Application of ANFIS in Prediction of Burst Area in Abrasive Water Jet Cutting of Granite

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Abstract: **Granite has vast range of application as construction material, architectural stone, a decorative stone, bridges and countertops. Black pearl granite is excavated in large blocks providing slabs of suitable sizes. Machining of rocks with conventional method has low surface finish and incorporates cost in final finishing. Abrasive water jet cutting is used for precise cutting of granite. Burst occurs at the other side of the material which is undesirable. The burst has to be minimum for high production and minimum wastage of cost. This work deals with the prediction of burst area by using ANFIS. The experiments were carried on Black pearl granite. By using Taguchi method a L27 Orthogonal Array was formed for deciding number of cuts. Input parameters such as traverse speed, abrasive flow rate and standoff distance were varied whereas water pressure and abrasive size were constant and burst area was the response which is to be calculated. After experimentation, with the help of ImageJ software area of burst is calculated for each cuts. Thereafter with the help of data acquired, coding was done in ANFIS in order to predict the burst area. The motive behind this is to increase the precision of machining and to reduce the cost behind the finishing of granite. Effect of these process parameters on the burst area were considered for prediction of burst area by using various Artificial Intelligence (A.I) techniques like ANN (Artificial Neural Network) and ANFIS (Artificial Neuro-fuzzy Inference System). The results were compared by comparing AI technique in prediction of response to get most accurate AI technique.**

Keywords- **Abrasive water jet, Granite, Burst, ImageJ, ANN, ANFIS**

I. INTRODUCTION

With increase demand for stone use in a wide variety of constructional application requires proper knowledge of stone availability and use. The most commonly used are granite, marble, limestone, etc. Granite is hardest of all building stones with very dense grain, making it virtually impervious to stain and uniquely applicable for any interior use. Due to its application cutting of granite should be economical. Abrasive Water Jet Cutting is used for cutting of these rocks, it is important to select proper input parameters in order get proper surface finishing with less burst and using AI techniques modeling the results of experiments and comparing them. The complete detailed study is shown in the giving chapter.

1.1 Background:

In an era of intensive competition, the new challenges faced by industrial manufacturing processes include maximizing productivity, ensuring high product quality, and reducing the production time while minimizing the production cost simultaneously. With the more precise demands of modern engineering products, the control of surface texture together has become more important. These processes work on a particular principle by making use of certain properties of materials which makes them most suitable for some applications and at the same time put some limitations on their use. These processes involve large number of respective process variables (also called as process parameters) and selection of exact parameters setting is very crucial for these highly advanced machining processes which may affect the performance of any process considerably. Due to involvement of large number of process parameters, random selection of these process parameters within the range will not serve the purpose. The situation becomes more severe in case if more number of objectives are involved in the process. Such situations can be tackled conveniently by making use of optimization techniques for the parameters optimization of these processes.

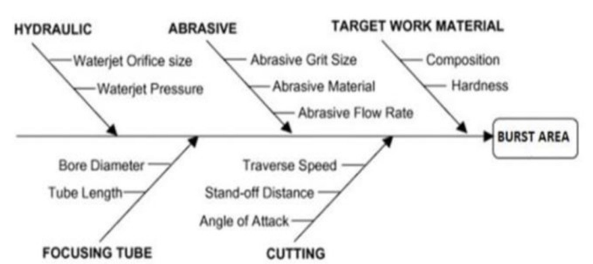


Fig 1.1 Parameters affecting Burst Area

Abrasive water jet (AWJ) is an unconventional method used in machining of difficult-to- machine materials like titanium, rocks, tool steels, super-alloys, hardened steels, glass, composites, metal matrix composites, laminates and advanced ceramics by high pressure, high velocity water jet. This list of materials expands daily as people apply the unique properties of fluid jets to industrial problems. This machining process is now a day's replacing the conventional machining processes due to their significant advantages in present industrial scenario. AWJ machining is a process in which a very high velocity stream of water is used to accelerate particles of an abrasive material, which in turn cuts the work piece material by erosion principle. It has a reservoir where water is stored, pump for supplying water, intensifier for increasing the water pressure, accumulator for temporary storage of water, control valve for flowing control of water, flow regulator for controlling flow of water and nozzle where kinetic energy of water is increased with addition on abrasive material. Various abrasive materials used in AWJM are silicon carbide or aluminum oxide.

Granite is igneous rock is formed from the process of magma cooling. It is composed mainly of quartz and feldspar with minor amount of mica, amphiboles and other minerals which gives granite a red, pink, grey or white color.

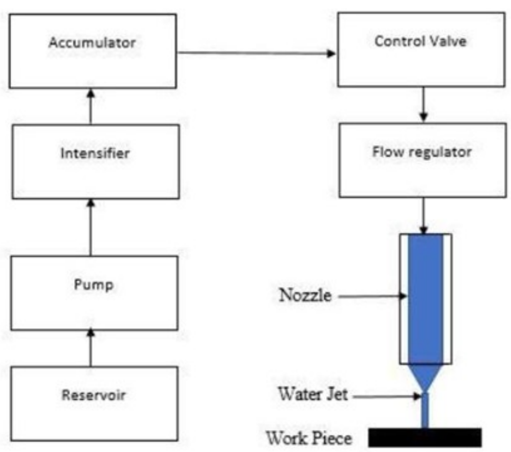


Fig 1.2 Water Jet cutting process

II. LITERATURE REVIEW

This Chapter includes study of research papers. On the basis of the rigorous study of literature, the problem definition and the objectives are framed.

2.1 Literature Survey: The survey considered in this work is categorized in the following subsections as abrasive water jet cutting of rocks and application of Artificial Intelligence in process monitoring.

2.1.1 Literature Survey on Abrasive Water Jet Cutting Of Rocks:

1. Karakurt et al [1] used Taguchi method to perform experiment by varying operating parameters i.e. traverse speed, abrasive flow rate, standoff distance, water pressure and abrasive size. Also regression modeling was used to build models for prediction of kerf angle. Further several statistical tests very conducted to test the adequacy of model. It was concluded that not only operating variables, but also the textural and mineralogical properties had effect on the kerf angle.

2. Lima et al [2] performed experimental analysis in AWJ cutting Agate (Gem stone). Here they considered effect of process parameters like traverse speed, abrasive mass flow and thickness on surface roughness and angle of striation. Further results are analyzed by ANOVA (analysis of variance). It was found that the machined surface finish varies according to the depth from the surface entrance and thickness of plate has no effect on surface finish. By ANOVA it is seen that transvers speed is more significance than abrasive mass flow rate with respect to surface finish.

3. Tae-Min Oh and Gye-Chun Cho [3] performed experiments with different energy (i.e. water pressure, traverse speed and abrasive feed rate), Standoff distance and uniaxial compressive strength (UCS). It is concluded from results that cutting depth efficiency increases with an increase in water pressure and traverse speed and with a decrease in the standoff distance and UCS.

4. Hlavac et al [4] performed experiments on several rock materials by varying traverse speed and comparing the taper inclination of cut wall. Further results where compared with regression equation obtained from previous experimentation on metals. It was seen that the kerf width of sandstones, marbles and limestone and granite for a particular traverse speed increases from inlet to outlet. And as traverse speed increases kerf width decreases either at inlet or outlet with respect to previous traverse speed respectively.

5. Polacek et al [5] performed experimental analysis on rocks under abrasive water jet cutting where they consider water pressure, material characteristics and pressure of air presence between nozzle outlet and sample surface as input and depth of penetration as a response. They found that as water pressure and material characteristics increases the depth of penetration decreases. And as air pressure decrease, depth of penetration also decreases.

6. Aydin et al [6] performed experimental study on depth of cut by abrasive water jet machining on rocks. Here they considered traverse speed, abrasive size, abrasive mass flow rate, water pressure and standoff distance as input and depth of cut as response. They applied Taguchi experimental design method to conduct an experiment and also applied regression method for prediction of depth of cut by operating input variables. They found that depth of cut increases as water pressure and abrasive mass flow rate increase. And it decreases when traverse speed increases and abrasive size decreases, also they found that stand of distance has discernible effect on depth of cut. Then they applied statistical analysis and they found that the model developed for rock had potential for practical analysis.

7. Tae min-oh et al [7] performed experimental study to explore the characteristics of rock fracturing induced by a high-pressure water jet. They considered stand of distance, water pressure and indentation depth as an input parameter and shear stress induction as a response. By applying shear stress analysis, they found that critical stand of distance increases when distance between water jet point of impact and the free surface boundary increases , along with increasing water jet power. And Pre-indentation helps to fracture the rock efficiently. It get maximized when the free surface boundary is far from the jet-impact point, and at low water jet power. And more shear stress generated when indentation depth is more along with higher water pressure and closer location from the water jet impact-point.

8. Karakurt et al [8] presents an experimental analysis in AWJ cutting of granite rocks. In this research paper they used kerf width instead of width of cut as an output parameter for analysis. The granitic rocks of known dimensions were used as specimen and the experimentation used were designed using Taguchi orthogonal arrays. The statistics were compared with predictive models. The results showed that SOD (standoff distance) and traverse speed had significant effects on kerf widths of tested rocks. The results also showed that various mechanical properties of rock like water absorption, unit weight, micro-hardness, maximum grain size of rock-forming minerals, and mean grain size had co-relations with kerf widths.

9. Aydin [9] investigated recycling ability of abrasives using cutting depth, kerf width, kerf taper angle and surface roughness as input process parameters. The abrasives and the rock particles were separated by using gravity separation technique. The abrasive particles with mass percentage above 106 micro metres were only selected for experimentation. The reusability of abrasives after first, second, third and fourth cuttings were 81.77%, 57.50%, 34.37% and 17.72% respectively. It was determined that the abrasives must not be recycled after three cuttings as there is excess disintegration of abrasives with further recycling. The results concluded that cutting depth, kerf width and surface roughness decreases with recycling of abrasives but there was no clear relation between kerf taper angle and recycling.

2.1.2 Literature Survey On Application:

1. GAO et al [10] developed a parameter optimization model using Genetic Algorithm (GA) and Artificial Neural Network (ANN) with Levenberg Maquardt algorithm adaptation which represents relation between material removal rate (MRR) and input parameters in Electric Discharge Machining (EDM).

2. Pradhan and Bhattacharyya [11] developed a mathematical model to optimize the machining characteristics like MRR, TWR and overcut (OC) using Response Surface Methodology and ANN with peak current, pulse on time, dielectric flushing pressure as input parameters in micro EDM.

3. Rajmohan et al [12] optimized machining parameters in drilling of hybrid aluminium metal matrix composites using the grey-fuzzy algorithm. Fuzzy rule-based reasoning integrated with Taguchi's method used to reduce the degree of uncertainty during the decision making. For producing high quality products at low cost L_{27} 3-level orthogonal array is used for experiments.

4. Pandey and Dubey [13] improved the geometrical accuracy of the Duralumin sheet in laser cutting and simultaneously minimized kerf width and kerf deviation on both top and bottom sides. Robust parameter design methodology and fuzzy logic theory used to compute fuzzy multi-response performance index.

5. Sen et al. [14] ANFIS modelling was utilized to predict the relationship between surface roughness, cutting force and cutting temperature with speed, feed, depth of cut and width of cut as in CNC milling of Inconel 690 using ANFIS. Machine learning algorithm is developed using fuzzy inference system (FIS) incorporated in the neural network (NN) environment.

6. Khan et al. [15] used artificial neural network(ANN) [Multilayer perceptron(MLP) with 3 hidden layer feed forward networks] to develop Artificial Intelligence (AI) model to predict surface roughness of Ti-15-3 alloy in Electrical discharge machining (EDM) with peak current, pulse on time, pulse off time, servo voltage as input parameters.

7. Maher et al. [16] predicted surface roughness of brass using ANFIS in CNC end milling. Spindle speed, feed rate, and depth of cut were used as predictor variables. Fuzzy inference system (FIS) incorporated in the neural network (NN) environment is used to design machine learning algorithm. This hybrid arrangement offers a twin benefit of human-like reasoning quality in conjunction with an adaptive network which is accountable for enlightening the fuzzy rules.

III. PROBLEM DEFINITION AND OBJECTIVE

This chapter includes problem definition, objective and methodology.

3.1 Problem Definition:

Granite has large scale application in ornaments as well as in municipal corporations (nowadays used in sewage system). Initially the rock material was cut by mechanical techniques (conventional methods) which involved high production cost due to wear in tool material and damage in work piece.

Water jet cutting is a non-conventional machining technique where in tool is abrasive water jet which solves the problem of tool wear in conventional method. But the problem faced in water jet cutting is that random selection of process parameters gives striation at the exit of abrasive water jet. The same problem can be solved by optimal selection of process parameters. Also the hybrid modeling techniques like ANFIS would help the operators in future to have the process parameters for required surface roughness.

3.2 Objectives:

- To minimize the burst area in water jet cutting of rocks.
- To find the effect of input process parameters towards the variation in burst area.
- To model the complete process by ANN, Fuzzy Logic and ANFIS.
- To compare the results of all the three A.I. techniques for the given responses.

3.3 Overall Methodology:

After the study of research papers on cutting of Granite rock. Then calculate the number of cuts required for experimentation using Taguchi Method. Then the study of research papers on Artificial Intelligence in process monitoring was used to find the appropriate method of getting results to process for optimizing the process parameters and prediction of burst area. Parameter selection is necessary for test trial after getting objective. Then the optimization is done using AI techniques like fuzzy logic to formulate a prediction model for burst area.

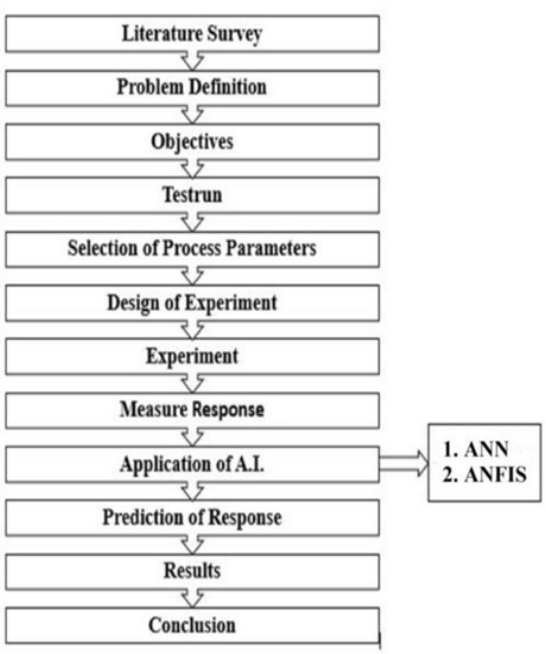


Fig 3.3: Overall Methodology Chart

IV. EXPERIMENTATION AND MEASUREMENT OF RESPONSE

In this chapter we briefly discuss about the Abrasive Water jet machine used for experimentation. Material selected for experimentation is Granite (Black Pearl). Taguchi method was used for deciding the various levels of process parameters for orthogonal array and input parameters where selected. Thereafter the response was decided which is to be calculated. After performing experiment and taking 27 cuts, with the help of ImageJ software the response (area of burst) was calculated for each cut.

4.1 Experimentation:

The AWJ cutting tests were carried on KMT Water jet STREAMLINE SL-V 30 Classic C machine with power rating of 30hp, pressure of 60000 psi, power supply of 10 amp and voltage of 24V. The experiments were performed on a sample of Black Pearl Granite marble whose average density lies between 2.65 and 2.75 g/cm^3, compressive strength above 200MPa and viscosity near STP is 3 – 6 * 10^{19} Pa.s. Granite ranks an incredible 7 on the Moh's hardness scale. The sample used for the experimentation had dimensions as 800 mm x 76 mm x 18 mm.

The detailed specifications of the Abrasive Water jet machine used are mentioned below:

Table No.4.1.1: Specification of Abrasive Water jet Machine

Description	Unit	Value
Nominal Power Rate	Hp	30
Maximum Pressure Range	Psi	60000
Max. water flow rate	gpm	0.6
Maximum Single Orifice Diameter	mm	0.279
Control Voltage	V	24
Power Supply	Amps	10
Max. Noise Level	dB	72.5
Length	M	1.7
Width	mm	914
Height	mm	1453
Weight	Kg	953

Fig 4.1.1. KMT Intensifier Pump

Fig 4.1.2. CNC unit

Taguchi method are statistical methods, or sometimes called robust design methods, developed by Genichi Taguchi to improve the quality of manufactured goods, and more recently applied to engineering, biotechnology, marketing and advertising. Dr. Taguchi of Nippon telephones and Telegraph Company, Japan developed a method based on "Orthogonal Array" experiments which gives much reduced "variance" for the experiment with "optimum setting" of control parameters to obtain best results in the Taguchi Method. Orthogonal Array (OA) provide a set of well balanced (minimum) experiments.

Taguchi proposed a standard 8 – step procedure for applying his method for optimizing any process,

Step-1: Identify the main function, side effects, and failure mode.

Step-2: Identify the noise factors, testing conditions, and quality characteristics.

Step-3: Identify the objective function to be optimized.

Step-4: Identify the control factors and their levels.

Step-5: Select the orthogonal array matrix experiment.

Step-6: Conduct the matrix experiment.

Step-7: Analyse the data, predict the optimum levels and performance.

Step-8: perform the verification experiment and plan the future action.

For this experimentation process, standoff distance, traverse speed and abrasive flow rate were considered as the input process parameters. Each input parameter had three different levels of operation. Therefore, by using Taguchi Method a L27 orthogonal array was formed. Thus 27 cuts were taken.

Table No. 4.1.2: Process Parameters and their levels considered for the experimentation

Machining parameters	Units	Level 1	Level 2	Level 3
Standoff distance	mm	1	3	5
Traverse speed	mm/min	1000	800	700
Abrasive flow rate	gm/min	200	250	300

Fig no. 4.1.3. Setup of material for experimentation

Table No. 4.1.3: Experimental Layout of 3^3 Orthogonal array

Experiment No.	Standoff Distance (mm)	Traverse Speed (mm/min)	Abrasive flow rate (gm/min)	Area of Burst (mm^2)
1	3	1000	200	17.004
2	3	1000	250	7.24
3	3	1000	300	87.039
4	3	800	200	78.457
5	3	800	250	96.745
6	3	800	300	63.155
7	3	700	200	101.149
8	3	700	250	87.294
9	3	700	300	6.665
10	1	1000	200	37.394
11	1	1000	250	122.284
12	1	1000	300	22.813
13	1	800	200	194.08
14	1	800	250	146.166
15	1	800	300	52.054
16	1	700	200	139.9
17	1	700	250	71.222
18	1	700	300	15.152
19	5	1000	200	76.614
20	5	1000	250	51.97
21	5	1000	300	54.993
22	5	800	200	173.172
23	5	800	250	78.743
24	5	800	300	50.421
25	5	700	200	99.814
26	5	700	250	105.872
27	5	700	300	28.606
28	5	600	300	7.651
29	5	900	200	69.227
30	2	775	250	61.717

4.2 Measurement:

After performing the experiments, the response (area of burst) needs to be calculated. For calculating the response ImageJ software is used. Following step are involved in calculating the area:

1. Set Scale (Reference): First the image is opened in the software and from the tool bar click on straight and draw a known distance then clicking on analyse in the toolbar click on set scale enter the known distance and unit and click Ok.

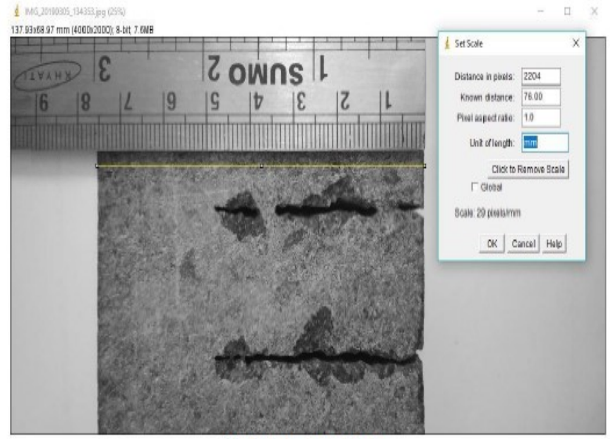


Fig 4.2.1. Setting of Scale.

2. *Tracing:*

After setting of the scale then selecting freehand selection from toolbar and tracing the area which is to be calculated.

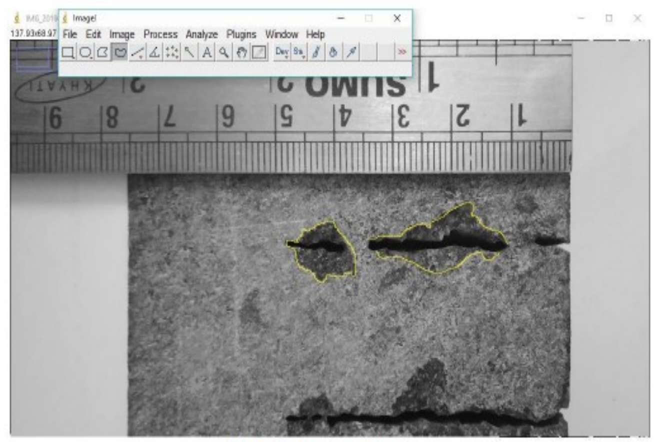


Fig 4.2.2. Tracing of burst.

Calculation:

After the tracing is done click on analyse in the toolbar and click measure then we get the area of the traced area.

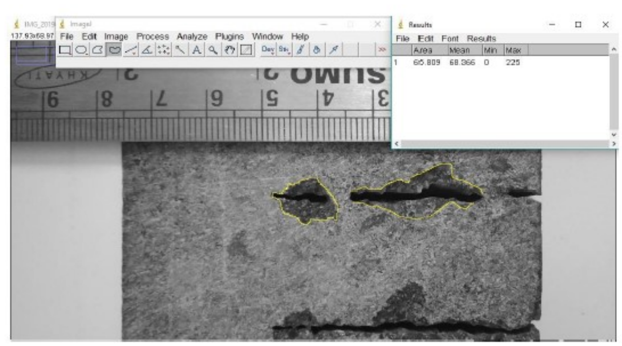


Fig 4.2.3. Measurement of traced area.

V. PREDICTION OF BURST AREA BY USING AI TECHNIQUES

Physics based process modeling using finite element method (FEM) has been integrated with the soft computing techniques like artificial neural networks (ANN), genetic algorithm(GA), adaptive-network-based fuzzy inference system (ANFIS), Fuzzy Logic to improve prediction accuracy of the model with less dependency on the experimental data. Researchers in Artificial Intelligence (AI) follow the algorithmic approach and try to capture the knowledge of an expert in some specific domain as a set of rules to create so called expert systems. For this experiment, we used two techniques for prediction of response:

- ANN
- ANFIS

5.1 Artificial Neural Network (ANN):

An Artificial Neural Network is a parallel, distributed information processing structure consisting of processing units (which can possess a local memory and can carry out localized information processing operations) interconnected via unidirectional signal channels called connections. Each processing unit has a single output connection that branches ("fans out") into as many collateral connections as desired; each carries the same signal - the processing unit output signal.

Artificial neural network (ANN) is an effective method to solve non-linear problem. ANN is inspired from the structure of biological neural networks and their way of encoding and solving problems. Artificial Neural Networks (ANN), also called neurocomputing, connectionism, or parallel distributed processing (PDP), provide an alternative approach to be applied to problems where the algorithmic and symbolic approaches are not well suited.

It includes

- Creation of Neural Network
- Training a Neural Network
- Validation of Neural Network
- Testing a Neural Network
- Prediction using Neural Network

5.1.1 Structure of Neural Network:

Amongst the architecture of ANN like 3-1-1, 3-2-1, 3-3-1; we choose 3-2-1 as neural network as shown in fig. no. 5.1 in which 3 are input layers, 2 are hidden layers and 1 is output layer i.e. burst area. Back Propagation Algorithm is considered for this network.

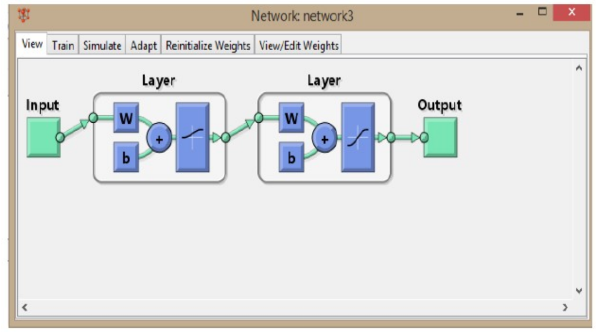


Fig. No. 5.1.1.: 3-2-1 Neural Network

Out of 64 samples, 44 samples are used for training, 10 used for validation and remaining 10 samples are used for testing to get accurate results. Mean Square Error (MSE) and Regression coefficient (R) of respective samples are shown in table no. 5.1.

Table No. 5.1 Results of ANN

	Samples	MSE	R
Training	44	7.59439e-2	9.76757e-1
Validation	10	2.8626e-1	9.20472e-1
Testing	10	8.94927e-1	8.71362e-1

5.1.2 ANN Result:

This topic shows the predicted values of burst area for sample of process parameters

- RMSE =0.532
- Regression Coefficient (R) =0.9327
- Best validation performance=0.826 at (epoch-3)
- Predicted values of burst area for given process parameters

Table No. 5.1.1: Prediction of burst area

Experiment No.	Standoff Distance (mm)	Traverse Speed (mm/min)	Abrasive flow rate (gm/min)	Actual Area of Burst (mm^2)	Predicted Area of Burst (mm^2)
1	3	1000	200	17.004	11.23
2	3	1000	250	7.24	4.2
3	3	1000	300	87.039	70.88
4	3	800	200	78.457	66.38
5	3	800	250	96.745	85.51
6	3	800	300	63.155	54.15
7	3	700	200	101.149	89.39
8	3	700	250	87.294	80.47

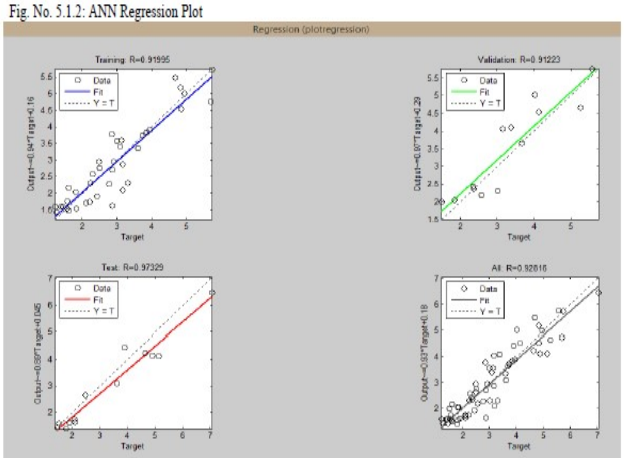
9	3	700	300	6.665	3.315
10	1	1000	200	37.394	29.98
11	1	1000	250	122.284	100.64
12	1	1000	300	22.813	13.94
13	1	800	200	194.08	148
14	1	800	250	146.166	122.09
15	1	800	300	52.054	37.22
16	1	700	200	139.9	111.46
17	1	700	250	71.222	41.89
18	1	700	300	15.152	5.568
19	5	1000	200	76.614	55.931
20	5	1000	250	51.97	31.35
21	5	1000	300	54.993	39.67
22	5	800	200	173.172	142.965
23	5	800	250	78.743	59.06
24	5	800	300	50.421	29.37
25	5	700	200	99.814	76.13
26	5	700	250	105.872	80.934
27	5	700	300	28.606	17.05
				Average error	17.243

5.1.3 ANN Plots:

After training of neutral network different plots comes up which shows the performance, fitting, regression and error of the neural network. 1st plot (fig. no. 5.1.3) shows the Regression plots for the training, validation and testing with respect to target data this plot gives the regression coefficient for the training, validation and test data 4th of the four plots of the regression plot mentioned below shows the all data points and gives the overall regression coefficient R=0.92816

From the plots we get a regression coefficient (R) and we have to train a data until we gets the best value of the R. Here in our case the regression coefficient r for the test is found to be 0.97329 which is close to 1.

Fig. No. 5.1.2: ANN Regression Plot



2nd plot (fig. no. 5.1.4) shows the ANN performance plot. In this plot the mean square error of the training state is plotted against the epochs (10 epochs were selected). This error should be as much as minimum as possible. To minimize this error the algorithm used is gradient descent algorithm. Here 3 types of errors training validation and testing errors becomes minimum at the epoch no.3. And the best validation performance is 0.26826 at epoch 3.

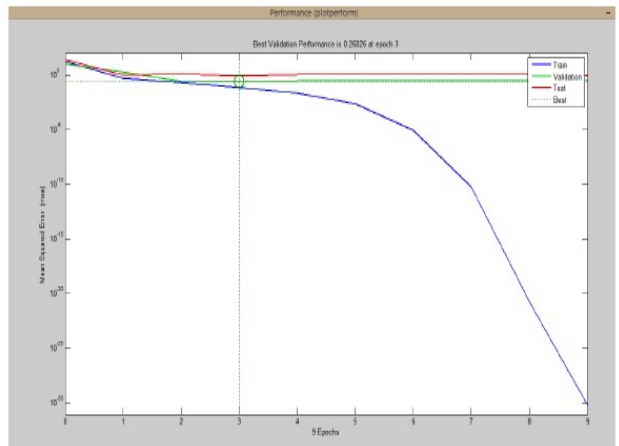


Fig. No. 5.1.3: ANN performance Plot

5.2 ANFIS (Adaptive Neuro Fuzzy Inference System):

The architecture and learning procedure underlying ANFIS (adaptive-network-based fuzzy inference system) is presented which is a fuzzy inference system implemented in the framework of adaptive networks. By using a hybrid learning procedure, the proposed ANFIS can construct an input-output mapping based on both human knowledge and stipulated input-output data pairs.

ANFIS uses both training data and user defined parameters in optimization procedures. User defined parameters include: number of membership functions per input, membership function type, step size, increasing and decreasing step size, and the number of epochs used in training.

It is a hybrid technique used for prediction of Response

It includes

- Generation of Fuzzy Inference System (FIS)
- Training of FIS using hybrid or back-propagation Algorithm Optimization Method
- Testing of a FIS/ checking of Data
- Prediction of a given process parameters using predicted results of ANN

5.2.1 The ANFIS Architecture:

It is a machine learning algorithm which utilizes fuzzy inference system (FIS) incorporated in the neural network (NN) environment. In ANFIS, Fuzzy logic membership functions are tuned with the aid of hybrid learning algorithm i.e. an amalgamation of the least-square method and back propagation gradient descent method for acclimatizing to the environments. The Fuzzy logic system conveys human-like interpretation features into the ANFIS. Such hybrid arrangement offers a twin benefit of human-like reasoning quality in conjunction with an adaptive network which is accountable for enlightening the fuzzy rules.

Actually, ANFIS structural design consists of five different layers. They are input layer, fuzzification layer, inferences process layer, defuzzification layer and the final output layer. Every single layer executes a particular job to promote the signals. It's a network structure consists of a number of nodes affixed through direct links. Here fig. no.5.1.2 illustrates the ANFIS algorithm.

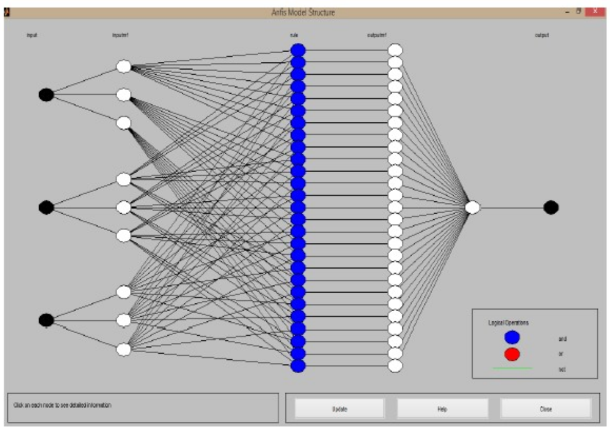


Figure 5.2.1 : The Anfis Architecture

In ANFIS to optimize the neural network we use the Fuzzy Inference System (F.I.S). The following figure No.5.3 shows the different membership functions which affects the optimized model of F.I.S. Membership functions of the inputs are of the gbellmf and output membership function is of triangular type

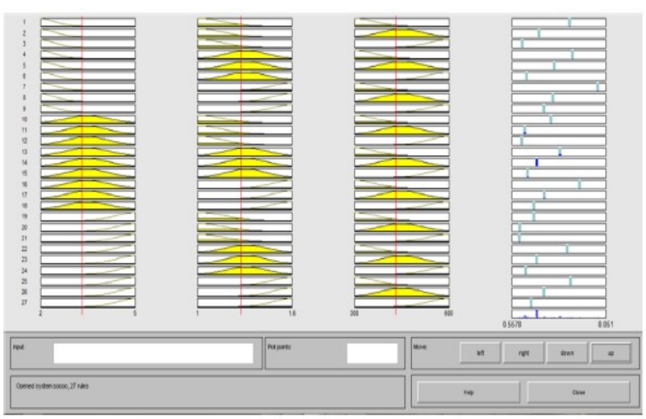


Fig. No. 5.2.2: Fuzzy Inference System (FIS)

- Average checking error- 0.40869
- Average Epoch error – 0.144

Calculation of predicted values of ANFIS by using predicted values of ANN and average checking error.

Table No.5.2.1: Prediction of burst area by ANFIS

Experiment No.	Standoff Distance (mm)	Traverse Speed (mm/min)	Abrasive flow rate (gm/min)	Actual Area of Burst (mm^2)	Predicted Area of Burst (mm^2)
1	3	1000	200	17.004	13.02
2	3	1000	250	7.24	5.53
3	3	1000	300	87.039	76.97
4	3	800	200	78.457	70.02
5	3	800	250	96.745	91.1
6	3	800	300	63.155	58.88
7	3	700	200	101.149	96.74
8	3	700	250	87.294	82.01
9	3	700	300	6.665	4.15
10	1	1000	200	37.394	32.17
11	1	1000	250	122.284	113.098
12	1	1000	300	22.813	89.42
13	1	800	200	194.08	165
14	1	800	250	146.166	132.098
15	1	800	300	52.054	43.81
16	1	700	200	139.9	123.5
17	1	700	250	71.222	50.02
18	1	700	300	15.152	8.95
19	5	1000	200	76.614	62.42
20	5	1000	250	51.97	40.62
21	5	1000	300	54.993	46.56
22	5	800	200	173.172	155.88
23	5	800	250	78.743	65.49
24	5	800	300	50.421	38.19
25	5	700	200	99.814	83.72
26	5	700	250	105.872	95.65
27	5	700	300	28.606	21.43
				Average error	10.904

5.3 ANFIS VS ANN Results:

Moreover, the ANFIS acquired results were compared with an Artificial Neural Network (ANN) model, developed on the identical parametric ranges. The Comparsion of the obtained results indicated that the ANFIS overtakes the ANN model in predicting the preferred response variables, which suggests the modesty of the ANFIS model.

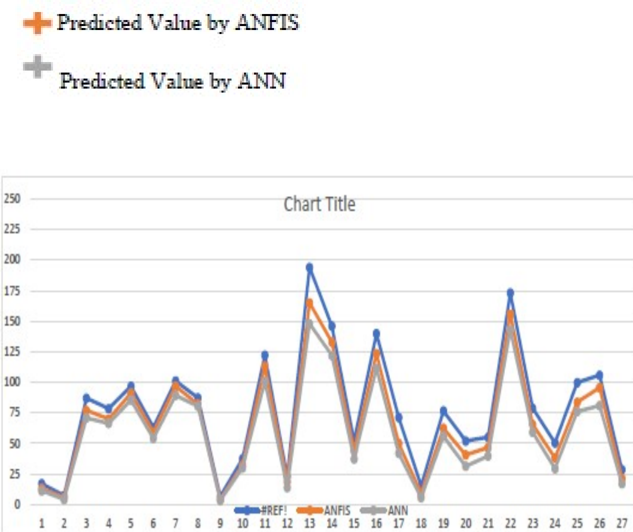


Fig. No. 5.2.3: ANN vs ANFIS

VI. RESULTS AND CONCLUSION

The results, conclusion and future scope of this project is explained below. The results show a successful prediction on response. The conclusion summarizes project results in a few sentences and state whether results support or contradict the hypothesis. The future scope summarizes what we are not able to do because of time constraint.

6.1 Results:

On account of experimental effort, ANFIS and ANN model have been built up to predict burst area. It is found that prediction of the output parameters of abrasive water jet cutting machine by means of ANFIS gave extraordinary correlation statistics as compared to ANN model. The precision of the ANFIS predicted machining parameters was admirable.

- This work predicted the burst area by ANN and ANFIS with average error of 17.24 and **10.9**.
- The maximum burst area was found **194.08** at the following setting: S.O.D. =1mm,
- A.F.R. =200 gm /min, T.R. =800 mm/min.
- Amongst the architecture of ANN **3-2-1** gave minimum error in prediction.

6.2 Conclusion:

We have described the architecture of adaptive-network based fuzzy inference systems (ANFIS) with 3-2-1 neural structure. By employing a hybrid learning procedure, the proposed architecture can refine fuzzy if-then rules obtained from human experts to describe the input- output behavior of a complex system. These results indicate that the ANFIS model with gbellmf is accurate and can be used to predict burst area in abrasive water jet machining.

- Image processing was successfully applied in prediction of burst area.
- The effects of different process parameters on variation produced on burst area found successfully.
- After comparing different AI techniques, ANFIS is the better hybrid technique.

6.3 Future Scope

In this research work, we have predicted the burst area using different AI techniques by keeping stand-off-distance, abrasive flow rate, and traverse rate as a process parameters. In future this work can be done as:

- Various process parameters can also be varied like water jet pressure, surface roughness, kerf length, grit embedment, etc.
- Also different hybrid techniques like GA-Fuzzy, GA-ANFIS, GA-Fuzzy-ANN, etc. can be used to predict the response.
- Most awaiting technique of Quantum Neural Networks (QNN) can be applied when no. of process parameters are more and the accuracy required is higher in quantum computers.
- Along with prediction techniques signal processing can be applied for online process monitoring.

REFERENCES

[1]. I. Karakurt, G. Aydin and K. Aydiner, “A study on the prediction of kerf angle in abrasive waterjet machining of rocks”, Journal of Engineering Manufacture 226(9) pp.1489-1499, 2012.
[2]. C. Edmundo de A. Lima, R. Lebran, A. Joao de Souza, N. Francisco Ferreira, P. Daniel Neis, “Study of influence of traverse speed and abrasive mass flow rate in abrasive water jet machining of gemstones”, Int J Adv Manuf Technol, 2015.
[3]. Tae-Min Oh, Gye-Chun Cho “Characterization of Effective Parameters in Abrasive Waterjet Rock Cutting”, Rock Mech Rock Eng, Vol.47, pp. 745-756, 2014.
[4]. L. M. Hlaváč, I. M. Hlaváčová and V. Geryk “Taper of kerfs made in rocks by abrasive water jet”, Int J Adv Manuf Technol, 2016.
[5]. J. Poláček and E. Janurová, “Impact of pressure of surrounding medium on plain water jet cutting of rocks”, Int J Adv Manuf Technol, Vol.90, pp. 2185-2191, 2016.
[6]. G. Aydin, I. Karakurt and K. Aydiner, “Prediction of the Cut Depth of Granitic Rocks Machined by Abrasive Waterjet”, Rock Mech Rock Eng, Vol.46, pp.1223-1235, 2012.
[7]. Tae-Min Oh, A. K. Prasidhi, Gye-Chun Cho and Jong-Ho Shin, “ Effect of water jet geometric parameters on rock

fracturing", KSCE Journal of Civil Engineering, Vol.18, pp.772-779. 2014.

[8]. I. Karakurt, G. Aydin and K. Aydiner," An investigation on the kerf width in abrasive waterjet cutting of granitic rocks", Saudi Society for Geosciences, 2013.

[9]. G. Aydin, "Recycling of abrasives in abrasive waterjet cutting with different types of granite", Saudi Society for Geosciences, 2013.

[10]. Q. GAO, Q. ZHANG, S. SU, J. ZHANG, "Parameter optimization model in electrical discharge machining process,"*Gao et al. / J Zhejiang Univ Sci A*, vol.9, no.1, pp.104-108, 2008.

[11]. B.B.Pradhan, B.Bhattacharyya, "Modelling of micro-electro discharge machining during machining of titanium alloy Ti–6Al–4V using response surface methodology and artificial neural network algorithm,"*Proc. IMechE Part B: J. Engineering Manufacture,* vol.223, pp.683-693, 2009.