Wire EDM failure prediction and process control based on sensor fusion and pulse train analysis

Abhilash Puthanveetil Madathil *, Dupadu Chakradhar

Department of Mechanical Engineering, Indian Institute of Technology Palakkad, Kerala, India, 678557

*Corresponding author: abhilashpm184@gmail.com, ORCID ID: 0000-0001-5655-6196

Abstract: The study aims to develop a neural network classification model to predict machining failures during wire electric discharge machining. Also, a process control algorithm retunes the process parameters based on remaining useful time before failure. In the proposed methodology, an artificial neural network (ANN) classifier receives four in-process discharge characteristics as input. These extracted features are discharge energy, spark frequency, open spark ratio and short circuit ratio. Output classes are labelled normal machining, wire breakage, and spark absence. 108 experiments were conducted according to a full factorial design to train the classifier model, with 90 % classification accuracy. An ANN model was trained to predict the remaining useful time before failure, based on which process parameters are retuned to restore the machining stability. The algorithm was successful in ensuring continuous failure-free machining.

Keywords *Wire electric discharge machining; pulse classification; condition monitoring; short circuit; neural network classification; wire breakage; process control*

1. Introduction

Wire electric discharge machining (wire EDM) is a non-traditional machining process which removes material through an electro thermal mechanism. It possesses several merits over conventional machining of superalloys and hard conductive materials due to the non-contact nature of material removal. However, the process efficiency is still questionable due to the frequent process failures like wire breakages [1, 2]. This affects the productivity and sustainability of the process due to time wastage during wire re threading, wastage of consumables, unwanted energy

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consumption, and machined part rejection due to surface damage. In order to achieve complete automation and to improve the competitiveness of the process, failure situations shall be predicted and avoided. The paper discusses a failure prediction and process control algorithm for wire EDM process using advanced pulse train analysis and machine learning techniques.

Earlier attempts of wire breakage prediction systems were based on spark frequency [3] and discharge energy [4]. Many fuzzy logic wire break prediction models based on spark energy and frequency were developed in this regard. Yan and Liao [5] developed a fuzzy logic wire break prediction system by monitoring spark frequency. Pulse off time is auto regulated to keep spark frequency within limits. Liao and Woo [6] developed a fuzzy logic servo controller to regulate the machine feed according to a reference power level. Also, to prevent wire breakages, the model monitors short circuit ratio and adjust the pulse off time. Bufardi et al. [7] attempted a combined offline-online fuzzy logic-based approach for wire EDM monitoring. Offline model sets the initial parameters and online model performs real time monitoring. Abhilash and Chakradhar have developed adaptive neuro fuzzy inference system (ANFIS) prediction model [8] and Naïve bayes based prediction model [9] to forecast the events of wire breakage during wire EDM. Here, a parameter called mean gap voltage variation (ΔV_m) was introduced as an indicator of machine health. Offline models are computationally fast and inexpensive to setup. However, due to the stochastic nature of the process, many uncontrollable factors can also affect the machining performance. Thus, the offline models which relates the input parameters and process failures can be inaccurate.

The modern condition monitoring systems are pulse classification based. A pulse classifier distinguishes the pulses into normal and abnormal pulses. Different pulse classification systems were developed by Janardhan and Samuel [10], Yan and Hsieh [11], Obwald et al. [12] and Conde

et al. [13]. Kwon and Yang [4] studied the advantages of a wire EDM monitoring system based on instantaneous discharge energy. The authors observed the limitations of earlier spark frequency-based monitoring systems. Cabenes et al. [14] developed an online monitoring system to alert the operator regarding a potential wire break failure. To study the process instabilities experiments were conducted under unfavorable conditions and the changes in discharge characteristics before wire breakages were observed. Different levels of alarms were programed based on discharge energy, peak current and spark frequency. Klocke et al. [15] developed a monitoring system to ensure surface quality during fir tree slot machining of Inconel 718. Mean gap voltage was monitored to keep R_a value within the required limits. This model however, has not considered the current pulses. Caggiano et al. [16] has proposed several feature extraction methodologies by sensor fusion. Caggiano et al. [17] has also developed an advanced signal processing methodology to extract discharge features by pattern recognition to identify unstable machining conditions. Bergs et al. [18] analysed the discharge characteristics to predict unstable machining behaviour. The study observed that the unstable process condition is indicated by increase in discharge energy, spark frequency and increase in abnormal pulse proportions. A sudden raise in discharge pulse frequency was observed before wire breakages. Rajeswari and Shunmugam [19] performed pulse train analysis to understand the process mechanism for EDM process. Two new discharge parameters, called energy expended and performance factor were introduced to evaluate the process performance. Marrocco et al. [20] analysed the voltage signals during micro EDM of Si_3N_4-TiN composite using power spectral density. The results indicated that higher number of normal discharges does not necessarily implies a higher energy density. Further, Marrocco et al. [21] studied the effect of various pulse types on productivity and tool wear. Mwangi et al. [22] studied the arcing phenomena with respect to discharge characteristics.

Even though several failure-alert systems were developed in the past, the existing models addressed only one mode of process failure, i.e., wire breakages. However, other modes of process failures like spark absence, which affects the productivity and efficiency of the process is yet to be considered in a wire EDM failure prediction system. Also, even though several of the existing models are capable of failure identification, an integrated adaptive control algorithm to bring back the process stability is not proposed by many of them [4, 14]. And, many of the existing process control models are not based on pulse classification algorithm, and thus the effect of harmful pulses can go unidentified [7, 23, 24]. A severity based variable process control, as proposed in this study, is not investigated before. Fuzzy logic is the most commonly used soft computing algorithm for wire EDM condition monitoring [5-7]. However, fuzzy logic is based on operators experience and a rule set connecting parameters and responses. For a process like wire EDM where the parameter – failure relationship is complex and stochastic, neural network models will perform better than fuzzy logic models, which is rarely attempted in previous literature. Also, most of the existing work have not reported the impact of such monitoring systems on the surface integrity of machined components.

The proposed model introduces a novel failure-severity based process control for wire EDM process based on remining useful life (RUL). RUL is previously used in condition monitoring to represent the time to failure, but it has not been used in the context of process control yet. The parameter however, can be a capable indicator of the failure severity as proposed in the current work. Also, unlike the existing models, the present work addresses both work breakage and spark absence failures, to prevent multiple cases that can reduce the process efficiency. Thirdly, the neural network prediction models are proven to be extremely capable of handling complex real-world phenomena. The current study proposes a monitoring and control system based on extracted

discharge characteristics from real time voltage and current pulse data. Relevant discharge characteristics, which can completely indicate the machine health status is identified. A neural network classifier predicts the machining outcome based on discharge energy, abnormal pulse proportions, and spark frequency. Finally, the effect of process control on the surface integrity is also studied.

2. Materials and Methods

Experiments are conducted on an Electronica Ecocut wire EDM machine. Wire electrode chosen is zinc coated brass electrode of 0.25 mm diameter. Dielectric fluid is deionized water having 20 µS/cm conductivity. Deionized water is the most common choice of dielectric for wire EDM due to its environmentally friendly nature, low viscosity and rapid cooling rate. High tool wear makes it non-ideal for conventional EDM, but that is compensated in wire EDM by continuous supply of fresh wire to the machining zone. Oil based wire EDM is reported to have high operational costs [1].

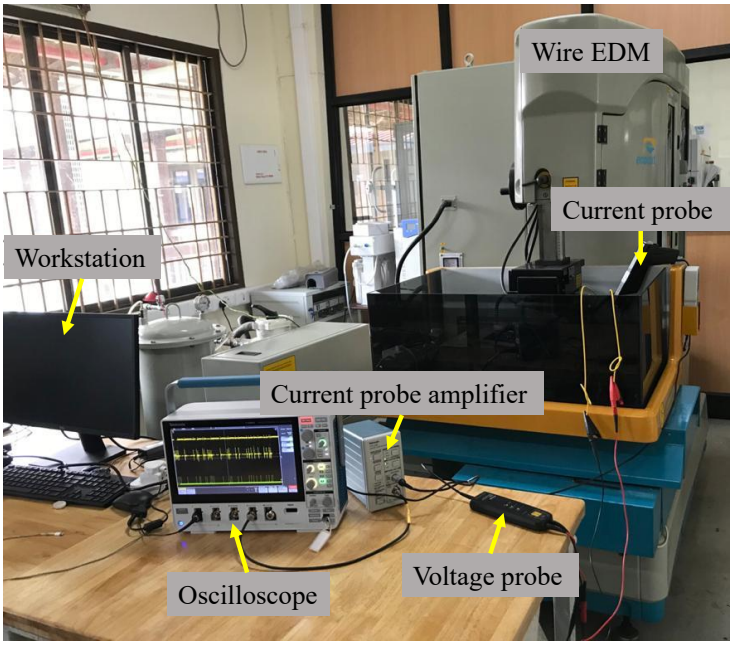


Fig. 1. Condition monitoring system components

The condition monitoring hardware includes a differential probe (Tektronix P 5200A), current probe (Tektronix TCP 303), current probe amplifier (Tektronix TCPA 300), oscilloscope (Tektronix MDO 34-200) and windows PC workstation. The probes and oscilloscope have a bandwidth of 200 MHz with suitable measuring range for real time measurement of current and voltage pulses. The oscilloscope has a sampling rate of 2.5 G Sa/s in each channel for better representation of individual pulse shapes. High bandwidth sensors are selected to capture maximum information / second. The primary challenges in real-time closed loop control are associated with the time lag associated with the data transfer and processing, and issues with data storage. The higher the sampling rate, the greater will be the data generated, and the slower will be the analysis and control. Two ways of addressing this is by down sampling the acquisition or improving the computational power of the PC. Authors have decided to control the sampling rate for faster data transfer and analysis. A very low sampling rate also runs the risk of affecting the quality of captured data. So, an ideal sampling rate of 250 Mega Samples/s was selected after several trials, which acquires signals without data loss, but enables fast computing. Even with this sampling rate, the signals acquired were with adequate level of details and the discharge characteristics are extracted accurately. Additionally, authors have also decided to clear the raw data from memory continuously to manage the storage requirements. The generated data is transferred to PC and only the extracted features are stored permanently.

The signal processing, feature extraction, and further analysis were conducted in MATLAB 2019a. The condition monitoring system installed on the wire EDM is shown in Fig. 1. The schematic of the monitoring system is shown in Fig. 2.

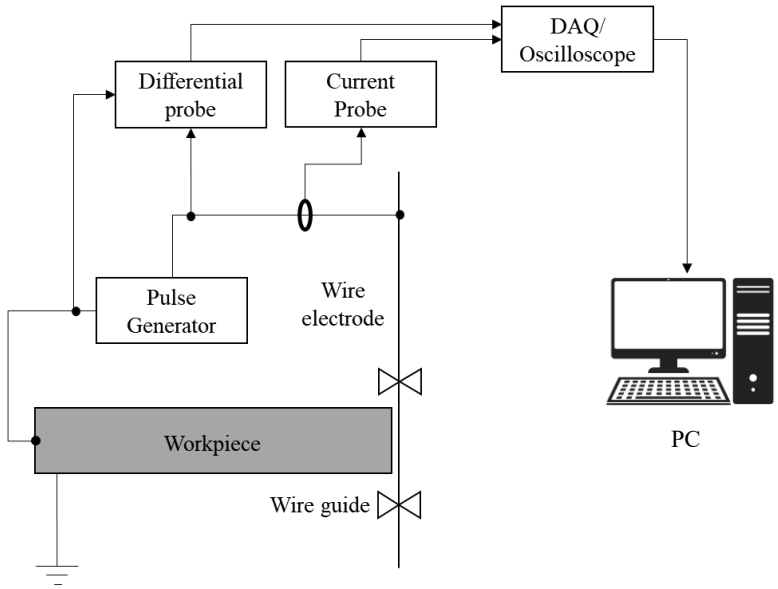


Fig. 2. Schematic of wire EDM condition monitoring setup

2.1 Workpiece material

The work material chosen is Inconel 718. The material is having great demand in aerospace industries due to its ability to retain its superior mechanical properties at higher temperatures. Additionally, the superalloy exhibits good corrosion, fatigue and creep resistance. Wire EDM machining of Inconel 718 is a topic of research interest due to the advantages it possesses over conventional techniques. The mechanical properties and chemical composition of Inconel 718 is given in Table 1 and Table 2.

Table 1 Properties of Inconel 718 [25]

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 [26]

Element	Ni	Fe	Cr	Nb	Mn	C	Co	Al	Si	Ti	Mo	Others
Weight (%)	51.05	19.43	18.70	5.7	0.07	0.04	0.2	0.56	0.08	1.01	3.1	0.06

2.2 Experimental plan

Experiments were conducted according to full factorial experimental design with three replications by varying input parameters like pulse on time, pulse off time, wire feed rate, servo voltage, and input current. The parameters and levels are given in Table 3. The input current is only varied in 2 levels because the machine model only allows two modes of operation, power pulse and fine pulse, having the input current 10 A and 40 A respectively. The wire feed rate is varied in 2 levels due to its lesser significance on the wire EDM failure phenomena compared to of pulse off time, pulse on time and servo voltage, as evident from the pilot experiments and existing literature. A few other parameters are fixed, as listed in Table 4, due to lesser relevance on process mechanism and due to wire EDM limitation. Pilot experiments were conducted to fix the parameters and levels. Total 108 experiments were conducted as the part of training dataset with the responses being machining outcome, surface roughness and profile length till failure. The machining outcome is categorized into three classes, normal machining, wire breakage, and spark absence. Wire breakage is the failure situation where the wire ruptures causing a process interruption. Spark absence is an inefficient machining condition resulting in near zero productivity when the discharge sparks die out due to longer than ideal spark gaps.

Table 3 Input parameters and levels

Process parameters	Symbol	Level 1	Level 2	Level 3
Pulse on time (µs)	T_{ON}	115	110	105
Pulse off time (µs)	T_{OFF}	50	40	30
Servo voltage (V)	SV	50	40	30
Wire feed rate (m/min)	WF	9	3	
Input current (A)	I_P	40	10	

Table 4. Constant machining parameters

Parameter	Value
Wire electrode diameter	250 µm
Open circuit voltage	12 V
Dielectric fluid pressure	1.9×10^5 N
Axial wire tension	10 N

3. Artificial neural network classification

Classification problem in machine learning (ML) refers to a supervised learning technique to predict the class label of a datapoint. Geometrically, if all the datapoints are laid out in a multi-dimensional space, the classifier comes up with decision boundaries (hyper surfaces), which separates the datapoints into different groups. Data points belonging to each group exhibits some common characteristics which are learnt by the algorithm during the training phase. Since this is a supervised prediction model, input dataset and their corresponding class labels are fed to the classifier as training data. For a complex and stochastic real-world problem, like failure mechanism of wire EDM, classifying the data points into failure and non-failure categories is challenging. This is because of the multi-dimensional, nonlinear nature of input output relationship. Artificial neural network (ANN) classifiers are known to perform extremely well in such cases.

ANN is a bio inspired soft computing tool which tries to emulate the human neurons. The neurons are highly interconnected with adjustable weights and biases associated with it. During the training phase, these will be tuned to minimize the error between actual prediction and true class label. Neural network is regarded as the best among the machining learning algorithms in its capability to learn the input-output relationships. ANN is proved to be capable of handling uncertain and higher order data which involves complex interaction effects between the considered parameters. Also, the technique handles non predefined relationships between the inputs and responses with good accuracy [27].

Wire EDM failure mechanism is an extremely stochastic phenomena which involves multiple parameter interactions and intervention of external uncontrollable factors. Therefore, a soft computing approach which can handle higher order interactions and stochastic mechanism is a necessity. This gives ANN an advantage over other machining learning models in modelling wire EDM process failures.

A feed forward back propagation neural network is selected for the study. The class labels in this case are the machining outcomes, namely normal machining, wire breakage and spark absence. The model inputs are real time discharge features like discharge energy, discharge frequency, short circuit ratio, and open circuit ratio. Pulse classifier gives the count of open and short circuit sparks and also total number of sparks. Open circuit sparks are the discharge sparks with an excessive ignition delay time or an absence of current discharge even after the entire pulse on duration. The ratio of number of open circuit sparks to total number of discharge sparks is called open circuit ratio. It is computed as:

$$Open\ circuit\ ratio\ = \frac{(Number\ of\ open\ circuit\ sparks)}{(Total\ number\ of\ sparks)}$$

The short circuit ratio is calculated as the ratio between total number of shorts - where shorts are the discharges which occur without an ignition delay time - divided by the total number of discharge sparks. It is computed as:

$$Short\ circuit\ ratio\ = \frac{(Number\ of\ short\ circuit\ sparks)}{(Total\ number\ of\ sparks)}$$

The discharge frequency is calculated as the number of current discharge sparks that happen between the wire electrode and workpiece, during the total duration of data acquisition. It is computed as:

$$Discharge\ spark\ frequency\ = \frac{(Total\ number\ of\ sparks)}{Total\ data\ aquisition\ duration\ (s)}$$

The ANN parameters are given in Table 5. The training algorithm considered, Levenberg-Marquardt, is an iterative algorithm which combines the advantages of gradient-descent and Gauss-Newton algorithms. Levenberg-Marquardt method interpolates between these two algorithms. Levenberg-Marquardt learning method converges extremely fast and is robust in comparison to Gauss–Newton algorithm (GNA). The algorithm finds a solution even when the starting point is far away from the final minima. Different ANN structures were employed to classify the dataset and the structure 4-11-3 is selected based on classification accuracy. A heuristic method was used to reach the proposed ANN structure. The number of hidden layers were increased from 1 to 15 and the structure which gave the maximum accuracy was selected. The number of neurons on each hidden layer was then changed for this structure, but the default value of 10 neurons per hidden layer was found to be most accurate in predictions. Fig. 3 shows the proposed ANN classification structure. Output layer neurons gives the output as the class probability (normal machining, wire breakage and spark absence). The ANN classifier predicts the event as the one with maximum probability. For example, if the output layer neuron predicts the

class probabilities are, P (NM) = 0.1, P (SA) = 0, and P (WB) = 0.9, the predicted event is wire breakage, since it has the maximum probability of occurrence.

Table 5. Parameters of neural network multiclass classifier

Parameter	Properties
Number of inputs	4
Input layer neurons	Spark frequency, discharge energy, short circuit spark ratio, open circuit spark ratio
Number of classes	3
Output layer neurons	Probability of normal machining, wire breakage, and spark absence
Number of hidden layers	11
Number of neurons in each hidden layer	10
Training algorithm	Levenberg-Marquardt

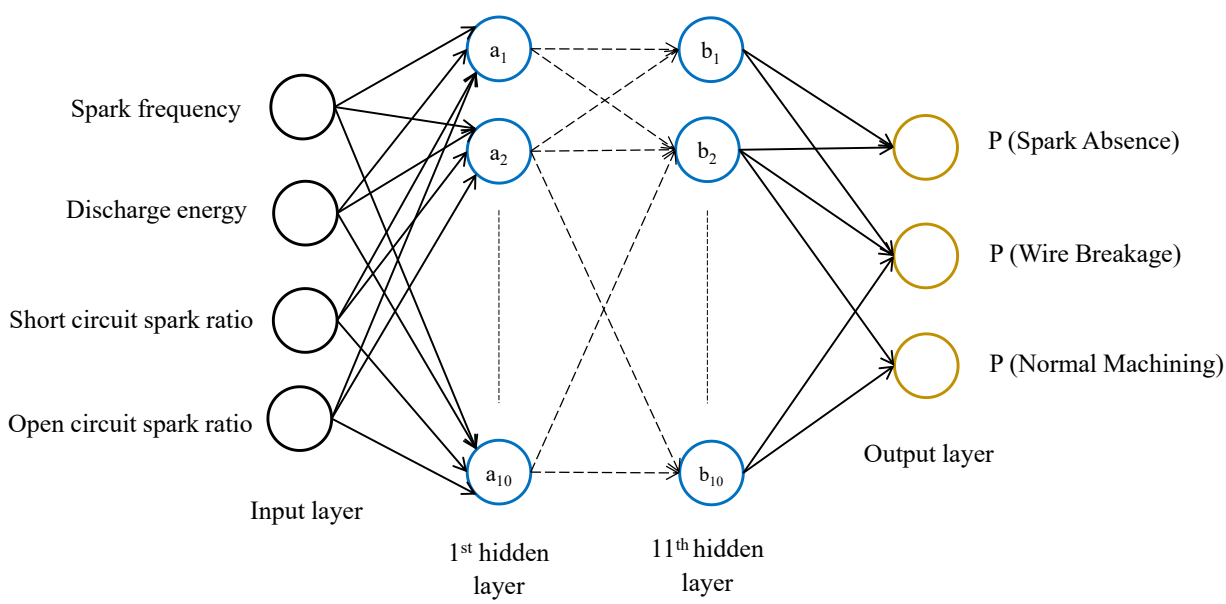


Fig. 3. ANN classifier structure

4. Results and Discussion

Wire EDM pulse cycle leading to wire breakage, spark absence and normal machining were observed to be significantly different from that of normal continuous machining. Wire breakage is

a well-documented failure mode where the machining process is interrupted by wire electrode rupture. Spark absence is an inefficient machining scenario where the sparks die out, halting the process, or resulting in near zero productivity [28]. Pulse cycle leading to wire breakage is observed to consist mostly of short circuit sparks with higher spark frequency and intensity. On the contrary, spark absence is indicated by longer ignition time pulses, with low discharge frequency and discharge energy. A comparison of the pulse train leading to both the situation is shown in Fig. 4.

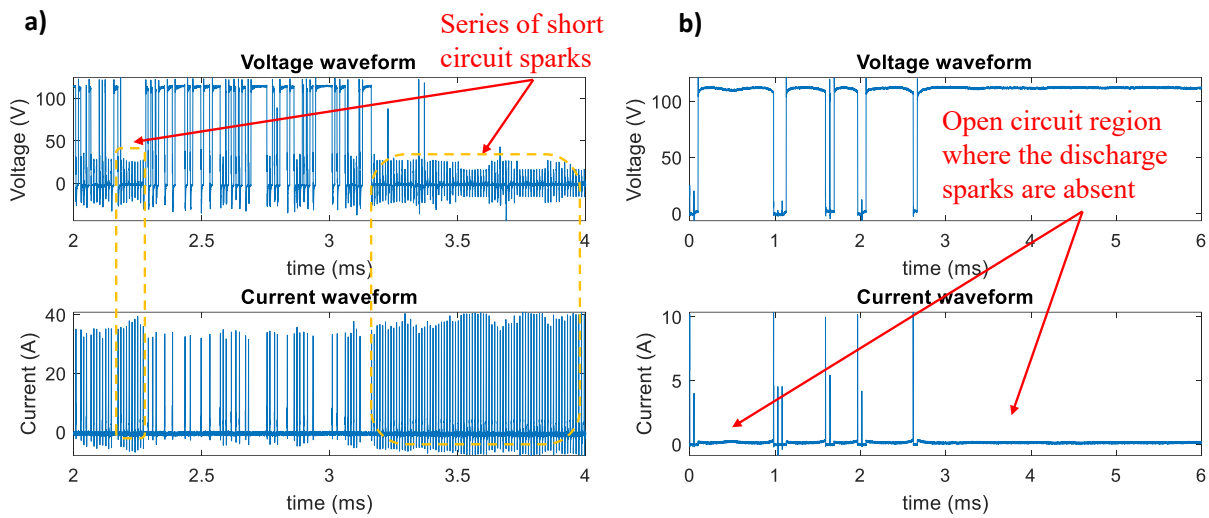


Fig. 4. (a) Pulse cycle leading to wire breakage (b) Inefficient pulse cycle leading to spark absence

A pulse classifier classifies the discharge pulses into normal, arc, short and open circuit pulses. A rule-based method is used for pulse classification, which categorizes individual pulses based on ignition delay duration (T_d). The pulses where T_d is absent ($T_d = 0$ µs) is classified as short circuit pulses and the pulses with negligible T_d ($T_d < 8$ µs) are classified as arc pulses. Open circuit pulses are the ones with unusually large T_d ($T_d > 160$ µs). Every other pulse with ideal ignition delay time is classified as normal spark discharges. Normal and arc contributes to material removal, whereas

the other two are unfavorable pulse causing wire breakages and inefficient machining. Based on these observations, discharge features considered to feed ANN classifier are discharge energy, spark frequency, short circuit ratio and open circuit ratio. Training dataset contains 108 sample data by machining 10 mm straight rough cuts. The trained ANN classifier was having an accuracy of 89

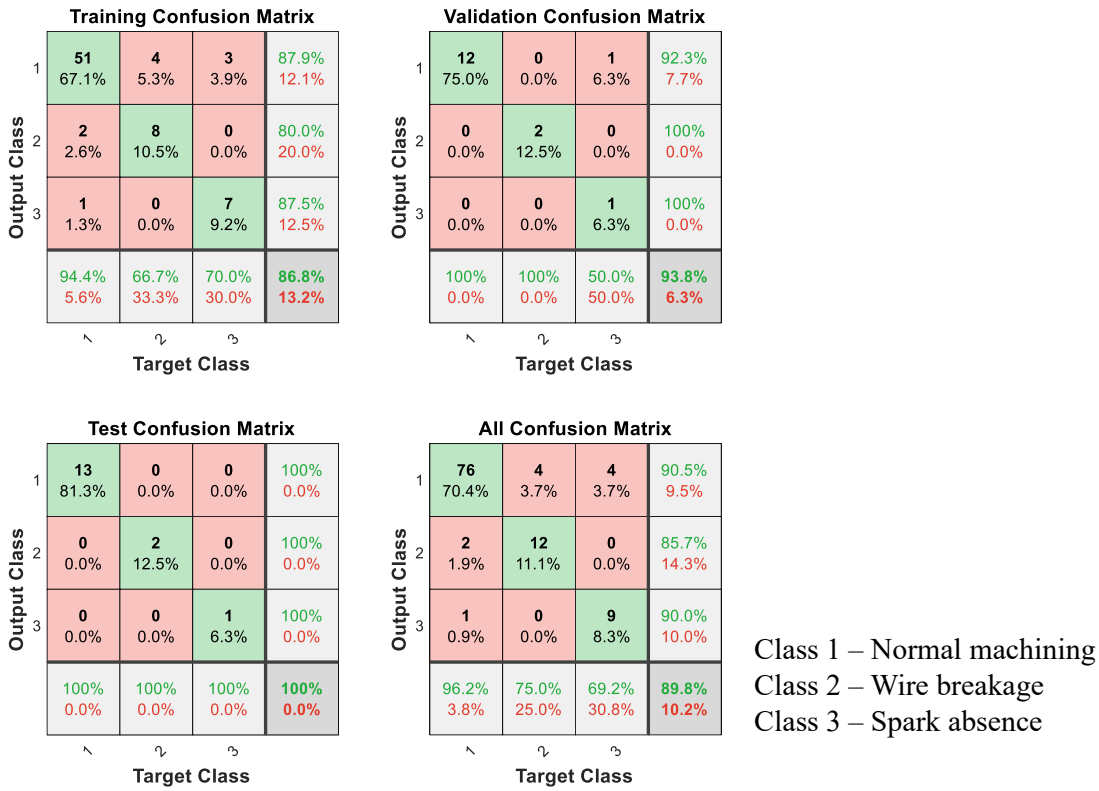


Fig. 5. Confusion matrix showing classifier performance

In the cases of wire break and spark absence, remaining useful life (RUL) was also noted as the response. The parameter RUL is defined as the time duration for which the machining process is likely to continue before repair or failure. It is calculated by recording the time till an event of failure is observed (either wire break or spark absence) by using a stopwatch. An ANN regression model is developed to predict the RUL parameter. This parameter is used to develop a process control algorithm which is discussed in the following subsection. The regression plots of the

trained ANN regression model are shown in Fig. 6. The obtained closeness coefficient (R value) is 0.988, which indicates a good prediction accuracy for the trained model.

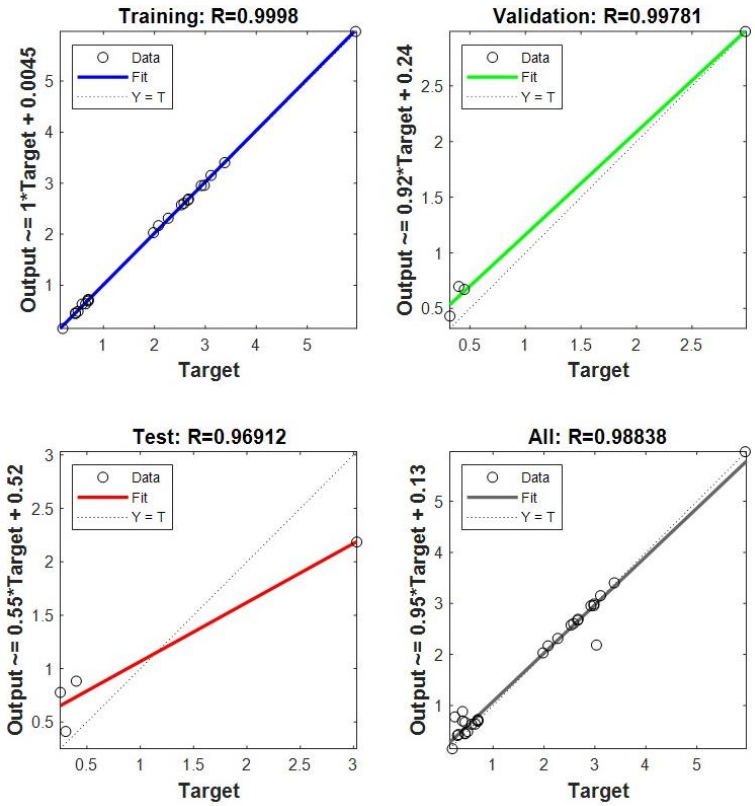


Fig. 6. Regression plot for trained neural network model to predict remaining useful life (RUL)

4.1 Process control algorithm

The process control algorithm framework is given in Fig. 7. The discharge features, extracted from process signals can be fed to a neural network classifier to predict the occurrence of process failure. If the classifier predicts a machining failure, then another neural network model predicts the remaining useful life (RUL) before failure. The parameter RUL, indicates the severity of the instability. Based on the outputs of these classifier and regression models, a process control methodology is proposed to re-establish the machining stability. In case of wire breakage two modes of failures are reported. Type I failure is an immediate failure where the failure happens as soon as the machining starts. Type I failure happens when there is physical contact between wire

and workpiece when the machining commences. Type II failure is a result of gradual build-up of machining instability [29].

Type II failure happens as a result of unideal spark gap conditions mostly resulting from debris accumulation and stagnation leading to spark gap bridging. This is a complex phenomenon depending upon many process variables and uncontrollable factors. Among controllable factors, discharge energy, pulse off time, and inter electrode gap (IEG) affects the gap stability. High discharge energy increases thermal load on the wire electrode and can have a negative effect on the wire strength. Additionally, high discharge energy implies more debris in the spark gap. Pulse off time (T_{OFF}) is the time duration between the discharge pulses, utilized for flushing away the suspended debris and restoration of dielectric properties in the spark gap. Lesser than optimum T_{OFF} results in partial removal of debris. Spark gap distance too has a similar effect on gap stability. A narrow spark gap enhances the tendency of gap bridging. Also, it makes removal of debris by dielectric flushing harder. Based on these observations, pulse on time, pulse off time, and servo voltage were selected for process control, in case of failure prediction.

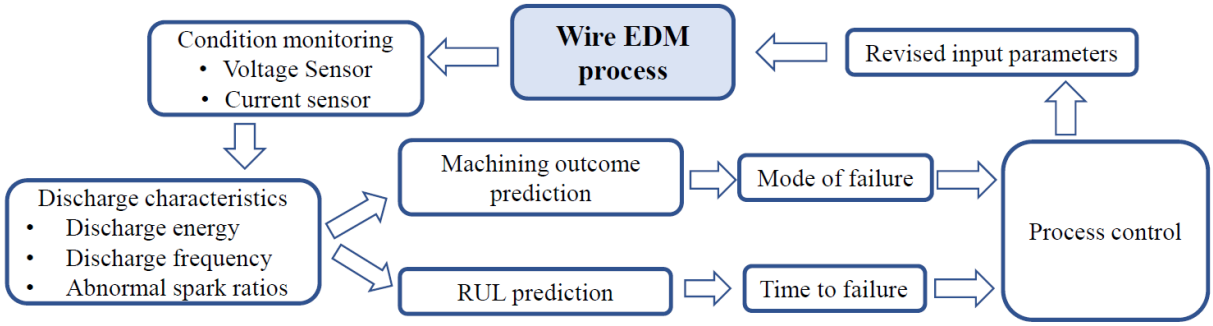


Fig. 7. Approach for wire EDM process control

A rule based heuristic approach is given in Fig. 8 for wire EDM process control. The mode of failure is predicted by the neural network classifier. In case a failure is predicted, an ANN model predicts the remaining useful life (RUL). A small RUL value indicates higher machining instability

and vice versa. In case of wire breakage, the unstable conditions are categorized into three based on predicted RUL. Shortest RUL (< 1 min) needs the maximum correction to restore the spark gap condition. Therefore, pulse off time, pulse on time and servo voltage is adjusted which increases the flushing time, decreases the discharge energy, and increases the inter electrode gap distance respectively. The intermediate category of instability (RUL between 1 to 5 min), needs adjustments in pulse off time and servo voltage. Finally, for the last case (RUL > 5 min), only the pulse off time is adjusted.

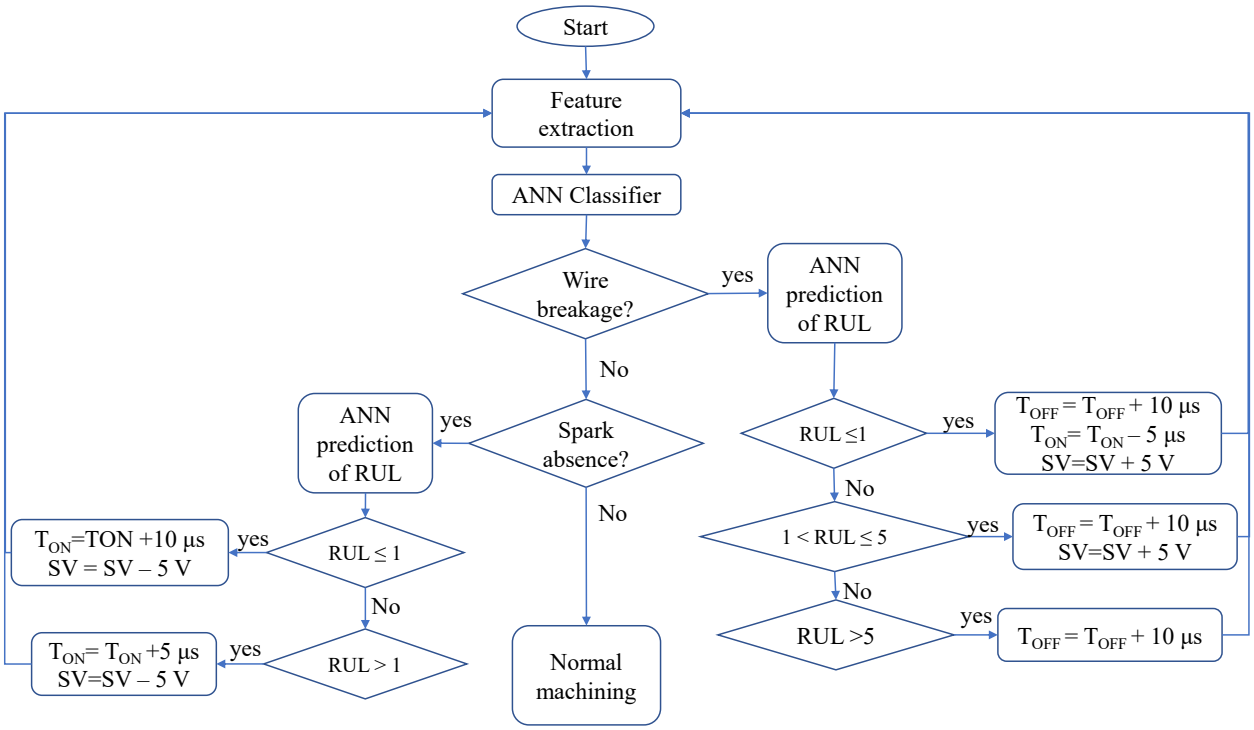


Fig. 8. Flowchart of process control

In case of spark absence, based on predicted RUL, measures are taken to ensure continuous normal spark pulses to restore the productivity back to the desired level. Pulse on time and servo voltage are varied by the proposed algorithm in this regard. This is because weaker sparks or their absence are mainly caused by higher and inappropriate inter electrode distance, or the energy is insufficient to breach the dielectric barrier. If RUL < 1 min, then pulse on time is increased and

servo voltage is decreased to increase the discharge energy and decrease spark gap distance respectively. If RUL > 1 min, then only the spark gap distance is adjusted.

4.2 Validation tests

Twelve validation trials were conducted by selecting random combination of input parameters to test the real-world performance of the developed models. The results of the validation tests are given in Table 6. It can be observed that the neural network classifier was able to rightly predict the machining outcomes in each of the 12 cases. Also, the RUL prediction by ANN regression was very accurate, based on which the process control was performed. Two such cases are discussed in detail separately in the upcoming subsection.

4.2.1 Case 1: Process control to prevent wire breakage

Validation Exp. No. 1 is considered to demonstrate the effects of process control on the signal characteristics, failure situation and surface integrity of machined components. ANN classifier predicts wire break failure and the predicted RUL falls in the second category for this case (RUL between 1 to 5 mins). For this category of machining instability, proposed algorithm increases pulse off time by 10 µs and servo voltage by 5 V. The controlled settings (T_{OFF} = 40 µs, SV = 40 V) resulted in continuous failure-free machining. A comparison of discharge pulse characteristics is shown in Fig. 9.

4.2.2 Case II: Process control to prevent spark absence

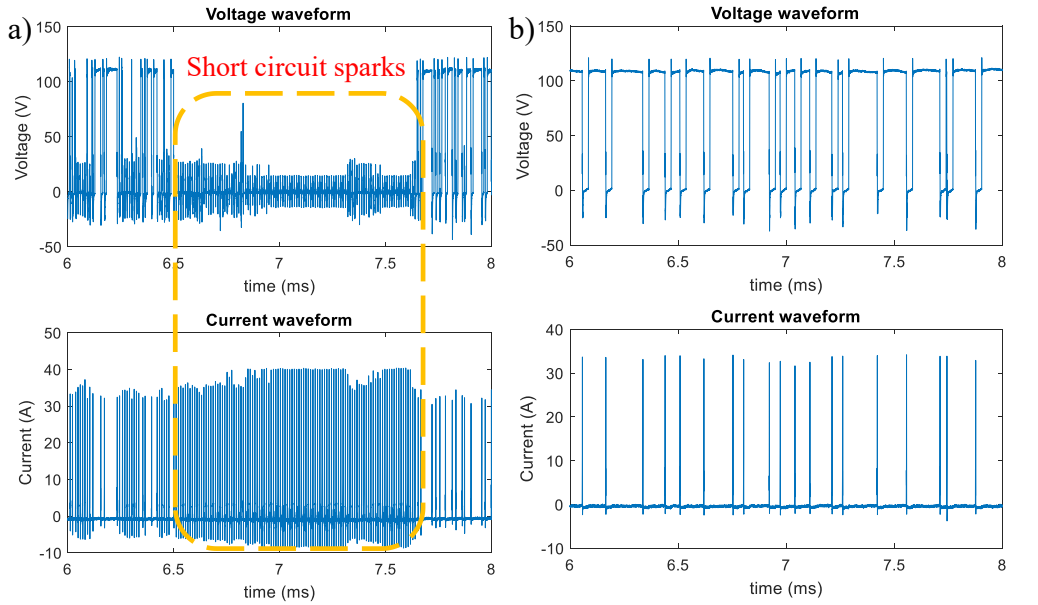
Validation Exp. No. 5 is considered to demonstrate the effects of process control for spark absence case. ANN classifier predicts spark absence and the predicted RUL falls in the second category for this case (RUL > 1 min). For this category of machining instability, proposed algorithm increases pulse on time by 5 µs and reduces servo voltage by 5 V. The controlled settings (T_{ON} = 110 µs, SV = 43 V) resulted in continuous machining. A comparison of discharge pulse

characteristics is shown in Fig. 10. The spark absence regions are replaced by repetitive normal discharge pulses.

Table 6. Results of neural network classification prediction during validation trials

S. No	T_{ON} (µs)	T_{OFF} (µs)	SV (V)	I_P (A)	WF (m/min)	DE (µJ)	SSR	OSR	SF (Hz)	Predicted Class Probability			Predicted Event	True Event	RUL Predicted (min)	RUL (min)
										NM	WB	SA				
1	113	30	35	40	3	1568.86	0.94	0.00	84600	0.00	**1.00**	0.00	WB	WB	2.23	3.2
2	115	32	33	40	3	1705.05	0.55	0.01	61200	0.00	**1.00**	0.00	WB	WB	10.07	9.58
3	110	33	31	40	3	990.31	0.26	0.08	21350	0.01	**0.99**	0.00	WB	WB	4.15	3.72
4	112	30	30	40	3	559.54	0.72	0.00	62500	0.04	**0.96**	0.00	WB	WB	6.55	5.21
5	105	50	48	10	3	58.58	0.17	0.50	300	0.35	0.00	**0.65**	SA	SA	3.05	2.91
6	107	45	50	10	3	49.30	9.73	4.09	550	0.21	0.00	**0.79**	SA	SA	3.36	2.7
7	108	40	55	40	3	433.39	0.04	0.08	9650	**0.99**	0.00	0.01	NM	NM	-	-
8	110	42	43	40	3	502.84	0.03	0.24	7600	**0.97**	0.00	0.03	NM	NM	-	-
9	110	38	36	40	3	801.76	0.08	0.18	7700	**1.00**	0.00	0.00	NM	NM	-	-
10	112	35	30	40	3	890.71	0.17	0.21	7450	**1.00**	0.00	0.00	NM	NM	-	-
11	110	50	38	10	3	53.28	0.17	0.01	32150	**1.00**	0.00	0.00	NM	NM	-	-
12	112	45	40	10	3	64.49	0.13	0.00	30150	**1.00**	0.00	0.00	NM	NM	-	-

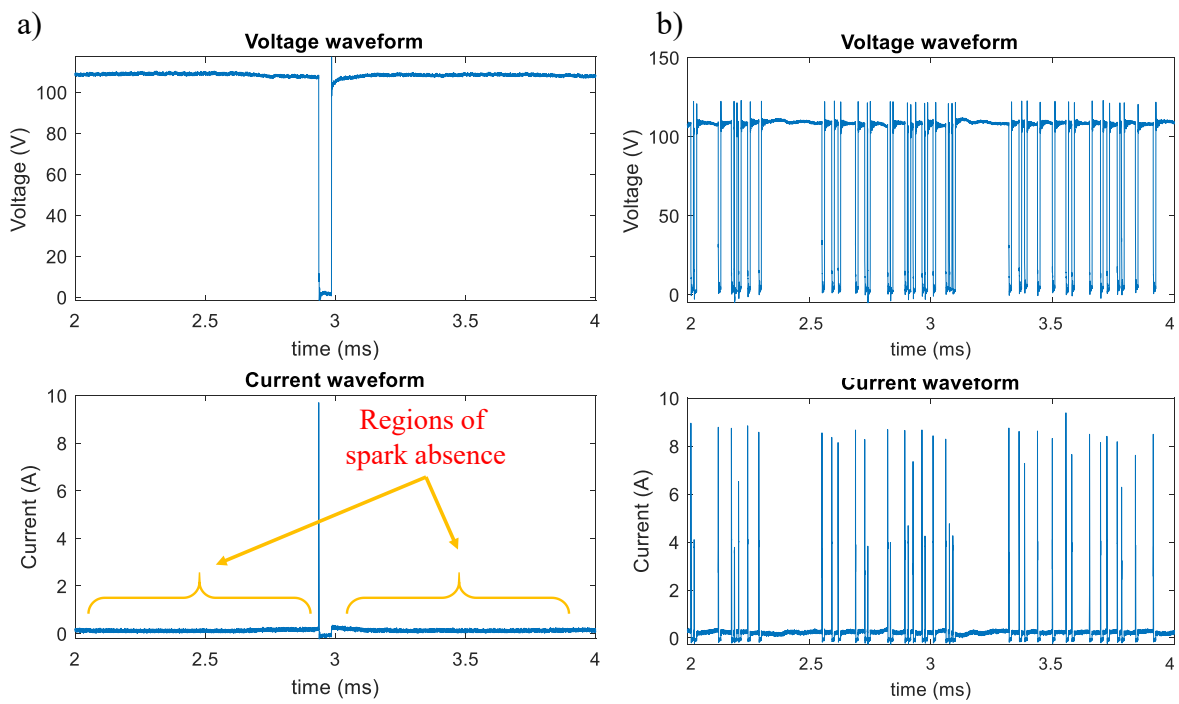
DE- discharge energy/spark, SSR- short circuit ratio, OSR- open circuit ratio, SF- spark frequency, NM- normal machining, WB- wire breakage, SA- spark absence, RUL- remaining useful life



Original parameter settings: T_{ON}= 113 µs, T_{OFF}= 30 µs, SV= 35V, WF= 3 m/min, I_p=40 A

Controlled parameter settings: T_{ON}= 113 µs, T_{OFF}= 40 µs, SV= 40V, WF= 3 m/min, I_p= 40 A

Fig. 9. (a) Original settings (Conf test: Exp. No. 1) (b) Controlled settings



Original parameter settings: T_{ON}= 105 µs, T_{OFF}= 50 µs, SV= 48V, WF= 3 m/min, I_p=10 A

Controlled parameter settings: T_{ON}= 110 µs, T_{OFF}= 50 µs, SV= 43V, WF= 3 m/min, I_p=10 A

Fig. 10. (a) Original settings (Conf test: Exp. No. 5) (b) Controlled settings

The improvement in machining stability after process control is also performed by microstructural analysis. SEM images of worn wire samples were compared for validation test Exp. No. 1. Fig. 11 (a) shows the worn wire surface with severe surface degradation. Zinc coating is observed to be removed in many areas, with debris impinged to the surface. Removal of zinc coating exposes the core brass electrode which is more susceptible to sudden rupture. Presence of debris indicates the debris stagnation and spark gap bridging. If the unstable process condition persists, the surface degradation continues till a limiting point where the wire will lose the strength to withstand the axial tension. At this point, the wire electrode starts to elongate at the region of maximum wire wear by reducing the cross section, until the eventual failure through rupture. Fig. 11 (b) shows the broken wire tip in conical shape. The situation can be avoided by retuning the process parameters at some point before the advent of wire elongation. The proposed control

strategy was successful in restoring the machining stability. This is the reason for minimal wire wear after process control as shown in Fig. 11 (c).

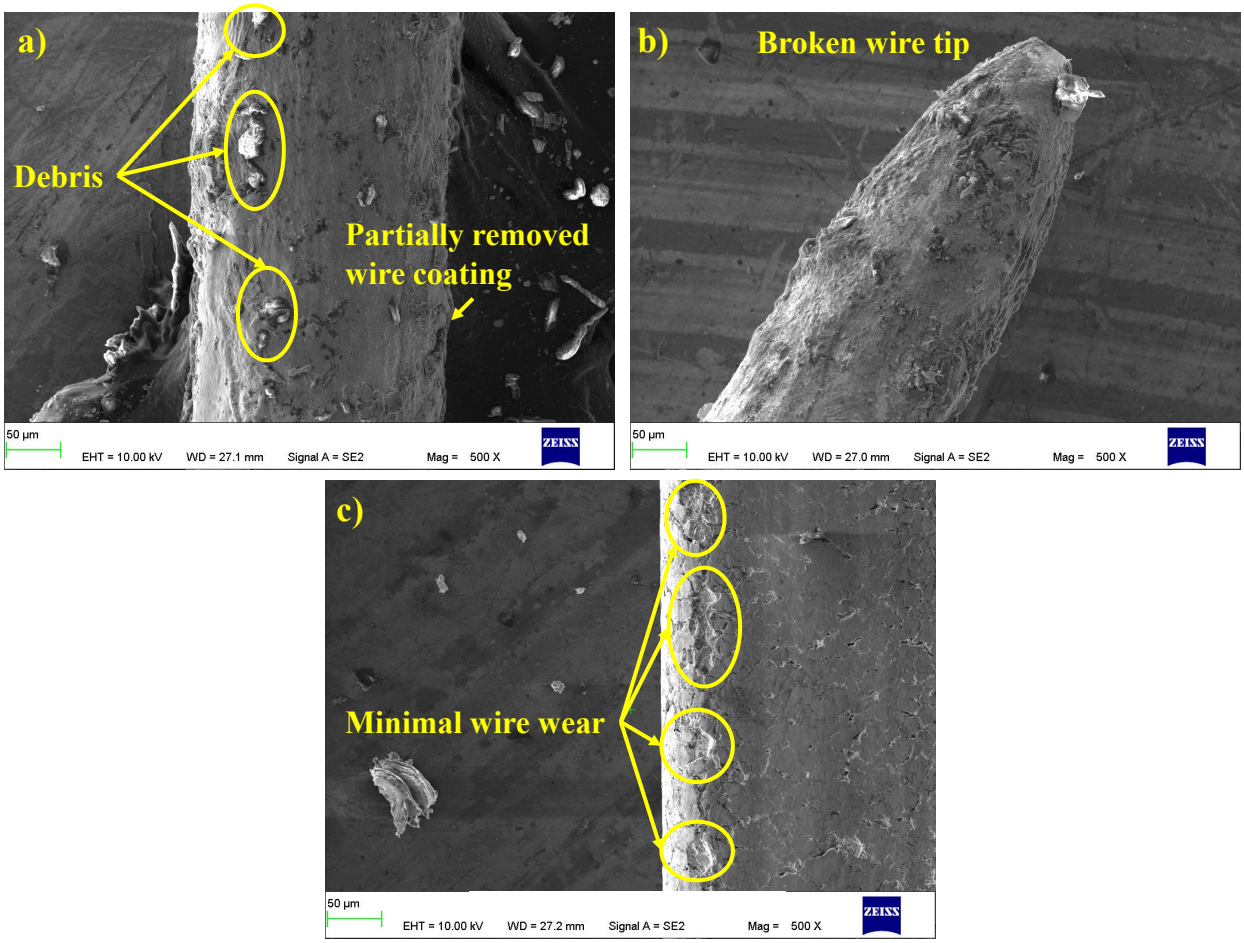


Fig. 11. (a) Severely degraded wire surface under original settings (b) Broken wire tip (c) Minimal wear after process control

The machined surface integrity also improves with process control as shown in Fig. 12. The surface is observed with various recast micro features like micro globules and pits under original settings corresponding to validation test Exp. No. 1. After process control, the machined surface is observed to be much smoother. Average surface roughness, R_a, of machined surfaces before and after process control is compared in Fig. 13 for all failure cases in validation tests. As proved by the reported data, the surface roughness is reduced after process control in each case. The

improvement of the surface finishing is more prominent in wire breakage cases, due to the reduction of undesirable discharge sparks, especially arc discharges, which are one of the main reasons for surface irregularities and damages.

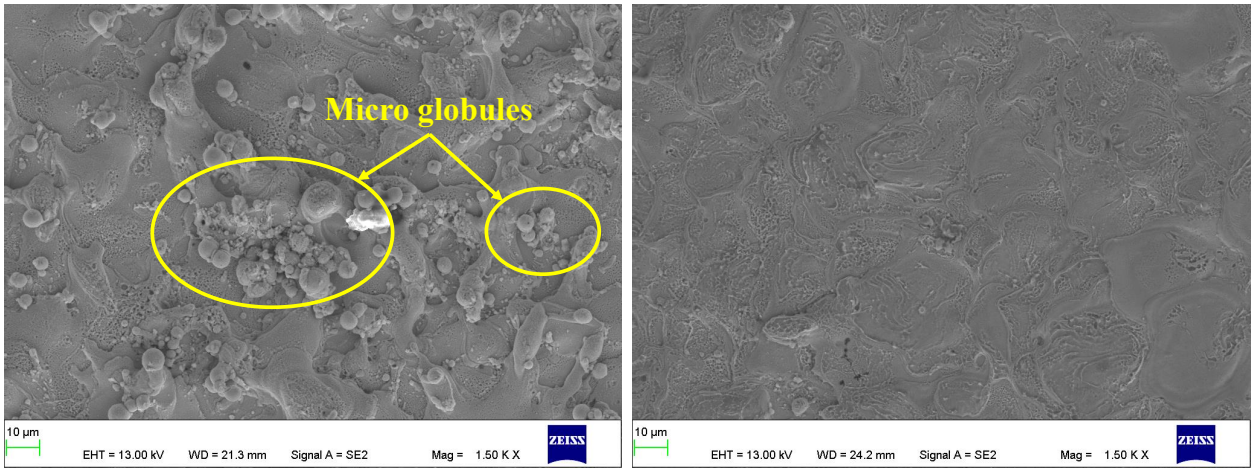


Fig. 12. SEM images of machined surface (a) under original settings (b) after process control

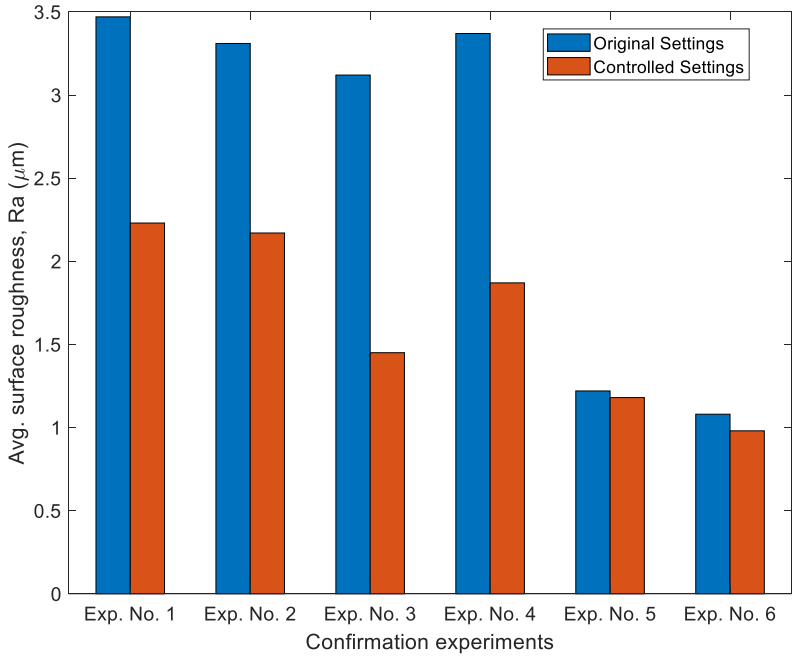


Fig. 13. Effect of process control on surface roughness of machined components

5. Conclusions

The current study proposes a machine learning (ML) based failure prediction and control system for wire EDM process. A condition monitoring system is setup consisting of current and voltage sensors. Relevant discharge characteristic features are extracted from the pulse train data. Failure detection is based on a neural network classifier, which categorizes the machining outcomes into failure and non-failure groups. If a potential failure is identified by classifier, another neural network model predicts the remaining useful life (RUL) till failure. Based on RUL value, a process control algorithm re-tunes the process parameters to restore the machining stability. To train the neural network models, 108 experiments were conducted. The proposed model was found capable of predicting and avoiding the process failures, which was proven by conducting additional validation tests. Through process control, not only a continuous, failure-free machining was ensured, but also the surface integrity of machined components was improved.

Appendix

Table 7. Details of the 108 experiments

S. No	T_{ON} (µs)	T_{OFF} (µs)	SV (V)	I_P (A)	WF (m/min)	DE /spark (µJ)	NSR	ASR	SSR	OSR	SF	MO	RUL (min)
1	105	30	30	40	3	1614	0.11	0.01	0.83	0.05	75000	WB	2.66
2	105	30	50	40	3	508	0.29	0.07	0.35	0.29	31000	NM	-
3	105	40	30	40	3	544	0.42	0.05	0.38	0.15	12000	NM	-
4	105	40	50	40	3	560	0.12	0.00	0.4	0.48	26000	NM	-
5	105	50	30	40	3	549	0.28	0.00	0.42	0.3	28500	NM	-
6	105	50	50	40	3	583	0.07	0.00	0.36	0.57	14000	NM	-
7	110	30	30	40	3	1044	0.24	0.06	0.38	0.32	56500	WB	0.32
8	110	30	50	40	3	1066	0.28	0.03	0.41	0.28	45000	WB	2.08
9	110	40	30	40	3	1034	0.27	0.02	0.31	0.4	22500	NM	-
10	110	40	50	40	3	987	0.17	0.02	0.52	0.29	69000	WB	3.11
11	110	50	30	40	3	1124	0.46	0.03	0.38	0.13	16000	NM	-
12	110	50	50	40	3	1002	0.15	0.02	0.51	0.32	50500	WB	5.95
13	115	30	30	40	3	1477	0.15	0.05	0.54	0.26	82500	WB	0.58
14	115	30	50	40	3	1596	0.60	0.00	0.11	0.29	9000	NM	-

15	115	40	30	40	3	1485	0.15	0.22	0.53	0.1	65500	WB	2.67
16	115	40	50	40	3	1646	0.59	0.00	0.17	0.24	11500	NM	-
17	115	50	30	40	3	1618	0.51	0.00	0.17	0.32	11500	NM	-
18	115	50	50	40	3	1659	0.70	0.00	0.2	0.1	5000	NM	-
19	105	30	30	10	3	157	0.59	0.07	0.23	0.11	25000	NM	-
20	105	30	50	10	3	77	0.32	0.04	0.33	0.31	24500	NM	-
21	105	40	30	10	3	135	0.42	0.03	0.24	0.31	34000	NM	-
22	105	40	50	10	3	48	0.30	0.08	0.04	0.58	12000	SA	0.7
23	105	50	30	10	3	32	0.66	0.03	0	0.31	13500	SA	0.7
24	105	50	50	10	3	43	0.17	0.08	0.31	0.44	19500	SA	0.3
25	110	30	30	10	3	141	0.39	0.00	0.38	0.23	6500	NM	-
26	110	30	50	10	3	145	0.22	0.14	0.34	0.3	39500	NM	-
27	110	40	30	10	3	239	0.39	0.06	0.39	0.16	13500	NM	-
28	110	40	50	10	3	123	0.34	0.04	0.37	0.25	37500	NM	-
29	110	50	30	10	3	253	0.21	0.05	0.36	0.38	21000	NM	-
30	110	50	50	10	3	43	0.10	0.00	0.45	0.45	14500	SA	0.5
31	115	30	30	10	3	135	0.61	0.14	0.14	0.11	27000	NM	-
32	115	30	50	10	3	161	0.49	0.02	0.16	0.33	32000	NM	-
33	115	40	30	10	3	122	0.63	0.04	0.28	0.05	57500	NM	-
34	115	40	50	10	3	139	0.25	0.03	0.41	0.31	19500	NM	-
35	115	50	30	10	3	241	0.34	0.04	0.24	0.38	22500	NM	-
36	115	50	50	10	9	66	0.36	0.03	0.13	0.48	15500	SA	0.45
37	105	30	30	40	9	1382	0.10	0.11	0.79	0	68450	WB	2.98
38	105	30	50	40	9	483	0.57	0.15	0.26	0.02	25150	NM	-
39	105	40	30	40	9	477	0.41	0.26	0.33	0	23400	NM	-
40	105	40	50	40	9	528	0.53	0.22	0.24	0.01	24000	NM	-
41	105	50	30	40	9	503	0.39	0.28	0.33	0	22800	NM	-
42	105	50	50	40	9	553	0.70	0.11	0.1	0.09	11500	NM	-
43	110	30	30	40	9	958	0.27	0.19	0.53	0.01	77000	WB	2.27
44	110	30	50	40	9	1031	0.55	0.11	0.15	0.19	7800	NM	-
45	110	40	30	40	9	981	0.14	0.21	0.62	0.03	55250	WB	2.98
46	110	40	50	40	9	1044	0.60	0.12	0.16	0.12	8950	NM	-
47	110	50	30	40	9	1059	0.56	0.19	0.24	0.01	12100	NM	-
48	110	50	50	40	9	1062	0.49	0.13	0.18	0.2	7550	NM	-
49	115	30	30	40	9	1627	0.27	0.22	0.51	0	48600	WB	1.98
50	115	30	50	40	9	1693	0.71	0.07	0.11	0.11	9150	NM	-
51	115	40	30	40	9	1643	0.37	0.20	0.42	0.01	55200	WB	2.53
52	115	40	50	40	9	1642	0.56	0.11	0.21	0.12	9400	NM	-
53	115	50	30	40	9	1631	0.56	0.18	0.26	0	12750	NM	-
54	115	50	50	40	9	1640	0.56	0.11	0.16	0.17	7550	NM	-
55	105	30	30	10	9	123	0.75	0.07	0.18	0	29950	NM	-
56	105	30	50	10	9	228	0.66	0.08	0.25	0.01	37900	NM	-
57	105	40	30	10	9	339	0.60	0.09	0.31	0	20750	NM	-
58	105	40	50	10	9	351	0.64	0.05	0.24	0.07	19650	NM	-

59	105	50	30	10	9	245	0.62	0.07	0.3	0.01	23950	NM	-
60	105	50	50	10	9	37	0.59	0.05	0.32	0.04	17650	SA	0.45
61	110	30	30	10	9	135	0.59	0.08	0.33	0	20550	NM	-
62	110	30	50	10	9	248	0.43	0.05	0.26	0.26	6600	NM	-
63	110	40	30	10	9	140	0.64	0.05	0.31	0	15900	NM	-
64	110	40	50	10	9	249	0.62	0.04	0.28	0.06	12400	NM	-
65	110	50	30	10	9	136	0.56	0.03	0.4	0.01	14700	NM	-
66	110	50	50	10	9	152	0.51	0.03	0.25	0.21	6550	NM	-
67	115	30	30	10	9	144	0.68	0.07	0.23	0.02	15450	NM	-
68	115	30	50	10	9	253	0.63	0.04	0.21	0.12	9400	NM	-
69	115	40	30	10	9	138	0.58	0.08	0.32	0.02	16300	NM	-
70	115	40	50	10	9	50	0.51	0.03	0.27	0.19	8400	NM	-
71	115	50	30	10	9	149	0.73	0.04	0.21	0.02	12600	NM	-
72	115	50	50	10	9	55	0.52	0.03	0.29	0.16	7950	NM	-
73	105	30	40	40	3	515	0.71	0.06	0.23	0	27950	NM	-
74	105	40	40	40	3	567	0.73	0.06	0.21	0	23000	NM	-
75	105	50	40	40	3	523	0.72	0.04	0.21	0.03	17400	NM	-
76	110	30	40	40	3	1650	0.36	0.07	0.57	0	46100	WB	2.92
77	110	40	40	40	3	1087	0.74	0.01	0.22	0.03	10950	NM	-
78	110	50	40	40	3	1104	0.79	0.02	0.16	0.03	10600	NM	-
79	115	30	40	40	3	1600	0.79	0.02	0.15	0.04	12800	NM	-
80	115	40	40	40	3	1654	0.53	0.03	0.41	0.03	50650	WB	3.03
81	115	50	40	40	3	1586	0.71	0.02	0.24	0.03	11500	NM	-
82	105	30	40	10	3	134	0.59	0.07	0.34	0	21900	NM	-
83	105	40	40	10	3	228	0.67	0.06	0.26	0.01	38500	NM	-
84	105	50	40	10	3	151	0.74	0.05	0.17	0.04	20400	NM	-
85	110	30	40	10	3	55	0.34	0.05	0.1	0.51	16200	SA	0.65
86	110	40	40	10	3	35	0.39	0.05	0.27	0.29	15150	SA	0.4
87	110	50	40	10	3	43	0.22	0.06	0.22	0.5	11800	SA	0.25
88	115	30	40	10	3	134	0.59	0.04	0.31	0.06	15850	NM	-
89	115	40	40	10	3	138	0.50	0.06	0.35	0.09	13200	NM	-
90	115	50	40	10	3	51	0.37	0.02	0.19	0.42	8400	SA	0.2
91	105	30	40	40	9	1542	0.63	0.06	0.31	0	39250	WB	3.38
92	105	40	40	40	9	554	0.74	0.05	0.21	0	28400	NM	-
93	105	50	40	40	9	541	0.82	0.03	0.14	0.01	16850	NM	-
94	110	30	40	40	9	512	0.55	0.06	0.39	0	27750	NM	-
95	110	40	40	40	9	1134	0.75	0.02	0.17	0.06	10250	NM	-
96	110	50	40	40	9	1101	0.74	0.03	0.21	0.02	11200	NM	-
97	115	30	40	40	9	1625	0.54	0.02	0.41	0.03	40900	WB	2.58
98	115	40	40	40	9	1554	0.72	0.04	0.19	0.05	11000	NM	-
99	115	50	40	40	9	1594	0.76	0.02	0.18	0.04	10050	NM	-
100	105	30	40	10	9	131	0.63	0.07	0.3	0	13350	NM	-
101	105	40	40	10	9	235	0.64	0.06	0.3	0	34000	NM	-
102	105	50	40	10	9	135	0.65	0.06	0.22	0.07	15750	NM	-

103	110	30	40	10	9	237	0.72	0.05	0.23	0	20750	NM	-
104	110	40	40	10	9	258	0.60	0.06	0.2	0.14	9900	NM	-
105	110	50	40	10	9	30	0.53	0.04	0.14	0.29	13400	SA	0.45
106	115	30	40	10	9	239	0.57	0.04	0.36	0.03	21100	NM	-
107	115	40	40	10	9	33	0.39	0.06	0.16	0.39	14350	SA	0.7
108	115	50	40	10	9	41	0.38	0.04	0.16	0.42	11750	SA	0.4

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References

1. Ho KH, Newman ST, Rahimifard S, Allen RD (2004) State of the art in wire electrical discharge machining (WEDM). Int J Mach Tools Manuf 44:1247–1259. https://doi.org/10.1016/j.ijmachtools.2004.04.017
2. Mandal A, Dixit AR (2014) State of art in wire electrical discharge machining process and performance. Int J Mach Mach Mater 16:1. https://doi.org/10.1504/IJMMM.2014.063918
3. K. P. Rajurkar; W. M. Wang (1991) On-Line Monitor and Control for Wire Breakage in WEDM. Ann CIRP 40:219–222. https://doi.org/10.1016/j.procir.2017.12.059
4. Kwon S, Yang MY (2006) The benefits of using instantaneous energy to monitor the transient state of the wire EDM process. Int J Adv Manuf Technol 27:930–938. https://doi.org/10.1007/s00170-004-2252-y

5. Yan MT, Liao YS (1996) A self-learning Fuzzy controller for wire rupture prevention in WEDM. Int J Adv Manuf Technol 11:267–275. https://doi.org/10.1007/BF01351284
6. Liao YS, Woo JC (2000) Design of a fuzzy controller for the adaptive control of WEDM process. Int J Mach Tools Manuf 40:2293–2307. https://doi.org/10.1016/S0890-6955(00)00036-5
7. Bufardi A, Akten O, Arif M, Xirouchakis P (2017) Towards zero-defect manufacturing with a combined online - offline fuzzy-nets approach in wire electrical discharge machining. 401–409
8. Abhilash PM, Chakradhar D (2020) ANFIS modelling of mean gap voltage variation to predict wire breakages during wire EDM of Inconel 718. CIRP J Manuf Sci Technol 31:153–164. https://doi.org/10.1016/j.cirpj.2020.10.007
9. Abhilash PM, Chakradhar D (2021) Sustainability improvement of WEDM process by analysing and classifying wire rupture using kernel - based naive Bayes classifier. J Brazilian Soc Mech Sci Eng 43:. https://doi.org/10.1007/s40430-021-02805-z
10. Janardhan V, Samuel GL (2010) Pulse train data analysis to investigate the effect of machining parameters on the performance of wire electro discharge turning (WEDT) process. Int J Mach Tools Manuf 50:775–788. https://doi.org/10.1016/j.ijmachtools.2010.05.008
11. Yan MT, Hsieh PH (2015) An on-line monitoring system for wire electrical discharge turning process. Proc Inst Mech Eng Part B J Eng Manuf 229:1945–1954. https://doi.org/10.1177/0954405414543488
12. Oßwald K, Lochmahr I, Schulze H-P, Kröning O (2018) Automated Analysis of Pulse Types in High Speed Wire EDM. Procedia CIRP 68:796–801. https://doi.org/10.1016/j.procir.2017.12.157
13. Conde A, Sanchez JA, Plaza S, et al (2018) Experimental Measurement of Wire-lag Effect and Its Relation with Signal Classification on Wire EDM. Procedia CIRP 68:132–137. https://doi.org/10.1016/j.procir.2017.12.035
14. Cabanes I, Portillo E, Marcos M, Sánchez JA (2008) An industrial application for on-line detection of instability and wire breakage in wire EDM. J Mater Process Technol 195:101–109. https://doi.org/10.1016/j.jmatprotec.2007.04.125
15. Klocke F, Welling D, Klink A, Perez R (2014) Quality assessment through in-process monitoring of wire-EDM for fir tree slot production. New Prod Technol Aerosp Ind - 5th Mach Innov Conf (MIC 2014)-Procedia CIRP 24:97–102. https://doi.org/10.1016/j.procir.2014.07.136
16. Caggiano A, Perez R, Segreto T, et al (2016) Advanced Sensor Signal Feature Extraction and Pattern Recognition for Wire EDM Process Monitoring. Procedia CIRP 42:34–39. https://doi.org/10.1016/j.procir.2016.02.181

17. Caggiano A, Teti R, Perez R, Xirouchakis P (2015) Wire EDM monitoring for zero-defect manufacturing based on advanced sensor signal processing. Procedia CIRP 33:315–320. https://doi.org/10.1016/j.procir.2015.06.065
18. Bergs T, Tombul U, Herrig T, et al (2018) Analysis of Characteristic Process Parameters to Identify Unstable Process Conditions during Wire EDM. Procedia Manuf 18:138–145. https://doi.org/10.1016/j.promfg.2018.11.018
19. Rajeswari R, Shunmugam MS (2019) Investigations into process mechanics of rough and finish die sinking EDM using pulse train analysis. Int J Adv Manuf Technol 100:1945–1964. https://doi.org/10.1007/s00170-018-2701-7
20. Marrocco V, Modica F, Fassi I (2019) Analysis of discharge pulses in micro-EDM milling of Si3N4-TiN composite workpiece by means of power spectral density (PSD). J Manuf Process 43:112–118. https://doi.org/10.1016/j.jmapro.2019.05.017
21. Marrocco V, Modica F, Bellantone V, et al (2020) Pulse-type influence on the micro-edm milling machinability of si3 n4 –tin workpieces. Micromachines 11 https://doi.org/10.3390/mi11100932
22. Mwangi JW, Bui VD, Thüsing K, et al (2020) Characterization of the arcing phenomenon in micro-EDM and its effect on key mechanical properties of medical-grade Nitinol. J Mater Process Technol 275:116334. https://doi.org/10.1016/j.jmatprotec.2019.116334
23. Mendes LA, Amorim FL, Weingaertner WL (2014) Automated system for the measurement of spark current and electric voltage in wire EDM performance. J Brazilian Soc Mech Sci Eng 37:123–131. https://doi.org/10.1007/s40430-014-0171-x
24. Zhidong L, Haoran C, Huijun P, et al (2014) Automatic control of WEDM servo for silicon processing using current pulse probability detection. Int J Adv Manuf Technol 76:367–374. https://doi.org/10.1007/s00170-014-6252-2
25. Thakur DG, Ramamoorthy B, Vijayaraghavan L (2009) Study on the machinability characteristics of superalloy Inconel 718 during high speed turning. Mater Des 30:1718–1725. https://doi.org/10.1016/j.matdes.2008.07.011
26. Reed RC (2006) The Superalloys Fundamentals and Applications. Cambridge University Press
27. Sargent DJ (2001) Comparison of artificial neural networks with other statistical approaches: Results from medical data sets. Cancer 91:1636–1642. https://doi.org/10.1002/1097-0142(20010415)91:8+<1636::aid-cncr1176>3.0.co;2-d
28. Abhilash PM, Chakradhar D (2021) Failure detection and control for wire EDM process using multiple sensors. CIRP J Manuf Sci Technol 33:315–326. https://doi.org/10.1016/j.cirpj.2021.04.009

29. Arunachalam C, Aulia M, Bozkurt B, Eubank PT (2001) Wire vibration, bowing, and breakage in wire electrical discharge machining. J Appl Phys 89:4255–4262. https://doi.org/10.1063/1.1355281