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Application of Fuzzy Logic Approach for Prediction of Machining Parameters by AWJM Process on Aluminium 6061 Alloy

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ABSTRACT

Last decades have witnessed a rapid growth in the development of harder, difficult and complexity to machine metals and alloys. AWJM is one of the recently developed nontraditional machining processes in processing various kinds of hard-to-cut materials nowadays. It is an economical method for heat sensitive materials that cannot be machined by processes that produce heat while machining. Machining parameters play the lead role in determining the machine economics and quality of machining. In this study the consequence of five AWJM process parameters on MRR and SR of an American element named Aluminium 6061 alloy which is machined by AWJM was experimentally performed and analyzed. According to RSM design, different experiments were conducted with the combination of input parameters on this American element. This paper investigates the prediction of MRR and Surface roughness on Aluminium 6061 alloy using three different types of membership function on Fuzzy logic (FL) approach.

KEY WORDS: Response Surface Methodology, Fuzzy Logic, Membership Function, Material Removal Rate, Surface Roughness.

1. INTRODUCTION AND PAST STUDIES

AWJC is the recently developed processes. This technique is suitable for machining of brittle materials similar to glass, ceramics and stones as well as for composite materials and ferrous and non-ferrous materials. From the literature review of Adel A. Abdel-Rahman in 2011 an elastic-plastic erosion model was implemented to build up an abrasive water jet model for machining brittle materials. Deam in 2006 reviewed that kerf geometry have been measured by the use of an optical microscope. With these measurements, an empirical correlation for kerf profile shape under various traverse speed have been developed that fits the kerf shape well. Liu (2004), in their research Computational fluid Dynamics (CFD) models for ultrahigh velocity water jets and abrasive water jets (AWJs) are established by the use of Fluent6 flow solver. Suganthi (2013), performed micro-electrical discharge machining and hybrid process of micro-wire electrical discharge grinding to assess the inaccuracies while machining. They examined the MRR, SR and TWR results by ANN and ANFIS and showed that the ANFIS model is better when compared with ANN. Çaydaş (2009), performed ANFIS model for surface roughness on D5 tool steel in WEDM process and examined the metallographic properties. Jang (1993) observed from Literature Review that AI techniques comprising of ANN, fuzzy logic and Taguchi based fuzzy systems have wide applications in modeling of WEDM process parameters. In this paper he modeled the process parameters with ANFIS which combines the ANN adaptive capability and Fuzzy Logic qualitative approach. Lei (2007), in their study modeled for surface roughness and white layer thickness after WEDM by using ANFIS by considering Pulse duration, dielectric flushing pressure, wire feed rate and open circuit voltage as parameters. Reddy (2012), in his study considered the prediction of surface roughness by ANFIS which is the output parameter and feed rate, current, and pulse on time are chosen as the independent variables in WEDM process.

2. EXPERIMENTAL WORK

Material: Aluminium 6061 alloy, an American element is a precipitation hardening Aluminium Alloy which is available in several forms such as tube, ingot, ribbon, wire, foil, bar, pipe and rod. It is one of the cheapest American element alloys. The important factor in selecting Aluminum 6061 alloy is their high strength to weight ratio, appearance, and their non-magnetic properties. Some of the applications of Aluminium 6061 alloy include Marine fittings, aerospace maintenance, transport, bicycle frames, brake components, valves couplings etc. It is also applied in paint removal, surgery, peening, drilling turning etc. It has good surface finish and can be anodized. Its density is 2.7g/cm3 and its Modulus of Elasticity E = 80GPa. The dimension chosen to cut the Aluminium 6061 alloy for this study is 150mm x 50mm x 50mm is depicted in Fig. 1.

Fig.1.Aluminium 6061 Alloy

Fig.2.Experimental Setup of AWJM with Mixing Chamber

Response Surface Methodology: RSM is a collection of mathematical and statistical techniques that are useful to find the correlation between the response and the variables. The work which initially generated interest in the package of techniques was a paper by Box and Wilson, Iqbal and Khan have been involved in developing prediction models using this renowned RSM for their advanced machining studies. This method is now broadly used in many fields, such as chemistry, biology and manufacturing. In the present study five process parameters are chosen and varied in three levels as shown in Table 1.

Table.1.Levels of parameters used in experiment

Levels	Water Pressure (P) Bar	Abrasive Flow Rate (m_f) Kg/min	Orifice Diameter (d_o) mm	Focusing Nozzle Diameter (d_f) mm	Stand Off Distance (s) mm
Low	3400	0.4	0.3	0.9	1
Intermediate	3600	0.55	0.33	0.99	2
High	3800	0.7	0.35	1.05	3

Based on RSM, Box-Behnken design 46 sets of experimental design was selected. The parameters and its levels were selected based on the review of certain journals that have been acknowledged on AWJC on materials like 6063-T6 Aluminum alloy, Metallic Coated Sheet Steels, Metal Matrix Composites, and Ceramics.

Data Collection and Experimentation: The machine used to slice the nonferrous alloys is the AWJM machine with KMT ultrahigh pressure pump of 4000 bar designed pressure, shown in Fig. 2. The machine is equipped with an abrasive hopper, abrasive feeder system, a valve and a work piece table. By the use of controller which is fixed in control stand, SOD is set for different combination of machining parameters experiments. The AWJ system which is programmed through numerical control code adjusts the transverse speed and abrasives supplement. High pressure water of about 2000-4000bar is pumped using intensifier and when this water at high pressure is allowed to pass through the orifice which is of about diameter 0.2mm to 0.4mm, converts potential energy into kinetic energy of water, results high velocity abrasive water jet of about 1000m/s. This very high velocity of abrasive water jet as it comes throughout the nozzle slices the materials to the required shape and size.

For performing the experiments we have to design the combination of input parameters for each experiment and how many experiments has to be done. For this purpose using Minitab software according to the Box-Behnken design of Response surface methodology design of experiments, with five input parameters, 46 experimental design is selected and performed experimentally and machining time is observed for all experiments as shown in Table 2. The MRR is calculated by the formula;

$$MRR = (m_f - m_i) / t$$

Where, m_f = mass of the material after machining, m_i = mass of the material before machining and t = Machining Time. The surface roughness for the machined Aluminium 6061 alloy is measured using Portable surface roughness tester in National College of Engineering, Tamilnadu, India.

Fuzzy Logic: Fuzzy Logic (FL) incorporates a simple, rule based if x and y then z approach to a solving control problem rather than attempting to model a system mathematically. The FL model is empirically based, relying on an operators experience rather than their technical understanding of the system.

FL requires some numerical parameters in order to operate such as what is considered significant error and significant rate of change of error, but exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them. FL was conceived as a better method for sorting and handling data but has proven to be an excellent choice for many control system applications since it mimics human control logic. It can be built into anything from small, handheld products to large computerized process control systems. It uses an imprecise but very descriptive language to deal with input data more like a human operator. It is very robust and forgiving of operator and data input and often works when first implemented with little or no tuning. FL is used because,

a) It offers several unique features that make it a particularly good choice for many control problems.

b) It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth control function despite a wide range of input variations.

c) Since the FL controller processes user defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules.

d) FL is not limited to a few feedback inputs and one or two control outputs, nor is it necessary to measure or compute rate of change parameters in order for it to be implemented.

e) Because of the rule based operation, any reasonable number of inputs can be processed (1-8 or more) and numerous outputs (1-4 or more) generated, although defining the rule base quickly becomes complex if too many inputs and outputs are chosen for a single implementation since rules defining their interrelations must also be defined. It would be better to break the control system into smaller chunks and use several smaller FL controllers distributed on the

system, each with more limited responsibilities.
f) FL can control nonlinear systems that would be difficult or impossible to model mathematically. This opens doors for control systems that would normally be deemed unfeasible for automation.

Membership Functions: The MFs is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs and ultimately determines an output response. The rules use the input membership value as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. Once the functions are inferred, scaled and combined, they are defuzzified into a crisp output which drives the system. There are different MFs associated with each input and output response. Some of them are Gauss, trapezoidal and triangular.

Implementation of Using Gauss Membership Function FL: A FL unit comprises a fuzzifier, MFs, a fuzzy rule base, an inference engine and a defuzzifier. First, the fuzzifier uses MFs to fuzzy the MRR and SR. Next the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally the defuzzifier converts the fuzzy value into a Multiple Response Performance Index (MRPI). In the following, the concept of fuzzy reasoning is described briefly based on the five inputs and two outputs FL unit. The fuzzy rule base consists of a group of if then control rules with the five inputs P, m_f, d_o, d_n and s and two outputs MRR and SR that are given as follows.

Rule 1: If P is prmf1, m_f is afrmf1, d_o is odmf1, d_n is ndmf1, s is sodmf1 then MRR is mrrmf1
Rule 2: If P is prmf1, m_f is afrmf1, d_o is odmf1, d_n is ndmf1, s is sodmf2 then MRR is mrrmf2
Rule 3: If P is prmf1, m_f is afrmf1, d_o is odmf1, d_n is ndmf2, s is sodmf1 then MRR is mrrmf3
Rule 4: If P is prmf1, m_f is afrmf1, d_o is odmf1, d_n is ndmf2, s is sodmf2 then MRR is mrrmf4
Rule 5: If P is prmf1, m_f is afrmf1, d_o is odmf2, d_n is ndmf2, s is sodmf2 then MRR is mrrmf5
Rule 6: If P is prmf1, m_f is afrmf1, d_o is odmf2, d_n is ndmf1, s is sodmf2 then MRR is mrrmf6
Rule 7: If P is prmf1, m_f is afrmf1, d_o is odmf2, d_n is ndmf2, s is sodmf1 then MRR is mrrmf7
Rule 8: If P is prmf1, m_f is afrmf1, d_o is odmf2, d_n is ndmf2, s is sodmf2 then MRR is mrrmf8
Rule 9: If P is prmf1, m_f is afrmf2, d_o is odmf1, d_n is ndmf1, s is sodmf1 then MRR is mrrmf9
Rule 10: If P is prmf1, m_f is afrmf2, d_o is odmf1, d_n is ndmf1, s is sodmf2 then MRR is mrrmf10
Rule 11: If P is prmf1, m_f is afrmf2, d_o is odmf1, d_n is ndmf2, s is sodmf1 then MRR is mrrmf11
Rule 12: If P is prmf1, m_f is afrmf2, d_o is odmf1, d_n is ndmf2, s is sodmf2 then MRR is mrrmf12
Rule 13: If P is prmf1, m_f is afrmf2, d_o is odmf2, d_n is ndmf1, s is sodmf1 then MRR is mrrmf13
Rule 14: If P is prmf1, m_f is afrmf2, d_o is odmf2, d_n is ndmf1, s is sodmf2, then MRR is mrrmf14
Rule 15: If P is prmf1, m_f is afrmf2, d_o is odmf2, d_n is ndmf2, s is sodmf1, then MRR is mrrmf15
Rule 16: If P is prmf1, m_f is afrmf2, d_o is odmf2, d_n is ndmf2, s is sodmf2 then MRR is mrrmf16
Rule 17: If P is prmf2, m_f is afrmf1, d_o is odmf1, d_n is ndmf1, s is sodmf1 then MRR is mrrmf17
Rule 18: If P is prmf2, m_f is afrmf1, d_o is odmf1, d_n is ndmf1, s is sodmf2 then MRR is mrrmf18
Rule 19: If P is prmf2, m_f is afrmf1, d_o is odmf1, d_n is ndmf2, s is sodmf1 then MRR is mrrmf19
Rule 20: If P is prmf2, m_f is afrmf1, d_o is odmf1, d_n is ndmf2, s is sodmf2 then MRR is mrrmf20
Rule 21: If P is prmf2, m_f is afrmf1, d_o is odmf2, d_n is ndmf1, s is sodmf1 then MRR is mrrmf21
Rule 22: If P is prmf2, m_f is afrmf1, d_o is odmf2, d_n is ndmf1, s is sodmf2 then MRR is mrrmf22
Rule 23: If P is prmf2, m_f is afrmf1, d_o is odmf2, d_n is ndmf2, s is sodmf1 then MRR is mrrmf23
Rule 24: If P is prmf2, m_f is afrmf1, d_o is odmf2, d_n is ndmf2, is sodmf2 then MRR is mrrmf24
Rule 25: If P is prmf2, m_f is afrmf2, d_o is odmf1, d_n is ndmf1, s is sodmf1 then MRR is mrrmf25
Rule 26: If P is prmf2, m_f is afrmf2, d_o is odmf1, d_n is ndmf1, s is sodmf2 then MRR is mrrmf26
Rule 27: If P is prmf2, m_f is afrmf2, d_o is odmf1, d_n is ndmf2, s is sodmf1then MRR is mrrmf27
Rule 28: If P is prmf2, m_f is afrmf2, d_o is odmf1, d_n is ndmf2, s is sodmf2 then MRR is mrrmf28
Rule 29: If P is prmf2, m_f is afrmf2, d_o is odmf2, d_n is ndmf1, s is sodmf1 then MRR is mrrmf29
Rule 30: If P is prmf2, m_f is afrmf2, d_o is odmf2, d_n is ndmf1, s is sodmf2then MRR is mrrmf30
Rule 31: If P is prmf2, m_f is afrmf2, d_o is odmf2, d_n is ndmf2, s is sodmf1 then MRR is mrrmf31
Rule 32: If P is prmf2, m_f is afrmf2, d_o is odmf2, d_n is ndmf2, s is sodmf2 then MRR is mrrmf32

Similarly the fuzzy rules for SR are also generated. By taking the maximum minimum compositional operation, the fuzzy reasoning of these rules yields a fuzzy output. Finally, a defuzzification method, called the center of gravity method, is adopted here to transform the fuzzy inference output into non fuzzy value. Without defuzzification, the final output from the inference stage would remain the same as fuzzy set.

Table.2.Planning Matrix of the Experiments

P (Bar)	**m_f (Kg/min)**	**d_o (mm)**	**d_f (mm)**	**s (mm)**	**MRR mm^3/min**	**SR (µm)**	**P (Bar)**	**m_f (Kg/min)**	**d_o (mm)**	**d_f (mm)**	**s (mm)**	**MRR mm^3/min**	**SR (µm)**
3400	0.55	0.33	0.99	3	48.6111	3.57	3600	0.4	0.35	0.99	2	49.2264	2.29
3600	0.55	0.33	0.9	1	53.6399	2.08	3600	0.4	0.33	0.9	2	48.9168	2.36
3600	0.55	0.3	1.05	2	51.8519	2.21	3600	0.55	0.35	0.99	3	51.1696	2.50

3600	0.55	0.33	0.9	3	50.8352	2.55	3600	0.7	0.33	0.9	2	55.9552	2.14
3800	0.55	0.33	0.9	2	62.2222	1.90	3400	0.55	0.33	0.99	1	49.2264	2.65
3600	0.55	0.33	0.99	2	51.8519	2.19	3600	0.7	0.3	0.99	2	56.7721	2.18
3400	0.4	0.33	0.99	2	45.7516	3.20	3600	0.55	0.33	1.05	1	50.8352	1.90
3600	0.7	0.35	0.99	2	53.6399	1.80	3600	0.55	0.3	0.99	1	51.8519	1.99
3800	0.55	0.33	0.99	3	61.2423	2.07	3800	0.7	0.33	0.99	2	64.8148	1.70
3800	0.55	0.3	0.99	2	62.2222	2.05	3600	0.4	0.33	1.05	2	48.6111	2.40
3600	0.55	0.33	0.99	3	51.1696	2.54	3600	0.55	0.3	0.99	3	52.1999	2.68
3400	0.55	0.33	1.05	2	47.7164	3.08	3600	0.55	0.33	0.99	2	52.9101	2.20
3600	0.4	0.33	0.99	1	50.1792	1.99	3800	0.55	0.33	1.05	2	59.8291	1.99
3600	0.55	0.33	0.99	2	52.9101	2.17	3400	0.7	0.33	0.99	2	51.8519	2.80
3600	0.55	0.35	0.9	2	54.3901	2.08	3600	0.55	0.35	1.05	2	51.1696	2.34
3600	0.55	0.3	0.9	2	51.8519	2.79	3400	0.55	0.3	0.99	2	48.9168	3.23
3400	0.55	0.33	0.9	2	48.6111	3.30	3600	0.4	0.33	0.99	3	48.3092	2.69
3600	0.55	0.33	0.99	2	52.9101	2.19	3600	0.55	0.33	0.99	2	53.2725	2.18
3600	0.4	0.3	0.99	2	47.7164	2.36	3600	0.55	0.35	0.99	1	52.5526	1.80
3400	0.55	0.35	0.99	2	48.3092	2.95	3800	0.55	0.35	0.99	2	59.3724	1.82
3800	0.4	0.33	0.99	2	58.4785	1.89	3600	0.7	0.33	1.05	2	56.7721	2.03
3600	0.7	0.33	0.99	3	54.7731	2.25	3600	0.55	0.33	1.05	3	51.1696	2.73
3600	0.7	0.33	0.99	1	56.3607	1.68	3800	0.55	0.33	0.99	1	61.2423	1.72

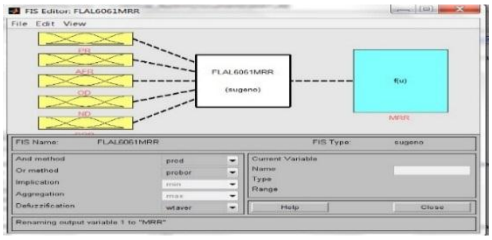


Fig.3.FL for Input and Output Variable

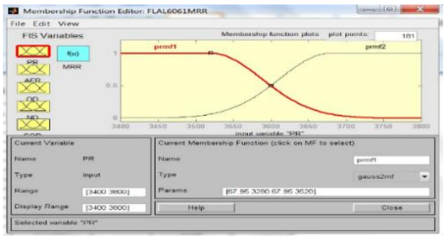


Fig.4.Gauss MF for Pressure

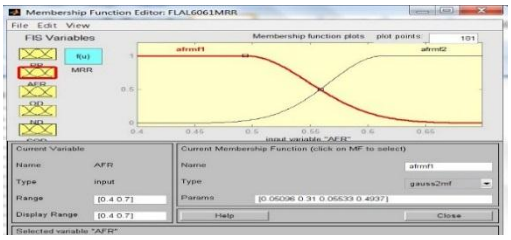


Fig.5.Gauss MF for Abrasive Flow Rate

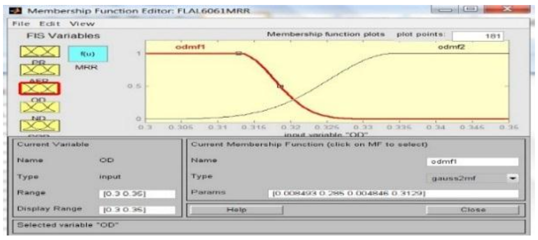


Fig.6.Gauss MF for Orifice Diameter

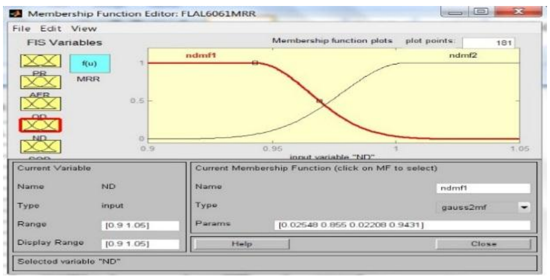


Fig.7.Gauss MF for Nozzle Diameter

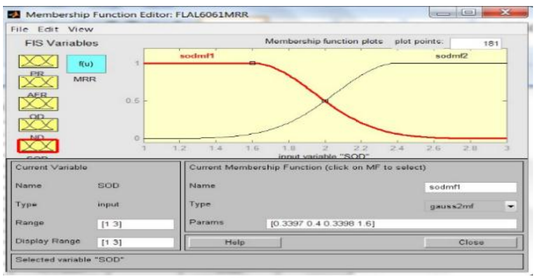


Fig.8.Gauss MF for Stand Off Distance

Table.3.Optimized Output Value of MRR and SR for Aluminium 6061 Alloy through Gauss Membership Function Fuzzy Logic

Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR (μm)	Predicted SR (μm)	Error SR	Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR (μm)	Predicted SR (μm)	Error SR
48.6111	48.3	0.63997	3.57	3.56	0.2801	49.2264	49.6	0.75894	2.29	2.29	0
53.6399	53.6	0.07438	2.08	2.08	0	48.9168	48.8	0.23877	2.36	2.36	0
51.8519	51.9	0.09276	2.21	2.21	0	51.1696	50.9	0.52687	2.5	2.51	0.4

50.8352	50.9	0.12747	2.55	2.55	0	55.9552	55.9	0.09865	2.14	2.14	0
62.2222	62.3	0.12503	1.9	1.9	0	49.2264	48.9	0.66305	2.65	2.65	0
51.8519	52.8	1.82847	2.19	2.19	0	56.7721	56.8	0.04914	2.18	2.18	0
45.7516	45.7	0.11278	3.2	3.21	0.3125	50.8352	51.3	0.91432	1.9	1.89	0.5263
53.6399	53.9	0.4849	1.8	1.8	0	51.8519	51.8	0.10009	1.99	2	0.5025
61.2423	60.9	0.55892	2.07	2.07	0	64.8148	64.8	0.02283	1.7	1.7	0
62.2222	62.3	0.12503	2.05	2.04	0.4878	48.6111	48	1.25712	2.4	2.39	0.4166
51.1696	51.2	0.05941	2.54	2.54	0	52.1999	52.2	0.00019	2.68	2.69	0.3731
47.7164	48	0.59434	3.08	3.09	0.3246	52.9101	52.8	0.20808	2.2	2.19	0.4545
50.1792	50.4	0.44002	1.99	1.99	0	59.8291	60.1	0.45279	1.99	2	0.5025
52.9101	52.8	0.20808	2.17	2.19	0.9216	51.8519	51.8	0.10009	2.8	2.81	0.3571
54.3901	54.3	0.16565	2.08	2.08	0	51.1696	50.6	1.11316	2.34	2.34	0
51.8519	52.2	0.67133	2.79	2.79	0	48.9168	48.9	0.03434	3.23	3.22	0.3096
48.6111	48.6	0.02283	3.3	3.3	0	48.3092	48.5	0.39495	2.69	2.69	0
52.9101	52.8	0.20808	2.19	2.19	0	53.2725	52.8	0.88694	2.18	2.19	0.4587
47.7164	47.7	0.03437	2.36	2.36	0	52.5526	52.2	0.67094	1.8	1.81	0.5555
48.3092	48.6	0.60195	2.95	2.94	0.3389	59.3724	59.7	0.55177	1.82	1.81	0.5494
58.4785	58.4	0.13423	1.89	1.9	0.5291	56.7721	56.4	0.65542	2.03	2.02	0.4926
54.7731	54.9	0.23168	2.25	2.25	0	51.1696	51.7	1.03655	2.73	2.72	0.3663
56.3607	56.5	0.24715	1.68	1.68	0	61.2423	60.9	0.55892	1.72	1.71	0.5814

Fig. 3 shows the Fuzzy Logic for input and output variables. Figs. 4 to 8 shows the Gauss Membership functions of Pressure, abrasive flow rate, orifice diameter, nozzle diameter and stand off distance. The table 3 shows the errors between the experimental and predicted values for MRR and SR using Gauss membership function FL for Aluminium 6061 Alloy and the comparison between the experimental values of MRR, SR and Predicted values of MRR, SR using Gauss membership function FL for Aluminium 6061 alloy is shown in Fig. 9. Fig. 10 shows the Fuzzy Rule Viewer of MRR and SR for Aluminium 6061 Alloy.

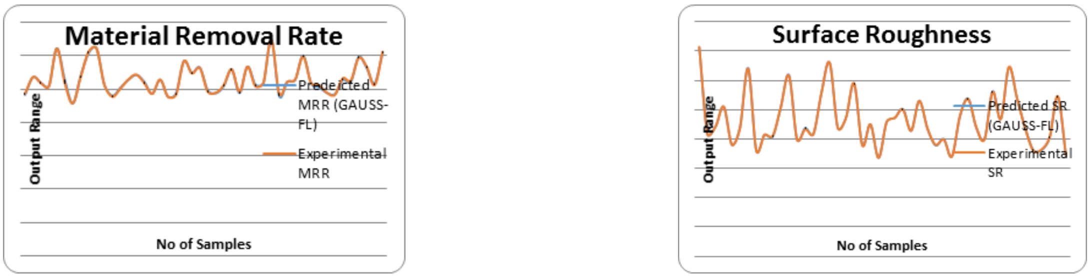


Fig.9.Comparison of Experimental and Predicted MRR and SR using Gauss MF

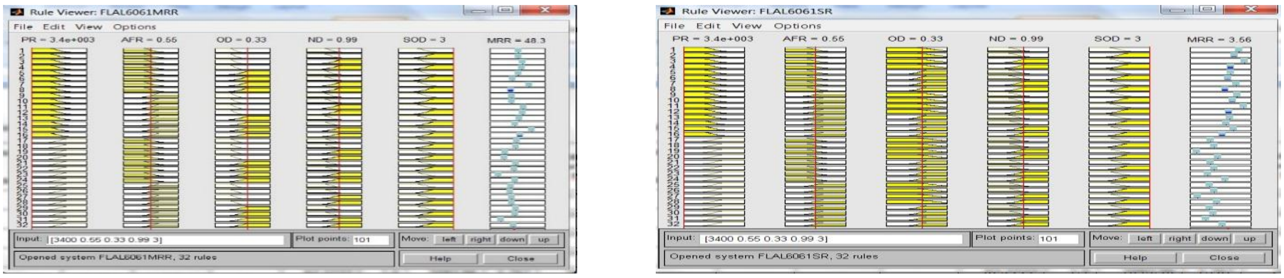


Fig.10.Fuzzy Rule Viewer of MRR and SR using Gauss MF

Implementation of Using Trapezoidal Membership Function FL: Figs. 11 to 15 shows the Trapezoidal Membership functions of Pressure, abrasive flow rate, orifice diameter, nozzle diameter and stand off distance.The table 4 shows the errors between the experimental and predicted values for MRR and SR using Trapezoidal membership function FL for Aluminium 6061 Alloy and the comparison between the experimental values of MRR, SR and Predicted values of MRR, SR using Trapezoidal membership function FL for Aluminium 6061 alloy is shown in Fig. 16 and Fig. 17 shows the Fuzzy Rule Viewer for MRR and SR of this alloy.

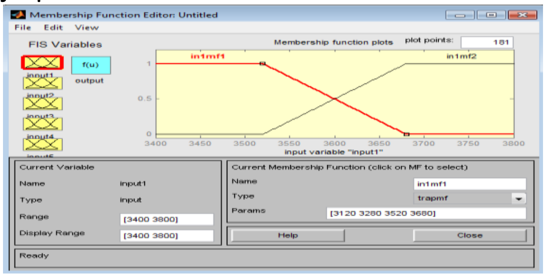


Fig.11.Trapezoidal MF for Pressure

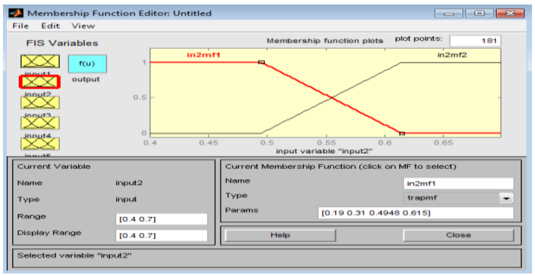


Fig.12.Trapezoidal MF for Abrasive Flow Rate

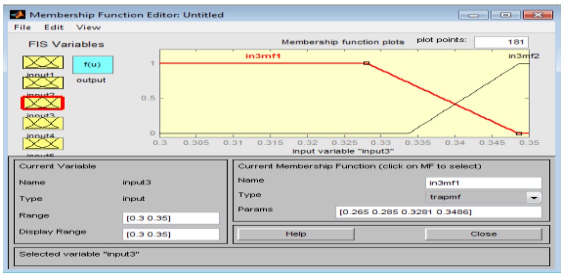


Fig.13.Trapezoidal MF for Orifice Diameter

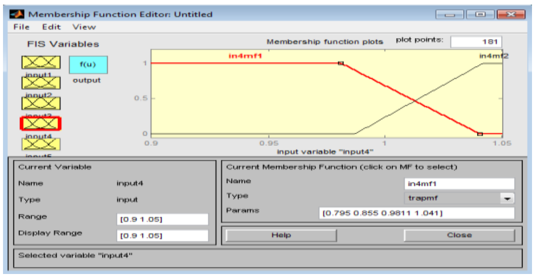


Fig.14.Trapezoidal MF for Nozzle Diameter

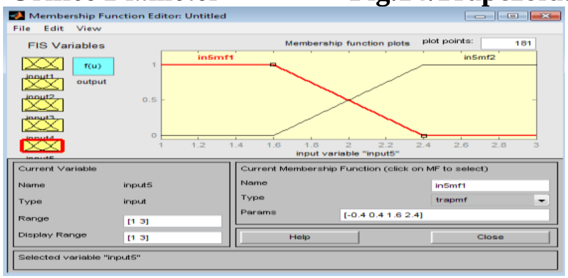
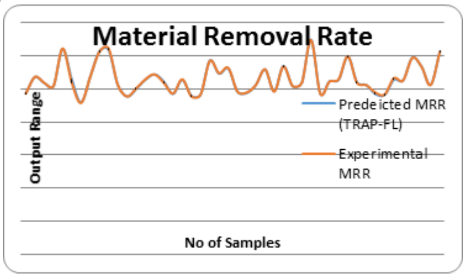


Fig.15.Trapezoidal MF Stand Off Distance

Table.4.Optimized Output Value of MRR and SR for Aluminium 6061 Alloy through Trapezoidal Membership Function Fuzzy Logic

Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR (µm)	Predicted SR (µm)	Error SR	Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR (µm)	Predicted SR (µm)	Error SR
48.6111	48.7	0.182880	3.57	3.56	0.280	49.2264	49.2	0.053629	2.29	2.29	0
53.6399	53.6	0.074384	2.08	2.08	0	48.9168	48.8	0.238772	2.36	2.36	0
51.8519	51.8	0.100092	2.21	2.21	0	51.1696	51.2	0.059410	2.5	2.51	0.4
50.8352	50.8	0.069243	2.55	2.55	0	55.9552	55.9	0.098650	2.14	2.14	0
62.2222	62.1	0.196392	1.9	1.91	0.526	49.2264	49.3	0.149513	2.65	2.64	0.377
51.8519	52.8	1.828476	2.19	2.19	0	56.7721	56.9	0.225286	2.18	2.18	0
45.7516	45.9	0.324360	3.2	3.2	0	50.8352	50.8	0.069243	1.9	1.9	0
53.6399	53.6	0.074384	1.8	1.8	0	51.8519	51.9	0.092764	1.99	2	0.502
61.2423	61.4	0.257501	2.07	2.06	0.483	64.8148	64.9	0.131451	1.7	1.7	0
62.2222	61.8	0.678535	2.05	2.04	0.487	48.6111	48.6	0.022834	2.4	2.39	0.416
51.1696	51.2	1.427410	2.54	2.54	0	52.1999	52.3	0.191762	2.68	2.69	0.373
47.7164	47.7	1.710942	3.08	3.09	0.324	52.9101	52.8	0.208088	2.2	2.19	0.454
50.1792	50	0.357120	1.99	1.99	0	59.8291	59.8	0.048638	1.99	2	0.502
52.9101	52.8	0.208088	2.17	2.19	0.921	51.8519	52	0.285621	2.8	2.8	0
54.3901	54.4	0.018201	2.08	2.08	0	51.1696	51.2	0.059410	2.34	2.33	0.427
51.8519	52.2	0.671335	2.79	2.79	0	48.9168	48.5	0.852059	3.23	3.22	0.309
48.6111	48.5	0.228548	3.3	3.31	0.303	48.3092	48.2	0.226043	2.69	2.69	0
52.9101	52.8	0.208088	2.19	2.19	0	53.2725	52.8	0.886949	2.18	2.19	0.458
47.7164	47.9	0.384773	2.36	2.36	0	52.5526	52.6	0.090195	1.8	1.81	0.555
48.3092	48.3	1.222955	2.95	2.94	0.338	59.3724	59.4	1.637798	1.82	1.81	0.549
58.4785	58.6	0.207768	1.89	1.89	0	56.7721	56.8	0.049143	2.03	2.02	0.492
54.7731	54.6	0.316031	2.25	2.25	0	51.1696	51.2	1.818267	2.73	2.73	0
56.3607	56.2	0.285127	1.68	1.68	0	61.2423	61.3	0.094215	1.72	1.71	0.581



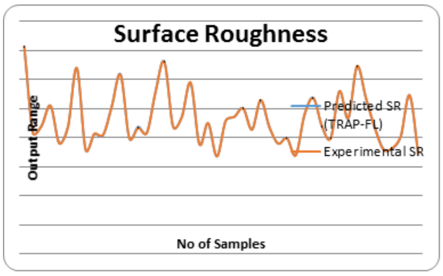


Fig.16.Comparison of Experimental and Predicted MRR and SR using Trapezoidal MF

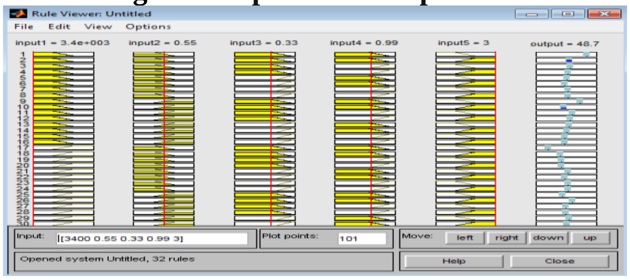
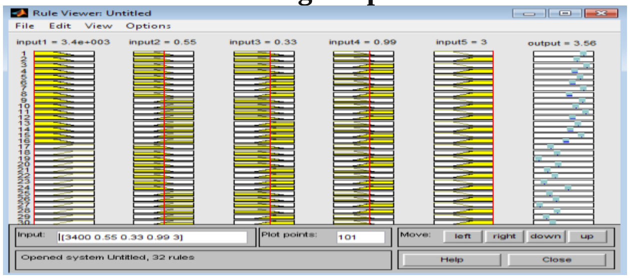



Fig.17.Fuzzy Rule Viewer of MRR and SR using Trapezoidal MF

Implementation of Triangular Membership Function FL: Figs. 18 to 22 shows the Triangular Membership functions of Pressure, abrasive flow rate, orifice diameter, nozzle diameter and stand off distance. The Table 5 shows the errors between the experimental and predicted values for MRR and SR using Triangular membership function FL for Aluminium 6061 Alloy and the comparison between the experimental values of MRR, SR and Predicted values of MRR, SR using Triangular membership function FL for Aluminium 6061 alloy is shown in Fig. 23 and Fig. 24 shows the Fuzzy Rule Viewer of MRR and SR for Aluminium 6061 Alloy.

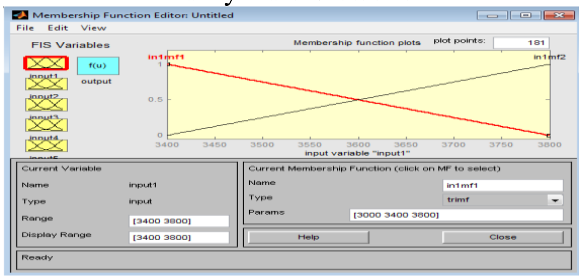


Fig.18.Triangular MF for Pressure

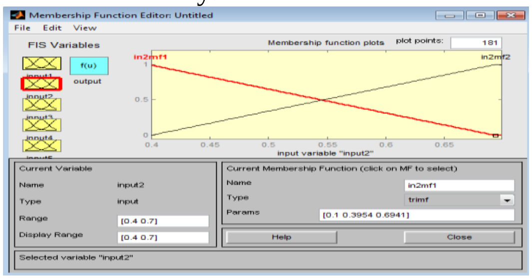


Fig.19.Triangular MF for Abrasive Flow Rate

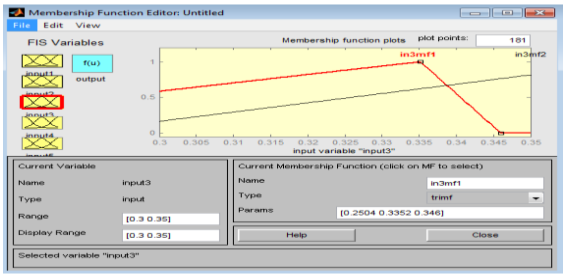


Fig.20.Triangular MF for Orifice Diameter

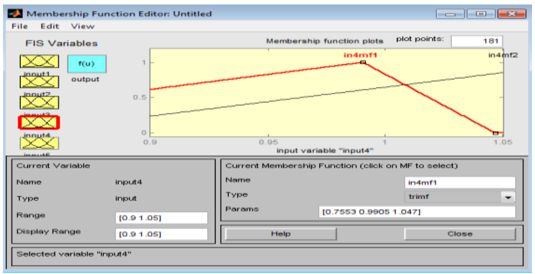


Fig.21.Triangular MF for Nozzle Diameter

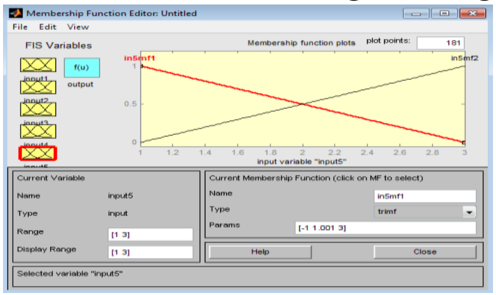


Fig.22.Triangular MF for Stand Off Distance

Table.5.Optimized Output Value of MRR and SR for Aluminium 6061 Alloy through Triangular Membership Function Fuzzy Logic

Experimental MRR (mm³/min)	Predicted MRR (mm³/min)	Error MRR	Experimental SR (µm)	Predicted SR (µm)	Error SR	Experimental MRR (mm³/min)	Predicted MRR (mm³/min)	Error MRR	Experimental SR (µm)	Predicted SR (µm)	Error SR
48.6111	48.6	0.02283	3.57	3.56	0.28011	49.2264	49.3	0.1495	2.29	2.3	0.43668
53.6399	53.8	0.29847	2.08	2.08	0	48.9168	48.8	0.2387	2.36	2.36	0
51.8519	51.8	0.10009	2.21	2.2	0.45249	51.1696	51.2	0.0594	2.5	2.51	0.4
50.8352	51	0.32418	2.55	2.55	0	55.9552	55.1	1.5283	2.14	2.14	0
62.2222	62.3	0.12503	1.9	1.91	0.52632	49.2264	49.2	0.0536	2.65	2.64	0.37736
51.8519	52.8	1.82847	2.19	2.19	0	56.7721	57	0.4014	2.18	2.18	0
45.7516	45.8	0.10578	3.2	3.2	0	50.8352	50.9	0.1274	1.9	1.91	0.52632
53.6399	53.7	0.11204	1.8	1.81	0.55556	51.8519	52.7	1.6356	1.99	1.99	0
61.2423	61.2	0.06906	2.07	2.06	0.48309	64.8148	64.9	0.1314	1.7	1.7	0
62.2222	62	0.35710	2.05	2.05	0	48.6111	48.6	0.0228	2.4	2.4	0
51.1696	50.7	0.91773	2.54	2.54	0	52.1999	52.2	0.0001	2.68	2.68	0
47.7164	48.6	1.85177	3.08	3.09	0.32468	52.9101	52.8	0.2080	2.2	2.19	0.45455
50.1792	50	0.35712	1.99	1.99	0	59.8291	59.8	0.0486	1.99	2	0.50251
52.9101	52.8	0.20808	2.17	2.19	0.92166	51.8519	51.9	0.0927	2.8	2.8	0
54.3901	55.4	1.85677	2.08	2.07	0.48077	51.1696	51.9	1.4274	2.34	2.32	0.8547
51.8519	51.7	0.29294	2.79	2.79	0	48.9168	48.7	0.4432	3.23	3.23	0
48.6111	48.6	0.02283	3.3	3.31	0.30303	48.3092	48.2	0.2260	2.69	2.69	0
52.9101	52.8	0.20808	2.19	2.19	0	53.2725	52.8	0.8869	2.18	2.19	0.45872
47.7164	47.9	0.38477	2.36	2.36	0	52.5526	52.9	0.6610	1.8	1.81	0.55556
48.3092	48.3	0.01904	2.95	2.95	0	59.3724	59.3	0.1219	1.82	1.82	0
58.4785	58.6	0.20776	1.89	1.89	0	56.7721	56.8	0.0491	2.03	2.03	0
54.7731	54.6	0.31603	2.25	2.25	0	51.1696	51.9	1.4274	2.73	2.74	0.3663
56.3607	56.2	0.28512	1.68	1.68	0	61.2423	61.2	0.0690	1.72	1.71	0.5814

Fig.23.Comparison of Experimental and Predicted MRR and SR using Triangular MF

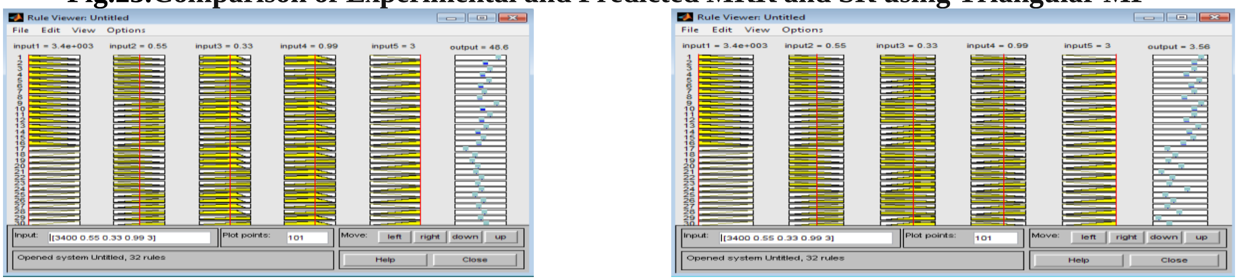


Fig.24.Fuzzy Rule Viewer of MRR and SR using Triangular MF

Table.6.Comparison of Gauss, Trapezoidal and Triangular Membership Functions Fuzzy Logic Least Mean Square Error for MRR and SR for Aluminium 6061 Alloy

Error MRR Using Gauss MF	Error MRR Using Trapezoidal MF	Error MRR Using Triangular MF	Error SR Using Gauss MF	Error SR Using Trapezoidal MF	Error SR Using Triangular MF	Error MRR Using Gauss MF	Error MRR Using Trapezoidal MF	Error MRR Using Triangular MF	Error SR Using Gauss MF	Error SR Using Trapezoidal MF	Error SR Using Triangular MF
0.639977	0.182880042	0.022834291	0.28011	0.28011	0.28011	0.758942	0.05362976	0.149513269	0	0	0.43668
0.074385	0.074384926	0.298471847	0	0	0	0.238773	0.238772773	0.238772773	0	0	0
0.092764	0.100092764	0.100092764	0	0	0.45249	0.526875	0.059410275	0.059410275	0.4	0.4	0.4
0.127471	0.069243359	0.324184817	0	0	0	0.09865	0.098650349	1.52836555	0	0	0
0.125036	0.196392927	0.125035759	0	0.52632	0.52632	0.663059	0.149513269	0.05362976	0	0.37736	0.37736
1.828477	1.828476874	1.828476874	0	0	0	0.049144	0.225286717	0.401429575	0	0	0

0.112783	0.324360241	0.10578865	0.3125	0	0	0.914327	0.069243359	0.127470729	0.52632	0	0.52632
0.4849	0.074384926	0.11204346	0	0	0.55556	0.100093	0.0927642	1.63561991	0.50251	0.50251	0
0.558927	0.257501759	0.069069908	0	0.48309	0.48309	0.022834	0.131451459	0.131451459	0	0	0
0.125036	0.678535957	0.35710727	0.4878	0.4878	0	1.25712	0.022834291	0.022834291	0.41667	0.41667	0
0.05941	1.427410025	0.917732404	0	0	0	0.000192	0.191762819	0.000191571	0.37313	0.37313	0
0.594345	1.71094215	1.851774233	0.32468	0.32468	0.32468	0.208089	0.208088815	0.208088815	0.45455	0.45455	0.45455
0.440023	0.357120082	0.357120082	0	0	0	0.45279	0.048638539	0.048638539	0.50251	0.50251	0.50251
0.208089	0.208088815	0.208088815	0.92166	0.92166	0.92166	0.100093	0.285621163	0.0927642	0.35714	0	0
0.165655	0.018201842	1.856771729	0	0	0.48077	1.113161	0.059410275	1.427410025	0	0.42735	0.8547
0.671335	0.671335091	0.292949728	0	0	0	0.034344	0.852059006	0.443201518	0.3096	0.3096	0
0.022834	0.228548624	0.022834291	0	0.30303	0.30303	0.394956	0.226043901	0.226043901	0	0	0
0.208089	0.208088815	0.208088815	0	0	0	0.886949	0.886949176	0.886949176	0.45872	0.45872	0.45872
0.03437	0.384773369	0.384773369	0	0	0	0.670947	0.090195347	0.661051975	0.55556	0.55556	0.55556
0.601956	1.222955462	0.019043992	0.33898	0.33898	0	0.551772	1.637798034	0.121942182	0.54945	0.54945	0
0.134237	0.207768667	0.207768667	0.5291	0	0	0.655428	0.049143858	0.049143858	0.49261	0.49261	0
0.231683	0.316031044	0.316031044	0	0	0	1.036553	1.818267096	1.427410025	0.3663	0	0.3663
0.247158	0.285127757	0.285127757	0	0	0	0.558927	0.094215926	0.069069908	0.5814	0.5814	0.5814
Least Mean Square Error MRR using Gauss MF									0.083599		
Least Mean Square Error MRR using Trapezoidal MF									0.096096		
Least Mean Square Error MRR using Triangular MF									0.104317		
Least Mean Square Error SR for using Gauss MF									0.048535		
Least Mean Square Error SR using Trapezoidal MF									0.048588		
Least Mean Square Error SR for using Triangular MF									0.050194		

CONCLUSION

In this paper, the prediction of MRR and SR for Aluminium 6061 alloy by machining through Abrasive water jet machining process using three MFs of Fuzzy Logic. All the Fuzzy Logic predictions using Gauss, Trapezoidal and Triangular membership functions are closer to the experimental findings of MRR and SR. Also the least MSE for Gauss Mf Fuzzy Logic Modeling is very less compared to Trapezoidal and Triangular MF Fuzzy Logic Modeling. Thus Gauss Fuzzy modeling technique could be an economical and successful method for prediction of AWJM output parameters for Aluminium 6061 alloy according to input variables.

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