Chapter

Optimization of Surface Roughness of D2 Steels in WEDM using ANN Technique

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Abstract

Attempt has been made to investigate the experimental process and surface roughness (SR) optimization of cold working (high carbon and high chromium) hard die steel (D2) during wire electrical discharge machining processes (WEDM). It is very difficult to determine optimal cutting parameters for improving cutting performance has been reported. Wire electrical discharge machining process relies heavily on the operators' technologies and experience because of their numerous and diverse range as using complicated cuts can made through difficult to machine electrically conductive components, WEDM process was developed to generate precise cutting on complicate, hard and difficult to machine materials. Tan-sigmoid and purlin transfer functional with bias based four layered back propagation artificial neural network (BPANN) approach have been used to investigate the effect of six independent parameters 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) along with corresponding material removal rate (MRR). A fractional factorial design of experiment of three level were employed to conduct 80 rows of experiment on (D2) steel with chrome coated copper alloy wire electrode. The predicted response, CLA values of SR and corresponding MRR were observed by the approach of BPANN from experimental (55 rows for training, 15 rows for validation and 10 for testing) data. Software instructed programme has been used individually for training, validation and testing in MATLAB 2010a to find the corresponding prediction output. Two fold cross over technique (TFCT) were used to developed distinguish (S1 and S2) models and also developed more models depending on numbers of neurons used in primary and secondary hidden layers. The model adequacy is very satisfactory as correlation coefficient (R^2) is found to be 99.1% and adjusted ($R_{adj.}{}^2$) statistics is 98.5. It is found those spark time ON/OFF, wire feed rate, wire tension, gap voltage and flush rate and few of their interactions have significant effect on SR.

Keywords: WEDM, BPANN, SR, MRR, TFCT

1. Introduction

Wire electrical discharge machining is the metal removal process by means of repeated spark created between the wire electrode and work piece. It is considered as unique adaptation of the conventional EDM, which used an electrode to create the sparking within kerfs [11]. However, WEDM utilizes a continuously traveling chromium coated copper wire electrode ranging diameter 0.05–0.35 mm, which is capable to achieve very good sharpness of edge [4]. Very high temperature ranging 8000–10,000°C creates within the kerfs gap during machining, so that material removal may takes place by not only melting but directly vaporizations also. WEDM is used for the high precision machining to all type of electrically conductive metallic alloys, tool and die, graphite, and few ceramic and composite materials of any hardness which cannot be machined easily by conventional machining methods [1, 5].

Manufacturing processes (WEDM) has been chosen depending on the material characteristics and the type of responses required to be evaluating. The present study aimed to optimization of responses i.e. surface roughness with corresponding MRR of D2 steel by conducting 80 rows of experimental data using frictional factorial (2^{6-2}) design of experiment of five different set at three levels [3]. Four layered BPANN architecture has been used for modeling, where independent process variables are V_g, F_r T_{on}, T_{off}, W_f and W_t to get the précised and optimized values of responses R_a [6, 8, 10]. Best model S2 has been found on the basis of correlation coefficient (R^2) between observed and predicted responses (SR) [12]. The response (SR) is expressed as the irregularities of material resulted from various machining operations. It is represented as '$\mathbf{R_a}$' symbol and used to be called center line arithmetic average roughness for the sampling length [2].

The optimum process parameters are much essential to achieve better surface finish with adequate material removal rate (MRR) or shrink of total machining time; lot of research attempts has been reported for modeling and investigation of WEDM process parameters [7], but sum of root mean square error (SRMSE) approach have been used to optimize the process parameters by taking 55 rows of training data [9].

2. Experimental setup

2.1 Selection of wire electrode and work piece

A chrome coated cylindrical pure copper wire electrode having 0.25 mm in diameter and high tensile strength were selected for conducting machining operation on 18 mm diameter of D2 steel rod to cut 5 mm thickness of disk using Electronica Maxicut, WEDM process. It is very clear that D2 is hard die steel and conducting material with high carbon and chromium content (**Table 1**).

The experiment has carried out on Wire Electrical Discharge Machine, model ELECTRONICA-MAXICUT, SLNO -250, (F:09:0002:01) 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 characteristics of screening test.

C	SI	Cr	Mo	V	HRC	Conductivity
1.50%	0.30%	12.00%	0.80%	0.90%	56	22 (W/mk)

Table 1.
Metallurgical component analysis: D2 steel.

Figure 1.
D2 steel machining using WEDM process.

Figure 2.
Surftest SJ-210 (Mitutoyo).

Commercials grade of deionized water (density = 832 kg/m^3) was used as dielectric fluid. 18 mm cylindrical rod of D2 steel was used as the work piece with negative polarity and the power supply has the provision to connect the 0.25 mm chromium coated pure copper tool electrode with positive polarity so that the material removal may takes place by influence of heat generated within kerfs due to applied voltage within it (**Figure 1**).

The surface roughness R_a of the processed material have been measured precisely by using Surftest SJ-210 tester having center line average value (CLA), where least count of the equipment is 0.001 μm for the travel length of 0.85 mm (**Figure 2**).

2.2 Design of experiment and objective

Five different set of fractional factorial (2^{6-2} = 16) experimental design have been selected at two levels, so that 80 rows of experimental data can be observed at three level of replication on D2 using WEDM. In this study the main aim to minimize the surface roughness of D2 on best possible maximum MRR during WEDM (**Table 2**).

2.3 ANN architecture and training

The hit and trail method based on literature have been adapted to find 7 and 10 neurons in primary and secondary hidden layers respectively, which effects on the R-square statistics for best prediction modeling. Tan sigmoid activation (squashing) function used as the (infinite input to finite output range) learning capability by the

Factors/three level (coding)	1	2	3
Gap voltage (Vg): (volt)	30	60	90
Flush rate (Fr): (L/min)	4	6	8
Pulse on time (Ton): (μS)	1.05	1.15	1.25
Pulse of time (Toff): (μS)	130	160	190
Wire feed rate (Wf):(m/min)	2	5	8
Wire tension (Wt): (g)	300	600	900

Table 2.
Factors for screening test.

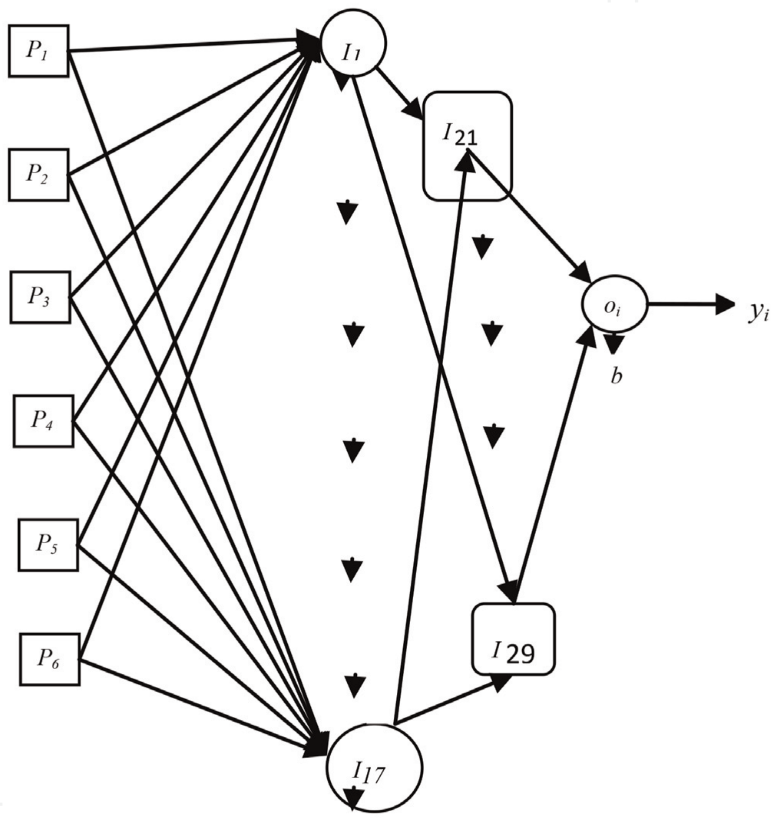

Figure 3.
Artificial neural network approach.

controllable instructed programme in MATLAB 2010a. Steepest descent problem used for the training algorithm to train the multilayer network, where the values of gradient was smallest because of the small changes in weight and biases. p_1, p_2, p_3, p_4, p_5 and p_6 are the six input layer neurons and O_i is the single neurons in output layer, whereas I_{11}-I_{17} and I_{21}-I_{29} (7 neurons present in primary and 10 in secondary hidden layers) are the hidden layers (**Figure 3**).

3. Experimentation

Two models (S1 and S2) were developed from 80 rows of experimental data performed of D2. Only training result of best performing model (S2) of 55 rows is

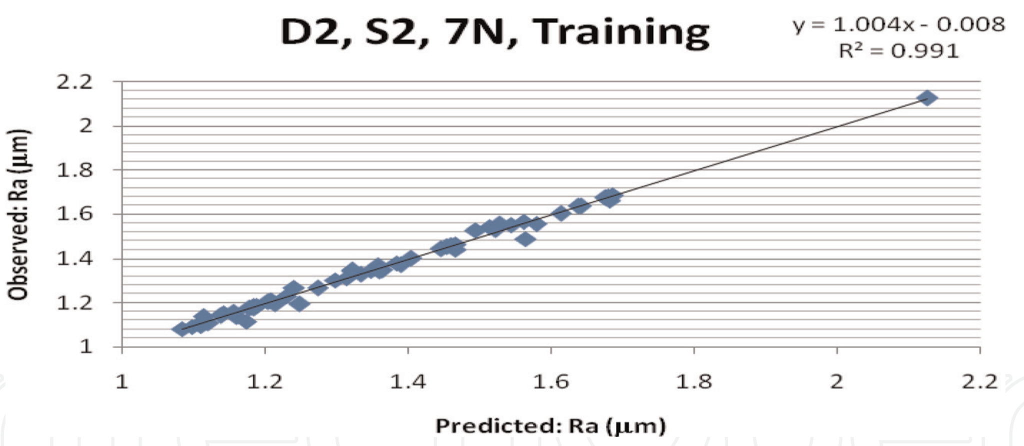

Figure 4.
Predictions against observations of R_a for model-D2, S2, 7 N (training dataset).

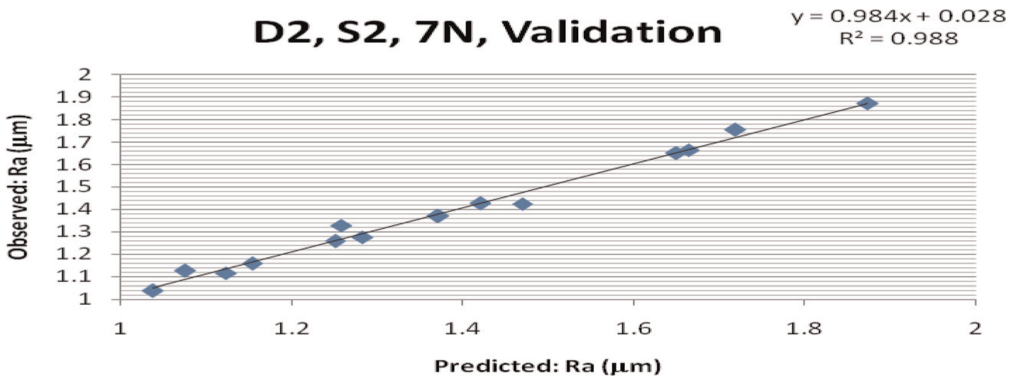

Figure 5.
Predictions against observations of R_a for model-D2, S2, 7 N (validation dataset).

presented here for achieving the aimed to optimization of influencing process parameters (**Figures 4** and **5**).

OPTIMIZATION OF PROCESS PARAMETER R_a: D2, 7 Neurons in hidden layer.

The best model needs to be predicted among Model-S1 and S2, in D2 steel. Effect of individual input parameters will be observed on the R_a (**Tables 3–6**).

4. Optimization of process parameters

It is evident from **Table 3**, that each independent influencing input parameter has corresponding values of their square of residuals at each three levels. Two values at each level (2 × 3 = 6 rows) has been taken for each inputs, where lowest possible square of residuals are available, to draw the **Figure 6(a–f)**.

5. Result

Figure 6(a–f) shows the relations between individual influencing parameters (V_g, F_r, T_{on}, T_{off}, W_f and W_t) to their optimized response, surface roughness (R_a) with corresponding values of MRR. **Table 5** also indicates that unique values of each influencing parameters (corresponding to its serial numbers of **Table 5**) gives optimum responses, which has been highlighted.

SN	Gap voltage (V_g)	Flush rate (F_r)	Spark time (T_{ON})	Spark time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a) Obs.	Surface roughness (R_a) Pred.	Material removal (MRR)	Square of residuals
	(V)	(Lit./min)	(μS)	(μS)	(m/min)	(g)	(μm)	(μm)	(mg/min)	$(\mu m)^2$
1	30	4	1.05	130	2	300	1.6858	1.6863	102	2.5E−07
2	30	4	1.05	160	2	600	1.4452	1.4451	92	1E−08
3	30	4	1.15	130	5	600	1.3884	1.3713	133	0.0002924
4	30	4	1.15	160	5	300	1.4658	1.4428	95	0.000529
5	30	6	1.05	130	5	600	1.3836	1.3788	125	2.304E−05
6	30	6	1.05	160	5	300	1.5278	1.5553	110	0.0007562
7	30	6	1.15	130	2	300	1.676	1.6756	97	1.6E−07
8	30	6	1.15	160	2	600	1.564	1.4909	95	0.0053436
9	60	4	1.05	130	5	300	1.1772	1.1754	104	3.24E−06
10	60	4	1.05	160	5	600	1.2076	1.2083	88	4.9E−07
11	60	4	1.15	130	2	600	1.273	1.2663	136	4.489E−05
12	60	4	1.15	160	2	300	1.3476	1.3455	116	4.41E−06
13	60	6	1.05	130	2	600	1.3322	1.3277	110	2.025E−05
14	60	6	1.05	160	2	300	1.1598	1.1371	115	0.0005153
15	60	6	1.15	130	5	300	1.248	1.1945	118	0.0028623
16	30	8	1.15	160	8	900	1.5124	1.5422	145	0.000888
17	30	8	1.15	190	8	600	1.363	1.3482	108	0.000219
18	30	8	1.25	160	5	600	2.1256	2.128	206	5.76E−06
19	30	8	1.25	190	5	900	1.6794	1.6823	101	8.41E−06
20	90	4	1.15	160	8	600	1.1098	1.1096	88	4E−08
21	90	4	1.15	190	8	900	1.1096	1.0952	63	0.0002074

SN	Gap voltage (V_g)	Flush rate (F_r)	Spark time (T_{ON})	Spark time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a) Obs.	Surface roughness (R_a) Pred.	Material removal (MRR)	Square of residuals
	(V)	(Lit./min)	(μS)	(μS)	(m/min)	(g)	(μm)	(μm)	(mg/min)	$(\mu m)^2$
22	90	4	1.25	160	5	900	1.3572	1.3664	107	8.464E-05
23	90	4	1.25	190	5	600	1.3218	1.3425	88	0.0004285
24	90	8	1.15	160	5	900	1.2286	1.2292	91	3.6E−07
25	90	8	1.15	190	5	600	1.1194	1.1062	64	0.0001742
26	60	6	1.15	160	5	600	1.4038	1.4023	155	2.25E−06
27	60	8	1.05	130	5	900	1.4592	1.459	162	4E−08
28	60	8	1.05	160	5	600	1.3601	1.3441	139	0.000256
29	60	8	1.25	130	2	600	1.5208	1.5302	202	8.836E−05
30	60	8	1.25	160	2	900	1.5435	1.5535	168	0.0001
31	90	6	1.05	130	5	600	1.3127	1.3118	78	8.1E−07
32	90	6	1.05	160	5	900	1.2973	1.3023	72	2.5E−05
33	90	6	1.25	130	2	900	1.1823	1.1867	117	1.936E−05
34	90	6	1.25	160	2	600	1.0832	1.0812	105	4E−06
35	90	8	1.05	130	2	900	1.2396	1.2696	89	0.0009
36	90	8	1.05	160	2	600	1.1838	1.1739	81	9.801E−05
37	90	8	1.25	130	5	600	1.1413	1.1524	92	0.0001232
38	90	8	1.25	160	5	900	1.1125	1.1364	112	0.0005712
39	60	6	1.05	130	2	600	1.4536	1.4546	128	1E−06
40	60	6	1.05	160	2	900	1.3208	1.3474	114	0.0007076
41	90	8	1.05	130	2	900	1.1369	1.1423	96	2.916E−05
42	90	8	1.05	160	2	600	1.0962	1.0905	78	3.249E−05

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SN	Gap voltage (V_g)	Flush rate (F_r)	Spark time (T_{ON})	Spark time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a) Obs.	Surface roughness (R_a) Pred.	Material removal (MRR)	Square of residuals
	(V)	(Lit./min)	(μS)	(μS)	(m/min)	(g)	(μm)	(μm)	(mg/min)	$(\mu m)^2$
43	90	8	1.25	130	5	600	1.1551	1.1551	99	0
44	90	8	1.25	160	5	900	1.1723	1.1153	74	0.003249
45	30	4	1.15	160	2	300	1.6813	1.6628	112	0.0003422
46	30	4	1.15	190	2	900	1.5782	1.5577	108	0.0004202
47	30	4	1.25	160	8	900	1.4935	1.5283	163	0.001211
48	30	4	1.25	190	8	300	1.4658	1.4666	155	6.4E−07
49	30	6	1.15	160	8	900	1.6402	1.6368	121	1.156E−05
50	30	6	1.15	190	8	300	1.6128	1.6021	132	0.0001145
51	30	6	1.25	160	2	300	1.6368	1.6354	103	1.96E−06
52	30	6	1.25	190	2	900	1.5609	1.5668	108	3.481E−05
53	60	4	1.15	160	8	300	1.2136	1.1945	123	0.0003648
54	60	4	1.15	190	8	900	1.1871	1.1878	128	4.9E−07
55	60	4	1.25	160	2	900	1.2036	1.2035	148	1E−08
				Average				1.3654	113.8	

Table 3.
D2, S1, 7N, training data (combined parameters).

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SN	Gap voltage (V_g)	Flush rate (F_r)	Spark ON time (T_{ON})	Spark OFF time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a) obs.	Surface roughness (R_a) predicted.	$(Residual)^2$	Material removal predicted (MRR)
	(V)	(Lit./min)	(µS)	(µS)	(m/min)	(g)	(µm)	(µm)	$(\mu m)^2$	(mg/min)
1	30	4	1.05	130	2	300	1.6858	1.6863	2.5E−07	105
2	30	4	1.05	160	2	600	1.4452	1.4451	1E−08	95
3	30	4	1.15	130	5	600	1.3884	1.3713	0.0002924	119
4	30	4	1.15	160	5	300	1.4658	1.4428	0.000529	102
5	30	6	1.05	130	5	600	1.3836	1.3788	2.304E−05	115
6	30	6	1.05	160	5	300	1.5278	1.5553	0.0007562	116
7	30	6	1.15	130	2	300	1.676	1.6756	1.6E−07	114
8	30	6	1.15	160	2	600	1.564	1.4909	0.0053436	102
9	60	4	1.05	130	5	300	1.1772	1.1754	3.24E−06	108
10	60	4	1.05	160	5	600	1.2076	1.2083	4.9E−07	96
11	60	4	1.15	130	2	600	1.273	1.2663	4.489E−05	131
12	60	4	1.15	160	2	300	1.3476	1.3455	4.41E−06	123
13	60	6	1.05	130	2	600	1.3322	1.3277	2.025E−05	111
14	60	6	1.05	160	2	300	1.1598	1.1371	0.0005153	117
15	60	6	1.15	130	5	300	1.248	1.1945	0.0028623	112
16	30	8	1.15	160	8	900	1.5124	1.5422	0.000888	136
17	30	8	1.15	190	8	600	1.363	1.3482	0.000219	105
18	30	8	1.25	160	5	600	2.1256	2.128	5.76E−06	189
19	30	8	1.25	190	5	900	1.6794	1.6823	8.41E−06	97
20	90	4	1.15	160	8	600	1.1098	1.1096	4E−08	79

SN	Gap voltage (V_g)	Flush rate (F_r)	Spark ON time (T_{ON})	Spark OFF time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a) obs.	Surface roughness (R_a) predicted.	$(Residual)^2$	Material removal predicted (MRR)
	(V)	(Lit./min)	(µS)	(µS)	(m/min)	(g)	(µm)	(µm)	$(µm)^2$	(mg/min)
21	90	4	1.15	190	8	900	1.1096	1.0952	0.0002074	70
22	90	4	1.25	160	5	900	1.3572	1.3664	8.464E−05	110
23	90	4	1.25	190	5	600	1.3218	1.3425	0.0004285	92
24	90	8	1.15	160	5	900	1.2286	1.2292	3.6E−07	101
25	90	8	1.15	190	5	600	1.1194	1.1062	0.0001742	69
26	60	6	1.15	160	5	600	1.4038	1.4023	2.25E−06	153
27	60	8	1.05	130	5	900	1.4592	1.459	4E−08	158
28	60	8	1.05	160	5	600	1.3601	1.3441	0.000256	143
29	60	8	1.25	130	2	600	1.5208	1.5302	8.836E−05	208
30	60	8	1.25	160	2	900	1.5435	1.5535	0.0001	163
31	90	6	1.05	130	5	600	1.3127	1.3118	8.1E−07	74
32	90	6	1.05	160	5	900	1.2973	1.3023	2.5E−05	93
33	90	6	1.25	130	2	900	1.1823	1.1867	1.936E−05	122
34	90	6	1.25	160	2	600	1.0832	1.0812	4E−06	111
35	90	8	1.05	130	2	900	1.2396	1.2696	0.0009	97
36	90	8	1.05	160	2	600	1.1838	1.1739	9.801E−05	86
37	90	8	1.25	130	5	600	1.1413	1.1524	0.0001232	81
38	90	8	1.25	160	5	900	1.1125	1.1364	0.0005712	106
39	60	6	1.05	130	2	600	1.4536	1.4546	1E−06	135
40	60	6	1.05	160	2	900	1.3208	1.3474	0.0007076	111

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SN	Gap voltage (V_g)	Flush rate (F_r)	Spark ON time (T_{ON})	Spark OFF time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a) obs.	Surface roughness (R_a) predicted.	$(Residual)^2$	Material removal predicted (MRR)
	(V)	(Lit./min)	(µS)	(µS)	(m/min)	(g)	(µm)	(µm)	$(µm)^2$	(mg/min)
41	90	8	1.05	130	2	900	1.1369	1.1423	2.916E−05	96
42	90	8	1.05	160	2	600	1.0962	1.0905	3.249E−05	74
43	90	8	1.25	130	5	600	1.1551	1.1551	0	94
44	90	8	1.25	160	5	900	1.1723	1.1153	0.003249	88
45	30	4	1.15	160	2	300	1.6813	1.6628	0.0003422	117
46	30	4	1.15	190	2	900	1.5782	1.5577	0.0004202	100
47	30	4	1.25	160	8	900	1.4935	1.5283	0.001211	158
48	30	4	1.25	190	8	300	1.4658	1.4666	6.4E−07	163
49	30	6	1.15	160	8	900	1.6402	1.6368	1.156E−05	115
50	30	6	1.15	190	8	300	1.6128	1.6021	0.0001145	141
51	30	6	1.25	160	2	300	1.6368	1.6354	1.96E−06	112
52	30	6	1.25	190	2	900	1.5609	1.5668	3.481E−05	109
53	60	4	1.15	160	8	300	1.2136	1.1945	0.0003648	123
54	60	4	1.15	190	8	900	1.1871	1.1878	4.9E−07	125
55	60	4	1.25	160	2	900	1.2036	1.2035	1E−08	144
				Average				1.3654	0.002642	114.8

Table 4.
Training data for model: S2, R_a, N7, D2 steel.

SN	Gap voltage (V_g)	Flush rate (F_r)	Spark time (T_{ON})	Spark time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a)	Material removal (MRR)	Square of residuals (R_a)
	(V)	(Lit./min)	(μS)	(μS)	(m/min)	(g)	(μm)	(mg/min)	$(\mu m)^2$
	V_g								
2	30	4	1.05	160	2	600	1.4452	92	1E−08
7	30	6	1.15	130	2	300	1.676	97	1.6E−07
27	60	8	1.05	130	5	900	1.4592	162	4E−08
54	60	4	1.15	190	8	900	1.1871	128	4.9E−07
20	90	4	1.15	160	8	600	1.1098	88	4E−08
43	90	8	1.25	130	5	600	1.1551	99	0
		F_r							
1	30	4	1.05	130	2	300	1.6858	102	2.5E−07
55	60	4	1.25	160	2	900	1.2036	148	1E−08
7	30	6	1.15	130	2	300	1.676	97	1.6E−07
31	90	6	1.05	130	5	600	1.3127	78	8.1E−07
27	60	8	1.05	130	5	900	1.4592	162	4E−08
43	90	8	1.25	130	5	600	1.1551	99	0
			T_{on}						
41	90	8	1.05	130	2	900	1.1369	96	2.916E−05
42	90	8	1.05	160	2	600	1.0962	78	3.249E−05
54	60	4	1.15	190	8	900	1.1871	128	4.9E−07
20	90	4	1.15	160	8	600	1.1098	88	4E−08
55	60	4	1.25	160	2	900	1.2036	148	1E−08
43	90	8	1.25	130	5	600	1.1551	99	0
				T_{off}					
7	30	6	1.15	130	2	300	1.676	97	1.6E−07
27	60	8	1.05	130	5	900	1.4592	162	4E−08
55	60	4	1.25	160	2	900	1.2036	148	1E−08
36	90	8	1.05	160	2	600	1.1838	81	9.801E−05
21	90	4	1.15	190	8	900	1.1096	63	0.0002074
54	60	4	1.15	190	8	900	1.1871	128	4.9E−07
					W_f				
34	90	6	1.25	160	2	600	1.0832	105	4E−06
2	30	4	1.05	160	2	600	1.4452	92	1E−08
43	90	8	1.25	130	5	600	1.1551	99	0
31	90	6	1.05	130	5	600	1.3127	78	8.1E−07
48	30	4	1.25	190	8	300	1.4658	155	6.4E−07
16	30	8	1.15	160	8	900	1.5124	145	0.000888

SN	Gap voltage (V_g)	Flush rate (F_r)	Spark time (T_{ON})	Spark time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a)	Material removal (MRR)	Square of residuals (R_a)
	(V)	(Lit./min)	(μS)	(μS)	(m/min)	(g)	(μm)	(mg/min)	$(\mu m)^2$
						W_t			
7	30	6	1.15	130	2	300	1.6760	97	1.6E−07
1	30	4	1.05	130	2	300	1.6858	102	2.5E−07
2	30	4	1.05	160	2	600	1.4452	92	1E−08
31	90	6	1.05	130	5	600	1.3127	78	8.1E−07
54	60	4	1.15	190	8	900	1.1871	128	4.9E−07
21	90	4	1.15	190	8	900	1.1096	63	0.0002074

Correlation coefficient (R^2): Training data of D2 steel (best performing model S2) using 7 and 10 neurons in primary and secondary hidden layers.

Table 5.
D2, S2, 7N, training data (individual parameters corresponding to least square of residuals).

Material	Model	R^2 value	Equation of lines (correlation between obs. and pred. values of Ra)	Average predicted R_a (μm)	Root mean square error (μm)	Percentage RMSE (%)	Average % RMSE RMSE
D2	S1 Training	0.983	y = 1.005x - 0.010	1.3864	0.003401	0.2453	0.8129 **0.7353**
	S1 Validation	0.967	y = 1.067x - 0.090	1.3008	0.01077	0.8279	
	S1, Testing Testing	0.963	y = 0.879x + 0.154	1.4016	0.01914	1.3655	
	S2 set, Training Training	**0.991**	**y = 1.004x - 0.008**	**1.3654**	**0.002642**	**0.1934**	**0.3865**
	S2 validation	0.988	y = 0.984x + 0.028	1.3888	0.007015	0.5051	
	S2, testing testing	0.979	y = 1.006x - 0.006	1.4232	0.006565	0.4612	

Table 6.
Summary of R^2 values of training validation and testing data: 7 N in 1st and 10 N in 2nd L, R_a.

Again experiment has been conducted on D2 steel using WEDM by setting the individual optimum parametric combinations (V_g, F_r, T_{on}, T_{off}, W_f and W_t) as 90 (V), 8 (Lit./min), 1.05 (μS), 190 (μS), 2 (m/min) and 900 (g) respectively and found the values of Ra = 0.9638 (μm) at MRR = 105 (mg/min) (**Table 7**).

6. Conclusion

It has been concluded that the best fitted model (S2) for material removal rate and surface roughness of D2 steel has been achieved by artificial neural network

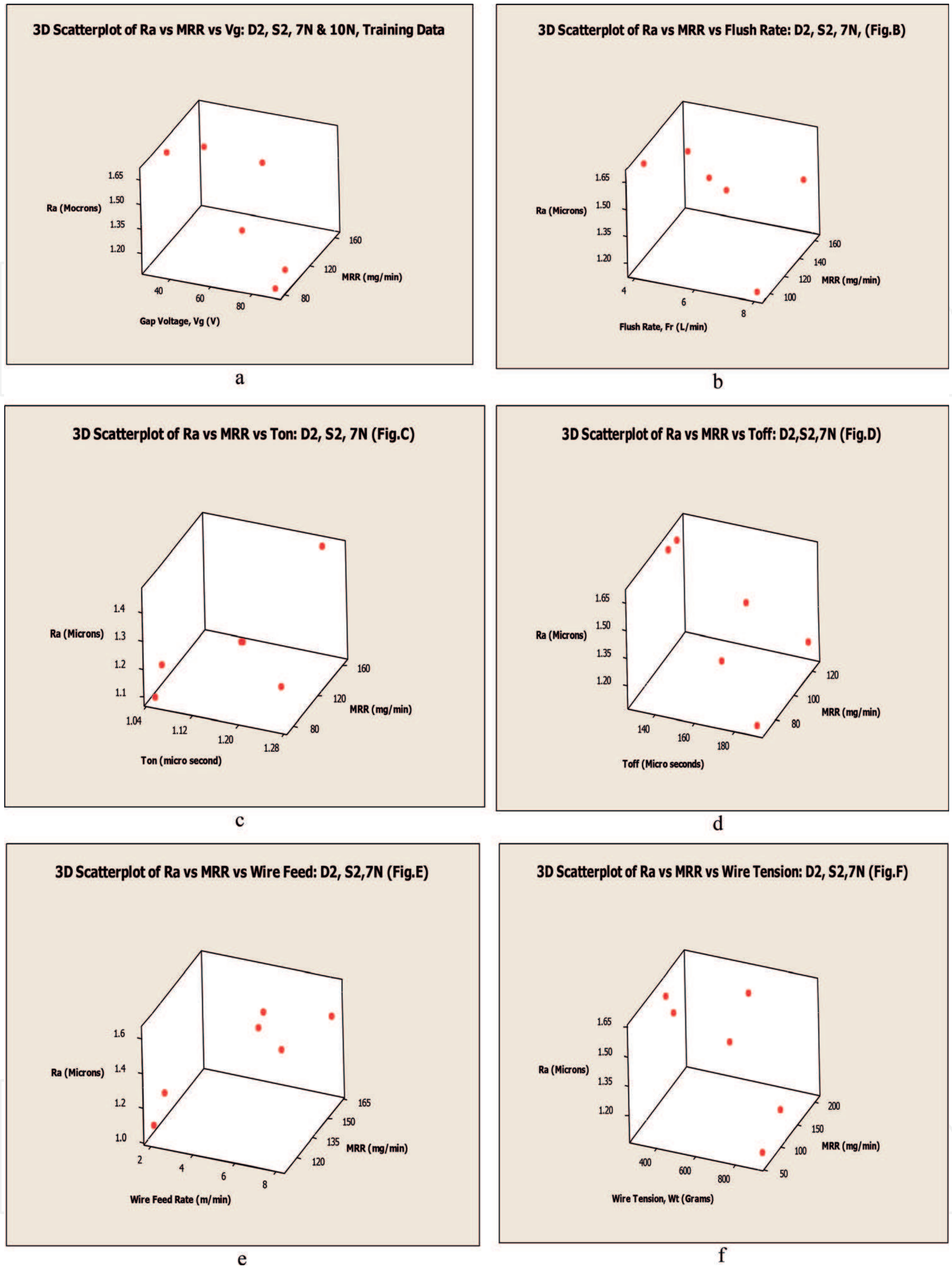

Figure 6.
(a–f) 3D scattered plot between Ra vs. MRR vs. individual independent parameter.

using WEDM. From best modeled training data, optimum parametric combinations (V_g, F_r, T_{on}, T_{off}, W_f and W_t) observed as 90 V, 8 Lit./min, 1.05 μS, 190 μS, 2 m/min and 900 g respectively and found the values of R_a = 0.9638 μm at MRR = 105 mg/min, whereas the average Ra = 1.3654 μm at MRR = 114.8 mg/min. It has been concluded that ANN modeling technique is best fitted for surface roughness prediction and able to successfully minimize (SR) is 29.41% with 8.53% decreases the MRR from its average values on D2 steel using BPANN under WEDM. Such combinations may be applied for industrial application, where it is needed.

SN	Gap voltage (V_g)	Flush rate (F_r)	Spark time (T_{ON})	Spark time (T_{OFF})	Wire feed (W_f)	Wire tension (W_t)	Surface roughness (R_a) obs.	Surface roughness (R_a) predicted	(Zero residual)^2	Material removal predicted (MRR)
	(V)	(Lit./min)	(μS)	(μS)	(m/min)	(g)	(μm)	(μm)	$(\mu m)^2$	(mg/min)
20	**90**	4	1.15	160	8	600	1.1098	1.1096	4.00E−08	79
43	90	**8**	1.25	130	5	600	1.1551	1.1551	0	94
42	90	8	**1.05**	160	2	600	1.0962	1.0905	3.25E−05	74
54	60	4	1.15	**190**	8	900	1.1871	1.1878	4.90E−07	125
34	90	6	1.25	160	**2**	600	1.0832	1.0812	4.00E−06	111
54	60	4	1.15	190	8	**900**	1.1871	1.1878	4.90E−07	125

Table 7.
Best parametric combination with their possible responses.

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