Fuzzy Logic Approach on Lead Tin Alloy for Prediction of Machining Parameters by AWJM Process

K.S. Jai Aultrin, M. DevAnand, S. MuthuSherin, R. Rajesh

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 process 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 Lead Tin 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 Lead Tin Alloy using three different types of membership function on Fuzzy logic (FL) approach.***

Keywords--- ***Response Surface Methodology, Fuzzy Logic, Membership Function, Material Removal Rate, Surface Roughness.***

I. INTRODUCTION AND BACKGROUND OF 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 Waterjet (AWJ) model for machining brittle materials [1]. C. Ma, R.T. 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 [2]. H. Liu,J.Wang, N. Kelson, R.J. Brown in 2004 in their research Computational Fluid Dynamics (CFD) models for ultrahigh velocity waterjets and (AWJs) are established by the use of Fluent6 flow solver [3].Suganthi et al. 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 [4]. Çaydaş et al., performed ANFIS model for surface roughness on D5 tool steel in WEDM process and examined the metallographic properties [5]. Jang 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 [6]. Lei, He, &Zi, 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 [7]. Reddy, C. B., Reddy, V. D., Reddy, C. E. 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 [8].

II. EXPERIMENTAL WORK

Material

Lead is achemical elementin thecarbon groupwith symbol $P_b$andatomic number 82. Lead is a soft,malleableandheavypost-transition metal. Metallic lead has a bluish white color after being freshly cut, but it soontarnishesto a dull grayishcolor when exposed to air. Lead has a shiny chrome-silver luster when it is melted into a liquid. It is also the heaviest non-radioactiveelement (some radioactive elements, liketechnetium, are lighter). Lead is used in building construction,lead-acid batteries,bulletsandshot, weights, as part ofsolders,pewters,fusible alloys, and as aradiation shield.

If ingested, lead ispoisonousto animals and humans, damaging thenervous system and causingbraindisorders. Excessive lead also causes blood disorders in mammals. Lead is aneurotoxinthat accumulates both in soft tissues and the bones.

Lead poisoninghas been documented fromancient Rome,ancient Greece, and ancient China. Lead alloys are generally melted and cast into molds to produce useful shapes.

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The alloys of Lead are also rolled, extruded, and forged. The primary use for Lead alloys is in the production of battery parts for Lead acid batteries.

Smaller but significant uses are ammunition, cable sheathing, sheet for roofing and construction, insoluble anodes, solders, and special low melting point materials. The significant factor in choosing the alloy is its high strength to weight ratio and nonmagnetic properties. The applications of this alloy comprise of aircraft & aerospace industry,military and defence, telecommunications industry. It has good surface finish and can be anodized. The density of this alloy is 11.035g/cm^3 and Modulus of Elasticity, E = 80GPa. The work piece material chosen for this study is Lead Tin Alloy plate of 150mm x 50mm x 50mm dimensions size has been used for performing the experiments.

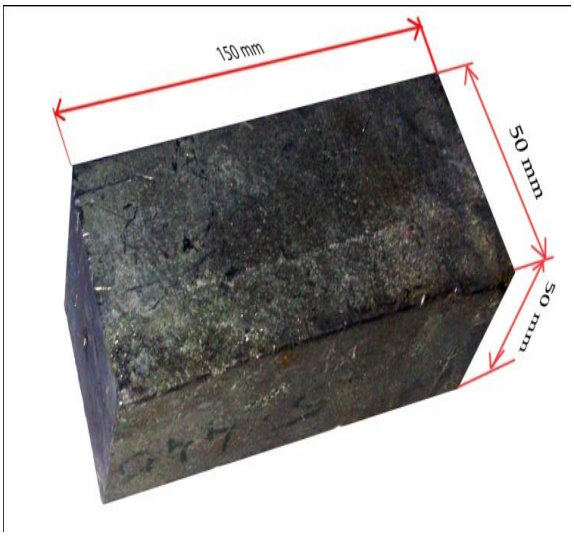

Figure 1:Lead Tin Alloy

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 Press	Abrasive Flow Rate	Orifice Diame	Focusing Nozzle	Stand Off Distance
Low	3400	0.4	0.3	0.9	1
Interme	3600	0.55	0.33	0.99	2
High	3800	0.7	0.35	1.05	3

Based on response surface methodology, 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 [9], Metallic coated sheet steels [10] Metal Matrix Composites [11] and Ceramics [12].

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 Figure 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.

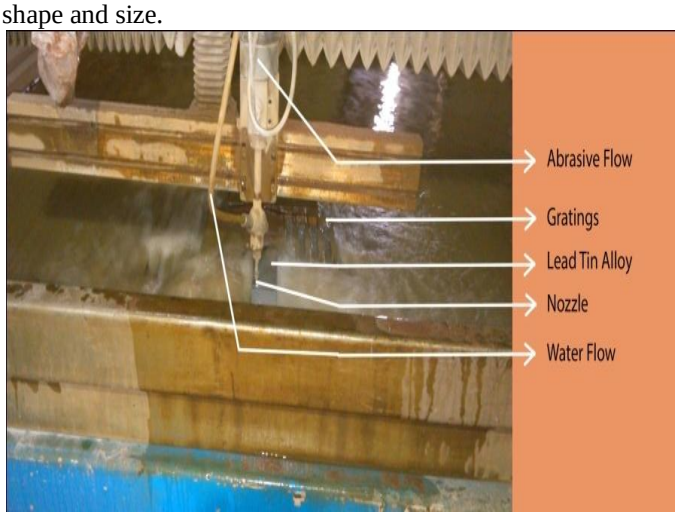

Figure 2: Experimental Setup of AWJM

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 MRR = (mf – mi) / 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 Lead Tin Alloy is measured using Portable surface roughness tester in National College of Engineering, Tamilnadu, India.

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Table 2: Planning Matrix of the Experiments

Sl.No.	P(Bar)	m_f (Kg/min)	d_o (mm)	d_f (mm)	S (mm)	MRR mm^3/min	SR (µm)
1.	3400	0.55	0.33	0.99	3	1709	2.45
2.	3600	0.55	0.33	0.9	1	2014.86	1.415
3.	3600	0.55	0.3	1.05	2	1970.09	1.624
4.	3600	0.55	0.33	0.9	3	1916.85	2.2
5.	3800	0.55	0.33	0.9	2	2182.26	0.788
6.	3600	0.55	0.33	0.99	2	1997.84	1.609
7.	3400	0.4	0.33	0.99	2	1688.65	2.109
8.	3600	0.7	0.35	0.99	2	1997.84	1.52
9.	3800	0.55	0.33	0.99	3	2085.98	1.201
10.	3800	0.55	0.3	0.99	2	2149.19	0.801
11.	3600	0.55	0.33	0.99	3	1896.34	2.1
12.	3400	0.55	0.33	1.05	2	1746.88	1.905
13.	3600	0.4	0.33	0.99	1	1943.11	1.887
14.	3600	0.55	0.33	0.99	2	2009.16	1.571
15.	3600	0.55	0.35	0.9	2	1948.44	1.53
16.	3600	0.55	0.3	0.9	2	2003.48	1.709
17.	3400	0.55	0.33	0.9	2	1751.19	1.9
18.	3600	0.55	0.33	0.99	2	2003.48	1.566
19.	3600	0.4	0.3	0.99	2	1842.16	1.91
20.	3400	0.55	0.35	0.99	2	1751.19	1.899
21.	3800	0.4	0.33	0.99	2	2136.25	1.211
22.	3600	0.7	0.33	0.99	3	1891.29	1.999
23.	3600	0.7	0.33	0.99	1	2055.75	1.431
24.	3600	0.4	0.35	0.99	2	1866.4	2.013
25.	3600	0.4	0.33	0.9	2	1842.16	1.945
26.	3600	0.55	0.35	0.99	3	1916.85	2.008
27.	3600	0.7	0.33	0.9	2	1970.09	1.5
28.	3400	0.55	0.33	0.99	1	1800.08	1.789
29.	3600	0.7	0.3	0.99	2	1937.8	1.699
30.	3600	0.55	0.33	1.05	1	2049.81	1.707
31.	3600	0.55	0.3	0.99	1	2009.16	1.5
32.	3800	0.7	0.33	0.99	2	2142.69	0.62
33.	3600	0.4	0.33	1.05	2	1866.4	1.934
34.	3600	0.55	0.3	0.99	3	1916.84	2.309
35.	3600	0.55	0.33	0.99	2	2014.86	1.597
36.	3800	0.55	0.33	1.05	2	2162.3	0.8
37.	3400	0.7	0.33	0.99	2	1800.08	1.9
38.	3600	0.55	0.35	1.05	2	2020.6	1.704
39.	3400	0.55	0.3	0.99	2	1768.66	2.102
40.	3600	0.4	0.33	0.99	3	1842.16	2.345
41.	3600	0.55	0.33	0.99	2	2020.6	1.64
42.	3600	0.55	0.35	0.99	1	2079.86	1.634
43.	3800	0.55	0.35	0.99	2	2162.3	0.881
44.	3600	0.7	0.33	1.05	2	1970.09	1.539
45.	3600	0.55	0.33	1.05	3	1922.04	1.997
46.	3800	0.55	0.33	0.99	1	2223.3	0.8

III. 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 ofthe 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.

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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,

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

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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.

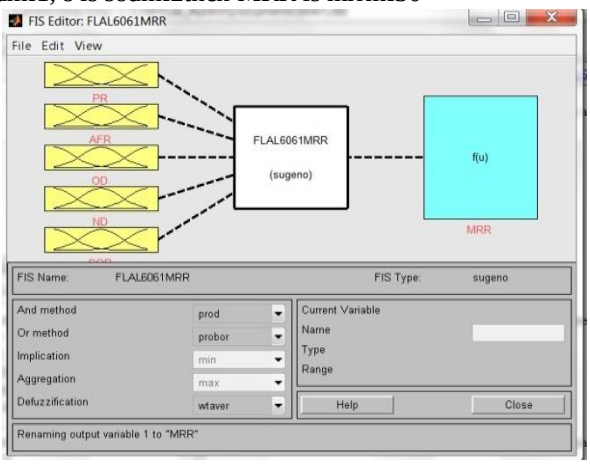

Figure 3: FL for Input and Output Variable

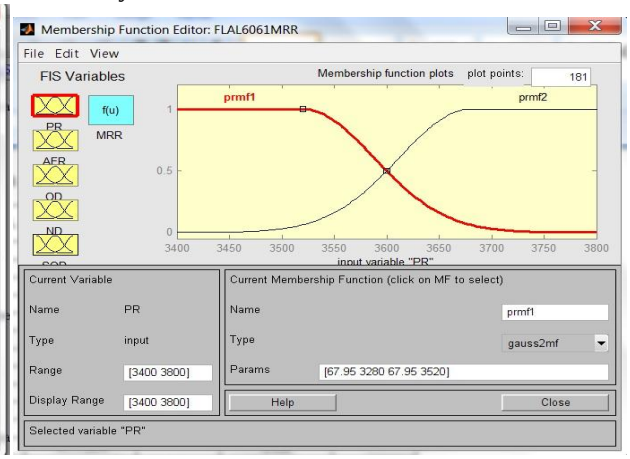

Figure 4: Gauss MF for Pressure

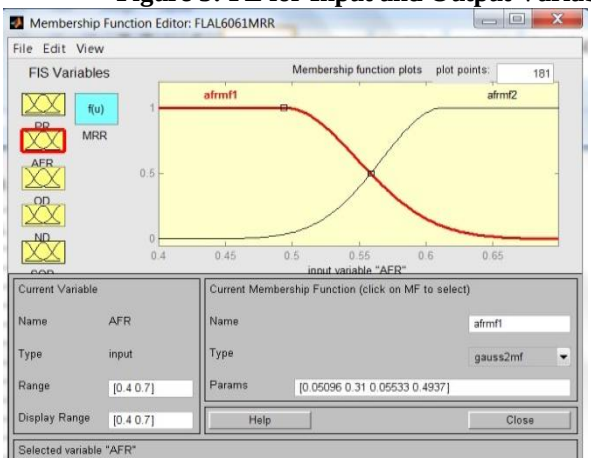

Figure 5: Gauss MF for Abrasive Flow Rate

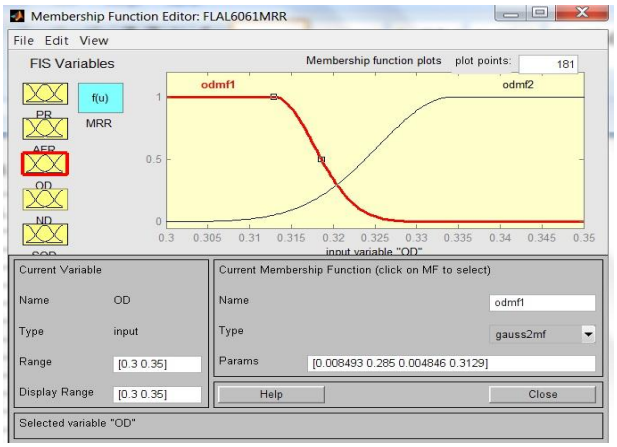

Figure 6: Gauss MF for Orifice Diameter

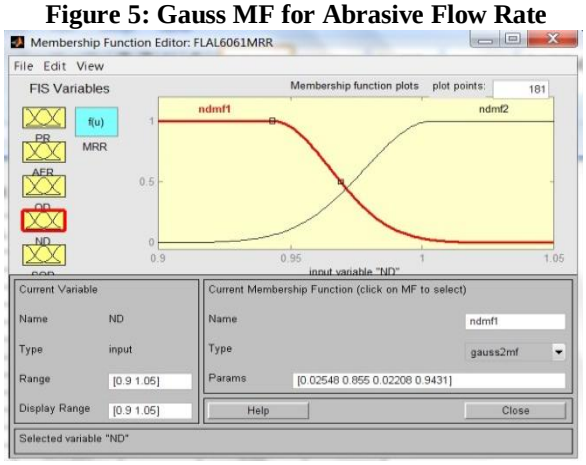

Figure 7: Gauss MF for Nozzle Diameter

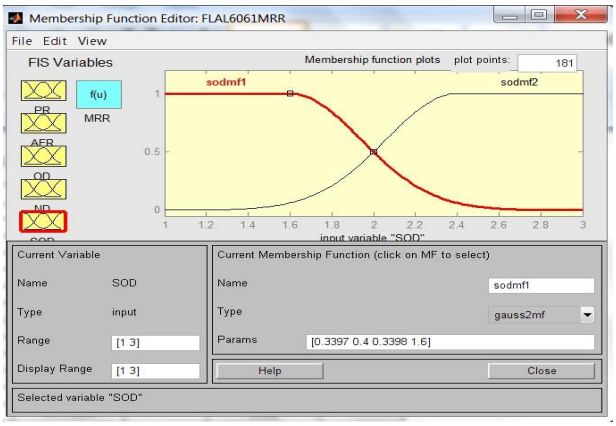

Figure 8: Gauss MF for Stand Off Distance

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Table 3: Optimized Output Value of MRR and SR for Lead Tin Alloy through Gauss Membership Function Fuzzy Logic

Sl. No	Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR (µm)	Predicted SR (µm)	Error SR
1.	1709	1710	0.058514	2.45	2.45	0
2.	2014.86	2010	0.241208	1.415	1.41	0.35336
3.	1970.09	1970	0.004568	1.624	1.62	0.24631
4.	1916.85	1920	0.164332	2.2	2.2	0
5.	2182.26	2180	0.103562	0.788	0.793	0.63452
6.	1997.84	2010	0.608657	1.609	1.6	0.55935
7.	1688.65	1690	0.079946	2.109	2.11	0.04742
8.	1997.84	1990	0.392424	1.52	1.51	0.65789
9.	2085.98	2090	0.192715	1.201	1.19	0.9159
10.	2149.19	2150	0.037689	0.801	0.799	0.24969
11.	1896.34	1900	0.193003	2.1	2.1	0
12.	1746.88	1740	0.393845	1.905	1.92	0.7874
13.	1943.11	1940	0.160053	1.887	1.89	0.15898
14.	2009.16	2010	0.041809	1.571	1.6	1.84596
15.	1948.44	1950	0.080064	1.53	1.53	0
16.	2003.48	2000	0.173698	1.709	1.71	0.05851
17.	1751.19	1750	0.067954	1.9	1.91	0.52632
18.	2003.48	2010	0.325434	1.566	1.6	2.17114
19.	1842.16	1840	0.117254	1.91	1.91	0
20.	1751.19	1760	0.503086	1.899	1.89	0.47393
21.	2136.25	2140	0.175541	1.211	1.21	0.08258
22.	1891.29	1900	0.460532	1.999	2.01	0.55028
23.	2055.75	2060	0.206737	1.431	1.44	0.62893
24.	1866.4	1870	0.192885	2.013	2	0.6458
25.	1842.16	1840	0.117254	1.945	1.95	0.25707
26.	1916.85	1910	0.357357	2.008	2.03	1.09562
27.	1970.09	1980	0.503023	1.5	1.5	0
28.	1800.08	1800	0.004444	1.789	1.78	0.50307
29.	1937.8	1940	0.113531	1.699	1.7	0.05886
30.	2049.81	2050	0.009269	1.707	1.69	0.9959
31.	2009.16	2010	0.041809	1.5	1.5	0
32.	2142.69	2130	0.592246	0.62	0.622	0.32258
33.	1866.4	1870	0.192885	1.934	1.93	0.20683
34.	1916.84	1920	0.164855	2.309	2.31	0.04331
35.	2014.86	2010	0.241208	1.597	1.6	0.18785
36.	2162.3	2160	0.106368	0.8	0.817	2.125
37.	1800.08	1790	0.559975	1.9	1.9	0
38.	2020.6	2020	0.029694	1.704	1.71	0.35211
39.	1768.66	1770	0.075764	2.102	2.1	0.09515
40.	1842.16	1840	0.117254	2.345	2.35	0.21322
41.	2020.6	2010	0.524597	1.64	1.6	2.43902
42.	2079.86	2070	0.47407	1.634	1.65	0.97919
43.	2162.3	2170	0.356102	0.881	0.871	1.13507
44.	1970.09	1980	0.503023	1.539	1.54	0.06498
45.	1922.04	1920	0.106137	1.997	1.98	0.85128
46.	2223.3	2220	0.148428	0.8	0.793	0.875

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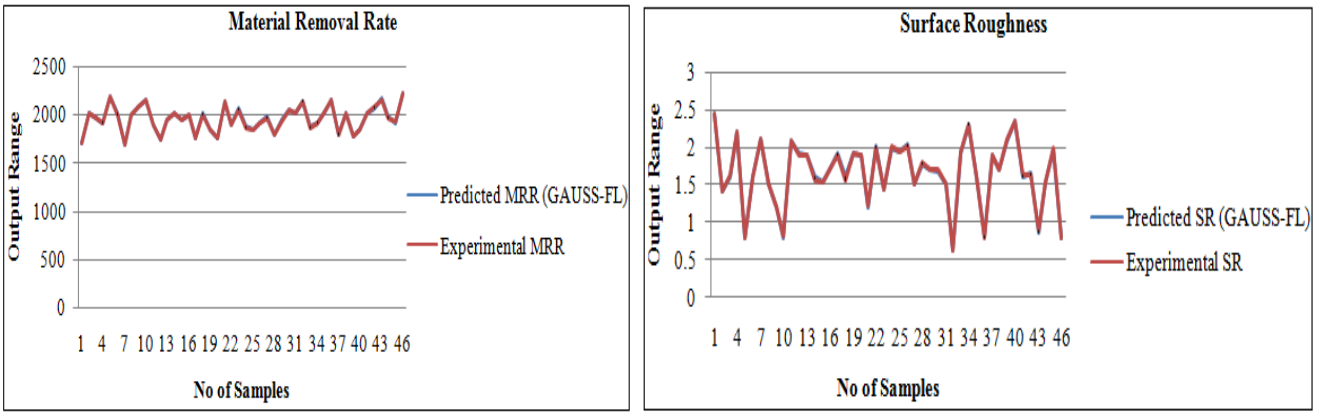

Figure 11: Comparison of Experimental and Predicted MRR and SR Using Gauss MF

Figure 3 shows the Fuzzy Logic for input and output variables. Figures 4 to 10 shows the Gauss Membership functions of Pressure, abrasive flow rate, orifice diameter, nozzle diameter, stand off distance, MRR and SR. The table 3 shows the errors between the experimental and predicted values for MRR and SR using Gauss membership functionFL for Lead Tin Alloy and the comparison between the experimental values of MRR, SR and Predicted values of MRR, SR using Gauss membership function FL for Lead Tin Alloy is shown in Figure 11. Figure 12 shows the Fuzzy Rule Viewer of MRR and SR for Lead Tin Alloy.

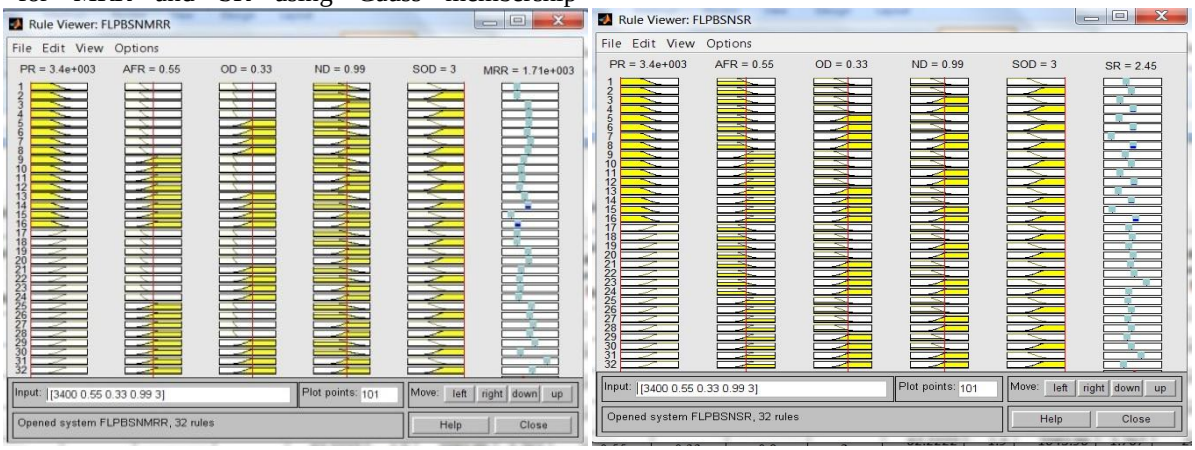

Figure 12: Fuzzy Rule Viewer of MRR and SR Using Gauss MF

Implementation of Using Trapezoidal Membership Function FL

Figures 13 to 17 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 Lead Tin Alloy and the comparison between the experimental values of MRR, SR and Predicted values of MRR, SR using Trapezoidal membership function FL for Lead Tin Alloy is shown in Figure 18. Figure 19 shows the Fuzzy Rule Viewer for MRR and SR of this alloy.

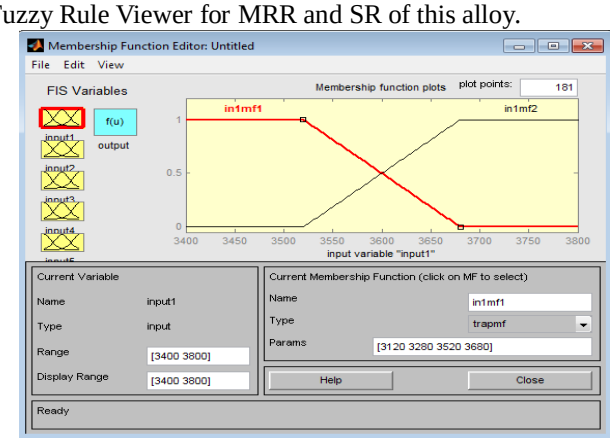

Figure 13: Trapezoidal MF for Pressure

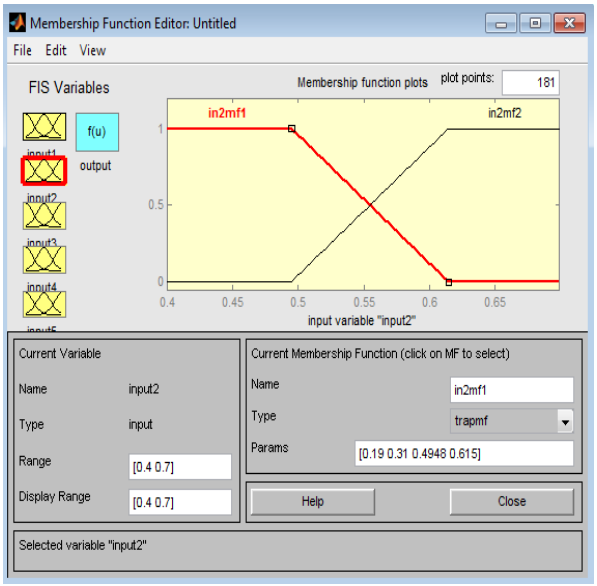

Figure 14: Trapezoidal MF for Abrasive Flow Rate

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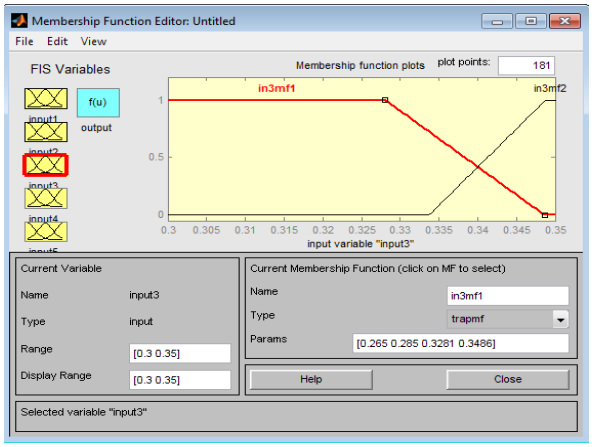

Figure 15: Trapezoidal MF for Orifice Diameter

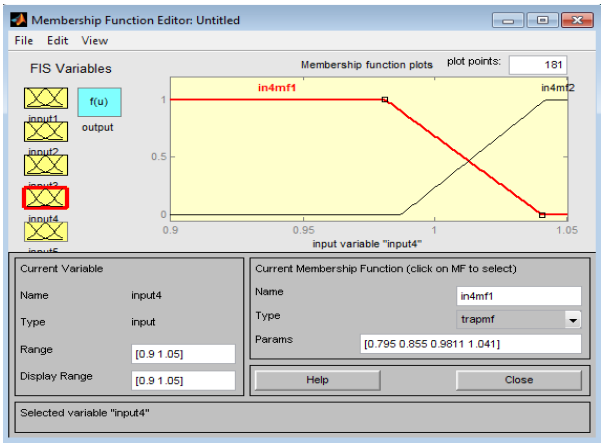

Figure 16: Trapezoidal MF for Nozzle Diameter

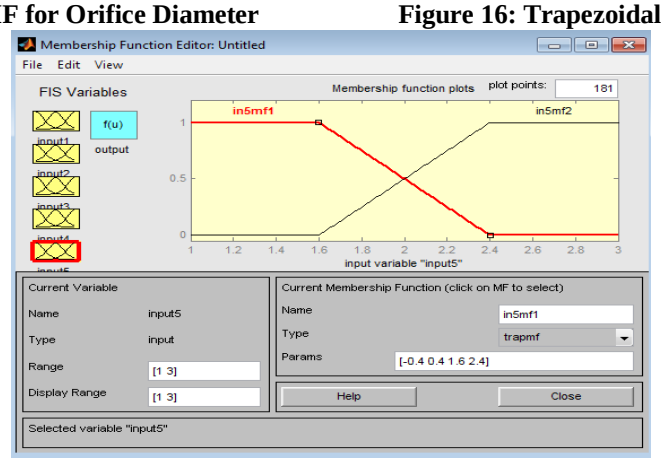

Figure 17: Trapezoidal MF Stand Off Distance

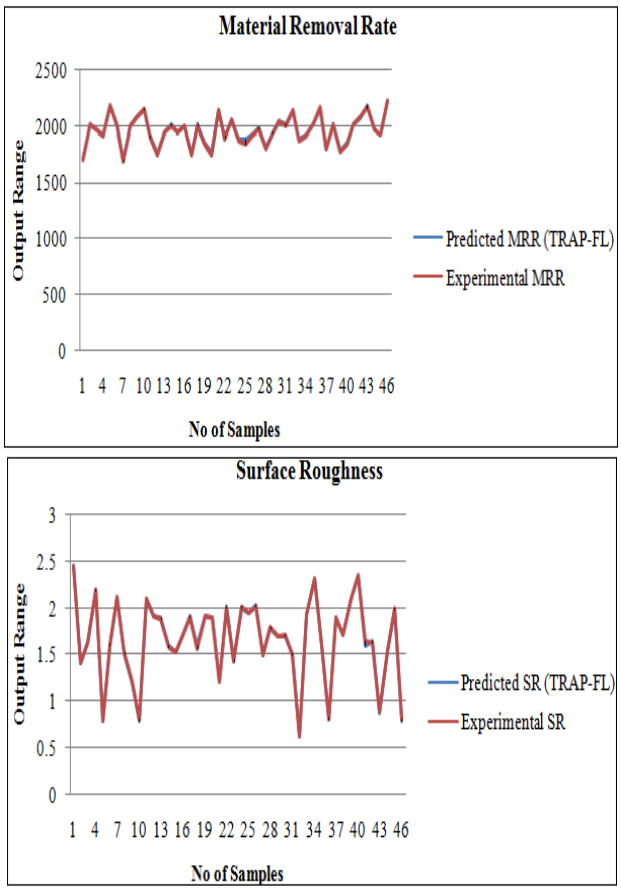

Figure 18: Comparison of Experimental and Predicted MRR and SR using Trapezoidal MF

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Table 4: Optimized Output Value of MRR and SR for Lead Tin Alloy through Trapezoidal Membership Function Fuzzy Logic

Sl.No.	Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR (µm)	Predicted SR (µm)	Error SR
1.	1709	1710	0.05851375	2.45	2.45	0
2.	2014.86	2014	0.04268287	1.415	1.41	0.35336
3.	1970.09	1970	0.00456832	1.624	1.63	0.36946
4.	1916.85	1922	0.26866995	2.2	2.19	0.45455
5.	2182.26	2182	0.01191425	0.788	0.792	0.50761
6.	1997.84	2010	0.60865735	1.609	1.6	0.55935
7.	1688.65	1692	0.19838332	2.109	2.11	0.04742
8.	1997.84	1997	0.04204541	1.52	1.51	0.65789
9.	2085.98	2091	0.24065427	1.201	1.2	0.08326
10.	2149.19	2150	0.03768862	0.801	0.797	0.49938
11.	1896.34	1901	0.24573652	2.1	2.1	0
12.	1746.88	1746	0.05037553	1.905	1.92	0.7874
13.	1943.11	1943	0.00566103	1.887	1.89	0.15898
14.	2009.16	2012	0.14135261	1.571	1.6	1.84596
15.	1948.44	1953	0.23403338	1.53	1.53	0
16.	2003.48	2003	0.02395831	1.709	1.71	0.05851
17.	1751.19	1751	0.01084977	1.9	1.91	0.52632
18.	2003.48	2014	0.52508635	1.566	1.6	2.17114
19.	1842.16	1842	0.00868546	1.91	1.91	0
20.	1751.19	1760	0.50308647	1.899	1.89	0.47393
21.	2136.25	2141	0.22235225	1.211	1.21	0.08258
22.	1891.29	1900	0.46053223	1.999	2.01	0.55028
23.	2055.75	2063	0.35266934	1.431	1.44	0.62893
24.	1866.4	1871	0.24646378	2.013	2	0.6458
25.	1842.16	1874	1.72840578	1.945	1.94	0.25707
26.	1916.85	1916	0.04434358	2.008	2.03	1.09562
27.	1970.09	1985	0.75681822	1.5	1.5	0
28.	1800.08	1800	0.00444425	1.789	1.78	0.50307
29.	1937.8	1942	0.21674063	1.699	1.69	0.52972
30.	2049.81	2050	0.00926915	1.707	1.69	0.9959
31.	2009.16	2012	0.14135261	1.5	1.51	0.66667
32.	2142.69	2139	0.17221343	0.62	0.623	0.48387
33.	1866.4	1871	0.24646378	1.934	1.93	0.20683
34.	1916.84	1922	0.26919305	2.309	2.32	0.4764
35.	2014.86	2014	0.04268287	1.597	1.6	0.18785
36.	2162.3	2162	0.01387412	0.8	0.815	1.875
37.	1800.08	1796	0.22665659	1.9	1.9	0
38.	2020.6	2020	0.02969415	1.704	1.72	0.93897
39.	1768.66	1771	0.13230355	2.102	2.1	0.09515
40.	1842.16	1842	0.00868546	2.345	2.35	0.21322
41.	2020.6	2019	0.0791844	1.64	1.6	2.43902
42.	2079.86	2079	0.04134894	1.634	1.65	0.97919
43.	2162.3	2184	1.00356102	0.881	0.869	1.36209
44.	1970.09	1980	0.5030227	1.539	1.54	0.06498
45.	1922.04	1922	0.00208112	1.997	1.98	0.85128
46.	2223.3	2231	0.34633203	0.8	0.795	0.625

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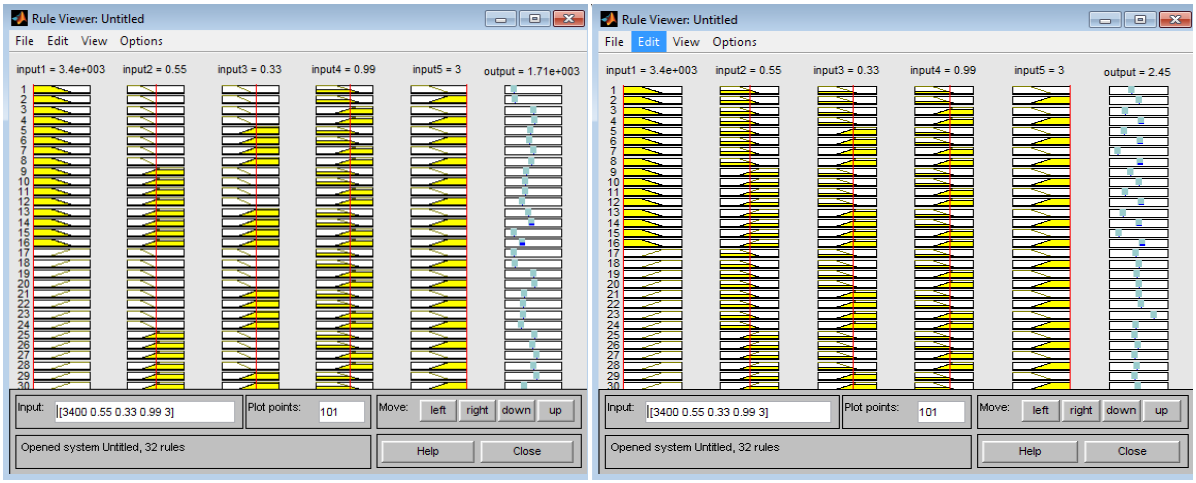

Figure 19: Fuzzy Rule Viewer of MRR and SR using Trapezoidal MF

Implementation of Triangular Membership Function FL

Figures 20 to 24 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 forMRR and SR using Triangular membership function FL for Lead Tin Alloy and the comparison between the experimental values of MRR, SR and Predicted values of MRR, SR using Triangular membership function FL for Lead Tin Alloyis shown in Figure 25. Figure 26 shows the Fuzzy Rule Viewer of MRR and SR for Lead Tin Alloy.

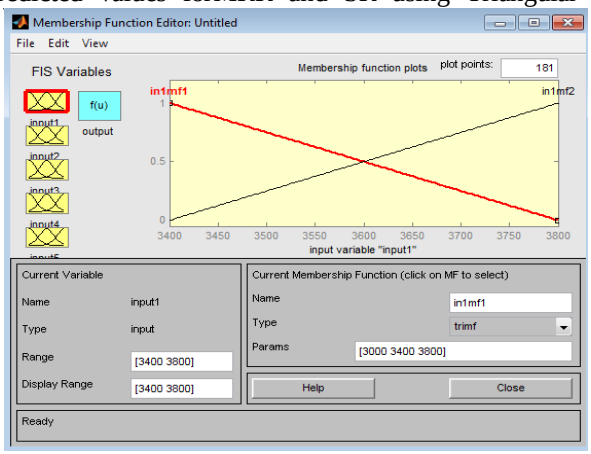

Figure 20: Triangular MF for Pressure

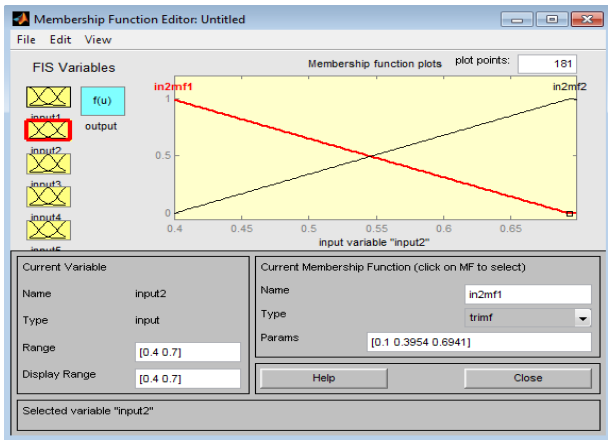

Figure 21: Triangular MF for Abrasive Flow Rate

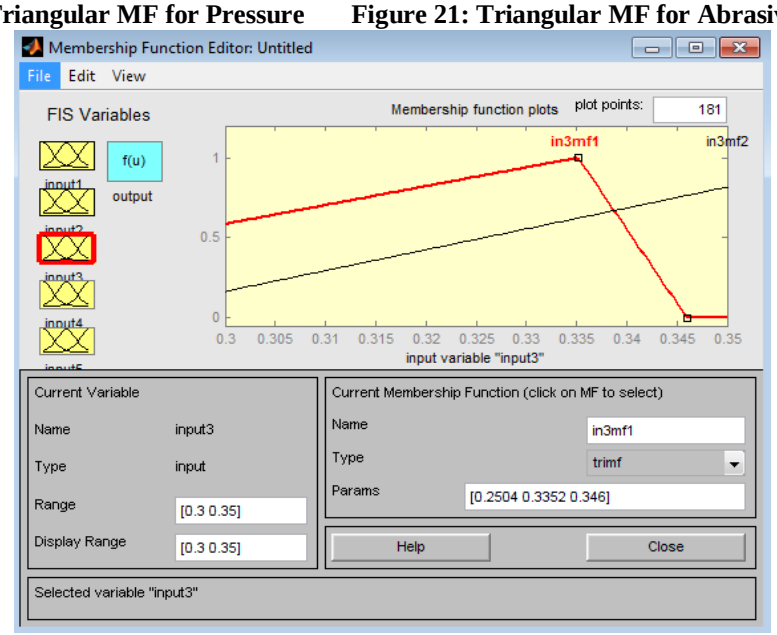

Figure 22: Triangular MF for Orifice Diameter

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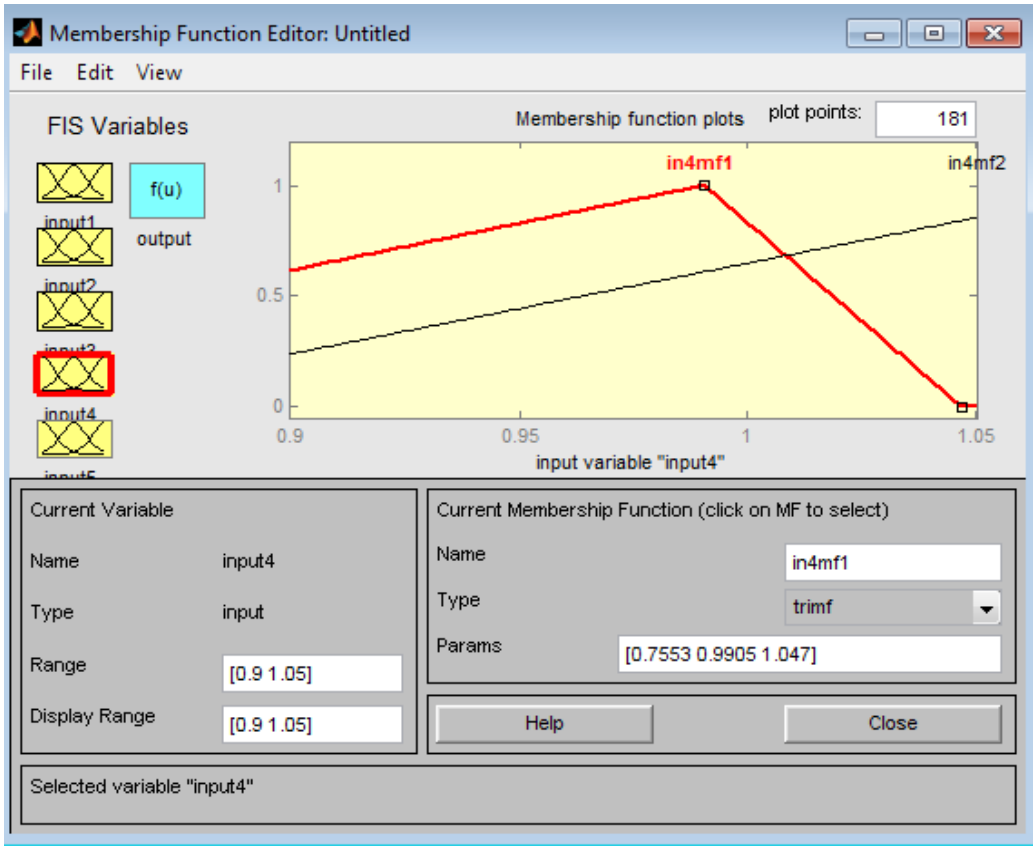

Figure 23: Triangular MF for Nozzle Diameter

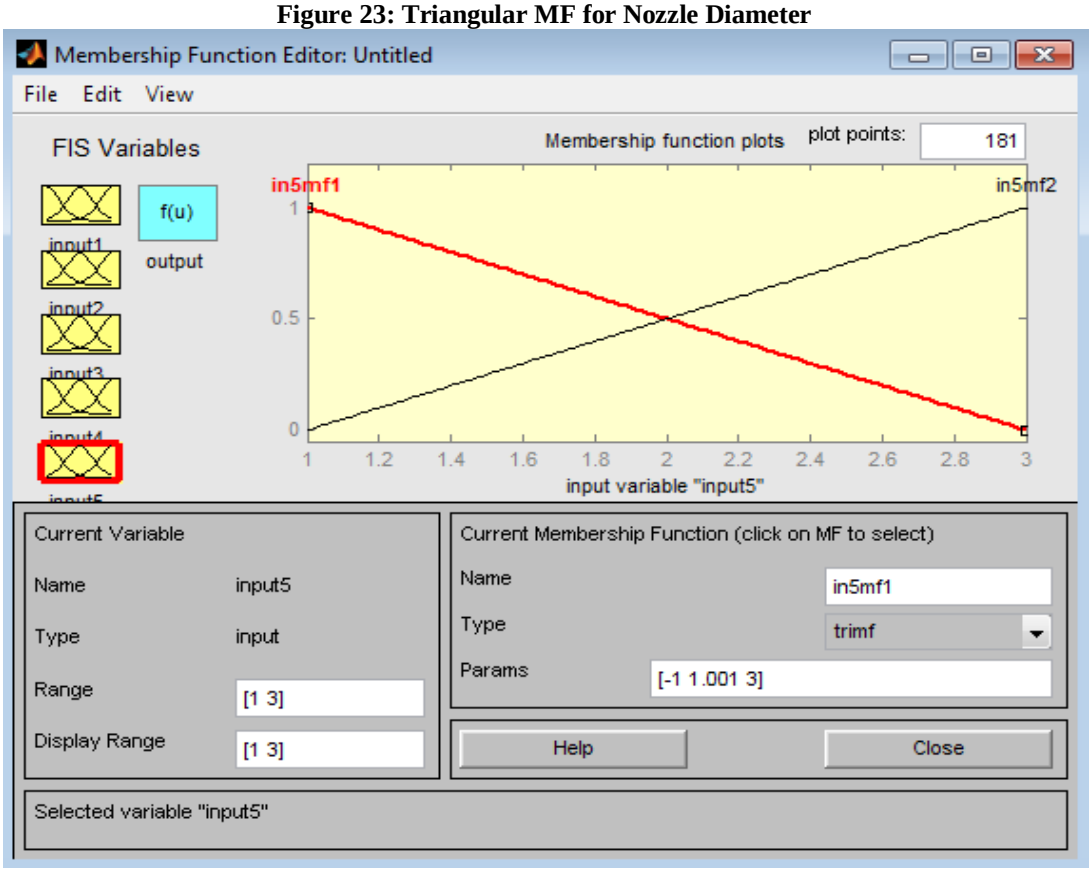

Figure 24: Triangular MF for Stand Off Distance

Table 5: Optimized Output Value of MRR and SR for Lead Tin Alloy through Triangular Membership Function Fuzzy Logic

Sl.No.	Experimental MRR (mm^3/min)	Predicted MRR (mm^3/min)	Error MRR	Experimental SR (µm)	Predicted SR (µm)	Error SR
1.	1709	1710	0.05851375	2.45	2.45	0
2.	2014.86	2014	0.04268287	1.415	1.41	0.3533569
3.	1970.09	1970	0.00456832	1.624	1.62	0.2463054
4.	1916.85	1924	0.3730078	2.2	2.2	0.4545455
5.	2182.26	2182	0.01191425	0.788	0.793	1.0152284
6.	1997.84	2011	0.65871141	1.609	1.6	0.5593536
7.	1688.65	1690	0.07994552	2.109	2.11	0.0474158
8.	1997.84	2001	0.15817082	1.52	1.51	0.6578947
9.	2085.98	2091	0.24065427	1.201	1.19	0.0832639
10.	2149.19	2150	0.03768862	0.801	0.799	1.1235955
11.	1896.34	1921	1.30039972	2.1	2.1	0
12.	1746.88	1746	0.05037553	1.905	1.92	0.7874016
13.	1943.11	1943	0.00566103	1.887	1.89	0.1589825
14.	2009.16	2010	0.04180852	1.571	1.6	1.845958
15.	1948.44	1952	0.18271027	1.53	1.53	0
16.	2003.48	2003	0.02395831	1.709	1.71	0.0585138
17.	1751.19	1751	0.01084977	1.9	1.91	0.5263158
18.	2003.48	2013	0.4751732	1.566	1.6	2.1711367
19.	1842.16	1842	0.00868546	1.91	1.91	0
20.	1751.19	1762	0.61729453	1.899	1.89	0.4739336
21.	2136.25	2142	0.26916325	1.211	1.21	0.0825764
22.	1891.29	1891	0.01533345	1.999	2.01	0.5502751
23.	2055.75	2060	0.2067372	1.431	1.44	0.6289308
24.	1866.4	1875	0.46078011	2.013	2	0.1490313
25.	1842.16	1842	0.00868546	1.945	1.95	0.2570694
26.	1916.85	1916	0.04434358	2.008	2.03	1.0956175
27.	1970.09	1985	0.75681822	1.5	1.5	0
28.	1800.08	1800	0.00444425	1.789	1.78	0.5030743
29.	1937.8	1941	0.16513572	1.699	1.7	0.0588582
30.	2049.81	2054	0.20440919	1.707	1.69	0.9958992
31.	2009.16	2017	0.39021283	1.5	1.5	0
32.	2142.69	2135	0.35889466	0.62	0.622	0.1612903
33.	1866.4	1871	0.24646378	1.934	1.93	0.2068252
34.	1916.84	1916	0.04382212	2.309	2.31	0.0433088
35.	2014.86	2014	0.04268287	1.597	1.6	0.1878522
36.	2162.3	2162	0.01387412	0.8	0.817	1.875
37.	1800.08	1795	0.28220968	1.9	1.9	0
38.	2020.6	2020	0.02969415	1.704	1.71	0.3521127
39.	1768.66	1778	0.52808341	2.102	2.1	0.0951475
40.	1842.16	1842	0.00868546	2.345	2.35	0.2132196
41.	2020.6	2018	0.12867465	1.64	1.6	2.4390244
42.	2079.86	2079	0.04134894	1.634	1.65	0.9791922
43.	2162.3	2174	0.54109051	0.881	0.871	1.4755959
44.	1970.09	1984	0.70605911	1.539	1.54	0.0649773
45.	1922.04	1922	0.00208112	1.997	1.98	0.8512769
46.	2223.3	2231	0.34633203	0.8	0.793	0.5

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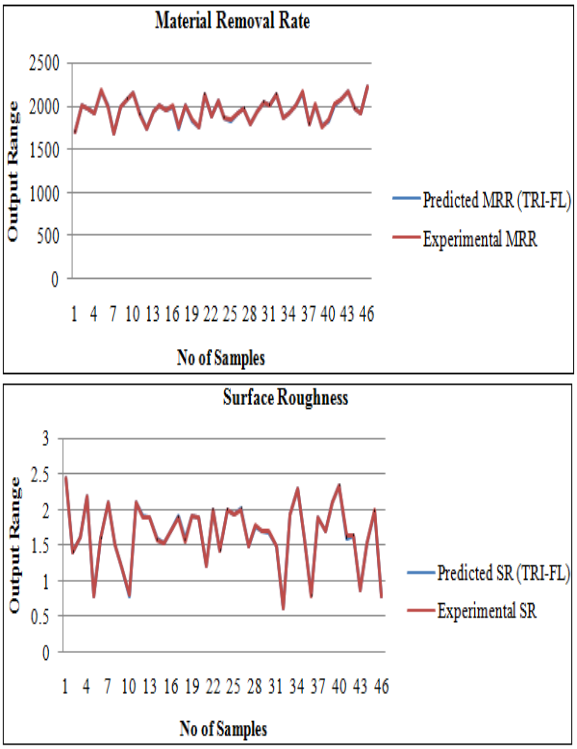
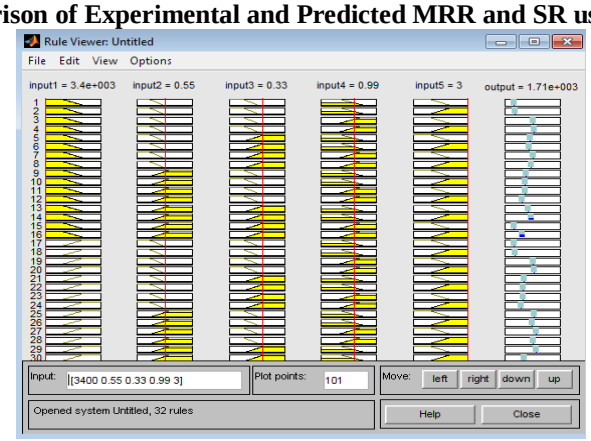


Figure 25: Comparison of Experimental and Predicted MRR and SR using Triangular MF



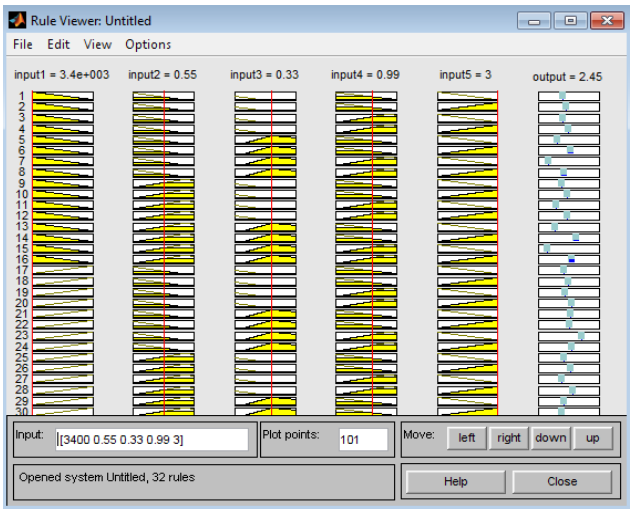


Figure 26: Fuzzy Rule Viewer of MRR and SR Using Triangular MF

Table 6: Comparison of Gauss, Trapezoidal and Triangular Membership Functions Fuzzy Logic Least Mean Square Error for MRR and SR for Lead Tin Alloy

Sl.No	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
1.	0.058514	0.058514	0.058514	0	0	0
2.	0.241208	0.042683	0.042683	0.35336	0.35336	0.35336
3.	0.004568	0.004568	0.004568	0.24631	0.36946	0.24631
4.	0.164332	0.26867	0.373008	0	0.45455	0.45455
5.	0.103562	0.011914	0.011914	0.63452	0.50761	1.01523
6.	0.608657	0.608657	0.658711	0.55935	0.55935	0.55935
7.	0.079946	0.198383	0.079946	0.04742	0.04742	0.04742
8.	0.392424	0.042045	0.158171	0.65789	0.65789	0.65789
9.	0.192715	0.240654	0.240654	0.9159	0.08326	0.08326
10.	0.037689	0.037689	0.037689	0.24969	0.49938	1.12359
11.	0.193003	0.245737	1.3004	0	0	0
12.	0.393845	0.050376	0.050376	0.7874	0.7874	0.7874
13.	0.160053	0.005661	0.005661	0.15898	0.15898	0.15898
14.	0.041809	0.141353	0.041809	1.84596	1.84596	1.84596
15.	0.080064	0.234033	0.18271	0	0	0
16.	0.173698	0.023958	0.023958	0.05851	0.05851	0.05851
17.	0.067954	0.01085	0.01085	0.52632	0.52632	0.52632
18.	0.325434	0.525086	0.475173	2.17114	2.17114	2.17114
19.	0.117254	0.008685	0.008685	0	0	0
20.	0.503086	0.503086	0.617295	0.47393	0.47393	0.47393
21.	0.175541	0.222352	0.269163	0.08258	0.08258	0.08258
22.	0.460532	0.460532	0.015333	0.55028	0.55028	0.55028
23.	0.206737	0.352669	0.206737	0.62893	0.62893	0.62893
24.	0.192885	0.246464	0.46078	0.6458	0.6458	0.14903
25.	0.117254	1.728406	0.008685	0.25707	0.25707	0.25707
26.	0.357357	0.044344	0.044344	1.09562	1.09562	1.09562
27.	0.503023	0.756818	0.756818	0	0	0
28.	0.004444	0.004444	0.004444	0.50307	0.50307	0.50307
29.	0.113531	0.216741	0.165136	0.05886	0.52972	0.05886
30.	0.009269	0.009269	0.204409	0.9959	0.9959	0.9959
31.	0.041809	0.141353	0.390213	0	0.66667	0
32.	0.592246	0.172213	0.358895	0.32258	0.48387	0.16129
33.	0.192885	0.246464	0.246464	0.20683	0.20683	0.20683
34.	0.164855	0.269193	0.043822	0.04331	0.4764	0.04331
35.	0.241208	0.042683	0.042683	0.18785	0.18785	0.18785
36.	0.106368	0.013874	0.013874	2.125	1.875	1.875
37.	0.559975	0.226657	0.28221	0	0	0
38.	0.029694	0.029694	0.029694	0.35211	0.93897	0.35211
39.	0.075764	0.132304	0.528083	0.09515	0.09515	0.09515
40.	0.117254	0.008685	0.008685	0.21322	0.21322	0.21322
41.	0.524597	0.079184	0.128675	2.43902	2.43902	2.43902
42.	0.47407	0.041349	0.041349	0.97919	0.97919	0.97919
43.	0.356102	1.003561	0.541091	1.13507	1.36209	1.4756
44.	0.503023	0.503023	0.706059	0.06498	0.06498	0.06498
45.	0.106137	0.002081	0.002081	0.85128	0.85128	0.85128
46.	0.148428	0.346332	0.346332	0.875	0.625	0.5
LMSE of MRR using Gauss, Trapezoidal, Triangular MF					**0.042188**	**0.057164**	**0.051499**
LMSE of Error SR for using Gauss Trapezoidal, Triangular MF					**0.118503**	**0.119533**	**0.118709**

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IV. CONCLUSION

In this paper, the prediction of MRR and SR for Lead Tin 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 Lead Tin Alloy according to input variables.

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