Estimation and Comparison of Electrode Wear and AE Parameters of Titanium and Stavax Materials in Wire Electric Discharge Machining using ANN

[1]Prathik Jain S, [2]H V Ravindra, [3]G Ugrasen
[1] Research Scholar, Department of Mechanical Engg, PESCE, Mandya,
[2] Professor, Department of Mechanical Engg, PESCE, Mandya,
[3] Department of Mechanical Engg, BMSCE, Bengaluru.
[1]prathik9@gmail.com,[2] mailhovera@yahoo.com, [3]ugrasen.g@gmail.com

Abstract— Wire Electrical Discharge Machining (WEDM) is a specialized thermal machining process capable of accurately machining parts with varying hardness or complex shapes, which have sharp edges that are very difficult to be machined by the main stream machining processes. Selection of process parameters for obtaining higher cutting efficiency or accuracy in WEDM is still not fully solved, even with most up-to-date CNC wire EDM machine. It is widely recognized that Acoustic Emission (AE) is gaining ground as a monitoring method for health diagnosis on rotating machinery. The advantage of AE monitoring over vibration monitoring is that the AE monitoring can detect the growth of subsurface cracks whereas the vibration monitoring can detect defects only when they appear on the surface. This study outlines the machining of titanium and stavax material using L'16 design of experiment and comparing the electrode status for each material. Titanium is used in engine applications such as rotors, compressor blades, hydraulic system components and nacelles. Stavax finds its application in the molding of medical components such as syringes and analysis vials. Each experiment has been performed varying different process parameters like pulse-on, pulse-off, current and bed speed. Among different process parameters voltage and flush rate were kept constant. Molybdenum wire having diameter of 0.18 mm was used as an electrode. Optimization of these process parameters are carried out to know the effect of most influencing parameters on the responses. Simple functional relationships between the parameters were plotted to arrive at possible information on electrode wear and AE signals. But these simpler methods of analysis did not provide any information about the status of the electrode. Hence more sophisticated method of analysis was used viz., Artificial Neural Network (ANN) for the estimation of the experimental values. EW and AE parameters prediction was carried out successfully for 50%, 60% and 70% of the training set for Stavax material using ANN. Among the selected percentage data, at 70% training set showed remarkable similarities with the measured value then at 50% and 60%.

Keywords: AE, Electrode Wear, ANN

I. INTRODUCTION

The wire-cut type of machine arose in the 1960s for the purpose of making of tools (dies) from hardened steel. The tool electrode in WEDM is simply a wire. To avoid the erosion of material from the wire causing it to break, the wire is wound between two spools so that the active part of the wire is constantly changing. The earliest Numerical Controlled (NC) machines were conversions of punched-tape vertical milling machines. WEDM is an alternative competitive process to manufacture complex part geometries. Acoustic Emission (AE) techniques are very useful for fast and easier measurement of machining performances which is difficult to recognize by other methods.

The present work was carried out for a detailed study on estimation of Electrode Wear (EW) and AE parameters of titanium and stavax materials in WEDM. Process parameters such as pulse-on time, pulse off time, current and bed speed were varied. The measured EW and AE parameters namely signal strength and RMS was compared with predicted values of ANN, and estimation of theoretical results and experimental results were compared. Titanium is used in engine applications such as rotors, compressor blades, hydraulic system components and nacelles. Its application can also be found in critical jet engine rotating and airframes components in aircraft industries. Stavax finds its application in the moulding of medical components such as syringes and analysis vials. It is recommended for the production of optical parts like sunglasses, cameras and lenses. It is suitable for large moulds because of its high hardenability feature. In the past, researchers have investigated the effect of ZrO_2-TiN blanks at higher cutting dimensions in WEDM using brass wire. Different finishing steps were used to obtain cause for Metal Removal

Mechanism (MRM) and low Surface Roughness (SR). Results from SEM images shows that with proper WEDM setting higher finish can obtained in the machined specimen and MRM was mainly due to melting and evaporation [1]. The evolution of the EDM wire electrode technologies from using copper to the widely employed brass wire electrodes and from brass wire electrodes to the latest coated wire electrodes. Wire electrodes have been developed to help user demand and needs through maximum productivity and quantity by choosing the best wire. It was found that the productivity of WEDM process can be increased by using zinc coated wire material than any other wire materials [2]. A new polishing method in which surface modification by an oxidizing treatment is combined with flow polishing using abrasives was developed to remove the surface defects generated in cemented carbide with fine holes by WEDM. In this method, although it is desirable to avoid a thermal process if possible, the oxidizing treatment is added to process. Thus, on-the-machine surface modification technology in WEDM has already been developed for the purpose of completely removing the surface defects [3].

Comparative study on materials viz., Rolled Homogeneous Armour (RHA) steel and aluminium alloy using Buckingham pi theorem for modelling parameters viz., MRR and SR using brass wire in WEDM. The experimental methodology determines the parameters viz., pulse on time, input power, flushing pressure, latent heat of vaporization and thermal diffusivity. It was found that as there was an increase in the pulse on time surface finish deteriorates and MRR increases. [4]. One of the main challenges in WEDM is avoiding wire breakage and unstable situations as both phenomena reduce process performance and can cause low quality components. The methodology has been followed as applied to process instability and wire breakage detection in WEDM. First, an acquisition system has been developed aimed at storing an extensive experimental database based on stable and unstable tests. The results of a preliminary analysis of a set of tests have revealed the influence on wire breakage of discharge variables, such as peak current, discharge energy and ignition delay time. Related to these discharge variables, wire breakage indicators have been defined [5]. The influence of different process parameters on MRR, SR and tool wear in EDM has been studied for Inconel 718 material. Regression model was used to know the deviation of peak count, SR, EW and MRR. Results show that the most influencing parameter for MRR and SR is current intensity whereas for electrode wear and peak count it is pulse time [6]. The effect of design factors viz., pulse time, open-circuit voltage, duty cycle, intensity and flushing pressure, on MRR and EW while machining reaction bonded silicon carbide (SiSiC) material in die sinking EDM. Results show that the most influential design factors for MRR were open-circuit voltage and intensity; in order to obtain a high value of MRR, both the design factors should be fixed as high as possible. [7]. AE signal as the frame of reference for determining the acoustic time lag, the proof-of-concept of the applications of AE discharge mapping for the respective identification of electrode length and workpiece height in fast-hole EDM and WEDM are presented. Additional work in terms of acquisition and processing of AE signals is warranted to further develop this technology towards its real-time implementation, as well as its extension to sink EDM [8]. The two different ANN models viz., BPNN and RBFN for the prediction of SR of AISI D2 material in die sinking EDM was carried out. The process parameters considered for the machining were duty cycle, pulse current and pulse duration with a constant voltage of 50V. It was found that the neural models could predict the process performance with reasonable accuracy, under varying machining conditions. RBFN is faster than the BPNN but BPNN is reasonably more accurate. [9].

II. EXPERIMENTAL WORK

The experiments were performed on CONCORD DK7720C 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 CONCORD DK7720C allows the operator to choose input parameters according to the material and height of the work piece. The WED machine has several special features. Unlike other WED machines, it uses the reusable wire technology. i.e., wire can’t be thrown out once used; instead it is reused adopting the re-looping wire technology. To avoid the erosion of wire from the material causing it to break, thus the wire is constantly changing before each experiment. The experimental set-up for the data acquisition is illustrated in the Fig. 1.

The WEDM process generally consists of several stages, a rough cut phase, a rough cut with finishing stage, and a finishing stage. But in this WED machine only one pass is used. The gap between wire and work piece is 0.02 mm and is constantly maintained by a computer controlled positioning system. Molybdenum wire having diameter of 0.18 mm was used as an electrode.

Fig. 1. Experimental Set-up during machining

III. THEORETICAL ANALYSIS

A. Artificial Neural Network (ANN)

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. As the machining process is non-liner and time-dependent, it is difficult for the traditional identification methods to provide an accurate model. Compared to traditional computing methods, ANN's are robust and global. ANN's had the characteristics of universal approximation; parallel distributed processing, learning and adaptations. Because of this ANN's are widely used for system modeling, commission optimizing, and image processing and intelligent control. ANN's give an implicit relationship between the input and output by learning from a data set that represents the behavior of a system.

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 [10]. The output signal of a neuron is fed to other neurons as input signals via interconnections Fig. 2 shows a simple ANN.

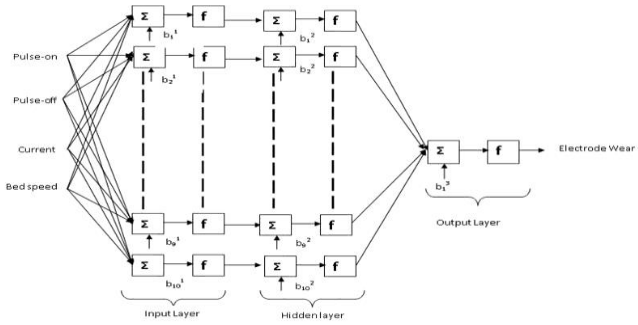

Fig. 2. Network Architecture

IV. RESULT AND DISCUSSION

A. Parametric Influence on EW and AE signals (Signal strength and RMS)

Selection of the optimal process parameters is essential to obtain desired values in response variable such as EW, surface roughness etc which usually impacts economy. An appropriate technique shall provide optimum parameters, essential to achieve several conflicting objectives of the process. The optimal data pertaining to EW and AE_{SS} (Signal Strength) and AE_{RMS} for titanium and stavax materials to predict the raw data plot is presented below.

Fig 3 and 4 shows the response parameter plot on EW for titanium and stavax materials respectively, from the figure it can noted that the 1st most influencing parameter is pulse on time and 2nd most influencing parameter is current. This is due to the fact as the pulse on time and current since as the current increases causes increase in spark energy resulting in higher wear. Further spark energy and the period to transfer this energy into the electrodes increases with increase in pulse on time which results in increase of the wear [11]. Table 1 and 2 shows the optimum parameter, R-Sq value and F value for the response parameters for titanium and stavax materials respectively.

Table 1. Response and Optimal parameter for titanium material

Parameters	Titanium Material		
	EW (µm)	F Value	R-Sq
Pulse on time	20	18.39	96.31%
Pulse off time	4	3.69	
Current	4	9.17	
Bed speed	25	2.88	

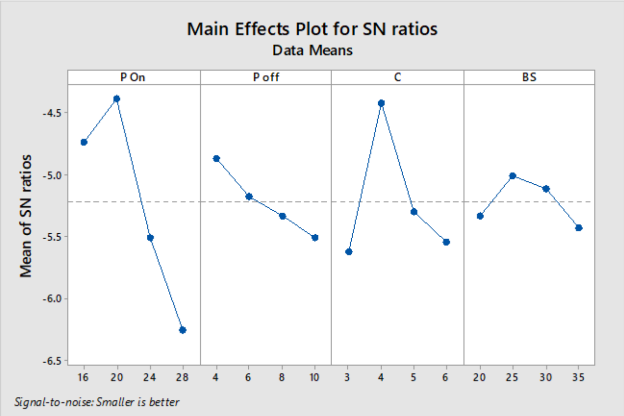

Fig. 3. Response Plot on EW for titanium material

Table 2. Response and Optimal parameter for stavax material

Parameters	Stavax Material		
	EW (µm)	F Value	R-Sq
Pulse on time	16	14.15	95.94%
Pulse off time	6	5.55	
Current	5	8.78	
Bed speed	35	3.15	

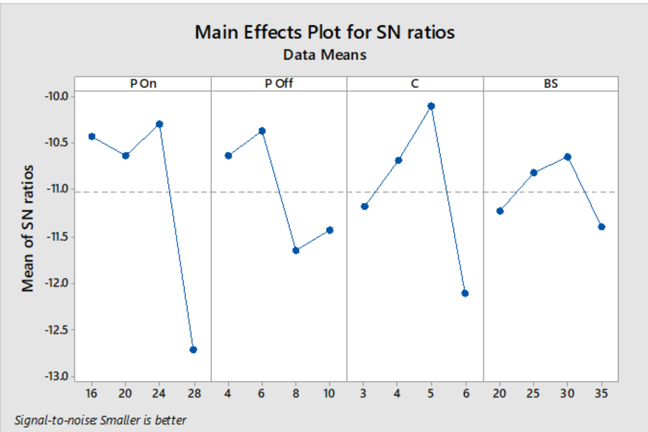

Fig. 4. Response Plot on EW for stavax material

It was also noted that the most influencing parameters for AE_{SS} and AE_{RMS} were also pulse on time and current. Hence for the further machining process, only the variation of the pulse on time and current are considered by keeping pulse off time and bed speed constant i.e. by considering the most repeated value of pulse off time (4 µs) and bed speed (25 µm/s).

B. Raw data analysis for the variation of pulse on time and current to know the electrode status and machining performance status.

Electrode diameter was measured before the machining and the wear of the electrode was measured at the regular intervals to know the status of the electrode. Fig. 4 and 5 shows the effect of EW against machining time for the various pulse on time (16 µs, 20 µs, 24 µs, 28 µs) at constant pulse off time 4 µs, current 5 A and bed speed 25 µm/s for titanium and stavax materials respectively.

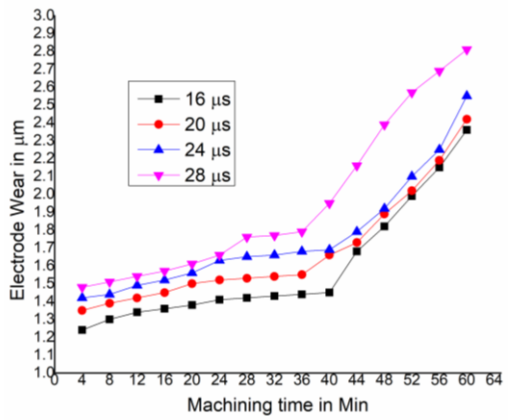

Fig 4 : EW v/s Machining Time for titanium material

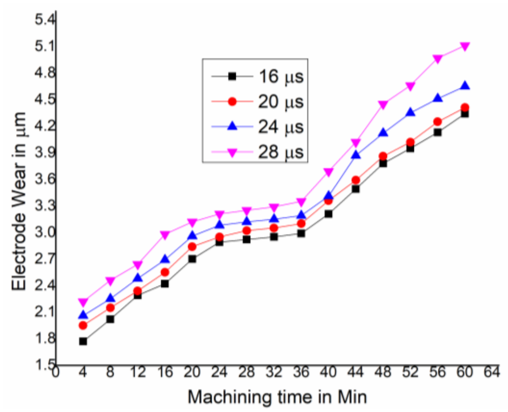

Fig 5 : EW v/s Machining Time for stavax material

From the plots it can be revealed that at higher pulse on time higher values of the EW was observed, because increasing the pulse on time means increases the amount of heating flux for a longer time. This will cause an increase of the heat that is conducted onto workpiece and tool electrode causing an increase in the wear of the electrode [12]. As shown from plots it can be seen that higher wear is found in stavax material then in titanium material this is because higher hardness material requires more amount of heating flux for machining hence the material removal rate will also be high along with the electrode wear.

AE signals (SS and RMS) were measured at the regular intervals using AE sensors to know the status of the machining performance. Fig. 6 and 7 shows the effect of AE_{SS} against machining time for the various current (3 A, 4 A, 5 A, 6 A) at constant pulse on time 20 µs, pulse off time 4 µs and bed speed 25 µm/s for titanium and stavax materials respectively. Fig. 8 and 9, shows the effect of AE_{RMS} against machining time for the various current at constant pulse off time, pulse on time and bedspeed.

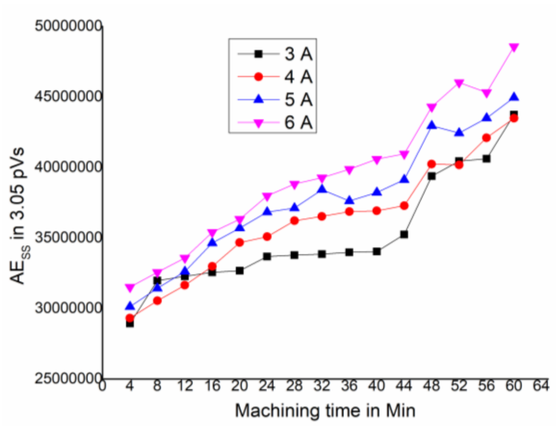

Fig 6: AE_{SS} v/s Machining Time for titanium material

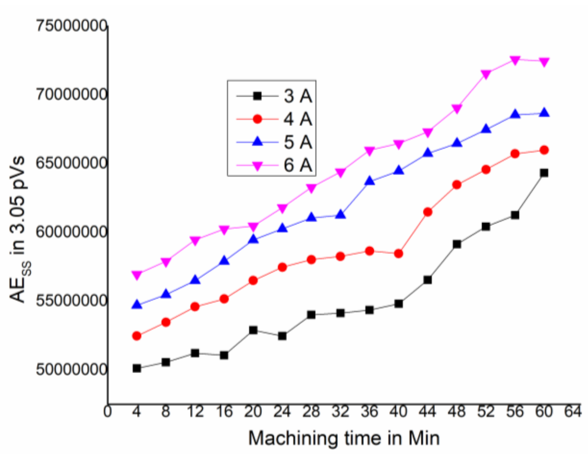

Fig 7: AE_{SS} v/s Machining Time for stavax material

From the plots higher gradient of AE_{SS} and AE_{RMS} was found at higher current. From the plots it can also be observed that as hardness of the material increases AE signals captured due to melting (fracture) are also high, hence higher values of AE_{SS} and AE_{RMS} are found in stavax material when compared to titanium material. Better correlation was obtained in AE_{RMS} when compared to AE_{SS}. Hence only AE_{RMS} was used for the estimation by ANN. It can also be concluded that signals variation was more in the maximum and minimum condition of the process parameters.

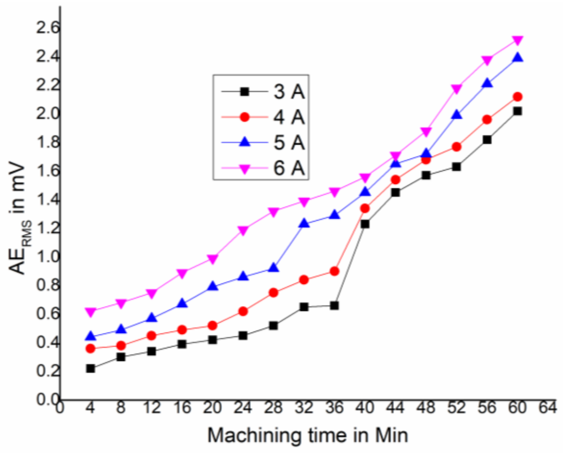

Fig 8: AE_{RMS} v/s Machining Time for titanium material

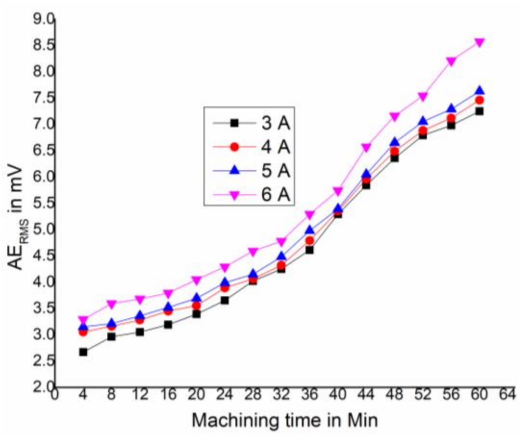

Fig 9: AE_{RMS} v/s Machining Time for stavax material

C. Estimation by ANN.

Neural network (NN) is biologically stimulated; i.e., it is consisting of elements that perform in a way similar to elementary functions of biological neurons. ANN is a mapping technique between input and output data based on biological nervous system simulation, such as the brain, on a computer. The actual supremacy and benefit of NN lies in their capability to characterize both non-linear and linear relationships and in their ability to learn these relationships directly from the data being modelled. Artificial Neural Networks (ANN's) is used to validate the results obtained and also to predict/estimate the behaviour of the system under any condition within the operating range. The accuracy of theoretical estimation using the NN is superior to that using other regression methods. The estimation of the ANN was carried out by varying the percentage of data in the training set, i.e. it was varied in three set viz., 50%, 60% and

70%. It was found that Least Mean Squared Error (MSE) and best fit was obtained when 70% of data is used in the training set. Fig. 10 and 11 shows the estimation of AE_{RMS} for minimum and maximum pulse on time at constant pulse off time 4 µs, current 5 A and bed speed 25 µm/s through which a clear insight can be obtained about the signal for titanium and stavax materials respectively

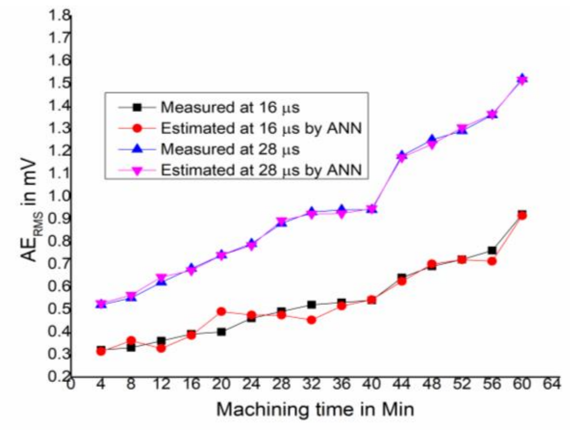

Fig. 10: Measured and Estimated by ANN for AE_{RMS} of titanium material

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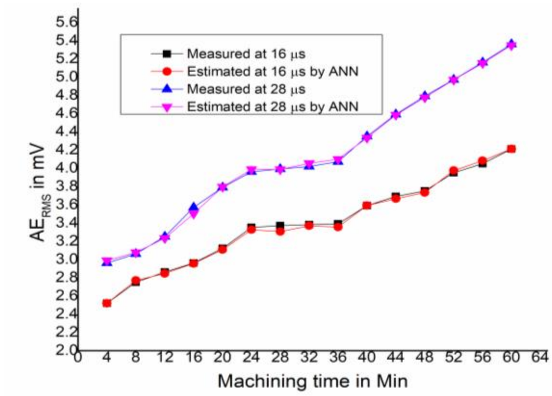

Fig. 11: Measured and Estimated by ANN for AE_{RMS} of stavax material

From the figure it can be observed that at maximum condition of pulse on time measured value correlates well with the estimated value with the least MSE value for all the materials then in minimum condition.

Fig. 12 and 13 shows estimation of EW for minimum and maximum current at constant pulse on time 20 µs, pulse off time 4 µs, and bed speed 25 µm/s through which a clear insight can be obtained about the signal for titanium and stavax materials respectively. From the plots it can be observed that minimum condition of the current correlates well with the estimated values then in the maximum condition.

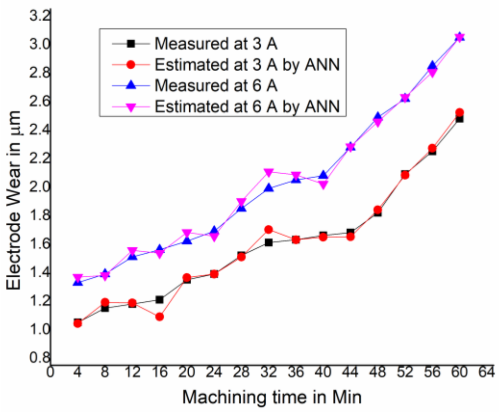

Fig. 12: Measured and Estimated by ANN for EW of titanium material

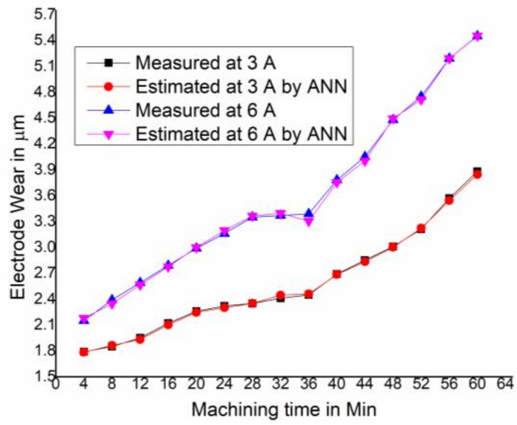

Fig. 13: Measured and Estimated by ANN for EW of stavax material

CONCLUSION

Optimization of the process parameters showed that pulse on time and current as the most influencing process parameters on EW and AE signals. Electrode Status has been assessed through AE signals viz., AE_{SS} and AE_{RMS}. All the response parameters for both the materials increased along with the machining time for the variation of pulse on time and current. Higher values of EW, AE_{SS} and AE_{RMS} are found at higher pulse on time (28 µs) and higher current (6A) then in lower and medium condition of these process parameters. Higher values of EW, AE_{SS} and AE_{RMS} were found in stavax material then in titanium material. ANN estimation model was build using 50%, 60% and 70% data in the training set. By considering 4 input parameters, 1 hidden layers and 9 hidden neurons were found to produce a regression coefficient 'R' closer to 1 and Mean Squared Error closer to zero. The best fit and better correlation with the measured values were found at 70% of data in the training set in ANN.

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