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Data Availability

The data that support the findings of this study are available from the corresponding author, [mostafa.a.hamed@uotechnology.edu.iq], upon reasonable request.

Author Contributions

All authors contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript

ORIGINAL STUDY

Surface Roughness of Aluminum Alloy 7024 Predicted by Linear Regression and Neural Network Model in Abrasive Water Jet Machining

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Abstract

A prediction model using a linear regression model and Artificial Neural Network for the abrasive water jet machining of Aluminum-alloy 7024 was the main objective of this study. The abrasive water jet experiments were carried out based on the Taguchi Design. The influence of three independent variables such as pressure (200, 250, 300, and 350 MPa), feed rate (40, 60, 80, and 100 mm/min), and Gap or standoff distance (1, 2, 3, and 4 mm) as input and use Surface Roughness (Ra) were examined using analysis of variance (ANOVA) as output. The ANOVA response graphs show that pressure has the greatest impact on Ra as a function of feed rate and Gap. The regression model was sophisticated between the studied factors and the response. The confirmation tests show that the regression models are in well approval. The estimated determination of the coefficient value was (0.96). As a result, the maximum error between the obtained Artificial Neural Network (ANN) and experimental data is less than the regression model. The prediction model of ANN was found to be more accurate when compared with the regression model. The ANN results have a good acceptance between the predicted and experimental data, with a mean square error of training indices equal to (0.001).

Keywords: Artificial neural network, AWJM, Regression model, Taguchi design, Surface roughness

1. Introduction

Abrasive Water Jet (AWJ) is a non-traditional machining technology used in mechanical machining operations [1,2]. A rapidly accelerated abrasive jet impinges on the target material, causing the substance to be sliced by the sharp abrasive edges [3,4]. Abrasive water jet machining can be used to cut materials that would be difficult to cut otherwise. Abrasive water jet machining is utilized in a wide range of industries and products, including metals, ceramics, polymers, and composite materials [5,6]. One mechanically developed nonconventional machining process is Water Jet Machining (WJM). In this process, water at a very high speed is utilized to erode a small portion of the surface of the workpiece. Water jet machining performed early removal of coating, cleaning, and cutting of soft materials. Another machining technology, Abrasive Water Jet Machining (AWJM), was developed to machine hard materials such as metals and granite [7]. During this process, no residual stresses and no heat-affected zones. Non-contact and dynamic in the AWJM process, other major advantages are small kerf width, a low heat impacted zone, and higher flexibility during material removal with very small cutting forces. Many types of abrasives are usually used during AWJM like silicon carbide (SiC), silica-sand, aluminum oxide (Al_2O_3), olivine, etc. [8]. AWJM is utilized in various sectors, including automotive, aerospace, medical, and food. Current applications include stripping and cutting fish, cutting automobile carpets, removing coatings from engine components,

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and cutting composite fuselages for airplane construction. The impact of water alone is sufficient to machine a material; however, the inclusion of abrasive increases the material removal rate in the process by many orders of magnitude [9]. Nader and Shather (2022) investigated the effect of stand-off distance, feed rate, and jet pressure on material removal rate through carbon steel metal workpiece abrasive water jet cutting. The Material Removal rate (MRR) was determined using precision balance equipment and sixteen tests to determine the weight loss to total cutting time ratio. The Taguchi technique was used to carry out the trials and identify the important relevant process factors on MRR. The testing findings revealed that the jet pressure and feed rate had the greatest effect on the material removal rate [10]. The higher MRR value was 3.71 g/min at a 4 mm standoff distance, 30 mm/min feed rate, and 300 MPa jet pressure. Khudhir et al. (2022) conducted experiments to evaluate the AWJM technique's performance kerf angle (Ka) and surface roughness (Ra). The process parameters used are abrasive flow rate (AFL), traverse speed (TS), and stand-off distance (SOD) using aluminum alloy 2024-T3 as the workpiece material. The image processing approach was used to calculate the Ka values. The results show that the ideal AWJM technique solutions yield the lowest value of Ra and minimize Ka, which are two mm, twenty mm/min, and one hundred g/min for the stand of distance, traverse speed, and abrasive flow rate, respectively [11]. Murugan et al. (2018) used a self-developed low-cost water jet machine to examine the performance of an AWJM technique at minimal cutting pressure. Its goal is to investigate the viability of machining diverse materials at low pressure, which will assist in the creation of a more effective low-cost WJM. At a low pressure of 34 MPa, three distinct materials were machined. The materials used are mild steel, aluminum alloy 6061, and Delrin plastics, with a traverse rate of one to three mm/min. Cutting performance at low pressure was investigated for several materials regarding surface roughness, kerf taper ratio, and depth penetration. Results revealed that all samples could be machined with varied quality at low cutting pressure and that the penetration depth reduces as the traverse rate rises [12]. Anu Kuttan et al. (2021) studied several modeling methods in AWJM, including dimensional analysis, statistical modeling, differential equations, neural network modeling, numerical modeling, and analytical modeling [13]. A Zr-based bulk metallic glass (BMG) was machined utilizing abrasive waterjet (AWJ), electrical discharge, ns-pulsed laser engraving, and traditional dry-milling processes, according to [14]. Characterization of the treated material revealed that AWJ retains the amorphous phase and provides the necessary speed and flexibility to rapidly create tiny three-dimensional pieces, whereas the other approaches did not. As a proof-of-concept, an orthopedic implant-like screw was quickly machined from the BMG utilizing AWJ. Madival (2023) Experiment using abrasive water jet machining (AWJM) on the machinability of a hybrid rice straw/*Furcraea foetida* composite. Furthermore, the AWJ process factors and the concentration of rice straw are adjusted, and their impacts on machining quality are investigated. The Taguchi L27 orthogonal array is used to produce the experimental trials, and then an analysis of variance (ANOVA) is done. Extensive experiments show that the concentration of rice straw is the most important element (93.5%) in determining the SR. The traverse speed (TS) contributes the most to the material removal rate (MRR), top (TKW), and bottom kerf widths (BKW), with 93.13%, 55.50, and 55.70%, respectively. However, the interplay between fiber concentration and traversal speed contributes the most (35.04%) to the kerf taper (KT). A second-order response surface model is created to investigate the impacts of process factors on the KT, BKW, TKW, SR, and MRR in any experimental area. Finally, the microstructural properties of the machined surfaces are explored, including microcracks, debonding, and fiber pullout [15]. Ramulu et al. (2016) investigated the machinability of one mm thick Ti/Gr laminate sheets using the Abrasive Water jet machining process in terms of material removal rate and kerf properties. By systematically measuring operating variables (traverse speed and Abrasive flow rate) with a fully crossed Design of the experiment (DOE) method and statistically analyzed with ANOVA (Analysis of variance), the parametric impact of AWJ operating factors on machining performance was explored. To quantify these influences and forecast the effect of process factors on overcut in straight cutting, kerf taper, entrance damage breadth, and material removal rate, empirical models were created [16]. (Smith, 2018) compared regression and neural network AWJM surface roughness prediction algorithms. Experimental data is used to build and validate models. Neural network models surpass regression models in accuracy and prediction. The neural network accurately predicts surface roughness with an R-squared of 0.93 [17]. Chen (2018) proposed an AWJM method surface roughness regression and artificial neural network model. Experimental cutting parameter data trains and validates the models. The models accurately estimate surface roughness.

The neural network model has 93% accuracy, whereas the regression model has 0.91 R-squared. Models adjust cutting parameters for higher surface quality [18]. Wang (2019) analyzed regression and artificial neural network methods to predict AWJM surface roughness. Models are built and compared using experimental data. The outcome of the neural network model illustrates that the regression model with an R-squared value of 0.94 compared to 0.89. Neural network models estimate surface roughness well [19]. Liu and Zhang (2019) predicted AWJM surface roughness using regression and neural network models. Changing the cutting parameters yields a complete dataset and models for evaluation. Both models make correct predictions, however, the neural network model outperforms the regression model by 91%–87%. Models can optimize cutting parameters for surface quality [20]. Zhang and Wang (2019) presented an AWJM surface roughness prediction model using multiple regression and artificial neural network models. Models are built and compared using experimental data. The neural network model outperforms the regression model with an R-squared value of 0.93 compared to 0.88. Neural network models estimate surface roughness well [21]. Lee and Kim (2020) optimized AWJM surface roughness prediction using regression and neural network models. Genetic algorithms develop and optimize models. As a result, the optimized models are more accurate, with the neural network model having an R-squared value of 0.95 and the regression model 0.90. The approach can optimize cutting parameters for better surface quality [22]. Gupta and Singh (2020) compares regression and neural network AWJM surface roughness prediction algorithms. Models are built and tested utilizing cutting parameters from experiment data. The neural network model outperforms the regression model with an R-squared score of 0.92 versus 0.89. Both models provide reliable predictions. The neural network model estimates surface roughness [23]. Sharma (2020) presented a hybrid regression-neural network approach for AWJM surface roughness prediction. Experiment data builds and validates models. The hybrid model outperforms the regression model (0.88) and the neural network model (0.91) with an R-squared score of 0.94. Hybrid models accurately predict surface roughness [24]. Patel (2020) predicted AWJM surface roughness using regression and neural network models. After collecting operational data, models are created and compared. The neural network model outperforms the regression approach with 92% accuracy [25]. The neural network model can optimize cutting settings for desired surface quality Nguyen (2021) compared regression and neural network methods for AWJM surface roughness prediction. Models are built and validated using experimental data from various cutting conditions. The neural network model outperforms the regression model in accuracy, with an R-squared value of 0.93 versus 0.88. Neural network models estimate surface roughness precisely [26]. Kim (2021) introduced a hybrid regression-neural network model for AWJM surface roughness predictions. Particle swarm optimization builds and optimizes models. The hybrid model outperforms the regression model in accuracy, with an R-squared value of 0.96 versus 0.90. The method improves surface roughness prediction [27]. Wang (2021) Regression and deep neural network algorithms measure surface roughness in AWJM. Models are generated and compared using experimental data from various cutting situations. The results illustrated that the deep neural network model outperforms the regression model with an R-squared score of 0.95 versus 0.89. Deep neural networks increase surface roughness prediction [28]. Singh (2022) presented an AWJM surface roughness prediction model using optimization, regression, and artificial neural network models. Genetic algorithms construct and optimize models. 96%

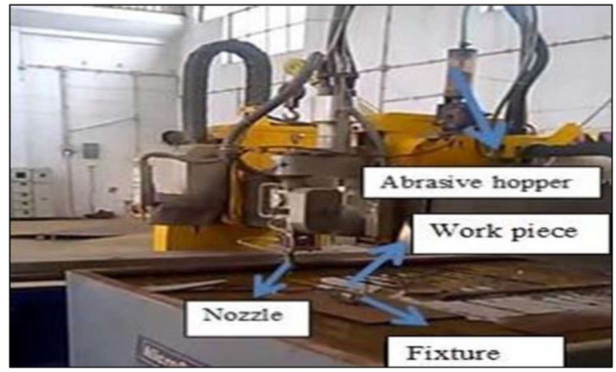

Fig. 1. Abrasive water jet element.

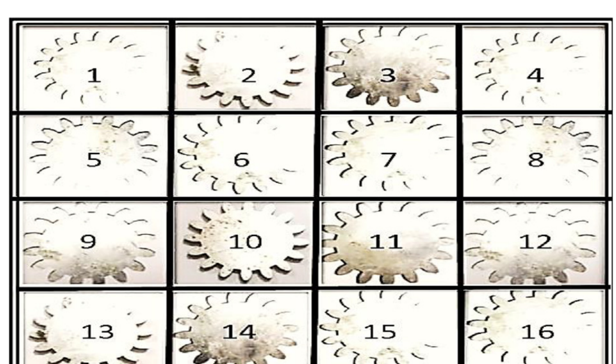

Fig. 2. The machined workpieces.

Table 1. Predicted data of surface roughness using a regression model.

No.	Pressure (Mpa)	Feed Rate (mm/min)	Gap or standoff distance (mm)	Surface Roughness (Measured) (μm)	Surface Roughness (Predicted) (μm)	Error %
1	200	40	1	2.76	2.772	0.435
2	200	60	2	3.28	3.224	1.707
3	200	80	3	3.26	3.410	4.601
4	200	100	4	3.88	3.794	2.216
5	250	40	2	2.70	2.758	2.148
6	250	60	1	3.08	3.086	0.195
7	250	80	4	3.49	3.436	1.547
8	250	100	3	3.60	3.616	0.444
9	300	40	3	2.63	2.554	2.889
10	300	60	4	2.91	3.046	4.673
11	300	80	1	3.11	3.040	2.251
12	300	100	2	3.36	3.384	0.714
13	350	40	4	2.51	2.532	0.876
14	350	60	3	2.89	2.820	2.422
15	350	80	2	2.99	2.978	0.401
16	350	100	1	3.12	3.198	2.500

accuracy beats regression in the optimal neural network model. The models optimize cutting parameters to increase surface quality [29]. Somani (2023) The best surrogate model was used to develop a complex objective function for use in firefly algorithm-based optimization of input machining parameters for minimization of the output responses.

Sharma (2022) compared regression and artificial neural network methods for predicting surface roughness in abrasive water jet machining. Experimental data develops and validates the models. The neural network model predicts surface roughness better than the regression model. The neural network can estimate surface roughness with a 0.93 R-squared score [30]. Patel (2023) optimized AWJM surface roughness prediction using regression and neural network models. Particle swarm optimization builds and optimizes models. The optimized models are more accurate, with the neural network model having an R-squared value of 0.96 and the regression model 0.92. The approach can optimize cutting parameters for better surface quality [31]. Kumar (2023) compared regression and artificial neural network approaches for forecasting abrasive water jet machining surface roughness. Models are built and compared using experimental data. As a result, both models provide accurate predictions, however, the neural network model outperforms the regression model with an R-squared value of 0.94 versus 0.89. Neural network models estimate surface roughness well [32].

Al-Kubaisi (2018) This study examined the Artificial Neural Network (ANN) model to predict these effects. Longer stone columns lowered bending moment, settlement, and vertical stresses while

Table 2. Predicted data of the neural network model data.

No.	Pressure (Mpa)	Feed Rate (mm/min)	Gap or standoff distance (mm)	Surface Roughness (Measured) (μm)	Surface Roughness (Predicted) (μm)	Error %
1	200	40	1	2.76	2.760	0.000
2	200	60	2	3.28	3.264	0.487
3	200	80	3	3.26	3.275	0.460
4	200	100	4	3.88	3.781	2.552
5	250	40	2	2.70	2.701	0.100
6	250	60	1	3.08	3.083	0.097
7	250	80	4	3.49	3.476	0.401
8	250	100	3	3.60	3.600	0.000
9	300	40	3	2.63	2.628	0.076
10	300	60	4	2.91	2.975	2.234
11	300	80	1	3.11	3.108	0.064
12	300	100	2	3.36	3.357	0.300
13	350	40	4	2.51	2.521	0.438
14	350	60	3	2.89	2.899	0.311
15	350	80	2	2.99	2.991	0.033
16	350	100	1	3.12	3.067	1.699

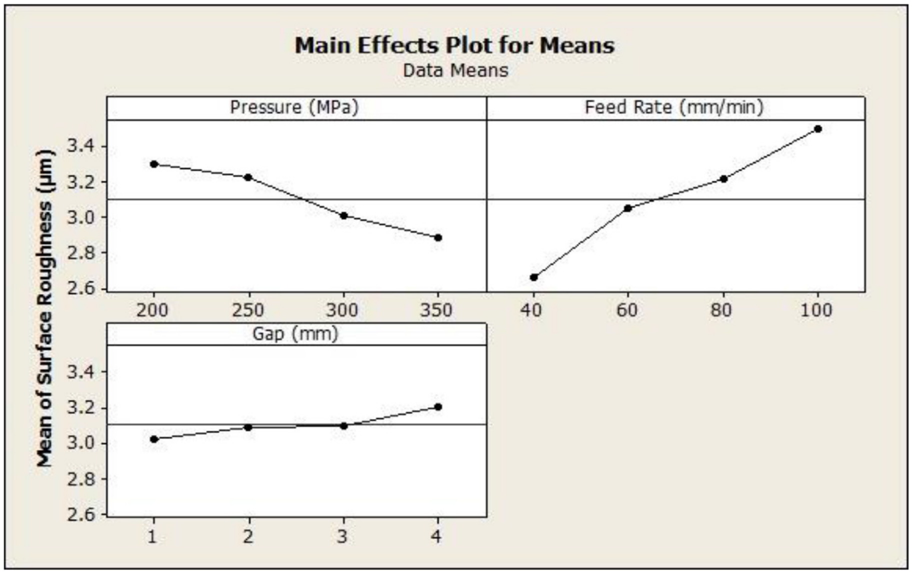

Fig. 3. The influence plot by surface roughness.

increasing horizontal stress and shear force. An ANN model showed a significant connection between predicted and calculated results [33]. Al-Musawi (2016) This work was used to build an AAN model to estimate iron concentrations at the Al-Wahda water treatment plant in Baghdad. The ANN model was made with SPSS. Iron levels in raw water were input from 2004 to 2011. Since 2012 and 2013 verification findings revealed good accuracy, the ANN model could predict future iron concentrations [34]. Al-Saady (2022) ANN will be used to anticipate maintenance costs and times in the study by creating two wastewater project maintenance cost and time models using artificial neural networks (ANN). The results show a 95.4% correlation (R) between real and projected costs [35]. Al-Saady (2023) The models were constructed utilizing the researcher's artificial neural network technology. R between actual and anticipated values was 99.4% and (94.5%) for the cost and time models. The results of this study found that ANN models have a high correlation and accuracy, making them efficient and cost- and time-predictive [36]. (Das, A.2022) Abrasion and adhesion were revealed to be the primary wear processes. Speed leads to increased tool wear. Cutting force was shown to grow fast at higher speeds (70, 80, and 90 m/min). Cutting force was reduced at both low and middle speeds (40, 50, 55, and 60 m/min). Increased levels of feed and depth of cut resulted in increased cutting force. Machined surface morphology and roughness deteriorated as the depth of cut varied [37].

This study aims to create a prediction model for abrasive water jet machining of Aluminum-alloy 7024 utilizing a linear regression model and an Artificial Neural Network (ANN). The research includes doing abrasive water jet experiments using the Taguchi Design approach.

2. Elements of abrasive water jet machine

The AWJM is comprised of multiple pieces of equipment, as shown in Fig. 1, including the following:

- Hydraulic Pump Unit (comprised of a hydraulic pump, an electric motor, accumulator, tubing, and an intensifier).
- Water Feeding Unit: tungsten carbide and synthetic sapphire nozzles. And 200 h of operation, which are damaged by dirt particles.
- Abrasive Feed Unit: two particles (abrasive slurry feed and dry abrasive delivery) are available.
- Nozzle: There are two types of nozzles: multiple-central and single-jet feed.
- Worktable: There are widely available shapes and sizes ranging from little to extremely large.
- Catcher System and Drain (The nozzle moves while the workpiece remains stationary, and the

Table 3. ANOVA affected parameter.

Source of variance	DOF	Sum of squares	Variance	P-value (%)
Pressure (MPa)	3	0.447	0.149	21.40%
Feed rate (mm/min)	3	1.4955	0.4985	71.61%
Gap (mm)	3	0.065	0.033	3.13%
Error,e	10	0.120		20.6%
Total	15	2.088		100

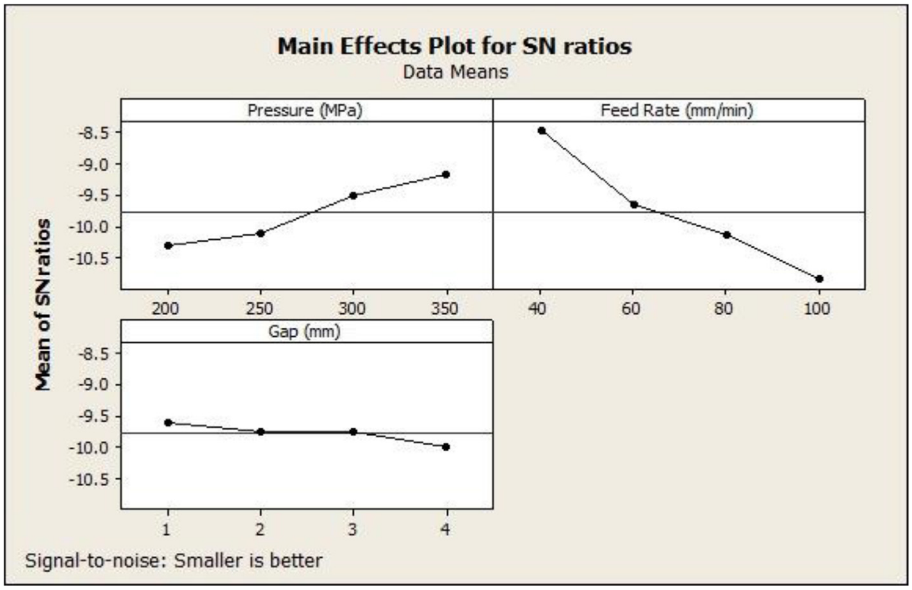

Fig. 4. The main effect plot of the SN ratio.

workpiece moves while the nozzle remains stationary).

3. Experimental procedure

3.1. Tool

AWJ machines use the kinetic energy of particles transported in water as a cutting tool by impinging on the material's surface at a large velocity through a nozzle.

3.2. Work piece

Workpiece materials are chosen according to allowable stresses, mechanical properties, and chemistry. The material removal rate decreases due to the lower kinetic energy of the abrasives induced by the hard material's resistance. In this job, Aluminum-alloy 7024 with dimensions (100*100*5) mm to cut gear shape was used, as shown in Fig. 2.

4. Results and discussion

The predicted and measured surface roughness data using the regression model are listed in Table 1. The neural network model data are illustrated in Table 2.

From the main effect plot of Ra illustrated in Fig. 3, the feed rate reduction in AWJ cutting of Aluminum Alloy type 7024 resulted in better surface quality, increasing the feed rate due to large inaccuracy and surface roughness. However, when the process feed rate rises, the Ra increases because fewer particles travel through a unit region when the process advances quickly. As a result, fewer impacts and cutting edges are available per unit area, resulting in a rougher surface depicting the link between the feed rate and the surface roughness. Table 3 Shows the influence of water pressure on surface roughness. Surface finish is greatly influenced by jet pressure. The surface becomes smoother as the jet pressure increases. Brittle abrasives break down into tiny particles when jet pressure increases. When the abrasive size is lowered, the surface gets smoother. Again, when the jet pressure rises, the particles'

Table 4. Signal-to-noise ratio response table.

Level	Pressure	Feed Rate	Gap or standoff distance
1	−10.308	−8.472	−9.601
2	−10.113	−9.658	−9.756
3	−9.524	−10.132	−9.766
4	−9.165	−10.848	−9.988
Delta	1.142	2.376	0.387
Rank	2	1	3

Table 5. Means response table.

Level	Pressure	Feed Rate	Gap or standoff distance
1	3.300	2.654	3.024
2	3.224	3.044	3.086
3	3.006	3.216	3.100
4	2.882	3.498	3.202
Delta	0.418	0.844	0.178
Rank	2	1	3

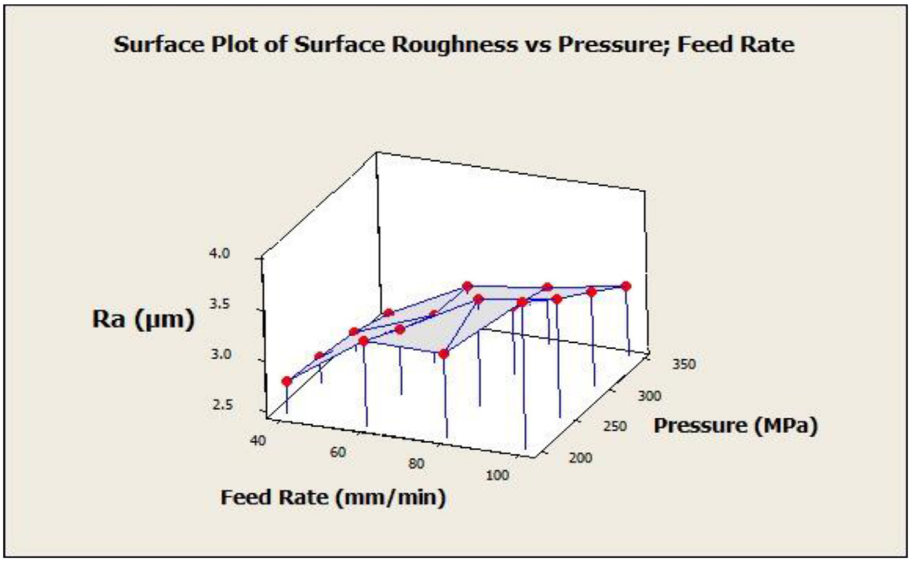

Fig. 5. Surface roughness plotted against pressure and feed rate.

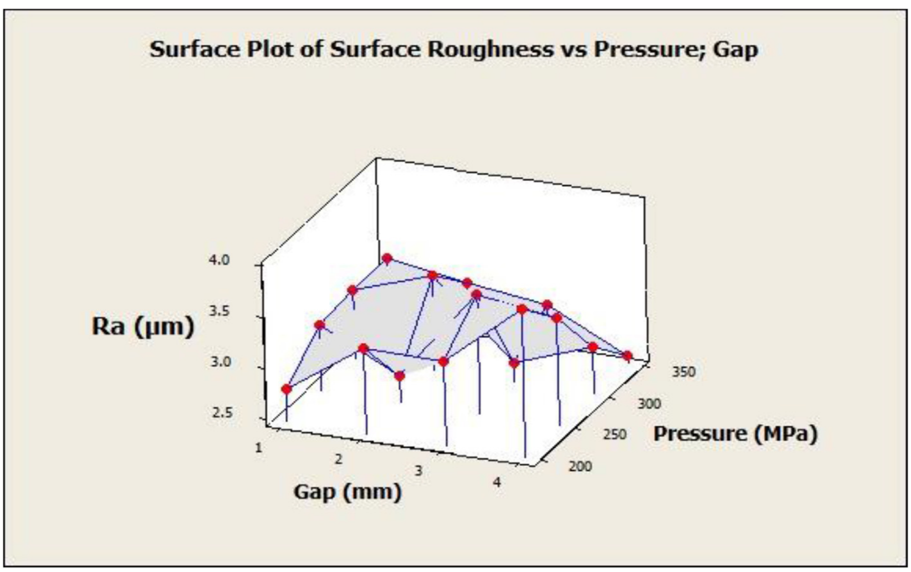

Fig. 6. The surface roughness plot vs. pressure, gap.

kinetic energy rises, resulting in a smoother machined surface. Surface roughness increases as the gap distance increases. Fig. 3 depicts this. Higher standoff distances, in general, enable the jet to expand before impingement, which may increase sensitivity to external drag from the surrounding environment. As a result of the increasing spacing, the jet diameter increases as cutting begins, reducing the kinetic energy of the jet upon impingement. As a result, the surface roughness increases as the distance widens. A smaller gap is preferable since it may result in a smoother surface due to higher kinetic energy. The product surface is smoother towards the surface's top and gets rougher as one descends from the top influence plot of the SN ratio is illustrated in Fig. 4.

The response table for signal noise ratios and response table for means are illustrated in Tables 4 and 5 Respectively.

The obtained linear regression model for the prediction equation is:

$$Ra = 2.83 - 0.00294\ P + 0.0135\ F + 0.0548\ G \quad (1)$$

Where:

Ra = Surface Roughness (µm)

P= Pressure (MPa)

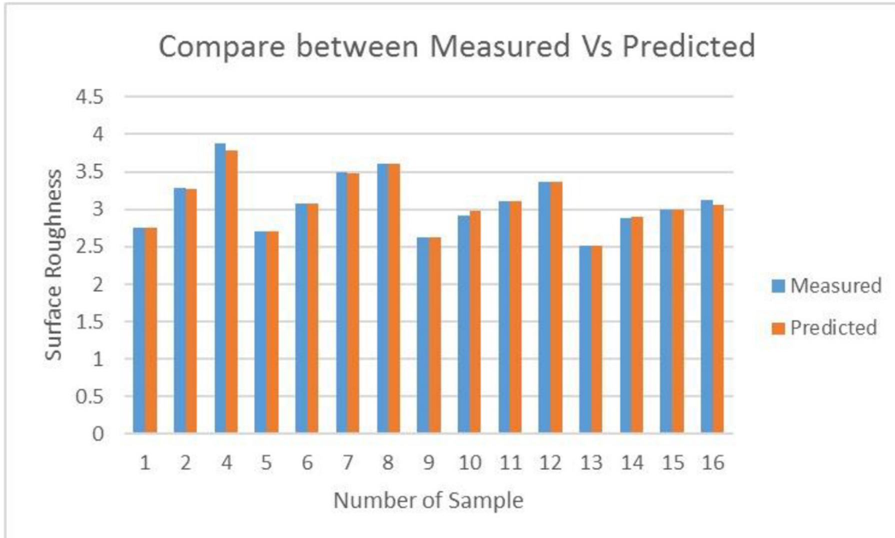

Fig. 7. The experimental and predicted ANN data of surface roughness.

F= Feed Rate (mm/min)
G = Gap or Standoff distance mm

The surface plot of pressure value vs. surface roughness value and feed rate value is illustrated in Fig. 5. The surface plot of surface roughness value vs. pressure value and gap value is defined in Fig. 6.

The experimental and predicted data on surface roughness value using the ANN prediction model as shown in Fig. 7.

The dissertation shows normal probability curves in Fig. 8. Normal probability plots show if a dataset is normal or follows a normal distribution. They

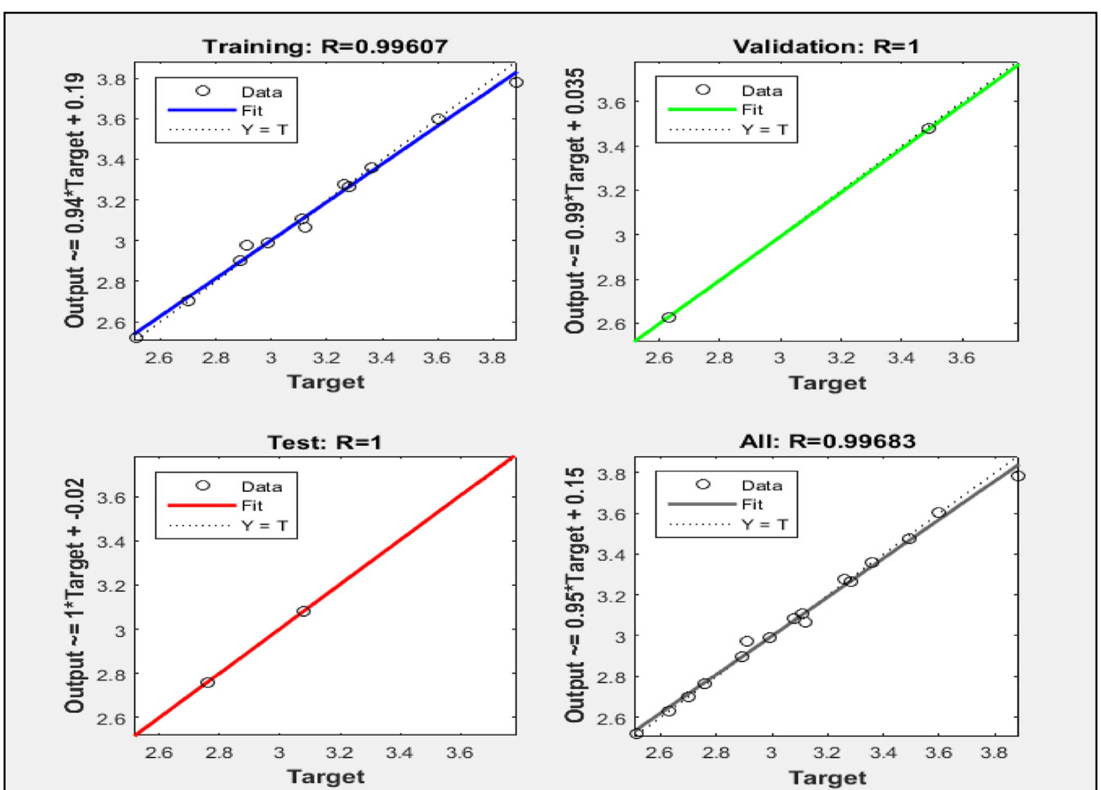

Fig. 8. The normal probability plot.

offer observed and expected data with a normal distribution. The normal probability plot shows data values against their z-scores or percentiles. Normal data exhibits essentially straight lines. Points that vary substantially from a straight line suggest an abnormality.

5. Conclusions

In this work, surface roughness has been investigated on Aluminum Alloy type 7024 by two methods linear Regression model and neural network Model prediction using the Abrasive Water jet process. The following conclusions are listed:

1. The influence of three independent variables such as increased pressure decreased Surface Roughness, increased feed rate and Gap (standoff distance) increased Surface Roughness were analyzed through ANOVA agree with [15].
2. The maximum Ra occurs at sample (4) pressure (200 MPa), feed rate (100 mm/min), and Gap or (standoff distance) (4 mm) on the Surface Roughness (3.88 μm).
3. A good agreement between the experimental and predicted data round of 96% in the ANN results with the mean square error of training indices equal to (0.001), allowing manufacturing industries to choose the better set based on application agree with [21,36].
4. The maximum effect parameter was feed rate with (72%) and The minimum effect parameter was Gap (standoff distance) with (4%).

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