

Tool condition monitoring based on the fractal analysis of current and cutting force signals during CFRP trimming

Maryam Jamshidi (✉ maryam.jamshidi.1@ens.etsmtl.ca)

Ecole de technologie superieure <https://orcid.org/0000-0002-8792-0656>

Jean-François Chatelain

Xavier Rimpault

Marek Balazinski

Research Article

Keywords: CFRP, Trimming, Tool condition, Fractal analysis, Electric current, Cutting force

Posted Date: April 12th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1510190/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Abstract

Carbon Fiber Reinforced Plastic (CFRP) is becoming more popular in the aerospace industry due to its high strength-to-weight ratio and low weight. Machining CFRP to achieve the required surface quality, on the other hand, remains a challenge. High temperature in the cutting zone area affects the tool life and surface quality of the machined part. A thermally affected matrix makes an inaccurate interpretation of the surface quality. Then, the roughness parameters cannot be an appropriate indicator for surface evaluation of the CFRP. In the aerospace industry, however, ensuring the acceptable surface quality of a part is essential. Minimizing and controlling tool wear is necessary to avoid degrading the finished surface and losing the dimensional accuracy of the final part. Early detection of tool wear and appropriate surface quality in finishing operations can be achieved using online tool condition monitoring. Cutting forces and electric current signals related to the spindle during machining are very responsive to cutting conditions and can accurately represent tool condition changes. Fractal analysis, as a new approach in the online tool condition monitoring, can assess the tool condition during machining. This research investigates the fractal analysis of the spindle electric current signal and the total cutting force signal while trimming CFRP using a CVD end mill through three different tool life conditions, e.g. new tool, moderately worn tool, and severely worn tool. The empirical fractal index is also introduced to assess the tool condition and ensure the acceptable surface qualities in the finishing operations. The effectiveness of fractal analysis as a decision-making method in the tool condition monitoring was successfully proven in this study.

1. Introduction

The utilization of Carbon Fiber Reinforced Plastic (CFRP) is increasing in the aerospace industry due to its high strength-to-weight ratio and low weight [1]. However, machining of CFRP to achieve the required surface quality remains a challenge. During machining of CFRP, abrasion and chipping are known as the major tool wear issues. Tool wear affects the rate of material removal and the quality of the machined surface [2]. While machining CFRP, the cutting tool must maintain a suitable level of edge sharpness in order to provide a clean cut at the end. During composite machining, minimizing and controlling tool wear is critical to avoid degrading the finished surface and losing dimensional accuracy of the final part [2]. Any failure may result in workpieces being rejected in the production line. Fiber pull-out or breakage, matrix smearing, or delamination may occur during the machining of CFRP [3]. To ensure product quality at the end of the finishing operation, direct or indirect methods of tool condition monitoring can be used [4]. In the direct method, the geometric parameters of the cutting tool are measured using an optical microscope with a high degree of accuracy [5]. This method has real-time limitations since it requires interrupting the cutting process to estimate the tool wear. Moreover, the direct method requires appropriate laboratory equipment, which is a limitation in harsh industrial machining applications [4]. The indirect method for tool wear monitoring is instead based on real-time analysis of signal acquisition during machining. This online approach is more appropriate for industrial applications that require few laboratory equipment and seek for automation of production processes to increase product quality and

decrease operating costs [6]. It has been shown that such tool condition monitoring in an automated machining center can lead to early detection of tool wear, boost cutting processes speed by 50 percent, and lower the manufacturing costs from 10 percent to 40 percent [7, 8]. Recently, Hassan *et al.* [9] developed the Wavelet Scattering Convolution Neural Network (WSCNN) technique to extract distortion-stable features from vibration signals generated by tool wear. Large-scale experimental validation tests under various cutting conditions revealed that the WSCNN method could achieve 98 percent detection accuracy in tool conditions and minimize system training by up to 97 percent.

Due to the sensitivity of cutting forces related to cutting conditions, the force signals have been widely used in tool condition monitoring [7]. Hu *et al.* [10] could predict distinct tool wear states, using statistical features of cutting force and acoustic emission signals during machining titanium alloy. This study employed Mutual Information (MI) and ν -Support Vector Machine (ν -SVM) for model training and prediction. The proposed strategy could successfully predict different tool wear states, with a prediction accuracy of 98.9 percent. Despite the capability of cutting force signal to detect tool wear, the acquisition of cutting forces requires sensors, such as dynamometers, which are not practical or cost-effective to use in production [7]. Alternatively, any changes in the cutting state can be reflected in the electric current signal of machine tools. Jeong and Cho [11] succeeded in estimating the cutting forces normal to a machined surface using the stationary feed motor current with less than 20 percent error. Current sensors are generally inexpensive and reliable and can be located far from the machining area [12]. However, developing a reliable method to reveal inherent patterns hidden in the current signal remains a challenge. Different approaches have been developed to analyze various online tool condition monitoring signals. Recently, an Artificial Neural Network (ANN) was applied during machining to classify the tool wear states in real-time using acceleration data [13] and acoustic emission signals [14]. Fuzzy logic was also introduced as another possible approach for tool condition monitoring by analyzing the uncertainties in acoustic emission signals [15]. Fractal analysis was recently developed as a new approach in tool condition monitoring. For the first time, the concept of fractal was used by B.B. Mandelbrot to estimate the length of the British coastline. Fractal objects are irregular shapes with affine structure and a sort of self-similarity. They have a fractal dimension that is greater than the topological dimension [16]. Fractal analysis was widely applied in advanced surface roughness evaluation [17], and it was also utilized in machine maintenance and diagnosis improvement [18]. Recently, Jamshidi *et al.* [19] analyzed the cutting force signal using fractal analysis to monitor the tool condition. In this study, fractal parameters of cutting force signals while drilling CFRP/titanium stacks of material was estimated to identify distinct wear stages of the cutting tool.

The present study investigates the online tool condition monitoring using fractal analysis of the spindle current signal and the total cutting force signal while trimming Carbon Fiber Reinforced Plastics (CFRP). The proposed approach investigates the feasibility of using an electric current signal to monitor tool condition and achieve the desired dimensional accuracy or surface integrity. Inexpensive and reliable current sensors, which meet industrial requirements, provide helpful information about the tool condition. This study aims to demonstrate the robustness of the fractal analysis as a decision-making system in tool condition monitoring using electric current signal.

2. Methodology

The use of spindle electric current signal and cutting force signal to monitor tool condition was investigated in this study. During the composite machining, signals were acquired and analyzed using fractal analysis. A cutting tool in three different conditions was used to highlight the three distinct wear stages in the cutting tool lifespan. Surface quality was assessed to evaluate the effect of cutting tool condition on machined surface. An infrared camera is used to evaluate the temperature in order to examine the influence of temperature on surface quality.

2.1. Materials and experimental setup

Six Carbon Fiber-Reinforced Plastics (CFRP) plates were manufactured using the hand lay-up method and cured in an autoclave [2]. The stacking sequence of each plate was as follows: $[0/90]_5$. Three separate experiments were carried out, including trimming the CFRP plates using 1) a new end mill, 2) a moderately worn end mill, and 3) a severely worn end mill tool to provide three different tool conditions. These conditions reflect the well-known phenomena of tool wear along with a whole lifespan of a cutting tool characterized with three distinct stages (Fig. 1). Due to the high pressure between the workpiece and a small contact area, tool wear is rapid in the first stage. Next, the wear is characterized by a relatively constant rate in the second stage. Then, the final wear stage occurs when the tool rapidly wears out until its end of life [19].

In the present study, the cutting tool was a 6mm diameter multi-layer CVD coating end mill having four flutes. The tool wear was estimated as the average of the maximum flank tool wear on each of the tool's four cutting edges, which is represented in Table 1.

Table 1
Tool wear at the beginning and the end of each experiment.

ID	Tool condition	Average flank wear at the beginning of the experiment	Average flank wear at the end of the experiment
1	New tool	0	0
2	Moderately worn tool	0.06 mm	0.09 mm
3	Severely worn tool	0.102 mm	0.148 mm

Two CFRP plates, with dimensions of 300 mm x 300 mm x 3 mm, were placed side by side in each experiment to allow a total cutting length of 5.7 m, with 3 m in the X direction and 2.7 m in the Y direction (Fig. 2). The red arrows indicate the cutting toolpath in Fig. 2. Dry trimming was performed using a K2X10 Huron® high-speed machining center equipped with a dust extraction system. The cutting speed and feed rate for all experiments were 226 m/min (12000 RPM) and 0.24 mm/rev (2880 mm/min), respectively, according to Bérubé [20]. The spindle electric current signal was acquired using the internal

sensor of the machine tool through a static synchronized action programmed with the Application Programming Interface (API) of the SIEMENS SINUMERIK 840D controller. The signal data was recorded with a 333 Hz frequency. The current signal can reflect any changes in the cutting condition, and it is expected that it may be utilized as an online tool condition monitoring, considering the development of an innovative analysis approach. Cutting force signals were recorded using a three-axis dynamometer table (Kistler 9255B). The cutting force signals were amplified and collected at a rate of 6 kHz. Cutting force signals are extremely sensitive to any changes in the cutting state and are widely used in tool condition monitoring, as stated in the literature review. To observe the cutting temperature, a VarioCAM® HD head 900 infrared camera with a 60 Hz frame rate was used to take a thermal image of the tool and workpiece in the same window. The infrared camera was mounted onto the spindle head to follow the cutting tool (Fig. 3). The emissivity of the cutting tool and CFRP specimens were calculated based on the ASTM international standard [21] and adjusted within the camera's settings. The emissivity of the CVD coating end mill tool and CFRP specimens were 0.52 and 0.94, respectively.

The 3D images of the machined surface and areal surface roughness parameters were estimated using Keyence VR-5000 optical profiler. The quality of the machined surface was assessed using areal surface roughness parameters.

2.2. Fractal analysis

Fractal analysis was recently developed as a new approach in tool condition monitoring. Different techniques, such as correlation analysis, information analysis, regularisation analysis, box-counting method, can calculate fractal dimension. Regularization analysis was used in the present study because of its reasonably strong repeatability, as demonstrated in recent works [22, 23]. In the regularization analysis, signal (s) can be regularized by convolution with different kernels such as Gaussian kernel (g_a). The convolution product s_a can be defined as:

$$s_a = s * g_a \quad (1)$$

Gaussian kernel (g_a) has the width (a) and the smoothed signal (s_a) is hypothesized to have a finite length (I_a). The regularization dimension can be calculated using:

$$D = 1 - \lim_{a \rightarrow 0} \frac{\log I_a}{\log a} \quad (2)$$

The limit in this equation is calculated as the slope in the area where the Gaussian kernel's width (a) tends to 0 and the R^2 of the linear regression is close to 1 [23]. The fractal dimension (D) is defined as the slope of the graph ($\log I_a$ vs. $\log a$) in the linear region, as shown in Fig. 4. Fractal dimension is an indication of the signal "roughness".

To ensure the accuracy of the results, a common region in the $\log I_a$ vs. $\log a$ graph with better linearity and sufficient points for linear regression must be chosen. Herein, the fractal parameters were calculated in the 9 to 16 points for spindle current signal (Region 1) and 5 to 22 points for total cutting force signal (Region 2) as illustrated in Fig. 5. Fractal dimension is conventionally determined as the slope in these regions where the (a) value is close to 0 and the R^2 of the linear regression is close to 1. Additional fractal parameters were defined to extract complementary characteristic features of the signal. The coefficient of determination of the linear regression (R^2) was defined to represent the auto-scale regularity of the signal. A fractal index was also introduced to support online tool condition monitoring and introducing a decision-making system. The empirical fractal index (I) was defined as follows:

$$I = (R^2)^D \quad (3)$$

3. Results And Discussion

The results of machining CFRP utilizing three distinct tool conditions are discussed in the following chapter. The obtained signals, including spindle current and total cutting force, are examined using both conventional and fractal analysis. The analysis outputs are used in online tool condition monitoring to verify that the desired surface quality is achieved at the end of the machining process.

3.1. Spindle current signal

3.1.1. Conventional analysis of spindle current signal

In this study, a CVD end mill tool in three different conditions was used to trim two plates of CFRP. Three separate experiments were conducted, including trimming of the CFRP using new, moderately worn and severely worn end mill tool. The spindle current signal was obtained using the machine tool's internal sensor with the least noise level, as shown in Fig. 6. During the tool engagement phase, this figure illustrates four separate zones. Zone I indicates the cutting tool's engagement with the workpiece, which causes the current to increase. Zone II is the steady state where the CVD end mill is trimming the CFRP plate. The cutting tool disengages from the workpiece in Zone III, where the electric current decreases until the cutting tool entirely exits the workpiece. Zone IV represents the air-cutting section where the tool is not in contact with the workpiece.

The average of spindle electric current is shown in Fig. 7. Air-cutting sections were removed from signals, so the average of current is plotted as a function of the cutting length. During trimming, the average current using the new cutting tool was higher than when the worn cutting tool was used in some areas, as indicated in the zoom-in section in Fig. 7. It may be explained by the effect of cutting tool edge radius on the cutting forces and then the electric current. The forces involved in machining are inextricably linked to the spindle electric current, since they both reflect the amount of power used during the cutting process [24]. This higher average value for the current signal using a new tool may result from the sharper cutting

edges that cut fibers in smaller chunks than those using a worn tool. This leads to high variations in the cutting force signal as well. Those cutting force high variations are often considered noise in the signal and then filtered out to extract the main shape of the cutting force signal. During the tool wear increase, composite fibers tend to be cut into bigger chunks when the cutting tool becomes dull and the edge radius increases. Then, bunches of fibers buckle or are pushed aside, delamination occurs between layers, and less power is consumed.

3.1.2. Fractal analysis of the spindle current signal

The fractal analysis results of the spindle current signal during the trimming of CFRP are filtered and illustrated in Fig. 8. The current signal can reflect any changes in the cutting condition, and it can be used in online tool condition monitoring. Only the inherent patterns hidden in the signal need to be revealed. The fractal dimension has traditionally been used to evaluate surface or curve complexity. Fractal parameters have recently been applied in signal analysis. The degree of complexity of the signal shape and variation of signal are represented by the fractal dimension [25]. As shown in Fig. 8, the fractal dimension of the new cutting tool is greater than the worn cutting tool. When the new cutting tool trims the CFRP, more complex shapes and more significant variations can be detected in the current signal. The fractal dimension in the first 3 m of cutting (trimming in the X direction as shown in Fig. 2) remains constant for the worn and new cutting tools, even when the quantity of the current fluctuates, as can be seen in Fig. 8. The fractal dimension continues to decrease for the new cutting tool while trimming in the Y direction (Fig. 2). This behavior can be explained by the effect of the cutting direction on the shape of the current signal, and clearly, it affects the result of the fractal dimension and other fractal parameters. For the first 3 m of cutting, the coefficient of determination of the linear regression (R^2) remains constant for both worn and new cutting tools, with a progressive rise in the graphs. The value of R^2 when the worn cutting tool is utilized is higher than when the new cutting tool is used. Then, even the R^2 results can reflect the tool condition. The fractal parameters calculated from trimming with a severely worn and a moderately worn cutting tool are relatively similar, particularly the R^2 results.

Each fractal parameter characterizes a specific feature of the signal. Then, the combination of the fractal parameters can express more information about the current signal and improve the accuracy of the decision-making system. The empirical index of fractal analysis of the spindle electric current signal is also shown in Fig. 8. As the tool wear increases, all graphs show a progressive rise. The fractal index can be used as a decision-making system based on experimental data to support online tool condition monitoring. The experimental result of the fractal index while trimming with a new cutting tool is used to determine a threshold value. The fractal index could be adjusted to a threshold value and a warning could be sent before the wear is detected on the cutting tool. Early detection of tool wear leads to appropriate surface quality in finishing operations. This value can guarantee high machining quality at the end of the trimming operation. The threshold value of I for the spindle electric current signal could be adjusted to 0.958 or less based on tool condition (trimming using new cutting tool). This value can guarantee the cutting tool is still in perfect operating order with no signs of wear, which is essential for finishing operations of CFRP material.

3.2. Total cutting force signal

3.2.1. Conventional analysis of total cutting force signal

The total cutting force signal as a function of machining time and the average of the total cutting force signal as a function of cutting length during the trimming of CFRP are illustrated in Fig. 9. For the worn cutting tool, the total cutting force average is lower in some areas than for the new cutting tool. This behavior can be explained by the effect of cutting tool temperature on matrix softening, where the softer matrix requires less cutting force. Generally, due to the composite material's low thermal conductivity, the high temperature tends to stay in the cutting zone area during the machining of composite parts [26]. High temperature in the cutting zone area affects the tool life and surface quality of the machined part. The strength and properties of CFRP are degraded by matrix softening and decomposition at temperatures over the resin's glass transition temperature [26, 27]. The average temperature of the CFRP in the cutting zone area and the average temperature of the cutting tool are illustrated in Fig. 10. These temperatures were estimated using the infrared camera installed on the spindle head with the frame rates of 60 Hz, and it is graphed for the first 3 m length of cut. The cutting tool temperature was estimated when the tool exited the workpiece. The average temperature of the worn cutting tool during the trimming of CFRP is higher than the average temperature of the new cutting tool, as shown in Fig. 10. Moreover, the average temperature of the CFRP (in the cutting zone area) is also higher when the worn cutting tool is utilized. Wear on the cutting tool generates a rise in temperature in the cutting area, causing the matrix to soften and burn. The temperature of a new cutting tool reaches 300°C after 3 m of cutting; while for the moderately worn and severely worn cutting tool, the temperature reaches 320°C and 394.1°C, respectively. Figure 11 shows the 3D images of the surface texture for the last 50 mm of cut with the new and severely worn cutting tool. The thermally impacted matrix creates a smooth surface, as seen in Fig. 11, which is a false interpretation of the surface evaluation.

R_a is the arithmetical mean height of a line and it estimate the roughness of a profile. S_a is the extension of R_a to a surface. S_a is the average value of the absolute value of height at each point in the area [28]. The result of S_a (Arithmetical Mean Height) indicates that the surface improves when the worn cutting tool is utilized (Fig. 12). The moderately worn tool makes a smooth machined surface with S_a less than 10 μm . However, when the surface is trimmed by the new cutting tool, the S_a rises to 20 μm . High temperature in the cutting zone area leads to matrix softening and inaccurate interpretation of surface quality. It is concluded that roughness parameters cannot be an appropriate indicator for surface evaluation of the CFRP, as Hamedanianpour [29] and Ghidossi *et al.* [30] also mentioned in their studies.

3.2.2. Fractal analysis of total cutting force signal

Cutting force signals have frequently been used to monitor the tool condition. However, they are not practical or cost-effective to be used in production lines. Because of its sensitivity to the cutting state, the cutting force signal can be utilized as an alternate option for tool condition monitoring depending on

equipment availability. The fractal analysis result of the total cutting force signal during the trimming of CFRP is filtered and illustrated in Fig. 13. The result of fractal dimension reveals that during the trimming of CFRP with worn cutting tools, less complicated shapes and less variation can be found in the total cutting force signal. The result of the coefficient of determination of the linear regression (R^2) for the worn cutting tools remains constant throughout the cutting length, and the results of severely and moderately worn cutting tools are very similar. However, for the new cutting tool, the R^2 results fell to a low point of 0.968 after 3.8 m of trimming and subsequently, the graph shows a rise. A threshold value of 0.98 or less for the fractal index can be selected (trimming using a new cutting tool). This value can ensure the desired dimensional accuracy or surface integrity of the machined surface at the end of finishing operation.

4. Conclusion

Machining of CFRP is challenging due to the elevated temperature that remains in the cutting zone area. According to the results, the average temperature of the worn cutting tool during the trimming of CFRP was much higher than the new cutting tool's average temperature. A thermally affected matrix made an inaccurate interpretation of the surface quality. According to the result of S_a , roughness parameters cannot be an appropriate indicator for surface evaluation of the CFRP. The tool wear was selected as a comparative factor for the results.

This study investigated the online tool condition monitoring using fractal analysis of the spindle current signal and the total cutting force signal during the trimming of CFRP. Based on the results, fractal parameters of the total cutting force signal can be used to assess the tool condition during machining CFRP. The fractal dimension describes the regularity of the signal, while the coefficient of determination of the linear regression describes the auto-scale dependency of the signal. Index computation using a combination of fractal parameters allows for merging the key detection performances of each parameter. This index provides a more precise monitoring of tool wear and surface quality during the machining of CFRP. A threshold value of 0.98 or less for the fractal index of the cutting force signal has been determined to ensure the desired surface quality at the end of the trimming operation based on proposed experiments. For production environments where no force acquisition systems are implemented, this study demonstrates that fractal analysis of the spindle electric current signal is as appropriate to extract the tool wear information as the force signal is during the trimming of CFRP. The threshold value for the fractal index of this signal has been determined as 0.958 or less to ensure excellent tool condition, with no sign of wear, for the trimming operation proposed. This empirical fractal index is introduced as a decision-making parameter to support online tool condition monitoring. This study effectively demonstrated the efficiency of fractal analysis as a decision-making method in tool condition monitoring.

Declarations

Funding The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Conflicts of interest The authors state that they have no known competing financial interests or personal relationships that could have influenced the research presented in this study.

Availability of data and material Not applicable.

Code availability Not applicable.

Ethics approval The authors confirm to the work's novelty and state that it has not been submitted to any other journal.

Consent to participate The authors give consent to participate.

Consent for publication The authors give their consent for their work to be published.

References

1. U.P. Breuer, Commercial aircraft composite technology, 1 ed., Springer, Cham, Switzerland, 2016.
2. J. Ahmad, Machining of polymer composites, 1 ed., Springer, Boston, MA, 2009.
3. M. Altin Karataş, H. Gökkaya, A review on machinability of carbon fiber reinforced polymer (CFRP) and glass fiber reinforced polymer (GFRP) composite materials, *Defence Technology* 14(4) (2018) 318-326.
4. R. Teti, K. Jemielniak, G. O'Donnell, D. Dornfeld, Advanced monitoring of machining operations, *CIRP Annals- Manufacturing Technology* 59(2) (2010) 717-739.
5. M. Nouri, B.K. Fussell, B.L. Ziniti, E. Linder, Real-time tool wear monitoring in milling using a cutting condition independent method, *International Journal of Machine Tools and Manufacture* 89 (2015) 1-13.
6. H.K. Abdul-Ameer, G.A. Al-Kindi, H. Zughaer, Towards computer vision feedback for enhanced CNC machining, *IEEE 3rd International Conference on Communication Software and Networks*, Xi'an, China, 2011 pp. 754-760.
7. M.T.N. Hidayah, J.A. Ghani, M.Z. Nuawi, C.H.C. Haron, A review of utilisation of cutting force analysis in cutting tool condition monitoring, *International Journal of Engineering & Technology IJET-IJENS* 15(03) (2015).
8. A.G. Rehorn, J. Jiang, P.E. Orban, State-of-the-art methods and results in tool condition monitoring: a review, *The International Journal of Advanced Manufacturing Technology* 26(7-8) (2005) 693-710.
9. M. Hassan, A. Sadek, M.H. Attia, Novel sensor-based tool wear monitoring approach for seamless implementation in high speed milling applications, *CIRP Annals- Manufacturing Technology* 70(1) (2021) 87-90.
10. M. Hu, W. Ming, Q. An, M. Chen, Tool wear monitoring in milling of titanium alloy Ti-6Al-4 V under MQL conditions based on a new tool wear categorization method, *The International Journal of Advanced Manufacturing Technology* 104(9-12) (2019) 4117-4128.

11. Y.H. Jeong, D.-W. Cho, Estimating cutting force from rotating and stationary feed motor currents on a milling machine, *International Journal of Machine Tools & Manufacture* 42 (2002) 1559–1566.
12. E. Soliman, F. Ismail, Chatter detection by monitoring spindle drive current, *The International Journal of Advanced Manufacturing Technology* 13 (1997) 27-34.
13. D.F. Hesser, B. Markert, Tool wear monitoring of a retrofitted CNC milling machine using artificial neural networks, *Manufacturing Letters* 19 (2019) 1-4.
14. M. Elforjani, S. Shanbr, Prognosis of bearing acoustic emission signals using supervised machine learning, *IEEE Transactions on Industrial Electronics* 65(7) (2018) 5864-5871.
15. Q. Ren, L. Baron, M. Balazinski, R. Botez, P. Bigras, Tool wear assessment based on type-2 fuzzy uncertainty estimation on acoustic emission, *Applied Soft Computing* 31 (2015) 14-24.
16. B.B. Mandelbrot, *The fractal geometry of nature*, W.H. Freeman, New York, 1982.
17. X. Zuo, H. Zhu, Y. Zhou, J. Yang, Estimation of fractal dimension and surface roughness based on material characteristics and cutting conditions in the end milling of carbon steels, *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 231(8) (2015) 1423-1437.
18. X. Rimpault, M. Balazinski, J.-F. Chatelain, Fractal analysis application outlook for improving process monitoring and machine maintenance in manufacturing 4.0, *Journal of Manufacturing and Materials Processing* 2(3) (2018).
19. M. Jamshidi, X. Rimpault, M. Balazinski, J.-F. Chatelain, Fractal analysis implementation for tool wear monitoring based on cutting force signals during CFRP/titanium stack machining, *The International Journal of Advanced Manufacturing Technology* 106(9-10) (2020) 3859-3868.
20. S. Bérubé, *Usinage en détournage de laminés composites carbone/époxy*, Mechanical engineering École de technologie supérieure, Montréal, 2012.
21. ASTM, *Standard practice for measuring and compensating for emissivity using infrared imaging radiometers*, E1933-14, ASTM International, West Conshohocken, PA, 2018.
22. Z. Feng, M.J. Zuo, F. Chu, Application of regularization dimension to gear damage assessment, *Mechanical systems and signal processing* 24(4) (2010) 1081-1098.
23. X. Rimpault, J.-F. Chatelain, J.-E. Klemberg-Sapieha, M. Balazinski, Fractal analysis of cutting force and acoustic emission signals during CFRP machining, *Procedia CIRP* 46 (2016) 143-146.
24. A. Akbari, M. Danesh, K. Khalili, A method based on spindle motor current harmonic distortion measurements for tool wear monitoring, *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 39(12) (2017) 5049-5055.
25. X. Rimpault, E. Bitar-Nehme, M. Balazinski, J.R.R. Mayer, Online monitoring and failure detection of capacitive displacement sensor in a Capball device using fractal analysis, *Measurement* 118 (2018) 23-28.
26. W. Hintze, C. Klingelhöller, Analysis and modeling of heat flux into the tool in abrasive circular cutting of unidirectional CFRP, *Procedia CIRP* 66 (2017) 210-214.

27. T. Yashiro, T. Ogawa, H. Sasahara, Temperature measurement of cutting tool and machined surface layer in milling of CFRP, *International Journal of Machine Tools and Manufacture* 70 (2013) 63-69.
28. ISO, Geometrical product specifications (GPS) – Surface texture: Areal – Part 2: Terms, definitions and surface texture parameters, ISO 25178-2, 2012, p. 47.
29. H. Hamedanianpour, J.F. Chatelain, Effect of tool wear on quality of carbon fiber reinforced polymer laminate during edge trimming, *Applied mechanics and materials* 325-326 (2013) 34-39.
30. P. Ghidossi, M. El Mansori, F. Pierron, Edge machining effects on the failure of polymer matrix composite coupons, *Composites Part A: Applied Science and Manufacturing* 35(7-8) (2004) 989-999.

Figures

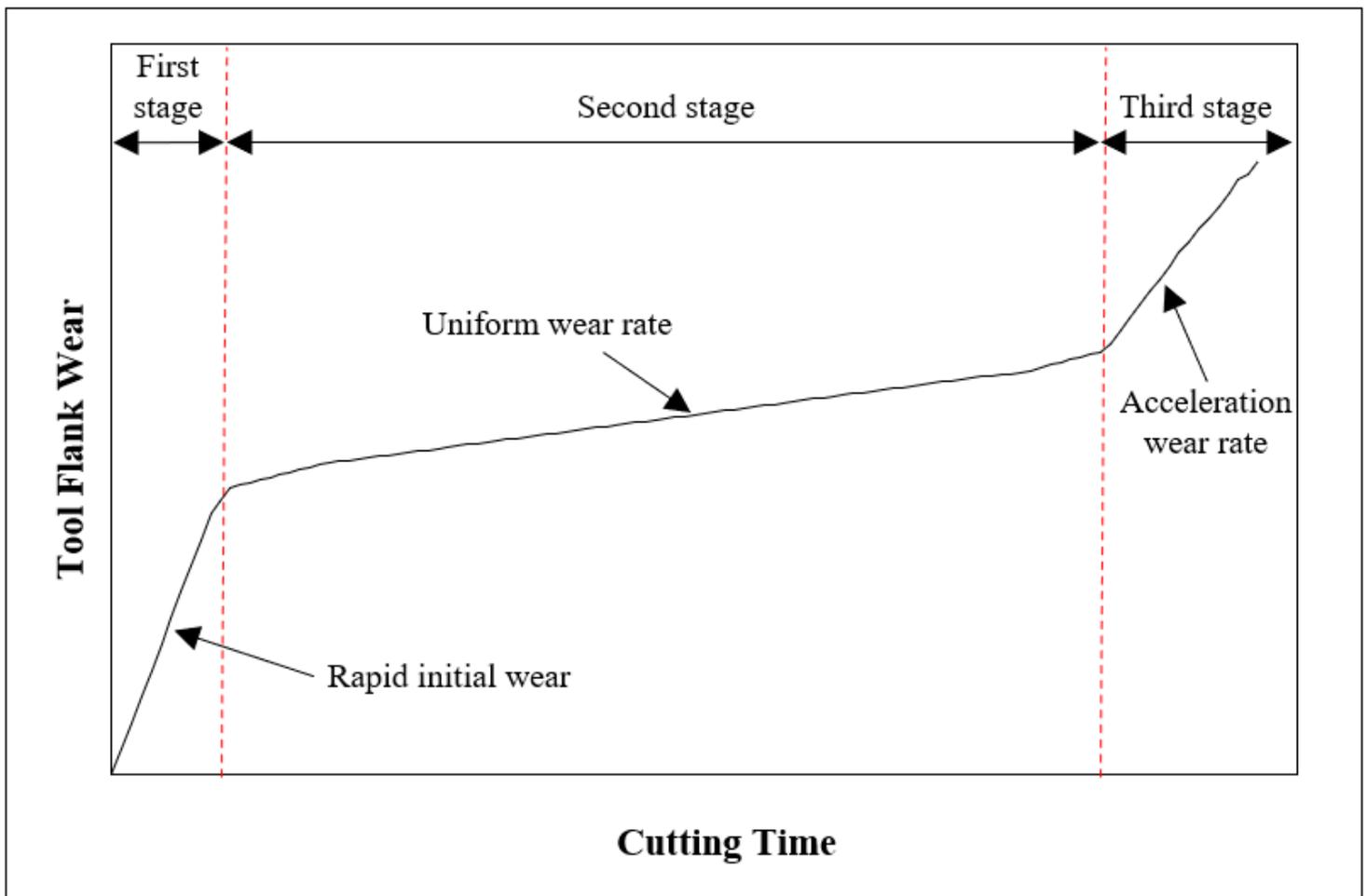


Figure 1

Tool wearing phenomena [19]



Figure 2

The experimental setup, and the direction of trimming specified with the red arrows

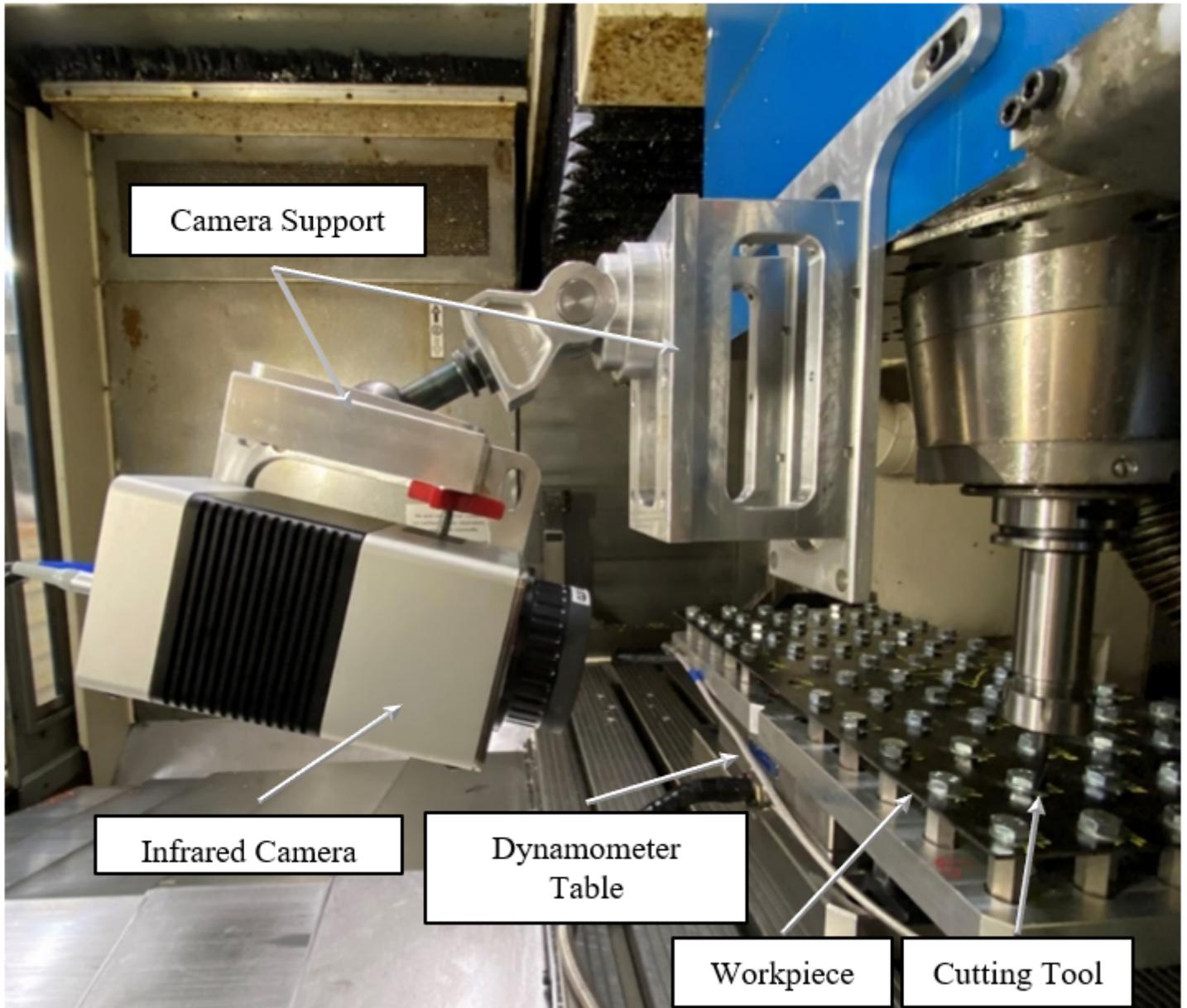


Figure 3

Infrared camera series VarioCAM® HD head 900 installed on the spindle head

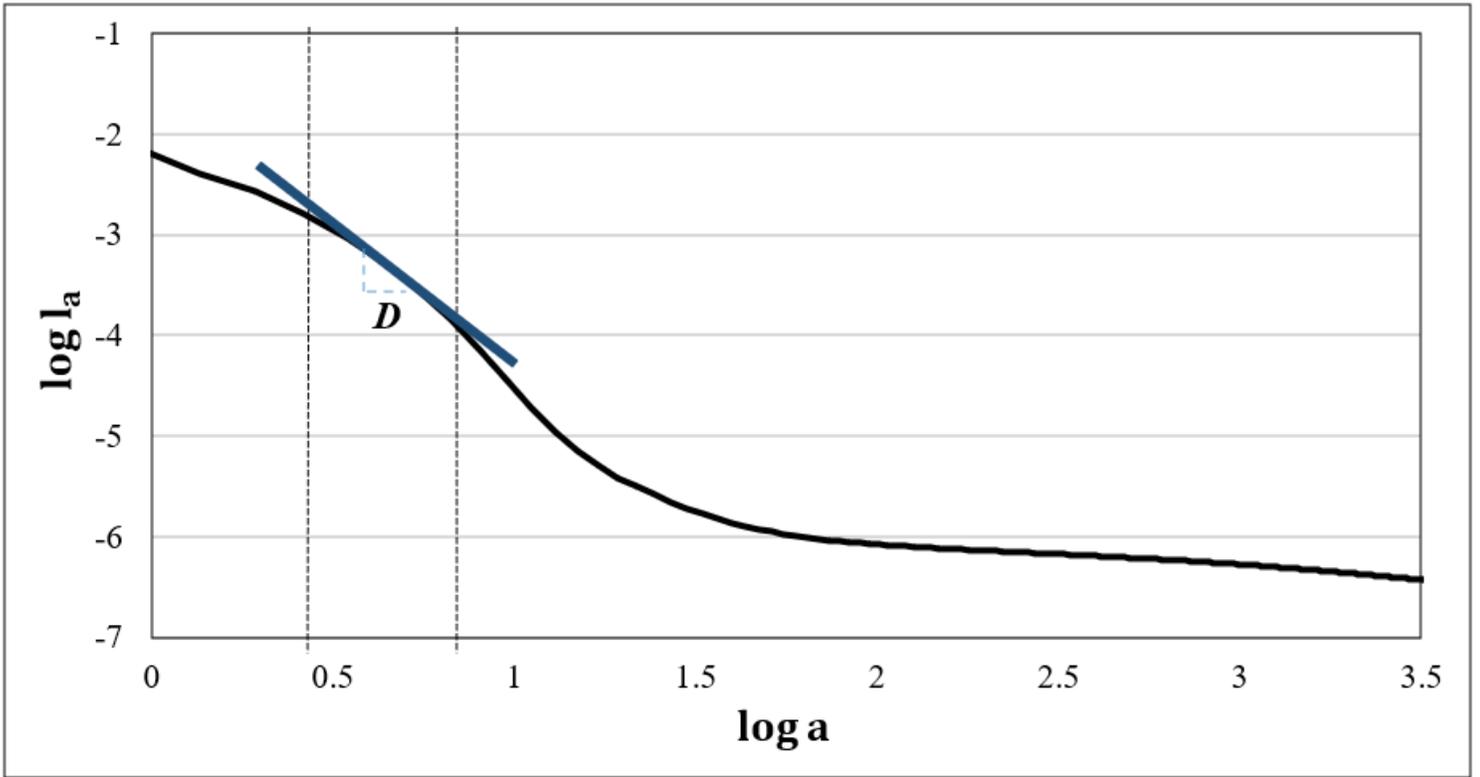


Figure 4

Example plot illustrating regularization analysis. The plot expresses vs. (a) in log-log format for the spindle current signal

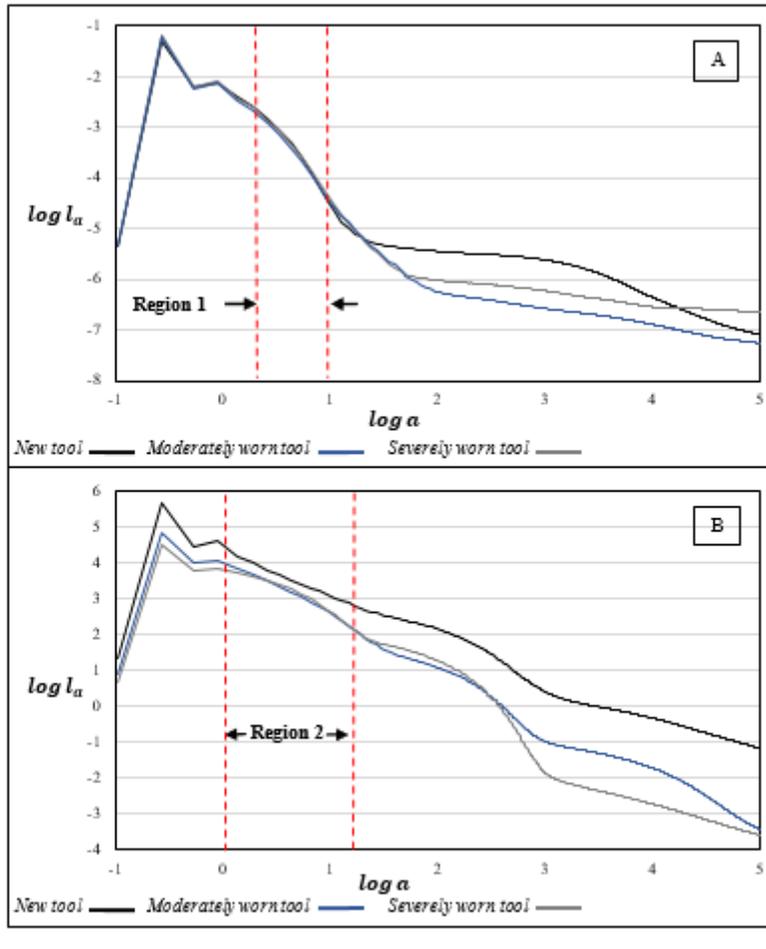


Fig.5 $\log l_a$ vs. $\log a$ graph for A) the spindle current signal and B) total cuttice signal

Figure 5

See image above for figure legend

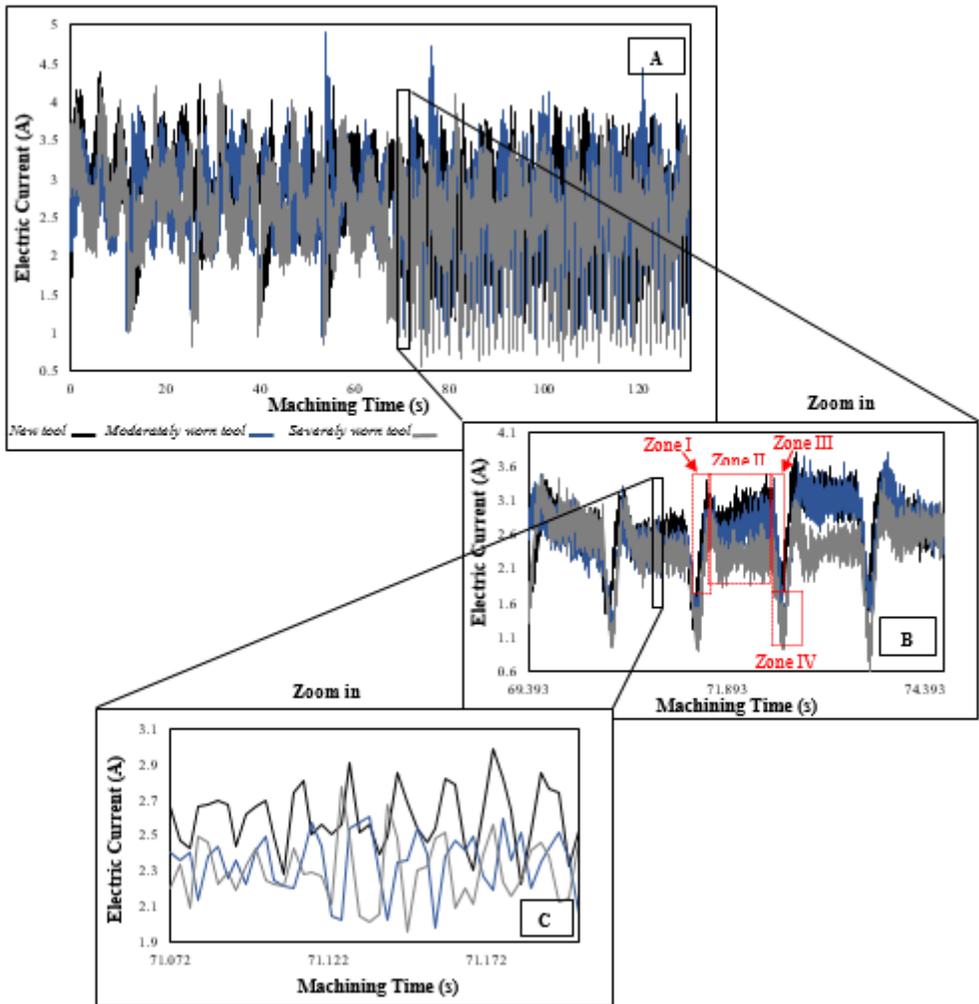


Figure 6

A) The spindle electric current signals during trimming of CFRP using the new, the moderately worn, and the severely worn CVD end mill tool. **B)** Zoom in section of the spindle current signals including Zone I to Zone IV **C)** Zoom in section of the spindle current signals

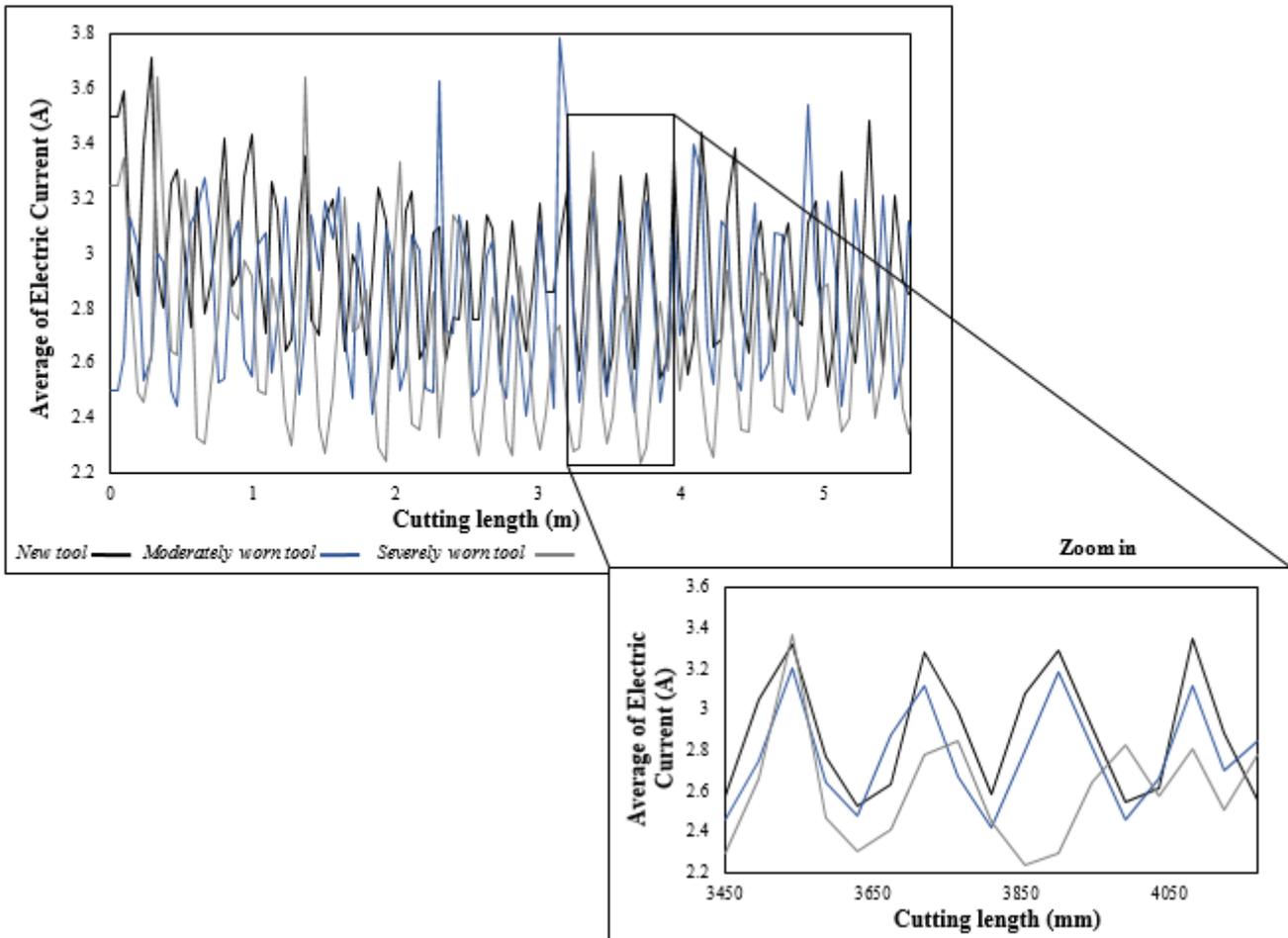


Figure 7

Average of the spindle electric current as a function of cutting length during trimming of CFRP using the new, the moderately worn, and the severely worn CVD end mill tool

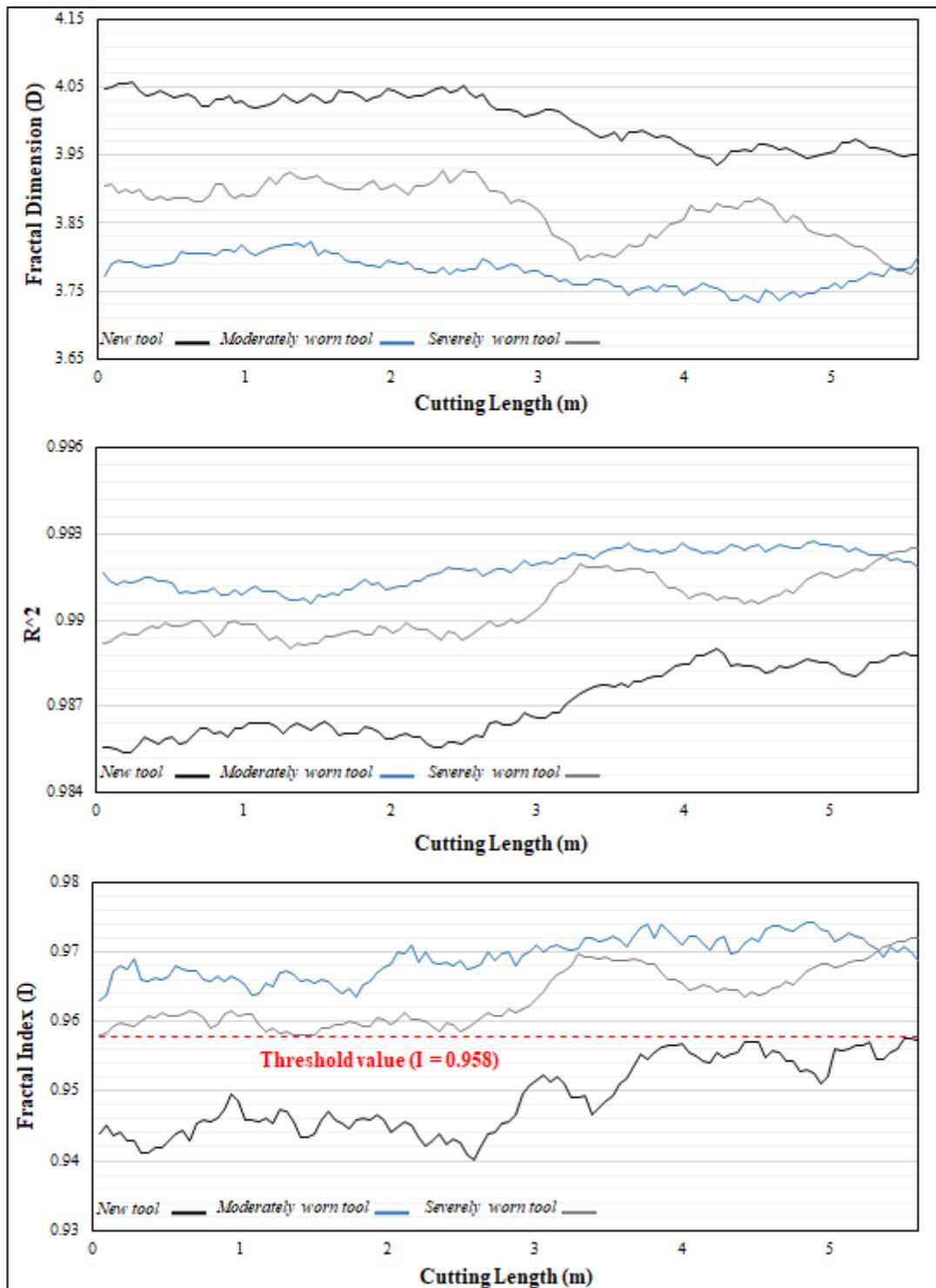


Figure 8

Fractal analysis of the spindle electric current signal during trimming of CFRP using the new, moderately worn, and severely worn CVD end mill tool

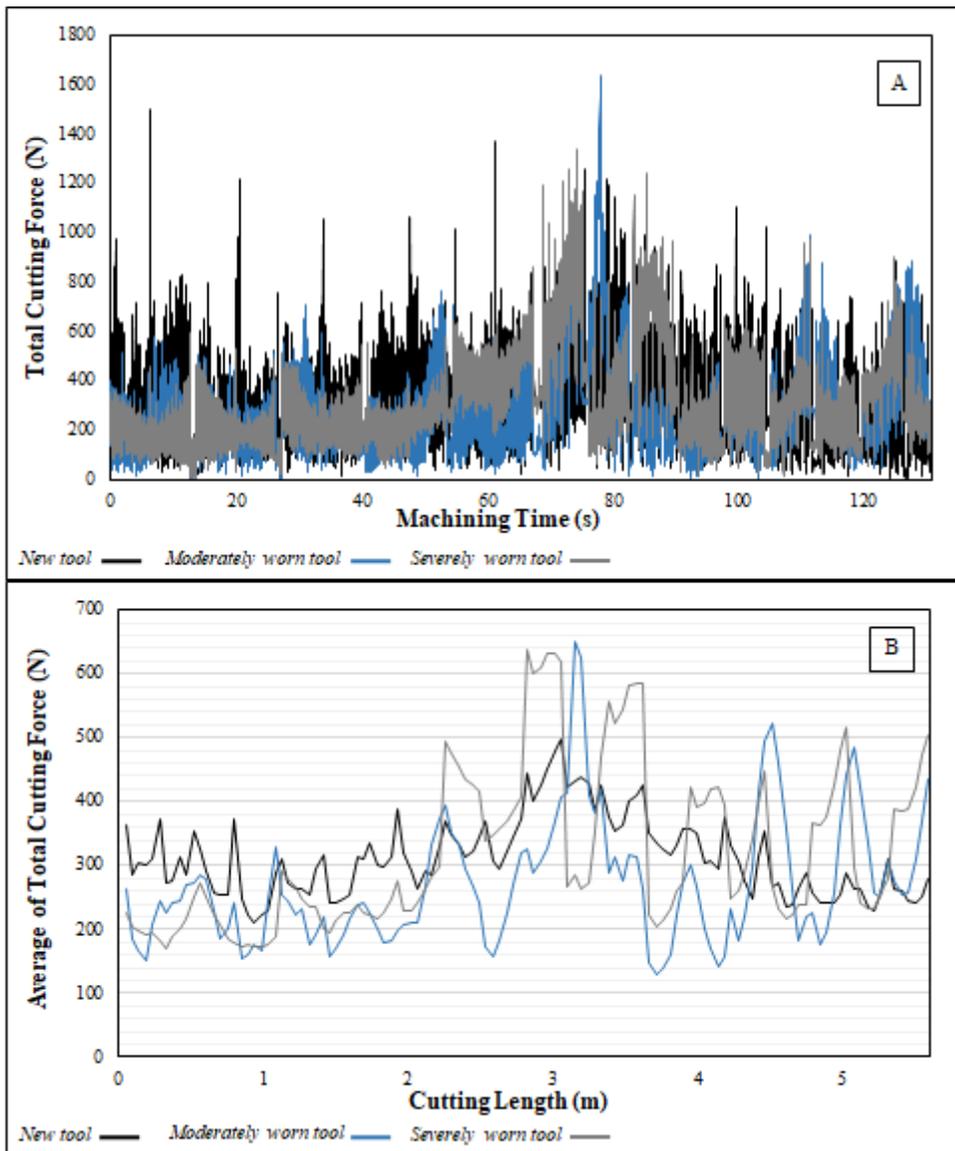


Figure 9

A) Total cutting force signal during trimming of CFRP using the new, the moderately worn, and the severely worn CVD end mill tool. **B)** Average of total cutting force signal as a function of cutting length

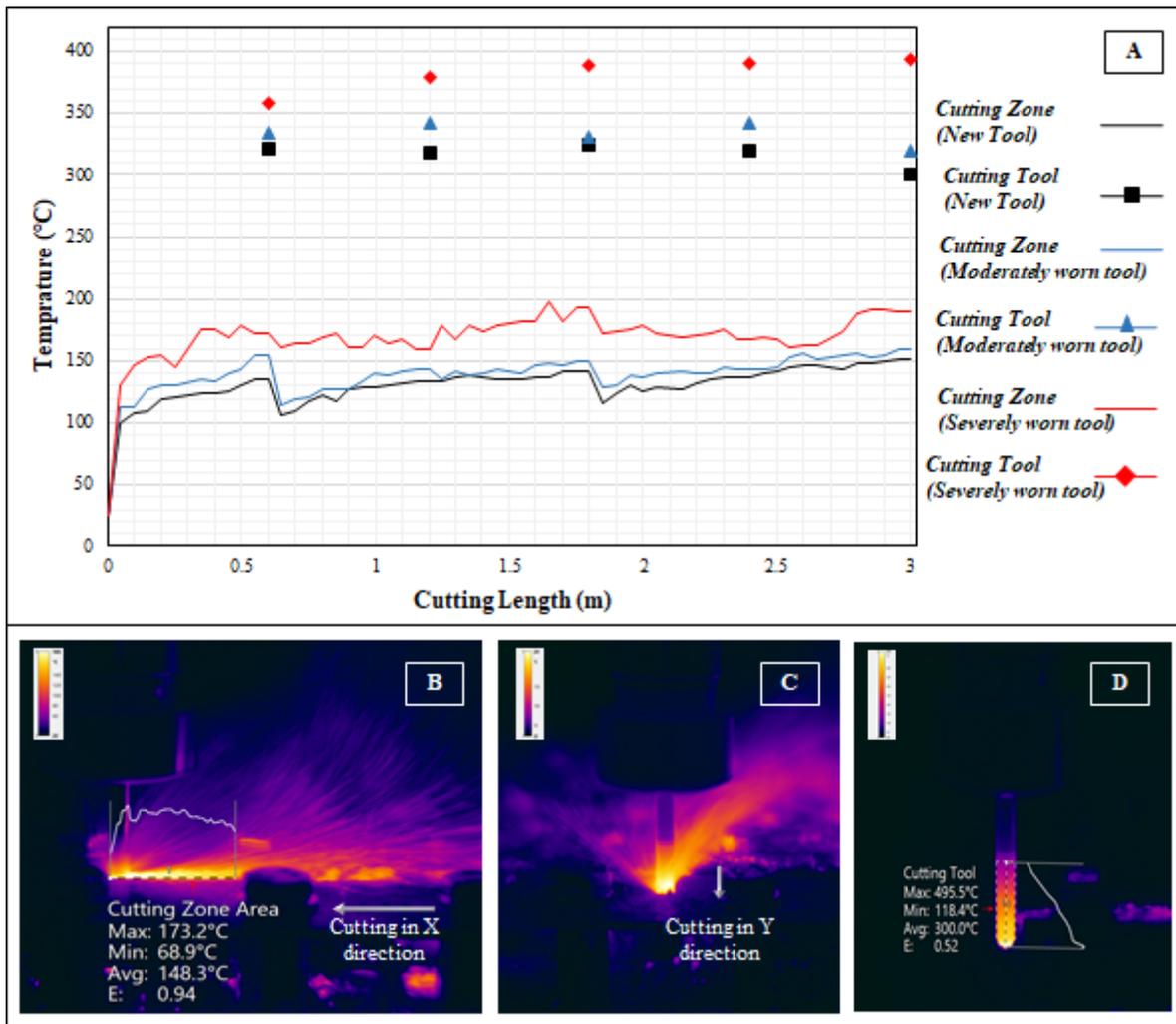


Figure 10

A) The average temperature of the workpiece in the cutting zone area and the average temperature of the cutting tool during trimming of the CFRP in the first 3 m length of cut using the new, the moderately worn, and the severely worn CVD end mill tool. **B)** Photo taken using infrared camera during cutting in X direction. **C)** Photo taken during cutting in Y direction. **D)** Photo taken when the cutting tool is out of the workpiece to estimate the temperature of the cutting tool

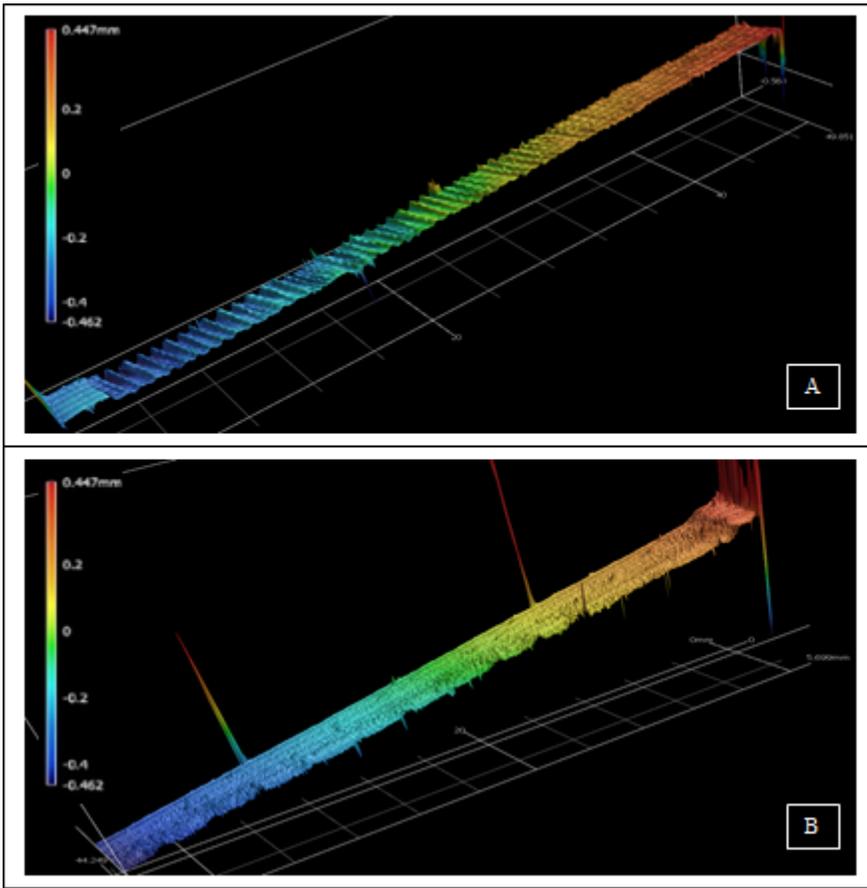


Figure 11

The 3D images of the surface texture for the last 50 mm of the cutting using A) the new CVD end mill tool B) the severely worn CVD end mill tool

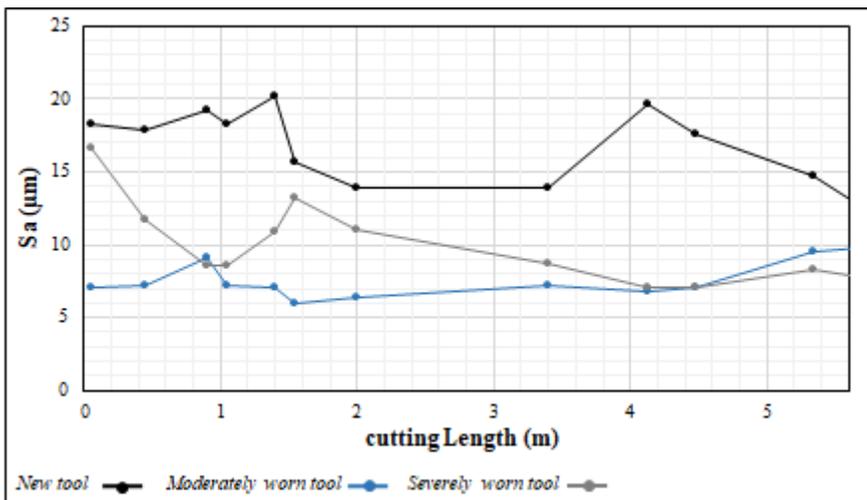


Figure 12

Areal surface roughness parameter (S_a) when the new, moderately worn and severely worn cutting tool is utilized

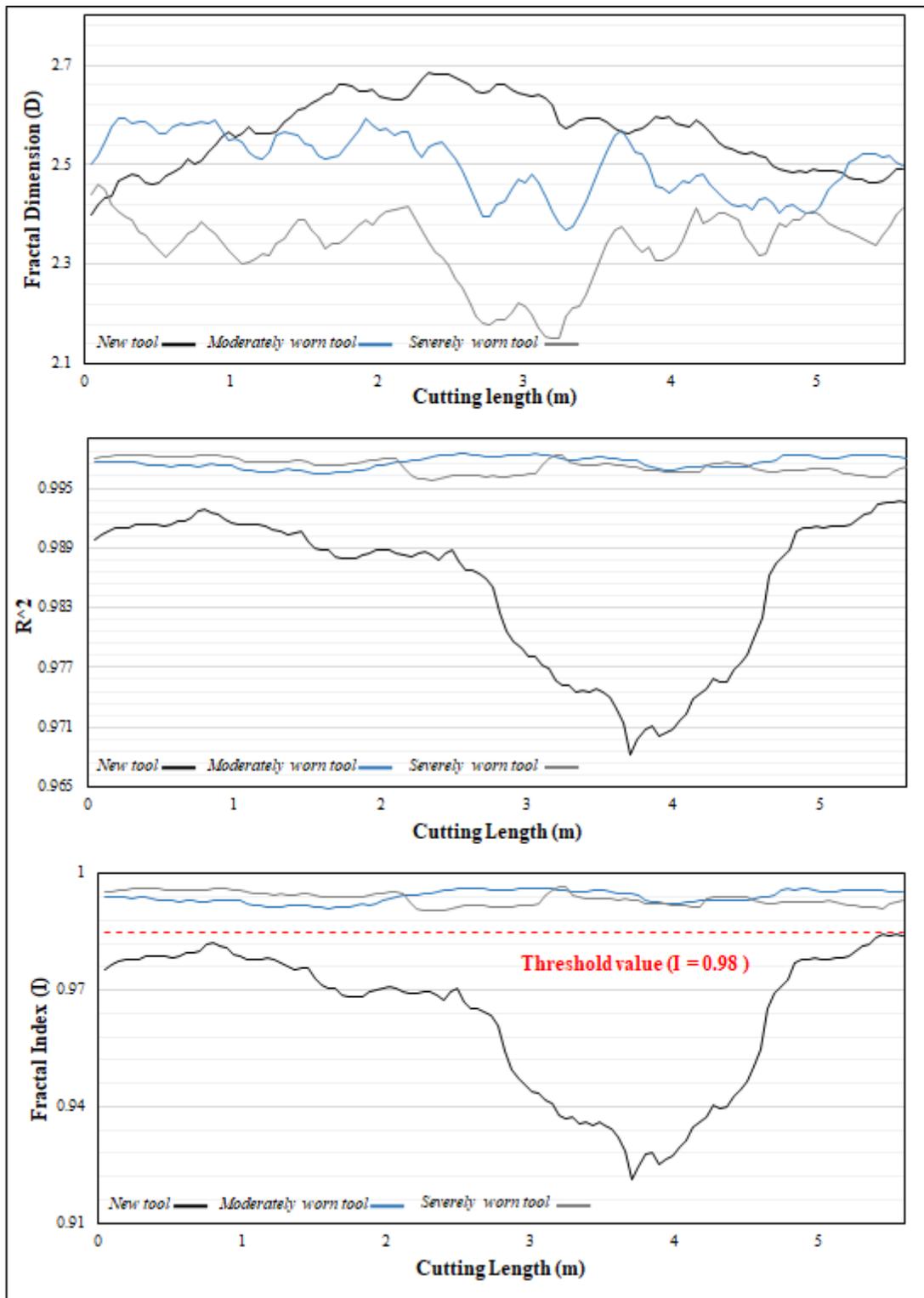


Figure 13

Fractal analysis of the total cutting force signal using the new, the moderately worn, and the severely worn CVD end mill tool

