Surface Finish Analysis of D2 Steel In WEDM Using ANN & Regression Modelling with Influence of Fractional Factorial Design of Experiment

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Abstract

Wire electrical discharge machining (WEDM) is an important metal removal process in precision manufacturing of mould and dies, which comes under non traditional machining processes. It is also quite difficult to find the correct input parametric combinations to give lowest possible values of surface roughness of D2 steel under WEDM.. Non-conventional WEDM process under low temperature dielectric (DI water) is more robust and powerful approach than conventional machining process to obtaining better surface finish in low temperature treated tool steels. Low temperature dielectric cooling medium implementation generally used as secondary treatment to enhance the surface smoothness. Present work aimed to effect of WEDM parameters on surface finish of low temperature treated AISI D2 tool steel is investigated. Montgomery fractional factorial design of experiment, L16 orthogonal array was selected for conducting the experiments. The surface roughness and its corresponding material removal rate (MRR) were considered as responses for improving surface finish. The Analysis of variance (ANOVA) was done to find the optimum machining parametric combination for better surface finish. The experimental result shows that the model suggested by the Montgomery's method is suitable for improving the surface finish. Regression (RA) analysis method and Artificial Neural Network (ANN) were used to formulate the mathematical models. Based on optimal parametric combination, experiments were conducted to confirm the effectiveness of the proposed ANN model.

Keywords

Montgomery method, WEDM, ANOVA, ANN, RA and surface finish.

1. Introduction

Unconventional processes like Wire electro discharge machining (WEDM) plays an important role in precision manufacturing of automobile, aerospace parts and dies industries. WEDM process is the metal removal process by means of repeated spark created between wire electrode and work piece. It is considered as unique adaptation of the conventional EDM which uses an electrode to create sparks within kerfs. WEDM process utilizes a regular travelling wire anode made up of very thin copper, tungsten and brass materials of diameter ranging 0.05- 0. 35 mm this is used to find very good edge sharpness (Ho K.H et al., 2004). The thermal erosion mechanism during WEDM, primarily makes use of electrical energy and then turns into thermal energy through a series of discrete electrical discharges occurring between thin wire electrode and conductive material work piece immersed in a dielectric medium (Tsai, H.C et al., 2003). The thermal energy generates a channel of plasma between wire electrode and the conductive and hard work material (Shobert, E.I. (1983). However, it is concluded that very high local temperature ranging 8000° C - 12000° C creates within the kerfs gaps during machining so that material removal may takes place by not only melting but directly vaporization also (Boothroyd, G.; Winston, A.K. .1989). WEDM Resistance and Capacitance (R-C) circuits converts electrical energy to generate the pulsating or intermittent discharge in the form of sparks with maintaining desire gap between the existing electrodes (Bawa, H.S. (2004).

Lot of researchers (Khan 2008, Lee 2008, Das 2009, Pujari et al.2011) have tried to investigate and improve the

Surface finish of different materials namely AISI D1, H13, D2, STD 11, aluminium alloy, alloy steels etc. It is noted that the electrical conductivity and higher hardness are significant properties affecting the surface roughness and tool wear. Therefore high hardness and rigidity of material will produce finer surface and low rigidity material like Aluminum alloys produce high surface roughness (Lee 2008, Daset al. 2009).

WEDM is also used for high precision material removal process to all types of electrically conductive metallic alloys, graphite, tool & die, and a few composite materials as well as ceramic of any hardness which cannot be machined easily by traditional machining methods and it has been reported that V_g, T_{on}, and T_{off} are influencing parameters on surface roughness and MRR for tool steels (Puertas I. et al 2003). WEDM machining performance such as R_a, electrode wear rate and MRR with copper electrode on AISI: H3 tool steel work piece and input parameters taken as Ip, T_{on}, and T_{off} the optimum condition for R_a was obtained at low I_p, low T_{on} and high T_{off} and I_p was the major factor effecting both the responses MRR and R_a respectively (Jaharah et al 2008). A lot of modelling techniques have already been developed for surface roughness of different conducting work materials under WEDM. The prediction of MRR by ANN modelling by Panda DK et al 2005 and Pradhan M.K. et al 2010 worked on four parameters i.e. voltage, current, T_{on} and duty cycle for the prediction of MRR. Hybrid models of ANN and GA have been developed to predict the surface roughness of tool & die steel materials, machining time, current and voltage being input parameters (Krishna Mohana Rao, G, et al., 2009). The data obtained from various experiments is analyzed in three different ways. Firstly, the significant factors were determined using analysis of variance (ANOVA). Secondly, Regression analysis model is used to establish a relationship between selected parameters and response variables. Thirdly, Signal to noise ratio is calculated and analyzed to find out the optimal parameter settings and their levels. Finally, confirmation experiments were conducted with the optimized parameter combination to identify the effectiveness of the proposed method.

Nowadays the many industries have started using very low temperature dielectric medium in WEDM for AISI D2 tool steel for manufacturing dies and punches because of its improved electrical and thermal characteristics. No evidence has been found in any literature on optimization of WEDM parameters for AISI D2 tool steel using low temperature dielectric. Therefore, it is tried to study, investigate and optimize the effect of WEDM parameters on very low temperature DI water. The optimum surface finish process parameters are essential to achieve with adequate material removal rate (MRR). A lot of research techniques have been reported for response optimization but present work uses sum of root mean square error (SRMSE) approach and achieves improvement approx more than 28% in surface smoothness under WEDC process.

2. Experimental setup:

Chromium coated cylindrical pure copper wire [Electrical Conductivity (σ) = 5.96×10^7 $(ohm\text{-}m)^{-1}$ or (S/m)] electrode having 0.25 mm in diameter and high tensile strength has been selected. This wire electrode is suitable, as far as conductivity is concerned, for performing cutting operation on 18 mm diameter rod of D2 grade steel to cut disks of 5 mm thickness using Electronica Maxicut: Sl - 250, WEDM shown in Fig.1. Cold working hard die steel and conducting material (D2 steel) has been selected due to its wide scope in tool and dies manufacturing industries. The chemical composition of D2 steel is mentioned in table.1 below:

Table 1: Chemical Combination: D2 grade steel.

C	Si	Cr	Mo	V	HRC	Conductivity
1.45 %	0.34 %	12.1 %	0.82 %	0.93 %	57	1.236×10^6 (S/m)

The experiments were run on a CNC operated Wire Electrical Discharge Machine, model ELECTRONICA-MAXICUT,SL NO-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. Present experiments are aimed at considering significant effects of several controllable and independent parameters on surface roughness of D2 steel during WEDM. The spark is created depending upon gap voltage applied between the conductive work piece and electrode. The machining performance is influenced by major independent process parameters which have been selected for experiment as characteristics of screening test. Commercials grade of deionised water [(Density= 832 kg/m^3), (Electrical conductivity= 5.5 x 10 $^{-6}$ S/m)] has been used as dielectric fluid. 18 mm cylindrical rod of D2 steel has been 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. The surface roughness R_a of the material have been measured precisely by using Surftest SJ-210 in Fig 2, surface roughness tester having least count 0.001µm for the travel length of 0.85 mm.

Fig.1: WEDM

Fig.2: Surftest SJ-210 (Mitutoyo).

2.1 Design of Experiments: Five different sets under fractional factorial design of experiments (2^{6-2} = 16) have been selected at two levels so that 80 rows of experimental data may be taken at three levels of replication on D2 using WEDM. Screening test on D2 steel has been performed.

Table 2: Factors for screening test

Factors/Three Levels(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
WireFeedRate (Wf):(m/minn)	2	5	8
Wire tension (Wt): (grams)	300	600	900

Apart from controllable and independent variables as mentioned inTable.2, there are many parameters which are kept constant. Experiments were carried out randomly using suitable table, so that repetitions of the runs were not done throughout.

Factors	Constant values (coded)
Jog Feed	2
Low Jog	7
Toff1	6
Sensitivity	7

Table 3: Constant Factors during WEDM

2.2 ANN Architecture & Training: Many studies have been reported on the development of neural networks based on different architectures. Basically, one can characterize neural networks by its important features, such as the architecture, the learning algorithms and the activation functions. Each category of the neural networks would have its own input output characteristics, and therefore it can only be applied for modelling some specific processes. In this present work, fast Levenberg- Marquardt algorithm BPANN is employed for modelling. In order to improve the generalisation and early stop, are often employed. There are two different ways in which this algorithm can be implemented: incremental mode and batch mode. In the incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In the batch mode all of the inputs are applied to the network before the weights are updated. There are many variations have been observed in the back propagation algorithm. The simplest implementation of back propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly - negative of the gradient. A iteration of this algorithm can be written as

$$\boxed{X_{t+1} = X_t - \alpha_t\, g_t}$$

Where, X_{t+1} are a vector of current weight and bias, X_t is the current gradient, α_t is multiplying factor and g_t is the learning rate. The hit and trial method based on literature as well as soft computing methods have been adopted to find critical 7 Nos. and 10 Nos. of neurons in primary and secondary hidden layers respectively which affects R- square statistic. Tan sigmoid activation (squashing) function is used for the modelling for the best prediction of R_a using instructed programme in MATLAB 2010a. Steepest descent method is used to train multilayer network where values of gradients are smallest because of small changes in weights and biases i.e. p_1, p_2, p_3, p_4, p_5 and p_6 which are six input layer neurons and O_i is single neuron in output layer, whereas I_{11}-I_{17} and I_{21}-I_{30} are 7 and10 neurons in primary and secondary hidden layers respectively as mentioned in Fig.3.

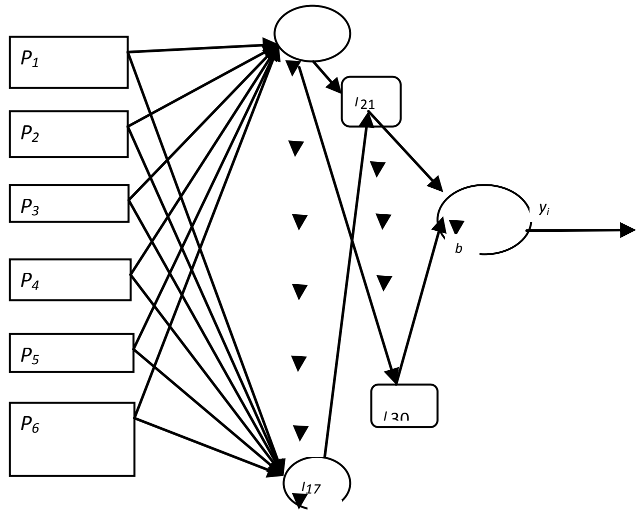
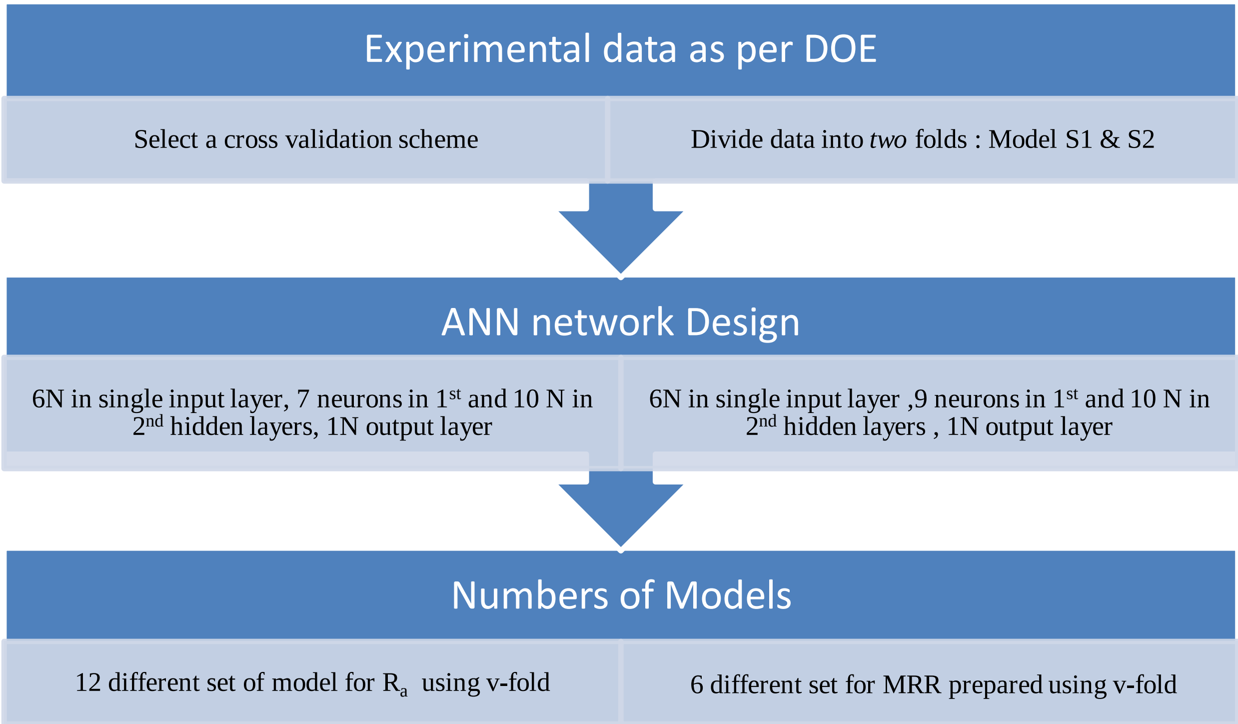


Fig 3: Artificial Neural Network Approach

3. Design of Experiments:

Fractional factorial (2^{6-2}) design has been implemented to conduct the five set of experiment. Also v- folds crossover technique used for get data homogeneous, which may be explained as-



3.1 Modelling Result:

Table 4: Modelling result comparisons

Material	Model	R^2 Value	Equation	Average Prediction (μm)	Root Mean Square Error (μm)	Percentage RMSE (%)	Average % RMSE
AISI: D2 steel modelling by ANN	S1 Training	0.983	y = 1.005x - 0.010	1.3864	0.003401	0.2453	0.8129
	S1 Validation	0.967	y = 1.067x - 0.090	1.3008	0.01077	0.8279	
	S1, Testing	0.963	y = 0.879x + 0.154	1.4016	0.01914	1.3655	
	S2, 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	0.979	y = 1.006x - 0.006	1.4232	0.006565	0.4612	

AISI: D2 steel modelling by regression	S1 Training	0.946	y = 1.009x - 0.050	1.3961	0.004536	0.2453	0.9675
	S1 Validation	0.931	y = 1.027x - 0.090	1.4053	0.01132	0.8239	
	S1, Testing	0.927	y = 0.849x + 0.152	1.4013	0.01414	1.3755	
	S2, Training	0.992	y = 1.002x - 0.002	1.3354	0.003642	0.1931	**0.5572**
	S2 Validation	0.983	y = 0.984x + 0.028	1.3888	0.007015	0.5051	
	S2, Testing	0.969	y = 1.006x - 0.003	1.4532	0.007565	0.4615	

3.2 Experimentation:

Table 5: Experimental Ra- WEDM

	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**
	Volt	**Lit./min**	**µS**	**µS**	**m/min**	**Grams**	**µm**	**µm**	**mg/min**	**$(\mu m)^2$**
1	30	4	1.05	130	2	300	1.685	1.6863	102	2.5E-07
2	30	4	1.05	160	2	600	1.445	1.4451	92	1E-08
3	30	4	1.15	130	5	600	1.388	1.3713	133	0.0002924
4	30	4	1.15	160	5	300	1.465	1.4428	95	0.000529
5	30	6	1.05	130	5	600	1.383	1.3788	125	2.304E-05
6	30	6	1.05	160	5	300	1.527	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	1.177	1.1754	104	3.24E-06
10	60	4	1.05	160	5	600	1.207	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	1.347	1.3455	116	4.41E-06
13	60	6	1.05	130	2	600	1.332	1.3277	110	2.025E-05
14	60	6	1.05	160	2	300	1.159	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	1.512	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	2.125	2.128	206	5.76E-06

19	30	8	1.25	190	5	900	1.679	1.6823	101	8.41E-06
20	90	4	1.15	160	8	600	1.109	1.1096	88	4E-08
21	90	4	1.15	190	8	900	1.109	1.0952	63	0.0002074
22	90	4	1.25	160	5	900	1.357	1.3664	107	8.464E-05
23	90	4	1.25	190	5	600	1.321	1.3425	88	0.0004285
24	90	8	1.15	160	5	900	1.228	1.2292	91	3.6E-07
25	90	8	1.15	190	5	600	1.119	1.1062	64	0.0001742
26	60	6	1.15	160	5	600	1.403	1.4023	155	2.25E-06
27	60	8	1.05	130	5	900	1.459	1.459	162	4E-08
28	60	8	1.05	160	5	600	1.360	1.3441	139	0.000256
29	60	8	1.25	130	2	600	1.520	1.5302	202	8.836E-05
30	60	8	1.25	160	2	900	1.543	1.5535	168	0.0001
31	90	6	1.05	130	5	600	1.312	1.3118	78	8.1E-07
32	90	6	1.05	160	5	900	1.297	1.3023	72	2.5E-05
33	90	6	1.25	130	2	900	1.182	1.1867	117	1.936E-05
34	90	6	1.25	160	2	600	1.083	1.0812	105	4E-06
35	90	8	1.05	130	2	900	1.239	1.2696	89	0.0009
36	90	8	1.05	160	2	600	1.183	1.1739	81	9.801E-05
37	90	8	1.25	130	5	600	1.141	1.1524	92	0.0001232
38	90	8	1.25	160	5	900	1.112	1.1364	112	0.0005712
39	60	6	1.05	130	2	600	1.453	1.4546	128	1E-06
40	60	6	1.05	160	2	900	1.320	1.3474	114	0.0007076
41	90	8	1.05	130	2	900	1.136	1.1423	96	2.916E-05
42	90	8	1.05	160	2	600	1.096	1.0905	78	3.249E-05
43	90	8	1.25	130	5	600	1.155	1.1551	99	0
44	90	8	1.25	160	5	900	1.172	1.1153	74	0.003249
45	30	4	1.15	160	2	300	1.681	1.6628	112	0.0003422
46	30	4	1.15	190	2	900	1.578	1.5577	108	0.0004202
47	30	4	1.25	160	8	900	1.493	1.5283	163	0.001211
48	30	4	1.25	190	8	300	1.465	1.4666	155	6.4E-07
49	30	6	1.15	160	8	900	1.640	1.6368	121	1.156E-05
50	30	6	1.15	190	8	300	1.612	1.6021	132	0.0001145
51	30	6	1.25	160	2	300	1.636	1.6354	103	1.96E-06
52	30	6	1.25	190	2	900	1.560	1.5668	108	3.481E-05
53	60	4	1.15	160	8	300	1.213	1.1945	123	0.0003648
54	60	4	1.15	190	8	900	1.187	1.1878	128	4.9E-07
55	60	4	1.25	160	2	900	1.203	1.2035	148	1E-08
	Average							**1.3654**	**113.8**	

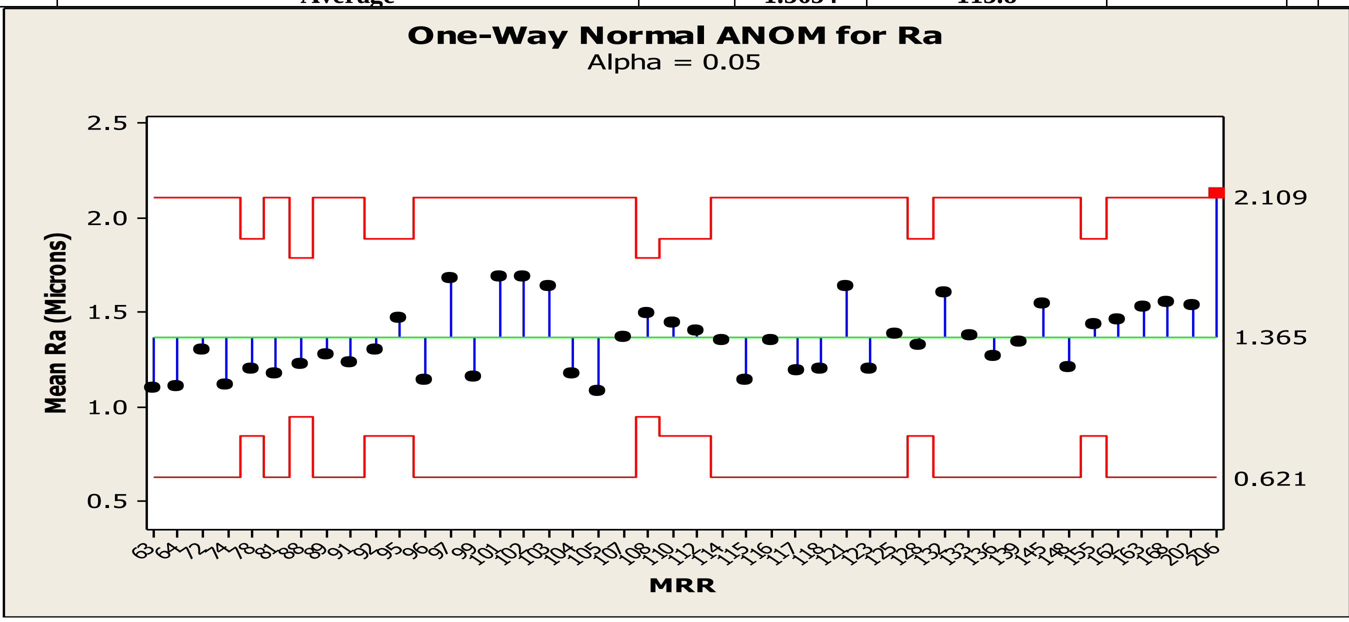


Fig 4: One way normal ANOM for Ra within limit

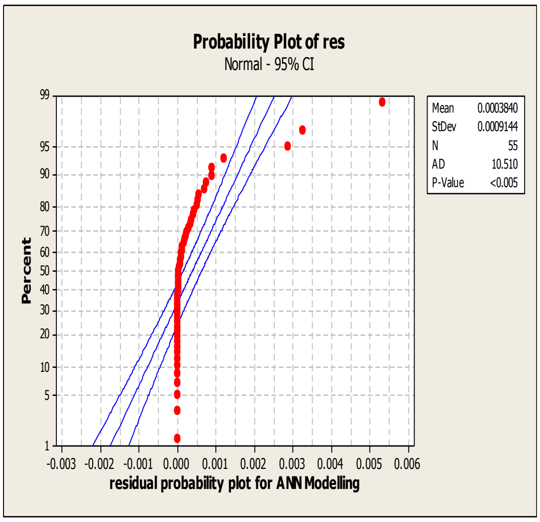


Fig 5: Probability plot for residuals

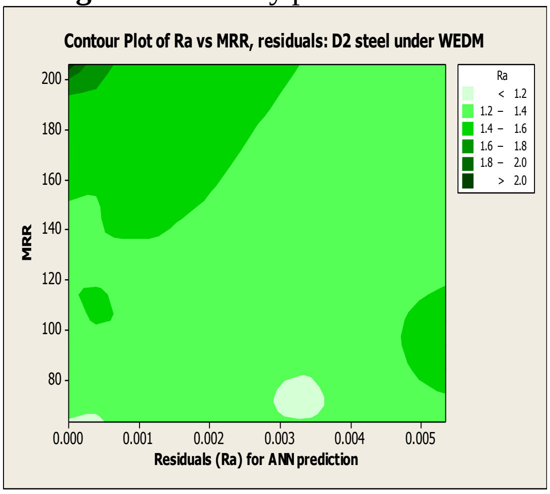


Fig 6: Contour plot for ANN prediction

4. Data Analysis

4.1. Analysis of Variance (ANOVA)

The Analysis of Variance helps to identify the significant and non significant parameters affecting the performance and can be used to control the process variation. Before ANOVA analysis the assumptions made for the analysis can be verified by Anderson (AD) statistics. The normal probability plot of residuals for surface roughness and p-value are shown in the Figure2. Normal probability plot is nothing but a graph of the cumulative distribution of the residuals on the graph paper with the scaled ordinate so that a straight line can be obtained for the cumulative normal distribution. The p value (0.294) is higher than α –level of confidence (0.05), hence it can be concluded that the residual error is normally distributed. This shows that the error normality has been proved, so the ANOVA analysis can be performed and the conclusions made on the basis of its table will be correct.

The ANOVA Table3 shows the effect of individual parameters and Fisher test values for surface roughness of AISI D2 tool steel. Here D.F. is the degree of freedom, SS is the sum of square, V is the variance, F is the Fisher value and % P is the percentage of contribution. Based on ANOVA calculations and P values it is observed that, the parameter Ton (77.58 % contribution) is most significant, Ip (11.72 % contribution) and Sv (9.48% contribution) are significant and Toff(1.32% contribution) is less significant on performance measured.

5. Regression Mathematical Model

Multiple regression (MLR) models are suitable to formulate the complicated problems with many dependant variables and independent variables within certain range. It gives the relationship between independent variables and response. In this paper the simple regression analysis is carried out to estimate the surface roughness as Response. The mathematical model suggested is as given in Equation 1.

Exptl. SR= 1.1124
ANN Predicted. SR= 1.005

$$SR= -7.79261+ 0.08448* Ton - 0.00212* Toff - 0.00797 * Sv +$$

6. Confirmation Experiment

The results obtained by Taguchi's design of experiments analysis are to be validated by conducting the confirmation experiments. The experiments were conducted as per the optimized levels of machining parameters. The last step in the process is to Equation (1) verified the improvement in performance characteristics. This is done by comparing the predicted values and the experimental results obtained with optimum parameters. The predicted S/N ratio of machining parameters at optimum level can be calculated by Equation (2)

$$\eta opt = \eta m + \Sigma k$$

$$j=1 \; (\eta j - \eta m)(4)$$

Where: η opt The predicted optimal S/N ratio , η m -Total mean of the S/N ratios, ηj Mean S/N ratio at the optimal levels and k -Number of main design parameters.

Based on ANOVA and S/N ratio calculations, it is observed that the parameters Ton is the most significant factor (77.78 % contribution), IP and SV are significant factors (11.70 % & 9.18% contribution respectively) whereas T_{off} is the least significant factor (1.32% contribution) for surface roughness. The product of pulse on time and current is known as discharge energy. With increase in Ton and Ip the discharge energy increases. This increases the surface irregularities due to the increased melting and re solidified metal. This forms the large debris on the surface which cannot be machined by wire as it moves forward and increases the roughness. So in order to compensate the higher current, its time period should be minimized and the frequency of higher density spark can be increased by keeping Ton and T_{off} values at minimum level. This helps in continuous machining and avoids the formation of debris and re solidification of molten metal. Thus, the surface quality is improved by reducing the roughness. Here, the reduced surface roughness is obtained at Ton = 1.05, T_{of} = 190 and Ip = 90.

The spark gap voltage is related to the generation of electric field in the gap. The increase in spark voltage means generation of strong electric field with the same gap. This helps to discharge the spark more easily for continuous removal of material with each discharge and thereby reduces the roughness. Since the AISID2 tool steel is tough and hard enough due to cry treatment higher values of Sv are preferred for generation of strong spark for easy machining. The minimum surface roughness is obtained at Sv=45.

7. Conclusion

In this research work the effect of pulse on time, pulse off time and spark gap are experimentally investigated in wire electro discharge machining of cryo treated AISI D 2 tool steel. The factor Pulse on time (Ton) is the most significant factor and Spark gap voltage (Sv) is significant factors where as Pulse off time (Toff) is the least significant factor in improving the surface roughness. The mathematical model developed using linear regression method and ANN confirms the suitability of model in predicting the surface roughness in WEDM of cryotreated AISI D2 tool steel. The confirmation test results and improved S/N ratio shows that the surface quality of cryotreated AISI D2 tool steel can be improved by reducing surface roughness using present statistical analysis. The proposed ANN model has successfully predicted the result which matches with the experimental values. Based on experimental results and the present analysis it can be stated that the optimum parameter combination and developed mathematical model is useful for predicting and machining hard cryotreated tool steel materials with reduced surface roughness. Thereby, it confirms the usefulness of cryotreated AISI D2 tool steel and WEDM for manufacturing dies and punches in sheet metal industries.

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