GLOBAL JOURNAL OF ADVANCED ENGINEERING TECHNOLOGIES AND SCIENCES

STUDY OF FUZZY MODELLING ON ELECTRICAL DISCHARGE MACHINING (EDM) OF TOOL DIE STEEL

D.Paparao
Department of Production Engineering, National Institute of Technology Tiruchirapalli, Tamilnadu, India

DOI: 10.5281/zenodo.1302243

ABSTRACT
Estimating the performance becomes necessary in today's modern world in order to reduce the number of experiments in precision manufacturing, especially in electrical discharge machining (EDM). Hence, in the present investigation fuzzy-based algorithm using MATLAB software for prediction of Material Removal Rate (MRR), Tool Wear Rate (TWR), and Surface Roughness (SR) in the EDM processes. The discharge current, pulse duration, and pulse-off time are selected as input variables and the responses like MRR, TWR, and SR are estimated. The proposed fuzzy model developed in this study provides a more precise and easy selection of any EDM input parameters for the required responses which leads to better machining conditions and decreases the machining costs. Observations indicate that the fuzzy modeling results of EDM were in good agreement with experimental findings demonstrating 90% predictions can be achieved.

KEYWORDS: Electrical discharge machining (EDM); Material removal rate(MRR); Tool wear rate(TWR); surface roughness(SR);Fuzzy modelling; MATLAB.

INTRODUCTION
Electro Discharge Machining (EDM) is an electro-thermal non-traditional machining Process, where electrical energy is used to generate electrical spark and material removal mainly occurs due to thermal energy of the spark. EDM is mainly used to machine difficult-to-machine materials and high strength temperature resistant alloys. EDM can be used to machine difficult geometries in small batches or even on job-shop basis. Work material to be machined by EDM has to be electrically conductive.EDM has been replacing drilling, milling, grinding and other traditional machining operations and is now a well-established machining option in many manufacturing industries throughout the world. And is capable of machining geometrically complex or hard material components, that are precise and difficult-to-machine such as heat treated tool steels, composites, super alloys, ceramics, carbides, heat resistant steels etc. being widely used in die and mould making industries, aerospace, aeronautics and nuclear industries. Electric Discharge Machining has also made its presence felt in the new fields such as sports, medical and surgical, instruments, optical, including automotive R&D areas.
Electrical discharge machining is one of the non-conventional machining process that can be effectively used for difficult to machine materials by conventional methods. It is possible to control machining rate by properly controlling EDM parameters. The machining time and cost can be reduced by fuzzy logic modeling without doing further experiments. Therefore, fuzzy logic can be efficiently applied to process. In present work, a fuzzy rule based system is developed for better and user friendly selection of EDM parameters. Furthermore, an experimental data is required in order to predict the other output results.

EXPERIMENTAL RESULTS
The performance characteristics for this experiment like metal removal rate, tool wear rate and surface roughness were calculated.

2.1)L9 orthogonal array:

Table 1: L9 orthogonal array

FACTORS	LEVEL 1	LEVEL 2	LEVEL 3
CURRENT -1	9	12	15
PULSE ON TIME -2	100	175	300
PULSE OFF TIME-3	20	30	40

2.2) Observed data on experiment:

Table 2: Experimental results

Ex No	Current (A)	Pulse on Time (μs)	Pulse off Time (μs)	Electrode(g)		Work-piece (g)	
				Initial	Final	Initial	Final
1	9	100	20	153.8385	153.8364	80.2180	80.2135
2	9	175	30	141.7857	141.7843	80.1066	80.1004
3	9	300	40	144.2555	144.2510	80.1287	80.1066
4	12	100	30	137.2819	137.2795	80.0822	80.0699
5	12	175	40	138.7078	138.7064	80.1004	80.0822
6	12	300	20	147.1194	147.1169	80.1464	80.1287
7	15	100	40	134.0590	134.0579	80.0697	80.0420
8	15	175	20	150.1463	150.1454	80.1838	80.1464
9	15	300	30	153.7077	153.7066	80.2135	80.1836

2.3)The performance characteristics:

Table 3: Performance characteristics

Ex No	MRR (mm^3/min 10^{-8})	TWR (mm^3/min 10^{-2})	SR,(μm)
1	2.96	1.17	2.03
2	4.07	0.78	2.09
3	14.53	2.52	2.70
4	8.09	1.34	2.10
5	11.97	2.84	2.04
6	11.64	1.40	2.84
7	18.22	0.61	2.11
8	24.60	0.50	2.96
9	19.53	0.61	2.80

FUZZY LOGIC

3.1) Fuzzy logic introduction:

Fuzzy logic has a long history in mathematics and philosophy. It begins with the insight that not all statements are true or false to the some degree. Some claims are truer than othersand so truth is a matter of degree. The

ISSN 2349-0292
Impact Factor 3.802

definition of performance characteristics such as lower-the-better, higher-the-better and nominal-the-better contains the degree of uncertainty andvagueness. Fuzzy logic has become a common tool to handle such information.

It uses linguistic terms to develop reasonable relationship between input and output variables. In this paper the fuzzy model has been designed for selecting better EDM parameters. There are three main stages during the development of the model: formation of membership function (fuzzification), definition of the expert rules, and selecting defuzzification method.

3.2) Membership function (MF):
Membership function characterizes the fuzziness in a fuzzy set whether the elements in the set are discrete or continues in graphical form. There is an infinite number of methods to graphically depict the membership function that describes fuzziness. Since the membership function essentially embodies all fuzziness for the particular fuzzy set, its description is the essence of a fuzzy property or operation. Because of the importance of the shape of the membershipfunction, a great deal of attention has been focused on development of these functions: triangular, trapezoidal and Gaussian are some types of membership function shapes. In selectingthe membership functions for fuzzification, the events and types of membership function are mainly dependent upon the relevant event. So far there has been no standard method of choosing the proper shape of the membership functions for the fuzzy sets of thecontrol variables. Trial and error methods are usually exercised.

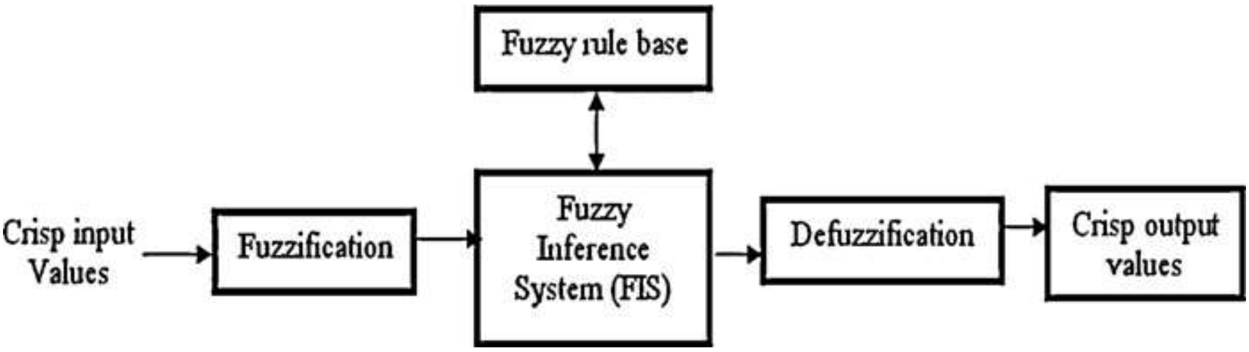


Fig 1:Scheme of fuzzy

3.3) Fuzzy expert rules:
The relationship between the input and output in a fuzzy model is characterized by a set of linguistic statement called fuzzy rules. They are defined based on experimental work and engineering knowledge. All of these rules are in the form of if-then. For examplein this paper one of these rules is: If current is VS and pulse duration is M then MRR is VS and TWR is M and SRis S.

3.4) Defuzzification:
Defuzzification refers to the method in which a crisp value is extracted from a fuzzy set as a representative value. In general there are several methods for defuzzifying fuzzy sets. Centroid of area is the most widely adopted defuzzification strategy which is reminiscent of the calculation of expected values of probability distributions. In this paper this method has been used.

3.5) Methods of Defuzzification:
There are many methods for defuzzification .One of the more common types of defuzzification technique is the maximum defuzzification techniques. These select the output with the highest membership function. They include:

- First of maximum
- Middle of maximum
- Last of maximum
- Mean of maxima
- Random choice of maximum

ISSN 2349-0292
Impact Factor 3.802

Given the fuzzy output:

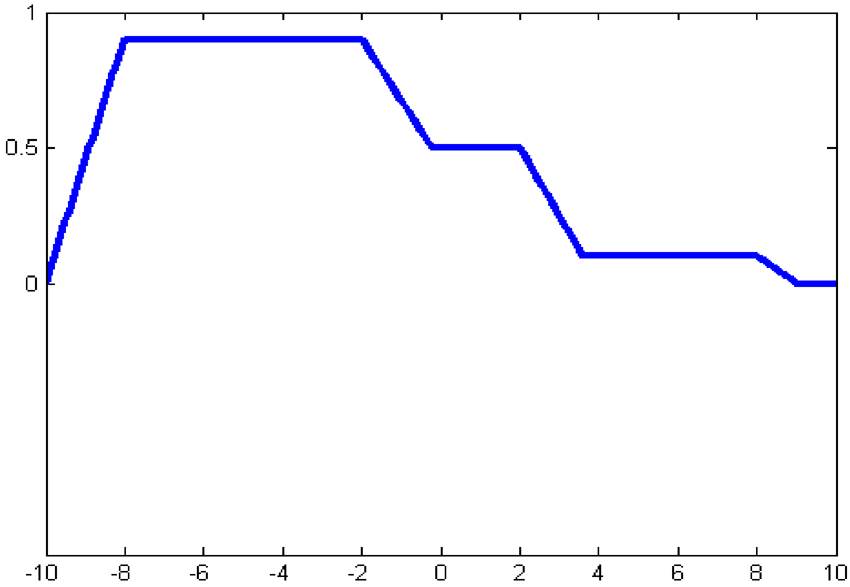
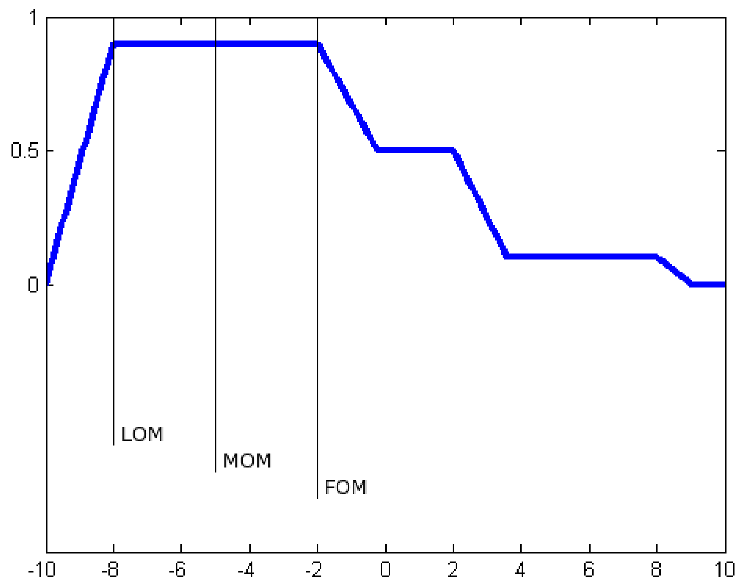


Fig 2:Defuzzification method

The first of maximum, middle of maximum, and last of maximum would be -2, -5, and -8 respectively as seen in the above diagram.The mean would give the same result as middle unless there is more than one plateau with the maximum value



Two other common methods are:
Centre of gravity:

- Calculates the center of gravity for the area under the curve

Bisector method:

- Finds the value where the area on one side of that value is equal to the area on the other side

 ISSN 2349-0292
Impact Factor 3.802

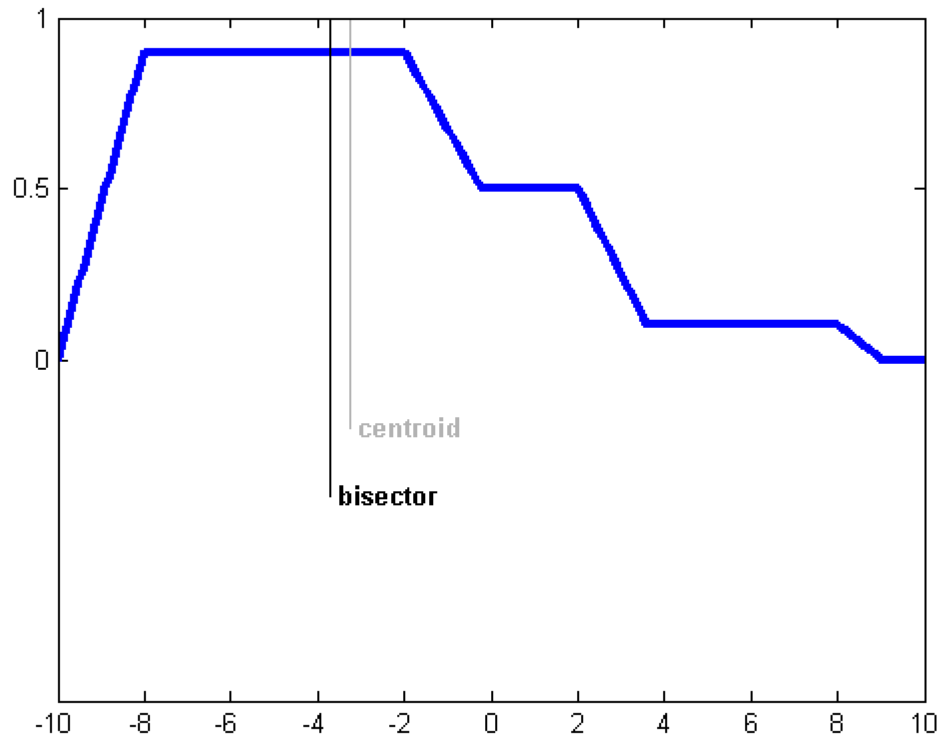


Fig 3:Center of gravity and Bisector method

3.6)Factorial design and fuzzy expressions:

Design of experiments (DOE) is a powerful tool for analysis of the influence of process variables on the machining characteristics. The prediction of EDM process, based on the input parameters and machining conditions by fractional-factorial methods i.e. Taguchi method is rather difficult. Therefore, full-factorial method was used in this study. The full factorial design was determined based on both discharge current, pulse duration and pulse off time input data. Each parameter consists of 3 levels (9,12 and 15A for the current and 100,175 and 300µs for the pulse duration and 20,30 and 40µs for pulse-off time.). Considering factorial designtechnique, the number of experimentations was 3*3 = 9.Tables 3.2 and 3.3illustrate the settings for input and output variables. By using of trial and error method, it can be concluded that the triangular and trapezoidal membership functions give better results (Figs. 5.1–5.6). As shown in Figs. 5.1–5.6the number of fuzzy sets for discharge current (I), pulse duration (Ti), surface roughness(SR), material removal rate (MRR) and tool wear rate (TWR) in EDM process are 3,3,9,9 and 9. In EDM VVS,VS, S, SM,M,ML,ML, L,VL and VVL are very very small,very small, small,small medium, medium, medium large, medium large, large, very large and very very large respectively. A part of fuzzy rules for EDM process in linguistic form are shown in Table 5.1. Total number of fuzzy rules used for these experiments are 9.

ISSN 2349-0292
Impact Factor 3.802

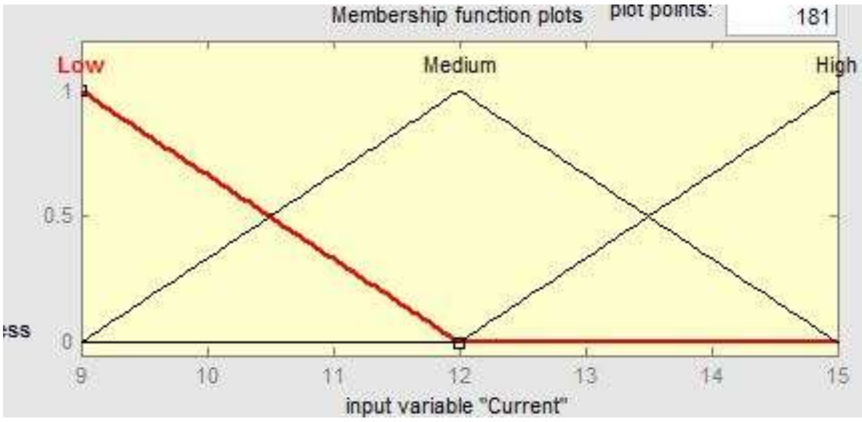


Fig 4:Membership function for current

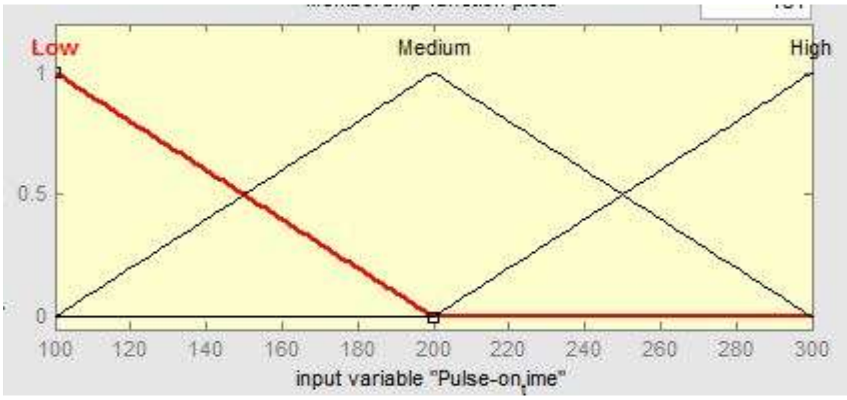


Fig 5:Membership function for Pulse-on time

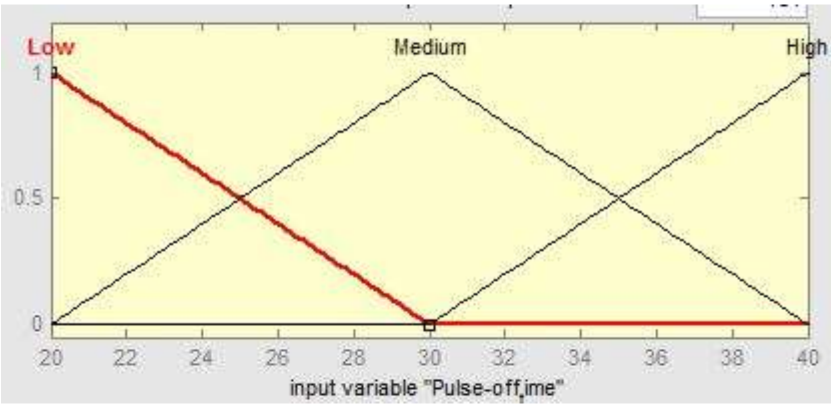


Fig 6:Membership function for Pulse-off time

ISSN 2349-0292
Impact Factor 3.802

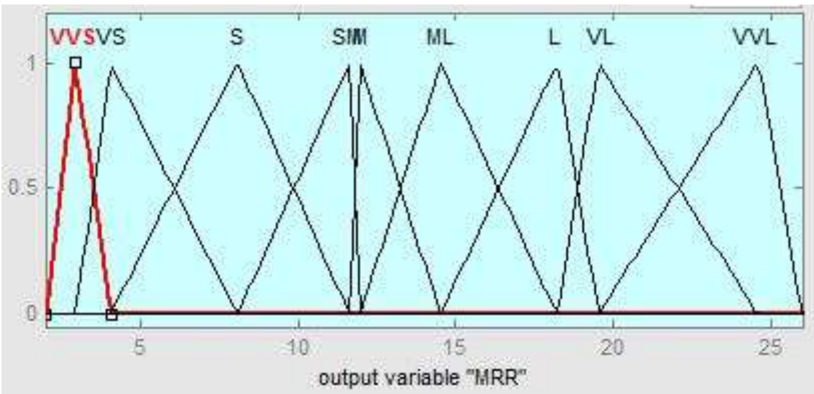


Fig 7:Membership function for MRR

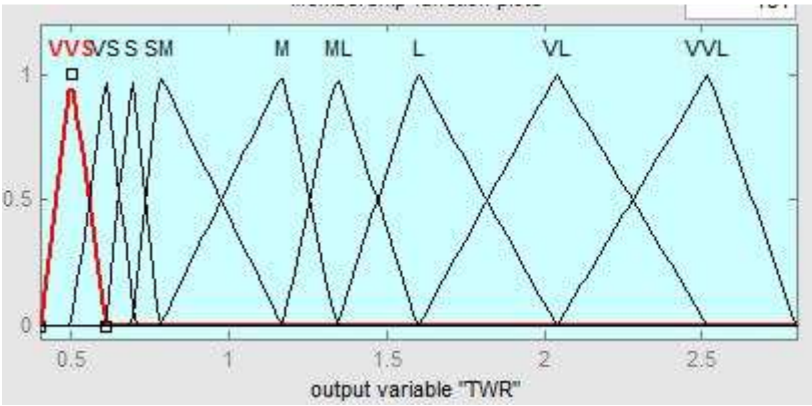


Fig 8: Membership function for TWR

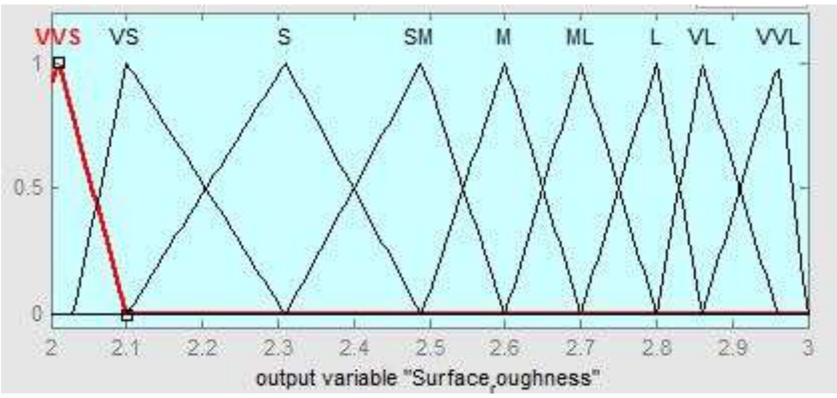


Fig 9:Membership function for surface roughness

Table 4: Fuzzy expert rules

1. If (Current is Low) and (Pulse-on_time is Low) and (Pulse-off_time is Low) then (MRR is VVS)(TWR is M)(Surface_roughness is VVS) (1)
2. If (Current is Low) and (Pulse-on_time is Medium) and (Pulse-off_time is Medium) then (MRR is VS)(TWR is SM)(Surface_roughness is S) (1)
3. If (Current is Low) and (Pulse-on_time is High) and (Pulse-off_time is High) then (MRR is ML)(TWR is VVL)(Surface_roughness is ML) (1)
4. If (Current is Medium) and (Pulse-on_time is Low) and (Pulse-off_time is Low) then (MRR is S)(TWR is ML)(Surface_roughness is SM) (1)
5. If (Current is Medium) and (Pulse-on_time is Medium) and (Pulse-off_time is Medium) then (MRR is M)(TWR is VL)(Surface_roughness is VS) (1)
6. If (Current is Medium) and (Pulse-on_time is High) and (Pulse-off_time is High) then (MRR is SM)(TWR is L)(Surface_roughness is VL) (1)
7. If (Current is High) and (Pulse-on_time is Low) and (Pulse-off_time is Low) then (MRR is L)(TWR is S)(Surface_roughness is M) (1)
8. If (Current is High) and (Pulse-on_time is Medium) and (Pulse-off_time is Medium) then (MRR is VVL)(TWR is VVS)(Surface_roughness is VVL) (1)
9. If (Current is High) and (Pulse-on_time is High) and (Pulse-off_time is High) then (MRR is VL)(TWR is VS)(Surface_roughness is L) (1)

DISCUSSIONS

By Mamdani inference, the fuzzy linguistic values and their membership values for the outputs were obtained. Afterwards, the defuzzification method by the centroid of area was used to calculatethe crisp values as the final outputs. Graphical representation of fuzzy surface and comparisonof experimental results and fuzzy prediction are illustrated in table 6.1 to 6.3.

Table 5:Experimental results Vs. modelling results for MRR:

S.No	Current (A)	Pulse on time(μs)	Pulse off time(μs)	Experimental MRR(mm^3/min 10^{-2})	Modeling MRR (mm^3/min 10^{-2})	Accuracy
1	9	100	20	2.96	3.02	97.9
2	9	175	30	4.07	5.09	79.49
3	9	300	40	8.09	7.54	93.2
4	12	100	20	11.64	10.93	93.9
5	12	175	30	11.97	11.12	92.89
6	12	300	40	14.53	13.96	96.07
7	15	100	20	18.22	19.10	95.17
8	15	175	30	19.53	20.27	95.90
9	15	300	40	24.60	25.40	96.74

Table 6:Experimental results Vs. modelling results for TWR:

S.No	Current (A)	Pulse on time(μs)	Pulse off time(μs)	Experimental TWR(mm^3/min 10^{-2})	Modeling TWR (mm^3/min 10^{-2})	Accuracy
1	9	100	20	0.5	0.41	82
2	9	175	30	0.61	0.51	83.6
3	9	300	40	0.69	0.79	85.5
4	12	100	20	0.78	0.88	87.18
5	12	175	30	1.17	1.06	90.59
6	12	300	40	1.34	1.48	89.55
7	15	100	20	1.6	1.41	88.12
8	15	175	30	2.04	1.81	88.72
9	15	300	40	2.52	2.73	91.66

Table7:Experimental results Vs. modelling results for surface roughness:

S.No	Current (A)	Pulse on time(μs)	Pulse off time(μs)	Experimental SR (μm)	Modeling SR (μm)	Accuracy
1	9	100	20	2.03	2.03	100
2	9	175	30	2.1	2.3	90.47
3	9	300	40	2.31	2.7	83.11
4	12	100	20	2.49	2.79	87.95
5	12	175	30	2.6	2.85	90.38
6	12	300	40	2.7	2.98	89.62
7	15	100	20	2.8	3.01	92.5
8	15	175	30	2.86	3.02	94.4
9	15	300	40	2.96	3.18	92.56

CONCLUSIONS

Thus the fuzzy logic modeling system for the selection of the electrical discharge machining (EDM) parameters has been successfully carried. The fuzzy models were developed based on the experimental data of EDM machining of tool die steels using copper tool. Observations indicate that the fuzzy modeling results of EDM was in good agreement with experimental findings demonstrating 90% predictions can be achieved. Experimental results showed that, in machining of tool die steels, the material removal rate and surface roughness increased with an increase in pulse duration and discharge current. In addition, tool wear ratio decreased with an increase in pulse duration and discharge current. Comparison and validation of fuzzy results with experiment findings proves its high accuracy. Furthermore, if more the experimental data is available then the accuracy can be improved. Thus, the fuzzy modeling technique could be an economical and successful method for prediction of EDM output parameters according to input variables.

REFERENCES

[1] Yih-fongTzengand Fu-chen Chen (2006),Multi-objective optimisation of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach.
[2] Ozlem Salman and M. CengizKayacan(2007),Evolutionary programming method for modeling the EDM parameters for roughness.
[3] Ibrahem Maher, LiewHui Ling, Ahmed A. D. Sarhan,and M. Hamdi(2015),Improve wire EDM performance at different machining parameters – ANFIS modeling.
[4] S. Dewangan, S. Gangopadhyay and C.K. Biswas(2014), Study of surface integrity and dimensional accuracy in EDMusing Fuzzy TOPSIS and sensitivity analysis.
[5] OguzhanYilmaz , Omer Eyercioglu and Nabil N.Z. Gindy(2005), A user-friendly fuzzy-based system for the selection of electric discharge machining process parameters.
[6] Chen-Chun Kao, Albert J. Shih(2009),Design and tuning of a fuzzy logic controller for micro-hole electrical discharge machining.
[7] S.N. Joshi and S.S. Pande(2010),Intelligent process modeling and optimization of die-sinking electric discharge machining.
[8] JambeswarSahu, Chinmaya P. Mohanty and S.S. Mahapatra(2008),A DEA approach for optimization of multiple responses in Electrical Discharge Machining of AISI D2 steel.
[9] Sengottuvel.P, Satishkumar.S and Dinakaran(2004), Optimization Of Multiple Characteristics Of EDM Parameters Based On Desirability Approach And Fuzzy Modeling.
[10] R. K. Bhuyan, ShaliniMohanty and B.C. Routara(2016),RSM and Fuzzy logic approaches for predicting the surface roughness during EDM of Al-SiCp MMC.
[11] Chandramouli S and EswaraiahK(2016),Optimization of EDM Process parameters in Machining of 17-4 PH Steel using Taguchi Method.
[12] Manish Gangil, M. K. Pradhan, Rajesh Purohit(2016),Review on modelling and optimization of electrical discharge machining process using modern Techniques.
[13] ShaileshDewangan, SoumyaGangopadhyay and Chandan Kumar Biswas(2015),Multi-response optimization of surface integrity characteristics of EDM process using grey-fuzzy logic-based hybrid approach
[14] Ahmed A.D. Sarhan, Lim Siew Fen, Mum Wai Yip, M. Sayuti(2015),Fuzzy Modeling for Micro EDM Parameters Optimization in Drilling of Biomedical Implants Ti-6Al-4V Alloy for Higher Machining Performance.
[15] AmitKohli, AashimWadhwa, TapanVirmani, and UjjwalJain(2012), Optimization of Material Removal Rate in Electrical Discharge Machining Using Fuzzy Logic