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Advanced die sinking EDM process monitoring based on anomaly detection for online identification of improper process conditions

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Abstract

Die sinking EDM processes are widely employed in advanced aerospace applications where part quality and machining time are main concerns. The aim of this research work is to develop an advanced EDM process monitoring procedure in the perspective of Zero Defect Manufacturing based on the identification of correlations between die sinking EDM process parameters and improper process conditions that could increase machining time and cause unacceptable part quality. To this purpose, the Real Time Acquisition (RTAQ) module installed on a AgieCharmilles FORM P 600 sinker spark erosion machine tool is utilized to monitor and acquire online data related to 8 selected process parameters with 32 ms sampling interval. An anomaly detection methodology is then applied to timely identify improper process conditions based on relevant features extracted from the EDM process parameters.

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Keywords: Die sinking EDM; Process monitoring; Feature extraction; Anomaly detection

1. Introduction

In the last few years, the employment of electrical discharge machining (EDM) processes in the aerospace industry is increasing due to the large range of applications which includes very small holes, precise cutting of tough, hard and heat resistant metals, machining of cavities with complex geometry [1]. In particular, die-sinking EDM processes are largely utilised for the realization of slots characterised by high depth-to-width ratio on aeroengine components such as turbine blades made of difficult-to-machine materials like Nickel-based alloys [2,3].

In these advanced aerospace applications, part quality and machining time are main concerns. The resulting white layer thickness, metallurgical properties, residual stress, fatigue behaviour, need to be controlled in order to satisfy the quality specifications for the final part, which can be very restrictive in some application fields. In many cases, very conservative EDM process parameters values must be employed, which makes the EDM process extremely inefficient. Machining duration can be negatively affected by several phenomena, such as the decrease of erosion speed which occurs due to the excessive deposit of debris at the bottom of narrow cavities or due to tool electrode wear, which also affects the geometry of the cavity [1]. Moreover, process modelling is particularly challenging due to the stochastic nature of the die sinking EDM process [1,4].

In this framework, the development and implementation of advanced sensor monitoring procedures can be critical to the identification of correlations between die sinking EDM process parameters and improper process conditions responsible for increased machining time and unacceptable part quality. To this purpose, in this research work, an advanced die sinking EDM process monitoring technique

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based on anomaly detection was developed [5–7].

An experimental campaign of die sinking EDM was carried out on a AgieCharmilles sinker spark erosion machine tool, largely employed in the aerospace industry, with different process settings to simulate both standard and anomalous process conditions. The Real Time Acquisition (RTAQ) module installed on the machine tool was employed to monitor and acquire online data related to 8 selected process parameters with 32 ms sampling interval. An anomaly detection procedure was then developed using the features extracted through statistical analysis in the time domain, in order to classify the good machining conditions and identify the improper machining conditions. The final goal is to employ the advanced sensor monitoring procedure for monitoring the EDM process in the perspective of Zero Defect Manufacturing and enhance the productivity by lowering the machining time while fulfilling the restrictive quality requirements imposed on the workpiece surface integrity.

2. Experimental campaign of die sinking EDM

An experimental testing campaign was designed with the aim to reproduce anomalous conditions which could occur during machining of thin slots. First of all, the standard process was tested in order to collect data concerning the good process conditions. Afterwards, selected technological parameters were modified in order to force the degeneration of the die sinking EDM process so as to trigger the occurrence of improper machining conditions.

2.1. Experimental setup

The EDM experimental testing campaign was carried out on a AgieCharmilles FORM P 600 sinker spark erosion machine tool equipped with a Real Time Acquisition (RTAQ) module to acquire online data on selected process parameters.

The workpiece was a 1.2343 steel plate (Fig. 1). A fine graphite tool electrode with dimensions L 35 mm × T 0.4 mm × D 25 mm was employed to realise cavities (slots) with a depth of 6 mm. In each test, 6 consecutive slots with a distance of 1.125 mm between centres were realised with the same tool electrode. After the machining of each slot, tool electrode dressing was performed in order to refresh the electrode erosion surface and remove the pyrolytic graphite deposits which grow on the corners of the electrode. The dressing operation was performed using a reverse polarity technology on a copper workpiece to achieve a 0.5 mm length reduction on the electrode (Fig. 2).

2.2. Experimental testing campaign

In order to develop the anomaly detection methodology, 6 tests (each consisting of 6 consecutive slots) were carried out under standard conditions (“good conditions”). The aim is to collect data on the standard process to be used as a reference for training the system on the identification of anomalous process conditions. The most relevant technological parameters employed in the experimental tests under standard conditions are summarised in Table 1.

Afterwards, 5 different tests (each consisting of 6 consecutive slots) were carried out under modified conditions (“anomalous conditions”) to gather data to be used for the validation of the anomaly detection procedure (Table 2). In particular, defects and improper process conditions were generated by varying the following technological parameters:

- OFF Time (modified to 150 μs)
- Machine Sensitivity (modified to +/-2, +/-3)

Fig. 1. Steel workpiece and tool electrode setup for the EDM tests.

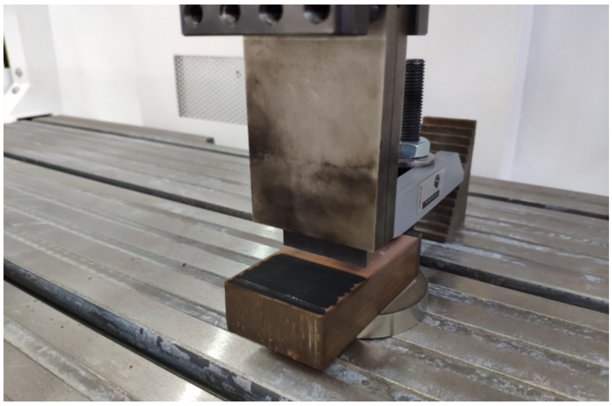


Fig. 2. Copper workpiece setup for tool electrode dressing.

Table 1. Technological parameters used in tests under standard conditions.

Technological parameters	Value
Pulse Current [A]	24
ON Time [μs]	60
OFF Time [μs]	200
Ignition Voltage [V]	220
Machine Sensitivity	0

Table 2. Tests carried out under standard and modified process conditions.

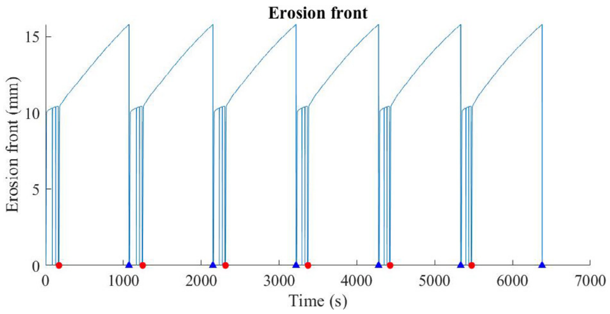
Technological parameters	No. of tests	Total no. of slots
Standard parameters	6	36
OFF Time = 150 μs	1	6
Machine Sensitivity = +2	1	6
Machine Sensitivity = -2	1	6
Machine Sensitivity = +3	1	6
Machine Sensitivity = -3	1	6

2.3. RTAQ data acquisition

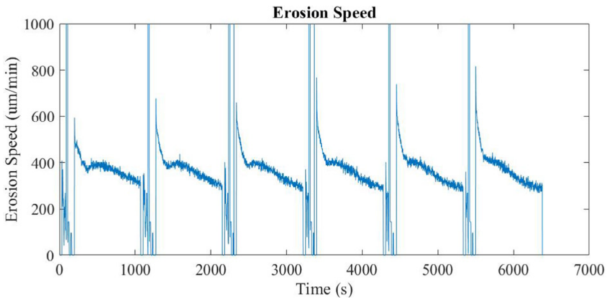
During the experimental tests, the RTAQ module was employed for the acquisition of the following 8 parameters considered significant for monitoring the EDM process:

- Erosion Front [mm]: the relative position of the lower surface of the electrode.
- Pause Average LF [V]: voltage value in the pause.
- Effective Sparks [Sparks/s]: total number of sparks per second, including short circuits.
- Short [Sparks/s]: number of short circuits per second.
- Arc [Sparks/s]: number of arcs per second.
- Erosion Speed [um/min]: current speed of the electrode.
- Spark Voltage [V]: average voltage value during the spark.
- StDevEservo [%]: standard deviation of real adjustment value and target value of the servo-regulator.

The signals related to the listed parameters were acquired form the RTAQ module with a sampling period of 32 ms. Each acquired signal contains the data of the entire machining test, i.e. of the 6 consecutive slots realised woth the same tool electrode (Fig. 3 a-h).



(a)



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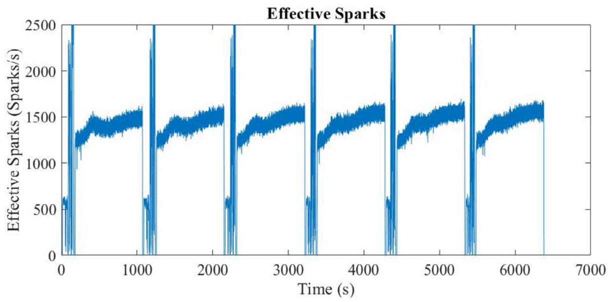

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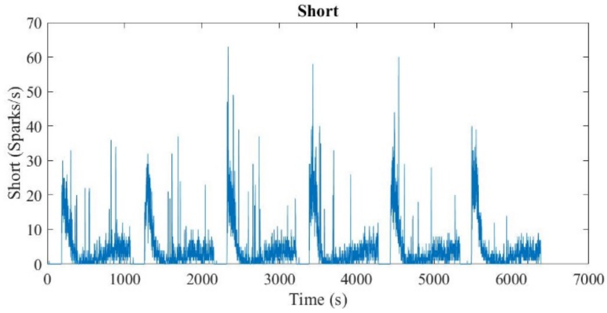

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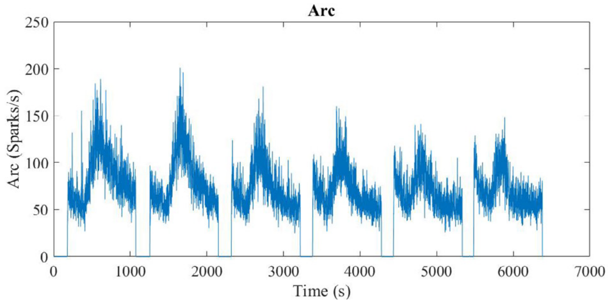

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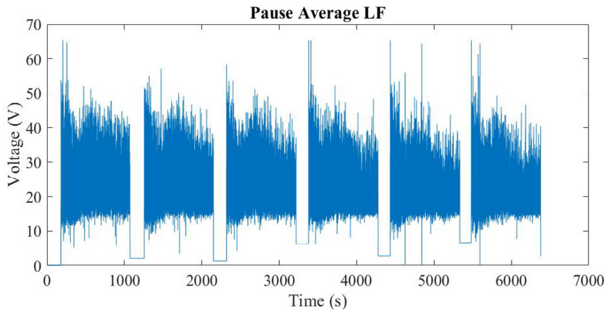

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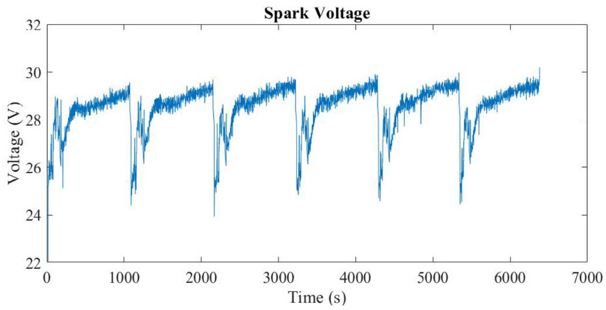
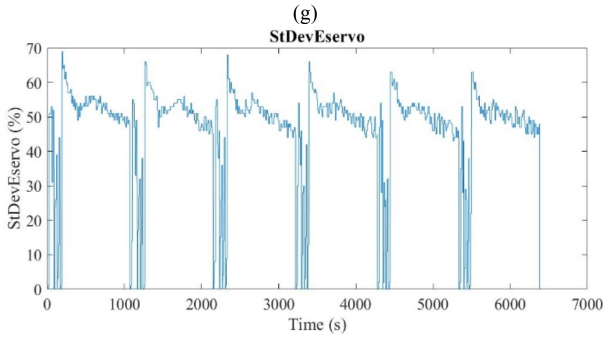


(g)



(h)

Fig. 3. Examples of signals acquired during an experimental test: (a) erosion front, (b) erosion speed, (c) effective sparks, (d) short, (e) arc, (f) pause average, (g) spark voltage, (h) StDevEservo.

3. RTAQ data processing and feature extraction

In order to separate the 6 segments of each signal corresponding to the single slots, a signal segmentation procedure was developed [8]. The Erosion front signal (Fig. 3a), as most representative signal of the EDM progression giving information on the position of the electrode, was used to identify the start and end points for signal segmentation.

For each signal segment relative to a single slot (Fig. 4), the following statistical features were extracted:

- Mean value
- Variance
- Skewness
- Kurtosis

After that, the results of each test were reported into a global graph (Fig. 5) in order to have a graphical summary of the features development and to perform a visual analysis of the anomalies. A total number of 28 features, 4 features for each of the 7 acquired signals, were extracted for each slot.

4. Anomaly detection methodology

The anomaly detection methodology applied in this research work consisted of two phases, see Fig. 6. The first phase was the system training, which was carried out by using as training dataset the statistical features extracted from the signals relative to the slots machined under standard conditions. Accordingly, the training set was made of 36 values for each of the 28 statistical features. The second phase consists in the system testing: to this aim, the tests performed under anomalous conditions were used for building the testing dataset composed of 66 values for each of the 28 features.

Testing was carried out by using the six sigma approach which is based on the calculation of the mean value μ and the standard deviation σ of the input data [9–11]. By setting the standard deviation range the percentage of the training set values included in the acceptability range is obtained. The range was set at 6 σ (Fig. 7) in order to include 99.999998% of training set good values: the values outside this range during the testing phase were classified as anomalies.

5. Results and discussion

By observing the behaviour of the extracted features, reported in the graphs, it is clear that significant variations occurred when the technological parameters were varied. Moreover, it can be observed that the features extracted under standard machining conditions are grouped in a limited range of values. This behaviour seems encouraging for the the anomaly detection procedure because it allows a clear distinction between good and anomalous values (e.g. Fig. 8).

Despite the variability of the feature values shown in Fig. 8, the related anomaly detection analysis registered no abnormal value, as all the feature values were classified within the six sigma range (the two red lines in Fig. 9). The importance and the effectiveness of this analysis is shown in Figs. 10-13, reporting two different cases of outliers.

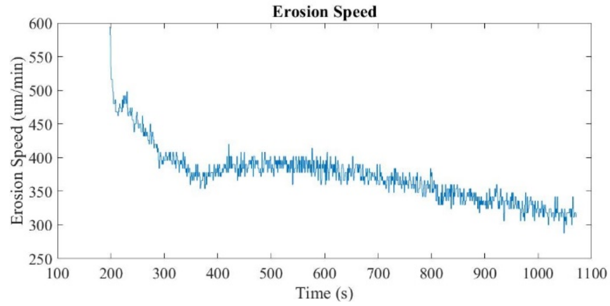


Fig. 4. Segmented erosion speed signal (single slot).

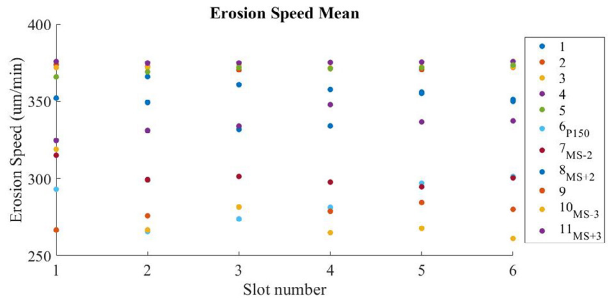


Fig. 5. Overall average value of the erosion speed signal vs slot number.

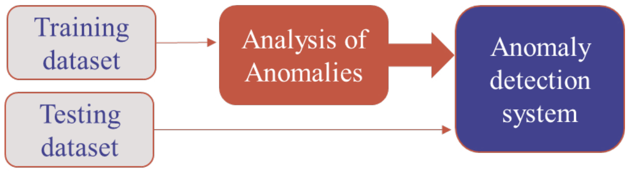


Fig. 6. Anomaly detection methodology scheme.

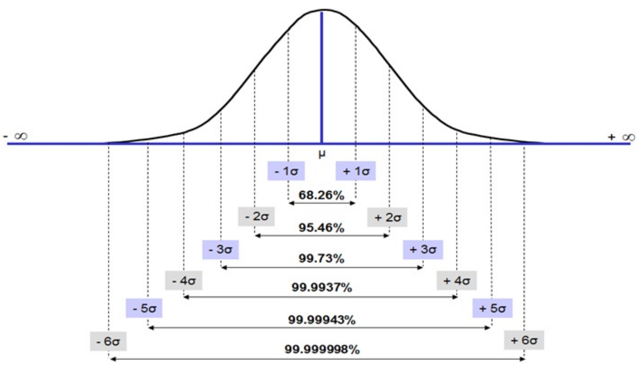


Fig. 7. Standard deviation scheme for six sigma approach.

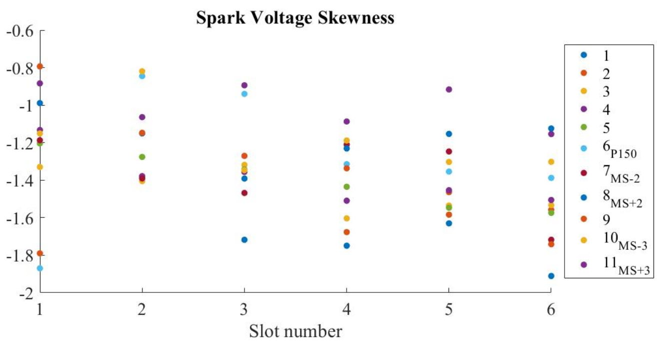


Fig. 8. Overall skewness value of the spark voltage signal vs slot number.

The spark voltage variance of the first slot of test 1 (Fig. 10), which seemed to be an outlier as clearly separated from the main group of standard values, was actually correctly not identified as an anomaly as inside the six sigma range in the histogram (Fig. 11). Instead, in Figs. 12-13, the two point series of the effective sparks variance belonging to tests under improper process conditions were actually identified as anomalies as falling out of the histogram acceptability range.

As regards the spark voltage kurtosis reported in Fig. 14, a critical issue concerns test 2: after the overall anomaly detection analysis it was not identified as anomalous (Fig. 15) but it represents an anomaly if considering just the slot n. 1. This circumstance suggests that also an in-depth analysis concerning the single slot EDM process has to be performed with the aim to detect the occurrence of anomalies during machining of the single cavity. Thus, the overall anomaly detection analysis, which concerns the analysis of the whole tests including 6 consecutive slots, will be integrated with an anomaly detection analysis at different depth ranges during machining of a single slot, by further segmenting the signal acquired during the EDM process (Fig. 16).

6. Conclusions

The anomaly detection analysis for the identification of improper EDM process conditions, trained using standard process data, provided excellent results after the testing phase carried out on the entire dataset including standard and anomalous conditions.

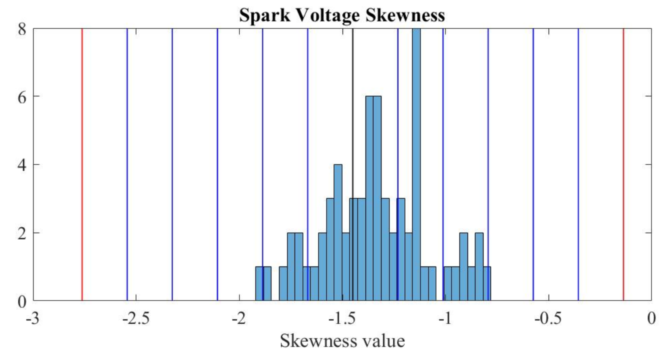


Fig. 9. Anomaly detection analysis of Spark voltage skewness.

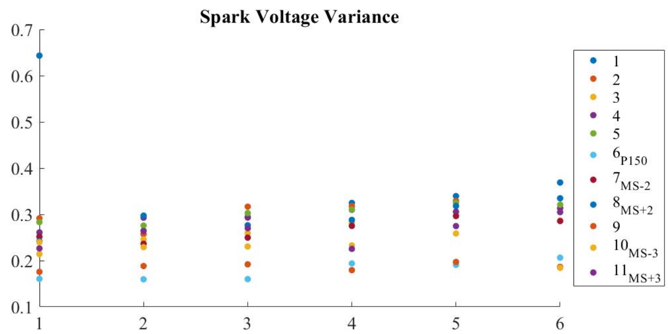


Fig. 10. Overall variance value of the spark voltage signal vs slot number.

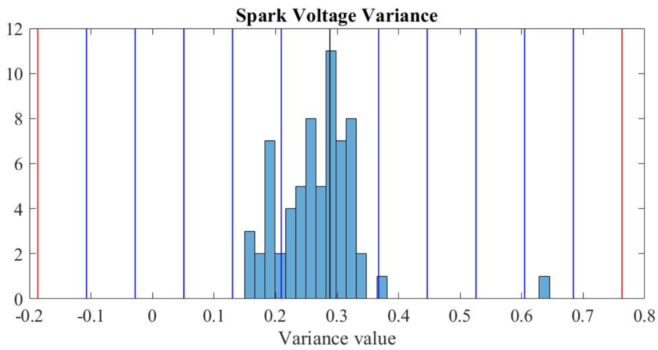


Fig. 11. Anomaly detection analysis of Spark voltage variance.

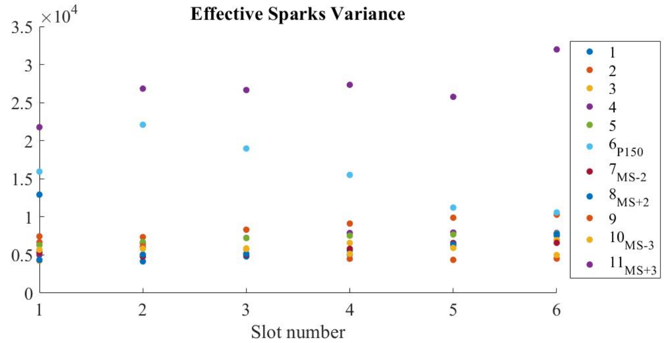


Fig. 12. Overall variance value of the effective sparks signal vs slot number.

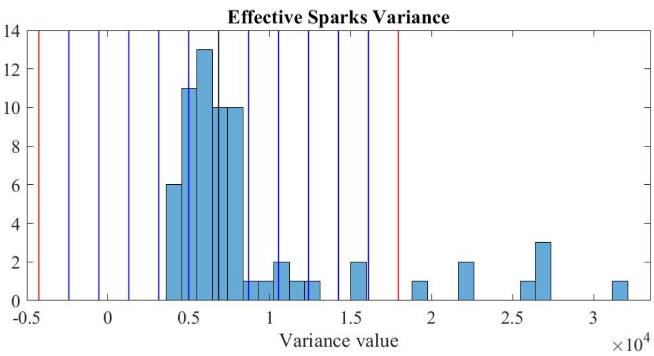


Fig. 13. Anomaly detection analysis of Effective spark variance.

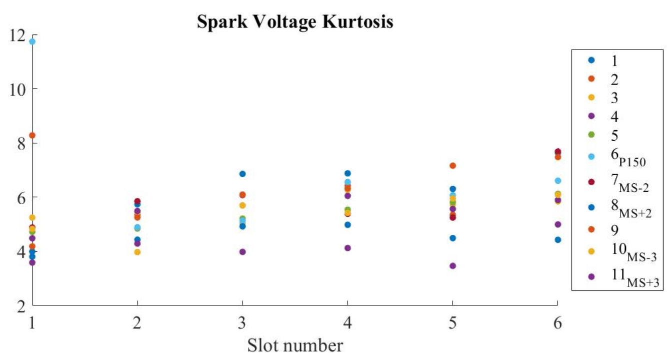


Fig. 14. Overall kurtosis value of the spark voltage signal vs slot number.

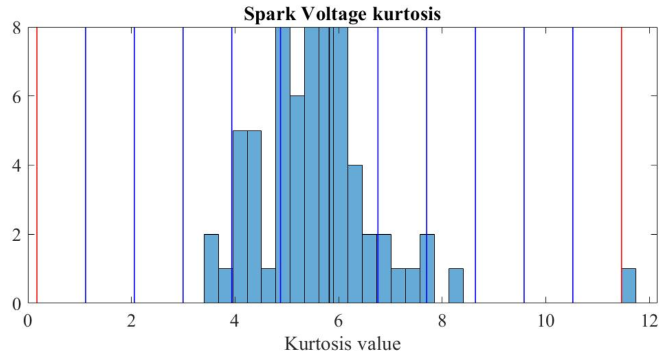


Fig. 15. Anomaly detection analysis of Spark voltage kurtosis.

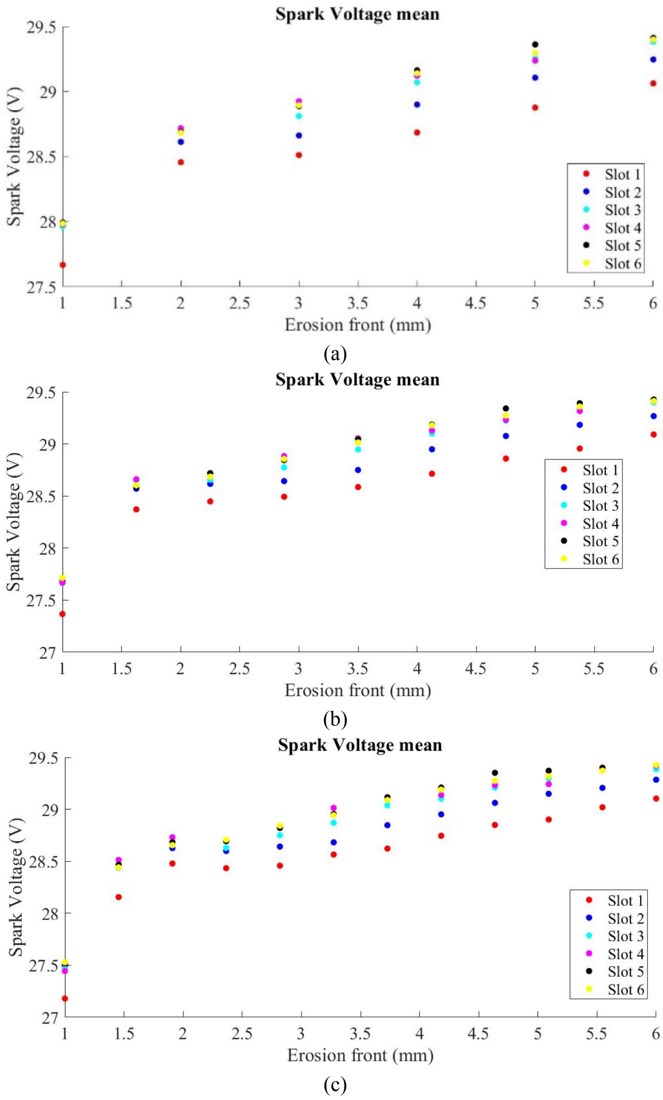


Fig. 16. Mean value of the Spark voltage resulting from single slot analysis: (a) 6 divisions, (b) 9 divisions, (c) 12 divisions.

Further analysis will be performed considering the single slot EDM and analysing the process behaviour at different depth ranges with the aim to obtain additional information about the occurrence of anomalies during the EDM process. Moreover, the studied methodology will be applied to die-sinking EDM of Inconel 718, largely employed in aeronautic industry for turbine blades production. The final objective is represented by the implementation of this methodology in the RTAQ software for online monitoring of process conditions.

Fig. 17. Appearance of current, voltage and machine control board signals on the oscilloscope screen.

Finally, as each RTAQ signal is based on the analysis of current and voltage signals acquired from the machine control board, an advanced study of raw current and voltage signals will be performed. A high frequency oscilloscope will be used for this study to investigate the primary conditions which lead to anomalies (Fig. 17).

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