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Published in:
Journal of Machine Engineering

Publication date:
2017

Document Version
Publisher's PDF, also known as Version of record

Citation (APA):
Puthumana, G. (2017). Micro-EDM process modeling and machining approaches for minimum tool electrode wear for fabrication of biocompatible micro-components. *Journal of Machine Engineering*, *17*(3), 97-111.

Journal of Machine Engineering, Vol. 17, No. 3, 2017

Received: *06 January 2017* / Accepted: *17 May 2017* / Published online: *28 September 2017*

biocompatibility, micro devices, electrical discharge machining, modeling, multiple linear regression, artificial neural networks

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MICRO-EDM PROCESS MODELING AND MACHINING APPROACHES FOR MINIMUM TOOL ELECTRODE WEAR FOR FABRICATION OF BIOCOMPATIBLE MICRO-COMPONENTS

Micro-electrical discharge machining (micro-EDM) is a potential non-contact method for fabrication of biocompatible micro devices. This paper presents an attempt to model the tool electrode wear in micro-EDM process using multiple linear regression analysis (MLRA) and artificial neural networks (ANN).The governing micro-EDM factors chosen for this investigation were: voltage (V), current (I), pulse on time (T_{on}) and pulse frequency (f). The proposed predictive models generate a functional correlation between the tool electrode wear rate (TWR) and the governing micro-EDM factors. A multiple linear regression model was developed for prediction of TWR in ten steps at a significance level of 90%. The optimum architecture of the ANN was obtained with 7 hidden layers at an R-sq value of 0.98. The predicted values of TWR using ANN matched well with the practically measured and calculated values of TWR. Based on the proposed soft computing-based approach towards biocompatible micro device fabrication, a condition for the minimum tool electrode wear rate (TWR) was achieved.

1. INTRODUCTION

Metals are used as biomaterials in order to fabricate micro-devices due to their biocompatibility, favorable mechanical properties and ability to deform plastically. Among the metals, titanium-based implant materials including pure titanium and Ti-6Al-4V are widely used because they do not induce allergic reactions, causes formation of an oxide film over the surface, have low density and have excellent corrosion resistance [1,2]. Titanium alloys are characterized by a high superficial energy, because of which, after implantation, helpful body reactions are generated [2]. The Ti6Al4V alloy is used as a standard material to manufacture dental, spinal, trauma and orthopedic implants.

The key issues of Ti6Al4V alloy to be employed in micro-device fabrication include poor manufacturing accuracy for cutting leading to issues with articulations of surfaces and poor attachment to the bone resulting in loosening of the implant [3]. In addition, Ti6Al4V alloy do not react with the human tissues, causing undesirable movements in the boundary of the implant and the tissue, eventually resulting in crack formation on the implant.

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One of the existing methods also to compensate for the manufacturing inaccuracy during fabrication of the implants using Ti6Al4V alloys the application of bioactive coatings [4], which improves the bonding of the implant with the bone and consequently increases the life of the implant. Since the thermal expansion coefficients of the implant and the coating are generally different, thermal stresses are generated during fabrication leading to crack formation and crack propagation at the implant-coating interface [2,5]. Also, the chemical reactions among the coating and Ti6Al4V alloy constantly deteriorates the strength of the interface.

Several conventional ‘contact machining’ methods have been used for fabrication of micro-devices and components using Ti6Al4V alloy [6-9]. The problems with these methods include formation of residual stresses and crack formation on micro-device surfaces, low dimensional accuracy of machined features and non-uniform removal of material during fabrication [8]. One of the advanced ‘non-contact’ micromachining technologies used to fabricate biomedical micro-devices is micro-electrical discharge machining (micro-EDM), and an attempt to apply ultrasonic vibration-assisted micro-EDM for fabrication of a biocompatible micro-channel has been reported in [10].

The micro-EDM technology is a precision machining technique for micro fabrication using Ti6Al4V alloy, and has several advantages over the conventional machining methods [11-14]. Some researchers have attempted to investigate micro-EDM drilling process of Ti6Al4V alloy [11]. A fundamental investigation aiming at developing a correlation between the properties of Ti6Al4V alloy and productivity was described in [12]. A multi-objective optimization of Ti6Al4V for minimum tool wear ratio, maximum material removal rate and minimum surface roughness was attempted [13]. Recently in [14], the capability of the micro-EDM process in machining of Ti6Al4V alloy using soft material brass (electrode –tool) have been demonstrated.

Nevertheless, one of the challenges in micro-EDM of Ti6Al4V alloy is tool electrode wear, leading to inaccuracy in the manufacturing of the micro-device. Being a complementary machining technology [10], the dimensional inaccuracy on the tool electrode because of the tool wear is directly reflected on the biomedical device fabricated using Ti6Al4V alloy. Tool electrode wear causes variations of 20-30% in the geometrical dimensions of blind micro-slots of Ti6Al4V alloy machined using micro-EDM, even at the same processing conditions [14]. A few research papers have been published with a comparative analysis of tool electrode materials [11], identification of best parameters [13] and analysis of surface roughness [10] for machining of Ti6Al4V alloy. In spite of several investigations demonstrating the capability of Ti6Al4V alloy for fabrication of micro devices using micro-EDM and other similar processes, no attempts have been made so far, to address the issue of tool electrode wear in micro device fabrication, and to model the phenomenon. Therefore, the objective of this paper is to analyze and model the tool electrode wear in micro-EDM of Ti6Al4V alloy material for drilling kinematic. The tool wear characteristics are modeled with the use of linear regression technique and artificial neural network methods. The micro-EDM controllable factors taken into consideration during the modeling are: discharge current, discharge frequency, pulse ‘on-time’ and gap voltage. Based on the wear modeling, the results of tool wear are analyzed for achieving the minimum tool electrode wear in micro-EDM of Ti6Al4V alloy.

2. METHODOLOGY

The aspects of the process capabilities of micro-EDM, which enables it as an appropriate and efficient technique for biocompatible micro device fabrication has been elaborated in [10]. Melting and vaporization is the basic material removal mechanism in micro-EDM process. In a recent work on micro-EDM of Ti6Al4V alloy [15], systematic statistical design using L_{18} orthogonal array was used and an experimental approach was followed to identify the significant parameters and to optimize the performance characteristics. In electrical discharge-based processes, because the erosion of material occurs from anode and cathode electrodes, investigations on tool wear involves an estimation of the ratio of the tool wear to the material removal [13,16]. Considering the smaller dimensions of the tools and continuous changes in the dimensions and shape of the tool over time, the tool wear needs to be studied and assessed independently to facilitate effective tool wear compensation. Accordingly, in this work, an alternative approach for understanding the tool wear phenomenon involving process modeling using regression analysis and artificial neural networks is detailed. The tool, workpiece dielectric properties are presented in Table 1.

Table 1 Tool electrode, workpiece and dielectric properties

<table>
<tr><td colspan="3">Tool electrode (WC)</td><td rowspan="3">Ø400 μm
Working length = 1500 μm</td></tr>
<tr><td>Young's modulus
630 GPa</td><td>Ultimate tensile strength
344 MPa</td><td>Density
15.63 g/cm^3</td></tr>
<tr><td>Thermal conductivity
110 W/mk</td><td>Melting point
3100 K</td><td>Electrical resistivity
0.2 μΩm</td></tr>
<tr><td colspan="3">Workpiece (Ti6Al4V)</td><td rowspan="3">20 mm × 10 mm × 1 mm
wt (%)
Ti: 89-90%
Al: 5.0-7.0%
V: 3-5%
Fe: 0.25%
O: 0.2%</td></tr>
<tr><td>Young's modulus
119 GPa</td><td>Ultimate tensile strength
1020 MPa</td><td>Density
4.5 g/cm^3</td></tr>
<tr><td>Thermal conductivity
7.2 W/mk</td><td>Melting point
1900 K</td><td>Electrical resistivity
1.7 μΩm</td></tr>
<tr><td colspan="3">Dielectric (Hydrocarbon oil)</td><td rowspan="2">Applied in the form of a jet from the side of the tool axis</td></tr>
<tr><td>Kinematic viscosity
0.02 cm^2/s</td><td>Mass density
0.8 g/cm^3</td><td>Electrical conductivity
2×10^{-8} μΩcm^{-1}</td></tr>
</table>

Fig. 1 shows a schematic of the methodology of this work. The tool electrode wear phenomenon in the micro-EDM process is analyzed by considering the governing processing conditions, as discussed in the literature. The tool wear rate is mathematically expressed as,

$$TWR = (\pi/4) \times D_t^2 \times L_t \tag{1}$$

where, D_t is the diameter of the tool electrode in µm and L_t is the linear tool electrode wear (µm) during the process.

The tool wear rate (TWR) is modeled on a preliminary basis using linear regression analysis. Further, the artificial neural network (ANN) is used for modeling. The optimum configuration of the ANN is selected based on the criterion of minimum mean square error (MSE). This is followed by selection of the processing conditions for the minimum tool electrode wear for fabrication of biocompatible micro devices, and in this investigation, a simple case involving drilling of holes of nominal Ø400 µm and depth of 1000 µm is considered. The governing micro-EDM processing conditions, range of factors controlling these processing conditions and reasons for selection are presented in Table 2. Various parameters and their levels based on the past experience and the review of literature.

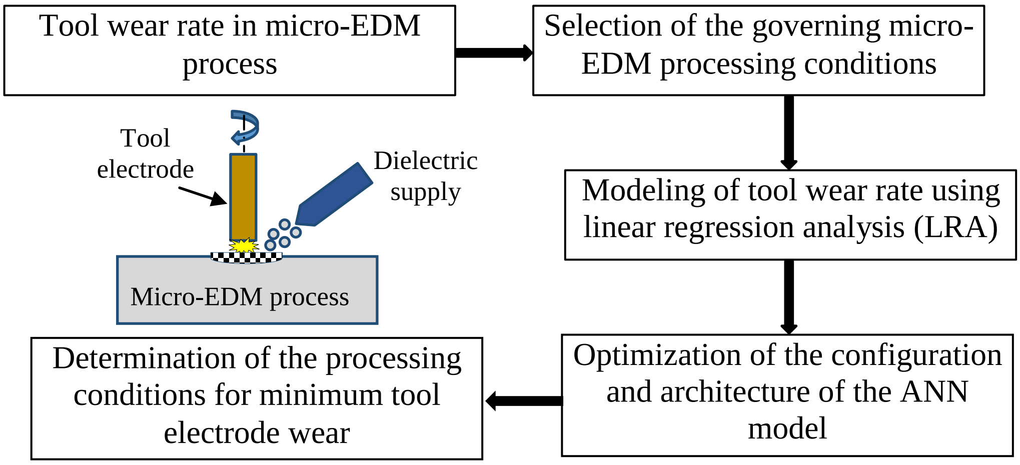

Fig. 1. A schematic of methodology for modeling and machining approaches for minimum tool electrode wear in biocompatible micro-device (holes) fabrication using micro-EDM

Table 2. Selection of micro-EDM processing conditions, range of factors and reason for selection of factors for modeling and analysis

Governing Micro-EDM factor	Unit	Range of factors	Effect on tool electrode wear	Reason for selection
Voltage (*V*)	V	80 to 150	Increases [13]	Directly controls the electric field and discharge energy during micro-EDM
Current (*I*)	index	20 to 80	Increases [17]	Influences the discharge energy and heating of tool surface.
Pulse on-time (T_{on})	µs	0.5 to 2.0	Decreases [18-19]	A factor that affects distribution of thermal energy on tool surface.
Pulse frequency (*f*)	kHz	150 to 250	Increases [20]	The current density on the surface of tool electrode varies with the frequency of discharges.

In the Sarix EDM machine, the measurement unit of peak current is expressed as an index and there is not a direct correlation with the actual value of current expressed in Ampere. During the micro-EDM process, the current value in amperes varied between 1 A to 15 A, the values are based on earlier measurement results at similar processing conditions [21-23]. Though the exact magnitudes of the peak current corresponding to the indexes and pulse shapes are not accurately measured at each instant, it is observed that the current indexes are proportional to the magnitude of currents in Amperes. In this analysis, the current indexes are varied between 20 and 80.

3. RESULTS AND DISCUSSION

The experimental data of tool wear rate (TWR) is presented in Fig. 2. In the figure, though all the data points are represented, the trial numbers with spacing of five are only presented. A maximum TWR of 175000 $\mu m^3/s$ is observed from the data chosen for this analysis. It shows a variation in the magnitude of TWR even by 12 times, considering all the variations in the processing conditions. This is because, when a tool electrode of circular cross-section is used for spark machining of micro-features, tool material is worn out both from the front as well as the side [24]. The lateral wear could be attributed to the effect of abrasion of debris particle and discharges occuring between these particles and the side walls of the tool, see Fig. 3. The removal of material from the tool electrode depends on the intensity of electric field, which in turn vary in a random manner in accordance with the sparking control factors in micro-EDM.

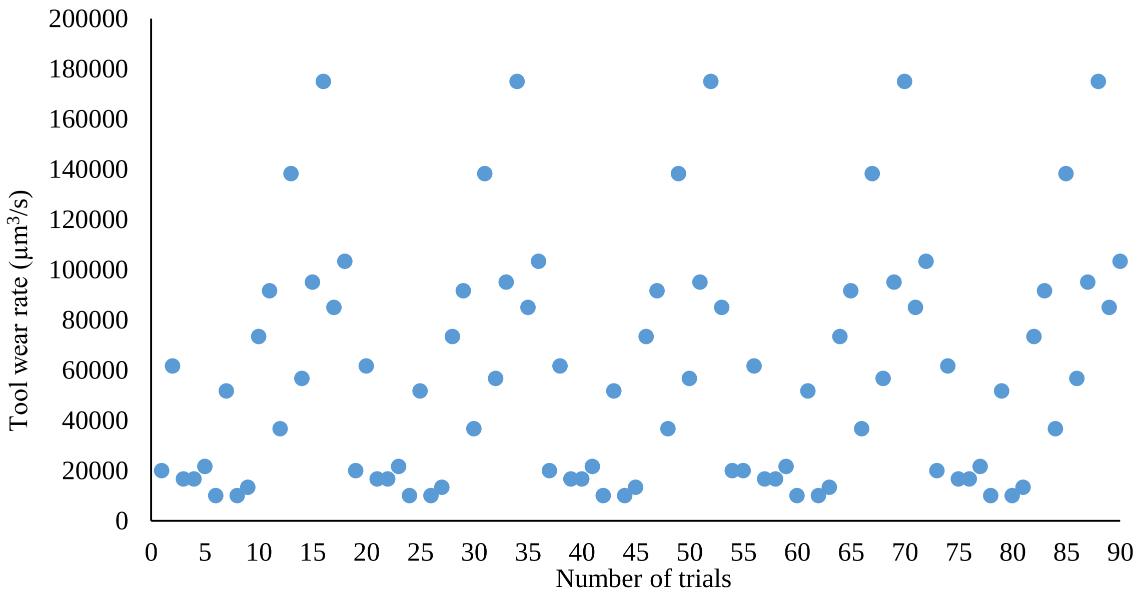

Fig. 2. Variation in the magnitude of tool wear rate with the number of trials

Therefore, it is necessary to express the TWR as a function of the input processing conditions for the micro-EDM process using modeling approach. Models for prediction of TWR are developed from the data, based on linear regression analysis and artificial neural network.

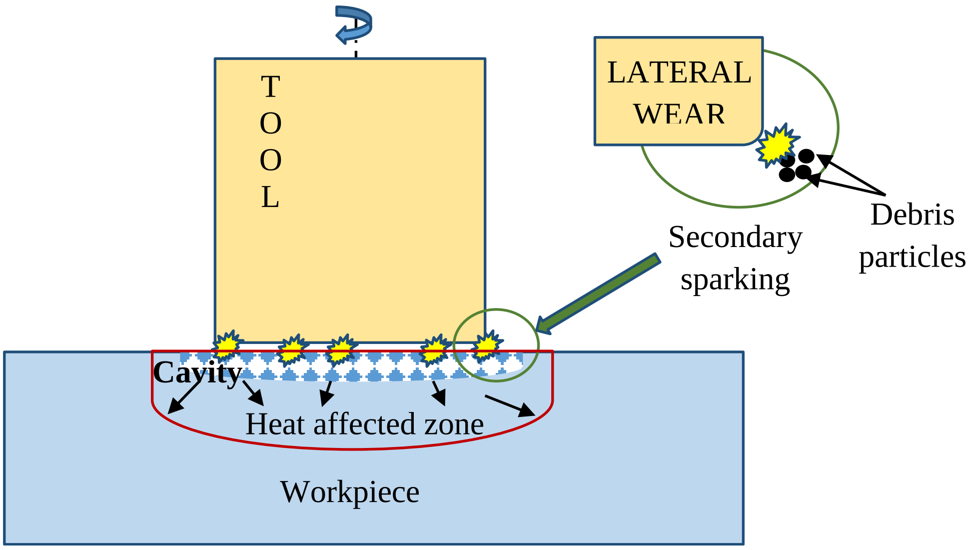

Fig. 3. Phenomenon of lateral tool wears due to secondary discharges in micro-EDM

3.1. MODELING OF TWR USING MULTIPLE LINEAR REGRESSION ANALYSIS (MLRA)

The linear regression technique [25-27] is used to predict the TWR based on the variations in the input processing conditions. The trial numbers of 90 is sufficient to predict a relationship between the TWR and the governing micro-EDM factors. As the number of data points are large, normality of the data is not evaluated [26,28] further, and the statistical significance of the model using a confidence interval based on the probability could be directly applied on the TWR model. The developed model was found to be statistically significant at 90% confidence level. As can be observed from Fig. 4, the regression model could predict 92.2% of the variations in the TWR. The terms used for prediction using the model have also been presented.

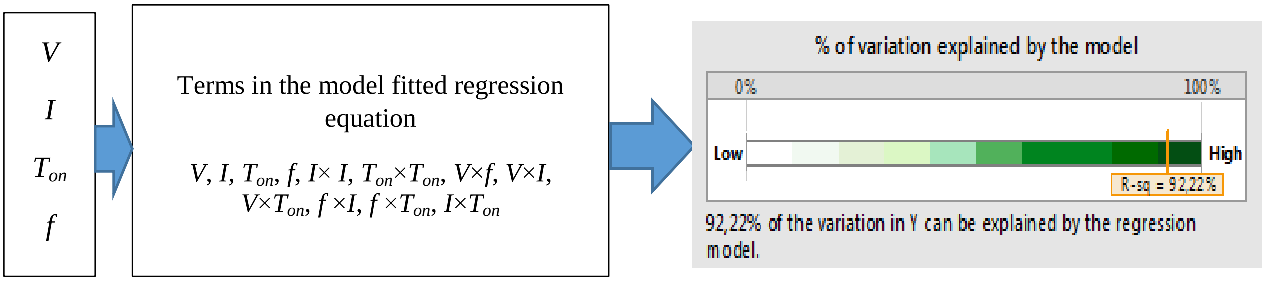

Fig. 4. An overview of multiple linear regression analysis of TWR

Fig. 5 shows the results of multiple regression analysis plots of the average TWR with the interactions of governing micro-EDM factors voltage, frequency, current and pulse-on time. From the plots, it is evident that an interaction voltage × current leads to an increase in the TWR that directly affects the accuracy of the fabricated micro device. It is envisaged that with a strong interaction between V and I, as seen from the linear relationship in the plot, the energy of the plasma as well as that of the striking electrons on the tool electrode frontal surface increases, resulting in a higher TWR [29]. A similar effect is noted by taking into account the interaction voltage × pulse on-time.

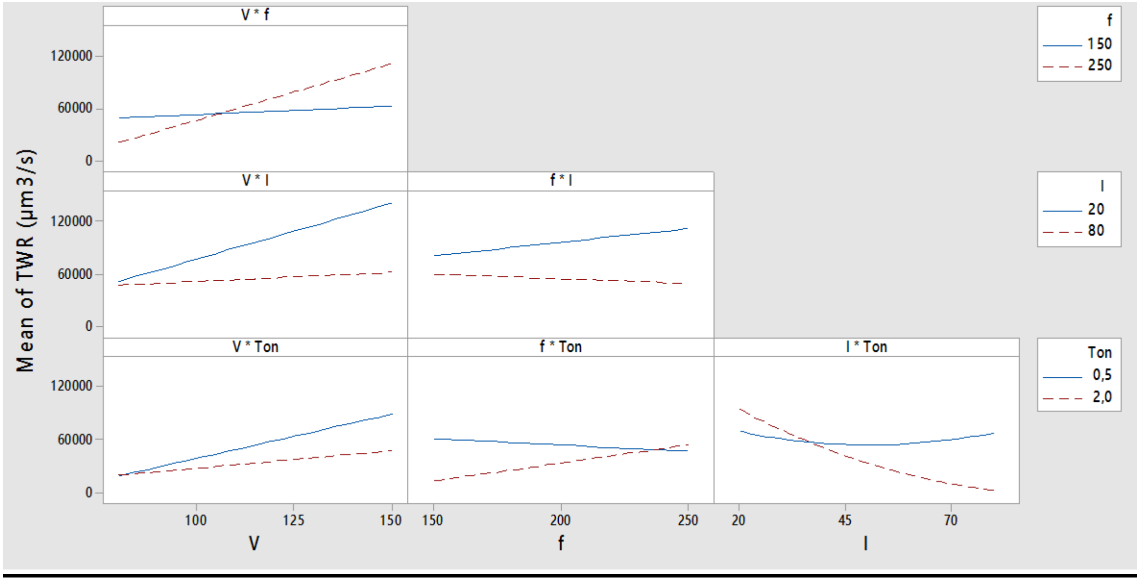

Fig. 5. Interaction plots for TWR based on multiple linear regression analysis

The results presented in Fig.5 could be interpreted based on statistical treatment of data presented in Fig. 2. In order to obtain the information on statistical model adequacy, the mean and standard deviation of TWR calculated are mean, m_s = 58889 μm^3/s, and standard deviation, σ = 38148 μm^3/s. Therefore, it is evident that the TWR value change with process parameters, but the contribution from the randomness of the process also exists. It is envisaged that the process parameters and their two-factor interactions plays a role in the control of the TWR in the micro-EDM process in the investigation.

In micro-EDM process, even for constant process settings of voltage, current and pulse on-time, a large variation in the discharge energies are observed because of the charging and discharging of the RC circuit [30,31]. Therefore, a control on the frequency settings is essential to maintain the productivity of the technology (material removal) even at lower discharge energy levels. However, in contradiction, a direct correlation between the energy E and the tool wear rate could be developed. Fig. 6 shows a schematic representation of the interaction between the discharge plasma and the electrodes in the micro-EDM process. Considering the plasma channel as a time dependent disc heat source with uniform heat flux profile [32], the heat flux q from the plasma channel of energy E can be expressed as:

$$q = (V\times I \times T_{on} / \pi\, r_p^{2}) \qquad (2)$$

where, $r_p$is theradius of the heat source. Therefore, the interaction between voltage, current and pulse on time controls the heat flux and consequently, the tool wear. Moreover, a relationship between boiling temperature of the electrode (θ_b), r_p , discharge power (P) and fraction of discharge energy entering the electrode (F) is expressed as:

$$\theta_b = (P \times F \times 10^6) / (\mathrm{k} \times r_p \times \pi^{3/2}) \times \tan^{-1}((4 \times a \times T_{on} \times 10^6) / r_p^{\,2})^{1/2} \tag{3}$$

where, k is the thermal conductivity of the material in w/mK and a is the thermal diffusivity of the electrode material [33]. Investigations on spark machining of Ti6Al4V have revealed that lower thermal diffusivity and lower thermal conductivity of the material leads concentration of thermal energy on the workpiece during the action of heat flux on it [34]. The consequential effect is on the erosion of material from the tool electrode. Looking at the results obtained from the MLRA, it can be observed that the tool wear could be directly correlated with the process settings controlling the energy of the plasma E.

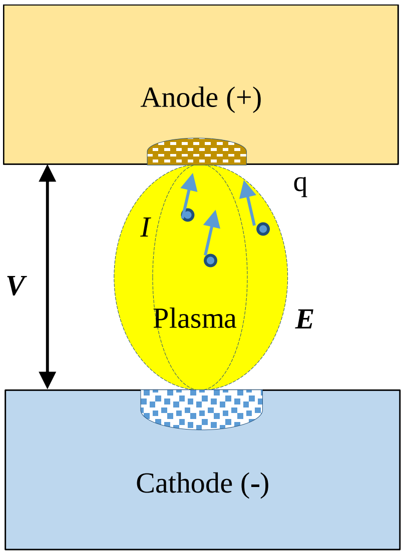

Fig. 6. A schematic representing the direct role of energy of the plasma on tool wear in micro-EDM

The other interactions are relatively less effective in controlling the erosion of material from the tool electrode, and therefore, do not have a direct impact on the precision of the micro-devices fabricated. Nevertheless, the MLRA approximation depicting the relationship between the tool wear and the process control factors would develop an understanding on the calculation of the applied wear compensations for the specific tool-workpiece-dielectric combinations. The final MLRA equation for TWR is obtained as,

$$\begin{aligned} TWR\ (\mu\mathrm{m}^3/\mathrm{s}) = {} & 55033 - 80 \times V - 1234 \times f + 2257 \times I + 79413 \times T_{on} + \\ & 16.46 \times I \times I - 28255 \times T_{on} \times T_{on} + 10.88 \times V \times f - 17.74 \times V \times I - \\ & 403 \times V \times T_{on} - 6.94 \times f \times I + 370.2 \times f \times T_{on} - 1003 \times I \times T_{on} \end{aligned} \tag{4}$$

The sequence of building the multiple linear regression model is presented in Fig. 7. The multiple linear regression model is developed by including each of the factors expressed as V (X1), f (X2), I (X3) and T_{on}(X4). The model is developed using 10 steps in total.

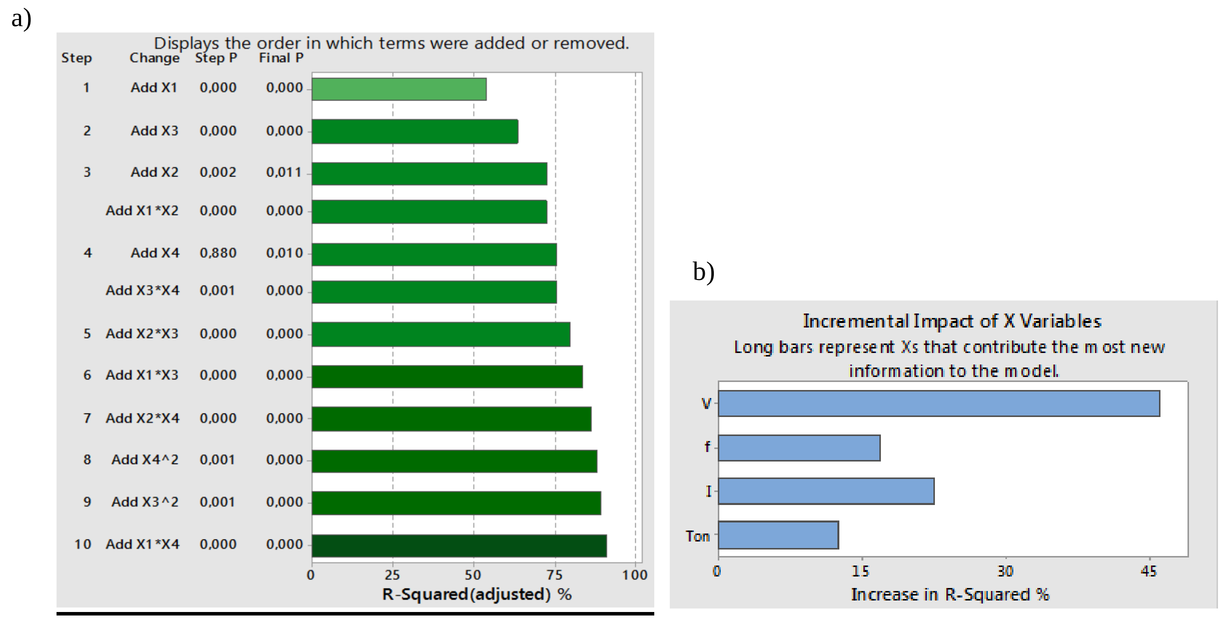

Fig. 7. A schematic showing: a) the TWR model building process by addition of individual micro-EDM control factors and their interactions, and b) relative impact of the governing micro-EDM factors

3.2. MODELING USING ARTIFICIAL NEURAL NETWORK

Artificial network is an advanced modeling technique that shows excellent learning and prediction capabilities suitable in any system encountered by minor uncertainties [35]. In this work, an intelligent algorithm for prediction of TWR is implemented as a function of the governing micro-EDM factors. The ninety observations included in this study is randomly divided into training (70%), validation (15%) and testing (15%). The observations used for training is used for adjusting the network in accordance with the errors. In validation, the network generalization is measured and when the generalization of the network stops improving, the training is stopped. The observations used for testing provides an independent measure of the network performance during the training and after the training.

The artificial neural network is optimized based on the mean squared error (MSE). MSE is an estimator used to measure the squares of the difference between the predicted and actual values of a variable [25-27]. MSE is the average squared difference between the outputs and the targets. Lower values of MSE are better for this study. The multiple regression model provides a good estimate of the erosion of material from the tool electrode and the model helps to provide the micro-EDM factors for minimum tool wear. An approach towards a better approximation would be possible by constructing artificial neural networks for the minimum MSE.

In order to obtain the correct network architecture, the numbers of hidden layers were varied from 1 to the maximum numbers allowed for the configuration (10000) for the minimum mean squared error (MSE) and R-sq value. The results of these iterations are presented in Table 2. The mean squared error was found to be very high for the number of hidden layers from 1 to 6. The architecture of the network with the minimum number of hidden layers, minimum MSE and high R-sq value was acceptable with 7 hidden layers. Therefore, the input layers contain four inputs (voltage, current, pulse on-time and frequency). Fig. 8 shows the optimum architecture of the neural network with 7 hidden layers corresponding to the minimum MSE and the structure of the ANN model for prediction of the TWR based on Fig. 8 and Table 3 is shown in Fig. 9. The network structure shows voltage, current, pulse on time and frequency as the inputs (input layer), 7 hidden layers and 1 output layer for predicting the tool wear rate.

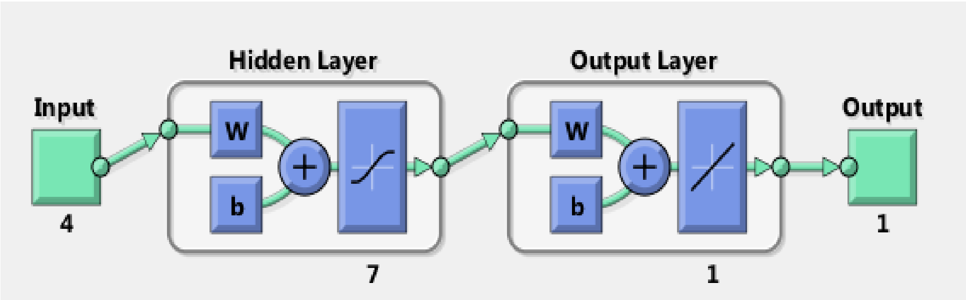

Fig. 8. The optimum architecture of the neural network with 7 hidden layers (minimum MSE and acceptable R-sq value of 0.98)

Table 3. Results of the iterations of the neural network architecture with different hidden layers

Sl. No	Number of hidden layers	Mean squared error (MSE)	R-sq value	Remarks
1	1	high	0.77	not acceptable, high MSE
2	2	high	0.96	
3	3	high	0.98	
4	4	high	0.94	
5	5	high	0.99	
6	6	high	0.99	
7	7	0.91	0.98	Acceptable, minimum MSE
8	8	high	0.98	not acceptable, high MSE
9	9	high	0.98	
10	10	high	0.99	
11	11	high	0.99	
12	15	high	0.98	
13	20	high	0.98	
14	10000	0.97	0.99	Low MSE, but Large number of hidden layers

The selected neural network was trained based on Levenberg-Marquardt algorithm to fit the four input factors and the values of TWR. 62 samples are used as the input to the network for training, and the network is adjusted in accordance with the error. The network testing data (14 samples) generates an independent measure of the performance of the network after the training. The validation data (14 samples) controls the training with the network generalization [36]. The Levenberg-Marquardt back propagation algorithm is a robust method for training of the data because it is reliable to determine a solution at all starting conditions of the controlling variables.

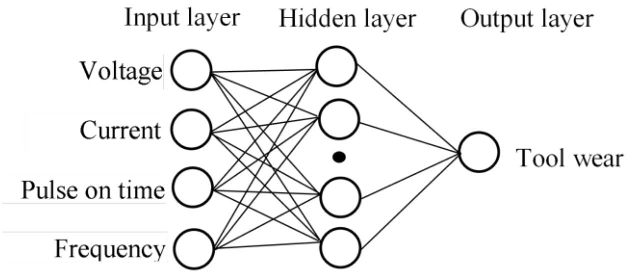

Fig. 9. Structure of the ANN model for prediction of tool wear rate (TWR)

The performance of the developed ANN model is presented in Fig. 10. It is evident that for both training and validation the minimum MSE is achieved at epoch 7 based on the current configuration of the network. To analyze the training and validation of the data using the network, a correlation plot is generated.

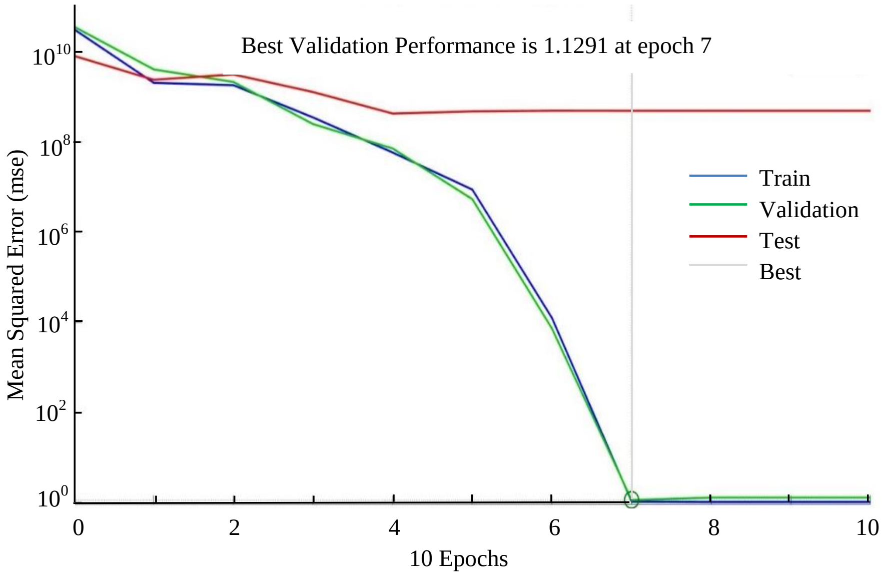

Fig. 10. Performance curve of the ANN model

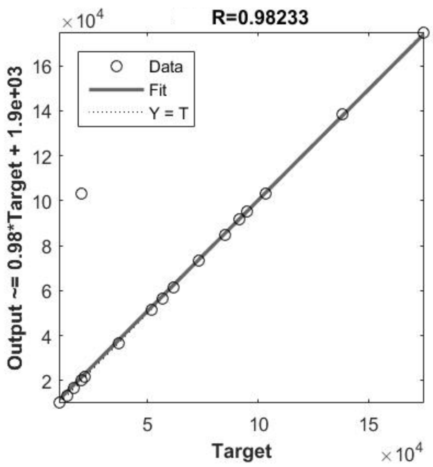

Fig. 11 Correlation plot between network output and target

A plot indicating the confirmation of the correlation between the predicted and experimental values of TWR is presented in Fig. 11. As can be observed from Fig. 9, the between the values of TWR predicted using the network (outputs) and the experimentally calculated values (target) shows an excellent fit.

3.3. CONDITIONS FOR MINIMUM TWR

In this work, the optimization algorithm provides a combination of input factors for the minimum TWR. Fig. 12 shows the prediction and optimization plot for TWR. The black lines indicate the trends of predicted values of TWR and the blue dashed lines are the optimized settings. Except the input factor frequency, all other factors follow a decreasing trend of TWR for the range of values selected for this investigation.

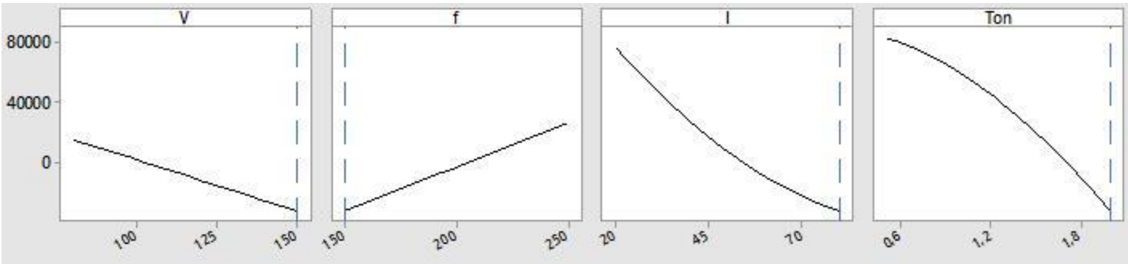

Fig. 12. Prediction and optimization plot for TWR

Based on this analysis, five different solutions are obtained as presented in Table 4. Among the processing conditions achieved, the lowest predicted TWR is observed corresponding to the process settings of voltage: 80 V, pulse frequency: 200 kHz, current index: 80 and pulse on time: 2 µs. Therefore, it is envisaged that for biocompatible micro device fabrication on Ti-6Al-4V alloy, the effective machining method would be based on these process settings.

Table 4. Predicted TWR closest to the optimum solution

Solutions	Voltage (X_1) (in V)	Frequency (X_2) (in kHz)	Current (X_3) (in index)	Pulse on time (X_4) (in µs)	Predicted minimum TWR ($\mu m^3/s$)
1	80	200	80	2	**6282.1**
2	80	250	80	0.5	14107.2
3	80	200	20	0.5	15087.4
4	80	150	80	2	15185.5
5	80	250	50	2	20267.3

4. CONCLUSIONS

A soft computing-based approach for modeling of tool wear rate (TWR) in micro-EDM using MLRA and ANN towards biocompatible micro device fabrication at minimum TWR is presented in this paper. Based on this work, the following conclusions can be drawn:

1. The phenomenon of tool electrode wear during fabrication of micro devices using Ti-6Al-4V alloy was modeled using multiple linear regression analysis and artificial neural network techniques. It is envisaged that the approximation would generate pathways for understandings on computation of the wear compensation and wear corrections.
2. The variation in the TWR values upto 12 times clearly indicates that even with a minor variation in the chosen governing micro-EDM process factors (V, I, T_{on} and f) causes larger changes in the TWR, and hence, a systematic modeling is necessary. Because of poor thermal conductivity and thermal diffusivity of Ti6Al4V, each discharge causes accumulation of thermal energy, which probably is the main cause for reaction forces on the tool electrode that leads to fluctuations in the amount of tool wear.
3. The developed multiple linear regression model could predict with the governing micro-EDM factors and their two-factor interactions could predict variations in the TWR upto 92.2%, and the model was found to be significant at 90% confidence level. Therefore, this model could be applicable to the predictions in which a high precision is not necessary. The model results show a direct correlation between discharge energy and the tool wear. However, the developed model has a limitation that the input current value is represented only as current index, not in amperes.
4. An ANN model was developed to predict the TWR corresponding to the governing micro-EDM factors and only for machine-tool applied in experiments. The TWR data was used for training, testing and validation. The MSE of the network was observed to be the minimum corresponding to 7 hidden layers with an R-sq value of 0.98. The TWR outputs generated using the network and the TWR data available was found to match thoroughly with an excellent fit.
5. Based on this analysis of TWR for efficient biocompatible micro device fabrication, five different solutions for the process settings corresponding to the lowest TWR have been obtained. Among the predicted values, a TWR of 6282.1 $\mu m^3/s$ was achieved at V = 80 V, Current index of 80, T_{on}= 2 μs and f = 200 kHz.

ACKNOWLEDGEMENTS

The research leading to these results has received funding from the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme (FP7/2007-2013) under REA grant agreement no. 609405 (COFUNDPostdocDTU).

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