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Comparative study of Surface Roughness and AE Signals while Machining Titanium Grade 2 & Stavax Materials using MRA and GMDH in WEDM

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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 cutting parameters for obtaining higher cutting efficiency or accuracy in WEDM is still not fully solved, even with most up-to-date CNC WEDM machine. It is widely recognised 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 estimation of surface roughness and AE parameters viz., signal strength, absolute energy in the WEDM while machining titanium and stavax (modified aisi 420) steel materials. Among different process parameters voltage and flush rate were kept constant. Parameters such as pulse-on time, pulse-off time, current and bed speed was varied. Molybdenum wire having diameter of 0.18 mm was used as an electrode. Simple functional relationships between the parameters were plotted to arrive at possible information on surface roughness and AE signals. But these simpler methods of analysis did not provide any information about the status of the work material. Thus, there is a requirement for more sophisticated methods that are capable of integrating information from the multiple sensors. Hence, methods like Multiple Regression Analysis (MRA) and Group Method of Data Handling (GMDH) have been applied for the estimation of surface roughness, AE signal strength and AE absolute energy. Different models of GMDH was obtained by varying the percentage of data in the training set and the best model can be selected from these, viz., 50%, 62.5% and 75%. From the results it was observed that, AE parameters and estimated surface roughness values were correlates well with GMDH when compare to MRA

Keywords: *AE, Surface roughness, MRA, GMDH*

1. 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.

In the past, researchers have investigated the workpiece productivity & integrity when WEDM Udimet 720 nickel based super alloy and Ti-6Al-2Sn-4Zr-6Mo titanium alloy, using Cu core coated wires (ZnCu50 and Zn rich brass). Surfaces measuring ~ 0.6μm Ra, with near neutral residual stresses and almost zero recast were produced following two trim passes. Cross-sectional micrographs of specimens following rough machining (~180mm2/min) showed the recast to be < 7µm thick (up to 11µm for uncoated wire), with comparable results for both alloys (1). The effects of heat treatments on the surface machined by WEDM; four different machining methods are considered. In general, heat treatments after WEDM improve the quality in terms of microstructures and surface roughness. It can be concluded that the quality of a press die prepared by the high temperature heat treatment after WEDM could be as good as that by traditional manufacturing processes of the method. Cemented carbide, which is about two times harder than high-speed steel, exhibits superior wear- and heat resistance properties (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).

The effect of parameters like gap voltage, pulse on time, pulse off time, wire feed and percentage reinforcement on the response Material Removal Rate (MRR) as well as on surface roughness while machining aluminium alloy (Al413)/flyash/ boran carbide hybrid composites using WEDM. They have used Taguchi's L_{27} orthogonal array for experimental work. ANOVA has been used to determine the design parameters significantly influencing the response. They have reported that the gap voltage is the most influential parameter which significantly affects the MRR. Gap voltage and wire feed are the most influential parameter which significantly affects the surface roughness (4). The influences of peak current, pulse duration and the movement speed of wire electrode in machining Si3N4 material in WEDM. The simulation for temperature field tells that, with the boiling removal form hypothesis, the material removal volume during single discharge is increasing with the increment of peak current and pulse duration but decreasing with the raising of wire electrode movement speed. Meanwhile, in the simulation of thermal stress, the material removal form for Si3N4 is mainly to be boiling when peak current less than 20A (Ton=5µs V=8m/s). When peak current is beyond 20A, the effect of thermal stress is increased gradually (5). 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 (6).

The mechanism of material removal in EDM which was investigated by AE technique. Twice burst AE wave was detected by optical fiber sensor during single pulse discharge As the results, it was found that burst AE wave was detected in air and in oil without gap region medium. In the case of electrical discharge in air, the burst AE wave was detected only once. On the other hand, in the case of electrical discharge in oil, the burst AE waves were detected several times. Moreover, single pulse discharge was occurred near aluminium plate without direct electrical discharge on the plate. There were several burst AE wave as same as cathode was aluminium plate. It was considered that the reason of occurrence several times burst AE wave was cavitations behaviour (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). Comparison of electrode wear estimation in WEDM using MRA and GMDH for EN-8 and EN-19 material were studied based on Taguchi's L'_{16} array. Three different criterion functions of GMDH viz., regularity, unbiased and combined have been tried for electrode wear estimation. Different models of GMDH by built by varying the number of data in training set to 50%, 62.5% and 75% of the total data. They have found that the least error of estimation and best fit were found for 62.5% of data in training set for EN-8 material and 62.5% and 75% of data in training set for EN-19 material. Comparison of two theoretical methods for estimation of electrode wear, they have found that regularity criteria function of GMDH has an edge over MRA method (9).

2. 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. The design of the experiment is as shown in table 1.

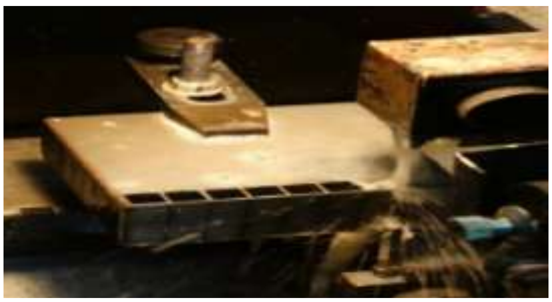

Fig. 1. Experimental Set-up during machining

Table 1: Design of Experiment

Run	Pulse On	Pulse Off	Current	BedSpeed
1	16	4	3	20
2	16	6	4	25
3	16	8	5	30
4	16	10	6	35
5	20	4	4	30
6	20	6	3	35
7	20	8	6	20
8	20	10	5	25
9	24	4	5	35
10	24	6	6	30
11	24	8	3	25
12	24	10	4	20
13	28	4	6	25
14	28	6	5	20
15	28	8	4	35
16	28	10	3	30

3. Results and Discussions

3.1 Multiple Regression Analysis (MRA)

The objective of MRA is to construct a model that explains as much as possible, the variability in a dependent variable, using several independent variables. The model fit is usually a linear model, though some timer nonlinear models such as log-linear models are also constructed. When the model constructed is a linear model, the population regression equation is

$$Y_i = \alpha + ß_1 X_{1i} + \ldots\ldots\ldots\ldots\ldots + ß_m X_{mi} + e_i \tag{1}$$

Where Y_i is the dependent variable and X_{1i} ……… X_{mi} are the independent variables for i^{th} data point and e_i is the error term. Error term is assumed to have zero mean. The co-efficients α, $ß_1$,………$ß_m$ are not known and estimates of these values, designated as a, b_1…….b_m have to be determined from the sampled data. For this least squares estimation is used, which consists of minimizing with respect to each of the co-efficients a, b_1…..b_m.

$$SS = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (Y_i - a - b_i X_{1i} \ldots\ldots - b_m X_{mi})^2 \tag{2}$$

This will give k+1 equations from which a, b_1…..b_m, can be obtained. These least squared estimates are the best linear unbiased estimates and hence give the best linear unbiased estimate of the dependent variable.

$$Y = a + b_1 X_1 + b_2 X_2 + \ldots\ldots\ldots\ldots + b_m X_m \tag{3}$$

3.2 Group Method of Data Handling Technique (GMDH)

One of the widely used methods for empirical analysis of data and model building is the multiple regressions. One of the major problems associated with use of regression has been the need to specify functional formulation. It would be preferable in such cases to use the data to determine both the nature of function and parameters of the function. This is the motivation for the development of self-organizing methods in modeling, GMDH is one such method. Data with the largest variance is put in the training set. The variance for ith data point is given by

$$D_i^2 = \sum_{i=1}^{m} \left(X_{ij} - X_j\right)^2 / \sigma_j^2 \qquad (4)$$

Where, D_i = measure of variance for ith data point, σ_j = variance for jth input variable, X_j = mean for jth variable and

$$\sigma_j^2 = (1/n) \sum_{i=1}^{n} \left(X_{ij} - X_j\right)^2 \qquad (5)$$

Initially, an attempt was made to obtain a clear insight involved in the process by plotting measured surface roughness, AE signal strength, AE absolute energy and AE RMS values against machining time.

3.3 Effect of minimum and maximum pulse on time on signal strength, absolute energy and surface roughness

Fig. 2 shows the surface roughness (Ra) curves for minimum pulse on of 16 µs with the varying in other process parameters for titanium material. From the Fig. 2, it can also be observed that at higher process parameters, the Ra value increases drastically.

Fig. 3 shows the roughness curves for maximum pulse on of 16 µs with varying in other process parameters for stavax material. From the Fig.3 it can also be observed that at moderate and higher process parameters, the Ra value increases drastically with the machining time.

Fig. 4 shows the absolute energy curves with machining time for maximum pulse on of 28 µs with varying other process parameters for titanium material. The plot reveals as the pulse on increases the need of absolute energy for machining is less.

Fig. 5 shows the signal strength curves with machining time for maximum pulse on of 28 µs with varying other process parameters for stavax material. From the Fig. 5 it can also be observed that at maximum pulse on and at lower process parameters the need of absolute energy for machining is more.

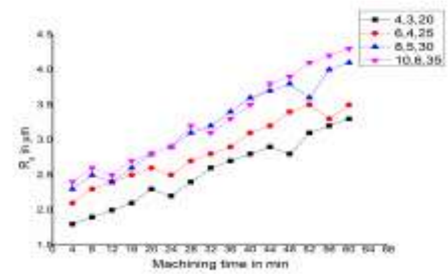

Fig. 2. Measured surface roughness for different machining time at minimum Pulse on of 16µs for titanium material

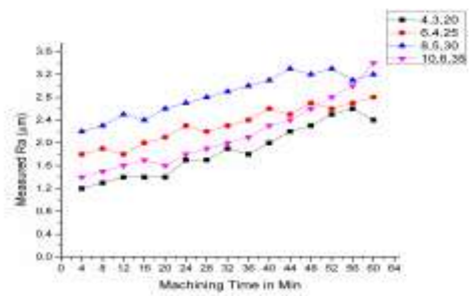

Fig.3. Measured surface roughness for different machining time at minimum Pulse on of 16µs for stavax material

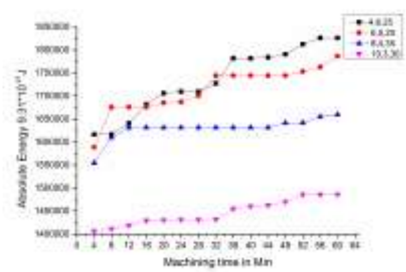

Fig. 4. Measured absolute energy for different machining time at maximum Pulse on of 28µs for titanium material

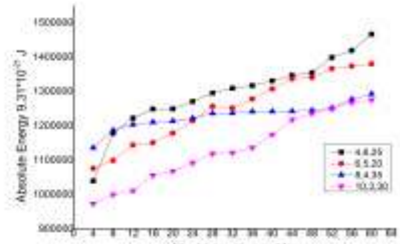

Fig. 5. Measured Absolute energy for different machining time at maximum Pulse on of 28µs for stavax material

3.4 Effect of minimum and maximum current on signal strength, absolute energy and surface roughness

Fig. 6 shows the signal strength curves with machining time for minimum current of 3 amps for titanium material. The plot reveals that during the machining, signal strength had higher gradient was found in moderate and higher process parameters. Fig. 7 shows the signal strength curves with machining time for minimum current of 3 amps for stavax material. The plot reveals that during the machining, the signal strength has little higher gradient with lower process parameters.

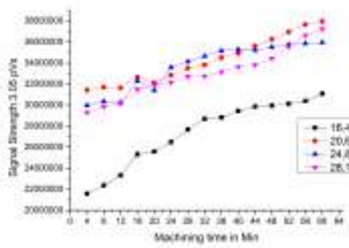

Fig. 6. Measured Signal strength for different machining time at a constant current 3 amps for Titanium material

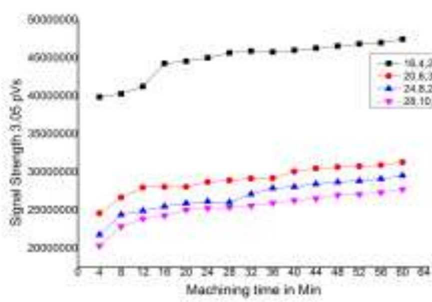

Fig. 7. Measured Signal strength for different machining time at a constant current 3 amps for Stavax material

3.5 Surface roughness, Signal strength and absolute energy estimation by MRA

MRA method is used for the estimation of Surface roughness and AE parameters like signal strength and absolute energy. Both maximum and minimum cutting conditions were estimated. Pulse on time, pulse off time, current, bed speed and machining time were considered as the independent variables to estimate surface roughness and AE parameters like signal strength and absolute energy. The variations of the measured and estimated values with time have been presented in the form of graphs for further discussion and comparison.

Fig.8 & 9 shows multiple regression estimates of Surface roughness for both titanium and stavax material respectively, at various pulse off time (4 µs,6 µs,8 µs,10 µs), current (3 amps,4 amps,5 amps,6 amps), bed-speed (20 µm/s,25 µm/s,30 µm/s,35 µm/s) at constant pulse on time 28 µs. From the Fig. 8, it is observed that the measured value at lower and higher process parameters correlates well with the estimated value. From the Fig. 9, it is observed that the measured value correlates well with the estimated value at all the process parameters.

Fig. 10 and Fig. 11 shows multiple regression estimates of absolute energy for both titanium and stavax material at various pulse on time (16µs, 20µs, 24µs, 28µs), pulse off time (10µs,8µs,6µs,4µs), bed-speed (35µm/s, 20µm/s, 30µm/s, 25µm/s) at constant current of 3 amps respectively. From Fig. 10 it is observed that the measured absolute energy correlates well with estimated values at lower and moderate process parameters for titanium material & from Fig 11for stavax material it is observed that the measured absolute energy correlates well with estimated values in all process parameters.

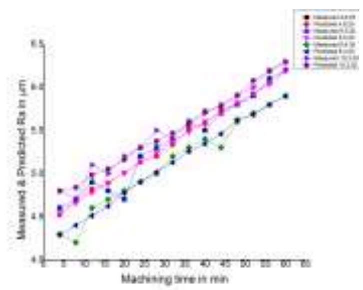

Fig. 8. Regression analysis estimates of surface roughness for various machining time for Maximum pulse on 28 µs for Titanium material

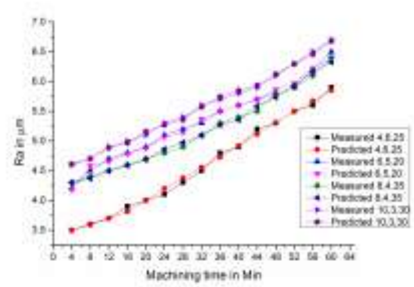

Fig. 9. Regression analysis estimates of surface roughness for various machining time for Maximum pulse on 28 µs for Stavax material

Fig. 12 and Fig. 13 shows multiple regression estimates of signal strength for both titanium and stavax material at various pulse on time (16µs, 20µs, 24µs, 28µs), pulse off time (10µs,8µs,6µs,4µs), bed-speed (35μm/s, 20μm/s, 30μm/s, 25μm/s) at constant current of 6 amps respectively. From the plots it can be observed that that signal strength at lower & moderate process parameters correlates with the estimated value for titanium material & for stavax material at lower and moderate process parameters correlates well with the estimated value.

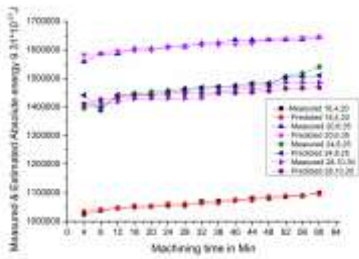

Fig. 10. Regression analysis estimates of Absolute energy for various machining time for maximum current 3 amps for titanium material

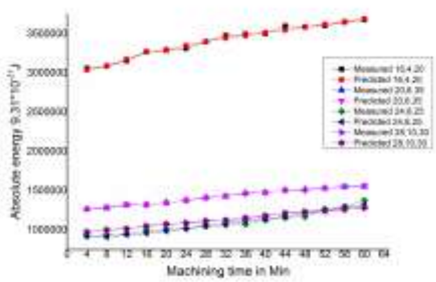

Fig. 11. Regression analysis estimates of absolute energy for various machining time for minimum current 3 amps for Stavax material

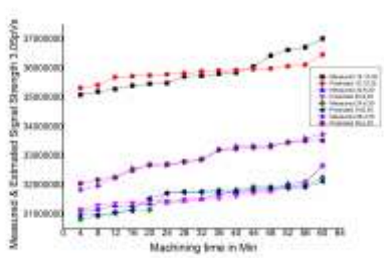

Fig. 12. Regression analysis estimates of signal strength for various machining time for maximum current 6 amps for Titanium material

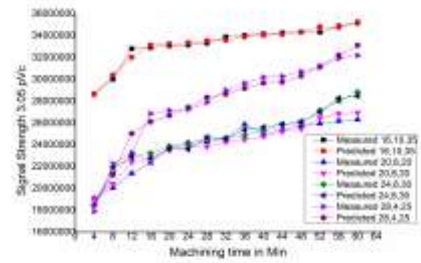

Fig. 13. Regression analysis estimates of signal strength for various machining time for maximum current 6 amps for stavax material

3.6 Surface roughness, Signal strength, RMS and Absolute energy estimation by GMDH

GMDH was also tried out for the estimation of surface roughness, signal strength and absolute energy for various process parameters based on the data obtained from the machining trials on stavax material. The independent variables were used as the input to the GMDH algorithm, which estimated surface roughness, signal strength, RMS and absolute energy (output) as a polynomial function of the supplied input. In designing the GMDH model, it is necessary to determine the number of input nodes and the level at which the output is estimated or the number of layers in between the input and output layer. In the present study, the number of data in the training set was considered to be at least 50% of total experimental data and it was varied in steps of 12.5% up to 75%. Hence, 50%, 62.5% and 75% of experimental data was considered in the training set.

3.6.1Study of GMDH criterion

To identify the best criterion the estimation of surface roughness, signal strength and absolute energy from the three criteria were compared with the measured values by plotting them against machining time Fig. 14 & 15, shows GMDH estimates of surface roughness from three criteria for titanium & Stavax material, for 50% of data in training set for pulse on 16μs, pulse off 6 μs, current 4amps, & Bed speed 25μm/s and for pulse on time 16 μs, pulse off time 10 μs, current 6 amps, and bed speed 35μm/s respectively.

Referring to the graphs, it was observed that, the surface roughness and signal strength obtained by regularity criterion correlates well with the measured surface roughness. Estimates from unbiased and combined criterion gave poor results.

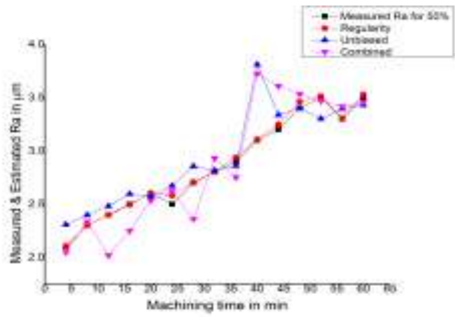

Fig. 14. GMDH estimates of surface roughness for 50% of data training set for titanium material

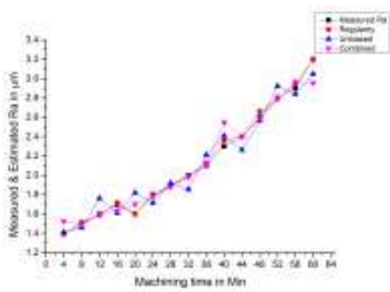

Fig. 15. GMDH estimates of Surface roughness for 50% of data in training set for stavax material

3.6.2Study of percentage of data in the training set

Results of GMDH were also studied to identify the best percentage of data in the training set to estimate the surface roughness, signal strength and absolute energy. Performance of GMDH for various percentages of data in the training set viz., 50%, 62.5% and 75% of data were studied. Fig. 16 & 17 shows the measured and GMDH estimates of absolute energy from regularity criterion, for various percentages of data in the training set Pulse on 24µs, Pulse off 4µs, Current 5amps, Bed speed 35µm/s and for Pulse on 28µs, Pulse off 8µs, Current 4amps, Bed speed 35µm/s for titanium & Stavax materials respectively. From these graphs, it was observed that, with the increase in the percentage of data in the training set, the estimation power of regularity criterion also increases and the best results were obtained at 75% training set.

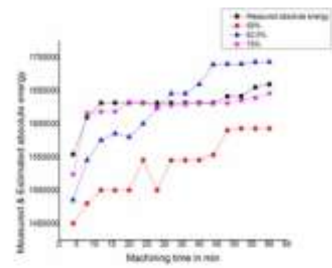

Fig. 16. GMDH estimates of Absolute Energy for various percentages of data in training set for titanium material

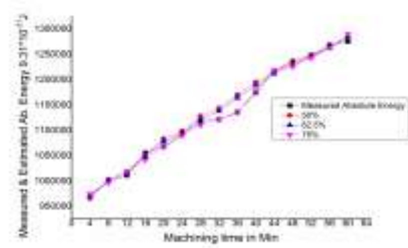

Fig. 17. GMDH estimates of Absolute energy for various percentages of data in training set for stavax material

3.7 Comparative study of MRA and GMDH

MRA and GMDH were used to estimate surface roughness, signal strength and absolute energy in WEDM based on the experimentally measured signals, machining time, and process parameters. In GMDH, regularity criterion with 75% of data in the training set gave better estimation than the other criteria and percentage of data. Based on the SE obtained the comparison of GMDH and MRA estimates for absolute energy at pulse on 28µs, pulse off 4µs, current 6amps and bed-speed 25µm/s for titanium material is as shown in Fig. 18. Fig. 19 shows the comparison of GMDH and MRA for absolute energy at pulse on time 28µs, pulse off time 10 µs, current 3amps and bed-speed 30µm/s Stavax material.

From the graphs it was observed that good estimation is obtained in both MRA and GMDH models. Among these, regularity criterion of GMDH gave better estimation than MRA. This is because; GMDH is a self-organizing method of modelling, which fits a high degree polynomial using a multilayered network like structure.

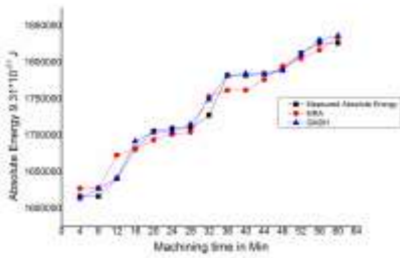

Fig. 18. Comparison of GMDH and multiple regression estimates of Absolute energy for titanium material

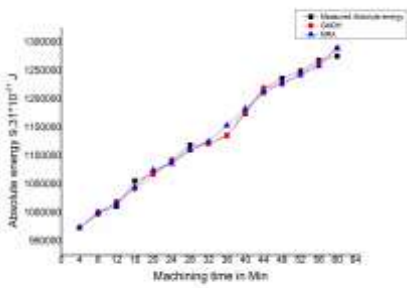

Fig. 19. Comparison of GMDH and multiple regression estimates of absolute energy for Stavax material

4. Conclusion

The present work involves machining of titanium grade 2 and stavax workpiece at various process parameters. During machining, different AE signal parameters viz., signal strength and absolute energy from the workpiece were acquired. Surface roughness was also measured after machining. The roughness plots have increased for maximum process parameters. Three different criterion functions of GMDH viz., regularity, unbaised and combined have been tried for surface roughness, signal strength and absolute energy estimation. The results from the present work show that the regularity criterion function provides good estimation than the other two functions. Different models of GMDH were built by varying the number of data in the training set to 50%, 62.5% and 75% of the total data. It was found that the least error of estimation and best fit was found at 75% of data in the training set. Measured surface roughness had a better correlation with the estimated one at lower process parameters. Measured signal strength correlates well with estimated one at moderate process parameters. Measured absolute energy correlates well with the estimated one at moderate process parameters for titanium material. Measured surface roughness had a better correlation with the estimated one at higher process parameters. Measured signal strength correlates well with estimated one at lower process parameters. Measured absolute energy correlates well with the estimated one at lower and higher process parameters for Stavax material. Comparison of the two theoretical methods for estimation of surface roughness, signal strength and absolute energy, it was found that regularity criterion function of GMDH had an edge over MRA method.

References

[1]Antar, Soo, Aspinwall, Jones and Perez, “Productivity and workpiece surface integrity when WEDM aerospace alloys using coated wires” Procedia Engineering Vol. 19, pp. 3 –8, (2011).

[2]Choia, Namb and Leec, “Effects of heat treatment on the surface of a die steel STD11 machined by W-EDM”, materials processing technology, Vol. 201 (Issue 1-3): pp.580–584, (2009).

[3]Tomura and Kunieda, “Analysis of electromagnetic force in wire-EDM”, Precision Engineering, Vol. 33, (Issue 3) pp. 255-262, (2009).

[4]Uday Prakash, Moorthy and Peter, “Experimental investigation on machinability of Aluminium Alloy (A413)/ Flyash/ B4C Hybird Composites using Wire EDM” Procedia Engineering, Vol. 64, pp.1344- 1353, (2013).

[5]Houa , Guoa , Suna and Deng, “Simulation of temperature and thermal stress filed during reciprocating traveling WEDM of insulating ceramics” Procedia CIRP Vol. 6 pp. 410 – 415, (2013).

[6]Cabanes, Portillo, Marcos and Sánchez,“An industrial application for on-line detection of instability and wire breakage in wire EDM”, materials processing technology, Vol. 195, (Issue 1-3): pp.101–109 (2008).

[7]Akematsu, Kageyama, Mohri and Murayama, “Effect of gap region medium on acoustic emission wave by single pulse discharge”,Optical Society of America ISBN code: 1-55752-817-9, (2006).

[8]Smith and Koshy, “Applications of acoustic mapping in electrical discharge machining", CIRP- Annals manufacturing technology, Vol. 62, (Issue 1) pp. 171-174, (2013).

[9]Ugrasen, Ravindra, Naveen Prakash and Vinay, “Comparative Study of Electrode Wear Estimation in Wire EDM using Multiple Regression Analysis

and Group Method Data Handling Technique for EN-8 and EN-19", International Journal of Industrial Engineering and Management Science, Vol. 4,(Issue 2), pp. 108-114, (2014).