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Prediction of Material Removal in Single Spark Micro-EDM Using Multiple Linear Regression and CART

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Abstract

Prediction of material removal in any machining process is usually based on the input machining parameters. However, apart from controllable parameters, there are various other parameters that needs to be monitored in real time to ensure better prediction of accuracy, especially in random processes. Hence, real time data monitoring using appropriate sensors in machining processes is extremely important as the input parameters cannot predict the output with high efficiency. In Micro EDM (MEDM), real time signal monitoring can yield various time domain features of individual current and voltage pulses that can help to enhance the prediction accuracy of material removal. In this study, an attempt has been made to predict the material removal in single spark MEDM based on two different modelling approaches i.e. multiple linear regression (MLR) and classification and regression tree (CART). A total number of 21 experiments were conducted on a specially designed single spark MEDM machine with input parameters viz. voltage and capacitance. Material removal measurements was carried out using Coherent Correlation Interferometer. Open source software "R-3.4.0" was used for building and prediction of the model. A total of 14 predictors (2-input and 12-time domain extracted predictors) and a single output i.e. material removal was used for prediction. Prediction model by multiple linear regression (MLR) showed root mean square error of 5.82 whereas that by CART showed 12.07. Hence, material removal in single spark MEDM can be predicted by MLR with better accuracy as compared to CART.

Keywords: Single spark micro EDM, multiple linear regression, Classification and regression tree (CART), signal monitoring, material removal

1. INTRODUCTION

Miniaturization of devices in the size range of micro to nano has led to rapid advancement in the fields of semiconductor, tribology, biomedical, microfluidics etc. Micro manufacturing deals with fabrication of devices in the micro domain. Micro manufacturing processes can be subdivided into subtractive, additive, mass containing and joining processes [1]. Most of the micro devices are extensively fabricated by subtractive processes viz. ultrasonic micromachining (USMM), laser beam micro machining, micro abrasive waterjet machining, micro electro discharge machining (MEDM), electrochemical micromachining (ECMM) etc. Of all the processes, MEDM is one of the most widely used process due to its ability to machine any conductive material irrespective of its hardness, machining of 3D structures, fabrication of micro tools for processes like USMM, ECMM and has the capability to machine high aspect ratio single or arrayed holes as well as pillars for various applications. Material removal in MEDM takes place by melting and/or vaporization depending on the spark energy. Wong et al found that at low spark energy, the efficiency of material removal is high with consistent size of micro craters [2]. With increase in spark energy, melting dominates and molten material re-solidifies and re-attaches on the parent material thereby decreasing the material removal. Hence, prediction of material removal in MEDM is very difficult due to transient behaviour of material removal from melting and vaporization at low energies to mostly melting at higher energies. Since, spark energies are calculated based on constant input parameters (voltage and capacitance) in RC circuit, real time signal monitoring of current and voltage can yield various time domain features of individual current and voltage pulses that can help to enhance the prediction accuracy of material removal that was otherwise calculated based on constant input energy only.

Predictive modeling is a process that use data mining techniques for prediction of response based on some or all predictors in the dataset. Data mining techniques can be divided into four stages [3] as shown in Fig. 1. The initial stage is the collection of large volume of data required for predicting the relationship between response and the predictors. This data is then transformed to obtain various time domain, frequency domain and/or time-frequency domain extracted features that are considered as predictors for building model. The third stage is creating a model based on a sample from the dataset (training data). The model is then used for prediction of response on the remaining sample (testing data). The final stage involves taking actions based on results of model. Different data mining techniques extensively used for prediction are multiple linear regression (MLR), classification and regression tree (CART), bagging, boosting, random forest, support vector regression etc. Though most of these techniques provide satisfactory results in case of large datasets, MLR and CART are capable of handling smaller data sets [4] as compared to other data mining

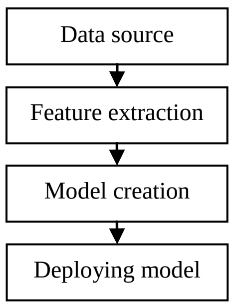

Fig. 1. Stages of data mining

techniques. Hence, an attempt has been made to predict material removal in single spark MEDM using MLR and CART and

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compare the results obtained from these two modeling techniques.

2. EXPERIMENTAL DETAILS

Experiments were carried out on a specially designed single spark MEDM machine (Fig. 2). A total of 21 experiments were conducted at different input parameters viz. voltage (75V, 90V, 100V, 120V, 125V, 140V, 150V) and capacitance (33pF, 100pF, 1000pF). Table 1 shows the materials for electrodes and parameters that were kept constant during experiments.

Fig. 2. Single spark MEDM

2.1. Real Time Data Acquisition

Real time signal monitoring of voltage and current pulses were captured using Tektronix DPO 3014 oscilloscope (100 MHz, 2.5 GSPS, 5 Mega point record length, 3.5 ns). Based on acquired signals, a MATLAB code was written to determine time domain extracted features from the dataset. The time domain extracted features for voltage are V_{max}, V_{mean}, V_{max}-V_{min}, V_{std}, V_{skew} and V_{kurt} whereas for current, the time domain extracted features are I_{max}, I_{mean}, I_{max}-I_{min}, I_{std}, I_{skew} and I_{kurt}. Therefore, for prediction of material removal, 14 predictors (2-input and 12-time domain extracted predictors) were used.

Table 1: Materials and parameters used

Material:			
Cathode (Rod)	Tungsten (Diameter = 50 µm)		
Anode (Plate)	Brass		
Parameters:	Values	Parameters	Values
Discharge pulses	RC circuit	Sensitivity	30%
Return time	100 µsec	Hold time	100 µsec
Electrode feed rate	1 µm/sec		

2.2. Measurement Procedure

Material removal during single spark was measured using Talysurf Coherent Correlation Interferometer (CCI) Lite. Fig. 3 shows the formation of micro crater due to material removal in single spark.

3. PREDICTION OF MATERIAL REMOVAL

3.1. Multiple Linear Regression (MLR)

Multiple linear regression is useful in predicting a response based on multiple predictors. It is an extension of a simple linear regression model with a single response and single predictor. MLR takes the form as shown in Eq. 1 where X_j represents the j^{th} predictor, β_j signifies the relation between the j^{th} predictor and the response (regression co-efficients) and Y is the response.

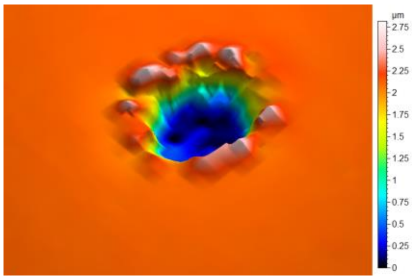

Fig. 3. Micro crater formation during single spark in MEDM

The procedure for calculating the regression co-efficients and finding out R^2, R^2_{adj} and residual standard error (RSE) is described elsewhere [5].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \quad \text{……………………………. (1)}$$

3.2. Classification and Regression Tree (CART)

CART is one of the most popular data mining techniques employed in engineering problems in which dependent variable can be either qualitative or quantitative. Since, dependent variable is quantitative in our case, regression tree (RT) algorithm is used which works on a binary-dividing procedure that splits the dataset from a root node further down to create sub nodes based on different yes/no questions of the independent variables [6]. The end result is a decision tree that results in optimum split with high purity (Fig. 4). The procedure for building an RT model is described by James et al [5].

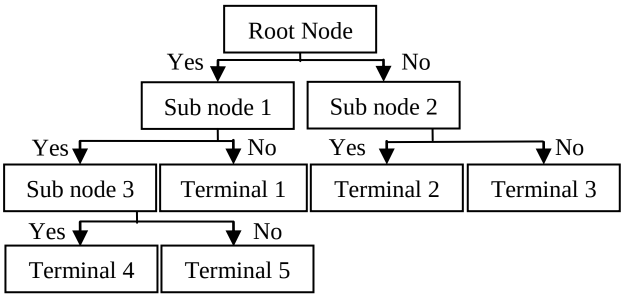

Fig. 4. Decision tree in RT modeling

3.3. Model selection criteria

The square root of mean squared error (RMSE) was used as a performance measure for comparing MLR and CART models. RMSE is defined as

$$RMSE = \sqrt{mean\,(PV - OV)^2} \quad \text{……………….. (2)}$$

where PV is the predicted value and OV is the observed value (response).

4. RESULTS AND DISCUSSION

R statistical package (Version 3.4.0) was used for prediction of material removal in single spark for both the cases. The dataset was divided into two parts. Out of a total of 21 data obtained from experiments, 15 were used for training the model and rest 6 were used for prediction. The results obtained from open source software and comparison of both models is described below.

4.1. Prediction by MLR

A number of iterations were carried out to determine the highly significant predictors among all. Table 3 shows the significant predictors responsible for controlling the response along with their respective regression co-efficients, *p*-values, R^2, R^2_{adj}, RSE and degrees of freedom (DOF). Two significant factors viz. V^2_{skew} and voltage were found to be contributing to material removal along with three interaction terms viz. voltage with V_{mean}, I_{skew} and I_{kurt} respectively.

Table 2: MLR output

Co-efficients	Predictors	p-value	
β_0	Intercept	0.001597	R^2:0.9188
β_1	V^2_{skew}	0.0000765	R^2_{adj}: 0.8736
β_2	Voltage	0.000518	RSE: 5.753
β_3	Voltage : V_{mean}	0.003969	DOF:9
β_4	Voltage : I_{skew}	0.023883	
β_5	Voltage : I_{kurt}	0.082461	

4.2. Prediction by CART

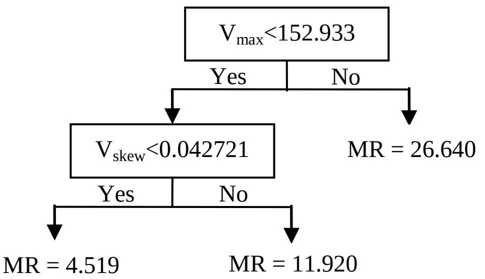

Fig. 5(a). Material removal prediction by CART (unpruned tree)

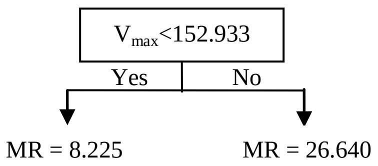

Fig. 5(b). Material removal prediction by CART (pruned tree)

Regression tree resulted in prediction of material removal to be dependent on maximum voltage and skewness of voltage (Fig. 5(a)). It is interesting to note that both these significant factors are not input parameters from experiments but are derived from signals obtained during machining. Skewness of voltage was found to be significant in both the models. Tree pruning (Fig. 5(b)) was done to investigate the effect of reducing the number of branches. Pruned tree showed maximum voltage to be the only significant factor responsible for material removal.

4.3. Significant parameters for prediction

Based on prediction results obtained from MLR and CART, it has been found that V_{skew} is one of the parameters obtained from signal analysis that is significant in material removal prediction for both cases. Fig. 6 shows a pie-chart depicting the percentage of material removed at every value of skewed voltage. It can clearly be seen that at high skewness of voltage (1.37), the contribution of material removal is highest (22.72%). Subsequently, for the lowest value of skewed voltage (0.03), the contribution of material removal is low (0.29%). This indicates that deviation of voltage profile from symmetry leads to higher material removal as compared to symmetric profile. Considering predictors based on real time data acquisition, it throws light on the fact that during actual machining in MEDM, dependence of material removal is not only on the input constant parameters of machine but also depends on various others factors that can only be found out in real time monitoring of signals.

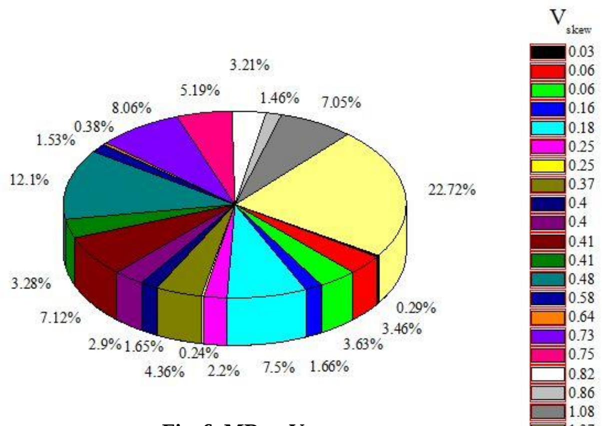

Fig. 6. MR vs V_{skew}

4.4. Comparison between MLR and CART

RMSE for MLR was found out for initial iteration when all predictors were considered as well as during final iteration. Similarly, RMSE for CART was also found out for unpruned and pruned tree. Fig. 7 shows the comparison for both the models based on RMSE. It was found that RMSE for MLR was the least for final iteration as compared to other iterations. Moreover, pruning of tree in CART didn't significantly decrease RMSE indicating that prediction by unpruned tree doesn't significantly vary by pruning. Prediction accuracy of CART is less as compared to MLR indicating that a linear model is better for material removal prediction in single spark MEDM.

5. CONCLUSIONS

An experimental study was conducted to predict material removal in single spark MEDM based on input parameters as well as features extracted from voltage and current signals. The following conclusions can be derived from this study.

- Time domain extracted features from real time data monitoring of signals provided a total of 12 predictors of which skewness of voltage (V_{skew}) was found to be significant parameters in determination of material removal in both models (MLR and CART). Apart from that, maximum voltage (V_{max}) was also found to another significant in CART. Hence, material removal not only depends on constant input parameters but it also depends on features extracted from real time signal monitoring data.

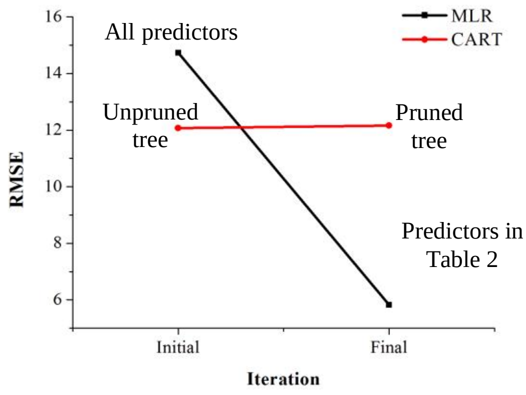

Fig. 7. Model comparison based on RMSE

- Higher V_{skew} contributed to high material removal. The more voltage profile deviates from symmetry (high skewness), more is the amount of material removal.
- Multiple linear regression (MLR) indicated two significant factors that led to material removal. One of these factors (V_{skew}) was derived from signal data and other significant factor was input voltage.
- Pruning of tree in CART didn't significantly change root mean square error (RMSE) as compared to unpruned tree.
- Prediction of material removal by MLR showed less RMSE as compared to CART indicating a linear trend between material removal and the predictors.

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Abbreviations			
V	Input voltage	**C**	Input capacitance
$\mathbf{V_{max}}$	Maximum voltage	I_{max}	Maximum current
$\mathbf{V_{mean}}$	Mean of voltage	I_{mean}	Mean of current
$\mathbf{V_{max}}$-$\mathbf{V_{min}}$	Voltage range	I_{max}-I_{min}	Current range
$\mathbf{V_{std}}$	Standard deviation of voltage	I_{std}	Standard deviation of current
$\mathbf{V_{skew}}$	Skewness of voltage	I_{skew}	Skewness of current
$\mathbf{V_{kurt}}$	Kurtosis of voltage	I_{kurt}	Kurtosis of current
MR	Material removal		