

Estimation and Comparison of Electrode Wear and AE Parameters in Machining of P-20 Tool Steel Material in Wire Electric Discharge Machining using MRA and GMDH

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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 wire EDM 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. P-20 tool steel material was machined using the L_{16} standard orthogonal array. 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. Methods like Multiple Regression Analysis (MRA) and Group Method of Data Handling (GMDH) have been applied for the estimation of electrode wear, AE signal strength, AE absolute energy and AE RMS from the multiple sensors. Different models can be obtained by varying the percentage of data in the training set and the best model can be selected from these, viz., 50%, 62.5% & 75%. The best model is selected from the said percentages of data. Three different criterion functions, viz., Root Mean Square (Regularity) criterion, Unbiased criterion and Combined criterion were considered for the estimation. From the results it was observed that, acoustic emission parameters and estimated electrode wear values for P-20 tool steel material correlates well with GMDH for regularity criteria at 75% data set when compared to MRA.

Keywords: AE, Electrode wear, MRA, GMDH.

1. INTRODUCTION

Machining referred to as the traditional or non-traditional machining process. Since the advent of new technologies such as Electrical Discharge Machining (EDM), Electro Chemical Machining (ECM), Electron Beam Machining (EBM), photochemical machining, and Ultrasonic Machining (USM), the retronym "conventional machining" can be used to differentiate those classic technologies from the newer ones. In current usage, the term "machining" without qualification usually implies the traditional machining processes. Wire Electric Discharge machine (WEDM) is spark erosion non conventional machining method to cut hard and conductive material with a help of wire electrode [1]. A wire EDM generates spark discharges between a small wire electrode and a work piece with de-ionized water as the dielectric medium and erodes the work piece to produce complex two and three dimensional shapes according to a numerically controlled path. One of the main challenges in WEDM is avoiding wire breakage and unstable situation as both phenomena reduces process performance and causes low quality performance [2]. The main goals of WEDM manufacturers and users are to achieve a better stability and higher productivity of the process. As newer and more exotic materials are developed, and, more complex shapes are presented, conventional machining operations will continue to reach their limitations. As these processes are material dependent, selection of electrode, optimization of surface finish metal removal rate (MRR) and electrode wear ratio (EWR) are remained the main concern [3]. WEDM manufacturers and users emphasize on achievement of higher machining productivity with a desired accuracy and

surface finish. Selection of optimal value of process parameters, such as pulse duration, pulse frequency, duty factor, peak current, dielectric flow rate, wire speed, wire tension, effective wire offset of WEDM is an important characteristic [4]. One of the main research fields in WEDM is related to the improvement of the process productivity by avoiding wire breakage. The mechanism of the electromagnetic force applied to the wire electrode in WEDM is important concern. The electromagnetic force is not only produced by DC components but also by AC components of the discharge current supplied in the wire [5]. The discharge current is influenced by the impedance of the wire and workpiece material which may vary depending on the diameter of the wire, height of the workpiece and materials of wire and workpiece even if the pulse condition are the same [6]. Tool wear is continuously evaluated during machining, and the actual wear compensation is adapted on the basis of this real-time wear evaluation. Simulations and experiments show the potential of the new method [7]. Different factors can lead to wire breakage such as a decrease in flushing pressure, inefficient removal of erosion debris, as well as other types of stochastic phenomena that appear during the machining process. In such a case, the catastrophic failure may occurs which will results in the failure of the workpiece.

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

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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. Molybdenum wire having diameter of 0.18 mm was used as an electrode.



Fig. 1. Experimental Set-up during machining

3. THEORETICAL ANALYSIS

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

$$Y_i = \alpha + \beta_1 X_{i1} + \dots + \beta_m X_{mi} + e_i \quad (1)$$

Where Y_i is the dependent variable and $X_{i1} \dots X_{mi}$ 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 $\alpha, \beta_1, \dots, \beta_m$ are not known and estimates of these values, designated as a, b_1, \dots, 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, \dots, b_m .

$$SS = \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (Y_i - a - b_1 X_{i1} - \dots - b_m X_{mi})^2 \quad (2)$$

This will give $k+1$ equations from which a, b_1, \dots, 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.

$$Y = a + b_1 X_1 + b_2 X_2 + \dots + b_m X_m \quad (3)$$

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 i^{th} data point is given by

$$D_i^2 = \sum_{j=1}^m (X_{ij} - X_j)^2 / \sigma_j^2 \quad (4)$$

Where, D_i = measure of variance for i^{th} data point, σ_j = variance for j^{th} input variable, X_j = mean for j^{th} variable and

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

4. RESULT AND DISCUSSION

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

4.1 Effect of minimum and maximum pulse on time on signal strength, absolute energy, RMS and electrode wear

Fig. 2 shows the absolute energy curves for maximum pulse on of 28 μ s with varying in other process parameters. From the Fig. 2 it can also be observed that at maximum pulse on and at higher process parameters the need of absolute energy for machining is more. Fig. 3 shows the electrode wear curves for minimum pulse on of 16 μ s with varying in other process parameters. From the Fig. 3 it can be observed that the value of electrode wear value for P-20 tool steel material has increased linearly with machining time in all the process parameters.

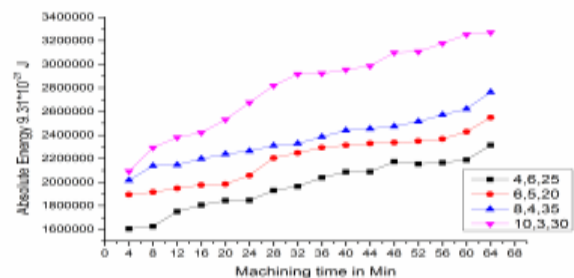


Fig. 2. Measured Absolute energy for different machining time at maximum Pulse on of 28 μ s for P-20 tool steel Material

4.2 Effect of minimum and maximum current on signal strength, absolute energy, RMS and electrode wear

Fig. 4 shows the RMS curves for minimum current of 3 amps with varying in other process parameters. From the Fig. 4 it can be observed that that during the machining, the RMS has little higher gradient with lower process parameters. Fig. 5 shows the signal strength curves with machining time for maximum current of 6 amps. The plot reveals that during the machining, the signal strength has higher gradient with lower process parameters.

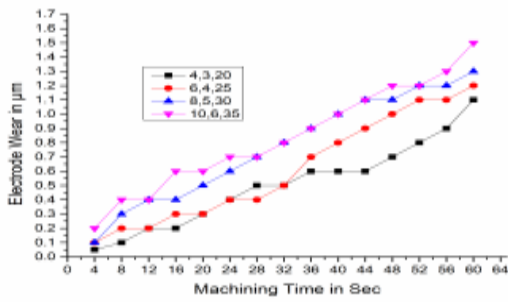


Fig. 3. Measured Electrode Wear for different machining time at minimum Pulse on of 16 μ s for P-20 tool steel Material

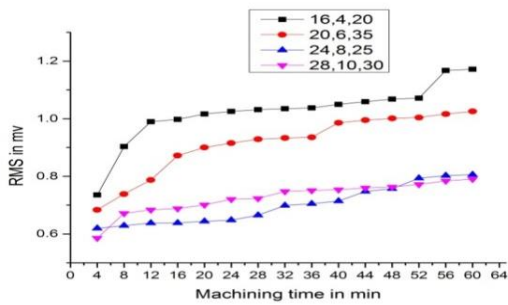


Fig 4 : Measured RMS value for different machining time at minimum current of 3 amps for P-20 Tool Steel material

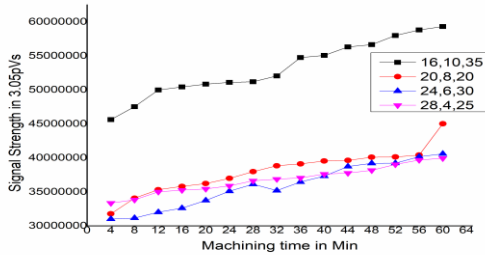


Fig 5 : Measured signal strength value for different machining time at maximum current of 6 amps for P-20 Tool Steel material

4.3 Estimation of electrode wear, signal strength, RMS and absolute energy by MRA

MRA method is used for the estimation of electrode wear and AE signals in the form of graphs to both minimum and maximum condition of pulse on time and current for further discussion and comparison.

Fig.6 shows multiple regression estimates of RMS for various pulse on time (16 μ s,20 μ s,24 μ s,28 μ s),pulse off time(4 μ s, 6 μ s, 8 μ s, 10 μ s), bed-speed (20 μ m/s,35 μ m/s, 25 μ m/s, 30 μ m/s) at constant current 3 amps. From the figure, it is observed that the measured RMS value at lower and moderate process parameters correlates well with the estimated value.

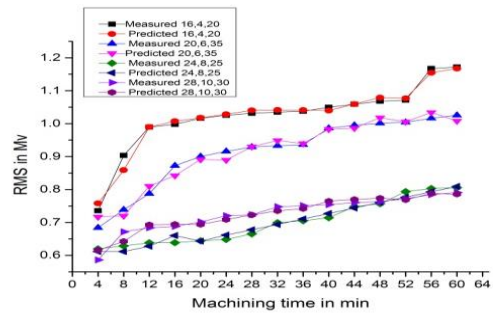


Fig 6: Regression analysis estimates of RMS for various machining time for minimum current of 3 amps

4.4 Electrode wear, Signal strength, RMS and Absolute energy estimation by GMDH

GMDH was also tried out for the estimation of electrode wear, signal strength, RMS and absolute energy for various process parameters based on the data obtained from the machining trials on P-20 tool steel material. The independent variables were used as the input to the GMDH algorithm, which estimated electrode wear, 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, first the GMDH criterion such as regularity, unbiased and combined were studied for the analysis and 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.

4.4.1 Study of GMDH criterion

Fig. 7 shows GMDH estimation of signal strength for P-20 tool steel material from three criteria, for 62.5% of data in training set for pulse on time 20 μ s, pulse off time 6 μ s, current 3 amps, & Bed speed 35 μ m/s. Referring to the graph, it was observed that the Signal strength obtained by regularity criterion correlates well with the measured signal strength. Estimates from unbiased and combined criterion gave poor results.

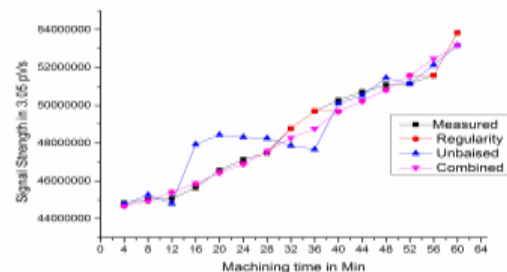


Fig 7: GMDH criterion estimates of signal strength for P-20 tool steel at 62.5% of data in training set

4.4.1 Study of percentage of data in training set

Results of GMDH were also studied to identify the best percentage of data in the training set to estimate the electrode wear, signal strength, RMS 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. 8 shows the measured and GMDH estimates of electrode wear from regularity criterion, for various percentages of data in the training set of pulse on time 24 μ s, pulse off time 4 μ s, current 5amps, bed speed 35 μ m/s.

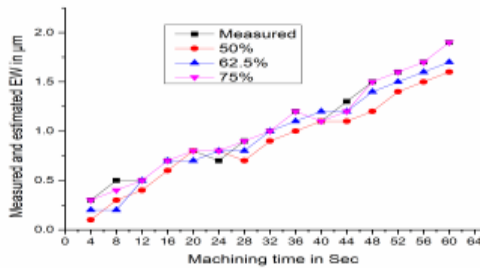


Fig 8: GMDH percentage of data in training set of electrode wear for P-20 tool steel in regularity criterion

From these graph, 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.

4.5 Comparative study of MRA and GMDH

MRA and GMDH were used to estimate electrode wear, signal strength, RMS 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 Multiple Regression for RMS at pulse on 28 μ s, pulse off 10 μ s, current 3amps and bed-speed 30 μ m/s. in fig 9. From the graphs it was observed that good estimation is obtained in both MRA and GMDH models. Among these, regularity criterion of GMDH at 75% of training set gave better estimation than MRA. This is because; GMDH is a self-organizing method of modeling, which fits a high degree polynomial using a multilayered network like structure.

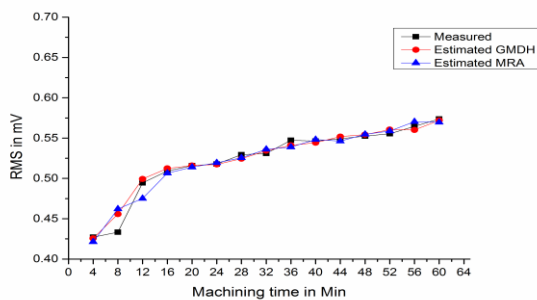


Fig 9: Comparison of GMDH and multiple regression estimates of RMS

5. CONCLUSION

The present work involves machining of P-20 tool steel workpiece at various process parameters. During machining, different AE signal parameters viz., signal strength, RMS and absolute energy from the workpiece were acquired. Electrode wear was also measured at regular intervals. Both experimental and theoretical approaches were used to estimate electrode wear, signal strength, RMS and absolute energy. Based on the experimental results, the following conclusions were drawn. The wear plots have increased for maximum process parameters. Signal level of AE parameters increased with the increase in machining time due to increase in load on the workpiece at higher process parameters. Measured electrode wear had a better correlation with the estimated one at lower and higher process parameters, Measured RMS correlates well with estimated one at with lower and moderate process parameters, Measured signal strength correlates well with estimated one at lower and moderate process parameters and Measured absolute energy correlates well with the estimated one at moderate and higher process parameters and comparison of the two theoretical methods for estimation of electrode wear, signal strength, RMS and absolute energy, it was found that regularity criterion function at 75% training set of GMDH had an edge over MRA method.

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