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# Hierarchical cluster analysis for pattern recognition of process conditions in die sinking EDM process monitoring

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## Abstract

Die sinking EDM processes require continuous monitoring due to the typically severe application requirements, especially in advanced aerospace parts machining, where part quality and machining time are main concerns. As the process conditions cannot be recognized based on the behaviour of a single monitored value, it is necessary to consider a number of relevant sensor signals together. The aim of this research work is to recognize the machining conditions which lead to an improper process performance, e.g. by increasing machining time and causing unacceptable part quality, and to highlight the most relevant sensorial features. Using the Real Time Acquisition (RTAQ) module installed on an AgieCharmilles FORM P 600 sinker spark erosion machine, eight process parameters are acquired. Hierarchical cluster analysis is then applied to identify different groups of improper process conditions based on relevant features extracted from the EDM process parameters.

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**Keywords:** Die sinking EDM; process monitoring; hierarchical cluster analysis

## 1. Introduction

The employment of electrical discharge machining (EDM) processes is progressively finding new applications in industry. In the last decades, they were successfully introduced in the aerospace industry and they have established their superiority in certain applications including machining of very small holes, precise cutting of tough, hard and heat resistant metals, and machining of cavities with complex geometry [1]. Nevertheless, EDM process modelling is particularly challenging due to the stochastic nature of the process [1, 2].

Die-sinking EDM is typically used to realise cavities with high depth-to-width ratio and high surface finish, called Seal Slots, on aeroengine components such as turbine blades made of difficult-to-machine materials like Nickel-based alloys [3, 4]. The constraints that have to be met in these advanced aerospace applications are the resulting white layer thickness, metallurgical properties, residual stress and fatigue behaviour. Moreover, machining time is a critical issue because the excessive deposit of debris at the bottom of narrow cavities or

due to tool electrode consumption lead to a decrease of the erosion speed resulting in an increase of machining time. Due to these concerns, very conservative EDM process parameters values are adopted in the industrial practice, resulting in extremely inefficient processes [1].

In this framework, the development and implementation of advanced sensor monitoring procedures to notably enhance the process effectiveness has become critical like in many other manufacturing fields [5]. In particular, the identification of the correlations between die sinking EDM process parameters and improper process conditions which negatively affect machining time and part quality is of utmost importance [6–8].

In this perspective, a first procedure to investigate abnormal machining conditions was proposed by the authors using the six sigma methodology for anomaly detection [8].

In the present research work, a pattern recognition technique detection [9, 10], based on Hierarchical Cluster Analysis (HCA) [11], has been developed and then compared with the previous anomaly detection method. The advantages offered by HCA are related to implementation simplicity as,

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once the suitable algorithm is chosen, it can autonomously discriminate different process conditions without any adjustment or supervision. Moreover, hierarchical clustering is able to perform the complete analysis of the whole data set including different signal features, as opposed to the six sigma analysis, which requires the comparison of the evaluation performed on each signal feature in order to obtain an overall analysis. Finally, this type of clustering is easy to understand as it provides a graphical output consisting of a dendrogram which visually helps understand the composition of each cluster and the existing relations between different clusters.

In order to reproduce different machining process conditions, an experimental campaign was design and carried out on a AgieCharmilles FORM P 600 sinker spark erosion machine tool, largely employed in the aerospace industry.

This machine tool was equipped with a Real Time Acquisition (RTAQ) module which was employed to monitor and acquire online data related to 8 selected process parameters with 32 ms sampling interval.

Then, by applying the weighted hierarchical clustering algorithm to the features extracted from these parameters through statistical analysis in the time domain, proper and improper machining conditions were classified.

The final goal of the developed advanced sensor monitoring procedure is to timely detect abnormal process conditions to improve the final part quality and enhance the EDM process productivity by lowering the machining time while fulfilling the restrictive quality requirements imposed on the workpiece surface integrity.

## 2. Experimental testing campaign

As mentioned in [8], the experimental testing campaign was designed to reproduce different machining conditions, including good and anomalous machining conditions, which can occur during the erosion of the seal slots. To this aim, specific technological parameters were purposely altered to cause EDM process degeneration.

### 2.1. Experimental setup

An AgieCharmilles FORM P 600 sinker spark erosion machine was employed to carry out the experimental testing campaign. The machine tool was equipped with a Real Time Acquisition (RTAQ) module allowing to acquire data samples of selected process parameters with a minimum sampling interval of 32 ms. The workpiece was a 1.2343 steel plate (Fig. 1) machined with a fine grain graphite tool electrode with size L 35 mm, T 0.4 mm, D 25 mm to realise 6 mm depth cavities (slots). In each test, 6 consecutive slots with a distance of 1.125 mm between centres were realised with the same tool electrode. A dressing operation of the tool electrode was performed after machining of each single slot. The aim of this operation is to refresh the erosion surface and remove the pyrolytic graphite deposits growing at the electrode corners. The electrode dressing operation was performed on a copper workpiece, using a reverse polarity technology, to achieve a 0.5 mm length reduction on the electrode (Fig. 2).

### 2.2. Experimental testing campaign

The experimental testing campaign consisted of 11 tests, 6 of which carried out under standard process conditions (good conditions) realizing 36 total slots in order to collect data on the standard process. Table 1 summarizes the most relevant process parameters employed in the standard conditions tests. Moreover, 5 tests were performed under modified conditions (anomalous conditions) with the aim to generate a set of diverse improper process conditions (Table 2).

In particular, defects and improper process conditions were generated by varying the following technological parameters:

- Pulse OFF Time (modified to 150  $\mu$ s)
- Machine Sensitivity (modified to +/-2, +/-3)

Pulse OFF Time is the time elapsed between two power supply ignitions, so it is the time during which the power supply is OFF and the dielectric fluid can clean the gap. By decreasing this value, the sparks become more frequent and the debris accumulation in the gap increases. Machine Sensitivity is related to the set of parameters which are evaluated by the machine control system. By increasing Machine Sensitivity, the control becomes more sensitive and adopts more conservative adjustments. Decreasing Machine Sensitivity allows for a faster machining process, but the final workpiece quality is affected by an increase of the abnormal sparks ratio.



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 of the EDM tests in standard conditions.

Technological parameter	Pulse Current [A]	ON Time [ $\mu$ s]	OFF Time [ $\mu$ s]	Ignition Voltage [V]	Machine Sensitivity
Value	24	60	200	220	0

Table 2. EDM tests under standard and modified process conditions.

Name	Technological parameters	No. of tests	Total no. of slots
ST	Standard parameters	6	36
P150	OFF Time = 150 $\mu$ s	1	6
MS+2	Machine Sensitivity = +2	1	6
MS-2	Machine Sensitivity = -2	1	6
MS+3	Machine Sensitivity = +3	1	6
MS-3	Machine Sensitivity = -3	1	6

### 2.3. RTAQ data acquisition

The RTAQ data acquisition module was set to acquire the following 8 parameters relevant for this research study:

- 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 [ $\mu$ m/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.

These data were acquired using a sampling period of 32 ms. Each acquired signal contains the entire machining test (6 slots) as it reports the data concerning the machining processes performed with the same electrode. Fig. 3 a-b shows two examples of acquired signals, i.e. the signal of the Erosion Front parameter and the signal of the Effective Sparks parameter for an entire machining test including 6 slots.

### 3. RTAQ data processing and features extraction

To separately analyse the EDM machining process of each single slot, a segmentation procedure [11, 12] was carried out to split each acquired signal into 6 different segments. The segmentation procedure was based on the detection of the start and end points of each machining process based on the Erosion front signal (Fig. 3a), which is the most representative of the process progression as it reports information about the depth of the erosion front in the machined cavity.

For each signal segment relative to a single slot (e.g. Fig. 4), the following 4 statistical features were extracted: Mean value, Variance, Skewness and Kurtosis [13-15].

All the 4 features extracted from each of the 6 signal segments of the parameters acquired during the machining tests were reported in a matrix covering the whole experimental testing campaign. The resulting matrix has dimensions 66 rows x 28 columns, i.e. 6 rows (corresponding to the single slots) for each of the 11 different tests, and 4 columns (corresponding to the statistical features) for each of the 7 acquired parameters (the erosion front was not included). This matrix was then used as input to feed the

hierarchical cluster analysis algorithm for pattern recognition of process conditions.

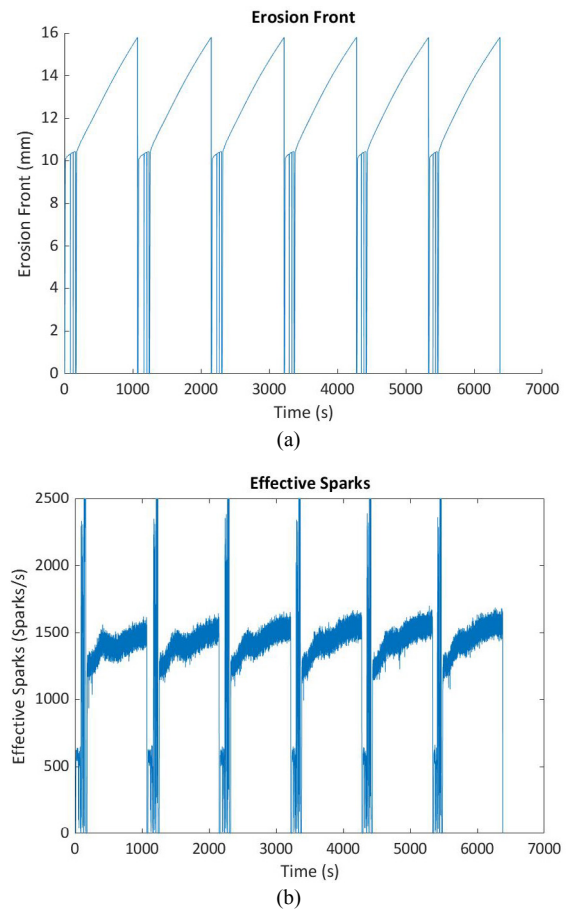


Fig. 3. Examples of: (a) Erosion Front signal; (b) Effective Sparks signal.

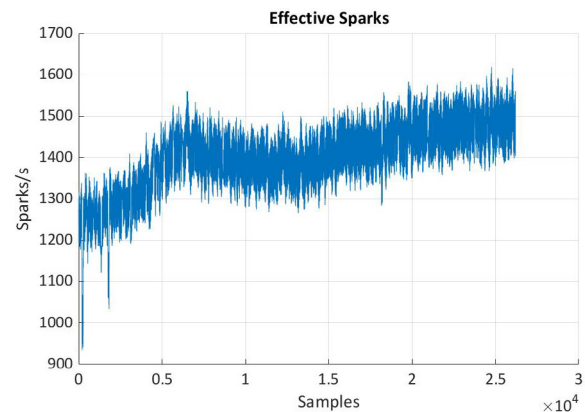


Fig. 4. Segmented Effective sparks signal (single slot).

### 4. Cluster analysis

To evaluate the machining process in a comprehensive way to recognize proper and improper machining conditions, cluster classification analysis was performed using the extracted signal features. In this analysis, each data point, which in this case is one specific feature referred to EDM machining of one slot, has an importance and a weight related to the other points belonging to the same process. This means that an anomaly, occurring in one feature, is not sufficient to affect the classification of the whole machining process if the

other features are not anomalous. This helps attribute more consistency to the machining classification method because the differentiation between proper and improper conditions depends on the whole machining process behaviour. This approach is different from the one applied using the anomaly detection method [8], where one isolated feature out of the six sigma range was considered enough to initiate the machining parameters correction by the supervision system.

Among the many different cluster analysis algorithms, hierarchical clustering was chosen for this application [16].

#### 4.1. Hierarchical cluster analysis

Hierarchical clustering or hierarchical cluster analysis (HCA) is an analysis method that aims at building a hierarchy of clusters where data or collections of data are grouped [17]. Two types of strategies can be used for HCA, agglomerative (bottom-up approach) or divisive (top-down approach). Each merge or split of the clusters is determined in a greedy manner and the results are presented in a dendrogram consisting of many *U*-shaped lines that connect data points in a hierarchical tree [18]. The height of each *U* represents the distance between the two data points being connected.

Different algorithms are classified under the definition of hierarchical clustering: the selected algorithm is the Weighted Pair Group Method with Arithmetic Mean (WPGMA). WPGMA is a simple agglomerative (bottom-up) hierarchical clustering method, generally attributed to [19]. The dendrogram (Fig. 5) constructed using WPGMA reflects the structure present in a pairwise distance matrix. The nearest two clusters, say *i* and *j*, at each step, are combined into a higher-level cluster *i* ∪ *j*. Then, considering another cluster *k*, the distance of *i* ∪ *j* and *k* is the arithmetic mean of the average distances between members of *k* and *i* and *k* and *j*:

$$d_{(i \cup j),k} = \frac{d_{i,k} + d_{j,k}}{2} \quad (1)$$

## 5. Results and discussion

In Table 3, the results of the WPGMA analysis are reported. Considering the types of expected anomalies

expected, a number of clusters equal to 5 was set in the hierarchical clustering algorithm. The final clusters identified by the algorithm are respectively composed by a total number of elements equal to 37, 16, 6, 6, and 1 (each element is a machining process of 1 slot). For ease of representation, the values in bold refer to full machining tests (all 6 slots), while the others refer to a specific single slot machining process.

As shown in Table 3, one main cluster (Cluster 1) includes the majority of machining processes with standard parameters. It includes also the whole machining test with increased machine sensitivity +2. The nearest cluster (Cluster 2) includes the whole fifth machining test with standard parameters and almost all the machining processes with decreased machine sensitivity. Cluster 3 contains the full machining test with decreased Pulse OFF Time. Cluster 4 comprises the full machining test with the greatest increase in machine sensitivity (MS +3). Cluster 5 contains just the first slot executed with standard parameters but with an electrode positioning error due to a superposition of the new slot with an already machined cavity present on the workpiece.

Table 3. Cluster classification of experimental tests resulting from WPGMA. MS: change in Machine Sensitivity; P: change in Pulse OFF Time; ST: standard parameters; STerr: standard parameters with positioning error.

Cluster no.	1	2	3	4	5
	STerr_2	<b>ST5</b>	<b>P150</b>	<b>MS+3</b>	STerr_1
	STerr_3	MS-2_2			
	STerr_4	MS-2_3			
	STerr_5	MS-2_4			
	STerr_6	MS-2_5			
	<b>ST1</b>	MS-2_6			
	<b>ST2</b>	MS-3_2			
	<b>ST3</b>	MS-3_3			
	<b>ST4</b>	MS-3_4			
	<b>MS+2</b>	MS-3_5			
	MS-2_1	MS-3_6			
	MS-3_1				
<b>Total elements</b>	<b>37</b>	<b>16</b>	<b>6</b>	<b>6</b>	<b>1</b>

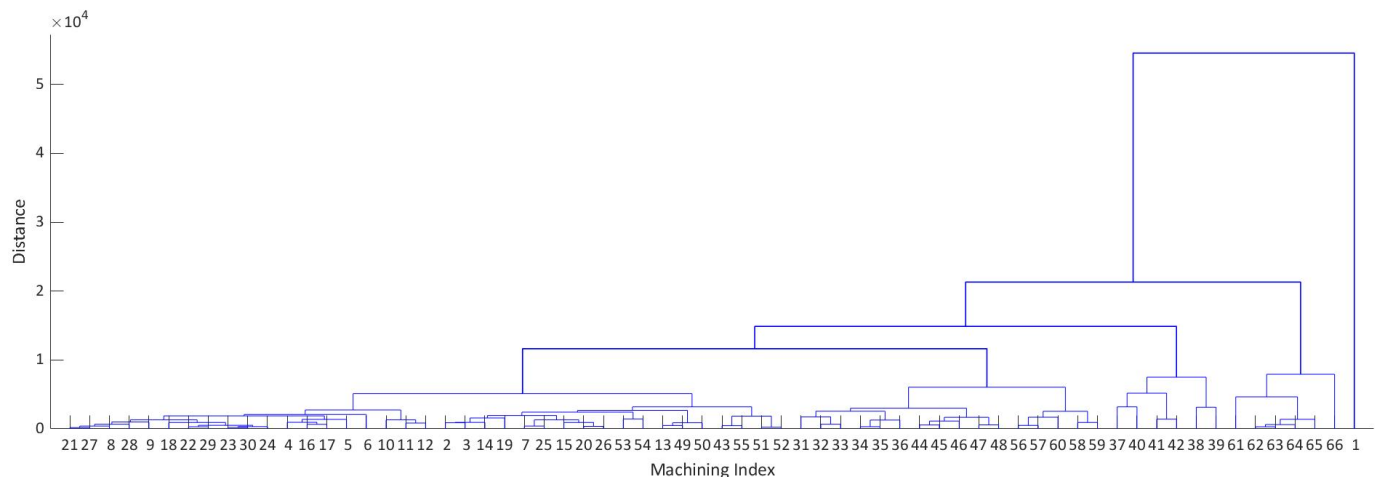


Fig. 5. WPGMA results: dendrogram of the whole experimental campaign. Machining index refers to machining of a single slot in the experimental campaign.

To summarize these results, Cluster 1 and Cluster 2 contain the features related to the machining conditions which are considered good, as a matter of fact the ST5 is in Cluster 2. Cluster 3 and Cluster 4 contain the features related to the machining conditions which are different from the standard parameters and that can be considered bad. And Cluster 5 contains the features related to the most anomalous machining condition because it corresponds to a partial machining due to the superposition with another cavity.

By observing that there are some features having high normalized standard deviation value (Fig. 6), after the cluster classification it was decided to reduce the dimension of the matrix of the features to be analysed from 28 to 8. The results obtained using the same algorithm for cluster analysis fed with the 8 newly selected features were the same in terms of group composition. This suggests that the following features can be properly used to feed the system for cluster classification and to construct the sensor fusion pattern vector: (i) Effective Sparks average, (ii) Arc ratio average, (iii) Erosion Speed average, (iv) Effective Sparks variance, (v) Arc ratio variance, (vi) Erosion Speed variance, (vii) StDevEservo variance, (viii) Short ratio kurtosis.

By comparing the results obtained using the previously developed anomaly detection method to the results obtained using hierarchical clustering, some observations can be made. The first point in Fig. 7, belonging to the machining test called STerr, is clearly an outlier. Similarly, the whole machining test represented by the light blue points and called P150 can be considered anomalous. However, the anomaly detection system doesn't detect any value outside the six sigma range (Fig. 8). The observation of the acquired signals confirms that the 5 clusters resulting from HCA properly separate the features belonging to different types of machining conditions (Fig. 9). The signals of the machining processes belonging to the same cluster as well as those belonging to the same machining test (e.g. ST1) appear graphically homogeneous (Figs. 10-11), suggesting good results for the hierarchical clustering method. Indeed, hierarchical clustering allows to group the machining processes considering all the relevant sensor features together and not the single sensor features separately.

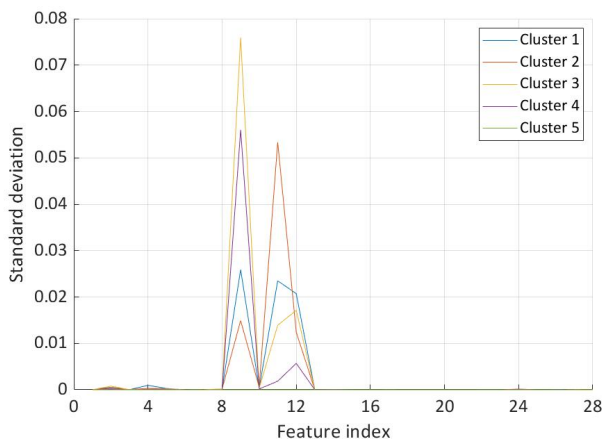


Fig. 6. Normalized standard deviation of the extracted features for all clusters.

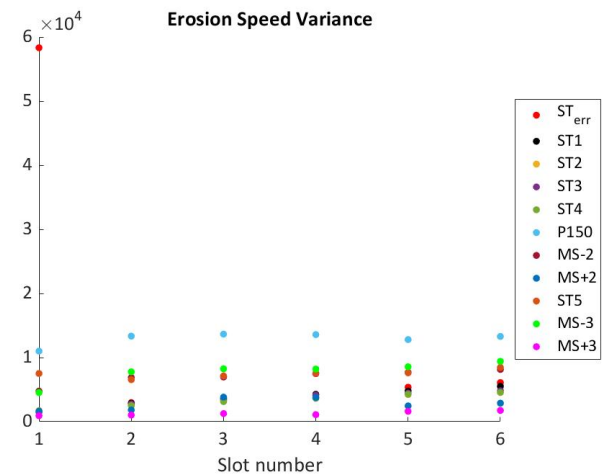


Fig. 7. Erosion speed variance of experimental tests.

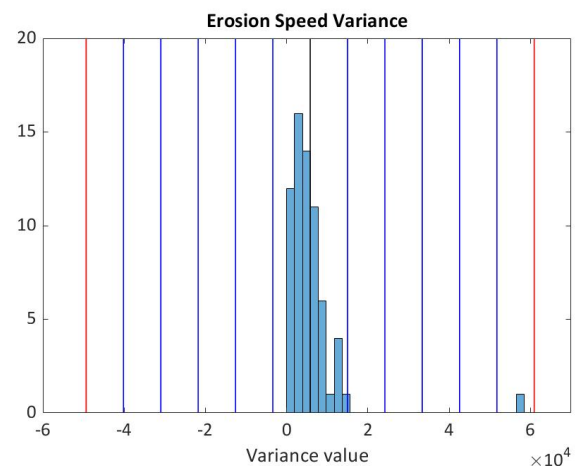


Fig. 8. Histogram of erosion speed variance.

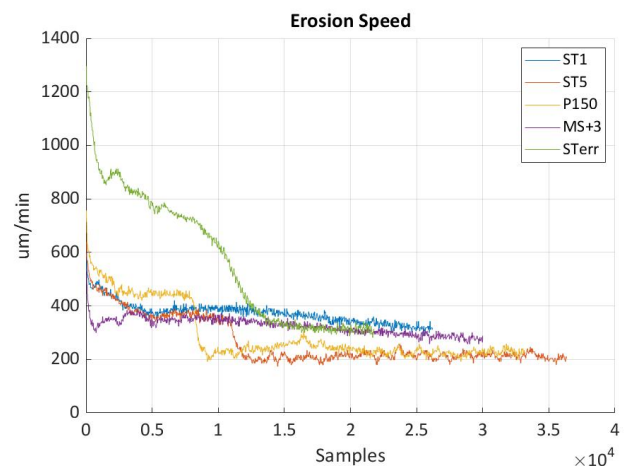


Fig. 9. Erosion speed signals of the 5 different clusters.

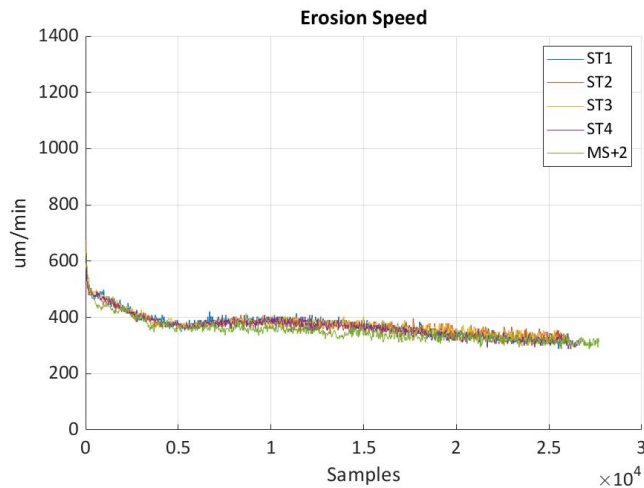


Fig. 10. Erosion speed signals of the first cluster.

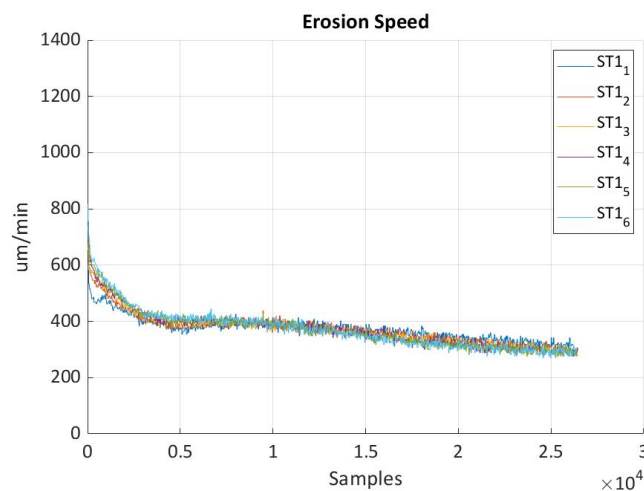


Fig. 11. Erosion speed signals of machining test ST1.

## 6. Conclusions

In this research work, a process monitoring technique based on Hierarchical Cluster Analysis (HCA) was developed with the aim to recognize improper process conditions negatively affecting machining time and part quality in EDM. The developed methodology was studied through an experimental testing campaign performed using standard and modified process conditions and its performance was compared with a previously developed anomaly detection method based on the six sigma strategy. The HCA method allowed to group proper and improper machining conditions produced through different modification levels of key technological process parameters, such as machine sensitivity and pulse OFF time, as well as due to an electrode positioning error causing superposition of the new slot with an already machined cavity on the part. Moreover, it was able to correctly recognize even the improper process conditions that, in many cases, were wrongly classified as not abnormal by the six sigma anomaly detection method. A key advantage of this unsupervised method is that the machining process evaluation and the cluster composition are carried out by observing all the relevant sensor features together and not by considering each feature independently from the others. Indeed, the classification of proper/improper process conditions was performed using 28

sensor signal features together. To reduce the computational load of hierarchical cluster analysis, the examination of the normalized standard deviation of the extracted features for all clusters allowed to reduce the dimension of the relevant features from 28 to 8 features, which is remarkable in the perspective of an on-line algorithm implementation in manufacturing industry. With particular reference to materials of interest for the aeronautical industry, similar procedures could be developed also for new applications involving other materials and other geometries, taking advantage of the effectiveness and the quickness of this procedure.

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