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Performance Analysis of Wire Electric Discharge Machining on D-3 Die Material by Artificial Neural Network

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Abstract: Demand in present industries which specialize in cutting complex shapes and geometries of conductive metals of any hardness that are difficult or impossible to cut with traditional machining process. WEDM is one of the most commonly used machining which is employed in machining of conductive hard metals. The literature survey has revealed that very lass work has been done in order to achieve optimal level of process parameters for D3 die material using coated wire electrode. This material has been selected keeping in view their application and machined using Electronica maxi cute. The main objective of the present work is to investigate the effect of different process parameters viz. pulse on time, pulse off time , spark voltage , peak current on the response parameters such as surface roughness and MRR using coated wire electrode (0.25 mm diameter). The taguchi design methodology is chosen for design of experiment and L18 orthogonal array are selected for present work. Estimation and comparision of response was done by using Artificial Nural Network (ANN).
Keywords: ANN, D-3, WEDM, Taguchi Method, MRR.

I. INTRODUCTION

Wire Electrical Discharge machining (WEDM) is a specialized thermal machining process capable of accurately machining parts of hard materials with complex shapes. WEDM has evolved as a simple means of making tools and dies to the best alternative of producing micro-scale parts with the highest degree of dimensional accuracy and surface finish. Copper wire is used in various applications which require very high tensile strength to provide a reasonable load carrying capacity in small diameter wire. The effect of process parameters on the material removal rate (MRR) and surface roughness is to be investigated experimentally in wire EDM. As the process depends of different parameters it is very tedious task to analyze the effectiveness of all the parameter for the process. So, different techniques are used to analyze the parameters for better utilization of the process. A Taguchi's standard orthogonal array is chosen for the design of experiments. The responses were predicted for 50%, 60% and 70% of the training set for D-3 die material using Artificial Neural Networks (ANN).

II. LITERATURE REVIEW

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 L18 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 NeuroGenetic 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 γTiAl 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.

III. EXPERIMENTAL WORK

The experiments were performed on Electronica Maxicut e 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 Electronica Maxicut e allows the operator to choose input parameters according to the material and height of the work piece. Copper wire having diameter of 0.25 mm was used as an electrode. The control factors and Process 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.

Fig. 1. Experimental Set up

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In this study, four machining parameters were used as control factors and each parameter was designed to have three levels denoted 1,2 and 3 as shown in Table 1.

Table 1. Machining settings used in experiments

Control Factor		Level 1	Level 2	Level 3
A	Ton	2	4	6
B	Toff	4	6	8
C	SV	70	65	60
D	IP	5	6	7

IV. RESULT AND DISCUSSION

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, lower surface roughness and higher MRR are indication of better performances.

Table 2. Experimental design using L18 orthogonal array

Ton	Toff	Spark Voltage	Peak Current	MRR	Surface roughness
2	4	70	5	6.481	3.058
2	6	65	6	5.265	3.04
2	8	60	7	2.51	2.89
4	4	70	7	5.368	3.114
4	6	65	5	6.602	3.01
4	8	60	6	3.389	3.222
6	4	65	7	6.502	2.783
6	6	60	5	4.252	2.985
6	8	70	6	5.216	3.321
2	4	60	5	3.982	3.112
2	6	70	6	3.466	2.887
2	8	65	7	4.499	3.221
4	4	65	6	5.76	3.324
4	6	60	7	3.888	2.882
4	8	70	5	6.675	2.989
6	4	60	6	4.682	3.014
6	6	70	7	6.162	3.411
6	8	65	5	5.481	3.389

A. 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. shows the network architecture of ANN.

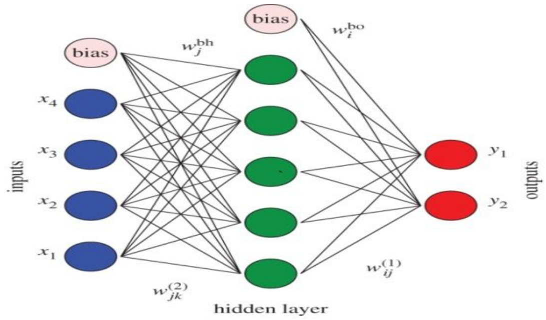

Figure 1. Network Architecture

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.

$$a_n = Wn\ Xn^T \quad \text{(i)}$$
$$O_n = f\ (a_n) \quad \text{(ii)}$$

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.

B. Prediction of Metal removal rate (MRR) and surface roughness (R_a) by ANN

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 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

MRR	Surface roughness
6.502	3.114
5.278	3.075
2.476	2.951
5.421	3.18
6.701	2.992
3.452	3.198
6.489	2.858
4.301	2.894
5.304	3.214
3.898	2.954
3.562	3.261
4.405	3.282
5.698	3.625
3.875	2.779
6.589	2.913
4.705	3.152
6.241	3.526
5.519	3.281

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Fig. 2 & Fig. 3 shows the comparison of measured and predicted surface roughness and MRR of different datasets viz., 50%, 60%, and 70% for D-3 die material. It is observed from the Fig. 2 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. 3 predicted VMRR of 70% of the data set exhibits better correlation with the measured VMRR than 50% and 60% of the data set.

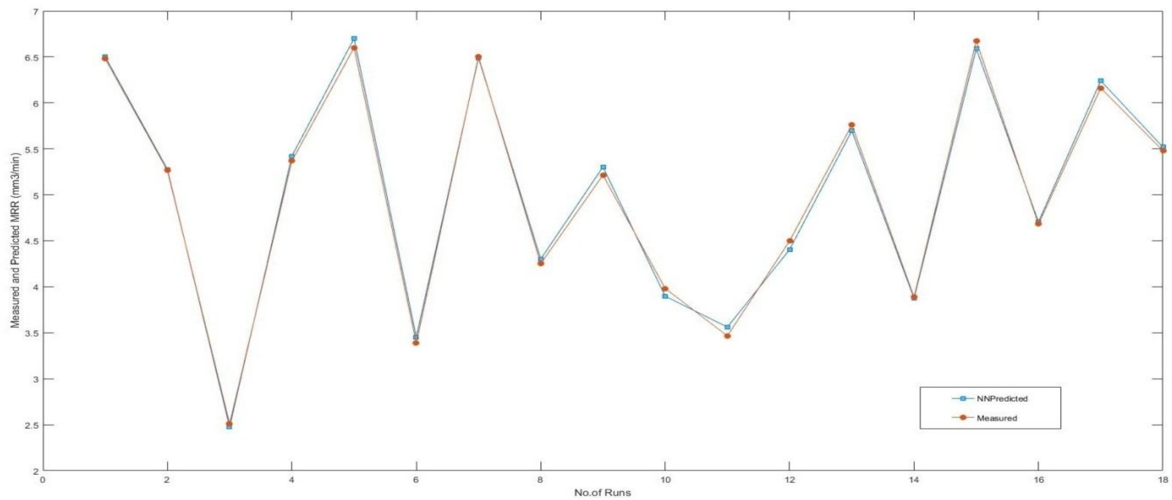

Figure 2. Comparision of measured and predicted MRR

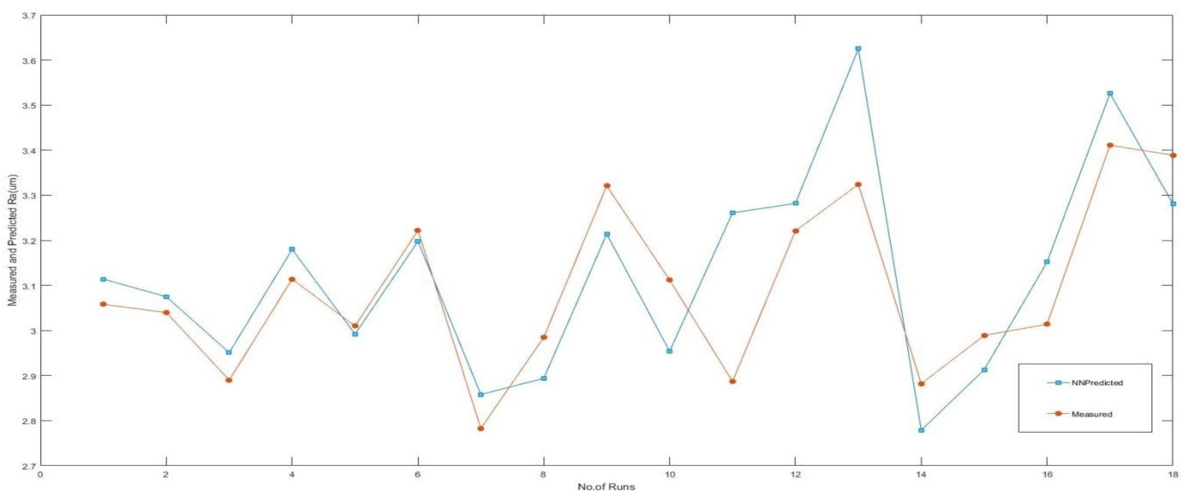

Figure. 3.measured and predicted surface roughness(R_a)

V. CONCLUSION

This paper has presented an investigation on optimization and the effect of machining parameters on surface roughness and MRR in WEDM operations. The control factors considered for the studies are Pulse-on, Pulse-off, Current and Spark voltage. Process parameters were selected based on Taguchi's L'18 orthogonal array. ANN is used to predict the response variable viz., surface roughness,MRR. Back propagation feed forward neural network (BPNN) is used to build and train the network. It is observed that neural network trained with 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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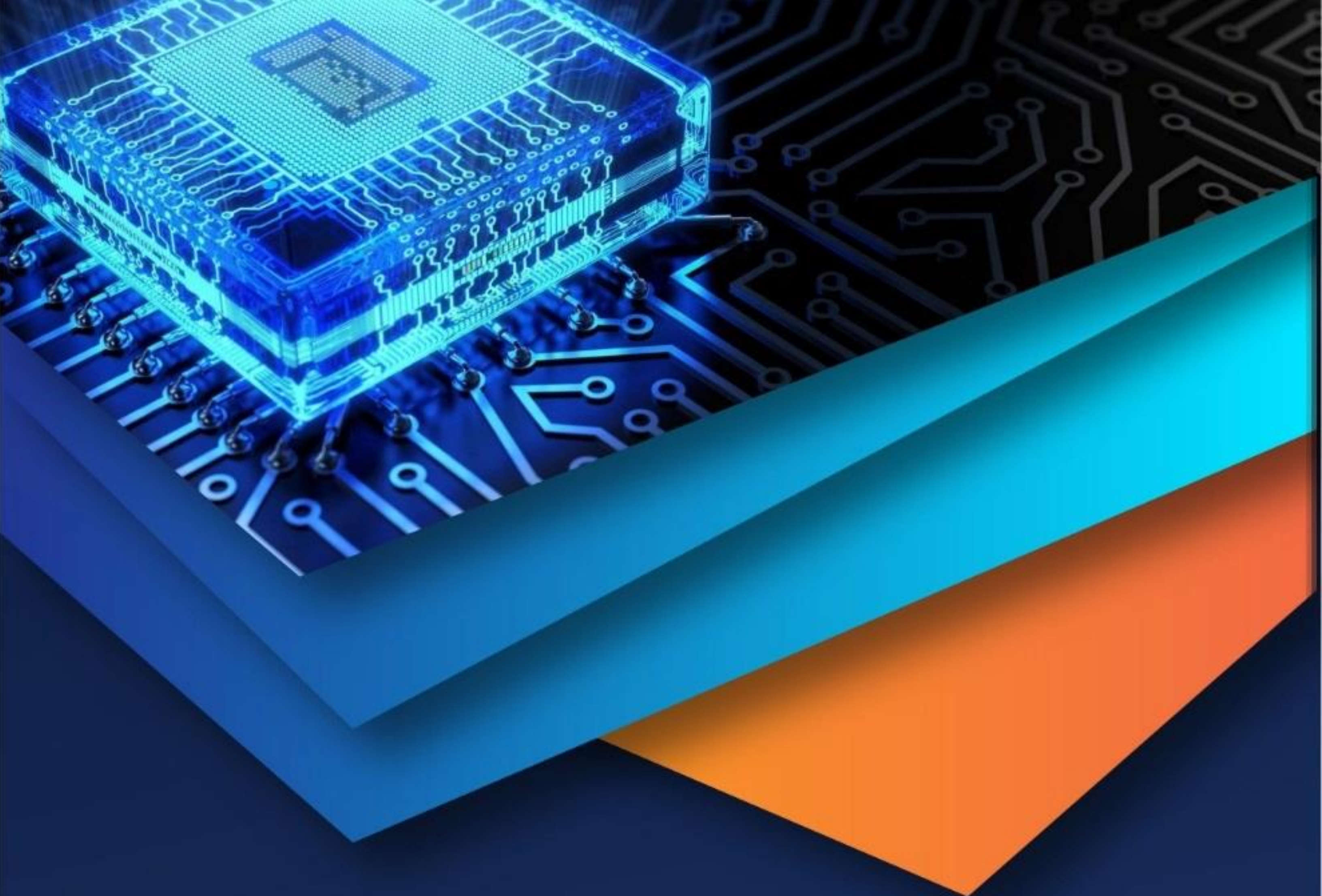

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