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Development of Hybrid Modeling and Prediction of SR in EDM of AISI1020 Steel Material Using ANFIS

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Abstract

Background/Objectives: Surface roughness plays a major role in determining how an original component will interact with its environment. For getting a good surface finish industries spent huge cost for introducing new technologies. The use of advanced engineering ceramics and composites in the aerospace and defense industries is continuous and increases day by day. Surface Roughness (SR) prediction plays a vital role in improving the surface finish in industries. The present work deals with predicting the surface roughness of AISI1020 steel material in Electrical Discharge Machining (EDM) by using Adaptive Neuro Fuzzy Inference System (ANFIS). **Methods/Statistical Analysis:** The discharge voltage, discharge current, pulse on time, pulse off time, gap between tool and workpiece and oil pressure are taken as the input parameters, whereas SR is the output machining parameter. Design of Experiment (DoE) is based on Response Surface Methodology (RSM). ANFIS model has been constructed using Gaussian membership function (Gaussmf) with 2 membership function for each and every input parameter and linear membership function for output parameter SR and MRR. **Findings:** We employed both the back propagation method and the hybrid method for membership function parameter training. Based on the conclusion from the comparison of ANFIS with two types of membership function parameter training, hybrid method provides accurate results. **Applications/Improvements:** It is further used that the maximum error when the network is optimized by the intelligent technique has been reduced considerably. Sensitivity analysis is also done to find the relative influence of factors on the performance measures. It is observed that type of material is having more influence on the performance measures.

Keywords: Adaptive Steganography, Enhanced Canny Operator, Ensemble Classifier, Least Significant Bit, Positive Predictive Rate

1. Introduction

EDM occupies an important position in modern manufacturing industries. It is one of the advanced methods to machining almost all kinds of electrically conductive metals. The main principle of EDM is done through erosion of material from the workpiece by producing high temperature electrical spark discharge between tool and workpiece. In this work, the electrode used for tool is copper electrode which acts as a cathode and workpiece is act as an anode. Both tool and the workpiece is connected to the D.C. power supply and which is submerged in a dielectric fluid medium like petroleum based hydrocarbon fluids, paraffin, white sprit, transformer oil, kerosene and mineral oil with poor conductivity of electricity. During the D.C. supply is given to the circuit, high temperature spark is produced in an interval of 10 to 30 microseconds with current density of 15 to 500 Ampere per mm^2. Due to the high temperature and pressure workpiece metal is melted and eroded. The removed material from the workpiece is carried out by a dielectric fluid. Since there is no cutting forces act on the workpiece, error due to elastic deformation is eliminated. To improve the quality of the surface finish of a components manufacturing in an industries with low cost at optimum

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time in a safety manner, modeling and optimization of manufacturing process plays a huge role in selection of a process parameters. Modeling and optimization comes under the category of artificial intelligence.

2. Literature Survey

Used input parameter as peak current, pulse on time, pulse duty factor and the output parameter as MRR and SR in EDM[1]. ANFIS has been developed to test for both forward and reverse mappings efficiently. Was developed a neuro fuzzy and regression model for predicting the MRR in EDM process using AISID2 tool steel with copper electrode and they consider discharge current, pulse duration and duty cycle as input parameters[2]. Consider pulse on time, duty factor and discharge current as input parameter in EDM for optimizing the output parameters electrode wear ratio, MRR and SR by using grey fuzzy logic based on orthogonal array[3]. Has been conducted an experiments on Ti6A14V, HE15, 15CDV6 and M-250 material in EDM to optimized the SR by developed a hybrid model[4]. They considered peak current and voltage as an input parameter. Multi-perceptron NN models were developed and optimized using [5]compared the MRR of the work for different material in EDM considering the change of polarity among six different NNs like Logistic Sigmoid Multi-Layered Perceptron (LOGMLP), hyperbolic Tangent Sigmoid Multi Layered Perceptron (TANMLP), Fast Error Back Propagation Hyperbolic Tangent Multi Layered Perceptron (error TANALP), Radial Basis Function Networks (RBFNs), Adaptive TANMLP, Adaptive TANMLP, ANFIS. Finally it can be concluded that ANFIS with Bell-Bell shape membership function provides accurate prediction. Analyzed the workpiece surface finish with variation of cutting velocity on wire EDMNN with back-propagation and SA algorithm is used to found an optimal parameter[6]. Has been developed an ANFIS for predicting the white layer thickness and the average SR achieved in a WEDM with input parameter as pulse duration, open circuit voltage, dielectric flushing pressure and wire feed rate[7]. Has been developed the prediction model of SR by using RSM and ANFIS for CNC turning machine with carbide cutting tool for machining Aluminium alloys and finally concluded that compared with using RSM, ANFIS produced good results[8].

Have been considered varying cutter axis inclination angle, spindle speed, feed rate, feed and depth of cut as input parameter[9]. Here the DoE is based on RSM and developed the ANFIS model with three Gaussian membership functions for predicted the SR of Aluminum for ball end milling operation. Compared the prediction of SR in end milling of Inconel-718 using optimal triangular and trapezoidal membership functions in ANFIS model with the results of real experiment and the proposed system produced good results[10]. Utilized three tools like ANFIS, NNs and regression for SR in turning process and they achieved good accuracy in using ANFIS when compared with others[11]. Has been developed a Graphical User Interface (GUI) and integrated to model laser machining process using ANFIS and they proved GUI implementation embedding ANFIS has been greatest prediction ability in modeling the complex and nonlinear behavior of laser processing responses[12]. Applied an ANFIS system to predict the output parameters like surface finish and tool life criteria of the lathe machine for machining of ST-37 steel[13]. Has been used ANFIS and ANN to predict the SR of workpiece in hard turning[14]. Has been developed a NN model for predict the SR in turning process and observed an accurate prediction by utilized small sized training and testing data sets[15].

From the literature survey it is observed that the input factors consider for machining the workpiece in EDM is up to three or four and ANFIS is widely used in EDM process for the prediction of output parameter. However ANFIS with any one type of method is used for membership function parameter training. In this paper utilized six input parameters are consider and creating ANFIS model with Gaussian membership function (Gaussmf) using both the back propagation method and the hybrid method for membership function parameter training.

3. Experimental Verification

Before going to machining the workpiece, it is for DoE at different cutting conditions. In this work DoE is based on RSM. For creating the RSM, Box-Behnken design is used. Which do not have axial points; this ensures the occurring of all points within safe operating zone. Based on Box-Behnken design the available design for six factors is 54 numbers of runs. Machining of workpiece by using the EDM setup is shown in the Figure 1. Here copper electrode is used as a tool and kerosene with poor conductivity of electricity is used as a dielectric fluid. SR measurement has been finished by using SR tester SJ-201 which is a transferable and self-contained device for surface roughness measurement is as shown in Figure 2. In case of SR measurement the average of three measurements should be taken as final experimental output. The different process variables and their corresponding measured responses are tabulated in Table 1.

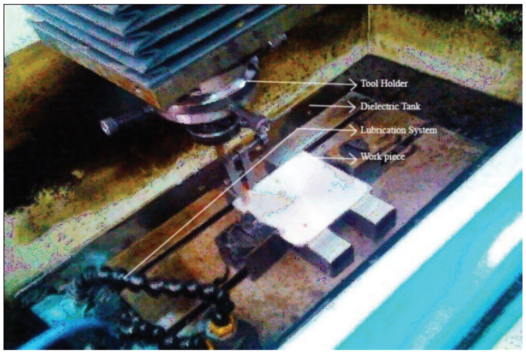


Figure 1. Photograph of the Electrical Discharge Machining Setup.

Table 1. Process variables and their corresponding Responses

Sl. No.	A Voltage (V)	B Current (A)	C Pulse On Time (µs)	D Pulse Off Time (Sec)	E Spark Gap (mm)	F Oil Pressure (kg/cm2)	G SR (µm)
1.	50	15	20	1.5	0.22	25	3.110
2.	50	15	20	2.0	0.22	25	3.163
3.	50	15	15	1.5	0.22	25	2.673
4.	75	15	20	1.5	0.22	25	2.950
5.	50	15	20	1.0	0.22	25	3.300
6.	25	15	20	1.5	0.22	25	2.371
7.	50	15	20	1.5	0.04	25	3.535
8.	50	25	20	1.5	0.22	25	3.490
9.	50	15	20	1.5	0.22	20	2.970
10.	50	15	25	1.5	0.22	25	2.750
11.	50	15	20	1.5	0.22	25	3.110
12.	50	15	20	1.5	0.40	25	3.468
13.	50	15	20	1.5	0.22	30	3.011
14.	50	5	20	1.5	0.22	25	2.391
15.	25	25	25	2.0	0.40	20	2.930
16.	25	5	15	2.0	0.04	30	0.870
17.	25	5	15	1.0	0.04	20	1.187
18.	50	15	20	1.5	0.22	25	3.110
19.	25	25	15	2.0	0.40	30	2.824
20.	75	25	15	1.0	0.04	20	2.986
21.	25	25	25	1.0	0.40	30	3.421
22.	75	5	15	2.0	0.40	30	2.640
23.	75	25	25	2.0	0.04	20	2.947
24.	75	5	15	1.0	0.40	20	2.379
25.	50	15	20	1.5	0.22	25	3.110

26.	75	5	25	2.0	0.40	20	2.410
27.	75	25	15	2.0	0.04	30	2.660
28.	75	5	25	1.0	0.40	30	2.682
29.	25	25	15	1.0	0.40	20	3.100
30.	25	5	25	2.0	0.04	20	1.040
31.	25	5	25	1.0	0.04	30	1.281
32.	75	25	25	1.0	0.04	30	2.648
33.	50	15	20	1.5	0.22	25	3.110
34.	50	15	20	1.5	0.22	25	3.110
35.	75	25	15	2.0	0.40	20	2.630
36.	25	25	25	2.0	0.04	30	2.960
37.	75	5	15	1.0	0.04	30	2.524
38.	25	25	25	1.0	0.04	20	3.413
39.	25	5	25	1.0	0.40	20	1.137
40.	75	5	15	2.0	0.04	20	2.660
41.	50	15	20	1.5	0.22	25	3.110
42.	75	25	15	1.0	0.40	30	2.816
43.	75	25	25	2.0	0.40	30	2.760
44.	50	15	20	1.5	0.22	25	3.110
45.	25	25	15	2.0	0.04	20	3.020
46.	25	25	15	1.0	0.04	30	3.076
47.	75	5	25	2.0	0.04	30	2.592
48.	75	5	25	1.0	0.04	20	2.560
49.	25	5	15	2.0	0.40	20	0.576
50.	50	15	20	1.5	0.22	25	3.110
51.	25	5	25	2.0	0.40	30	1.160
52.	75	25	25	1.0	0.40	20	2.730
53.	25	5	15	1.0	0.40	30	1.250
54.	50	15	20	1.5	0.22	25	3.110

Figure 2. EDM machined workpiece and set up for surface roughness measurement tester.

4. Adaptive Neuro Fuzzy Inference System

Artificial intelligence is the study of ideas that enable computers to be intelligent. It works with the help of artificial neurons and some scientific theorems, also it have an ability to find out the solution based on factors rather than on a preset series of steps. ANNs are composed of interconnecting artificial neurons. An artificial neuron is a function formed as a crude model or abstraction of biological neurons. The main goal of the ANN is to transform the input parameters into meaningful outputs parameters. FL dispense a more efficient and resourceful path to work out control systems. It is mainly based on some rule basis. For developing an intelligent systems ANN and FL are the natural complementary tools. When dealing with unanalyzed data NNs are bottom level computational anatomy, which accomplish effectively. FL mainly concerned with reasoning on an upper level, using linguistic data obtained from domain experts. However, FL system deficit the capability to acquire knowledge of and can't modify themselves to a current domain. At the same time, even though NNs can acquire knowledge of, they are non-transparent to the user. The integrated neuro fuzzy systems can merge the parallel computation and learning capacities of NN with the knowledge representation like a human being and explaining capacities of fuzzy systems. As a conclusion, a NN becomes huge translucent, while FL systems become capable of learning. An ANFIS utilizes a hybrid learning algorithm that merges the least square estimator and the gradient descent process. It is the sugeno fuzzy model which has been recommended for creating fuzzy rules from a given input output data set.

4.1 Structure of Adaptive Neuro Fuzzy Inference System

ANFIS model has been constructed with Gaussian membership function (Gaussmf) with 2 membership functions for all input parameters and linear membership function for output parameter. For ANFIS two types of optional optimization methods used for training the membership function parameter training. They are back propagation method and the hybrid method. In this paper we use both the back propagation method and the hybrid method. Hybrid method

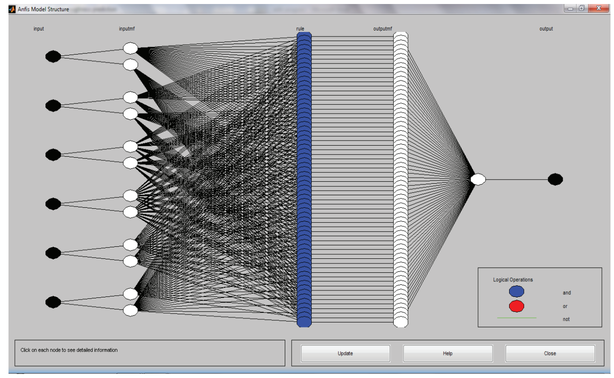


Figure 3. Proposed ANFIS model.

is a combination of least squares estimation with back propagation. All the input parameters are entered in to the adaptive neuro fuzzy inference system and trained with 100 epochs. The final ANFIS model with 6 input parameters and 1 output parameter is shown in the Figure 3. From the Figure 3, this shows the structure of proposed ANFIS model. Here the branches in the graphs are color coded and the blue color nodes which indicates the 'and' logical operations. The 6 inputs are represented by the left most black color nodes and the right most black color node indicates the output. The left side and right side white color nodes which indicates the corresponding membership function nodes for both inputs and output.

5. Results and Discussion

5.1 Back Propagation Method

First load the data from the workspace for training. From the Figure 4, which shows the data's are appears in the plot as a small blue color circles. The vertical axis is output and the horizontal axis is data set index. The data set index is the row from which the inputs were obtained. Then select the Gaussian membership function (Gaussmf) with two membership functions for all input parameters and linear membership function for output parameter with back propagation method which is shown in the Figure 5. The Figure 6 shows the generated ANFIS model, which have all six numbers of inputs and an output SR. In this all membership function of inputs are also shown in the Figures 7, 8, 9, 10, 11, and 12.

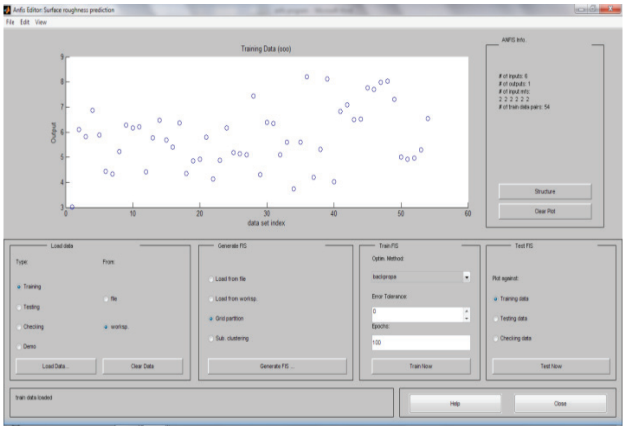


Figure 4. Plotting of Experimental Output.

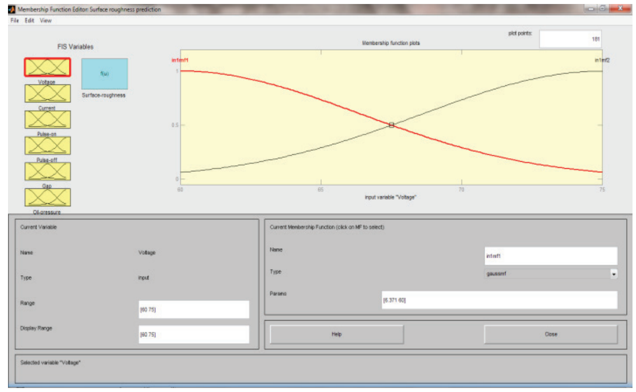


Figure 7. Membership Functions for an Input Voltage.

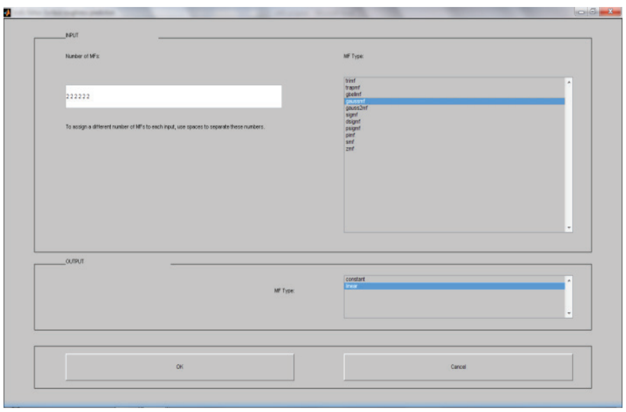


Figure 5. Selection of Membership Function.

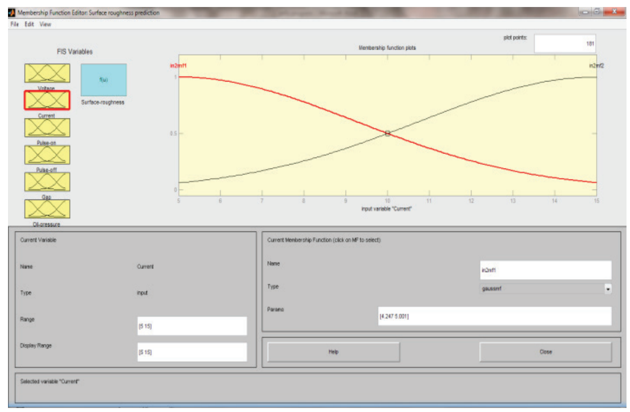


Figure 8. Membership Functions for an Input Current.

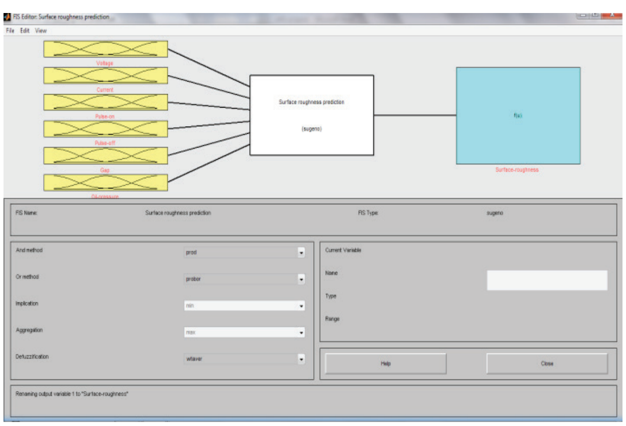


Figure 6. Generated Adaptive Neuro Fuzzy Inference System Model.

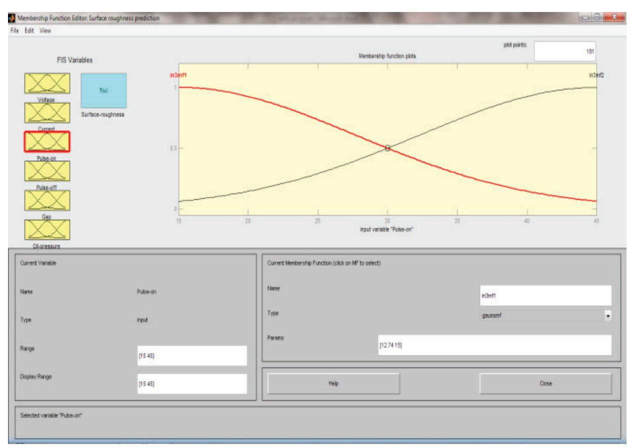


Figure 9. Membership Functions for an Input Pulse on Time.

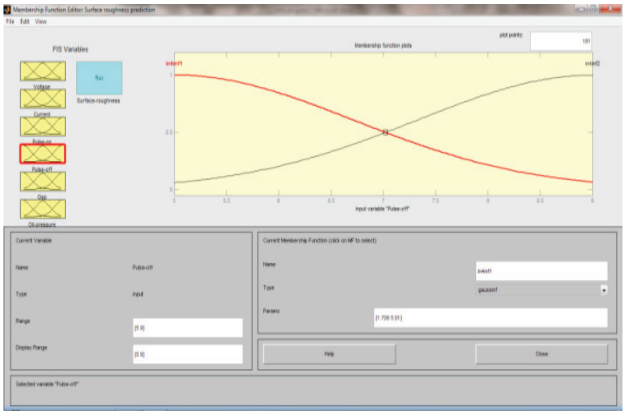


Figure 10. Membership Functions for an Input Pulse Off Time.

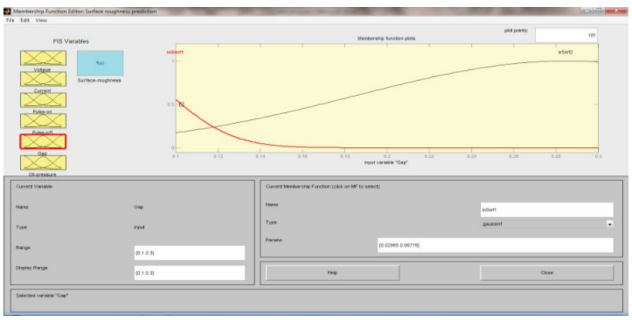


Figure 11. Membership Functions for an Input Gap.

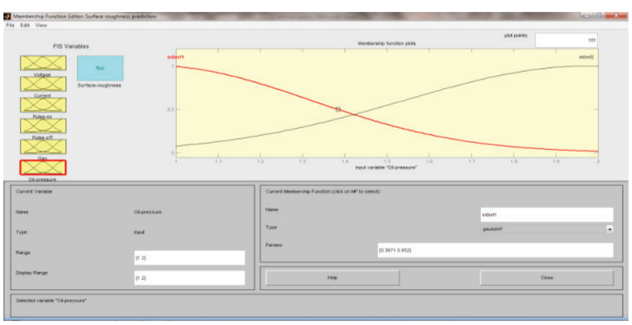


Figure 12. Membership Functions for an Input Oil Pressure.

Next train the ANFIS model with 100 epochs. The training is continued again and again until get an accurate results. Figure 13, which show the training curve. In this training curve, the error decreases gradually after every epochs and the training curve is in straight line. Figure 14 shows the plotting of actual experimental data's and the predicted output data's by using ANFIS model with Back propagation method. The error obtained in back propagation method

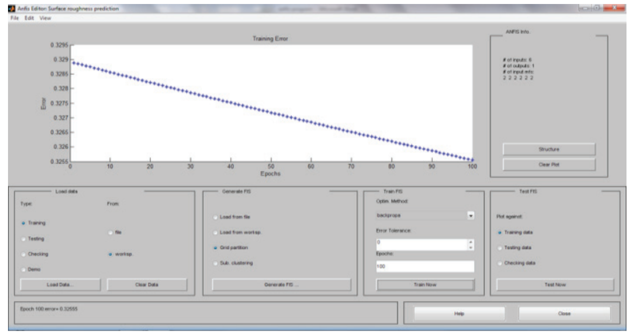


Figure 13. Train of ANFIS up to 100 Epochs Using Back Propagation Method.

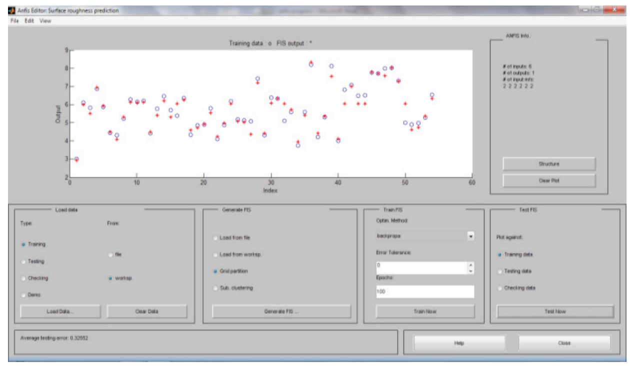


Figure 14. Variation between the Experimental and Predicted Output by the ANFIS Training Data Using Back Propagation Method.

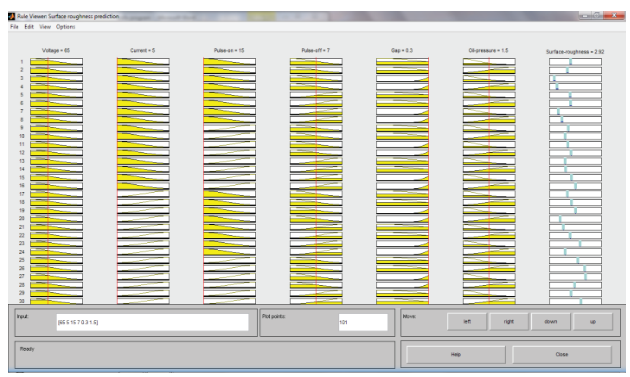


Figure 15. Rules Generated for an ANFIS Model with Back Propagation Method.

is 0.32555 and the average testing error is 0.32552. The output values are found out in the rule viewer as shown in the Figure 15. Here by changing the inputs the corresponding output values for the developed back propagation type ANFIS model is generated.

5.2 Hybrid Method

In case of hybrid method, by selecting the Gaussian membership function (Gaussmf) with two membership functions for all input parameters and linear membership function for output parameter with hybrid method. Next train the ANFIS model with 100 epochs. The training is continued again and again until get an accurate results. Figure 16, which show the training curve. In this training curve, the error decreases gradually after every seven epochs and after that the constant error is maintained up to 100 epochs. Figure 17 shows the plotting of actual experimental data's and the predicted output data's by using ANFIS model with hybrid method. The error obtained is 0.24562 and the average testing error is 0.24562. The output values are found out in the rule viewer for hybrid method is shown in the Figure 18. In this all membership function of inputs and outputs are also shown in the below Figures 19 (a-e) for back propagation method, and Figures 20 (a-e) for hybrid method respectively. Here by changing the inputs the corresponding output values for the developed hybrid type ANFIS model is generated. By using hybrid method trained the ANFIS model, which gives good result when compared with back propagation method.

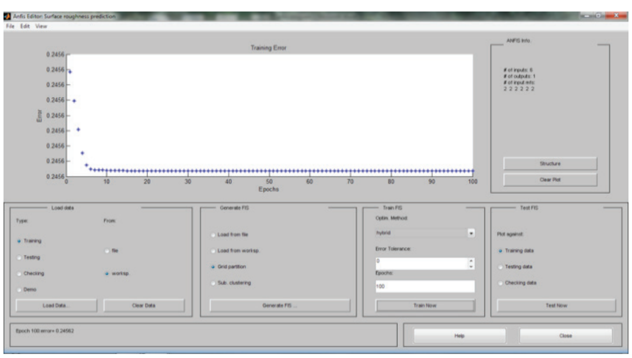


Figure 16. Train of ANFIS Up to 100 Epochs.

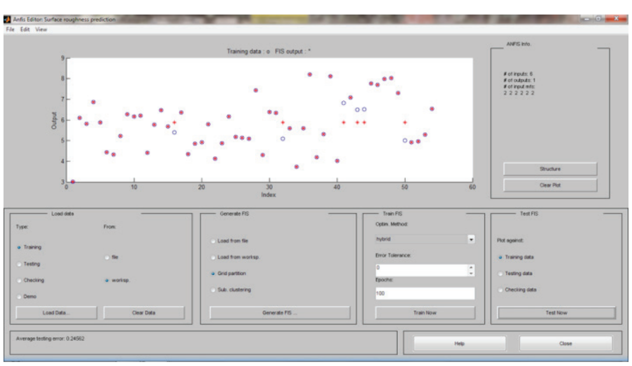


Figure 17. Variation between the Experimental and Predicted Output by the ANFIS Training Data Using Hybrid Method.

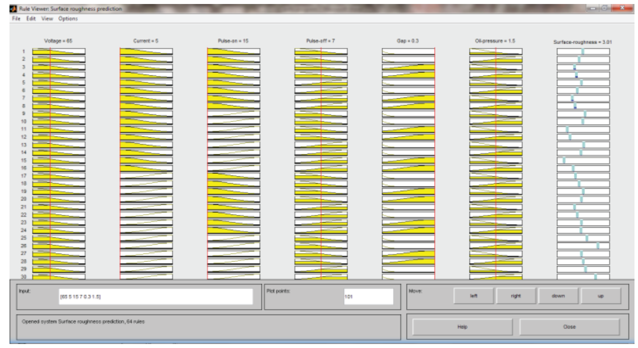


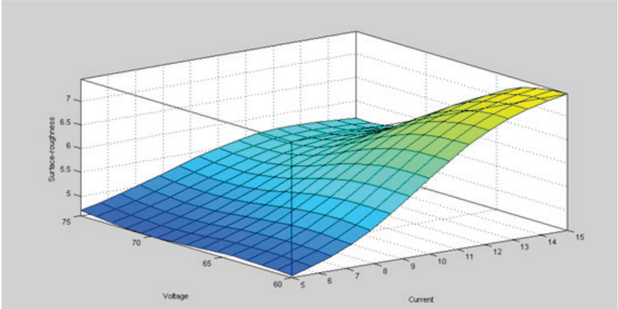
Figure 18. Rules Generated for an ANFIS Model with Hybrid Method.

From the above surface viewers, the surface shows the plotting of surface roughness in one axis and the input parameter current is fixed at one axis. All the other input parameters are varying at one axis and the surface which clearly shows that for getting a good surface roughness in the value at which the lowest value of current. The Table 2 shows the predicted outputs for both back propagation and hybrid method of ANFIS model.

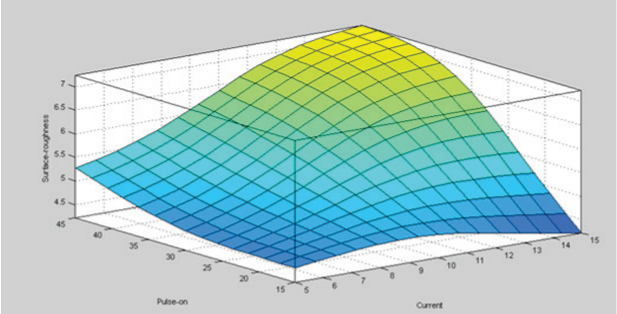
Table 2. Results obtained in back propagation and hybrid method

Sl. No.	SR (µm)H	Predicted SR (Back Propagation) (µm)H	Predicted SR (Hybrid) (µm)H
1.	3.110	2.920	2.750
2.	3.163	3.061	2.921
3.	2.673	2.132	2.132
4.	2.950	2.950	2.730
5.	3.300	3.100	2.802
6.	2.371	2.072	2.032
7.	3.535	3.213	3.051
8.	3.490	3.230	3.170
9.	2.970	2.532	2.335
10.	2.750	2.210	2.041
11.	3.110	2.910	2.813
12.	3.468	3.172	3.052
13.	3.011	3.011	3.011
14.	2.391	2.052	1.972
15.	2.930	2.510	2.323
16.	0.870	0.840	0.743
17.	1.187	1.052	1.052
18.	3.110	3.110	3.037
19.	2.824	2.513	2.375
20.	2.986	2.652	2.552

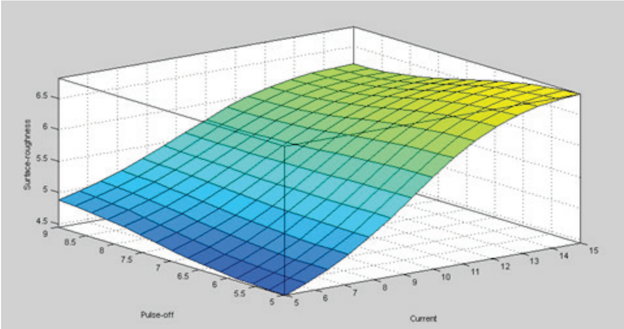
21.	3.421	3.213	3.201
22.	2.640	2.363	2.174
23.	2.947	2.572	2.331
24.	2.379	2.105	1.762
25.	3.110	2.820	2.572
26.	2.410	2.250	2.170
27.	2.660	2.220	2.130
28.	2.682	2.432	2.292
29.	3.100	2.732	2.573
30.	1.040	1.040	1.040
31.	1.281	1.172	1.064
32.	2.648	2.371	2.142
33.	3.110	2.540	2.334
34.	3.110	3.110	3.110
35.	2.630	2.234	2.142
36.	2.960	2.763	2.572
37.	2.524	2.340	2.220
38.	3.413	3.216	3.115
39.	1.137	1.034	1.022
40.	2.660	2.550	2.420
41.	3.110	2.530	2.430
42.	2.816	2.362	2.152
43.	2.760	2.510	2.530
44.	3.110	3.010	3.010
45.	3.020	2.720	2.570
46.	3.076	3.076	2.832
47.	2.592	2.343	2.343
48.	2.560	2.137	2.047
49.	0.576	0.576	0.576
50.	3.110	2.830	2.770
51.	1.160	1.140	1.100
52.	2.730	2.520	2.371
53.	1.250	1.130	1.130
54.	3.110	2.820	2.537



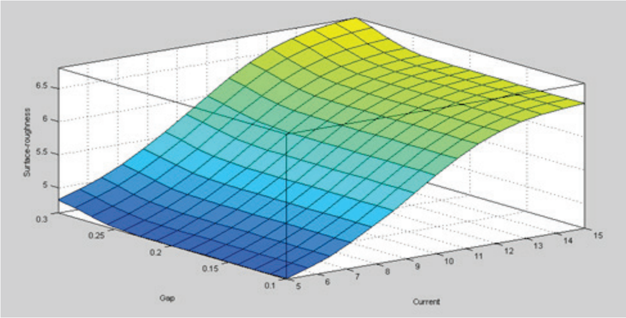
(a)



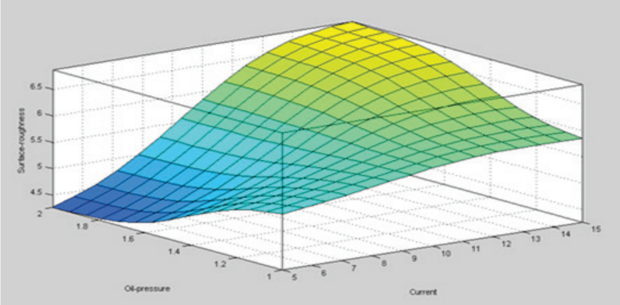
(b)



(c)

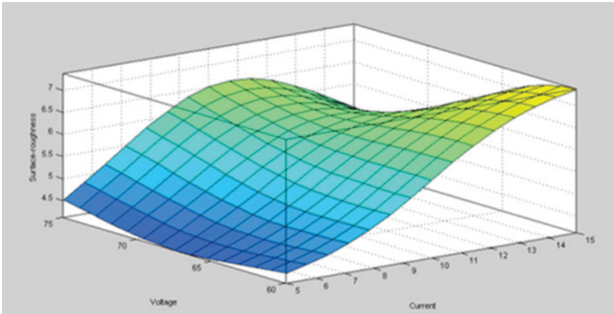


(d)

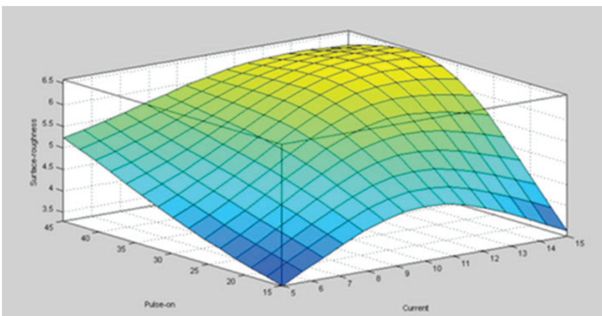


(e)

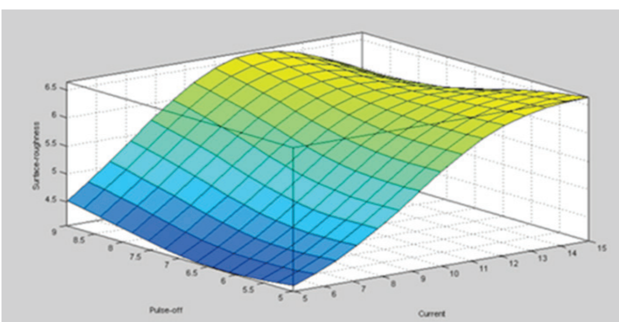
Figure 19 (a-e). Plot of Surface Roughness vs. Current and Voltage, Pulse On, Pulse Off, Gap, Oil Pressure for Back Propagation Method.



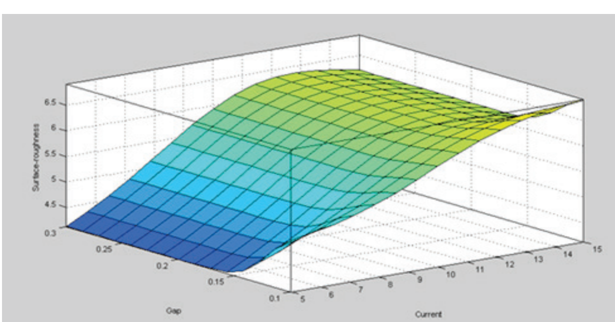
(a)



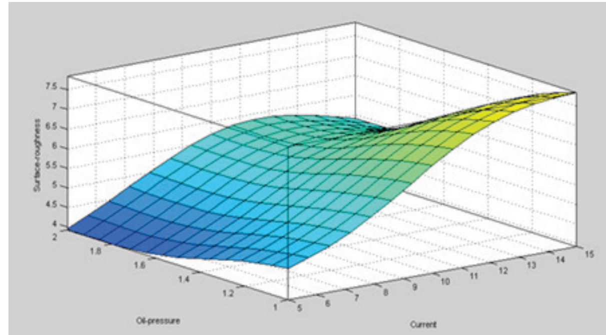
(b)



(c)



(d)



(e)

Figure 20 (a-e). Surface Plot of Roughness vs. Current and Voltage, Pulse On, Pulse Off, Gap, Oil Pressure for Hybrid Method.

The comparison chart Figures 21and 22 clearly shows the difference between the experimental SR and the predicted SR using back propagation method as well as hybrid method.

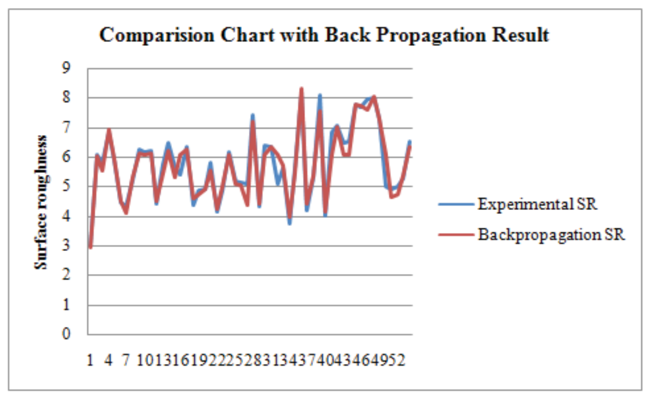


Figure 21. Comparison Chart of Experimental and Back Propagation Predicted Surface Roughness.

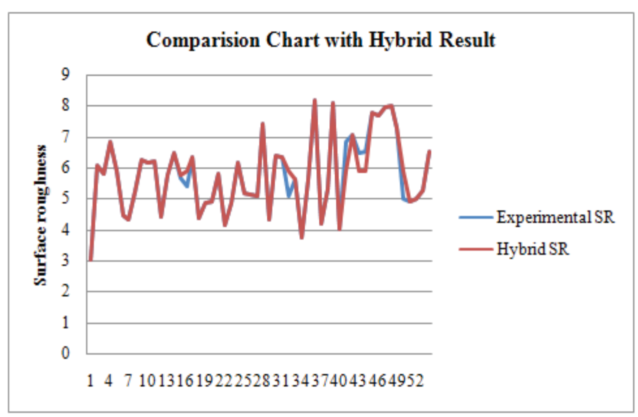


Figure 22. Comparison Chart of Experimental and Hybrid Predicted Surface Roughness.

6. Conclusions

An ANFIS model with Gaussian membership function (Gaussmf) using the back propagation method and the hybrid method for membership function is used for predicting the SR of AISI1020 steel material in EDM. From the results clearly shows that the predicted values using ANFIS model with Gaussian membership function (Gaussmf) using the hybrid method for membership function produced closer as well as accurate result, when compared with back propagation method. And hence ANFIS with hybrid method can be used as an effective prediction tool in EDM.

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