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ANN and RSM Modeling Methods for Predicting Material Removal Rate and Surface Roughness during WEDM of $Ti_{50}Ni_{40}Co_{10}$ Shape Memory Alloy

Hargovind Soni, S. Narendranath, M. R. Ramesh

Department of Mechanical Engineering, National Institute of Technology Karnataka, India

(hargovindsoni2002@gmail.com, narenbayalu@gmail.com, ramesdmt@gmail.com)

Abstract

Present study exhibits the comparison between experimental and predicted values. Where response surface method (RSM) and artificial neural network (ANN) were used as predictor for the prediction of wire electro discharge machining (WEDM) responses such as the material removal rate (MRR) and surface roughness (SR) during the machining of $Ti_{50}Ni_{40}Co_{10}$ shape memory alloy. It has been noticed from the literature survey that pulse on time and servo voltage are most important process parameters for the machining of TiNiCo shape memory alloy, hence there are five levels of these process parameters were chosen for the present study. For the present study selected alloy has been developed through vacuum arc melting and L-25 orthogonal array has been created by using Taguchi design of experiment (DOE) for experimental plan. During the present study ANN predicted values have been found to very close to experimental values compare to RSM predicted values, hence it can be say that ANN predictor gives more accurate values compare to RSM predicted values.

Key words

Artificial neural network, Response surface methodology, Wire electric discharge machining, $Ti_{50}Ni_{40}Co_{10}$ shape memory alloy.

1. Introduction

Due to excellent biocompatibility, TiNi based shape memory alloys (SMAs) are used for biomedical applications such as bone staple, stone extraction baskets, cardiovascular stents, catheter guide wires and other biomedical devices [1]. Addition of Co or ternary elements in TiNi which replaced Ni, improve its physical (shape memory effect, pseudoelasticity, transformation temperature and biocompatibility) and mechanical (strength, fatigue and cyclic loading and damping capacity) properties suitable for biomedical applications [2, 3]. Machining of such kind of alloys is difficult through conventional machining processes because they affect the internal properties (Pseudoelastic behaviour, shape memory effect, high chemical reaction, and work hardening) of alloys and with poor surface integrity, therefore non-conventional machining processes are more appropriate [4,5]. It has been proved in our previous work that servo voltage and pulse on time are most influential process parameters for the machining of TiNiCo shape memory alloy by using wire electro discharge machining therefor these process parameters will be considered for present study [6]. Many researchers have been predicted the responses of WEDM process, Ugrasen et al. [7] adopted ANN, Group Method Data Handling Technique (GMDH) and Multiple Regression Analysis (MRA) for the prediction of WEDM performances and found the ANN was more accurate others similarly Shandilya et al [8] also compared ANN and RSM predicted values with experimental values, Portillo et al. [9] used ANN for WEDM performances. From the literature survey, it has been found that ANN is the best predictor comparatively but the combination of RSM and ANN only researchers have been adopted for estimation. In the present study, TiNiCo shape memory alloy will be developed through vacuum arc melting furnace and confirmed the composition through EDX analysis. WEDM of developed alloy adopted L-25 orthogonal array which is created by Taguchi as design of experiments and measured outputs such as material removal rate and surface roughness and see the effects of each experimental run on its outputs. The present study is a comparison between experimental and predicted values of WEDM responses and also compared the both predicted values through ANN and RSM.

2. Materials and Methods

TiNiCo SMAs has been developed through a vacuum arc melting. The material homogeneity is achieved by carrying out melting for six times successively, followed by casting into rectangular blocks of size 50mm x 12mm x 10mm. WEDM (Model Electronica ELPULS15 CNC) was used for profile cutting of bone staple at optimized process parameters. The selected process parameters are given in Table 1 and L-25 orthogonal array (Table 2) has been used for experimental plan which is created by using Taguchi DOE. WEDM performances (MRR and SR), MRR is calculated by equation 1 [10] while surface roughness is measured by using "Telly surf (Mitutoyo)" surface roughness tester. The roughness of each machined surface was measured at three different locations and the average surface roughness (Ra) is reported in the present study, the cut off length 0.8 mm and an evaluation length of 3 mm was used and the stylus speed of 0.25 mm/s.

MRR = cutting speed (mm/min) x width of cut (mm) x height of work piece (mm) (1)

Where, width of cut (mm) = 2 x spark gap + diameter of wire (mm)

Table 1. input process parameters and their levels

Input process parameters	**Levels**
Pulse on time (µs)	105, 110, 115, 120, 125
Servo voltage (V)	20, 30, 40, 50, 60
Pulse off time (µs)	42
Wire speed (m/min)	4
Servo feed (mu)	2180
Brass wire	0.25mm

Table 2. L-25 orthogonal array

Run No.	Pulse on time	Servo voltage
1	105	20
2	105	30
3	105	40
4	105	50
5	105	60
6	110	20
7	110	30
8	110	40
9	110	50
10	110	60
11	115	20
12	115	30
13	115	40
14	115	50
15	115	60
16	120	20
17	120	30
18	120	40
19	120	50
20	120	60

21	125	20
22	125	30
23	125	40
24	125	50
25	125	60

3. Results and Discussion

3.1 Effects of the Each Experimental Run on MRR for Each Alloy

The effect of each experimental run on MRR is given in the Fig. 2. Black colour indicates the experimental values of MRR; similarly, red colour shows the ANN based predicted values for MRR while blue colour exhibit the RSM based predicted values for MRR at all experimental run. From the figure 2 it can be say that ANN based predicted values is closest to experimental values for MRR and also noticed that the material removal rate decreases up to experiment no 5 because servo voltage increases with constant pulse on time. When comes to the experiment no. 6 again material removal rate increases then, further it decreases till experiment run 10 because servo voltage increase. Similar trend has been noticed after each five experiments. Material removal rate decreases with increase in servo voltage because the increase in servo voltage results in larger spark gap thereby reducing the spark intensity and eventually lesser amount of material is removed from the surface of the workpiece. Others also observed similar kind of result during the wire electro discharge machining [11] of High- strength low-alloy steel (HSLA). Additionally, during the machining of $Ti_{50}Ni_{40}Co_{10}$ alloy at the run no. 21 and 22 noticed more frequent wire breakage due to higher pulse on time and lower servo voltage. Hence it can be say that combinations of 125µs pulse on time and 20-30V servo voltage are not suitable parameters for the machining of $Ti_{50}Ni_{40}Co_{10}$ alloy.

3.2 Effects of the Each Experimental Run on SR for Each Alloy

The effect of each experimental run on surface roughness is given in the Fig. 3. Black colour indicates the experimental values of SR; similarly, red colour shows the ANN based predicted values for SR while blue colour exhibits the RSM based predicted values for SR at all experimental run. From the figure 3 it can be say that ANN based predicted values is closer to experimental values for SR. It has been found (Fig. 3) that surface roughness decreasing till 1 to 5 experimental run similar trend has been observed during 6 to 10, 11 to 15, 16 to 20 and 21 to 25 experimental run this is because servo voltage is increasing with constant pulse on time and after each five-run pulse on time is increase and further it constant for five experiments. Surface roughness was decreased with increase servo voltage because at the higher servo voltage less amount of material is melted on machined surface; this can be easily flushed away from the machined surface through dielectric fluid leading to low surface roughness. Which is the same as other noticed for wire electro discharge machining for high carbon high chromium cold alloy tool (D-3) steel [12].

3.3 Response surface methodology for responses

RSM method is exhibits the relationship between WEDM inputs process parameters and its responses. Regression equation 1 and 2 are indicating the relationship between input process parameters and outputs process parameters. SR is predicted through equation 1 while MRR is predicted by equation 2 for the 25 experimental run and given in the Table 3.

$$SR = -4.804 + 0.06920 \text{ Pulse on time} - 0.02526 \text{ Servo voltage} \quad (2)$$

$$MRR = -15.07 + 0.2027 \text{ Pulse on time} - 0.1081 \text{ Servo voltage} \quad (3)$$

3.4 Artificial neural network for responses

ANN is an artificial illustration of human brain that tries to simulate its learning approach which is an interconnected pair of artificial neurons that uses a mathematical model for information processing based on a connectionist method to computation. Neural networks are non-linear mapping systems that consist of simple processors which are called neurons, linked by weighed connections. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. Among ANN models, the feed forward neural network based on back-propagation is the best general-purpose model. The network has two inputs of Ton and SV and two outputs MRR and SR. Matlab software was used for predicting the responses; in ANN prediction data will divide in two forms test data and training data. From the literature, it has been found that training data are 70% then it gives more accurate values of responses [7]. For present study 70% data was kept in training and rest of the data was test data during the prediction.

3.5 Error analysis

Figure 4 exhibit the percentage of error for MRR while figure 5 shows the percentage of error for SR. Maximum 6 % of error for MRR and 8% of error for SR has been recorded during the comparison of experimental values and ANN predicted values. At the same time if compared the RSM predicted values of outputs from the experimental values, 36% of error for MRR and 20% of error for SR has been noticed. Hence ANN predicted values of outputs found more accurate comparatively similar work has been reported by Shandilya et al. [8] during their comparative study on RSM and ANN based predicted values of cutting speed of wire electro discharge machining of SiC_p/6061 Al metal matrix composite.

Table 3. Experimental and Predicted (by ANN and RSM) MRR and SR

Run No.	Pulse on time	Servo voltage	Experimental MRR	Predicted MRR		Experimental SR	Predicted SR	
				ANN	RSM		ANN	RSM
1	105	20	3.51	3.5	4.0515	1.84	1.8405	1.9568
2	105	30	3.06	3.2499	2.9705	1.72	1.5756	1.7042
3	105	40	2.41	2.321	1.8895	1.58	1.4836	1.4516
4	105	50	1.69	1.69	1.8085	1.26	1.2604	1.199
5	105	60	1.04	1.0478	1.2725	1.18	1.1811	0.9464
6	110	20	3.71	3.668	5.065	1.98	2.0586	2.3028
7	110	30	3.06	3.2192	3.984	1.84	1.9745	2.0502
8	110	40	2.28	2.407	2.903	1.67	1.8038	1.7976
9	110	50	1.63	1.6296	1.822	1.49	1.4895	1.545
10	110	60	1.11	1.1086	0.741	1.2	1.2055	1.2924
11	115	20	5.92	5.9184	6.0785	2.45	2.4493	2.6488
12	115	30	4.81	4.7553	4.9975	2.31	2.4911	2.3962
13	115	40	3.51	3.5106	3.9165	2.26	2.3928	2.1436
14	115	50	2.41	2.4091	2.8355	2.15	2.1513	1.891
15	115	60	1.63	1.6082	1.7545	1.78	1.8274	1.6384
16	120	20	8.78	8.7757	7.092	3.41	3.4046	2.9948
17	120	30	6.31	6.3083	6.011	3.12	3.1195	2.7422
18	120	40	5.04	5.2061	4.93	2.2	2.3354	2.4896
19	120	50	3.84	3.8399	3.849	2.2	2.2002	2.237
20	120	60	2.47	2.47	2.768	2.17	2.1698	1.9844
21	125	20	9.68	9.5049	8.1055	3.63	3.6018	3.3408
22	125	30	6.55	6.5514	7.0245	3.3	3.3002	3.0882
23	125	40	5.6	2.6704	5.9435	2.45	2.7634	2.8356
24	125	50	4.9	4.8999	4.8625	2.26	2.2601	2.583
25	125	60	2.99	2.99	3.7815	2.13	2.1298	2.3304

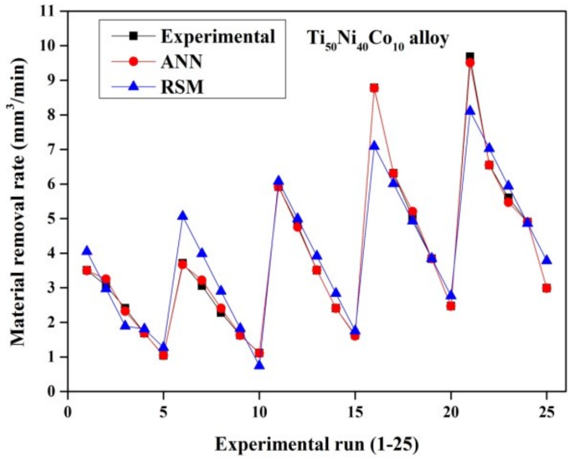

Figure 2. Experimental, ANN and RSM predicted values of MRR vs Experimental run

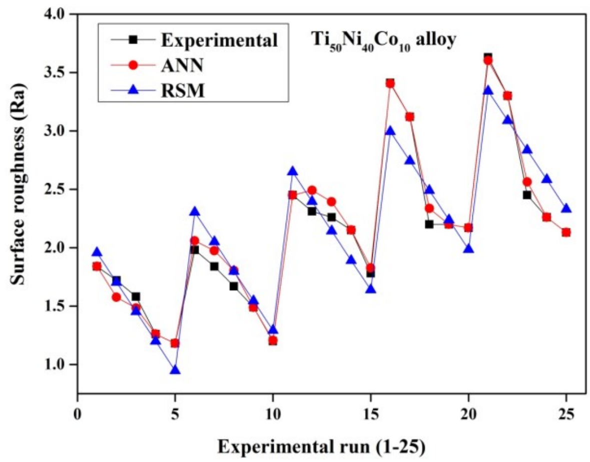

Figure 3. Experimental, ANN and RSM predicted values of SR vs Experimental run

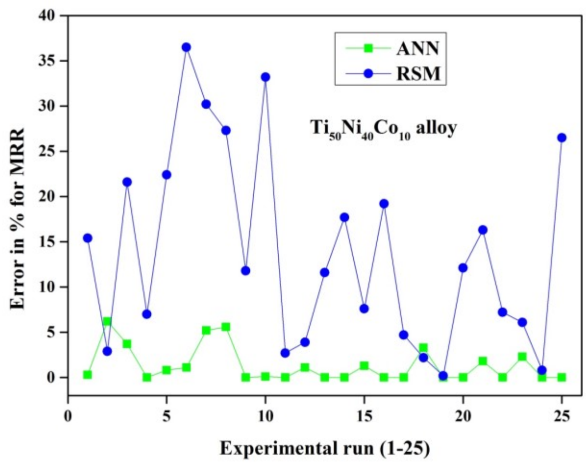

Figure 4. Comparison of error in % for MRR at all experiential run

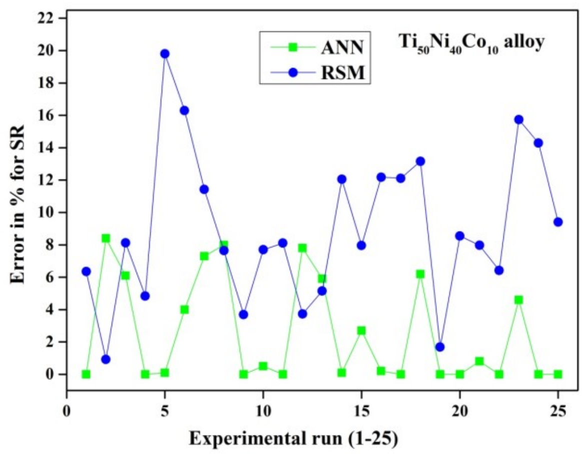

Figure 5. Comparison of error in % for SR at all experiential run

Conclusion

The Effects of each experimental run on MRR and SR has been seen and found that minimum values of theses outputs recorded at 105µs pulse on time and 60 V servo voltage while maximum values at the 125µs pulse on time and 20 V servo voltage. The present study compared the ANN and RSM based predicted values for MRR and SR during the WEDM process and ANN based predicted values of MRR and SR found more accurate compare to RSM predicted values for these responses. Maximum error 6 % for MRR and 8% for SR has been noticed when compare the ANN predicted values to experimental values while in case of RSM based predicted 36% for MRR and 20% for error observed.

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