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Research Article

Artificial neural network and multiple regression analysis for predicting abrasive water jet cutting of Al 7068 aerospace alloy

Fuat KARTAL[1,*], Arslan KAPTAN[2]

[1]*Department of Mechanical Engineering, Kastamonu University, Kastamonu, 37150, Türkiye*
[2]*Department of Motor Vehicles and Transportation Technologies, Sivas Technical Sciences Vocational School, Sivas Cumhuriyet University, Sivas, 58140, Türkiye*

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ABSTRACT

This study aims to predict machinability and high performance optimum surface roughness (R_a) by developing multiple regression models and artificial neural network (ANN) model for abrasive water jet cutting (AWJC) of Aluminum 7068 alloy. Important basic processing parameters such as pump pressure (3500-4000 Bar), nozzle distance (2-5 mm), abrasive flow rate (200-350 g/min), abrasive grain size (100-110 mesh), and nozzle traverse speed (240-300 mm/min) were selected in the study. To examine the effects of these parameters on R_a, 32 experiments were conducted using the L32 orthogonal array, and data was collected. Additionally, the most important factors and interactions affecting R_a were determined using multiple regression analysis and analysis of variance (ANOVA). The Artificial Neural Network (ANN) model was designed to have multiple hidden layers using MATLAB. The model was trained and evaluated using experimental data, and its performance was measured using mean squared error (MSE) and mean absolute error (MAE). The model was optimized using hyper parameter tuning and cross-validation techniques. As a result, it was determined that the best R^2 value of 95.65% from the multiple regression models created to estimate the surface roughness could be obtained from the linear regression model. While selecting the optimum process parameters for AWJC, it was determined that nozzle rotation speed, abrasive grain size and flow rate had the greatest effect by 35.5%, 25.4% and 21.9%, respectively. The optimized ANN model showed high accuracy in predicting R_a for different input parameter combinations. This study provides a reliable and efficient tool for predicting R_a in AWJC, which can contribute to improving process planning and control.

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***Corresponding author.**
*E-mail address: fkartal@kastamonu.edu.tr

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INTRODUCTION

Abrasive water jet cutting (AWJC) is an effective cutting method that uses a high-pressure water jet and abrasive particles and can be applied to a wide range of materials [1-3]. AWJC is preferred in many industries because it makes fast and precise cuts. The basic principle of cutting with AWJC is the mixture of water and abrasive particles cutting the material at high speed from a nozzle [3-5]. This process is suitable for cutting various materials such as metal, plastic, glass, ceramics, stone, and composites. Many conventional machining methods occur under serious temperature effects due to high friction between the work piece and the cutter, leading to damage to the material microstructure. However, AWJC allows the material to be cut without being exposed to thermal interaction due to the cooling effect of the water jet, which helps to maintain the structural integrity and properties of the material [1-6]. The process can also cut complex geometries and high tolerances. AWJC shows parallelism with various regulatory directives around the world in reducing waste after processing, as well as low energy consumption compared to other cutting methods. Being an environmentally friendly method, it is used for material cutting and shaping in various fields such as aviation and space, automotive, electronics, and construction.

Aluminum (Al) 7068 alloy maintains its reputation as a strategic material in the aerospace industry due to its ability to meet many industrial expectations such as a high strength-to-weight ratio, low density, good fatigue and corrosion resistance [7,8]. These features make the Al 7068 alloy suitable for use in industrial components where zero defects are expected, such as aircraft bodies, engine parts, landing gear, etc. On the other hand, it is also a material that meets many critical expectations in the aerospace industry, such as not creating too much weight with robotic units during transportation with a spacecraft, and being able to withstand harsh climate conditions for many years during landing on a planet surface under research.

Artificial neural networks (ANN) are a powerful tool for increasing process efficiency and reducing costs in the industrial field, as they have the ability to learn and generalize complex and non-linear relationships. ANN can be used to optimize and predict cutting processes with many input parameters, such as water jet cutting. The use of ANN in waterjet cutting provides the following advantages such as optimization of cutting parameters, surface roughness estimation, cutting time estimation, material strength and stress estimation [9-11].

Wang et al. conducted a comprehensive analysis on the AWJC process, specifically focusing on Al alloys. In their work, they developed and validated a mathematical model for predicting the cutting front profile based on the defined cutting conditions [12]. In a novel study by Kumar et al., the effects of abrasive water jet machining (AWJM) on Al alloy 7475 (AA7475) composites, reinforced with varying weight fractions of carbon nanotube (CNT) particles, were investigated. An optimization of outputs, including material removal rate and average roughness (R_a), was conducted using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method [13]. Wang et al. delved into the impacts of kerf taper in AWJM of Al alloy 6061-T6. Their results indicated that cutting speed and material thickness greatly affect the kerf taper, whereas the influences of water pressure and abrasive flow rate are less apparent. The study found that reducing cutting speed contributes to minimizing kerf taper, and kerf taper inversely correlates with material thickness. Building on these findings, the authors established a kerf taper prediction model, the effectiveness of which was substantiated through further experiments [14]. Ahmed et al. embarked on a mission to enhance the surface roughness in the AWJC process through the application of statistical modeling. The study aimed to comprehend the impact of AWJC parameters, including traverse speed, water pressure, and standoff distance, on the quality of surface roughness in the cutting process. The authors employed design of experiments and statistical modelling techniques to establish correlations between the control factors and output responses. Using the Response Surface Method (RSM) for surface roughness modeling, they discovered that surface roughness could be improved by increasing water pressure at low traverse speeds or decreasing the pressure at high traverse speeds [15]. Akkurt et al. concentrated their study on the effects of feed rate and work piece thickness on the surface roughness in AWJC applications. Various materials were examined, including pure Al, Al-6061 aluminum alloy, brass-353, AISI 1030 and AISI 304 steel, each cut at different feed rates. The research found that the improvement in surface roughness of pure Al remained within a narrow range, relative to the decrease in feed rate. Additionally, it was noted that the pressure of the AWJ adversely influences surface roughness as the thickness of the material decreases. For materials with higher strength than Al, such as brass and AISI 1030, higher surface roughness was observed in thinner workpieces. [16]. Bañon et al. explored the potential of AWJM as a technique for texturing thin Al alloy UNS A92024. The researchers highlighted that surface modification of metallic alloys could lead to hydrophilic or hydrophobic surfaces that enhance the material's functional performance. The study examined the impact of texturing with and without abrasives, finding that specific combinations without abrasive particles could yield surfaces of interest. The study determined the influence of texturing parameters such as hydraulic pressure, traverse speed, abrasive flow, and spacing on surface quality in terms of surface roughness parameter (Sa), maksimum surface height (Sz), and depth of core roughness (Sk), and wettability [17]. Lv et al. conducted a numerical study to explore the fatigue crack behavior of 2024 Al alloy specimens treated through AWJ peening. A numerical model for fatigue testing was also established to evaluate crack growth characteristics in the specimen, accounting for the residual compression introduced by peening. The findings suggested a reduction in

Table 1. Chemical composition of Al 7068 alloy [20]

Element	Si	Cu	Mg	Zn	Ti	Fe	Zr	Al
Weight (%)	0.1	2.1	2.4	7.74	0.07	0.11	0.06	Balance

both the effective stress intensity factor range and the crack propagation rate due to the residual stress induced by peening [18]. Sun et al. aimed to enhance the cutting quality of Al alloy machined by an AWJ operating at a relatively low pressure. To achieve high cutting quality at a lower pressure of 150 MPa, the researchers optimized AWJ process parameters using the RSM. Surface roughness (R_a) and kerf taper (Kt) were the metrics used to assess cutting quality. A Central Composite Design (CCD) model guided the design of the cutting experiment, with the effects of abrasive flow rate, standoff distance, and traverse speed on machining quality examined via the Analysis of Variance (ANOVA) method. [19].

In order to optimize the surface roughness to be obtained as a result of cutting with AWJ, Al 7068 alloy material was used and basic machining parameters such as pump pressure, nozzle distance, abrasive flow, abrasive particle size, nozzle advance speed were investigated. Data were collected by conducting 32 experiments using L32 orthogonal design, and the most important factors and interactions affecting R_a were determined using multiple regression analysis and ANOVA methods. In addition, an ANN model with multiple hidden layers was designed using MATLAB, and it was optimized by training it with experimental data. This optimized ANN model accurately predicted R_a for different input parameter combinations. This study provides a reliable and efficient tool for predicting R_a in AWJC and contributes to the development of process planning and control. In conclusion, the findings of this study provide solutions to problems related to surface roughness control in material-cutting processes. By understanding how these parameters influence R_a, manufacturers can optimize their AWJC processes, leading to increased productivity, improved quality, and reduced manufacturing costs. In conclusion, the novelty of this research lies in the application and optimization of AWJC process parameters for Al 7068 alloy and the development of a robust and accurate model to predict surface roughness. The findings from this study are anticipated to make a significant contribution to the field of AWJM and benefit the aerospace industry.

MATERIALS AND METHODS

Material

In this study, an Al 7068 alloy with a thickness of 30 mm was used which is a lightweight and high-strength material. Due to its higher strength performance and lower density compared to Al 7075 alloy, it contributes to weight reduction. The chemical composition of this Al-based alloy is shown in Table 1, and its mechanical properties are shown in Table 2. The novelty of this study in the investigation and optimization of AWJC parameters for Al 7068 alloy, a material extensively used in critical applications within the aerospace industry due to its high strength-to-weight ratio. Despite its popularity, there is a limited body of research focused on the optimization of AWJC parameters for this specific alloy. As AWJC is a versatile and effective method for cutting metals, it is essential to understand the optimal conditions to maximize efficiency and minimize R_a, enhancing the alloy's performance in subsequent applications.

Table 2. Mechanical properties of Al 7068 alloy [20]

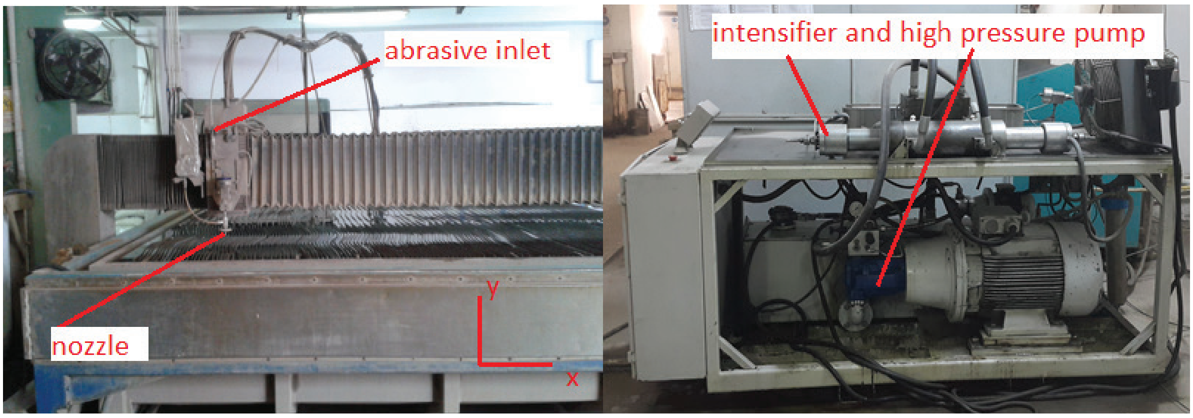
Specifications	Units	Value
Density	(kg/m^3)	2850
Yield strength	(MPa)	683
Ultimate tensile strength	(MPa)	710
Brinell hardness	(HB)	190
Fatigue strength	(MPa)	220
Fracture toughness	($MPa*m^{1/2}$)	35
Elasticity modulus	(GPa)	71
Elongation	(%)	10

Abrasive Water Jet Cutting

In this study, an AWJC machine with an intensifier-type pump with a power of 50 HP was used. Additionally, garnet abrasive material was used during the cutting process. The pressure value (P) was determined in the range of 3500-4000 Bar, the stand-off distance (d) was between 2-5 mm, the abrasive flow rate (m_v) was in the range of 200-350 g/min, the particle size (a) was between 100-110 mesh, and the cutting speed (V) was between 240-300 mm/min. The cutting unit of the Portal Type S brand water jet machine used in the experiments is shown in Figure 1.a, and the pump unit used is shown in Figure 1.b. Figure 2 shows the Al 7068 alloy work piece during the AWJC process with the pressurized water jet, nozzle, and cutting line. The technical specifications of the cutting unit are presented in Table 3.

Experimental Planning and Data Collection

In this study, 32 different experiments were conducted using an L32 orthogonal array design. L32 orthogonal design is an experimental planning method that allows obtaining



(a) (b)

Figure 1. (a) Water jet cutting table (b) high-pressure system.

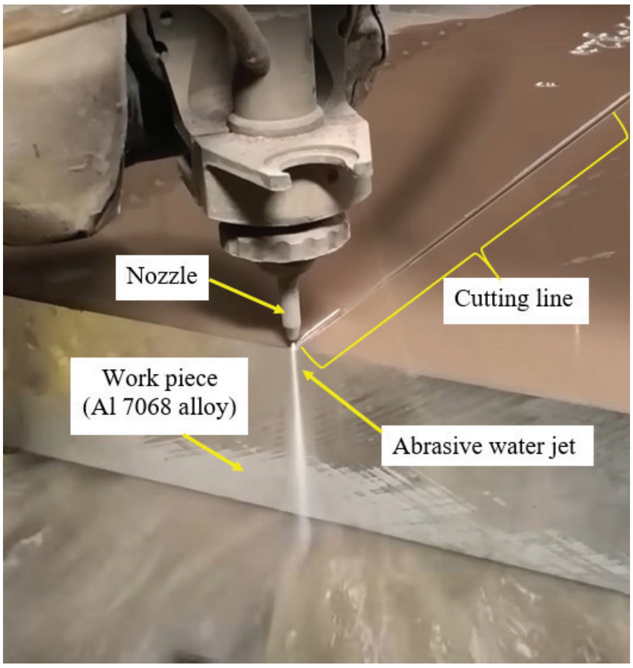


Figure 2. AWJC of Al 7068 alloy.

the most accurate results with the minimum number of experiments by minimizing the interaction between factors. Different parameter combinations were used for the AWJC process in each experiment. Factors such as pressure, nozzle distance, abrasive flow rate, abrasive particle size, and nozzle traverse rate were determined at commonly used levels. R_a values were measured using a Mitutoyo Surftest SJ-210 surface roughness device and the average value from three different points on the processed surface of the samples was calculated for further analysis. In this study, the 32 experiments conducted using L32 orthogonal array design provided an important data source for parameter optimization

Table 3. Specifications of AWJC unit

Properties	Values
Machine Model	Portal Type S-Standard
Pump Power	KMT 50HP
CNC Control System	Siemens
Max Error-Free Cutting Speed	12,000 mm/min
Positioning Accuracy	0.03 mm
Maximum Pump Flow Rate	3.8 L/min
Pump Pressure	≤ 4000 Bar
Nozzle Angle	90°
Nozzle Length	76.2 mm
Nozzle Outlet Diameter	0.76 mm
Table Capacity	2 m x 4 m

Table 4. Levels and values of the process parameters

Parameters	Unit	Low	High
Pressure (P)	Bar	3500	4000
Standoff distance (d)	mm	2	5
Abrasive flow rate (m_v)	g/min	200	350
Abrasive grit size (a)	mesh	100	110
Traverse speed (V)	mm/min	240	300
Surface roughness (R_a)	(μm)	Response	

of the AWJC process. The “Low” and “High” levels of the experiment parameters are presented in Table 4, and the experiment order and the training data set used for R_a are given in Table 5.

In AWJC operations, various parameters impact the R_a of the cut material. In this study, the selected input parameters are P, m_v, V, d, and a. These parameters were chosen based on their significance in affecting surface quality as outlined in previous research and their practical importance in industrial applications. Pump pressure (P), this is the hydraulic pressure at which water is pumped into the AWJC system. It directly influences the energy of the water jet, and thus, the material removal rate and the R_a. Too high a pressure can lead to increased roughness due to a greater amount of material being displaced. Conversely, too low a pressure may not provide enough cutting force, affecting the process efficiency. Abrasive flow rate (m_v): The quantity of abrasive particles mixed with the water jet significantly affects the cutting performance. Higher abrasive flow rates may result in a smoother surface finish due to the increased cutting action. However, an excessive flow rate may result in waste of abrasive and higher operating costs. Nozzle traverse speed (V): This is the speed at which the nozzle moves over the workpiece surface. It impacts the cutting time and the interaction time between the water jet and the material, thus affecting the surface roughness. A faster traverse speed may decrease the process time but could increase the surface roughness. Stand-off distance (d): It is the distance between the nozzle tip and the workpiece. The standoff distance has a significant effect on the energy density of the water jet, which can impact the material removal and the surface roughness. An improper standoff distance can result in a poor surface finish. Abrasive grain size (a): The size of the abrasive particles used in the AWJC system can affect the cutting performance and surface finish. Larger

Table 5. Training dataset used for test order and surface roughness

Exp. No	P (Bar)	d (mm)	m_v (g/min)	a (mm)	V (mm/min)	R_a (μm)
1	3500	2	200	100	240	4.87
2					300	4.97
3				110	240	4.92
4					300	5.04
5			350	100	240	4.96
6					300	5.03
7				110	240	5.10
8					300	5.10
9		5	200	100	240	4.89
10					300	4.96
11				110	240	4.96
12					300	5.03
13			350	100	240	4.95
14					300	5.02
15				110	240	5.02
16					300	5.09
17	4000	2	200	100	240	4.93
18					300	5.01
19				110	240	5.00
20					300	5.08
21			350	100	240	4.99
22					300	5.07
23				110	240	5.06
24					300	5.14
25		5	200	100	240	4.92
26					300	5.00
27				110	240	4.99
28					300	5.07
29			350	100	240	4.98
30					300	5.06
31				110	240	5.05
32					300	5.13

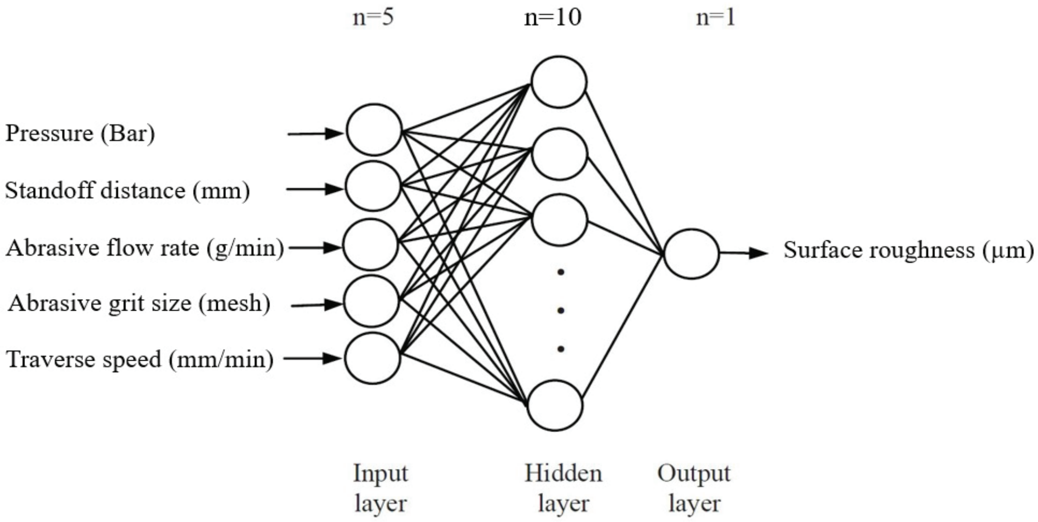


Figure 3. Architecture of ANN model.

particles may improve the cutting efficiency but could result in a rougher surface due to deeper indentations made on the material. Each of these parameters significantly impacts the AWJC process's performance, and their proper selection and control are essential to achieve the desired R_a and operational efficiency. Hence, the study is focused on these parameters to develop accurate models for predicting surface roughness in AWJC operations.

Multiple Regression Analysis

Multiple Regression Analysis is a statistical analysis method used to predict a target variable using multiple independent variables. This method has been used to examine the effects of parameters (P, d, m_v, a, and V) used in AWJC on cutting quality (surface roughness). Different models such as Linear regression, Lasso regression, Ridge regression, Support Vector Machines, Decision Trees, and Bagged Trees were used for multiple regression analysis. Mean Squared Error (MSE) was used to determine which model performed better among these models. MSE is a measure of the average squared difference between predicted and actual values. Lower MSE values indicate a better-performing model.

Artificial Neural Network (ANN) Model

An ANN model has been developed and trained to predict the effects of the cutting parameters used in AWJ on cutting quality. The developed model consists of a layer of 5 input parameters, 10 hidden layers, and 1 output layer, as shown in Figure 3. Parameters such as P, d, m_v, a, and V were used to predict their effects on cutting quality (R_a). The data set in Table 5 was divided into two parts; 70% of the data were used as the training data set (experiment group) and 30% were used to verify the validity of the models (control group). The ANN model was tested on data set samples during the learning process to improve accuracy. After the training process was completed, the ANN model was used to predict cutting quality and the predictions were compared with the actual measurements to evaluate the accuracy. Statistical parameters such as the correlation coefficient (R^2) and Mean Absolute Error (MAE) were used for model evaluation. In addition, the performance of the ANN model was improved using the optimized parameters, and the results of the optimization were analyzed. This study demonstrates that the use of ANN models can be beneficial for optimizing the AWJC process.

RESULTS AND DISCUSSION

In this study, the aim was to develop multiple regression and ANN models for predicting surface roughness in AWJC of Al 7068 alloy. The research aimed to eliminate surface roughness problems that increase operating costs.

According to analysis results, Table 5 presents the data used as the training set to build a multiple regression model to predict R_a in the AWJC process. The input parameters, P, d, m_v, a, and V, were systematically varied in 32 experiments to examine their effects on R_a. The R_a were measured for each experiment and recorded in the table. The multiple regression model was built using this data set and optimized to predict surface roughness values for new input parameter sets. As shown in Table 6, the best R^2 value among the models used was obtained with the Linear regression model, with a value of 95.65%. These results demonstrate that Linear regression model performs the best and could be considered in the selection of other prediction methods such as ANN model. The performance criteria of the other models used are also presented in Table 6.

Table 6. Performance comparison table of regression models

Model	MSE	R^2	Performance (%)
{'Linear'}	0.00029682	0.9565	95.65
{'Support Vector Machines'}	0.0008664	0.87304	87.30
{'Lasso'}	0.01019	-0.49329	49.33
{'Bagged Trees'}	0.004038	0.40828	40.83
{'Ridge'}	0.0083577	-0.22472	22.47
{'Decision Trees'}	0.0061625	0.096966	9.70

In the post-training phase, the results were obtained and compared with each other. The determinant coefficient R^2 was used as the comparison criterion. The comparative R^2 graph of the experimental study data clearly shows how accurate the ANN model predicts (Figure 4). Therefore, it was concluded that the developed ANN model is highly compatible and can be used with confidence intervals. Ficko et. all (2021) used ANN to predict surface roughness of stainless steel X5CrNi18-10 (1.4301) cut by AWJC and found that the ANN model had a higher R^2 value of 97.87% than the multiple regression model with 94.67%. The study also showed that the ANN model was more sensitive to the changes in the input parameters than the multiple regression model [21]. Experimentation and optimization of cutting parameters of AWJC on AA6082 through response surface methodology titled paper uses RSM to optimize the cutting parameters of AWJM for AA6082 alloy. The paper considers abrasive feed, stand-off distance, and nozzle speed as the input parameters, and surface roughness, material removal rate, and hardness as the output parameters. The paper reports that abrasive feed has the most significant effect on surface roughness, followed by nozzle speed and stand-off distance. The paper also suggests optimal values for each parameter to achieve minimum surface roughness and maximum material removal rate and hardness [22].

Furthermore, the results of both the experiments conducted with ANN and the accuracy of ANN in predicting the data have been analyzed. The analysis revealed that the results obtained from ANN and experimental studies are similar (Figure 5). This finding demonstrates the potential of ANN to obtain accurate results in the future.

The results of the experiments conducted with the ANN model and the success of the model in predicting the data have been analyzed. During the training phase of the network, regression curves for the corresponding outputs for the training, validation, and testing sets are shown in Figure 6. The results obtained for each stage of the design process (training, validation, testing, and system) have been analyzed and plotted with the regression process (Figure 6.a-d). As shown in Figure 6, the regression R values (top) and linear regression equations (y-axis) are shown on each graph. It can be observed from the figures that the ANN results are in good agreement with the experimental results. The training for the ANN model is 99%, and the confidence interval value obtained in the testing phase is 97%, which is higher than the accepted value of 95% in the prediction

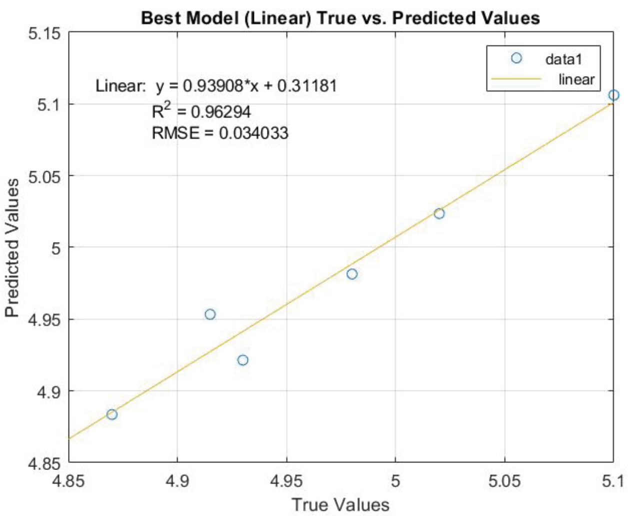


Figure 4. Comparative experimental-ANN results.

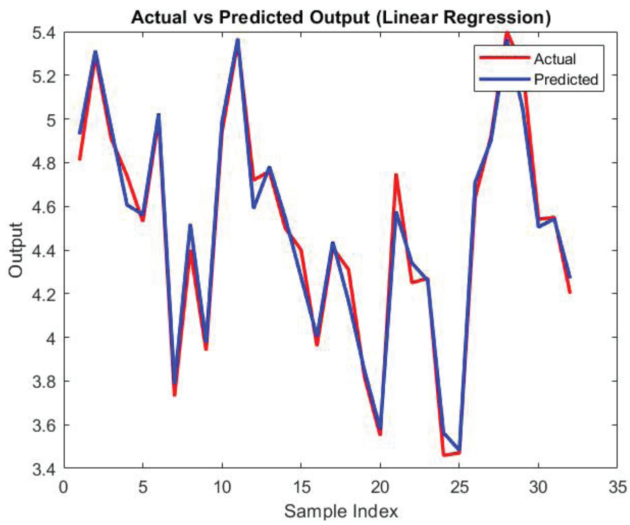


Figure 5. Experiment-ANN data comparison result graph.

analysis (Figure 6). In the graph shown in Figure 7, as the epoch number increases, the amount of error decreases, and the best validation performance is 0.011626 (MSE). When the real and predicted values were compared to evaluate the prediction power of the developed model, the error between them was found to be less than 1%. This indicates that the model has a high level of prediction accuracy. In the conducted ANN study and the linear regression model created, the parameters that affect the surface quality were used to show their effects. This figure shows the performance of the network during the training, validation, and testing processes. These results confirm that the ANN is suitable for modeling the processing process. The success rate for all cases is over 90%. It can be observed that the results obtained from both experimental and ANN models are very close to each other. The decreasing mean squared error of the values fabricated for the ANN experiments shows that the prediction accuracy increases. The least MSE for validation data was obtained in the fifth experiment. In the AWJC process, various parameters, such as pump pressure, standoff distance, abrasive flow rate, abrasive particle size, and nozzle advance rate, affect the surface roughness (R_a). Ćojbašić et al. (2016) developed a model for predicting surface roughness using an extreme learning machine (ELM) and AWJ. The papers use different input parameters, such as hydraulic pressure, stand-off distance, traverse speed, abrasive flow rate, abrasive grain size, angle of attack, cut depth, nozzle diameter, etc. The papers also use different output parameters, such as material removal rate, hardness, kerf geometry, etc. The papers use different methods to model and optimize the process parameters, such as ANN, ELM, FEM, Taguchi method, experimental evaluation, etc. The papers also use different materials for AWJM, such as ceramic tiles, AA6082 alloy, Al alloy 6061-T6, mild steel, Inconel 718 super alloy, etc [23].

Figure 8 presents the relative importance of the input parameters in affecting the surface roughness in AWJM, based on the developed ANN model. The results show

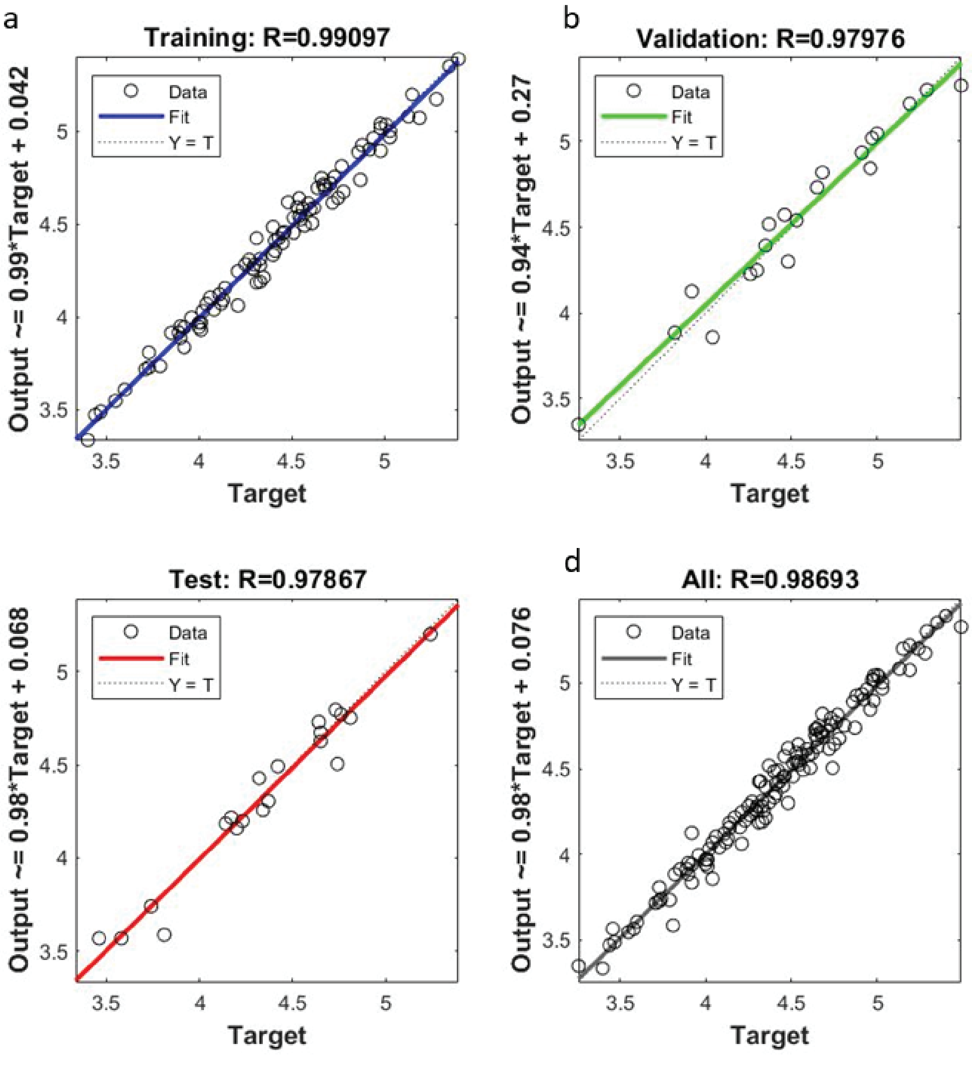


Figure 6. ANN outputs for surface roughness.

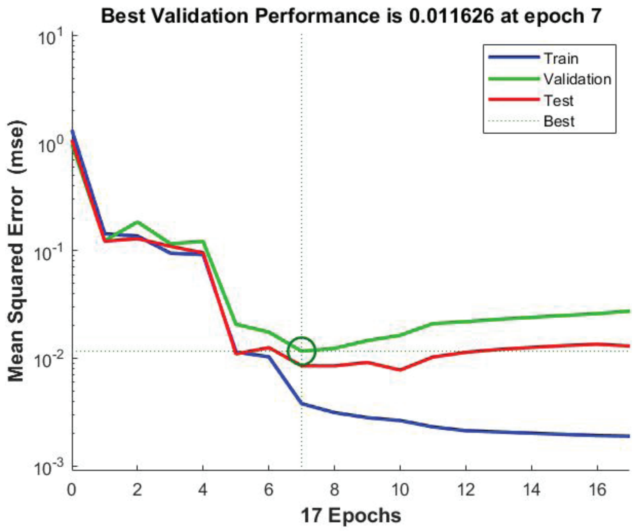


Figure 7. Performance graph of the neural network after training.

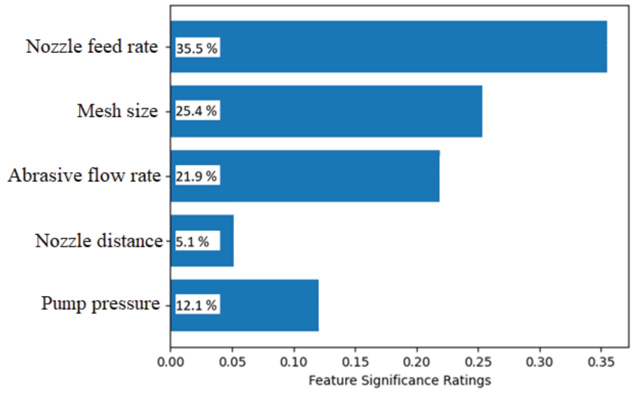


Figure 8. Significance of the effect of parameters on R_a.

that the most influential parameter on surface roughness is the nozzle traverse speed with a percentage of 35.5%. The abrasive grain size comes second with 26.8%, followed by the abrasive flow rate with 19.4%. The pump pressure ranks fourth with 10.4%, and finally, the standoff distance has the least effect on surface roughness with a percentage of 7.9%. These findings provide valuable information for selecting the optimum machining parameters for AWJM. Specifically, the results suggest that the nozzle traverse speed, abrasive grain size, and flow rate are the most important parameters to consider in achieving the desired surface roughness. These findings are consistent with previous research in the field and highlight the importance of selecting appropriate machining parameters to optimize the AWJM process. Ramakrishnan et. all used an ANN-based genetic algorithm (GA) and particle swarm optimization (PSO) to optimize the AWJC parameters for Ti-6Al-4V alloy. They considered water jet pressure, standoff distance, and abrasive flow rate as input parameters and surface roughness and kerf taper angle as output responses. They found that water jet pressure was the most significant factor affecting both responses [24]. Experimentation and optimization of cutting parameters of AWJC on AA6082 through response surface methodology, which uses response surface methodology and ANOVA to optimize the AWJC process parameters for reducing surface roughness and maximizing material removal rate and hardness of Al alloy [25].

The experiment with the lowest R_a value of 4.87 was obtained in Experiment No. 1. The parameters used in this experiment were as follows: the pressure (P) was set to 3500 Bar, the diameter (d) was 2 mm, the abrasive flow rate (m_v) was 200 g/min, the stand-off distance (a) was 100 mm, and the traverse speed (V) was 240 mm/min. In this experiment, the combination of these parameters resulted in the achievement of the lowest R_a value. The high pressure and moderate stand-off distance likely contributed to the efficient removal of material, resulting in a smoother surface. Additionally, the chosen diameter and abrasive flow rate may have played a role in controlling the cutting action and the overall surface finish. It is important to note that the specific material being machined, the nozzle type, and other factors can also influence the final surface quality. However, based on the given parameters, Experiment No. 1 demonstrated favorable results in terms of achieving a lower R_a value, indicating a relatively smoother and more refined machined surface. Microstructure images Figure 9 shows Scanning Electron Microscope (SEM) images of surfaces machined with different cutting parameters. These images play an important role in evaluating surface quality and roughness. The SEM image (Figure 9) of the machined surface obtained using an AWJ reveals several key features. The surface appears to be relatively smooth overall, with some visible irregularities and texture. The AWJ has effectively removed material, resulting in a clean and uniform surface with minimal residual debris. The image shows microscopic scratches and grooves, indicative of the cutting action of the abrasive particles in the water jet. The surface appears to have a matte finish, indicating a moderate level of surface roughness. Additionally, there are no apparent cracks or fractures observed, suggesting that the machining process has not induced any significant damage to the material.

This study introduces a new approach to optimizing R_a in the AWJC of Al 7068 alloy, a material favored in aerospace manufacturing due to its lightweight, high strength performance, and machinability. Instead of solely relying on conventional statistical models, this study employs an ANN model alongside multiple regression models. Critical processing parameters, such as pump pressure, nozzle distance, abrasive flow rate, abrasive grain size, and nozzle traverse speed, are chosen for the study. By using the L32 orthogonal array, the effects of these parameters on R_a are examined through 32 experiments, and data is collected. The study uses multiple regression analysis and Analysis of

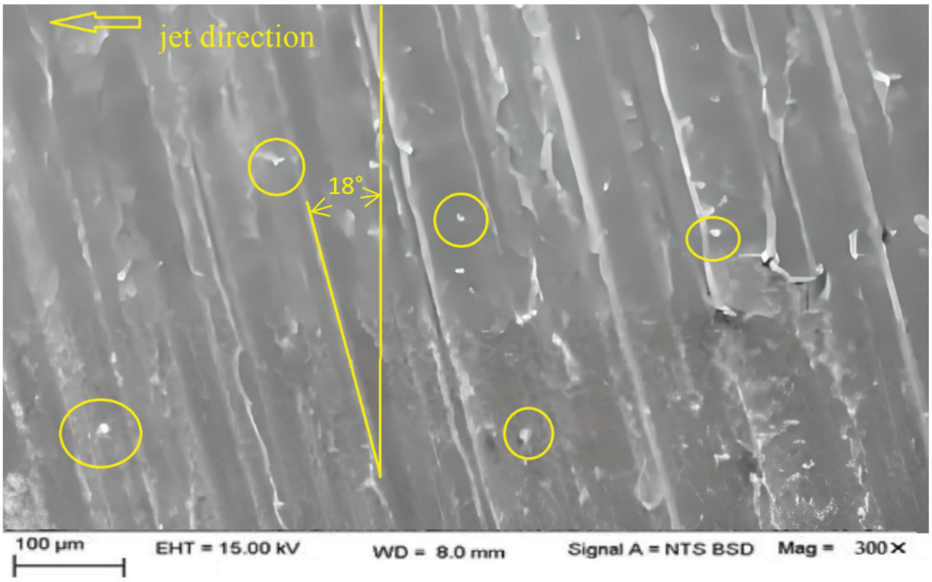


Figure 9. SEM image of machined Al alloy surface experiment no. 1. The parameters used in this experiment were as follows; P=3500 Bar, d= 2 mm, m_v= 200 g/min, a= 100 mm, and V= 240 mm/min.

Variance (ANOVA) to identify the most significant factors and interactions affecting R_a. The ANN model, designed with multiple hidden layers using MATLAB, is trained and assessed using experimental data, and its performance is gauged using mean squared error (MSE) and mean absolute error (MAE). The model is then optimized using hyper parameter tuning and cross-validation techniques. This approach provides a high-accuracy prediction of R_a for different input parameter combinations, representing a reliable and efficient tool for predicting R_a in AWJC, which could enhance process planning and control, thereby potentially reducing operational costs. This is a significant leap from earlier studies that focus on parameter optimization using methods like Response Surface Methodology (RSM) or Taguchi's experimental design. One key difference from the previous studies is the use of ANN, which allows for a more complex and nuanced analysis of the effects of various cutting parameters on surface roughness and other quality indicators. This stands in contrast to traditional regression or DOE methods, which, while effective, may not fully capture the complex interactions between different cutting parameters. Additionally, this approach can be more adaptive, learning from new data to improve predictions over time. Another point of differentiation is the focus on Al 7068 alloy, a high-performance material often used in aerospace applications. This might provide insights specific to this material that might not be gleaned from studies focusing on different types of Al alloys. However, it would be interesting to see a comparison of these modeling approaches with more traditional DOE methods in terms of their accuracy and reliability. Also, while the ANN approach can be more accurate, it's also more complex and may require more computational resources, which could be a disadvantage in some settings. The kerf taper in AWJC and how it is influenced by different processing parameters like cutting speed, material thickness, water pressure, and abrasive flow rate. While this research is crucial in its own right, it is narrower in focus compared to the in this study you mentioned. The in this study uses an ANN model to predict surface roughness across different parameters, providing a more holistic and possibly more accurate approach to optimize the cutting process. Both studies focus on the impact of processing parameters on the machining process, but the in this study has an edge in its ability to predict outcomes [14]. The optimization of the cutting process by adjusting different parameters to achieve optimal surface roughness. Although this study makes significant strides, its statistical modelling approach might not capture the complex interactions between different cutting parameters as efficiently as the ANN model in the in this study [15]. The research evaluates how the feed rate and thickness of work piece affect surface roughness during AWJC. It provides important insights into specific parameters and their impact, but may not cover the full range of interactions and influences that the ANN model in the in this study can account for. This points to a potentially more robust prediction capability in this study [16]. The texturing operations using AWJ, which is a distinct area of study compared to the in this study. While both studies involve altering the material surface, the newer study applies an ANN model for surface roughness prediction across various parameters, which could potentially offer more flexible and nuanced process optimization. [17]. The research investigates fatigue crack behavior in the context of AWJ peening, a very different focus from the in this study. In this study's use of ANN modelling for surface roughness prediction provides a method that might be applied to a broader range of AWJC applications, even though it may not directly tackle issues like fatigue crack behavior [18]. "Improving the cutting quality of Al alloy machined by AWJ with a relatively low pressure" - This study emphasizes the optimization of process parameters to enhance cutting quality at a low pressure. However, it does not make use of advanced methods like ANN modelling used in the in this study, which could potentially provide a more accurate and dynamic method for predicting and improving cutting quality [19].

CONCLUSION

Overall, the study demonstrates the potential of using both multiple regression analysis and ANN methods for predicting surface roughness in AWJ of Al 7068 alloy. The results show that ANN is a reliable tool for predicting surface roughness with reasonable accuracy, and can be used to improve process planning and control in the aerospace industry. The study also highlights the importance of optimizing process parameters such as nozzle traverse speed, abrasive grain size, and flow rate to achieve minimum surface roughness. It is worth noting that modeling each variable separately using regression analysis was found to be more efficient in terms of regression coefficients. Furthermore, the study found that the ANN model outperformed the multiple regression model, with a higher R^2 value of 99% in the training stage and a confidence interval of 97% in the testing stage. These results indicate that the ANN model has high prediction accuracy and can be reliably used in practice. The study also identified the nozzle traverse speed as the most significant parameter affecting surface roughness, followed by abrasive grain size and flow rate. The study's findings suggest that when selecting optimum process parameters for AWJC, nozzle traverse speed, abrasive grain size, and flow rate should be given priority over other parameters.

Overall, this study provides valuable insights into the use of multiple regression and ANN methods for predicting surface roughness in AWJC. It sheds light on the importance of optimizing process parameters to achieve minimum surface roughness and provides a useful tool for process planning and control in the aerospace industry.

The results also show that the pump pressure and the standoff distance have less effect on surface roughness in AWJM of Al 7068 alloy. This may be due to the fact that these parameters have more influence on other aspects of the AWJM process, such as cutting depth, kerf width, and material removal rate. Moreover, these parameters may have more significant effects on surface roughness when using higher pressures or larger standoff distances than those used in this study. Therefore, it is suggested to explore the effects of these parameters on surface roughness in AWJM under different pressure and standoff distance ranges.

LIMITATION AND FUTURE WORKS

The limitations of this study include the use of a single material (Al 7068 alloy), a single nozzle diameter (0.3 mm), and a limited number of experiments (32 pieces). These factors may limit the generalizability and robustness of the developed models for predicting surface roughness in AWJM. Future research could extend this study by using different materials, nozzle diameters, and experimental designs to improve the accuracy and reliability of the models. Furthermore, other methods such as fuzzy logic, support vector machine, and extreme learning machine could also be applied to compare their performance with multiple regression and ANN models for surface roughness prediction in AWJM.

This study has successfully utilized multiple regression and ANN models to predict surface roughness in AWJC of Al 7068 alloy. However, the findings of the study lead to several potential directions for future research. Material and nozzle diameter: This study has focused on a specific material (Al 7068 alloy) and a specific nozzle diameter (0.3 mm). Future experiments involving different materials and nozzle diameters could further expand our capacity to predict surface roughness in AWJC processes. This would help us better understand the effects of different materials and nozzle diameters on surface roughness in AWJC processes. Utilization of other prediction methods: This study used multiple regression and ANN models to predict surface roughness. In future studies, the application of other prediction methods, such as fuzzy logic, support vector machine, and extreme learning machine, could further expand our prediction capacity and enhance the accuracy and reliability of our results. Expanded experimental design: This study concentrated on a specific set of experiments. In the future, a broader experimental design could be utilized. This would allow us to work with a broader data set and further generalize our results. Different pressure and standoff distance ranges: In future studies, it might be possible to explore the effects of pump pressure and standoff distance on surface roughness in AWJC processes under different pressure and standoff distance ranges. This could help us better understand the impact of these parameters on surface roughness in AWJC processes. These potential studies have the capacity to extend the findings of the current study and enhance our ability to predict surface roughness in AWJC processes.

NOMENCLATURE

P	Pressure, Bar
d	Stand-off distance, mm
m_v	Abrasive flow rate, g/min
a	Abrasive grit size, mesh
V	Traverse speed, mm/min
R_a	Surface roughness, µm
K_t	Kerf taper, °

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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