Modelling of Process Parameters on D2 Steel using Wire Electrical Discharge Machining with combined approach of RSM and ANN

U.K.Vates[1], N.K.Singh[2], R.V.Singh[3]

1. Research Scholar, ME&MME, ISM Dhanbad India; u.k.vates@gmail.com
2. Associate Professor &Head (CWS), ME, ISMD India; nks_221@yahoo.co.in
3. Professor & Head, ME, FET, MRIU, Faridabad India, rvs5272@gmail.com

Abstract

Aimed to investigate the experimental process and surface roughness optimization of cold working, high carbon high chromium hardened die (D2) steel during Wire Electrical Discharge Machining processes. Response Surface Methodology (RSM) and an Artificial Neural Network (ANN) approaches have been applied to investigate the effect of six independent input parameter namely gap voltage (V_g), flush rate (F_r), Pulse on time (T_{on}), pulse off time (T_{off}), wire feed (W_f) and wire tension (W_t) over CLA value of surface roughness (R_a) and material removal rate (MRR). A fractional factorial Design of Experiment of two level were employed to conducted the experiment on D2 die steel with chromium coated copper alloy wire electrode . The responses, CLA values of SR and MRR were observed by combined approach of training, validation and testing programme in MATLAB 2010a and mathematical modelling using RSM on experimental data respectively. Significance coefficients were observed by performing analysis of variance (ANOVA) at 95% confidence level. Prediction against second order RSM mathematical modelling technique is the best performing to MRR and ANN Modelling has most significant for surface roughness by conducting only very less experimentation.

Keywords: *WEDM, RSM, ANN, SR, MRR, etc.*

1. **Introduction:** Wire Electrical Discharge Machining is the metal removal process by means of repeated discrete spark created between the wire electrode and work piece immersed in liquid dielectric medium. Repeated electrical spark created by electric pulse generator at very short interval between an electrode wire & part to be machined by the influence of conducting dielectric fluid. Very high temperature ranging 8000 C° - 10000 C° creates during machining, so that minute amount of material removal may takes place by not only melting but directly vaporizations, which are then ejected and flushed away by influence of dielectric fluid [1]. WEDM is used for the machining to electrical conductive, hard and composite materials and capable to machined accurately with varying hardness or complex shapes, which cannot be machined easily by conventional machining methods.

Manufacturing processes (WEDM) has been chosen depending on the material characteristics and the type of responses required to evaluating. Many attempts has been made to modelled the EDM processes for improving responses smooth surface with high MRR, but still it is challenging, which restrict the expended application of the technology [2]. A combined approach

ISSN 2229-5518

of hybrid artificial neural network and genetic algorithm has been incorporated for modelling and optimisation of EDM process parameters [3]. In addition to the study of more powerful modelling tool, ANN having the capabilities on learning the mathematical mapping between input and output nonlinear variables [4]. The present study aimed to incorporated the multi-layers perceptions based on back-propagation ANN and second order RSM modelling and optimization of responses i.e. surface roughness along with MRR monitoring by influence of independent process parameters, V_g, F_r T_{on}, T_{off}, W_f and W_t.

2. Experimental Setup:

2.1. Selection of Wire electrode and work piece:

A Chromium coated cylindrical copper wire having 0.25 mm in diameter were selected for conducting machining operation on AISI-D2 steel, which having 18 mm in diameter and 0.7 m in length were used to cutting approx 3 mm thickness of the disk under the machining controlled conditions. The experiment has carried out on Wire Electrical Discharge Machine model ELECTRONICA-MAXICUT -50zp, having the facilities to hold the work piece within the place provided by the help of conductive fixture, so that they can complete the circuit between electrode and work piece. The spark is created depending upon gap voltage applied between the conductive work piece, electrode, and machining performance influence the major independent process parameter which selected for experiment as per the characteristics of screening test. Commercials grade of ionized water (Density= 832kg/m^3) was used as dielectric fluid.

Table 01 : Metallurgical Analysis: Component of workpiece (AISI D2 Steel)

C	SI	Cr	Mo	V	HRC	Total alloys %	Electrical conductivity
1.50%	0.30%	12.00%	0.80%	0.40%	56	3.1	166

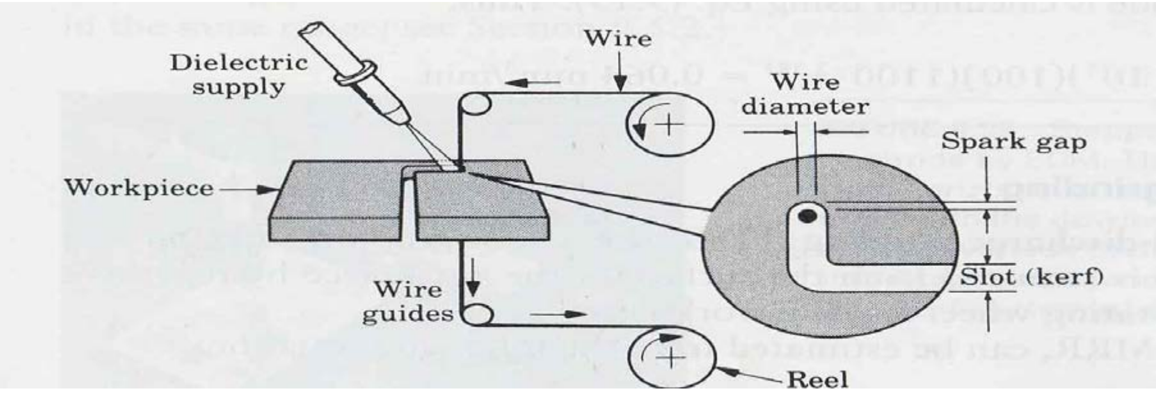

Fig 01: WEDM Principle with D2 steel workpiece [5].

ISSN 2229-5518

2.2 Design of Experiment: Fractional factorial ($2^{6-2} = 16$) experimental design have been selected by three different set of replication to conducting the experiment on D2 using WEDM.

Table 02: Factors for screening test

Factors/Three Level (Coding)	**1**	**2**	**3**
Gap Voltage (Vg)	3	6	9
Flush Rate (Fr)	4	6	8
Pulse on Time(Ton)	3	5	7
Pulse of Time (Toff)	3	6	9
Wire Feed Rate (Wf)	2	5	8
Wire tension (Wt)	300	600	900

2.3 **Model development (RSM & ANN):** Response surface methods (RSM) combined with a steepest ascent approach and second-order model has been used where, xi is factors for response y.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j=2}^{k}\sum + \varepsilon$$

Second order RSM approach

The above response surface methodology is unique to mathematical model between response and several variables [6]. RSM requires very less runs of experiment to stabilize the relations between response MRR and the independent variables under controlled condition.

An Artificial Neural Network (ANN) is the concept of biological neurons present in the human brain and worked as information carriers from brain to every part under multi-variant conditional circumstances. An ANN model has to be very clear among number of neurons in the hidden layers and also the number of total layers (including input and single output layer) present in the architecture [7-8], but It cannot be generalized for each and every response under different circumstances. Many researchers have given different approaches but according to Lawrence and Fredrickson (1998) suggested the following relationship to estimate the best number of training (*N*) facts:

$$2(i + h + o) < N < 10(i + h + o);$$

The number of neurons in the hidden layer suggested by the aforementioned rules is found to vary widely. Therefore it was decided to adopt a "brute force" trial and error approach for finding the optimum number of neurons. The number *h* was varied between 6 to 12 in steps of 1 and the performance accuracy of the ANNs was evaluated. In present circumstances, I have tested R-square by hit and trial and found 7 neurons with two hidden layers given best result [9].

ISSN 2229-5518

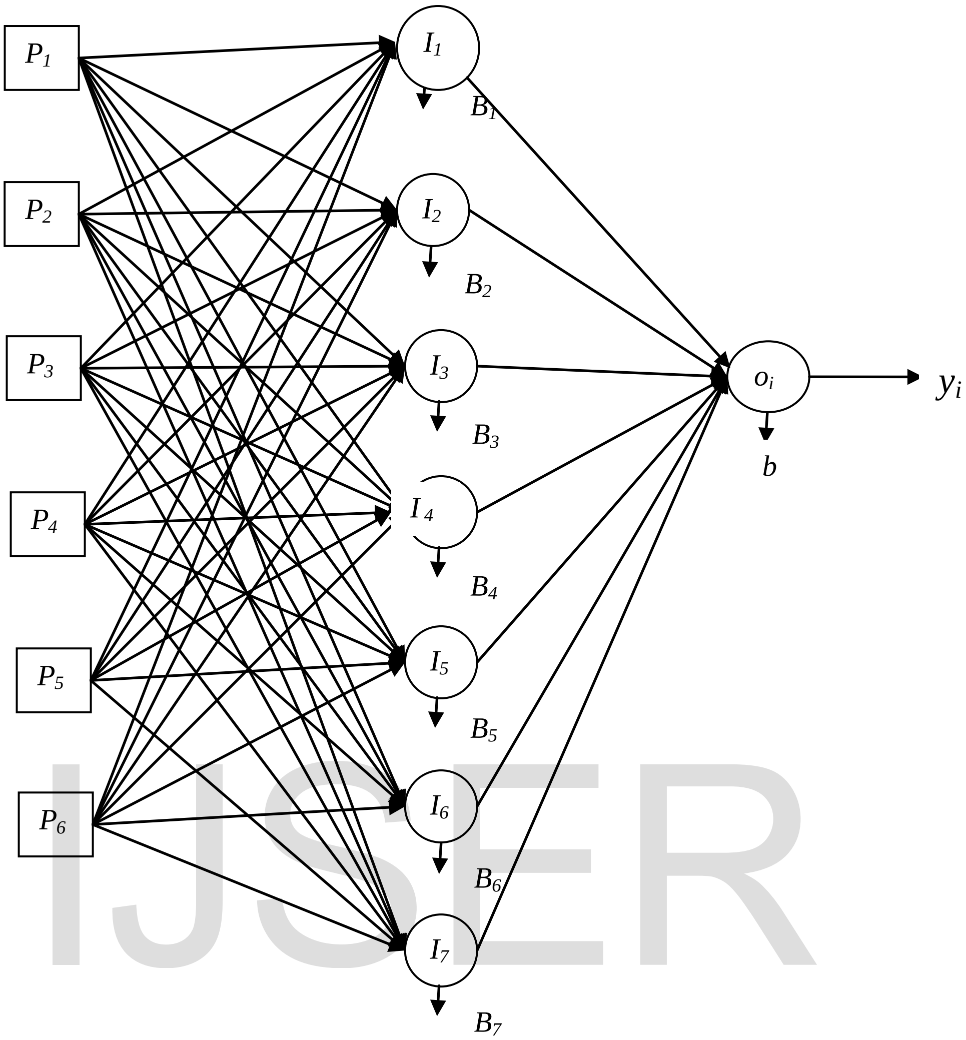

Fig 02: Artificial Neural Network approach (Architecture)

3. Experimentation:

3.1 Experimental Observation for Surface Roughness and MRR on D2 during WEDM

Table 03: Experimental data: MRR and Ra

Runs	Gap voltage (V_g)	Flush rate (F_r)	Spark time (T_{ON})	Spark time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	R_a (Average)	MRR
	Volt	Litre/ Min	µS	µS	Meter/ Min	N/m^2	µm	Mg/Min
1	3	4	3	3	2	300	1.6858	102
2	3	4	3	6	2	600	1.4452	92
3	3	4	5	3	5	600	1.3884	133
4	3	4	5	6	5	300	1.4658	95

5	3	6	3	3	5	600	1.3836	125
6	3	6	3	6	5	300	1.5278	110
7	3	6	5	3	2	300	1.676	97
8	3	6	5	6	2	600	1.564	95
9	6	4	3	3	5	300	1.1772	104
10	6	4	3	6	5	600	1.2076	88
11	6	4	5	3	2	600	1.273	136
12	6	4	5	6	2	300	1.3476	116
13	6	6	3	3	2	600	1.3322	110
14	6	6	3	6	2	300	1.1598	115
15	6	6	5	3	5	300	1.248	118
16	6	6	5	6	5	600	1.3714	110
17	9	6	3	3	5	600	1.2178	83
18	9	6	3	6	5	900	1.0376	98
19	9	6	7	3	2	900	1.1232	84
20	9	6	7	6	2	600	1.0751	77
21	9	8	3	3	2	900	1.1369	96
22	9	8	3	6	2	600	1.0962	78
23	9	8	7	3	5	600	1.1551	99
24	9	8	7	6	5	900	1.1723	74
25	3	4	5	6	5	600	1.6498	162
26	3	4	5	9	5	900	1.4692	148
27	3	4	7	6	8	900	1.7404	173
28	3	4	7	9	8	600	1.4566	144
29	3	8	5	6	8	900	1.5124	145
30	3	8	5	9	8	600	1.363	108
31	3	8	7	6	5	600	2.1256	206
32	3	8	7	9	5	900	1.6794	101
33	6	6	3	3	2	600	1.4536	128
34	6	6	3	6	2	900	1.3208	114
35	6	6	7	3	5	900	1.8731	132
36	6	6	7	6	5	600	1.6639	126
37	6	8	3	3	5	900	1.7185	144
38	6	8	3	6	5	600	1.5572	128
39	6	8	7	3	2	600	1.4918	115
40	6	8	7	6	2	900	1.4206	106
41	9	6	3	3	5	600	1.3127	78
42	9	6	3	6	5	900	1.2973	72
43	9	6	7	3	2	900	1.1823	117
44	9	6	7	6	2	600	1.0832	105
45	9	8	3	3	2	900	1.2396	89

46	9	8	3	6	2	600	1.1838	81
47	9	8	7	3	5	600	1.1413	92
48	9	8	7	6	5	900	1.1125	112

Table 04: Experimental data: Predicted values and residual by RSM and ANN

Runs	MRR for RSM			MRR for ANN			R_a for RSM			R_a for ANN		
	Observed	Predicted	Error	Observed	Predicted	Error	Observed	Predicted	Error	Observed	Predicted	Error
1	102	113	-11	102	100	2	1.6858	1.6754	0.0104	1.6858	1.6462	0.0396
2	92	94	-2	92	78	14	1.4452	1.3623	0.0829	1.4452	1.4723	-0.0271
3	133	132	1	133	134	-1	1.3884	1.3891	-0.0007	1.3884	1.2275	0.1609
4	95	89	6	95	95	0	1.4658	1.4636	0.0022	1.4658	1.4791	-0.0133
5	125	121	4	125	116	9	1.3836	1.2882	0.0954	1.3836	1.3822	0.0014
6	110	111	-1	110	105	5	1.5278	1.5601	-0.0323	1.5278	1.5713	-0.0435
7	97	98	-1	97	108	-11	1.676	1.562	0.114	1.676	1.6764	-0.0004
8	95	96	-1	95	94	1	1.564	1.5569	0.0071	1.564	1.5685	-0.0045
9	104	110	-6	104	110	-6	1.1772	1.2221	-0.0449	1.1772	1.1048	0.0724
10	88	87	1	88	93	-5	1.2076	1.2711	-0.0635	1.2076	1.1916	0.016
11	136	135	1	136	126	10	1.273	1.3303	-0.0573	1.273	1.3053	-0.0323
12	116	119	-3	116	115	1	1.3476	1.15	0.1976	1.3476	1.3572	-0.0096
13	110	111	-1	110	117	-7	1.3322	1.2458	0.0864	1.3322	1.4081	-0.0759
14	115	114	1	115	119	-4	1.1598	1.1391	0.0207	1.1598	1.1766	-0.0168
15	118	119	-1	118	111	7	1.248	1.1924	0.0556	1.248	1.2803	-0.0323
16	110	109	1	110	108	2	1.3714	1.3542	0.0172	1.3714	1.3714	0
17	83	84	-1	83	76	7	1.2178	1.1758	0.042	1.2178	1.2256	-0.0078
18	98	103	-5	98	99	-1	1.0376	1.1833	-0.1457	1.0376	1.0565	-0.0189
19	84	81	3	84	88	-4	1.1232	1.2229	-0.0997	1.1232	1.1033	0.0199
20	77	83	-6	77	67	10	1.0751	1.0963	-0.0212	1.0751	1.0757	-0.0006
21	96	97	-1	96	103	-47	1.1369	1.4664	-0.3295	1.1369	1.1641	-0.0272
22	78	78	0	78	101	-23	1.0962	1.0139	0.0823	1.0962	1.0888	0.0074
23	99	91	8	99	99	0	1.1551	1.1662	-0.0111	1.1551	1.1574	-0.0023
24	74	73	1	74	77	-3	1.1723	1.5188	-0.3465	1.1723	1.1773	-0.005
25	162	156	6	162	164	-2	1.6498	1.6302	0.0196	1.6498	1.6294	0.0204
26	148	148	0	148	144	4	1.4692	1.4243	0.0449	1.4692	1.4562	0.013
27	173	172	1	173	179	-6	1.7404	1.6404	0.1	1.7404	1.6831	0.0573
28	144	144	0	144	144	0	1.4566	1.4531	0.0035	1.4566	1.5268	-0.0702
29	145	149	-4	145	164	-19	1.5124	1.3756	0.1368	1.5124	1.5135	-0.0011
30	108	108	0	108	106	2	1.363	1.4008	-0.0378	1.363	1.3763	-0.0133
31	206	200	6	206	197	29	2.1256	1.9877	0.1379	2.1256	2.0915	0.0341
32	101	102	-1	101	100	1	1.6794	1.7303	-0.0509	1.6794	1.6466	0.0328
33	128	129	-1	128	124	4	1.4536	1.4534	0.0002	1.4536	1.4249	0.0287
34	114	114	0	114	114	0	1.3208	1.3455	-0.0247	1.3208	1.3243	-0.0035
35	132	131	1	132	137	-5	1.8731	1.8358	0.0373	1.8731	1.8832	-0.0101
36	126	127	-1	126	114	12	1.6639	1.6937	-0.0298	1.6639	1.6642	-0.0003
37	144	141	3	144	135	9	1.7185	1.7566	-0.0381	1.7185	1.7172	0.0013

38	128	128	0	128	122	6	1.5572	1.5737	-0.0165	1.5572	1.5267	0.0305
39	115	121	-6	115	116	-1	1.4918	1.6847	-0.1929	1.4918	1.4908	0.001
40	106	107	-1	106	106	0	1.4206	1.2222	0.1984	1.4206	1.4109	0.0097
41	78	79	-1	78	73	5	1.3127	1.4918	-0.1791	1.3127	1.3125	0.0002
42	72	72	0	72	77	-5	1.2973	1.4605	-0.1632	1.2973	1.2854	0.0119
43	117	121	-4	117	113	4	1.1823	1.1149	0.0674	1.1823	1.1956	-0.0133
44	105	98	7	105	101	4	1.0832	1.5662	-0.483	1.0832	1.0406	0.0426
45	89	95	-6	89	89	0	1.2396	1.2111	0.0285	1.2396	1.2118	0.0278
46	81	80	1	81	80	1	1.1838	1.3368	-0.153	1.1838	1.2088	-0.025
47	92	96	-4	92	98	-6	1.1413	1.2251	-0.0838	1.1413	1.1702	-0.0289
48	112	114	-2	112	106	6	1.1125	1.1256	-0.0131	1.1125	1.1129	-0.0004
Total			-19	Total		-1	Total		-1.03	Total		0.1453
RMSE			3.6	RMSE		10.5	RMSE		0.1308	RMSE		0.0262
% Grand Error			3.2	% Grand		9.43	% Grand Error		9.32	% Grand Error		1.90

Correlation coefficients:

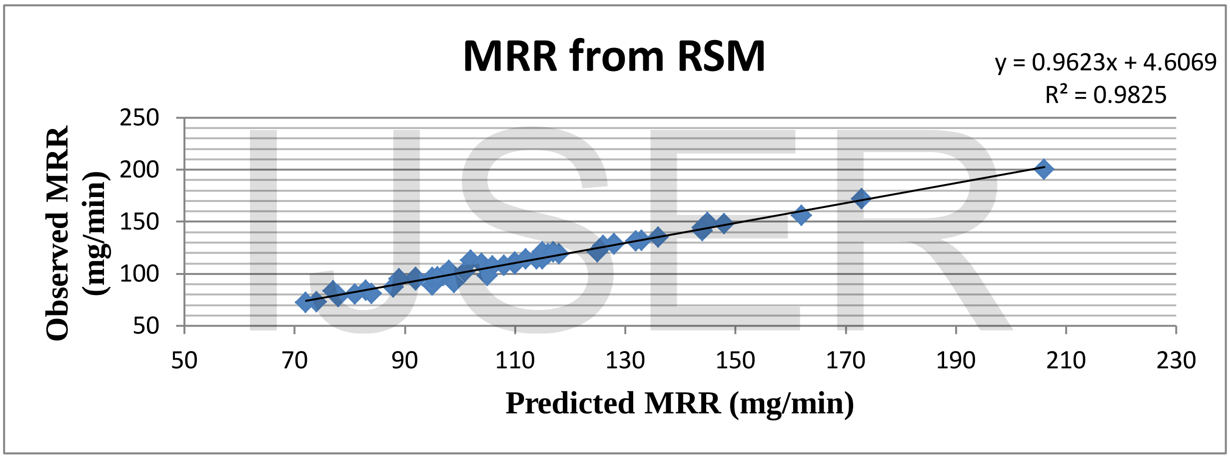

Fig 03: Observed vs predicted MRR relationship during RSM modelling

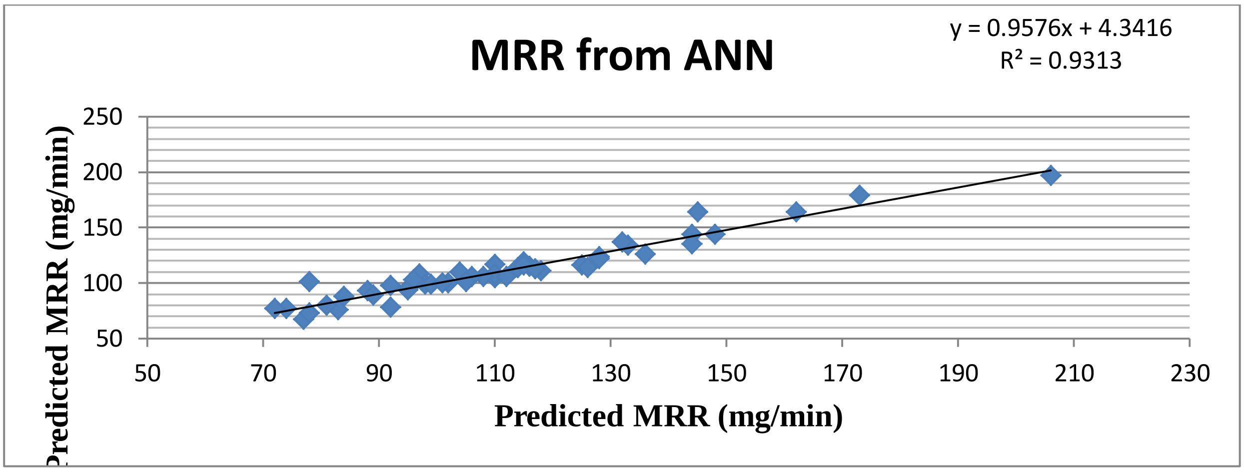

Fig 04: Observed vs predicted MRR relationship during ANN modelling

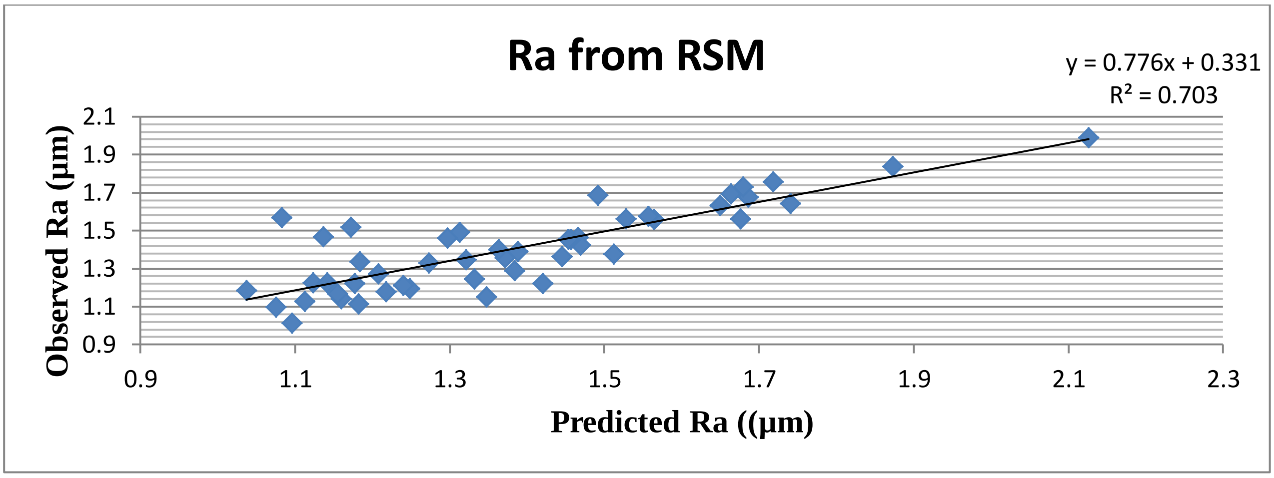

Fig 05: Observed vs predicted Ra relationship during RSM modelling

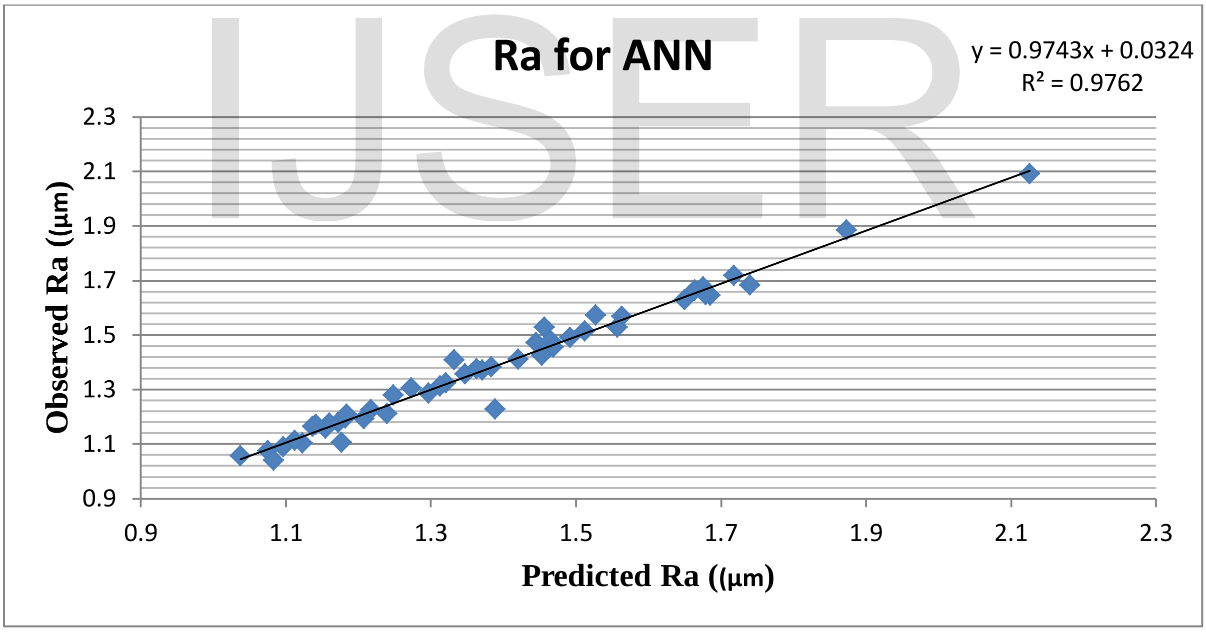

Fig 06: Observed vs predicted Ra relationship during ANN modelling

4. Conclusion:

Table 05: R- square values at different modelling conditions

Sl	Correlation Coefficient R^2	Modelling Condition	Application	% RMSE

1	0.703	Ra	RSM	9.322
2	0.982	MRR	RSM	3.211
3	0.976	Ra	ANN	1.90
4	0.931	MRR	ANN	9.434

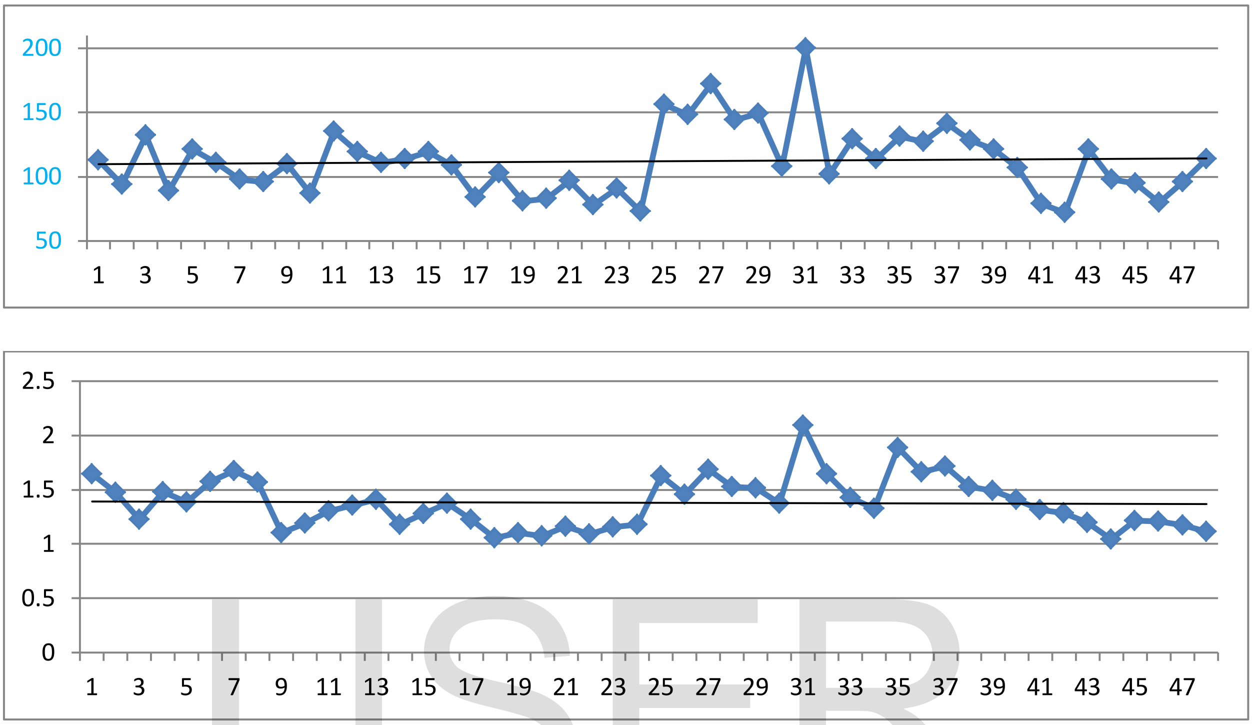

Fig 07 (a & b): Variations in MRR and Ra corresponding to runs of experiment

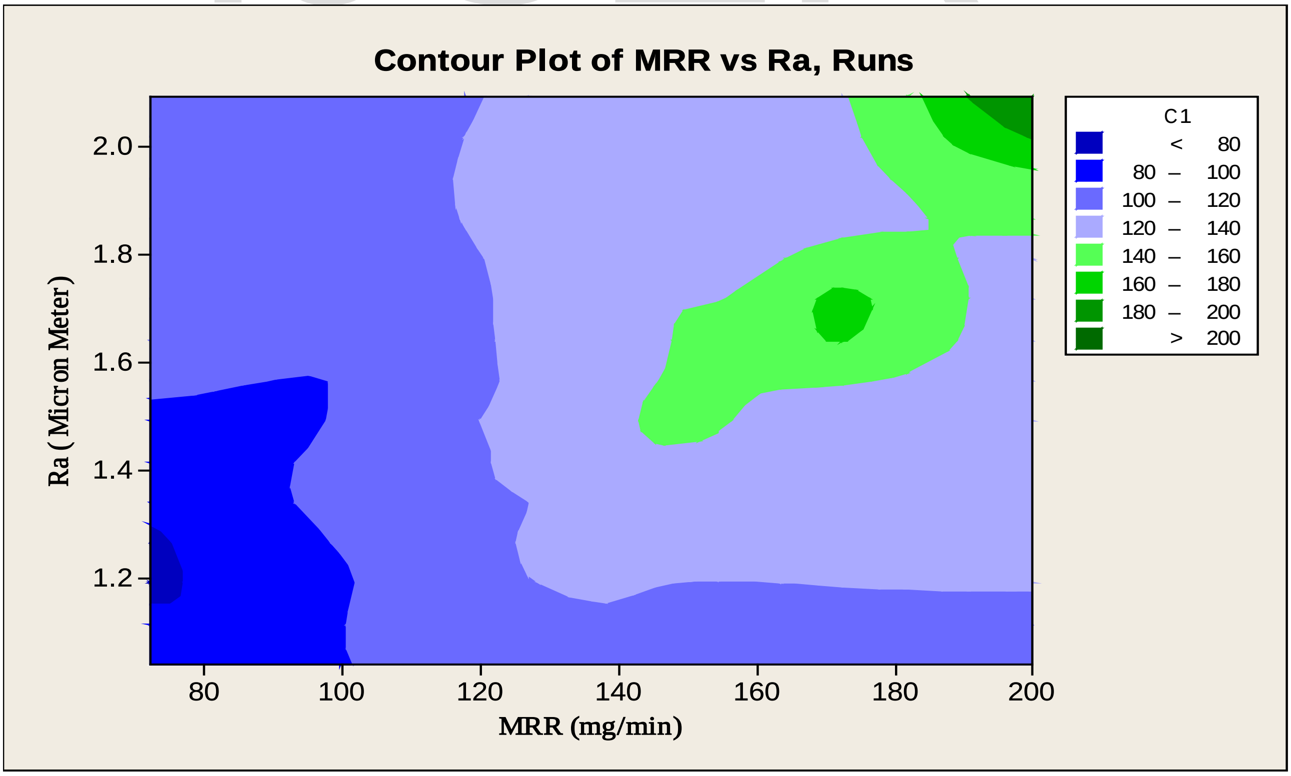

Fig 08: Contour plot for combined variations in MRR and Ra corresponding to runs of experiment.

It has been concluded that the best fitted modelling of material removal rate and surface roughness of D2 steel has been achieved by application of Response Surface Methodology and Artificial Neural Network respectively using WEDM under controlled condition. With the help of above graphical representation and predicted root mean square % (error = 1.90), it can be concluded that ANN is the best possible modelling tool for the surface roughness during WEDM machining. Surface roughness is proportional to the material removal rate. Good surface may be achieved at low material removal rate during machining of D2 steels using wire electrical discharge machining.

Reference:

[1] E.C. Jameson, Electrical Discharge Machining. Dearborn, Michigan: SME, 2001.
[2] K. Wang, H.L.Gelgete, Y.Wang, Q. Yuan,and M.Fang, "A hybrid intelligent method for modelling the EDM process" International journal of machine tool and manufacture, vol.43, pp. 995-999, Aug 2003 .
[3] Kuo-Ming Tsai, Pei-Jen Wang (2001) "Semi-empirical model of surface finish on electrical discharge machining" Int. J. of Machine Tools & Manufacture. Vol. 41, pp 1455-1477.
[4]. Jun Qu, Albert J. Shih (2002) "Development of the cylindrical wire electrical discharge machining process, part 1: Concept, Design, and Material removal rate", Journal of Manufacturing Science and Engineering, Vol. 124, pp 702-707.

[5]. Nandlal gupta (107ME053), B.Tech thesis "Optimization of micro wire EDM operation using grey Taguchi method " NIT Rourkela, India,fig. pp 5.
[6]. D.C. Montgomery, Design and Analysis of Experiments, Wiley, Singapore, 1991.
[7]. Bose, N.K., and Liang, P. (2004), Neural network fundamentals with graphs, algorithms, and applications, 7th reprint, Tata McGraw Hill Publication, New Delhi, India.
[8]. Hagan, M.T., and Demuth, H.B., (1996), Neural Network Design, PWS, Boston, Mass, USA.
[9]. Lawrence, M., and Fredricson, J. (1998), "Brainmaker's user's guide and reference manual," 7th edition, Nevada City, CA: California Scientific Software Press.

U.K.Vates is a Research Scholar at Dept. of Mechanical Engineering, ISM, Dhanbad, India. He received his M.Tech degree from MDU Rohtak, India , in Manufacturing & Automation Engineering in the year 2010. He has 10 years of teaching and research experience. His area of research interest includes modelling and analysis of manufacturing processes, and optimisation. He has published more than 10 research papers in the International/ national journal/conferences.