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Productivity and Quality enhancement in Powder Mixed Electrical Discharge Machining for OHNS die steel by utilization of ANN and RSM modeling

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Abstract: *Oil hardened steel are used as die material and also as tool steel owing to its high hardness. Machining hardened steel is a tedious task due to the difficulty in product complex profiles according to applications. For machining hardened material, non-traditional machining process is employed, which is suitable for producing the required shape on the material for dies. In this work, Powder Mixed Electrical Discharge Machining (PMEDM) process parameters is optimized during machining oil hardened steel material. To improve machinability, aluminum powders were added to the electrolyte. The input factors considered were, pulse ON-time, pulse OFF-time, current and percentage concentration of aluminum powders in electrolyte. Response surface methodology (RSM) and Artificial Neural Network (ANN) approach is considered for designing the experiments, optimization and modeling of output responses such as Surface Roughness (SR) and Material Removal Rate (MRR). ANOVA exposed that, powder concentration in the electrolyte is the most significant parameter towards the output responses. Higher material removal is sensed with lower surface roughness for higher concentration of aluminum powder. Prediction of outputs is carried out with the developed model with adequate precision values. The desirability value for ANN model is 0.908 which is higher than the desirability of RSM model which is 0.87. Hence it is advisable to use ANN model for prediction than RSM model.The most feasible combination of parameters was identified as Pon=641.44 µs, Poff=55.13 µs , I=7 µs and Cp=1% for multicriterion objective.*

Keywords: Powder Mixed Electrical Discharge Machining (PMEDM), Material Removal Rate (MRR), Surface Roughness (SR), Response Surface Methodology (RSM), Artificial Neural Network (ANN), Powder Concentration.

1. OVERVIEW

Manufacturing Industries face major issues in machining die steels due to its inherent property of being harder at situation where tools are used at higher speed even though having a great machinability. Advanced machining processes have been adopted to overcome the issues but at higher cost. Manufacturers strive hard to produce components at lower cost and of esteem quality as they have a direct impact over the profit earned by the firm. Hence, the productivity can be improved by increasing the material removal rate (or) by reducing the machining time of the product. The surface roughness was encountered to be much higher in EDM [31]. The surface quality can be improved by exercising better control over the machining parameters. The MRR was increased with reduced TWR was due to formation of large sparks due to increased electrical conductivity [20]. Cracks and craters of large sizes were formed in machining different materials with Electrical discharge machining process [2, 3]. Powder mixed Electrical discharge machining process can be used in machining harder to machine materials for reducing the cracks and craters on the machined surface [1]. Powder Mixed Electrical discharge machining is a development of EDM which involves enhancing the material removal rate, Surface Roughness and Tool Wear Rate by inclusion of conductive powders that result in earlier breakdown of dielectric fluid [2]. Addition of conductive powders such as copper [2], aluminium [1-3] of various sizes, chromium [4], Silicon carbide [11], CNT [20], Manganese [25], boron carbide [26], Graphene Nano powder [27], Graphite [30] etc,. to the dielectric fluid shall increase the MRR with reduced SR. The material removal rate can be improved by 1% to 33% when powder is mixed with dielectric fluid without compromising on the quality [8]. An increase in MRR due to non-uniform heat dissipation was identified resulting in dissipation of superfluous residual heat [14].

The mixing of Al powders of appropriate proportion to enhance the responses [9]. Inclusion of aluminium powder in specified quantity to the dielectric fluid showed better enhancement of MRR and SR in machining aluminium composite with copper electrode [3]. The material removal rate increased with reduced surface roughness when nano powders where used in Electrical discharge

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machining process [8]. Addition of nano aluminium powders improved the surface quality of the titanium alloy for biomedical applications with the formation of carbon enriched surface facilitating osseointegration [1]. The micro crack formation was reduced by adding CNT with improve stability in machining [20]. Mixing of chromium to the dielectric fluid produces chromium rich machined surface [17].

The surface Roughness shall be improved by controlling the powder concentration [26]. A mirror finish of components can be achieved by proper identification of powder size and concentration depending upon the workpiece and the degree of surface finish [15]. The addition of chromium powder in appropriate size and concentration helps in reducing the surface roughness along with reduced cracks and small crater size while machining H-11 die steel [4]. Proper selection of powder concentration can yield better results. The micro hardness of the machined surface shall also by increase with the increase in powder concentration [10]. The micro hardness shall be when dielectric fluid is mixed with manganese powder while machining OHNS die steel. A maximum of 8 % of the powder can be added in relation to the volume of dielectric fluid [1]. The MRR increased with inclusion of multi walled CNT until powder concentration of 8 gm/lit [8]. The ability of the materials to transfer current effectively also increases the MRR. The SR reduced till SiC powder concentration of 4 gm/lit when machining H 11 die steel. There was a small amount of material transfer to the workpiece from the electrode while adding SiC to dielectric fluid [5].

2. METHODS AND MATERIAL

OHNS die steel, molybdenum high speed tool steels and water-hardening die steels (W-series) have been tried as work materials in PMEDM only for few times [19]. The former researches have been concentrated on improving the micro hardness of the OHNS die steel by mixing manganese with dielectric fluid [25,29]. The micro hardness of OHNS die steel was improved by 73 %, when suspending manganese to the dielectric powder [25]. The MRR and SR have been analyzed with Cu-CrB2 compact electrodes [27]. Hence, OHNS is machined with PMEDM in the following research work to improve the surface integrity which is important in measurement instruments such as GO and NO GO gauges. The Chemical composition of the OHNS steel is shown in table 1. Kerosene is used as the dielectric fluid as it has improved the material removal rate up to 60 % when mixed with abrasive powders. The addition of Aluminium powders to the dielectric fluid improved the surface quality than copper powder and without additives. Kerosene is the by far best suitable dielectric fluid suitable for PMEDM process due to its excellent flushing capability and viscosity [12]. Aluminium powder of 44 microns was added to the dielectric fluid in an attempt to improve the MRR and reduce the SR in comparison with EDM [1].

Table 1. Chemical Composition of OHNS.

C	Mn	Cr	W	V
0.95	1.15	0.5	0.5	0.2

Table 2. Distinguished levels of parameters

Parameter/Levels	I	II	III
Pulse ON time (µs)	500	600	700
Pulse OFF time (µs)	40	50	60
Current (Ampere)	5	6	7
Powder Concentration (%)	0	0.5	1

(a)

(b)

Figure 1. (a) SPARKNOIX S 50 Model, (b) Machined Specimen

3. EXPERIMENTATION

Oil Hardened Steel (OHNS) is machined using the copper electrode of 12 mm diameter by varying the parameters such as Pulse ON time, Pulse OFF time and Current with three distinguished levels for each parameter. Totally, 81 experiments were carried out with varying powder concentrations of 0, 0.5 and 1 gm/lit. 27 experiments for each level of powder concentration were conducted. The input parameters and the levels are given in table 2. The results were recorded with the help of SPARKONIX S 50 model machine as shown in figure 1(a). The surface roughness was measured using TR100 surface roughness tester. The weights of the workpiece before and after machining were notes and the MRR was found with the following formulae. The pump is used to make sure that the powders do not settle at the foot of the container. Improper distribution of powder density results in decrement of MRR and increased SR [4]. The table 3 shows the investigational results. The machined sample is shown in figure 1 (b).

$$Material\ Removal\ Rate\ (MRR) = \frac{Weight\ before\ Machining - Weight\ after\ Machining}{Machining\ time} \quad (1)$$

4. OUTCOME ANALYSIS

Analysis of critical controlling parameters is essential for better process planning for any operation.Different methods have been adopted for identification of critical parameters, analyze and predict the suitable parameters such as Response surface Methodology, Taguchi methods, Utility concept [4-6,13]. Surface Roughness and Material Removal rate of the machined specimen can be predicted using Response Surface Methodology and Artificial Neural Network [18]. Response Surface Methodology is used for modeling and to understand the effect of input parameters over the response [3, 13, 18]. Two different models to predict the MRR, TWR and

SR was developed and the compatibility of those models were analyzed [4].

The impact of the input parameters over MRR is shown in (a) to (f) of figure 2. The material removal rate has been found to increase with increase in current after 5 amperes and dies down before it. The MRR has a very minor change with increase in Pulse ON time. The MRR has decreased with increase in pulse OFF time till 50 µs and increases slightly thereafter. With reference to the powder concentration the material removal has reduced upto 0.5 % and tends to increase exponentially thereafter. The powder concentration is the most substantial parameter that has a remarkable effect on MRR followed by current, Pulse ON time and Pulse OFF time.

Identification of most contributing parameter is accomplished by ANOVA analysis [7,32,33].The material Removal rate is expected to be at its peak for achieving greater production rates. The ANOVA analysis for MRR is shown in table 4. The model is feasible for determining the MRR since the P<-0.0001. The most contributing parameter is powder concentration which has a P<0.0001[2,6]. The Adequate precision value is 17.797 which proves that the developed empirical model is suitable for forecasting of MRR. The R-squared and Adjusted R squared values are noted as 0.931034 and 0.916623. The F value for the suggested 2nd order differential model is 64.6044.

$$\begin{aligned}&\textit{Material Removal Rate(MRR)}=(+1.60515E\text{-}003*A)+\\&(4.80404E\text{-}003*B)-(0.10893*C)+(0.025129*D)+\\&(1.65387E\text{-}006*A*B)+(2.24114E\text{-}005)*A*C)-\\&(1.98373E\text{-}005*A*D)-(3.63716E\text{-}004*B*C)+\\&(5.54844E\text{-}004*B*D)-(0.017466*C*D)-(1.48459E\text{-}\\&006*(A^{\wedge}2)+(5.43376E\text{-}005*(B^{\wedge}2)+(0.011582*(C^{\wedge}2)+\\&(0.14732*(D^{\wedge}2)\end{aligned}\tag{2}$$

The impact of the input parameters is shown from (a) to (f) of figure 3. The surface roughness varied in hyperbolic fashion with respect to all input parameters. The surface roughness has decreased with respect to the powder concentration. Powder concentration has been found to be the most influential parameter in controlling the SR, followed by current, Pulse OFF time and Pulse ON time [2,6]. The developed 2nd order differential model has an F value of 38.66 and can be used for forecasting of the SR. The Adequate precision value obtained is 10.82 which prove the model substantial for the intended purpose. The most substantial parameter for SR is identified as powder concentration as such for MRR with a P value of 0.0201. The developed model has an R-squared and Adjusted R-squared value of 0.889871 and 0.866859.

$$\begin{aligned}&\textit{Surface Roughness(SR)}=(-0.000533831*A)+\\&(0.022945*B)-(0.00958685*C)-(0.15366*D)-\\&(0.0000145907*A*B)-(0.000101756*A*C)-\\&(0.000161696*A*C)-(0.00209796*B*C)+\\&(0.00449512*B*D)-(0.035059*C*D)+\\&((0.00000163221)*(A^{\wedge}2))-((0.0000412621)*(B^{\wedge}2))+\\&(0.015767*(C^{\wedge}2))+(0.1511*(D^{\wedge}2))\end{aligned}\tag{3}$$

Table 5 shows the ANOVA for SR. The deviation of the investigational values from the anticipated values for MRR and SR is shown in figure 4 and figure 5. It emphasis on the fact, that the average deviation is very negligible. The values are 0.005 % for MRR and 0.003 % for SR, which is almost zero. This justifies that; the developed models can be used to predict the responses with very minimal error.

The optimal parameters for the PMEDM machined die steel shall be identified for both rough and finish cut [27]. The selection of most feasible combination of parameters can be selected by desirability study with the help of desirability chart. The combined desirability value of 0.872 proves that prediction of the responses will be of less error, since it is very closer to 1. The desirability value of 1 for surface roughness shows that model is best for forecasting the

Table 3. Investigational Results

Trail number	Pulse ON Time (µs)	Pulse OFF Time (µs)	Current (ampere)	0%		0.5%		1 %	
				Material Removal Rate (g/s)	Surface Roughness (microns)	Material Removal Rate (g/s)	Surface Roughness (microns)	Material Removal Rate (g/s)	Surface Roughness (microns)
1	500	40	5	0.092	0.48	0.074	0.25	0.194	0.25
2	500	40	6	0.099	0.48	0.098	0.23	0.207	0.23
3	500	40	7	0.131	0.35	0.134	0.49	0.258	0.28
4	500	50	5	0.088	0.48	0.073	0.33	0.152	0.55
5	500	50	6	0.100	0.3	0.093	0.37	0.256	0.32
6	500	50	7	0.127	0.38	0.113	0.33	0.293	0.35
7	500	60	5	0.097	0.29	0.090	0.34	0.172	0.34
8	500	60	6	0.082	0.35	0.103	0.36	0.196	0.35
9	500	60	7	0.091	0.47	0.126	0.34	0.325	0.34
10	600	40	5	0.147	0.23	0.100	0.29	0.148	0.28
11	600	40	6	0.121	0.47	0.092	0.25	0.287	0.25
12	600	40	7	0.157	0.48	0.263	0.39	0.398	0.39
13	600	50	5	0.095	0.34	0.075	0.33	0.140	0.32
14	600	50	6	0.107	0.39	0.118	0.34	0.214	0.33
15	600	50	7	0.135	0.47	0.140	0.26	0.388	0.26
16	600	60	5	0.092	0.44	0.106	0.43	0.237	0.42
17	600	60	6	0.120	0.35	0.112	0.27	0.244	0.27
18	600	60	7	0.154	0.46	0.163	0.24	0.287	0.24
19	700	40	5	0.092	0.49	0.090	0.36	0.177	0.36
20	700	40	6	0.097	0.47	0.085	0.37	0.141	0.33
21	700	40	7	0.123	0.45	0.158	0.32	0.291	0.31
22	700	50	5	0.079	0.46	0.101	0.33	0.239	0.33
23	700	50	6	0.101	0.35	0.106	0.35	0.214	0.27
24	700	50	7	0.127	0.49	0.155	0.27	0.401	0.26
25	700	60	5	0.093	0.39	0.101	0.26	0.239	0.37
26	700	60	6	0.087	0.44	0.100	0.37	0.196	0.34
27	700	60	7	0.143	0.23	0.140	0.34	0.375	0.34

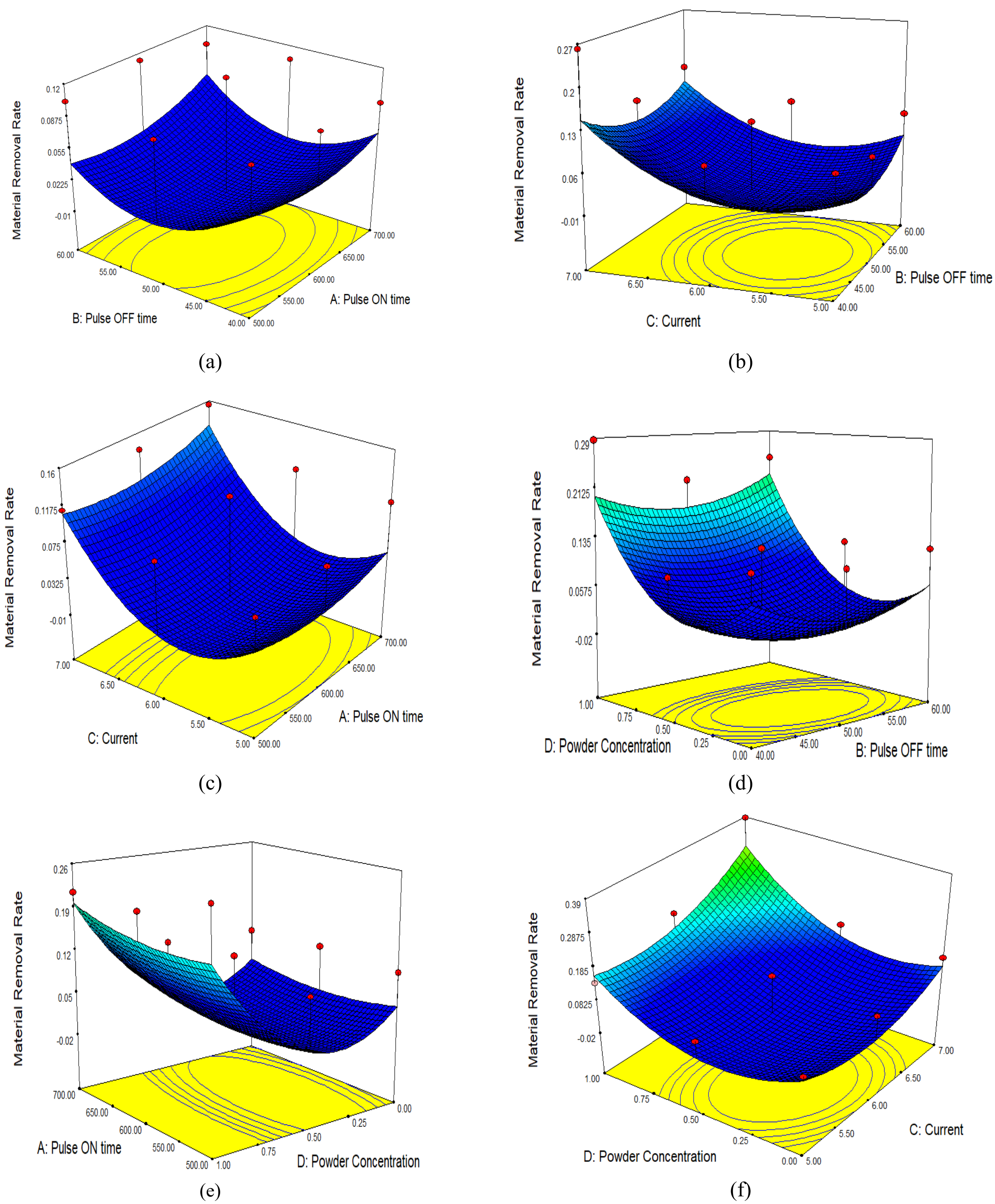

Figure 2. Effect of input parameters over Material Removal Rate

SR where as it is 0.760 for MRR. The desirability chart is shown in figure 6. The optimized results and the predicted response values are shown in figure 7 with the ramp chart.

Table 6 indicates the ideal combination of the considerations for best possible production rate and quality. RSM is used for drawing the combined ideal parametric conditions to obtain the best possible production rate and quality [3]. The confirmation experiment was conducted and the responses were found to be in harmony with the anticipated values. The anticipated MRR and SR were recorded as 0.322714 and 0.2299.

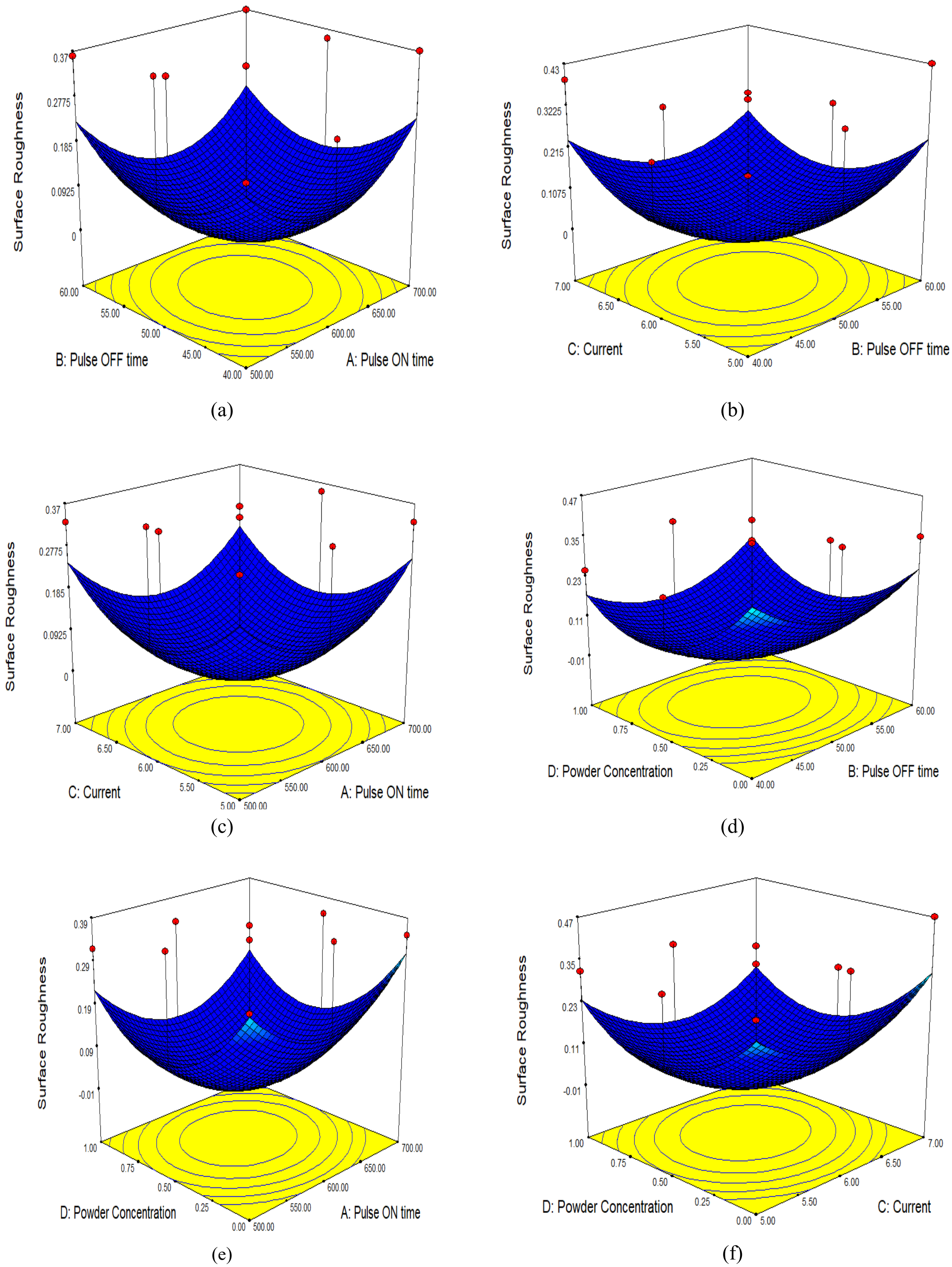

Figure 3. Effect of input parameters on Surface Roughness

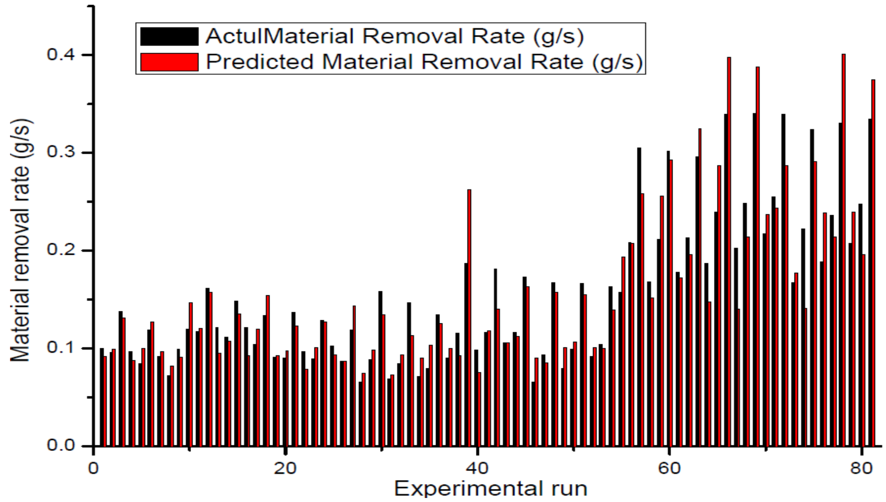

Figure 4. Actual (vs) Anticipated Material Removal Rate

Table 4. ANOVA of MRR

Source	Sum of Squares	Degree of Freedom	Mean Square	F value	P value	Status
Model	2.371348	14	0.169382	64.60644	< 0.0001	Significant
A-Pulse ON time	0.002788	1	0.002788	1.063278	0.3062	
B-Pulse OFF time	5.17E-06	1	5.17E-06	0.001973	0.9647	
C-Current	0.090869	1	0.090869	34.6595	< 0.0001	
D-Powder Concentration	0.252278	1	0.252278	96.22488	< 0.0001	
AB	1.41E-03	1	1.41E-03	0.536712	0.4664	
AC	0.000491	1	0.000491	0.187468	0.6664	
AD	9.50E-04	1	9.50E-04	0.362222	0.5493	
BC	0.001379	1	0.001379	0.525973	0.4708	
BD	0.002007	1	0.002007	0.765688	0.3847	
CD	0.028052	1	0.028052	10.69959	0.0017	
A^2	0.005541	1	0.005541	2.113345	0.1507	
B^2	0.033986	1	0.033986	12.96306	0.0006	
C^2	0.093139	1	0.093139	35.52557	< 0.0001	
D^2	0.233616	1	0.233616	89.10687	< 0.0001	
Residual	0.175657	67	0.002622			
Total	2.547005	81				

Std. Dev.	0.051203	R-Squared	0.931034
Mean	0.157488	Adj R-Squared	0.916623
C.V. %	32.51236	Pred R-Squared	0.904439
PRESS	0.243396	Adeq Precision	17.797

Table 5. ANOVA for Surface Roughness

Source	Sum of Squares	Degree of Freedom	Mean Square	F value	P value	Status
Model	9.351391	14	0.667957	38.66997	< 0.0001	Significant
A-Pulse ON time	7.41E-06	1	7.41E-06	0.000429	0.9835	
B-Pulse OFF time	0.000417	1	0.000417	0.024122	0.8770	
C-Current	0.000817	1	0.000817	0.047279	0.8285	
D-Powder Concentration	0.097963	1	0.097963	5.671364	0.0201	
AB	7.51E-03	1	7.51E-03	0.43484	0.5119	
AC	0.0036	1	0.0036	0.208415	0.6495	
AD	2.34E-03	1	2.34E-03	0.135244	0.7142	
BC	0.015625	1	0.015625	0.904577	0.3450	
BD	0.018225	1	0.018225	1.055099	0.3080	
CD	0.011025	1	0.011025	0.63827	0.4272	
A^2	0.327794	1	0.327794	18.97696	< 0.0001	
B^2	0.224341	1	0.224341	12.98775	0.0006	
C^2	0.324741	1	0.324741	18.8002	< 0.0001	
D^2	0.4544	1	0.4544	26.30657	< 0.0001	
Residual	1.157309	67	0.017273			

Std. Dev.	0.131428	R-Squared	0.889871
Mean	0.351481	Adj R-Squared	0.866859
C.V. %	37.39252	Pred R-Squared	0.845922
PRESS	1.619156	Adeq Precision	10.82059

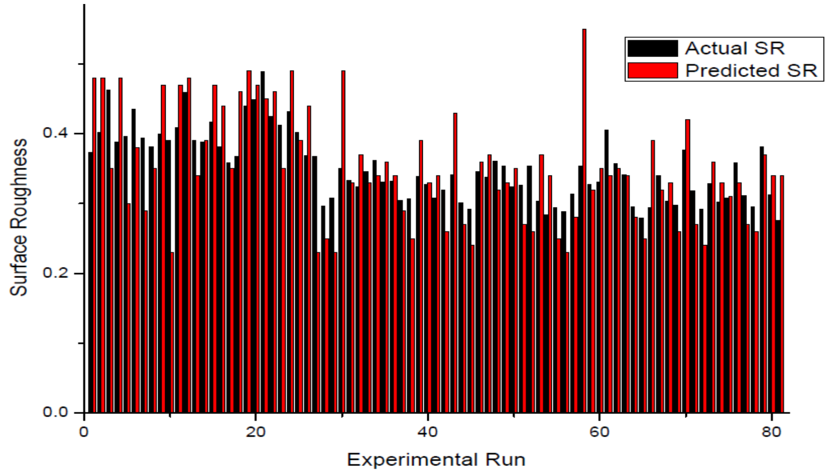

Figure 5. Actual (vs) Anticipated Material Removal Rate

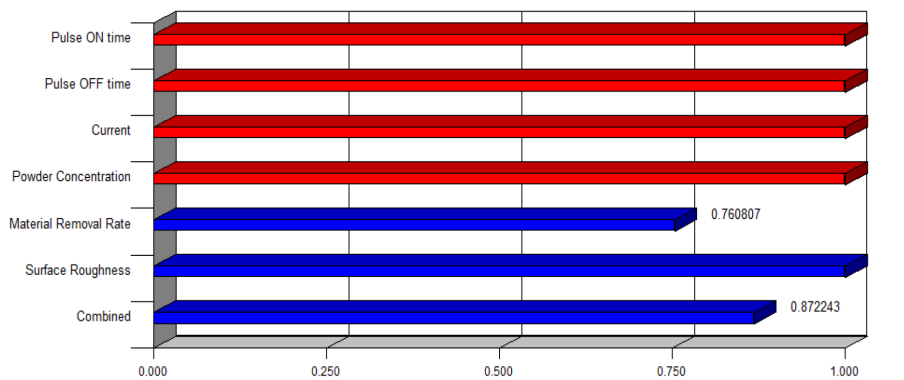

Figure 6. Desirability chart

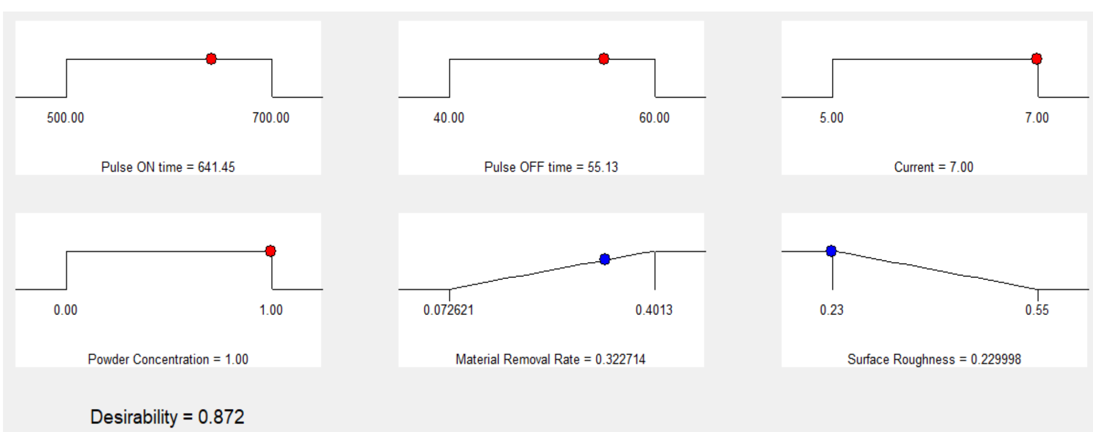

Figure 7. Ramp chart

4.1. Prediction using Artificial Neural Network

The output of any secondary manufacturing process can be predicted with the help of models economically [21]. The model has been built with 71 neurons and 16 neurons were used testing the trained neurons. The hidden layer of the model possess 10 neurons with the best learning rate of 0.02 and coefficient of moment as 0.7 to achieve the nominal R- Squared value. 20000 iterations were conducted and the change in MSE while training the ANN model under various epochs is shown in figure 8. The most compatible performance achieved at 0.0017 with very minimal MSE.

The regression models were developed and the regression coefficient of the developed model for the test, training and validation is

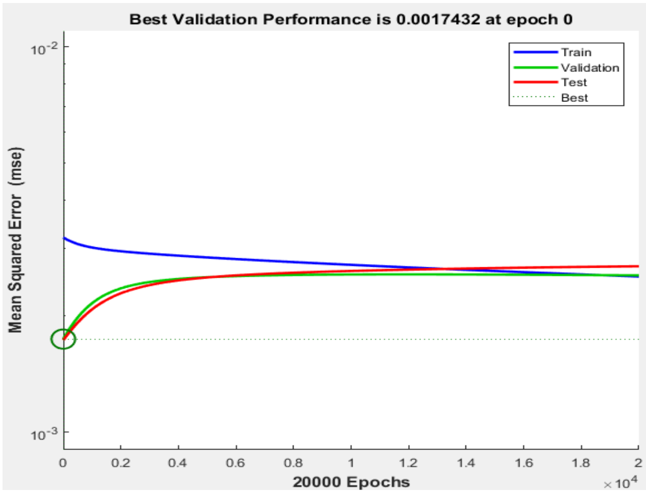

Figure 8. Mean squared error obtained during ANN training

shown in figure 9 and table 7. A gradient value of 0.00865 was encountered for 2000 epoch while validating the developed model. The gradient descent algorithm has been used to calculate the weight factor for minimizing the elapses in prediction. Figure shows the Validation and gradient vale plot.

Table 8 shows the experimental and predicted values of MRR and SR using ANN for the trained neurons for the prediction. It is evident that the ANN model is more efficient than the regression model. Hence it is advisable to use ANN model for better predictability. Figure 10 shows the gradient value and validation under training.

Figure 11 and 12 compares the predicted values using ANN and Regression model with the experimental results for both MRR and SR. It infers that there is minimal variation with the predicted and experimental values for both the models. The average error in predicting MRR and SR using ANN model is 2 % and 0.16 %.

5. CONCLUSION

The following conclusions were drawn from the above work when analyzed with Response Surface Methodology and ANN.

1. The material removal rate has improved with reduced surface roughness when powder concentration was increased while machining OHNS when mixing Al powders to dielectric powder.
2. Prediction models for both MRR and SR were developed with the assist of RSM and were found to be suitable for predicting the response with Adequate Precision value of 17.797 and 10.82059.
3. Powder concentration was identified as the most influential parameter followed by current for both MRR and SR through ANOVA.
4. The deviation from the anticipated using Regression and experimental analysis was noted to be 0.05 % for MRR and 0.03 % for SR which is almost zero.
5. The deviation from the anticipated using ANN and experimental analysis was noted to be 2 % and 0.16 %. This validates the fact that the developed models can be used for prediction of the responses.
6. The most feasible combination of parameters was identified as Pon=641.44 µs, Poff=55.13 µs , I=7 µs and Cp=1% for multicriterion objective.
7. The desirability value for ANN model is 0.908 which is higher than the desirability of RSM model which is 0.87. Hence it is advisable to use ANN model for prediction of MRR and SR than RSM model.

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Table 6. Ideal Combination

Factor	Parameters	Ideal level	Low Level	High Level
A	Pulse ON time	641.44	500	700
B	Pulse OFF time	55.13	40	60
C	Current	7	5	7
D	Powder Concentration	1	0	1

Table 7. Regression coefficients

S.no	Category	Regression coeeficient
1	Training	0.905
2	Validation	0.939
3	Test	0.928
4	All	0.908

Table 8. Comparison for experimental and predicted values using ANN and Regression Model

Trail no	Neuron Number	Experimental		ANN Predicted		Regression Predicted	
		MRR (g/sec)	SR (microns)	MRR (g/sec)	SR (microns)	MRR (g/sec)	SR (microns)
5	1	0.0999	0.3	0.1098	0.30	0.0844	0.40
10	2	0.1467	0.23	0.1417	0.21	0.1200	0.39
15	3	0.1350	0.47	0.1317	0.49	0.1484	0.42
20	4	0.0974	0.47	0.0954	0.47	0.0904	0.45
25	5	0.0934	0.39	0.0941	0.41	0.1020	0.40
30	6	0.1341	0.49	0.1291	0.48	0.1582	0.35
35	7	0.1031	0.36	0.0984	0.38	0.0792	0.33
40	8	0.0751	0.33	0.0806	0.33	0.0987	0.33
45	9	0.1632	0.24	0.1641	0.26	0.1733	0.29
50	10	0.1064	0.35	0.1089	0.35	0.0992	0.32
55	11	0.1938	0.25	0.1799	0.24	0.1573	0.29
60	12	0.2930	0.35	0.2018	0.33	0.3015	0.33
65	13	0.2867	0.25	0.1839	0.26	0.2397	0.28
70	14	0.2371	0.42	0.1805	0.43	0.2171	0.38
75	15	0.2912	0.31	0.2029	0.30	0.3244	0.31
80	16	0.1958	0.34	0.2031	0.34	0.2478	0.31

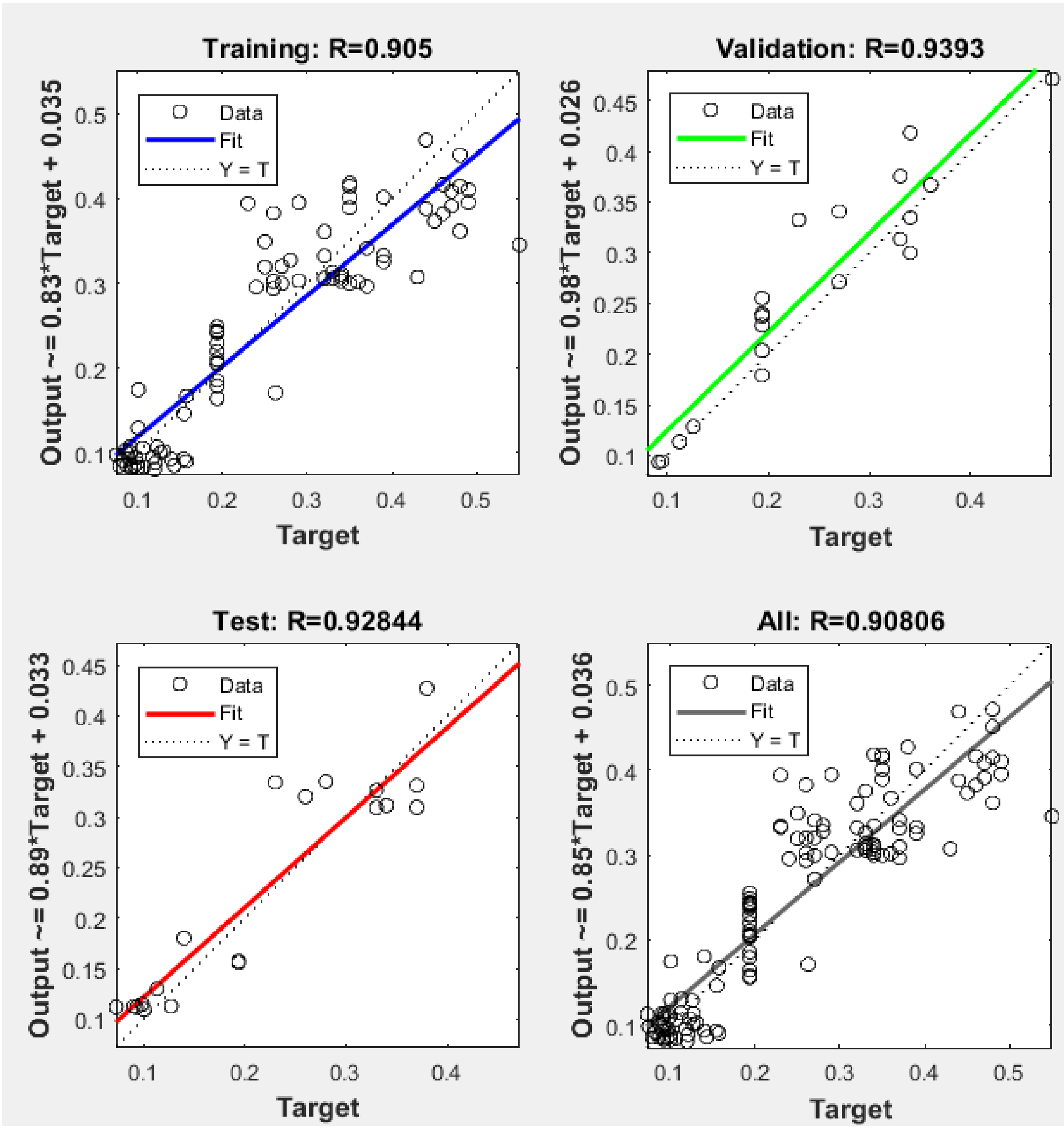

Figure 9. Plot for Regression while training

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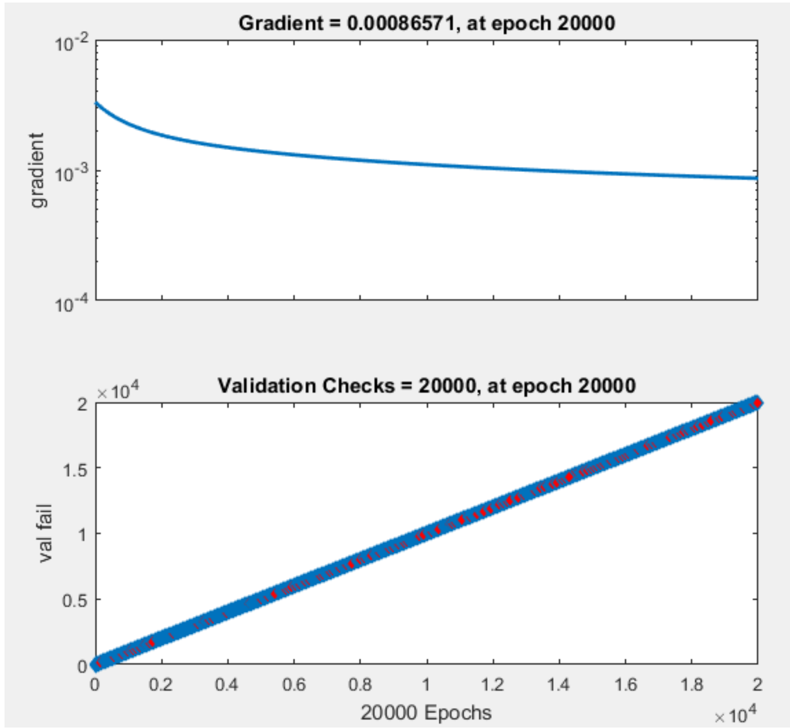

Figure 10. Gradient value and validation under training

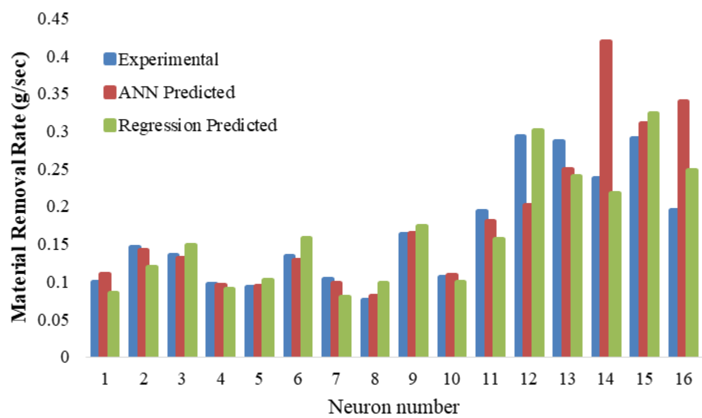

Figure 11. Experimental and predicted MRR

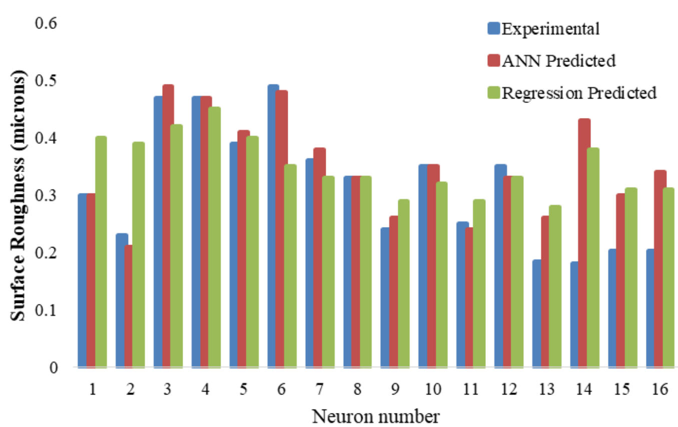

Figure 12. Experimental and predicted SR

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