Modelling of MRR during Wire-EDM of Ballistic grade alloy using Artificial Neural Network Technique

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Abstract. This research work presents an incorporated approach to modelling of WEDM of AA6063 using Artificial Neural Network (ANN) technique. The experimental investigation has been carried out with four input variables namely pulse-on time \(P_{ON}\), pulse-off time \(P_{OFF}\), servo-voltage \(V_s\) and peak-current \(I_p\). Material removal rate are measured as response parameter. 3\(^3\) full factorial design is used to design the experimental runs. It is apparent from this study that values anticipated by developed model are found closer to experimental results. Thus, it ensures appropriateness of model for prediction purpose and smart manufacturing. Machined surfaces are also examined by SEM to critically evaluate the process.

1. Introduction

WEDM is a variant process of EDM. It was introduced in the late 1960s. This process has many applications in industries (tool and die making, mould and metal working). Generally, components having complex profiles/shapes and strident edges which are tough to machine by other conventional and non-conventional machining techniques, can be easily machined by this process. Hence, this technique has vast application fields: aerospace, automobile, medical, electronic, etc. [1, 2]. The WEDM process is shown in Fig. 1. In WEDM, a sequence of discharge between wire-tool and workpiece produces huge amount of heat for very less time and removes material by melting and vaporizing in terms of craters. Both the tool and workpiece have to be electrically conductive in nature and should be submerged in dielectric fluid (deionized water). To prevent short circuiting a gap has to be sustained between tool and workpiece. A potential difference has to be applied between wire-tool and workpiece to generate an electric field. Usually the tool is having negative polarity and workpiece is having positive polarity. Free electrons on the tool surface experience an electrostatic force when electric field is established between tool and workpiece. Those free electrons which are having less bonding energy, emitted from the tool surface and directed towards the workpiece. The free electrons gain high velocity and energy and collide with dielectric molecules resulting ionization of dielectric molecule. A plasma channel (high concentration of ions and electrons) is generated between tool and workpiece. This plasma channel is having very less electrical resistance thus suddenly, a huge number of electrons flow towards workpiece. Thus high velocity and energy electrons strikes on workpiece surface and produces intense localised heat flux. Such high temperature melts and vaporizes little amount of material from the workpiece surface in the form of craters [3]. A detailed study of published...
research works has been executed (as shown in Fig. 2) on the basis of optimization and modelling technique employed.

![Fig. 1: Representation of WEDM process [10]](image)

It is obvious from the study that Taguchi technique (approx. 52%) is the most frequently used optimization/modelling technique while only 5% research works are reported for modelling with ANN [4-11].

![Fig. 2: Relative study of published research works on modelling techniques used in WEDM](image)

In this research, a full-factorial design (i.e. 81 experiments) is used to conduct the experiment. After that, ANN model has been developed by training the model with outcome of 81 experiments. In addition, validation of developed model has been carried out to evaluate the prediction capability of the model. Furthermore, WEDMed surfaces of highest and lowest MRR are examined by SEM to obtain better understanding of the technique.

2. Experimental Details
2.1. Selection of Workpiece, Wire-tool and Dielectric
For this research work, Aluminium Alloy 6063 (AA 6063) has been selected as workpiece material. AA 6063 is an Al-Si-Mg based alloy. This alloy is best suited for armour applications because of excellent properties namely, corrosion resistance, impact strength, low density, energy absorption and
stiffness [12-13]. EDX image of AA 6063 is shown in Figure 3. As a cutting tool a diffused brass wire (\(\Phi = 0.25\) mm) is used and dielectric medium is De-ionized water.

![Fig.3: EDX analysis of AA 6063](image)

2.2. Experimental Procedure

Wire electric discharge machine is used for experimental investigation. The book titled ‘Advanced Machining Processes’ has shown the in-depth utilities of each sub-element of WEDM [14]. In the current study, \(P_{on}\), \(P_{off}\), \(I_{p}\), and \(V_S\) are taken as input process parameters while, MRR is taken as response parameters. Table 1 shows the ranges and levels of input process parameters. The fixed parameters and their values are also given in Table 1. In current research, 3\(^k\) full factorial design is used to design the experimental runs. (k is number of controlled variables). The MRR is opted as process performance characteristic. It is quantified using Eq. (1).

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MRR(\text{mm}^3/\text{min}) = \text{cutting speed}(\text{mm/\text{min}}) \times \text{height of workpiece (mm)} \times \text{kerf width (mm)}
\] (1)

| Parameters | Levels | Parameters | Values | Fixing Criteria |
|------------|--------|------------|--------|----------------|
| \(P_{on}\) [\(\mu\)s] | L1 105 | \(P_{off}\) [\(\mu\)s] | L1 40 | Dielectric Fluid | De-ionized water | Literature review and pilot experiments |
| \(I_p\) [A] | L1 130 | \(V_S\) [V] | L1 40 | Peak Voltage | 2 m/c unit | |
| \(V_S\) [V] | L2 150 | Water Pressure | L2 1 m/c unit | | |
| | L3 170 | Wire Feed | L3 7 m/c unit | | |
| | | Wire Tension | L3 7 m/c unit | | |
| | | Servo Feed | L3 2050 m/c unit | | |
| | | Workpiece Material | AA 6063 (15cm\(\times\)10cm \(\times\)1.5cm) | Armour application | |

3. Results and Discussions

The minimum MRR of 1.141 mm\(^3\)/min is achieved for the experimental run where, \(P_{on}=105\)\(\mu\)s, \(P_{off}=60\)\(\mu\)s, \(I_p=170\)A, and \(V_S=80\)V. On the other hand, the maximum MRR of 18.103 mm\(^3\)/min is achieved for the experimental run where, \(P_{on}=115\)\(\mu\)s, \(P_{off}=40\)\(\mu\)s, \(I_p=150\)A, and \(V_S=40\)V. It is obvious that there is near about 94% improvement in MRR value owing to suitable setting of machining parameters. The relationship between input parameters and MRR are illustrated in Figure 4. It is evident that when \(P_{on}\) value increases from lower value to higher value the MRR also increases. The reason behind high roughness is high discharge energy. On the other hand \(V_S\) have contrary effect MRR of machined surface. The reason behind this is that at lower value of \(V_S\), there is decrease in
dielectric strength of medium resulting increase in discharge current. The value of \( I_p \) also has contrary effect on MRR. \( P_{off} \) has contrary effect on MRR, due to decrease in discharge energy.

![Relationship between input variables and process performance characteristic](image)

**Fig. 4:** Relationship between input variables and process performance characteristic

SEM images of WEDMed surface corresponding to LDE (low discharge energy) and HDE (high discharge energy) are illustrated in Fig. 5(a) and Fig. 5(b) respectively. Fig. 5(b) clearly demonstrates that the machined surface corresponding to HDE contains higher amount of craters, debris and cracks than the machined surface corresponding to LDE. Due to high discharge energy there is a high value of erosive power which vaporizes a large amount of material cause’s craters and cracks. In addition, HDE increases the depletion of wire tool material; residual particles of wire tool material get stick to the cutting surface and results in formation of rough surfaces.

![SEM micrographs of WEDMed surface](image)

**Fig. 5:** SEM micrographs of WEDMed surface (a) Expt. No: 5 (\( P_{on} = 105 \mu s, P_{off} = 60 \mu s, I_p = 170 A, V_S = 80 V \)) (b) Expt. No: 73 (\( P_{on} = 115 \mu s, P_{off} = 40 \mu s, I_p = 150 A, V_S = 40 V \))
4. ANN modelling

Artificial neural network mimics the human body’s nervous system to solve non-linear multivariate mathematical problem occurring in various engineering fields. It makes utilization of various neurons to acquire, store and utilize the experienced knowledge to find out the interrelation between different process variables. There are three type of layers in an ANN structure namely input layer (present the data to the network), hidden layer (perform essential intermediary computation) and output layer (present network’s response). The characterization of ANN structure is done by its weight vectors, topology and activation function which is used in model hidden and output layer. Neurons are connected to each other to make an ANN structure. Neural network models are of various types, among them feed forward neural network with backward propagation model performs well [15-18]. In the present study the ANN network has four no. of inputs namely, $P_{ON}$, $P_{OFF}$, $V_S$ and $I_P$ and one output of MRR (as shown in Figure 6). MATLAB software is used for the training of 81 input-output data using ANN tool box. Experimental data was divided randomly for training, testing and validation. There are one input layer, one hidden layer and one output layer in the network. The hidden layer is consist of ten neurons. The input layer consist four neurons and output layer have one neurons.

![Schematic diagram of the neural network for the estimation of the MRR](image)

**Fig. 6:** Schematic diagram of the neural network for the estimation of the MRR

4.1. ANN based result

In this research work back propagation multi-layered structure which works on gradient search method is used to train the ANN model. The corelation for MRR between ANN predicted data and experimental data are depicted by Figure 7. The value of R for ANN model is 0.9909. Figure 8 shows the data plot between predictions from ANN model and experimental runs. There is no particular trend between data points which vindicates that developed ANN model is a good demonstration of the current study.
5. Confirmation Experiments
To certify the developed model’s performance confirmation runs were carried out. Results of confirmation runs are shown in table below. From the table 2 it can concluded that the prediction error are only 3.898% which are under permissible limit.

| Pulse-on time (μs) | Pulse-off time (μs) | Peak current (A) | Servo voltage (V) | MRR Predicted | MRR Actual | Absolute % Error |
|-------------------|--------------------|-----------------|------------------|---------------|------------|------------------|
| 115               | 45                 | 170             | 40               | 15.724        | 16.464     | 4.494            |
| 115               | 60                 | 140             | 60               | 4.766         | 5.048      | 5.586            |
| 125               | 40                 | 160             | 60               | 14.275        | 14.048     | 1.615            |

Average absolute % error = 3.898
6. Conclusion
The present work consisted of experimental investigation and intelligent modelling of WEDM process while machining of Al6063. The numbers of 81 experiments were carried out based on full factorial design to investigate effects of $P_{ON}$, $P_{OFF}$, $V_S$ and $I_p$ on MRR. A comparative study of predictions from ANN model and experimental outcome has been carried out and it is found that the ANN process is best suited for modelling the WEDM process. The prediction error are only 3.898% which are under permissible limit. So this model can be used by various researchers and industry people for the prediction of MRR during machining of AA6063 using WEDM.

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