Engineering and Applied Science Research July – September 2020;47(3):264-274 Research Article

EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

Modeling and critical analysis of material removal rate in WEDM of Oil Hardening Non-Shrinking Die Steel (OHNS)

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Received 5 December 2019
Revised 7 February 2020
Accepted 24 February 2020

Abstract

Wire EDM is a complicated machining process that is used for producing complex 2D and 3D shapes. In this work, the process parameters associated with the wire electrical discharge machining (WEDM) of oil hardening non-shrinkage (OHNS) die steel material were investigated through response surface method (RSM) and an artificial neural network (ANN). A quadratic model developed through RSM was used to predict material removal rate (MRR) with appreciable precision. The various input variables, viz. pulse on time (P_{ON}), pulse off time (P_{OFF}), wire feed rate (WFR) and input current (I), have been considered. A comparison between the predicted and measured values of MRR was performed for each experiment. It was noted that the RSM predicted values are in a 95%confidence interval. Statistical analysis shows the capabilities of the developed models to predict the MRR more accurately. Also, ANN model estimates MRR with high precision compared using the RSM model. Support vector regression (SVR) is also used to analyze the impact of various process parameters. The results show that all approaches are strongly capable of predicting the response. Analysis the WEDM is a very effective. Of the three approaches ANN is superior.

Keywords: Wire EDM, Buckingham's Pi theorem, Dimensional analysis, Response surface method, Artificial neural network, Oil hardening non-shrinking die steel, Support vector regression

1. Introduction

Wire electrical discharge machining (WEDM) is a nonconventional machining process that is used to cut materials with an electrode following a definite pathway. Drilling in the workpiece is a major machining process required to shape complex and complicated products. In WEDM processing, each discharge produces a crater in the raw workpiece and a collision on the wire electrode. During the machining of a hard material, if the quantity of material being removed from the electrode surface is greater than the amount being removed from the workpiece surface, the wire electrode breaks and discharge is blocked. In this process a dielectric fluid acts as an insulator and coolant that controls the amount of heat generated during the process. WEDM has functional potential in a huge number of machining industries. Ilhan and Mehmet [1] focused on developing an experimental based surface roughness (SR) modeled through multiple regression and ANN for turning. Also, the authors investigated the effects of cutting speed, feed and depth of cut on the surface roughness. Phate and Tatwawadi [2-3] used a dimensional analysis (DA) approach to analyze the effect of different field variables during dry machining of ferrous material. The DA based models developed for the surface roughness, had a material removal rate (MRR) and power consumption with an acceptable correlation. The optimum set of input variables was found for the effective use of this process. Sensitivity analysis was performed to elucidate the impact of various factors on response variables. Gaitonde et al. [4] analyzed the performance of conventional and wiper ceramic inserts in hard turning through ANN. Girish and Kuldip [5] used two approaches to investigate machining processes, specifically ANN and genetic algorithms (GA) for machining parameter optimization to minimize surface roughness. Experiments were carried out to ensure model potentials in calculating and optimizing surface roughness. It was concluded that the present tools have been effectively used to analyze the machining process. Phate and Tatwawadi [6] proposed an ANN model to estimate the MRR in turning ferrous and non-ferrous materials on a small scale industry in India. The input parameters, viz. operator, workpiece, cutting process, cutting tool, machine and the environment, were used. A three layer feed forward backpropagation neural network (FFBPNN) was trained using the targeted datasets built during machining ferrous and nonferrous materials to achieve better

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doi: 10.14456/easr.2020.29

Table 1 Chemical composition of OHNS workpieces

Elements	C	Mn	Cr	Si	P	T	V
Wt %	0.85-0.95	1.0-1.3	0.4-0.6	0.2-0.4	0.03 max	0.4-0.6	0.20 max

performance in terms of contact. The developed model was used for testing and forecasting the complex relationships among the dependent and independent variables in turning operations. Bobbili et al [7] examined the machine variables, viz. P_{ON}, flushing pressure, input power, thermal diffusivity and latent heat of vaporization, on responses viz., MRR and surface roughness. Buckingham's Pi theorem was used for modeling the materials, i.e., aluminium alloy 7017 and rolled homogeneous armour. Phate et al. [8-9] used ANN to model and predict the responses during the turning of ferrous and non-ferrous materials. Pujari et al. [10] investigated the residual stresses developed in the machining of an aluminium alloy through a Taguchi method. Kolli and Kumar [11] applied a Taguchi method to analyze the impact of a dielectric fluid on discharge during WEDM of a titanium alloy. Different responses viz., MRR, SR, tool wear rate (TWR) and recast layer thickness (RLT), were considered. Mevada [12] investigated MRR and SR to find an optimal level for high MRR at low SR for an Inconel 600 material by varying P_{ON}, P_{OFF}, and peak current. Huang et al. [13]studied the effect of various process variables on SR, MRR and average gap voltage during WEDM of high hardness tool steel, YG15, using a regression model developed to optimize the cutting parameter combinations. The authors concluded that P_{ON}, cutting feed rate, and water pressure were more important than other factors during modelling of MRR. Tzeng et al.(2014) [14] proposed an important process variable optimization that combines Taguchi's parameter design method, RSM, FFBPNN, and GA on engineering optimization to express the best parameters for the WEDM process considering multiple responses. The effects of MRR and work piece surface finish on process variables while manufacturing by WEDM were considered. A Box-Behnken design with four factors and twenty seven runs was used for data collection. A polynomial equation was developed to explain WEDM performance. Phate et al. [15-17] investigated the influence of various process variables on composite material and optimized the process using an advanced optimization tool.

The aim of present work is to formulate a comprehensive model using ANN and RSM approaches during the machining of OHNS. There is a wide application of OHNS such as for making blanking and punching dies, rotary blades, cutting tools, cutters, gauging tools and chasers among others. For the aforementioned purpose, a full factorial experimental design was used to study the effect of different process parameters, viz., P_{ON}, P_{OFF}, WFR and I, on the MRR. An RSM model was tested using analysis of variance (ANOVA). The performance of a dimensional based model, RSM and ANN, were compared statistically. The projected methodology can be used efficiently to forecast MRR in the WEDM process.

2. Materials and methods

2.1 Materials and methodology

WEDM is a very popular advanced machining process used in manufacturing industries. The aim of the present work is to study the impact of various process parameters on the material removal rate. The work will help researchers to work in the suggested direction and improve the performance of WEDM. The experiments using the WEDM set up were conducted considering four input variables, viz., P_{ON}, P_{OFF}, WFR and I, using an L27 Orthogonal Array (OA). From literature, it was determined that these variables affect important performance measures. Table 1 illustrates the chemical composition of the OHNS workpiece. The said variables at the three levels shown in Table 2 were used. An OHNS workpiece with dimensions 200 X 75 X 10 mm and brass wire were used as tools for machining. The WEDM machining characteristic examined was MRR. The experimentation was planned and performed per Taguchi's methodology (L27 array). The MRR is the performance characteristic to estimate the WEDM process performance.

The MRR is given in Eq. (1):

$$\text{Material removal rate } \left(\frac{\text{mm}^3}{\text{sec}}\right) = \frac{\text{Volume of material removed from the workpiece}}{\text{Machining time}} \tag{1}$$

The experiments were conducted using EZEECUT NXG –Wire cut EDM with 320 x 400 mm axis travel and 360 x 600 mm maximum workpiece dimensions. Brass wire with a 0.2 mm diameter was used for the experiments. The experimental setup and the methodology adopted is shown in Figure 1. In total, twenty-seven experiments were conducted with three replicates of each. The average values were considered the response variable.

2.2 Modeling using RSM

RSM is a group of statistical and mathematical techniques that are helpful in the design of experiments as well as in optimizing process variables. RSM was applied to forecast the performance of a WEDM process in reference to MRR with various influencing parameters. The optimal values obtained from RSM were used to find the best response. In this experiment, WEDM process performance measured in terms of MRR is given by Eq.2:

$$\mathrm{Y} = \mathrm{K}_0 + \sum_{i=1}^{n} K_i\, X_i + \sum_{i=1}^{n} K_{ii}\, {X_i}^2 + \sum_{i<j}^{n} K_{ij}\, X_i\, X_j + \in \tag{2}$$

where, Y is the response variable, i.e., MRR. X_i and X_j are the input variables, considered in the *x* and *y* directions, X_j are the quadratic and interaction terms of the input variables. K_i, K_{ii} and K_{ij} are the regression coefficients. The coefficients of RSM were estimated using the proposed Box-Behnken design that used four factors and twenty seven runs. The presented model fits the second-order surface response very precisely.

2.3 Modeling using ANN

ANN is one of the most powerful modeling techniques used in many engineering research studies. ANN can be used to develop models for complex systems that are hard to express. This work focused on the use of ANN for analyzing a complex WEDM process. The presented networks have

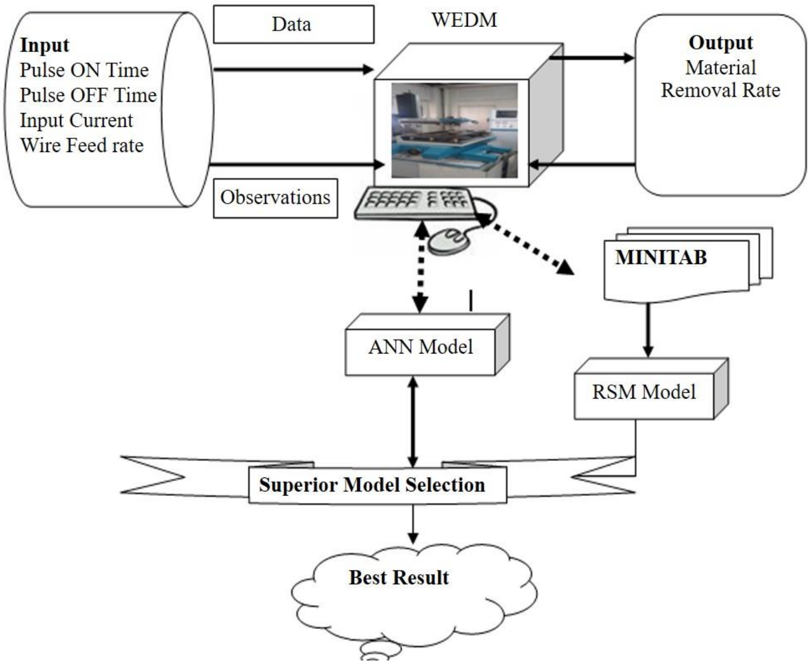

Figure 1 Flowchart representing the methodology adopted for WEDM analysis

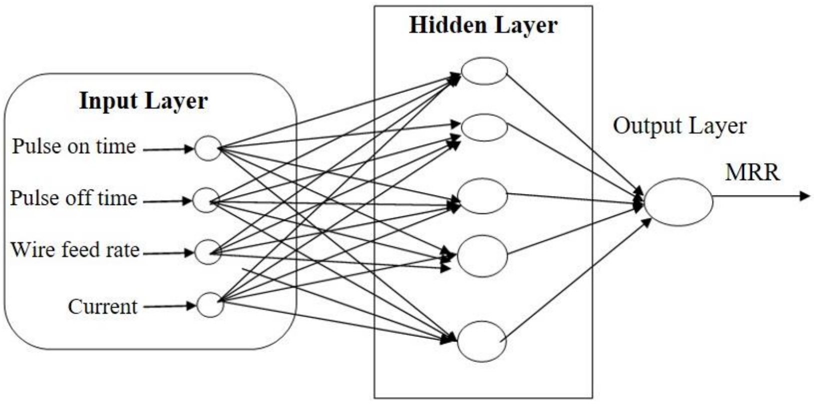

Figure 2 Schematic of a basic ANN structure

Table 2 Various input parameters and their selected levels

S.N.	Variables	Symbols	Low level (-1)	Medium Level (0)	High level (1)
1	Pulse in time	P_{ON} (μsec)	25	35	45
2	Pulse off time	P_{OFF} (μsec)	4	6	8
3	Wire feed rate	WFR (mm/min)	40	70	99
4	Input current	I (amp)	2	3	4

three layers. Various combinations are studied to find the best topology by varying the neuron count in the hidden layer. In this work, four neurons were used in the input layer, which correspond to P_{ON}, P_{OFF}, WFR, and I, while one neuron in the output layer corresponds to the MRR. For all networks, the tangent sigmoid transfer function 'tansig' was used as it takes into account nonlinearity of the ANN model. Figure 2 shows the basic ANN structure. Figure 3 shows the basic ANN neurons.

Various input variables and their selected levels are presented in Table 2.The experimental data is as shown in Table 3. In total, twenty seven different experiments were conducted at random per the Box-Behnken design with four factors. The various input/output parameters correlated with the aforementioned process are shown in Figure 4. The experimental data shown in Table 4 were used to develop an ANN model to predict MRR.

3. Results and discussion

3.1 Analysis of the RSM model

Statistical evaluation of the developed RSM model for the WEDM process was done by examining model competency. The model competency was determined using a "lack-of-fit" test which compares the residual error with the pure error from replicated design points. Based on the ANOVA in Table 5, it can be been clearly understood that the parameters

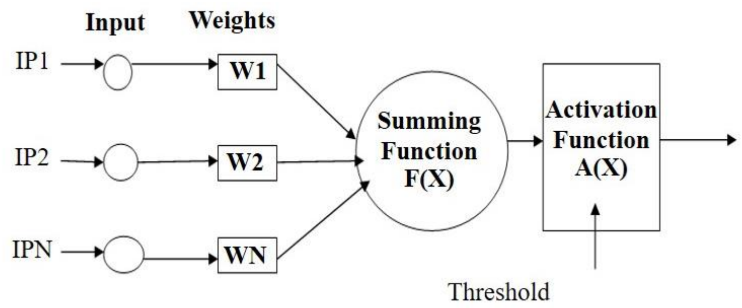

Figure 3 A model of ANN neurons

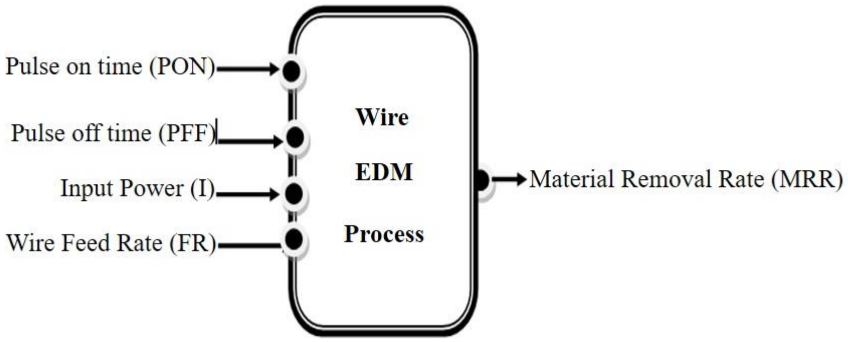

Figure 4 Schematic model of WEDM as an input-output process

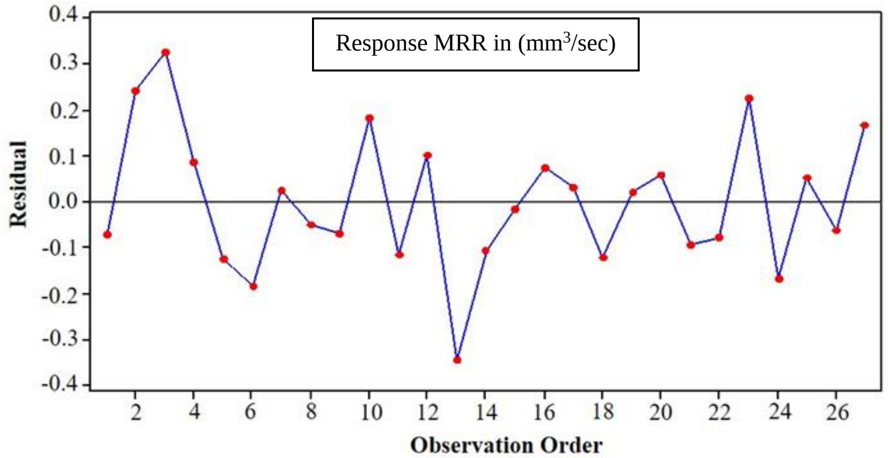

Figure 5 Residuals vs. order of experimentation

viz., P_{ON}, P_{OFF}, WFR, IP, interaction terms of the parameters and a pure quadratic effect of the process variables have significant effect on MRR. Figure 5 shows the residual error obtain in individual experiments. It indicates the error produced is in the acceptable confidence limit. Figure 6 shows a normal probability plot.

Figure 6 shows the normally distributed errors in RSM. Figure 7 depicts the randomly scattered residuals, which show that they are autonomous or independent. Statistical evaluation shows that RSM model predictions are in agreement with measured data. The coefficient of determination (R^2) for MRR prediction in the WEDM of OHNS is 0.9099. The develop RSM model is used to predict MRR with a coded unit as given in Eq. 3.

$$\begin{aligned} MRR = {} & 2.42400 + 0.0991667 * P_{ON} + 0.0405833 * P_{OFF} \\ & + 0.613250 * I + 0.215833 * WFR + 0.03475 * {P_{ON}}^2 \\ & + 0.573750 * {P_{OFF}}^2 + 0.0148750 * I^2 - 0.147500 \\ & * WFR^2 + 0.247750 * P_{ON} * P_{OFF} + 0.0320 * P_{ON} * I \\ & + 0.04375 * P_{ON} * WFR + 0.01175 * P_{OFF} * I - \\ & 0.17625 * P_{OFF} * WFR - 0.12110 * I * WFR \end{aligned} \tag{3}$$

From the RSM model, it is clear that the input current (I) is the most influential factor followed by the WFR, P_{ON} and P_{OFF} on MRR. An acceptable correlation (R^2 = 90.99%) between the measured and RSM predicted MRR is observed. The significance of interaction for the parameters, such as P_{ON}, P_{OFF} and WFR, has been identified. A similarly of significant square effect of some parameters, such as P_{ON} and I, were observed. Figure 7 shows a comparison of measured and predicted MRR values for RSM. It depicts closeness between the measured and predicted MRR. Table 5 shows an ANOVA table that was used to determine the dependency of MRR to select the various input parameters. The significance of the main effects of these parameters and their interactions

Table 3 Experimental results for MRR in WEDM of OHNS steel

Exp	P_{ON}	P_{OFF}	I	WFR	MRR
1	0	0	0	0	2.352
2	0	-1	0	1	2.928
3	0	0	-1	-1	1.669
4	0	0	0	0	2.511
5	0	-1	0	-1	1.777
6	0	1	0	-1	2.153
7	1	0	0	-1	2.177
8	-1	1	0	0	2.159
9	-1	0	0	1	2.316
10	0	1	0	1	2.599
11	1	0	0	1	2.554
12	0	0	-1	1	2.118
13	0	0	1	1	2.653
14	-1	0	-1	0	1.687
15	0	0	0	0	2.409
16	-1	0	0	-1	2.114
17	1	-1	0	0	2.359
18	0	0	1	-1	2.688
19	0	-1	1	0	3.078
20	1	1	0	0	2.962
21	0	-1	-1	0	1.76
22	-1	-1	0	0	2.547
23	-1	0	1	0	3.184
24	1	0	-1	0	1.76
25	0	1	1	0	3.214
26	0	1	-1	0	1.849
27	1	0	1	0	3.385

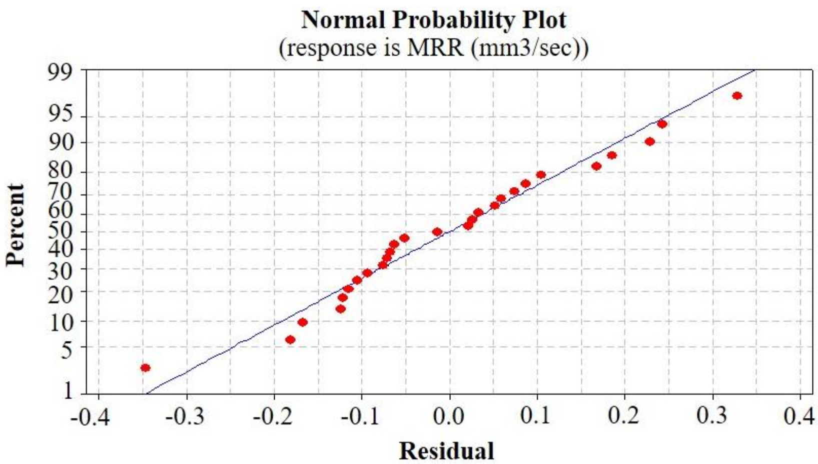

Figure 6 Normal probability plot of response MRR.

are presented in the Table 5. The ANOVA test was done using MINITAB software at a 95% confidence level. Since the p-value specified in Table 5 is less than 0.05, the developed RSM based MRR model is significant. According to the Taguchi hypothesis, if at least one of these p-values is sufficiently small or the coefficients are not equal to zero, the model will be accepted [1]. It can be observed from Table 5 that the RSM model is acceptable.

3.2 Analysis of the ANN model

An analytic examination of multilayer ANN structure with FFBPNN was applied to predict MRR in the WEDM of OHNS. The ANN model was trained using Levenberg-Marquardt backpropagation (trainlm). Various ANN networks were studied by varying the neuron count in the hidden layer and epoch sizes. However, the best correlation was found for the 4-3-1 ANN topology (As shown in Figure 8). This used four neurons in the input layer corresponding to four input parameters. Three hidden neurons and one neurons at output layer corresponds to the response, MRR. The neural network was trained using a built-in MATLAB tool box. The data found for the various ANN networks studied are shown in Table 6. Samples for training, testing and validation, neuron count in the hidden layer, learning rate and the processing function used are according to the MATLAB guidelines. The processing function (tansig) was used for prediction. Analysis showed that the network with three neurons in hidden layer yielded superior performance over other models studied. The number of epochs and the

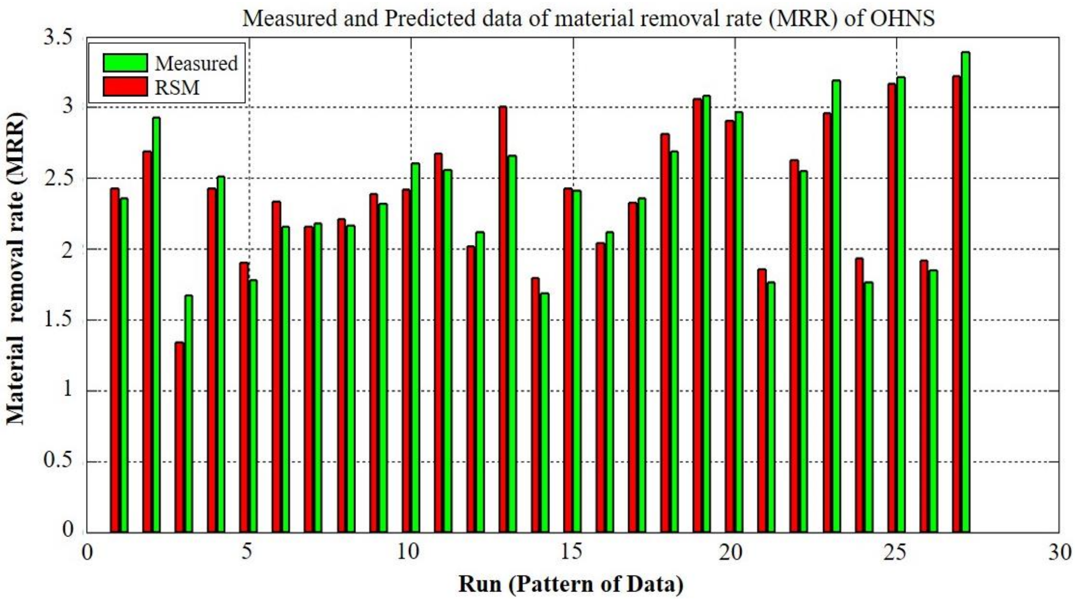

Figure 7 Measured and predicted MRR in WEDM of OHNS

Table 4 Various weights between the input (layer 1) and hidden layers (layer 2)

Neuron count (Hidden layer)	W_{1i} (Input 1)	W_{2i} (Input 2)	W_{3i} (Input 3)	W_{4i} (Input 4)
1	-0.09862	4.56317	1.69106	-1.69233
2	-1.58978	2.29238	-1.7884	3.18242
3	-0.30739	0.85561	1.5971	3.05177

Table 5 Analysis of variance (ANOVA) for the MRR in WEDM

Source	Degrees of Freedom	Sum of Squares	Mean Square	F Value	P-value Prob. >F	Influence
Regression	**14**	**5.85996**	**0.41857**	**8.66**	**0.000**	Significant
Linear	4	5.20969	1.30242	26.95	<0.001	Significant
P_{ON}	1	0.11801	0.11801	2.44	0.144	Significant
P_{OFF}	1	0.01976	0.01976	0.41	0.535	Significant
I	1	4.51291	4.51291	93.37	0.000	Significant
WFR	1	0.55901	0.55901	11.57	0.005	Significant
Square	**4**	**0.20963**	**0.05241**	**1.08**	**0.407**	Significant
P_{ON}*P_{ON}	1	0.01653	0.00664	0.13	0.721	Significant
P_{OFF}*P_{OFF}	1	0.05245	0.01756	0.36	0.558	Significant
I *I	1	0.02461	0.00118	0.02	0.878	Significant
WFR*WFR	1	0.11603	0.11603	2.40	0.147	Significant
Interaction	**6**	**0.44605**	**0.07344**	**1.52**	**0.253**	Significant
P_{ON}*P_{OFF}	1	0.24552	0.24552	5.08	0.044	Significant
P_{ON}*I	1	0.00410	0.00410	0.08	0.776	Significant
P_{OFF}*FWR	1	0.00766	0.00766	0.16	0.698	Significant
P_{OFF}*I	1	0.00055	0.00055	0.01	0.917	Significant
P_{OFF}*WFR	1	0.12426	0.12426	2.57	0.135	Significant
I *WFR	1	0.05856	0.05856	1.21	0.293	Significant
Residual Error	12	0.57998	0.04833			Significant
Lack-of-Fit	10	0.56700	0.056700	8.74	0.107	Not Significant
Pure Error	2	0.01298	0.00649	8.74	0.107	
Total	26	6.43994				

S = 0.219844 **Press** = 3.29511
R^2=0.9099 **R^2 (Pred)** = 0.8883 **R^2 (Adj)** = 0.8049

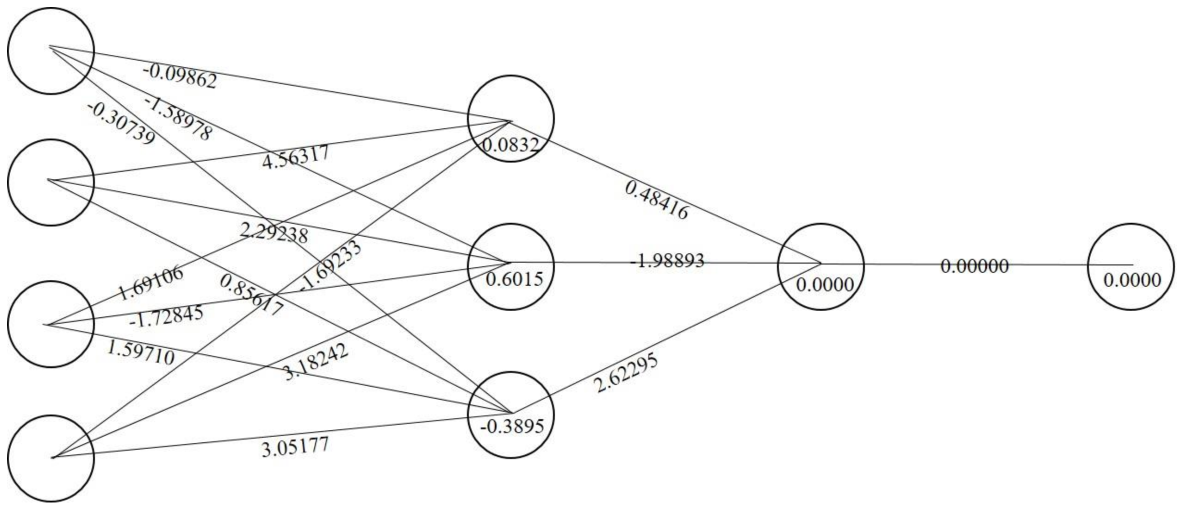

Figure 8 Developed 4-3-1 ANN with weights in each layer for the MRR

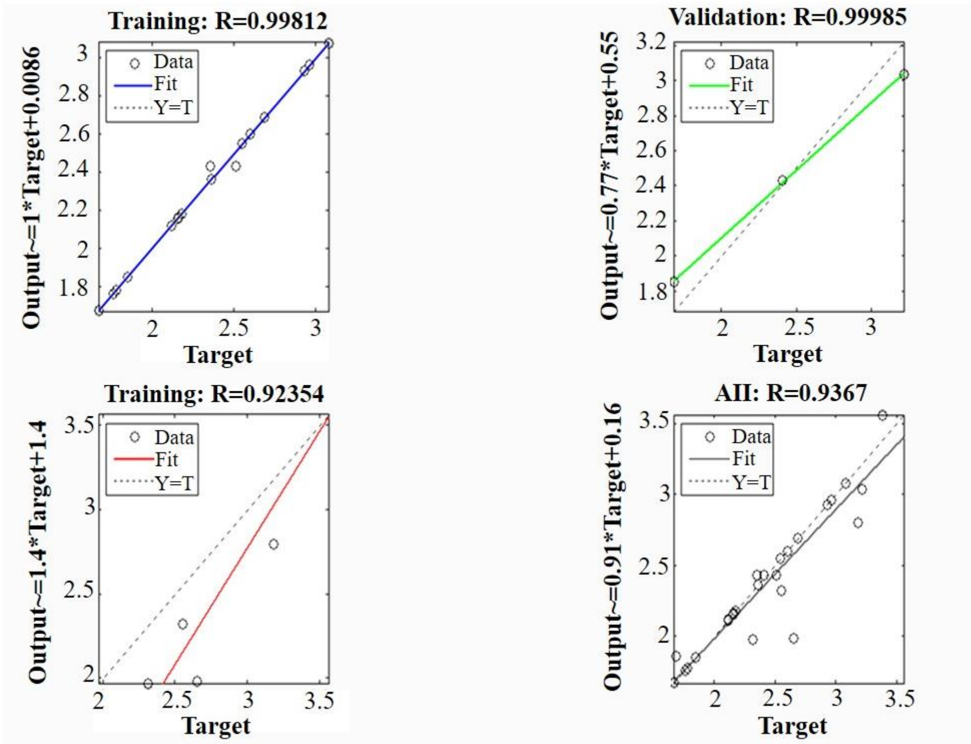

Figure 9 Details of the results obtain during training, validation and the testing data

learning rate used were 10,000 and 0.01 respectively. Figures 9-11 show the various results obtain to predict MRR using an ANN approach. Figures 11 and 12 show the ANN performance during training, testing, validation and for the whole dataset. Statistical parameters such as the mean squared error (MSE), mean absolute percentage error (MAPE), and the correlation coefficient (R) are satisfactory. The activation function used in this study is given as Eq. (4):

$$f_i = \frac{1-e^{-W_i}}{1+e^{-W_i}} \tag{4}$$

where W_i is the weighted sum of the input parameters and is calculated as Eq.(5):

$$W_i = W_{1i} * P_{ON} + W_{1i} * P_{OFF} + W_{1i} * I + W_{1i} * WFR \tag{5}$$

Hence, the ANN based equation for the material removal rate is given by Eq.(6):

$$MRR = \frac{1 - e^{-(0.48416\, f_1 - 1.98893\, f_2 + 2.62295\, f_3)}}{1 - e^{-(0.48416\, f_1 - 1.98893\, f_2 + 2.62295\, f_3)}} \tag{6}$$

where f_1, f_2 and f_3 are the weights between the hidden and output layers, as shown in Figure 8 The various weights between input layers corresponding to four input parameters and three neurons in the hidden layers are shown in Table 4. The network performance for the 4-3-1 ANN model is shown in Figure 9.

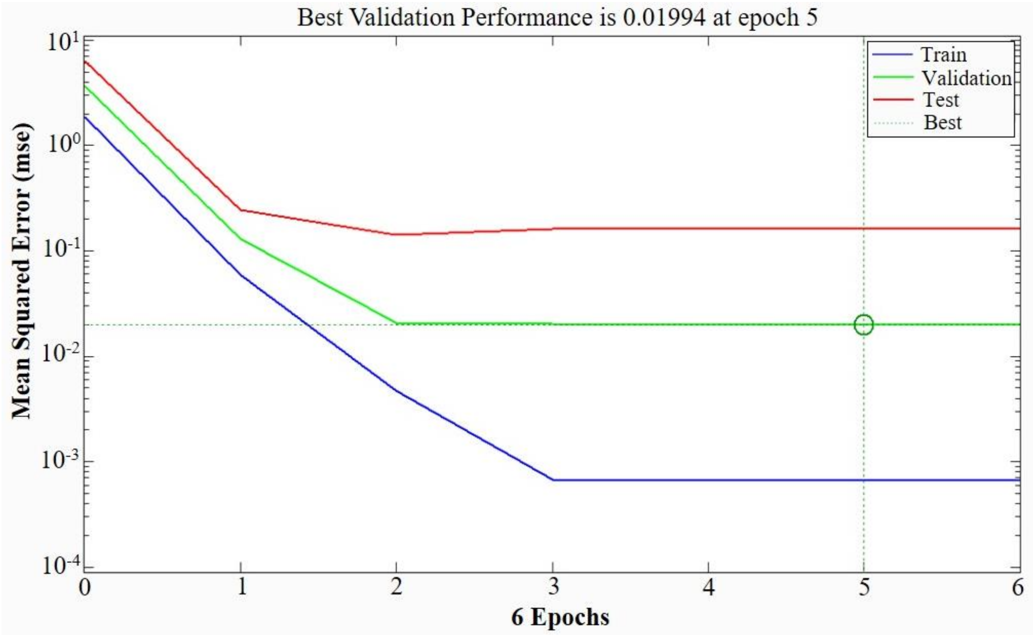

Figure 10 Details of best validation performance obtain during ANN prediction

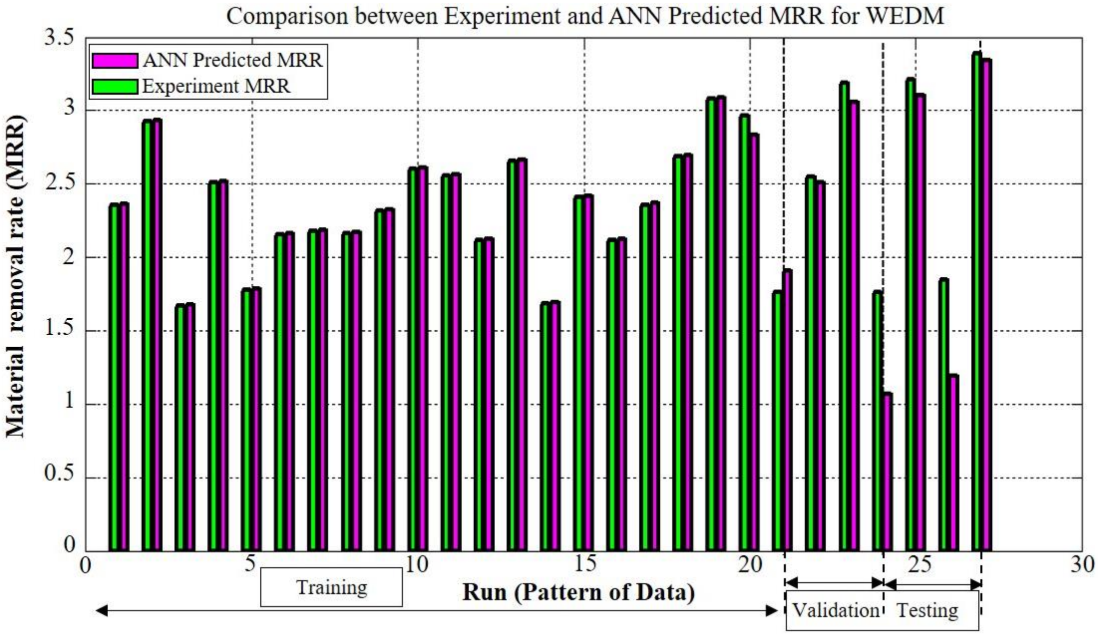

Figure 11 Comparison of experimental results and ANN during training, validation and testing

From the 4-3-1ANN network, it is clear that the weight related to I and WFR are the most influential. 70% of the total data (19 samples) was used for training, 10% (3 samples) was used for validation and remaining 20% (5 samples) was used for testing the network.

The models were developed to predict MRR in WEDM of OHNS material through RSM and ANN. Then, these formulated models were compared with measured MRR data (Table 7). The results obtained were statistically compared using several important statistical indices, viz. root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R^2), which are defined in Eq.7 (a-c).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - Y_{Ci})^2}{N}}; \tag{7a}$$

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n}\left|\frac{Y_i - Y_{Ci}}{Yi}\right|}{N} X100 \tag{7b}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(Y_i - Y_{Ci})^2}{\sum_{i=1}^{n}(Y_{Ci})^2}\right) \tag{7c}$$

where N is the run number or dataset. Y_i is the actual MRR and Y_{ci} is the predicted MRR values.

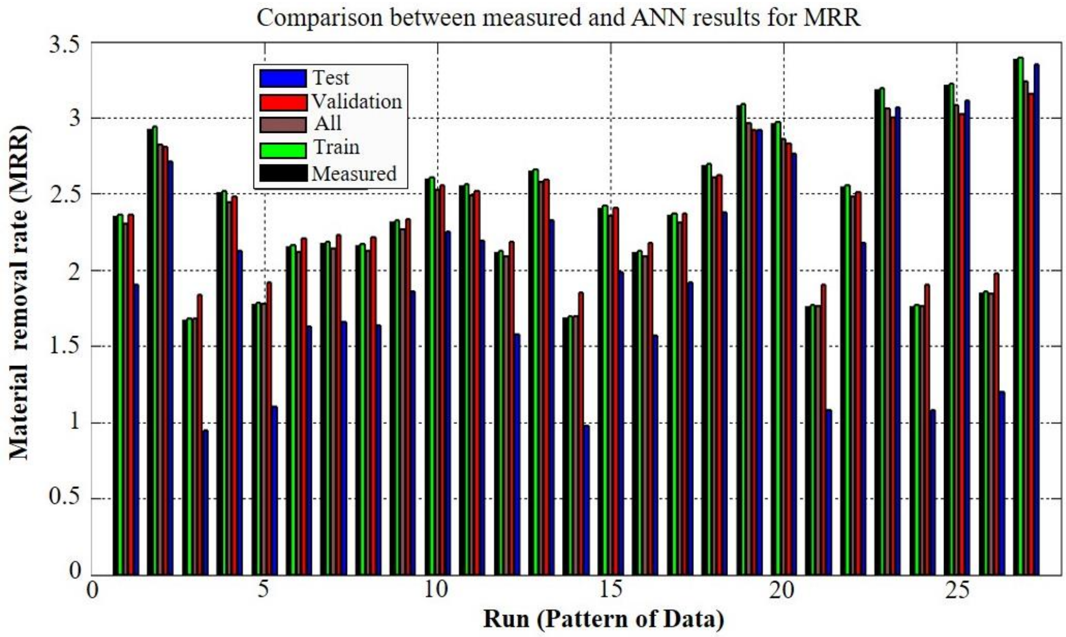

Figure 12 Comparison of experimental data and ANN model results over all data

Table 6 Details of various ANN models used for MRR prediction in WEDM

Algorithm/Neurons	**Training data (70%)**		**Validation data (10%)**		**Testing data (20%)**	
	MSE	R^2	MSE	R^2	MSE	R^2
LM with 5 neurons	0.000809921	0.998266	0.0087444	0.997681	0.253906	0.876632
LM with 4 neurons	0.00502730	0.992602	0.0280054	0.995412	0.077489	0.939618
LM with 3 neurons	**0.00066528**	**0.998123**	**0.0198400**	**0.999850**	**0.160520**	**0.933536**

Table 7 Details of the statistical parameters for the various model techniques used

Modeling method	**MAPE**	**R^2**	**RMSE**
RSM	0.3087	0.909928	0.146563
ANN	0.3727	0.998123	0.0086

Table 8 Details of various SVR model parameters for the MRR in WEDM

Regression Summary		**Model Specification**	**Value**
Observed mean	2.3497	Number of independents	04
Predictions mean	2.3490	SVM type	Regression1
Observed S.D.	0.4866	Kernel type	Radial basic function (RBF)
Predictions S.D.	0.4334	Number of SVs	17(6 bounded)
Mean squared error	0.0181	Decision constant	0.59581682229
Error mean	0.0007	Used random sampling	
Error S.D.	0.1381	Testing	75%
Abs. error mean	0.1183	Speed	1000
S.D. ratio	0.2837	Gamma	0.25
Correlation	0.9615	Max iteration	1000

3.3 MRR prediction using support vector regression (SVR)

A support vector machine or support vector regression (SVR) was also used for the prediction of the MRR. SVR was used for prediction of real responses. The parameters selected for the SVR are tabulated in Table 8. The effectiveness of the SVR prediction primarily depends on the selection of the kernel parameter. SVR predicted results during the training and the testing are shown in Figure 13(a). The actual and SVR predicted MRR values are compared as shown in Figure 13(b).

4. Conclusions

In this work, RSM and ANN models were developed to predict the MRR in the WEDM of OHNS. Parameters such as P_{ON}, P_{OFF}, I and WFR were examined by means of an L27 Taguchi array. The data obtained were used to develop various models for MRR prediction. From the results, it was observed that I is the most influential parameter on MRR followed by P_{OFF} and WFR. The FFBPNN training algorithms with Levenberg–Marquardt (LM) were used to predict the ANN response. The best co-relational model was

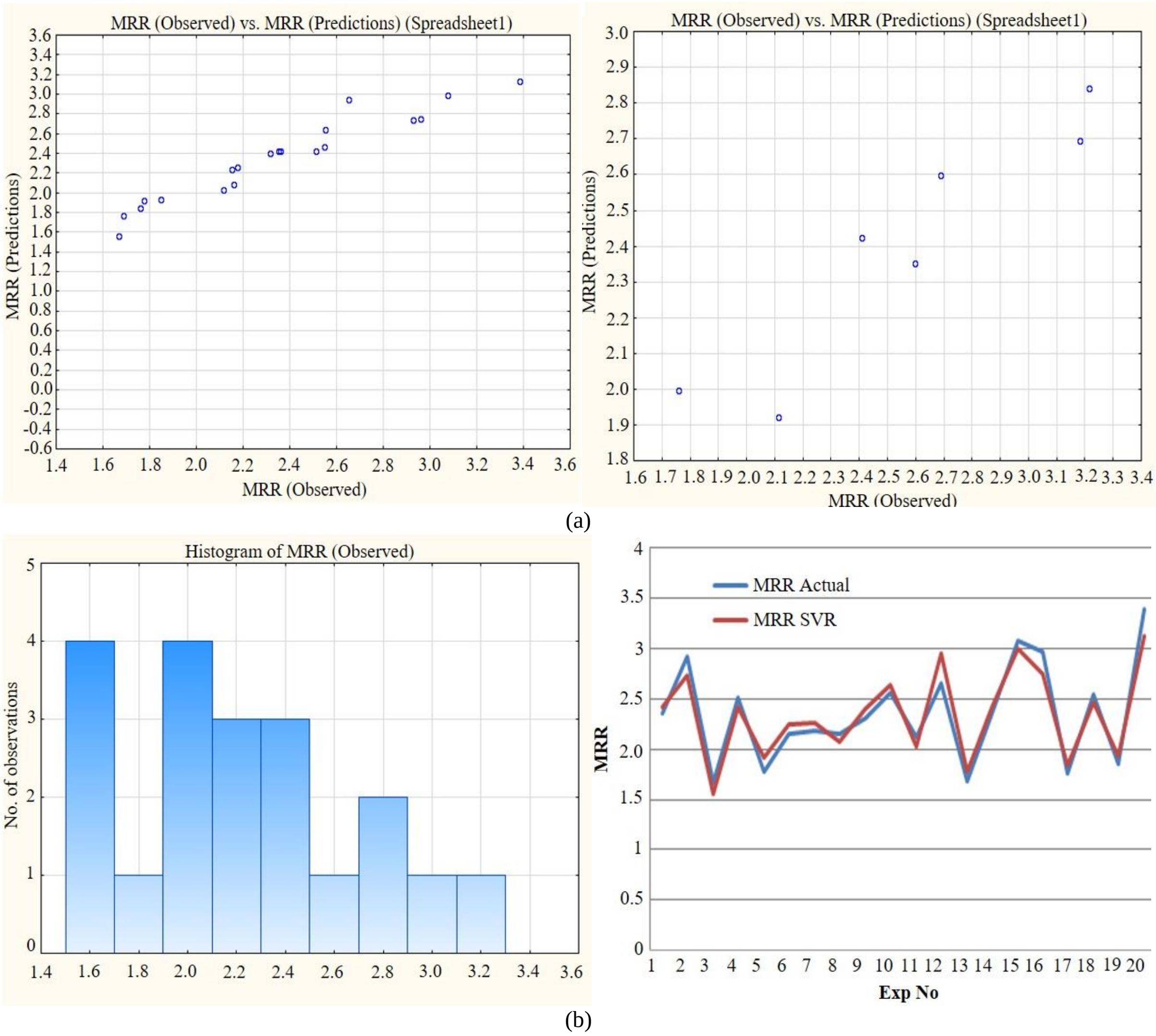

Figure 13 (a) MRR prediction using SVR in training and testing phase, (b) comparison between actual and SVR predicted MRR

obtained with a 4-3-1 ANN topology. The developed models were compared with the experimental values to judge their forecasting ability. The predicted values were found to be very close to their experimental counterparts. The formulated models can be successfully used to predict MRR in WEDM process. In the ANN model, the R^2 values found during training, validation and testing were 99.8266%, 99.7861% and 87.6632%, respectively, while it achieved a value of90.9928% in RSM. From the developed models, it was observed that the ANN model produced superior performance over RSM. ANN is an effective and efficient approach to predicting MRR. In the future, researchers can effectively use RSM, SVR and ANN toolsin other fields of engineering. SVR models show good performance to represent systems in a very effective way.

The approach suggested by this work was used to predict the performance of WEDM of OHNS steel. ANN modelling is suggested as a better approach to predict the performance of such systems. Effective use of ANN in such analyses can save time and expense. Our work will help operators to machine OHNS materials in a very effective and efficient way. This will help them to increase their profits and maximize utilization of their resources.

5. Acknowledgements

The authors wish to express their sincere gratitude to Kakade Laser, Narhe, Pune and Maharashtra, India for allowing their facilities to be used in this work.

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