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Development of a new model for predicting EDM properties of Cu-TaC compact electrodes based on artificial neural network method

[1,2]Mohammed Baba Ndaliman, [1]Muataz Hazza, [1]Ahsan Ali Khan and [1]Mohammad Yeakub Ali

[1]Department of Manufacturing and Materials Engineering, Kulliyyah of Engineering
International Islamic University Malaysia, P. O. Box 10, 50728 Kuala Lumpur, Malaysia
[2]Mechanical Engineering Department, Federal University of Technology, P. M. B. 65, Minna Nigeria

Abstract: Electrical discharge machining (EDM) is one of the non-traditional machining processes normally used in manufacturing very hard materials that are electrically conductive. Tool electrodes form one of the main components of the machining system. The major properties that determine the suitability of such electrodes are electrical conductivity, thermal conductivity and density. The objective of this paper is to present the use of Artificial Neural Network (ANN) architecture in modeling these properties. In the research, Cu-TaC electrode compacts were produced at two levels each of the composition and the compacting pressures from copper and tantalum carbide powders for use in EDM. The compositions of the Cu-TaC are made of 30 % and 55 % wt of TaC, while the compacting pressures are 1, 500 psi and 3,000 psi. They were subjected to sintering at temperatures of 450°C and 850 °C. The properties were measured before and after sintering. Results showed that the sintered electrodes are not suitable for EDM because they lost their electrical conductivity. The pre-sintered electrodes (green compacts) were however found to suitable for EDM. Artificial neural network technique with 16 experimental runs was used to develop the new models for predicting the electrical conductivity, thermal conductivity and density of the green compacted electrodes. The models were been built by using MATLAB 2009b. Results show that ANN models are capable of predicting the electrode properties with high degree of prediction accuracy compared to the experimental results.

Key words: Artificial Neural Network, EDM, Green Compact Electrode, Sintered Electrode, Cu-TaC, thermal conductivity, electrical conductivity.

INTRODUCTION

Electrical Discharge Machining (EDM) is one of the earliest non-traditional manufacturing processes. EDM is widely used for making mold and dies and finishing parts for automotive industry, aerospace and surgical components (Ho and Newman, 2003). The two principal types of EDM processes are the die sinking and the wire cut EDM process. In EDM process, the pair of the workpiece and the cutting tool acts as electrodes. One of these electrodes acts as the cathode while the other is the anode. However, the cutting tool is more commonly referred to as the electrode. The electrode has been a significant component of the EDM mechanism. It has been fabricated by quite a number of methods including conventional machining, rapid tooling (Anil and Cogun, 2008) and powder metallurgy (PM). Several types of them being used in cutting are available, ranging from copper, graphite, copper-tungsten etc. Youssef and El-Hofy observed that about 80–90% of EDM work is the manufacture of tool and die sets for the production of castings, forgings, stampings, and extrusions. Micromachining of holes, slots, texturing, and milling are also typical applications of the process.

A good number of research works on PM fabricated electrodes have been carried out. In their research work, Samuel and Philip (1996) examined the basic properties of the green compacts electrodes produced from electrolytic copper powder. These properties include electrical resistivity, and density of the electrodes. They found the electrodes suitable for use in EDM. Some of the electrodes are being used for conventional EDM with the focused on material removal rate (MRR), and surface roughness (Shu, and Tu, 2003; Hassan *et al*., 2009; Janmanee and Muttamara, 2010). Tsai *et al*. (2003) observed that higher MRR was realizable with the use of Cu-Cr PM electrode when they compared its performance with that of metallic copper electrode. Beri *et al*. (2008) proved that better surface finish is also attainable with the use of these electrodes. PM compacted electrodes have been also produced and used in pre-sintered or sintered conditions (Kwon *et al*., 2007; El-Taweel, 2009), while some are being used for machining in green compacted forms (Patowari, *et al*., 2010a; Ndaliman *et al*., 2011a).

Artificial neural networks (ANN) is a flexible modeling tool which has the capability of learning the mapping between input and output for any complex nonlinear system (Patowari *et al*., 2010b). It has superior tools which are capable of modeling of many aspects of EDM such as materials removal rate, surface

Corresponding Author: Mohammed Baba Ndaliman, Department of Manufacturing and Materials Engineering, Kulliyyah of Engineering International Islamic University Malaysia, P. O. Box 10, 50728 Kuala Lumpur, Malaysia
E-mail: mutaz_hazaa@yahoo.com

modification with PM electrodes etc (Patowari *et al*., 2010b; Yahya *et al*., 2011). However, the application of ANN in modeling the properties of EDM powder metallurgy electrodes has not yet been reported in literatures. This paper therefore focuses on the development of new models using ANN technique to estimate and predict the thermal conductivity, electrical conductivity and density of the new EDM electrodes produced from Tantalum Carbide (TaC) and Copper (Cu) powders in two different forms- the green compacted electrodes (GCE) and sintered electrodes (SE) by using PM method. These are important properties of EDM electrodes which will not only determine their suitability in machining, but also the level of surface integrity to be attained by the workpiece. The electrodes produced from these powders have earlier been investigated for suitability in EDM as well as capability in surface modification of workpiece (Ndaliman *et al*., 2011a; Ndaliman *et al*., 2011b).

Research Methodology:

Research Flow Chart:

The theoretical and the experimental work have been integrated and supported with the artificial intelligence tools to develop a new model to predict the thermal conductivity, electrical conductivity and density of the two different electrodes forms. The input variables are TaC composition, the compacting pressure, the sintering temperature and time. Figure 1 shows the flow chart of the details used in the investigation to achieve the target of developing the output model of the electrode properties.

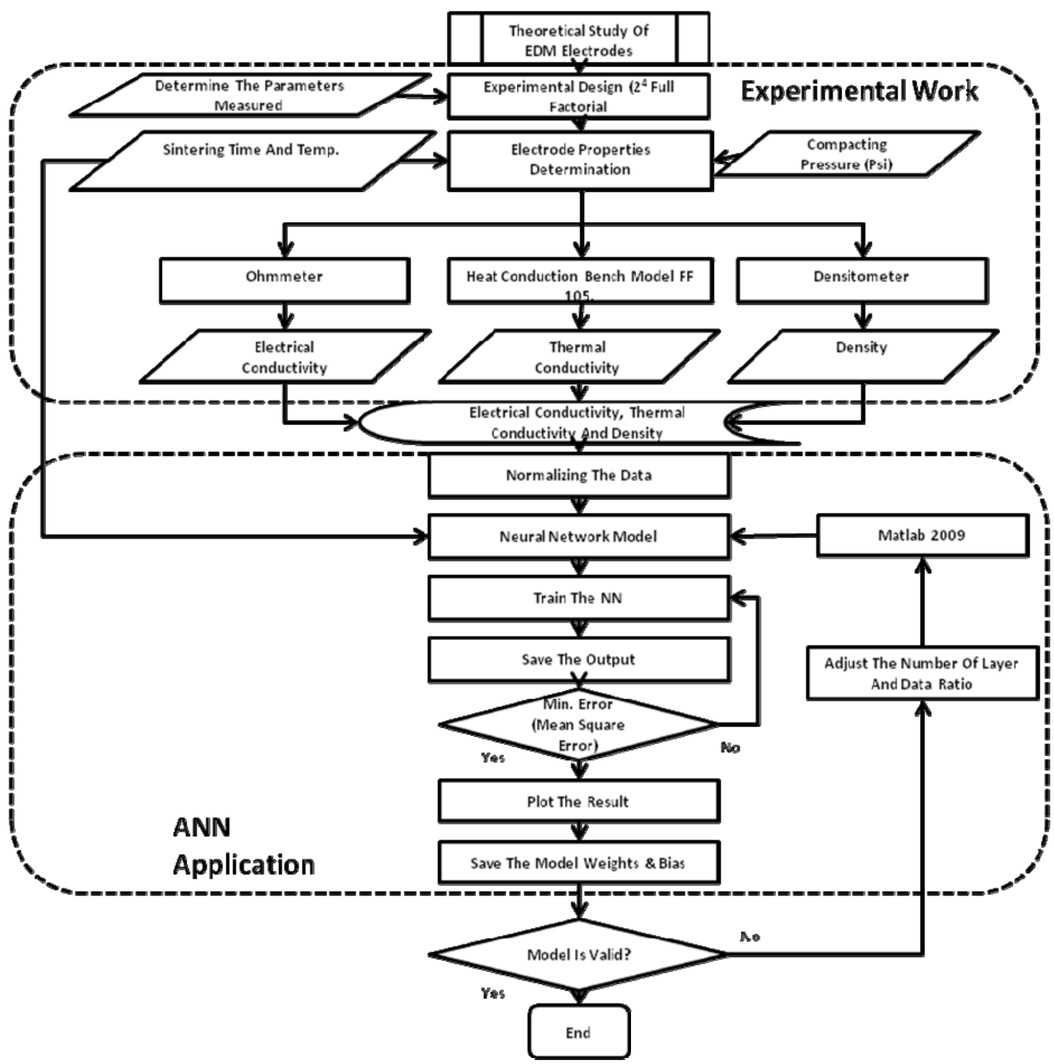

Fig. 1: Research flow diagram

Materials:

Materials have been used in the experiment were Cu and TaC powders. The Cu powder is of 99.9% purity and 200 mesh, while the TaC powder is of 99% purity, and between 200 and 325 mesh. The electrical conductivities of individual powders have been determined by measuring the compacted electrodes made of each of the powders. They were mixed into the following compositions: (Cu-TaC: 70-30% and 45-55%). A manual pellet press shown in Figure 2 was used to compact the electrodes which are of 13mm diameter. The compacting pressures used were 1,500 and 3,000 psi.

Fig. 2: The carver press used for compaction

They were then sintered at two levels of temperatures: 450 and 850°C, at 25 and 50 minutes. The densities were measured with densimeter, while the thermal conductivities were determined with the Heat conduction bench model FF 105. The electrical conductivities were measured by determining the resistances of the electrodes with Ohmmeter. The resistance, R_e, is related with resistivity, ρ, as shown in Equations 1 and 2 (Ndaliman and Khan, 2011).

$$\rho = R_e A / L \tag{1}$$

Where ρ – electrical resistivity (Ωm), A – Cross-sectional area (mm^2), L – Length of the electrode (mm)
For the circular cross section of the electrode, the resistivity becomes:

$$\rho = 0.786\ Rd^2/ L \tag{2}$$

Where d – Electrode's diameter
The electrical conductivity, σ, is the inverse of the resistivity and this can be represented in equation 3 as:

$$\sigma = 1/ \rho \tag{3}$$

Experimental Work:

In the experiment, 16 samples of data set have been collected based on a 2^4 full factorial experiments for each type. The factors of consideration are powder composition, compacting pressure, sintering temperature and time. The investigated responses were three: electrical conductivity, thermal conductivity and density. These properties were measured for the pre-sintered (green compacts) and sintered electrodes. Table 1 shows the summary of the factors and their level.

Table 1: Factors and their levels.

Factor	Low level	High level
TaC in composition (%)	30	55
Compacting pressure (psi)	1,500	3,000
Sintering temperature (°C)	450	850
Time (min)	30	50

Experimental Results:

The experimental results are presented in Table 2. The results showed that the compacted electrodes in green form can be suitable for EDM, since the electrical conductivities are very high (94.96 – 189.92$\Omega^{-1}m^{-1}$). The thermal conductivity is good (29.70 – 33.20W/ m K). The density ranges between 6.13 and 9.80 g/cm^3. The first major determinant in suitability of EDM electrode is electrical conductivity. It is also observed from Table 2 that the electrical conductivity of the sintered electrodes ranges between 0.0018 x 10^{-3} and 6.41 x 10^{-3} 1/Ω m. This implies that the sintered electrodes are electrically non-conductive, and are therefore unsuitable for use in EDM under these sintering conditions.

Table 2: Experimental results for the compacted electrodes (green compacted electrodes and sintered electrodes)

Run order	Factors				Green Compact Electrodes(GCE)			Sintered Electrodes(SE)		
	A (%)	B (psi)	C (C°)	D (min)	Therm. Cond. (W/m K)	Elect Cond (1/Ω m)	Density (g/cm^3)	Therm. Cond (W/m K)	Elect Cond (1/Ω m)x10^{-3}	Density (g/cm^3)
1	55	3000	450	50	30.8	120.53	7.240	29.1	1.3016	5.680
2	30	1500	450	50	31.2	157.78	8.750	30.3	2.0518	4.717
3	30	3000	850	30	33.2	154.86	8.519	29.3	0.8963	4.498
4	30	3000	450	30	30.1	178.96	6.969	30.0	1.8887	5.520
5	55	1500	450	50	31.2	94.96	9.411	30.0	1.7604	5.156
6	30	1500	450	30	30.4	157.78	8.620	29.8	1.1794	5.558
7	30	1500	850	50	30.6	123.13	8.425	31.4	0.0321	3.958
8	55	3000	450	30	29.7	129.05	9.801	30.1	6.4089	5.724
9	30	3000	850	50	31.2	132.70	8.504	29.9	0.0018	4.107
10	55	1500	450	30	30.5	124.18	8.995	31.6	2.7484	5.159
11	55	3000	850	30	31.3	143.66	9.710	30.9	0.0081	4.857
12	55	3000	850	50	31.4	175.31	7.520	30.0	0.0035	4.954
13	55	1500	850	30	32.3	144.87	6.374	31.0	0.0042	4.992
14	30	3000	450	50	30.8	189.92	7.026	29.4	4.2371	5.498
15	30	1500	850	30	32.2	150.47	6.128	29.1	0.0135	5.416
16	55	1500	850	50	31.9	107.74	8.953	28.4	0.0018	0.309

A: TaC in composition, B: Compacting pressure, C: Sintering temperature, D: Time

These results have been used to develop the neural network model to predict the electrical conductivity, thermal conductivity and density for Cu-TaC electrodes produced by Powder Metallurgy (PM) method for the green compacted electrodes which were confirmed to be suitable for EDM (Ndaliman *et al*., 2011).

Ann Modeling:

ANN Application:

Sixteen experimental runs each of the GCE and the SE samples were used to train the neural network and to adjust the weights and the biases of each unit in order to reduce the error between the desired output and the actual output. The NFTOOL box in the MATLAB 2009 was used. The back propagation training algorithm was applied to determine the layer's weights. This comprises of four steps: the weight commencement, feed-forward, back-propagation of errors and updating of the weights and biases (Patowari *et al*., 2010b). Table 3 gives the summary involving the architecture, learning system and specifications of the neural network model used in the development of the new model.

Table 3: Modeling by with artificial neural network

Tool	MATLAB 2009
Tool box	Nftool
Architecture	Feed forward
Learning system	Supervised learning
Algorithm	Back propagation Levenberg-Marquardt algorithm (LM)
Activation Function	Sigmoid (logistic function)
Number of layers, Data ratio	3 layers (input, hidden and output) 70:15:15
Number of hidden layers	20

Figure 3 shows the neural network structure that was generated by the software. A three-layer network comprising input, output and hidden layers of neurons was constructed. The architecture of the network is made up of four inputs, twenty hidden layers and three output layers. The network training was undertaken with Levenberg-Marquardt algorithm, thus *trainlm* in ANN Toolbox of MATLAB software.

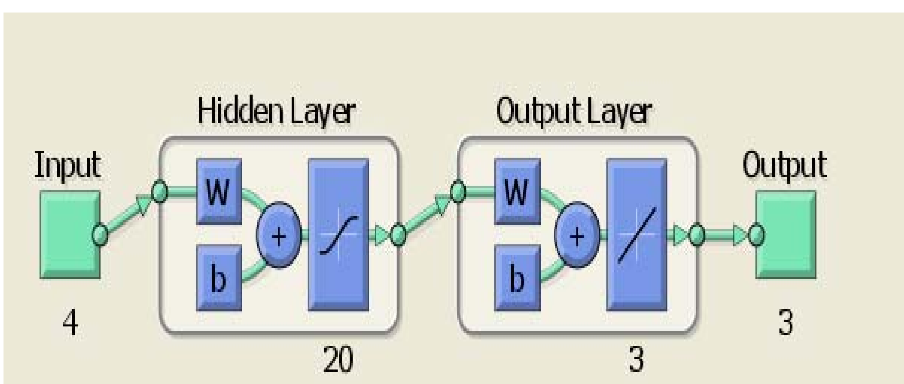

Fig. 3: Neural Network Structures with the input, output and hidden neurons

ANN Results:

The regression plot for training, testing and validating the model are presented in Figure 4. The plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line (dash line), where the network outputs are equal to the targets. For this study, the fits are found to be very good for all data sets, with the R value in each of the outputs were found to be above 0.98.

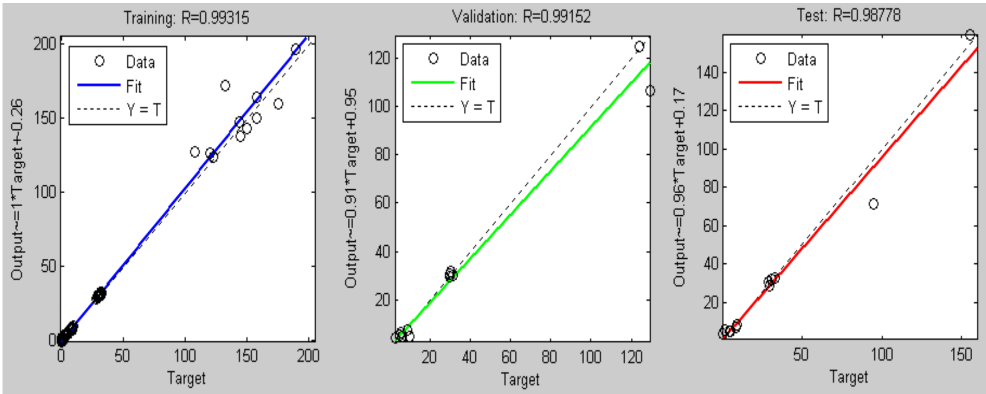

Fig. 4: Regression data plots for training, validation and, testing

Validation:

A comparision of the measured and the predicted values to determine the deviation between the theoretical and actual value that comes out from ANN models was then been conducted. The summary of the average deviations of the models with respect to each of the property is presented in Table 4. Figures 5 to 7 illustrate the average deviation in terms of point-to-point behavior between the actual and the predicted values by the neural network models for the three properties. The results show different percentages of accuracy with respect to individual properties.

From Figure 5, the model for thermal conductivity of the GCE shows better prediction of results compared to those of other properties. This is because it has fewer data points that are outside the prediction region. This is corroborated by its lowest deviation of 0.60%. in Table 4. Thermal conductivity is an important property of EDM electrodes as it affects the dissipation of the heat generated during the electrical discharges away from them (electrodes) to prevent their melting. However, since the electrical conductivity of the sintered electrodes is very low (almost non conductive), they cannot be used in EDM. Thus, the question of modeling of their properties would not arise. Attempt to model the electrical conductivity of SE can be an effort in futility as can be seen in the deviation of 47.30% in Table 4. This was also confirmed in the previous study with the same powders by the authors (Ndaliman and Khan, 2011). This is why the prediction / target diagrams for the properties of SE were not presented.

The results also show that the models of the remaining properties (electrical conductivity and density) of the GCE are valid. For the electrical conductivity, the predicted outputs indicate few points of variations (Figure 6) with the target. The 9.00% deviation is acceptable. Similarly the 4.70% deviation for the density is a good approximation to the target. This close approximation is also illustrated in Figure 7. Therefore, it would to appropriate to summarize that the use of ANN tools can give a good prediction of the properties of green compacted PM electrodes, especially those produced from Cu and TaC powders.

Table 4: Validation of the results

Property	GCE	SE
Thermal conductivity	0.60%	2.00%
Electrical conductivity	9.00%	47.30%
Density	4.70%	4.90%

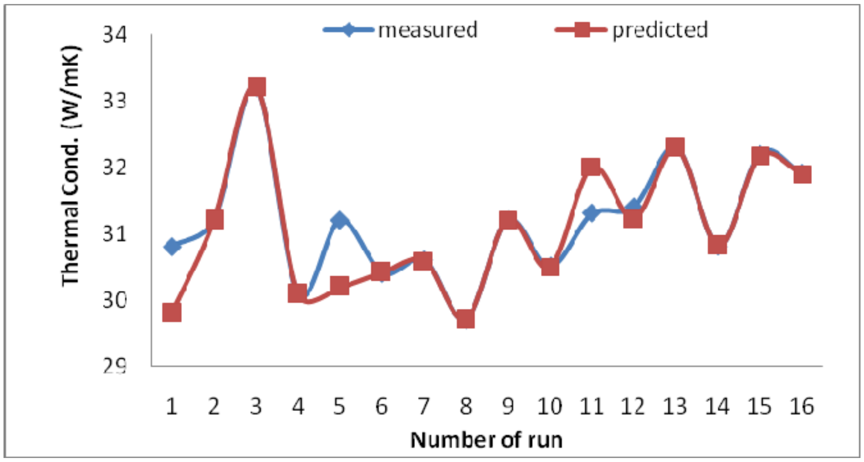

Fig. 5: Predicted thermal conductivity of GCE with their corresponding targets at different data points

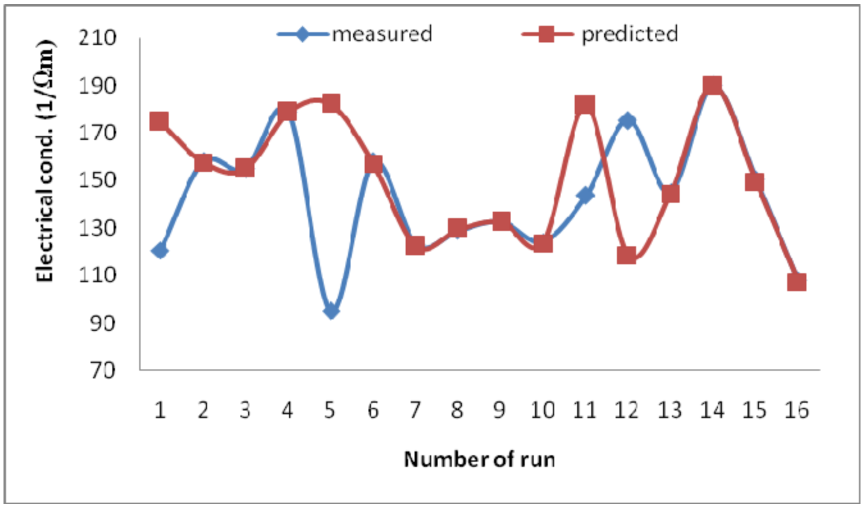

Fig. 6: Predicted electrical conductivity of GCE with their corresponding targets at different data points

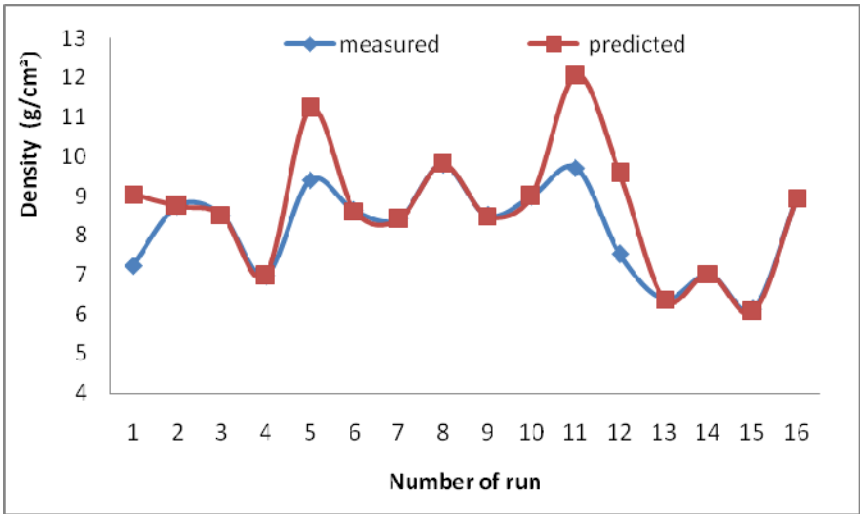

Fig. 7: Predicted density of GCE with their corresponding targets at different data points

Conclusions:

This study involves the use of ANN technique to develop behavioral models for predicting the values of electrical conductivity, thermal conductivity and density for Cu-TaC compacted electrodes produced by Powder Metallurgy method for use in EDM. Twenty hidden layer used with feed forward back-propagation hierarchical neural networks were designed with MATLAB 2009b Neural Network Toolbox. The new model was tested and validated for the properties. The properties of the green compact electrodes finally correlated in the models. The correlations between the predicted and observed values indicate that the models can validly predict the electrode properties with high degree of prediction accuracy.

LIST OF ABBREVIATIONS/NOTATIONS

A	Cross-sectional area of the electrode (mm^2)
ANN	Artificial neural network
Cu-TaC	Copper-Tantalum carbide PM compacted electrode
d	Electrode's diameter (mm)
EDM	Electrical discharge machining
GCE	Green compact electrode
L	Length of the electrode (mm)
MRR	Material removal rate
PM	Powder metallurgy
R	Deviation
R_e	Resistance (Ω)
SE	Sintered electrode
σ	Electrical conductivity (1/Ω m)
ρ	Resistivity (Ω m)

REFERENCES

Anil, D. and C. Cogun, 2008. Performance of copper-coated stereoligraphic electrodes with internal cooling channels in electrical discharge machining (EDM). Rapid Prototyping Journal, 14(4): 202-212.

Beri, N., S. Maheshwari, C. Sharma and A. Kumar, 2008. Performance evaluation of powder metallurgy electrode in electrical discharge machining of AISI D2 steel using Taguchi method. International Journal of Mechanical, Industrial and Aerospace Engineering, 2(3): 167-171.

El-Taweel, T.A., 2009. Multi-responses optimization of EDM with Al-Cu-Si-TiC P/M composite electrode. International Journal of Advanced Manufacturing Technology, 44: 100-113.

Hassan, N.H., Z.N. Mohd, M.S. Wahab and M. Ibrahim, 2009. Fabrication of MMC material for EDM electrode. Procceedings of IEEE Student Confernce on Research and Development, UPM, Serdang, November 16-18, 2009, Malaysia, pp: 262-265.

Ho, K.H. and S.T. Newman, 2003. State of the art electrical discharge machining (EDM). International Journal of Machine Tools & Manufacture, 43: 1287-1300.

Janmanee, P. and A. Muttamara, 2010. Performance of different electrode materials in electrical discharge machining of tungsten carbide. Energy Research Journal, 1(2): 87-90.

Kwon, Y., S. Chung, S. Lee, J. Noh, S. Park and R.M. German, 2007. Development of the high performance W-C electrode, in Advances in Powder Metallurgy and Particle Materials, Metal Powder Industries Federation.

Mohri, R., N. Saito, Y. Tsunekawa and K. Kinoshita, 1993. Metal surface modification by electrical discharge machining with composite electrode. CIRP Annals, 42(1): 219-222.

Ndaliman, M.B., A.A. Khan and Z.M. Zain, 2011a. Performance of PM compacted Cu-TaC electrodes during EDM. Presented at the 2nd International Conference on Mechanical and Manufacturing Engineering (ICME 2011), PICC, Putrajaya, Malaysia, June 6-8.

Ndaliman, M.B., A.A. Khan, and M.Y. Ali, 2011b. Surface modification of titanium alloy through electrical discharge machining (EDM). International Journal of Mechanical Materials Engineering, 6: 380-384.

Ndaliman, M.B. and A.A. Khan, 2011. Development of Powder Metallurgy (PM) compacted Cu-TaC electrode for EDM. Journal of Mechanics Engineering and Automation, 1(5): 385- 391.

Patowari, P.K., U.K. Mishra, P. Saha and P.K. Mishra, 2010a. Surface modification of C40 steel using WC-Cu P/M green compacted electrodes in EDM. International Journal of Manufacturing Technology and Management, 21(1/2): 83-98.

Patowari, P.K., P. Saha and P.K. Mishra, 2010b. Artificial neural network model in surface modification by EDM using tungsten-copper powder metallurgy sintered electrodes. International Journal of Advanced Manufacturing Technology, 51: 627- 638.

Samuel, M.P. and P.K. Philip, 1996. Properties of compacted, presintered and fully sintered electrodes produced by powder metallurgy for electrical discharge machining. Indian Journal of Engineering and Materials Science, 3(9): 229-233.

Shu, K.M. and G.C. Tu, 2003. Study of electrical discharge grinding using metal matrix composite electrodes. International Journal of Machine Tools Manufacture, 43: 845-854.

Tsai, H.C., B.H. Yan and F.Y. Huang, 2003. EDM performance of Cr/Cu-based composite electrodes. International Journal of Machines Tools Manufacture, 43: 245-252.

Yahya, A., T. Andromeda, A. Baharom, A. Abd Rahim and N. Mahmud, 2011. Material removal rate prediction of electrical discharge machining process using artifitial neural network. Journal Mechanics Engineering and Automation, 1: 298-302.

Youssef, H.A. and H. El-Hofy, 2008. Machining Technology: machine tools and operations. CRC Press Taylor & Francis Group.