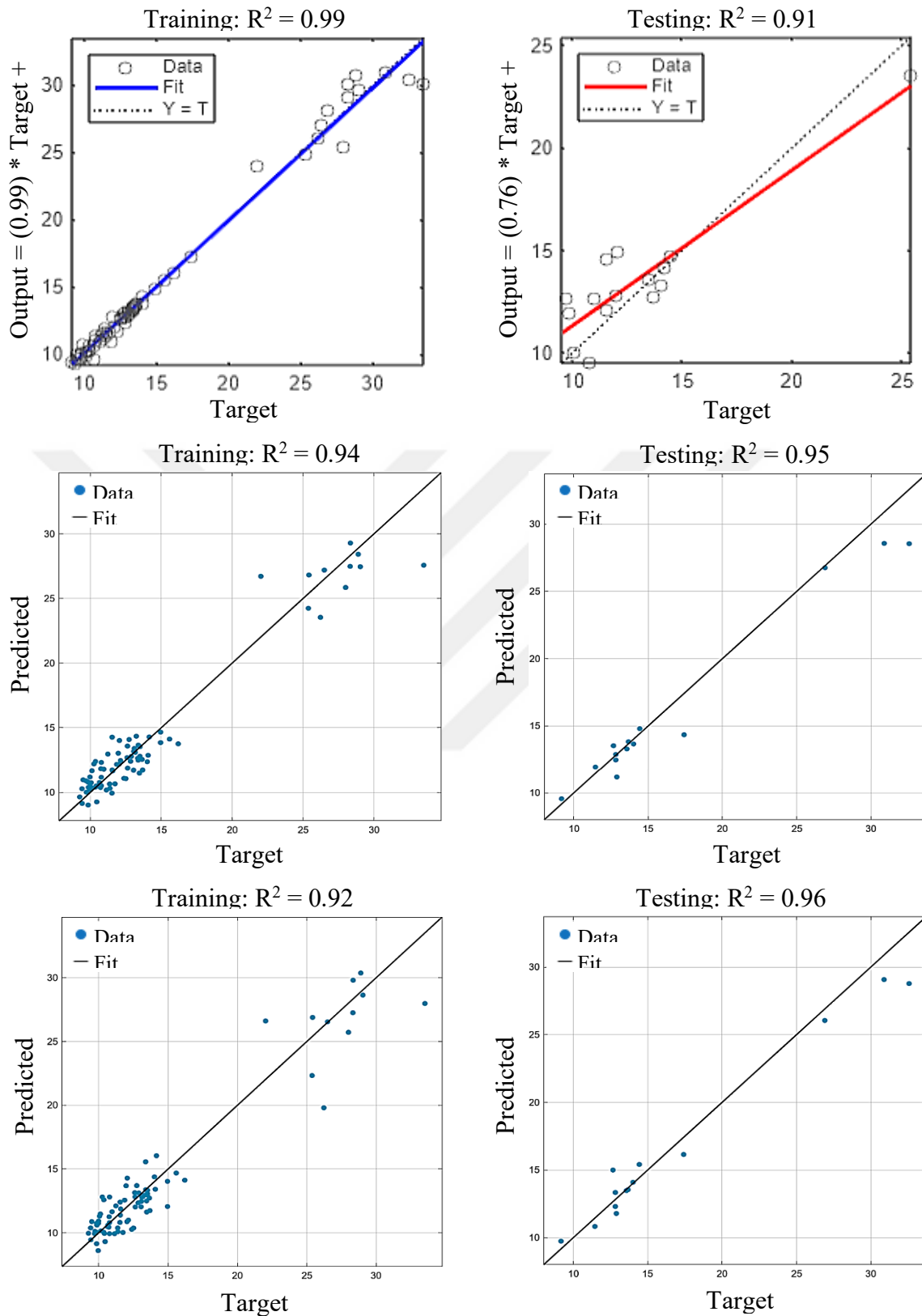


Figure 7.16. Actual vs predicted data and fits for the CWZ depth by the ANN model (a), the GPR model (b) and the SVM model (c)

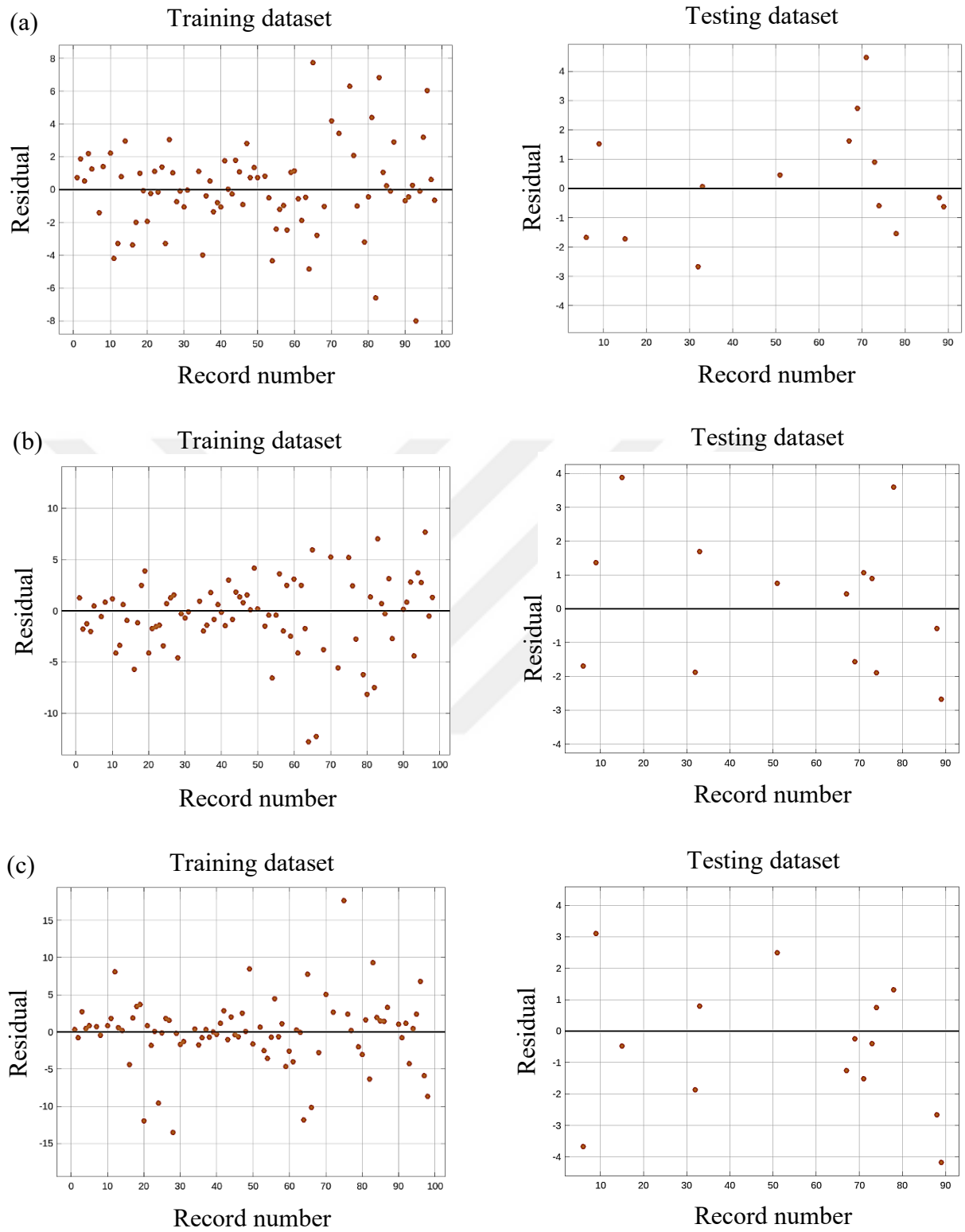


Figure 7.17. Residue plots for the cutting depth by the GPR model (a), ANN model (b) and the SVM model (c)

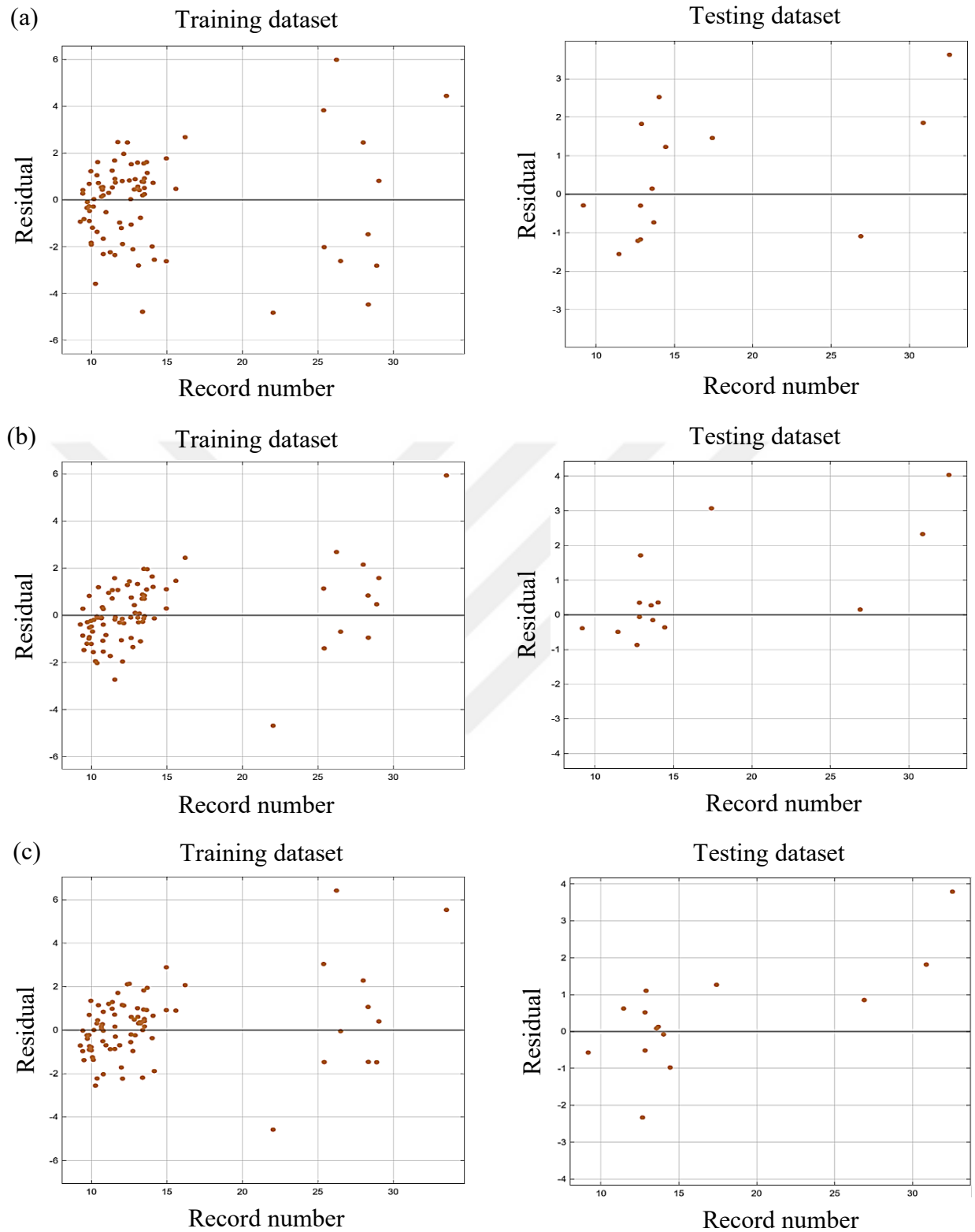


Figure 7.18. Residue plots for the CWZ depth by the ANN model (a), GPR model (b) and the SVM model (c)

7.2. Overall Evaluation of the Modelling Results

Beyond the performance of individual models and indicators, several important insights emerge from the overall modelling effort that merits broader discussion. First, it is evident that the use of machine learning (ML) algorithms is highly effective in capturing the complex and often non-linear interactions inherent in abrasive waterjet (AWJ) cutting of heterogeneous rock materials. The successful application of multiple ML approaches across a diverse set of output parameters—ranging from geometrical features like kerf characteristics to process-induced outcomes such as surface quality and wear zones—demonstrates the flexibility and robustness of data-driven modelling in this context (Li et al., 2024; Mahdevari et al., 2025). An important observation from this study is that the predictive models generally achieved better accuracy on the training datasets compared to testing sets. This outcome, expected in supervised learning contexts, highlights the importance of rigorous cross-validation and residual analysis to ensure generalization and avoid overfitting (Aydin et al., 2013). The residual plots and regression evaluations confirmed that the developed models retained reliable predictive performance even when applied to previously unseen data, thus validating their generalizability within the bounds of the experimental domain. Across all the performance indicators investigated, the ANN model consistently provided superior results, particularly in cases where non-linear interactions were dominant. GPR and GBDT models also performed well, especially for cutting depth and declination angle, respectively. The integration of response plots, regression analysis, error metrics, and residual diagnostics allowed for a robust evaluation of model quality. Another notable insight lies in the consistency of the modelling framework across varied outputs. Despite the differences in the physical meaning, scale, and measurement sensitivity among the investigated cutting performance indicators, the ML models were able to achieve a high level of predictive accuracy. This indicates that the input dataset—comprising both rock properties and operational parameters—was sufficiently rich to support accurate modelling across multiple outputs. It also reflects the success of the input selection strategy and pre-processing methodology adopted in the modelling phase. Furthermore, the structured comparative modelling approach, involving the parallel development and evaluation of multiple ML algorithms per indicator, allowed for the identification of the best-performing model in each case. While no single model was universally optimal across all outputs, the ANN model emerged as the most consistently

effective. This supports prior findings in similar domains where ANNs have shown strong performance in capturing complex non-linear relationships within manufacturing and geomechanically systems. The modelling process was supported by a multi-layered validation strategy, combining statistical metrics (R^2 , RMSE, MAPE) with diagnostic plots of predicted vs. actual values and residual distributions. This ensured that the models were not only accurate in prediction but also statistically sound and practically reliable for application in AWJ-based cutting processes.

Finally, the findings of this modelling effort suggest strong potential for practical implementation. The models developed can serve as foundational components in future real-time prediction systems, adaptive control strategies, or digital twin environments for AWJ machining of rocks. Their demonstrated performance across a range of indicators supports their use not only for forward prediction but also for inverse modelling or optimization tasks, where input parameters must be selected to achieve target output conditions efficiently and reliably.

8. OPTIMIZATION RESULTS AND DISCUSSION

Through Python software for the case of optimization, a detailed description of the optimization results, concentrating on the operational variables for achieving the best cutting performance indicators in AWJ multi – pass and forward angling the jet cutting of rocks, was presented in this chapter. Here, feature importances of both material (rock) and operational variables were also determined. Additionally, the codings for data normalization, feature importance and optimization procedures were presented in Appendix II, . Appendix III and Appendix IV respectively.

8.1. Optimization of the Kerf Width and Kerf Taper Angle

Figure 8.1(a,b) displays the feature importance plots, obtained by the RFR. Based on the related figure, the X3 and X4 have largest influence on the kerf width as material properties, while those are the FA and TS as the operational variables. As can be followed, 34.03% and 20.78% are the contributing rates for the X3 and X4, whereas 24.39% and 21.70% are the rates of the operational variables respectively. Additionally, Table 8.1 gives critical operational variables including the NP, TS, AFR, FA and WP for the tested rock types. In other words, Table 8.1 presents the optimum operating variables for achieving the best or minimum kerf widths based on the rock type. By adjusting these optimum operating variables, the best or minimum kerf widths that can be achieved are presented in Fig. 8.1(c). While R3, R4, R6 and R7 rock types are expected to have the minimum or best kerf widths of 1.32 mm, R3 and R5 rock types are expected to have the maximum kerf widths of 1.39 mm.

Table 8.1. Optimum operating variables for the best or minimum kerf widths based on the rock types

	R1	R2	R3	R4	R5	R6	R7
NP	3	1	2	3	2	2	1
TS (mm/min)	1120	520	820	1120	820	820	445
AFR (g/min)	450	300	450	300	450	300	300
FA (degree)	90	88	90	88	88	88	90
WP (MPa)	180	220	187	210	186	220	212

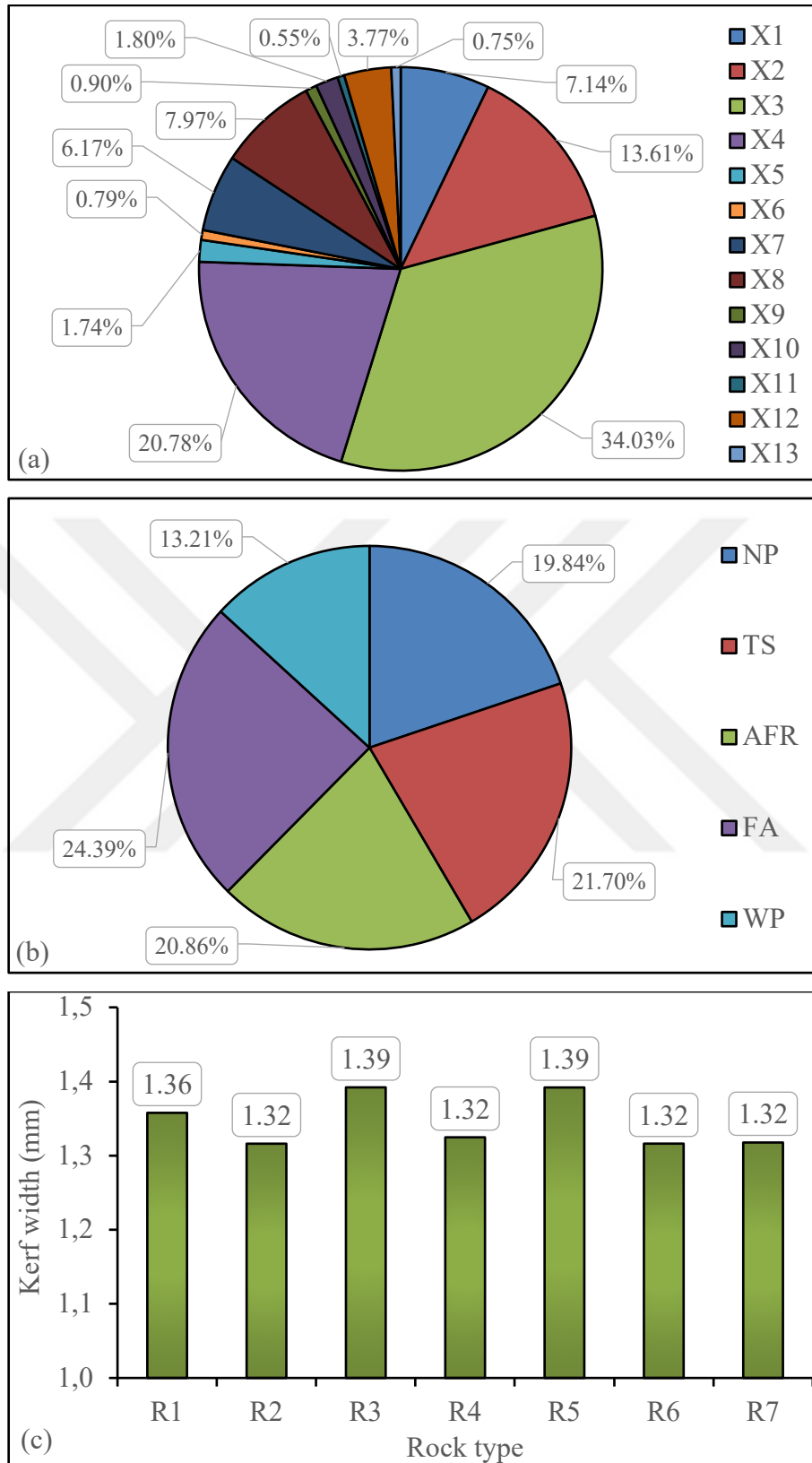


Figure 8.1. Importance of the material properties (a) and operating variables (b), and optimum kerf widths for the rock types (c)

The rock type of R1 is expected to have 1.36 mm when the optimum variable design, which is given in Table 8.1, is employed. Moreover, Fig. 8.2(a,b) presents the feature importance pie charts for the case of the kerf taper angle of the machined rocks. One can easily understand from the Figure that the material properties which are denoted as X8 and X2 have the largest influence on the kerf taper angles, while those are NP and TS as the operating variables. Contribution rates for these features are 17.76% and 17.23% for the X8 and X2, 35.52% and 33.25% for the NP and TS respectively. Moreover, while the critical or optimal design for the best kerf taper angles on the basis of the rock types, is presented in Table 8.2, the best or minimum kerf taper angles that can be achieved are presented in Fig. 8.2(c). Regarding the best kerf taper angles for the rock types, it can be deduced that R4 and R6 are expected to have the minimum kerf taper angles of 0.61 degrees, whereas R1 is expected to have the largest kerf taper angle of 0.79 degrees when the suggested design, as shown in Table 8.2 is applied.

Table 8.2. Optimum operating variables for the best or minimum kerf taper angles based on the rock types

	R1	R2	R3	R4	R5	R6	R7
NP	2	1	1	1	1	1	1
TS (mm/min)	584	300	300	300	300	300	350
AFR (g/min)	450	450	360	420	300	367	425
FA (degree)	90	90	89	89	90	89	90
WP (MPa)	188	180	180	180	180	185	180

8.2. Optimization of the Surface Roughness

The feature importance pie charts for the case of the surface roughness of the machined rocks in terms of the Ra is exhibited in Fig. 8.3(a,b). One can infer from the related Figures that two material properties as ultrasonic velocity (X12) and void ratio (X8) have the largest influence on the Ra, with the rates of 33.81% and 13.76% respectively. For the case of the operating variables, it can be concluded that two significant variables are the FA and AFR, with 29.54% and 20.99%. In addition to the feature importance, the optimal design for the best surface roughness in terms of the Ra on the basis of the rock types, is presented in

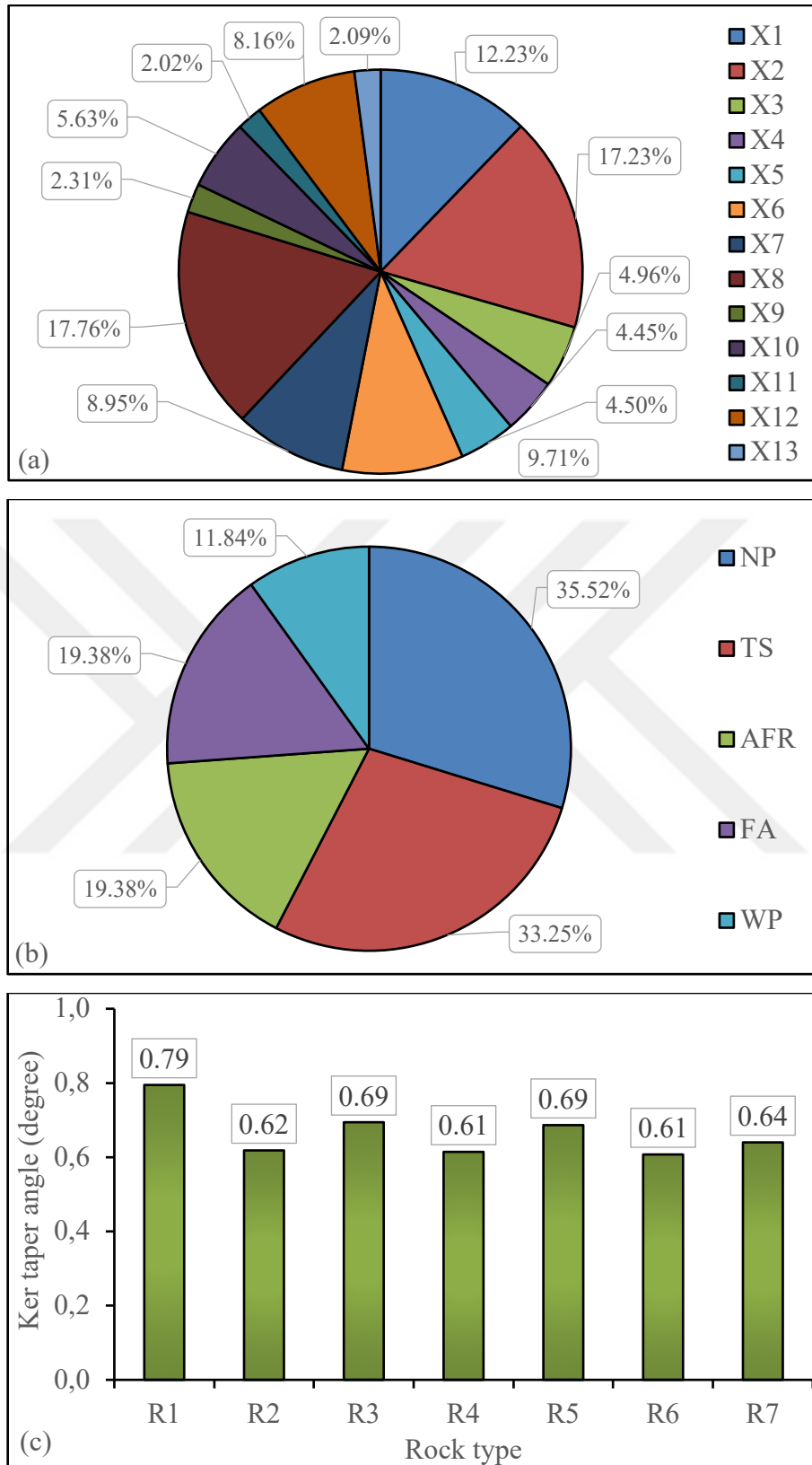


Figure 8.2. Importance of the material properties (a) and operating variables (b), and optimum kerf taper angles for the rock types (c)

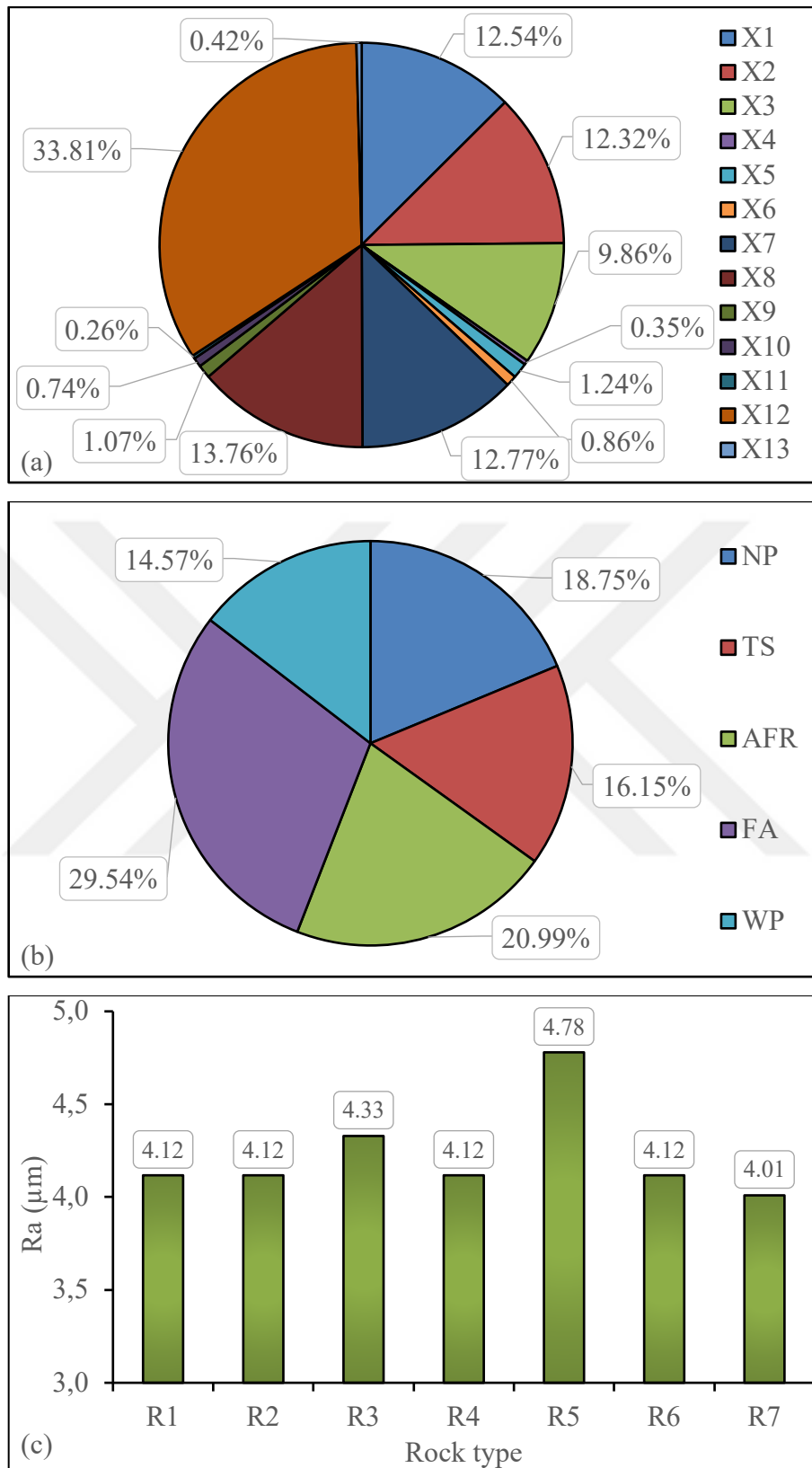


Figure 8.3 Importance of the material properties (a) and operating variables (b), and optimum Ra for the rock types (c)

Table 8.3. As it is exhibited in Fig. 8.3(c), the best Ra values can be achieved for the rock types with the helping of this design.

Table 8.3. Optimum operating variables for the best Ra based on the rock types

	R1	R2	R3	R4	R5	R6	R7
NP	1	1	2	1	2	1	2
TS (mm/min)	300	300	300	300	300	300	300
AFR (g/min)	300	300	300	300	450	300	300
FA (degree)	90	90	90	88	90	89	89
WP (MPa)	180	180	201	220	212	180	180

For the case of the Rz, Fig. 8.4(a,b) demonstrates that the ultrasonic velocity (X12) and effective porosity (X7) present the largest influences on the Rz with the contributing rates of 45.36% and 11.09% respectively. On the other hand, the FA and TS play critical roles as operating variables for achieving the best Rz. Regarding the optimal design for the best Rz or minimum Rz, Table 8.4 gives the operational variables based on the rock types. With the design given in Table 8.4, minimum 21.29 μm will be able to achieve for the Rz of R1, R4 and R6 [Fig. 8.4(c)].

Table 8.4. Optimum operating variables for the best Rz based on the rock types

	R1	R2	R3	R4	R5	R6	R7
NP	1	1	2	1	2	1	2
TS (mm/min)	300	380	300	300	300	380	363
AFR (g/min)	300	350	300	300	450	350	305
FA (degree)	89	89	90	90	90	89	88
WP (MPa)	180	180	201	180	212	180	182

8.3. Optimization of the Declination Angle

Figure 8.5(a,b) displays the RFR feature importance plots for the DAs. Based on the results, the NP has the largest influence on the DA with a contributing rate of 50.56%, while

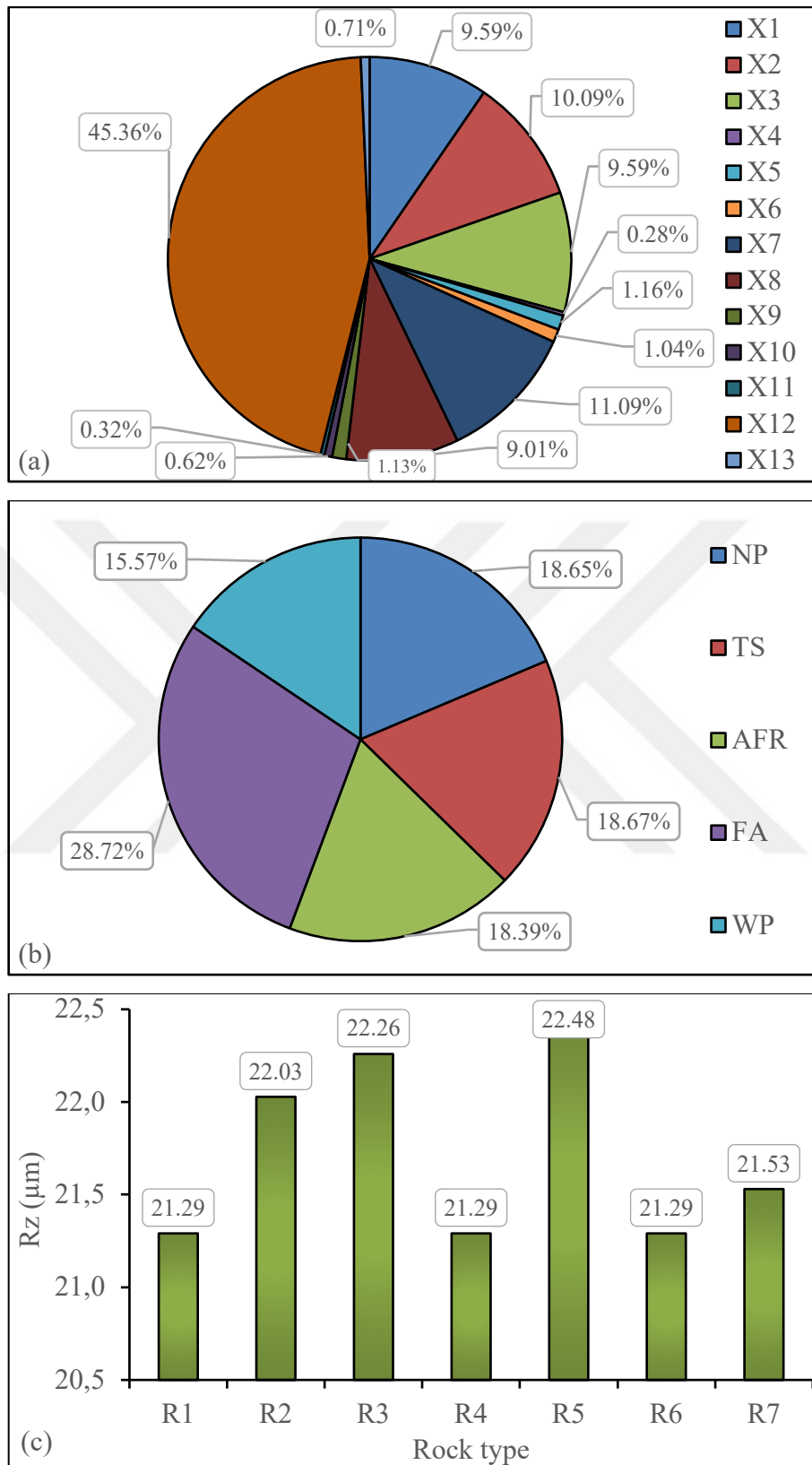


Figure 8.4. Importance of the material properties (a) and operating variables (b), and optimum Rz for the rock types (c)

the WP and FA have the least influences among the tested operating variables. The X1 and X6 ranked first and second most important material properties, influencing the DA. Their contribution rates were 15.07% and 10.27% respectively. On the other hand, Table 8.5 gives critical operational variables including number of pass, traverse speed, abrasive flow rate, forward angling, and water pressure for the tested rock types. In other words, Table 8.5 presents the optimum operating variables for the best DA based on the rock type. As shown in Table 8.5, TS, FA and NP play a significant role in achieving the best DA for the tested rock types. It can be concluded that the best DA will be achieved with settings such as 1200 mm/min for TS as four pass for all rock types and the FA at various angles from 85° to 90° on the basis of rock type. Additionally, Fig. 8.5(c) displays the lowest DAs that may be achieved by adjusting the optimum variables listed in Table 8.5. On the basis of Fig. 8.5(c), the R2 exhibits the highest DA, while the R7 presents the lowest.

Tablo 8.5. Optimum operating variables for the best DAs based on the rock type

	R1	R2	R3	R4	R5	R6	R7
NP	4	4	4	4	4	4	4
TS (mm/min)	1200	1200	1200	1200	1200	1200	1200
AFR (g/min)	300	300	300	300	300	300	300
FA (degree)	90	89.56	85.93	86.32	78.82	86.47	88.54
WP (MPa)	180	180	180	180	180	180	180

8.4. Optimization of the Cutting and Cutting Wear Zone Depths

Figures 8.6(a,b) and 8.7(a,b) exhibit the feature importance pie plots for the cutting and cutting wear zone depths respectively. The feature importance's outputs reveal that the X3 and X2 emerged as the most significant material properties, contributing to the variations in both cutting and CWZ depths respectively, with the rates of 20.04% and 13.90% for the cutting depth and 24.21% and 13.90% for the CWZ depth. Additionally, the feature importance analysis shows that the WP and NP were the most important operating variables for the cutting depth, while those were the FA and TS for the CWZ depth, with the contributing rates of 28.97% and 23.94% for the cutting depth and 27.66% and 21.56% for the CWZ depth respectively. Moreover, Table 8.6 and Table 8.7 present the optimum operating variables for the best cutting and CWZ depths based on the rock type respectively.

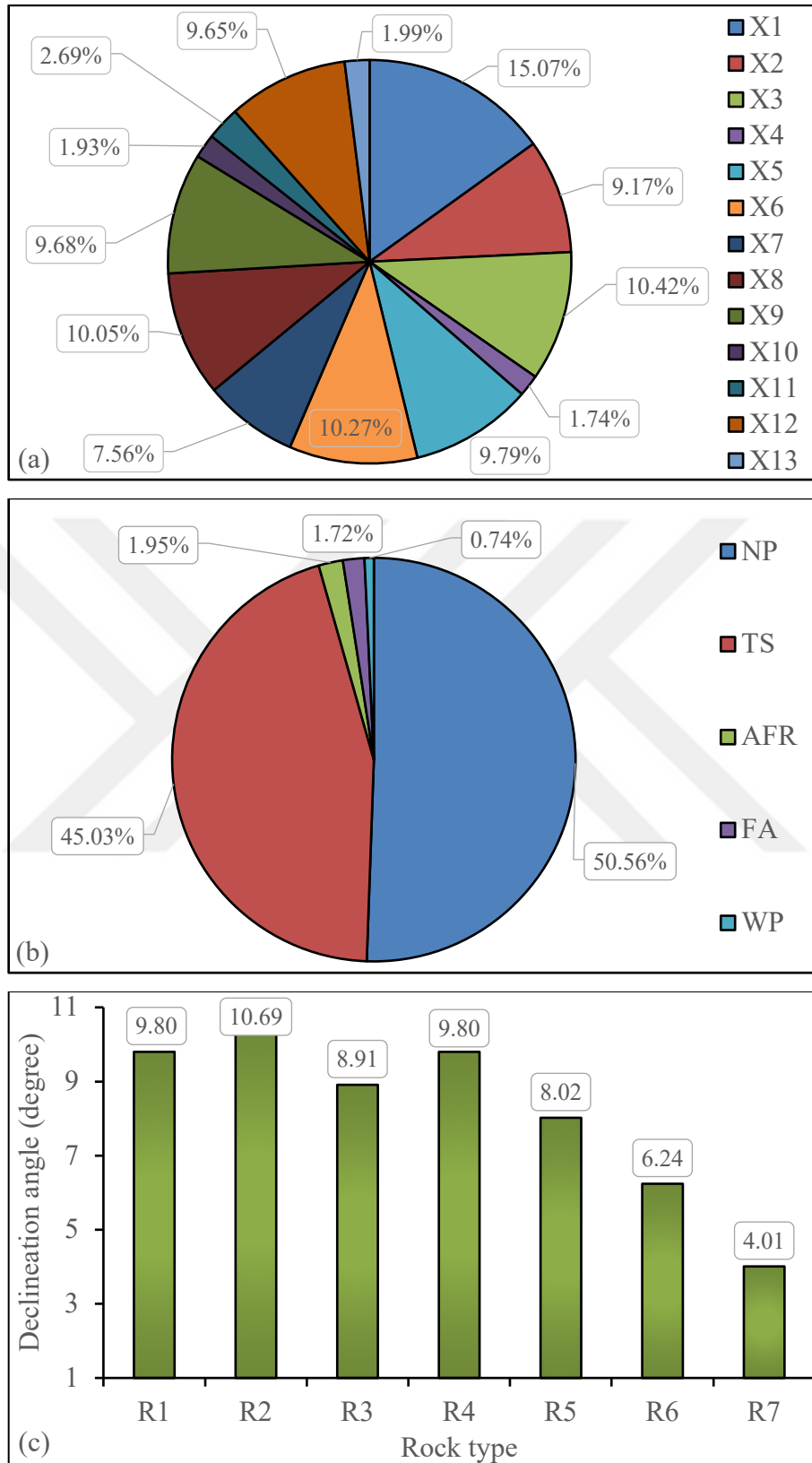


Figure 8.5. Importance of the material properties (a) and operating variables (b), and optimum DAs for the rock types (c)

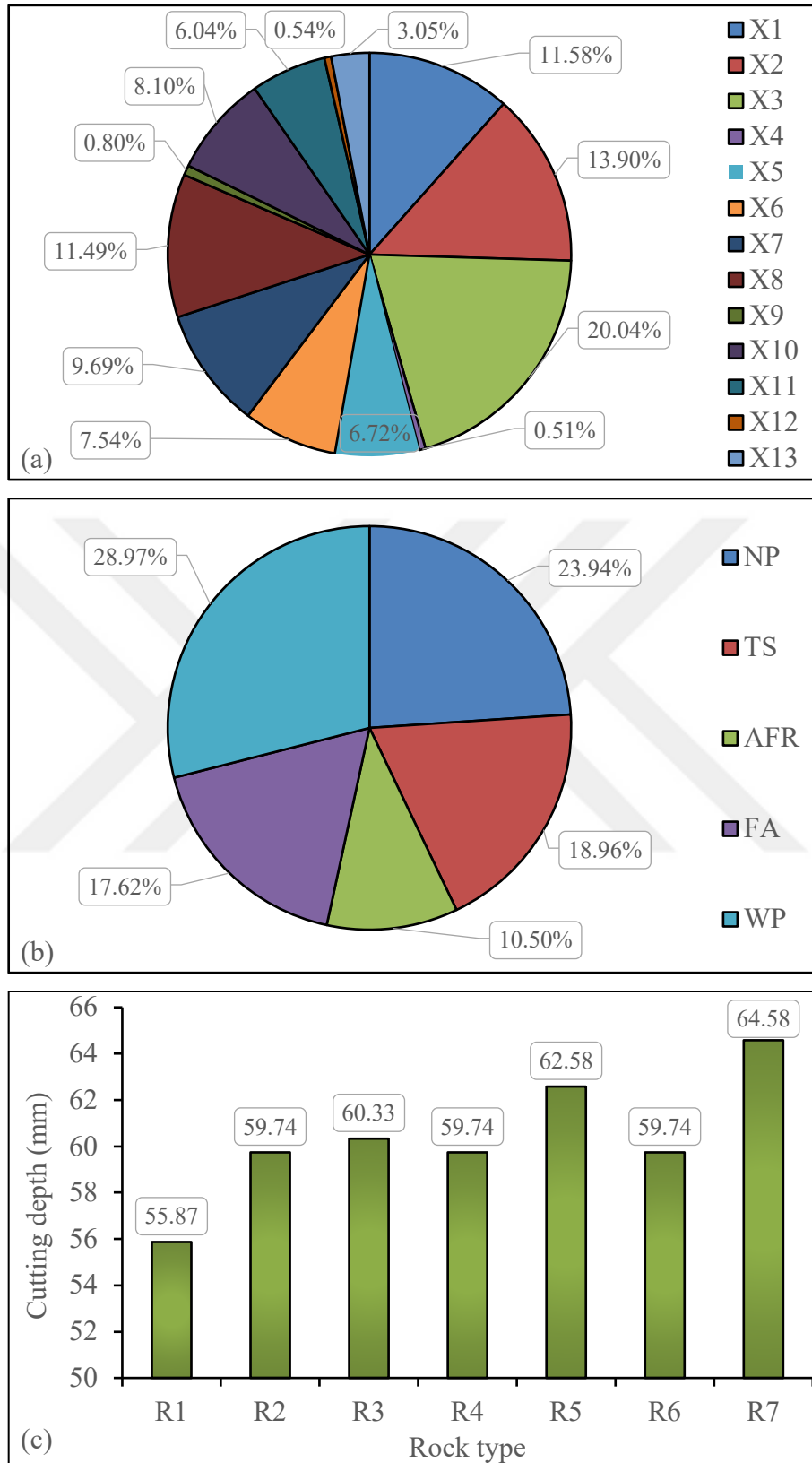


Figure 8.6. Importance of the material properties (a) and operating variables (b), and optimum cutting depths for the rock types (c)

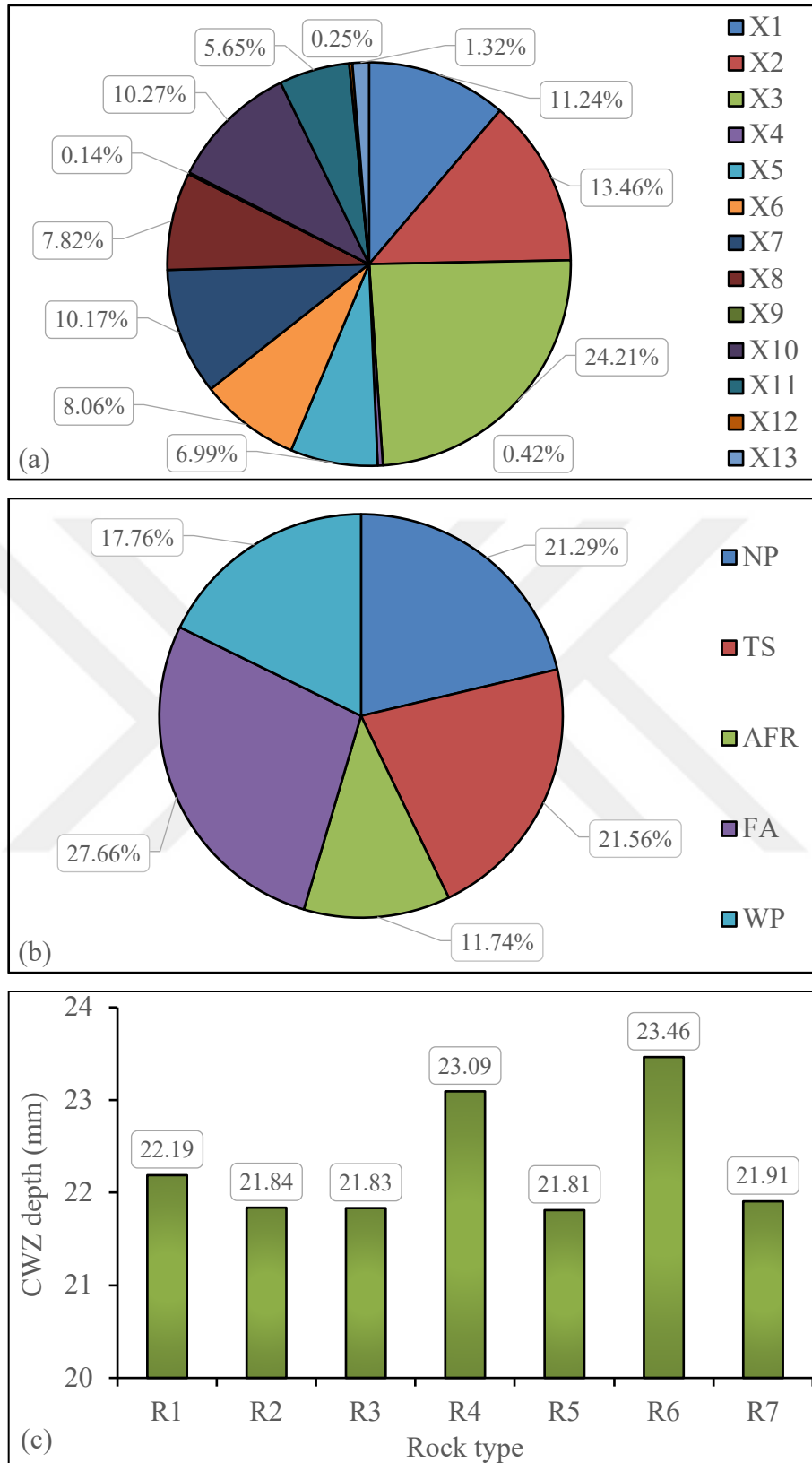


Figure 8.7. Importance of the material properties (a) and operating variables (b), and optimum CWZ depths for the rock types (c)

In case of applying these designs, which are indicated in the related Tables for the cutting and CWZ depths, largest cutting and CWZ depths may be achieved for the machined rock types as illustrated in Fig. 8.6(c) and 8.7(c).

Table 8.6. Optimum operating variables for the best cutting depths based on the rock type

	R1	R2	R3	R4	R5	R6	R7
NP	3	4	3	4	3	4	4
TS (mm/min)	1200	1200	1200	1200	1200	1200	1200
AFR (g/min)	450	450	450	450	450	450	450
FA (degree)	90	90	89	89	90	90	90
WP (MPa)	180	180	180	180	180	180	180

Table 8.7. Optimum operating variables for the best CWZ depths based on the rock type

	R1	R2	R3	R4	R5	R6	R7
NP	4	4	4	4	4	4	2
TS (mm/min)	1200	1200	1200	1200	1200	787	1200
AFR (g/min)	350	450	450	300	428	300	450
FA (degree)	90	90	88	89	90	90	90
WP (MPa)	180	180	198	220	180	220	180

9. CONCLUSIONS

Despite the significant superiorities of the AWJ technology over traditional and non-traditional technologies, the cutting depth and surface irregularities such as striations and roughness are still the most important problems, limiting its wide application. Thus, research and developments have been initialized and continued in order to enhance the technology's cutting capabilities in the form of cutting depth and surface irregularities in recent years. It is worth noting that it is not feasible to enhance the surface quality of the target materials and dimensional accuracy of the AWJ as this would result in an increase in machining time and expense. Instead, techniques should be employed that can achieve successful results without additional machining costs and time such as newly developed techniques of the multi-pass cutting, controlled nozzle oscillation and forward angling the jet. In this thesis, therefore, testing the AWJ multi-pass and forward angling the jet techniques in rock cutting applications reveals the conclusions that effort have been made in line with the emphasized purpose. In this regard, the main conclusions that have been reached in this thesis can be summarised as follow.

- a. It was determined that the AWJ multi-pass cutting substantially enhanced the cutting and CWZ depths across the various investigated rock materials, including sedimentary, igneous, and metamorphic stones. Similarly, the declination angles (DAs) of these rock specimens were positively influenced by the AWJ multi-pass cutting technique. In other words, the DAs were significantly reduced through the application of this method.
- b. It was concluded that the AWJ multi-pass cutting technique resulted in a decrease in the kerf widths of machined rocks other than R3 and R5, albeit at a low rate. On the other hand, it was seen that the AWJ multi-pass cutting technique decreased significantly the kerf taper angles up to 57.30% depending on the machined rocks with the exception of the R5.
- c. It was deduced that the AWJ multi-pass cutting technique caused an acceptable improvements in the surface roughnesses (both the Ra and Rz) of R3, R4, R5, R6 and R7, while it did not cause any noticeable improvement or decrease in the surface roughnesses of the R1 and R2.
- d. Unlike what is achieved with multi-pass cutting, it was observed that the forward angling the jet did not produce large cutting and CWZ depths for the machined rocks.

The cutting and CWZ depths of R5, R6 and R7 were only increased, albeit by very small amounts.

- e. Similar results which were achieved in the cutting and CWZ depths, were found for the kerf widths and kerf taper angles of the machined rocks. In other words; the kerf widths of four rock types such as R1, R2, R4 and R6 were reduced, while the kerf taper angles of the R1, R6 and R7 were decreased by the forward angling the jet cutting technique.
- f. Although high improvement rates were achieved for some rocks such as 25.40% for the R7 and 26% for the R4 in terms of the DA and Ra – Rz respectively, it was seen that the forward angling the jet cutting technique had limited improvements for the DA and surface roughness such as Ra – Rz.
- g. Based on their R^2 and other error indicators, it was concluded that the cutting performance indicators such as cutting and CWZ depths, surface roughness, DA, kerf width and kerf taper angle will be able to be modelled and optimized by MLAs.
- h. It was demonstrated that the ML – based models are the GPR, ANN and SVM for the cutting, while those are the ANN, GPR and SVM for the CWZ depth respectively. Additionally, it was seen that the ML – based models are ANN, SVM and GBDT for the Ra and ANN, SVM and GPR for the Rz respectively. Moreover, it was showed that the ML – based models are the ANN, GBDT and GPR for the DA, while this is only ANN for both kerf widths and kerf taper angles for the machined rocks.
- i. It was found that the the NP, TS and FA have the largest influences on the cutting performance indicators, depending on their contribution rates. In other words, one can deduce that the NP, TS and FA play crucial role in order to achieve the best cutting performance indicators in AWJ multi – pass and forward angling the jet cutting of rocks.

It can be finally concluded that this thesis demonstrated the superiority of multi – pass cutting over single pass cutting and highlighted effectiveness of MLAs in modeling and optimizing the cutting performance indicators, achieved by AWJ multi – pass and forward angling the jet techniques in cutting of various rocks.

10. RECOMMENDATIONS FOR FUTURE STUDIES

Although this thesis has yielded substantial results from an experimental, modelling and optimization perspectives, there are still the following limitations, regarding especially the generalization of the experimental results due to the rocks' inherent structure. Additionally, variable selection for modeling and optimization may result in another kind of limit for the current thesis as there are numerous factors influencing the cut-ability of rocks. Scholars who are studying and/or will study the subject could, therefore, address these limits indicated below in their investigations for the generalization of the achieved results.

- i. Rocks include numerous minerals with unique characteristics such as unusual textures and structures, resulted from their intrinsic genesis and geologic evolution (Arab and Celestino, 2020). That means, they are the materials composed of without the involvement of humans. Therefore, these minerals primarily govern how rocks react to any mechanical actions such as AWJ cutting. While the physical-mechanical characteristics of rocks were considered in the current thesis, the key textural characteristics, such as mineral grain size, their proportions or the status of cracks-fractures, were not. In order to advance the investigation to a further level, thus, addressing these key mineralogical and textural characteristics of the different rocks will be helpful.
- ii. Rock strength is widely acknowledged as one of the most significant factors influencing a rock's ability to break and/or failure when subjected to any mechanical impact such as AWJ cutting. In the current thesis, the studied rocks' strengths vary from almost 42 MPa to 155 MPa. These figures make it clear that there are significant variances between the rocks when they are compared on the basis of their strengths. This may restrict the generalization of the achieved results. Therefore, it will be more beneficial to study with the rocks that have comparable strength values in order to generalize the achieved results. It is strongly recommended that this situation should be taken into account in further studies.
- iii. Studying more levels of WP and AFR for both the AWJ multi – pass and forward angling the jet techniques will be able to present more precise interpretations in terms of the cutting performance indicators in rock cutting applications.

- iv. In the current thesis, the SD was kept constant. Therefore, in future studies, more levels can be studied to reveal the SD's effect precisely.
- v. It is a known fact that the diversity of the training data set is one of the significant determinant of the final performance of a ML – based model. This implies that the ML – based model's performance may improve with greater data diversity. Hence, future studies can test additional variables such as nozzle diameter, abrasive type and size, various levels of the standoff distance, added to the current training set of 20 variables to see how the model's performance varies.
- vi. Similar to the variable selection procedure and their effects for the modelling studies, the modelling and optimization techniques play an crucial role as well. Thus, studies that attempt to employ different techniques such as GAs, MAs and SA for modelling and GWO, ACO and BA for optimization of the cutting performances of the AWJ multi – pass and forward angling the jet techniques in rock processing applications will take the outcomes to a higher level.

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12. APPENDIXES



[illegible]

Appendix Table I. Continuing

[illegible]

Appendix Table II. Coding for data normalization through Python software

```
!pip install pandas --quiet
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from google.colab import files
print("Please upload your dataset (CSV format):")
uploaded = files.upload()
file_name = list(uploaded.keys())[0]
df = pd.read_csv(file_name)
print("Original Dataset:")
print(df.head())
numeric_columns = df.select_dtypes(include=[np.number]).columns
scaler = MinMaxScaler()
df_normalized = df.copy()
df_normalized[numeric_columns] = scaler.fit_transform(df[numeric_columns])
print("Normalized Dataset:")
print(df_normalized.head())
df_normalized.to_csv("normalized_dataset.csv", index=False)
print("Normalized dataset saved as 'normalized_dataset.csv'.")
from google.colab import files
files.download("normalized_dataset.csv")
```

Appendix Table III. Coding for feature importance analysis through Python software

```

from google.colab import files
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt

uploaded = files.upload()
df = pd.read_csv(list(uploaded.keys())[0])
print(df.head())
print("Columns in the dataset:", df.columns)
categorical_columns = df.select_dtypes(include=['object']).columns
label_encoder = LabelEncoder()

for col in categorical_columns:
    df[col] = label_encoder.fit_transform(df[col])

print("Categorical columns encoded.")

target_column = 'Ra'
if target_column not in df.columns:
    print(f'Column '{target_column}' not found. Please verify the correct name of the target column.')
else:
    X = df.drop(columns=[target_column])
    y = df[target_column]
    rf = RandomForestRegressor(n_estimators=100, random_state=42)
    rf.fit(X, y)
    feature_importances = rf.feature_importances_
    feature_importance_df = pd.DataFrame({
        'Feature': X.columns,
        'Importance': feature_importances
    })
    feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
    print("\nMost Important Features:")
    print(feature_importance_df)
    plt.figure(figsize=(10, 6))
    plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'])
    plt.xlabel('Feature Importance')
    plt.title('Feature Importance for Ra Surface Roughness Optimization')
    plt.show()

```

Appendix Table IV. Coding for optimization through Python software

```

from google.colab import files
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt
uploaded = files.upload()

df = pd.read_csv(list(uploaded.keys())[0])
print(df.head())
print("Columns in the dataset:", df.columns)
categorical_columns = df.select_dtypes(include=['object']).columns
label_encoder = LabelEncoder()

for col in categorical_columns:
    df[col] = label_encoder.fit_transform(df[col])

print("Categorical columns encoded.")
target_column = 'Ra'
if target_column not in df.columns:
    print(f'Column '{target_column}' not found. Please verify the correct name of the target column.')
else:
    X = df.drop(columns=[target_column])
    y = df[target_column]
    rf = RandomForestRegressor(n_estimators=100, random_state=42)
    rf.fit(X, y)
    feature_importances = rf.feature_importances_
    feature_importance_df = pd.DataFrame({
        'Feature': X.columns,
        'Importance': feature_importances
    })
    feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
    print("\nMost Important Features:")
    print(feature_importance_df)
    plt.figure(figsize=(10, 6))
    plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'])
    plt.xlabel('Feature Importance')
    plt.title('Variables Feature Importance for Ra Surface Roughness Optimization')
    plt.show()

```

RESUME

Imene Rogai She completed the primary, secondary, and high school education in her hometown. In order to earn a bachelor's degree, She started higher education in Mining Engineering Department at Abderrahman Mira University in Bejaia, which is a municipality in the Gulf of Bijaye in Algeria. During her higher education, she participated in several technical field trips to mining operations in the region. She completed also professional internships aligned with her area of study and graduated as the top of her class. Earned the bachelor's degree in Mining Engineering from Abderrahman Mira University, Ms. Rogai specialized in mine safety and environmental protection. Following the graduation from Mining Engineering at Abderrahman Mira University, She enrolled for the Master of Science (MSc.) degree in Mining Engineering at the same university. During her MSc. education, she has developed a software for blast design in surface mining, which was successfully tested at several mine sites across Algeria. In addition, Ms. Rogai served as a teaching instructor at the National Polytechnic School in Algeria, delivering both theoretical and practical courses in Mining Engineering Department. At the same time, she gained professional experience as a Mining Engineer at the General Directorate of the ENOF Group. Once she graduated from MSc., she started doctorate education (PhD.) in Mining Engineering Department at Karadeniz Technical University (K.T.U.) in Trabzon, which is a coastal city of Türkiye in 2020. Towards the end of 2023, She joined the *Mining & Energy Research Group (MERG)*, which has actively conducting research and development (R&D) activities withing Mining Engineering Department at K.T.U. During her doctoral education, she participated in international congresses and symposiums, held in various cities of Türkiye and abroad and presented a lot of papers related to her specialization. Moreover, Ms. Rogai became a member of the Arab Mining Engineers Association in 2022. And thus, she has also delivered annual lectures and participates in conferences on a variety of topics related to Mining Engineering. Ms. Rogai, who is still continuing her doctoral education, is single and speaks Arabic, French, English, Turkish and Spanish fluently.

Publications originating from this thesis

- 1) **Rogai, I.**, Karakurt, I., Aydin, G., Karabacak, E.Y., Avci, D.B., Kaya, S. 2025. An investigation into the abrasive waterjet cutting of rocks: Improving cutting performance

and leveraging the machine learning algorithms for modelling. Mining, Metallurgy & Exploration (Revision submitted).

- 2) **Rogai, I.**, Karakurt, I., Aydin, G., Karabacak, E.Y., Roudini, E.Y., Avci, D.B. 2025. Modeling and optimization of the declination angle generated by abrasive waterjet multi-pass and forward angling cutting using machine learning. Proceedings of the IMechE, Part E: Journal of Process Mechanical Engineering (Submitted).
- 3) **Rogai, I.**, Karakurt, I., Aydin, G., Karabacak, E.Y. 2025. Artificial neural network modelling of the kerf width in abrasive waterjet cutting of rocks (In preparation for submission to a conference or congress).
- 4) **Rogai, I.**, Karakurt, I., Aydin, G., Roudini, A. 2025. Optimal variable design for the kerf width in abrasive waterjet machining of rocks (In preparation for submission to a conference or congress).
- 5) **Rogai, I.**, Karakurt, I., Aydin, G. 2025. Enhancing the smooth depths of various rocks in abrasive waterjet machining. IV. International Bandırma Scientific Studies Congress, April 18 – 20, 2025 Balıkesir, Türkiye, pp. 408 – 414.
- 6) **Rogai, I.**, Karakurt, I., Aydin, G., Roudini, A. 2025. Machine learning – based optimization for the cutting depths of various rocks cut by abrasive waterjet. IV. International Bandırma Scientific Studies Congress, April 18 – 20, 2025 Balıkesir, Türkiye, pp. 417 – 424.
- 7) **Rogai, I.**, Karakurt, I., Aydin, G., Kaya, S. 2024. Usability of forward angling the jet in abrasive waterjet cutting of a natural stone. 8th. International Marmara Scientific Research and Innovation Congress, 27 – 28 October 2024, İstanbul, Türkiye, pp. 478 – 484.
- 8) **Rogai, I.**, Karakurt, I., Aydin, G., Kaya, S. 2024. Abrasive waterjet multi-pass cutting of different rock types: A comparative study. 8th. International Marmara Scientific Research and Innovation Congress, 27 – 28 October 2024, İstanbul, Türkiye, pp. 471 – 477.
- 9) **Rogai, I.**, Avci, D. B., Karakurt, I., Aydin, G., Kaya, S., 2024. Preliminary evaluation of a multi-pass abrasive waterjet cutting of an igneous rock. 8th. International Scientific Research and Innovation Congress, 22-23 June 2024, Baku, Azerbaijan, pp. 512 – 518.