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Process optimization and estimation of machining performances using artificial neural network in wire EDM

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Abstract

Wire electrical discharge machining (WEDM) is a specialised thermal machining technique that can precisely manufacture items with complex shapes or variable hardness that are highly challenging for conventional machining methods to handle because of their sharp edges. The development of a model and its use to improve WEDM machining settings utilising Taguchi's technique, which is based on resilient design, are both covered in this work. The Taguchi L'16 orthogonal array was used for the experimentation. Each experiment was run under a separate set of cutting parameters, including pulse-on, pulse-off, current, and bed speed. Voltage and flush rate were maintained constants among the various process variables. An electrode was created using molybdenum wire that had a 0.18 mm diameter. There have been three responses: accuracy, surface roughness, and volumetric material removal rate.

Keywords: WEDM, Optimization, Accuracy, Surface Roughness, VMRR, ANN.

1. Introduction

Using a sophisticated thermal machining technique called wire electrical discharge machining (WEDM), hard material pieces with intricate forms can be precisely machined. From a straightforward method of creating tools and dies to the greatest solution for creating micro-scale parts with the highest level of dimensional accuracy and surface polish, WEDM has grown. Only a few applications call for molybdenum wire, which has a very high tensile strength and a tiny diameter to offer a respectable weight carrying capacity. In wire EDM, it will be explored experimentally how process parameters affect accuracy, volumetric material removal rate (VMRR), and surface roughness. Analyzing the efficacy of every process parameter is a very laborious operation because the process depends on various parameters. Hence, different techniques are used to analyze the parameters for better utilization of the process. Several experiments are conducted to consider effects of pulse-on, pulse-off, current and bed speed, on the accuracy, surface roughness,VMRR.

A Taguchi's standard orthogonal array is chosen for the design of experiments. Analyses of variance (ANOVA) are performed on experimental data. The responses were predicted for 50%, 60% and 70% of the training set for stavax material using Artificial Neural Networks (ANN). Kannachai Kanlayasiri and Prajak Jattakul (2013) have discussed an optimal cutting condition of dimensional accuracy and surface roughness for finishing cut of wire-EDMed K460 tool steel. The cutting variables investigated in this study encompassed cutting speed, peak current and offset distance. Box–Behnken design was employed as the experimental strategy, and multiple response optimization on dimensional accuracy and surface roughness was performed using the desirability function. Results showed that both peak current and offset distance have a significant effect on the dimension of the specimen while peak current alone affects the surface roughness. Farnaz Nourbakhsh et al. (2013) have discussed the influence of zinc-coated brass wire on the performance of WEDM is compared with high-speed brass and also investigated the effect of seven process parameters including pulse width, servo reference voltage, pulse current, and wire tension on process performance parameters (such as cutting speed, wire rupture and surface integrity).

A Taguchi L_{18} design of experiment (DOE) has been applied. All experiments have been conducted using Charmilles WEDM. It was also found that the peak current and pulse width have significant effect on cutting speed and surface roughness. The Analysis of Variance (ANOVA) also indicated that voltage, injection pressure, wire feed rate and wire tension have non-significant effect on the cutting speed. Scanning Electron Microscopic (SEM) examination of machined surfaces was performed to understand the effect of different wires on work piece material surface characteristics. Compared with high-speed brass wire, zinc-coated brass wire results in higher cutting speed and smoother surface finish. High speed brass wire resistance against wire rupture in tough conditions, high pulse width and low time between two pulses, is much more than zinc coated wire. Venkata Rao and Kalyankar (2013) have proposed a newly developed advanced algorithm named 'teaching–learning-based optimization (TLBO) algorithm' is applied for the process parameter optimization of selected modern machining processes. The important modern machining processes identified for the process parameters optimization in this work are ultrasonic machining (USM), abrasive jet machining (AJM), and wire electrical discharge machining (WEDM) process. The examples considered for these processes were attempted previously by various researchers using different optimization techniques such as genetic algorithm (GA), simulated annealing (SA), artificial bee colony algorithm (ABC), particle swarm optimization (PSO), harmony search (HS), shuffled frog leaping (SFL) etc.

In case of USM process, the TLBO algorithm has given the improvement of approximately 12% over genetic algorithm and a considerable improvement over other algorithms used for the same model. Similarly, the improvement obtained in case of AJM process is 8% and 20% for brittle material and ductile material respectively over genetic algorithm and simulated annealing algorithm. In case of WEDM process, the TLBO algorithm has given considerable improvement over that of ABC results. Thus the TLBO algorithm is proved superior over the other advanced optimization algorithms in terms of results and convergence. Probir Saha et al. (2013) have proposed a Neuro-Genetic technique to optimize the multi-response of wire electro-discharge machining (WEDM) process. This technique was developed through hybridization of a radial basis function network (RBFN) and non-dominated sorting genetic algorithm (NSGA-II). The machining was done on 5 vol% titanium carbide (TiC) reinforced austenitic manganese steel metal matrix composite (MMC).

The process parameters namely pulse on-time and average gap voltage have great influence on the cutting speed and the kerf width. From the experimental results, an increase in the average gap voltage leads to the decrease of the cutting speed but increase in the kerf width, within the parametric range under consideration. It is also observed that an increase in pulse on-time increases both the cutting speed and kerf width. The proposed Neuro- Genetic technique was also compared with the weighted sum method based on single-objective GA. It was found that the proposed technique is superior to the weighted sum method. Behzad Jabbaripour et al. (2013) have proposed two series of machining tests are designed. Firstly the powder mixed electrical discharge machining (PMEDM) of γ- TiAl by means of different powders such as aluminum, chrome, silicon carbide, graphite and iron is performed to investigate the output characteristics of surface roughness and topography, material removal rate (MRR), electrochemical corrosion resistance of machined samples and also the machined surfaces are investigated by means of EDS and XRD analyses. Secondly after selection the aluminum powder as the most appropriate kind of powder, the current, pulse on time, powder size and powder concentration are changed in different levels for overall comparison between EDM and PMEDM output characteristics. In the first setting of input machining parameters, aluminum powder improves the surface roughness of TiAl sample about 32% comparing with EDM case and also aluminum particles with the size of 2 μm, in the second setting of input parameters lead to 54% enhancement of MRR comparing with EDM case. Rajarshi Mukherjee et al. (2012) have an attempt is made to apply six most popular population-based non-traditional optimization algorithms, i.e. genetic algorithm, particle swarm optimization, sheep flock algorithm, ant colony optimization, artificial bee colony and biogeography-based optimization for single and multi-objective optimization of two WEDM processes. Selection of the optimal values of different process parameters, such as pulse duration, pulse frequency, duty factor, peak current, dielectric flow rate, wire speed, wire tension, effective wire offset of wire electrical discharge machining (WEDM) process is of utmost importance for enhanced process performance.

The major performance measures of WEDM process generally include material removal rate, cutting width (kerf), surface roughness and dimensional shift. It is found that although all these six algorithms have high potential in achieving the optimal parameter settings, but the biogeography-based algorithm outperforms the others with respect to optimization performance, quick convergence and dispersion of the optimal solutions from their mean. Thus, the BBO algorithm can be used as a global optimization tool for finding out the parametric combinations of other machining processes too. Pragya Shandilya et al. (2012) have discussed the optimization of process parameters during machining of SiCp/6061 Al metal matrix composite (MMC) by wire electrical discharge machining (WEDM) using response surface methodology (RSM).

Four input process parameters of WEDM (namely servo voltage (V), pulse-on time (T_{ON}), pulse-off time (T_{OFF}) and wire feed rate (WF)) were chosen as variables to study the process performance in terms of cutting width (kerf). The analysis of variance (ANOVA) was carried out to study the effect of process parameters on process performance. ANOVA results show that voltage and wire feed rate are highly significant parameters and pulse-off time is less significant. Pulse-on time has insignificant effect on kerf. In addition mathematical models have also been developed for response parameter. Properties of the machined surface have been examined by the scanning electron microscopic (SEM). Vineet Srivastava and Pulak M. Pandey (2012) have discussed the parametric study on EDM process using ultrasonic assisted cryogenically cooled copper electrode (UACEDM) during machining of M2 grade high speed steel has been performed. Electrode wear ratio (EWR), material removal rate (MRR) and surface roughness (SR) was the three parameters observed. Discharge current, pulse on time, duty cycle and gap voltage were the controllable process variables. EWR and SR were found to be lower in UACEDM process as compared to conventional EDM for the same set of process parameters, while MRR was at par with conventional EDM process. The surface integrity of work piece machined by UACEDM process has been found to be better as compared to conventional EDM process. The shape of the electrode has also been measured and it was found that the shape retention was better in UACEDM process as compared to conventional EDM process. Thus in the present work UACEDM process has been established to be better than conventional EDM process due to better tool life, tool shape retention ability and better surface integrity. Harminder Singh and Shukla (2012) have discussed the variation of fraction of input discharge energy with the help of thermo-mathematical models during EDM of Tungsten-Carbide by varying the machining parameters current and pulse duration. The data calculated in this study can be further used in the existing thermophysical models, expecting to bring the models preciously more close to the real conditions. This data will also be helpful for numerically calculating the optimum parameters using optimum value of the fraction of energy transferred to the electrodes especially workpiece. The results obtained showed that the energy effectively transferred to the workpiece varies with the discharge current and pulse duration from 6.5% to 17.7%, which proves that the fixed value assumed in the models is not in line with real EDM process.

This study will help in prediction of optimum parameters using existing thermo-physical models by using the values of current and pulse duration where maximum fraction of energy is transferred to workpiece. Muthuraman and Ramakrishanan (2012) have discussed the multi parameter optimization of tungsten carbide cobalt metal matrix composites were done using desirability approach. A 0.25 mm diameter zinc coated copper wire was used as a tool electrode to cut the material. Experiments were designed and conducted using Taguchi's L'_{32} orthogonal array. They have selected, percentage of cobalt in the composite, pulse on time, delay time, wire feed, wire tension, ignition current and di-electric pressure are the input variables. Three trails were conducted and the average was chosen as the response at that particular experimental condition. Optimization of the multiple process variables were carried out using desirability function analysis. Conformation experiments were carried out to check the accuracy of the optimized results. For optimal machining conditions the percentage of cobalt binder phase needs to be 20% within tungsten carbide cobalt metal matrix composites. The optimal machining parameters are pulse on time15 μsec, delay time 10 μsec, wire feed 100 mm/min, wire tension 80 N, ignition current 20 Amps and di-electric pressure 40 Pascals. Using the composite desirability analysis, surface roughness is decreased from 2.52 μm to 1.90 μm and material removal rate is increased from 19.52 mm^3/min to 21.24 mm^3/min.

2. Experimental work

The experiments were performed on CONCORD DK7720C four axes CNC WED machine. The basic parts of the WED machine consist of a wire electrode, a work table, a servo control system, a power supply and dielectric supply system. The CONCORD DK7720C allows the operator to choose input parameters according to the material and height of the work piece. The WED machine has several special features. Unlike other WED machines, it uses the reusable wire technology. i.e., wire can't be thrown out once used; instead it is reused adopting the re-looping wire technology. The experimental set-up for the data acquisition is illustrated in the Fig. 1. The WEDM process generally consists of several stages, a rough cut phase, a rough cut with finishing stage, and a finishing stage. But in this WED machine only one pass is used.

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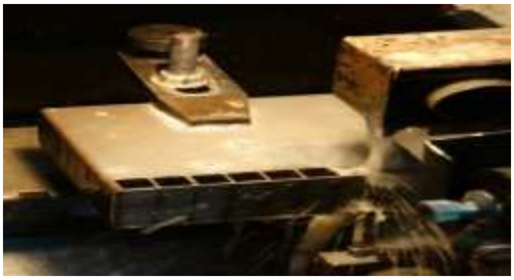

Fig. 1. Experimental Set-up

The gap between wire and work piece is 0.02 mm and is constantly maintained by a computer controlled positioning system. Molybdenum wire having diameter of 0.18 mm was used as an electrode. The control factors and fixed parameters selected are as listed in Table 1. The control factors were chosen based on review of literature and experts. Each time the experiment was performed, an optimized set of input parameters was chosen. In this study, five machining parameters were used as control factors and each parameter was designed to have four levels denoted I, II, III and IV as shown in Table 1.

Table 1. Machining settings used in experiments

		Level			
Control Factors		I	II	III	IV
A	Pulse –on	16	20	24	28
B	Pulse-off	4	6	8	10
C	Current	3	4	5	6
D	Bed speed	20	25	30	35

Results and Discussions

The analysis of variance was used to establish statistically significant machining parameters and the percentage contribution of these parameters on accuracy, surface roughness and VMRR. In Taguchi method a loss function is used to calculate the deviation between the experimental value and the desired value. This function is further transformed into signal to noise ratio. Taguchi's philosophy includes three general ways to evaluate the relationship between quality and variability they are: Nominal is better approach, Smaller is better approach, Larger is better approach. In WEDM, the lower accuracy, lower surface roughness and higher VMRR are indication of better performances.

Adopting the quadratic loss function, the objective function can be given by:

$$\eta \text{ (S/N ratio for Accuracy)} = -10 \log_{10} \left\{ \frac{1}{n} \sum_{i=1}^{n} y_{acc}^{2} \right\} \quad (1)$$

$$\eta \text{ (S/N ratio for Surface roughness)} = -10 \log_{10} \left\{ \frac{1}{n} \sum_{i=1}^{n} y_{R_a}^{2} \right\} \quad (2)$$

$$\eta \text{ (S/N ratio for VMRR)} = -10 \log_{10} \left\{ \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_{MRR}^{2}} \right\} \quad (3)$$

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After conducting the experiment, response values are noted down and analysis has been done. Taguchi analysis was conducted to determine the optimal parameters and ANOVA was also performed to estimate magnitude of factors effects on the responses. The experiment was conducted in the same environmental condition for all the runs so that environmental noise factors can be minimized. The response variables for Stavax material is shown in Table 2. The main effect plot for Stavax material for accuracy, surface roughness and VMRR are as shown in Fig. 3, Fig. 4 and Fig. 5 respectively. It is clear from the main effect plot, that the factor current has largest effect on the VMRR, dimensional accuracy and surface roughness as response variable. The optimum level for a factor is the level that gives the highest value of η (S/N ratios) in the experimental region.

Artificial Neural Network

A neural network is an artificial representation of human brain that tries to simulate its learning process. ANN is an interconnected group of artificial neurons that uses a mathematical model or computational models for information processing based on a connectionist approach to computation. The artificial neural networks are made of inter connecting neurons which may share some properties of biological neurons. ANN is an information processing paradigm that is inspired by procedure in the biological nervous system. 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. The output signal of a neuron is fed to other neurons as input signals via interconnections Fig. 2 shows the network architecture of ANN.

The neuron has a bias b, which is summed with the weighted inputs to form the net input n.

$$n = w1,1p1 + w1,2\ p2 + \ldots + w1,R\ pR + b \tag{4}$$

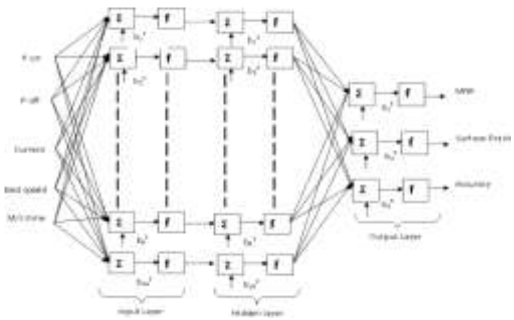

Fig. 2. Network Architecture

Various input to the neurons are represented by 'Xn'. Each of these inputs is multiplied by a connection weighed, represented by 'Wn' and added to the bias 'φ' to compute activation 'an' which is converted into the output 'On' via transfer function. Various input to the neurons are represented by 'Xn'. Each of these inputs is multiplied by a connection weighed, represented by 'Wn' and added to the bias 'φ' to compute activation 'an' which is converted into the output 'On' via transfer function.

$$a_n = W_n\, Xn^T + \varphi \tag{5}$$

$$O_n = f\,(a_n) \tag{6}$$

Since the capability of a single neuron is limited, complex functions can be realized by connecting many such neurons to form layers neuron network. The common type of ANN consists of 3 layers viz., Input layer, Hidden layer and Output layer. A layer of input units is connected to a layer of hidden units which is connected to layer of output units. Patterns are presented to the networks via the input layer, which communicates to one or more hidden layers where the actual processing is done via a system of weighed connections. The hidden layers then link to an output layer. A layer is defined as group of parallel neurons without and interaction between them.

Table 2. Experimental design using L'$_{16}$ orthogonal array

Run	Pulse-on (μs)	Pulse-off (μs)	Current (Amps)	Bed speed (μm/s)	Surface Roughness (μm)	VMRR mm3/min	Accuracy (μm)
1	16	4	3	20	2.392	5.522475	12
2	16	6	4	25	2.384	5.501599	11
3	16	8	5	30	2.526	5.362812	9
4	16	10	6	35	2.792	7.217242	20
5	20	4	4	30	2.631	6.803308	19
6	20	6	3	35	2.541	6.23702	18
7	20	8	6	20	2.843	7.350427	21
8	20	10	5	25	2.891	7.440031	23
9	24	4	5	35	3.317	9.73251	28
10	24	6	6	30	3.281	8.631387	24
11	24	8	3	25	2.476	6.059247	13
12	24	10	4	20	2.253	5.202805	11
13	28	4	6	25	3.024	8.58634	26
14	28	6	5	20	2.586	6.376812	17
15	28	8	4	35	2.482	6.085558	15
16	28	10	3	30	2.348	5.375764	10

Observations on Surface Roughness, VMRR and Accuracy

Fig. 3, Fig. 4 and Fig. 5 shows the main effect plot for stavax material of thickness 40 mm, for the surface roughness, VMRR and accuracy as the response variable based on S/N ratio. It is clear from the Fig. 3, Fig. 4 and Fig. 5; the main effect plot for stavax material that the factor current has larger effect on the surface roughness, VMRR and accuracy as the response variable.

The optimal level for a factor is the level that gives the highest value of η in the experimental region. The purpose of conducting the ANOVA is to determine the relative magnitude of the effect of each factor on the objective function η. The larger the F value, the larger will be the factor effect. Referring to the ANOVA, the largest value of F is in the factor current. That means the factor current has the more effect on the accuracy as the response variable. This can be seen from the main effect plot shown in the Fig. 3, Fig. 4 and Fig. 5.

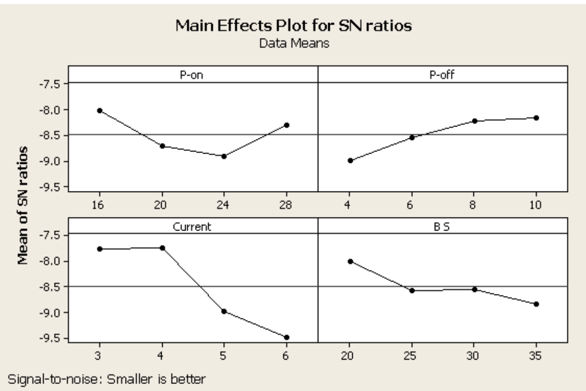

Fig. 3. Main effects plot for surface roughness

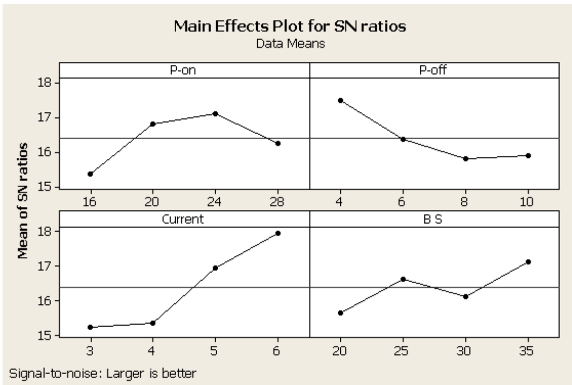

Fig. 4. Main effects plot for VMRR

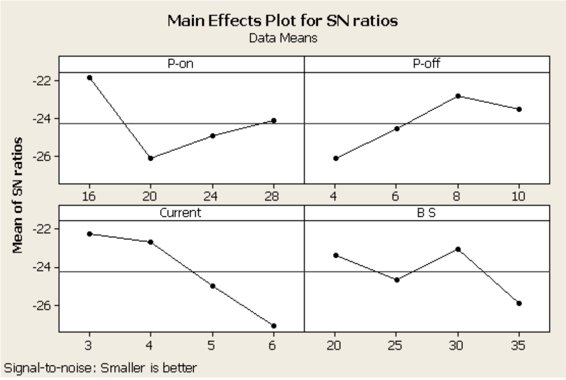

Fig. 5. Main effects plot for accuracy

Prediction of response variables of Stavax material

The prediction of responses was carried out using Neural Network Fitting Tool for various training sets of 50%, 60% and 70%. When the training is completed, it is necessary to check the network performance and determine if any changes need to be made to the training process, network architecture or the data sets. Table 3 shows the prediction of machining performances using neural networks at 70% of data in training set.

Table 3: Prediction of response variables using ANN

Prediction of Machining Performances by Ann		
Surface Roughness	VMRR	Accuracy
2.323	5.73117	12.0618
2.41675	5.75503	11.0014
2.42954	5.66445	9.10334
2.83018	7.48386	20.1846
2.62174	7.01174	18.9236
2.49399	6.52825	17.8726
2.84291	7.60382	20.9181
2.86634	7.73966	22.9547
3.20079	9.69693	28.2227
3.22279	8.84126	24.0482
2.56598	6.30971	12.893
2.30743	5.46249	11.0044
2.87147	8.54325	26.2127
2.57368	6.65388	16.8318
2.44671	6.29267	15.2406
2.37923	5.673	10.0138

Fig. 6, Fig. 7 and Fig. 8 shows the comparison of measured and predicted surface roughness, VMRR and accuracy of different datasets viz., 50%, 60%, and 70% for Stavax material. It is observed from the Fig. 6 predicted surface roughness of 70% of the data set exhibits better correlation with the measured surface roughness than 50% and 60% of the data set. Fig. 7 predicted VMRR of 70% of the data set exhibits better correlation with the measured VMRR than 50% and 60% of the data set. Fig. 8 predicted accuracy of 70% of the data set exhibits better correlation with the measured accuracy than 50% and 60% of the data set.

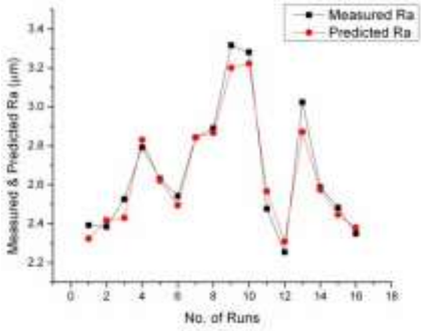

Fig. 6. Comparison of measured and predicted Surface finish

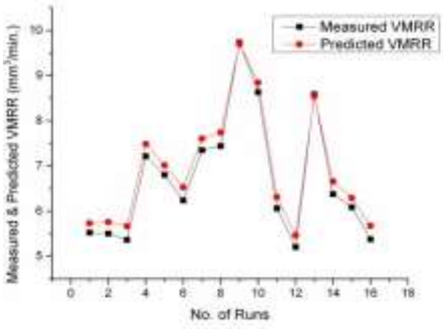

Fig. 7. Comparison of measured and predicted VMRR

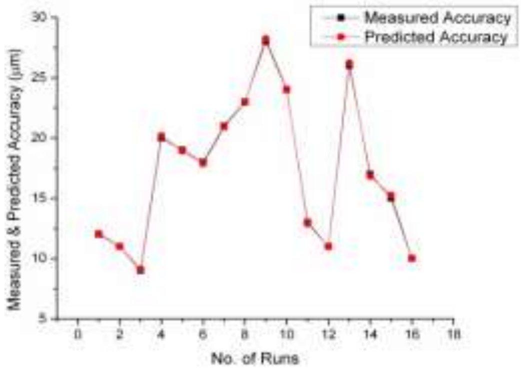

Fig. 8. Comparison of measured and predicted Accuracy

4. Conclusion

The examination into optimization and the impact of machining settings on accuracy, surface roughness, and VMRR in WEDM operations is provided in this work. ANOVA is used to assess the influence of the machining parameters on accuracy, surface roughness, and VMRR. The very effective parameters for surface roughness, VMRR, and accuracy were discovered as current based on the ANOVA approach. Pulse-on, Pulse-off, Current, and Bed speed are the control variables taken into consideration for the investigations. On the basis of Taguchi's L'16 orthogonal array, process parameters were chosen. Surface roughness, VMRR, and accuracy are the response variables that are predicted using ANN. The network is constructed and trained using the Levenberg-Marquardt algorithm (LMA) and the back propagation feed forward neural network (BPNN). The results of neural network training is 70% of the data in training set gives good prediction results when compared to the 50% and 60% of data in training set. Thus, predicted response variables of 70% training set correlates well with the measured response variables.

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