Online Tool Condition Monitoring Implementation using Fractal Analysis

by

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Mise en œuvre de surveillance en ligne de l'état des outils à l'aide de l'analyse fractale

Maryam JAMSHIDI

RÉSUMÉ

Le fraisage est une technologie de haute performance qui permet d'usiner efficacement des surfaces de formes complexes. La qualité de la pièce usinée est influencée directement par l'état de la fraise. Il est essentiel de surveiller l'état de l'outil de coupe pendant le processus d'usinage afin de contrôler la qualité de la pièce usinée et d'éviter le temps mort des équipements. La surveillance en ligne de l'état des outils est un pilier de la fabrication intelligente, en particulier dans les lignes de production hautement automatisées. L'objectif de la technique de surveillance est de produire une alerte avant que l'usure de l'outil n'atteigne un certain seuil pour éviter de dégrader la surface finie et de perdre la justesse dimensionnelle de la pièce finale. Le développement d'un système intégré de surveillance de l'état des outils qui minimise le temps de traitement et l'expertise requise représente un domaine crucial nécessitant une enquête plus approfondie. Dans cette étude, une méthode indirecte de surveillance de l'état des outils a été développée afin de surveiller l'état des outils en temps réel et de réagir rapidement si nécessaire. Cette méthode a été réalisée en corrélant les signaux de capteurs pertinents aux états d'usure de l'outil. Dans cette étude, des capteurs qui n'interfèrent pas avec le processus de coupe ont été utilisés. Les paramètres liés au moteur ont également été présentés, représentant le choix idéal en raison de leur grande sensibilité aux conditions de coupe et pour éviter une pause pendant l'usinage. Les efforts de coupe et les signaux de courant électrique liés à la broche se sont avérés très sensibles aux conditions de coupe et une représentation correcte des changements d'état de l'outil. Dans cette étude, le signal de courant électrique de la broche a été acquis à l'aide du capteur interne de la machine-outil grâce à une programmation d'actions synchrones.

La théorie des probabilités statistiques d'un signal peut ne pas être suffisamment juste pour étudier l'usure des outils lorsque le processus d'évolution présente une caractéristique chaotique. La théorie du chaos traite de cette imprévisibilité dans les systèmes et utilise des paramètres fractals pour prévoir tout changement dans la forme du signal. Dans cette étude, l'analyse fractale a été introduite comme une stratégie de prise de décision efficace demandant moins de temps de traitement et d'expertise pour extraire des informations du signal. Plusieurs matériaux et opérations d'usinage ont servi à valider cette méthode de surveillance de l'état de l'outil. Le perçage orbital, le détourage et le fraisage de contour ont été utilisés pour usiner un empilement multi-matériaux (titane (Ti6Al04V) / composite fibres de carbone époxy (CFRP)), un matériau CFRP ainsi que l'acier AISI 5140. L'analyse fractale a été appliquée aux signaux des efforts de coupe et au signal de courant électrique de la broche pour prévoir toute turbulence inattendue dans le signal et pour établir une valeur unique dans la machine-outil comme avertissement avant que l'usure de l'outil ne devienne sévère. Cette étude a démontré l'efficacité de l'analyse fractale comme méthode de support à la décision dans la surveillance de l'état des outils.

Mots clés : Fraisage, Surveillance de l'usure des outils, Efforts de coupe, Courant électrique, Analyse fractale

Online tool condition monitoring implementation using fractal analysis

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ABSTRACT

Milling is a high-performance technology, which makes it possible to efficiently machine complex shaped surfaces. The quality of the machined component is directly influenced by the condition of the milling cutter. It is essential to monitor the cutting tool condition during the machining process in order to control the quality of the machined part and avoid equipment downtime. Real time tool condition monitoring is a pillar of intelligent manufacturing, especially in the highly automated production lines. The objective of monitoring technique is to send a warning before tool wear reaches a certain threshold to avoid degrading the finished surface and losing the final part's dimensional accuracy. An integrated tool condition monitoring system with minimal processing time and expertise is one of the crucial areas that require further investigation. In the present study, indirect method of tool condition monitoring has been developed in order to monitor tool condition in real time and respond quickly as needed. This method is performed by correlating relevant sensor signals to the tool wear states. In this study, sensors that did not interfere with the cutting process were used. Motor-related parameters were also introduced as the ideal choice due to their high sensitivity to cutting conditions and the avoidance of a pause during machining. Cutting forces and electric current signals related to the spindle during machining were found to be highly responsive to cutting conditions and to properly represent changes in tool condition. In this study, the spindle electric current signal was acquired using the internal sensor of the machine tool through a static synchronized action programming.

In order to extract significant characteristic features of the signal, probability statistics theory may not be accurate enough to study tool wear when the evolution process exhibits a chaotic characteristic. The Chaos theory addresses this unpredictability in a system, and it uses fractal parameters to forecast any change in signal shape. In the present study, fractal analysis was introduced as an effective decision-making strategy with less processing time and expertise to extract information from the signal. Different machining operations and materials were conducted to validate this tool condition monitoring method. Orbital drilling, trimming and contour milling were used to machine a multi-material stack (titanium alloys (Ti6Al04V)/ Carbon Fiber Reinforced Plastics (CFRP)), a CFRP material as well as the AISI 5140 steel material. Fractal analysis was applied to the cutting force and spindle electric current signal to predict any unexpected turbulence in the signal and to establish a single value in the machine tool as a warning before tool wear becomes severe. The effectiveness of fractal analysis as a decision-making method in tool condition monitoring was demonstrated in this study.

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Keywords : Milling, Tool wear monitoring, Cutting force, Electric current, Fractal analysis

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LIST OF ABREVIATIONS

AE	Acoustic Emission
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
BUE	Built-Up Edge
CFRP	Carbon Fiber Reinforced Plastics
CWT	Continuous Wavelet Transform
D	Fractal dimension
DCT	Discrete Cosine Transform
DFT	Discrete Fourier Transform
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transform
FIS	Fuzzy Inference System

FTP	First Transition Point
G	Topothesy
GA	Genetic Algorithms
KB	Crater width
KM	Crater centre distance
KT	Crater depth
MI	Mutual Information
R^2	Coefficient of determination of the linear regression
R_a	Arithmetical mean height
RMS	Root Mean Square
RUL	Remaining Useful tool Life
S_a	Arithmetical mean height
STFT	Short-Time Fourier Transform
STP	Second Transition Point
SVM	Support Vector Machine

TCM	Tool Condition Monitoring
TFD	Torque-Force Distance indicator
VB_B	Average values of the flank wear width
$VB_B max$	Maximum values of the flank wear width
WPT	Wavelet Packet Transforms
ν -SVM	ν-Support Vector Machine

INTRODUCTION

Milling is a high-performance technology, which makes it possible to efficiently machine complex shaped surfaces in industrial, automotive, machinery, and many more sectors. The condition of the rotary milling cutter is directly influencing the quality of the machined component (Pimenov et al., 2022). The cutting tool needs to be replaced when tool wear becomes severe enough to affect the quality of the finished product. Successful wear determination helps prevent poor product quality, unscheduled downtime, and financial losses by tool failure. According to statistics, tool wear causes 7 to 20 percent of the average machine tool downtime, which significantly reduces productivity (Drouillet et al., 2016). Pre-setting a tool life is a common procedure on shop floors, despite being conservative and unrealistic. Such approach leads to either the early replacement of cutting tools, which raises tool costs and downtime, or the delayed replacement of worn cutting tools, which lowers the quality of the finished product and raises product cost. Statistics show that milling tools are often only utilized for between 50 percent to 80 percent of their functional lives (Yuqing Zhou & Xue, 2018). As an example, consider the production of an automotive engine part. Approximately thirty-forty operations from various machines are necessary to finish each component, wherein one machine is assigned to perform five to ten different machining operations that include turning, milling, drilling, *etc.* Failure or breakage of one or more tools in such a situation results in significant material loss, machine shutdown and downtime, which affects production and quality (Nath, 2020).

Real time tool condition monitoring becomes a pillar of intelligent manufacturing, especially in the highly automated production lines to make the necessary corrections as well as a quick and precise tool wear detection (N. Li, Chen, Kong, & Tan, 2016). Unmanned machining has been recognized as one of the key components to lower production costs in industries. This is accomplished with the use of automatic monitoring technology for all possible machining processes at once. The development of Tool Condition Monitoring (TCM) system has increased the quality of workpiece surfaces and extended tool life. By employing proper signal processing and pattern recognition algorithms, TCM system can save costs by 10 to 40 percent by reducing downtime and maximising the cutting tool life (Yuqing Zhou & Xue, 2018).

Successful application of a tool condition monitoring system in the industrial environment is still a big challenge. One of the important areas that require further investigation is an integrated tool condition monitoring system with minimal processing time and expertise. The objective of the present study is to develop a new method of tool condition monitoring with minimal processing time, expertise and devices that complies with industrial restrictions.

This PhD thesis is organized in six chapters, which are briefly described here. The thesis's research objectives along with its scope are described in **chapter 1**. The **chapter 2** provides an overview of recent researches on different tool condition monitoring systems. Additionally, a literature review about various signal processing techniques and decision-making strategies are discussed in this chapter. The **chapter 3** discusses the methodology, experimental measurements, and more specific information regarding the signal analysis.

The first published journal article is presented in **chapter 4**. This article focuses on online tool condition monitoring using the cutting force signal. In this study, the cutting force signal related to orbital drilling were analyzed while machining a stack of homogeneous and composite material (stack of Ti6Al4V titanium alloy and CFRP). It was shown that distinct wear stages of the cutting tool were adequately identified using fractal signal features of cutting forces, and low machining quality could be prevented without requiring extensive experimentation.

The second published journal article is described in **chapter 5**. This study aimed to achieve the required surface quality during machining of CFRP using online tool condition monitoring. It was found that the high temperature in the cutting zone area affected the tool life and surface quality of the machined part. This research investigated 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. The effectiveness of fractal analysis as a decision-making method in the tool condition monitoring was successfully proven in this study.

The third published journal article is presented in **chapter 6**. In this study, tool condition was monitored using fractal analysis of the spindle electric current signal during metal machining. The spindle electric current signal was acquired using the machine tool internal sensor, which met industrial constraints in their operating conditions. This study analyzed the electric current signal when milling AISI 5140 steel to develop monitoring techniques for wear classification of metal cutting processes. Fractal parameters were defined to extract significant characteristic features of the signal and to evaluate the tool condition and guarantee adequate surface quality during the machining process. This study successfully proved the efficiency of fractal analysis as a decision-making strategy in tool condition monitoring.

The conclusions from the present research work are addressed at the end of this Ph.D. thesis, along with some recommendations for more research in this area.

CHAPTER 1

PROBLEM STATEMENT, RESEARCH OBJECTIVES, AND ORIGINAL CONTRIBUTIONS

1.1 Problem statement and research objectives

In the industrial environment, milling is a high-performance technology that enables the efficient machining of both flat and complex shaped surfaces. The quality of the machined component is directly influenced by the condition of the cutting tool. When tool wear gets severe enough to impact the quality of the finished product, the cutting tool needs to be replaced. The critical challenge is how to anticipate tool life and when is it necessary to replace the cutting tool. Pre-setting a tool life is a common procedure on shop floors, despite being conservative and unrealistic. Such approach leads to either the early replacement of cutting tools, which raises tool costs and downtime, or the delayed replacement of worn cutting tools, which lowers the quality of the finished product and raises product cost. In order to produce high-quality parts, automated production lines require quick and accurate tool wear detection. Early detection of tool wear and appropriate surface quality can be achieved using online tool condition monitoring. Successful application of a tool condition monitoring system in the industrial environment is still a big challenge. One of the important areas that require further investigation is an integrated tool condition monitoring system with minimal processing time and expertise.

The **overall objective** of this study is to develop a new method of tool wear monitoring with minimal processing time, expertise and devices that complies with industrial restrictions.

The specific objectives of the present research are:

- Correlating different sensor signals to the tool wear states to examine the possibility of application in online tool condition monitoring. Different sensors, including cutting forces, acoustic emission, temperature, electric current sensors were examined to accurately assess the condition of the cutting tool.

- Developing an intelligent online tool condition monitoring system using different decision-making strategies to detect process irregularities and start corrective action without human involvement.

- Investigating the use of the internal data of the machine tool through a static synchronized action programming to monitor the condition of the cutting tool.

- Evaluating the effectiveness of fractal analysis as a decision-making strategy in the tool condition monitoring when machining different materials.

1.2 Original contributions of the study

One of the important areas that require further investigation is an integrated tool condition monitoring system with less processing time, expertise and sensors. The objective of real-time tool condition monitoring is to send a warning before tool wear reaches a certain level. In the present study, an indirect method of tool wear monitoring has been introduced and developed in order to build an integrated Tool Condition Monitoring (TCM) system in real time. This method was performed by correlating relevant sensor signals to the tool wear states. Cutting forces, acoustic emission, temperature, and electric current signals were acquired to feed the TCM system. It was found that motor-related parameters were the ideal choice for TCM systems due to their high sensitivity to cutting conditions and the avoidance of a pause in machining. For the first time, the spindle electric current signal was acquired using the internal sensor of the machine tool in the present study. Data acquisition was extremely fast and no external sensors were involved in this monitoring system. A static synchronized action programmed with the Application Programming Interface (API) of the SIEMENS SINUMERIK 840D controller was used to record the spindle electric current signal. In the present study, high performance key features of different signals were extracted using fractal analysis, to complete monitoring and prediction systems. Fractal analysis was found as an efficient decision-making technique with minimal processing time and expertise. Different cutting processes and materials were examined to validate this new tool condition monitoring technique.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of Tool Condition Monitoring (TCM) methods and explains why it is essential in a manufacturing process. The two main categories of tool condition monitoring; direct and indirect methods, are reviewed in section 2.2 alongside the most recent work in this field. An overview of data acquisition techniques that can be applied in TCM systems is provided in the section 2.3. The following sections (2.4 and 2.5) provide a description about the signal pre-processing and signal processing techniques that are required to extract information from the signals. The decision-making techniques for tool wear monitoring are discussed in section 2.6. This chapter concludes with an overview of an integrated tool condition monitoring system, which is one of the major gaps that have not yet been addressed and needs further investigation.

2.2 Tool condition monitoring systems

One of the primary concerns in modern autonomous and semi-autonomous machining production floors is a comprehensive, effective and trusted tool condition monitoring system (Nath, 2020). A common tool condition monitoring includes data acquisition, signal processing techniques, feature extraction and decision making process, as shown in Figure 2.1. Hardware is used for data or signal acquisition techniques, while software is used for the rest of the TCM systems. Figure 2.2 illustrates the two primary categories of tool condition monitoring: direct and indirect methods. The geometric characteristics of the cutting tool are precisely assessed in the direct method using optical, laser, electromechanical or ultrasonic methods (Nouri, Fussell, Ziniti, & Linder, 2015). Direct measurements of tool wear using machine vision and optical microscopy are a reliable method for tool condition monitoring (Figure 2.3). In this method, flank wear land and the other wear characteristics, such as, chipping, breakage, *etc.* can be accurately mapped using an optical microscope. However, optical measurement of tool condition has often been used in laboratories, and it is still impractical to use in the industrial production lines (Nath, 2020). This inspection process takes long time and process interruptions which is necessary for direct method to determine the tool's health state. This method is also unable to detect any unexpected cutting tool damage that occurs during the tool/workpiece engagement (Mohamed, Hassan, M'Saoubi, & Attia, 2022). Before 1990, the radioactive and electrical resistance technologies were also investigated as a direct method of tool condition monitoring. However, these methods appeared to be impractical because of safety concerns, slow processing times and variations in cutting force which led to false results (Nath, 2020). The machine vision technology was recently presented as the new direct tool condition monitoring technique. A high-quality optical camera sensor system was put in the machine chamber, and the tool images were captured and processed online using Artificial Intelligence (AI). The accuracy of flank wear, fracture, Built-Up Edge (BUE), and chipping estimation was reported to be about 97 percent. However, this method is still only a proof-of-concept, and more effective standards and algorithms are needed to cover a variety of cutting tools and cutting processes (Nath, 2020).

In order to monitor situation in real time and respond quickly as needed, indirect method of tool condition monitoring has been developed (Figure 2.3). The condition of the cutting tool is estimated using alternative parameters in the indirect technique. It is performed by correlating relevant sensor signals to the tool wear states. Different signals can be employed to monitor the tool condition in this method. This method correlates the tool health state with measured variables such as cutting forces (X. Rimpault, J.-F. Chatelain, J.-E. Klemberg-Sapieha, & M. Balazinski, 2016), acoustic emission (Barreiro, Fernández-Abia, González-Laguna, & Pereira, 2017), vibration (C. a. Zhou, Guo, & Sun, 2021), sound (Rehorn, Jiang, & Orban, 2005), temperature (He, Shi, Xuan, & Li, 2021), electric current and power signal (Drouillet et al., 2016). The indirect method of tool condition monitoring is more widely applicable and more affordable, but it is less accurate.

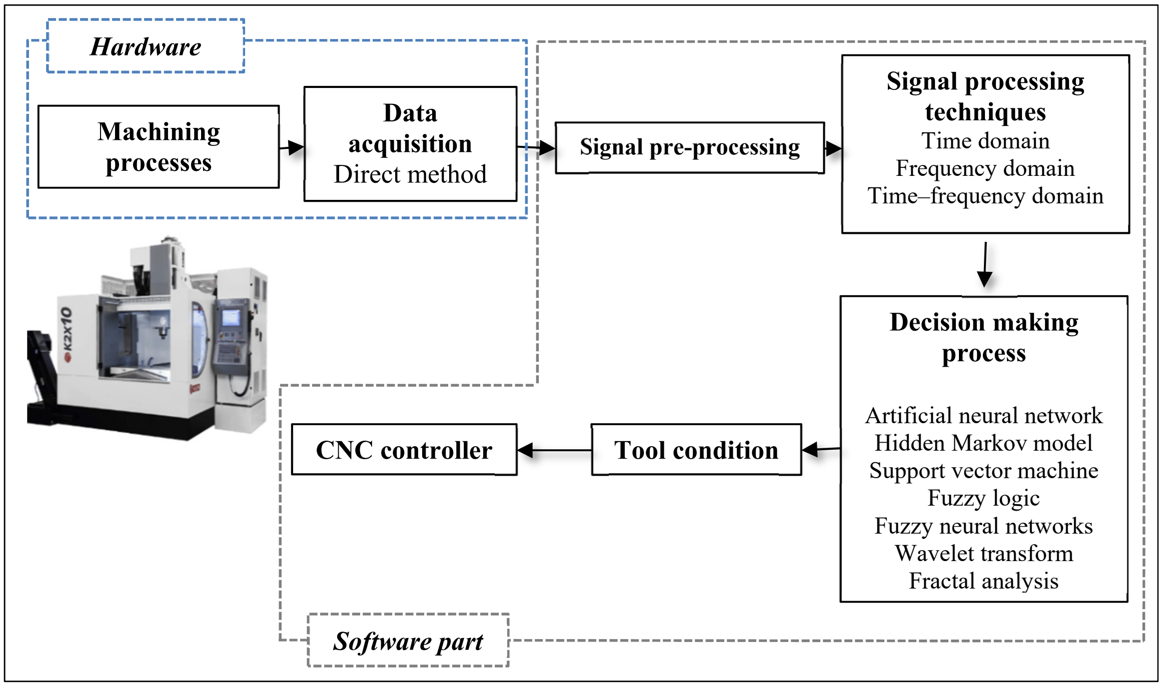

Figure 2.1 Tool Condition Monitoring (TCM) system's framework

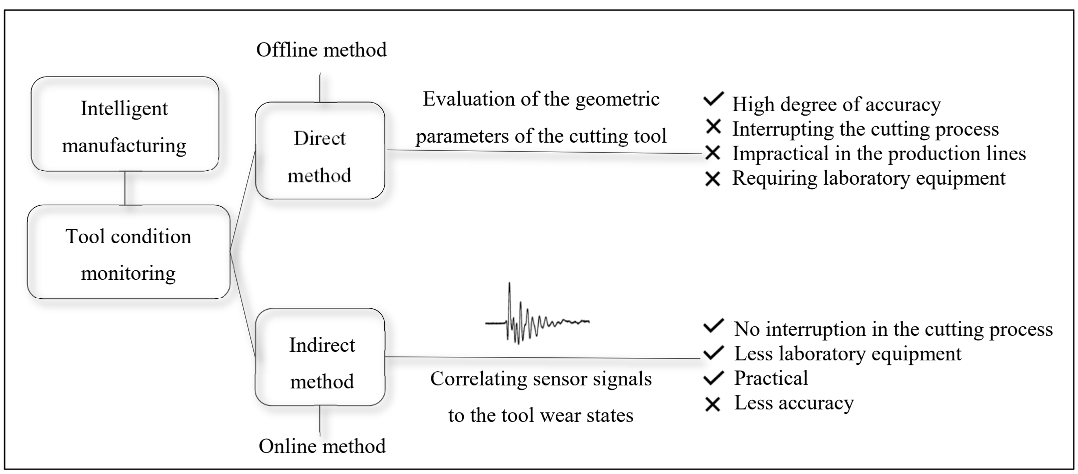

Figure 2.2 Description of direct and indirect tool condition monitoring methods

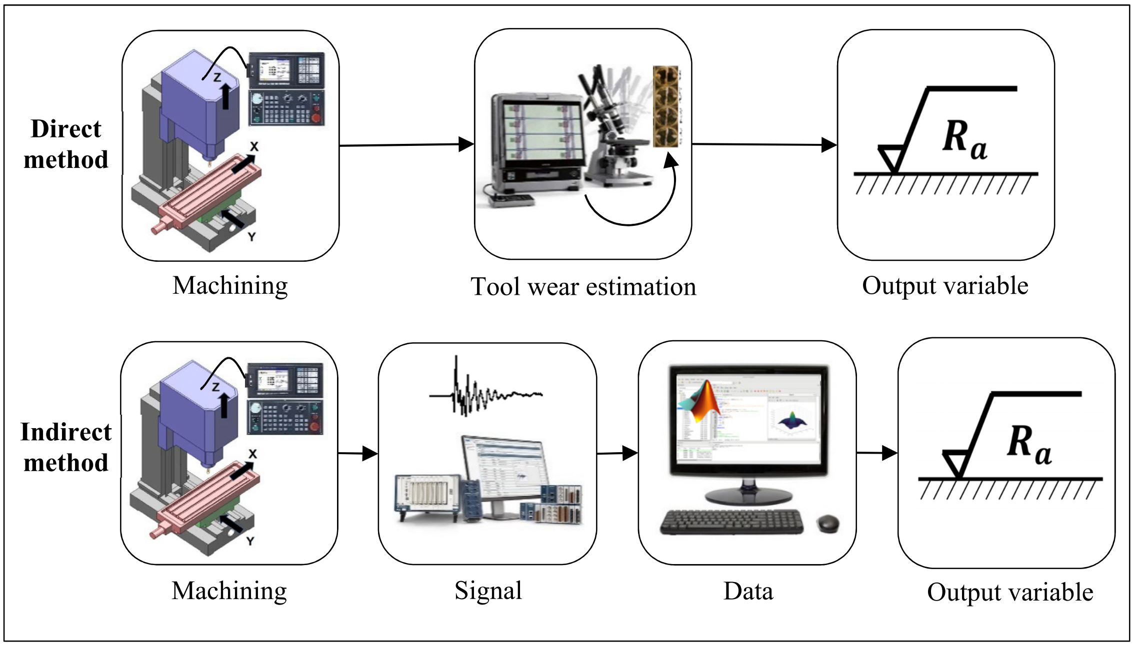

Figure 2.3 Representation of direct and indirect tool condition monitoring methods

2.3 Data acquisition techniques

To accurately assess tool condition, a tool condition monitoring system needs to be practically online for data collecting and processing. In the indirect method of tool condition monitoring, the systems assess the state of the cutting tool using alternative parameters. Such systems include, for example, cutting force sensors (Xavier Rimpault et al., 2016), acoustic emission sensors (Barreiro et al., 2017), vibration sensors (C. a. Zhou et al., 2021), sound sensors (Rehorn et al., 2005), temperature sensors (He et al., 2021) and electric current or power sensors (Drouillet et al., 2016).

2.3.1 Cutting force signal

The cutting force signal is the most dependable and stable variable in machining processes and is therefore the most frequently used signal in tool condition monitoring (Xavier Rimpault et al., 2016; Chang'an Zhou et al., 2020). Due to cutting forces high sensitivity, any changes in cutting state can be reflected in the cutting force signal (Mohamed et al., 2022). The friction force between the tool and the workpiece during machining increases when the cutting tool loses its sharpness and gets dull, but given the same cutting conditions, a greater cutting force is required to remove material from the workpiece. Other factors, such as the cutting conditions, cutting tool material and workpiece material can also be responsible for the increase in cutting forces. To emphasise the tool wear effect on the acquired signals and filter out all other aspects, a normalisation method is required (Mohamed et al., 2022).

Using statistical aspects of cutting force signals during the machining of titanium alloy, Hu *et al.* (Hu, Ming, An, & Chen, 2019) could predict distinct tool wear states. Mutual Information (MI) and ν-Support Vector Machine (ν -SVM) were used in this study for model training and prediction. With an accuracy rate of 98.9 percent, the suggested technique could accurately forecast various tool wear conditions. In another study, Liao *et al.* (Liao, Zhou, Zhang, Lu, & Ma, 2019) developed an automated tool condition monitoring technique using a cutting force sensor while machining steel alloy. In this monitoring technique, the Support Vector Machine (SVM) and Genetic Algorithms (GA) were used to accurately determine the level of tool wear. According to a review by Hidayah *et al.* (Hidayah, Ghani, Nuawi, & Haron, 2015), analysis of cutting forces is a robust approach for online tool condition monitoring. However, the acquisition of cutting force requires sensors, such as dynamometer, which is not practical or cost-effective to use in production line.

The dynamometer table is a well-known sensor for force measurements in the indirect tool condition monitoring method due to its great sensitivity and reliability. A dynamometer table can be used to detect small variations in the load. However, due to its high price, load and size restrictions, it cannot be used in industrial facilities (Mohamed et al., 2022). Moreover, when several machines are running together in a manufacturing line, various noise and vibration sources may interfere with the cutting force, which can cause some errors in tool condition monitoring systems. Additionally, the majority of force sensors are sensitive to the cutting fluid which can cause signal drifting and variations, so the cutting force results can be unreliable when cutting fluid is utilised during machining (Nath, 2020). The cutting force signals are therefore regarded as a reliable sensor in tool condition monitoring for academic research and not for the production line due to dynamometer's limitations.

2.3.2 Acoustic emission signal

Acoustic Emission (AE) is the intuitive transient elastic wave or energy that is released from materials as a result of plastic deformation at the cutting zone area (Nath, 2020). The AE signal has been employed to detect tool wear and breakage since its frequency bandwidth is higher than machine vibrations. By observing the acoustic waves produced during the unstable crack propagation at the prefailure stage, the AE signal can predict upcoming catastrophes, and provide the opportunity to take precautions actions (Mohamed et al., 2022). AE signals in the cutting process depend on the signal's source. During the milling operation, which is a discontinuous operation, transient AE signals can be generated. Continuous AE signals are produced by continuous interaction between the tool and the workpiece or the continuous chips (e.g., turning or drilling) (Nath, 2020). Similar to the vibration analysis, signal monitoring and analysis typically involves placing the sensor as near as possible to the cutting zone area. AE sensors are relatively cheap and easy to install on the machine. They need to be calibrated correctly before each experiment. The machine condition, the distance between the cutting tool and the sensor, and the signal transmission path can all affect the AE signal's quality. In order to effectively monitor the tool condition, AE sensors can be mounted on the spindle or on the workpiece. However, due to the closeness of the signal source and the short signal transmission path, more reliable signals can be recorded when sensors are mounted on the spindle (Mohamed et al., 2022). Barreiro *et al.* (Barreiro et al., 2017) presented the design of a TCM system using a combination of vibration and AE signals to detect the cutting tool condition while machining very high thickness and length steel plates. This research illustrated that each of these signals provided complimentary effects in several spectral bands with a totally distinctive nature. As a result, utilizing complementary signals was more relevant for monitoring systems than utilizing an individual signal.

Even though AE sensors are inexpensive and simple to install, it might be challenging to obtain accurate signal feature information from AE sensors. Results can be easily impacted by placing location, ambient noise, sensor alignment, fouling from chip and coolant, and sensitivity to parameter changes (Nath, 2020).

2.3.3 Vibration signal

In machining, vibration is a direct response to oscillations in cutting force during chip formation. Vibration is often classified as free, forced and self-excited vibration (Pimenov et al., 2022). In comparison to other sensors like AE sensors and dynamometers, a vibration sensor is inexpensive and simple to install. Utilizing piezoelectric or MEMS accelerometers, the cutting tool vibrations can be measured (Mohamed et al., 2022). Cutting-dependent and cutting-independent vibrations are two categories that can be used to categorise vibrations produced during metal cutting. Cutting-dependent vibrations are those created by the cutting process itself, such as interrupted cutting. Whereas, cutting-independent vibrations are those induced by machine parts, such as unbalanced rotating parts, and include forced vibrations as well. To accurately reflect tool wear, it is important to analyze the signal to separate the two types of vibrations (Mohamed et al., 2022).

Both the time and frequency domains are typically used to analyze the vibration signal. The analysis can assess the growth of a specific frequency harmonic and its amplitude in relation to the tool's current condition (Pimenov et al., 2022). According to a recent study, tool wear gradually increased the time domain characteristics of vibration signals, such as Root Mean Square (RMS), peak to peak, and kurtosis values. Additionally, it was demonstrated that the frequency level varied significantly depending on the tool conditions (Mohanraj, Shankar, Rajasekar, Sakthivel, & Pramanik, 2020). An integrated wireless vibration sensing tool holder system with outstanding dynamic balance features and a wide sampling frequency range was recently designed and manufactured by Zhou *et al.* (C. a. Zhou et al., 2021) to monitor the milling process. Based on singularity analysis of vibration signals, a tool condition monitoring approach was developed in this study. It was claimed that this method could detect the tool wear condition properly with an accuracy of 86.1 percent.

Due to low cost, simplicity of installation and the ability to produce a periodic signal shape which is similar to the cutting force, vibration sensors have been frequently used in TCM.

Using the mean power analysis, Rmili *et al.* (Rmili, Ouahabi, Serra, & Leroy, 2016) developed an automatic technique for monitoring tool wear based on the vibratory signatures generated during the turning operation. The suggested automatic detector was presented as a practical way to enhance a wear monitoring system in an industrial environment. However, the accuracy of TCM using vibration signals is limited by the characteristics of milling processes. Even when the tool is not engaged with the workpiece, vibrations are produced during machining operation. It is still difficult to accurately distinguish between cutting and air-cutting. Additionally, the vibration signals are extremely sensitive to the working environment. Choosing the proper filter to extract information from the vibration signal is another challenge. Moreover, the vibration signal can be impacted by the location of the sensor and the type of cutting fluid as well (Yuqing Zhou & Xue, 2018).

2.3.4 Sound signal

The friction between the tool and workpiece during machining leads in audible sound production. This sound, in contrast to AEs, is transmitted via air and it can be captured by microphones (Nath, 2020). However, there are several more sound sources on production lines, including neighbouring machines, air blows, robots, *etc.* To resolve this problem, a directional microphone is suggested (Rehorn et al., 2005), but it has not been properly tested. Therefore, it still seems impractical to use audible sound signals for a reliable tool condition monitoring.

2.3.5 Temperature

The majority of energy used by the machining system is converted into heat during the plastic deformation at the tool-workpiece-chip interface. The rate and volume of removed material, the mechanical properties of the material, the cutting tool shape, all can affect the cutting temperature (Pimenov et al., 2022). Mathematical models have revealed a strong correlation between mechanical abrasion/friction, tool wear, chemical dissolution and cutting temperature. The wear rate and temperature may be estimated by mathematical models, but it is difficult to predict the wear length without a database of the thermochemical properties of a specific tool-workpiece combination (Nath, 2020).

Different techniques, including infrared thermography, radiation pyrometer and thermocouple can be utilised to measure the temperature during the machining process. Infrared cameras are used to obtain a thermal image of the tool and workpiece in a single window. These cameras assess the cutting area temperature remotely in real time without physical contact. In a variety of fields, including the nuclear, aerospace, civil, electronic and mechanical engineering industries, infrared thermography is a frequently used method for condition monitoring (Bagavathiappan, Lahiri, Saravanan, Philip, & Jayakumar, 2013). The relatively low acquisition rate and resolutions are the main challenges to employ thermography as an online monitoring method (Pimenov et al., 2022).

There are certain drawbacks when utilizing a standard thermocouple or other contact method to measure temperature, such as limited access to sensor installation location and long response times (Mohanraj et al., 2020). He *et al*. (He et al., 2021) used a temperature signal from a thin-film thermocouple placed inside a cutter in turning operation to monitor the tool wear. Thin-film thermocouple was used to overcome the low response of the standard thermocouple. The authors reported strong prediction levels under different cutting conditions, demonstrating the reliability of such signals to improve wear predictions.

2.3.6 Electric current and power signal

The cutting tool condition and spindle power are directly correlated. The spindle power signal can be used to anticipate tool breakage accurately (Mohanraj et al., 2020). Using the stationary feed motor current, Jeong and Cho (Y.-H. Jeong & D.-W. Cho, 2002) were able to accurately predict the cutting forces normal to a machined surface with less than 20 percent error. The electric current signal can reflect any changes in the cutting state. Using this signal to monitor the tool condition is based on the theory that as the cutting tool wears out, the alternating current motor will experience a larger mechanical resistance, resulting in a decrease in spindle speed. As soon as the encoder notices it, the machining centre control unit will supply more electric current to compensate the drop, boosting the spindle speed to the pre-programmed settings. According to Stavropoulos *et al.* (Stavropoulos, Papacharalampopoulos, Vasiliadis,

& Chryssolouris, 2016), motor current signals had a stronger correlation with tool wear than the vibration signals, and because the motor current signal was less sensitive to external noise, it can be used to evaluate tool condition more precisely.

The electric current signals are often only analysed in the time domain because the frequency domain only contains information about the harmonics and frequency of the electrical grid (Pimenov et al., 2022). The spindle power signal was used by Drouillet *et al.* (Drouillet et al., 2016) to predict Remaining Useful tool Life (RUL). In this study, an Artificial Neural Network (ANN) method was employed. The cutting tool's predicted and actual RUL were found to be in good agreement. In another study, in order to forecast drill foreboding failure during steel alloy drilling, Choi *et al.* (Choi, Park, & Chu, 2008) developed a method based on the RMS of the feed and spindle motor currents. The suggested algorithm was able to predict impending failure before the drill broke, regardless of the type of cutting tool and cutting conditions. Current sensors can be positioned distant from the cutting area and are often cheap and reliable which are preferred in industrial environments (Soliman & Ismail, 1997). It is even more practical if the internal data of the machine tool's can be used for tool condition monitoring because data acquisition is extremely fast and no external sensors are involved. There is a gap in the literature in this area since no researchers have attempted to obtain the electric current data from the internal sensor of a machine tool.

2.3.7 Multi-signal approach

Multi-sensor tool condition monitoring has been developed due to the limitations of single-sensor systems. This system can cover a wider range of phenomenon frequencies and boost system robustness and information resolution (Mohamed et al., 2022). However, a comprehensive analysis is required to identify and optimize the key sensors and their characteristics in order to avoid an increase in manufacturing and maintenance expenses (Mohamed et al., 2022). Some researchers have concentrated on developing a reliable online TCM system by merging multiple signal acquisition techniques. Ghosh *et al.* (Ghosh et al., 2007) examined different signal combinations, such as cutting forces, spindle vibration, spindle current and sound pressure level to estimate the average flank wear of the cutting edge. This study recommended that the electric current and force-based TCM system can be used in the high-value machining industry. In another study, a sensor fusion model based on the combination of AE, vibration, force and machine vision techniques was examined by Jemielniak *et al.* (Jemielniak, Urbański, Kossakowska, & Bombiński, 2012). It was concluded that the vibration and AE signal features offer the best results. Kuljanic and Sortino (Kuljanic & Sortino, 2005) introduced a new variable called the Torque-Force Distance indicator (TFD) in the face milling operation based on the combination of torque and cutting force signal. The TFD demonstrated a strong correlation with tool wear and it was independent of the cutting parameters.

Type and quantity of sensors used in TCM processes are important. The number of sensors cannot be excessive since as the number of sensors rises, the production and maintenance expenses increase. Furthermore, the TCM model's accuracy may deteriorate from the redundant data provided by many sensors. In that case, using a selected key sensor is preferable to using all available sensors (Yuqing Zhou & Xue, 2018).

2.4 Signal pre-processing

Signal pre-processing is frequently necessary before or after signal digitalization, because of the characteristics of the sensor and the interference from mechanical, electrical and environmental disturbances (Mohamed et al., 2022). Amplification, sampling, filtering and segmentation are examples of signal pre-processing approaches as illustrated in Figure 2.4.

Due to the low-level output signal, the signal is often amplified at an early stage. Amplification of the signal improves the signal-to-noise ratio while reducing unwanted interference. To obtain the higher accuracy, the signal maximum voltage range should match the maximum input range condition of the analog-digital converter (Teti, Jemielniak, O'Donnell, & Dornfeld, 2010). The acquired signal should be sampled after amplification. The Nyquist-Shannon sampling theorem (Marwala, 2012) states that the sample rate for the obtained signal should be greater than twice the highest frequency of interest seen in the signal. In the next step, the acquired signal should be filtered using a high-pass, low-pass or band-pass filter to remove unwanted signal frequency components (Mohamed et al., 2022). Segmentation is another pre-processing approach for sensor data which is optional. When the tool comes into contact with the workpiece material, segments of the signal are extracted since only these segments include information about the tool condition. The simplest and most popular method of signal segmentation is the employment of a predetermined threshold in a user-defined time window. Producing repeated patterns based on tool rotation to extract segments is another segmentation technique (Mahmoud Hassan, Sadek, Attia, & Thomson, 2017; Mohamed et al., 2022).

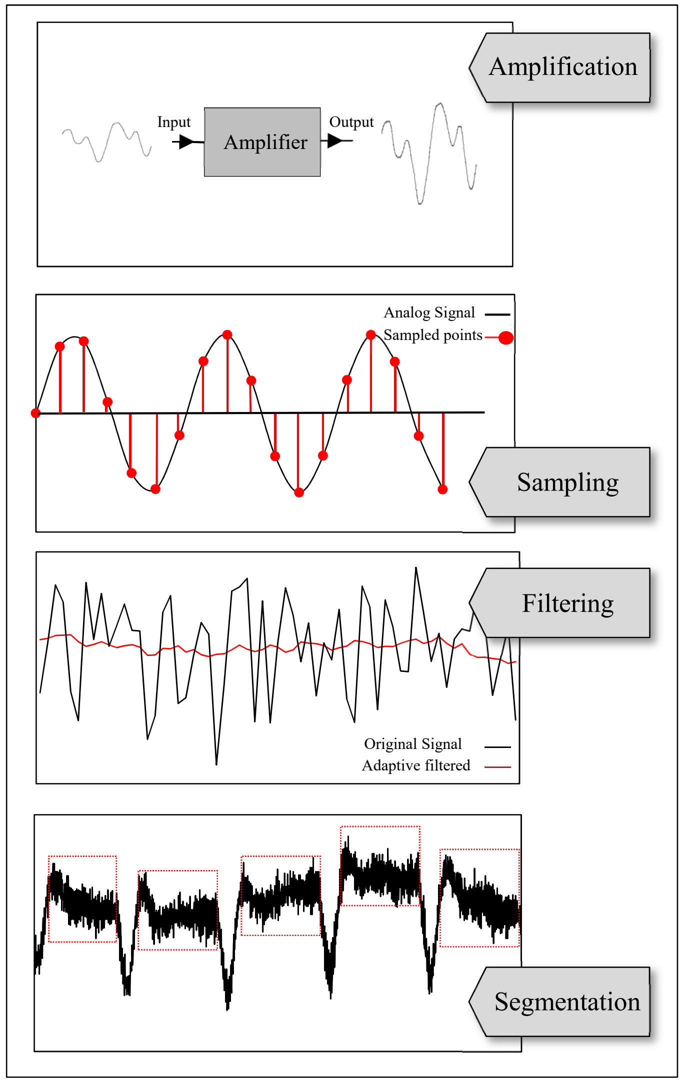

Figure 2.4 Signal pre-processing approach including amplification, sampling, filtering and segmentation

2.5 Signal processing techniques

The acquired signals in machining operations are noisy, nonstationary and nonlinear. As a result, the raw data subject to preprocessing and extraction procedures in order to acquire useful tool condition information (Mohamed et al., 2022). The main goals of the feature extraction module are to greatly reduce the dimensions of the original information in the time or frequency domains and to extract the feature parameters of the signals that are closely associated with the tool state (Yuqing Zhou & Xue, 2018). The classification of features becomes more complex when all characteristics are used, and there is a chance that some of the features will be redundant, noisy or irrelevant. This problem can be solved by using dimensionality reduction methods to choose the most useful features in the decision-making algorithm (Mohamed et al., 2022). The preprocessed data are extracted using different domains throughout the data extraction stage, including time, frequency and time-frequency domain.

2.5.1 Time domain features

Time domain features are the frequent and simple features in terms of extraction and computations. Time series analyses combined with statistical parameters are used to extract feature information in regards to the cutting tool condition (Yuqing Zhou & Xue, 2018). The average, maximum/minimum, Root Mean Square (RMS) and peak-to-peak amplitude of the signal are the most common time domain statistical features. The variance, crest factor, skewness, and kurtosis are typically extracted to describe the probability distribution of acquired data (Abubakr, Hassan, Krolczyk, Khanna, & Hegab, 2021; Bektas, Jones, Sankararaman, Roychoudhury, & Goebel, 2019). Additionally, time series modelling factors such as autoregressive, moving average and autoregressive moving average have been utilized in different studies for tool condition monitoring (Teti et al., 2010). Figure 2.5 provides an illustration of some time domain statistical features, such as average, RMS, peak-to-peak, kurtosis and skewness.

Using statistical features of cutting force and acoustic emission signals during the machining of titanium alloy, Hu *et al.* (Hu et al., 2019) were able to predict distinct tool wear states. In another study, in order to anticipate drill foreboding failure during steel alloy drilling, Choi *et al.* (Choi et al., 2008) developed a technique based on the RMS of the feed and spindle motor currents. Using the feed motor current signal, the suggested technique detected impending failure before the drill started breaking.

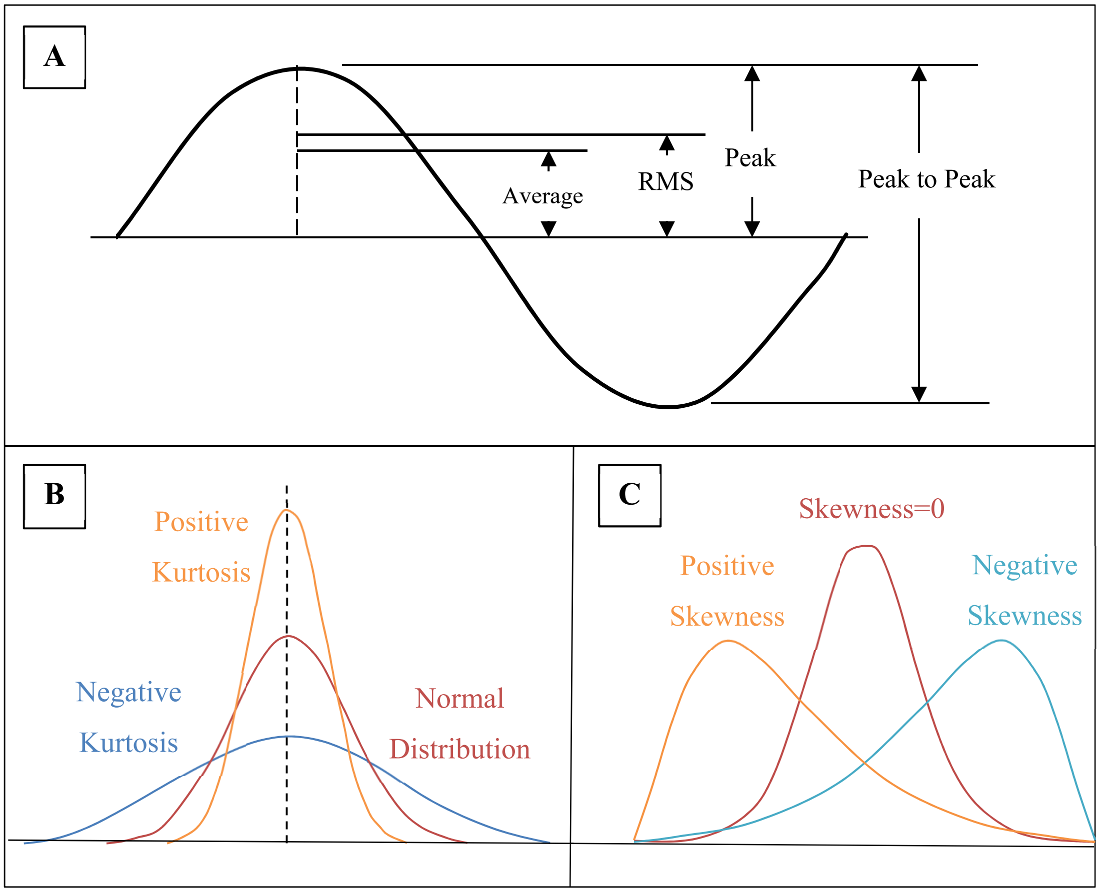

Figure 2.5 Time domain statistical features including **A)** average, RMS, peak-to-peak **B)** kurtosis and **C)** skewness

2.5.2 Frequency domain features

In the frequency domain analysis, the feature information related to the tool condition is extracted from the frequency dimension of the signal based on the frequency structure and harmonic components. This technique first uses the Fast Fourier Transform (FFT), the Discrete Fourier Transform (DFT) or Discrete Cosine Transform (DCT) to convert signals from the time domain into the frequency domain, and then the features characteristics such as the power spectrum, peak-to-peak amplitude and tooth frequency are extracted (Yuqing Zhou & Xue, 2018). In comparison to the time domain analysis, frequency domain analysis has the advantage of being able to quickly identify and separate the specific frequency components of interest (Mohanraj et al., 2020).

Analysis of cutting force in the frequency domain showed that the amplitude of typical frequency cutting force signal increased monotonically with the tool wear. However, the amplitude dropped sharply at the point of entry into the final wear stage where the cutting tool was rapidly wearing out. Additionally, a sharp decline was also reported before the tool fracture (Lee, Lee, & Gan, 1989). Despite the fact that the frequency domain may successfully detect various tool wear characteristics, it is still challenging to identify the characteristic spectral bands that are sensitive to tool wear. Additionally, it is yet unclear why tool wear affects some particular frequencies (Siddhpura & Paurobally, 2013).

2.5.3 Time-frequency domain features

Time-frequency domain characteristics can assess the signal localization in the both frequency and time domain. It is mainly based on wavelet transforms, which can offer essential information about the singularity of a signal. Recently, this area has received a lot of attention for TCM systems (Mohamed et al., 2022). Continuous Wavelet Transforms (CWT), Discrete Wavelet Transforms (DWT), Wavelet Packet Transforms (WPT), Short-Time Fourier Transform (STFT), and Empirical Mode Decomposition (EMD) can be used to extract characteristics from the acquired signal (Cabrera, Araujo, & Castello, 2017; Ferrando Chacón et al., 2021; Chang'an Zhou et al., 2020; Y. Zhou & Sun, 2020). The average energy of wavelet coefficients and wavelet domain statistics (*e.g.* RMS, mean, variance and *etc.*) are among the features that can be extracted. According to Scheffer *et al.* (Scheffer, Kratz, Heyns, & Klocke, 2003), the most stationary parts of force signals can be determined using time-frequency analysis. Because metal cutting is a dynamic phenomenon, it's essential to determine the signal's most stationary part. Zhu *et al*. (Zhu, Wong, & Hong, 2009) reviewed the different applications of wavelet analysis in TCM systems. It was indicated that this analysis method is very effective in analysing sensor signals from non-stationary machining. It was concluded that wavelet analysis offers a lot of potential for identifying sudden alterations in tool conditions and it can be very helpful in TCM systems. Although wavelet transform in the time-frequency domain offers a lot of potential for TCM, further investigation is required to demonstrate its superiority to all other methods.

2.6 Decision making for tool wear monitoring

An intelligent online TCM system is required in the fully or even partially automated production systems to detect process irregularities and start corrective action without human involvement. The system needs to be able to state the current tool condition based on acquired and processed signals. Decision-making strategies that rely on classifiers are essential for online TCM systems. After extracting features from the experimental data, tool condition can be predicted using different decision making algorithms. To automate the TCM systems, a variety of methods have been considered, including Artificial Neural Network (ANN), Hidden Markov Model (HMM), Support Vector Machine (SVM), Fuzzy Logic (FL), Fuzzy Neural Networks (FNNs) and fractal analysis.

2.6.1 Artificial Neural Network (ANN)

Artificial Intelligence (AI) accelerates data processing as a result of development in computational power. The relationship between the sensor signal and the flank wear is non-linear. As a result, Artificial Neural Network (ANN) with fault tolerance and reduces noise is an appropriate model for TCM. The input layer, hidden layer, and output layer of ANN are each composed of a certain number of neurons as illustrated in Figure 2.6. All the neurons in each layer are connected to each other. To strengthen the link between the neurons, weight and bias are applied (Mohanraj et al., 2020). In the TCM system, the input layer of ANN contains the features extracted from the feature extraction module and a number of cutting parameters (such as cutting speed, feed rate and depth of cut). The output layer represents the tool condition or tool wear value (Yuqing Zhou & Xue, 2018). The error on the predicted results appears to be bigger initially when ANN approximated the results based on the small amount of data. In order to forecast results more accurately, more experiments with continuous feeding of the data are required (Nath, 2020). Recently, an artificial neural network was used to determine the condition of cutting tool in real-time using acceleration data (Hesser & Markert, 2019) and acoustic emission signals (Elforjani & Shanbr, 2018). Cutting force and sound signals were also used by Shankar *et al.* (Shankar, Mohanraj, & Rajasekar, 2019) to monitor the flank wear during milling of aluminium alloy.

The advantage of ANN is that it does not need an analytical model to determine the complicated tool deterioration mechanism because the neural network can preserve the tool condition (Pimenov et al., 2022). However, to achieve great performance, ANN needs a lot of training data, which is time-consuming and expensive. Moreover, a key element of ANN performance is the choice of the number of hidden layers and neurons in the network structure. There are different available network structures, but finding the best one for the TCM is still unknown (Yuqing Zhou & Xue, 2018).

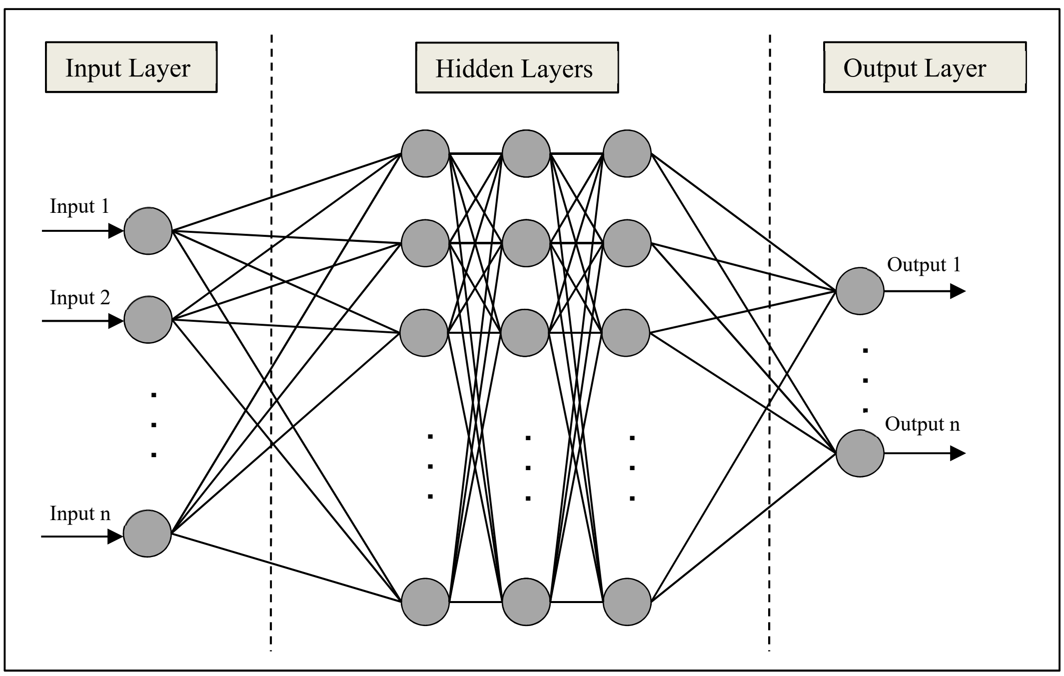

Figure 2.6 The input layer, hidden layer and output layer of Artificial Neural Network (ANN) and their connections

2.6.2 Hidden Markov Model (HMM)

A Markov process with implied unknown parameters is called Hidden Markov Model (HMM). Two random process sequences are included in the HMM. As shown in Figure 2.7, the series in the upper part is an unobservable random process sequence, while the sequence in the lower part is an observable random process. The objective is to learn about the state of the sequence of unobservable random process through observing the state value of the observable sequence, because the above sequence cannot be directly observed. The HMM can be defined by the state transition probability matrix (A), the observation probability matrix (B) and the initial state probability vector (C), which can be stated as $\lambda = [A, B, C]$ (Liang et al., 2018).

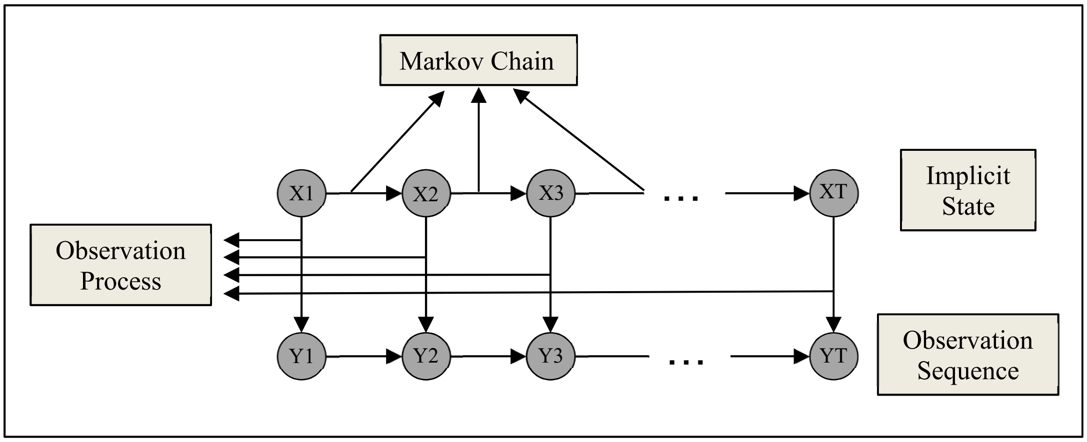

Figure 2.7 Hidden Markov Model (HMM)

Since HMM systems are capable of representing the behavior of machining operations as a dynamic model as compared to a static model, they can consider features that change over time. Yu *et al.* (Yu, Liang, Tang, & Liu, 2016) proposed a weighted HMM approach for tool wear monitoring. In this study, vibration signals were employed as a cutting tool health indicator. The experimental results indicated that the weighted HMM method is capable of producing precise wear estimates and RUL predictions. HMM systems are useful for exploring the mechanisms of tool wear evolution. However, a large amount of training data is needed for HMM similar to ANN-based methods (Yuqing Zhou & Xue, 2018).

2.6.3 Support Vector Machine (SVM)

The Support Vector Machine (SVM) approach is based on statistical learning theory. SVM uses a kernel function to input samples from the original space to a high-dimensional feature space. In this approach, a linear algorithm in the high-dimensional feature space is created which corresponds to the original space's non-linear problem's solution. SVM is an appropriate method for the TCM, which involves small sample sizes and high-dimensional non-linear data (Yuqing Zhou & Xue, 2018). In the case of detection of tool wear, several studies have shown that SVM-based algorithms performed better than ANN-based methods (Cho, Binsaeid, & Asfour, 2010; Madhusudana, Kumar, & Narendranath, 2017). In order to successfully determine the condition of the cutting tool, Liao *et al.* (Liao et al., 2019) recently proposed an automated tool condition monitoring method using the cutting force sensor. The suggested monitoring system's used SVM and Genetic Algorithms (GA) which leaded to accurately determine the level of tool wear. The SVM approach, however, has some drawbacks. The performance of this method is greatly influenced by the choice of the kernel function and its parameters. They can only be chosen through a method of trial and error which greatly complicates their selection (Yuqing Zhou & Xue, 2018).

2.6.4 Fuzzy Logic (FL)

Fuzzy logic (FL) has been originally introduced by Zadeh in 1965 (Zadeh, 1965). When there is ambiguity, in order to make decisions, fuzzy logic can be employed. FL basically enables the consideration of logic that is fairly accurate, rather than the exact one. Input and output membership functions, fuzzy logical operators, and "if-else" rules are all components of the Fuzzy Inference System (FIS). Fuzzification of the input, fuzzy rules and defuzzification of the output are the steps in the application of fuzzy logic as shown in Figure 2.8. Input and output values are converted into fuzzy crisp sets during fuzzification. "If-else" rules are created based on the operator's knowledge (Mohanraj et al., 2020). Ren *et al.* (Ren, Baron, Balazinski, Botez, & Bigras, 2015) presented a tool condition monitoring method by applying type-2 fuzzy logic to acoustic emission signals. It was concluded that, using this technique, it is possible to automate online diagnosis of the cutting tool condition at the precision scale. The fuzzy logic system is quicker than a neural network system due to its simplicity, however a specialist is required to determine the functional connection between inputs and outputs (Nath, 2020).

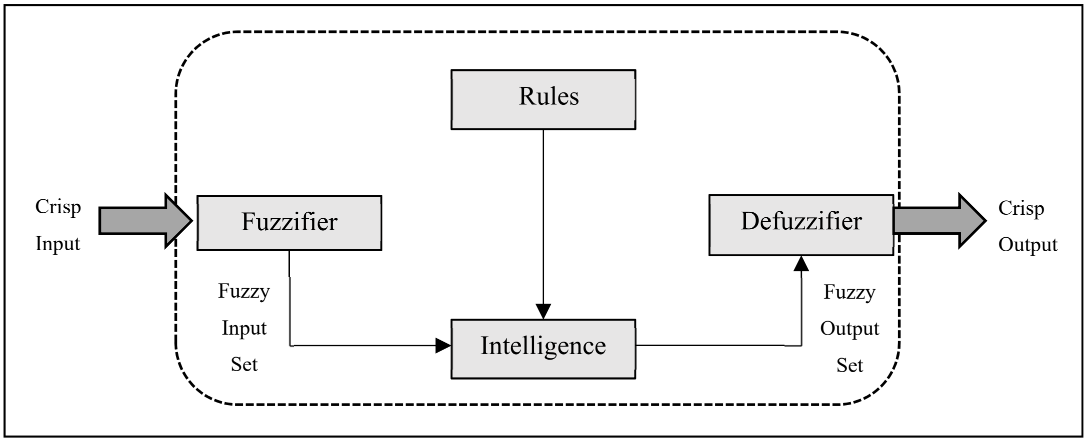

Figure 2.8 Fuzzy Logic (FL) model

2.6.5 Fuzzy Neural Networks (FNNs)

Fuzzy Neural Networks (FNNs), also referrer as Neuro-fuzzy inference methods, combine Fuzzy Logic (FL) and Neural Network (NN) models. Because of the long training duration, it can be a little challenging to apply NN system in production lines, however, FL system has a quick processing time. Yet, the FL system needs a qualified operator to analyze and correlate the cutting tool condition with the input signals. FNNs approach was proved to be more effective than FL in tool condition monitoring with less processing time and expertise (Balazinski, Czogala, Jemielniak, & Leski, 2002; Nath, 2020). Rao and Srikant (Rao & Srikant, 2004) applied different artificial intelligence techniques including ANN, FL and the FNNs technique to assess their potential for monitoring the manufacturing processes. In this study, the FNNs technique produced better results than the other two techniques in a tool condition estimation during machining of EN-8 steel. The limitation of FNNs is that the calibrated model can only predict tool wear for the exact cutting parameters for which it was trained. Consequently, the model needs to be retrained whenever the parameters are changed (Nath, 2020).

2.6.6 Fractal analysis

The probability statistics theory may not be accurate enough to study tool wear when the evolution process exhibits a chaotic characteristic. The Chaos theory addresses this unpredictability in a system, and it uses fractal parameters to forecast any change in signal shape. The term "fractal" was first used by B.B. Mandelbrot in the middle of the 1970s to estimate the length of the British coastline. Fractals are irregular objects that cannot be categorized as geometric shapes. They exhibit some degree of self-similarity and affine structure. Fractal objects have fractal dimension which is greater than the topological dimension (Mandelbrot, 1982). Fractal theory becomes an effective tool for forecasting and analyzing the behavior of complicated dynamic systems. Fractal analysis is an excellent noise quantifier which can be used to explain and extract specific features of signal behavior. It is possible to use this theory in the sciences of chemistry, physics, and geology (Chuangwen & Hualing, 2009). Numerous methods, including correlation analysis, regularisation analysis, information analysis and box counting can be employed to estimate the fractal dimension. However, the following three steps for all the techniques is essential:

1. A property of an object is evaluated at various scales
2. A least-squares regression line needs to be fitted through the points on a logarithmic graph (*log* (measured quantities) *vs. log* (step sizes))
3. Fractal dimension is calculated as the slope of the regression line.

A system's complexity and irregularity can be described by the fractal dimension, which is a single numerical value. The fractal dimension is determined by:

$$D = \lim_{\varepsilon \to 0} \frac{\ln N(\varepsilon)}{\ln\left(\frac{1}{\varepsilon}\right)} \tag{2.1}$$

Where $N(\varepsilon)$ is the number of pieces (self-similar pieces) and ε is a scaling factor. In this section to illustrate the definition of the fractal object, the Koch flake is displayed.

A Koch flake is created by splitting a straight line into three equal pieces, taking out the middle segment, and replacing it with the other two segments. In the following step, the same procedure is performed for every straight segment as shown in the Figure 2.9. At all scales, this curve is self-similar and has a constant dimension. The Koch flake's fractal dimension is determined as follows:

$$D = \lim_{k\to\infty} \frac{\ln N(k)}{\ln\left(\frac{1}{\varepsilon_k}\right)} = \lim_{k\to\infty} \frac{\ln 4^k}{\ln 3^k} = 1.2619 \tag{2.2}$$

Where N is the number of pieces of the first stage with the length of $\varepsilon = \frac{1}{3}$, and after k stages, the number of pieces is $N(k) = 4^k$ and the length measurement is $\varepsilon_k = \frac{1}{3^k}$ (Prasanta Sahoo, Tapan Barman, & J. Paulo Davim, 2011).

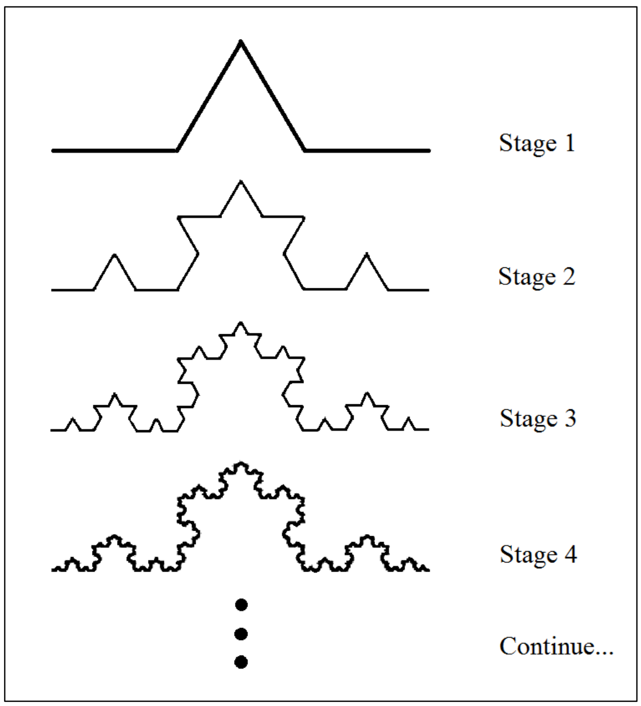

Figure 2.9 Koch curve formation
Taken from Chuangwen et al. (2009)

High performance key features can be extracted using fractal analysis, which is a sensitive and robust technique, and it could be used to complete monitoring and prediction systems. To identify abnormal machine states, Xing *et al.* (Xing, Rimpault, Mayer, Chatelain, & Achiche, 2019) evaluated several fractal parameters from the volumetric error vectors with magnitude-based quantities. It was demonstrated that fractal parameters could extract information about the maximum and mean volumetric error values, which is additional and complimentary to the information provided by the typical VEs vector magnitude processing. Advanced surface roughness evaluation and machine maintenance made extensive use of fractal analysis because of its good characterization of noise (Xavier Rimpault, Balazinski, & Chatelain, 2018; Zuo, Zhu, Zhou, & Yang, 2015).

It may not be accurate enough to study tool wear using the probability statistics theory when the evolution process of tool wear has a chaotic characteristic. Rimpault *et al.* (X. Rimpault, J. F. Chatelain, J. E. Klemberg-Sapieha, & M. Balazinski, 2017) demonstrated that fractal analysis of the cutting force signal can evaluate tool condition more accurately than statistical parameters. A combination of cutting conditions (speed and feed) were examined in this study. It was indicated that the fractal parameters depend on the cutting parameters less than the statistical parameters. As the industry 4.0 philosophy grows among machining centers, fractal analysis can give the control system the non-traditional information from sensor signals. This information can be used to monitor and optimize processes.

2.7 Integrated tool condition monitoring system

One of the important areas that need further investigation is an integrated tool condition monitoring system with less processing time, expertise and sensors. Successful application of a tool condition monitoring system in the industrial environment is a big challenge. The effectiveness and reliability of a TCM system are evaluated using precise tool condition prediction, repeatability, and sustainability for continuous production with almost no human intervention (Nath, 2020). The objective of real-time tool condition monitoring is to send a warning before tool wear reaches a certain level. 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 can be achieved using online tool condition monitoring. Indirect methods of tool condition monitoring have been developed in order to monitor tool condition in real time and respond quickly as needed. These methods are performed by correlating relevant sensor signals to the tool wear states. Overview of several tool condition monitoring studies are provided in Table 2.1. Different signal processing and decision-making algorithms were employed in these studies. Despite the capacity of different sensors (*e.g.* cutting forces, acoustic emission, vibration, sound and temperature sensors), using those sensors in the production line is not practical or cost-effective. Low-cost sensors that do not interfere with the cutting process are preferred in industrial environments (X. Li, Liu, Yue, Liang, & Wang, 2022). In industrial applications, motor-related parameters are the ideal choice due to their high sensitivity to cutting conditions and the avoidance of a pause in machining. It is more practical if the internal data of the machine tool's can be used for tool condition monitoring because data acquisition is extremely fast and no external sensors are involved. There is a gap in the literature in this area since no researchers have attempted to obtain the electric current data from the internal sensor of a machine tool. The electric current signal of machine tools can reflect any changes in the cutting state. Effective decision-making strategies with less processing time and expertise are also essential for online TCM systems. Fractal analysis is able to characterize the changes in the signal shape with a single value and effectiveness of this method as a decision-making system in tool condition monitoring was proven. As will be detailed in the subsequent sections of this thesis, it has been determined that fractal analysis of the spindle electric current signal can be utilized to forecast tool condition and develop an integrated system that complies with industry restrictions, as illustrated in Figure 2.10.

Table 2.1 Overview of studies in tool condition monitoring

Year of publication	**Authors**	**Signal acquisition method**	**Signal processing techniques / Decision-making algorithms**
1989	Lee *et al.*	Cutting force signal	Frequency domain analysis
2004	Rao and Srikant	Cutting force signal	Artificial neural network, fuzzy logic and fuzzy neural networks
2005	Kuljanic and Sortino	Torque and cutting force signal	Statistical analysis
2007	Ghosh *et al.*	Cutting forces, spindle vibration, spindle current and sound signal	Neural network-based sensor fusion model
2008	Choi *et al.*	Feed and spindle motor current signal	Statistical analysis
2009	Zhu *et al*.	Cutting force signal	Wavelet analysis
2012	Jemielniak *et al*	Vibration and AE signal	Time-frequency domain analysis
2015	Ren *et al.*	Acoustic emission signal	Type-2 fuzzy logic
2016	Yu *et al*.	Vibration signal	Hidden markov model
2016	Drouillet *et al.*	Electric current signal	Artificial neural network
2016	Stavropoulos *et al.*	Motor current and vibration signal	Statistical analysis
2016	Rmili *et al.*	Vibration signal	Statistical analysis
2017	Rimpault *et al.*	Cutting force signal	Fractal analysis
2017	Barreiro *et al.*	Vibration and AE signals	Time and frequency domain analysis
2018	Elforjani and Shanbr	Acoustic emission signal	Artificial neural network
2019	Hu *et al.*	Cutting force and acoustic emission signal	Mutual information and ν-support vector machine
2019	Shankar *et al*.	Cutting force and sound signal	Artificial neural network
2019	Liao *et al.*	Cutting force signal	Support vector machine and genetic algorithms
2019	Hesser and Markert	Acceleration data	Artificial neural network
2021	He *et al*.	Temperature signal	Stacked sparse autoencoders model
2021	Zhou *et al.*	Vibration signal	Support vector machine algorithm

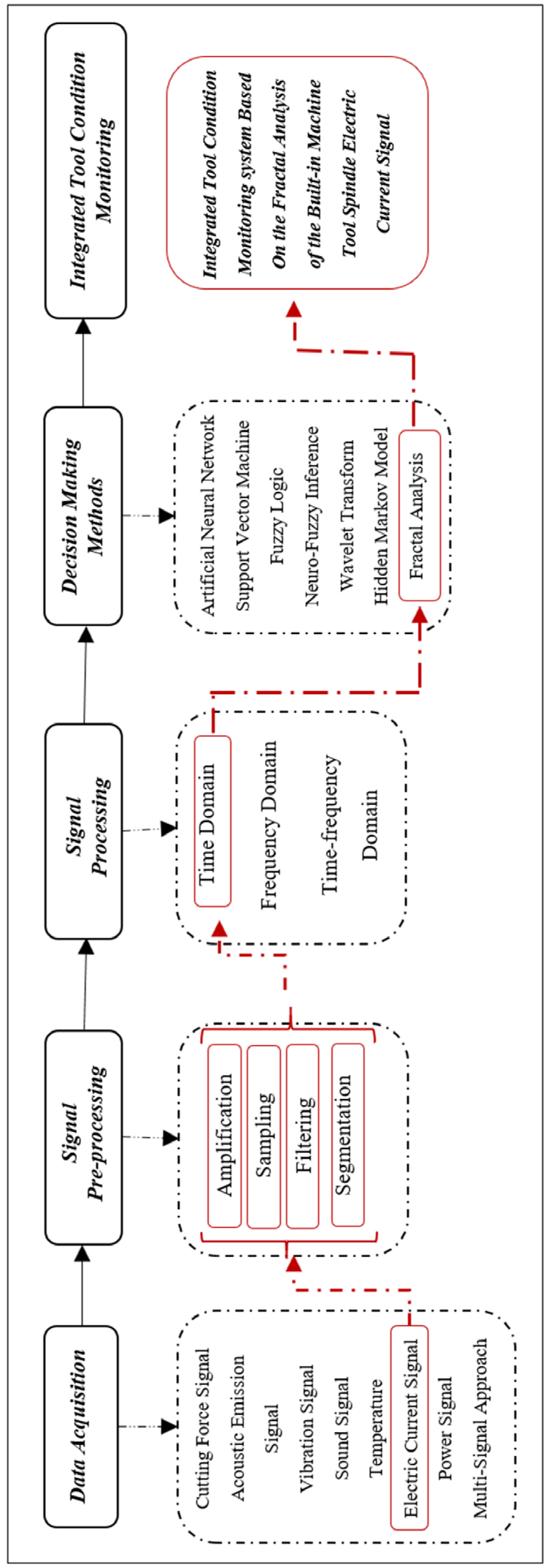

Figure 2.10 Integrated tool condition monitoring system based on the fractal analysis of the built-in machine tool spindle electric current signal

CHAPTER 3

METHODOLOGY

A Tool Condition Monitoring (TCM) system should practically be online for data collection and processing in order to assess tool condition accurately. In the present study, the system evaluated the cutting tool's condition using different parameters in the indirect approach of tool condition monitoring. Cutting forces, acoustic emission, temperature and electric current signals were acquired to feed the TCM system. High performance key features were extracted using fractal analysis, and it was used to complete monitoring and prediction systems. In all steps, the cutting tool wear and surface roughness parameters were measured at the end of each experiment.

In the **first approach** of the present study, online tool condition monitoring during orbital drilling of a stack of homogeneous and composite material was studied. In this approach, the cutting force signal related to orbital drilling was analyzed while machining a stack of Ti6Al4V titanium alloy and Carbon Fiber Reinforced Plastics (CFRP). The cutting tool was a carbide end mill with a TiAlSiN/TiSiN/TiAlN coating. Using the new cutting tool, drilling was proceeded until the cutting tool broke and 20 holes were produced. The fractal parameterization of the cutting force time series was used to identify different stages of tool wear.

In the **second approach**, the utilization of spindle electric current and cutting force signal in the TCM system during composite machining was studied. Six Carbon Fiber Reinforced Plastics (CFRP) plates were manufactured using the hand lay-up method and cured in an autoclave. 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. The cutting tool was a multi-layer CVD coating end mill. An infrared camera is used to evaluate the temperature in order to examine the influence of temperature on surface quality. This study investigated the online tool condition monitoring using fractal analysis of the spindle electric current signal and the total cutting force signal during trimming of CFRP.

In the **last approach**, online tool condition monitoring during shoulder milling of metal was studied. A four-flute solid carbide AlTiN coated end mill cutter was used to machine a block of AISI 5140 steel. The spindle electric current signal was sampled using the machine tool internal sensor, which meets industrial requirements. Fractal analysis was applied to the spindle electric current signal to predict any unexpected turbulence in the signal and to establish a single value in the machine tool as a warning before tool wear becomes severe.

Despite the fact that the selected machining operations (drilling, trimming and shoulder milling) were performed in this study, it is assumed that fractal parameters are less dependent on cutting parameters and more sensitive to the workpiece material and the type of machining. Rimpault *et al.* (X. Rimpault et al., 2017) proved that fractal analysis of cutting force signal is more efficient to estimate the tool wear than the statistical parameters can be. In this study, different set of cutting conditions (speed and feed) were investigated. It has been demonstrated that the fractal parameters are less dependent on the cutting parameters than the statistical parameters during machining of CFRP.

Each of these approaches that have been published as journal articles are described in the following chapters (chapter 4,5 and 6). However, the published papers did not provide many of the extra information that is included in the following sections. Then, more information is provided in the following sections.

3.1 Tool wear

In machining, tool wear is a major challenge. Generally, tool wear raises the temperature and cutting force while lowering the precision and surface quality of finished parts. Tool geometry and material, workpiece material, cutting condition, as well as machine tool characteristics, all affect tool wear. Premature tool failure and progressive tool wear are the two main categories of tool wear. Premature tool failure commonly occurs when the cutting-edge breaks as a result of the rapid growth of crater wear or previously present cracks in the cutting tool, and it results in tool failure. The useful tool life is always determined by progressive tool wear. It is comprised of flank wear and crater wear (Kai Cheng, 2009). As illustrated in Figure 3.1, in order to estimate the flank wear, the main cutting edge is divided into three zones: C, B, and N. Zone B is the straight portion of the cutting edge that lies between zones C and N, while zone N is the quarter of the worn cutting edge from the tool corner and zone C is the curved part of the cutting edge. The average (VB_B) and maximum ($VB_B max$) values of the flank wear width are typically measured on the flank face as shown in this figure. The variables that are often measured on the rake face include the crater width (KB), crater depth (KT), and crater centre distance (KM) (Stephenson & Agapiou, 2016). In the present study, tool wear was estimated as the average of the maximum flank tool wear, and it was measured using "Keyence VHC-500F Microscope".

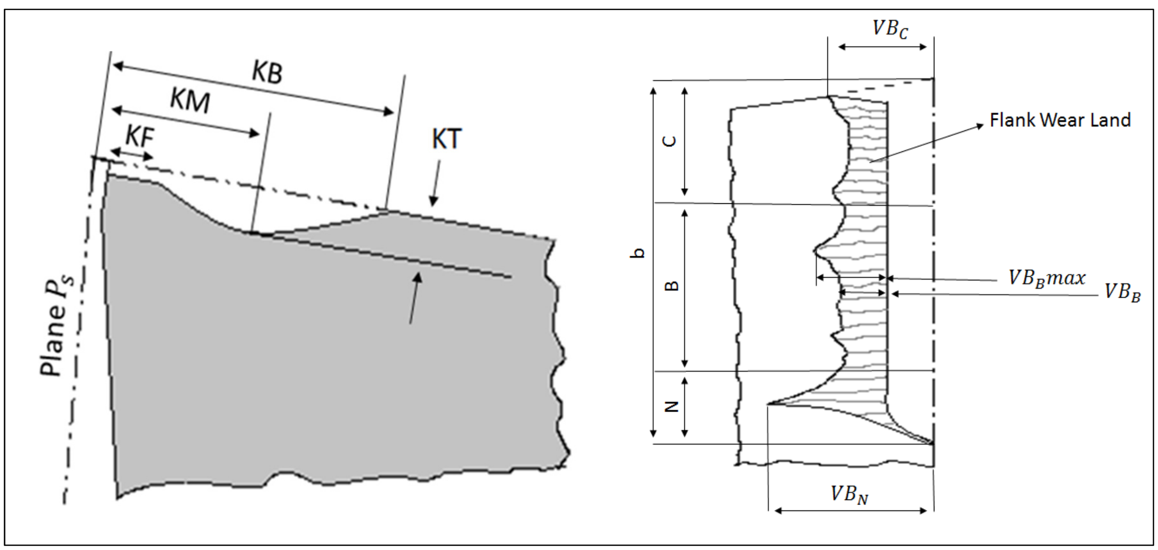

Figure 3.1 Crater wear and flank wear classifications
Taken from Jamshidi (2018)

3.2 Cutting tool lifespan

Figure 3.2 illustrates how the flank wear rate progresses through three stages as it changes over time in a typical cutting situation. The "primary" or "initial" stage is when wear on the cutting tool starts. Due to increased pressure between the workpiece and the cutting tool in a small contact area, tool wear increases quickly in this step. The second wear stage, known as the "steady-state" stage, includes a wear rate that is generally consistent. The "accelerated wear" stage is the third and last wear stage. The tool is wearing out very fast at this stage. Temperature and cutting force both increase significantly. The tool's useful life reaches its end when the third stage begins; as a result, the cutting tool needs to be changed before this point (Stephenson & Agapiou, 2016). In the present study, the First Transition Point (FTP) is defined as the transition point between the first and second wear stages which is shown in Figure 3.2, and the Second Transition Point (STP) is defined as the transition point between the second and third wear stages where the cutting tool needs to be replaced (Jamshidi, 2018).

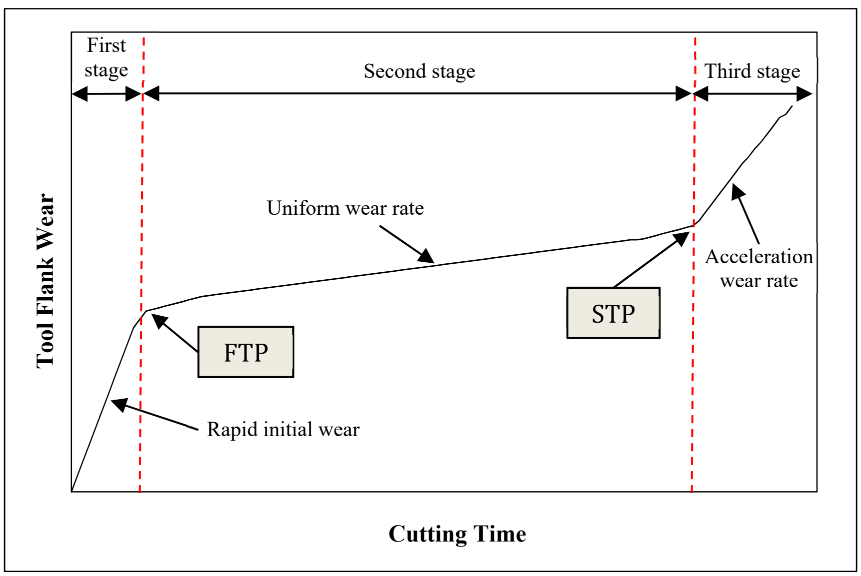

Figure 3.2 Typical tool wear stages

3.3 Surface finish quality

The performance of the cutting tool deteriorates during machining, which has an effect on the machined surface. Several factors, such as the condition of the cutting tool, the machining process parameters, the relative vibration between the tool and the workpiece, and machining dynamics, all have an impact on surface roughness during the milling process (M.-X. Guo et al., 2022). The surface condition is mainly characterized using roughness profile parameters.

R_a is the arithmetical mean height of a line and it is defined as the average absolute deviation of the roughness irregularities as illustrated in Figure 3.3 (Gadelmawla, Koura, Maksoud, Elewa, & Soliman, 2002). The mathematical definition R_a is as follow:

$$R_a = \frac{1}{l}\int_0^1 |y(x)|dx \tag{3.1}$$

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|y_i| \tag{3.2}$$

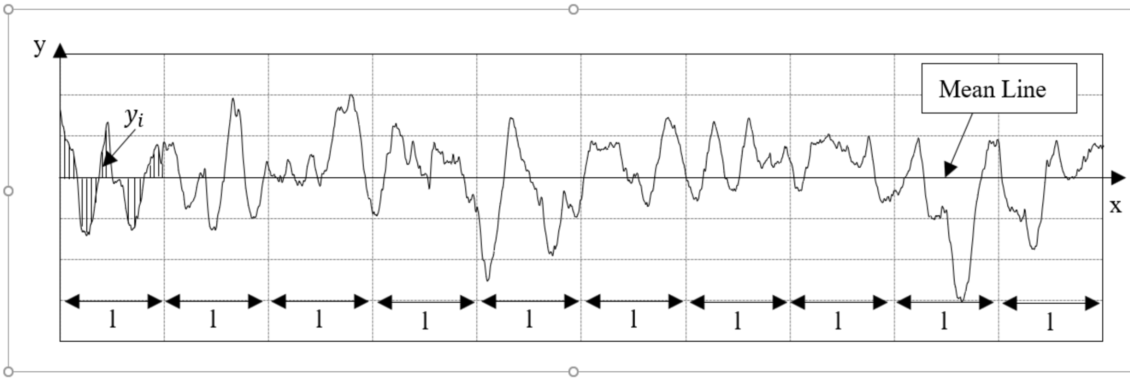

Figure 3.3 Definition of the arithmetic mean height R_a
Taken from Gadelmawla et al. (2002)

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 as illustrated in Figure 3.4 (ISO, 2012). The following is the mathematical definition of S_a:

$$S_a = \frac{1}{A}\iint |Z(x,y)|dxdy \tag{3.3}$$

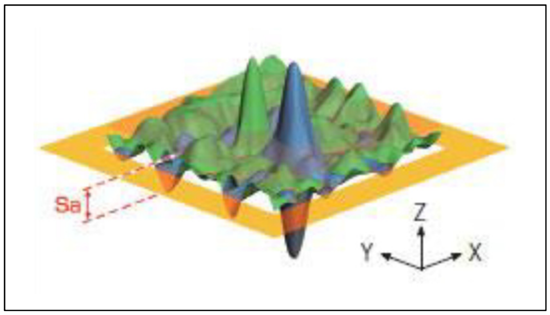

Figure 3.4 Definition of the arithmetic mean height S_a
Taken from ISO (2012)

In this study, surface roughness parameters were estimated using Keyence VR-5000 optical profiler. The 3D images of the machined surface and areal surface roughness parameters were estimated after each experiment. The quality of the machined surface was assessed using areal surface roughness parameters.

3.4 Cutting force signal

The cutting force signal is the most often used signal in tool condition monitoring since it is the most reliable and stable variable in machining processes. Any changes in the cutting condition can be reflected in the cutting force signal because of its high sensitivity. A dynamometer table can be used to detect small variations in the load. In the present study, the cutting forces were acquired by a three-axis dynamometer (Kistler 9255B) which is shown in Figure 3.5. Calibration was done before each experiment. The technical specifications of the dynamometer are presented in Table 3.1. The cutting force signals were recorded using LabVIEW software, and data processing was completed using MATLAB software.

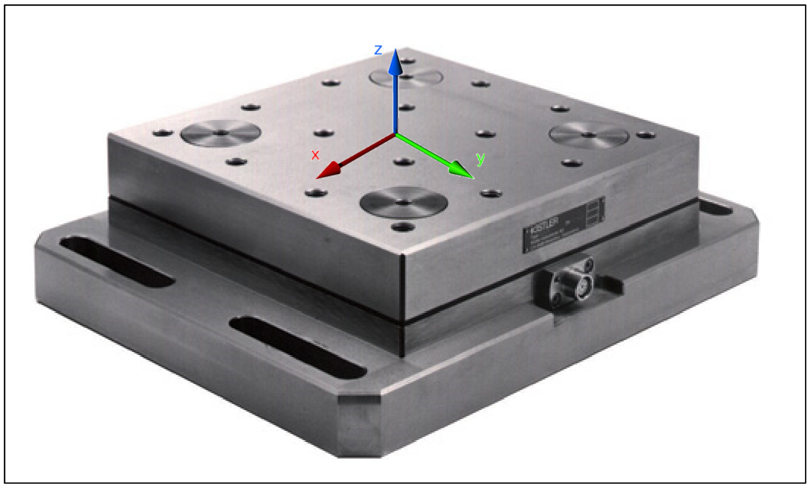

Figure 3.5 Three-axis dynamometer (Kistler 9255B)

Table 3.1 Technical specifications of Kistler 9255B

Machine type	Three-axis dynamometer
Manufacturer	Kistler
Measuring range	Fx, Fy: -20…20 kN Fz: -10…40 kN
Sensitivity	Fx, Fy: -8 pC/N Fz: -3.7 pC/N
Natural frequency	fn(x,y): 1.7 – 3 kHz fn(z): 2– 3 kHz

3.5 Acoustic emission signal

Acoustic emission (AE) is the intuitive transient elastic wave or energy that is released from materials as a result of plastic deformation at the cutting zone area (Nath, 2020). Acoustic emission sensors need to be located as near as possible to the cutting zone area. Before each experiment, they should be accurately calibrated. In the present study, "PCB piezotronics AE systems" were used to record AE signals. In order to effectively monitor the tool condition, AE sensors were mounted on the workpiece as shown in Figure 3.6. However, the experiments showed that accurate signal information from the AE sensors could not be obtained since many disturbances were found during machining. As a result, this data was not included in this study and was abandoned in the contribution of tool condition monitoring.

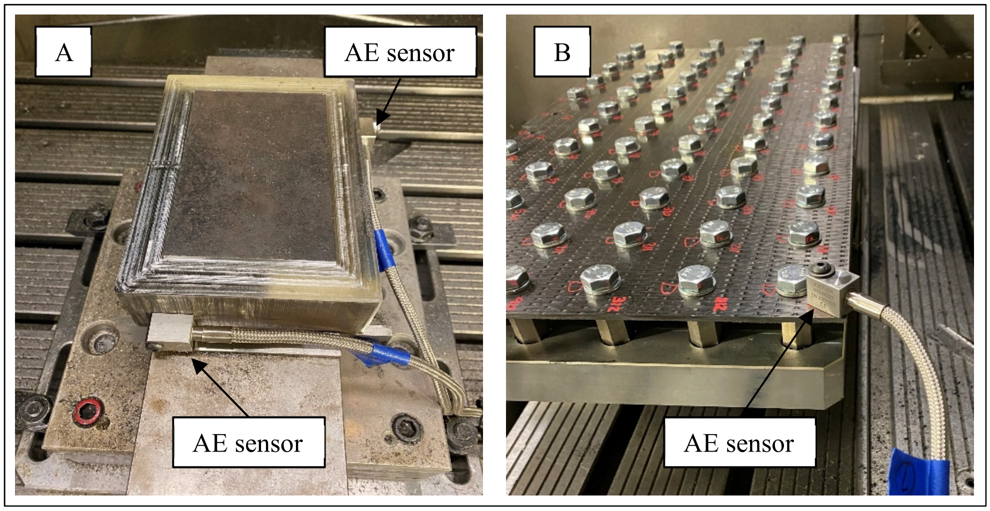

Figure 3.6 Acoustic emission sensors mounted on **A)** steel block **B)** CFRP plate

3.6 Spindle electric current signal

The electric current signal represents any change in the cutting condition. This signal was utilized in the online tool condition monitoring, considering the development of an innovative approach in the present study. For the first time, the spindle electric current signal was acquired using the internal sensor of the machine tool (K2X10 Huron® high-speed machining center). A static synchronized action programmed with the Application Programming Interface (API) of the SIEMENS SINUMERIK 840D controller was used to record the signal. A synchronized action was defined in an asynchronous subprogram (ASUP) that was activated by the PLC, and R variables of machine tool were used to save electric current data. In this study, the NCU of K2X10 Huron® high-speed machining center has an interpolator cycle time of 3 ms and the acquisition rate through synchronous actions was considered as 333Hz.

3.7 Temperature

Temperature is a factor that needs to be considered during the monitoring process. The high temperature of the cutting tool can affect tool life and quality of the machined part. During machining of composite, the elevated temperature tends to remain in the cutting zone area due to the low thermal conductivity of the composite. In order to capture thermal images of the cutting tool and workpiece in a single window and to remotely measure the cutting temperature in real time, an infrared camera was utilized in this study. As illustrated in Figure 3.7, a support was designed to fix the camera on the spindle head of the machine tool while tracking the cutting tool with the least amount of vibration. 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 only experiment that utilized an infrared camera was the composite material machining test, because the camera's lens needs to be protected while machining hard materials (like steel). There was no lens protector available for this research.

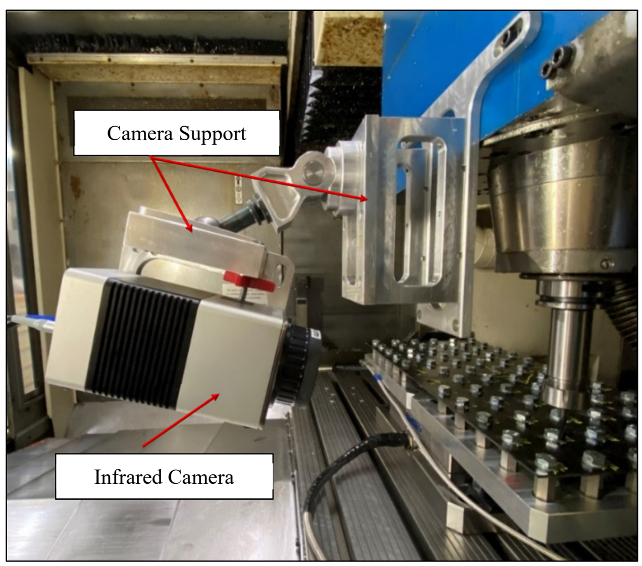

Figure 3.7 Infrared camera series VarioCAM® HD head 900 installed on the spindle head

When working with infrared cameras, the reflected and transmitted energies need to be considered. These energies need to be estimated and filtered out to avoid measurement errors in temperature estimation (ASTM, 2010, 2017). In this study, transmitted energy was zero and reflected temperature was estimated based on the standard method as follows (ASTM, 2017);

The infrared camera's emittivity was set to 1.00. As illustrated in Figure 3.8, the camera was mounted on a tripod and oriented at the specimen where the reflected temperature needed to be measured. A piece of crumpled and re-flattened aluminum foil placed in front of the specimen (aluminum foil was considered as a reflector with reflectance close to 1.00). Using an infrared camera, the foil's surface temperature was measured and recorded as a reflected temperature. The average reflected temperature was obtained by repeating this procedure three times and averaging the results. In this study, the calculated reflected temperature was 25.2º c.

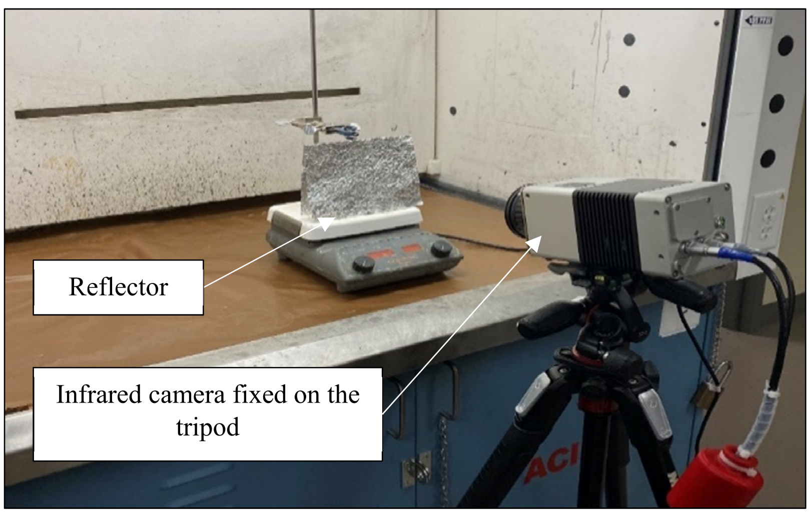

Figure 3.8 Standard test method for measuring reflected temperature using the infrared camera

In order to have the temperature close to the actual temperature, emissivity of the material needs to be calculated. Emissivity is the ability of the object to emit thermal radiation. Emissivity of common materials are introduced in different literature, but the emissivity of an object can change with the change in some factors like; temperature, surface and environmental conditions (Caniou, 1999). In order to have an accurate temperature, the emissivity of the material needs to be estimated at least 10 °C warmer or cooler than the ambient temperature based on the standard (ASTM, 2018). The following procedure was used to determine the cutting tool's and the CFRP specimen's emissivity based on the standard (ASTM, 2018);

As seen in Figure 3.9, the camera was mounted to the tripod. The calculated reflected temperature was entered into the camera’s software. The specimen was equipped with thermocouples. Since emissivity can change with temperature, the value of emissivity should be computed under actual experimental conditions. The temperature of the specimen was increased using a hot plate. Thermocouples calculated the specimen's temperature. The camera's emissivity was modified to reflect the thermocouples recorded temperature. The emissivity value was averaged after this process had been conducted three times. The emissivity of the CVD coating end mill tool and CFRP specimens were 0.52 and 0.94, respectively.

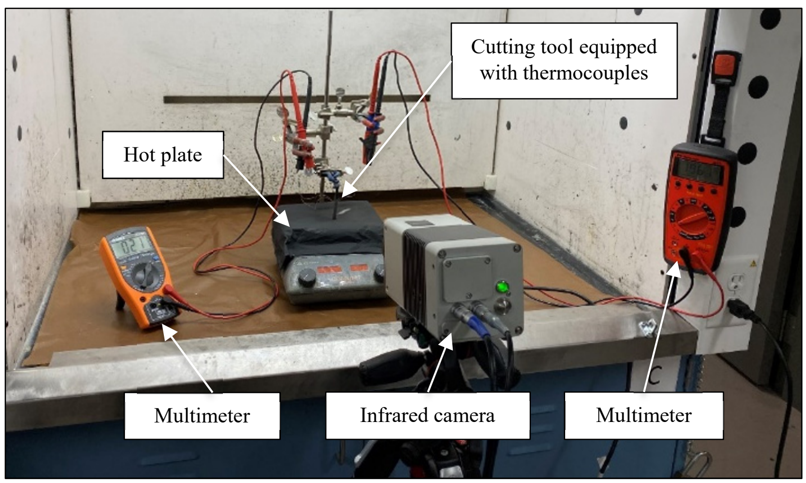

Figure 3.9 Calculation of the emissivity of the cutting tool

3.8 Signal feature extraction

3.8.1 Fractal analysis

Fractal theory turns into a useful tool for analyzing and predicting the behavior of complex dynamic systems. Additionally, it can be utilized to identify and extract particular signal behavior characteristics. A number of fractal analysis techniques, including correlation analysis, information analysis, regularisation analysis, and the box-counting method, can be used to estimate the fractal dimension of a profile. Some of this methodology, such as box-counting, showed relatively low robustness in many studies (Xavier Rimpault et al., 2018;

Xavier Rimpault et al., 2016). Because regularization analysis has a relatively great repeatability, as shown in recent researches (Feng, Zuo, & Chu, 2010; Xavier Rimpault et al., 2016), it was adopted in the present study.

3.8.1.1 Regularization analysis

In 1998, Roueff and Lévy Véhe (Roueff & Lévy Véhe, 1998) proposed a novel method to explain a graph's regularity. They used the following definition to characterize the regularization dimension.

$\mathit{\Gamma}$ is defined to be the graph of a bounded function $f : \mathbb{R} \longrightarrow \mathbb{R}$. $\chi(t)$ is defined to be a kernel function of Schwartz class S, so

$$\int \chi = 1 \tag{3.4}$$

$\chi_a(t) = \frac{1}{a}\chi\left(\frac{t}{a}\right)$ is the dilated version of χ at scale a, and f_a can be the convolution of f with χ_a:

$$f_a = f * \chi_a \tag{3.5}$$

Equation 3.4 shows, when a goes to 0, χ_a tends to Dirac distribution and f_a tend to f. Because $f_a \in S$, then the length of its graph Γ_a on K is finite and it can be calculated using following equation:

$$L_a = \int_K \sqrt{1 + f_a'(t)^2 dt} \tag{3.6}$$

Then the regularization dimension can be calculated as follows;

$$dim_R(\mathit{\Gamma}) = 1 + \lim_{a \to 0} \frac{\log(L_a)}{-\log(a)} \tag{3.7}$$

$dim_R(\mathit{\Gamma})$ is called regularization dimension which is referred as fractal dimension (*D*) in the present study.

The limit in this equation is calculated as the slope in the area where *a* tends to 0 and the R^2 of the linear regression is close to 1 (Xavier Rimpault et al., 2016). As shown in Figure 3.10, the fractal dimension (D) is defined as the slope of the graph ($log\, l_a$ *vs.* $log\, a$) in the linear region. Fractal dimension is an indication of the signal "roughness". Topothesy is taken as the y-intercept from the same regression and expresses the ruggedness of the signal.

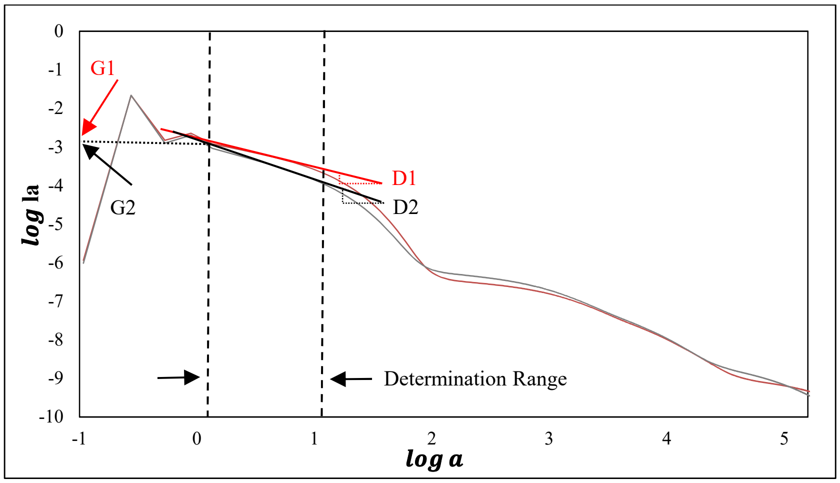

Figure 3.10 Example plot illustrating regularization analysis. The plot expresses l_a *vs.* (a) in *log-log* format

CHAPTER 4

FRACTAL ANALYSIS IMPLEMENTATION FOR TOOL WEAR MONITORING BASED ON CUTTING FORCE SIGNALS DURING CFRP/TITANIUM STACK MACHINING

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4.1 Abstract

Hybrid structures of metals and composite materials are increasingly common in aerospace industry and the optimization and monitoring of the machining of these stacks are an area of active research. Online tool condition monitoring in particular is a valuable capability and is facilitated by real-time treatment of cutting force signals. Cutting force signals are considered one of the most important measures for tool condition monitoring. The present work treats online cutting force time series with fractal analysis. The signal features generated are central to tool wear assessment. This work evaluates the fractal dimension of the cutting force signals from orbital drilling of a stack of Carbon Fiber Reinforced Plastics (CFRP) and Ti6Al4V titanium alloy as a measure of the "roughness" of these signals. It is shown that distinct wear stages are adequately identified using fractal signal features. Low machining quality may thereby be prevented. Additionally, to address the inconvenient need for long machining tests when studying the application of these techniques to CFRP and titanium alloys, a novel fractal index is proposed to improve the monitoring process without requiring extensive experimentation.

Keywords: Tool wear, Drilling, Carbon fiber reinforced plastics, Titanium, Cutting force, Fractal

4.2 Introduction

Aerospace industry requires materials possessing at once low weight and high strength, stiffness, resistance to corrosion. Multi-material stacks, such as those made of titanium alloys (Ti6Al04V) and Carbon Fiber Reinforced Plastics (CFRP) enable innovative configurations meeting these needs (Pecat & Brinksmeier, 2014). CFRP is increasingly popular, owing to its elevated specific strength. The drawbacks of CFRP include limited loadbearing capability, poor wear resistance and low elastic modulus. Stacking titanium alloys with CFRP can address the limitations of CFRP. Titanium alloys provide elevated specific strength and good fatigue toughness but low corrosion resistance (Sha & Malinov, 2009). Such hybrid structures are popular among manufacturers. The Boeing 787 Dreamliner provides an example with its use of stacked CFRP and titanium between the wing and fuselage (Xu & El Mansori, 2016). Although effective and currently employed in commercial production, assembly of parts made with multi-material stacks remains difficult. Combined wear mechanisms escalate the tool wear problem.

Drilling of Ti-CFRP stacks has been addressed before in the open literature. Abrasion, adhesion, attrition, and chipping have been identified as issues. Abrasion has been singled out as particularly aggressive, owing to the toughness of the carbon fibers (Pramanik & Littlefair, 2014; Xavier Rimpault et al., 2016). Online tool condition monitoring can alleviate these difficulties. According to Hidayah *et al*. (Hidayah et al., 2015), tool condition monitoring can enable speed increases up to 50 percent and similar cost savings.

As a matter of nomenclature, tool wear monitoring schemes may be described as either direct or indirect. Direct monitoring involves inspection of the cutting tools themselves, such as with offline examination of tool surfaces and textures. Indirect methods are popular research topics for manufacturers and can help reduce costs and ensure quality. Online methods may prevent tool breakage, which can be particularly important with costly workpieces. Online methods can also support timely replacement of worn tools. Indirect methods may function in real time, during machining (Jantunen, 2002).

Operationally, tool wear is complex. The process involves the materials of the tool and workpiece; tool geometry; cutting speed, feed rate, and depth of cut; cutting fluids; and the machine tool itself. Worn tools require more cutting force, generate more heat, and produce inferior dimensional accuracy and surface integrity (Kai Cheng, 2009). Cutting force was proposed by Kious *et al*. (Kious, Boudraa, Ouahabi, & Serra, 2008) as an effective means for detection of tool failure. A review of cutting force analysis for tool condition monitoring was written by Hidayah *et al.* (Hidayah et al., 2015). Analysis of cutting forces was described as a robust approach to online monitoring. Research involving online cutting forces is active because cutting forces respond strongly to changes in the behavioral mode of the cutting (Fang et al., 2015; Hidayah et al., 2015).

The present study builds upon prior work with orbital drilling rather than axial drilling. In the orbital drilling, the end mill tool rotates by itself and also has helical movement through the material. In comparison with axial drilling, orbital drilling requires lower thrust force. Orbital drilling also produces smaller burrs and causes less delamination (H. Wang, Qin, Ren, & Wang, 2011).

The present work treats cutting force time series data with fractal analysis. Ti-CFRP stacks are drilled for this purpose. Similar work has been done before. Recently, Caggiano *et al.* (Caggiano et al., 2018) reported extraction of signal features from torque and thrust force during CFRP stack drilling. An Artificial Neural Network (ANN) took these features as input to produce tool life estimates. Conventional statistical methods augmented the ANN's abilities, producing the best tool life estimation method for aerospace assembly. Another study, by Rimpault *et al.* (Rimpault, et al., 2018), treats the signals from capacitive displacement sensors using fractal analysis. Rimpault *et al.* were thus able to detect abnormalities. An index of sensor failure was proposed based upon fractal parameters. The index was shown to be effective. In the literature, acoustic emission signals have also been shown to be effective for online tool condition monitoring (Lachaud, Piquet, Collombet, & Surcin, 2001).

4.3 Methodology

Orbital drilling was performed on a multi-material stack. The stack was composed of quasi-isotropic CFRP and Ti6Al4V. The machine tool employed was a high-speed 3-axis. A dust extraction mechanism was used for health. The experimental setup was shown in the Figure 4.1. 5.85 mm holes were drilled. Drilling continued until tool failure at 20 holes. The operation parameters and tool geometry are listed in Table 4.1. The cutting speed, feed rate, and helix step were selected based upon cutting tests prior to the experiment. The CFRP was 3.3 mm thick. A 3.0 mm layer of Ti6Al4V sat below the CFRP, as depicted in Figure 4.2. Online monitoring data were acquired from a dynamometric table that produced cutting force time series. The signal was amplified and collected at a rate of 48 kHz.

After the cutting tests, photographs of the cutting tool were taken to evaluate tool wear. Orbital drilling contains a discontinuous cutting on the side cutting edge and a continuous cutting on the front edges. In the present work, tool wear on the side cutting edge was negligible, so tool wear on the front edges was calculated. The “maximum tool wear” parameter is taken as the mean of the maximum tool wear (VB_Bmax1 on Figure 4.3) on each of the tool’s four cutting edges (front edges). This value is listed as “VB_Bmax”.

Table 4.1 Operation parameters and tool geometry

Orbital drilling tool		
Type	End mill, carbide, four-fluted, with TiAlSiN/TiSiN/TiAlN coating	
Mill diameter	4 mm	
Helix angle	30°	
Cutting Parameters		
CFRP	Feed rate	800 mm/min
	Feed rate by tooth	4.5 mm/tooth
	Cutting speed	11000 RPM
	Helix step	0.7 mm
Titanium	Feed rate	300 mm/min
	Feed rate by tooth	1.3 mm/tooth
	Cutting speed	3200 RPM
	Helix step	0.35 mm

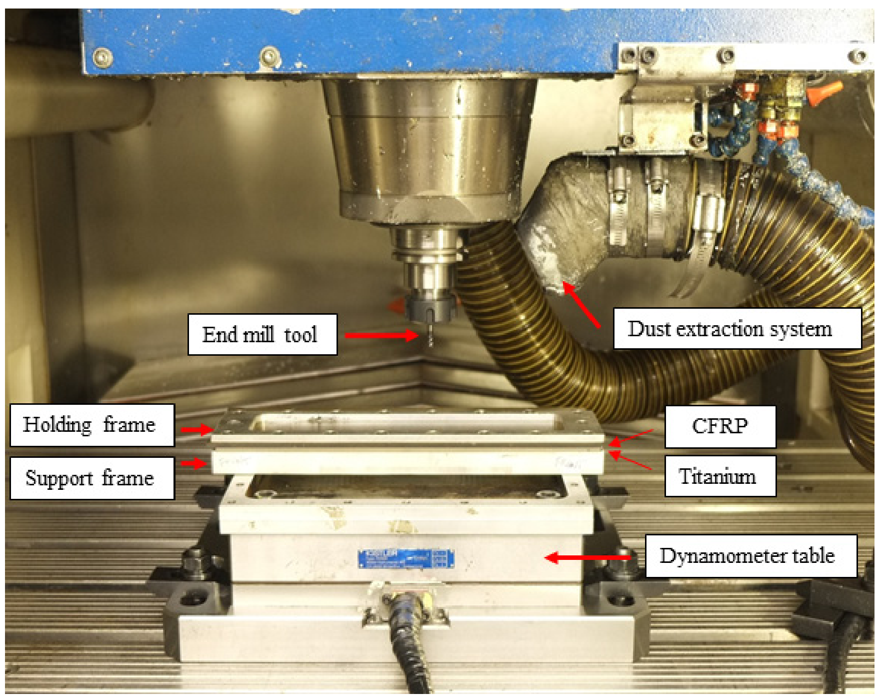

Figure 4.1 The experimental setup

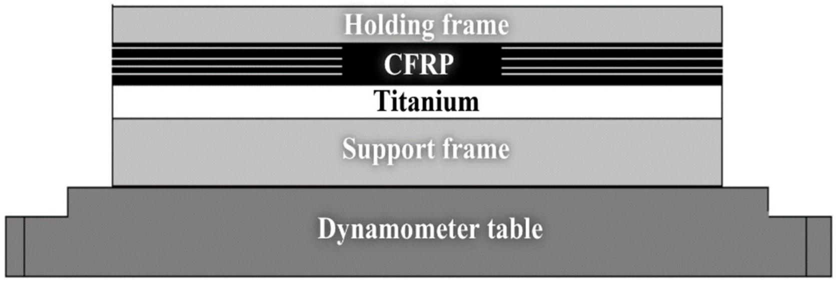

Figure 4.2 Schematic of the hybrid stack and mounting

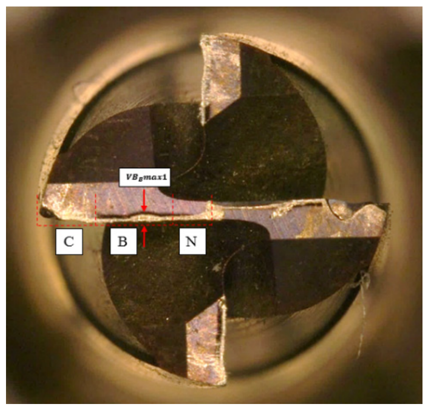

Figure 4.3 The "maximum tool wear" parameter is calculated as the mean of the maximum tool wear (VB_Bmax1) on each of the tool's four cutting edges. This value is listed as "VB_Bmax"

The cutting force time series from the first hole is illustrated in Figure 4.4. The three Cartesian components of force are shown. The cutting process in this stack is divided into three phases. The first phase corresponds with machining of the CFRP. Likewise, the third phase corresponds with the drilling of the titanium alloy and the cutting parameters used within each layer are listed in Table 4.1. The second phase corresponds to the transition between layers, also called the interface-machining phase. In the second phase, the CFRP was cut using the operation parameters of the third phase (which are suited to cutting the titanium alloy). The interface-machining phase is complex due to the transition between laminated materials.

The Cartesian components of force relayed by the dynamometric table which readily describe the resultant (net, or total) force. The present work infers its conclusions from analysis of the resultant (net) force from the first and third phases (which correspond, respectively, to the cutting of the CFRP and the Ti alloy). The resultant force is shown in Figure 4.5. The resultant force signal is relatively stable in the portions delimited by the dashed lines. The effects of the ingress and egress of the tool are neglected. The resultant force in the machining of titanium part increased suddenly. During machining CFRP, it was indicated that severe abrasive tool wear and edge chipping on the tool led to increase of cutting force during titanium machining (X. Wang, Kwon, Sturtevant, Kim, & Lantrip, 2014).

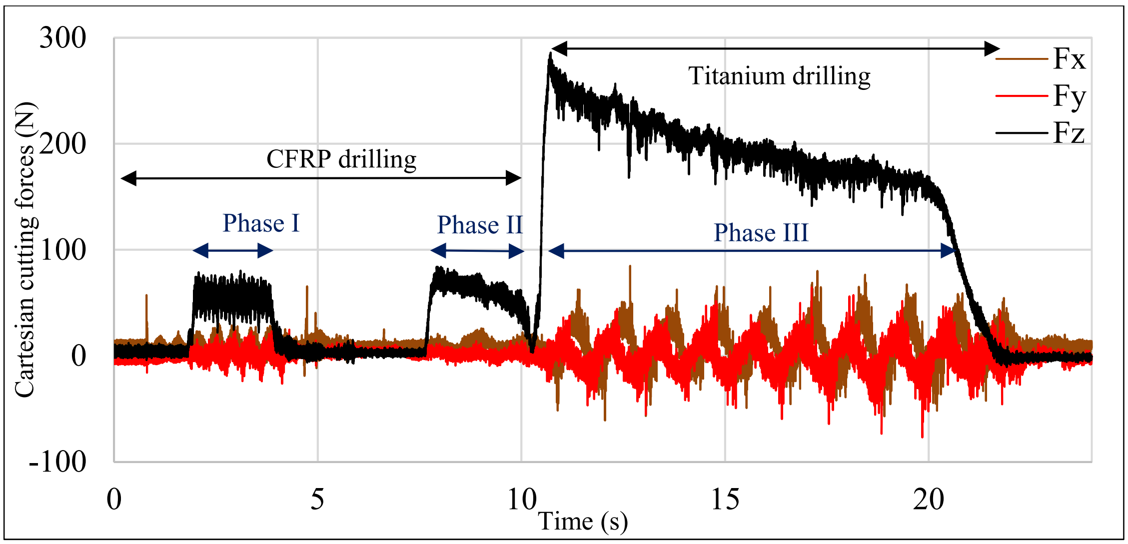

Figure 4.4 Cartesian cutting forces during the drilling of the first of twenty holes

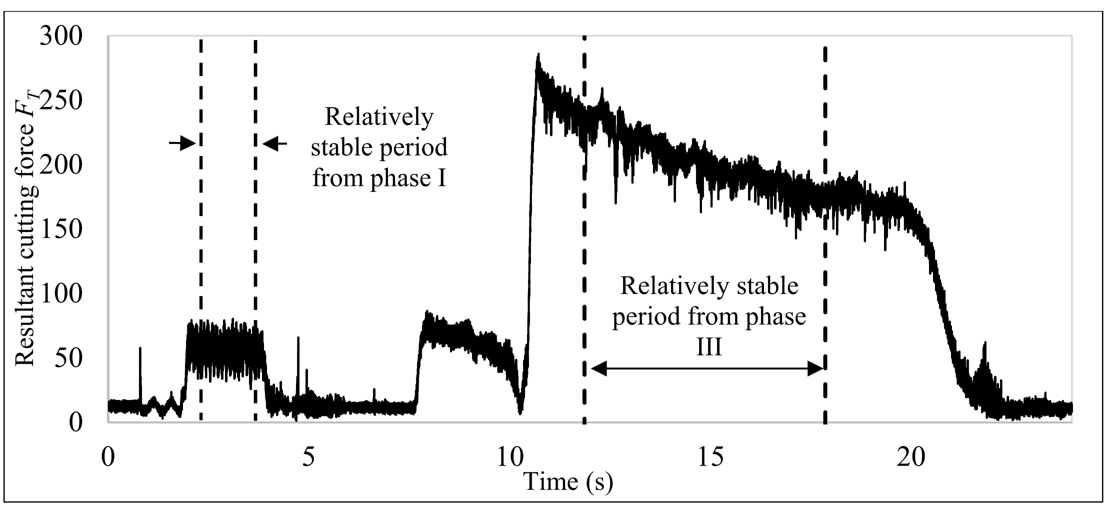

Figure 4.5 Resultant force corresponding to Figure 4.4

In order to evaluate the evolution of the tool during the third phase (Ti alloy), the resultant cutting force from that phase was divided into three sections along the time axis. These sections are shown in Figure 4.6 and are labelled A, B, and C.

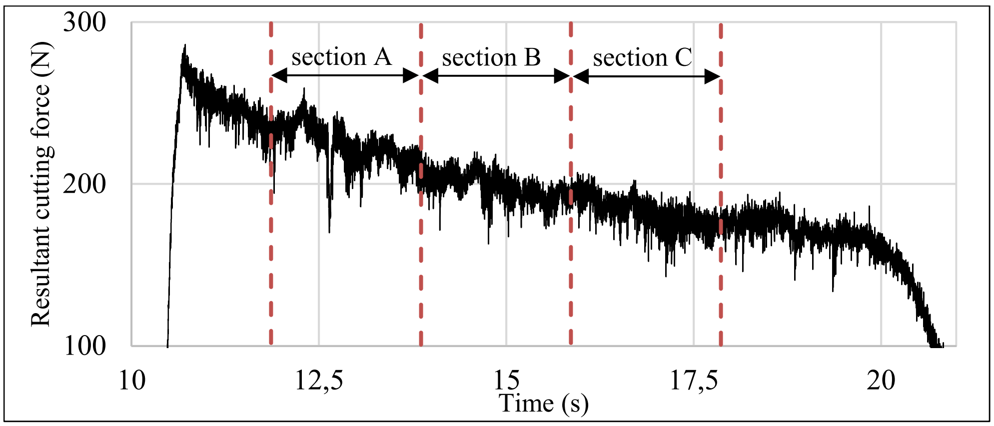

Figure 4.6 The resultant cutting force from the third phase stable period from Figure 4.5. Three sections along the time axis, labelled A, B, and C, are (arbitrarily) drawn within the waveform

The resultant cutting forces from the three sections during the titanium alloy cutting phase may be averaged to produce a value corresponding to that particular drilled hole. That value is plotted in Figure 4.7 as a function of chronological hole number. The trend of this plot is more or less linear and therefore does not inform us about tool life. Consequently, average cutting force is not recommended as a measure of tool wear. To extract useful information from such a plot, many experiments under tightly controlled conditions would be required. As may be seen in Figure 4.7, the sections from the first three holes drilled follow alphabetical order. This result is characteristic of a stable process. By contrast, the final holes follow the opposite, anti-alphabetical order. This suggests that, once the tool is fully engaged in the Ti alloy, the cutting force rises and the process becomes unstable.

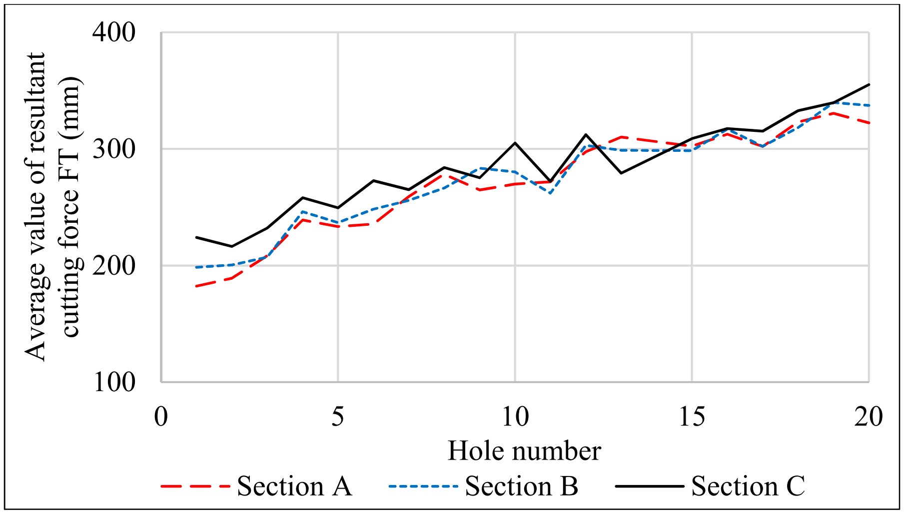

Figure 4.7 Evolution of total cutting force average along hole drilling

For illustration, the variability of the resultant cutting force during cutting of the titanium alloy is shown in Figure 4.8. Each section has a duration of two seconds. The blown-up graphs on the right describe one rotation of the tool. The variations in resultant cutting force are the consequence of the cutting condition evolving, given that the only factor changing is the age of the tool. The resultant force rises as the tool ages until a maximum is reached in hole twenty. The increasing force is due to rising friction. The blown-up portion of Figure 4.8 shows that the moving average of the resultant force is more or less invariant. The signal becomes more ragged for later holes. Arches also become apparent. Also of note is that the force from hole eight is irregular and involves an increase in force magnitude and a change in the general aspect of the time series, and this in all three sections. The change apparent at hole eight corresponds with the transition from the steady-state tool wear regime to the accelerated tool wear regime which will be discussed in the next section.

4.4 Fractal dimension

In the 1970s, Mandelbrot (Mandelbrot, 1982) coined the term “fractal” to describe patterns which are interrupted and possess structure at all scales. Fractals possess self-similarity. They are also affine structures. Fractals may be described using “fractal dimension,” the value of which for an object is always greater than that object’s topological dimension. Fractal dimension may be used to express the irregularity of shape, and so finds application in signal analysis (Feng et al., 2010).

The use of fractals to describe cutting force time series from machining of multi-material stacks is an area of active interest (X. Rimpault, J.-F. Chatelain, J. E. Klemberg-Sapieha, & M. Balazinski, 2017; X. Rimpault et al., 2017). Fractal dimension may be estimated in a variety of ways, including correlation analysis, information analysis, regularization analysis and box counting. The present works evaluates fractal dimension using regularization analysis. This technique is robust (Feng et al., 2010; X. Rimpault, J. F. Chatelain, J. E. Klemberg-Sapieha, & M. Balazinski, 2016). Regularization analysis can be interpreted as a measure of signal "roughness". Convolution with Gaussian kernels g_a of width a constitutes regularization. In the present work, the time series were regularized, and consequently smoothed, using the derivative of the Gaussian function. The regularized function has length l_a. This length is finite and blows up to infinity for vanishing Gaussian kernel width a. "Regularization dimension" expresses how quickly l_a blows up for a tending to zero (Feng et al., 2010).

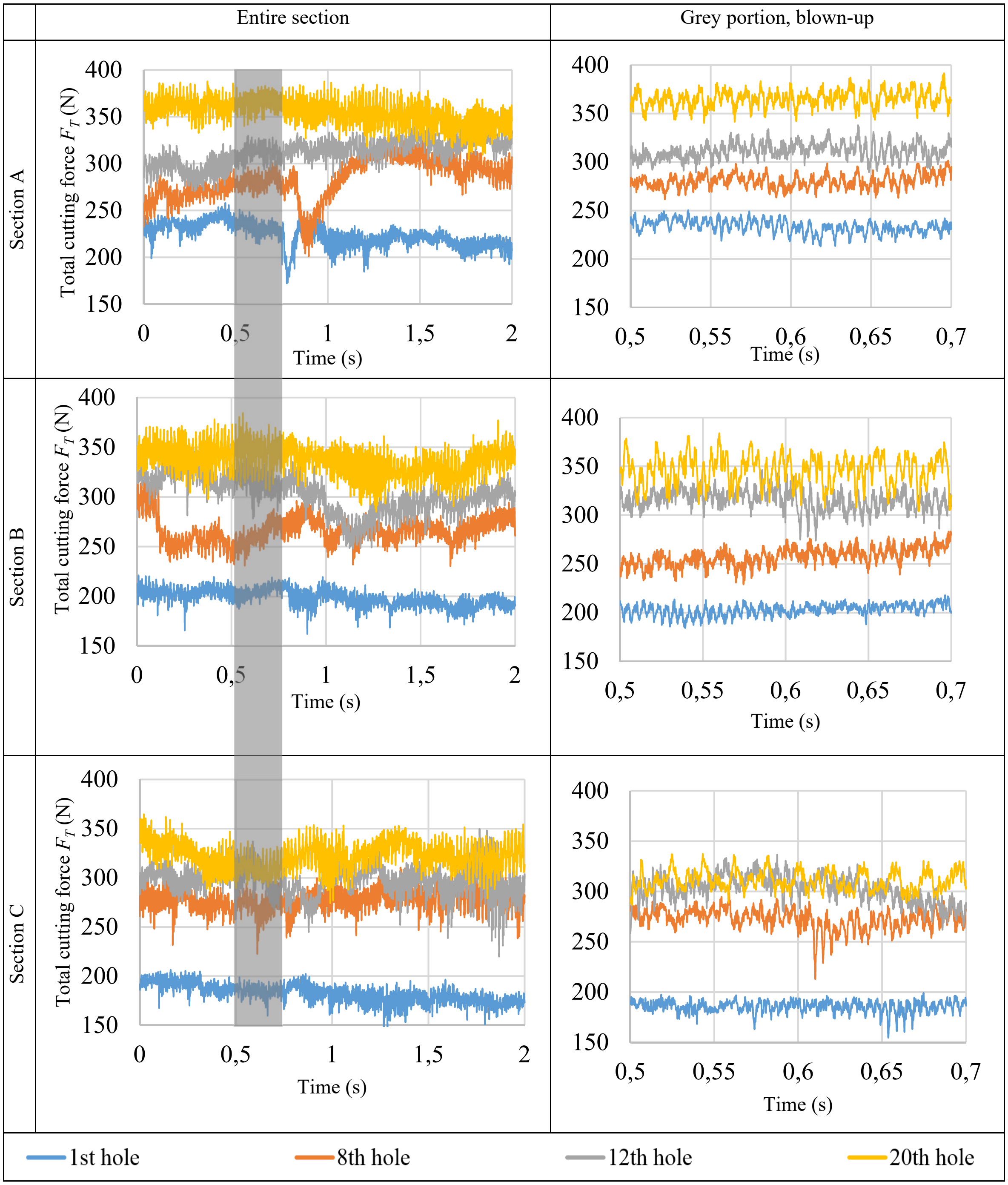

Figure 4.8 The evolution of resultant force over tool life. Only the drilling of titanium alloy is shown. Holes 1, 8, 12, and 20 are shown on each plot. From top to bottom, the plots illustrate sections A, B, and C. The grey stripe in each left-hand plot is plotted blown up in the right-hand plots

Some algebraic exposition is in order. The quantity f_a is taken to express a signal f convoluted with a kernel g_a of width a:

$$f_a = f * g_a \tag{4.1}$$

Let l_a represent the length of f_a. The quantity l_a explodes as a vanishes.
Let D be defined as the "regularization dimension" as follows:

$$D = 1 - \lim_{a \to 0} \frac{log\, l_a}{log\, a} \tag{4.2}$$

A linear regression may be performed relating $log\, l_a$ to a. A value of the coefficient of determination R^2 of this regression approaching unity indicates that the D successfully expresses fractal dimension.

An example is shown in Figure 4.9. In the figure, $\log l_a$ vs $\log a$ is depicted from cutting tests, specifically from the drilling of the titanium alloy layers. The fractal dimension, among other fractal parameters, was estimated using regularization analysis. The vertical dashed lines delimit portions of the signals for each of the A, B, and C sections. The delimited portions were used for preliminary analysis using 7 to 19 sampling points. Analysis of the CFRP-drilling phase used 14 to 32 points. The quantity D was estimated from a portion of each graph and was taken to be the slope of the $\log l_a$ vs $\log a$ plot within the appropriate interval.

Fractal dimension was augmented with two other fractal parameters, G and R^2. These are respectively topothesy and the coefficient of determination of the line fit to the *log-log* plot. Topothesy was taken as the *y*-intercept from the same regression.

All three fractal parameters, D, G, and R^2 have been considered in the present work to serve tool wear monitoring. D expresses the irregularity of the time series. G expresses the ruggedness of the signal. R^2 expresses auto-scale regularity. All three parameters were estimated for each section from each hole.

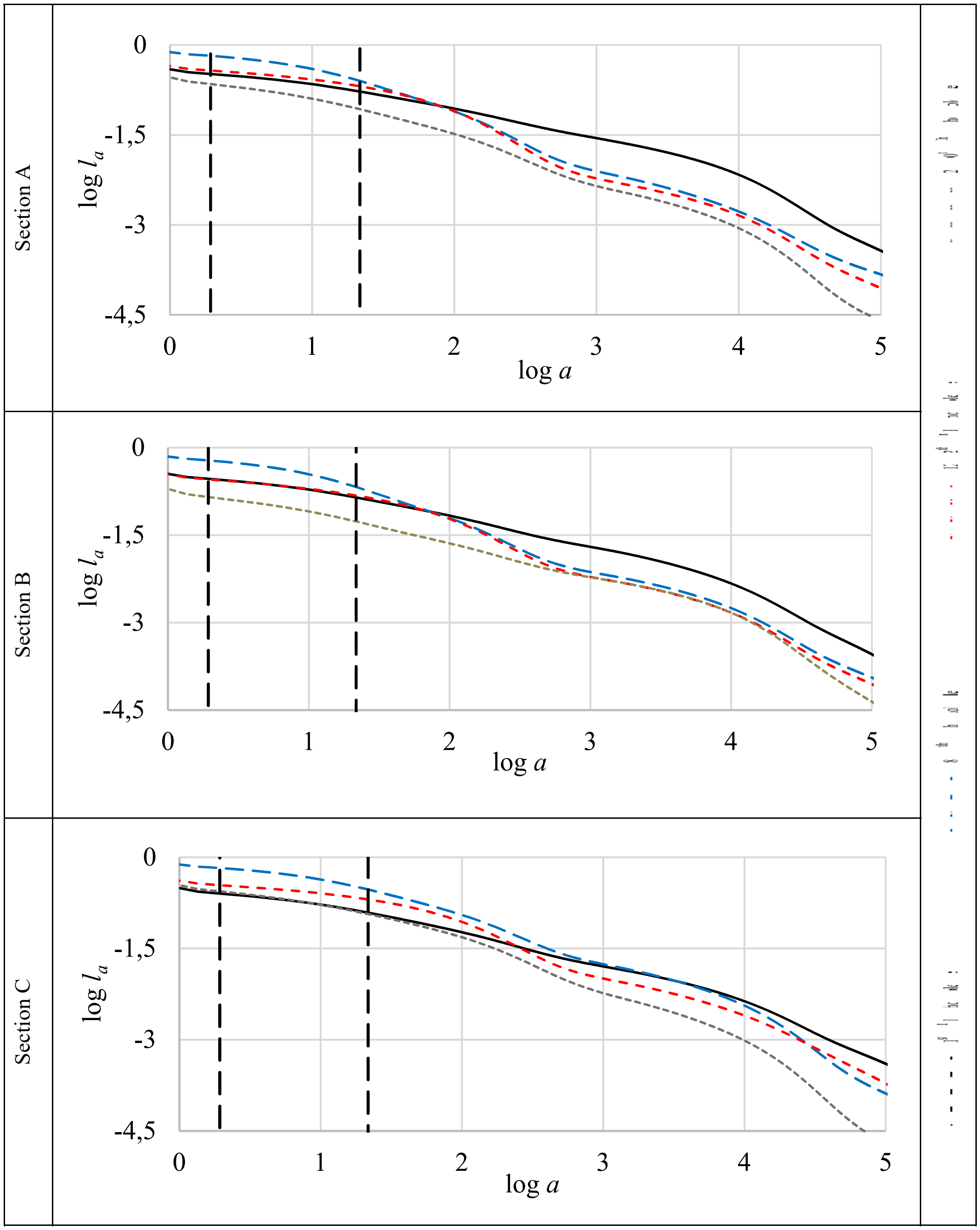

Figure 4.9 Example plots illustrating regularization analysis. The plots express la vs a in log-log format for the A, B, and C sections during the Ti-drilling phase

4.5 Result and discussion

The well-known three stages of cutting tool wear are illustrated in Figure 4.10. Wear begins in the “primary” or “initial” stage. In this stage, tool wear is rapid due to elevated pressure between the workpiece and a small contact area. The second wear stage, the “stead-state” stage, consists of a reasonably constant wear rate. The third and final wear stage is the “accelerated wear” stage. In this stage, the tool wears rapidly. Cutting force and temperature rise dramatically. The tool’s useful life reaches its end when the third stage begins; consequently, tools are replaced before this happens. Identifying the transition between the second and third stages is helpful for replacing a worn tool at a cost-efficient moment during its service life.

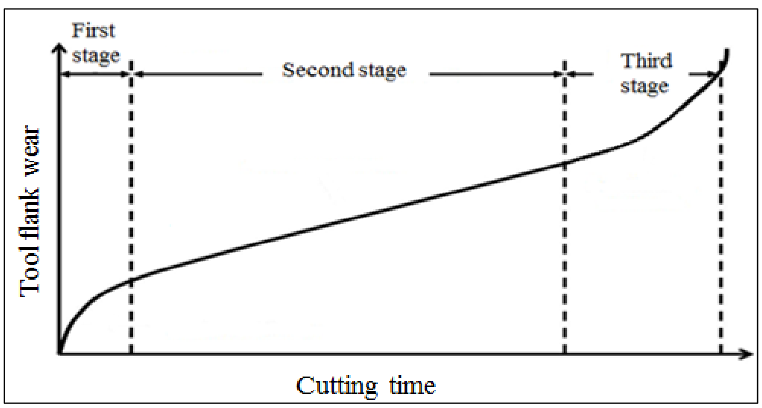

Figure 4.10 The well-known stages of cutting tool wear

Figure 4.11 illustrates the end mill at several points in its life. Chipping, abrasion, adhesion, and attrition were all observed. Abrasion was the dominant tool wear mode and this fact is attributed to the hardness of the CFRP’s carbon fibers. According to Wang *et al.* (X. Wang et al., 2014), drilling of CFRP-Ti hybrid stacks cause 10 percent more flank wear land than does drilling of CFRP alone. The 10 percent increase is therefore attributed to the drilling of the titanium alloy in the stack. The wear from the titanium is therefore nine times smaller than the wear from the CFRP.

Tool wear, expressed as VB_Bmax, is shown in Figure 4.12 as a function of tool age. The initial tool wear stage appears to occur during the drilling of the first hole or thereabouts. The steady-state tool wear stage lasts until the eighth hole, at which point the tool wear reaches 0.3 mm. In 2014, Kalpakjian and Schmid (Kalpakjian & Schmid, 2014) published guidelines for the tolerable average wear land, tabulated by tool and operation. By that guide, the tolerable wear for carbide milling tools is up to 0.3 mm. Naturally, wear below this limit supports better machining results.

At twelve holes, the process generated sparks. Hole sixteen sees the steady-state wear stage end. At hole twenty, a flame erupted and the tool became practically unusable. Figure 4.12 includes a color gradient to reflect the advanced wear beginning at hole twelve, with combustion and sparking. The tool broke at hole twenty.

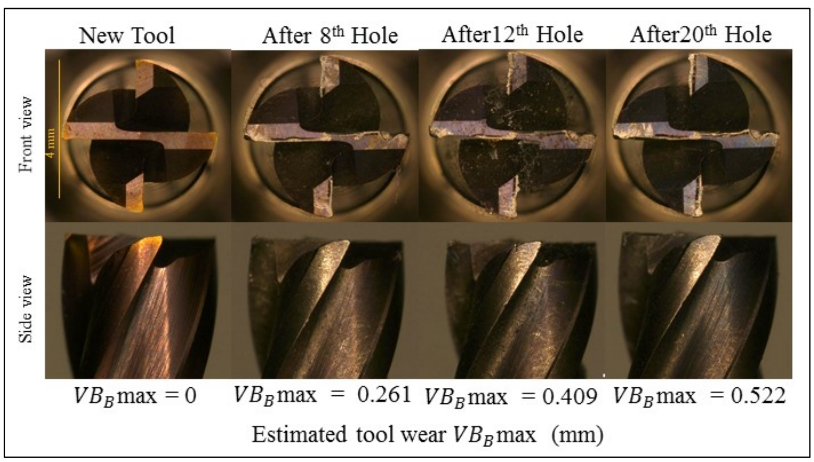

Figure 4.11 Photographs of the end mill after drilling 8, 12, and 20 holes

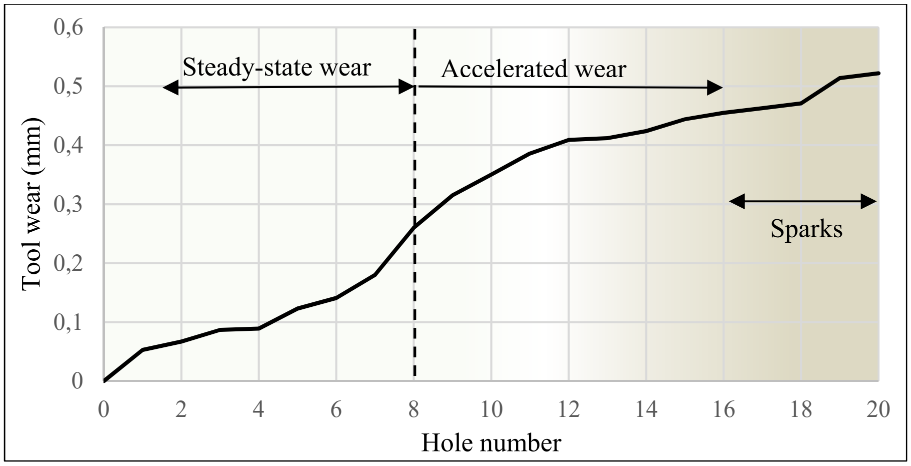

Figure 4.12 Tool wear from the end mill used for orbital drilling, expressed as VB_Bmax, as a function of tool age, expressed by chronological hole number

Fractal dimension through tool life is shown in Figure 4.13. Fractal dimension cannot be used to detect the transition from initial wear to steady-state wear because this transition occurs during the first hole. From hole one to eight, the fractal dimension tends to decline down to the eighth hole. This is taken to indicate the transition from steady-state wear to accelerated wear. Machining quality decreases rapidly during that stage and heat and force increase dramatically. The fifteenth hole sees a drop in fractal dimension which lasts until the twentieth hole. At that point, the tool's temperature rose rapidly and combustion was visible. Comparing the sections, section A values are lower than the section B values, which likewise are below the section C values. It is therefore inferred that when comparing force signals between holes, like sections must be compared.

The fractal dimension for the CFRP drilling reaches a minimum at hole eight. It then rises until the fifteenth hole. The character of the time series changes at hole eight, becoming rough and complex. This corresponds with the transition to accelerated wear. The fractal dimension then continues to increase until the twentieth hole. At elevated temperature, the cutting process is complex and the fractal dimension amid the sparking does not follow the same trend for CFRP as for titanium alloy. It would appear from these results that the transition from steady-state wear to accelerated wear coincides with minimum fractal dimension.

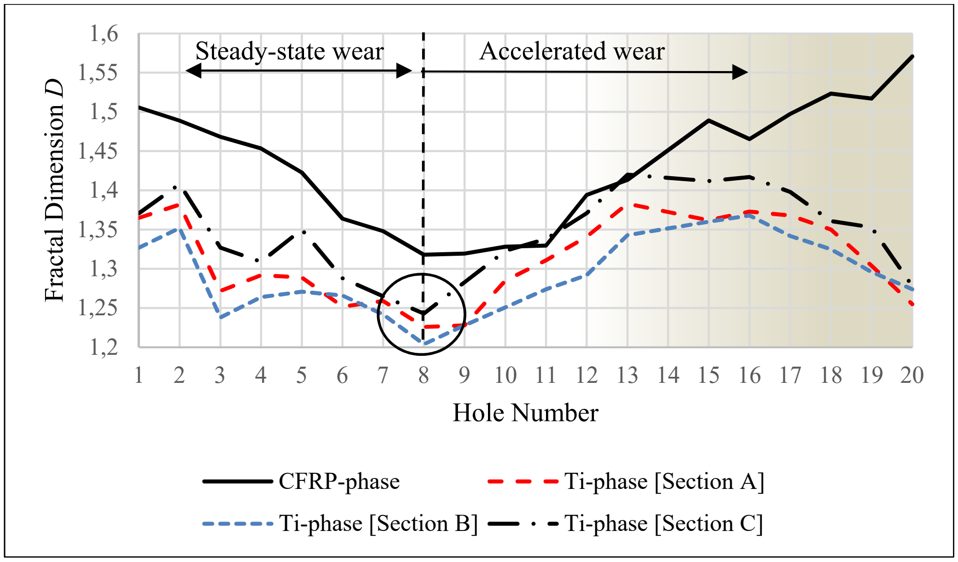

Figure 4.13 Fractal dimension as a function of tool age

The R^2 and G parameters, respectively the topothesy and the coefficient of determination, are shown in Figures 4.14 and 4.15 as a function of chronological hole drilled. The CFRP-drilling phase shows a tendency for topothesy to increase. In the titanium-drilling phase, the topothesy shows no particular trend until the accelerated wear stage begins. The R^2 parameter shows no trend for CFRP-phase cutting, but the R^2 for the titanium shows clear transition points in wear behavior. The R^2 rises from the fifth to the eighth hole for Ti. A maximum is achieved at the eighth hole and the accelerated wear stage begins. The R^2 value then drops rapidly until hole sixteen. For the Ti, the R^2 and topothesy appear to vary less by section. Nevertheless, the C section data show more variability.

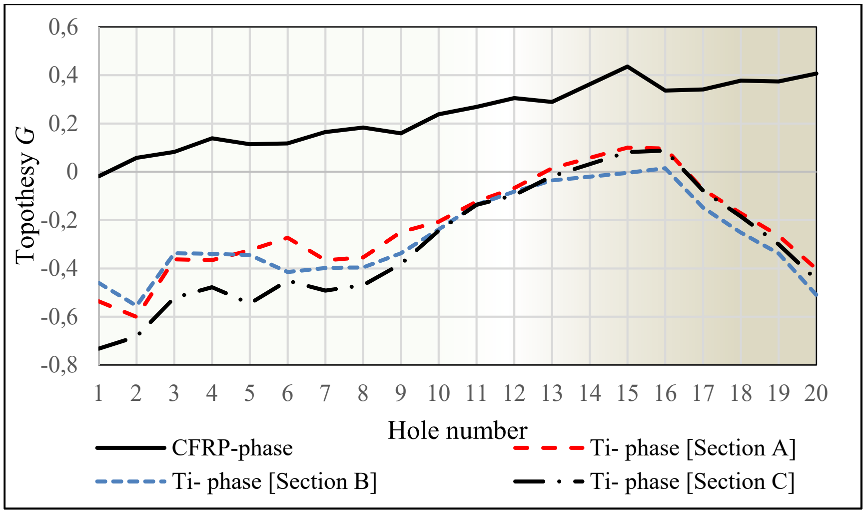

Figure 4.14 Topothesy G by hole

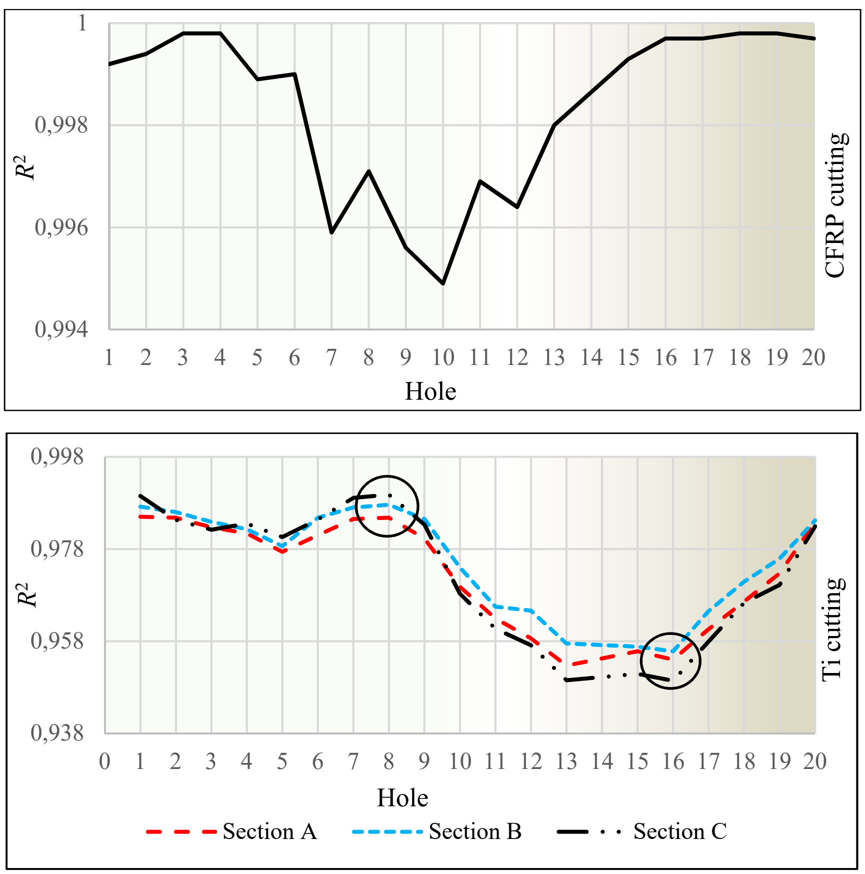

Figure 4.15 The R^2 coefficient of determination by hole

The cutting force time series has been parametrized by fractal parameters. It is reasonable that combinations of fractal parameters can express more information about the signal than can a single parameter. A decision-making system is here proposed on the basis of a fractal index I. Parameter I was created from working with experimental data and can support online tool wear monitoring. A threshold value can be selected for each application in order to help determine the transition from steady-state wear to accelerated wear and thus ensure part quality. Parameter I is defined:

$$I = (D - G) * (R^2)^2 \tag{4.3}$$

Again, D, G, and R^2 are respectively the fractal dimension, topothesy and coefficient of determination. Figure 4.16 illustrates the tendency for I to decrease for both CFRP and Ti and in all three sections A, B and C. The fractal index I decreases as the tool wear increases.

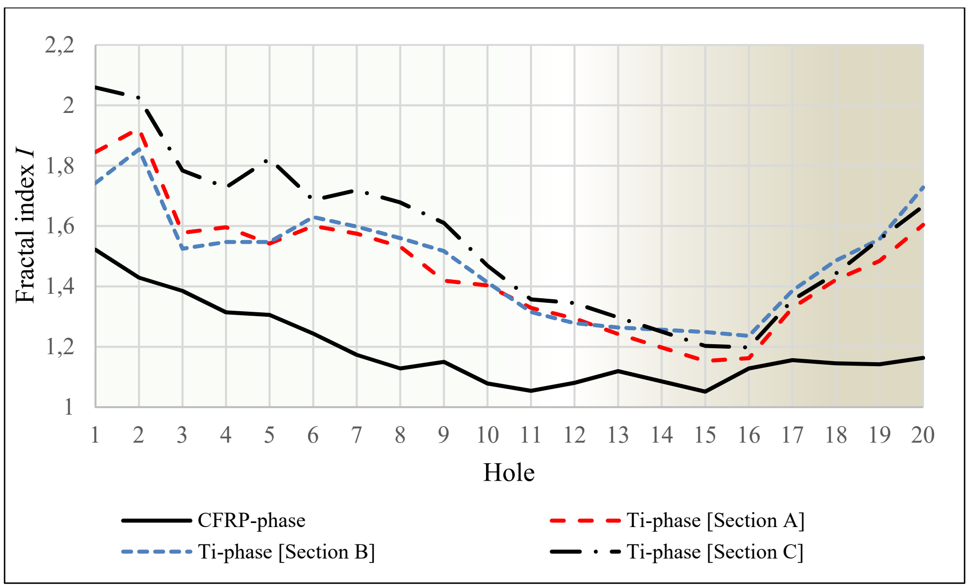

Figure 4.16 Fractal index I by hole

The tool wear and fractal index are compared in Figure 4.17. The data in Figure 4.7 may be drawn in parallel. Usage of a threshold value to flag transition to accelerated wear can ensure good machining quality. As discussed, the transition to accelerated wear appears to be around hole eight, so the threshold value of I could be 1.7 for section C.

The C section from the drilling of the titanium alloy has the greatest variation and therefore may be a reliable source of information. Consequently, monitoring I is reasoned to be more effective at the end of the titanium drilling when compared with the beginning.

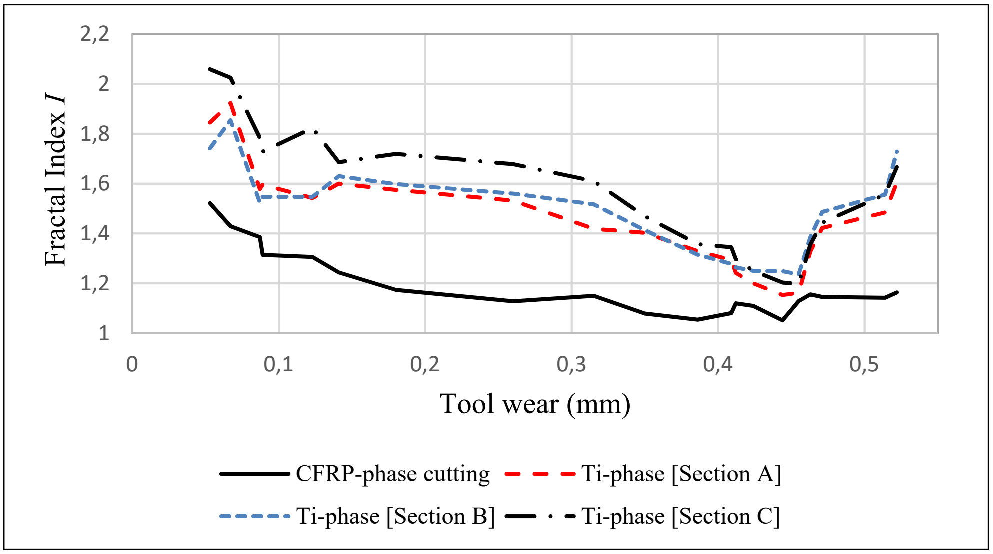

Figure 4.17 Fractal index I compared with tool wear VB_Bmax

4.6 Conclusion

The present work supports online tool wear monitoring for orbital drilling of CFRP-titanium alloy hybrid stacks. This is done via description of cutting force signals using fractal parameters. This machining process and similar multi-material drilling processes are challenging and are the subject of active research. Regularization analysis was selected as the method for generating fractal parameters. Among these is fractal dimension. The fractal parametrization of the cutting force time series demonstrates clear trends that highlight the transitions between the stages of tool wear.

Traditional statistical parameters may therefore be augmented by these fractal parameters. For this purpose, a fractal index I is proposed in the current work. A threshold critical value for I may be selected for a given process. Usage of this parameter in combination with some appropriate limit value may help ensure part quality.

It was shown that the fractal index *I* can express the transition between wear stages during orbital drilling of CFRP-Ti alloy hybrid stacks without the need for time-consuming experimentation. This fractal parameter method might also be adaptable to other online monitoring signals, such as acoustic or accelerometric information.

CHAPTER 5

TOOL CONDITION MONITORING BASED ON THE FRACTAL ANALYSIS OF CURRENT AND CUTTING FORCE SIGNALS DURING CFRP TRIMMING

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5.1 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.

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

5.2 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 (Breuer, 2016). 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 (Ahmad, 2009). 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 (Ahmad, 2009). 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 (Altin Karataş & Gökkaya, 2018). To ensure product quality at the end of the finishing operation, direct or indirect methods of tool condition monitoring can be used (Teti et al., 2010). In the direct method, the geometric parameters of the cutting tool are measured using an optical microscope with a high degree of accuracy (Nouri et al., 2015). 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 (Teti et al., 2010). 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 (Abdul-Ameer, Al-Kindi, & Zughaer, 2011). 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 (Hidayah et al., 2015; Rehorn et al., 2005).

Due to the sensitivity of cutting forces related to cutting conditions, the force signals have been widely used in tool condition monitoring (Hidayah et al., 2015). Hu *et al.* (Hu et al., 2019) 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 line (Hidayah et al., 2015). Alternatively, any changes in the cutting state can be reflected in the electric current signal of machine tools. Jeong and Cho (Y. H. Jeong & D.-W. Cho, 2002) 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 (Soliman & Ismail, 1997).

The process of extracting reliable, intelligible data from enormous data sets to enhance decision-making is known as data mining. There are numerous approaches for data mining and extracting information from a particular signal (K.-S. Wang, 2013). Hassan *et al.* (M. Hassan, Sadek, & Attia, 2021) 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. Recently, an Artificial Neural Network (ANN) was applied during machining to classify the tool wear states in real-time using acceleration data (Hesser & Markert, 2019) and acoustic emission signals (Elforjani & Shanbr, 2018). Fuzzy logic was also introduced as another possible approach for tool condition monitoring by analyzing the uncertainties in acoustic emission signals (Ren et al., 2015). The combination of time and frequency domain analysis (Choi et al., 2008), genetic algorithms (Liao et al., 2019), fast Fourier transform (Pyatykh, Savilov, & Timofeev, 2022) and other methods have been used to analyze the acquired signals in the online tool condition monitoring. However, the robustness of these methods needs to be examined, though, as any modifications to the cutting condition or process parameters can change the result. 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 (Mandelbrot, 1982). Fractal analysis was widely applied in advanced surface roughness evaluation (Zuo et al., 2015), and it was also utilized in machine maintenance and diagnosis improvement (Xavier Rimpault et al., 2018). Rimpault *et al.* (X. Rimpault et al., 2017) proved that fractal analysis of cutting force signal is more efficient to estimate the tool wear than the statistical parameters can be. In this study, different set of cutting condition (speed and feed) were investigated. It has been demonstrated that the fractal parameters are less dependent on the cutting parameters than the statistical parameters during machining of CFRP. Moreover, recently, Jamshidi *et al.* (Jamshidi et al., 2020) 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 electric current signal and the total cutting force signal while trimming Carbon Fiber Reinforced Plastics (CFRP). For industrial applications, using the machine tool's internal data, such as electric current signal, is more practical, due to the quick data acquisition and lack of external sensors. In this study, it is indicated that, in the integrated system that complies with industrial restrictions, the machine tool spindle electric current signal or total cutting force signal are used to predict the tool condition. This method is an innovation since it enables online tool condition monitoring utilizing fractal parameters of the electric current signal or cutting force signal, as shown in Figure 5.1. This study aims to demonstrate the robustness of the fractal analysis as a decision-making system in tool condition monitoring.

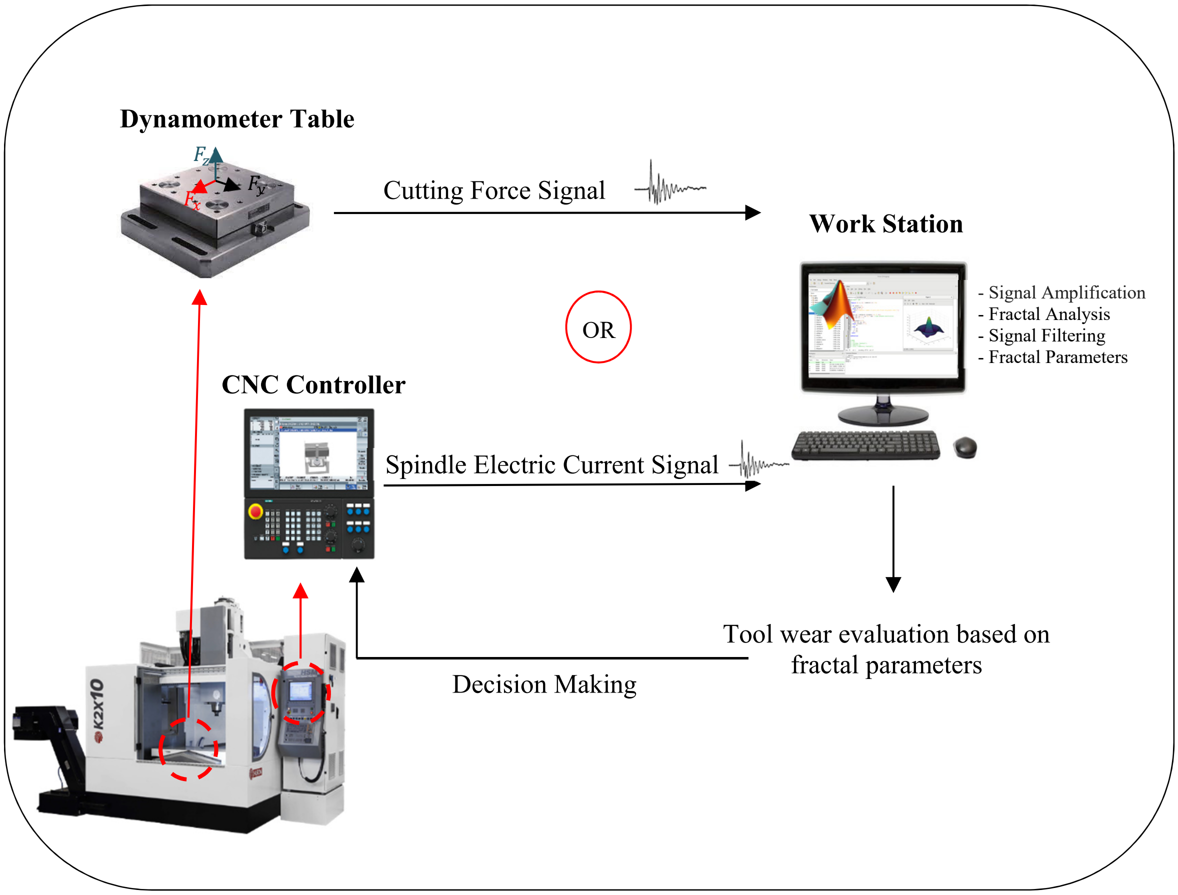

Figure 5.1 Indirect method of tool condition monitoring using spindle electric current signal or total cutting force signal

5.3 Methodology

The use of spindle electric current signal and cutting force signal to monitor tool condition was investigated in this study. Correlating relevant sensor signals to the tool wear states will be performed. 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.

5.3.1 Materials and experimental setup

Six Carbon Fiber Reinforced Plastics (CFRP) plates were manufactured using the hand lay-up method and cured in an autoclave (Ahmad, 2009). 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 (Figure 5.2). 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 (Jamshidi et al., 2020).

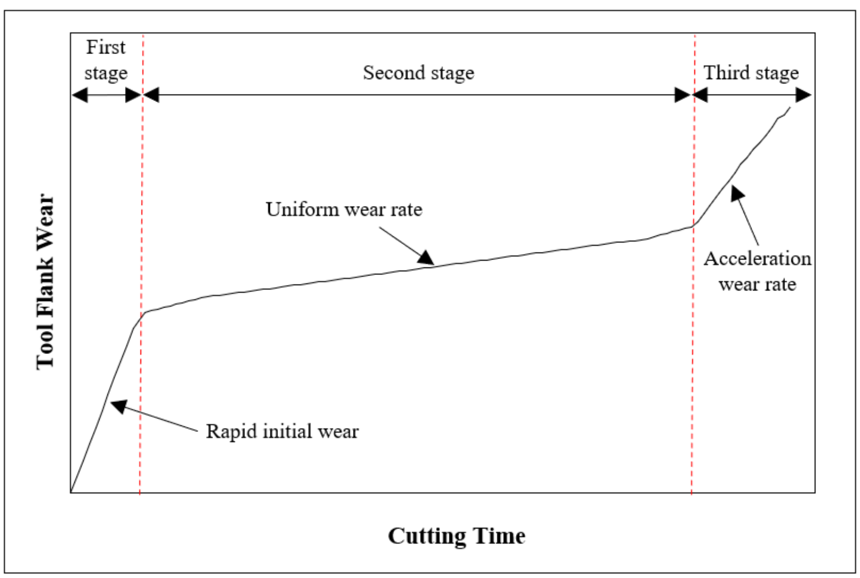

Figure 5.2 Tool wearing phenomena

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 5.1.

Table 5.1 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 (Figure 5.3). The red arrows indicate the cutting toolpath in Figure 5.3. 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 (Bérubé, 2012). 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 (Figure 5.4). The emissivity of the cutting tool and CFRP specimens were calculated based on the ASTM international standard (ASTM, 2018) 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 after each experiment. The quality of the machined surface was assessed using areal surface roughness parameters.

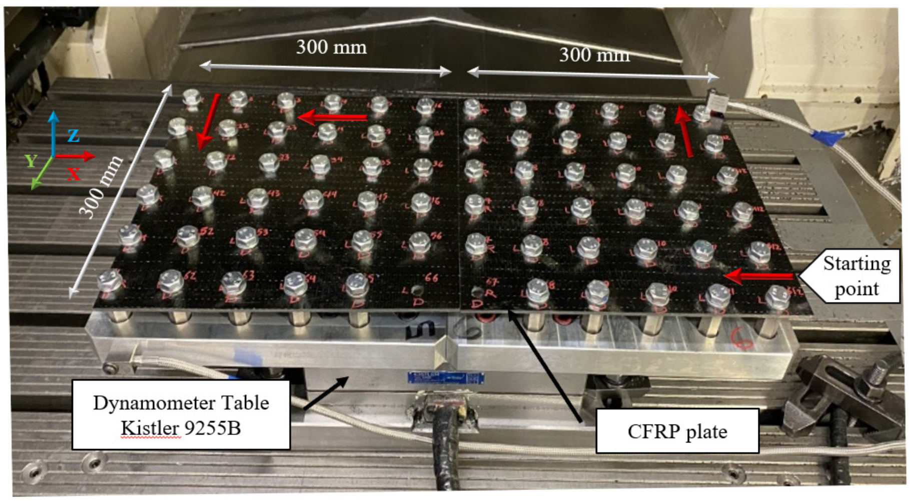

Figure 5.3 The experimental setup, and the direction of trimming specified with the red arrows

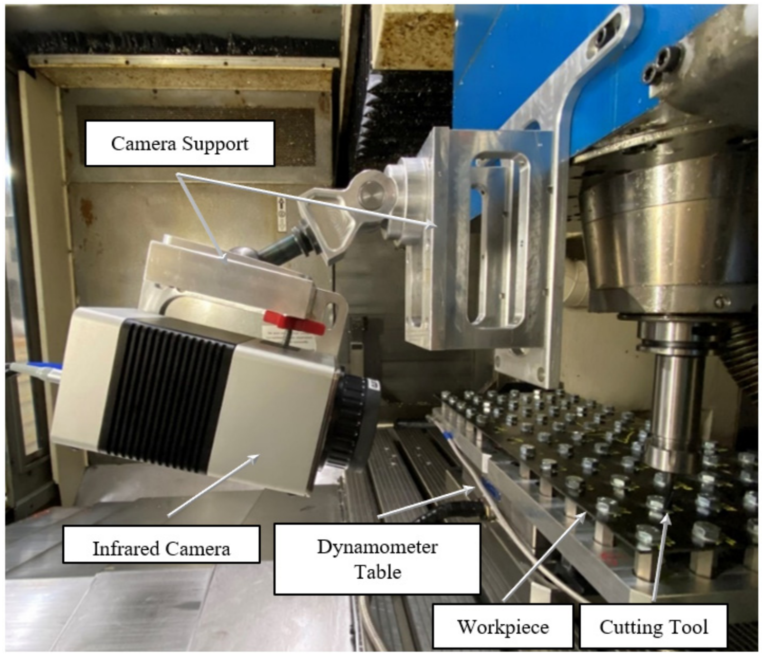

Figure 5.4 Infrared camera series VarioCAM® HD head 900 installed on the spindle head

5.3.2 Fractal analysis

Some irregular geometries were initially represented by fractal dimensions. Mathematicians discovered that "rough" surfaces exhibit self-affine behavior and may be measured in terms of fractal dimension. It is difficult to determine the fractal dimension of an object or a curve. The Weierstrass-Mandelbrot (WM) function enables the sketching of a self-affine curve (Majumdar & Tien, 1990; X. Rimpault et al., 2017).

$$z(x) = G^{D-1} \sum_{n=n_1}^{\infty} \frac{\cos 2\pi\gamma^n x}{\gamma^{(2-D)n}} \tag{5.1}$$

Two factors, D and G, which are unaffected by sampling frequency or length, define the shape of the profile. The fractal dimension from a profile (D) can be obtained using a variety of fractal analysis approaches such as correlation analysis, information analysis, regularization analysis and box-counting method. In different studies, some of this methodology such as box-counting, exhibited relatively low robustness (Xavier Rimpault et al., 2018; Xavier Rimpault et al., 2016). Regularization analysis was used in the present study because of its reasonably strong repeatability, as demonstrated in recent works (Feng et al., 2010; Xavier Rimpault et al., 2016). Roueff and Lévy Véhe (Roueff & Lévy Véhe, 1998) proposed a novel method to assess the regularity of a graph in 1998. They defined regularization dimension using following definition.

Γ is defined to be the graph of a bounded function $f : \mathbb{R} \longrightarrow \mathbb{R}$. $\chi(t)$ is defined to be a kernel function of Schwartz class S, so

$$\int \chi = 1 \tag{5.2}$$

$\chi_a(t) = \frac{1}{a}\chi\left(\frac{t}{a}\right)$ is the dilated version of χ at scale a, and f_a can be the convolution of f with χ_a:

$$f_a = f * \chi_a \tag{5.3}$$

Equation 5.2 shows that χ_a tend to Dirac distribution, and f_a tend to f, when a goes to 0. Because $f_a \in S$, then the length of its graph Γ_a on K is finite and it can be calculated using following equation:

$$L_a = \int_K \sqrt{1 + f_a'(t)^2 dt} \tag{5.4}$$

Then the regularization dimension can be calculated as follow;

$$dim_R(\Gamma) = 1 + \lim_{a \to 0} \frac{\log(L_a)}{-\log(a)} \tag{5.5}$$

$dim_R(\Gamma)$ is called regularization dimension which is referred as fractal dimension (*D*) in the present study.

The limit in this equation is calculated as the slope in the area where *a* tends to 0 and the R^2 of the linear regression is close to 1 (Xavier Rimpault et al., 2016). The fractal dimension (*D*) is defined as the slope of the graph ($log\ l_a$ *vs.* $log\ a$) in the linear region, as shown in Figure 5.5. Fractal dimension is an indication of the signal “roughness”.

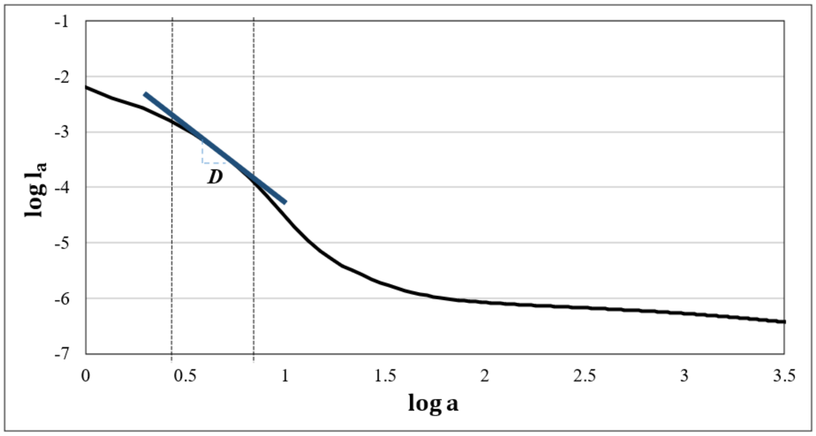

Figure 5.5 Example plot illustrating regularization analysis. The plot expresses l_a vs. (a) in *log-log* format for the spindle electric current signal

To ensure the accuracy of the results, a common region in the $\log l_a$ *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 electric current signal (Region 1) and 5 to 22 points for total cutting force signal (Region 2) as illustrated in Figure 5.6. 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:

$$I = (R^2)^D \tag{5.6}$$

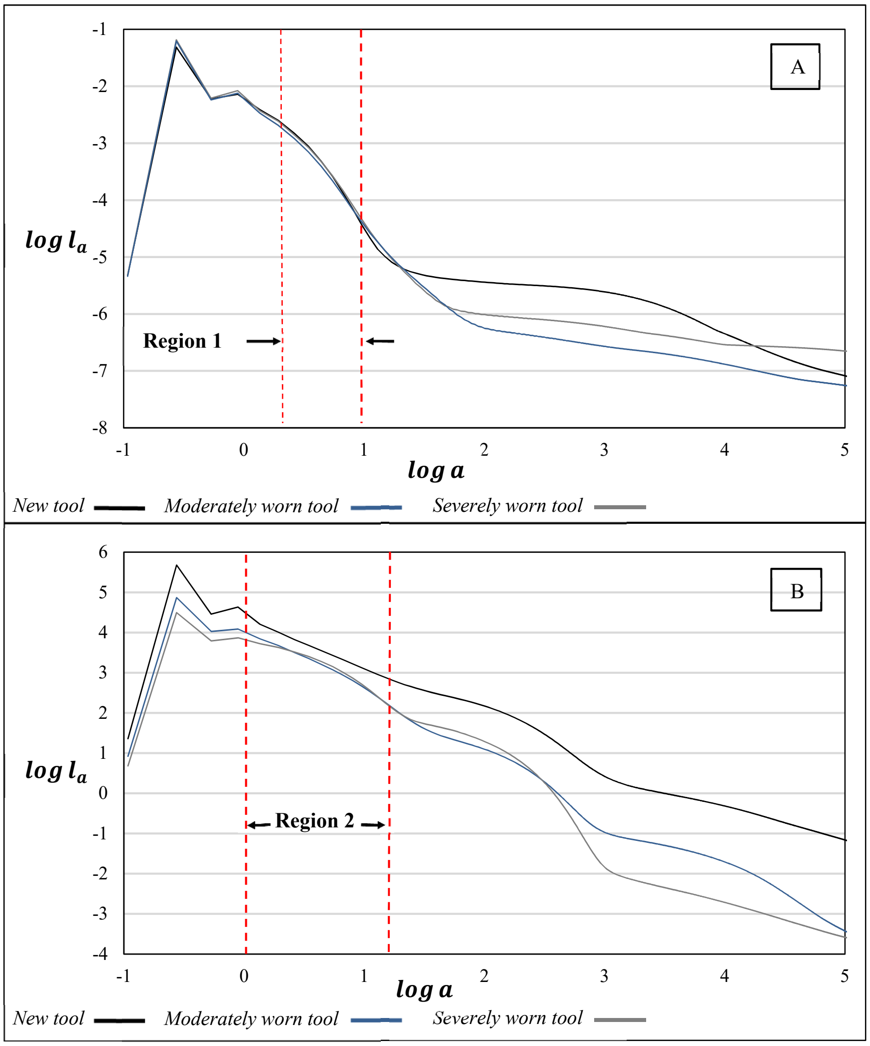

Figure 5.6 $log\ l_a$ *vs.* $log\ a$ graph for **A)** spindle electric current signal and **B)** total cutting force signal

5.4 Results and discussion

The results of machining CFRP utilizing three distinct tool conditions are discussed in the following chapter. The obtained signals, including spindle electric 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.

5.4.1 Spindle electric current signal

5.4.1.1 Conventional analysis of spindle electric 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 electric current signal was obtained using the machine tool's internal sensor with the least noise level, as shown in Figure 5.7. 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 Figure 5.8. 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 Figure 5.8. 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 (Akbari, Danesh, & Khalili, 2017). 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. In this study, it is not possible to evaluate the condition of the cutting tool using the statistical parameters of the electric current signal during CFRP machining. Average, standard deviation, kurtosis, and skewness of electric current signal were calculated; however, fluctuations of these parameters did not appear to correlate with tool condition due to unexpected changes and excessive variation.

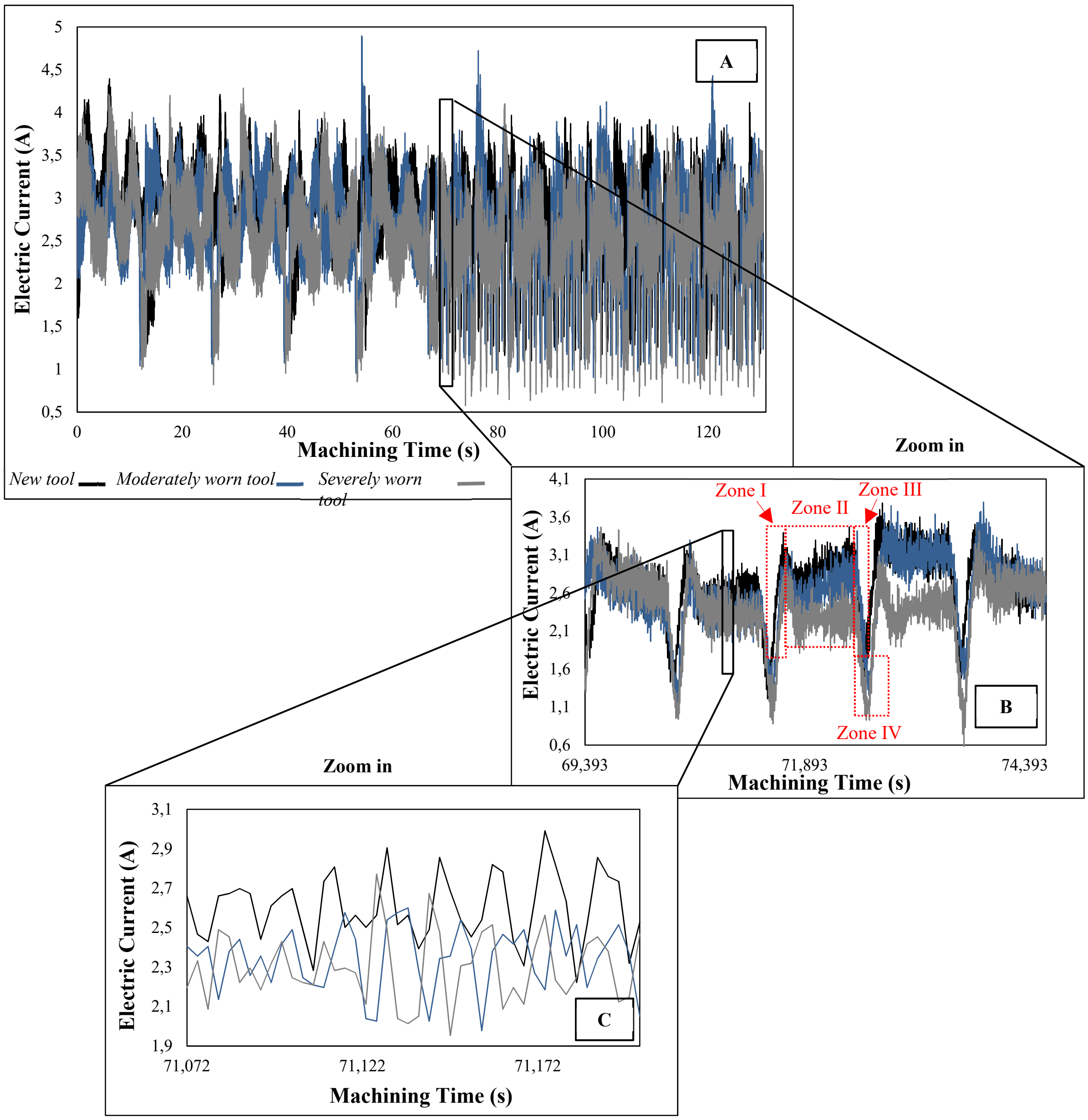

Figure 5.7 **A)** The spindle electric current signals during trimming of CFRP using the new, the moderately worn, and the severely worn CVD end mill tool. **B)** Zoom in section of the spindle electric current signals including Zone I to Zone IV **C)** Zoom in section of the spindle electric current signals

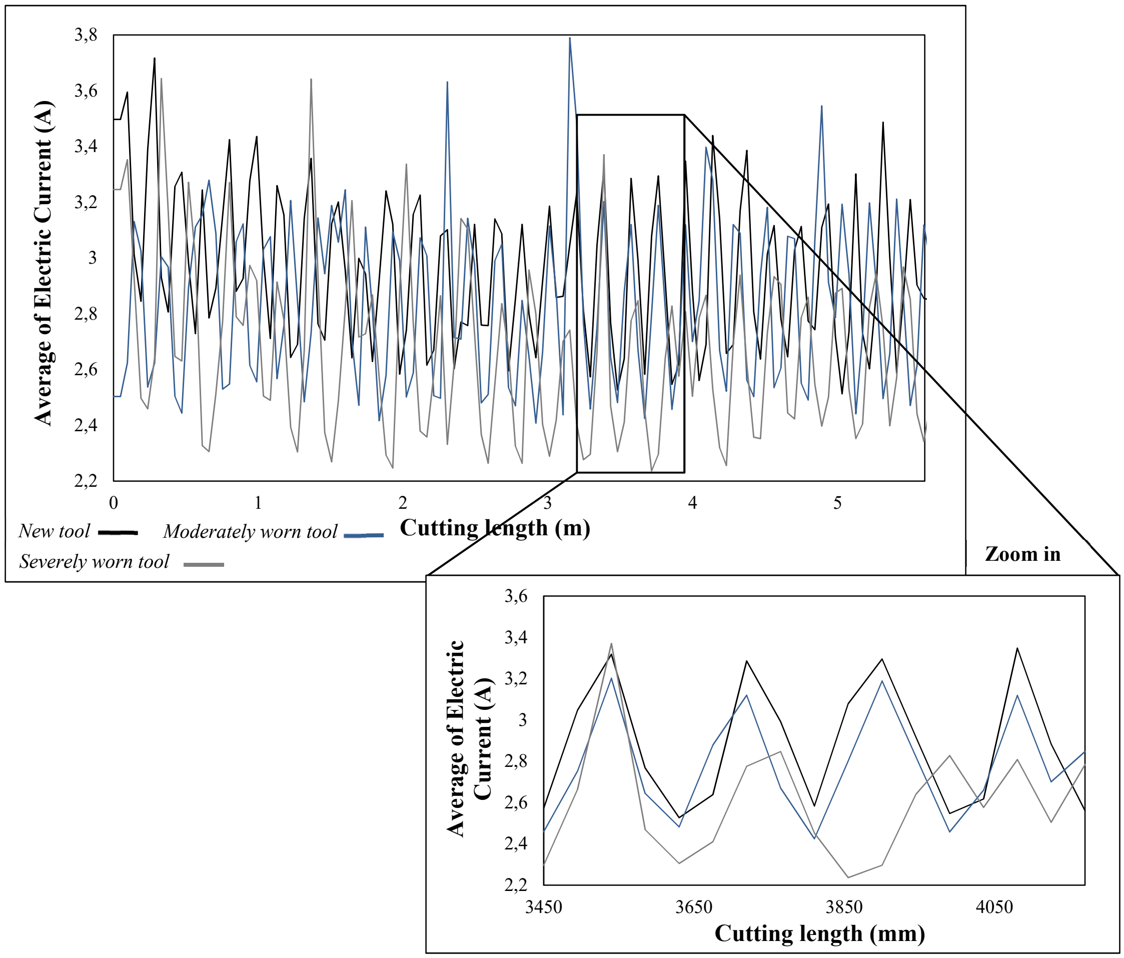

Figure 5.8 Average of the spindle electric current as a function of cutting length during trimming of CFRP using the new, the moderately worn, and the severely worn CVD end mill tool

5.4.1.2 Fractal analysis of the spindle electric current signal

The fractal analysis results of the spindle electric current signal during the trimming of CFRP are filtered and illustrated in Figure 5.9. Fractal parameters are less dependent on the cutting parameters than the statistical parameters during machining of CFRP as stated in the literature review. 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

(X. Rimpault et al., 2018). As shown in Figure 5.9, 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 electric current signal. The fractal dimension in the first 3 m of cutting (trimming in the X direction as shown in Figure 5.3) remains constant for the worn and new cutting tools, even when the quantity of the current fluctuates, as can be seen in Figure 5.9. The fractal dimension continues to decrease for the new cutting tool while trimming in the Y direction (Figure 5.3). This behavior can be explained by the effect of the cutting direction on the shape of the electric 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 electric current signal and improve the accuracy of the decision-making system. This empirical index was designed to feed the controller with a single value based on the combination of all fractal parameters. Therefore, before feeding it to the controller, an appropriate threshold value for each experiment must be chosen. The empirical index of fractal analysis of the spindle electric current signal is also shown in Figure 5.9. 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 to feed the controller. 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.

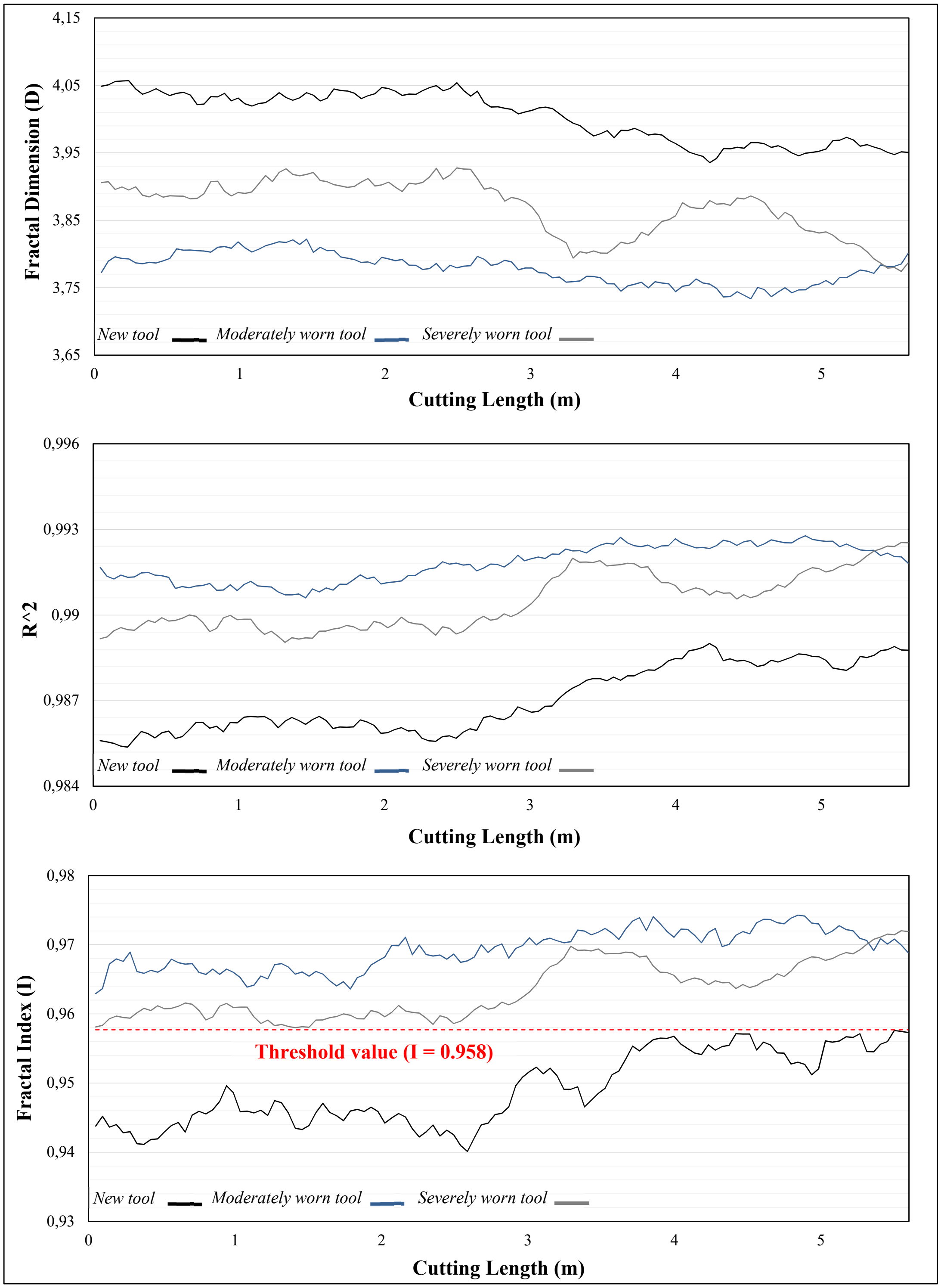

Figure 5.9 Fractal analysis of the spindle electric current signal during trimming of CFRP using the new, moderately worn, and severely worn CVD end mill tool

5.4.2 Total cutting force signal

5.4.2.1 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 Figure 5.10. 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 (Hintze & Klingelhöller, 2017). 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 (Hintze & Klingelhöller, 2017; Yashiro, Ogawa, & Sasahara, 2013). The average temperature of the CFRP in the cutting zone area and the average temperature of the cutting tool are illustrated in Figure 5.11. 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 Figure 5.11. 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 5.12 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 Figure 5.12, 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 (ISO, 2012). The result of S_a (arithmetical mean height) indicates that the surface improves when the worn cutting tool is utilized (Figure 5.13). 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 *et al.* (Hamedanianpour & Chatelain, 2013) and Ghidossi *et al.* (Ghidossi, El Mansori, & Pierron, 2004) also mentioned in their studies.

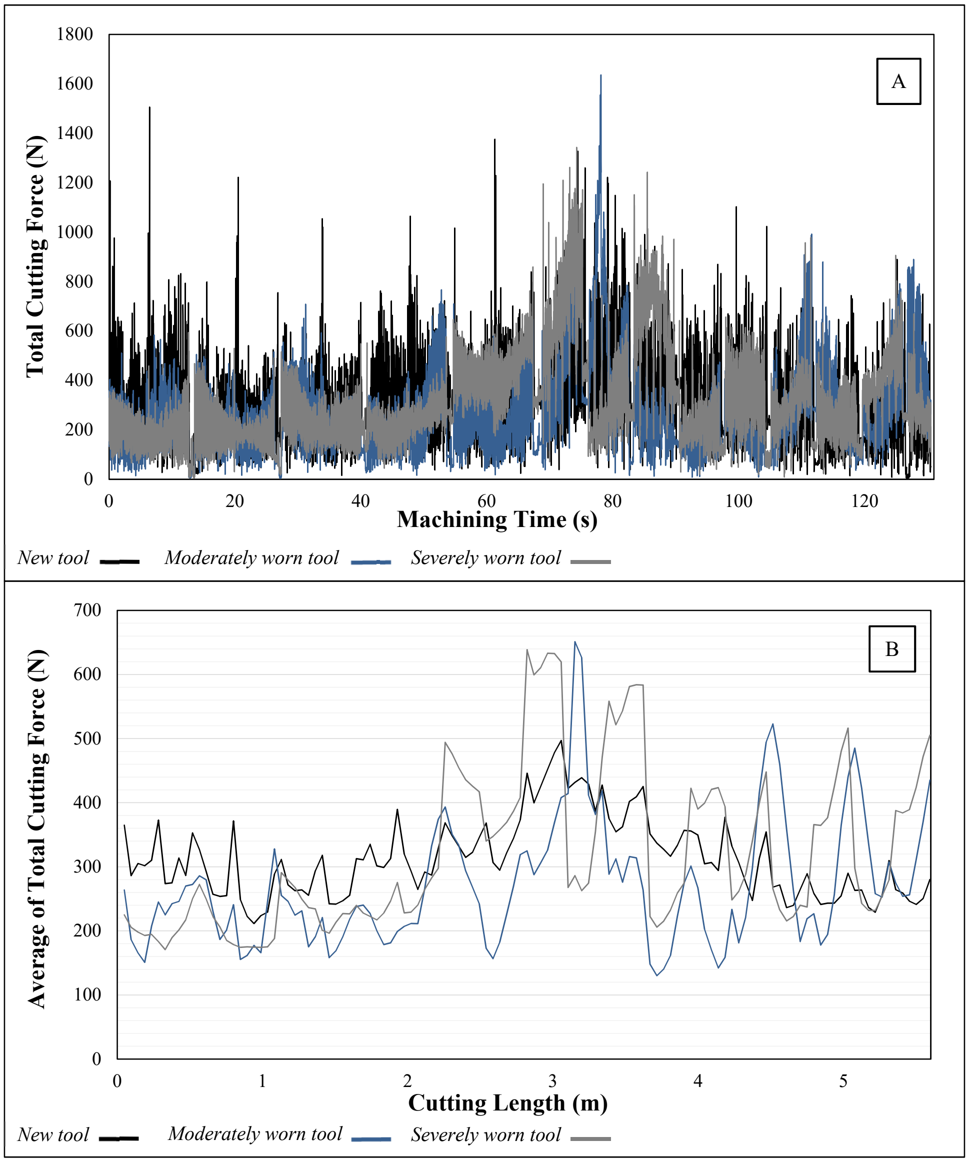

Figure 5.10 **A)** Total cutting force signal during trimming of CFRP using the new, the moderately worn, and the severely worn CVD end mill tool. **B)** Average of total cutting force signal as a function of cutting length

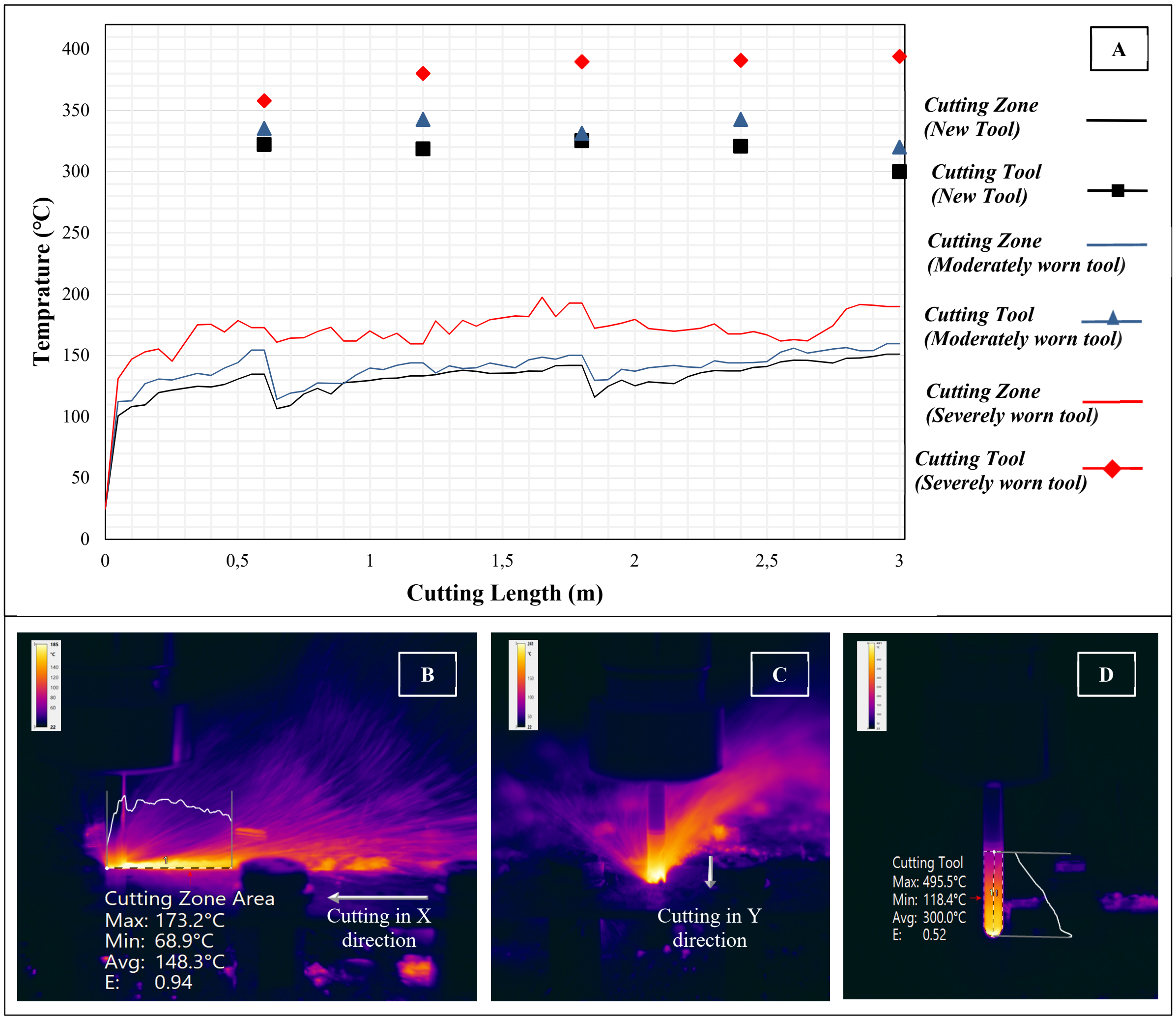

Figure 5.11 **A)** The average temperature of the workpiece in the cutting zone area and the average temperature of the cutting tool during trimming of the CFRP in the first 3 m length of cut using the new, the moderately worn, and the severely worn CVD end mill tool. **B)** Photo taken using infrared 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

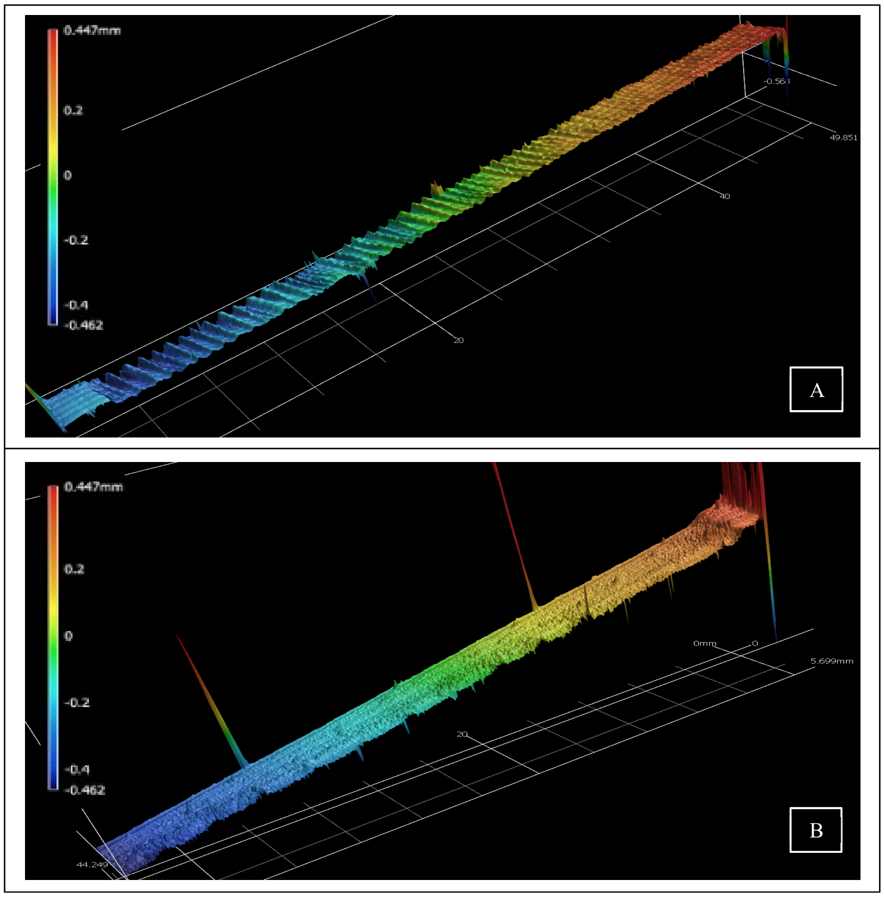

Figure 5.12 The 3D images of the surface texture for the last 50 mm of the cutting using **A)** The new CVD end mill tool **B)** The severely worn CVD end mill tool

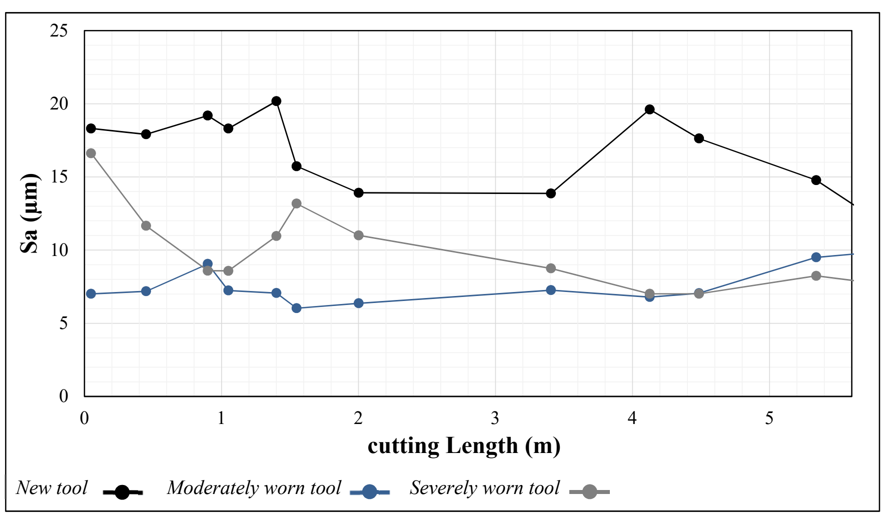

Figure 5.13 Areal surface roughness parameter (S_a) when the new, moderately worn and severely worn cutting tool is utilized

5.4.2.2 Fractal analysis of total cutting force signal

Cutting force signals have frequently been used to monitor the tool condition. However, the acquisition of cutting forces needs sensors like dynamometers, which are not practical or cost-effective to utilize in production lines. Depending on equipment availability, the cutting force signal can be used as an alternate option for tool condition monitoring. Due to unforeseen changes and excessive fluctuation, the statistical parameters of the total cutting force signal during CFRP machining were insufficient to determine the condition of the cutting tool. Then, fractal analysis was used to extract the hidden information of the cutting force signal. The fractal analysis result of the total cutting force signal during trimming of CFRP is filtered and illustrated in Figure 5.14. 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 empirical index was created to provide the controller with a single value based on the combination of all fractal parameters. This value can ensure the desired dimensional accuracy or surface integrity of the machined surface at the end of finishing operation.

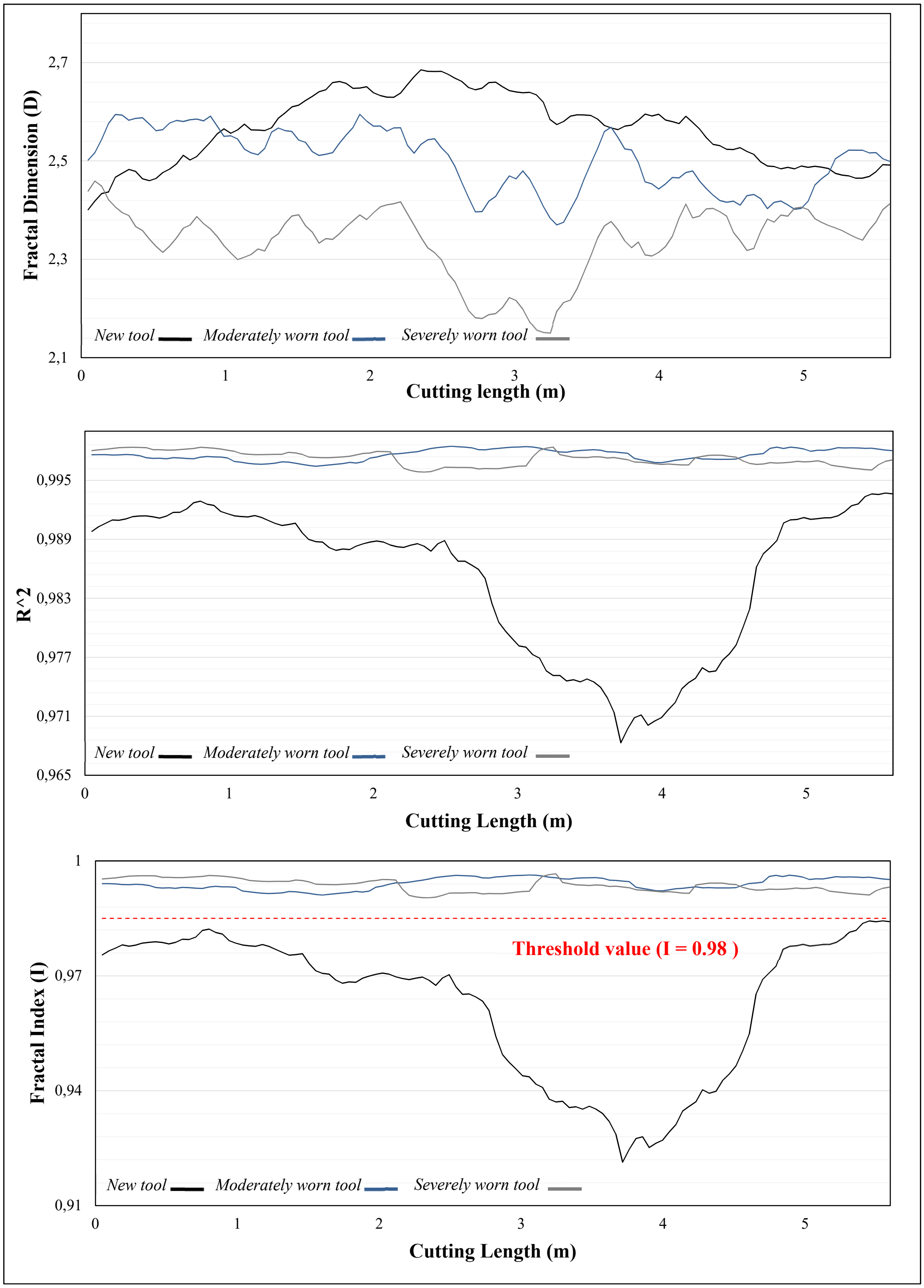

Figure 5.14 Fractal analysis of the total cutting force signal using the new, the moderately worn, and the severely worn CVD end mill tool

5.5 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 electric 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. 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. This study effectively demonstrated the efficiency of fractal analysis as a decision-making method in tool condition monitoring.

CHAPTER 6

TOOL CONDITION MONITORING USING MACHINE TOOL SPINDLE ELECTRIC CURRENT AND MULTISCALE ANALYSIS WHILE MILLING STEEL ALLOY

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6.1 Abstract

In the metal cutting process, the tool condition directly affects the quality of the machined component. To control the quality of the cutting tool and avoid equipment downtime, it is essential to monitor its condition during the machining process. The primary purpose is to send a warning before tool wear reaches a certain level, which could influence product quality. In this paper, tool condition is monitored using fractal analysis of the spindle electric current signal. The current study analyzes the monitoring of cutting tool when milling AISI 5140 steel with a four-flute solid carbide end mill cutter to develop monitoring techniques for wear classification of metal cutting processes. The spindle electric current signal is acquired using the machine tool internal sensor, which meets industrial constraints in their operating conditions. As a new approach, the fractal theory is referred to analyze the spindle electric current signal and then assess the tool wear condition during the metal cutting process. Fractal parameters were defined to extract significant characteristic features of the signal. This research provides a proof of concept for the use of fractal analysis as a decision-making strategy in monitoring tool condition.

Keywords: Steel, Milling, Tool condition, Fractal analysis, Electric current

6.2 Introduction

The cutting tool is vital in the metal cutting process, and the tool condition directly influences the quality of the machined component. When tool wear is severe enough to influence product quality, the cutting tool needs to be replaced. In real time, successful determination of wear can avoid insufficient product quality, unplanned downtime, and economic losses associated with tool failure. The average machine tool downtime due to the tool wear was estimated to be 7–20 percent, resulting in significant productivity loss (Drouillet et al., 2016). Abrasion, fracture, plastic flow and built-up edge were reported as the main wear mechanisms during the machining of the AISI 5140 steel (Grzesik, 2009).

Real time tool condition monitoring is a pillar of intelligent manufacturing, especially in the highly automated production lines (N. Li et al., 2016). Tool condition monitoring has been classified into two categories: direct and indirect methods. In the direct method, the geometric parameters of the cutting tool are evaluated with a high degree of accuracy using an optical microscope (Nouri et al., 2015). This method has real time limitations since it requires interrupting the cutting process to estimate tool wear. Furthermore, the direct method requires specific laboratory equipment, which is a constraint in the harsh industrial machining environment (J. Guo et al., 2022). However, the indirect method contains a simpler setup, and it is performed by correlating relevant sensor signals to the tool wear states. Different signals can be employed to monitor the tool condition. The cutting force signal is the most reliable monitoring signal, and it is very sensitive to the tool condition changes (Jamshidi et al., 2022a; N. Li et al., 2016). Li *et al.* (N. Li et al., 2016) introduced a force based tool condition monitoring system based on ν-Support Vector Regression (ν-SVR) and correlation analysis. Experimental results proved the prediction accuracy up to 96.76 percent during the turning of steel alloy. Recently, Liao *et al.* (Liao et al., 2019) developed an automated tool condition monitoring scheme using a cutting force sensor to guide decision-making in milling steel alloy effectively. The proposed monitoring system correctly indicated the degree of tool wear using

Support Vector Machine (SVM) and Genetic Algorithm (GA). The SVM approach, however, has some drawbacks. The performance of this method is greatly influenced by the choice of the kernel function and its parameters. They can only be chosen through a method of trial and error which greatly complicates their selection.

Despite the cutting force signal's capacity to assess tool condition during machining, obtaining cutting forces requires specialized sensors such as dynamometers. Using those sensors in the production line is not practical or cost-effective. Low cost sensors that do not interfere with the cutting process are preferred in industrial environments (X. Li et al., 2022). Rmili *et al.* (Rmili et al., 2016) developed an automatic system for monitoring tool wear based on the vibratory signatures produced during the turning operation using the mean power analysis. The proposed automatic detector introduced as a useful method for improving a wear monitoring system in an industrial environment. However, the accuracy of Tool Condition Monitoring (TCM) using vibration signal is limited by the characteristics of machining processes and the vibration signal is extremely sensitive to the environment. Moreover, the vibration signal can be impacted by the location of the sensor and the type of cutting fluid as well.

For industrial applications, it is more practical to use the machine tool's internal data, such as power and electric current because data acquisition is extremely fast and no external sensors are involved (D.-D. Li, Zhang, Li, Xue, & Fleischer, 2020). Drouillet *et al.* (Drouillet et al., 2016) used the spindle power sensor data to predict Remaining Useful tool Life (RUL). A curve fitting method of Artificial Neural Network (ANN) was used to anticipate the RUL. The predicted and actual RUL of the cutting tool were found to be in good agreement. However, to achieve great performance, ANN need a lot of training data, which is time consuming and expensive. Choi *et al.* (Choi et al., 2008) developed a method based on the Root Mean Square (RMS) of the feed and spindle motor currents to predict drill foreboding failure during steel alloy drilling. Regardless of the cutting tool type and cutting conditions, the proposed algorithm identified impending failure before breakage of the drill using the feed motor current signal. Moreover, Jamshidi *et al.* (Jamshidi et al., 2022a) showed that the electric current signal from the spindle was extremely responsive to the cutting conditions and could precisely depict tool condition changes during milling. Implementing a monitoring system based on the spindle electric current signal is accessible, and no modification is required to the workpiece fixture or machine tool.

Data mining is commonly defined as the process of obtaining valid, understandable data from massive data sets in order to improve decision-making process. For data mining and extracting information from a specific signal, a variety of techniques are available (K.-S. Wang, 2013). As previously indicated, conventional statistical methods (Arslan, Osman Er, Orhan, & Aslan, 2016), the combination of time and frequency domain analysis (Choi et al., 2008), genetic algorithms (Liao et al., 2019), fast Fourier transform (Pyatykh et al., 2022), artificial neural networks analysis (Drouillet et al., 2016) and other methods have been used to analyze the acquired signals in the tool condition monitoring while machining steel alloys. However, a method with shorter training duration and quicker processing time is required for TCM. Recently, fractal analysis was introduced as a new approach in tool condition monitoring while machining composite parts. Fractal analysis was introduced to reveal inherent patterns hidden in the acquired signals such as cutting force signal (Jamshidi et al., 2022a; Jamshidi et al., 2020) and electric current signal (Jamshidi et al., 2022a). According to the literature review, fractal parameters depend on cutting parameters less than statistical parameters. Recently, Jamshidi *et al.* (Jamshidi et al., 2022a) referred to fractal analysis to monitor the tool condition using cutting forces and electric current signal while machining composite parts. During machining of Carbon Fiber Reinforced Plastic (CFRP), fractal characteristics were evaluated to determine discrete wear stages of the cutting tool.

In this study, it is proposed to use the built-in machine tool spindle electric current signal to anticipate the tool condition in an integrated system without any use of external device which meets industrial constraints. This research provides a proof of concept for the use of fractal analysis as a decision-making strategy in monitoring tool condition. This approach is an important innovation, allowing to assess the tool condition in real time as shown in Figure 6.1. This study intends to demonstrate the possible outcome of the fractal analysis of the built-in machine tool spindle electric signal in the online tool condition monitoring during the metal cutting process as the effectiveness of this method was proved during composite machining (Jamshidi et al., 2022a).

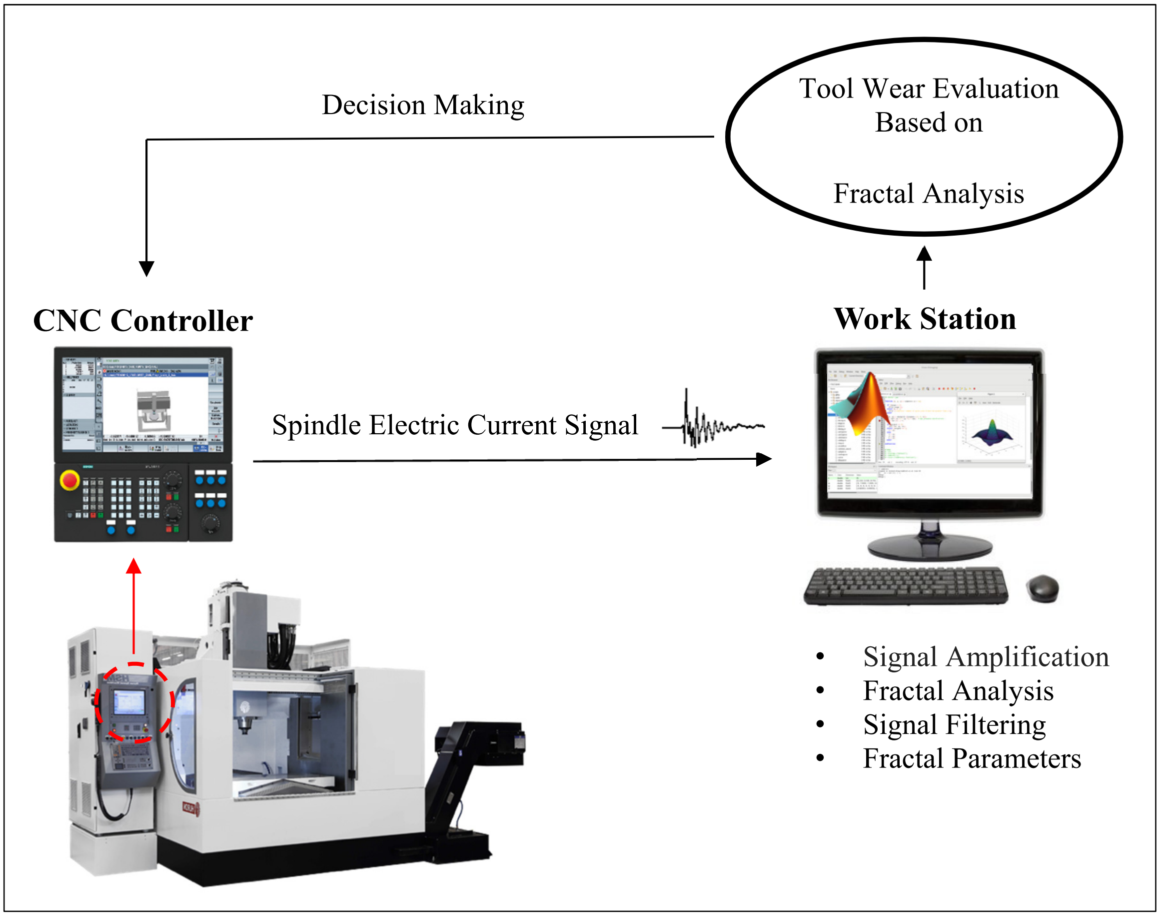

Figure 6.1 Indirect method of tool condition monitoring using spindle electric current signal

6.3 Methodology

In this study, the spindle electric current signal was acquired during shoulder milling of AISI 5140 steel block using a four flute solid carbide end mill cutter. The experiments lasted 50 minutes and the overall cutting length was 23.3 meters. As shown in Figure 6.2, the cutting toolpath consisted in a contour-parallel. The machining was paused every three contours for tool wear measurement. Following the contouring operations, the areal roughness parameter was estimated on each contour resulting surface.

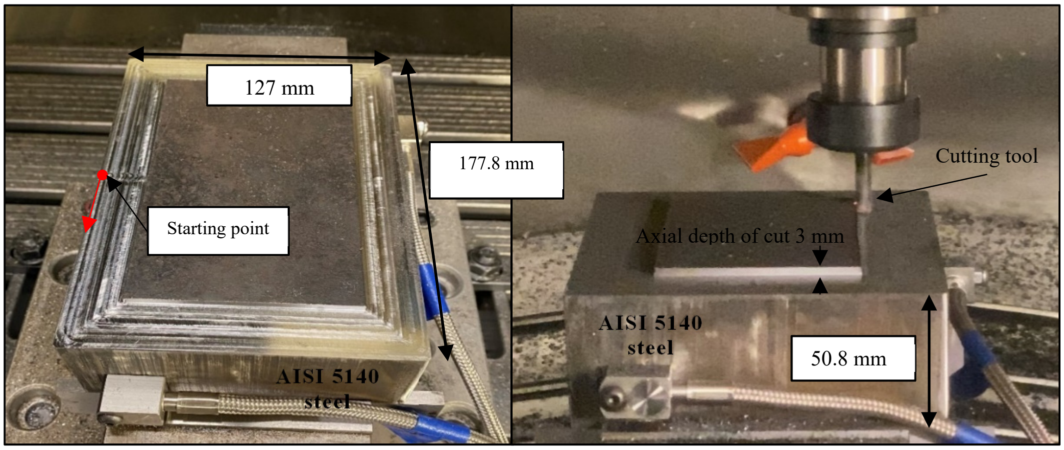

Figure 6.2 The experimental setup

6.3.1 Materials and experimental setup

A four flute solid carbide AlTiN coated end mill cutter having a 6.35 mm (1/4") diameter was used to machine a block of AISI 5140 steel with dimensions of 177.8 mm x 127 mm x 50.8 mm as displayed in Figure 6.2. Tables 6.1 and 6.2 demonstrate the chemical composition and mechanical properties of AISI 5140 steel, respectively. The cutting conditions recommended by the cutting tool manufacturer were selected to conduct this experiment, as specified in Table 6.3. Tool wear was estimated by averaging the flank wear on each of the four cutting tool edges. The photographs of the tool were taken using a Keyence VHX-500F digital microscope. A reading of the flank wear was taken after every three contour machining until the tool met the ISO-8688-1 wear criterion of 0.3 mm (ISO, 1989). A K2X10 Huron® high-speed machining center equipped with a dust extraction system was used for the dry milling contouring process.

Table 6.1 General chemical properties of AISI 5140 steel.

Element	**Fe**	**Mn**	**Cr**	**C**	**Si**	**S**	**P**
Content (%)	97.395-98.07	0.7-0.9	0.7-0.9	0.38-0.43	0.15-0.3	≤ 0.04	≤ 0.035

Table 6.2 Mechanical properties of AISI 5140 steel.

Properties	**Tensile strength**	**Yield strength**	**Elastic modulus**	**Poisson's ratio**	**Hardness**
	570 MPa	295 MPa	189998-210000 MPa	0.27-0.30	167 (Brinell)

Table 6.3 Cutting conditions.

Cutting speed	**Feed rate**	**Radial depth of cut (RDOC)**	**Axial depth of cut (ADOC)**
18336 RPM	465.73 mm/min	0.64 mm	3 mm

The spindle electric current signal is very responsive to cutting conditions and can accurately describe tool condition changes. The data acquisition of this signal was done through an internal sensor of the machine tool and a static synchronized action, programmed using the Application Programming Interface (API) of the SIEMENS SINUMERIK 840D controller. The signal data was recorded at a frequency of 333 Hz. The electric current signal requires a lower frequency than the cutting force signal because the electric current variation is a portion of the requested power and its variation is less reliant on the cutting parameters. In this study, the NCU of K2X10 Huron® high-speed machining center has an interpolator cycle time of 3 ms and the acquisition rate through synchronous actions was considered as 333Hz. The machined surface quality was evaluated using the areal surface roughness parameter. The Keyence VR-5000 optical profiler was used to record the 3D images of the machined surface as well as the areal surface roughness parameter.

6.3.2 Fractal analysis for feature extraction

The concept of fractals was initially introduced by B.B. Mandelbrot (Mandelbrot, 1982). Using fractal analysis, he calculated the length of the British coastline. Fractal objects have irregular shapes and an affine structure, and they are self-similar. They have fractal dimension which is greater than the topological dimension (Mandelbrot, 1982). Fractal theory can be a valuable tool for forecasting and analyzing the behavior of complex dynamic systems and explaining and extracting properties from signals. This theory can be applied to chemistry, physics, and geology (Chuangwen & Hualing, 2009). Fractal analysis was widely used in the advanced surface roughness evaluation (Prasanta Sahoo, Tapan Barman, & J. Paulo Davim, 2011; Zuo et al., 2015). The fractal theory has recently been introduced as a novel method in tool condition monitoring systems (Jamshidi et al., 2020).

Fractal dimension can be calculated using a variety of techniques, including correlation analysis, information analysis, regularization analysis, and the box-counting method. Regularization analysis was chosen in this study because it has a significant degree of repeatability, as evidenced by recent studies (Feng et al., 2010; Jamshidi et al., 2022a; X. Rimpault et al., 2017). In the regularization analysis, signal (s) can be regularized by convolution with different kernels, such as the Gaussian kernel (g_a). Convolution product is defined as:

$$s_a = s * g_a \tag{6.1}$$

The smoothed signal (s_a) is theorized to have a finite length (l_a) and the Gaussian kernel (g_a) has the width (a). The regularization dimension can be estimated using the following equation:

$$D = 1 - \lim_{a \to 0} \frac{\log l_a}{\log a} \tag{6.2}$$

The slope in the area where the Gaussian kernel's width goes to 0 and the R^2 of the linear regression is close to 1 is determined as the limit in this equation (X. Rimpault et al., 2018). A typical region in the $\log l_a$ *vs.* $\log a$ graph with greater linearity and sufficient points for linear regression must be selected to ensure the results accuracy. Herein, a determination range was chosen based on preliminary computations for the spindle electric current signal, identified in Figure 6.3 by dash lines. The fractal parameters were calculated in the 5 to 15 points range. In Figure 6.3, two graphs were illustrated as an example. The linear regression slope (*D*) and *y*-intercept slope offset (*G*) were calculated for each curve in this range. 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 is used to compute fractal dimension which indicates the signal's roughness as well as the irregularity and complexity of a system. Additional fractal parameters were established to obtain complementary signal characteristics; topothesy (*G*) and the coefficient of determination of the linear regression (R^2). The signal's ruggedness was represented by topothesy and the auto-scale regularity of the signal was defined as the coefficient of determination of the linear (R^2).

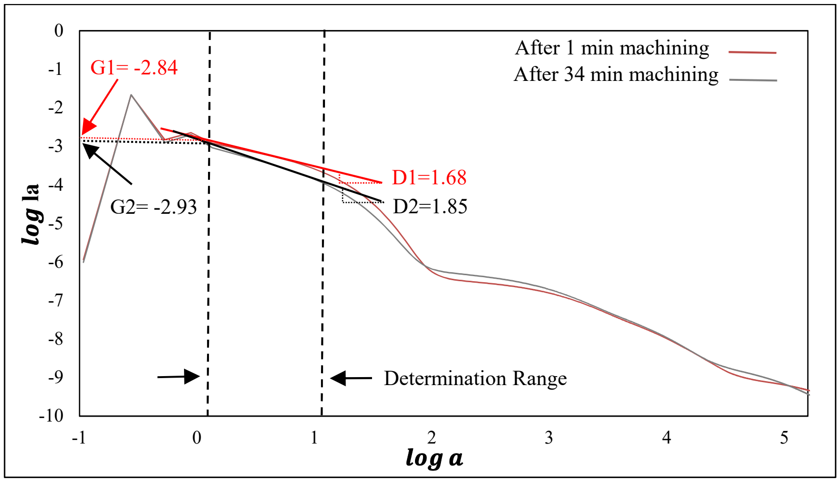

Figure 6.3 Regularization analysis of the spindle electric current signal. The plot expresses two graphs as an example in *log* format

6.4 Results and discussion

6.4.1 Conventional analysis

The experimental results of shoulder milling of AISI 5140 steel block using the solid carbide end mill tool are discussed in this section. During machining, the tool performance degrades and directly impacts the machined surface. The tool wear evolution curve of the solid carbide end mill for 23.3 meters of contour milling is depicted in Figure 6.4. This curve has three separate stages. At the initial stage, the wear increased more quickly due to the high pressure in the small contact area. Up to the third stage, the wear rose at a slower, more consistent rate. In this area, tool wear was considered normal. The wear increased faster at the final stage until the tool achieved its wear criteria of 0.3 mm according to ISO-8688-1 (ISO, 1989). The First Transition Point (FTP) was defined as the transition point between the first and second wear stages after 1.3 meters of machining. The Second Transition Point (STP) was defined as the transition point between the second and third wear stages after 18.8 meters of machining (Figure 6.4). To avoid any change in the workpiece surface quality, the cutting tool must be replaced before the second transition point. In the present study, the procedure generated sparks after 14 meters of cutting in the second stage of tool wear because of the elevated temperature at the tool-workpiece interface. The quantity of sparks increased considerably in the third stage, when the cutting tool lost its initial cutting geometry and generated a new contact surface.

The areal roughness parameter was obtained in this study to evaluate the surface quality of the steel block. Surface roughness is influenced by a variety of elements throughout the milling process, including the cutting tool condition, machining process parameters, relative vibration between the tool and the workpiece, and machining dynamics (M.-X. Guo et al., 2022). R_a is a roughness parameter based on the arithmetical mean height of a line. S_a is the extension of R_a to a surface. The average absolute value of the height for each point in the area is determined by S_a (ISO, 2012). The result of S_a (arithmetical mean height) is displayed in Figure 6.5. With S_a less than 1.5 μm in the first 18 meters of cutting, the surface is acceptable; however after 18 meters of machining, S_a increased, and surface quality dropped. Figure 6.6 illustrates the 3D image of a section of a steel block to demonstrate how the surface deteriorates as the tool wear increases. When tool wear got severe, and sparks rose, the arithmetical mean height (S_a) of the surface reached 3.13 μm at the end of the machining.

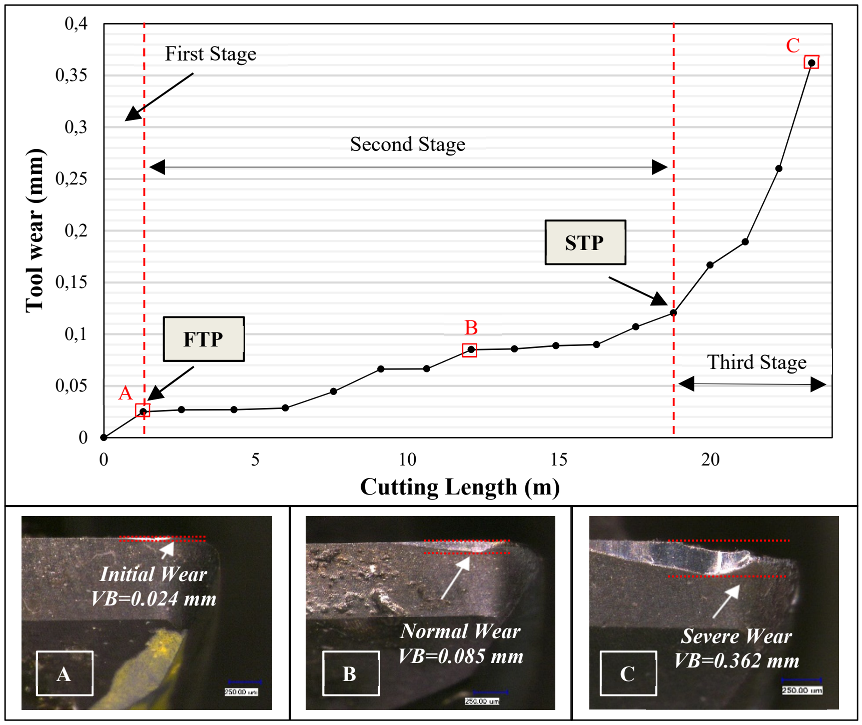

Figure 6.4 Tool wear evolution curve of the solid carbide end mill for 23.33 meters of shoulder milling of AISI 5140 steel block

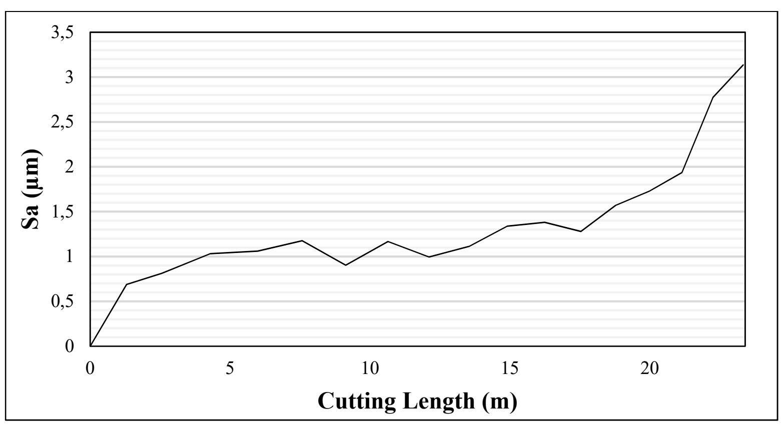

Figure 6.5 Areal surface roughness parameter (S_a) as a function of cutting length

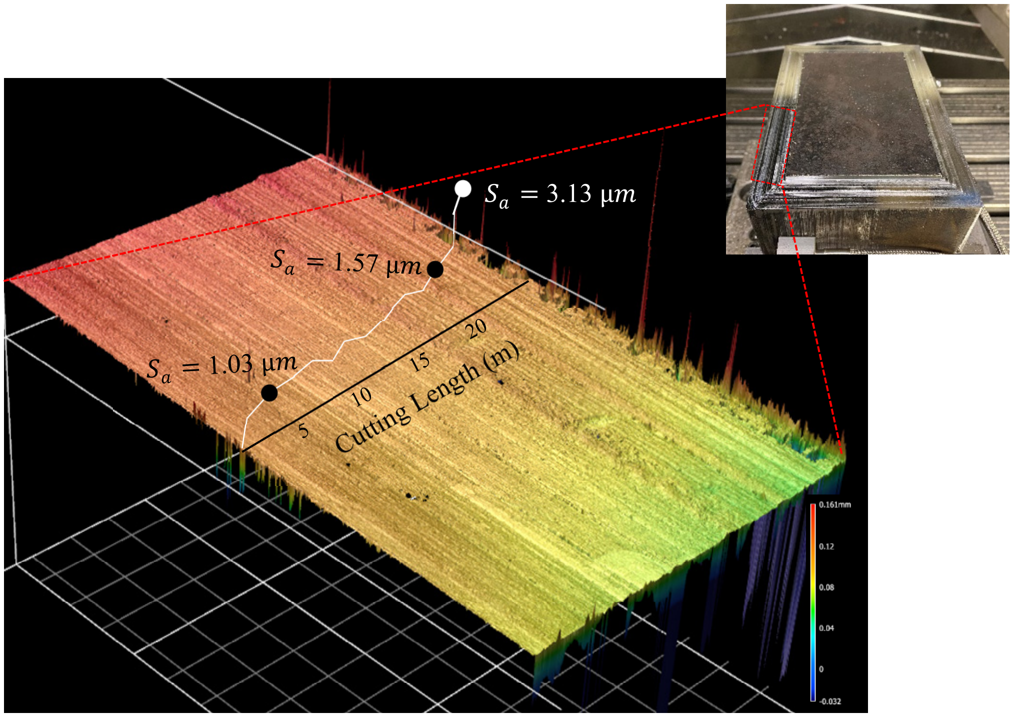

Figure 6.6 Image and surface map of a steel block; areal surface roughness parameter (S_a) as a function of cutting length

Figure 6.7 shows the electric current signal related to the spindle sampled utilizing the machine tool internal sensor with the least noise level. To emphasize the electric current changes over time, this figure also contains a moving average of the spindle electric current signal with a 30-second window of calculation. After 2.8 and 40.3 minutes of machining, the moving average of the electric current signal displays two notable rises. Since the cutting condition remained constant over time, these two peaks respectively represent the FTP and STP points in the tool wear evolution curve, as previously showed in Figure 6.4.

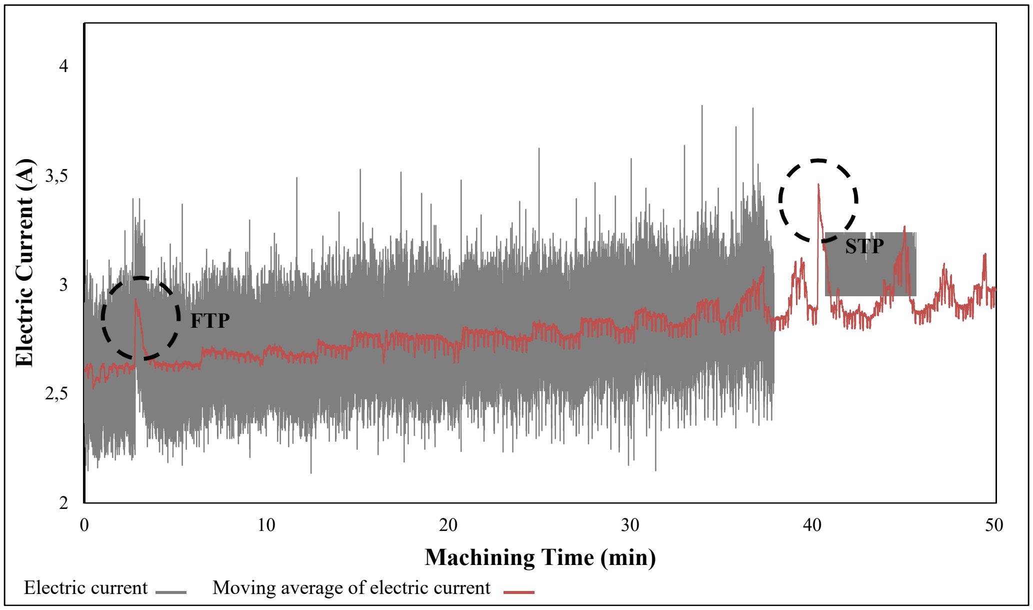

Figure 6.7 Electric current signal related to the spindle as a function of machining time

The conventional statistical analysis (average, standard deviation and kurtosis) was considered in this study to extract more information from the spindle electric current signal, as shown in Figure 6.8. Generally, the mechanical force required to remove material from the workpiece is provided by electric drives and spindles. The cutting forces are directly related to the spindle electric current. As the cutting tool wears out, the cutting force increases, requiring more power to machine the workpiece, which result in the electric current increase. The average of the spindle electric current signal as a function of the cutting length is illustrated in Figure 6.8A. The first and second transition points of tool wear clearly appear in the electric current signal average, where the current rose suddenly after 1.3 and 18.8 meters of cutting. Tool wear causes a slight increase in the electric current in the second wear stage between FTP and STP. When tool wear becomes severe (third stage of tool wear), the spindle electric current fluctuates, and several peaks appear. The standard deviation of the electric current signal is also shown in Figure 6.8B. A merely constant region can be seen in this graph, where the current readings are close to the mean with minor variation. Tool wear was expected in this area, and the machined surface quality was acceptable. However, after 18.8 meters of cutting, a disruption in the signal appears, where the electric current values spread out over a broader range of mean. Herein, instead of a transition point, a transition area that comprises STP is visible, where the standard deviation increases significantly. This area can also be seen in the kurtosis of the electric current signal, where the kurtosis drops significantly after a merely constant area. Generally, kurtosis describes how a distribution peak and tails depart from the normal distribution. As shown in Figure 6.8C, there is a disturbance in the electric current signal between 18.8 meters to 19.9 meters of cutting. The cutting condition remained constant throughout the experiment, the only variation in this experiment was the wear on the cutting tool. This disturbance could therefore be linked to the status of the cutting tool, where the cutting tool wear had become severe enough to modify cutting forces and, as a result, cause a significant alteration in the electric current signal. This unpredictable behavior in a system is the subject of the Chaos theory, where the fractal parameters are utilized to predict any change in the signal shape. The next section discusses the fractal analysis of the electric current signal to set a single value as a warning in the machine tool before tool wear reaches a specific level.

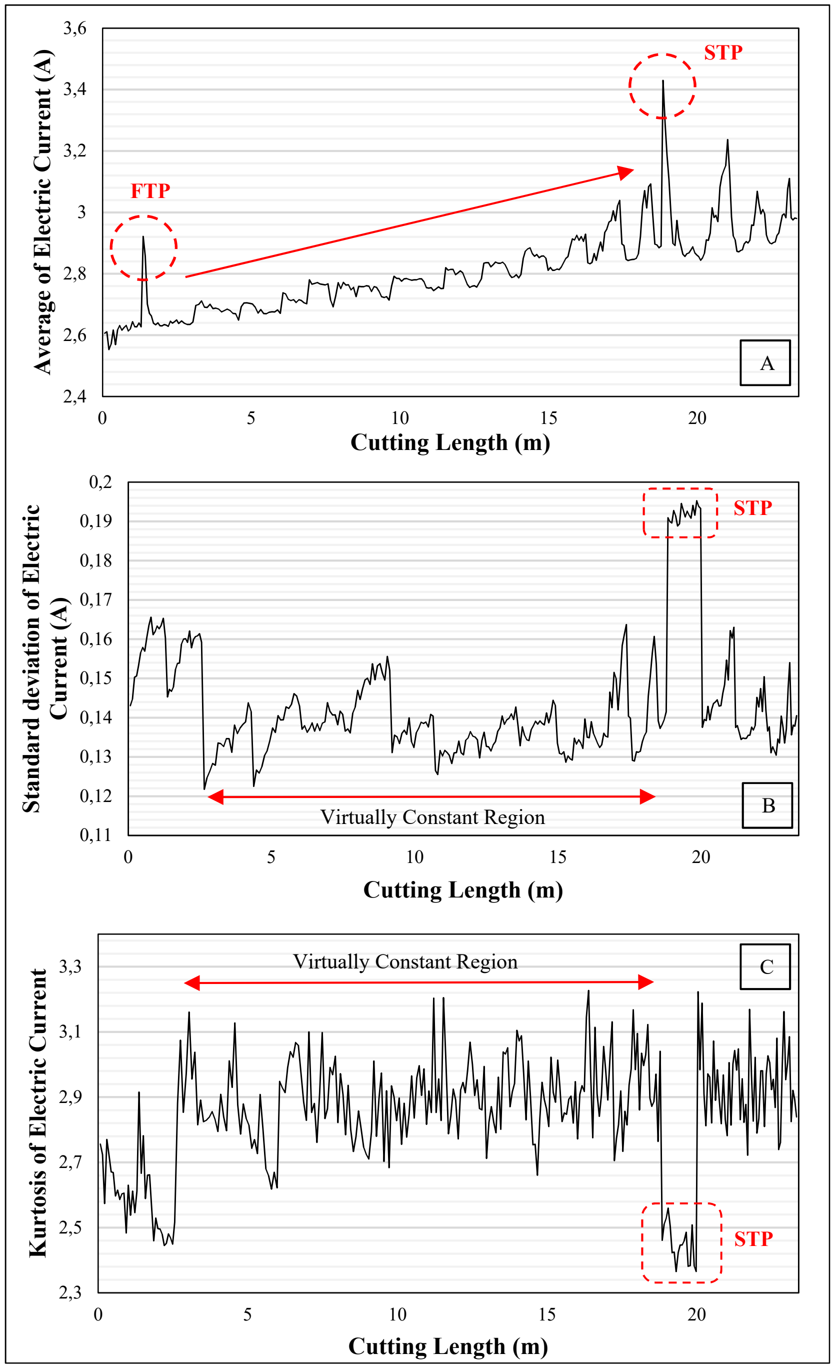

Figure 6.8 The conventional statistical analysis of the spindle electric current signal **(A)** The average of the spindle electric current signal as a function of the cutting length **(B)** The standard deviation of the electric current signal as a function of the cutting length **(C)** The kurtosis of the electric current signal as a function of the cutting length.

6.4.2 Fractal analysis

Figure 6.9 represents the fractal analysis results of the spindle electric current signal during milling of the AISI 5140 steel block. As stated in the previous section, the current signal represents any change in the cutting tool condition. This is of major importance since it may lead to the implementation of an online tool condition monitoring system. The fractal theory attempts to explain and extract properties from the signal so that any change in it may be predicted. Fractal dimension is an indication of the signal "roughness". As previously indicated, the First Transition Point (FTP) and Second Transition Point (STP) were defined as the points between the first and second wear stages, as well as the second and third wear stages. As seen in Figure 6.9, fractal dimension (*D*) exhibited a periodic behavior at the beginning of the machining process and attempted to maintain a consistent behavior at the end. However, due to signal turbulence in the cutting window of 18.8 to 19.9 meters, the fractal dimension dropped to an approximate value of 1.5, where the Second Transition Point (STP) of tool wear happens. The result of topothesy also follows the same pattern as fractal dimension; a cyclical behavior at the beginning and a consistent trend at the end. The signal turbulence in the transition area of tool wear, causes a sudden increase in the topothesy result. Topothesy represents ruggedness of the signal. The auto-scale regularity of the signal was measured by the coefficient of determination of the linear regression (R^2), which is also shown in Figure 6.9. A merely constant region could be seen during the cutting process, where the tool wear was normal. R^2 drops within the cutting window of 18.8 to 19.9 meters and then tend to resume its stable behavior for the remaining cutting length.

A fractal index is also evaluated to assist the online tool condition monitoring and establish a decision-making system based on all fractal parameters. Using fractal parameters in a combination can express more information about the spindle electric current signal and increase the decision-making system accuracy. The empirical fractal index (*I*) is defined as follows:

$$I = D \times G \times R^2 \tag{6.3}$$

Figure 6.9 illustrates the empirical index of the current signal as a function of the cutting length. The magnitude of the fractal index gradually decreases with the cutting length and exhibits a damping behavior until the cutting window of 18.8 to 19.9 meters. This turbulence in the signal is identified with a single value. This value is used in online tool condition monitoring as a threshold value to prevent workpiece surface damage due to severe tool wear. The threshold value for the present study was set at -3.6 or lower based on turbulence prediction in the spindle electric current signal to guarantee the cutting tool still is in a perfect operating condition.

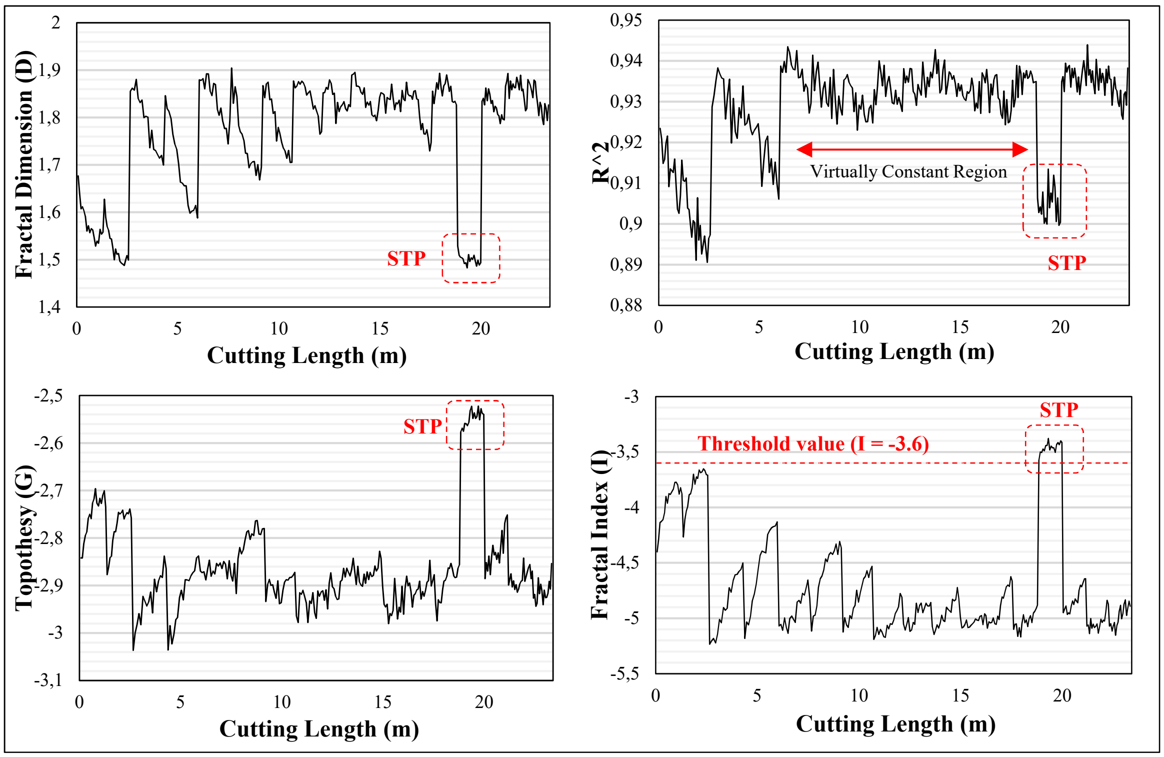

Figure 6.9 The fractal parameters of the spindle electric current signal during shoulder milling of the AISI 5140 steel block

6.5 Conclusion

In smart manufacturing, real time tool condition monitoring is crucial. The purpose of real time monitoring is to issue an alert before tool wear reaches a critical value. For industrial applications, motor-related parameters for detecting this value are preferred because the machining does not need to be disrupted. In this study, the spindle electric current signal was used for online tool condition monitoring during shoulder milling of AISI 5140 steel block using a solid carbide end mill. The spindle electric current signal was sampled using the machine tool internal sensor, which meets industrial requirements. Two transition points in the tool wear evolution curve were introduced; First Transition Point (FTP) and Second Transition Point (STP). These transition points were easily recognized on the average of the spindle electric current signal graph. Turbulence was discovered in the spindle electric current signal when standard deviation increased, and kurtosis decreased unexpectedly between 18.8 and 19.9 meters of cutting. Fractal analysis was applied to the spindle electric current signal to predict any unexpected turbulence in the signal and to establish a single value in the machine tool as a warning before tool wear became severe. The empirical fractal index (I) was defined based on a combination of the fractal parameters to express more information about the spindle electric current signal and improve the accuracy of the decision-making system. This research provides a proof of concept for the use of fractal analysis as a decision-making strategy in monitoring tool condition. The effectiveness of fractal analysis of the built-in machine tool spindle electric current signal as a decision-making method in tool condition monitoring was demonstrated in this study. However, to evaluate the repeatability of the method, further additional investigation is required.

CONCLUSION

The complex shaped components can be manufactured easily using milling operations. The condition of milling cutter has a direct impact on the quality of the machined surfaces. It is essential to check the cutting tool condition during the machining process in order to maintain the quality of the machined parts and prevent equipment downtime. Real time tool condition monitoring intends to issue a warning before tool wear reaches a predetermined threshold to prevent deteriorating the finished surface and losing the dimensional accuracy of the product. In order to monitor tool condition in real time and take appropriate action as needed, an indirect method of tool condition monitoring has been proposed in this study. This procedure involved correlating relevant sensor signals to the cutting tool condition. Motor-related parameters were suggested as the best option due to their high sensitivity to cutting conditions and the ability to prevent a pause in machining.

In this study, fractal analysis was demonstrated as an efficient decision-making technique with minimal processing time and expertise. This method was utilized to extract information from different signals for tool condition monitoring system. Different cutting processes and materials were used to validate this tool condition monitoring technique. The multi-material stack (made of titanium alloys and CFRP), CFRP plates, and a steel block were machined using orbital drilling, trimming, and contour milling, respectively. Fractal analysis was applied to the spindle electric current signal and cutting force signal to predict any unexpected turbulence in the signal and to establish a single value in the machine tool as a warning before tool wear became severe. The effectiveness of fractal analysis as a decision-making method in tool condition monitoring was demonstrated in this study.

RECOMMENDATIONS

Algorithms for machine learning rely on distinguishing properties obtained from different sensor signals. The performance of the machine learning algorithm and, consequently, the dependability of the related control system, depend on identifying and optimizing essential features. The interesting subject is using fractal characteristics to feed artificial intelligence systems in order to improve the tool condition monitoring method. The combination of artificial intelligence with fractal analysis can then be the subject of future research.

In this study, only monofractal analyses were performed. Instead of using different fractal parameters, it is feasible to examine multifractal analysis to identify the primary fractal dimensions. Additionally, chaos theory tools including Lyapunov analysis could be beneficial for tool condition monitoring in future research.

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