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Optimization of Material Removal Rate in Wire-EDM using Genetic Algorithms

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Abstract

The current study focus on developing mathematical model for MRR in wire EDM using artificial neural network. The experiment is designed using L27 Taguchi orthogonal array. The process parameters selected are pulse on time, pulse off time, flushing pressure, wire tension, servo voltage and wire feed rate. A feed forward neural network with back propagation algorithm is trained to find better MRR. MATLAB program is used to develop neural network model and trained model is simulated. The network model result is compared with experimental result and it find that error is minimum. Then optimum process parameter is identified using genetic algorithm. The obtained optimum parameter is experimentally verified.

Keywords: WEDM, Artificial neural network (ANN), genetic algorithm, Taguchi technique

INTRODUCTION

WEDM is thermo-electrical unconventional machining process. The material is removed by successive spark between the work piece and wire electrode. The gap between the wire electrode and workpiece is completely filled with dielectric fluid. It will flush away the removed material from the spark gap [1]. Material removal rate is an important process characteristic need to be studied in WEDM. Selection of process parameter is an important element to study the process characteristics in EDM [2]. Somashekhar et al developed a neural network model for MRR using artificial neural network in WEDM process. The well trained model was developed using MATLAB and it found effective in estimating the MRR. The well trained model is optimized using genetic algorithm [3]. Pragya Shandilya et al have modelled the optimized the selected process parameter in WEDM process using ANN and Genetic algorithm. The selected parameters were pulse-on time, pulse-off time, wire feed rate and servo voltage, [4].

Bijaya BijetaNayak and Siba SankarMahapatra optimized the selected process parameter in EDM during taper cutting of Inconel718 material. Taguchi design experiment technique was used to run the experiment. Part thickness, taper angle, pulse duration, discharge current, wire speed and wire tension were considered as a process parameter. ANN model was developed to understand the relationship between process parameter and output responses [5]. G.Sankara Narayanan and D.Vasudevan developed a functional model relating process parameter and response variables using artificial neural network (ANN) for SKD11 tool steel material in WEDM. The trial experiments were conducted to get the experimental data to train the neural network. The program for train the model is developed using Mat lab [6]. ANN was an effective technique to predict input process parameters for optimal process performance [7]. Genetic algorithm was an effective optimization technique used for machining process [8]. In this paper ANN is used for modelling and GA is employed to optimize the MRR during WEDM.

EXPERIMENTATION

The experiment is performed on Electra Spring cut 734 four axis WEDM. The experiment is designed using Taguchi method. 27 experiments are conducted at different level of input process parameter. As six input process parameters namely pulse on, pulse off time, Current, Servo voltage wire feed and fluid pressure are chosen for the experiments. Input process parameters and their levels are shown in table 1.

Table 1: Input variable and their levels

S.No	Symbol	Input process parameter	Levels		
			I	II	III
1	A	Pulse on Time- Ton (µs)	110	115	120
2	B	Pulse off time T-off (µs)	40	45	50
3	C	Flushing Pressure (kgf/cm2)- Fp	8	10	12
4	D	Wire Tension (kgf)-Wt	550	750	950
5	E	Servo Voltage (volt)- Sv	15	20	25
6	F	Wire feed rate (m/min)- Wf	6	8	10

The range of input process parameter is selected based on the literature survey and the preliminary experiments. Few parameters are fixed as available in the machine. The fixed parameters are shown in table 2.

Table 2: Fixed Parameters

S.No	Fixed parameter	Set value
1	Wire material	Molybdenum wire of diameter of 0.25 mm
2	Peak current	230 Amps
3	Pulse in peak voltage	2
4	Servo feed setting	250

The response parameter material removal rate (MRR) is calculated by weighing the workpiece before and after machining with respect to time. The observed results for MRR are shown in table 3.

Table 3: Experiments using L27 orthogonal array

Run	Ton	Toff	Fp	Wt	Sv	Wf	MRR
1	110	40	8	550	15	6	6.5826
2	110	40	8	550	20	8	6.096
3	110	40	8	550	25	10	5.7664
4	110	45	10	750	15	6	6.0711
5	110	45	10	750	20	8	5.7778
6	110	45	10	750	25	10	5.4864
7	110	50	12	950	15	6	5.6018
8	110	50	12	950	20	8	5.4668
9	110	50	12	950	25	10	4.978
10	115	40	10	950	15	6	8.3965
11	115	40	10	950	20	8	7.748
12	115	40	10	950	25	10	7.2169
13	115	45	12	550	15	6	7.029
14	115	45	12	550	20	8	6.6949
15	115	45	12	550	25	10	6.338
16	115	50	8	750	15	6	5.9778
17	115	50	8	750	20	8	5.777
18	115	50	8	750	25	10	5.4474
19	120	40	12	750	15	6	8.5164
20	120	40	12	750	20	8	8.1123
21	120	40	12	750	25	10	7.9431
22	120	45	8	950	15	6	8.1194
23	120	45	8	950	20	8	7.8864
24	120	45	8	950	25	10	7.8596
25	120	50	10	550	15	6	7.6905
26	120	50	10	550	20	8	7.1651
27	120	50	10	550	25	10	6.9987

Artificial neural network (ANN)

The back propagation training algorithms has been implemented for training the neural architectures. In this study single hidden layer was used throughout analysis. It because single hidden layer is enough for back-propagation neural network to define the input-output mapping. The number of neuron in the input layer and the output layer are fixed for this study. The input process parameters and responses of Wire - EDM process are fixed for this analysis and also the mapping is to be established between input and output parameters.

Genetic algorithm

The genetic algorithm is a probabilistic local search algorithm that iteratively transforms a Population into mathematical objects, each with an associated fitness value into a new population of offspring objects. The objective of this study is to maximize the MRR

MRR = f(Ton_Toff_ Fp_Wt_Sv_ Wf)

Subject to constraints

$110 \leq Ton \leq 120$

$40 \leq Toff \leq 50$

$8 \leq Fp \leq 12$

$550 \leq Wt \leq 950$

$15 \leq Sv \leq 25$

$6 \leq Wf \leq 10$

Where Ton, Toff, Fp, Wt, Sv and Wf are pulse on, pulse off time, Current, Servo voltage wire feed and fluid pressure respectively. Genetic algorithm parameter and their value is shown in table 5. The limitation range of the input process parameters are assigned based on experimental setup. f represents relationship between material removal rate and six input process parameters. For every iteration of Genetic algorithms, material removal rate values are predicted by artificial neural network models for a specified population size. The Genetic algorithm randomly generated a real valued population of possible process parameter chromosomes. A new population for the next generation is created based on old population using different operator functions. MATLAB is used for the optimization. Optimized parameter value is shown in table 6.

Table 4: Predicted Value

S.No	MRR-Actual	ANN MRR-Predicted
1	6.5826	6.20119
2	6.096	6.10152
3	5.7664	5.77725
4	6.0711	6.14578
5	5.7778	5.82429
6	5.4864	5.62399
7	5.6018	5.97842
8	5.4668	5.70123
9	4.978	5.08302
10	8.3965	8.30814
11	7.748	8.03780
12	7.2169	7.58424
13	7.029	6.94590
14	6.6949	7.03865

S.No	MRR-Actual	ANN MRR-Predicted
15	6.338	6.76547
16	5.9778	6.21164
17	5.777	5.71987
18	5.4474	5.42603
19	8.5164	8.39569
20	8.1123	8.33866
21	7.9431	8.15525
22	8.1194	8.14779
23	7.8864	7.92659
24	7.8596	7.90579
25	7.6905	7.83080
26	7.1651	7.24643
27	6.9987	6.66245

Table 5: Genetic Algorithm parameter and their values

number of generations	500
population size	20
crossover rate	0.8
crossover mechanism	Two point
mutation rate	0.01

Table 6: Optimum process parameter

Process parameter						MRR		Error
Ton	**Toff**	**Fp**	**Wt**	**Sv**	**Wf**	predicted	Experimental	
115	40	10	750	15	8	7.728	7.964	3.05%

DISCUSSION

ANN is trained with different nodes in the hidden layer using experimental data. Model accuracy is improved of low value of RSME model. In this study two layer and six hidden neurons per layer is selected. The predicted value of MRR is compared with the experimental model and shown in table 4. To predict MRR for nonlinear responses tansig transfer function introduced in the neural network.

The selection of important input process parameter is essential in manufacturing process because these factors determine performance of WEDM process. The result shows that artificial neural network model would be successfully applied in WEDM process to predict the machining response.

ANN- GA is combined to predict the optimum input process parameter for the WEDM process. The obtained results are shown in Table 5. The obtained results are verified with experimental results. The results are valid for the range of parameters considered in this analysis.

CONCLUSIONS

In this research work MRR was predicted by feed-forward neural network with back propagation algorithm for the given range of input process parameter. The following conclusion were made from the study,

1. The proposed ANN algorithm useful for reduction in production time and set-up time, along with the reduction in cost in WEDM processes.
2. The developed artificial neural network model results are close agreement with experimental values.
3. Optimum process parameter was derived from gentic algorithm process. The obtained optimum parameters are 115Ton of 114, Toff of 40, Fp of 10, Wt of 750, Sv of 15 and Wf of 8.

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