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*Full Length Research Paper*

# Modeling of machining parameters of Ti-6Al-4V for electric discharge machining: A neural network approach

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**This paper presents the artificial intelligence model to predict the optimal machining parameters for Ti-6Al-4V through electrical discharge machining (EDM) using copper as an electrode and positive polarity of the electrode. The objective of this paper is to investigate the peak current, servo voltage, pulse on- and pulse off-time in EDM effects on material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR). Radial basis function neural network (RBFNN) is used to develop the artificial neural network (ANN) modeling of MRR, TWR and SR. Design of experiments (DOE) method by using response surface methodology (RSM) techniques are implemented. The validity test of the fit and adequacy of the proposed models has been carried out through analysis of variance (ANOVA). The optimum machining conditions are estimated and verified with proposed ANN model. It is observed that the developed model is within the limits of the agreeable error with experimental results. Sensitivity analysis is carried out to investigate the relative influence of factors on the performance measures. It is observed that peak current effectively influences the performance measures. The reported results indicate that the proposed ANN models can satisfactorily evaluate the MRR, TWR as well as SR in EDM. Therefore, the proposed model can be considered as valuable tools for the process planning for EDM and leads to economical industrial machining by optimizing the input parameters.**

**Key words:** Ti-6AL-4V, material removal rate, tool wear rate, surface roughness, radial basis function neural network, response surface method.

## INTRODUCTION

Titanium is a very strong and light metal which is stronger than aluminum but as strong as steel. It is 45% lighter than steel and only 60% heavier than aluminum. Their applications to automobile industry have been limited except for racing cars and special-purpose cars because of their high cost despite the strong interest shown in titanium materials by the industry in terms of lightweight, fuel efficiency, and performances (Rahman et al., 2010; Rahman and Abdullah, 2010; Rahman et al., 2011a,b). Titanium alloy also has increasing use in many industrial and commercial applications due to its outstanding corrosion resistance, fatigue resistance and sufficient corrosion resistant in many environments especially in high strength applications. The largest consumer of titanium alloys is the aerospace industry and is increasingly more used in chemical machine building, shipbuilding, oil and gas industry, food industry, medicine and civil engineering (Moiseyev, 2006).

EDM is a non conventional, thermo electric process in which the material from work pieces is eroded by series of discharge sparks between the work and tool electrode immersed in a liquid dielectric medium (Yang et al., 2009; Khan et al., 2011). EDM technology is developed and is widely used in applications such as die and mold machining, micro-machining, and prototyping. Among all EDM processes, die sinker EDM is widely used (Fonda et al., 2008, Rahman, 2010). Die sinking EDM is a machining process, where the positive feature shapes on the workpiece are mapped from the negative features in the electrode. It is a relatively low machining process and it require electrode made especially for machining of a given product. The advantage of EDM machine is its ability to produce small, even micro features. The EDM process is used mostly for making dies and moulds (Valenticic et al., 2009). In order to get good quality parts with minimum cost, there are several parameters in the EDM that have to be controlled. The polarity, pulse-on duration, discharge voltage and discharge current are several parameters that need to be controlled. Servo voltage specifies a reference voltage for servo motions to keep gap voltage constant. Peak current is the maximum current during spark. Pulse on time is the time in which current is applied to the electrode during each EDM cycle while the pulse off time is the waiting interval during two pulse-on periods.

Advance in information and communication technology have forced industrial activities to use computers in each phase of manufacturing process. This has put computerization at the forefront of competitive factors in manufacturing business. Hence, artificial intelligence (AI) is introduced into the industry. There are a lot of different tools in AI. ANN is one of the tools used in AI. ANN is a computational model of the human brain that assumes that computation is distributed over several simple interconnected processing elements called neurons or nodes, which operate in parallel. ANNs can capture domain knowledge from examples. ANNs can be employed as mapping devices, pattern classifiers or pattern completers. It had been found that the value of MRR, EWR and surface roughness has the tendency to increase with increasing current density and pulse duration (Hascalik and Caydas, 2007, Rahman et al., 2011c). Investigation has been done in choosing which electrode material is better at offering higher MRR and lower TWR. The investigation shows that work piece machine by copper and aluminum electrodes offer higher MRR. Copper and copper tungsten over comparatively low electrode wear for the tested work material. At high values of the currents, copper and aluminum offer low surface roughness, hence copper is a better electrode material (Shankar et al., 2004). Tsai and Wang (2001) presented comparative study on prediction of surface finish. They illustrated six different neural-networks and a neuro-fuzzy network model. A research work was carried out for the development and application of a hybrid artificial neural network and genetic algorism methodology to modeling and optimization of EDM performance material removal rate and surface roughness (Wang et al., 2003). Graphite electrode and nickel-base alloy workpiece were employed to conduct the experiments. Mandal et al. (2007) developed an artificial neural network with back propagation algorithm to model and genetic algorithm-II to optimize the material removal rate and tool wear rate for C40 steel. They picked up peak current, pulse on time, pulse off time as input variables and copper as tool. An investigation was fulfilled to study the effect of current and tool dimension on MRR and surface roughness (SR) for machining mild steel work piece (Dave et al., 2008). Machining of EDM with different parameters is being carried out to investigate the effect of this parameter on the MRR, TWR and SR of titanium alloy (Ti-6AL-4V) with copper as an electrode. ANN model is used to predict the responses. In order to achieve this objective, various level of input parameters namely servo voltage, peak current, pulse on time and pulse off time are used to find the optimized machining parameters. Development of ANN using RBFN model is validated by using experimental data. This paper is to develop an ANN model to predict the output of the machining of Ti-6Al-4V by using EDM die sinking machine.

## MATERIALS AND METHODS

### Experimental setup

The experiments were designed on the basis of axial point central composite designs using response surface method. CNC EDM wire cut is used to cut the workpiece into the desire size from a plate of Ti-6AL-4V. A number of experiments were carried out according to the design of experiment (DOE) generated by using RSM method to investigate the influence of various machining factors on EDM process. Four variables such as peak current, pulse on time, pulse off time and servo voltage were considered to ascertain their effect on material removal rate, TWR and SR. Peak current ($I_p$) is the maximum current during spark. Pulse on time ($T_{on}$) is the duration of time the current is allowed to flow per cycle while the pulse off-time ($T_{off}$) is the duration of time between two consecutive sparks (Puertas et al., 2009; Rahman et al., 2011b). Servo voltage ($S_v$) specifies a reference voltage for servo motions to keep gap voltage constant. When gap voltage is higher than servo voltage, the electrode advances for machining; when it is lower, the electrode retracts to open the gap. The titanium alloy material Ti-6Al-4Sn was machined with copper tool electrode. The electrode polarity was retained as positive polarity. Kerosene was used as dielectric fluid. The experiments were performed on a numerical control programming EDM AQ55L. The workpiece are cut into the desired dimension of 21.50 × 21.00 × 13.16 mm by using EDM wire cut. The weights of the workpiece before and after machining were measured by a digital balance (AND GR-200) with readability of 0.1 mg. Figure 1 shows the workpiece and electrode dimension. The machining was usually carried out for a fixed time interval. Table 1 shows the machining parameter and their coded levels generated from the central composite design method. The experimental settings are shown in Table 2.

The weight of both the workpiece and electrode are weighted by using precision balance before and after the machining process. Each machining was operated for 40 min. The sets of combination parameter that was set earlier serve as the input data. The

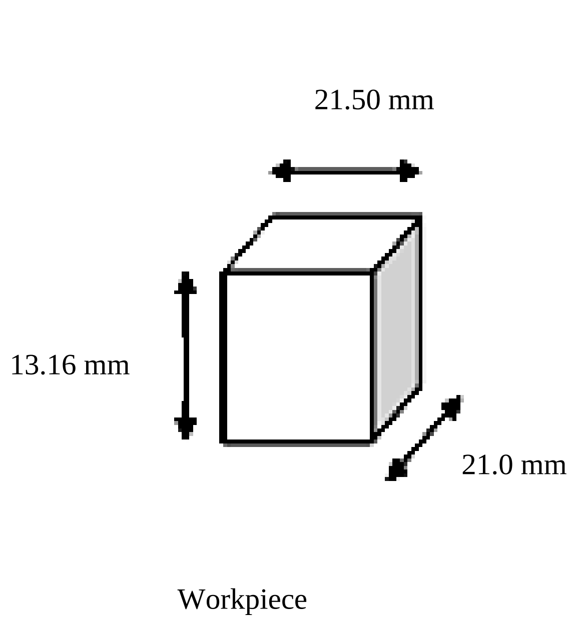



**Figure 1.** Workpiece and electrode dimension.

**Table 1.** Machining parameter and their levels.

| Process parameter | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 |
|---|---|---|---|---|---|
| | -2 | -1 | 0 | 1 | 2 |
| Peak current (A) | 1 | 8 | 15 | 22 | 29 |
| Pulse on time (µs) | 10 | 95 | 180 | 265 | 350 |
| Pulse off time (µs) | 60 | 120 | 240 | 180 | 300 |
| Servo voltage | 75 | 85 | 95 | 105 | 115 |

**Table 2.** Experimental settings.

| Parameter | Description |
|---|---|
| Work piece material | Ti-6Al-4V |
| Work piece size | 25 × 25 × 20 mm |
| Electrode material | Copper |
| Electrode size (diameter × length) | 20 × 44 mm |
| Electrode polarity | Positive |
| Dielectric fluid | Commercial Kerosene |
| Applied voltage | 120 V |
| Servo voltage | 70 V |
| Flushing pressure | 1.75 MPa |
| Machining time | 40 min |

experiments were performed at constant voltage ($V$) which is 120 V. A total of thirty-one machining is being done according to the generated parameter. The material removal rate is calculated as Equation (1):

$$MRR = \frac{WRW}{T}$$

Where $WRW = W_{w1} - W_{w2}$ (1)

Where, $W_{w1}$ is the weight of workpiece before machining and $W_{w2}$ the weight of workpiece after machining, WRW is the weight loss of the workpiece and T time taken for the machining.

The tool wear rate is the amount of electrode being used in the machining process and is represented by Equation (2):

$$\text{EWR} = \frac{100 \times W_e}{\rho_e \times T}$$

Where $W_e = W_1 - W_2$ (2)

Where, $W_e$ is the weight loss of the electrode in gm, $\rho_e$ is the density of the electrode material (Density of Cu is 8.93 g/cm$^3$), $W_1$ is initial weight of electrode, $W_2$ is final weight of electrode, T is the machining time in minutes.

The surface roughness of the work-piece can be expressed in different ways including arithmetic average ($R_a$), average peak to valley height ($R_z$), or peak roughness ($R_P$), etc. Generally, the SR is measured in terms of arithmetic mean ($R_a$) which according to the UNE-EN ISO 4287:1999 is defined as the arithmetic average roughness of the deviations of the roughness profile from the central line along the measurement (Wu et al., 2005). Arithmetic mean or average surface roughness, $R_a$ is considered in this study for assessment of roughness. The experimental data are shown in Table 3.

### Artificial neural network model

#### ANN model

In order to develop an ANN model to predict the MRR, TWR and SR; radial basis function neural network (RBFN) model is used to develop the ANN model. RBFN is built into a distance criterion with respect to a center and is applied in neural network as replacement for sigmoid hidden layer characteristic in Multi-Layer Perceptrons. RBFN have two layers of processing. Input is mapped onto each RBF in the hidden layer. The output layer is a combination of hidden layer values representing the mean predicted output. The interpretation of this output layer is like a regression model in statistics. The output layer is a typical sigmoid function of a linear combination of hidden layer values representing the mean predicted output. The interpretation of this output layer value is like a regression model in statistics.

The training and testing of neural network is performed by using experimental data which is shown in Table 3. The mathematical relation between the performance factors and response are described in Equation (3).

$$Y = f(X, W); \quad v = \sum_i w_i x_i \tag{3}$$

Where, Y represents the performing parameter, X is the response to the neural network, W is the weight matrix, f is the model of process that is being used in the training, v represents the induced local field produced, x as the input signal and w as the synaptic weight.

The inputs of the network at the nodes of the hidden layer and the output layer are combined by using Equation (4).

$H_l = f(v_l) = f(\sum_i w_{li} x_i)$ and $Z_j$ = fi $(H_l)$, $O_k = f(Z_j)$ and $Y_o = f(O_k)$ (4)

Where $H_l$, $Z_j$ and $O_k$ are the output at the hidden layer one, two and three respectively; $Y_o$ is the output at the output layer and $w_{li}$ is the synaptic weight from input neuron *i* ($x_i$) to the neuron *l* in the first hidden layer. Combining Equations 3 and 4, the relation for the output of the network can be set as Equation (5):

$$Y_o = f(O_k) = f(\sum_k w_{ok} f(\sum_j w_{kj} f(\sum_l w_{jl} f(\sum_i w_{li} x_i)))) \tag{5}$$

Where $w_{jl}$ is the synaptic weight from neuron l in the first hidden layer to the neuron j in the second hidden layer, $w_{kj}$ is the synaptic weight from neuron j in the second hidden layer to the neuron k in the third hidden layer and $w_{ok}$ is the synaptic weight from neuron k in the last hidden layer to the output neuron o. Neuro solutions package is used to develop the model.

#### Network topology, training and testing

The model used is RBFN with three hidden layer. The architecture of RBFN is shown in Figure 2. The model used is RBFN with three hidden layer. Hyperbolic tangent function of sigmoid (TanhAxon) is used to calculate the output at both the hidden layer and also the output layer. The function of TanhAxon is shown in Equation (6) and the output was compared with the measured output using mean square error (MSE) as in Equation (7). For training, levenberg-manquardt is used and the threshold was set at 0.0001. The model was trained in batch mode. The maximum number of epoch used is 1600.

TanhAxon function, $f(v) = tanh(v)$ (6)

MSE, $E = \frac{1}{N}\sum_{o=1}^{N}(T_o - Y_o)^2$ (7)

A number of networks are constructed, each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The general network is supposed to be 4–3–3, which implies four neurons in the input layer, 3 neurons in the hidden layer and 3 neurons in the output layer.

## RESULTS AND DISCUSSION

Table 4 shows the convergence of the output error MSE with the number of iterations (epochs) during the training of the network. After 311 epochs, the MSE between the desired and actual output was 0.004272003 where the training is stopped. The value of output at the beginning of the training is far from the targeted value but it gets nearer to the target value as epochs increases. Initially, the output from the network is far from the target value. The output slowly and smoothly converges to the target value with more epochs and the network learns the input/output relation of the training samples. Table 4 also

**Table 3.** Experimental data.

| Number of experiment | Input data | | | | Output data | | |
|---|---|---|---|---|---|---|---|
| | Servo voltage (V) | Peak current (A) | Pulse on time (µs) | Pulse off time (µs) | SR (µm) | MRR (mg/min) | TWR |
| 1 | 95 | 15 | 180 | 180 | 4.319 | 2.0268 | 0.0229 |
| 2 | 85 | 8 | 265 | 240 | 1.747 | 1.0878 | 1.5291 |
| 3 | 95 | 29 | 180 | 180 | 6.110 | 6.5512 | 0.0234 |
| 4 | 95 | 15 | 180 | 180 | 4.326 | 1.9854 | 0.0934 |
| 5 | 75 | 15 | 180 | 180 | 4.660 | 2.9146 | 0.1096 |
| 6 | 95 | 15 | 180 | 180 | 5.334 | 0.9366 | 0.1641 |
| 7 | 85 | 8 | 95 | 120 | 2.529 | 1.7244 | 1.3197 |
| 8 | 85 | 22 | 265 | 240 | 5.983 | 4.2902 | 0.1017 |
| 9 | 105 | 8 | 265 | 240 | 3.108 | 0.4878 | 4.0550 |
| 10 | 95 | 15 | 180 | 180 | 4.268 | 2.2561 | 0.0259 |
| 11 | 105 | 8 | 95 | 240 | 2.851 | 0.3927 | 2.8713 |
| 12 | 95 | 15 | 180 | 60 | 3.461 | 2.6220 | 0.0242 |
| 13 | 85 | 8 | 265 | 120 | 2.638 | 1.3122 | 1.1896 |
| 14 | 105 | 22 | 95 | 120 | 4.358 | 3.0707 | 0.0045 |
| 15 | 105 | 22 | 95 | 240 | 4.043 | 3.1634 | 0.0616 |
| 16 | 105 | 8 | 95 | 120 | 2.976 | 0.5415 | 0.8153 |
| 17 | 105 | 22 | 265 | 240 | 5.402 | 3.3854 | 0.1376 |
| 18 | 85 | 22 | 265 | 120 | 5.617 | 5.8120 | 0.0721 |
| 19 | 95 | 1 | 180 | 180 | 1.999 | 0.1415 | 6.4310 |
| 20 | 95 | 15 | 180 | 180 | 4.799 | 2.4293 | 0.0270 |
| 21 | 95 | 15 | 180 | 300 | 5.413 | 1.7098 | 0.1054 |
| 22 | 95 | 15 | 180 | 180 | 4.684 | 2.1146 | 0.0188 |
| 23 | 85 | 22 | 95 | 240 | 5.544 | 3.4195 | 0.1405 |
| 24 | 105 | 22 | 265 | 120 | 6.535 | 3.8024 | 0.0783 |
| 25 | 85 | 22 | 95 | 120 | 6.041 | 4.4465 | 0.2660 |
| 26 | 115 | 15 | 180 | 180 | 6.213 | 1.3415 | 0.564 |
| 27 | 105 | 8 | 265 | 120 | 3.989 | 0.8488 | 0.0676 |
| 28 | 95 | 15 | 10 | 180 | 4.322 | 1.2073 | 0.4202 |
| 29 | 85 | 8 | 95 | 240 | 2.316 | 1.3780 | 0.7611 |
| 30 | 95 | 15 | 350 | 180 | 3.833 | 2.7024 | 0.0298 |
| 31 | 95 | 15 | 180 | 180 | 3.709 | 2.0488 | 0.0452 |

represents the error between the desired output and predicted ANN output. It shows the error of output generated by using ANN compare to the desire output.

The learning behaviour of ANN is shown in Figure 3. The data is further analyzed for sensitivity to identify the influence of the varied input process parameters on output response including MRR, TWR and SR. Sensitivity analysis is performed by continuous testing by using Neuro Solution package. The obtained results are shown in Figure 4 and Table 5. From the result, it is apparent that the peak current has more influence on the performance measures. After peak current, the pulse off time possesses more influence then

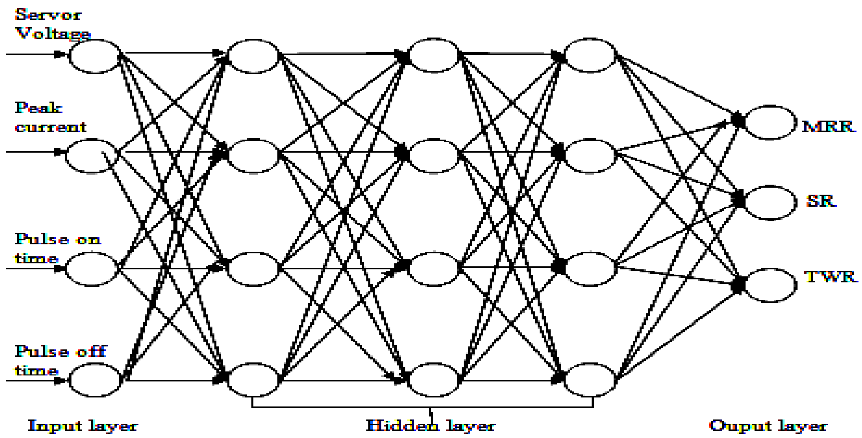



**Figure 2.** Architecture of RBFN model.

**Table 4.** Error analysis of MRR, SR and TWR for the network.

| Performance | SR | MRR | TWR |
|---|---|---|---|
| MSE | 0.050349143 | 0.044880613 | 0.000562047 |
| NMSE | 0.02929424 | $7.22888\times10^{-5}$ | 0.000296066 |
| MAE | 0.086654387 | 0.066741027 | 0.009289403 |
| Min Abs Error | $2.05565\times10^{-9}$ | $1.1966\times10^{-9}$ | $1.29688\times10^{-11}$ |
| Max Abs Error | 0.842714268 | 1.034485717 | 0.107342856 |
| r | 0.98524401 | 0.999963855 | 0.999851956 |
| | | | |
| **Best network** | | **Training** | |
| Number of Epoch | | 474 | |
| Minimum MSE | | 0.001194516 | |
| Final MSE | | 0.001194516 | |

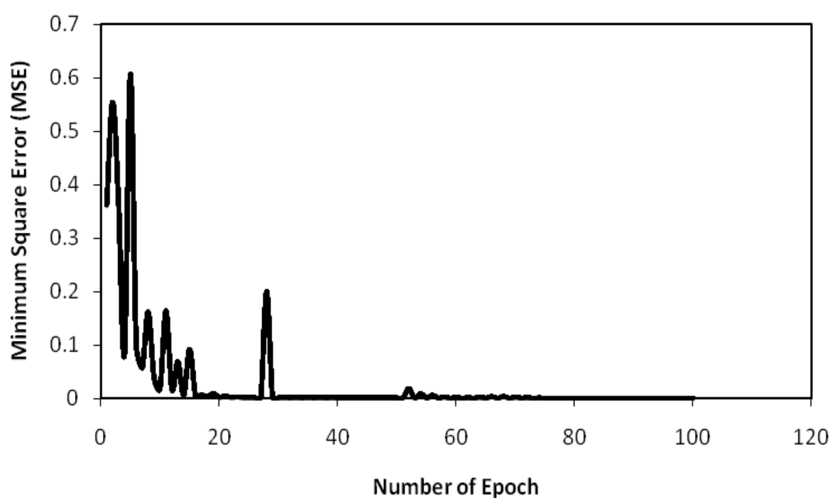



**Figure 3.** Learning behavior of ANN model.

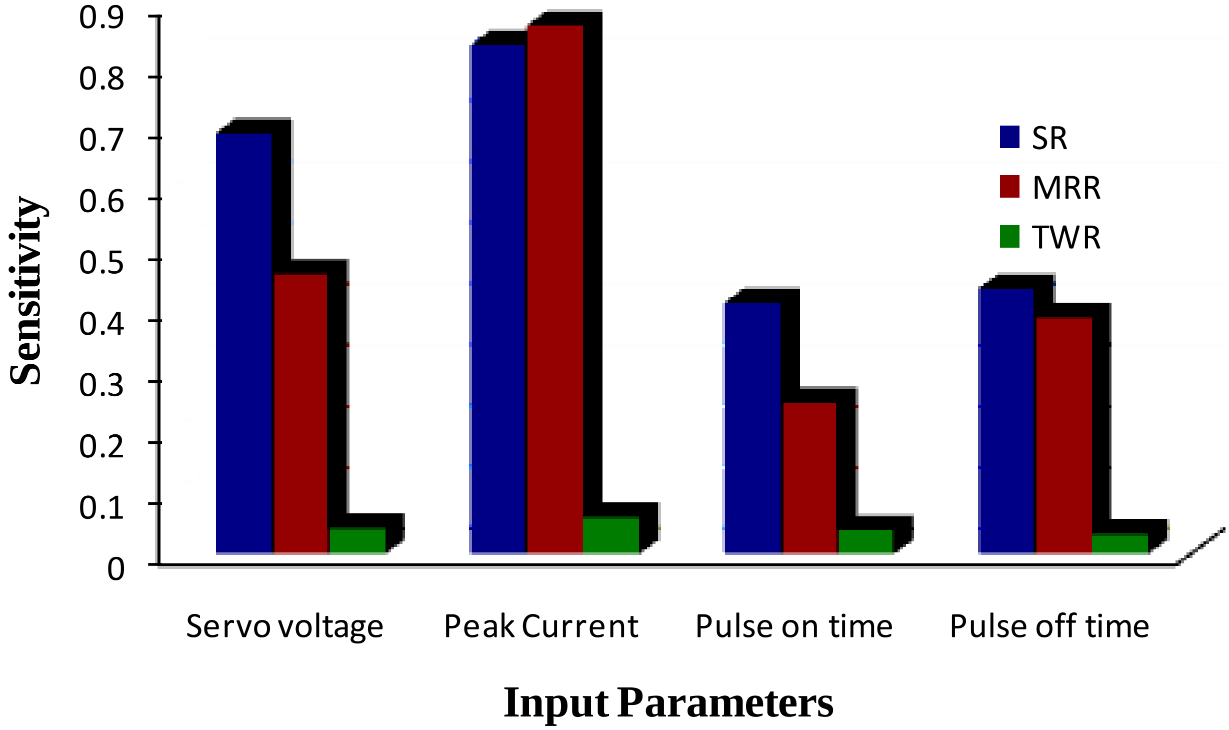



**Figure 4.** Effect of different input parameter with responses.

**Table 5.** Sensitivity analysis.

| Sensitivity | SR | MRR | TWR |
|---|---|---|---|
| Servo voltage | 0.688406544 | 0.458291076 | 0.042164026 |
| Peak Current | 0.831760848 | 0.864021914 | 0.060062428 |
| Pulse on time | 0.410801856 | 0.248125045 | 0.038801849 |
| Pulse off time | 0.433807762 | 0.387179951 | 0.033671973 |

the other two factors as on time and servo voltage. From the results generated, a graph of output versus each input parameter can be generated. Each input parameter gives different effect to the output. The optimum input is lowest in SR and TWR, and highest in MRR. Figure 5 shows the effect of each input parameter to the output.

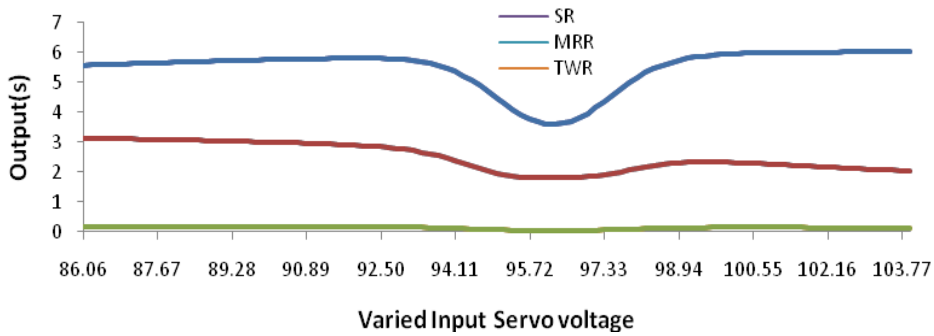
## Confirmation test

The ANN predicted results are in concurrence with experimental results and the network can be employed for production. Hence, the production data sets are applied. The electrical discharge machining conditions used in the confirmation tests are presented in Table 6. It is evident from Table 7 that, the output of the network in terms of mean squared error during training of the network and the error between the desired response and ANN predicted is in the range of 2 to 4%. ANN is demonstrated to be a practical and effective way for the evaluation of EDM performance parameters including MRR, electrode wear rate and SR.

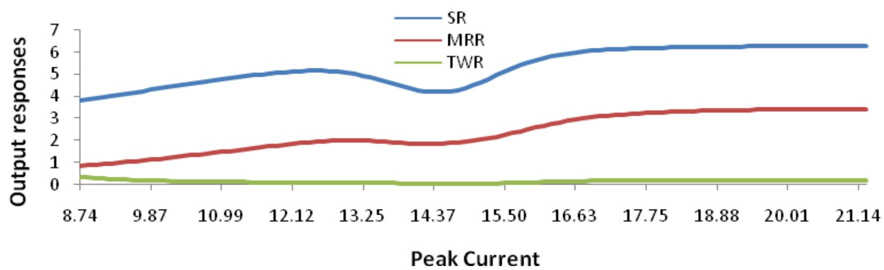
## Conclusion

ANN model is developed for four parameters which can predict the behavior of these parameters when machined on Ti-6Al-4V. The developed model is within the limits of agreeable error when experimental and model values are compared for all performance measures considered.

From the sensitivity analysis, it is concluded that peak




(a)

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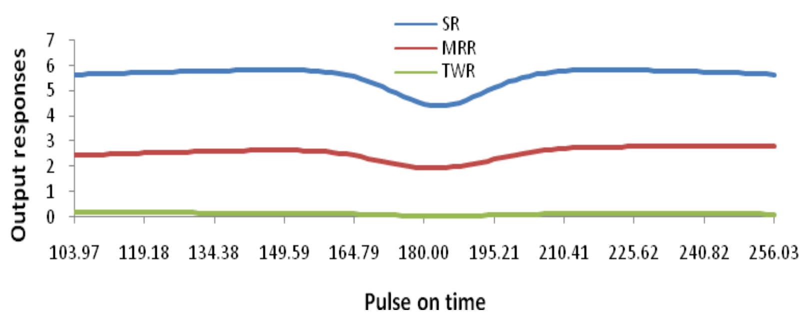


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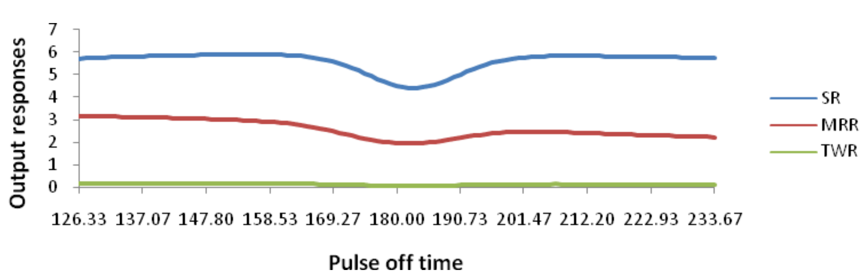


(d)

**Figure 5.** Sensitivity analysis of SR, MRR, TWR versus input parameters.

**Table 6.** EDM input parameters for confirmation test.

| Peak current (A) | Pulse on time (μs) | Pulse off time (μs) | Servo voltage (V) |
|---|---|---|---|
| 8 | 265 | 300 | 85 |
| 15 | 180 | 180 | 105 |
| 22 | 265 | 180 | 85 |

**Table 7.** Error for ANN predicted results with experiment.

| No. of experiment | Experiment | Prediction | Error (%) |
|---|---|---|---|
| **Material removal rate** | | | |
| 1 | 1.3450 | 1.378 | 2.45 |
| 2 | 2.6161 | 2.702 | 3.28 |
| 3 | 1.7497 | 1.841 | 5.21 |
| Average error | | | 3.65 |
| **Tool wear rate** | | | |
| 1 | 0.8151 | 0.7811 | 4.17 |
| 2 | 0.0287 | 0.0298 | 3.83 |
| 3 | 0.5845 | 0.5676 | 2.84 |
| Average error | | | 3.61 |
| **Surface roughness** | | | |
| 1 | 2.226 | 2.316 | 4.04 |
| 2 | 3.783 | 3.751 | 0.85 |
| 3 | 4.654 | 4.491 | 3.50 |
| Average error | | | 2.80 |

current is having highest influence on all performance measures. Around 15 A peak current, 85 μs pulse on time, 232 μs pulse off time and 95 V servo voltage yields the best surface roughness. The electrode wear rate initially decreases with pulse on time henceforth increase as on time increase. The similar effect is observed in the case of pulse off time; nevertheless, the longest on time generates maximum TWR while the same result occurred at shortest off time. As for MRR and TWR, the servo voltage is around 85 and 95V as well as the peak current of 21 and 8 A, respectively. The results reveal that the lower the ampere, the higher the electrodes wear rate and vice versa. The lowest value of electrode wear rate is acquired while the peak current is around 18 A. At high peak current and longer pulse on time, the MRR increases.

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