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Machine Learning Based Classification and Analysis of Wire-EDM Discharge Pulses

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Abstract—**Wire electrical discharge machining (wire-EDM) process is having immense potential over conventional machining methods due to its non-contact nature of material removal. However, frequent and unanticipated machining failures like wire breakages negatively affect the productivity, sustainability and efficiency of the process. In this context, there is a wide scope to improve the process efficiency through online condition monitoring. A prominent aspect of EDM condition monitoring is discharge pulse discrimination. The threshold based methods which are currently being used has low accuracy and is reliant on operator's experience. In this study, a machine learning (ML) based pulse classification based on the extracted discharge characteristics is proposed. The features are extracted from the raw voltage and current senor signals collected from the machining zone during the wire EDM operation. Among the various ML models, Artificial Neural Network (ANN) classifier is found to have the maximum prediction accuracy of 98 %. Also, the effects of different discharge pulses on the productivity, surface finish and machining failures are investigated. The short circuit and arc discharges are found to cause wire breakage failure if they predominate the pulse cycle by more than 80 %. Also, short and arc sparks increase the surface roughness significantly, by up to 70 %.**

Keywords- Wire EDM; Condition Monitoring; Signal Processing; Pulse Classification; Machine Learning; ANN

I. Introduction

Wire-EDM is a non-traditional machining process which uses controlled and repeated spark erosions for material removal. Due to the non-contact nature of material removal, the hardness of the material doesn't restrict the machinability during wire EDM process [1, 2]. Thus, wire-EDM has found wide applications in machining 'difficult-to-cut' alloys like Ni based superalloys and Ti-alloys. Even though the process is having these aforementioned merits, wide industrial adoption of the process is still lagging due to the lesser efficiency and sustainability of the process caused by frequent machining failures. There is a need for thorough investigation and eradication of machining failures like wire breakages and spark absence through pulse cycle analysis and online condition monitoring to make the process more efficient, robust and dependable [3, 4]. The principal challenge for condition monitoring of wire EDM process is the stochastic nature of the spark discharges. Due to the ever varying nature of the inter electrode gap (IEG), there is often no consistent pattern to the sparks which makes the process difficult to control [5]. The primary task to develop an online process control system will thus be to investigate, identify, and classify the discharge pulses in a wire EDM pulse cycle. If a robust model is designed to automate the pulse categorization, it will be the right step forward for real-time monitoring and process control of wire-EDM. This study, thus focuses on developing a machine learning (ML) model to classify the discharge pulses and further investigate its effects on the machining failures, part quality and productivity.

The research conducted thus far on pulse classification has been threshold based models. Liao and Woo [6] used voltage and current signals to classify the wire EDM discharge pulses, and then investigated the machining instabilities based on the type of pulses. Later, for wire electrical discharge turning, Janardhan and Samuel [7] proposed a strategy to identify short, and arc discharges by a rule based algorithm. The pulses were classified based on experimentally found threshold values for current and voltage signals. Klocke et al. [8] has developed a model to predict surface quality based on voltage pulses. However, this model has only considered voltage signals and thus the functionality is limited. Yan and Hsieh [9] performed hardware based pulse classification using a signal processor card, which however adds to the cost and complexity of the classifier. Subsequently, a two stage pulse classification using random forest regression and support vector mechanism was proposed by Zhang et al. [10]. Various thresholding techniques to extract different discharge characteristics were proposed by Caggiano et al. [11].

The limitations with such rule-based or threshold-based pulse classification models are that, the developer should have deep knowledge on the physics of the process to define the rules/thresholds. And since the pulse generator and machining parameter values and operating ranges varies from one EDM manufacturer to another, it is difficult to set a generic ruleset. These thresholds would require machine specific recalibration to work with a separate machine. Another shortcoming is that such models aren't trainable - i.e., they don't have the capability to 'learn' new patters and improve over the time with new training data. So, the models discussed thus far cannot be used a generic outline for the development of a pulse classification system for wire EDM.

To minimize the limitations of the threshold based classification models proposed so far, a machine learning based classification model is proposed in this study. Here the classifier predicts the probability of each discharge spark, whether it is normal, short, arc, or open spark based on its discharge characteristics. With sufficient training data, the proposed methodology can be used for any wire EDM machine to classify the discharge pulses. Since the model automatically captures the distinguishable characteristic features from the training data, there is no need to manually set up the thresholds / rules to perform the pulse classification. The predicted classes are investigated with respect to their effect on process failures, productivity and part quality. The automated pulse classification proposed in this study will enable the development of better real-time condition monitoring and process control systems in the future.

II. MATERIALS AND METHODS

A. *Materials*

Workpiece material chosen is Inconel 718 due to its wide industrial applications in the areas of aerospace, oil and gas, and cryogenics. Zinc coated brass wire of 0.25 mm diameter is chosen as the wire electrode due to its better overall performance over other wire electrodes. 50 mm long straight cuts are performed on a 10 mm thick workpiece for analyzing the pulse signals.

B. *Experimental Details*

Machining is carried out in an Electronica Ecocut wire EDM machine. Various machining situations are simulated by varying servo voltage, pulse on time and pulse off time as shown in TABLE 1. Hardware for signal acquisition includes a current sensor (Tektronix TCP 303-50 MHz bandwidth), a current signal amplifier (Tektronix TCP 300), a differential probe (Tektronix P 5200A-50 MHz bandwidth) and an oscilloscope (Tektronix MDO 34-200 – Sampling rate/channel 2.5 GSa/S). Signal processing operations were carried out in MATLAB 2021a. The current and voltage signals acquired by the sensors are preprocessed to reduce the signal noises using a low pass filter. An appropriate pass band frequency of $5 \times 10^{-10}\ \pi$ radians/sample is used for filtering.

TABLE I. WIRE EDM PROCESS PARAMETERS

Parameters	**Values**
Wire diameter (mm)	0.25
Wire feed rate, WF (m/min)	4, 8
Discharge current, I_p (A)	10, 40
Servo Voltage, SV (V)	25, 40, 55
Pulse on time, T_{ON} (μs)	100, 110, 120
Pulse off time, T_{OFF} (μs)	35, 50, 65

C. *Methodology*

The voltage and current discharge pulses undergoes several key characteristic variations during the wire EDM process. It is well documented that analyzing these pulse signals will aid in the analysis and prediction of machining failures like wire breakage and spark absence. The machining failures are related to the machining instabilities caused by the inefficient removal of debris from the spark gap. Once the pulses are classified, debris accumulation can be implicitly understood by monitoring the type of discharge pulses occurring between the electrodes.

The features extracted from the raw voltage and current signals are discharge duration, ignition delay time, input current, and discharge voltage. Ignition delay time is the time taken for the dielectric fluid in the spark gap volume to ionize and break the dielectric barrier. Discharge duration is the overall time duration of the discharge current between the two electrodes. Discharge voltage is the instantaneous inter-electrode voltage during the discharge. The proposed methodology to classify the discharge pulses is given as follows:

(a) Several experiments are conducted at normal and limiting EDM machining conditions to acquire the raw current and voltage signals. Limiting conditions includes the machining failure situations generated by a combination of higher discharge energy and inefficient flushing conditions (narrow spark gap, less pulse off time etc.). An extensive research have already been conducted on wire-EDM failures by the research group [12–15].

(b) The wire EDM discharge pulses are labelled based on their characteristic features (More about discharge pulses are further elaborated in the upcoming section). The labelled data points will constitute the training data for the ML model. Overall training dataset for this study contains 1000 datapoints, i.e., 250 data points per class.

(c) The inputs to the ANN model are discharge duration, ignition delay time, input current, and discharge voltage, plus its corresponding class label. The input dataset thus is of the size 1000 x 5. The ANN model is trained with 5-fold cross validation sampling strategy. Cross validation ensures better data utilization and generalization of the model. Appropriate ANN structure is to be chosen by varying the number of hidden layers and neurons/layer based on model performance. The model is then compared with other ML classification algorithms against its performance. Finally, the model performance is validated over unseen dataset containing 100 datapoints.

(d) The final step is the investigation of the effect of discharge pulse types on machining performance and wire EDM failures.

The overall pulse classification approach and experimental setup is given in FIGURE 1.

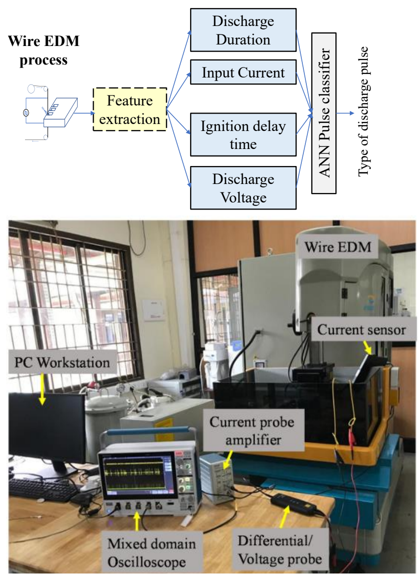

FIGURE 1. (A) PULSE CLASSIFICATION APPROACH (B) EXPERIMENTAL SETUP

D. ANN Classification

For complex manufacturing systems like wire EDM, prediction of events based on the available data can be an extremely difficult task. For such scenarios, supervised learning models like classifiers are usually recommended.

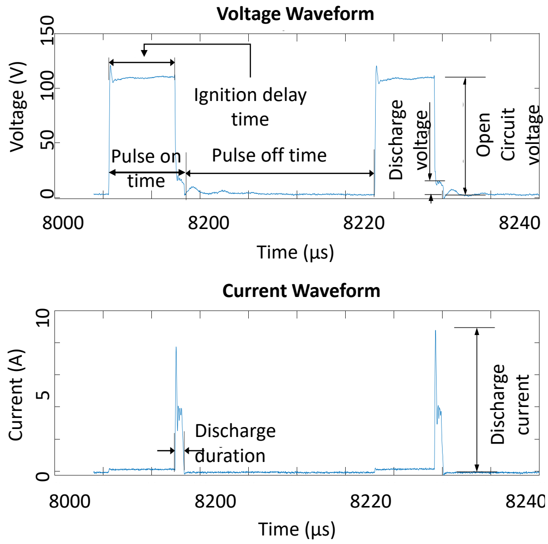

FIGURE 2. TYPICAL DISCHARGE PULSE CYCLE IN WIRE-EDM

Classification is an ML technique which predicts or identifies the group to which a data point(s) belongs to. Geometrically, the technique finds a decision boundary that separates a group of points from one another in space. Depending on the dimensions of the datapoints, the decision boundary can be a curve, surface, or hyper surface. When the datapoints are multidimensional and have higher order interaction, the classification becomes complex and demands high computational power. Among several classifier available, ANN classifier is widely regarded as the best in terms of its prediction accuracy, flexibility, generalization capability, and workability with noisy data.

ANN uses a network of neurons in multiple layers to perform complex computational tasks. The weights and biases associated with the neuron connections can be tuned during the training phase, to iteratively improve the prediction accuracy of the model. The number of neurons in each layer, and the number of layers can be varied which adds to the modelling flexibility. A detailed description of ANN classification and its application in wire EDM response prediction is given in [16].

III. TYPES OF DISCHARGE PULSES

The typical pulse cycle for wire-EDM process contains several characteristic features as depicted in FIGURE 2. Once the voltage is applied across the electrodes, the current discharge ideally happens after a certain time duration. This time gap, called ignition delay time is utilized for the ionization of dielectric in the inter electrode volume. After the narrow discharge channel is ionized; the dielectric barrier is breached and a current discharge occurs between the electrodes. The pulse off time is utilized to flush away the debris to restore the dielectric property in the inter electrode gap before the upcoming spark cycle. Such repetitive sparks are called normal sparks which occurs when the machining is stable and the flushing is efficient.

During unideal circumstances, the pulse cycle can be identified with other harmful types of sparks which are considered to be indicators of unstable machining. Those are discussed in the subsequent section. Overall, four different types of discharge sparks were identified from pulse train analysis.

Wire EDM discharge pulses are predominantly of 4 types.

- Normal sparks (NS): These are the ideal discharges which happens after a sufficient ignition delay time. A predominance of normal sparks in a discharge cycle implies stable machining.
- Arc sparks (AS): Arc discharges are higher energy discharges caused due to some percentage of debris accumulation in the spark gap due to inefficient flushing. The spark is characterized by negligible ignition delay time.
- Short sparks (SS): Short circuit discharges (short sparks) are indicators of spark gap bridging due to debris accumulation. Such sparks occur without a voltage discharge peak. Predominance of short sparks in a pulse cycle is an extremely undesirable scenario which leads to wire breakages and causes severe part quality deterioration. A series of high frequency short sparks are often regarded as an indicator of immediate wire breakage.
- Open sparks (OS): The absence of a current discharge between the electrodes is called open sparks. Such sparks lead to machining failure due to spark absence.

The theoretical shape of various discharge sparks is given in FIGURE 3.

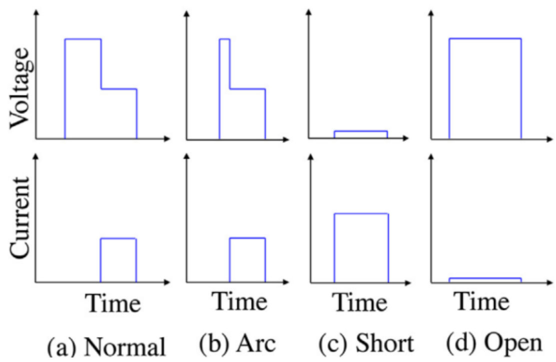

FIGURE 3. TYPES OF WIRE-EDM DISCHARGE PULSES [14]

IV. RESULTS AND DISCUSSION

Various discharge pulses identified from the acquired pulse cycles are shown in FIGURE 4. The pulse shapes are observed to vary significantly from their ideal shapes reported thus far. Also, several variations can be spotted within the short sparks itself, including pulse shapes, peaks, frequency and duration. Similar is the case with arc and normal discharges as well. It is thus clear that finding a common threshold that defines a particular pulse type is impossible due to their inter-group variations. This emphasizes the need for a better model than the threshold based models to classify the discharge pulses.

A. *Pulse classification*

Five ML models are compared for performance against the same input dataset (described in the methodology section) with 5-fold cross validation sampling strategy. The models considered are decision tree, Naïve Bayes, Support Vector Mechanism (SVM), K-Nearest Neighbor, and ANN. Among them, maximum prediction accuracy was observed for ANN model as shown in TABLE II.

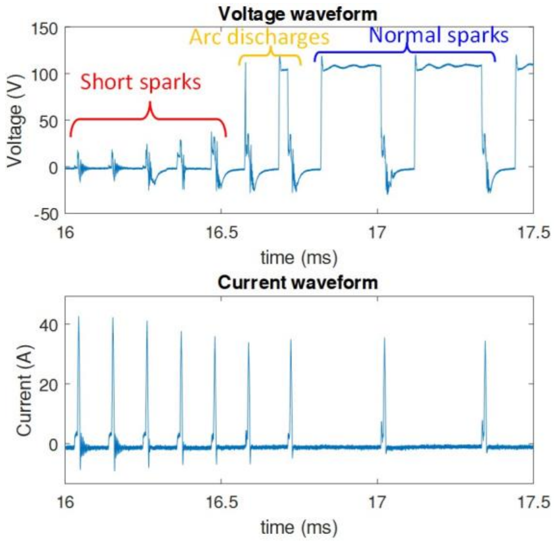

FIGURE 4. WIRE EDM DISCHARGE PULSES FROM PULSE CYCLE

TABLE II. COMPARISON OF ML MODEL PERFORMANCES

ML model	Validation Accuracy
Decision Tree	87.6 %
Naïve Bayes	89.1 %
SVM	90.7 %
KNN	92.3 %
ANN	**98.3 %**

The ANN architecture used for this application is 4-20-20-20-4, i.e., 3 hidden layers, having 20 neurons each as shown in FIGURE 5. This structure is selected by varying the number of hidden layers from 1 to 10 (i.e., 4-20-4, 4-20-20-4, 4-20-20-20-4, … etc.) by keeping number of neurons in each hidden layer as 20. Each model accuracy was noted and the structure with 3 hidden layers gave the maximum prediction accuracy. During training, the weights and biases of the model are tuned to minimize the predation error. Based on the input discharge characteristics, the model predicts the probability that the data can fall into each of the 4 discharge categories. The model output is the one with maximum probability. The predicted class label is then compared with the true class label to evaluate the model performance. The model's prediction accuracy was 98.3% during validation stage. i.e., 983 out of 1000 predictions were accurate with respect to pulse category. The details of the ANN model can be seen in TABLE III.

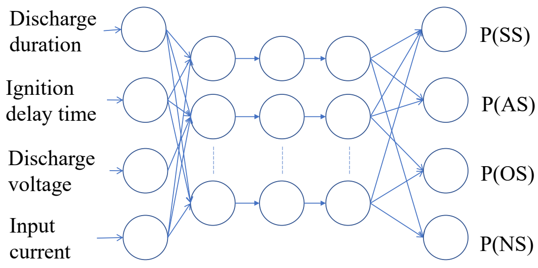

FIGURE 5. STRUCTURE OF ANN CLASSIFICATION MODEL

TABLE III. ANN CLASSIFIER MODEL DETAILS

Model Feature	Details
Number of fully connected layers	3
NN structure	4-20-20-20-4
Activation	ReLU
Iteration limit	1000
Cross validation	5-fold
Model Accuracy (Validation)	98.30%

FIGURE 6 shows the confusion matrix to evaluate the class wise prediction performance of the model. In the matrix, the classes are labelled as follows: Class 1 = Normal spark; Class 2 = Arc spark; Class 3 = Short Spark; Class 4 = Open Spark. The diagonal blue elements of the matrix show the right predictions among each labelled class category. The red elements show the prediction errors. For example, the first row of the confusion matrix indicates that, when a spark is actually a normal spark (true class label is Class 1), it is correctly identified by the ANN classifier as normal spark on 98.4 % instances, as arc spark on 0.4 % and as open spark on 1.2 % instances. Similarly, the prediction accuracy of arc, short and open sparks are 98.4 %, 98.4 % and 98 % respectively.

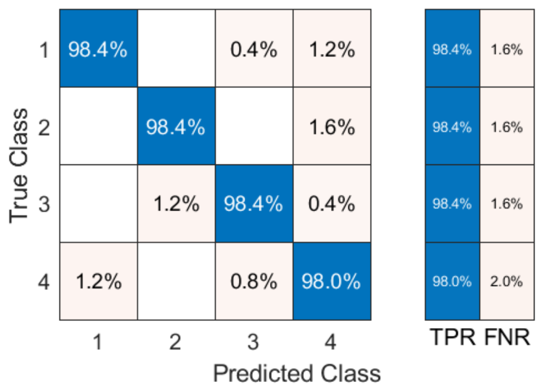

FIGURE 6. ANN CONFUSION MATRIX

A receiver operating characteristic (ROC) curve is shown in FIGURE 7 to further represent the model performance. To demonstrate, ROC for class 1 is considered here with class 2, 3, and 4 as negative classes. For a perfect/ideal classification model, the ROC curve passes through the coordinates (0,1), which implies 100 % true positive rate and 0 % false positive rate. The closer the

ROC curve passes to this coordinate, better is the prediction accuracy. As it can been seen in the figure, the model passes through the coordinates (0,0.98) for class 1. Similar trends were observed for other classes as well. This affirms the prediction accuracy of the model.

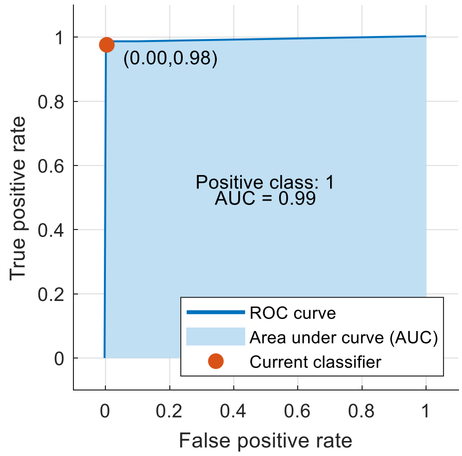

FIGURE 7. RECEIVER OPERATING CHARACTERISTIC (ROC) CURVE

B. *ANN performance verification*

A confusion matrix is used to validate the real world performance of the trained ANN classifier. For this, 100 unseen datapoints are selected and the model is tested for performance and the results are given in FIGURE 8. The model displayed an overall prediction accuracy of 98%. Class wise prediction accuracy is 96 %, 96 %, 100 % and 100 % for classes 1 to 4 respectively.

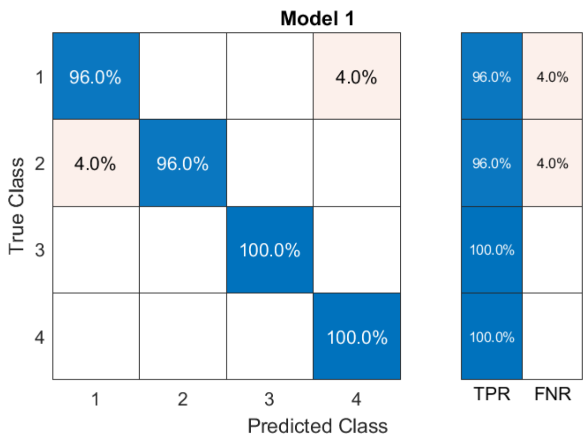

FIGURE 8. ANN CONFUSION MATRIX DURING VERIFICATION TRIALS

C. *Effects of discharge pulses on machining performance*

This section discusses the effect of discharge pulses on the part quality, productivity and machining failures during wire EDM of Inconel 718. To analyse the effect of various discharges on these responses, proportion of each pulse types are computed. This is done by designing a pulse counter and finding the ratio of each pulse count to that of the total pulse counts.

Short circuit sparks and arc sparks influences the surface quality negatively. Such sparks often happen at higher than normal frequency and are having high discharge energy. This causes deeper craters and thus coarser surfaces. FIGURE 9 (A) and FIGURE 9 (B) shows the machined surface comparison when the proportion of sum of arc and short sparks are 0.6 and 0.2 respectively. In the former case, the surface can be observed with several undesired surface features like micro globules, and other recast layer depositions. On the contrary, lesser arc and short sparks has resulted in an even and smooth surface due to the ideal overlapped micro craters.

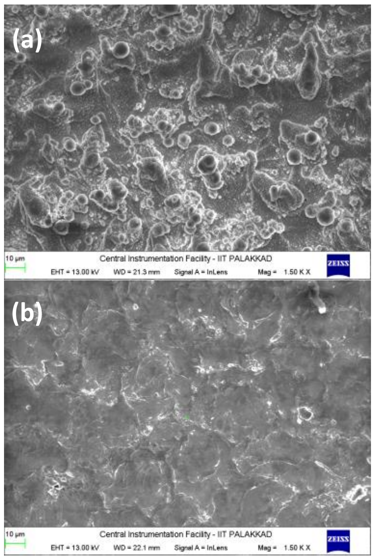

FIGURE 9. SEM IMAGE COMPARISON WHEN (AS+SS) IS (A) 0.6 (B) 0.2

In situations where AS+SS is higher, material removal rate could be higher but with compromised part quality. This is evident from the plot for cutting speed and R_a in FIGURE 10. Apart from causing inferior machined surfaces, the predominance of short and arc discharges in a pulse cycle is an indicator of potential instability which may lead to wire breakages. In the figure, it can also be noted that a predominance of AS + SS (over 80 %), leads to wire breakages. Several researchers have attempted to develop failure prediction models based on this idea, however the inaccuracies in the pulse classification have limited the functionalities of such monitoring systems.

FIGURE 11 shows the effect of different pulse proportions on machining failures. During wire breakage, short sparks were predominating and during spark absence, open sparks were predominating the pulse cycle.

V. CONCLUSIONS

The study proposes a pulse classification model and investigates the effects of different pulse types on wire EDM responses and failures. Four different pulses, namely, normal, arc, short and open are identified through pulse train analyses. Various ML models were compared and among them, ANN model with 98.3 % accuracy was found to have the maximum pulse classification accuracy. During verification tests, the ANN model performed with an overall accuracy of 98 %. The short and arc pulses were found to have a detrimental effect on the part quality with 74.1 % increase in R_a at higher arc and short spark ratios. At more than 80 % short and arc sparks, machining failure was reported.

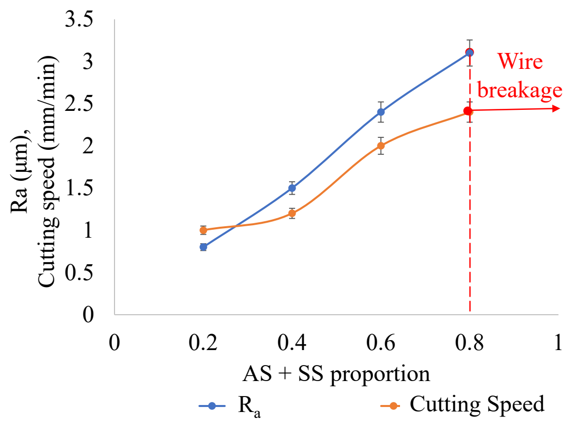

FIGURE 10. VARIATION OF SURFACE ROUGHNESS AND CUTTING SPEED WITH RESPECT TO ARC AND SHORT SPARK PROPORTIONS

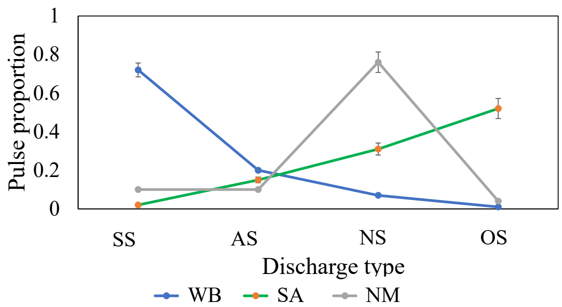

FIGURE 11. EFFECT OF PULSE PROPORTIONS ON MACHINING OUTCOMES

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