REST Journal on Emerging trends in Modelling and Manufacturing
Vol:3(1),2017
REST Publisher
ISSN: 2455-4537

Website: www.restpublisher.com/journals/jemm

Neural Network Prediction and Analysis of Material Removal Process during Wire Cut Electrical Discharge Machining

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Abstract

This article illustrates the response surface methodology and artificial neural network primarily based mathematical modelling for average machining parameters of powdered activated carbon and 7075 Al metal matrix composite throughout wire spark machining. Four WEDM parameters particularly Discharge current, pulse-on time, pulse-off time and servo speed were chosen as machining technique parameters. A back propagation neural network was developed to envision the maneuver model. The performance of the developed ANN models were connected with the RSM mathematical models of average machining parameters like material removal rate and surface roughness. The comparison clearly indicates that the ANN models offer much correct prediction compared to the RSM models. Combined impact of input methodology parameters on machining parameters shows that servo speed could be a heap of necessary parameter on input machining parameter than pulse-off time and discharge current.

Keywords: Response surface Methodology, Artificial neural network, AA7075, Metal matrix composites

I. Introduction

Wire discharge machining could also be a specialized thermal machining technique capable of accurately machining shapes of hard materials like aluminium, atomic number 22 etc. regarding region applications, MMCs presently have a tried price of accomplishment as thriving engineering materials as a result of the properties like high strength-to-weight quantitative relation, sensible wear resistance, and capability of operational almost temperatures [1]. Response surface methodology (RSM) can be a assortment of mathematical and applied math techniques for empirical model building. By careful sort of experiments, the target is to optimize a response of output variable that's influenced by several freelance variables of input variables associate experiment can be a series of tests in this changes unit of measurement created among the input variables therefore on spot the reasons for changes among the output response. The use of ancient machining processes to machine arduous composite materials causes serious tool wear attributable to abrasive nature of reinforcing particles thus shortening tool life [2]. Although, non-traditional machining techniques like water jet machining and beam machining(LBM) could also be used but the machining instrumentality pricey, height of the work piece could also be a constraint, and surface end obtained is not sensible [3], in line with Patiland Brahmankar throughout WEDM is correct and economical machining operation whereas not compromising machining performance is feasible. Motorcu and Sahin have machined the hardened AISI 1040 steel with triangular and sq. tools in varied machining conditions and sculptured the surface roughness statue maker has formulized experimental results of surface roughness and cutting forces by statistical procedure, and sculptural the implications of them in his study victimization S55C steel [4]. Effective and cost effective of work published on combined approach of ANN and RSM modelling of process parameters on the performance of during machining of PAC and 7075 Al MMCs. The most necessary performance live in WEDM is Material removal rate (MRR) and Surface Roughness (SR) intensive experimental work is therefore needed to analysis and optimize the strategy parameters to understand their impact on product quality. Response surface methodology (RSM) is one rising technique, that helps in ending the analysis of experiments with the littlest quantity experimental effort [5]. ANN approach is a good tool to predict process parameters; it will generate the outputs for a collection of inputs that area unit inside the vary of the initial inputs throughout the training part [6]. The current investigation aims at work the machining speed predictive models supported RSM and ANN throughout WEDM of PAC/7075 Al MMC. The models of average machining parameters were developed with the discharge current (I_A), pulse-on time (T_{ON}), pulse-off time (T_{OFF}) and servo speed (*rpm*) as the WEDM method parameters. The input-output information required to develop every RSM and ANN models area unit obtained through Box-Behnken style (BBD) of experiments.

II. Materials And Method

The experiments were conducted with three controllable four level factors and 3 levels. Twenty seven experiments were conducted in this element as per the Box-Behnken design. It shows four controllable factors with three levels for each factor. The cutting parameters are set to the pre-defined levels for all the experiments. The material used for work piece was AA7075 with PAC composition metal matrix composites. The wire cut Electric Discharge machine usually consists of a machine tool, a power supply unit and flushing unit. Wire travels through the work piece from higher and lower wire guides. In wire cut EDM method the brass conductor was used because the tool and work piece.

III. Response Surface Methodology For Predict Machining Parameters

Response surface methodology (RSM) approach is that the procedure for determinant the link between numerous methodology parameters with various machining criteria and exploring the results of these method parameters on the coupled responses. So as to check the impact of WEDM method parameters of 7075/PAC Al MMC on machining parameters a mathematical model response equation has been matured can be adapted into the sequent equation. The WEDM method was studied in line with the BBD for four factors are given in Table a pair of. During this investigation twenty seven experiments were conducted. Table a pair of illustrates the order, combination and elegance of the experiments supported the coded surfaces and experimental results of the specified response surface. The determined knowledge from the set of experiments were used because the inputs to coach the ANN prophetic model.

Table I: Input Process Parameters and Their Levels

Parameters	***symbol***	***Level 1***	***Level 2***	***Level 3***	***Units***
Current	I_A	1500	1750	2000	A
Pulse on Time	T_{on}	5	10	15	µs
pulse off time	T_{off}	25	50	75	µs
Servo speed	SS	50	100	150	RPM

Mathematical model supported RSM for correlating response i.e. machining parameters MRR and SR with numerous settings of method parameters throughout WEDM of Al7075/PAC MMC are established, and is painted within the following response equation. Where A is Discharge Current (I_A), B is pulse-on time (µs), C is Pulse off time (µs) and D is Servo speed (RPM). Table 3 shows the Experimental ideals for response design for the 27 experimental conditions. The combined impact of input technique parameters on machining responses were analyzed on the premise of mathematical model expression obtained through experimental ideals and response surface methodology. Fig. 1(a) shows the surface plots of the predicted values of material removal rate versus servo speed and pulse-off time for 7075/PAC Al MMC. From this figure, the valued result of current and Toff is described at lower values of discharge current and better values of servo speed a rise in material removal rate is discovered. Fig. 1(c) This figure displays surface plot that the rate of material removal rate increases with decrease in servo speed and decrease in pulse on time.

Table II: RSM Design with Four Parameters and Experimental Average Machining Parameters

Exp No	**IA**	**Ton**	**Toff**	**SS**	**MRR*(mm3/min)***	**SR *(µm)***
1	1750	5	50	150	9.54	3.37
2	1750	10	75	50	6.84	4.03
3	1500	10	75	100	8.2	3.79
4	2000	10	50	150	7.99	3.43
5	1750	10	50	100	8.82	3.69
6	1750	10	50	100	8.82	3.69
7	1750	10	25	150	10.8	3.54
8	1500	10	50	150	10.26	3.71
9	1500	15	50	100	8.45	3.83
10	1750	5	75	100	7.56	3.32
11	2000	15	75	100	9.66	3.72
12	2000	5	75	150	9.6	3.3
13	1750	15	75	50	8.14	4.01
14	1750	10	25	100	9.36	3.71
15	1750	15	75	50	7.62	3.11
16	1750	15	50	150	11.1	3.71
17	1750	10	75	100	8.34	3.63
18	2000	10	25	50	8.04	3.68
19	1750	5	50	100	8.04	3.47
20	1750	5	25	100	8.58	3.43
21	1750	15	25	100	11.62	3.66
22	2000	10	50	100	7.98	3.53
23	1500	15	50	100	9.57	4.01
24	1500	10	25	100	9.31	3.47
25	1500	10	50	50	6.98	4.05
26	1750	10	50	100	8.82	3.89

27	2000	10	75	100	8.64	3.57

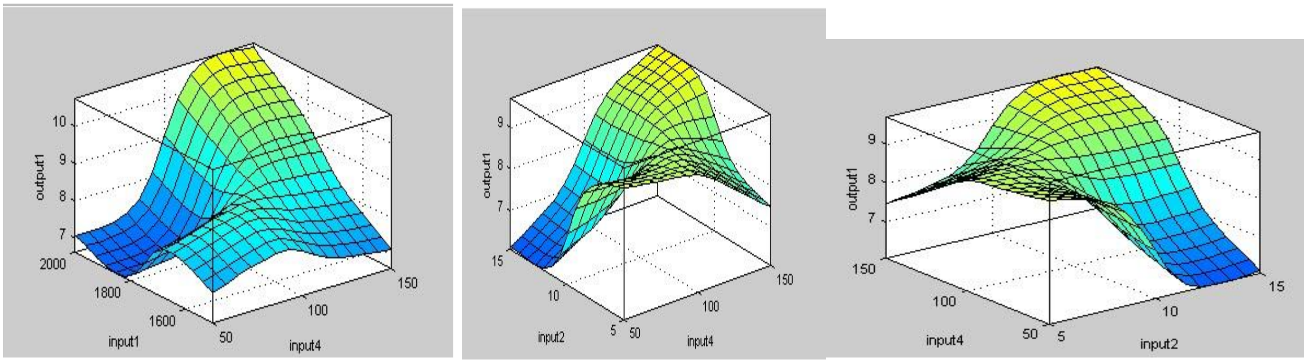

Fig. 1(a) Surface response for (a) average SR versus Discharge current and servo speed of PAC/7075Al MMC (b) average MRR versus Pulse on Time and servo speed of PAC/7075AlMMC, (c) average MRR versus servo speed and pulse on time of PAC/7075AlMMC

An artificial neural network is area unit typically given as systems of interconnected that exchange messages between each other. The connections have numeric weights which is able to be tuned supported expertise, creating capable of learning. Among varied neural network models, the feed forward neural network promoted back-propagation is that the simplest general model. The network has four inputs and the outputs are material removal rate and surface roughness. The coaching of the ANN for twenty seven input-output patterns has been dole out mistreatment the Neural Network accessible in MATLAB computer code. The network consists of 1 input layer, one hidden layer and one output layer. Hidden layer have fifteen neurons, wherever as input and output layer have four and one neurons severally to coach every network, Associate in Nursing equal learning rate (and momentum constant 0.04 and 0.9 was used. The activation functions of hidden and output neurons was chosen as a hyperbolic tangent, and conjointly the error goal (mean sq. error, MSE) was set at 0.0001, which implies the coaching epochs area unit continuing till the MSE fell below this worth. Desired output values extracted as coaching dataset, obtained with the assistance of style of experiments (DOE). Response values reminiscent of coaching knowledge were obtained from experimental runs generated by Box Behnken design supported RSM the knowledge set generated by the design is shown in Table 3. Testing is carried through two stages. In the beginning it's tested with seen computer file sets. Within the second part, the network is tested with unseen computer file sets. Training of the neural network model was performed on twenty seven experimental information points as explained in on high of section. Table four shows ANN expected values for the response knowledge for the twenty seven coaching set.

IV. Comparison of the RSM and ANN Models

The Response surface and back propagation neural network model of MRR and SR prophetic models thus advanced were compared on the concept of their prediction information set. At the same time the ANN training using LM training algorithm the mean square error decreased from 0.005 to 0.000005. The LM model has made absolute fraction of variance (R2) values regarding one for the coaching knowledge, 0.9725 for validation as seen from Figure 2(b).

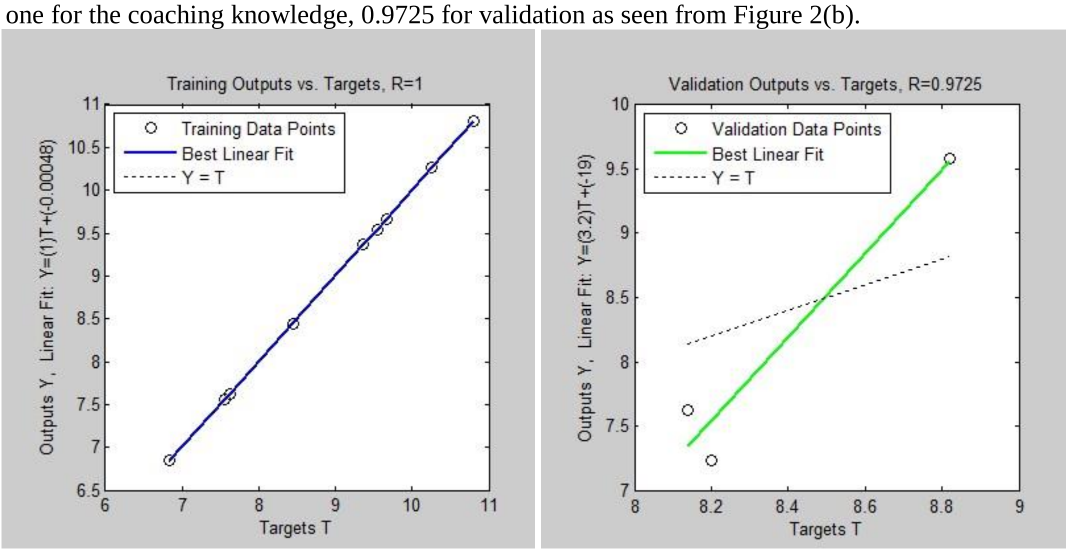

Fig.2 (a) Post training the Artificial Neural Network, (b) Post Validation the Artificial Neural Network

Fig. 3(a) illustrates the comparison of error profile for Material removal rate, for the 27experimental information set of the work patterns the utmost absolute proportion error inside the ANN prediction of Material removal rate was found to be around of 4.85%, while for the RSM model, it absolutely was around 8.24% so it is all over that the ANN predictors increased precisely than the Response model. This comparison is shown in Fig. 3(b). It is ascertained from this figure that the prediction of surface roughness with ANN and RSM values from each models closely consider that of experimental values.

Table III: List of Ann Predictions and RSM Predictions with Experimental Data Values

Exp No	Material Removal Rate (mm3/min)			Surface Roughness (µm)		
	Exp MRR	***ANN Prediction***	***RSM Prediction***	***Exp SR***	***RSM Prediction***	***ANN Prediction***
1	9.54	9.49	9.38	3.37	3.34	3.35
2	6.84	6.78	6.83	4.03	3.67	4.25
3	8.2	8.48	7.58	3.79	3.77	3.87
4	7.99	8.21	8.52	3.43	3.4	3.12
5	8.82	8.74	8.62	3.69	3.54	3.58
6	8.82	9.18	8.62	3.69	3.54	3.59
7	10.8	9.95	10.11	3.54	3.44	3.29
8	10.26	10.24	10.06	3.71	3.61	3.68
9	8.45	9.01	8.91	3.83	3.69	3.94
10	7.56	7.48	8.15	3.32	3.45	3.58
11	9.66	9.45	9.47	3.72	3.52	3.67
12	9.6	8.99	8.46	3.3	3.54	3.24
13	8.14	8.13	7.84	4.01	3.71	3.87
14	9.36	9.35	9.44	3.71	3.46	3.7
15	7.62	7.68	7.74	3.11	3.18	3.78
16	11.1	11.28	10.57	3.71	3.58	3.98
17	8.34	9.05	8.41	3.63	3.59	3.53
18	8.04	7.98	8.17	3.68	3.35	3.54
19	8.04	7.87	7.85	3.47	3.41	3.45
20	8.58	8.47	8.17	3.43	3.35	3.41
21	11.62	10.58	11.11	3.66	3.49	3.56
22	7.98	7.56	7.91	3.53	3.39	3.54
23	9.57	9.47	8.91	4.01	3.69	4.02
24	9.31	8.87	9.74	3.47	3.59	3.54
25	6.98	7.52	6.69	4.05	3.81	4.15
26	8.82	8.54	8.62	3.89	3.54	3.87
27	8.64	8.65	8.24	3.57	3.42	3.48

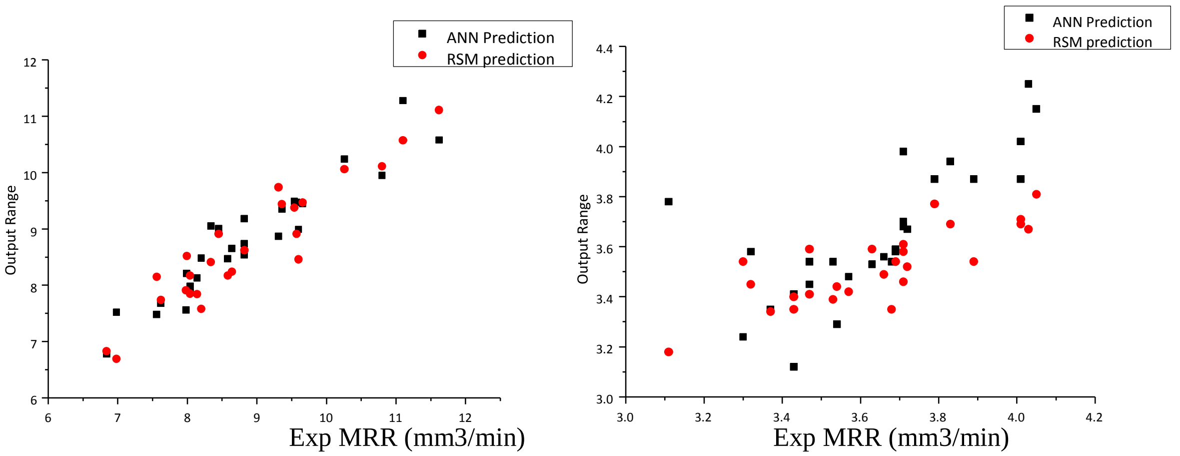

Fig. 3(a) Comparison of error profile for Material Removal Rate, (b) Comparison of error profile for Surface Roughness

The effectiveness of the observational relationships is tested by drawing scatter diagram with the experimental worth and foretold worth on X axis and Y axis severally as shown in fig. The scattered plots square measure terribly on the point of the road that indicates the right fitness of the developed empirical relationships. Experiments were conducted to verify the effective of the developed observational relationships. 5 experimental were created victimization completely different values of things save for those employed in style matrix and their material removal rate and surface roughness were calculable. The obtained results square measure shown in table 5. The result shows that the anticipated values square measure quite acceptable than substantial error.

V. Conclusion

In this work the predicted values from artificial neural network and Response surface methodologies were compared and promoted prediction efficiency for output range values throughout WEDM of PAC/7075 Al MMC. ANN model showed better least error percentage profile than RSM model. The prediction expected of ANN model was regarding higher than RSM. The utmost absolute proportion error within the ANN prediction of MRR was found to be around of 4.85%, whereas for the RSM model, it had been around 8.24%. On the idea of error profile the prediction accuracy of ANN model is above RSM model. Result of input method parameters shows that servo speed and pulse on time is a lot of vital parameter on MRR and surface roughness than pulse-off time and Discharge current for 9% PAC/7075 Aluminium Metal matrix composites.

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