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STUDY OF ACOUSTIC EMISSIONS IN ELECTRICAL DISCHARGE MACHINING WITH COPPER AND GRAPHITE ELECTRODES

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Abstract. *Electrical discharge machining (EDM) is an unconventional machining process that involves the removal of material from a workpiece through successive electrical discharges submerged in a dielectric fluid. The phenomena associated with EDM are continually being studied to understand its behavior and its relationships with machine parameters, dielectrics, and the materials used in the process. Unlike conventional machining methods, EDM operates with the tool electrode in close proximity to the workpiece but without physical contact, enabling material removal. Material is removed from the part through electroerosion, which overheats the material on the surface of the work gap. This study aims to investigate the behavior of EDM phenomena in the machining of AISI H13 steel, considering variations in machining parameters, electrolytic copper, and graphite electrodes. The experimental characterization employs Acoustic Emission (AE) signals resulting from the process, along with Machine Learning (ML) tools for data analysis. The results demonstrate a satisfactory accuracy of 97.7%, highlighting the superior control of machining phenomena when using graphite electrodes compared to electrolytic copper electrodes. These results are achieved by detecting the excited frequencies and amplitudes of AE signals from EDM tests using Fast Fourier Transform (FFT) for data processing.*

Keywords: *Electrical Discharge Machining, Acoustic Emission, Machine Learning, Fast Fourier Transform.*

1. INTRODUCTION

Throughout the course of technological development aimed at meeting the basic needs of humanity, the production of high-quality products and consumer goods in large quantities has been achieved through various types of mechanical manufacturing processes. One such process is electrical discharge machining (EDM) (Schmenner, 2009). EDM is an unconventional machining process that involves the removal of material from a pair of working electrodes through electrical discharges, without the need for physical contact between them (Banu and Ali, 2016). This unique characteristic sets EDM apart from conventional machining methods.

Since its inception, EDM has involved the application of a potential difference between the tool and the workpiece, both submerged in a dielectric liquid. With the progress of technology, computer numerical control (CNC) can be integrated into the process to enhance efficiency. In the past two decades, extensive research has been conducted in the field of EDM to explore methods for improving efficiency, including novel experimental concepts that deviate from the traditional EDM phenomenon. Despite the diverse range of approaches, recent studies in EDM share common goals of achieving more efficient metal removal, reducing electrode-tool wear, enhancing surface quality, and comprehending the underlying phenomena within the process (Ho and Newman, 2003).

EDM is particularly advantageous for machining high hardness materials and facilitating the production of complex geometries. This capability has been instrumental in its widespread adoption for the manufacturing of punch holders, molds, and dies used in industries such as stamping and injection molding (Mouralova et al., 2022). During the EDM process, when an electrical discharge is applied to the submerged pair of electrodes, sparks are generated in the working gap. This phenomenon occurs as ions impact the surfaces of the workpiece and electrode, resulting in the superheating of a portion of the material within the gap's surface. In some cases, temperatures exceeding 35,000 °C can be reached. Depending on the composition of the electrode pair and the dielectric used, the excessive heat can cause a small amount of the heated metal to vaporize (Cesarotti et al., 2019).

Electrolytic copper and graphite electrodes are commonly used in EDM. Graphite, with its higher melting point (3,650ºC) compared to copper (1,083ºC), offers several advantages. Firstly, graphite electrodes have a lower acquisition cost, making them more economical. Additionally, graphite is easier to machine, allowing for the manufacture of electrodes with specific geometries. This characteristic enables the fabrication of more intricate and complex geometries in EDM processes.

Moreover, graphite electrodes possess a low expansion coefficient, which contributes to greater dimensional control of the workpiece during operation. This property ensures precision in achieving the desired dimensions of the final product. Furthermore, graphite electrodes exhibit reduced wear compared to copper electrodes, enhancing their longevity and overall performance (Ferreira et al., 2022).

Electrolytic copper electrodes offer a notable advantage in high-scale production scenarios due to their cost-effectiveness. They are well-suited for large-scale manufacturing processes while maintaining a low cost. In the medical equipment industry specifically, copper electrodes possess a significant edge over graphite electrodes due to their polishability. This characteristic allows for achieving superior surface finishes of the machined parts, resulting in higher-quality end products. Additionally, the use of copper electrodes during machining helps minimize particle degradation, ensuring cleaner and more precise machining processes (Tsai, Yan and Huang, 2003).

The machining parameters of an EDM machine have a direct influence on various aspects of the process, including production speed, surface finish quality, material removal rate (MRR), and overall operational efficiency. Higher electrical currents are often suggested to achieve higher MRR by increasing the incidence of ions on the workpiece surfaces, leading to the heating and melting of a larger volume of material. However, this increase in current tends to result in poorer surface finishes of the final part.

Furthermore, higher electrical currents can lead to lower efficiencies in the EDM process, as the increase in energy for material removal is not proportional. Large electrical currents also contribute to increased electrode wear, which reduces dimensional accuracy during machining (Bonfá et al., 2019).

Pulse duration time and pulse interval are important parameters in EDM. Longer pulse duration times generate a greater amount of molten material, resulting in higher MRR but lower process efficiency. Longer intervals between pulses contribute to improved process stability, better cleaning of the work gap by removing debris, and enhanced cooling of the areas subjected to electrical discharges. Consequently, longer pulse intervals tend to produce better surface finishes of the final part (Luzia et al., 2019).

The study of parameter and material influences in EDM machining is crucial for enhancing process efficiency and minimizing waste. Although EDM has been utilized for almost a century, numerous phenomena and behaviors associated with the process remain unknown. However, several researchers have presented methodologies and findings that shed light on this field of activity, such as the studies conducted by Bonfá et al. (2019) and Ferreira et al. (2022).

For instance, Wang et al. (2018) propose a mathematical model for EDM devices, demonstrating the random behavior of phenomena within the process. Zhang et al. (2015) suggest an electrode length compensation prediction method in micro EDM to improve efficiency in machining high hardness materials. The results show that the relative error of the simulation compared to experimental data falls within 4% under the specified machining conditions, and the model can predict the machined surfaces of both the tool and workpiece. Ferreira et al. (2022) present results on the relationship between EDM parameters and process outcomes using acoustic emission (AE) signals, establishing an excellent correlation between the study's input and output variables, while also examining carbon deposition on the eroded material surfaces.

AE signals are pressure waves that propagate through a material as a result of a sudden release of energy. This emission occurs due to elastic waves arising from spontaneous variations in energy within the solid state, resulting in local, dynamic, and irreversible changes in the material's microstructure. Acoustic emission demonstrates a high level of confidence in characterizing various phenomena within the scientific community, including its application in material removal, making it widely applicable in engineering (Maia et al., 2015).

This study aims to contribute relevant results and conclusions regarding the EDM machining process using acoustic emission generated during machining with different electrode materials and a range of EDM parameters. The collected data will be subjected to signal processing techniques, and subsequently analyzed using Machine Learning (ML) methods. ML has emerged as a powerful tool in computer science, with many practical applications in engineering for solving complex problems that traditionally require human intelligence. ML-based prediction applications for engineering tasks are becoming increasingly prevalent, including hybrid approaches that combine the advantages of multiple learning tools (Pham et al., 1999).

A crucial aspect of EDM studies is the comprehensive understanding of the variables under investigation to facilitate effective signal processing. One widely employed technique in AE signal processing is the Fast Fourier Transform (FFT), which transforms the input signal into a frequency-amplitude graph. This analysis provides rich information, where each process phenomenon excites its respective frequency with an amplitude corresponding to its intensity. By leveraging the ability to distinguish phenomena through their frequency characteristics, solid conclusions can be derived (Marrocco and Fassi, 2019).

2. EXPERIMENTAL PROCEDURE

The objective of this research is to investigate the EDM phenomena and establish their relationship with process parameters and variables, such as pulse interval time, electrical current, and electrode material. To analyze and interpret the results, Machine Learning techniques are employed for data analysis and the generation of predictive scenarios. This section outlines the complete methodology utilized in this study.

The experimental study focuses on conducting EDM tests using varying pulse interval times, electrical currents, and different electrode materials while machining AISI H13 steel. The specific parameters and materials employed in the EDM process to observe the behavior of AE phenomena and signals are described in detail below.

2.1 Materials

The workpieces utilized in this research were made of AISI H13 steel, which is a widely employed material in various industrial applications such as hot forging, injection molds, and extrusion dies. This steel possesses a remarkable combination of hardness and fracture resistance. Additionally, AISI H13 steel exhibits favorable characteristics including good toughness, high temperature resistance, thermal fatigue resistance, and thermal shock resistance (Vieira et al., 2022).

Table 1 provides a simplified representation of the chemical composition of the steel used in this study, presented in weight percentage. The tests were conducted using solid blocks of AISI H13 steel with dimensions of 100 mm x 100 mm x 25 mm each.

Table 1 - Weight percentage of the chemical composition of the AISI H13 steel used in the research.

C	Mn	P (max)	S (max)	Si	Cr	Mo	V
0,32 - 0,45	0,20 - 0,50	0,03	0,03	0,80 - 1,20	4,75 - 5,50	1,1 - 1,75	0,8 - 1,2

Two types of electrodes were proposed in this study: electrolytic copper electrodes with a copper content of 99.96% by weight, and commercial graphite electrodes. Both types of electrodes were manufactured in a cylindrical geometry with a diameter of 15 mm and a useful length of 40 mm.

The experimental setup employed an EDM machine model EDM 440 NC, which featured three working axes and was manufactured by AGIE CHARMILLES LTDA. This machine allowed for a maximum electric current application of 34.5 A during the machining process. The electrode holder and tool head were supported by linear guides and a recirculating ball screw, driven by a stepper motor.

To capture acoustic emission signals, a piezoelectric transducer of the Physical Acoustics brand, model R15i, was utilized. This transducer had an operating frequency range of 50 to 400 kHz and was coupled to the EDM machine tank. The signal conditioner, a Physical Acoustics model Spartan 2000, was used to collect the sensor data. The data acquisition system was managed using a data acquisition board, LABVIEW software, and a computer.

The data acquisition board used in this study was a PCI-6251 model manufactured by National Instruments, capable of a maximum acquisition rate of 1.2 MS/s. It was installed in a computer with an AMD Fusion A8 Quad-Core 2.9 GHz processor, 4 MB cache and Vision Radeon HD6550D video card.

For the EDM tests, a blast washing system was employed, which is a commonly used option in the industry and eliminates the need for drilling holes in the electrodes or workpieces. An industrial hydrogenated hydrocarbon dielectric fluid manufactured by Archem was used. This configuration allowed for the circulation of the dielectric fluid, facilitating the removal of chips and debris from the gap between the workpiece and tool electrodes during the machining processes.

2.2 Methods

The acoustic emissions of the EDM machine were captured using a signal transducer, and the data conditioner provided structured information for further processing in the data analysis software. The signal transducer captured the acoustic emission signals generated during the operation of the EDM machine, and the data conditioner prepared the data for analysis using a dedicated routine within the data processing software. Figure 1 illustrates the flowchart outlining the data processing steps undertaken to derive the conclusions of this experimental research.

Figure 1 - Data processing scheme.

The processing of the acquired signals was performed using a specially developed program in the MATLAB platform. The signals were collected during a 4-second acquisition period, and intervals corresponding to material removal phenomena were delimited based on the characteristic shape of the signal, which exhibited higher amplitudes and variability during the erosion phenomena.

In the next step, Fast Fourier Transform (FFT) signal processing was applied to identify the frequencies and amplitudes of the responses associated with the erosion phenomena. This provided valuable information for further analysis and utilization in the machine learning model.

Signal acquisitions were conducted at a rate of 1.2 MHz for 4 seconds during each test, resulting in a matrix containing the signal amplitudes and their respective time stamps. The piezoelectric sensor, coupled to the structure of the EDM machine, collected all the necessary information, which was then fed into the data acquisition software on the LABVIEW platform. Subsequently, the collected data was processed in MATLAB, forming the database for analysis and prediction using machine learning techniques.

MATLAB software was utilized for data preparation, treatment, and analysis of the acquired data from the EDM tests. The training and generation of machine learning models for this research employed the regression application available within MATLAB.

2.3 Procedures

Using the EDM machine, solid blocks of AISI H13 steel, data acquisition equipment, electrolytic copper electrodes, and graphite electrodes, EDM tests were conducted with the following parameters: Test 1: Pulse interval of 18.75 µs and electrical current of 9 A (equivalent to a current density of 5.09 A/cm²); Test 2: Pulse interval of 18.75 µs and electrical current of 15 A (equivalent to a current density of 8.49 A/cm²); Test 3: Pulse interval of 12.21 µs and electrical current of 9 A (equivalent to a current density of 5.09 A/cm²) and; Test 4: Pulse interval of 12.21 µs and electrical current of 15 A (equivalent to a current density of 8.49 A/cm²).

Other parameters remained constant across all tests, including positive electrode polarity, a voltage of 100 V, pulse duration time of 75 µs, erosion time of 1 second, and a fixed distance of 1 mm between the electrode and the machined surface of the workpiece after each second of erosion. Table 2 provides a summary of the parameters utilized in each test according to the VDI 3402 standard, which governs the EDM parameters for penetration EDM machines.

Table 2 - Summary of parameters used in EDM tests.

Parameters	Unit	Work Regime Test 1	Test 2	Test 3	Test 4
Electrode polarity	+/-	+	+	+	+
Voltage	*V*	100	100	100	100
Electric current	*A*	9	15	9	15
Pulse duration	*µs*	75	75	75	75
EDM machine standard transistor	-	3	5	3	5
EDM machine duty cycle	*%*	86%	86%	80%	80%
Time between pulses	µs	18.75	18.75	12.21	12.21
Current density	*A/cm 2*	5.09	8.49	5.09	8.49
Erosion Time	*s*	1	1	1	1
Electrode setback in relation to the machined surface of the part	*mm*	1	1	1	1

A total of 40 EDM tests were performed, consisting of 5 tests for each parameter combination using both electrolytic copper and graphite electrodes. Each test was repeated 5 times, resulting in a total of 200 minutes of machining time. During each minute of machining, acoustic emission signals were acquired for 4 seconds. This generated a dataset of 13.3 minutes of captured AE signals, which were subsequently processed, analyzed, and applied to the prediction models.

It is important to note that the geometry of the electrodes does not influence the erosion phenomena, and therefore, it does not impact the results of the AE signals (Ferreira et al., 2022). The materials used in the process and the EDM parameters are the factors that affect both the machining results and the AE signals. Hence, the test results are valid for any electrode geometry and EDM variation.

3. RESULTS AND DISCUSS

The findings of this research will be discussed based on the determination of electroerosion, followed by the analysis of the acoustic emission (AE) signals, and concluding with the results of the Machine Learning (ML) predictions using the collected and stored data.

3.1 Electric Discharge Machine

Following the execution of the EDM tests and the capture of AE signals from the 20 tests conducted using electrolytic copper electrodes (Figure 2) and 20 tests with graphite electrodes (Figure 3), the observation of the results begins. In Figure 2, which depicts the result with copper electrodes, both the workpiece and electrodes exhibit a dark coloration on the surfaces due to the carbon deposition resulting from the dissociation that occurs in the dielectric during electrical discharges. The carbon from the dielectric is transferred to the resolidified layer, enhancing the hardness and wear resistance of the affected surfaces. The amount of carbon deposition is influenced by the process parameters, with more aggressive parameters leading to a greater penetration of carbon onto the part's surface (Gill and Kumar, 2015).

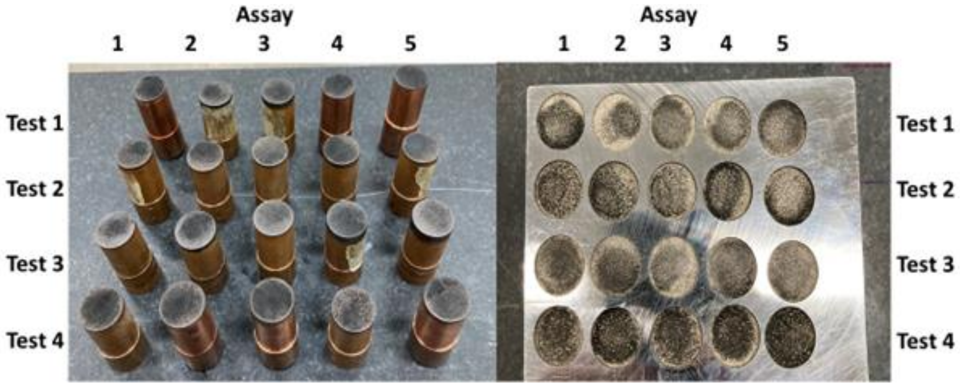

Figure 2 - EDM result of electrolytic copper electrodes on AISI H13 steel part.

For the results obtained with graphite electrodes shown in Figure 3, a similar carbon deposition on the workpiece surface is observed. The carbon deposition is generated by the same phenomenon as observed with the copper electrodes, involving the dissociation of carbon from the dielectric during electrical discharges in the working gap. However, due to the chemical and physical characteristics of graphite, it is not visually possible to observe the same deposition on the graphite electrode itself.

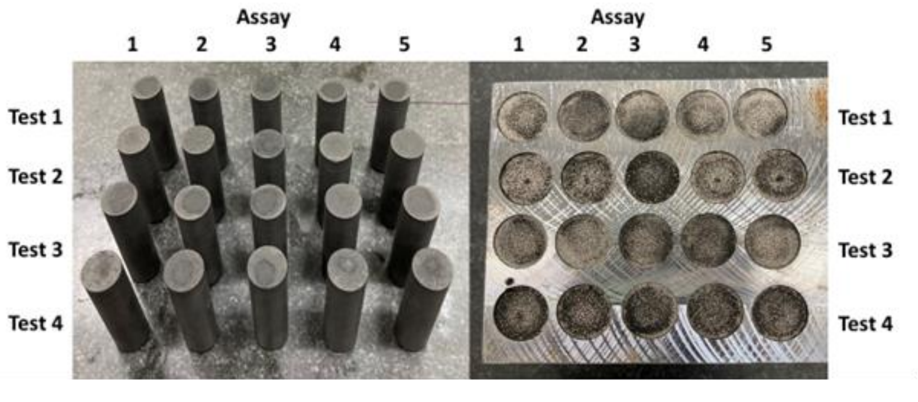

Figure 3 - EDM result of graphite electrodes on AISI H13 steel part.

As demonstrated in previous research, the surface finish achieved with copper electrodes is superior to that obtained with graphite electrodes (Liao et al., 2021). This is attributed to the higher melting point and greater porosity of graphite, which concentrate the electrical discharges during EDM and cause molten pools to penetrate deeper into the workpiece material. In contrast, copper exhibits better polishing ability during electroerosion, and the discharges occur more uniformly, resulting in a smoother surface finish with lower roughness.

3.2 Acoustic Emission

Analyzing the data from the 200 signal forms obtained in the 40 performed EDM tests, which resulted in a storage size of over 10 GB, the signals were observed in the form depicted in Figure 4. It was identified that during the period of effective material removal, the Acoustic Emission responded with the highest amplitude. Conversely, the periods where the signal remains close to the abscissa represent the moments when the electrode moves away from the workpiece by 1 millimeter and then returns to a position close enough for the subsequent erosion period (as per the parameter used in the study).

A MATLAB routine was developed to identify the signals with the highest amplitudes within each captured signal. This allowed for the extraction of clips from the original 4-second signals, containing only the signals that corresponded to the material removal periods. These highlighted signals are also depicted in Figure 3.

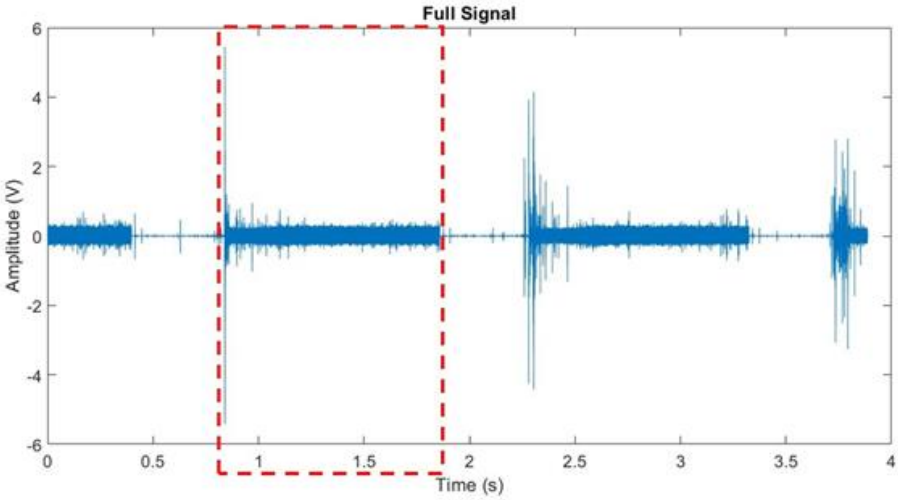

Figure 4 - Signal amplitude over time with an emphasis on the material removal period.

For each of the 200 signal acquisitions obtained during the 40 trials, the erosion period clips were subjected to FFT transformation. This process generated results similar to Figure 5 for each captured and stored signal. In each data processing step, the excited amplitude and frequency of the signal were recorded, resulting in a database rich in information about the phenomena present in the EDM process.

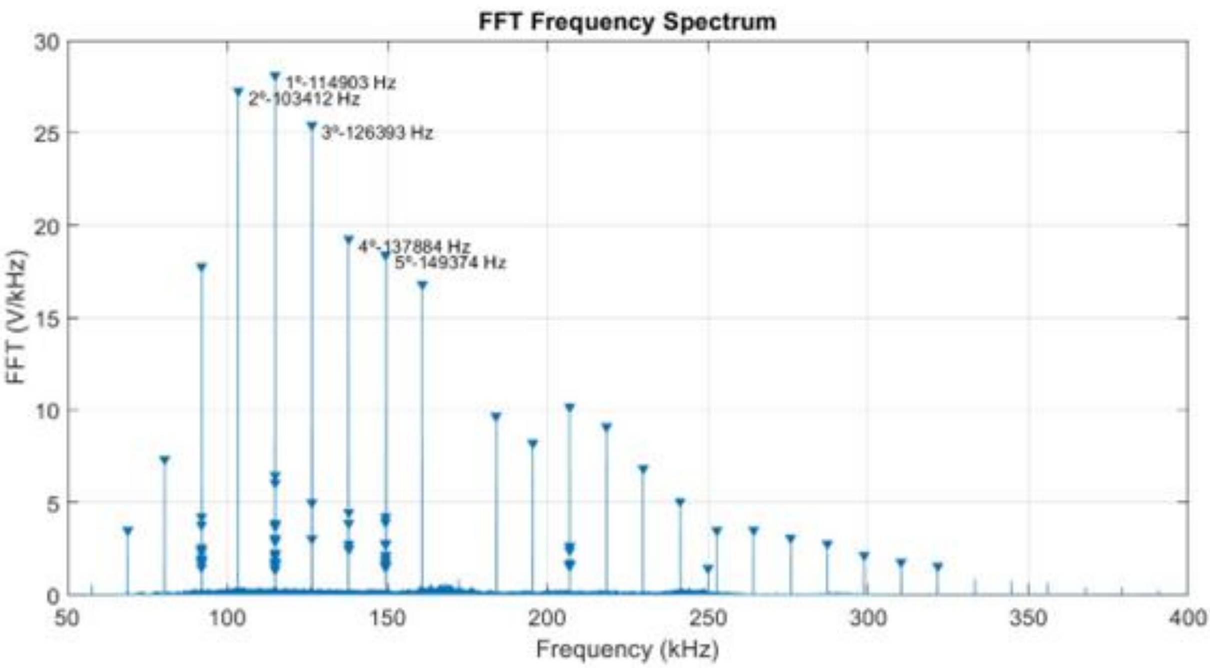

Figure 5 - FFT of a machining period.

Before proceeding, it is important to note that the parameters applied to the EDM machine, which generated periodic electrical discharges at frequencies ranging from 10.67 kHz (Tests 3 and 4 - 93.75 μs) to 11.47 kHz (Tests 1 and 2 - 87.21 μs), are outside the range of 50 kHz to 400 kHz. This range represents the working range of the transducer used in this research. Thus, the signals collected and presented here only contain frequencies related to the responses of the process phenomena and do not include the main frequencies and harmonics of the applied electrical discharges.

The spectrum of frequencies shown in Figure 4 highlights that there are several frequencies with different amplitudes involved in the EDM process. For instance, in the example provided, the highest amplitude is observed at a frequency of 114.9 kHz, followed by the frequency of 103.4 kHz with the second highest amplitude, and so on.

Although the graph in Figure 4 is presented for all 200 signal acquisitions, it is not possible to draw standardized conclusions regarding the machining parameters based solely on the signal responses. Therefore, a database is created, containing information about the electrode material, machining parameters, test, assay, amplitude, and frequency. This database is then utilized in Machine Learning, a powerful tool that will aid in establishing patterns, making predictions, and drawing conclusive findings.

3.3 Machine Learning

Based on the treatment of AE signals for each test and EDM trial, a database comprising 64,182 records was generated. These records included information about the electrode material, pulse duration time, interval time between pulses, applied electrical current, process duration, signal amplitude, and excited frequency. The FFT results from this database were then used to train various Machine Learning models available in MATLAB, with the regression technique known as Tree yielding the best result.

The Tree regression technique builds a decision tree by conducting a series of small tests on the input data to classify the output signal being studied. The selection of attributes is based on a strategy of dividing the original set of examples into subsets. The learning program constructs a decision tree that accurately classifies the given set of examples. This decision tree represents the generalized knowledge derived from the specific examples provided in the database. Chen et al. [40] provide an example of how the Tree technique can be used to handle situations not explicitly covered by the dataset.

The best regression result obtained using the Tree technique resulted in a Root Mean Square Error (RMSE) of 0.63068 for the FFT results. RMSE is a measure used to quantify the differences between the predicted values and the actual values provided by machine learning. In this case, the predicted peak amplitude values achieved a model accuracy of 97.7%, indicating relatively small deviations. Other works utilizing a similar methodology for tool wear prediction and analysis of machining process variables have reported larger errors ranging from 4% to 15% (Valentinčič, Filipič and Junkar, 2009).

To further analyze the Machine Learning results, graphs depicting the amplitude predictions for the studied parameters as a function of frequency were generated. Upon observing the behavior of the amplitudes, it is evident that the highest amplitudes are associated with the most aggressive machining conditions, namely test 2 and test 4, which involved an electrical current 66% higher than that of tests 1 and 3. Regarding the frequency bands observed in each test, test 1 exhibited a band ranging from 101.6 to 160.9 kHz, test 2 ranged from 85.5 to 160.9 kHz, and tests 3 and 4 encompassed a band from 91.9 to 160.9 kHz. Figure 6 provides a graphical comparison of these frequency bands.

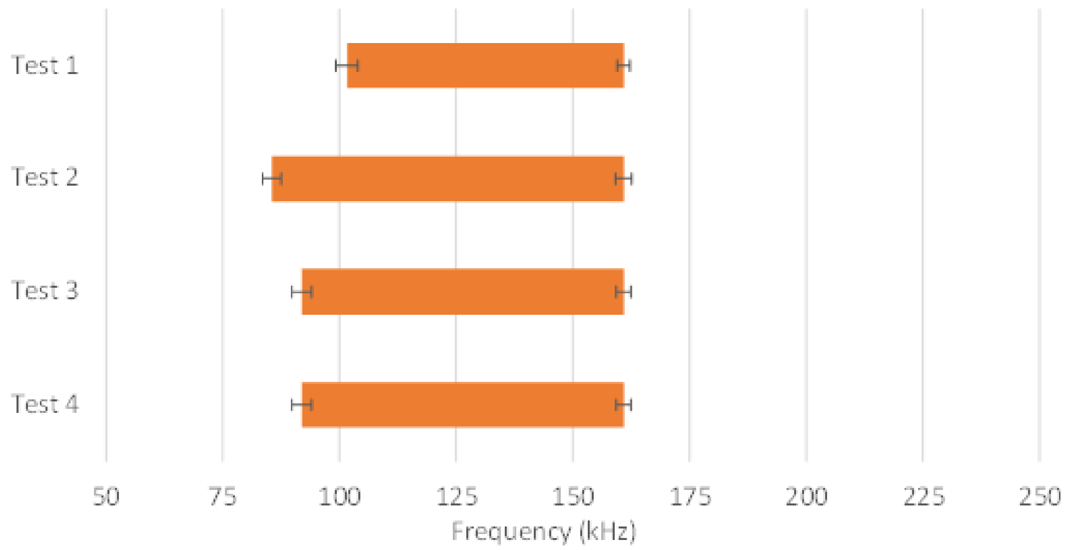

Figure 6 - Frequency band of tests with Electrolytic Copper electrodes.

The results obtained highlight that there is indeed a variation in the frequency bands between the tests, which is influenced by the machining parameters. It is also observed that tests with higher energy input exhibit larger excitation bands, specifically tests 2 and 4.

Figure 7 illustrates the prediction of the frequency spectrum for the FFT results obtained with graphite electrodes. The comparison is based on the same parameters applied in the previously described tests. When examining the amplitudes of the signals obtained with graphite electrodes, a similar effect to that observed in the FFT prediction of copper electrodes is noted. Tests 2 and 4, which involved a higher electrical current parameter, exhibit greater amplitudes, indicating a greater material removal during the EDM process compared to tests 1 and 3.

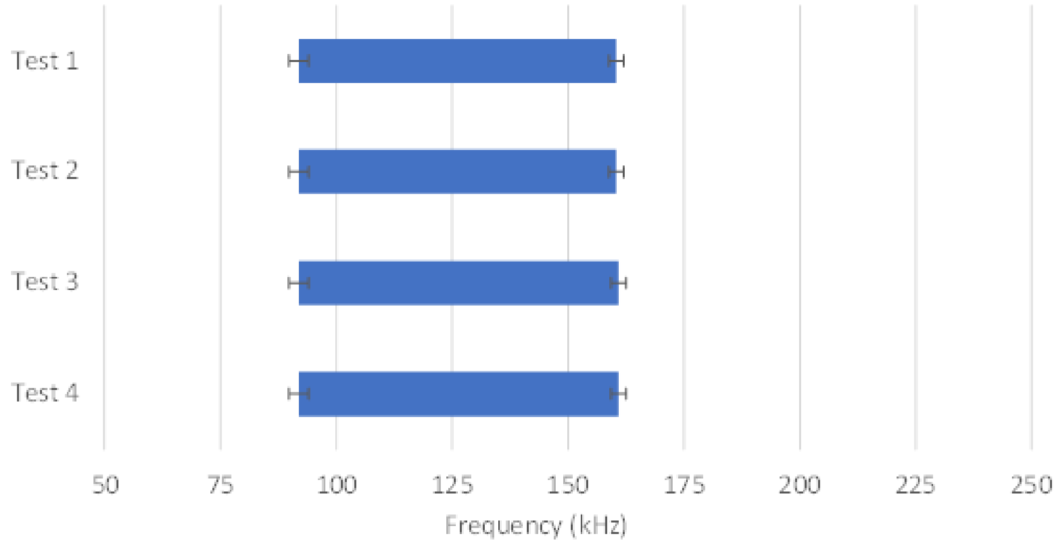

Figure 7 - Frequency band of tests with graphite electrodes.

Regarding the frequency bands associated with the graphite electrode, all four tests demonstrate an excited frequency band ranging from 91.9 to 160.4 kHz. Figure 7 visually presents these results. Notably, there is no variation in the excitation band of the AE signals among the tests conducted with graphite electrodes when analyzed using FFT. This suggests that in machining with graphite electrodes, the phenomena are better controlled, and their excitation frequencies are less sensitive to changes in machining parameters, in contrast to the findings observed with copper electrodes.

The results obtained further support the finding that an increase in electric current leads to higher amplitudes and a broader frequency range in the excited acoustic emission signals for copper electrodes. However, this phenomenon is not observed in the case of graphite electrodes, where an increase in electric current does not result in a significant increase in the excited frequency band. This highlights the greater stability of the phenomena generated during electrical discharges when using graphite electrodes.

Comparing the behavior of copper and graphite electrodes, it is evident that graphite electrodes exhibit more stable and controlled phenomena compared to copper electrodes. This can be attributed to the physical characteristics of graphite, such as its higher melting temperature and greater porosity. These properties allow graphite to better regulate the electrical discharge phenomena compared to electrolytic copper electrodes.

Since the energy of each individual discharge is the same for all tests, the stability of the material when subjected to this energy plays a crucial role in controlling the material removal phenomena. As a result, the acoustic emission signals generated by graphite electrodes are more contained compared to those produced by electrolytic copper electrodes. Based on these comparisons, it can be concluded that graphite electrodes enable a more efficient EDM process than electrolytic copper electrodes, as evidenced by the smaller excited frequency band observed.

4. CONCLUSIONS

In conclusion, this study highlights the importance of a comprehensive approach to understand the behavior of material removal phenomena in EDM processes by analyzing acoustic emission signals through FFT and Machine Learning. The machining parameters significantly influence the acoustic emission signals, while the electrode material also plays a crucial role in shaping the phenomena observed during the process.

By employing FFT and Machine Learning techniques, it becomes possible to analyze and draw conclusions about the erosion of materials, predicting behaviors and phenomena that may not have been effectively tested. The accuracy achieved by the proposed model, with a 97.7% accuracy rate, demonstrates the effectiveness of this intelligent data analysis approach.

The acoustic emission signals, treated through FFT and ML, exhibit sensitive responses in terms of amplitudes and frequencies throughout the material erosion period, reflecting the underlying phenomena in the process. Changes in electrode material and machining parameters affect the variation in the acoustic emission signal results.

Graphite electrodes demonstrate better control over the phenomena associated with erosion compared to electrolytic copper electrodes. This is evidenced by the narrower frequency excitation band observed in the spectra, which is 17% smaller for graphite electrodes. These results can be attributed to the physical and chemical characteristics of each electrode material, with graphite having a higher melting point and greater porosity in its structure.

Electrolytic copper electrodes exhibit a higher sensitivity to machining phenomena and parameters, as indicated by the variation in the excited frequency band. Furthermore, the frequency band tends to be larger with an increase in the energy applied during the electrical discharge process. The frequency band excited by machining processes with electrolytic copper electrodes ranges from 85.83 to 160.9 kHz, varying depending on the specific parameters used. Conversely, the frequency band excited by machining processes with graphite electrodes remains relatively consistent, ranging from 91.92 to 160.9 kHz, even with variations in the machining parameters.

Overall, this research contributes to the understanding of EDM processes and provides valuable insights into the influence of electrode material and machining parameters on acoustic emission signals. These findings have practical implications for optimizing EDM operations and enhancing the control and efficiency of the process.

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