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An Experimental Investigation on EDM Machines with Advanced Machine Learning to Predict High MRR For Aerospace Application

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Abstract
Now EDM (Electrical Discharge Machining) are playing a vital role in industries to produce very precise and complex profiles in the harden materials. They are used in aerospace, medical, die and mould making industries to where the intricate geometrical output and high precision is required. In aerospace industries EDM machines are used to produce the turbine blades, sensor housing, engine sparts and high tolerance parts housing. Die-sinker EDM machines are used in the blind cavities in the dies and molds. Extremely high-harden materials are used, which is crucial for aerospace applications. This die – sinker EDM process ensure the high tolerance with minimal tolerance level. In this machine process the material stress level will be reduced to maintain the material integrity with tight tolerance. In this paper we study about the MRR (Material Removal Rate) in the die sinker EDM machine for the aerospace grade materials Ti-6Al-4V and Inconel 718 using copper electrode. There is a challenge in the die sinker machine to predict the MRR. Because it's a significant factor to make the production plan. Without estimated MRR value, industries cannot plan the production chart. Here the study is about the MRR prediction on the materials used in the aerospace industries for the making the rocket engines, turbine blades, satellites sensors and other aircraft related spare parts. Here the dataset trained by four different types of supervised learning algorithm to predict the MRR value. Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM) and XGBoost machine learning algorithms are used for the prediction by computing several machining parameters like current, ton, toff, duty cycle, flushing etc. In this paper shows the experimental prediction is reliable with the actual result but there is a deviation of 3% fall in the experimental result when compared to the actual result.
Keywords: *EDM, Tolerance, Machining parameters, ANN, SVM, RF.*

1. Introduction
EDM – In the recent years the employment of the EDM machines is tremendously increasing due to the precise cutting of a harden materials, very small hole machining in tough heat-resistant material and geometrical complex shapes which are used in aerospace application. In the entire machining process the part quality and machining time will be the main concern. Some of the factors like metallurgical property, fatigue nature of the material, stress level to be controlled to maintain the result quality level. Here the MRR can be affected by several phenomena like huge debris deposition in the machining area and tool wear. This can be eliminated by applying some revamped machining methodology and machining parameters instead of using the conservative factors. In this paper, MRR predication will be structured out of several cycles to choose the best prediction accuracy level of the model. EDM machines are a prominent non – conventional machines that are operated by thermoelectric discharge. A high frequency spark is applied between the electrode and workpiece. Here the electrode and the workpiece act like an anode and cathode but both submerged in a dielectric medium. This process

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produces a plasma channel due to the spontaneous bombardment of ions and electrons, and it's generated a high temperature between 8000°c to 12000◦c. There is no direct contact between the workpiece and the electrode so that high geometrical complex shapes can be achieved with high precision accuracy. In the Artificial Intelligence (AI) filed persistent to progress of application in the prediction of non – conventional machine performance with gained prominence. ANN model can be able to model complex nonlinear relationships between the variables with the minimal statistical training model data. It can uncover the intricate interlinkage between the actual and prediction values and deliver multiple process training algorithm for the different optimization of the machining parameters. In general, maintaining the quality parameters is quite difficult because of the stochastic nature of the die sinker EDM machine. This paper shows the enhancement of MRR by the higher current, Ton and peak voltage. Also, the Toff gives its less contribution in the MRR enhancement of EDM process because the Toff is inversely proportional to the MRR. Anyways the debris should be removed recurrently by applying an adequate amount of the flushing. Deposition of debris will impact the MRR performance factor and the quality parameters of the output. The changes in the current values contributed to the higher MRR significantly, but the Toff changes have a very less drastic change in the MRR [1].

2. Experimental Setup

Conservative pulse is used in EDM. Figure 1. Shows the theoretical how the pulse current flow over the electrode and visualize the spark function during the machining process.

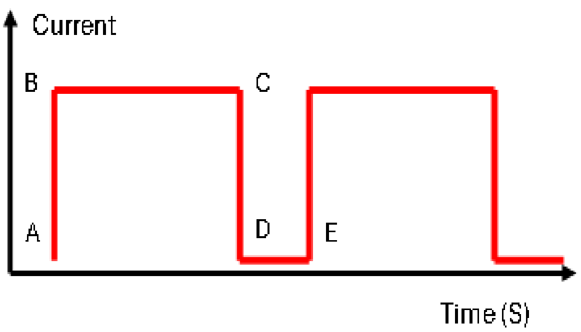

Figure 1 Duty Cycle

In the figure.1 shows the bank of extrinsic capacitor charged at a point and it's get discharged during the Ton to produce a spark to erode the distinct material from the workpiece and then the debris are flushed out during the Toff time where is spark is off, after flushed out the debris the cycle will be ready for the next Ton pulse to generate the spark. AB – current value, AD – Ton, DE- Toff, AE- cycle, AE/AD – duty cycle, 1/AE – Frequency rate [2].

$$A = \int_0^T I(T)\,dt = \int_0^{Ton} I(T)\,dt = I_P t_{on}$$

Current value can be derived from the above equation. Here the current value plays the major role. The current and Ton are linearly proportional to the MRR factor, whereas applying the Toff value even after removing the debris from the materials is waste of timing. Various methods are used to predict the MRR, here we see two manuals that are used to predict the MRR.

$$\mathbf{MRR} = \frac{644\, I_P}{(I_m)^{1.23}}$$

Where,

MRR - Material removal rate (mm^3 / sec)
Ip - Current (A)
Tm -Workpiece melting point (°C)

The Material removal rate () can convert into Material removal rate = for cycle time calculation. Ti-6A1-4V material is used as work piece which is widely used in the aerospace industries, and we choose the copper as the electrode to attain the rated MRR with the nominal surface finish. The melting point of the Ti-6A1-4V is around 2500°C but in the EDM process spark delivers the heat approximately 8000°C to 12000°C.

Another method, to calculate the MRR through manual calculations using the differential weight of the workpiece before and after the machining process with respect to the cycle time required to complete the entire machining process [3].

$$MRR = \frac{W_i - W_f \ x\ 1000}{\rho \ x\ t}$$

Where,

Wi and Wf - initial and final weights of the workpiece
P - material density (g/mm³)
T – machining time (min)
Workpiece weight will be measured before the

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machining process and again it will be measured once the machining process gets complete. The difference in weight has been considered as an MRR for a particular interval of time. In this manual calculation, time consumption is more and need to set a manual data sheet for every workpiece. Industry people need to prepare data sheets for different workpieces and electrodes for the different profile data. This is there will be delay in the production plan. In this paper the MRR prediction shown by implementing various machine learning techniques using ANN, SVM, RF and XGboost. Consider six essential parameters like Ton, Toff, Current, Voltage, Duty cycle and Flushing to design a model. Generating three sets of data capturing to eliminate the error value and find the average accuracy level of the model. Variations are plotted in the boxplot to find the outliers. In most of the literature surveys demonstrated the very low MRR predication by setting the lower current value. In this paper, the MRR predication will be more to achieve the productivity level than the author stated in their research work. Here, the experimental research carried out in the Skitek 600 NC machine by setting the maximum current value as 60 A to show the maximum MRR experimental value. To start the machining process, the workpiece materials Ti-6Al-4V and Inconel 718 the top surface has been made even and smooth through the grinding process and the respective copper electrodes have been designed by the conventional milling machine according to application requirements. In EDM process, electrode materials with high melting point, so that low electrode wear rate can be achieved. Electrodes are defined in the shape of the process requirement. The workpiece will reflect the minor image of the electrode at the end of the EDM process. In this paper various machine algorithms are used to predict the MRR and make the comparison between the experimental and predicted values. will compare the experimental and predicted value. Using ANN several algorithms are added to design the model, In the paper Random Forest (RF), XGBoost and Supervised Vector Regression (SVR) techniques are included. In RF, various decision trees are combined to generate the output by reducing the variance value. In XGboost, it can be capable of making the output very regularized to maintain the accuracy level Shown in Figure 2 EDM Machining Process [4].

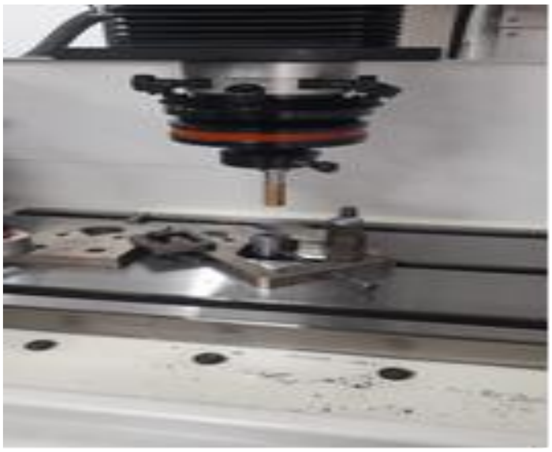

Figure 2 EDM Machining Process

The SVR algorithm will be helpful to discover the hidden data associated with the functions throughout the implementation. Here genetic algorithm is used to select the EDM machine optimized parameters to design the validate the model. There are several parameters involved in the EDM process but only some parameters are responsible for the MRR Shown in Table 1 Optimized EDM Parameters.

Table 1 Optimized EDM Parameters

Pulse Current (A)	Ton (µs)	Toff (µs)	Voltage (V)	Duty Cycle	Flushing (Mpa)
40	100	50	80	0.6	0.3
50	110	40	80	0.7	0.35
60	120	30	80	0.8	0.45

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Different experimental test conducted by including the parameters like current (A), Ton pulse (Ton) and Toff pulse (Toff), Flushng rate, Duty cycle and voltage (V). Data collection processed before designing the model and the outliers are plotted in the boxplot. Recursive feature elimination is used with correlation matrix to establish parameters that influence the MRR more. Model evaluation and validations are made by the various machine learning model parameters [5].

Mean Squared Error (MSE)

$$\boldsymbol{RSME = \sqrt{MSE}}$$

Root Mean Square Error (RMSE)

$$\boldsymbol{MSE = \frac{1}{n}\sum_{i=1}^{n}(y_l - \hat{y}_i)^2}$$

Coefficient Of Determination (R^2)

$$\mathbf{R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}}$$

Table 2 ML model Performance Parameters for MRR Prediction

Model	MSE	RSME	R²
ANN	27.75	5.27	0.9982
XGBoost	30.12	5.49	0.9979
RF	28.65	5.35	0.9975
SVM	35.40	5.39	0.9960

In the above Table 2; ANN shows the best prediction value with the coefficient rate of 0.9982. XGBoost model somehow matches the ANN prediction value with 0.9979 and RF model also have prediction accuracy like XGBoost with the value of 0.9975 but the SVM model techniques give the low prediction value 0.9960 when compared to the other models. Here the ANN model is considered as the best model for the MRR prediction, this can be used in the EDM machines by considering the optimized EDM parameters. Model output calculated by these parameters and accuracy level will be validated Figure 3 Performance Metrics [6].

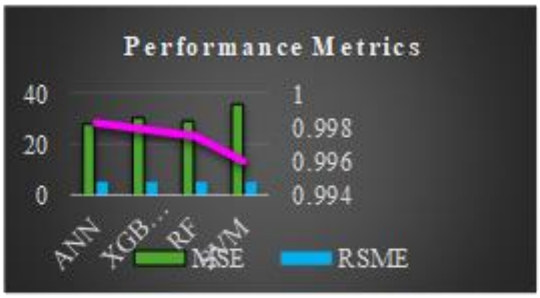

Figure 3 Performance Metrics

3. Discussion of Result

ANN model gives the best MRR prediction value when compared to the other model which has been tested by making multiple trials. The ANN model shows the deviation within 3% for the overall trials. Table 3; shows the comparison of the predicated and experimental MRR for the maximum current value as 60A for the aerospace grade materials Ti-6Al-4V and Inconel 718 and the copper electrode Shown in Figure 4 Prediction Vs Experimental [7-10].

Table 3 Prediction Vs Experimental Comparison

Trail	Predicted MRR (mm³/min)	Experimental MRR (mm³/min)	Deviation (%)
1	369.25	360.1	2.48
2	418.75	408.5	2.45
3	448.8	438.2	2.36

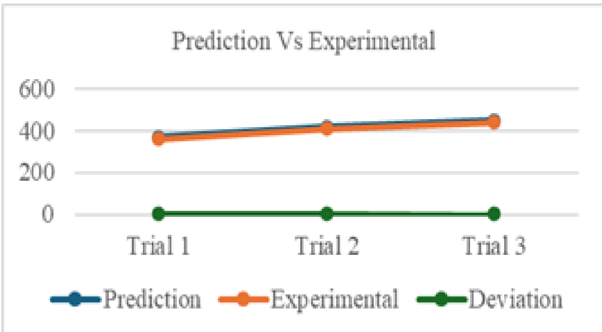

Figure 4 Prediction Vs Experimental

The low RSME and high R^2 value is achieved by the ANN model so this shows ANN model is capable to address the MRR prediction in the field with the best accuracy rate. This ANN model performed well during the MRR experimental test. The ANN model has several optimized EDM parameters to train and test the model. The best fit model structure has been defined by the criteria performance evaluation of the train set [11-15].

Conclusion

In this work the experimental and prediction analysis of MRR for EDM machine has been shown for the Ti-6Al-4V aerospace grade material. The MRR value predicted by different sets of trials using various control factors. The MRR prediction using the ANN model shows the best result with the low RMSE value of 5.27 and high coefficient R^2 value as 0.9982 when compared to the other model RF, XGboost and SVM which has tested during the model evaluation. The highest R^2 values of the ANN models shows the harmony between the prediction and experimental results. Thus, the machine learning algorithm can examine and design the EDM process effectively and become useful in making the mass production plan by giving the estimated MRR value before doing the machining process. The genetic algorithm must be highly effective to define the valid optimized EDM parameters to derive the best accurate result of the MRR. ANN model explored the effect of inputs utilized in the process and demonstrated that among all inputs the current value plays the major role and that impacts the MRR value in more.

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