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Optimization and Prediction of Machining Responses Using Response Surface Methodology and Adaptive Neural Network by Wire Electric Discharge Machining of Alloy-X

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Abstract. Wire electric discharge machining non-contact machining process based on spark erosion technique. It can machine difficult-to-cut materials with excellent precision. In this paper Alloy-X, a nickel-based superalloy was machined at different machining parameters. Input parameters like pulse on time, pulse off time, servo voltage and wire feed were employed for the machining. Response parameters like cutting speed and surface roughness were analyzed from the L25 orthogonal experiments. It was noted that the pulse on time and servo voltage were the most influential parameters. Both cutting speed and surface roughness increased on increase in pulse on time and decrease in servo voltage. Grey relation analysis was performed to get the optimal parametric setting. Response surface method and artificial neural network predictors were used in the prediction of cutting speed and surface roughness. It was found that among the two predictors artificial neural network was accurate than response surface method.

Introduction

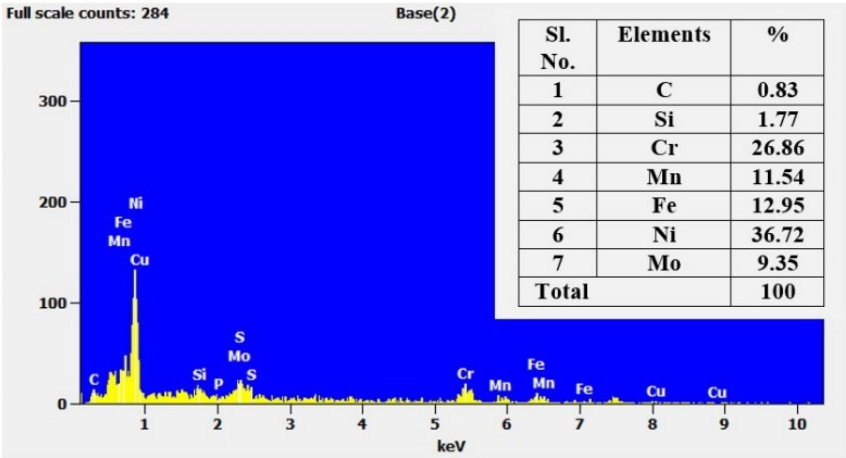
Nickel-based superalloys are having excellent mechanical properties such as fatigue strength, high strength, high thermal resistance, and high corrosion resistance with thermal stability. Such alloys not only have a vast application but also poses a challenge to manufacturers during machining or processing [1-3]. Non-conventional machining techniques are majorly preferred for machining of such alloys, where wire electric discharge machining gives an assuring solution in terms of surface integrity and precision [4-7]. The required response characteristics can be achieved by parametric study and optimization of machining parameters in such processes. Many researchers have carried out different optimization of cutting speed and surface roughness as follows. Manoj et al. [8-10] have investigated the effects of cutting speed on the material that was machined at different angles. Huang et al. [11] have employed regression models and signal-to-noise ratio for getting optimized material removal rate and surface roughness at different conditions to balance cutting efficiency and surface finish. Manjaiah et al. [12] have made a tradeoff in material removal rate and surface roughness using Taguchi based utility approach. It was observed that the pulse on time and servo voltage are the most dominant parameters affecting material removal rate and surface roughness. Dey and Pandey [13] have given a hybrid approach called Grey-Response Surface Methodology (GRSM) for optimization. Improvement was observed in cutting speed (3.234%), kerf width (2.7415%) and surface roughness (7.053%) during machining at optimal parameters. Kumar et al. [14] used response surface methodology coupled with grey relation analysis for optimizing the responses variables material removal rate (MRR), surface roughness and Kerf width. Kavimani et al. [15] have performed multi-response optimization material removal rate and surface roughness based on Taguchi-grey relation analysis. A trade-off between material removal rate and surface roughness was successfully made by utilizing Taguchi-grey relation analysis. Durairajet al. [16] have optimized cutting to attain the minimum kerf width and the best surface quality simultaneously and separately using grey relational theory and Taguchi optimization. Saha and Mondal [17] have employed a novel hybrid approach combining grey relational analysis for optimizing performance characteristics like material removal rate, machining time and surface roughness. It was found that the discharge pulse time a most important parameter for both brass and zinc-coated brass wires. Azhiri et al. [18] utilized a grey relational analysis has been used to maximize cutting velocity and minimize surface roughness. Among the parameters pulse on time and current were found the effect on cutting velocity and surface roughness. Shivade and Shinde [19] performed grey relation analysis during WEDM of during intricate machining of D3 tool steel. Influence of pulse-on time, pulse-off time, peak current and wire-speed on material removal rate, dimensional deviation, gap current and machining time was analyzed. Raj and Prabhu [20] made use of grey relation coupled with principle component analysis. Simultaneous maximization of material removal rate and minimization of surface roughness was attempted in machining titanium alloy using molybdenum wire. Chiang and chang [21] have used grey relation analysis for optimizing the response parameter where the cutting removal rate was accelerated from 7.504 to 15.201 mm^2/min and maximum surface roughness is greatly reduced from 3.214 to 2.051 μm. Chakraborty, Bose [22] have improved the accuracy of machining curve profile in WEDM process by selecting optimized parameters by entropy-based grey relation analysis.

Abhilash and Chakradhar [23] have used 31 experiments based on the central composite design for analyzing parametric behaviour and wire breakage instances are documented as a response. It was found that with the aid of response surface methodology, there were 96.7% accurate in wire breakage predictions. Singh and Misra [24] have explored box-behnken design technique with response surface methodology and artificial neural network (ANN) in the prediction of surface roughness. It was found that ANN predicted results are 99% in agreement with the experimental results. Manoj et al. [25] analyzed the effect of the machining parameters on profile areas and ANN prediction of profile areas at different angles for various parameters. Yusoff et al. [26] explored cascade forward back-propagation neural network (CFNN) and it was found to be the best network type among the selected data set having 5.16% error. Nain et al. [27] explore two methods for prediction of surface roughness and waviness. BP-ANN method reveals insignificant result over the fuzzy logic method for the evaluation of the WEDM of aeronautic superalloy. Phate and Toney [28] formulated a model in dimensional analysis and artificial neural network for material removal rate and surface roughness. It was found that artificial neural network predictor was superior that dimensional analysis predictor. Shandilya et al. [29] have also performed the prediction using ANN models and RSM mathematical models of average cutting speed. It was found ANN was accurate than RSM models for prediction. Conde et al. [30] employed a new type of Artificial Neural Network (ANN) configuration for prediction of radius to understand the variations inaccuracy during WEDM. Diaz et al. [31] have formulated a mathematical model using Artificial Neural Network for relating process parameters and operating parameters WEDM.

From the above literature, it was comprehended that the behaviour of cutting speed and surface roughness has to be optimized for maintaining the quality of the component. Grey relation analysis method can be used for optimization. Different predictors are used for forecasting the response parameters and this also reduces the experimental trials. In the present investigation different WEDM parameters like pulse on time, pulse off time, servo voltage and wire feed were employed in the machining of alloy-X. It is observed form L25 orthogonal taguchi experiments and ANOVA that pulse off time and wire-speed were insignificant on cutting speed and surface roughness whereas the pulse on time and servo voltage were the significant factors. As the pulse on time increased, the cutting speed and surface roughness also increased. Both response parameters showed contrasting behaviour to pulse on time, in the case of servo voltage. As the servo voltage increased both cutting speed and surface roughness decreased. The RSM and ANN predictors were used for the prediction of response parameters. It was observed that the ANN predictor is the most accurate compared response surface methodology predictor.

Material

Hastelloy X is also known as Alloy-X and it possesses exceptional strength and oxidation resistance up to 2200°F. It can be used in aircraft parts such as nozzles, jet engine tailpipes, furnace, afterburners, and cabin heaters etc. It was solution heat-treated at 2150°F (1177°C) and rapidly cooled [32]. Fig.1 shows the EDX of the material used for machining in WEDM.



Sl. No.	Elements	%
1	C	0.83
2	Si	1.77
3	Cr	26.86
4	Mn	11.54
5	Fe	12.95
6	Ni	36.72
7	Mo	9.35
Total		100

Fig. 1 EDS of Alloy-X

Experimental Procedure

The material was initially machined into 260x25x10 mm and fixed on the WEDM table as shown in fig.2 (a). The Alloy-X acts as workpiece material and zinc-coated copper wire acts as an electrode. This electrode is maintained in a small gap to the workpiece. This gap is always engulfed with the dielectric fluid circulated from the WEDM tank. Both workpiece and electrode were maintained at a very high potential which induces ionization and release of spark. This spark melts the material. The melted material cools down and would be carried out as debris by the dielectric fluid. The fig.2 (b) shows the machined alloy at different machining parameters.

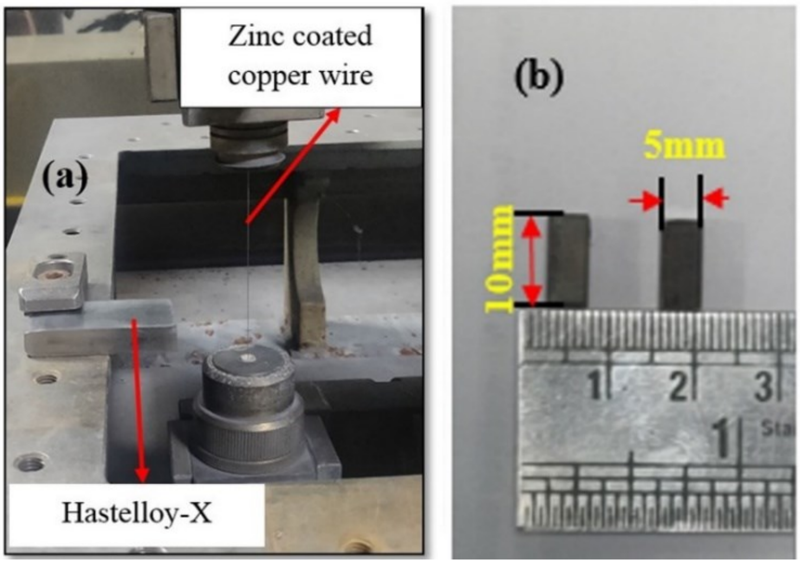


Fig. 2 (a) Alloy-X fixed in WEDM table (b) Machined Piece

Machining Parameters

The parameters of WEDM were chosen based on the preliminary experiments carried on the wire-workpiece material combination. It can be seen in table 1 all the machining parameters that were employed in the study. The pulse on time, pulse off time, wire feed and servo feed parameters were chosen for investigation in machining. These parameters were taken in 5 levels as shown in table 2. L25 orthogonal array was utilized and responses were recorded in the study.

Table 1 Machining parameters

Wire diameter (μm)	250
Wire Material	Zinc coated copper wire
Dielectric Fluid	Deionized water
Polarity	Positive
Peak Current (A)	12
Pulse on time (μs)	105,110,115,120,125
Servo voltage (V)	20,35,50,65, 80
Wire feed (m/min)	4,5,6,7,8
Servo feed (mm/min)	20
Pulse off time (μs)	28, 36, 44,52,60
Wire guide distance (mm)	60

Table 2 Parameters used in WEDM

Parameter	Unit	Level 1	Level 2	Level 3	Level 4	Level 5
Pulse-on time (t_{on}) (A)	μ sec	105	110	115	120	125
Pulse-off time (t_{off}) (B)	μ sec	28	36	44	52	60
Servo voltage (SV) (C)	V	20	35	50	65	80
Wire feed (WF) (D)	m/min	4	5	6	7	8

Results and Discussion

The surface roughness and cutting speed of 25 iterations were recorded as shown in table 3. The cutting speed was calculated from the instantaneous machining speed noted from WEDM machine. The surface roughness was an average of 5 surface roughness values from the 'Mitutoyo SJ-301' surface roughness tester. The 120 (Ton), 44(Toff), 20(SV), 7(WF) gave the highest response of 1.79 mm/min cutting speed and 3.58 µm surface roughness. To get optimal speed, the grey relation analysis was carried out as shown in table 2 which gave optimal parameters as (A1, B3, C4, D4) pulse on time 105 µ sec, pulse off time 52 µ sec, servo voltage 65 V, wire feed 7 m/min.

Table 3 L25 orthogonal array with response parameters with response data

Sl. No	T_{on}	T_{off}	SV	WF	SR (µm)	CS (mm/min)	GRE Grades	Rank
1	105	28	20	4	2.06	1.14	0.489045494	20
2	105	36	35	5	1.70	1.00	0.482835214	22
3	105	44	50	6	1.11	0.49	0.562769118	10
4	**105**	**52**	**65**	**7**	**0.93**	**0.17**	**0.690806517**	**1**
5	105	60	80	8	0.75	0.31	0.61352657	5
6	110	28	35	6	1.71	1.02	0.480415887	24
7	110	36	50	7	1.37	0.67	0.526713632	13
8	110	44	65	8	1.20	0.36	0.612696794	6
9	110	52	80	4	1.10	0.20	0.681643132	3
10	110	60	20	5	1.90	1.14	0.476583783	25
11	115	28	50	8	1.99	1.10	0.488865589	21
12	115	36	65	4	1.14	0.43	0.583960786	9
13	115	44	80	5	1.11	0.24	0.661385294	4
14	115	52	20	6	2.14	1.25	0.481988073	23

15	115	60	35	7	1.64	0.92	0.4920343	18
16	120	28	65	5	2.04	0.88	0.527586698	12
17	120	36	80	6	1.30	0.39	0.606273172	7
18	**120**	**44**	**20**	**7**	**3.58**	**1.79**	**0.68389662**	**2**
19	120	52	35	8	2.80	2.04	0.489592902	19
20	120	60	50	4	2.14	1.09	0.502631795	16
21	125	28	80	7	1.50	0.65	0.538795682	11
22	125	36	20	8	3.30	2.05	0.584070796	8
23	125	44	35	4	2.72	1.77	0.496359752	17
24	125	52	50	5	1.99	1.17	0.515656415	15
25	125	60	65	6	2.76	0.91	0.51831555	14

ANOVA and Main effects plot. The fig.3 and Table 4 shows the main effects of plots and ANOVA for the response parameters. It can be observed that pulse off time and wire feed have minimum influence on cutting speed and surface roughness. In the case of pulse on time, it can be noticed from the effects plot that as it increases the cutting speed also increases. This increase was due to an increase in the sparks at the wire and workpiece interface. This leads to an increased generation of discharge energy at the interface. This increases the melting rate of the workpiece material in turn increasing the cutting speed. In the case of surface roughness due to higher discharge, there are deeper and larger craters on the area exposed to the spark as observed in litrature [33, 34]. This increases the surface roughness of the machined surface.

In the case of servo voltage, as it increases the gap between work material and wire electrode also increases. This results in low ionization of dielectric medium which leads to decrease in the discharge energy. Therefore the cutting speed decreases as the servo voltage increases. At higher servo voltage, the ionization of the dielectric medium decreases leading to weaker sparking due which shallow and smaller craters were formed on surface. This phenomenon decreases the surface roughness of the machined surface [33, 34]. From the regression analysis, the equations for the surface roughness and cutting speed were formulated as shown in eq. 1 and eq. 2.

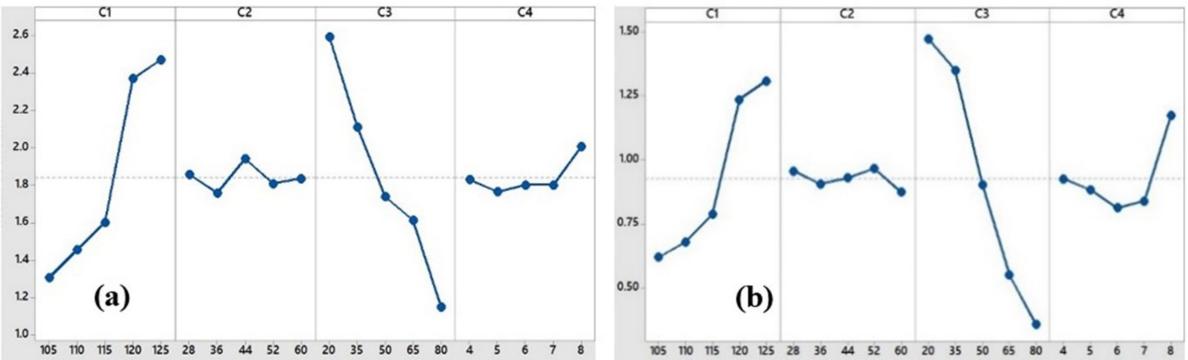


Fig. 3 Main effects plot of **(a)** surface roughness **(b)** cutting speed

Table 4 Analysis of variance

Sl. No.	Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Surface roughness							
1	Regression Model	4	11.408	2.852	21.05	0.001	Significant
2	Pulse-on time (Ton)	1	5.392	5.392	39.81	0.001	Significant
3	Pulse-off time (Toff)	1	0.0003	0.00029	0.28	0.964	Insignificant
4	Servo voltage (SV)	1	5.876	5.876	43.38	0.001	Significant
5	Wire feed (WF)	1	0.139	0.139	1.03	0.322	Insignificant
6	Error	20	2.709	0.135			
7	Total	24	14.117				
Cutting Speed							
1	Regression Model	4	5.518	1.379	17.39	0.001	Significant
2	Pulse-on time (Ton)	1	0.790	0.791	9.97	0.005	Significant
3	Pulse-off time (Toff)	1	0.174	0.174	2.19	0.154	Insignificant
4	Servo voltage (SV)	1	4.472	4.472	56.37	0.001	Significant
5	Wire feed (WF)	1	0.083	0.083	1.04	0.320	Insignificant
6	Error	20	1.586	0.079			
7	Total	24	7.105				

Regression Equation for surface roughness

Surface roughness = -4.90 + 0.0657 pulse on time - 0.00030 pulse off time - 0.02285 servo voltage + 0.0528 wire feed. (1)

Regression Equation for cutting speed

Cutting Speed = -0.988 + 0.02515 pulse on time - 0.00737 pulse off time - 0.01994 servo voltage + 0.0406 wire feed. (2)

Prediction by RSM and ANN of Cutting Speed and Surface Roughness

Response surface methodology predictor. The response surface methodology can be used for mapping the relationship between the machining and response parameters. The regression equations indicate the relation between the input and output parameters. It is a collection of statistical and mathematical techniques used for designing the experiments, fitting a hypothesized (empirical) model to data obtained and determining optimum conditions. The RSM model is as follows [35]

$$L = \gamma_o + \sum_{x=1}^{k} \gamma_x m_x + \sum_{x=1}^{k} \gamma_{xx} m_x^2 + \sum_{x,y=1\, x\neq y}^{k} \gamma_{xy} m_x\, m_y + \varepsilon. \quad (3)$$

Where ε is the noise or error observed in the response L. m_x is the linear input variables, m_x^2 and $m_x m_y$are the squares and interaction terms, respectively, of these input variables. The unknown second-order regression coefficients are $\gamma_o, \gamma_x, \gamma_{xx}, \gamma_{xy}$, which should be determined in the second-order model, are obtained by the least square method.

Artificial neural network predictor. The artificial neural network is computing systems used for prediction of indefinite solutions inspired by the biological neural networks. It consists of a group of connected units or nodes called artificial neurons. It was employed for the prediction of response parameters [25]. Table 5 shows the network parameters that was employed for the prediction of response parameters. The regression plots generated during the training, validation, testing data sets is as shown in fig. 4. Table 6 and 7 show the prediction of response parameters both by RSM and ANN predictor. It can be noticed from fig. 5 and table 6, 7 that ANN predictor was more accurate than the RSM predictor. It was noticed that the RSM predictor error percentage varied from 0-22% whereas ANN predictor gave an error percentage ranging from 0-5%.

Table 5 ANN parameters

Sl. No.	Network parameters	Values
1	Network structure	4-5-1-1
2	Total number of training/validation/testing data sets	15/5/5(25 experiments)
3	Network algorithm	Feedforward backpropagation
4	Type of transfer function	Tangential sigmoid
5	Type of training function	TRAINLM
6	Learning function	LEARNGDM
7	Performance function	MSE

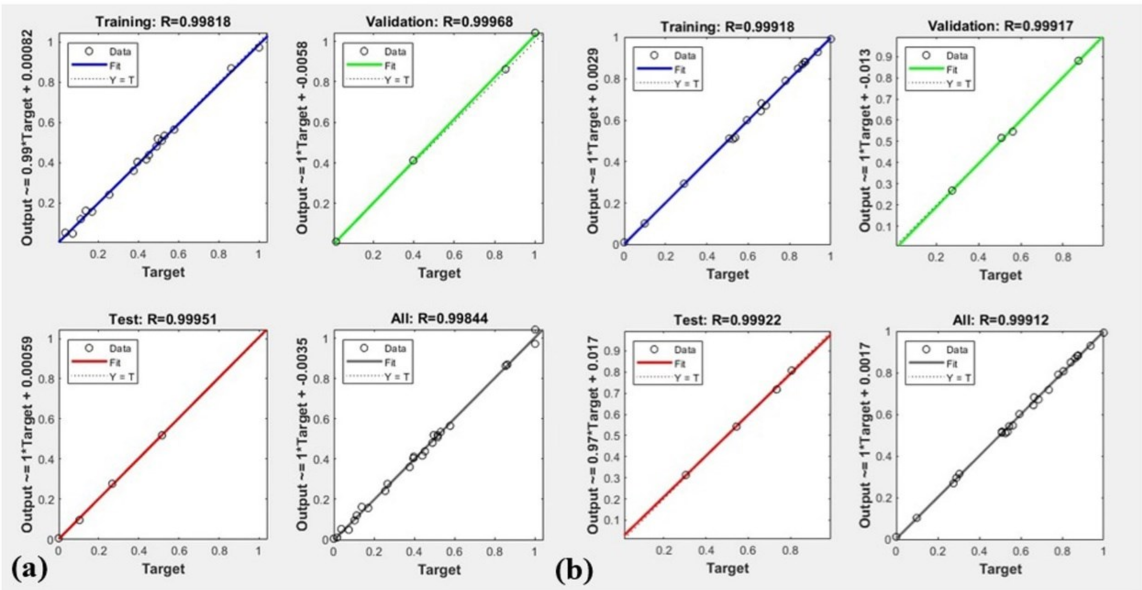


Fig. 4 Main effects plot of (a) surface roughness (b) cutting speed

Table 6 Prediction of cutting speed

Sl. No	CS (mm/min)				
	Experimental	RSM Predicted	% Error	ANN Prediction	% Error
1	1.14	1.26	10.87	1.14	0.46
2	1.00	0.91	16.36	0.95	4.28
3	0.49	0.58	2.58	0.48	2.47
4	**0.17**	0.27	0.18	**0.18**	**4.89**
5	0.31	0.10	0.56	0.31	0.89
6	1.02	0.99	11.54	0.99	2.54
7	0.67	0.69	20.36	0.69	2.62
8	0.36	0.30	13.09	0.35	4.05
9	0.20	0.10	2.83	0.20	0.94
10	1.14	0.81	9.63	1.13	1.15
11	1.10	0.98	11.17	1.14	3.82
12	0.43	0.50	15.58	0.45	3.74
13	0.24	0.26	6.07	0.22	7.82
14	1.25	1.19	3.52	1.23	1.88
15	0.92	0.90	10.16	0.94	2.85
16	0.88	0.78	10.53	0.85	3.48
17	0.39	0.34	12.04	0.40	2.89
18	1.79	1.56	7.70	1.80	0.81
19	2.04	2.14	0.02	1.99	2.49
20	1.09	0.72	19.16	1.07	1.50
21	0.65	0.35	1.15	0.62	3.97
22	2.05	1.93	17.41	2.13	3.92
23	1.77	1.45	7.78	1.79	1.03
24	1.17	1.00	15.34	1.17	0.67
25	**0.91**	**0.50**	**21.05**	0.93	1.65

Table 7 Prediction of surface roughness

Sl. No	SR (µm)				
	Experimental	RSM Predicted	% Error	ANN Prediction	% Error
1	2.06	2.16	4.85	2.12	2.80
2	1.70	1.48	12.45	1.65	2.92
3	1.11	1.04	6.28	1.09	2.00
4	0.93	0.83	10.69	0.95	2.08
5	0.75	0.85	13.92	0.77	3.01
6	1.71	1.88	9.94	1.76	2.76
7	1.37	1.39	1.45	1.34	2.03
8	1.20	1.13	5.90	1.18	1.95
9	1.10	1.01	8.18	1.08	1.62
10	1.90	1.70	10.32	1.88	1.09
11	1.99	1.80	9.20	2.03	2.20
12	1.14	1.28	12.70	1.12	1.79
13	1.11	1.15	3.73	1.09	1.85
14	2.14	2.30	7.48	2.12	1.07
15	**1.64**	**2.01**	**22.50**	1.68	2.41
16	2.04	1.55	9.55	2.05	0.26
17	1.30	1.36	4.62	1.30	0.34
18	3.58	2.97	17.04	3.55	0.92
19	2.80	2.63	6.07	2.82	0.71
20	2.14	1.97	7.90	2.13	0.45
21	1.50	1.63	9.19	**1.55**	**3.18**
22	3.30	3.71	12.42	3.29	0.32
23	2.72	2.65	2.57	2.69	1.01
24	2.09	2.43	16.27	2.14	2.29
25	2.76	2.45	11.23	2.75	0.50

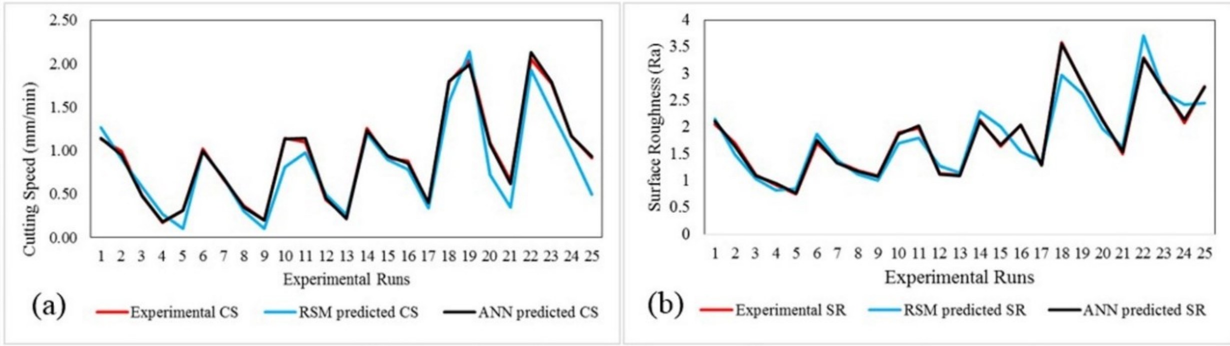


Fig. 5 Prediction plot of (a) surface roughness (b) cutting speed

Conclusion

From the above study, Alloy-X was machined at different machining parameters using zinc-coated copper wire from WEDM. The 120 (Ton), 44(Toff), 20(SV), 7(WF) gave the highest response of 1.79 mm/min cutting speed and 3.58 µm surface roughness. Grey relation analysis was performed and the optimal setting was calculated to be A1, B3, C4, D4. The pulse on time and servo voltage were major influential parameters on the cutting speed and surface roughness. It was observed as the response parameters increased when the pulse on time was increased and servo voltage was decreased. The ANN predictor was more efficient than the RSM predictor as the errors varied between 0-5 per cent.

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