Sustainability improvement of WEDM process by analysing and classifying wire rupture using kernel-based naive Bayes classifier

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Abstract: The current work aims to improve the sustainability of wire electric discharge machining by predicting the wire breakages. Wire breakages are process interruptions which increases the machining time, energy wastage and material consumption. The study is a novel approach to predict process continuity by binomial classification of machining outcomes using kernel based naive Bayes algorithm. The two classes are labelled wire breakages and continuous machining. Training data set consists of 31 experiments according to central composite design (CCD) of response surface methodology (RSM) and wire breakage instances are recorded as response. The input data set contains four machining parameters namely pulse on time, pulse off time, servo voltage and wire feed rate, whereas mean gap voltage variation is derived from in-process data. The trained model was 96.7 % accurate in wire breakage predictions. Further, nine confirmation tests were conducted to check model adequacy in real world situations. The model predicted all instances of wire breakages accurately. The stages of wire wear up to wire rupture was studied by conducting microstructural analysis.

Keywords: Wire EDM, sustainability, naive Bayes, wire rupture, mean gap voltage, process interruption

Article Highlights

- The study aims to improve the sustainability of wire EDM process by analysing and predicting process interruptions through wire rupture.

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- The study uses a probabilistic classifier called naive Bayes classifier for wire rupture prediction. The model was observed to be extremely accurate in its predictions.
- The wire rupture mechanism was analysed for coated wire electrodes. The study is industrially relevant in making the process more sustainable by improving the productivity, part quality and energy consumption.

1. Introduction

Wire electric discharge machining (WEDM) is a non-conventional machining process which is suitable to machine any electrically conductive material irrespective of its hardness. Since the wire electrode does not come in contact with the workpiece, the process possesses many advantages over the conventional machining techniques. The process uses the discharge energy of electric sparks to melt and vaporise the workpiece which is flooded in a dielectric fluid [1]. Machining stability is regarded as one of the most critical aspects in wire EDM with respect to part quality and process interruptions [2].

Uninterrupted machining is very significant for the process to be sustainable. Wire breakages are associated with the debris accumulation in the inter electrode gap (IEG) between the wire electrode and the workpiece [3]. This causes short circuit pulses, having extremely high discharge energies. Such sparks increase the temperature and deteriorates the wire strength which ultimately results in wire rupture. Once the wire breaks, either automatic or manual rethreading is necessary. In either case, the productivity is affected due to the time taken for rethreading [3]. Other than that, the energy utilization also goes up as observed by Gamage and Desilva [4]. They have reported a 48% higher energy utilization in the wire breakage cases. Also, the short circuit sparks will affect the machined part quality by causing surface damages. Thus, the wire breakages are observed to cause decreased productivity, reduced part quality and environmental implications.

Pramanik et al. [5] explored the sustainability aspects of wire EDM process by studying the wire breakage mechanism.

Rajurkar and Wang [6] developed an online monitoring system to detect and prevent wire breakages by correlating spark frequency with wire breakages. Rajurkar et al. [7] developed an adaptive control system that optimizes the sparking frequency according to the workpiece height to avoid wire breakages. A non-linear model was used for online estimation of workpiece height using cutting speed and spark frequency. Yan and Liao [8] developed a fuzzy logic-based monitoring system for wire breakage monitoring and control. The system automatically controls the pulse off time to avoid wire breakages if the sparking frequency is above a threshold value. Kao and Tarng [9] used a feed forward back propagation neural network for pulse classification and wire EDM process monitoring. Lio et al. [10] developed a pulse discrimination strategy to characterize the voltage waveform and found that excessive sparking frequency and presence of arc sparks are the reasons for wire breakages. Zhang et al. [11] developed an intelligent pulse discrimination system based on recurrent neural network. Rajeswari and Shunmugam [12] investigated the EDM process mechanism using pulse train analysis.

Kwon and Yang [13] observed that monitoring instantaneous energy of sparks instead of spark frequencies is advantageous to monitor wire EDM process. Cabanes et al. [14] developed an early detection system for wire breakage control. The system uses a set of indicators based on discharge energy, maximum discharge current and ignition delay time to detect wire breakages and instability. Caggiano [15] developed a multi sensor monitoring system to discriminate the pulses. Various signal features were extracted through multi sensor fusion to predict abnormal conditions which causes part defects and wire breakages. Obwald et al. [16] developed a condition monitoring system for automatic pulse classification. Short circuit pulse type was observed to reduce part quality and process interruptions. Caggiano et al. [17] developed a real time process monitoring system to detect improper machining conditions. They developed an anomaly detection technique for this purpose. Mwangi et al. [18] characterised arching phenomenon in micro EDM process and studied its effects on machining performance. Xia et al. [19] developed a failure detection method by classification of machining state graphs during EDM drilling.

A naive Bayes classifier is widely considered in machining learning as an effective and computationally efficient algorithm [20-22]. Karandikar et al. [23] developed the naive bayes classifier to predict the tool wear in end milling operation from the force data features in frequency and time domains. Sharma et al. [24] developed a condition monitoring system for roller bearings using naive Bayes classifier algorithm. The features were extracted from the sound signal for fault diagnosis and the results were compared with Bayes net and decision tree algorithm. Elangovan et al., [25] developed a condition monitoring system of single point carbide cutting tool by using naive Bayes classifier vibration signal features.

From the literature survey it was found that, the identification of process parameters and process mechanism that leads to machining interruption is of paramount importance to make the wire EDM process sustainable. However, research conducted in this area is not adequate. The current study aims to introduce a novel approach to improve the process sustainability and resource utilization by predicting and controlling the process interruption. The objective is to classify the machining outcomes into process interruption and otherwise using naive Bayes classifier based on kernel density estimation.

1.1 Naive Bayes Classifiers with kernel density estimation

Naive Bayes (NB) is a classification algorithm in machine learning, based on the Bayes theorem. NB classifier is thus a probabilistic classifier which could be coupled with kernel density estimation for improved accuracy. The biggest advantage of the classifier is the requirement of a smaller training data [26]. Since the wire EDM process have lesser productivity comparatively, the size of training data set is a limitation when comes to model classifiers. NB classifier was thus a suitable choice compared to ANN or fuzzy based classifiers with regard to size of required training data set. NB classifier is computationally fast and simple compared to other classifiers due to the independence assumption, since calculation of covariances are eliminated [27, 23]. Since the failure predictions are to be fast and in real time, NB classifier is better suited to the application than other classifiers [25]. The classifier is said to work well in many complex and stochastic real-world problems, for which wire EDM process is a typical example [28].

Bayes theorem incorporates probability of occurrence of an event based on the prior knowledge of a condition related to the event. Let y be the class variable which is the event of 'wire breakage' here. Let P(y) be the class probability and X be the predictor (input) dataset. The predictor dataset X has the input dataset members as its elements namely x_1= pulse on time, x_2= pulse off time, x_3=servo voltage, x_4=wire feed rate and x_5=mean gap voltage variation. The likelihood that the event y happening, given that the predictor dataset is X is given by $P(y/X)$ Bayes' rule gives the posterior belief about the event y, after knowing the predictor dataset. The rule states

$$P(y/X) = \frac{P(X/y)\,P(y)}{P(X)} \qquad (1)$$

where $X = (x_1, x_2, x_3, x_4, x_5)$

Now naive Bayesian classifier assumes independence of predictors within each class. It is known that if A and B are mutually independent, then for any A and B, $P(A \cap B) = P(A)\,P(B)$. Hence the following result is reached

$$X = (x_1 \cap x_2 \cap x_3 \cap x_4 \cap x_5) \tag{2}$$

$$P(y/X) = \frac{P\left({}^{x_1}/_{y}\right) P\left({}^{x_2}/_{y}\right) P\left({}^{x_3}/_{y}\right) P\left({}^{x_4}/_{y}\right) P\left({}^{x_5}/_{y}\right) P(y)}{P(x_1)\ P(x_2)\ P(x_3)\ P(x_4)\ P(x_5)} \tag{3}$$

$$P(y/X) \propto P\left({}^{x_1}/_{y}\right) P\left({}^{x_2}/_{y}\right) P\left({}^{x_3}/_{y}\right) P\left({}^{x_4}/_{y}\right) P\left({}^{x_5}/_{y}\right) P(y) \tag{4}$$

The classifier model computes the value of $P(y/X)$ for all possible cases of class variable y and will pick the class which fetches maximum probability.

$$y = argmax\left[P\left({}^{x_1}/_{y}\right) P\left({}^{x_2}/_{y}\right) P\left({}^{x_3}/_{y}\right) P\left({}^{x_4}/_{y}\right) P\left({}^{x_5}/_{y}\right) P(y)\right] \tag{5}$$

In the current case, y is a binomial class variable with values 1 or 0 referring to class labels ‘wire breakage’ or ‘continuous machining’ respectively. The various naive Bayes classifiers differ in their assumptions on the probability density function (PDF) of the predictor element x_i. The distribution of $P(x_i/y)$ thus differs based on the type of naive Bayes classifier. Gaussian NB classifier assumes gaussian distribution for each variable x_i of input dataset. NB classifier coupled with kernel density estimator can improve the accuracy of the classifier. Here the kernel distribution estimates the pdf of the predictor variables [20, 21].

1.2 Kernel weighting function

The kernel distribution is defined by a smoothing function and a bandwidth value. Kernel density estimator (KDE) estimates the pdf of predictor having a distribution of unknown density.

If x_i is randomly chosen samples from the predictor distribution, the KDE is given by the following formula

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \tag{6}$$

where n is the sample size, K is the kernel (non-negative smoothing function), and h is a non-negative smoothing parameter called bandwidth. The naive Bayes classifier computes discrete KDE for each class depending on the training dataset for that class. The normal kernel is selected as default, and a bandwidth is selected automatically by the classifier for each class and predictor [20, 21].

2. Experimental procedure

The experiments were conducted in Electronica wire cut electric discharge machine. The electrode used is hard zinc coated brass wire of 0.25 mm diameter. Deionized water of conductivity 20 µS/cm is used as the dielectric fluid. Straight rough cuts of 10 mm length were machined. The mean gap voltage is noted from the integrated computer screen. The naive Bayes classification model was developed using MATLAB software.

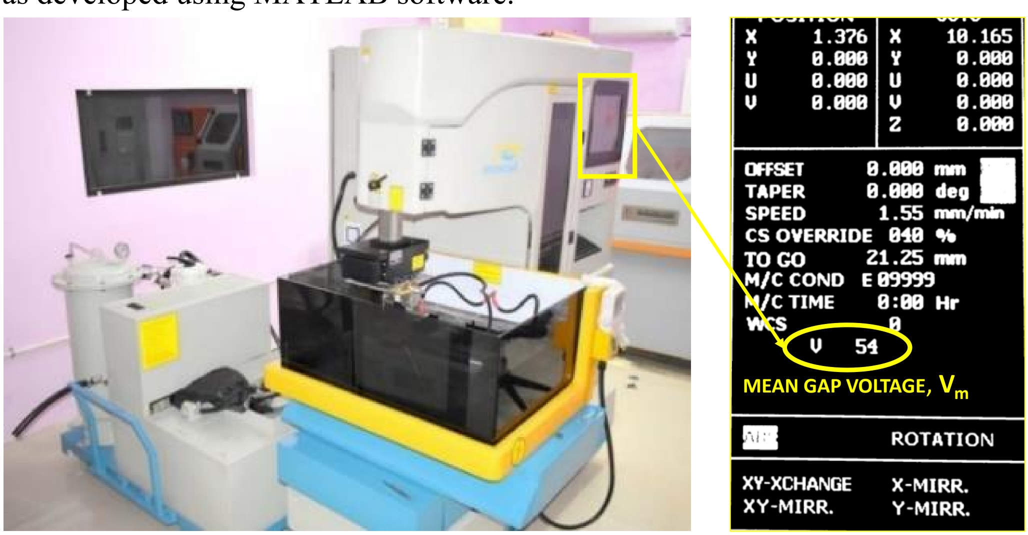

Fig. 1 (a) Machine tool (b) Integrated computer displaying mean gap voltage

The difference between the servo voltage value and mean gap voltage (V_m) is called mean gap voltage variation (ΔV_m) and this is a major factor that effects the gap stability and process interruptions. Fig. 1 shows the wire EDM machine and the displayed mean gap voltage readings. Fig. 2 shows the approach in computing ΔV_m.

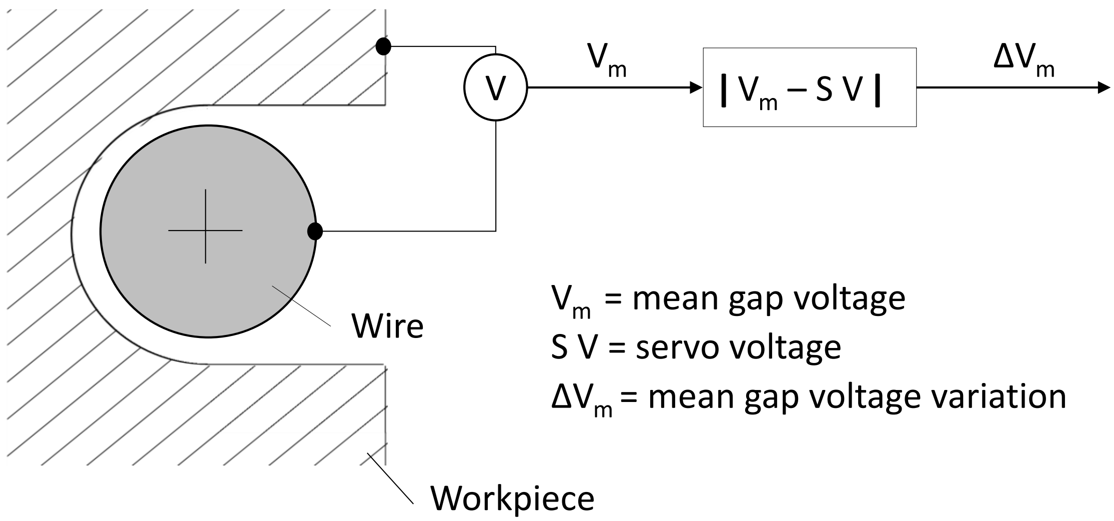

Fig. 2 Method of determining mean gap voltage variation

2.1 Workpiece material

Inconel 718 is chosen as the workpiece material because of its high temperature application especially in gas turbine industries. Apart from its superior mechanical properties at elevated temperatures, the superalloy is known for corrosion resistance, fatigue and creep resistance. The properties and chemical composition of Inconel 718 is given in Table 1 and Table 2 respectively.

Table 1. Properties of Inconel 718 [29]

Property	Value
Density	8.19 g/cm^3
Melting Point	1260 – 1336 ºC
Specific Heat	435 J/kg K
Average Coefficient of thermal expansion	13 µm/m K
Thermal Conductivity	11.4 W/m K
Ultimate Tensile strength	1240 MPa

Table 2. Chemical composition of Inconel 718 [30]

Element	**Ni**	**Fe**	**Cr**	**Nb**	**C**	**Al**	**Ti**	**Mo**
Weight (%)	Balancing	18.5	19	5.1	0.04	0.5	0.9	3

2.2 Experimental plan

The experimental plan is according to the central composite design (CCD) of response surface methodology (RSM). Totally 31 experiments were conducted considering the process parameters pulse on time, pulse off time, servo voltage and wire feed rate. These parameters are chosen to feed the classifier because of their greater influence on the wire wear phenomena discussed in section 3.1. Discharge energy increases with pulse on time and can accelerate wire wear. Pulse off time and servo voltage determines the time and space available to clear the debris produced. Lesser servo voltage implies narrower spark gap and lesser pulse off time results in ineffective flushing of spark gap. The resultant effect is spark gap bridging causing short circuit sparks and wire breakages. Also, when the wire feed rate is less, higher are the chances of repetitive sparks occurring from the same wire spot, which can lead to wire break failure [31]. The parameter levels and ranges were chosen based on pilot experiments and literature survey. Since the objective is to study the process interruptions, the ranges are chosen in such a way that wire breakages possibilities are more. The experiments were repeated thrice to avoid experimental errors. Table 3 shows the process parameters and its levels according to RSM design.

Table 3. RSM input parameters and levels

Process parameters	Level 1	Level 2	Level 3	Level 4	Level 5
Pulse on Time (μs)	120	115	110	105	100
Pulse off Time (μs)	70	60	50	40	30
Servo voltage (V)	70	60	50	40	30
Wire feed rate (m/min)	2	4	6	8	10

3. Results and discussion

Thirty-one experimental runs were conducted according to CCD of RSM. Table 4 shows the experimental design with input dataset and corresponding labels. The classifier model requires a training data set containing input data and corresponding class labels. Input dataset contains process parameter and signal features. Since the current model is trained for binomial classification, the datapoints are classified into two classes. The two class labels are 'interrupted machining' and 'uninterrupted machining'. The responses are recorded as '0' or '1' based on the class labels assigned to each input dataset. The value 1 is assigned when the wire breakage was observed, otherwise the case is labelled 0. The classification model 'learns' the feature pattern which results in wire breakages. 5-fold cross validation procedure is followed for this model to prevent overfitting and biases [32]. The trained model can predict the class of any new input dataset. The model is then tested for prediction accuracy by considering a new dataset which is not the part of training data. The steps involved in training testing and prediction are shown in Fig. 3.

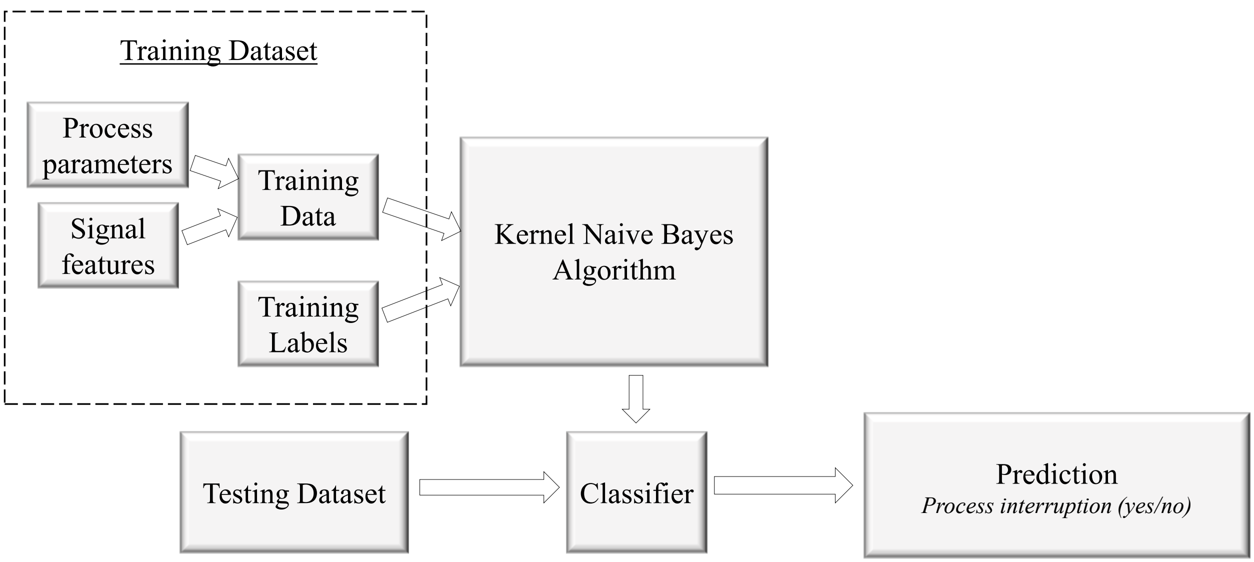

Fig. 3 The steps involved in developing a Naive Bayes classification model

Table 4. Experimental data and model predictions

S. No.	Ton (*µs*)	Toff (*µs*)	SV (*V*)	WF (*m/min*)	ΔV_m (*V*)	Actual event	Predicted event
						WB – WIRE BREAKAGE CM – CONTINUOUS MACHINING	
1	115	40	60	4	9.56	CM	CM
2	110	50	50	6	4.9	CM	CM
3	105	60	60	4	1.63	CM	CM
4	110	50	50	6	4.6	CM	CM
5	110	50	50	2	4.62	CM	CM
6	105	40	40	8	3.7	CM	CM
7	120	50	50	6	14.96	WB	WB
8	110	50	50	10	5.4	CM	CM
9	100	50	50	6	1.63	CM	CM
10	110	50	50	6	5.2	CM	CM
11	105	60	60	8	1.63	CM	CM
12	105	60	40	8	1.63	CM	CM
13	115	40	40	4	11.74	WB	WB
14	115	40	60	8	8.54	CM	CM
15	110	50	50	6	3.5	CM	CM
16	110	50	50	6	3.9	CM	CM
17	105	40	60	8	1.63	CM	CM
18	110	50	70	6	2.08	CM	CM
19	110	70	50	6	2.08	CM	CM
20	105	60	40	4	1.63	CM	CM
21	115	40	40	8	11.74	WB	WB
22	115	60	60	4	9.88	CM	CM
23	105	40	60	4	1.63	CM	CM
24	115	60	40	4	11.4	WB	WB
25	110	50	50	6	4.55	CM	CM
26	110	30	50	6	12.3	WB	WB
27	105	40	40	4	3.7	CM	CM
28	110	50	30	6	7.5	CM	CM
29	115	60	40	8	8.48	CM	CM
30	110	50	50	6	6.01	CM	CM
31	115	60	60	8	10.41	WB	CM

The prediction accuracy in case of classification models is given by confusion matrix shown in Fig. 5 (a). The model was 96.7 % accurate in classifying the datasets into wire breakage cases and otherwise. The model performance is also evaluated by receiver operating characteristic curve (ROC) curve shown in Fig. 5 (b). The curve which plots the true positive cases against false positive cases, shows the diagnostic ability of a binary classifier. Area under the curve (AUC) value indicates the model's capability to discriminate classes. AUC will have a value between 0 and 1 and higher the value, better is the model's discriminating ability. The current model has an AUC value of 0.96 which indicates that the model is extremely effective in binomial classification.

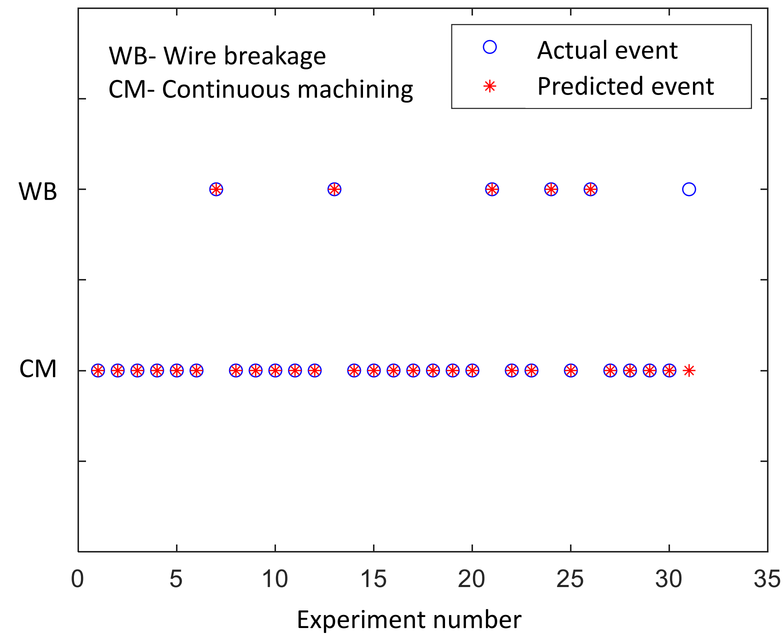

Fig. 4. Evaluation of model performance by comparing actual and predicted events

KNB classifier was specifically chosen based on its ability to perform accurately with smaller training datasets. Five different classifiers were trained with this dataset and the KNB technique fetched the maximum accuracy of 96.7%. Table 5 compares the classification accuracies of various supervised classification techniques. To test the model performance in real world situations, nine more confirmation tests were conducted and the model predictions were true in all the nine cases.

Table 5. Comparison of classifier performances

S. No.	Machine learning classifier technique	Accuracy
1	Logistic regression	87.10%
2	Linear Support Vector Machine	83.90%
3	Gaussian Support Vector Machine	80.60%
4	K-Nearest Neighbour	80.60%
5	**Kernel Naive Bayes**	**96.70%**

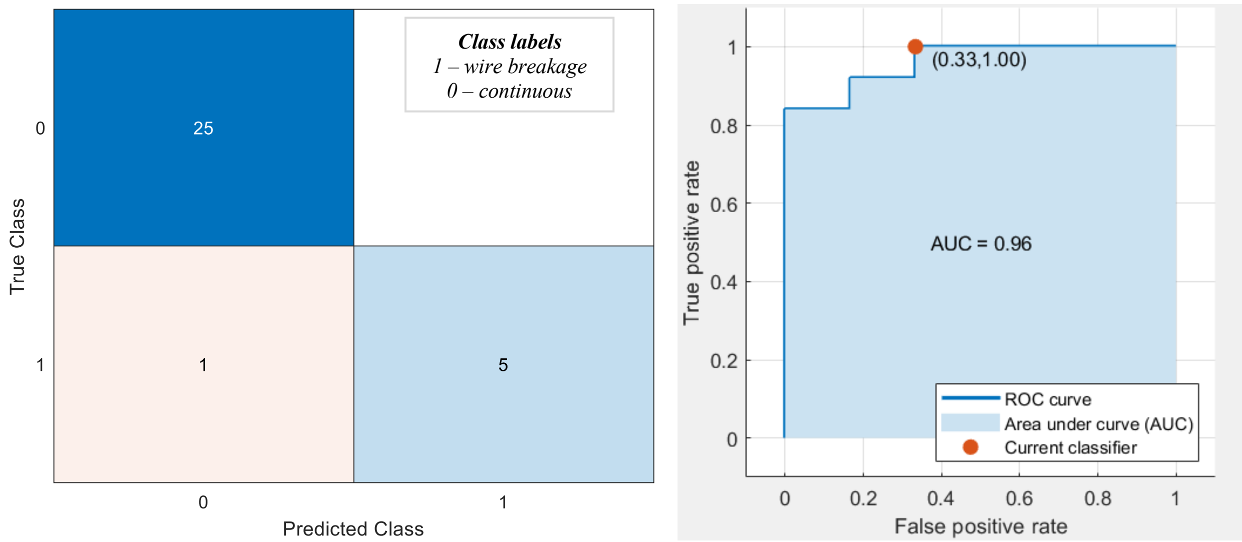

Fig. 5 Performance evaluation of the model (a) Confusion matrix (b) ROC curve

Table 6. Confirmation test results

S. No.	Ton (µs)	Toff (µs)	SV (V)	WF (m/min)	ΔV_m (V)	Actual event	Predicted event
1	115	40	30	3	8.8	CM	CM
2	115	30	40	3	8.4	CM	CM
3	120	30	30	7	15.2	WB	WB
4	120	30	40	4	10.8	WB	WB
5	105	45	40	5	3.5	CM	CM
6	110	35	40	10	8.05	CM	CM
7	118	33	39	4	12	WB	WB
8	112	43	49	9	7.25	CM	CM
9	103	33	31	5	2.5	CM	CM

WB – WIRE BREAKAGE
CM – CONTINUOUS MACHINING

Nine confirmation tests were conducted by the random selection of process parameters to test the model performance in real world machining situations. The model was able to accurately classify the datasets into wire breakage cases and otherwise. The results of the confirmation tests are shown in Table 6.

After these experiments, the wire samples were collected and the morphology of the wires were analysed to have an insight on the mechanism of wire rupture. Based on the mechanism of material removal, it is known that a process combination of high pulse on time (T_{on}), low pulse off time (T_{off}) and low servo voltage is most likely to result in sever wire damage and vice versa. Based on this, the worn wire samples collected after experiment numbers 1, 8 and 9 from confirmation experiments are expected to represent three stages of wire wear, i.e., minimal wire degradation, intermediate wire degradation and severe wire degradation.

3.1 Wire wear analysis

The wire rupture mechanism was studied with the help of scanning electron micrograph (SEM) images. Wire coatings are reported to protect the inner core from thermal shock by 'heat sink effect'. However, rapid removal of wire coatings will expose the inner core which will then be susceptible to wire wear. Rate of removal of coatings depend on discharge energies [33]. Furthermore, the harmful sparks like arc and spark discharges accelerate the wire wear. The progressive levels of wire wear were observed under SEM as shown in Fig. 6. Fig. 6 (a), (b) and (c) shows the wire surfaces collected after experiment number 9, 8 and 1 respectively. Fig. 6 (a) shows minimal damage to the wire surface and the coating is still visible. Fig. 6 (b), shows partial removal of wire coatings further exposing the brass core. Fig 6 (c) shows substantial wire wear with a highly uneven wire surface. The coatings are completely removed and are not identifiable at this stage. Moreover, re-solidified debris are seen impinged on the wire surface. This indicates that, at this stage, the wire damage is caused by excessive short circuit/ arc pulses due to debris accumulation and spark gap bridging.

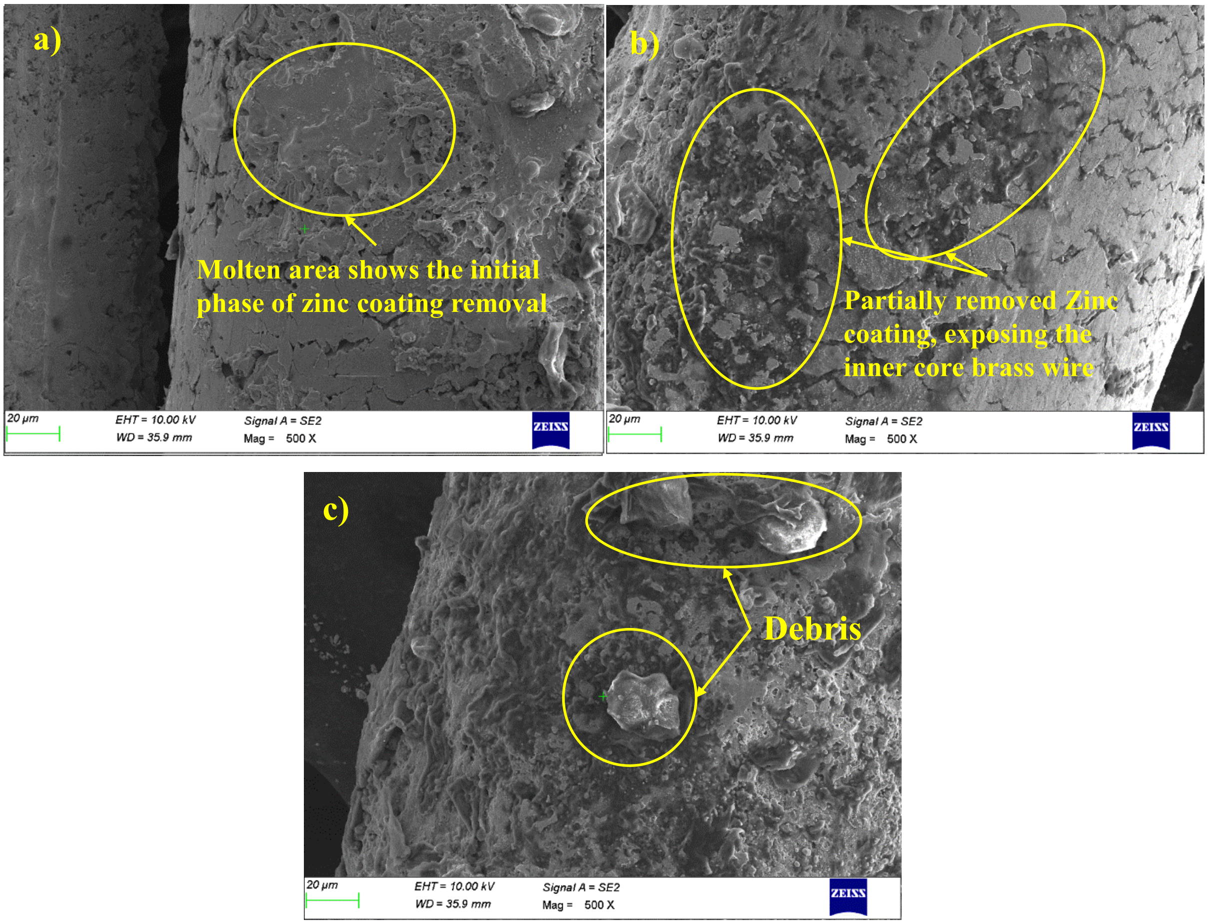

Fig. 6 Stages of wire wear (a) minimal degradation (Exp. No. 9) (b) intermidiate degradation (Exp. No. 8) (c) Severe degradation (Exp. No. 1)

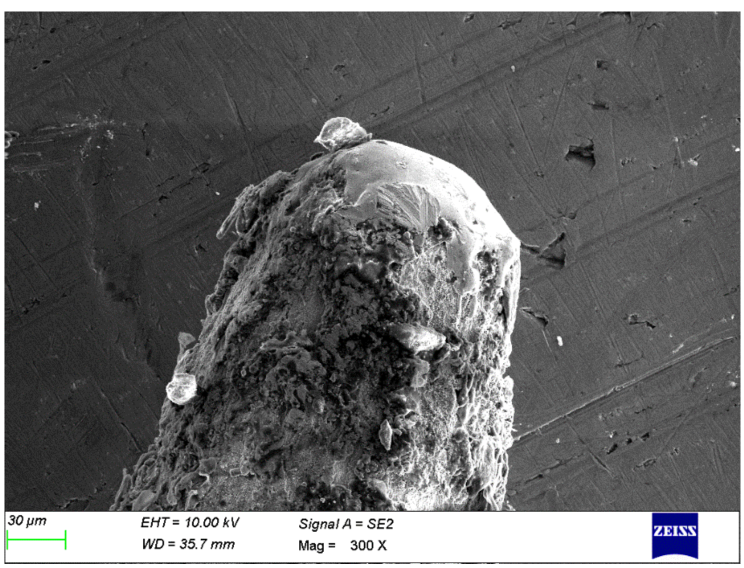

Fig. 7 SEM image of failed wire tip

The wire rupture happens when the short circuit pulses are predominating the discharge pulse cycle [31, 34]. This usually is the result of excessive debris accumulation in the spark gap. The short circuit sparks lead to sudden temperature rise causing rapid removal of wire coatings. Once the wire coatings are completely removed, the core copper wire is exposed. Extensive wire wear will happen by formation of craters and cracks, and a critical point will be reached where the wire is unable to bear the load due to the wire tension. The wire thus elongates reducing the wire diameter further and finally fails by rupturing at the point of minimum cross-sectional area. Fig. 7 shows the failed wire tip which is conical in shape as the result of wire elongation and diameter reduction.

4. Conclusions

A novel approach to improve the sustainability of wire EDM process by predicting process interruptions using kernel based naive Bayes classifier is proposed. Such a model is extremely relevant to improve the wire EDM process efficiency by reducing the wastage of consumables, energy and machining time. One of the limitations to model wire EDM process with ML techniques is the lack of large training data sets. The proposed NB model overcomes this limitation by its ability to perform with smaller datasets. The following are the salient conclusions from the work conducted. Kernel based NB classifier with kernel density estimator was trained by features from process parameters and in-process data. An approach to extract the in-process data feature, mean gap voltage variation (ΔV_m), was proposed. Kernel based NB classifier was found to be an efficient and accurate method to predict the process interruptions by wire breakages. The NB classifier was compared with five alternate classifier models and the model performed the best with 96.7 % accuracy in classifying wire breakage cases. The real-world performance of the model was tested by conducting verification experiments and the classifier was accurate in its prediction at every instance. The wire wear stages and the rupture mechanism were explored with the help of SEM images. The stages of coating removal and core wire exposure leading to wire rupture were analysed.

An integration of this offline Naïve Bayes classifier with an online condition monitoring system for wire EDM process is planned as a future work. Naïve Bayes classifier being fast and computationally simple can be used to set the initial process parameters, and the process can be further monitored in real time by an online system using voltage and current sensors.

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Declarations

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Conflicts of interest/Competing interests – The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material – Not applicable

Code availability – Not applicable

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