OPTIMISING TOOL WEAR AND WORKPIECE CONDITION MONITORING VIA CYBER-PHYSICAL SYSTEMS FOR SMART MANUFACTURING

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DECLARATION

I, Isaac Opeyemi Olalere, do hereby declare that this dissertation is the result of my own investigation and research, except to the extent indicated in the Acknowledgements and References.

I declare that all materials presented in this dissertation are my own work and any published work of another person has been duly acknowledged and referenced.

This work is being submitted for the degree of Doctor of Engineering (D. Eng.) in the Department of Industrial Engineering. It has not been submitted to any other university for any other degree or examination.

20/02/2023

Olalere, Isaac Opeyemi Date

17/04/2023

Dr. O.A. Olanrewaju Date

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DEDICATION

This research work is dedicated to Almighty God for being my constant help and for taking me this far in life.

I also dedicate this research work to my late parents Mr. and Mrs. O.A. Olalere. I admire the legacy you left us, and may your souls rest in peace (Amen).

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ABSTRACT

Smart manufacturing has been developed since the introduction of Industry 4.0. It consists of resource sharing and networking, predictive engineering, and material and data analytics (Kusiak 2018). This development is gradually reducing human operations and replacing them with computerized systems capable of varying a system's response to different situations and requirements. In the manufacturing system, a major concern of manufacturers is utilizing tools and machines to the end of their useful life before they are replaced, while also avoiding scrapped workpieces, downtime, and poor product finish due to system failure based on avoidable conditions (Tayal *et al.* 2021). This has opened the way for several research works on Tool Condition Monitoring (TCM) systems to reduce production cost, lower production downtime, and improve product quality output. Available literature has referred to TCM systems that predict tool condition by indicating tool failure from generalized key tool condition features focused on an indirect TCM system. According to Kamarthi, Kumara and Cohen (2000), tool wear is the most common phenomenon that is considered in several manufacturing processes such as drilling, turning and milling operations. An extensive literature review indicates that many research works have considered TCM and product quality output, while others have attempted integrating both product surface quality (roughness parameter) and TCM. The challenge with the implementation of these approaches is that product quality (precision in workpiece dimension and surface finish requirements) output is dynamic and the tool condition for each product quality requirement may thus differ. The limitation to these approaches is that the feedback system is not dynamic, which may indicate that the method will fail to generalize under different operating conditions such as product quality requirements, workpiece material, and cutting tool type. Furthermore, another major drawback with the present Tool Condition Monitoring (TCM) system is that it focuses on both the pre-failure and post-failure (i.e., after the start of a catastrophic failure) phases. Therefore, it is imperative to develop an approach that can self-compare real-time cutting conditions with the consideration of tool condition and the workpiece surface quality requirements for determining the output of the process in terms of the cutting tool condition and the workpiece surface finish properties.

The research has developed a smart precision machining system that captures cutting tool conditions through a non-obstructive approach that incorporates and integrates smart sensors, IoT

controllers, cloud computing for data capturing, a machine learning algorithm for data, and signal analyses for decision-making. The approach has developed a tool and workpiece condition monitoring (TWCM) system that indicates the condition of the tool and workpiece in real time during the turning operation through the classification of the condition into developed knowledge-based classes of tool and workpiece parameters. The system captures, processes and analyses real-time process data and features the installed IoT sensor network using advanced signal processing techniques and machine learning techniques for indicating the condition of both the tool and workpiece during cutting processes. To develop the TWCM system, generalized features of the tool and workpiece are first correlated, and the offline threshold of the parameters is captured for condition mapping and analysis. This study has non-obstructively classified the real-time condition of the tool and workpiece into known knowledge-based classes indicating the tool condition and the corresponding surface profile parameters output of the workpiece to determine and monitor the deviation from target output requirement in real-time during machining. This step in the approach focuses on first measuring the surface parameters (of the tool flank face) of the new cutting tool (100% life), used good tool, rough tool, and worn tool classes, and also the surface of the workpiece before commencing the turning operation on the lathe machine. This is to establish the classes of tools using ISO 3685:1993 standards based on their flank wear parameters. This was done using a surface and edge wear measuring device that measures twenty-one (21) parameters. The parameters were filtered based on their sensitivity to tool wear and workpiece surface finish using MANOVA analysis, hence six (6) parameters, namely, arithmetic mean roughness, R_a, mean roughness depth, R_z, max valley depth, R_y, root mean square deviation, R_q, total height of roughness profile, R_t, and max roughness depth, R_{max} were selected based on the acceptance of null hypothesis on the condition that $p-value$ is less than the alpha value (α = 0.025) of the MANOVA analysis. The threshold of these parameters from both the cutting tool and workpiece were classified into four (4) classes, which are the new tool, good tool, rough tool and worn tool. The corresponding vibration signal of the tool and workpiece during the turning operation was progressively captured using an advanced industrial vibration sensor, IoT gateway, and cloud server in real-time, which together form the cyber-physical system. This was done to progressively establish the resultant effect of tool wear conditions on the surface condition of the workpiece during operation. Thereafter, the parameters were captured experimentally at the same heartbeat (30 seconds) as the vibration sensor in the time domain. The wear conditions (measured parameters) were grouped into classes using the knowledge base gathered from the experimental result and advanced signal techniques were applied for feature extraction from the vibration signal as a means of classifying the output. Digital filters were first applied to the vibration data to eliminate the varying low contribution due to the alignment of the accelerometer (vibration sensor) to the gravitational field. Since the signal from the condition monitoring is non-stationary and non-linear, the empirical mode decomposition (EMD) method was applied to the signals to separate the signals into components for detailed insight into the inherent features rather than estimating the Power Spectra Density (PSD) of the signals after applying the digital filters that apply FFT using a uniform trigonometric function (sine, cosine) for its analysis. The captured vibration signals were decomposed using EMD into a finite number of Intrinsic Mode Functions (IMFs) and residuals. Hilbert Huang Transform (HHT) was used to determine the instantaneous properties of the signal that were used for discriminating signals under different conditions. HHT was applied to the IMFs to evaluate instantaneous properties such as instantaneous frequencies, amplitude, and energy of the signal. A total of twelve (12) features were computed from the IMFs after applying HHT to the decomposed signals. The aim of the features was to precisely capture the tool and workpiece conditions by classifying the class of the extracted features from the analyzed vibration signal from both the tool and workpiece during the cutting operation.

The process of classifying the features indicating the condition of the tool and workpiece during operation was done using a machine learning approach. To optimize the computational time and cost of the classification algorithm, the genetic algorithm (GA), using the Roulette Wheel (RW) method was used for feature selection. The convergence curve after 100 iterations showed that the model converged at the twenty-second (22nd) iteration even though the iteration still proceeded to 100 iterations as shown in Figure 5:5. Four features were selected from the twelve (12) computed features and these features were used for the ML classification algorithm. The classification was first performed using Neural Network Feed Forward Backprop with SCG algorithm. The input layers were four (4) while the output layers were four (4), with one hidden layer with eighteen (18) nodes in the network. Precision in manufacturing considering the tool and workpiece condition is reflected in the minutest range of several classes of parameters indicated through on-condition real-time signal analysis, which predicts the conditions accurately with a confidence level of about 89.8% and an error of 0.102 after 44 iterations. K-nearest neighbour (KNN) and Support Vector Machine (SVM) ML algorithms are also applied for classifying the tool and workpiece condition to evaluate the best classification algorithm in terms of performance. The *K*-fold cross-validation technique was applied and the error loss of each classification model was determined and plotted with *K* being five (5) and ten (10). With the 5-fold cross-validation, the overall error loss for the five SVM models was 0.5031, while for the KNN model it was 0.0318. This indicated that KNN models performed better under 5-fold cross-validation than SVM models and Feed Forward neural network with the SCG model for tool condition classification during the machining process. The overall error loss for the SVM models with 10-fold classification was 0.5009 while the error loss for KNN models was 0.0343, which also showed that KNN is a better model in terms of performance accuracy. Toledo-Pérez *et al.* (2019) reviewed the SVM-based model of EMG signal classification and reported that many sounds, vibration signals and images have been classified using the SVM classification algorithm, achieving more accuracy without feature selection and 5% less with feature selection. Therefore, to determine if the SVM model would perform better without feature selection, the models were evaluated with the 12 features, and the loss function was determined. The performance of both models for 5-fold cross-validation with all the feature vectors showed that for SVM models, the performance improved much more compared to when feature selection was implemented. The overall average error loss when 5-fold cross-validation was performed on all the features was 0.1668 compared to 0.5031 when feature selection was performed. However, for KNN models using 5-fold cross-validation with feature selection, the overall average error loss increased from 0.0318 to 0.2202. These results showed that while feature selection improved the performance of KNN models in classifying the conditions of the tool, it was not the case with the accuracy and performance of the SVM model.

The 10-fold cross-validation error loss for SVM and KNN classification models developed without applying feature selection also indicated that the performance of SVM models was more accurate without feature selection. The error loss for 10-fold cross-validation for SVM models when feature selection was applied was 0.5009, while it was reduced to 0.1578 without feature selection. On the other hand, the performance of KNN models when feature selection was adopted was 0.0343, while it increased to 0.2172 without feature selection. Therefore, the KNN algorithm performed better overall in classifying the condition of the cutting tool during the machining operation with the KNN8 model being the best-performed model with an error loss of 0.0106. The fitted KNN8 was then optimized by applying hyperparameter optimization with the objective function being the error loss of the model and the constraints being the distance metrics. The optimal distance metrics using the *kdtree* neighbour searcher method was then determined. The '*crossbar*' distance metrics were observed to minimize the 10-fold KNN8 model, while the estimated objective function value was 0.01416 and the observed objective function value was 0.014.

The condition of the tool and the workpiece during operation can be classified at an interval of the sensor's heartbeat which is 30 seconds but can be set to one (1) second. Since the system makes use of IoT-enabled industrial sensors, it implies that the condition of the tool and workpiece can both be remotely monitored and re-configured. The knowledge-based classification differentiates the condition of the tool and workpiece during operation into classes that detail the range of correlated surface profile parameter values with the corresponding tool parameters. Varying conditions of the tool can be matched with the product requirement and the classes and the tool can invariably be put to optimal use which makes this novel approach a useful method in precision manufacturing. Therefore, the model was again tested with a test set, and the error loss in the classification was evaluated as 0.0106. This research directly impacts the local manufacturing industries through product quality improvement by matching manufacturing operations with product quality requirements through real-time condition classification and avoiding a lower bound approach (damage to product), and also optimizing their system through optimal tool useful life usage and tool and workpiece wear condition classification.

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4IR FOUTH INDUSTRIAL REVOLUTION

AE ACOUSTIC EMISSION

AI ARTIFICIAL INTELLIGENCE

ANN ARTIFICIAL NEURAL NETWORK

ANOVA ANALYSIS OF VARIANCE

CNC COMPUTER NUMERICALLY CONTROLLED

DFT DISCRETE FOURIER TRANSFORM

DMLP DEEP MULTILAYER PERCEPTION

DRL DEEP REINFORCEMENT LEARNING

FFT FAST FOURIER TRANSFORM

FPGA FIELD PROGRAMMABLE GATE ARRAY

GDP GROSS DOMESTIC PRODUCT

HHT HILBERT HUANG TRANSFORM

HMI HUMAN MACHINE INTERFACE

ICT INFORMATION AND COMMUNICATION TECHNOLOGY

IIOT INDUSTRIAL INTERNET OF THINGS

LSTM LONG SHORT-TERM MEMORY

MANOVA MULTIPLE ANALYSIS OF VARIANCE

MQL MINIMUM QUALITY LUBRICATION

PR PATTERN RECOGNITION

PSD POWER SPECTRAL DENSITY

SEM SCANNING ELECTRON MICROSCOPE

SVM SUPPORT VECTOR MACHINE

TCM TOOL CONDITION MONITORING

TWCM TOOL AND WORKPIECE CONDITION MONITORING

WPT WAVELET PACKET TRANSFORM

WT WAVELET TRANSFORM

RESEARCH OUTPUTS

Published Articles:

Olalere, I.O. and Olanrewaju, O.A., Tool and Workpiece Condition Classification using Empirical Mode Decomposition (EMD) with Hilbert Huang Transform (HHT) of Vibration Signals and ML models. *Applied Sciences*. 2023; 13(4):2248. https://doi.org/10.3390/app13042248

Olalere, I.O. and Olanrewaju, O.A., 2022. Optimising Turning Operation in Precision Manufacturing using Fused IoT Devices and Machine Learning Approach. IFAC-PapersOnLine, 55(10), pp.1551-1555.

Articles Submitted to Journals for Review:

Olalere, I.O. and Olanrewaju, O.A., *Parameter Extraction for Smart Tool and Workpiece Condition Monitoring System Using MANOVA Analysis*. Submitted to: South African Journal of Industrial Engineers (SAJIE) 2022.

Articles Prepared for Submission to Journals for Review:

Olalere, I.O. and Olanrewaju, O.A., *Tool and Workpiece Conditions Optimisation Using Advanced Signal Analysis and Machine Learning Approach*. Prepared for submission to: Journal of Engineering and Applied Science. SpringerOpen.

Conference Paper Proceedings:

Olalere, I.O. and Olanrewaju, O.A., 2020. Optimising Production through Intelligent Manufacturing. In *E3S Web of Conferences* (Vol. 152, p. 03012). EDP Sciences.

CHAPTER 1 : INTRODUCTION

1.1 Introduction

This chapter discusses the introduction to the research, the research background, the research aim and objectives, research justification, research scope, thesis structure and the conclusion. Highlights on the current condition of the machine and cutting tool in relation to product output (in terms of workpiece surface finish) from the workstation are also discussed. The significance of the research and its scope is also highlighted.

The emergence of Industry 4.0 has given rise to several concepts and innovations that have increased the efficiency and effectiveness of the production and manufacturing processes. Smart manufacturing has been developed under the advent of Industry 4.0 and it consists of resource sharing and networking, predictive engineering, and material and data analytics (Kusiak 2018). It is gradually reducing human operations and replacing them with computerized systems capable of varying a system's responses to different situations and requirements. The Industrial Internet of Things (IIoT) has enabled intelligent manufacturing through the network of connected sensors, actuators and controllers to machines and production processes. This has had a significant positive impact on the product quality, resource utilization, production cost, and performance of most machines and systems. To achieve this in the machining industry, advanced investigations using a Tool and Workpiece Condition Monitoring system are required to have an optimized, smart, and efficient system. The three important components at a machining station are the cutting tool, the machine tool, and the workpiece. To achieve an efficient machining operation, these components need to be carefully observed and improved at a machining station. Since product requirements vary from one customer to another, this has made machining operations more dynamic than static. This range in terms of the product quality requirement which may differ from one product to another, and the material specification of the product may also be varying factors that differentiate the machining process of one product from another. These factors directly influence the condition of the cutting tool during machining operation and vice versa. In addition, they also affect the measurable parameters of the machine tool during operation, while the condition of the machine tool may also directly influence both the product quality output as well as the cutting tool condition during operation. Furthermore, another factor of concern at a machining station is the obstructive nature of the operation during the machining operation. Machining involves the cutting tool reciprocating against the rotating workpiece that forms the workpiece into a required shape. Because the operation involves two or more alloys of metals rubbing against each other, this produces noise, heat in the form of temperature in the cutting region, and vibration. A holistic consideration of the entire machining station requires a painstaking approach for an improved and enhanced production system. Therefore, there are concerted efforts being made towards initiating and developing new technologies and methods for improving cutting tool performance and workpiece/product surface quality output to offer solutions to challenges facing the manufacturers in this sector.

1.2 Research Background

The main industries in South Africa are the manufacturing, mining and agriculture sectors which approximately contribute about 17% of the GDP, with manufacturing industries accounting for 14% (Steenkamp, Hagedorn-Hansen and Oosthuizen 2017). With the growing concerns about the effects of the covid-19 pandemic on the economic sectors of countries globally, it has become very important to consider optimizing metal cutting processes in order to sustain this particular industry amidst global challenges. In machining processes, the objective of most production outlay is to produce a product at the lowest possible cost while sustaining the quality of the production output. For instance, in high-speed precision cutting processes, product quality is mostly affected by defective tools which, if they have not been replaced recently, may lead to breakdown of machine tools, requiring re-work on jobs and scrapped parts. Conversely, if the cutting tool is replaced timeously, it would imply that the cutting tool is under-utilized as it is discarded before its useful life has been fully utilized. In both scenarios, the result is the high cost of production. With much focus being placed on cutting tool condition as a measure of optimizing the cutting process, not much has been done on reflecting on the surface roughness of the workpiece as a measure of the condition of the cutting tool itself. This may help in utilizing the cutting tool to the end of its useful life for a particular operation before being discarded.

A recent survey conducted to examine productivity in the South African manufacturing sector suggests that most industries with high ICT integration perform better than their counterparts in terms of productivity and quality output (Lefophane and Kalaba 2020). The intelligent manufacturing system, which is also known as smart manufacturing, optimizes production using advanced information and manufacturing technologies (Zheng *et al.* 2018). Intelligent manufacturing can be classified into three processes, which are digital manufacturing, digital networked manufacturing, and new generation Intelligent manufacturing that integrates advanced manufacturing with Artificial Intelligence (AI) (Zhou *et al.* 2020). The concept as it applies to machining relates system optimization to continuous improvement of product quality, performance, and resource utilization. As will be discussed in Chapter 2 (Literature Review), several tool condition monitoring systems have been carried out using fused sensor networks, AI, IIoT, and predictive models but many have given more attention to the cutting tool condition but failed to adapt different working conditions such as the workpiece surface finish requirement with respect to different materials. Similarly, a few research studies on cutting tool condition monitoring may have been carried out on milling processes and drilling to predict tool failure and wear with consideration to operating parameters captured with sensors. However, an extensive literature search shows that less research has been done on turning operation, with the most recent research focusing on optimizing cutting tool life by fine-tuning machining parameters to achieve the desired surface roughness. The limitation of this is that the feedback system is not in real-time and dynamic, which may indicate that the method will fail to generalize under different operating conditions such as workpiece material and cutting tool type. The Analysis of Variance (ANOVA) method suggested that feed rate is the most important factor contributing to tool wear and surface roughness in the turning operation unlike the existing literature that postulated cutting speed as the factor with the most effect (Tayisepi 2017). A more in-depth approach is required to not only intelligently monitor and analyze the conditions, but also to suggest the best possible levels for each considered operating parameter that could adapt to varying workpiece material in real-time relative to the cutting tool type. Furthermore, a major drawback with the present Tool Condition Monitoring (TCM) system is that it focuses on the post-failure (i.e. after the start of a catastrophic failure) and pre-failure (i.e. predicting sudden tool failure) phases (Hassan *et al.* 2018b). The fact that no optimized model can self-compare and self-configure real-time cutting conditions regardless of the cutting tool type and the workpiece material also represents another gap that needs to be addressed.

1.3 Problem Statement

Smart machining manufacturing is taking over from the conventional methods in precision manufacturing and optimization of facility outlay for improved productivity. The concern with machining operation is the tool condition and the quality of the product output. While the former affects the latter, the specifications of the product quality finish determine whether or not the product will be accepted, or will need to be reworked or scrapped. Damage to the cutting tool during the machining process may result in either an upper bound or lower bound approach during the machining process. The former affects only the cutting tool while in the latter approach, damage to the cutting tool directly affects the workpiece, causing it to be scrapped. This increases the cost of production directly as both the tool and workpiece have to be replaced. Many machining stations have resulted in a just-in-time maintenance policy that replaces the cutting tool at a specified time before the end of its useful life (Rudek 2022). The drawback of this approach is that the cutting tool is under-utilized, which also increases the running cost during machining. This has forced many research approaches to investigate smart manufacturing that factors in product quality requirements, cutting tool conditions and manufacturing conditions into production using fourth industrial revolution technology such as smart sensors, smart IoT devices, cloud computing, and machine learning (ML) techniques (Dani 2022). Several research studies have been done in order to optimize tool and product/workpiece conditions during machining operation.

Most approaches have adopted parameters from the cutting tool, workpiece and machine tool to support decision making at the machining station. Workpiece condition has been determined by its surface roughness parameter, R_a, (Pathiranagama and Namazi 2019; Sarnobat and Raval 2019; Kuntoğlu *et al.* 2021) which is the arithmetic mean roughness, while the cutting tool is assessed by the wear, crack or chip parameters. While the arithmetic mean surface roughness, R_a, parameters of the workpiece can indicate a quality characteristic that is essential in terms of the customer and product specification, more detailed parameters can be extracted for intelligent condition diagnosis of both the workpiece and cutting tool during machining operation. There are several other surface roughness parameters such as total height of roughness profile, R_t, maximum roughness dept R_{max}, maximum valley dept, R_y, root mean square deviation, R_q, average maximum height of profile, R_z, kurtosis, R_{ku}, skewness, R_{sk} and others, which can be measured to evaluate the quality condition of a material's surface. While most research efforts into optimizing and improving machining operation have limited the surface quality parameter of the product or workpiece to just the arithmetic mean surface roughness, R_a. Munhoz *et al.* (2020) evaluated the surface roughness of a workpiece in an abrasive flow process considering three surface parameters, R_a, R_t and R_z that make use of a paste. Even though the research focused on an abrasive flow process, a knowledge base on the significance of other surface roughness parameters in abrasive flow can be drawn from the study. Existing studies have applied only a surface roughness parameter in developing the knowledge base for tool and workpiece condition monitoring for a machining turning operation. Studies on the optimization of cutting tools and workpieces for a machining operation (Kuntoğlu *et al.* 2020; Akkuş and Yaka 2021; Kuntoğlu *et al.* 2021; Skrzyniarz *et al.* 2021; Usca *et al.* 2022) have placed emphasis on the arithmetic mean roughness, R_a, surface parameter of the workpiece. A study conducted by (Kang, Derani and Ratnam 2020) using a simulation approach adopted both arithmetic mean roughness, R_a, and total height of roughness profile, R_t, to evaluate the vibration effect on the surface finish in a turning operation and there was significant impact on both surface roughness parameters from the simulated study.

There is therefore a gap in experimentally and analytically identifying and applying other significant surface roughness parameters that could build the knowledge base in indicating both the tool conditions as well as product/workpiece quality during machining for smart manufacturing. Other surface parameters of the workpiece and cutting tool may correlate significantly to factors of influence, which are the different conditions during the cutting operation. Developing a Tool and Workpiece Condition Monitoring (TWCM) system with correlated parameters will increase the accuracy of classifying the conditions of the tool and workpiece during operation. After classifying the tools using ISO 3685:1993 standards, determining the class of the signals generated during the turning operation depends on the classification algorithm used for developing the model. Classifying the tool condition based on signal processing and analysis during operation provides a non-obstructive process of the TWCM system during operation which is capable of reducing downtime.

1.4 Research Questions

In line with the considerations and research gaps identified in the problem statement, the following research questions have been raised.

- What are the measurable surface roughness parameters that can be captured from the workpiece or product surface?
- What are the surface roughness parameters that correlate with the varying conditions and classes of the cutting tool based on flank wear?
- Can the tool and workpiece condition be simultaneously determined using a numerical classifier rather than categorical data?
- What algorithm performs better in optimizing the classification algorithm to minimize the errors on the test data and also reduce the cost function?

1.5 Research Aim and Objectives

The aim of this work is to develop a non-obtrusive real-time Tool and Workpiece Condition Monitoring (TWCM) system that classifies the tool wear and workpiece surface roughness parameters level and an optimized machine learning (ML) algorithm in real-time operating conditions. The objectives of this research are as follows:

1. To analytically determine the workpiece surface roughness parameters that correlate with the cutting tool conditions for a turning operation.
2. To analytically determine the range of data values for each class of surface profile parameter for a tool and workpiece condition monitoring classification system.
3. To capture real-time signals for a tool and workpiece surface condition using non-obstructive hardware with characteristic industrial applications and advanced signal analysis.
4. To compute and derive features vectors of physical properties from raw captured sensor signals using the advanced signals processing technique capable of discriminating and classifying different tool and workpiece conditions during turning operation in real-time.
5. To determine the optimal features through hyperparameter optimization for selection of important features for the ML algorithm.
6. To optimize the ML models developed for tool and workpiece condition classification by applying different ML algorithms with k-fold cross-validation techniques.

The first objective aims to experimentally and analytically determine the roughness parameters that correlate with the varying conditions of the tool during a cutting operation. Several workpiece surface roughness parameters can be captured from a machined part; however, to develop a knowledge base for determining the condition of the cutting tool and the corresponding quality output of the workpiece, it is pertinent to observe and determine the roughness parameters that relate to the varying condition of the cutting tool during operation. This can be achieved by first classifying the cutting tool conditions to be used for the experiment. Also, the type of cutting tool to be used for the study must be determined, and the properties of the tool identified based on the type of workpiece to be used for the study. While some studies have monitored the tool conditions during the machining or turning operation, some have also considered monitoring the tool wear alongside the workpiece surface roughness; however, the available literature has only considered one surface roughness parameter, which is the arithmetic mean roughness. Another study has considered two (2) roughness parameters but adopted a simulation study to determine the corresponding output of tool condition on both. No existing studies have developed a knowledge-based system for the TWCM system that considers and classifies the tool conditions alongside the corresponding surface roughness parameters that correlate with the effect of the tool conditions.

The second objective is to analytically determine the range of data values for each class of surface profile parameter for the tool and workpiece condition monitoring classification system. This objective seeks to determine the range of data of the correlated parameters for each class of tool and workpiece used for generating signals from the real-time turning operation. The surface parameters of the workpiece and cutting tool that correlate with different conditions of the tool as decided by the first objective are evaluated to determine the range of values for each class. This is done by evaluating the range of data of the parameters after conducting several repeated experiments. Subsequent classification will reference the range of data of the parameters to interpret and determine the condition of each tool class.

The third objective is to adaptively determine and capture real-time signals for tool and workpiece edge/surface wear conditions through a developed inter-connected non-obstructive hardware with advanced signal analysis. Several signal types can be used in studying the corresponding effect of tool wear or conditions on the workpiece. It is therefore important to determine the signals that are capable of depicting the tool and workpiece conditions during machining operation without intermittently stopping the machining process for condition assessment. This objective therefore considers the available signals for monitoring the conditions of the tool and workpiece during the machining process without machine downtime, or intermittently stopping the operation.

The fourth objective of the study is to determine and evaluate features that are capable of discriminating between and classifying different tool and workpiece conditions during the turning operation using advanced signal processing techniques. The signals captured during the machining operation may not be directly used for analysing the condition of the tool and workpiece based on the nature of operation, the type of signal or the processing method, hence it is essential that the signals are further analysed and processed into features with properties that can be deployed for classifying and discriminating the various conditions of the tool and the workpiece during the machining operation. Furthermore, while some techniques may already have been used, a superior approach could lead to a more accurate and precise result. It is therefore important to determine the approach for extracting features through signal processing techniques to discriminate between the tool and workpiece conditions during the machining process.

The fifth objective is to determine the optimal features through hyperparameter optimization for the selection of important features for the Machine Learning (ML) algorithm. Implementing the ML algorithm on several features with extensive samples of data can be computationally expensive and also time consuming. Several parameter optimization algorithms have been implemented to reduce the number of features to fewer important features capable of analysing and classifying the various conditions of the classes. Similarly, this approach has been adopted to determine and select the optimal features that would determine the condition of the tool and workpiece for the training algorithm.

The sixth objective of the study is to optimize the ML algorithm used for tool and workpiece condition classification in order to determine the model with the least classification error loss. The focus of this objective is to determine the ML model with the best performance in terms of the accuracy in predicting the tool and workpiece class during the machining process. To avoid misclassification and bias, the k-fold cross-validation technique is implemented to determine the model with the highest classification accuracy. Another neural network algorithm, that can classify tool wear by varying workpiece surface finish signature, is also adopted for learning and training features extracted from the processed signals for the TWCM system. The optimal model and the error loss are determined and compared with the result and performance in the available literature reviewed.

To achieve the objectives of the study, it was important to develop a robust real-time signal processing and decision-making system capable of classifying tool wear and workpiece surface finish features into classes that indicated the conditions of the tool and workpiece parameters. Unlike most available literature that seeks to predict failure of the cutting tool so as to communicate an informed decision regarding machine operation before the workpiece is damaged, this study focused on firstly, capturing several sensorial data from the cutting operation, tool and workpiece conditions, and then analysing and processing the signals, extracting the significant features and applying a machine learning algorithm to intelligently classify the condition of the cutting tool and workpiece roughness parameters based on the trained network. Real-time signals from the system were captured, analyzed and optimized for product output and tool condition classification based on the operating monitored condition. The system firstly focused on the quality output of the workpiece based on some surface roughness parameters with regard to the tool wear conditions during the machining process. The system also reduced unnecessary downtime and adapted to varying workpiece material, cutting tool conditions and operating parameters.

1.6 Research Scope

In general, this work targeted the development of a robust smart intelligent TWCM system for tool wear and workpiece surface finish monitoring, and considered some monitored parameters using fused sensor networks and a machine learning approach. Much research has been done on tool condition monitoring systems in a milling process across some applications; however, this research focused on the turning operation carried out on a lathe machine. An application of this research work was found in the turning processes for small automobile parts (approx. 12mm diameter by 40mm cylindrical length) made up of steel alloys etc. This work targeted commonly used indexable tungsten cutting tools with CCMT09T3034 carbide inserts cutting tools with the same geometric parameters but different cross-sectional areas (thickness). It considered two different workpiece materials which are, namely, a 070M55 Black Steel Bar (EN9) with 0.5% carbon steel, and a 080A42 Bright Steel Bar (EN8) with 0.4% carbon steel for the research observations and learning. The study also made use of indexable cutting tools because of the precision requirement for the cutting part. The wear on the cutting tool was measured to capture up to 0.005mm R_a and 0.02mm R_z and the surface roughness of the workpiece was measured down to the same threshold with additional parameters such as R_t, R_q, R_v and R_p and other surface parameters captured as further discussed in Chapter 3. This research first selected the measured parameters that could indicate the varying conditions of tool wear and workpiece surface roughness parameter. It aimed at capturing and optimizing some operating conditions of the tool and workpiece during the turning operation such as the vibration, thermal image, and acoustics to analyze the edge/surface roughness parameters of the tool and workpiece. Machine conditions were captured in real-time using highly sensitive industrial-built sensors with enhanced Industrial Internet of Things (IIoT) capabilities and cloud computing which together constituted the cyber-physical system for the tool and workpiece condition monitoring system. Monitoring of some parameters, such as axial vibration of the machine tool, acoustic emission, and temperature during operation to learn and diagnose the cutting condition, is discussed in the literature reviewed. Recent literature has considered image processing for analyzing the tool condition on a milling machine (Mikołajczyk *et al.* 2018); however, this work uniquely optimized the condition of the tool wear and workpiece surface roughness during turning operation in real-time by capturing the axial vibration parameter of the machine tool during turning operation and applying advanced signal processing techniques for feature extraction which was not available in literature at the time of conducting this research. The captured data were analyzed using the Machine Learning AI method for classifying the conditions using Neural Network algorithm.

1.7 Overview of the Methodology

This study adopted a smart manufacturing approach that incorporates underpinning 4IR technology, the advanced signal processing method, and the AI classification algorithm. This is a data-driven approach that experimentally investigates the tool and workpiece conditions during a turning operation, determines the surface profile parameters that correlate with the tool condition, evaluates the range of values of the surface profile parameters for classes of tool and workpiece conditions, and captures the sensor signals for condition monitoring. The tool is classified based on its flank wear using ISO 3685:1993 standards and the corresponding workpiece quality is measured and recorded. Each tool class used for the turning operation and the corresponding surface quality parameters are measured and recorded. Each tool class is indicated with a label representing the tool type used. Sensors are used to capture signals during operation for indirectly processing and analysing the condition of the tool and workpiece for the classification of conditions. The approach is aimed at optimizing the tool and workpiece at the machining station by classifying the conditions to avoid damage leading to scrap or rework. Advanced signal processing techniques with ML are thereafter applied to the captured signal. A different ML classification algorithm is used for the classification model, which is optimized for optimal performance. Hence, the condition of the tool and the workpiece during operation can be classified into respective classes indicating the state of the tool and workpiece, without intermittent and non-obstructive stoppage during the machining operation.

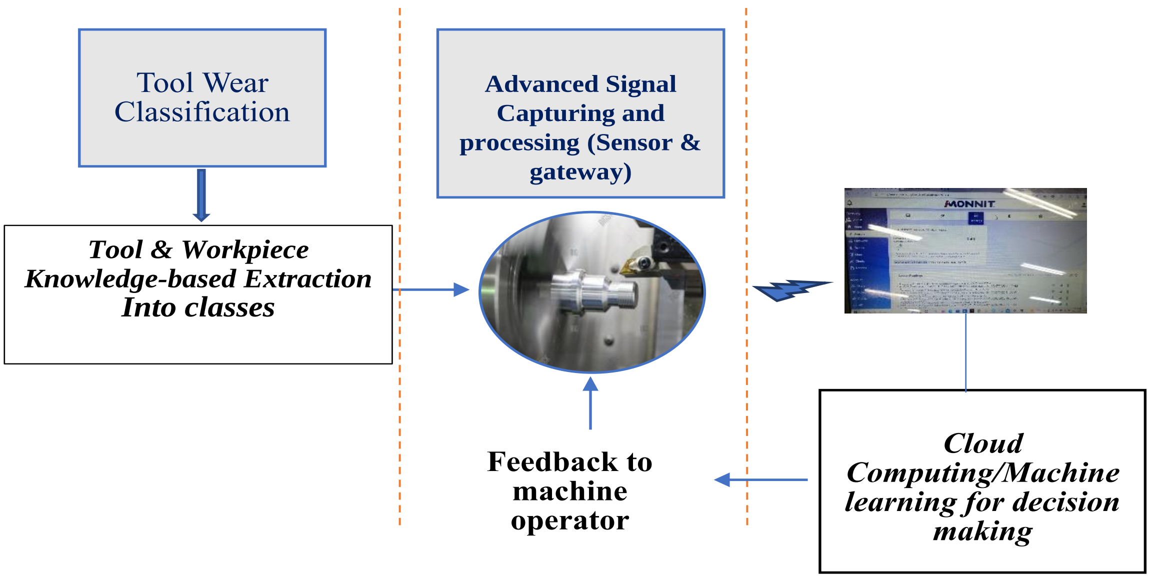

Figure 1:1: Research Approach Overview

The tool and workpiece conditions were classified into four (4) classes and the signal during operation was captured using advanced sensors and gateway.

1.8 Research Contribution

The approach in this study focused on the development of a knowledge-based system for tool and workpiece condition classification, advanced signal processing and analysis, feature vectors extraction, hyperparameter optimisation, and tool and workpiece condition classification using ML algorithms to determine the condition of the cutting tool during the machining operation without intermittent stoppage of the machining operation. It also determined the optimal classification algorithm for the tool and workpiece condition.

The following were the research contributions and observations:

- Tool classification based on the flank wear according to ISO 3685:1993 has indicated the severity range of flank wear for the tool but this study applies flank wear classification as a measurement threshold for product/workpiece quality output. Tolerance in a machining process is incorporated into tool condition classification which includes new, good, rough, and worn tool classes.
- Tool condition is analytically proven to correlate with some surface profile parameters of the workpiece such as arithmetic mean roughness R_a, the average maximum height of profile, R_z, maximum valley depth, R_y, root mean square deviation, R_q, maximum surface roughness dept, R_{max}, and the total height of the roughness profile, R_t using MANOVA analysis with Pillai's trace test. These parameters are therefore built into the knowledge-based classification attributes for the tool and workpiece condition monitoring system. Several studies have focused on R_a parameter for the workpiece condition with a few others adopting two (2) surface profile parameters. This research has expanded this knowledge area by showing that other surface profile parameters are influenced by the tool conditions, and the quality output of the product can be measured and classified based on the parametric range of values of these parameters of the workpiece.
- The KNN classification model performs much better than the Feedforward Backprop with SCG, and SVM model regardless of the implementation of the hyperparameter optimization and k-fold cross-validation techniques. It is also observed that KNN models perform better with the implementation of hyperparameter optimization compared to when all the feature vectors are used with the error loss being 0.0109 compared to an error loss of 0.1870.
- SVM classification models perform optimally without feature selection compared to when hyperparameter optimization is implemented, as the least error loss for the former is 0.1021, while the latter is 0.4752.
- The 10-fold cross-validation technique gives a better performance than the 5-fold cross-validation technique in optimizing the performance of the classification model.

1.9 Thesis Outline

The First Chapter discusses the research questions and objectives, while the Chapter 2 discusses the literature review and background to the research. Chapter 3 enumerates the experimental set-up and design method, and describes the developed tool and workpiece condition monitoring (TWCM) system. Chapter 4 discusses the surface parameter extraction for smart tool and workpiece condition monitoring system using MANOVA analysis, and Chapter 5 discusses the results of tool condition and workpiece characterization for wear detection and monitoring. The last chapter, which is Chapter 6, provides the conclusion and recommendations and also recommends the possible future extension of this research and related works. A detailed description of the contents of the thesis is as follows.

1. Chapter 1 presents a general idea of the relevance of the research question and the motivation behind the work. It provides a brief introduction, research background, problem statement, research aim and objectives, the scope of the research, thesis outline, and conclusion.
2. Chapter 2 discusses the research work that has been done and reported in the available literature on tool wear detection and workpiece surface finish monitoring. More attention is paid to the sensor-based monitoring system and its signal processing methods. Furthermore, the chapter also discusses research work done, as detailed in the literature, on artificial intelligence based on the TWCM system, machine learning for sensor-fusing and optimized turning operation. The chapter also covers the signal processing techniques and discusses the missing links that need to be addressed in this research work.
3. Chapter 3 presents a description of experimental setups in terms of the selected machine tool, sensor selection, and usage. It discusses the installation of the sensors for signal capturing during operation for the implementation of the developed TWCM system. It also discusses the signal-processing approach adopted for the study.
4. Chapter 4 discusses the surface parameter evaluation for smart tools and workpiece condition monitoring systems using the MANOVA analysis. It also presents the experimental investigations of the surface parameters of the workpiece conditions, the experimental set-up of the experiment, and the MANOVA data analysis.

5. Chapter 5 discusses the experimental results of the tool wear and workpiece surface finish detection system on a turning operation. It also presents the real-time features and data captured by the TWCM system. It further presents the signal processing and decision-making algorithm to provide a real-time TWCM system. This includes feature extraction and network training of data to detect the tool and workpiece conditions with high accuracy.
6. Chapter 6 presents the conclusion and recommendation on the research work. It further presents recommendations for future research.

1.10 Conclusion

This chapter has given some background information on the research area that centres on tool and workpiece condition monitoring (TWCM) systems. The key area of focus included the research background, which seeks to intelligently optimize both the tool and workpiece condition in a real-time condition during operation, the problem statement that highlights what the current situation is with the tool and workpiece condition monitoring system, the aim and objectives of the research, as well as the research scope. The chapter further highlighted the research objectives and discussed how each of the objectives would be addressed. The objectives were highlighted and discussed based on the content and significance of the study. The chapter also highlighted the structure of the thesis and provided an overview of its content.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

This chapter discusses the literature on tool deterioration and workpiece surface finish, the Tool and Workpiece Condition Monitoring System (TWCM), the application of the TWCM system, sensor selection for TWCM, signal processing techniques, and fused multi-sensor based TWCM. The literature is discussed under each sub-heading as it relates to past research work and current efforts in the specific areas.

Traditional manufacturing is rapidly being driven into intelligent manufacturing through technologies such as big data, Internet of Things (IoT), cloud computing, cyber-physical systems, and artificial intelligence. This is because of the lack of manual inspection which often results in increased production cost due to scrapped workpieces and damaged tools during manufacturing. Downtime in a machining station is mostly caused by tool failure, which accounts for 7-20% of the total downtime while the associated cost is approximately between 3-12% of the total cost (Zhou, Sun and Sun 2020). Another major concern at a machining station is the cost incurred on re-work and scrapped workpiece due to damage, and inferior quality of production output. To avoid these costs, proper and reliable manufacturing of parts requires accurate tool and workpiece condition monitoring to control the variations of the cutting process. This requires a detailed investigation of the varying conditions during the cutting process as well as the tool and workpiece conditions, and the introduction of adaptive operating conditions. This is aimed at standardizing the quality of the manufactured parts and reducing production costs incurred based on production error, system failure and unnecessary downtime. A concerted effort has been made towards developing an intelligent system capable of monitoring and predicting tool conditions in a bid to prevent sudden tool failure that leads to loss of production time, increased downtime of the machines, and increased production costs due to tool change and workpiece damage. In the following sections, different research contributions and findings on efforts made towards improving the TCM system and operating parameters reported on in the available literature reviewed for this research are enumerated with particular attention given to turning operations on the lathe machine. In addition, research gaps, as well as the background to different signal processing and decision-making algorithms employed in tool and workpiece condition monitoring systems, are highlighted and discussed.

2.2 Tool Deterioration and Workpiece Surface Finish

The phenomenon of tool failure and its effect on a product's quality output in terms of workpiece surface finish is significantly important and needs to be understood. Failure of a cutting tool is a complex concept that requires painstaking study as the effect is manifested in diverse ways. It occurs in the following different ways during its useful life.

- Crack/fracture (chipping): This happens when a small fragment breaks off the cutting tool (Vereschaka *et al.* 2017).
- Wear: This is a gradual change in the geometry of the cutting tool due to progressive removal of materials (Rech *et al.* 2018).
- Breakage: This is the breakage of the cutter edge of the cutting tool (Xu, Chen and Zhou 2019).

Gradual or sudden deterioration of the cutting tool's condition often results in any of the abovementioned failures depending on the operating conditions. These failures are mostly due to two mechanisms, which are either abrasion/friction between the interface of the tool and the workpiece, or adhesion due to plastic deformation of the workpiece material (Melkote *et al.* 2017), which makes the unified study on both the tool and workpiece condition necessary. Both the failure of the cutting tool and the surface roughness of the workpiece are linked to the operating parameters during the turning operation. Khan and Gupta (2020) carried out a study on the effect of operating parameters on cutting tool wear, considering cutting velocity, feed rate, depth of cut, and texture pattern of the cutting tool and stated that tool wear was found to be increasing and was the result of increased feed rate and depth of cut. Similar research was conducted by Roy *et al.* (2020) and the results showed that cutting speed and depth of cut is significant and impactful towards principal and flank wear, with the latter lower than the standard limit of $0.2mm$ with the maximum surface roughness of $0.99\mu m$. Another study was conducted on cutting tool wear morphology by optimizing the tool life reliability considering two operating parameters, cutting speed/velocity, and feed rate. The experimental study showed a resulting indication of varying tool wear such as crater wear resulting in cutting edge damage at $V_c = 175m/min$ and $f = 0.02mm/r$; tool fracture at $V_c = 55m/min$ and $f = 0.3mm/r$; tool chipping and tipping at $V_c = 85m/min$ and $f = 0.2mm/r$; and tool breakage at $V_c = 175m/min$ and $f = 0.05mm/r$ and different levels of cutting speed and feed rate (Liu *et al.* 2020). This further justifies that the cutting parameters influence cutting tool wear. However, there are other factors that also affect cutting tool wear during operations. A comparative study was carried out on tool fault using vibration and cutting force signals to classify the conditions of tool into healthy, worn flank, broken insert and extended tool (Aralikatti *et al.* 2020). The study indicated that the condition of the machine tool during operation could influence and depict the tool condition and could be used as a factor for evaluating the condition of the cutting tool. Another study was carried out by Rizal *et al.* (2017) to classify different tool wear (flank wear) under the milling process using cutting force, torque, vibrations and tool tip temperature and the result showed that medium and critical wear stages of the cutting tool can be detected in real-time by taking the same on-condition state of the machine tool into account considering that the condition of the machine tool during operation could indicate the state of the cutting tool at different stages of deterioration. Sun, Hu and Zhang (2020) also developed an automatic system that is built in to detect tool breakage using the Acoustic Emission (AE) signal technique which shows an accuracy of 91.18% in detecting breakages.

Furthermore, the condition of the cutting tool is believed to affect the surface roughness of the workpiece, hence it is important to study the available literature in this regard. A study was carried out on the effect of vibration and cutting zone temperature on surface roughness and tool wear in eco-friendly Minimum Quantity Lubrication (MQL) at a constant cutting depth and feed rate, and the result showed that at a reduced vibration signal and temperature, there is also reduced tool wear and surface roughness of the workpiece (Özbek and Saruhan 2020). It further established that there is either a linear or nonlinear relationship between tool wear and surface roughness of the workpiece (measured between $0.32\mu m - 3.26\mu m$) and the conditions, such as vibration and temperature of the machine tool, during cutting operation. An increased vibration signifies increased tool wear and surface roughness of the workpiece, and vice versa. Another study on cutting tool failure and surface finish analysis showed that surface quality of the turned workpiece is mostly affected by the cutting speed and the depth of the cut which also have a significant effect on the principal and auxiliary wear of the cutting tool (Roy *et al.* 2020). The study revealed the significance of some operating parameters on the workpiece surface finish during the cutting operation. An experimental investigation of the surface roughness of the workpiece under high speed machining using the Inconel 817 cutting tool revealed that at different cutting speeds $60m/min$, $90m/min$, $190m/min$, and $255m/min$, the resultant quality of the machined surface indicated that the best quality was achieved at $190m/min$ (D'addona, Raykar and Narke 2017). The study revealed that the optimal operating condition of the machine tool during the cutting operation may not follow a linear pattern, hence implementing an optimization model for the parameters may be necessary.

The literature discussed has enumerated the correlation between the operating parameters and the cutting tool deterioration as well as the on-condition state of the machine tool and the cutting tool condition. It has clearly shown how operating parameters (such as cutting speed, feed rate, depth of cut) affect the cutting tool deterioration pattern and how those parameters could be used to classify, detect and predict different deterioration stages of the cutting tool (wear, chipping or breakage stage). Similarly, the literature has also considered how the on-condition state of the machine tool (such as vibration, AE, tool temperature and cutting force) indicates the condition of the cutting tool deterioration pattern. Similarly, some other studies (Aslan 2020; Mohanraj *et al.* 2020; Kuntoğlu *et al.* 2021) have illustrated the existing link between operating parameters (such as cutting speed, feed rate, depth of cut) and the workpiece surface finish. The same applies to the correlation between the on-condition state of the machine tool and the surface finish of the workpiece. However, to the best of this author's knowledge no research has yet been done that factors in all four (4) pertinent components (operating parameters, on-condition of machine, tool condition, and workpiece surface finish) of the machining operation into an optimization. Hence this research aimed at developing a tool and workpiece surface finish monitoring system that adaptively standardizes the four (4) factors of machining for improved tool performance and workpiece condition, which addresses the second objective of the research.

2.3 Tool and Workpiece Condition Monitoring System

The workpiece and cutting tool are the most essential components of a machining station that determine the productivity of a manufacturing firm. Their primary objective is mainly to machine products in line with the quality requirement of the customers at the lowest possible cost. This involves utilizing a cutting tool to the end of its useful life, reducing tool damage, reducing re-work, and reducing the number of scrapped workpieces while ensuring that the product quality in terms of surface finish is not compromised. Presently, most manufacturers use a time period as a conventional tool replacement strategy subject to the operator's experience (Mourtzis, Angelopoulos and Panopoulos 2020). This type of strategy often results in either early replacement (under-utilizing the tool) or late replacement which often causes damage both to the machine tool and the workpiece. The result of this approach is either an increased production cost or poor product quality output from the system. Therefore, the Tool and Workpiece Condition Monitoring (TWCM) system has been considered as one of the key enabling technologies for manufacturing optimization (Zhang *et al.* 2018). The system estimates the tool condition by either deploying sensor-based models or analytical models (Abubakr *et al.* 2021). Both the analytical method and the fused sensor-based method measure the wear dynamics of the tool during operation and estimate the condition. Several studies have considered tool condition monitoring with little consideration for the product quality output, i.e., the workpiece surface quality (Patra *et al.* 2017; Coady *et al.* 2019; Jain and Lad 2019; Nath 2020). An extension of the tool monitoring system to include workpiece condition monitoring would optimize the entire turning operation, rather than investigating only the tool. Therefore, developing a robust tool and workpiece condition monitoring system could help overcome the complexities of the machining operation and optimize the manufacturing system. Since an effective real-time sensor based TCM system is capable of protecting the workpiece by keeping the cutting tool under surveillance, rather than it being left to the uncertainties of analytical tool life (Hassan 2019), it would equally be of interest to extend the condition monitoring system to the workpiece and the operating condition of the machine tool (maintenance) for more robust optimization.

The sensor based TWCM system is comprised of fused highly sensitive sensors, integrated with IoT controllers that help with signal interpretation, analysis and decision making. Like TCM, it can be divided into two broad methods, which are the direct and indirect methods (Ong, Lee and Lau 2019). The direct TCM method directly measures the changes in the geometry of the cutting tool during the cutting process while the indirect TCM method measures the online operating parameters as a way of detecting tool deteriorating conditions based on the relationship between the process parameters (such as vibration, AE, cutting forces, or power) and the cutting tool. The obstructed nature of the cutting region during the process, however, makes the direct TCM method challenging. Moreover, direct TCM methods are difficult to implement online, which has led to most studies adopting indirect TCM methods (Prior and Shen 2019). In addition, there has been very little interest in online TCM methods applied for turning operation as evidenced in the available literature. Similarly, TCM methods can be extended to monitor the surface quality of the workpiece using the same online approach. This would imply that the TWCM system would integrate monitoring the condition of the tool as well as the workpiece online to measure both the quality output and the performance of the tool. Therefore, due to the complexity of the operation, the advanced signal processing approach is required to extract important features from the received signals.

Currently, efforts are being made to investigate a better approach for extracting features from the signals captured from fused multi-sensors developed for indirect TCM systems. Despite concerted efforts being made to ensure a standardized methodology for developing a TCM system, which would be similar to the TWCM system, a perfect method that accurately detects tool and workpiece conditions in real-time has yet to be found. Uekita and Takaya (2017) investigated an interrupted cutting operation and noted that there may be a false alarm in respect of tooth fractures generated during operation with shock impulses during the entry and exit of each individual tooth to the workpiece, equal in magnitude to that generated during tooth fractures. Plaza, López and González (2019) revealed that not all vibration feature extraction methods are appropriate for real-time monitoring of surface finish and proposed the vibration signal with Wavelet Packet Transform (WPT) method, which can effectively be used for real-time surface finish monitoring with high accuracy, reliability, and a low computational cost in CNC machining. The study showed that the vibration signal is a better feature than AE in monitoring the surface finish of the workpiece. In addition, Kiew *et al.* (2020) showed that tool wear and the machine vibration signal are related to each other at varying depths of the cut and feed rate in different experiments. Even though Ochoa *et al.* (2019) found that the AE sensor, when mounted on the tool holder rather than the workpiece, could provide a more the reliable TCM system, in contrast, Deja and Licow (2020) disproved the ability of AE sensors to distinguish between the new and worn-out tool when mounted on either the tool holder or the workpiece. It may therefore be of interest to note that the vibration signal is an important parameter in the TWCM system for depicting the state of the tool and the workpiece during turning operation.

2.4 Application of TWCM System

Several models have been developed to evaluate and predict the condition of the cutting tool and sometimes the machined part surface finish using diverse indirect methods using the installation of sensors on the machine parts for both the milling and turning processes. The available literature has shown that more focus has been on the cutting tool compared to the workpiece surface finish, while some studies have evaluated the effect of conditions on both (Jadhav *et al.* 2019; Saleem and Mumtaz 2020). Optimizing the entire manufacturing process requires reducing the production cost, (i.e., the cost of tool damage, cost of re-work, cost of scrapped workpiece, and cost of system downtime) which entails monitoring the conditions of both the cutting tool and workpiece surface finish. Several studies done on monitoring the condition of the cutting tool focused on using the cutting tool to the end of its useful life by predicting tool wear, tool chipping and tool breakage (Corne *et al.* 2017; Hu *et al.* 2019; Ma *et al.* 2021). However, optimizing machining operation should also consider product quality output as well as monitoring the condition of the cutting tool. This implies that at some levels of cutting tool wear, based on the product surface quality requirement, the cutting tool might still be in its useful life stage, hence the need for a robust monitoring system that simultaneously monitors both the tool condition and the workpiece. Even though recent studies have tried to predict tool wear condition in real-time industrial application, the evidence is that very little work has been done focusing on optimizing machining operation by detecting tool wear and workpiece surface using indirect sensors that capture both the operating parameters and machine on-condition for analysis and decision making. The research efforts in these areas are discussed in the following subsections.

2.4.1 Tool Wear/Chipping/Breakage Monitoring

Tool wear/chipping/breakage monitoring is an important action during machining operation. In a bid to achieve an efficient production process, monitoring the condition of the cutting tool becomes paramount during the machining process. Hence, monitoring the ongoing condition of the cutting tool to detect tool wear/chipping requires a robust method that integrates relevant features with sensor fusion and deep analysis. Monitoring the cutting tool condition during turning operation entails varying the existing operating parameters to extract the most significant parameters that could indicate the changing conditions of the cutting tool during the turning process. This may include the cutting tool type, workpiece type, machine on-condition parameters, and the process parameters. With the existence of highly sensitive sensors, several features of the operating condition can be captured and analyzed for intelligent decision-making during operation. For example, the geometry of the cutting tool could reveal much about the deteriorating pattern of the cutting tool during operation as well as indicate the correlation it has to the workpiece surface finish. Sudden or abrupt changes in the geometry could affect the machine operating conditions as vibrations, AE, acquired force signals, and the interaction between the cutting tool and the workpiece.

Okokpujie *et al.* (2018a) investigated tool wear in a high-speed turning of Al-1061 alloy and considered some cutting parameters such as cutting speed, feed rate, and radial depth of cut with 27 samples and measured tool wear using a scanning electron microscope (SEM) after each sample. They developed a mathematical model using the least square method for predicting tool wear during operation; however, the interval between the tool condition measurements is long enough to allow several tool transformations in geometry to be missed. The method also focused on the tool condition with respect to changing cutting parameters for optimal performance and tool wear prediction. Yıldırım *et al.* (2020) established that there is a linear relationship between cutting speed and temperature, noting that at an increased cutting speed from 50m/min to 75m/min, the temperature increased by 7.2% while it increased by 15.5% at 100m/min. This revealed that operating parameters may directly impact the on-condition of the machine during operation. Heigel *et al.* (2017) in turn investigated the effect of cutting temperature on tool condition and reported that an increased temperature in the cutting zone might imply a chipped or worn cutting tool. This therefore indicates that there is a correlation between the cutting parameter, i.e., cutting speed and temperature, and between the temperature and the tool condition. Prasad, Prabha and Kumar (2017) also concluded that temperature gradually increases as edge wear and deformation develops while cutting speed and feed rate proved to be influential parameters on the depicted temperature with depth of cut proving to be less influential. An equation that connects the four operating parameters is presented in equation 1 (Behera, Ghosh and Rao 2018).

$$\boldsymbol{F = kd^{\sigma}V^{\gamma}f^{\alpha}} \qquad 1$$

Where F is the cutting force, k is the coefficient of the cutting force, d is the depth of cut, V is the cutting speed, f is the feed, while σ, γ, and α are exponents relating to the non-linear relationships between the force and the process variables. Linear relationship exists if, at a consistent increase in magnitude of the cutting force, there is a constant increase in the resultant measured parameters such as cutting speed and feed rate, hence the σ, γ, and α value remains constant while, if there are irregular resulting parameters, the relationship becomes non-linear. In the latter case, σ, γ, and α assume a real, or integer number that is not one (1). In addition, Okokpujie *et al.* (2018b) carried out an experiment to determine the linear relationship of vibration and some operating parameters such as cutting force and cutting speed, and concluded that at a reduced displacement of the workpiece in the radial direction, reduced tool rake angle, and a reduced cutting zone temperature during vibration cutting, there is a reduced tool wear distribution along the circumference of the cutting tool. Therefore, there is an established relationship between some operating parameters, the condition of the machine during operation, and the condition of the tool and workpiece. A more sensitive monitoring of some of the operating parameters and a robust deep analysis could delineate the condition of the tool and workpiece.

2.4.2 Workpiece Surface Roughness Monitoring

Machining operation entails manufacturing a component on a machine tool. The three important components of a machining station are the machine tool, the cutting tool and the workpiece. While ensuring that the machine tool is in a proper condition through maintenance, it is equally imperative to monitor the condition of the cutting tool, and ultimately the workpiece being manufactured into the required product. Several optimization studies have focused more on the cutting tool, being a serviceable part/component, with less attention being paid to the condition of the workpiece. However, monitoring the condition of the machined part can help to optimise the process by maximising the tool life.

Yıldırım *et al.* (2020) investigated the surface roughness/topography of an alloy 625 workpiece during turning operation at three cutting speeds 50, 75 and 10m/min, while the cutting depth was 0.5mm and a feed rate of 0.12mm/rev was fixed with the lowest roughness value derived at 75m/min. This proved that the cutting speed affects the surface roughness of the workpiece. Another experiment was carried out by Kang, Derani and Ratnam (2020) to investigate the effect of vibration on surface roughness in a finished turning operation and they asserted that average roughness may increase continuously or fluctuate randomly depending on the magnitude of vibration added to the vibration-free workpiece profile. The vibration parameter during the machining operation could either emanate from the condition of the fusion of the cutting process or the machine itself due to its maintenance state. It is therefore very important to identify the source of the vibration signal captured during operation. Şahinoğlu, Karabulut and Güllü (2017) studied the relationship between the spindle vibration and surface roughness in turning Aluminium alloy, AI 7075 and the effect of cutting parameters on surface roughness and spindle vibration was determined. The result showed that feed-rate has the most effect on cutting parameter, spindle vibration and surface roughness, while depth of cut and cutting speed have the least effect on surface roughness and spindle vibration. The condition of the machine tool is another factor causing vibration as it deteriorates with time. Ito and Matsumura (2017) found that the vibration of the turning centre spindle running with a used or damaged jaw, for example, would have a different vibration level from that running with a new jaw. To eliminate this factor, the jaw needs to be in proper working condition. Kumar *et al.* (2019) studied the effect of the radial vibration of the spindle during turning operation on the surface roughness of the workpiece and found that vibration has a strong effect on the surface roughness of the workpiece.

Therefore, to obtain the desired variables, such as surface finish and tool wear during a turning process, optimising the cutting parameters while also monitoring the machine tool condition in response to varying cutting parameters and deterioration over time is needed. The most readily controlled parameters in cutting operations are cutting speed, feed rate, depth of cut, and insert nose radius (Zhang *et al.* 2020). Feed rate, cutting speed, and insert nose radius are the parameters which have a significant influence on surface roughness, while depth of cut has shown the least effect (Patel and Gandhi 2019).

2.5 Sensor Selection for a Tool and Workpiece Condition Monitoring System

Turning operation is characterised by several physical qualities, which can be transformed into electrical signals with the help of appropriate sensors. The qualities which are of research interest can be classified into cutting parameters, machine on-condition parameters, and the parameters that measure the condition of the cutting tool and the workpiece. Earlier literature discussed on TWCM systems presented differing opinions on sensor selection for detecting the tool condition and the workpiece surface finish (product output). In addition, the emergence of newly developed and highly sensitive sensors and data processing techniques have made TWCM systems more robust. This section analyses the usage of these sensors in TWCM applications.

2.5.1 Vibration Sensors

Accelerometer sensors are devices that sense the displacement of a component or machine from its mean position. A vibration effect during the cutting operation may result from a number of factors. A broken or worn-out cutting tool during the cutting operation can cause a resultant vibrating effect on the machine tool, and similarly, a faulty jaw can also induce spindle vibration that affects both the tool condition and the workpiece (Feng 2019). The severity of the signal captured from the system and the ability to interpret the signal for adequate decision making depends on the installation position of the accelerometer sensors.

Chen, Bian and Ding (2019) detected varying conditions such as abnormal spindle, unbalanced rotor, gearbox crack, and bearing crack on a CNC machine tool by analysing vibration signals captured by accelerometer sensors installed on the spindle surface near the bearing. This captures the vibration signal resulting from malfunctioning of the machine tool component, which, in turn, would affect the surface roughness of the workpiece and tool wear. In contrast, Munawar, Mufti and Iqbal (2009) deployed a magnetic type accelerometer attached to the spindle bearing housing to capture the vibration signals from the machine tool during machining of AISI 1040 Carbon Steel. The research also concluded that the feed rate and vibration signal captured by the sensor when attached to the spindle bearing housing has an effect on the surface roughness but the inserted nose radius has a more significant effect. Furthermore, Gao *et al.* (2019) noted that an abrupt increase in the spindle rotation frequency compared to the natural rotation frequency of the spindle structure would increase spindle vibration, which degrades both the surface of the workpiece and also the spindle performance. Therefore, capturing the vibration signals using an accelerometer sensor is of great importance in monitoring the surface roughness of the workpiece and the tool condition.

2.5.2 Acoustics sensors

Acoustics emission sensors are used to capture the radiation of acoustics waves in solids that occur when a material undergoes irreversible changes on its internal structure resulting from crack formation or plastic deformation (Cai *et al.* 2017). Acoustics parameters on a machining station may equally give a valuable diagnosis on the condition of the cutting tool and the workpiece. Due to the poor processing environment of a CNC machine and the defects of sampling devices, the acquired sensor signals from the CNC machine might produce various noises which inhibit the sensors from picking up accurately the required acoustic signals from the system (Wu *et al.* 2018). Therefore, positioning an acoustic emission sensor on the machine tool to capture acoustic signals during operation is important. To detect the condition of the cutting tool and workpiece surface roughness accurately using acoustic emission generated at the tool tip, Murakami *et al.* (2021) used a spindle with a built-in acoustic emission sensor placed in direct contact with the tool end surface inside the shaft floated by air. This presents a more accurate method of positioning acoustic sensors for capturing acoustic emissions during operation without much interference from the noise within the environment. The result of the experiment showed that by using a spindle with a built-in acoustic emission sensor, the contact of the small diameter tool tip with the workpiece surface could be detected with damage to the workpiece at the sub-micrometre level on average.

2.5.3 Dynamometers

A dynamometer is essentially used in measuring the cutting force, which is an important requirement in tool condition monitoring (Qin *et al.* 2017). The study further proposed the use of a novel cutting force dynamometer that measures axial force and torque in the milling process. Rizal *et al.* (2018) observed and measured spindle torque, T_q; tool vibration in the z-axis, A_z; and tool tip temperature, T_m as the three components of the cutting force in a milling process using an embedded multi-sensor system on a rotating dynamometer and concluded that the sensor system is suitable for detecting machining condition. In another experiment that considered parameters such as cutting speed, feed rate, and depth of cut in monitoring the tool's condition, the convectional tool post of the lathe machine was removed and the tool dynamometer fixed in its place (Bagga *et al.* 2021). However, Xie *et al.* (2021) claimed that the use of a dynamometer is restricted by the high price, installation limitation, and interference with cutting performance, with the result that direct methods are not fully satisfactory and are seldom used in actual products, and hence proposed an indirect method which generates the cutting energy indirectly using an experimental model. The measurement mechanism model of the dynamometer system is established by the transformation relationship between deflection and strain under external force which limits its application due to the turning operation environment (Zhang *et al.* 2019).

2.5.4 Current and Power Sensors

Current and power monitoring at the main terminal of a CNC machine tool was proposed to have the potential to indicate the condition of the cutting tool and the surface roughness of the workpiece (Neef, Bartels and Thiede 2018). Current measurement devices could also detect the energy related measurements of the machine tools because of their non-intrusive nature, low cost and flexibility of the measurement using sensors. The current signal was captured by current transformers installed at the terminal block and also by a voltage signal via direct wiring for monitoring the progression of tool wear through a developed energy consumption model in a milling process (Shi *et al.* 2018).

2.5.5 Thermocouple

The friction between the cutting tool and workpiece material during the cutting operation generates some form of heat, or increase in temperature. Measuring the cutting zone temperature could give an indicator of the tool condition. This is because the cutting zone temperature varies as the tool progressively wears due to changes in the tool geometry which also affect the contact surface area with the workpiece (Abdulkadir and Abou-El-Hossein 2019). There are several temperature sensors that can be deployed for measuring the temperature around the cutting zone during operation. Thermocouples, thermal resistant elements, and semiconductors are a few temperature sensors that can be engaged for measuring cutting zone temperature. A K-type thermocouple (Omega) sensor with diameter $0.25mm$ was inserted in a drilled hole of diameter $0.53mm$ on a tool-insert to capture the cutting zone temperature (Bagherzadeh and Budak 2018). The research showed that at high cutting speed and feed rate, and given the proximity of the hole to the cutting edge, the cutting edge of the insert became susceptible to breakage. To overcome this problem, the test was repeated using new inserts until a stable temperature was measured. Prasad, Prabha and Kumar (2017) used an infrared radiation thermography sensor to measure the temperature of the cutting zone and found that the cutting temperature gradually increased as the edge wore and deformation developed. However, due to the harsh environment of the cutting zone, contact temperature sensors have made it challenging to adopt this parameter for tool and workpiece condition monitoring extensively. An emerging method to overcome this challenge is the use of contactless temperature measuring equipment. New sensors with infrared technology are gradually making temperature measurement feasible for tool and workpiece condition monitoring during the cutting operation.

2.5.6 Other Sensors

There are a few other sensors that have been used for monitoring the condition of the cutting tool and workpiece as well as the machine. While some methods have remained a challenge due to the nature of the environment during turning operation, others were found not to be feasible for industrial applications for the same reason. For example, vision sensors were used to measure the flank wear of a cutting tool during a turning operation by Szydłowski *et al.* (2016), and they concluded that due to the hostility of the cutting environment, current vision sensors could only be used between cutting cycles. In structured light sensing for monitoring both the tool and workpiece surface finish, the distortion of parallel lines of laser light gave a measure of crater depth. This method is, however, not feasible in the industry due to the nature of the work environment.

2.6 Signal Processing Techniques for TWCM Systems

There are different techniques of processing signals for a tool and workpiece condition monitoring system to diagnose the status during operation or intermittent operation. Signals captured from the monitoring devices installed on the machine tool can be classified into two categories. The first category is the steady state signals captured when the condition of the machine is stable during operation. This generally cuts across signals captured on the machine condition during operation. The second category of the captured signals from the machine tool during operation is the dynamic/transient signals. This signal category indicates an unstable state or condition of the machine tool system as the signal fluctuates during operation due to some external factors, or abnormalities which may be of interest in diagnosing the state of the cutting tool, the workpiece surface finish, and the condition of the machine. These two distinctive categories of signals captured from the machine tool are analysed using different techniques and methods to extract intelligent information that is useful in depicting the state of the process. There are different signal processing methods that can be adopted for the TWCM system. While time domain analysis techniques evaluate physical signals and mathematical functions with reference to time (Li *et al.* 2013; Hong and Dhupia 2014; Khorasani, Littlefair and Goldberg 2014; Vasilevskyi *et al.* 2017), frequency domain techniques analyse signals, or mathematical functions with reference to frequency instead of time (Miao, Wang and Huang 2010; Wu and Chen 2012; Chen *et al.* 2019). However, signals can be converted from either time domain to frequency domain or vice versa with an operator called $transforms$. Early research on the TCM system adopted Fourier transform which converts time function into an integral of sine waves of various frequency; however, it has been shown to be deficient in analysing non-periodic and non-stationary signals, hence other types of $transforms$ have been developed. WPT has shown a better result as a computational method for time-frequency signal conversion, and as a result has been widely used in tool condition monitoring research (Zhu, San Wong and Hong 2009; Chen *et al.* 2018; Pahuja and Ramulu 2019; Zhang *et al.* 2019). Other transforms exist for signal decomposition and computing time-frequency conversion such as the Hilbert-Huang transform (Vazirizade, Bakhshi and Bahar 2019). In addition, the artificial intelligence technique is another signal processing method which is used in TCM systems (Shankar, Mohanraj and Rajasekar 2019). The robustness and strength of this technique in the analysis of large volumes of data and the development of intelligent models for predicting the condition of the workpiece and tool has meant that this method has been used extensively recently in TCM systems (Pimenov, Bustillo and Mikolajczyk 2018; Ranjan *et al.* 2020). There are several AI algorithms that have been deployed in either predicting or classifying tool or workpiece conditions in a machining station. The Support Vector Machine (SVM) algorithm has been applied in many TCM systems for classifying tool conditions (Gouarir *et al.* 2018; Yang *et al.* 2020). The ANN algorithm has been used widely for predicting the condition of tool and workpiece (Yan *et al.* 2020). A recently evolved deep learning AI algorithm finding its way into the TCM system is the Convolutional Neural Network (CNN) (Aghazadeh, Tahan and Thomas 2018). The CNN algorithm takes in input data in the form of images, processes them by extracting their features, and evaluates the cutting tool's condition. Ambadekar and Choudhari (2020) developed a tool wear prediction system to monitor flank wear of a cutting tool using CNN and concluded that this method gives a good response to the data in the form of images with an accuracy of 87.26%. This method proved to be significantly accurate because it measures the cutting tool condition directly; however, this is done intermittently during operation which means there is still the probability of the tool failing and damaging the work piece in-between measuring intervals.

In tool and workpiece condition monitoring, the aim is to apply appropriate sensor signal processing and pattern recognition techniques to identify and predict the cutting state so as to reduce the loss brought about by tool failure and workpiece rework or scrap. Gradually, knowledge-based systems are being developed around this area but not much research has been done into tool condition and workpiece surface roughness monitoring using CNN for processing thermal images captured during the turning operation. The third objective of this research was to apply the direct method of thermal image capturing for TWCM system using CNN which addresses the gap of intermittent capturing of tool and workpiece conditions while applying the direct method. The techniques that are applicable to TCM and workpiece surface roughness monitoring can be divided into two main types, namely, pattern recognition and trend analysis techniques.

2.6.1 Pattern Recognition Techniques

The recent advancement in technology and the sudden development of Industrial 4.0 has led to the evolution of several machine learning techniques for analysing and classifying data for intelligent decision making. Pattern recognition (PR) can be explained as a branch of machine learning that employs a variety of statistical, probabilistic and optimization tools to learn from past events and examples, and then use that prior learning to classify new data and find new patterns (Kim *et al.* 2012). Data in historical knowledge modules form the backbone of developing patterns for the newly captured data. Features extracted from segmented patterns are compared to pre-processed ones extracted from a healthy tool or system through a supervised learning method to define a pattern for the tool condition. Inducting a supervised cut on the tool and extracting features from the signals captured during operation could also be deployed for segmenting a pattern for an unhealthy tool condition. It is, however, very important to select an appropriate PR method to use when applying the technique on machine data. For example, time and frequency sensitivity may play a significant role in the development of a PR classifier for tool conditions in a machining process depending on the condition under which the operation is being carried out. Pattern recognition application consists of five steps, which are signal conditioning, segmentation, features extraction, features selection, and supervised classification. The first step involves treating the signals for any inclusive bias and filtering. This is aimed at removing unwanted noise present in the acquired signals while retaining only the signals that represent the actual condition of the turning operation process. The filtered signals are then segmented in the second step. This is done in order to have signals that are an exact indication of the tool and workpiece condition during operation. The segments should be from a repetitive pattern of the actual turning process, i.e., a complete rotation of the workpiece in a turning operation, or fixed-time segments may also be applied. Segment size and the fixed-time approach should carefully be determined as they affect the feature extraction in the following step. Moreover, if the segment is small with few sampling points, frequency and or time-frequency domain analysis may not be adopted. This is simply because the techniques cannot accurately represent frequency content with such a small segment. Therefore, the features extracted from the segments are limited to a time domain analysis such as mean, variance or root mean square. Step four focuses on accurate detection of the tool condition. This step entails extracting the features that are important for analysis of the tool condition so as to prevent a 'dimensionality problem' caused by the use of too many features. Hence, features that are highly sensitive to the tool condition are selected in step four. The last step is the supervised classification of the segments based on the trained data set from historical data learned. Features extracted from the segment are assigned to one of the classes which could be two or more (e.g., worn tool, healthy tool etc.).

Labelled data are generated from the extracted features and ascribed to the PR classifier as training data. The PR classifier is further validated using the cross-validation set. This is to avoid the model overfitting the dataset. There are several pattern recognition methods that have been applied for monitoring the condition of the cutting tool, some of which are Artificial Neural Networks (ANN) (Dhobale *et al.* 2020; Wong, Chuah and Yap 2020; Yan *et al.* 2020), Naïve Bayes (NB) (He *et al.* 2017; Dave *et al.* 2020), Support Vector Machine (SVM) (Madhusudana *et al.* 2018; Guo and Sun 2021), Linear Discriminant Analysis (LDA) (Xie *et al.* 2019; Bakshi *et al.* 2020), K-Nearest Neighbour (kNN) (Guo *et al.* 2019; Lee *et al.* 2020), and Decision Trees (DT) (Madhusudana, Kumar and Narendranath 2017; Li *et al.* 2020). The drawback of these techniques despite them being an effective approach is their high dependence on the probabilistic and optimization technique that they are based on. The classification techniques are also based on dataset that are a problem-determined experimental result (Hassan *et al.* 2018a); however, a carefully designed experiment with a choice of high sensitive features can help achieve high accuracy of the PR method.

2.6.2 Trend Analysis Techniques

Trend analysis techniques aim at detecting abnormal events in the signal trend when compared to the signal history (Hassan *et al.* 2018b). As the machining operation starts, the condition of the cutting tool, machine tool as well as the resulting workpiece changes with time. Analysis of sensor signals captures the trend of events applied in the time, frequency and time-frequency domain in the tool condition and workpiece monitoring system. Trend analysis techniques include extracting features using mean computation, variance, root mean square, and peak value. This technique has been used previously but because of the drawback, which is that the captured signal is also dependent on the parameters of the turning operation, it makes it difficult to analyse the signal trend. For instance, tool breakage during the turning operating can be observed in the vibration trend as it suddenly surges, suggesting a change in the geometry, or orientation of the cutting tool. However, the vibration trend would exhibit the same trend when either of the operating parameters is changed, making it difficult to link the tool condition to the trend of the monitored parameter. In addition, a faulty or malfunctioning machine tool would also result in the same trend in the captured data, hence requiring a painstaking approach and experimental set-up in order to accurately and successfully apply this technique.

The signals captured during a machining operation are non-linear and non-stationary signals, which requires that the signal conversion used for feature extraction, either in a frequency or time-frequency domain, must be carefully considered for accuracy. The Fast Fourier Transforms (FFT) signal processing method is suitable for extracting features of linear and stationary signals in the frequency domain (Wang *et al.* 2017). Even though it can achieve the same result much faster than Discrete Fourier Transforms (DFT) (Sanabria-Villamizar *et al.* 2019), they are both still not a suitable algorithm for machining signal processing. Wavelet Transforms (WT) performs well, and it is widely used for extracting features in the time-frequency domain of non-linear and stationary signals (Varanis *et al.* 2020). It is not suitable for signal transformation and extracting features from a non-stationary signal, which makes it not suitable for machining signal processing. A more suitable analysis of a non-linear and non-stationary signal for feature extraction is Hilbert Huang Transforms (HHT) (Song *et al.* 2008; Lenka 2015; Sharma and Pachori 2017). This transform can be used for signal processing of captured signals from machining operation as it is non-linear and non-stationary. It provides a more precise definition of events in time-frequency space than wavelet analysis and offers a better interpretation of the underlying dynamic process.

2.6.3 Multi-Signal Processing TWCM Systems

Multi-signal processing for TWCM systems may provide a more robust and deeper analysis of the condition of both the cutting tool and the workpiece during operation. Trend analysis technique and pattern recognition may both be combined and applied to provide more intelligence and signal information about the TWCM system even though it requires more processing time. Both pattern recognition and trend analysis techniques combined have been used in literature for the analysis of signals to obtain better diagnoses and information (Wu *et al.* 2019). Recently, a few research studies have been done to identify tool conditions under different cutting parameters (Zhou and Xue 2018a; Cai *et al.* 2020). However, none of the systems reviewed in the available literature, which use trend analysis, pattern recognition or a combination of both, were successful in unmasking the effect of cutting parameters, and the machine tool condition (maintenance) on the acquired signals and only underscored the tool and workpiece condition effect. Therefore, a novel signal processing system is required to identify the tool condition relative to the surface roughness requirement or measurement of the workpiece under varying cutting parameters and machine conditions in a turning operation.

2.7 Multi-Sensor TWCM Systems

There are many TCM systems that have recently been deploying multi-sensors for capturing the different signals that can reflect the condition of the cutting tool during operation (Lenz, Wuest and Westkämper 2018). This is due to the absence of a stand-alone sensor that can capture the conditions of the cutting tool during operation under varying cutting conditions due to the dynamic nature of the turning operation. Most of the TCM systems in the available literature have shown that a reliable online TCM system must be sensitive to the tool condition and geometry (Danai 2017), provide signal information that reflects the tool condition type (Zhu and Yu 2017), possess a high degree of certainty in decision making, and have a good response time for a signal processing and feedback system (Hassan *et al.* 2018b). Due to the dynamic nature of machining operation, tool monitoring systems have limited application to independently monitor the tool condition or workpiece by extracting features from signals captured from the tool or workpiece, which also consider the cutting parameter. The recent application of artificial intelligence has further widened the prospect of a generalized and optimized condition monitoring system capable of integrating information, extracting features and making more reliable decisions on the cutting tool and workpiece condition. This method, however, would require more integrated sensors, signal conditioner/amplifiers, and a robust network platform for information processing and dissemination.

An emerging AI technique, Deep Learning (DL) method, with much processing capabilities is gradually being implemented. DL methods have achieved revolutionary success in diverse industries. Deep Multi-layer Perception (DMLP), Long-Short Term Memory (LSTM), Convolutional Neural Network (CNN), and Deep Reinforcement Learning (DRL) are among the most preferred methods of DL used in recent years (Serin *et al.* 2020).

2.8 Cyber-Physical Manufacturing

Traditional manufacturing is rapidly being driven into intelligent/smart manufacturing through technologies such as big data, IoT, cloud computing, cyber-physical systems and artificial intelligence. Liu *et al.* (2019) developed a digital twin-based machining process planning that assesses whether the process planning is reasonable, or feasible or not, based on real-time data acquisition. It further identified three common practical production problems with machining as uncontrollability of the quality of the machining process, uncontrollability of the machining cost due to dynamic change in machining cutting parameters, and uncontrollability of machining efficiency due to uncertainty of equipment failure. The structure of cyber-physical manufacturing in the development of a digital twin virtual machine was enumerated by Cai *et al.* (2017) as monitoring, analysis, simulation and management of a CNC machine. However, due to the requirements for digital twin development, which entails fusion of multi-sensors, IoT devices, deep processing of manufacturing data (Big data), cloud computing and an efficient feedback system, implementing the digital twin process has been challenging.

2.9 Tool Wear and Workpiece Monitoring: Trends and Challenges

Research has shown that cutting conditions affect tool wear and surface roughness during turning operation. An early study by Dureja *et al.* (2009) evaluated the relationship between machining parameters, workpiece roughness, and tool flank wear by applying ANOVA analysis and an interaction graph to show that there is correlation and influence between these factors in a machining operation. The study established through experimentation that captured a tool wear and surface roughness profile using Scanned Electron Microscope (SEM) and Energy Dispersion X-ray (EDX) analysis, that machining parameters such as cutting speed and feed rate have an effect on the tool flank wear, while the tool flank wear also affects the surface roughness of the workpiece. Several other studies have also indicated that there is a strong correlation between the machining parameters, tool wear condition, and workpiece surface roughness during machining operation (Bonifacio and Diniz 1994; Khidhir and Mohamed 2011; Chuangwen *et al.* 2018; Usca *et al.* 2022). A study by Roy *et al.* (2020) also showed that cutting parameters, and cutting depth and speed are significant and impactful towards principal and flank wear with the latter being lower than the standard limit of 0.2mm and surface roughness of 0.99μm. This study indicated that the operating condition of the machine tool has a significant effect on tool wear and the surface roughness of the workpiece. Machining operators have therefore placed emphasis on the operating parameters, surface roughness of the workpiece, and the cutting tool conditions in order to achieve optimal productivity. During a turning operation at any machining station, the cutting parameters at the machining station are independent variables, while tool wear parameters and the surface roughness are dependent variables. This implies that while the cutting parameters may be carefully chosen during operation, their corresponding effects on tool wear and surface roughness cannot be predicted, which further reveals the reason why so much research effort is being put into monitoring the condition of the tool and the workpiece roughness at a machining station.

Tool and workpiece condition monitoring may be classified into two methods, or approaches based on the ways and approach of observing the targets, or measuring both the tool and workpiece conditions, which are namely the direct and the indirect monitoring methods (Zhou and Xue 2018b). These methods have been extensively deployed in monitoring the conditions of both the cutting tool and workpiece quality output, with the direct method being the earlier approach while the indirect monitoring method is the more recently used approach.

2.9.1 Direct Tool and Workpiece Condition Monitoring Approach for Machining Operation

Direct tool wear and workpiece roughness monitoring relies on directly measuring and analysing the tool wear and workpiece profile by using high precision instruments such as contact detectors or industrial cameras (Zhu and Yu 2017). The contact instrument is used for evaluating the wear and the surface roughness condition of the tool and workpiece area of estimation. The effect of feed rate was examined on tool wear and surface roughness, Ra, in a drilling process using a direct method with the flank wear of the tool range being within 114 to 193µm. The feed rate in the study was the independent variable while the corresponding tool wear and surface roughness of the workpiece was measured using a direct method of intermittent image capturing. M'Saoubi *et al.* (2012) studied the surface profile of the workpiece focusing on the effect of tool wear during the turning of Inconel 718. The surface profiles were produced by both a new cutting tool and a worn tool, and measured using a contact instrument (direct method) while the electron images of the workpiece surface profile produced were noticed to become wavier as the tool wear increased considering a multiple length scale. Similarly, Fu (2017) applied the direct method of tool wear and workpiece condition monitoring by designing and adopting a compact flexible camera fixture with a low distortion telecentric lens imaging system to capture the tool image by adjusting the gap in the cutting process, combined with a fast automatic image calculation algorithm for fast measurement. Another study by Čerče, Pušavec and Kopač (2015) suggested a direct measurement method to measure the spatial wear of the tool using a laser contour sensor with the possibility of determining a three-dimensional tool wear profile. Furthermore, Boy, Yaşar and Çiftçi (2016) applied the direct method to investigate and model surface roughness, Ra, and the resultant cutting force in turning of AISI H13 steel. The surface roughness was measured using a Mahsurf PS1 device and a Kistler 9257 B piezoelectric dynamometer for measuring the cutting force while the mathematical model was developed to establish the relationship between the two (2) parameters. An investigation into the effect of cutting parameters on the machining process of a cryogenically treated aluminum alloy with treated carbide tool inserts was also carried out using a direct method by Samtaş and Bektaş (2021). The experiment was performed by varying the cutting speed and feed rates, and after each experiment the surface roughness and wear values of the cutting inserts were measured, the latter after repeating the experiment five times to establish the effect on the tool and workpiece surface roughness. All the highlighted studies have applied the direct approach in monitoring the conditions of both the tool and the workpiece to investigate and establish the effect of machining parameters. However, the limitations of the nature of the operation have encouraged many research studies to opt for the indirect method of monitoring the tool and workpiece surface profile for a machining operation.

2.9.2 Indirect Tool and Workpiece Condition Monitoring Approach for Machining Operation

The indirect method measures tool wear and workpiece roughness by monitoring alterations or changes in some parameters, or signals such as vibration, cutting temperature, force, acoustics and others by constructing the relationship model between characteristics signals and tool wear and indirectly inferring the tool wear and workpiece roughness state (Kang *et al.* 2019). Even though the implementation of this method is computationally more challenging compared to the direct method of tool and workpiece condition monitoring, advancement in sensing technology, cloud computing, and the increasing number of different sensors and modern CNC machines with in-built sensors have altogether enhanced this approach. This approach is a data-driven method that evaluates the tool and workpiece conditions by the intelligent analysis of signals captured during the machining operation. Since tool wear directly results in the increase of the product roughness, the decrease of the machining accuracy of the workpiece, the size being outside the tolerance limit, and the increase of the cutting temperature, a serious increase in vibration will lead to abnormal operation of the processing equipment, which has a negative impact on the workpiece with a high accuracy requirement (Cheng *et al.* 2023), the captured data in this method is mostly deployed for the prognosis of tool and workpiece condition. The most popular data-driven approaches to prognostics in machine tool condition monitoring, or system health management include ANNs, Decision-tree, and SVMs (Wu *et al.* 2017). These, and many other intelligent data processing techniques, together with the available smart devices and technologies, have expanded the scope of studies using the indirect method for data capturing, analysis and decision making. An intelligent approach for predicting tool wear and workpiece surface profile during machining is by adopting a tool and workpiece monitoring system based on vibration signals and signal processing techniques for extracting time domain, frequency domain and time-frequency domain features of cutting force and vibration (Cheng *et al.* 2020). The prediction model was built using support vector regression (SVR) and optimized by Genetic Algorithm (GA) and Grid Search (GS) using cutting force and vibration to make a prediction with GA-SVR having 97.32% accuracy and GS-

SVR being 96.72%. The wear stages were bench-marked based on the gray level processing techniques of the gray co-occurrence matrix of the surface texture.

The vibration effect during the cutting operation may result from several factors. A broken or worn cutting tool during the cutting operation can cause a resultant vibration effect on the machine tool, and the same can happen with a faulty jaw, which also induces spindle vibration that affects both the tool condition and the workpiece (Amici *et al.* 2020). Cheng and Dang (2017) detected varying conditions such as abnormal spindle, unbalanced rotor, gearbox crack, and bearing crack on a CNC machine tool by analysing vibration signals captured by accelerometer sensors installed on the spindle surface near the bearing. This captures the vibration signal resulting from malfunctioning of the machine tool component, which in turn would affect the surface roughness of the workpiece and tool wear. In contrast, Munawar, Mufti and Iqbal (2009) deployed a magnetic-type accelerometer attached to the spindle bearing housing to capture the vibration signals from the machine tool during the machining of AISI 1040 Carbon Steel. Another study by Kuram and Ozcelik (2017) optimized tool wear, surface roughness and cutting force measured in the machining of Ti6Al4V titanium alloy and Inconel 718 workpiece materials using Taguchi's signal-to-noise ratio. The study captured the acoustics signals generated during the machining process and applied the regression model on fitting and predicting tool wear, surface roughness and the cutting force in the machining of Ti6Al4V. Other signals have been captured during the machining process using different sensors as earlier discussed in section 2.3; however, vibration signals have been widely used because of their potential, ability, and robustness in sensing and analysing different conditions of the system during operation.

Signals captured from the monitoring devices installed on the machine tool can be classified as steady-state signals and dynamic/transient signals. The former are captured when the condition of the machine is stable during operation, while the latter are captured during the unstable operating condition of the machine tool. These two distinctive categories of signals captured from the machine tool are analysed using different techniques and methods to extract intelligent information that is useful in depicting the state of the process. Different signal processing methods can be adopted for the TWCM system. While time domain analysis techniques evaluate physical signals and mathematical functions with reference to time (Li *et al.* 2013; Hong and Dhupia 2014; Khorasani, Littlefair and Goldberg 2014; Vasilevskyi *et al.* 2017), frequency domain techniques analyse signals or mathematical functions with reference to frequency instead of time (Miao, Wang and Huang 2010; Wu and Chen 2012; Chen *et al.* 2019). Signals can be converted from either the time domain to the frequency domain or vice versa with an operator called transforms. Early research on the TCM system adopts Fourier transform, which converts time function into an integral of sine waves of various frequencies; however, it is not efficient in analysing non-periodic and non-stationary signals, hence other types of transforms have been developed (Hurley 2018). Wavelet Packet Transform (WPT) models have shown a better result as a computational method for time-frequency signal conversion, and as a result, have been widely used in tool condition monitoring research (Zhu, San Wong and Hong 2009; Chen *et al.* 2018; Pahuja and Ramulu 2019). A comparative study to predict bearing degradation by Bhavsar *et al.* (2022) using Discrete Wavelet Transform (DWT), Tabular Generative Adversarial Networks (TGAN), and ML models also showed that DWT is an efficient signal processing tool in decomposing signals that are non-stationary signals. Another transform model exists for signal decomposition and computing time-frequency conversion such as the Hilbert-Huang transform (Vazirizade, Bakhshi and Bahar 2019). In addition, the artificial intelligence technique is another signal-processing method used for TCM systems (Shankar, Mohanraj and Rajasekar 2019). This technique was adopted for fault prognosis and condition monitoring using previously obtained data to predict the Remaining Useful Life (RUL) of the component using various regression/degradation models by Bhavsar and Vakharia (Bhavsar and Vakharia 2022). The robustness and strength of this technique in the analysis of large volumes of data and the development of intelligent models for predicting the condition of the workpiece and tool have seen this method gain more usage recently in TWCM systems (Pimenov, Bustillo and Mikolajczyk 2018; Ranjan *et al.* 2020). Several AI algorithms have been deployed in either predicting or classifying tool or workpiece conditions in a machining station. The Support Vector Machine (SVM) algorithm has been applied in many TCM systems for classifying tool conditions (Gouarir *et al.* 2018; Yang *et al.* 2020), and the ANN algorithm has been used widely for predicting tool conditions and workpieces (Yan *et al.* 2020).

The possibilities of existing and emerging signal and data processing techniques have helped in the improvement and optimization of the components of machining operations. This entails the optimization or improvement of the operating parameters, and the product surface roughness (quality output), or extending the tool life by monitoring the tool wear during turning operation. Debnath, Reddy and Yi (2016) studied the influence of cutting parameters and fluids on surface roughness and tool wear in a turning process and stated that feed rate contributes a significant factor of about 34.3% to surface roughness of the workpiece, while the cutting speed and depth contributes factors of 43.1% and 35.8% respectively. The study hence optimized the cutting parameters with the goal of determining the optimum cutting conditions for the desired surface roughness and tool condition and the results indicated that the optimal cutting condition was at a high level of cutting speed, medium depth of cut and low feed rate. The significance of this study was that, provided the cutting conditions are kept constant, and at the optimal cutting conditions stated, the effect of the signals indicating the condition between the tool and the workpiece can be studied and determined using the intelligent approach. Sahu and Choudhury (2015) optimized the surface roughness of hardened steel (AISI4340 steel) under high-speed turning by determining the tool conditions, whether coated or uncoated, that produced the better surface morphology and prediction of tool wear. The study concluded that the tool and surface morphology was improved by using coated tools. Furthermore, some optimization attempts have simply improved the prediction accuracy of a model that determines the tool wear condition and surface roughness parameter of the workpiece. Su *et al.* (2021) tried to achieve process optimization by improving the prediction model for specific energy consumption of machine tool and surface roughness considering tool wear evolution while turning AISI 1045 steel experiment. The prediction model is based on the Support Vector Regression (SVR) algorithm for determining the model elements, such as tool wear, cutting parameters and surface roughness, that give a better prediction accuracy. As more improved algorithms are introduced, better models in terms of performance and accuracy are being implemented for tool and workpiece condition monitoring systems.

2.9.3 Challenges with Tool Wear and the Workpiece Condition Monitoring Approach

TWCM approaches have been investigated through applying both the direct and indirect methods of monitoring conditions during the machining process. Since the direct method relies on direct measurement and analysis using high precision instruments, it tends to be more accurate and precise. When compared to the indirect method, it produces more accurate measurement of the observations. However, direct methods come with some limitations such as lightning conditions, cutting fluid, and chip interference during machining, hence the method is only applied for tool wear and workpiece roughness measurement offline (Jantunen 2002). Also, direct measurements are difficult to implement because of the continuous contact between the tool and the workpiece, and almost impossible to implement due to the presence of coolant fluids (Zhu, San Wong and Hong 2009). Furthermore, due to the obstruction of the cutting region during machining operation, it requires that the operation be stopped for the readings or measurements to take place, hence limiting the approach as it increases the downtime of the machine tool.

Even though the precision of the indirect method is generally lower than the direct monitoring method, its flexibility and practicability has made it achievable for intelligent and smart tool wear monitoring (Cheng *et al.* 2023). Indirect methods such as those based on sensing of the cutting forces (Altintas 1988; Altintas and Yellowley 1989; Elbestawi, Papazafiriou and Du 1991; Du, Elbestawi and Wu 1995; Saglam and Unuvar 2003; Sutter and Molinari 2005), vibrations (El-Wardany, Gao and Elbestawi 1996; Chen and Chen 1999; Dimla Sr and Lister 2000a; Dimla Sr and Lister 2000b; Abu-Mahfouz 2003; Heyns 2007; Madhusudana, Kumar and Narendranath 2016; Gierlak *et al.* 2017; Aralikatti *et al.* 2020; Chang *et al.* 2022; Sapthagiri *et al.* 2022), acoustic emission (AE) (Pai and Rao 2002; Liu, Tseng and Tran 2019; Papandrea *et al.* 2020; Twardowski *et al.* 2021; Dhobale, Mulik and Deshmukh 2022), and motor/feed current (Xiaoli 1999; Li, Tso and Wang 2000; Li 2001; Tonshoff, Li and Lapp 2003) have been the most employed and reported for TCM. Furthermore, the high robustness in computational capacity, has increased its accuracy in terms of the intelligent and smart tool wear and workpiece monitoring system. Even though this approach has some comparative advantages over the direct method, the challenge of this approach is ambiguity in the computational approach and analysis of the signals for the interpretation of the tool and workpiece condition. This has therefore led to many models and algorithms being used in an attempt to improve and optimize the signal processing techniques.

Tool wear has been the most common phenomenon considered in manufacturing processes such as turning, milling, or drilling operations (Kamarthi, Kumara and Cohen 2000). While tool wear has been estimated using Taylo's equation for tool life expectancy (Johansson *et al.* 2017), recent approaches have applied sensing technology and smart intelligent systems in diagnosing wear conditions. Several other studies have considered the workpiece surface finish alongside the condition of the cutting tool (Patra *et al.* 2017; Coady *et al.* 2019; Nath 2020). A study was conducted by Melkote *et al.* (2022) to predict the surface roughness parameter, Ra, value for as low as 0.18 – 0.2μm with ceramic wiper tools by applying multiple linear regression models and neural network models. The tool flank wear in the study reached a tool life criterion value of VB_c

= 0.15mm before or around 15 minutes of cutting time at high cutting speed due to increased temperature. The experimental study aimed at investigating the influence of cutting parameters on tool flank wear and surface quality in hard turning of AISI D2 cold work steel using ceramics inserts with wiper nose geometry. Another study by Schoop, Sales and Jawahir (2017) established that tool wear distinctively influences surface roughness, R_a. The study showed surface roughness values as low as R_a = 40nm for cryogenic precision manufacturing during high-speed machining of Titanium alloys with $VB_c < 10$ µm after 65 minutes of cutting at $V_c = 240m/min$ with PCD tools. Workpiece condition has been determined by its surface roughness parameter (Pathiranagama and Namazi 2019; Sarnobat and Raval 2019; Kuntoğlu *et al.* 2021), while the cutting tool condition has been determined by the wear, crack or chip parameters. While the surface roughness parameter, Ra, of the workpiece can indicate a characteristic quality that is essential to the customer and product specification, more detailed parameters may be needed for intelligent condition diagnosis of both the workpiece and cutting tool during machining operation and also for meeting the customer's requirement for smart precision manufacturing. With much emphasis on the arithmetic mean roughness, Ra, parameter of the workpiece, other surface profile parameters have been less explored for condition monitoring of both the tool and the workpiece. There are several surface parameters, such as Rz, which is the mean roughness depth, Rz1max, maximum depth of roughness, Rt, total height of roughness profile, Rku, Kurtosis, Rsk, Skewness, Ra, Average Roughness etc., that can be measured experimentally from the surface of a workpiece based on the high precision instrument used in carrying out the task. These surface roughness parameters may in a significant way contribute to the study on condition monitoring and optimization of both the tool wear and surface roughness of the workpiece for a machining operation. Munhoz *et al.* (2020) evaluated the surface roughness of a workpiece in an abrasive flow process considering three surface parameters. Even though this process is not a turning or milling operation, it does, however, project that other surface roughness parameters could help in the study of tool and workpiece conditions. Another simulation study was done by Kang, Derani and Ratnam (2020) that adopts both arithmetic mean roughness, Ra, and total height of roughness profile, Rt, to evaluate the vibration effect on the surface finish in a turning operation and there was a significant impact on both surface roughness parameters from the simulated study. It therefore becomes imperative to determine other surface parameters properties of a workpiece, evaluate the significance to tool wear and workpiece condition and also incorporate the parameter for determining the workpiece class based on the tool condition evaluated by the captured signal during operation. It is therefore important to determine the measured parameters from the cutting tool and the surface condition of the workpiece that could be used as a knowledge base for determining the condition of the tool as well as the workpiece during machining for smart manufacturing.

2.10 Conclusion

This chapter has discussed the relevant literature available on the TWCM system. The chapter included a review of literature on tool deterioration and workpiece surface finish, the TWCM system, application of the TWCM system, tool wear chipping/breaking monitoring, workpiece surface roughness monitoring, sensor selection for the TWCM system, vibration sensors, acoustics, dynamometers, current and power sensors, other sensors, signal processing techniques, pattern recognition techniques, trend analysis techniques, multi-sensor TWCM systems and cyber-physical systems for turning operation. The chapter also discussed the TWCM system trend and challenges by highlighting the available approach/method used for the TWCM system, enumerating some studies and their significance, and also putting into perspective the advantages, pitfalls, and challenges of implementing each method as they were described in the available literature.

From the literature review discussed in the sections of this chapter, the following conclusions can be drawn.

- An integrated tool and workpiece condition monitoring system has been discussed. Studies have been conducted on the effects of machining parameters, such as cutting speed, force, feed rate and depth of cut on tool and workpiece, and the effect of tool wear on workpiece surface roughness, Ra.
- Data driven approach/methods for TCM have given rise to the introduction of many intelligent and smart analytical methods for predicting and diagnosing the tool wear condition as well as the workpiece surface roughness parameters during machining operation.
- More research studies have been done on the TCM systems compared to the workpiece surface quality output for a machining operation. Many existing studies on both tool wear

and workpiece surface roughness have majorly considered the arithmetic mean roughness Ra parameter for evaluating workpiece condition, while a few other studies have considered two (2) other surface parameters for the study. This has prompted this study to experimentally evaluate the correlated surface profile parameters to tool and workpiece, and establish six (6) surface profile parameters for classifying tool and workpiece conditions in real-time during operations that has not been done previously.

- An acoustic emission signal can capture acoustic waves radiation resulting from structural deformation of the cutting tool during turning operation but it is difficult to implement due to a poor processing environment (signal contamination due to the nature of the operating environment).
- Vibration signals generated from the contact of the tool with the workpiece during machining operation are effective for diagnosing, or predicting, the condition of both the tool and workpiece during machining operation but require painstaking data processing.
- Signals generated during the machining operation are non-stationary and non-linear continuous signals.
- Time domain trend analysis techniques are not suitable for TWCM systems.
- Frequency domain or time-frequency domain analysis using FFT are useful signal processing methods suitable for TWCM systems; however, the Wavelet Transform and HHT method offers a greater advantage.
- A reliable TWCM system requires the combination, or fusion of multi-sensors together with multiple signal processing types but is challenging to implement. Signal processing types include pattern recognition, trend analysis and AI.
- Advancement in the development of sensors and Internet of Things (IoT) devices has given rise to cyber-physical manufacturing and smart manufacturing, with an emerging interest in machine digital twin, IoT enabled devices and sensors, and the power of cloud computing has enabled advancement in this area; however, only a few studies have applied machine digital twin for tool and workpiece condition monitoring.
- Several optimization approaches have been implemented based on machining parameters, tool wear condition, and surface roughness.
- There is both direct and indirect monitoring of the TCM system as well as the workpiece surface finish. The indirect monitoring method is mostly adopted because of the obstructive

nature of the machining environment and the robustness and flexibility of the method but it is challenging to implement because it is a data-driven approach.

- Capturing the cutting zone temperature using a thermocouple is effective in detecting tool wear but challenging to implement. Existing methods employ the installation of a temperature sensor in a hole drilled on the cutting insert which needs to be constantly changed to avoid tool breakage.
- An infra-red thermocouple has been used for measuring cutting zone temperature; a similar implementation approach may be adopted for cutting zone thermal image for tool wear monitoring.

This study therefore closed the gap in the area of surface parameters that could be used for determining the conditions of the Tool and Workpiece during operation by experimentally investigating the parameters that are significant for determining the condition of the Tool and Workpiece during turning operation. It has further contributed to knowledge in the area of the indirect TWCM system through the processing and evaluation of vibration signals and ML techniques for classification of the Tool and Workpiece conditions during operation.

CHAPTER 3 : EXPERIMENTAL SET-UP AND DESIGN METHOD

3.1 Introduction

This chapter discusses the research experimental set-up and design for the study. It describes the machine tool, workpiece materials, cutting tools, sensor selection, the installation of a sensor on the machine tool, features extraction, and advanced signal analysis. In addition, the set-up of the experiment used for the test conducted is also discussed in this chapter. In this research, the test was carried out on the lathe machine tool for a turning operation under different workpiece materials, cutting tool classes, machine tool conditions, and fixed cutting conditions. The experiments were conducted to optimize the manufacturing system (with the focus on the turning operation) by capturing both the tool and workpiece conditions with the focus on meeting product quality output requirements, while also monitoring the condition of the machine tool during operation. The focus of the study was to develop an intelligent Tool Wear and Workpiece Surface Finish monitoring system, that determines the tool wear and workpiece surface parameters during machining through the processing and analysis of the signals captured during the working condition of the machine tool. Since machine operating conditions affect tool wear and surface roughness parameters, these factors were kept constant during the machining experiment in order to monitor the impact and effect of the factors of concern during machining operation.

The machining experiment was performed to determine the corresponding parameter output from each tool class. A vibration sensor was installed to capture the signal from the tool and workpiece, while the signal was analysed using an advanced processing technique in order to correlate and evaluate the tool condition relative to the workpiece surface quality requirement. This was carried out by conducting a turning operation to develop and validate sensor-based models to optimize tool and workpiece surface conditions due to tool wear and operating conditions. A feature analysis and classification method using machine learning was used on the captured data as later indicated in Chapter 5. This chapter comprises the following subsections: Introduction, Research Method Design, Machine Tool for Turning Operation, Cutting Tool, Workpiece Material, Sensor Selection, Assessment of the Cutting Tool Condition, Assessment of the Workpiece Surface Roughness, Experimental Set-up, Tool and Workpiece Surface Parameters Selection using MANOVA analysis, Real-Time Tool and Workpiece Condition Monitoring, and Summary. The hardware used for the experiment is also discussed together with its capabilities.

3.2 Research Method Design

Several studies have been carried out on evaluating tool conditions and workpiece roughness. In this study, tool conditions were classified based on flank wear. Four (4) different classes of cutting tools were used for this research, namely, new tool, good tool, rough tool, and worn tool, according to the ISO 3685:1993 standard. The first step was therefore to classify the classes of tools and the range of flank wear for each of the tool classes. The surface parameters for each cutting tool class were experimentally determined by performing a turning operation with each class of cutting tool at constant operating parameters. The surface roughness parameters were measured after each turning operation with the wear measuring instrument and the data recorded. The experiment was repeated by performing another turning operation at a fixed operating parameter with the same tool and using the same measuring instrument. The corresponding quality output of each tool class was experimentally determined by measuring the surface roughness parameters of the workpiece. Figure 3:1 illustrates the flow chart of the processes and stages of the research design.

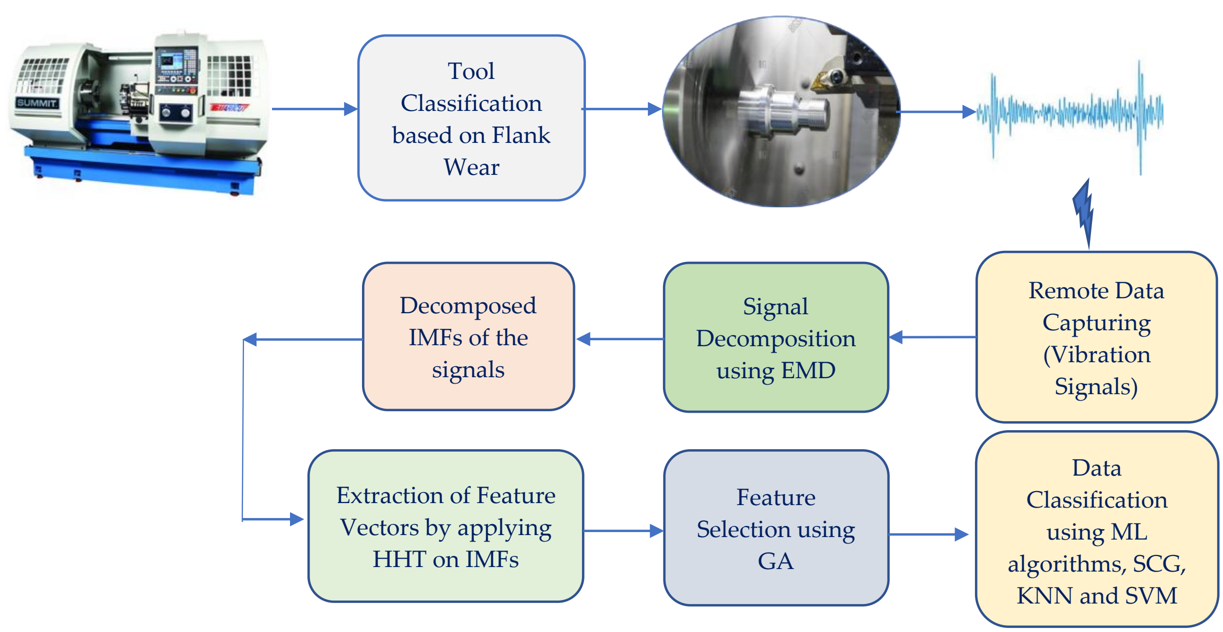

Figure 3.1: Flow Chart of the Research Method

The vibration signals were captured during machining operations using IoT-enabled sensors (advanced vibration sensor from iMonnit) and gateways. The vibration data was captured on the cloud server, enabling remote access and robust data analysis. The experiment (turning operation) was performed at constant operating parameters of the machine tool, such as speed, feed rate, cutting force etc. Each cutting tool class was used for the turning operation and the label indicating the tool type was recorded against the captured vibration signal. Many studies have applied digital filters to the signals captured from devices and systems; however, the signal must be stationary and linear as the method applies Fast Fourier Transform (FFT). Since Fast Fourier Transform (FFT) is ideal for linear and stationary signals due to the uniform trigonometric function, Wavelet Transform (WT) has been introduced as an alternative to extracting time-frequency resolutions of a signal, and are unique because of its sparse representation of signals. However, the EMD method is a better approach for analysing non-linear and non-stationary signals. This is because the EMD method is based on data compared to most other methods which are not. The signals are decomposed by applying the EMD method to the raw vibration signals. This method was applied because of the nature of the vibration signals captured from the machining process. The signals are unsteady (non-uniform) and the waves are deformed (non-linear) and therefore require additional harmonics. EMD decomposes the data set into a finite number of Intrinsic Mode Functions (IMFs). HHT were applied to the resulting IMFs from the decomposition to extract the feature vectors that were used for classifying the cutting tool. To optimise the classification algorithm and make it computationally less expensive, a Genetic Algorithm (GA) was used for feature selection. Finally, the features selected using the GA model after applying HHT on the decomposed signals were fed into ML models to classify each tool condition and the corresponding quality output. The classification was done using three different ML models, and the error loss of each model was evaluated. Neural networks with SCG, KNN, and SVM algorithms were used to develope the classification models. K-fold cross-validation techniques were applied to eliminate bias and obtain the optimal model in terms of performance hence, 5-fold and 10-fold cross validation was performed on both the SVM and KNN algorithms and the classification error loss was evaluated. Hyperparameter optimisation was performed on the fitted model and the objective function value and the function evaluation time was observed. The objective function value is the classification error loss of the model while the constraints are the distance metrics of the model. Optimization seeks to determine the distance metrics using the distance function that gives the least classification error loss. The error loss of each model was evaluated to determine the optimal algorithm for the classification problem. The outcome of this study can provide an alternative solution to intermittently stopping the machining process to evaluate the tool and workpiece condition during the machining process.

3.3 Machine Tool for Turning Operation

The focus of the research was on the turning operation and the study was carried out on the lathe machine Colchester NG200 CNC with a turning centre as shown is Figure 3:2. The rotating spindle power of this machine tool is 36 KW with a rotating speed of 4200 rpm. The maximum turning length of the machine tool is 750 mm, with a swing diameter overbed of 500 mm, and the turning diameter with external tool is 50 mm.

Figure 3.2: Lathe Machine Tool for Turning Operation

Figure 3.3: Lathe Machine Tool Post for Vibration Sensor Attachment

Figure 3.3 indicates the location of the vibration sensor on the machine tool during the experiment. The vibration sensor was installed on the tool post of the lathe machine and the corresponding vibration signals at varying tool classes and workpiece conditions were measured, while the cutting conditions were kept constant.

3.4 Cutting Tool

The research experiment focused on the turning operation on the lathe machine tool, hence the type of cutting tool considered in this study was the indexable tungsten cutting tool with tool insert. A set of varying geometrical shape indexable tungsten cutting tool with CCMT09T3034 carbide insert was used for the turning operations. The set of indexable cutting tools used has different geometrically shaped tool inserts fixed on the tool holders. Some studies have indicated that the tool wear effects on the surface roughness of a workpiece were not obvious under the condition of special tool edge geometry and machining methods (Hughes, Sharman and Ridgway 2006; Aspinwall *et al.* 2007; Niaki and Mears 2017). The tool's geometrical structures and shapes are shown in Figure 3:4 but with the main operation being a turning operation, parting tools were not used for the study. Two seemingly similar tools with almost the same geometry were used for the experiment since other tools were used for parting while one was a left-handed tool. The cutting inserts were replaced with the corresponding class of cutting tool for the experiment and the roughness parameters were measured and the signals captured by the vibration sensor. The set of hardened carbide tipped cutting tool inserts with the holders may have the tool tips replaced when they wear out.

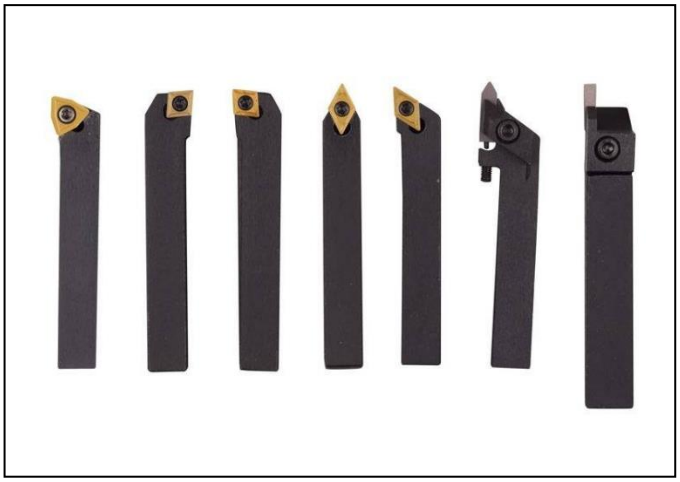

Figure 3.4: Cutting Tool Set

The set has left, right, and centre cutting tips. The parting tool shaft size is 12 mm while the shaft thickness is 10 mm. Each weighs about 0.52 kg, and has a dimension of 178 x 124 x 10 mm. The cutting tool is suitable for turning materials such as stainless steel and ordinary steel such as 45 steel, A3 steel, and other soft materials such as 201, 304 etc.

3.5 Workpiece Material

There are many types of materials used in manufacturing parts at a machining station; however, since the focus of this work was on the application of TWCM for automobile parts manufacturing, two (2) different carbon steel bars were selected for the study: BS 970 080m40 (EN8) and BS 970 070m55 (EN9). They are suitable for the manufacturing of parts such as general-purpose axles and shafts, gears, bolts, studs and other general engineering parts. EN8 carbon steel is much stronger than mild steel, because it is an hardened medium carbon steel and it is readily machinable in any condition, even though it is generally supplied in its untreated condition. EN9 workpiece material has a lower wear rate in rotating parts, which may be due to a higher carbon content resulting in an increased yield strength and ultimate strength. It has 0.5% carbon steel giving rise to higher tensile strength than EN8. Both the two types of workpieces (BS 970 080m40 and BS 970 070m55) come in two different forms which are the bright EN8 and EN9 bars and the black bar types. While the chemical composition of both the bright and black bars are the same, the formation process differs as black bars are formed through the ‘rolling process’ under heating conditions while the bright bars are formed through the ‘drawing process’ in cold-reduction mills at room temperature.

Table 3.1: Mechanical Properties of the Workpiece Materials

Material	*BS 970 080m40 (bright)*	*BS 970 080m40 (black)*	*BS 970 070m55 (bright)*	*BS 970 070m55 (black)*
Tensile Strength (MPa)	660	550	700	600
Yield Strength (MPa)	530	280	>=415	>=310
Brinell Hardness	201 - 255	201 – 255	201-255	201-255
Elongation (%)	7	16	20	13

Bright steel bars are marked with higher physical strength over the hot rolled (black steel) bars of the same composition. The bright carbon steel EN8 and EN9 bars are of interest in the research study. Table 3:1 shows the mechanical properties of the used workpiece materials while Table 3:2 shows the chemical components of the used workpiece materials.

Table 3.2: Chemical Composition of the Workpiece Material

Workpiece Material	*BS 970 080m40*	*BS 970 070m55*
Silicon	0.05 – 0.35 %	0.05 – 0.35 %
Manganese	0.6 – 1.0 %	0.5 – 0.8 %
Sulphur	0.050 % Max	0.04 % Max
Phosphorus	0.06 % Max	0.04 % Max
Carbon	0.36 – 0.44 %	0.5 – 0.6 %
Chromium	--	--
Nikel	--	--
Molybdenum	--	--

3.6 Sensor Selection

The TCWM system used in this research focused basically on both single axial or triple axial vibration, the thermal image and the surface roughness parameter of the workpiece. The condition of the machine tool in an off-load operational mode was evaluated based on the vibration parameter. The system was also evaluated during turning operation to monitor and capture the condition of the cutting tool and the workpiece based on the vibration parameter of the system. A long-range wireless advanced vibration meter sensor MNS 2-9-W2-AC-ADV was used to capture the vibration data from the system. This sensor was integrated into a wireless adapter gateway to enable remote data capturing. Both devices are manufactured by iMonnit, and are equipped with industry-based specifications. Figure 3.5 A shows the image of the sensor and B is the sensor adapter gateway to the network. In addition, the sensor adapter helps with signal processing and transfer to the remote cloud server that is accessible online, bringing about the implementation of the cyber-physical system for the smart machining process. The vibration sensor has the capability of measuring the vibration along a single and three axes (the x, y and z axes) accurately. Also, the heartbeat of the vibration sensor can be adjusted to capture at different operating intervals, such as in seconds or minutes. For the study, the heartbeat was set to 10 seconds for prompt capturing of the trend of event during manufacturing and also for reducing the cost of computation due to data size if otherwise reduced.

The temperature of the cutting zone can be measured using a thermal image camera FLIRONE PRO LT, P/N 435-0015-03 M/N0015 with thermal sensitivity of 0.15^0C. The thermal image sensor has a resolution of 50 x 60 pixels and can capture temperature variations in the cutting zone between the range of -10^0C to 330^0C. The sensor device was positioned to capture the temperature variations of the cutting zone during the machining operation while being connected to a screen via a USB cable connector. However, the obstruction of the region of the cut made it impossible to capture the thermal image without creating a narrow gap between the cutting tool and the workpiece. Hence, capturing the thermal image would entail that the process be stopped intermittently during operation to enable accurate capturing. Since the study focused on developing a TWCM system that captures and diagnoses the condition of the tool and workpiece surface during operation non-obstructively, the thermal image capturing was discarded.

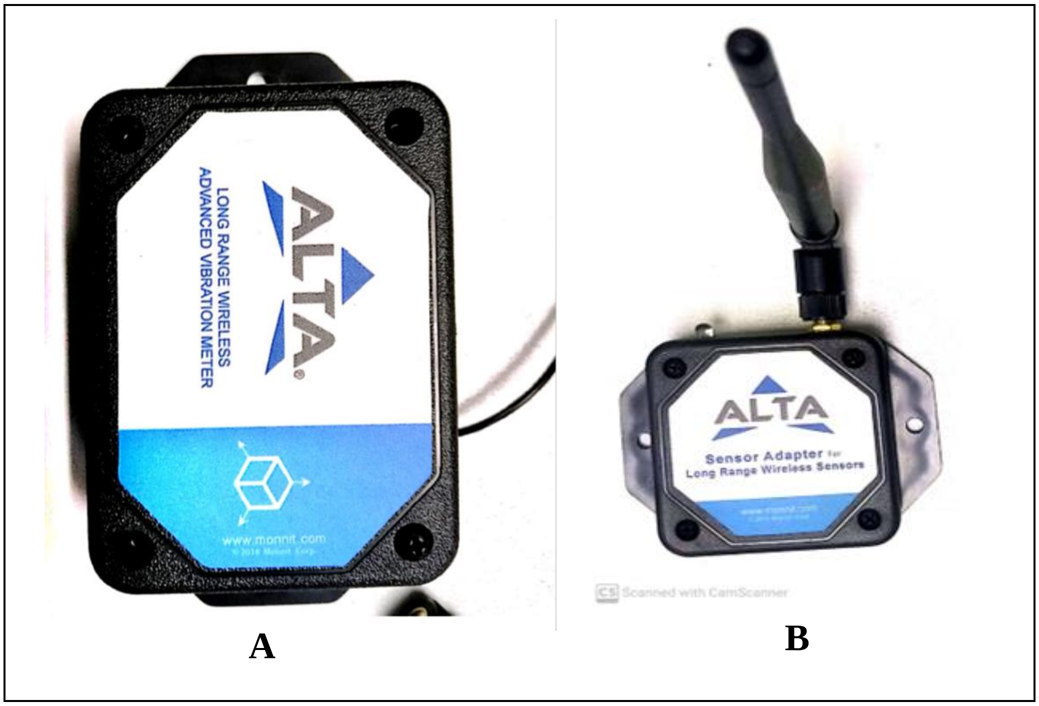

Figure 3.5: Wireless Vibration Sensor and Sensor Adapter

The workpiece surface finish was measured using the surface roughness tester equipped with the precision sensor. This equipment is highly sensitive and robust, with DSP chip control and data processing with high speed. The device measures about 20 parameters including R_a, R_z, R_q, R_t, R_p, R_y etc. with a large measurement range of about $160\mu m$. These intuitive parameters with graphical display are applied for deducing and analysing the flank wear condition of the cutting tool intermittently during operation and the data is recorded to develop the knowledge base system for diagnosing the tool and workpiece condition during operation. The surface roughness tester consists of the following parts, which are the sensor, the display (HMI), the key area, the adjustable support, USB charger, power switch and the calibrator. The image of the device is shown in Figure 3.6.

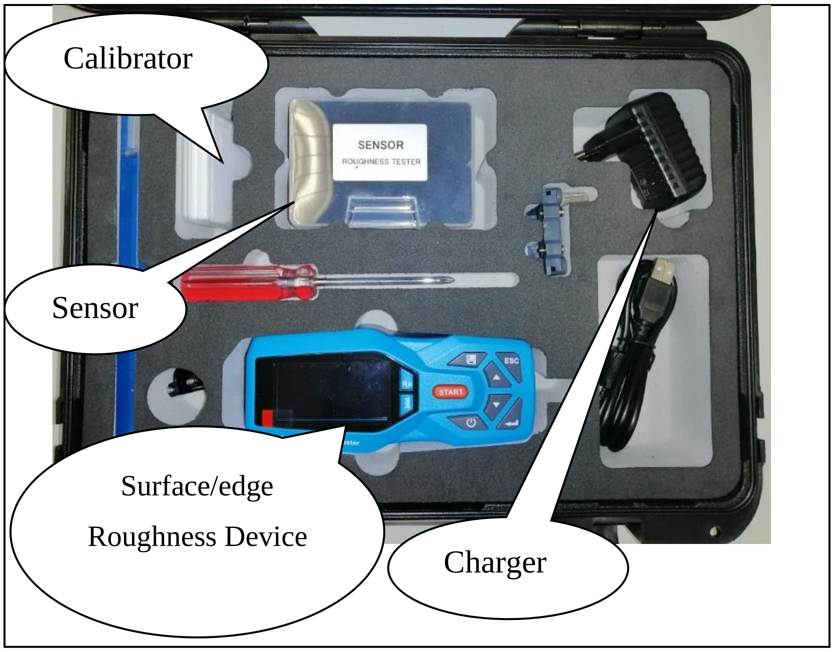

Figure 3.6: Surface/edge Roughness Tester

The surface and edge roughness measuring device is also used to capture and monitor the wear profile of the cutting tool. The cutting tool flank wear is used for classifying the classes and range of quality output of the surface parameters of the workpiece produced during machining for optimal productivity. This is a novel approach developed on the basis of the related surface parameters derived from the measurements taken using the instrument. The approach embraces the data analytics approach using the machine learning AI method for detecting cutting tool wear and the roughness signature on the workpiece material.

3.7 Assessment of the Cutting Tool Condition

Evaluating and assessing the state of the cutting tool before and during the cutting operation is very important as it determines the quality of the output produced and reduces the running cost of production. Tool wear occurs in different forms depending on the change in the geometry of the cutting edge and flanks. As this may be a common challenge at a turning machining station, another tool deterioration phenomenon that needs to be monitored during machining operation is tool chipping, which can be defined as the loss of small fragments of tool material due to the occurrence of cracks in the cutting part of a tool (Colpani *et al.* 2019). Chipping in most cases affects the cutting ability of the cutters, hence it is important to detect it early to prevent damage to the workpiece. Excessive vibration of the machine tool could cause tensile stress on the cutting edge which may result in chipping of the cutting tool, while cutting with a chipped cutting tool will also increase the vibration of the system which in turn affects the surface smoothness of the workpiece. Hence, monitoring the vibration parameter at a machining station becomes imperative in order to have an optimized system. In this work, an advanced vibration meter was used to capture the vibration parameter and analyze it using the machine learning AI method to classify the condition of the cutting tool and machine tool. Each class of cutting tool with a known flank wear range was used to perform a turning operation while the vibration signal during the operation was captured by the vibration sensor installed on the tool post of the machine tool. The corresponding surface parameters of the workpiece were measured and recorded. The turning operation was repeated five times to measure the accurate data range of the workpiece surface parameters for each tool class.

3.7.1 Real Time Tool Assessment

Monitoring the condition of the cutting tool during a turning operation requires a painstaking approach due to the obstructive nature of the cutting environment. An advanced vibration meter MNS 2-9-W2-AC-ADV captures the real time condition of the system by sending the vibration signal to a remote server for analysis and condition diagnosis. Abrupt change in the monitored condition with a corresponding excitation in the vibration parameter is an indication of a likely damaged cutting tool or other condition deterioration. The artificial intelligence method uses the machine learning algorithm to train a model to intelligently detect the condition of the cutting tool and workpiece from the series of events learnt during the operational data training process. The signals captured during the turning operation for each class of tool were noted and labelled accordingly. This was to enable the machine algorithm to train the model to identify the subsequent condition of the tool and workpiece surface parameters during operation without stopping the machining process. The vibration signals captured during the turning experiments cannot be used directly for the classification process as the signals are in a time series and transient. Therefore, advanced signal processing techniques were applied to the signals to extract physical properties capable of discriminating between the signals based on different conditions of the tool and workpiece during the machining process. The vibration signals were captured at a heartbeat of 10s on the remote cloud server and the data analyzed to ascertain the condition of the cutting tool in real time. The vibration data was measured during each turning stroke by the cutting tool and the resulting tool wear and workpiece surface finish parameters were measured using the surface/edge wear measuring device. This was repeated within the interval of the heartbeat and the data were trained for feedback on real-time condition assessment for classification of the resulting production output. The remote monitoring system of the condition during the turning operation was designed to achieve the Third Objective of determining and capturing real-time signals for detecting tool and workpiece surface wear condition through developed inter-connected, non-obstructive hardware with advanced signal analysis.

3.7.2 Offline Tool Assessment

Cutting tool inserts were assessed using the surface and edge wear measuring device after each predefined machining interval during the turning operation to evaluate the wear and chipping characteristics. Flank wear and chipping were measured carefully using the surface roughness device to monitor the wear during the turning operation. This was to determine whether or not the tool class remained the same or changed in the course of the turning operation. Different tool conditions such as brand-new tool, good but used tool, rough tool, and worn tool were measured before commencing the turning operation and classified using the ISO3685:1993 standard. Uniform and maximum flank wear was evaluated from the parameters measured by the surface roughness tester. Figure 3.7 represents the sketch of the cutting tool inserts with the features such as the rake face, cutting edge, chipped zone and others. The flank wear was of particular interest during the study because it was used as the basis for classifying the cutting tools. The flank wear of each tool insert was therefore measured after each turning operation.

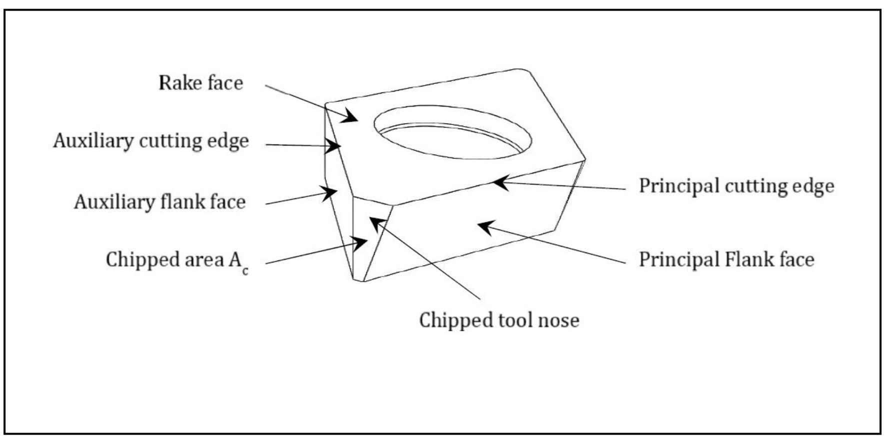

Figure 3.7: Cutting Tool Inserts Features with the Chipped Area

3.8 Assessment of Workpiece Surface Roughness Parameters

The surface finish of a workpiece is an integral part of precision manufacturing for a turning operation. The surface finish parameter of a workpiece dictates the functionality of the components as well as the number of scrapped workpieces during production due to deviation from the specified surface requirement. The surface roughness parameters of the workpiece are measured using the sensitive precision instrument to assess the workpiece condition. Surface parameters that are of interest to the study were determined by evaluating those parameters influenced by different tool flank wear conditions. This implies that the factor of influence is the flank wear condition of the cutting tool. The parameters were evaluated by applying MANOVA analysis on the surface roughness parameters captured by all the four (4) classes of cutting tool. The analysis is discussed in detail in Chapter 4. For each tool class, the corresponding range of values for the surface parameters that respond to the factor of influence were evaluated and recorded. Automobile parts, which are an internal member, coupled parts, or a rotating component are often required to have a specified level of surface finish. Therefore, measuring the quality level of the surface being machined becomes particularly significant during operation. This study monitored and picked up the conditions that indicate the levels of surface roughness of a workpiece, integrating the operating parameters and the tool conditions as well as the machine on-condition. The approach was evaluated both in real time and offline to assess the workpiece.

3.9 Real Time Assessment of the Workpiece

The development of a workpiece surface roughness monitoring system entails evaluating the workpiece surface condition during the cutting process. However, because of the obstructive nature of the turning operation, indirect measurement considering the vibration parameter in real time analysis was utilized. The vibration heartbeat was firstly captured at 10 minutes to allow for direct measurement of the tool surface and edge parameters for each vibration measurement and then at 30 seconds once the data was trained for predicting the output class of each captured signal. The real time assessment of the workpiece was achieved through a data-driven approach that classified the signal captured during operation into a data range based on prior knowledge generated from the experiment and modelling approach. The vibration signal captured was processed and used to determine the class the workpiece being machined belonged to. The corresponding vibration signal for each tool and workpiece surface and edge condition was analyzed using mathematical functions to extract features that would indicate the difference in classes of the condition of each tool and workpiece. The machine learning method, neural network algorithm using SCG algorithm, SVM and KNN were used to classify the extracted features from the signal while it was evaluated against the cutting tool condition and the measured surface roughness value of the workpiece using the surface and edge roughness tester. Two workpiece materials, bright carbon steel BS 970 080m40 and BS 970 070m55 were used to learn more about the effects of different tool wear classes on varying workpiece material.

3.9.1 Offline Workpiece Assessment

The surface roughness parameters of the workpiece were assessed after each predefined machining interval during the turning operation to correlate the corresponding measured operating vibration parameter to the surface roughness values. The research work sought to find the correlation between the tool wear, machine operating condition (vibration of the machine tool), and the surface profile parameters of a workpiece. A highly sensitive surface roughness tester that measures about twenty (20) surface features of the workpiece material was used. The data from the measured features were recorded and analyzed for the workpiece surface profile properties before the turning operation began to determine the significance of tool condition on the surface finish of the workpiece and the machine operating condition (vibration of the machine). The surface profile parameters of the workpiece were also measured and recorded after each turning operation to measure the range of the parameter values for each tool class. The result was used in developing the knowledge base for classifying the output of each tool class using the machine learning classification algorithm.

3.10 Experimental Set-up

The development of the TWCM system requires that the static signals for each monitored parameter are first captured before commencing operation. The surface smoothness of both the cutting tool inserts as well as the workpiece material was measured using the surface and edge wear measuring device. The workpiece is a cylindrical medium carbon steel bar, and the surface measurement was taken along the longitudinal surface of the workpiece, while the block-shaped rectangular cutting tool insert was also measured. The flank face area of the cutting tool insert was mapped out for surface roughness testing using the testing instrument, and the cutting edge of the cutting tool insert was methodically held for flank and edge wear measurement. This approach of developing a knowledge-based system, that optimizes the tool and workpiece condition by classifying the relative range of the tool and workpiece surface conditions with its corresponding significant surface profile parameters, had not been found in the existing literature at the time of conducting the research. Twenty (20) measured features were captured for all the surface roughness measurements, and the data was analysed to understand the significant parameters that indicated the wear and edge condition of the tool and workpiece before cyclic impact of load from the operation. The analysis was done using MANOVA analysis as earlier mentioned. This analysis is discussed further in Chapter 4. The illustration for the measurement of the flank wear of the tool insert in an offline condition is shown in Figure 3.8.

Figure 3.8: Surface Roughness Measurements for Cutting Tool and Workpiece

In addition, the vibration signal of the machine tool was captured while performing the turning operation to learn about the pattern of mean excitation of the machine before the start of the turning operation. This would also project into the condition of the machine tool when in a stable working state, normal loaded working condition, and faulty or abnormal working condition. A data classification technique using neural network feed forward backprop with SCG algorithm was deployed to learn about the behaviour of the system under varying circumstances and reconciled with the corresponding output of the signal. Besides the Feed Forward Backprop with SCG, the SVM and KNN algorithm was also deployed for the classification of the tool and workpiece conditions. These models are optimized by applying Genetic Algorithm (GA) for feature selection in order to improve the performance of the model in terms of time. Also, to optimize the training algorithm, the k-cross validation technique was adopted. This helps to eliminate bias and also optimise the learning algorithm to get the model with the best performance. The error loss was evaluated for the learning algorithm and the results plotted for comparison of the result output for determining the model with the best performance. Real time sensor data captured during the operation of the machine tool and workpiece may be integrated into a machine tool simulation to produce the digital twin of the machine tool; however, that was outside the scope of this research as the data were intelligently analyzed to evaluate the state of both the cutting tool and workpiece during operation.

3.11 Tool and Workpiece Surface Parameters Selection Using MANOVA Analysis

The parameters measured by the surface and edge wear measuring device provide many details and much information regarding the condition of both the cutting tool and the product output. It is, however, important to know the parameters that are of the utmost significance to the condition of both the cutting tool and the workpiece. To effectively identify those parameters out of the twenty-one measured parameters by using the surface and edge wear measuring device Multiple Analysis of Variance (MANOVA analysis) was used. This analysis takes into consideration the group mean and grand mean of the distributed data group. It is based on a null hypothesis that states:

$$H_0\colon\ \mu_1 = \mu_2 = \cdots\ \mu_L\ \ Null\ Hyphethesis$$

$$H_1\colon\ \mu_1 \neq \mu_M\ \ Alternative\ \ Hyphethesis$$

MANOVA analysis evaluates some parameters from the different groups of data and determines if the null hypothesis is to be accepted or rejected. The condition for acceptance or rejection of the model is stated as:

If the evaluated F − value (F) is larger than the f critical value ($F\ crit$) or

If the p − value is smaller than your chosen alpha level.

The rejection of the null hypothesis indicates that the relative tool condition does have a significant effect on a particular parameter/s and vice versa. Hence, the null hypothesis must be considered in classifying tool and workpiece condition during a turning operation. In this study, the alpha level of the model was chosen as 0.05 and therefore any p-value less than α- value (0.05) meant that the null hypothesis was rejected and hence, the relative tool condition (based on wear) did not have a significant effect on any of the parameters being evaluated. This analysis is discussed in detail in Chapter 4.

3.12 Real Time Tool and Workpiece Condition Monitoring (TWCM)

The TWCM system comprises of hardware components configured for data acquisition with internet capabilities for both an offline and online monitoring system. While some monitoring devices are industrial reconfigurable IoT devices with a pre-existing online platform for implementing and optimizing algorithms for captured data, some hardware are just simply stand-alone instruments that require connections with HMIs and storage devices for data analysis. These two types of instruments are integrated into the monitoring system for improved flexibility and scalability of implementation for data acquisition and signal processing tasks. In addition, since the monitoring system captures the condition of the cutting tool, the workpiece as well as the machine tool, it therefore becomes imperative to simultaneously acquire signals and extract advanced features from the signals in order to capture the real-time conditions of the tool and workpiece during operation.

The monitoring system schematic can be divided into two (2) robust layers. The first layer is the user interface layer which accepts inputs from the user, displays the decision output, and presents the visual dashboard of the overall monitoring system. The second layer is the application layer that interprets the real time data, applies a processing algorithm for feature extraction and decision making and presents the operator with an optimized output condition of the workpiece and the tool. In the case where the machine tool is using a Field Programmable Gate Array (FPGA), optimized signal outputs can be sent to the real-time controller of a FPGA for automatic self-adjustment and re-configuration; however, this study was limited to classifying the output class of the product and cutting tool output, allowing the operator to be aware of the wear conditions of both the tool and the workpiece. The industrial IoT wireless vibration sensor used in this study has an existing platform, API, built for signal capturing, processing and decision making using some existing optimized algorithm library. The platform has the capability of accepting the new optimized method or model for signal processing and decision making. In addition to the existing IoT front and backend platform for vibration data analysis, feature extractions were done on MATLAB programme/software codes for signal processing and analysis for the TWCM system. Other monitored signals and parameters were integrated into the software for real-time optimized analysis and decision making. Figure 3.9 shows the schematic of the implementation of the TWCM systems. The two (2) integral layers of the system are illustrated including the hardware components of the TWCM system. The remote monitoring system for capturing the condition during turning operation was designed to achieve the Third Objective of determining and capturing real-time signals for tool and workpiece surface wear condition through a developed inter-connected, non-obstructive hardware with advanced signal analysis.

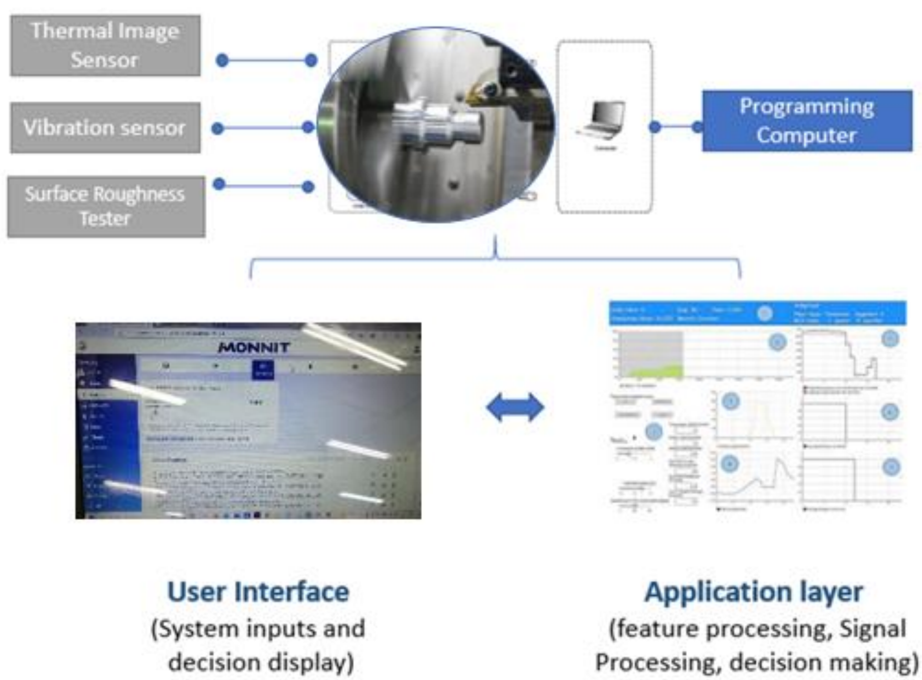

Figure 3.9: Schematic of TWCM System Implementation

3.12.1 Advanced Data Analysis Techniques for TWCM Systems

Adopting the recently advanced technologies of IoT, Cloud Computing, and AI is a good approach in precision manufacturing; however, the analysis and synthesis of data that is captured by the smart devices provides the strength for the method. While the artificial neural network with feed forward backprop algorithm, SVM and KNN, are used for training and classifying the processed signals into possible classes, several functions are used in extracting features from the captured signals from the machine tool.

3.12.1.1 *Tool and Workpiece Parameters Classification*

In this study, the output was classified into four (4) classes based on the conditions of the cutting tool and the resulting outcome of the production (workpiece surface measurement). The four (4) classes of cutting tools such as brand-new cutting tool, used but good cutting tool, rough cutting tool, and worn cutting tool, were considered for the study. The surface and edge measuring device was used to capture the edge wear parameters of each of the classes of cutting tool and their resulting production output. The same wear measuring device was used to capture the surface roughness/smoothness parameters of the corresponding workpiece produced by each tool category. The vibration signals during operation using each category of cutting tool were captured and the resulting workpiece surface quality was measured. Table 3.3 shows the representation of the categories of tools and the corresponding range of roughness parameters denoting the surface and edge wear of the cutting tool using ISO 3685:1993.

Table 3.3: Tool and Workpiece Classification

Para	**New**	**Good**	**Rough**	**worn**
Ra	0	< 0.15	0.15 – 0.25	0.25 – 0.35

Table 3.3 shows the classification of tools and the corresponding wear/edge parameters of each of the cutting tools, with the columns indicating the range of parameter values for the cutting tool. while the range of parameter values for the resulting surface finish of the workpiece can be

measured and recorded as well. The range of values is derived by measuring the flank wear/edge wear parameters of the cutting tool before the turning operation, as well as afterwards, while capturing the vibration signal during the operation, and measuring the resulting surface finish of the workpiece after each stroke at constant feed rate and speed. These classes are essentially the output of the TWCM system during operation for determining the condition of the tool and workpiece and are given a label one (1) to four (4).

3.12.1.2 *Advanced Signal Analysis and Feature Extraction*

Signal or data analysis is an integral component of the TWCM system as it provides the interpretation of the data and signals for the decision-making algorithm. Vibration signals captured during the turning operation are a dimensional parameter which, however, can be synthesized into several pertinent components capable of interpreting conditions and systems during operation. The thermal image capturing experiment for analysing the TWCM system in the cutting failed for two (2) reasons. Firstly, due to the obstructive nature of the turning operation, the image of the contact region could not be exclusively captured. To capture the thermal image and temperature of the cutting region, it is very important that the point of contact between the cutting tool and the workpiece be captured, which failed in the experiment due to the region of cutting. Secondly, since there was relative movement of the cutting tool against the rotating workpiece, it became extremely difficult to capture a static thermal image accurately during operation.

Therefore, the vibration signal was carefully captured, and the advanced analytical tools and approach was adopted for extracting features from the signals to capture both the detail and the transient condition of the cutting tool and workpiece during operation.

3.12.1.3 *Application of Digital Filters on Vibration Signal*

Vibration signals captured during turning operation are quantitative data that require signal manipulations, and some parameter estimation before being used for further detailed analytical functions. The advanced industrial vibration sensor used for the study captures vibration in three different units, which are acceleration, mm/s^2 , vibration in mm/s and gravity, g. The unit of the vibration on the cloud server was chosen as accelerometer in mm/s^2. Digital filters were applied to signals to separate their individual components and either enhance or reduce them using some mathematical functions. This helped to visualize the variation of the signals over time. The filter function can generally be represented as in equation 1 below.

$$V_f = filter(b, a, V)$$

Where V_f is the filtered vibration signal, while V is the input raw vibration signal, and a and b are numerator and denominator coefficients of the rotational transfer function.

The main objective of applying the filter was to eradicate the slowly varying contribution due to the alignment of the vibration sensor (accelerometer) to the rotational field. However, since the signal was non-stationary and non-linear, a better approach, which is the signal decomposition method, was adopted.

3.12.1.4 *Signal Decomposition Using the EMD Method*

The EMD method is a better approach for analysing non-linear and non-stationary signals. The EMD method decomposes signals into components to gain insight into inherent features. The signal is decomposed into a finite number of IMFs (real part) and the residual (imaginary part) as indicated in equation 2.

$$f(t) = \sum_i imf_i + res \ldots \ldots \ldots \ldots \ldots \ldots (2)$$

Where imf_i is the intrinsic mode functions and the residual. The EMD function evaluates the local extrema of the signal and fits the maxima ($E_{up}(t)$) and the minima ($E_{low}(t)$) to an individual envelope. The mean of the upper and lower envelope is determined as indicated in equation 3.

$$E_{mean}(t) = \frac{(E_{up}(t) + E_{low}(t))}{2} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (3)$$

The residual component of the signal is determined as indicated in equation 4.

$$res(t) = f(t) - E_{mean}(t) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (4)$$

Since the process is finite, the stopping criterion is determined by equation 5.

$$\sum t = \frac{(res(t) - f(t))^2}{f(t)^2} < \in \cdots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (5)$$

Therefore, the decomposition stops when the residual approaches a monotonic function. The signal is decomposed into IMFs and residuals. The IMFs are then further processed by applying HHT transform to extract the physical features from the signals.

To determine the instantaneous properties from the decomposed IMFs and res, HHT is applied. HHT is applied to compute the instantaneous energy and instantaneous frequency of each IMF mode. For each IMF, x_i, the HHT function computes the components as indicated in equation 6.

$$x_i = f(i) + iH\{f(t)\} = A(t)e^{i\varphi(t)} \dots\dots\dots\dots\dots\dots\dots.. \quad (6)$$

Where H$\{x_i\}$, is the Hilbert Transform of x_i and A(t) is amplitude, φ instantaneous phase. The amplitude and phase are expressed in equations 10 and 11 respectively

$$(t) = \sqrt{f^2(t) + H\{f(t)\}^2} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (7)$$

$$\varphi(t) = arctan\left(\frac{H\{f(t)\}^2}{f(t)}\right) \dots\dots\dots\dots\dots\dots\dots\dots..\dots\dots\dots (8)$$

Hilbert Transform provides a unique imaginary component, $H\{f(t)\}^2$with the instantaneous energy given in equation 9 and the instantaneous frequency in equation 10.

$$\rho = |A(t)|^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (9)$$

$$\omega(t) = \frac{d\varphi(t)}{dt} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots (10)$$

Since most frequencies are not continuous, Hilbert Transform is based on the discrete Fourier Transform.

The feature vectors for classifying the conditions of the tools are computed by applying Hilbert Transform on the IMFs of the decomposed signals. The features are therefore the instantaneous frequencies, energy, and amplitude of the IMFs as indicated in equations 8, 9, and 10 respectively. Since the instantaneous energy is very dependent on the amplitude, the feature vectors are usually the instantaneous frequency and energy for classification models. In this study a total of 12 features were computed from the IMFs of the decomposed signals.

To reduce the computational cost of the classification model, feature selection was performed through optimization using the GA model to select the features that were essential for the learning algorithm. The number of features was reduced to four (4) features after feature selection was done using the GA model, using the Roulette Wheel (RW) method. The fitness probability of a single chromosome in the generation is determined by equation 11.

$$Fp = \frac{F_i}{\sum_{i=1}^{n} F_i} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (11)$$

Where F_p, is the fitness probability of *i*th chromosome, F_i, is the fitness value of *i*th chromosome.

3.12.1.5 *Classification of Tool and Workpiece Conditions Using Artificial Neural Network Feed-Forward Backprop with SCG, SVM and KNN Algorithm for TWCM System*

Interpretation of the extracted features from the signal buffer is a daunting task as it indicates the condition of the tool and workpiece based on the existing measured parameters from the classes of tools and workpiece and the corresponding vibration signals propagated during turning operation. Several classification algorithms using AI techniques exist that determine the class of a set of data buffer based on the knowledge of a trained network of data. There are 12 features that were extracted as the instantaneous properties from the evaluated IMFs obtained from the decomposed signals using EMD. These features are extracted by applying HHT on the decomposed signals to obtain the instantaneous properties, such as instantaneous energy, instantaneous frequency, and instantaneous amplitude. While the features are very important for the classification algorithm, this may just as well be optimized by selecting very essential features from the 12 extracted features using the intelligent feature selection methods. The result of the performance of the model is then compared against when the feature selection approach was not used. For this study, the GA feature selection algorithm was used and the number of features was reduced from 12 features to 4 features and the result was computed. A feed forward neural network backprop algorithm type with one (1) hidden layer using scaled conjugate gradient for training the data was used for classifying the condition TWCM system. The SVM and KNN algorithm was also applied and the optimal model was determined from the result by computing the model with the least error loss. The input layer was twelve (12) while the hidden layer had eighteen (18) nodes, and the output was four (4) while, when the GA feature selection was applied, the input features were reduced to four (4). The algorithm trains the network using a push of data set that adapts internal parameters of the network so that it can identify the right tool and workpiece condition class. The k-fold cross-validation techniques were also adopted to optimize the best grouping for training, validation and test set for each of the models and the one with likely optimal performance. Hyperparameter optimization was performed on the best model selected after applying the k-fold cross-validation techniques. The objective of the optimization was to minimize the classification error loss of the model and the constraints were the distance metrics of the model. The distance metrics with the least classification error loss were determined.

In addition, the classes in this research based on the wear parameters of the tool and workpiece conditions were four (4) hence, numbers from 1 to 4 were used as the labels to represent each of the classes. These labels were converted to dummy variables to allow the MATLAB function to read them as an output of the trained network. It therefore implies that many more classes of tool and workpiece condition may be considered by the method. The overall performance of the neural network is indicated in the confusion matrix. The bottom right box of Figure 5.9 indicates the estimate of the percentage accuracy of the trained network, while some error in calculation can also be visualized on the same confusion matrix. With more data buffer available for training, the algorithm can be improved upon.

3.13 Conclusion

This chapter described the experimental set-ups for the TWCM system, including the machine tools for turning operation, the workpiece materials, and the cutting tools. The research focused on turning operation, therefore, a variety of cutting tool inserts with geometries was used for the operation. This was employed to examine the effect of tool geometry on the TWCM system. Furthermore, four (4) kinds of workpiece materials were used for the experiment to test the effect of different workpiece materials on the TWCM system. The chapter thereafter discussed the machine tool for turning operation, the cutting tool, the workpiece materials, and sensors selection.

In addition, the assessment of the cutting tool condition, which was discussed in sub-sections, namely, Real Time Tool Assessment, and Offline Tool Assessments was described. Assessment of workpiece surface roughness was also discussed in the sub-sections Real Time Assessment of Workpiece Condition, and Offline Workpiece Assessment. The properties of each parameter discussed were also included in those subsections for clarity. The experimental set-up for the TWCM system was also described in this chapter. This included the sensors selection, parameters selection, measuring range and connections. The properties of the workpiece materials were also presented and the specification of the systems hardware as well as the position and orientation of mounting were shown.

Furthermore, the real time tool and workpiece condition monitoring system, which includes the hardware and the software, was discussed. The schematics of the layers of the experiment were also described in this chapter. Since Section 3.11 addresses the Third Objective, which was to develop a non-obstructive tool and workpiece condition monitoring system that optimizes the tool condition and workpiece during turning operation, advanced signal processing techniques used for feature selection and extraction were discussed in this section. Experimental analysis of the vibration signal and thermal image indicated that the thermal image of the cutting zone during turning operation on the lathe could not be accurately captured due to the obstruction of the cutting region during cutting and the motion of the cutting tool during operation. Therefore, the signal considered for TWCM system was basically the vibration signal from an advanced industrial IoT vibration sensor that transmits data to the cloud which is a dedicated gateway. This implies that data can be remotely monitored and analyzed because of the cyber-physical devices, the gateway, cloud platform and IoT vibration sensor used for the experiment, which achieved the Third Objective of the study. Section 3.10.1 discussed the method for feature extraction which therefore addressed the Fourth Objective which was to extract features from advanced signal measurement and analysis capable of discriminating and classifying different tool and workpiece conditions during turning operation in real-time. Physical properties of the signals captured during the turning operation were extracted as features by applying some signal processing techniques and analyses on the captured signals. Feature selection was then performed using GA to reduce the computational cost and the time of the process. This was the Fifth Objective of the research which was to determine the optimal features through hyperparameter optimization using GA for selection of important features for the ML algorithm. The feature vector was trained for data classification using the ML classification algorithm. The Neural Network SCG algorithm was first applied to train the data for classification. Furthermore, SVM and KNN learning models were also used for the classification model and the best-performing model was essentially determined from the loss function of each model. The sub-section highlighted in this section includes Tool and Workpiece

Parameters Classification, Advanced Signal Analysis and Feature Extraction, Application of Digital Filters on Vibration Signal, Evaluating the EMD of the signals, and application of HHT on the corresponding IMFs generated after the decomposition, classification of tool and workpiece conditions using Feed Forward Backprop Neural Network with SCG algorithm, SVM and KNN for TWCM system. The last Objective was achieved by optimizing the ML classification model developed for the Tool and Workpiece Condition Classification in order to determine the model with the least classification error loss.

CHAPTER 4 SURFACE PARAMETER EXTRACTION FOR SMART TOOL AND WORKPIECE CONDITION MONITORING SYSTEM USING MANOVA ANALYSIS

4.1 Introduction

There are several surface profile parameters that can be measured from any given surface, regardless of the type of material and the geometrical shape of the object. The characteristic properties of the surface are interpreted based on several thresholds measured by the precision instrument and may be seen as significant to the study of tool and workpiece condition monitoring especially in a smart manufacturing system. The product quality requirement at a machining station is considered to be important, subject to the tool conditions during operation. In precision manufacturing, the surface profile parameters as well as the dimensions are very important for any machined part at a machining workstation. This chapter discusses the analysis and evaluation of significant surface profile parameters for a smart TWCM system using MANOVA analysis.

Several turning operations were performed by using different classes of tool and the corresponding product surface profile parameters were measured. The experiment was performed intermittently to allow for precision in the measurement of the surface profile parameters. It is however, important to determine the surface parameter that correlates with the factor of influence, which is the tool wear condition during the machining operation. This chapter therefore describes the experimental investigation of the surface parameters of the workpiece conditions, the evaluation of the significant surface parameters to factor of influence (tool condition) using MANOVA analysis, and the range of surface parameters for each tool classes.

4.2 Experimental Investigation of the Surface Parameters of the Workpiece Condition

The first objective was to analytically determine the workpiece surface roughness (measured surface profile parameters) parameters that correlate with the cutting tool conditions for a turning operation. The significant surface parameters are used for developing the knowledge base system for determining the tool and workpiece condition during machining. The characteristic of each parameter needs to be determined to assess if it is critical to the study using the null hypotheses in MANOVA analysis. Since MANOVA allows the probing of several dependent variables simultaneously with a convenient way of managing the Family-Wise-Error-Rate (FWER), the analysis/approach was adopted to determine if the factor of influence was significant on the measured dependent parameters.

4.3 Experimental Set-up

To determine whether there are any other significant parameters measured from the surface of the workpiece relative to the cutting tool, four (4) cutting tool categories were used for the machining experiment. An indexable tungsten cutting tool with CCMT09T3034 carbide inserts was used for the turning operations. The first class of tools is the brand-new tool, the second class is the used good tool, while the third and fourth tools are the rough and worn tools respectively. The cutting tools are classified into new, good, rough and worn tools according to the international standard, ISO 3685:1993 based on the flank wear. Rizal *et al.* (2017) stated that the ranges of flank wear values are divided into three classifications, normal wear (VB = 0 – 0.15 mm), medium wear (VB = 0.15 – 0.25), and critical wear (VB = 0.25 – 0.35 mm), adhering to the ISO 3685:1993 standard. Similarly, this study classified tools using flank wear where the new tool is presumed to have 0 flank wear, the good tool is taken to have the same range with the normal wear (VB = 0-015mm), the rough tool has medium wear (VB = 0.16 -0.29mm) and the worn tool is taken as having flank wear similar to the critical wear range (VB > 3.0mm). As tools gradually move from one phase of useful life to another during turning operations it becomes very important to monitor the conditions in order to optimize production by reducing product quality not meeting the required conditions. Bright Carbon Cylindrical Steel Workpiece Material, BS 970 080m40 was used for running the test and after the turning operation, the workpiece surface profile parameters were measured.

The experiment was repeated by performing the turning operation and measuring the surface profile parameters from the respective cutting tool class used for the machining process. The data was recorded on a spreadsheet and can be illustrated as shown in Figure 5.4. The surface parameters were measured using the surface/edge roughness tester by Mitutoyo that captures twenty (20) relative surface/edge parameters of both the workpiece and cutting tool. To examine whether there was any effect of the factor of influence on the cutting tool conditions, the results were analysed using the multivariate MANOVA analysis. This helped determine the surface parameters to be used as part of the classification for the tool and workpiece condition monitoring system, as well as the range of values for each of these classes.

4.4 MANOVA Data Analysis

MANOVA, just like ANOVA, is based on the general linear model given in equation (12) (John 1998):

$$Y = \beta X + \epsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

However, for MANOVA analysis, Y is an n x m matrix of dependent variables, X is an n x p matrix of predictor variables, β is an p x m matrix of regression coefficients, and ϵ is an n x m matrix of residuals.

Least square regression for calculating the SS for each is performed in MANOVA in a similar way to ANOVA. By applying the conservation of variation law, the cross products are evaluated as in equation (13) below:

$$\mathrm{C}P_{total} = CP_{model} + CP_{residual} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . (13)$$

For MANOVA analysis, the simplest experiment with two (2) dependent variables (dv1, dv2) can be represented in equation (14) as indicated:

$$CP_{total} = \sum_{i=1}^{n} (y_i, dv1 - \bar{y}_{grand}, dv1)(y_i, dv2 - \bar{y}_{grand}, dv2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

From equation (14), if there are ‘k’ number of dependent variables, the formula will become equation (15):

$$CP_{total} = \sum_{i=1}^{n} [\prod_{j=1}^{k} (y_i, dv_k - \bar{y}_{grand}, dv_k)] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

The cross product for variation associated with the group means is:

$$CP_{model} = \sum_{j=1}^{m} n\, x\, \left(\bar{y}_{group_j}, dv_1 - \bar{y}_{grand}, dv_1\right)\left(\bar{y}_{group_j}, dv_2 - \bar{y}_{grand}, dv_2\right) .. (16)$$

Since the investigation considered more than two dependent variables, for ‘k’ number of dependent variables, equation (16) is evaluated to equation (17):

$$CP_{model} = \sum_{i=1}^{m} n\, x\, [\prod_{j=1}^{k} (y_{group}, dv_k - \bar{y}_{grand}, dv_k)] \ldots\ldots\ldots\ldots (17)$$

Similarly, the cross product, CP, for residual variation is evaluated in equation 13 for two dependent variables:

$$CP_{residual} = \sum_{i=1}^{n} \left(\bar{y}_i, dv_1 - \bar{y}_{group_i}, dv_1\right)\left(\bar{y}_i, dv_2 - \bar{y}_{group_i}, dv_2\right) \dots \dots \dots (18)$$

For this study, k number of dependent variables was considered, hence the cross product for residual variations across k dependent variables is given in equation (19):

$$CP_{residual} = \sum_{i=1}^{n} \left[\prod_{j=1}^{k} \left(\bar{y}_i, dv_j - \bar{y}_{group_i}, dv_j\right)\right] \dots \dots \dots \dots \dots \dots \dots (19)$$

To evaluate the overall variation, partitioning of the overall variation is required. The cross product as well as their relative sum of squares, *SS*, are assembled into matrices such as *T*, *H*, and *E* matrices representing total, hypothesis, and error variations respectively. From ANOVA analysis, each matrix representation for each variation can be expressed as follows;

$$T = \begin{pmatrix} SS_{total,dv1} & CP_{total} \\ CP_{total} & SS_{total,dv2} \end{pmatrix} \dots \dots \dots \dots \dots \dots \dots \dots \dots (20)$$

$$H = \begin{pmatrix} SS_{model,dv1} & CP_{model} \\ CP_{model} & SS_{model,dv2} \end{pmatrix} \dots \dots \dots \dots \dots \dots \dots \dots \dots (21)$$

$$E = \begin{pmatrix} SS_{residual,dv1} & CP_{residual} \\ CP_{residual} & SS_{residual,dv2} \end{pmatrix} \dots \dots \dots \dots \dots \dots \dots (22)$$

In MANOVA, with k dependent variables each variation can be evaluated in the following matrix representations illustrated in equations 23, 24 and 25. The novelty of MANOVA analysis is that the CP computes the variation associated with all possible relationships between each dependent variable unlike ANOVA analysis, which accounts for the variation between the dependent variables by only evaluating the SS parameter.

$$T = \begin{bmatrix} SS_{total,dv1} & CP_{total,dv1xdv2} & \cdot & \cdot & \cdot & CP_{total,dv1xdvk} \\ CP_{total,dv2xdv1} & SS_{total,dv2} & \cdot & \cdot & \cdot & CP_{total,dv2xdvk} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ CP_{total,dvkxdv1} & CP_{total,dvkxdv2} & \cdot & \cdot & \cdot & SS_{total,dvk} \end{bmatrix} \dots \dots (23)$$

$$H = \begin{bmatrix} SS_{model,dv1} & CP_{model,dv1xdv2} & . & . & . & CP_{model,dv1xdvk} \\ CP_{model,dv2xdv1} & SS_{model,dv2} & . & . & . & CP_{model,dv2xdvk} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ CP_{model,dvkxdv1} & CP_{model,dvkxdv2} & . & . & . & SS_{model,dvk} \end{bmatrix} ..(24)$$

$$E = \begin{bmatrix} SS_{residual,dv1} & CP_{residual,dv1xdv2} & . & . & . & CP_{residual,dv1xdvk} \\ CP_{residual,dv2xdv1} & SS_{residual,dv2} & . & . & . & CP_{residual,dv2xdvk} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ CP_{residual,dvkxdv1} & CP_{residual,dvkxdv2} & . & . & . & SS_{residual,dvk} \end{bmatrix} ....(25)$$

Unlike ANOVA analysis, the variation within each dependent variable is evaluated via SS, which limits the significance of being able to evaluate the variance between the dependent variables being considered for analyzing the condition of the tool as well as the workpiece, or product quality output. The total variation may therefore be evaluated from both the model variation and the residual variation.

The simple algebraic relationship for matrix addition is applied together with the rule of conservation of variation. This is illustrated in equation 26:

$$T = H + E \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(26)$$

The variations that occur across the dependent variables of the parameters evaluating the condition of both the cutting tool and the surface finish of the workpiece based on the factor of influence, are evaluated from the matrices derived from equation 26. The focus of the analysis is to evaluate those dependent variables that could intelligently indicate the condition of the tool and workpiece considering the factors of influence during machining operation. While ANOVA analysis evaluates F-statistics from the ratio of the model variance with df_1 degrees of freedom to residual variance with df_2 degrees of freedom, MANOVA essentially determines F-statistics with matrix determinants. From statistical analysis, the latter gives more pertinent details of the variations between the dependent variables and the factor of influence compared to the former. The congeners to ANOVA's model and residual variances in MANOVA are the hypothesis *H* and error *E* matrices with h and e being the degrees of freedom respectively. The degrees of freedom of the matrices are denoted as h and e degrees of freedom respectively and the test statistic for determining F-statistic and p-values are evaluated from deriving the eigenvalues of matrices $HE^{-1}, H(H+E)^{-1}$, $and\ E(H+E)^{-1}$ (as Covariates 2018). The eigenvalue is evaluated as stated in equation 27:

$$AX = KX \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (27)$$

Therefore, for a given matrix, A multiplied by the eigenvector X gives the eigenvector X multiplied by the scalar constant K.

Many statistical approaches for test statistics adopt Wilk's lambda; however, this study applied the Pillai test due to its robustness in multivariate MANOVA test statistics and the testing conditions assumptions. The test estimates F-test statistic from eigenvalues of matrix $H(H+E)^{-1}$. The test is derived from equation 28:

$$V = trace\ (H(H+E)^{-1}) = \sum_{i=1}^{n} \theta_i \quad \dots\dots\dots\dots. (28)$$

Where:

$\boldsymbol{\theta_i}$ Is the ordered eigenvalue of $H(H+E)^{-1}$

$\boldsymbol{p}$ is the rank of matrix $(H+E)$

q is the rank of generalized inverse of $(H+E)^{-1}$

s is the min (p, g)

$m = (|p-q|-1)/2$

$n = (v-p-1)/2$

To determine whether to accept or reject the hypothesis, i.e., whether the factor of influence plays any significant role on the dependent variables measured from the surface and edge conditions of the tool and the workpiece, the F-test statistic is evaluated. This is derived from equation 30:

$$F = \frac{2n+s+1}{2m+s+1} * \frac{V}{s-V} \dots\dots\dots\dots\dots\dots\dots\dots\dots (29)$$

P-values can therefore be estimated from the value of F with 2n+s+1 and 2m+s+1 degree of freedom from F-distribution table. With different tool conditions classified into X1, X2, X3 and X4 of different tool life, the dependent factors that correspond to the conditions are determined.

Rather than using tool life as a direct factor of influence in correlating the tool condition to the vibration signal emanated during the operation, it is used as a means of evaluating and validating some critical to quality parameters of the flank/edge wear measurement of the cutting tool. MANOVA analysis evaluates some parameters from the different classes of data and determines if the null hypothesis is to be accepted or rejected. The conditions for accepting or rejecting the model are stated as:

F: The value of F is larger than the f critical value (F crit) or

p: The value is smaller than the selected alpha level 0.05

The rejection of the null hypothesis indicates that the tool life which is the factor of influence does have a significant effect on a parameter and vice versa. Hence the parameter can be used for classifying the tool as well as the workpiece conditions during operation. Each cutting tool is also experimentally used for machining a workpiece at constant feed rate, speed and depth and the surface parameters for each tool are read and recorded and data for different output of each measured tool class is recorded.

4.5 Conclusion

This chapter has described the approach for analysing and evaluating the surface profile parameters of the workpiece to determine intelligent classification of the tool and workpiece condition during online tool and workpiece condition monitoring. Existing studies have mainly focused on the arithmetic mean roughness parameters for evaluating the workpiece condition alongside the tool condition for a machining operation. Some of the measured parameters of the edge/surface of the tool and workpiece are Rz, which is the mean roughness depth, Rz1max, maximum depth of roughness, Rt, total height of roughness profile, Rku, Kurtoisis, Rsk, Skewness, Ra, Average Roughness etc. Any of the parameters that reject the null hypothesis indicate that they are significant in analysing the condition of the tool as well as the workpiece. However, the novelty of the study is that rather than adopting categorical data based on tool life as the root knowledge behind the classification of signals produced by each condition, or classifying the tool condition based on the workpiece roughness parameter Ra, this study provides more detail about the parameters of the corresponding product/workpiece quality output (in terms of the correlated surface profile parameters) with the flank wear range of the cutting tool that generates the captured signal (vibration). The developed classification model therefore predicts the class, which details the range of the flank wear of the cutting tool as well as the range of values of the significant surface profile parameters of the workpiece. These will help in optimizing the tool requirement for each product and machining task based on the surface quality finish required by the customer.

This chapter has highlighted the method applied in the evaluation of the significant surface parameters of the workpiece used for developing the condition monitoring system for the tool and workpiece during a turning operation, which addresses the First Objective of the study. The experiment, detailing the turning operation with the corresponding tool class, has been discussed and explained. The classification of the tool class based on ISO 3685:1993 standard has also been highlighted. The mathematical analysis of the approach, MANOVA analysis, for determining which of the surface profiles are significant, has also been provided and enumerated in detail.

CHAPTER 5 : TOOL CONDITION AND WORKPIECE CHARACTERIZATION FOR WEAR DETECTION AND MONITORING

5.1 Introduction

This chapter discusses the results of the tool condition and workpiece characterization for condition monitoring for wear and surface finish of the production output. The critical components that are the focus of this study are the cutting tool, machine tool, and the workpiece for a machining turning operation. The condition of either of the three (3) components significantly affects the performance, or overall output, of the operation. The focus of this research was to optimally develop a tool and workpiece monitoring system that considers the product output requirement in terms of surface finishing and tool condition without necessarily intermittently stopping the operation before the classification of the condition, which addresses the Second Objective of the research. The parameters range for each class of tool and workpiece condition was determined, and the machine learning classification algorithm analytically and intelligently determined the class of tool and workpiece based on vibration signals captured during machining operation.

This chapter therefore describes the experimental investigation of the tool and workpiece conditions before use for signal appraisal for wear detection, experimental results of signals from offload machine operation, surface and edge wear parameters selection results using MANOVA analysis, vibration signal characteristics from different tool classes, vibration signal processing and analysis for real-time tool and workpiece condition monitoring, signal features extraction results, and detection of tool and workpiece conditions from extracted feature classification, validating the TWCM system by experiment.

5.2 Experimental investigation of the conditions of the tool and workpiece before use for signal appraisal for wear detection

This section focuses on measuring the threshold conditions of both the cutting tool before use (at 100% useful life) and the workpiece for wear analysis conditions using the surface and edge wear measuring device. The research is also aimed at investigating Cutting Tool Wear Characteristics by analyzing the surface wear parameters of different tool classes in a similar way to the workpiece. There are four (4) classes of cutting tool used for the investigation of tool condition and the corresponding condition of the workpiece. The first class of tools are the brand- new tools, and the second class is the used good tool, while the third and fourth tools are the rough and worn tools respectively. The tool classes are based on the ISO 3685:1993 standard that basically draws the distinction using the tool flank wear measurement with normal wear being less than 0.15mm, medium wear being between 0.15 – 0.25mm, and critical wear being 0.25mm – 0.35mm. The new tool has 100% useful life while the completely worn tool has zero (0%) useful life remaining. The good tool has a useful life of about 70% or more, while a worn tool has less than 50% useful life; however, it can still be used depending on the surface finish requirement of the job or product. Tools gradually move from one phase of useful life to another during the turning operation and it becomes very important to monitor the condition in order to optimize production by reducing the probability of the product quality not meeting requirement. The first task is to measure the flank surface/edge wear parameters of the tools. The experiment in this section measured the cutting tool flank surface/edge wear parameters using the Surftonic surface/edge roughness measuring device for both the cutting tool and the workpiece before commencing the cutting operation. The vibration parameter was not considered at this stage since the turning operation was yet to commence. The measured parameters were carefully observed and recorded to capture the variation in the conditions due to wear during the cutting operation as highlighted in the next section.

Table 5.1: Cutting Tool Classification

Tool Label	Tool Caption	Flank Wear
X1	New	0
X2	Good	0-0.15
X3	Rough	0.15 – 0.25
X4	Worn	0.25 – 0.35

5.2.1 Experimental Pre-Condition Results of the Cutting Tool and Workpiece

There are twenty (20) parameters that were measured by the surface/edge wear measuring device. The stylus was carefully positioned to measure the surface/edge roughness parameters using a holding device with four (4) degrees of freedom to allow for adjustment and re-positioning. To ensure an accurate measurement, the measuring instrument and the tool or workpiece must be held in a stable position and the stylus position must be set to be in the middle position as shown in Figure 5.1.

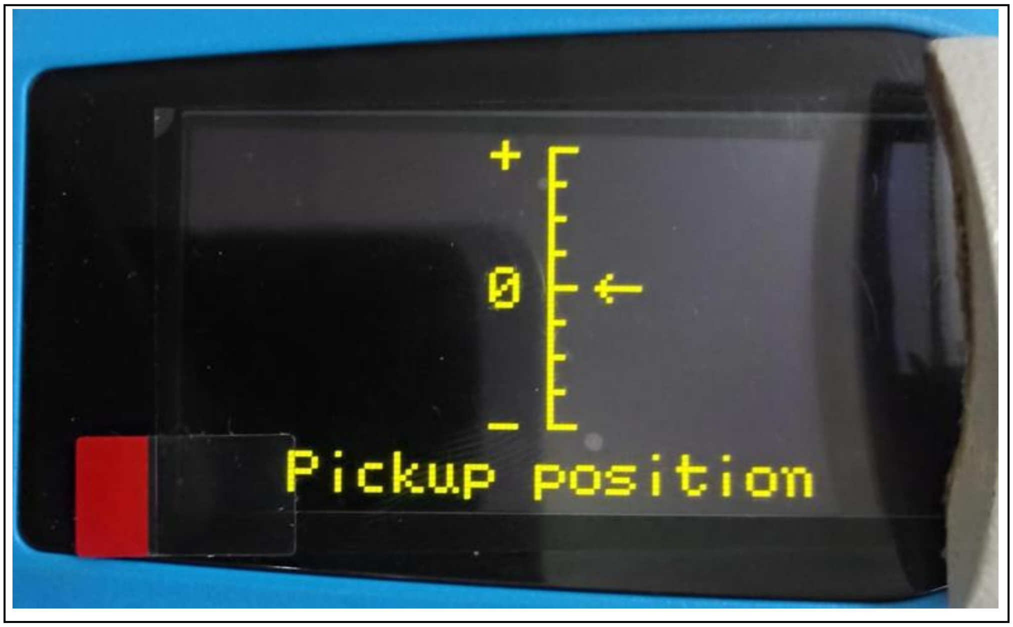

Figure 5.1: Stylus Position during Roughness Measurement

The measurement of the four (4) classes of tools was carefully done and the results recorded in a table format. The detail overview of the parameters measured from different tool condition showed that there might be some parameters which might not indicate any significant effect when the tool condition changed. In order to determine and select the parameters that were significant to the tool and workpiece surface edge wear detection, MANOVA analysis was adopted as described in chapter 4.

As discussed in Section 4.4, MANOVA analysis evaluates some surface profile parameters from the different groups of data and determines if the null hypothesis is to be accepted or rejected. The condition for accepting the model is if the $\mathrm{p}-\mathrm{value}$ is smaller than alpha level 0.05 while it is rejected if the p-value is greater than alpha. The set of data of a parameter, for example, R_a, from a new tool is analysed against the same parameter, R_a, from a rough tool and two other (2) classes of tools. As detailed in the analysis highlighted in section 4.4 of chapter four (4), the codes are written in MATLAB for the computations of f and p-values of the model. Some built-in mathematical functions in the MATLAB library were also applied for the computation and analysis of some parameters in order to derive both f and p -values. The result of the MANOVA analysis of all the surface profile parameters based on all the classes of tools are presented in Table 5.2. The result shows that the p-value of R_a is 0.010577, which indicates that the hypothesis can be rejected, and the variation in the tool surface/edge roughness has a significant effect on the parameter. Hence, the parameter, R_a, is a good indicator of the surface or edge roughness of either the tool or workpiece.

Table 5.2: Table of Surface Parameters Value with MANOVA Analysis

Dependent Var	df_{Btw-g}	df_{Wtn-g}	**F**	**p-values**	**Hypothesis**
R_{max}	1	18	17.95	0.000495	Accept
R_t	1	18	9.422	0.006604	Accept
R_z	1	18	33.78	0.000017	Accept
R_y	1	18	17.83	0.000512	Accept
R_q	1	18	19.39	0.000343	Accept
R_a	1	18	19.40	0.010500	Accept
R_{sk}	1	18	1.933	0.340893	Reject
R_v	1	24	0.001	0.980000	Reject
R_p	1	24	3.062	0.097000	Reject
R_{3z}	1	24	0.307	0.632200	Reject
R_{3y}	1	24	0.026	0.874000	Reject
R_{zJIS}	1	24	0.012	0.001000	Accept
R_{sm}	1	24	0.916	0.348000	Reject
R_{ku}	1	24	0.159	0.694000	Reject
R_{pc}	1	24	1.786	0.194000	Reject
R_{vk}	1	24	1.990	0.75200	Reject
M_{r1}	1	24	0.231	0.63500	Reject
M_{r2}	1	24	0.307	0.42700	Reject
R_{3y}	1	24	0.026	0.87400	Reject

The p -value of parameter, R_s, from the result table is given as 0.340893, which is greater than the alpha value of 0.05. This means that the null hypothesis was accepted, and that the parameter had no significant variation when the tool or workpiece surface or edge roughness changed. Therefore, this parameter was disregarded when classifying the tool and workpiece conditions for the TWCM system. Table 5.2 shows other significant parameters to the surface/edge roughness of the tool and workpiece using MANOVA analysis and the range of measurement recorded by the measuring instrument. This addresses the First Objective of the study which was to experimentally determine the surface parameters that correlated with the varying conditions of the tool during cutting operation. The parameter denoted as R_{zJIS}, is the Japanese standard for R_z, which also met the acceptance criteria. Hence, R_{zJIS}, was discarded since it represented the same parameter with R_z.

Therefore, six (6) parameters were considered for optimizing the classification of the cutting tool and workpiece surface/edge wear monitoring and analysis for the TWCM system. Table 5.3 shows the significant parameters to the surface/edge roughness of the tool and workpiece after computing using the MANOVA analysis method, and the range of measurement recorded by the measuring instrument is illustrated. These surface profile parameters were considered for tool and workpiece condition classification and a brief description of each parameter was also stated. This therefore achieved Objective One, which was to evaluate the surface profile parameters that correlated with the varying tool conditions. In this study, the cutting tool condition has been classified based on its flank wear using the ISO 3685:1993 standard. There was also a need to find the range of values for each of the significant parameters captured from the workpiece surface profile per each class of tool.

Table 5.3: Significant Surface Parameters Range for Tool and Workpiece

Measured Parameters	*Measuring Range*	*Description*
R_a	0.005 μ m ~ 16 μ m	Arithmetical mean edge/surface roughness value
R_z	0.02 μ m ~ 160 μ m	Mean roughness depth
R_y	0.02 μ m ~ 160 μ m	Max. Valley depth
R_q	0.005 μ m ~ 16 μ m	Root mean square deviation
R_t	0.02 μ m ~ 160 μ m	Total height of the roughness profile
R_{max}	0.02 μ m ~ 160 μ m	Max surface/edge roughness depth
	--	--

The measuring range for each of the parameters considered is also indicated in Table 5.3. The next section discusses the classification of the tool and workpiece condition based on the measured parameters of the classes of tool and the output workpiece surface quality after each turning operation.

Some of the data for the surface/edge wear parameters of the Cutting Tool and the Workpiece recorded before commencing the turning operation are shown in Table 5.4.

Table 5.4: Cutting Tool and Workpiece Measured Wear Parameters Before Operation

Ra	Rz	Rq	Rt	Rp	Rv	R3z	R3y	RzJIS	Rsk	Rku	Rsm	Rs	Rpc	Rk	Rpk	Rvk	Ry	Mr1	Mr2	Rmax
0.59	3.724	0.772	5.803	1.64	2.084	2.368	3.276	2.4	-0.25	3.08	0.03	0.02	232	1.573	0.754	1.236	5.803	12.1	84.6	5.8
0.549	3.43	0.682	4.41	1.831	1.599	1.888	2.45	2.1	0.24	3.19	0.03	0.02	240	1.773	0.662	0.719	3.662	8.8	90.9	3.66
0.566	3.436	0.705	4.462	1.811	1.625	2.012	2.321	2.2	0.16	3.02	0.16	0.02	240	1.794	0.723	0.66	3.843	8.6	88.9	3.84
0.45	2.873	0.573	4.153	1.465	1.408	1.687	2.038	1.85	0.16	3.37	0.03	0.02	256	1.437	0.673	0.615	3.895	10	92.1	3.89
0.435	2.837	0.564	4.617	1.207	1.63	1.64	2.063	1.75	-0.38	3.33	0.02	0.02	296	1.274	0.536	1.214	4.153	10.9	91.1	4.15
0.535	3.724	0.73	7.222	1.842	1.883	1.733	2.063	2.05	0.02	4.56	0.03	0.02	216	1.408	1.278	0.852	5.391	12.2	87.1	5.39
0.467	3.111	0.607	5.004	1.47	1.64	1.568	1.934	1.85	-0.17	3.79	0.03	0.02	256	1.431	0.721	0.856	3.998	11.1	91.3	4
0.596	3.91	0.748	4.668	1.836	2.074	2.027	2.321	2.33	0.24	3.07	0.03	0.02	320	1.877	0.752	0.999	4.307	9.8	90.3	4.31
0.59	3.724	0.772	5.803	1.64	2.084	2.368	3.276	2.4	-0.25	3.08	0.03	0.02	232	1.573	0.754	1.236	5.803	12.1	84.6	5.8
0.549	3.43	0.682	4.41	1.831	1.599	1.888	2.45	2.1	0.24	3.19	0.03	0.02	240	1.773	0.662	0.719	3.662	8.8	90.9	3.66
0.566	3.436	0.705	4.462	1.811	1.625	2.012	2.321	2.2	0.16	3.02	0.16	0.02	240	1.794	0.723	0.66	3.843	8.6	88.9	3.84
0.45	2.873	0.573	4.153	1.465	1.408	1.687	2.038	1.85	0.16	3.37	0.03	0.02	256	1.437	0.673	0.615	3.895	10	92.1	3.89
0.435	2.837	0.564	4.617	1.207	1.63	1.64	2.063	1.75	-0.38	3.33	0.02	0.02	296	1.274	0.536	1.214	4.153	10.9	91.1	4.15
0.535	3.724	0.73	7.222	1.842	1.883	1.733	2.063	2.05	0.02	4.56	0.03	0.02	216	1.408	1.278	0.852	5.391	12.2	87.1	5.39
0.467	3.111	0.607	5.004	1.47	1.64	1.568	1.934	1.85	-0.17	3.79	0.03	0.02	256	1.431	0.721	0.856	3.998	11.1	91.3	4
0.596	3.91	0.748	4.668	1.836	2.074	2.027	2.321	2.33	0.24	3.07	0.03	0.02	320	1.877	0.752	0.999	4.307	9.8	90.3	4.31
0.584	4.127	0.765	5.416	1.79	2.337	2.461	2.708	2.6	-0.35	3.61	0.2	0.02	256	1.684	0.785	1.056	5.416	12.5	88	5.42
0.624	4.307	0.8	6.319	1.955	2.352	2.28	2.579	2.59	-0.32	3.62	0.03	0.02	256	2.028	0.676	1.062	5.881	8.2	90	5.88
0.632	4.214	0.812	6.087	1.754	2.461	2.43	2.811	2.63	-0.38	3.61	0.03	0.02	288	1.984	0.676	1.053	5.52	9.8	89.9	5.52
0.616	3.884	0.79	5.829	1.573	2.311	2.383	2.708	2.47	-0.65	3.72	0.03	0.02	256	1.813	0.519	1.137	5.545	7.1	85.1	5.55
0.567	4.364	0.805	7.196	1.305	3.059	1.713	1.883	2.09	1.68	6.78	0.04	0.03	200	1.187	0.72	1.864	5.829	10.9	83	5.83
0.635	4.354	0.81	6.783	1.769	2.584	2.44	3.172	2.65	-0.44	3.37	0.03	0.02	224	1.906	0.665	1.275	6.783	8.3	88	6.78
2.832	12.38	3.42	17.17	6.928	5.447	3.276	5.932	5.14	0.26	2.30	0.08	0.05	104	9.224	5.308	4.588	17.18	6.9	94	17.18
2.913	13.94	3.55	26.57	7.867	6.077	3.549	6.242	5.72	0.28	2.38	0.08	0.06	120	8.926	4.197	5.127	25.57	7.9	89.2	26.57
2.793	14.41	3.48	25.82	7.371	7.036	3.838	6.087	5.86	0.25	3.19	0.08	0.06	104	8.933	3.511	4.312	21.28	8.3	89.5	21.28
2.467	13.02	3.070	16.46	7.552	5.463	7.113	8.640	7.34	0.30	2.73	0.06	0.05	144	7.602	4.245	2.699	16.46	15.1	92	16.46
2.489	12.74	3.031	16.53	7.475	5.267	7.206	9.878	7.27	0.40	2.70	0.06	0.05	128	7.969	3.654	2.860	14.86	13	95	16.58

5.2.2 Classification of Tool and Workpiece Condition Based on Experimental Results

To capture the wear propagation of both the cutting tool and workpiece, the turning operation was intermittently paused to measure the surface/edge wear parameters, and the vibration signals were captured during the turning operation while keeping the cutting parameters constant. Hence, the tool and workpiece surface/edge roughness were measured and recorded, the IoT vibration sensor was powered on, and the turning operation was started while capturing the vibration signal during the forward and backward stroke. Since the heartbeat was initially set to 10 seconds, the surface/edge roughness parameters of the tool and workpiece were measured, and the turning was commenced 30 seconds before the vibration was captured so that the vibration during the cutting operation could be recorded. This experiment was done using the four classes of tools, and the corresponding range of surface/edge roughness parameters of the tool and workpiece was recorded and evaluated for each of the significant surface profile parameters of the workpiece as shown in Table 5.5. The evaluation was done using the statistical tool for evaluating the range of a set of data and the result for each of the columns indicating the range was recorded.

Table 5.5: Tool and Workpiece Surface/Edge Roughness Classification

parameters	*New Tool*		*Good Tool*		*Rough Tool*		*Worn Tool*	
	Tool	Wkp	Tool	Wkp	Tool	Wkp	Tool	Wkp
R_a	0.2 - 0.5	0.4– 0.7	0.9-1.5	0.7-2.0	2.5-5.0	3.0-5.5	>5.5	>5.5
R_z	2.5- 4.0	2.5-4.7	4.1 - 6.8	4.0 -7.2	6.9 – 9.6	7.3-10	>9.7	>10
R_y	3.5 -4.8	3.5-5.0	4.6-5.9	4.8-5.9	5.8-6.9	5.9-7.0	>7.0	>7.0
R_q	0.5-0.78	0.5-0.79	0.8-0.95	0.85-1.0	1.0-1.9	0.9-2.5	>3.0	>3.0
R_t	3.5-6.5	3.5-7.0	6.6-8.0	7.0-8.4	8.5- 10	8.5-10.5	>10	>10.3
R_{max}	3.5-4.5	3.5-5.0	5.0-6.0	5.0-6.4	6.0-7.0	6.5-7.1	>7.0	>7.0
Label	**1**		**2**		**3**		**4**	

The measured parameters for each class of tool and its corresponding surface roughness output of workpiece varied only very slightly when compared to each other. This indicated that the Cutting Tool Condition, i.e., the threshold in most parametric values, directly impacted the surface quality output of the workpiece. Table 5.5 illustrates the ranges of measured values of the significant wear parameters of both the cutting tool insert and the workpiece before and after each turning operation. The label for each class of tool and workpiece condition during operation is shown in the last row of Table 5.5 representing the output class for classifying the conditions for the TWCM system giving room for smart and precision manufacturing. This is in line with the Second Object of the study that entails analytically evaluating the range of data values for each class of the surface profile parameters for the tool and workpiece condition monitoring classification system based on the tool condition and its corresponding significant surface parameter quality output where class one (1), new tool, indicates the condition of the cutting tool and the corresponding significant surface profile output of the workpiece, class two (2), good tool, indicates the condition of the cutting tool and the corresponding significant surface profile output of the workpiece, class three (3), rough tool, indicates the condition of the cutting tool and the corresponding significant surface profile output of the workpiece, and lastly, class four (4), worn tool, indicates the condition of the cutting tool and the corresponding significant surface profile output of the workpiece. The Machine Learning AI approach was then applied for intelligently classifying the condition of the tool and workpiece during the machining operation by computing and processing the vibration signals captured during operation. The AI ML model created was optimized to accurately classify the condition of the tool and workpiece during the turning operation. Each predicted class would project the characteristic experimental class in Table 5.7 derived from the experiment for both the tool and workpiece condition. Production was therefore optimized by optimal usage of the tool based on condition monitoring for classification. This was the Sixth Objective of the study and the result analysis is discussed in a subsequent section. The data measured together with the vibration signals captured provided detailed insight into wear and crack propagation resulting from the turning operation by analyzing and classifying the signals using the machine learning algorithm for intelligent decision-making.

5.2.3 Vibration Data Capturing via Cyber-physical System

An industrial vibration sensor equipped with Internet of Things (IoT) technology, in connection with a gateway and cloud platform has made room for cyber-physical system integration into the TWCM system. The gateway connects the vibration sensor to the server that allows for data transmission to and from the sensor to the cloud platform. The online platform called the iMonnit online allows for configuration of the sensor, the gateway, and monitoring and collection of data from the sensor. This implies that the conditions can be monitored remotely and on site and the threshold level can also be set to trigger notification in a case where the level exceeds a pre-set value. The heartbeat of the vibration sensor was set to 10 minutes, which allowed for the intermittent measuring of the surface/edge roughness parameters of the tool and the workpiece during operation. The heartbeat of the gateway was set to two (2) minutes, which means it checked in every two (2) minutes for any available data to be transmitted. The unit of the vibration sensor was selected as unit of acceleration, the data mode as single axis vibration, and the frequency set to 50Hz. All these configurations could be adjusted or changed within a split second in the case of a response to a new working condition. The Human Machine Interface (HMI) of the surface/edge measuring device displayed the measured values which were also downloaded to the memory device, or hardware for further data processing.

The initial vibration data were captured along a single axis and the corresponding surface/edge roughness data was recorded against the class label. The data on the spreadsheet was arranged in three columns and the rows represented the number of samples, which were a thousand samples. The first column is the axial vibration signal, the second column is the time interval of measurement taken, which is same as the heartbeat of the sensor, while the last column is the label that indicates the tool class being used. This addressed the Third Objective, which was to adaptively determine and capture real-time signals for tool and workpiece surface wear condition through a developed inter-connected, non-obstructive hardware with advanced signal analysis. The surface/edge roughness parameters were measured in micro-metres ($10^{-6}m$) while the vibration was measured in metres per second square (ms^{-2}). The vibration signal was then analyzed using advanced signal analysis techniques and the Feedforward Neural Network algorithm with SCG, SVM and KNN classification algorithm employed for classifying the signals into each condition class. This is explained in the next section.

5.3 Advanced Signal Analyses Results for TWCM system

Processing and analyzing data are important skills that need to be mastered in order to interpret and analyze the signal to process and filter out essential components for decision making. Several new techniques and approaches are being proposed and introduced for processing and analysing signals for the purpose of improving the performance and accuracy of the results. This section discusses the results and analysis of the signals, the extraction of features, and the classification of extracted features using a machine learning approach. The vibration data with a known class label and the time interval were captured on a spreadsheet and this was imported into the MATLAB program for advanced signal processing. The results are highlighted in the following subsections.

5.3.1 Application of Digital Filters on the Vibration Data

The plotting of vibration data against time would give some insight into the distribution of the data over time and the threshold. The magnitude of the signal varies basically due to the class of tool conditions used for the turning operation. Figure 5.2 shows the plot of the vibration data against time and several points of excitation were noticed on the plot. The graph shows different vibration excitations as the tool class was changed. The vibration of the tailstock from the start of the turning operation for about 120 minutes shows the vibration range to be between 0 and 1.1 ms^{-2} for the new cutting tool. The vibration slightly increased when a used good tool was replaced after about 120 minutes and increased again when the third class of tool was fitted on the machine tool after 270 minutes. The vibration excitation became more pronounced when the rough tool was replaced with a worn tool after about 360 minutes before being replaced again with a new tool.

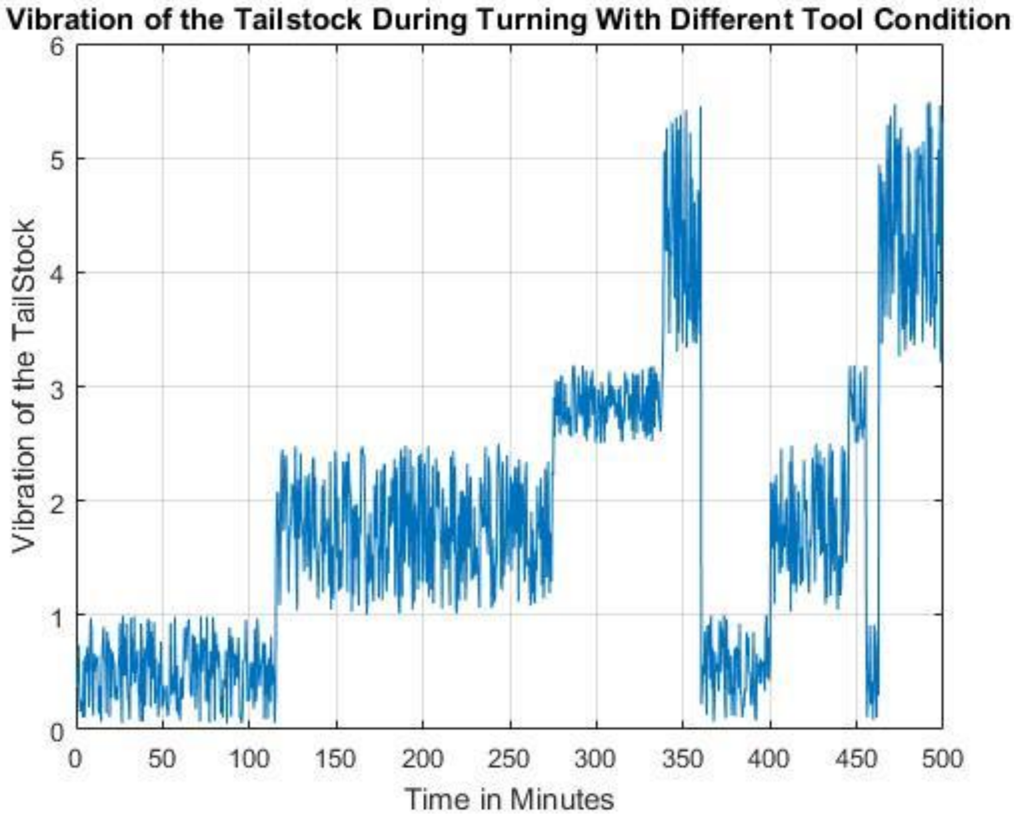

Figure 5.2: Vibration Plot Against Time

This indicated that as the condition of the cutting tool changed as shown in the classification of the tools, the vibration excitation also changed. This also implies that the vibration signal, when accurately analysed and measured, can produce an accurate judgement of the TWCM system during operation without necessarily obstructing or stopping the operation and thus addresses the Third Objective of the research. To visualize the different classes of tools and their corresponding vibration excitations during operation, a plotting of the vibration produced by each cutting tool was indicated in different colours against time as shown in Figure 5.3. The graph shows the difference in vibration signals against time and the legends indicate the varying classes of tool condition used for the turning operation on the lathe.

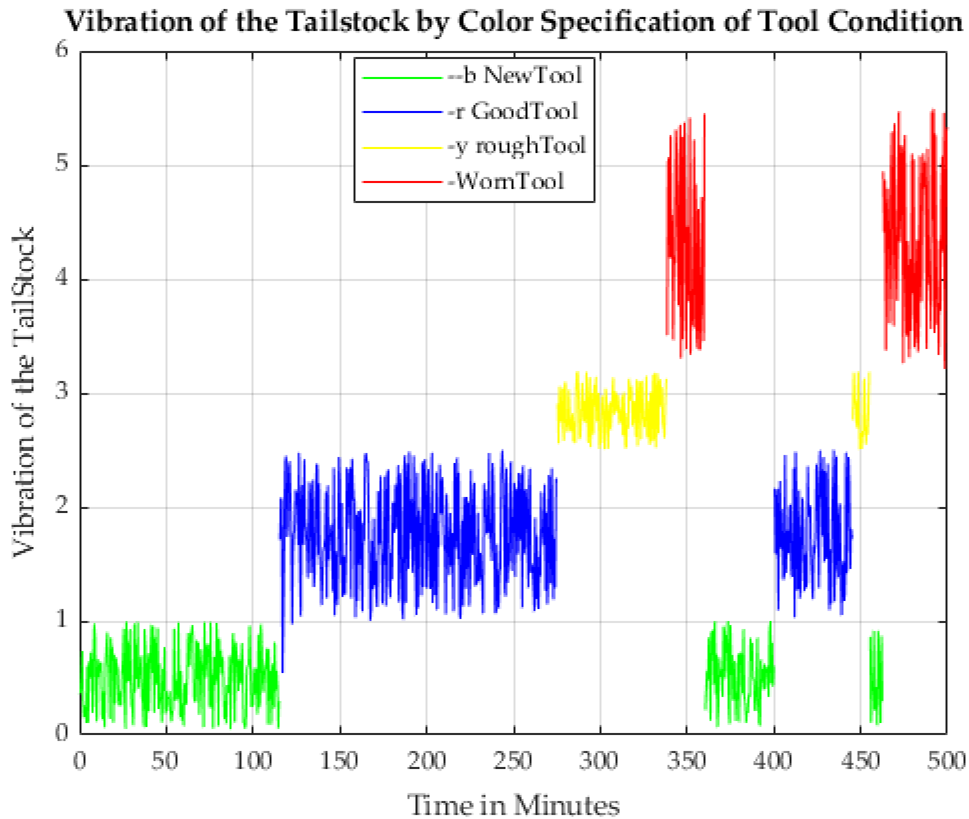

Figure 5.3: Graph of Vibration by Colour against Time

Figure 5.3 shows that once the tool was replaced with a new tool condition, the vibration signal captured also changed, with a damaged or worn tool generating the highest level of vibration excitation. This was caused firstly by the alignment of the accelerometer (vibration sensor) to the gravitational field and secondly by the power generated due to the reaction between the cutting tool and the workpiece during turning operation. The vibration signal may vary fairly evenly as it gradually moves from one phase of condition to another, therefore, to be able to discriminate the signals propagated as the tool condition changes, a new signal that can be differentiated based on the shape of oscillation and how quickly the signals vary over time was created. The new signal was created by applying digital filters on the vibration signals. Figure 5.4 shows the specification pane of the filter design as earlier explained in Chapter 3. The filter was designed using the following parameters F_{stop} is 0.4Hz/s, F_{pass} is 0.8, A_{stop} is 60, A_{pass} is 2, and F_s is 50Hz. The value of F_{stop} is very significant for the designed filter and it indicates that all oscillations slower than 0.4Hz/s are made a thousand times smaller than their original size. The signals produced after applying digital filters on the initial vibration data can be seen to eradicate the offset produced because of the acceleration due to gravity on the measured vibration data.

In addition, the transient behaviour of the signal can be visualized once a new condition kicks in during operation.

$$y(n) = \sum_{k=0}^{\infty} h(k)x(n-k) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(30)$$

A digital filter can in general be represented by its impulse response, h(k) (k=0,1,). Since the impulse response exists indefinitely, an infinite impulse response filter, Chebyshev was selected. It was also noticed that the digital filter function had eradicated the varying low contribution as a result of the alignment of the accelerometer to the gravitational field. This approach is, however, based on FFT and since FFT is ideal for linear and stationary signals due to the Uniform Trigonometric Function, WT was introduced as an alternative to extracting time-frequency resolutions of a signal. However, the EMD method is a better approach for analysing non-linear and non-stationary signals. This is because the EMD method decomposes signals into components to gain insight into inherent features.

5.3.2 Signal Analysis through the Application of EMD and HHT

Bokde *et al.* (2019) showed that 80% of the most recent analyses of non-stationary and non-linear wind turbine signals adopted EMD for signal analysis for the prediction models. The signal is decomposed into a finite number of IMFs (real part) and the residual (imaginary part) as highlighted in equation 5. As earlier explained in Section 3.12.1.4 of Chapter 3, the vibration signal was decomposed into imaginary and real parts with the application of equations 6 and 32. The result is illustrated in Figure 5:3 with the signal decomposed into six (6) IMFs and one (1) residual after the application of the empirical mode decomposition method. The iterative decomposition was stopped using the stopping criteria indicated in the expression below:

$$[IMFs, \quad res] = emd(data);$$

A *101 x 1000* matrix of sparse data of decomposed signals was derived from the decomposition of the signals. This data, however, could not be used for the training algorithm for discriminating the tool and workpiece condition during machining operation. The instantaneous properties of the signals were obtained by applying HHT on the IMFS as explained in equation 9. The outcome of the application of HHT on the IMFs produced the signal analysis in Figure 5.4, which indicates the extraction of instantaneous properties of signals after decomposition. Instantaneous properties such as the instantaneous frequency, instantaneous energy and instantaneous amplitude are derived from the decomposed signals when HHT is applied. Therefore, the transient behaviour of the signals during the machining operation could be discriminated from the extracted features (instantaneous properties) derived after applying HHT on the decomposed signals.

Therefore, the TWCM system for optimising machining operation by classifying the product quality and the tool condition during turning operation non-obstructively could be developed from the instantaneous properties from the processed signals. The feature vectors obtained as the instantaneous properties were twelve (12) features. These included the instantaneous frequencies, amplitude, and energy evaluated from the IMFs. Hyperparameter optimisation was also performed on the computed signal in order to optimise the ML algorithm by reducing the time for computation and the computational space. The feature selection was therefore made by applying the GA model on the computed feature vectors. The selected features after the hyperparameter optimisation were four (4) features out of the twelve (12). This addressed the Fourth Objective of the study which was to determine and evaluate features capable of discriminating and classifying different tool and workpiece conditions during the turning operation using advanced signal processing techniques. These features were fed into the ML algorithm for classifying the varying signals from each tool and workpiece class type.

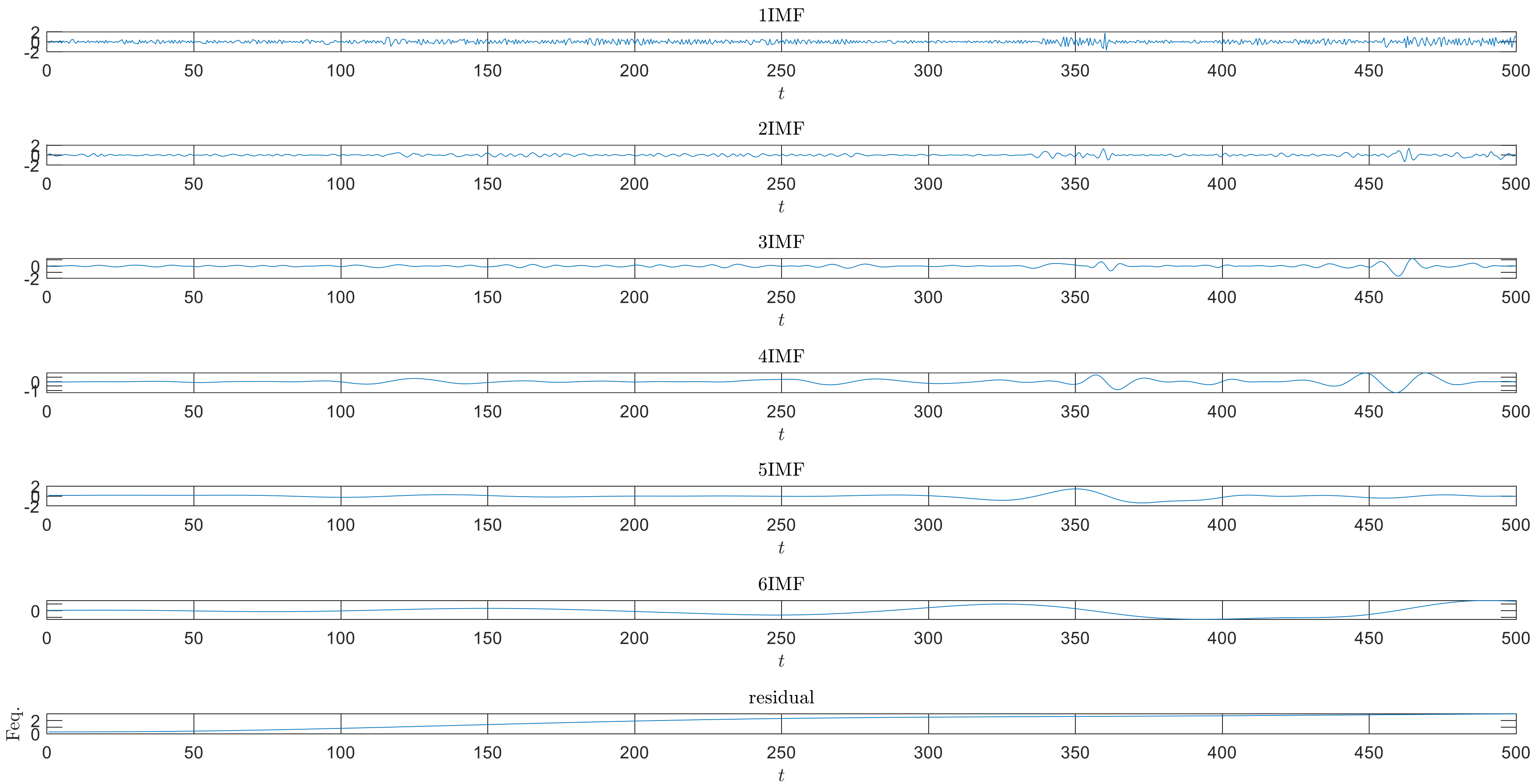

Figure 5.4: Decomposed Signals into IMFs and Residuals using EMD

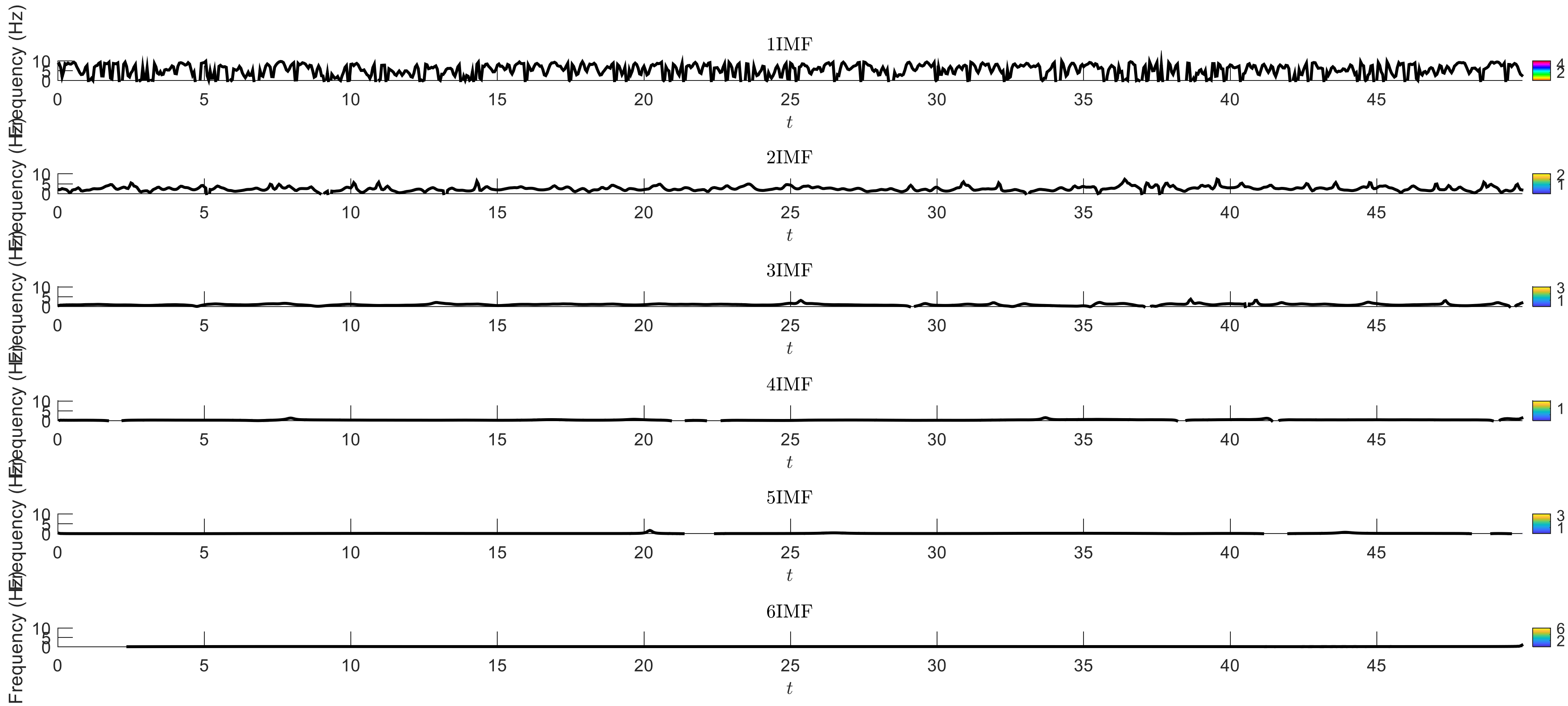

Figure 5.5: Applying HHT on the IMFs Evaluated from EMD Function

5.3.3 Feature Selection

Deploying the Machine Learning AI algorithm for smart manufacturing is a data-driven approach which relies on the level of data processing and optimization done in order to increase the level of accuracy of the model. The performance of the ML model therefore depends on the feature vectors that are taken as input into the model. Even though several features may be extracted from the vibration signals through an advanced signal processing method, feature selection is performed on the extracted features to optimise the classification process of the algorithm, The feature selection procedure makes the classification process computationally less expensive as it reduces the time and space required for the computation process.

Therefore, to reduce the computational cost of the classification model, hyperparameter optimization using the GA model was applied to the feature vectors extracted from the analysed signals captured during machining operation.

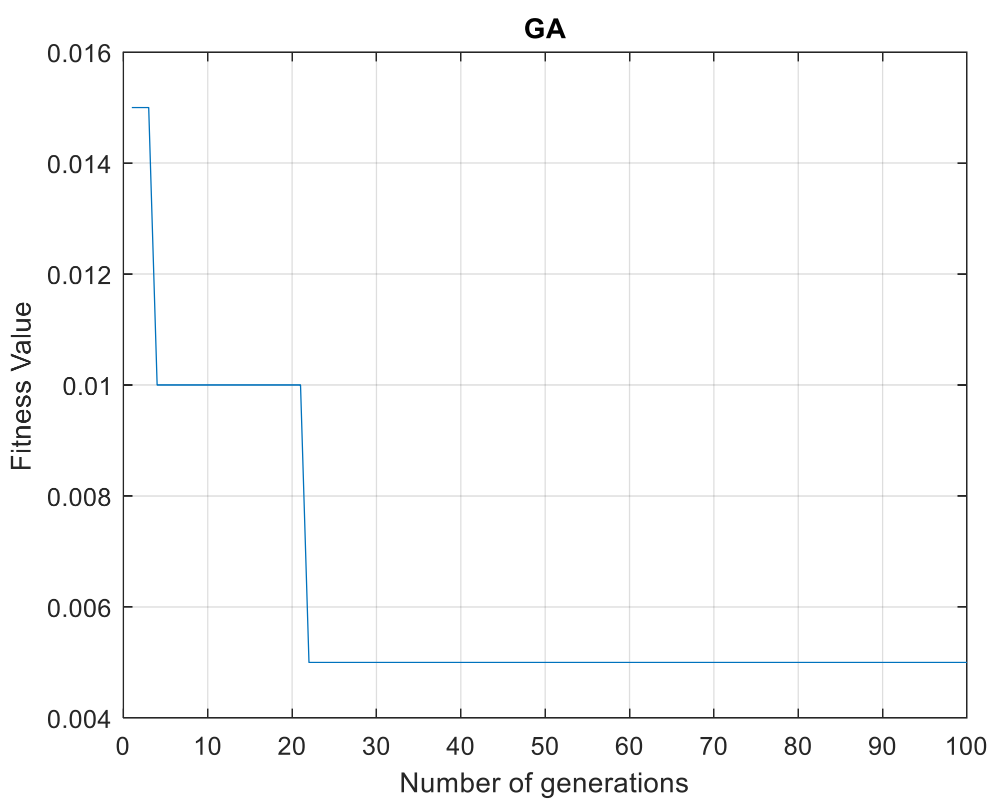

Figure 5.6: Convergence Curve for Feature Selection Method

The GA algorithm was implemented by applying the RW method as illustrated in equation 11. Where the number of chromosomes in the analysis was given as 12 from the extracted instantaneous properties of the signals, the fitness probability of a single chromosome in the generation was determined by equation 14 and the number of features selected from the algorithm were four (4) features. The convergence curve after 100 iterations is shown in Figure 5.5 and it can be seen that the model converges at the twenty-second (22) iteration even though the iteration still proceeded to 100 iterations.

For a given set of twelve (12) features computed as the instantaneous physical properties of the signal captured during the machining operation, with columns 1 – 12, four (4) features were selected, being columns 5, 6, 9 and 12. These features were the input feature vectors for the ML classification algorithm for evaluating the condition of the tool and workpiece. The condition is classified as any of the four classes, while the detail parameters of each of the classes have been highlighted in Section 5.2.2. This section therefore addresses the Fifth Objective of the study which was to determine the optimal features through Hyperparameter Optimization for selection of important features for the ML algorithm.

5.4 Feature Classification for Tool and Workpiece Conditions for TWCM system

Extracting features from the advanced signal analysis performed on the data helps to provide detailed information of each signal buffer produced by different classes of tool and workpiece condition for the purpose of optimising manufacturing by determining the suitable tool condition for a workpiece surface profile output based on the classification in Table 5.7. This implies that the condition of the tool and workpiece can accurately be determined during production while avoiding machine downtime, meeting job requirements, and reducing scraps due to product damage (surface quality exceeding the required standards).

The research study has described the development of the tool and workpiece condition monitoring system by highlighting the detailed procedures and steps in accomplishing the task as mentioned in the research design in Section 3.2. These steps entailed classifying the tool conditions based on the flank wear using the ISO 3685:1993 standard. Thereafter, the surface profile parameter for developing the knowledge base for tool and workpiece condition classification was developed and the corresponding vibration signals were also measured and recorded during operation. Advanced signal processing techniques were applied on the vibration signals for process and extracting feature vectors with instantaneous physical properties from the captured signals. Feature classification was essentially the last data processing task performed on the signal for the purpose of predicting the condition of the cutting tool and workpiece for optimisation during turning operation. This implies that if the product surface quality requirement was within, for example, a rough class for tool and workpiece condition, a gradually degrading tool from a good condition to a rough condition could still be used for the turning operation. That means the tool life of the cutting tool can be used optimally based on the product quality requirement.

The feature vectors were first trained using a Feedforward Neural Network model with a scaled conjugate gradient (SCG) algorithm. The features of the model were four (4), while the hidden layer had eighteen (18) nodes, and the output of four (4) classes was used. The label for the data to be trained had one (1) column and a thousand (1000) samples. The network trained the data set (that is, divided it into the ratio 7:2:1 for training, validation and test set respectively) using 44 iterations and the confusion matrix was used to evaluate the performance of the network. The best validation performance as shown in Figure 5.7 was 0.047349 at epoch 103.

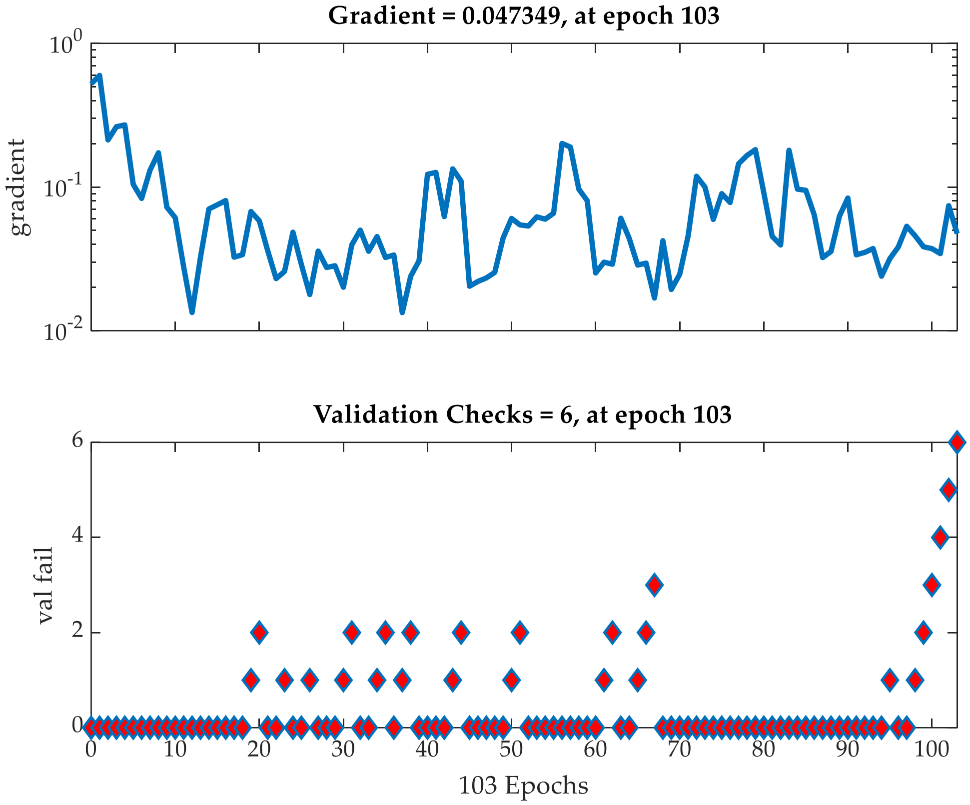

Figure 5.7: Training State of Neural Network with SCG Algorithm

The neural network with a SCG algorithm error histogram indicated the classification prediction error after training the feed-forward backprop neural network. It presented how the prediction class differed from the target class in a training example. This was very important in determining the accuracy of the trained network to classify new samples of data. The error histogram has 20 bins which indicated that the range of error bars on the histogram was divided into 20 samples as indicated in Figure 5.8.

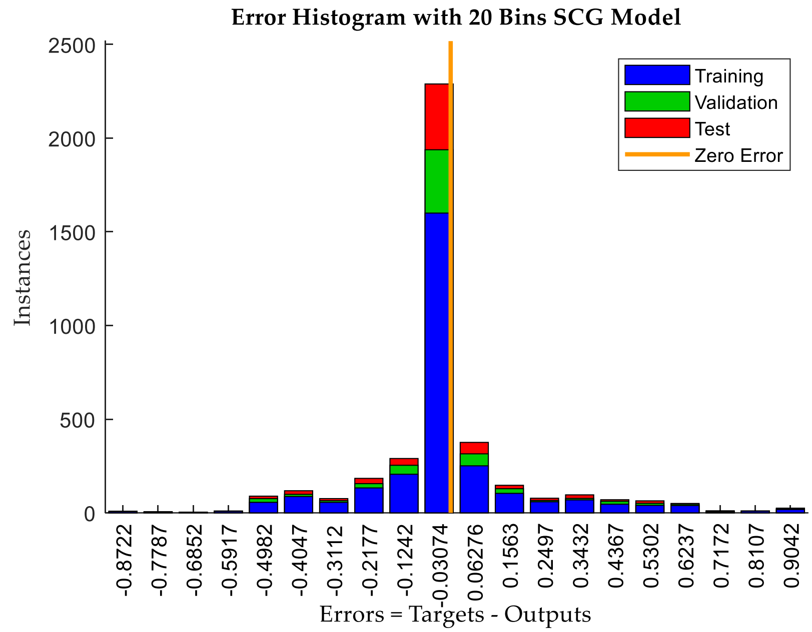

Figure 5.8: Error Histogram of SCG Neural Network Model

This was evaluated by first determining the upper limit and the lower limit of the error as shown in the error histogram.

The upper limit of the error bin was 0.06276 and the lower limit of the error as indicated in Figure 5.8 was -0.03074. The width of a bin is given by;

$$Bin\ width = \frac{(Right\ limit - Lower\ limit)}{20} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (33)$$

$$Bin\ width = \frac{(0.06276 - (-0.03074))}{20} = 0.0935$$

The bin width in Figure 5.8 can be evaluated to be 0.0935. While the classification algorithm performed very well from the error histogram, there were, however, other error distributions to the left and right of the zero-error line. To analyse the error in more detail, the range of the errors for the training algorithm were evaluated.

The confusion matrix in Figure 5.9 shows that the accuracy of the classification algorithm was 89.8%.

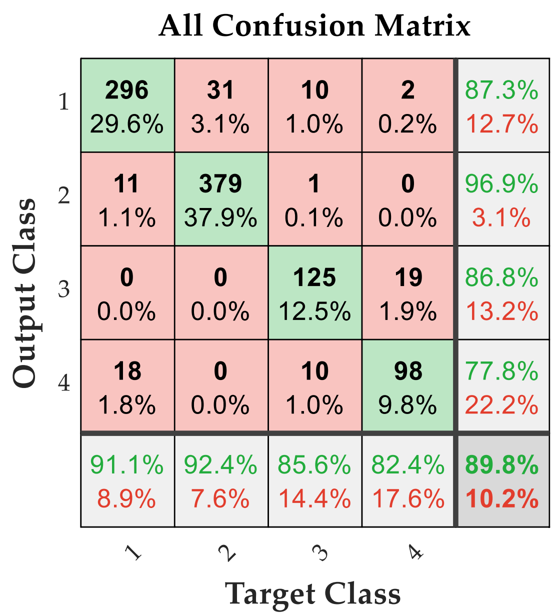

Figure 5.9: All Confusion Matrix for SCG Neural Network Model

To further examine the accuracy of the classification algorithm, the confusion matrix was also considered. Figure 5.9 represents the confusion matrix and the bottom right corner box of the matrix carries the most significant numerical value about the algorithm. It represents the degree of accuracy of the classification algorithm. In this case, the classification accuracy of the algorithm is seen to be 89.8% indicating that the algorithm has a very low probability of misclassification of the tool and workpiece condition during turning operation.

However, to further determine the accuracy of the classification algorithm, another ML classification algorithm was considered for classifying the conditions of the cutting tool during the machining operation from extracted vibration signals. SVMs are powerful techniques used in data classification and regression analysis as they have become one of the most used classification methods due to their good theoretical foundation and good generalization capacity (Cervantes *et al.* 2020). Kaya *et al.* (2020) applied SVM and Logistic Regression (LR) for classifying the vibration signals at varying bearing speeds and the result showed that the LR model yielded a poorer prediction. Similarly, while Chen *et al.* (2019) classified vibration signals based on variational mode decomposition (VMD) and energy entropy using the SVM technique for fault diagnosis in rotating bearings, Glowacz *et al.* (2019) applied Linear Support Vector Machine

(LSVM) for classification of data between two classes of signals captured from the vibration of an induction motor machine by finding the best hyperplane.

However, Altaf *et al.* (2022) classified EMD features and FFT features extracted from vibration signals for diagnosing bearing fault without any statistical information using KNN classifiers with the method yielding a reduction percentage of 96.64%. The result of this classification algorithm showed good performance, even though the study applied FFT on the decomposed signal as opposed to this study that applied HHT on the decomposed signal. Similarly, Han *et al.* (2021) applied both KNN and SVM on features extracted from vibration signals processed through FFT and Principal Component Analysis (PCA) and showed that vibration signals were sufficiently rich in information about the machine for precision machining that stated that 100% classification accuracy could be achieved. Hence, SVM and KNN were applied to the extracted features for the classification of the conditions in order to determine which classification model performed optimally for classifying tool classes.

The bias and misclassification error are mostly a challenge when applying ML algorithms and techniques in classification problems; therefore, to avoid these, k-fold cross-validation techniques are applied. This study applied 5-fold and 10-fold cross-validation and the models were compared to determine the one with the best performance in terms of error loss in classification. For the 5-fold cross-validation technique, the models were developed and tested by determining the error loss for both SVM and KNN to determine the model with better performance. Figure 5.10 illustrates the error loss of each model of the SVM and KNN method, with the colour blue representing SVM models and brown representing KNN models.

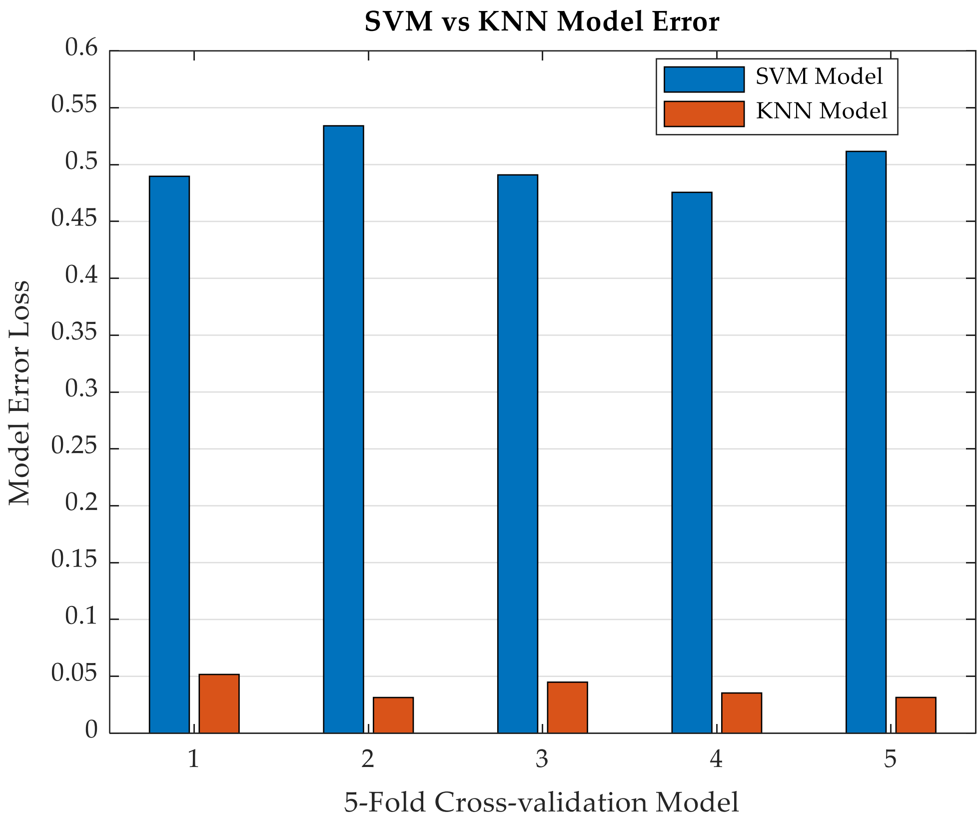

Figure 5.10: Error Loss for SVM vs KNN Classification with 5-fold Cross-Validation

The result showed that the KNN algorithm performed better than SVM in classifying the cutting tool classes during the machining operation. To determine the overall error loss for each of the models, equation 34 was applied.

$$E = \frac{1}{k}\sum_{i=1}^{k} E_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (34)$$

Where k represents the number of folds being considered and E is the error loss. Therefore, the overall error loss for the five SVM models was 0.5031, while for the KNN model it was 0.0318. This indicated that KNN models performed better under the SVM models for tool condition classification during the machining process.

For the 10-fold cross-validation technique, both models were also developed to determine their performance. Figure 5.10 shows that the KNN models all performed better than the SVM models. Each SVM model from 1 through to 10 had a higher error loss function compared to KNN models.

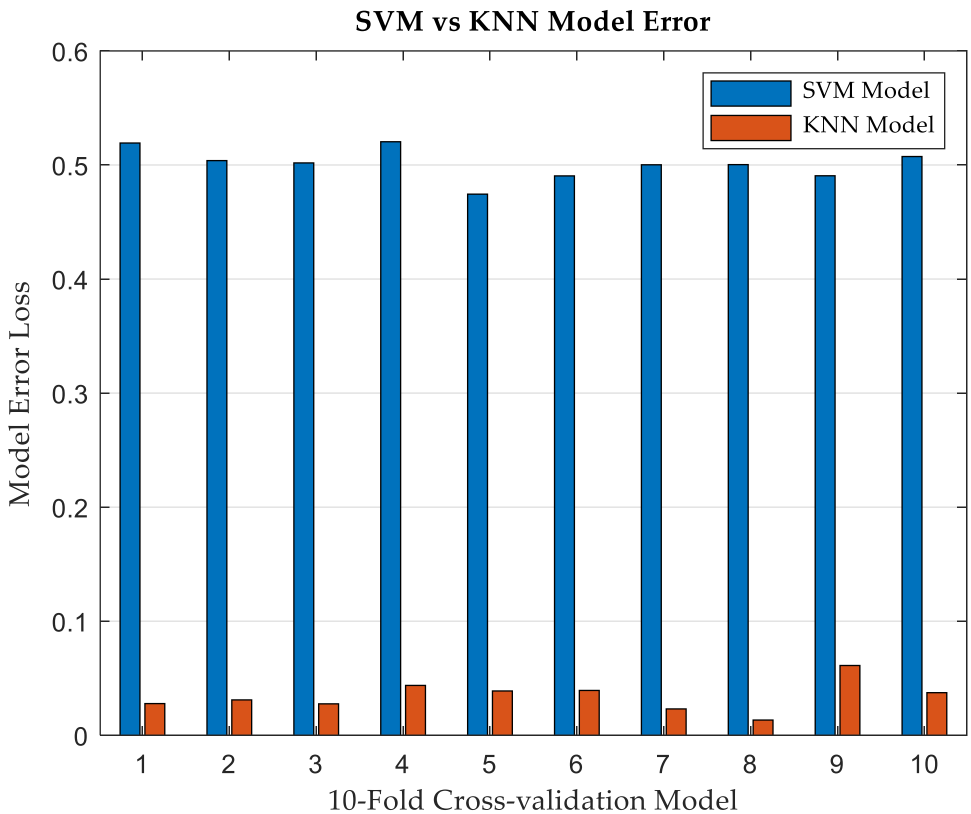

Figure 5.11: Error Loss for SVM vs KNN Classification with 10-fold Cross-Validation

The overall error loss for the SVM models with 10-fold classification was 0.5009 while the error loss for KNN models was 0.343. The general performance of the two (2) models showed that SVM slightly improved in the error loss when the 10-fold cross-validation technique was used compared to the 5-fold cross-validation technique. Furthermore, the performance of KNN models was better with the 5-fold cross-validation technique compared to the 10-fold cross-validation technique. Figure 5.11 shows the KNN8 model had the least error loss while the SVM5 model for the 10-fold cross-validation had the higher error loss. Toledo-Pérez *et al.* (2019) reviewed the SVM-based model of EMG signal classification and reported that a lot of sounds, vibrations signals, and images have been classified using SVM classification algorithm, achieving more accuracy without feature selection and 5% less with feature selection. Therefore, to determine if the SVM model would perform better without feature selection, the models were evaluated with the 12 features, and the loss function was determined. The performance of both models for 5-fold cross-validation with all the feature vectors are illustrated in Figure 5.12 and it shows that for SVM models, the performance improved greatly compared to when feature selection was implemented. The overall average error loss when 5-fold cross-validation was performed on all the features was 0.1668 compared to 0.5031 when feature selection was performed. However, for KNN models using 5-fold cross validation with feature selection, the overall average error loss increased from 0.0318 to 0.2202. These results show that while feature selection improved the performance of KNN models in classifying the conditions of the tool, it was not the case with the accuracy and performance of the SVM model.

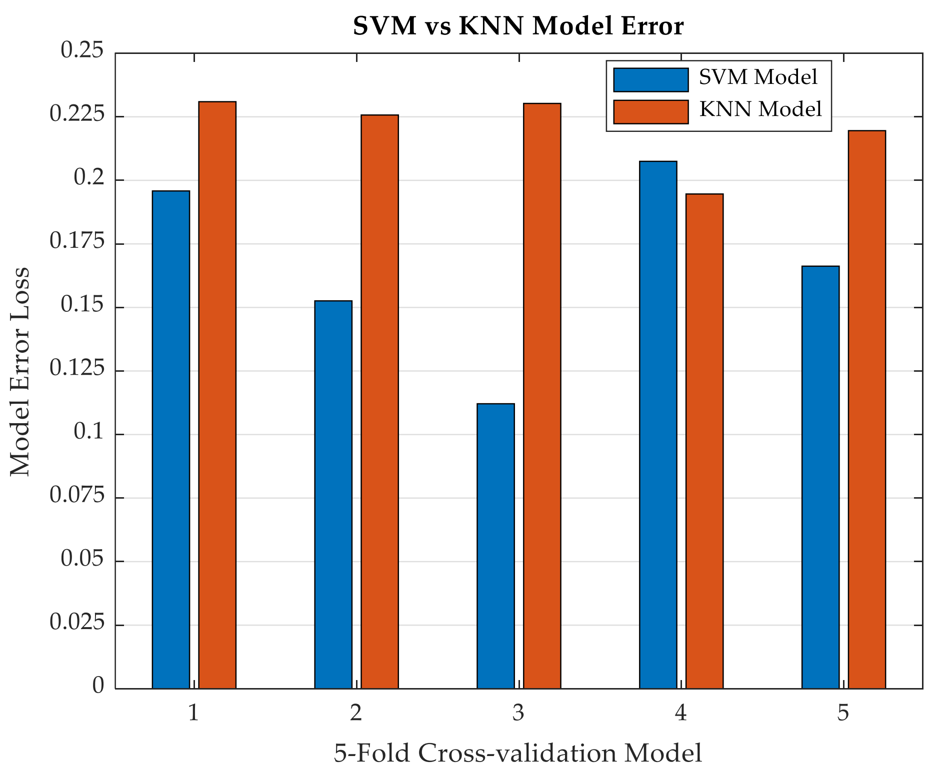

Figure 5.12: Error Loss for SVM vs KNN classification with 5-fold Cross-validation without feature selection

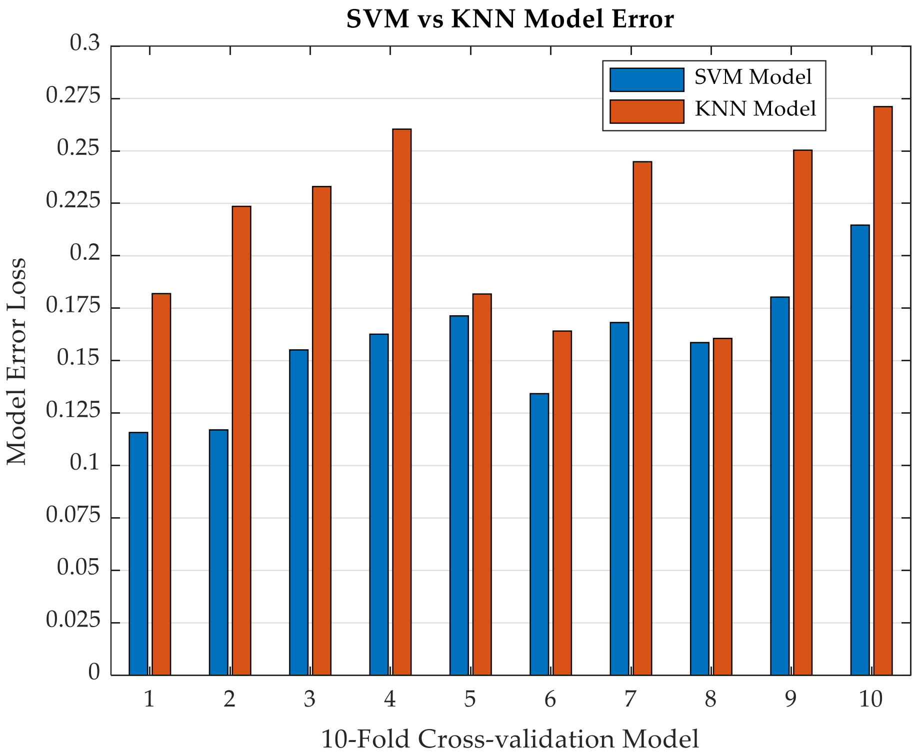

Figure 5.13: Error Loss for SVM vs KNN classification with 10-fold cross-validation without feature selection

The result shown in Figure 5.13 for the 10-fold error loss for SVM and KNN classification models developed without applying feature selection also indicated that the performance of SVM models was more accurate without feature selection. The error loss for 10-fold cross-validation for SVM models when feature selection was applied was 0.5009 while it was reduced to 0.1578 without feature selection. On the other hand, the performance of KNN models when feature selection was applied was 0.0343, while it increased to 0.2172 without feature selection. Therefore, the KNN algorithm performed better in classifying the condition of the cutting tool during the machining operation. The KNN8 model for 10-fold cross-validation set with the feature selection algorithm provided the optimal result in terms of accuracy in classification, hence, this model was adopted for discriminating and classifying the condition of the tool and workpiece during machining operation. This addresses the Sixth Objective of the study which was to optimize the ML Models used for tool and workpiece condition classification by applying different ML algorithms and k-fold cross-validation techniques. Model KNN8 produced the optimal classification accuracy for the tool and workpiece condition monitoring system.

5.5 Hyperparameter Optimization

Since the best model was observed when the *i*th partition for the 10-fold cross validation was 8, the model with the best performance when the error loss was considered was KNN8. This was also evaluated with the test set and the loss for the model was 0.0106.

The fitted KNN classifier was optimized to find the hyperparameter that minimized the 10-fold cross-validation loss by using automatic optimization and for reproducibility the seed was set to random and the 'expected-improvement-plus' acquisition function was used. The objective function model after hyperparameter optimization is shown in Figure 5.14. The objective of the optimization is to indicate the classification error loss of the model while the constraints are the distance metrics and number of neighbours of the model.

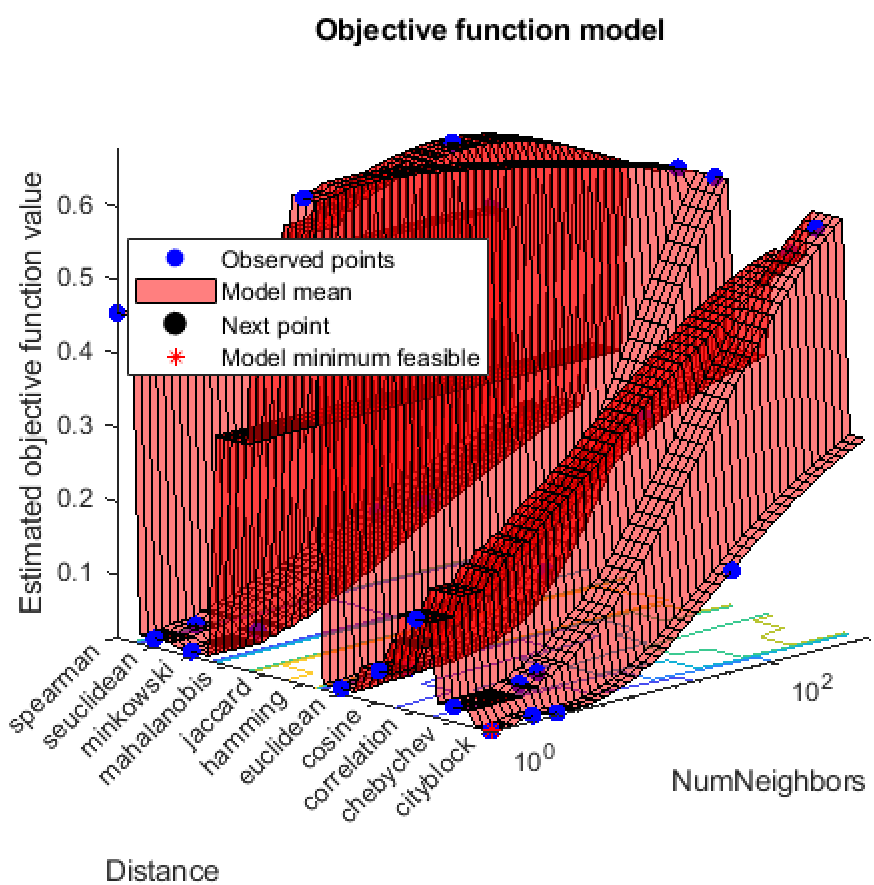

Figure 5.14: Hyperparameter Optimisation Objective Function Model

The objective function of the model after hyperparameter optimisation specified 'cityblock' distance metrics using the '*kdtree*' neighbour searcher method to perform optimally with the fitted model, hence the 'cityblock' distance was therefore used as the distance metrics for the trained model. From Figure 5.15 the estimated objective function value of the optimized model is 0.01416 while the observed objective function value is 0.0140, which indicated the model had been improved. The estimated function evaluation time and the actual function evaluation time was very close, being 0.14396 and 0.13112 respectively, while the NumNeighbour was 4. Cityblock is a special case of Minkowski distance where p is equal to 1 and evaluated by applying the equation:

$$d_{st} = \sqrt[p]{\sum_{j=1}^{n} |X_{sj} - y_{ij}|^{p}} \ldots\ldots\ldots\ldots (31)$$

This section addressed the Sixth Objective of the study which was to optimize the ML algorithm used for tool and workpiece condition classification in order to determine the model with the least classification error loss.

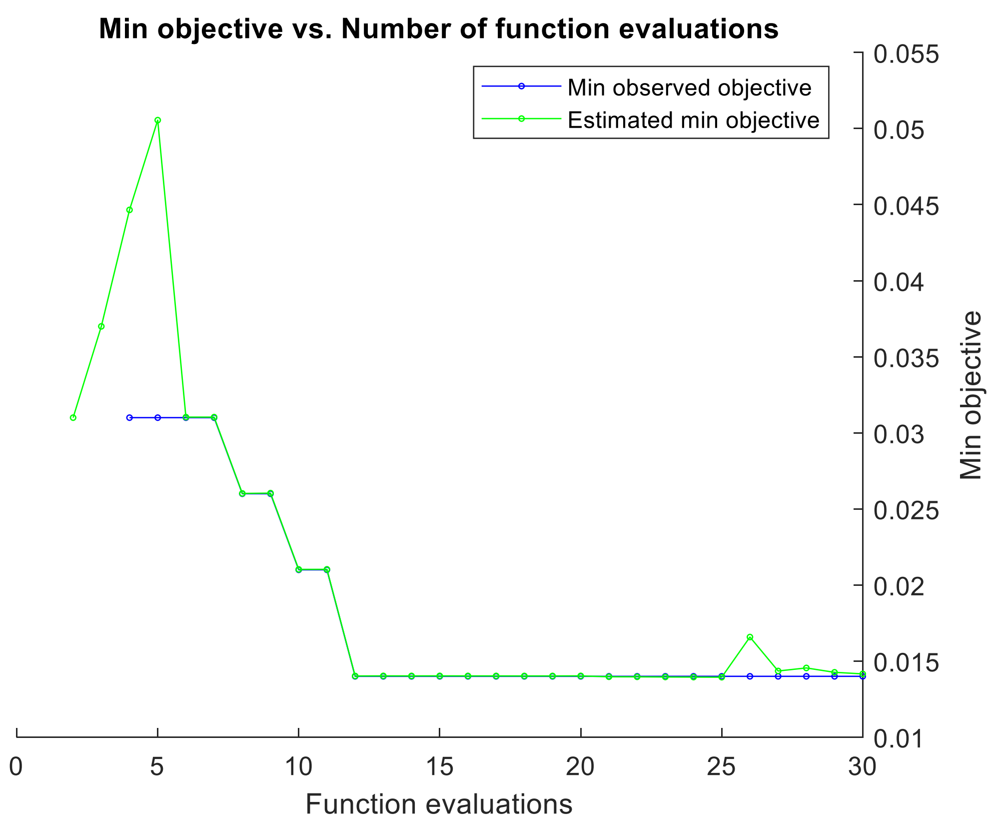

Figure 5.15: Function evaluation vs Minimum Objective

5.6 Conclusion

This chapter analysed the results of the advanced signal analysis using several methods, functions and algorithms for determining and classifying the conditions of Tools and Workpiece into four (4) as illustrated in Table 5:6. It discussed the investigation of the conditions of the tool and workpiece before commencing the turning operation. This involved the surface/edge wear parameters measured on the Tool and Workpiece Conditions. The first subsection under the investigation of the conditions of the tool and workpiece was the experimental pre-condition results of the cutting tool and workpiece. It presented in detail the evaluated parameters that highlighted the surface/edge roughness characteristics of the cutting tool using MANOVA analysis in determining the parameters that were significant when varying tool conditions were considered. Six (6) parameters were streamlined from about twenty (20) parameters captured by the surface/edge roughness measuring device. This addressed the First Objective of the study which was to determine the workpiece surface roughness parameters that correlated with the cutting tool conditions for a turning operation. Subsection 5.2.2 discussed the classification of Tool and Workpiece Condition for TWCM system. The subsection presented the parameters that classify the varying types of cutting tool conditions used and the corresponding detail values of the range of data for the workpiece surface roughness parameters during operation. This addressed the Second Objective of the study which was to analytically determine the range of data values for each class of surface profile parameters for tool and workpiece condition monitoring classification.

Table 5.6: Table indication of the Range of Parameters Values for the Classes

parameters	*New Tool*		*Good Tool*		*Rough Tool*		*Worn Tool*	
	Tool	Wkp	Tool	Wkp	Tool	Wkp	Tool	Wkp
R_a	0.2 - 0.5	0.4– 0.7	0.9-1.5	0.7-2.0	2.5-5.0	3.0-5.5	>5.5	>5.5
R_z	2.5- 4.0	2.5-4.7	4.1 -6.8	4.0 -7.2	6.9 – 9.6	7.3-10	>9.7	>10
R_y	3.5 -4.8	3.5-5.0	4.6-5.9	4.8-5.9	5.8-6.9	5.9-7.0	>7.0	>7.0
R_q	0.5-0.78	0.5-0.79	0.8-0.95	0.85-1.0	1.0-1.9	0.9-2.5	>3.0	>3.0
R_t	3.5-6.5	3.5-7.0	6.6-8.0	7.0-8.4	8.5- 10	8.5-10.5	>10	>10.3
R_{max}	3.5-4.5	3.5-5.0	5.0-6.0	5.0-6.4	6.0-7.0	6.5-7.1	>7.0	>7.0
Label	**1**		**2**		**3**		**4**	

The third subsection explained vibration data capturing via cyber physical systems by giving a detailed approach to implementing the non-obstructive tool and workpiece condition monitoring during the turning operation. The hardware components of the TWCM system were highlighted and configuration of the hardware components was also discussed. Several signal types were proposed for the TWCM system; however, the vibration signal was eventually adopted because it met the aim of the study, which was to non-obstructively monitor the conditions of the tool and workpiece during the machining process. This addressed the Third Objective of the study which was to adaptively capture real-time signals for tool and workpiece surface/edge condition using a non-obstructive hardware with characteristic industrial applications and advanced signal analysis.

The next section discussed the advanced signal processing and analysed results for the TWCM system. The subsequent subsection discussed the advanced signal analysis results with the application of digital filters on the vibration signal. This was done to eradicate the effect due to the offset of the gravitational field on the vibration sensor. However, this approach was not applied in the study because of the nature and type of the signal capture at the machining station which was non-stationary and non-linear. The next section discussed the decomposition of the vibration signal using the EMD method. The vibration signal was decomposed into real and imaginary parts, the IMFs and residuals. The HHT was applied to the IMFs to derive the instantaneous physical properties of the signals which were the feature vectors for classifying the tool and workpiece condition monitoring system. A total of 12 features were generated from the vibration signals, comprising the instantaneous energy, amplitude and instantaneous frequencies of the signals. This addressed the Fourth Objective of the study which was to compute and extract feature vectors of instantaneous physical properties from raw captured signals using advanced signal processing techniques capable of discriminating and classifying different tool and workpiece conditions during turning operation in real time.

Thereafter, the next section discussed the feature selection using the GA algorithm on the vibration signals. This section applied the GA algorithm for selecting essential features from the computed feature vectors of the instantaneous physical properties of the processed signal. The purpose of this computation was to reduce the computational cost of the ML classification algorithm and to reduce the processing time. The original extracted features were twelve (12) and four (4) features were selected using the genetic algorithm. This addressed the Fifth Objective of the study which was to determine the optimal features through hyperparameter optimization for the selection of important features for the ML algorithms.

The last section discussed the classification of the conditions of the tool and workpiece during operation by classifying the selected features from the processed features using different ML models and optimising the models to obtain the one with the optimal result or accuracy. The last section of the chapter discussed feature classification for tool and workpiece conditions for the TWCM system. Neural network feedforward backprop with SCG algorithm, SVM and KNN were used in classifying the conditions of the tool and workpiece during operation. The error loss in the classification of each algorithm was evaluated to determine the model with the best performance. To optimise the model, the k-fold cross-validation technique was applied for the classification. Both 5-fold cross-validation and 10-fold cross-validation were applied on the classification models and the error loss of each of the models was determined and plotted. The model with the least error loss would perform the best in classifying the condition of the tool and workpiece during operation into either of the four (4) classes of tool and workpiece conditions. Furthermore, SVM and KNN algorithms were also applied to all the twelve (12) features without feature selection. Impressively, the performance of SVM improved considerably. The error loss for SVM models marginally dropped, which may imply that the model performed better when all the computed features were used compared to when only the feature selection algorithm was used. Overall, the KNN8 model gave the least error loss and therefore it was judged the optimal model for classifying the condition of the tool and workpiece during machining operation from captured and analysed signals. Hyperparameter optimization was performed on the fitted KNN8 classifier and the distance metrics was specified as '*cityblock*' using the *kdtree* neighbour searcher method, which addressed the Sixth Objective. The objective function of the optimization was the classification error loss while the distance metrics were the constraints considered. This therefore also addressed the Sixth Objective which was to optimize the ML models developed for tool and workpiece condition classification by applying different ML algorithms with k-fold cross-validation technique.

Therefore, the overall aim of the study was achieved, which was to develop a TWCM system that classified the condition of the tool and workpiece through non-obstructive online monitoring. This implies that this study avoided downtime due to intermittent stoppage of the machining operation or process.

CHAPTER 6 : CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

This chapter discusses the research conclusion, highlighting the research objectives and stating how each of the objectives was addressed. It also explains in general terms the underpinning research approach used in developing the Tool and Workpiece Condition Monitoring System that can evaluate and classify the conditions of both the cutting tool and workpiece surface profile parameters during turning operation. Optimizing the turning operation requires a painstaking approach that evaluates the condition of the tool and its corresponding workpiece surface quality output during machining operation, provides a means for determining the threshold of the condition by capturing and processing vibration signals during the operation, and thereafter intelligently classifying the condition of the tool and workpiece during operation using trained ML classification algorithms. The chapter also discusses the results of the implemented approach and the methods and techniques adopted. This chapter also offers some recommendations based on the challenges encountered in the course of the experiment and data capturing that can in future be reviewed. A brief discussion of the experimental work and its limitations is also given.

Further research work that can be done in optimising turning operation by using the existing smart technology techniques and the robust data processing capabilities is also discussed in the chapter. Lastly, further general recommendations on the research area, which basically cut across the experimentation, data processing techniques and signal analysis are also highlighted.

6.2 Research Conclusion

Machining operation is an important manufacturing process as it is undertaken by both companies manufacturing new products and companies that produce parts for maintenance services. Turning operation is performed when parts with mostly cylindrical geometry are to be produced and this is done on the lathe or CNC lathe machine tool. Unlike a milling or drilling operation with a rotating cutting tool and fixed workpiece, a turning operation consists of a rotating workpiece and a fixed cutting tool on the tool post that allows only forward, backward and tapered directional movement against the workpiece as it cuts. Several research works have been done in the area of monitoring the tool condition to prevent failure and damage, which in turn affects the workpiece during operation. This most often leads to a lower bound approach, which is basically the damage done to the workpiece because of sudden damage to the cutting tool. Because the tool failure is not anticipated, breakage of the cutting tool during operation often damages the workpiece hence increasing the number of scraps and practically increasing the production cost. This phenomenon also increases the downtime at a machining station as production time is lost due to replacement of the cutting tool and workpiece, and, in cases where the event causes machine fault, time is lost to machine repair or machine reconfiguration as the case may be. This generally increases the cost of production due to lost production time, increased cost of cutting tool replacement, increased cost of scrapped workpiece, and cost of machine tool repair or reconfiguration. This situation has prompted several studies directed towards research into tool failure, and its prediction to reduce the cost of production caused by damage. As the available literature online revealed, more research work has been done on milling operation than drilling or turning operation on the lathe.

The upper bound approach due to a degenerating tool condition may not only cause scrapped workpiece due to the failing condition but also increases the production time due to re-work and often increases the number of scrapped workpieces in precision manufacturing. In precision manufacturing, product quality requirements are strict and some high alert guidelines must be observed in the manufacturing of the part These may include the dimensions, the surface finish of a product as well as many other aspects. These two characteristics of a product are often affected by the tool condition as it moves from one stage of condition to another more serious one. In precision machining, the quest for achieving the requirement of high quality has led to many machining stations not utilizing the tool to the end of its useful life due to the policy of uniformly replacing the tool after a specific production time. This strict replacement policy avoids rework and reduces the number of scraps at the machining station but will increase the production cost due to under-utilization of the cutting tool to the end of its useful life. This study therefore attempts to implement a tool wear and workpiece surface parameter monitoring system that classifies the tool and workpiece condition, or state into four classes during production, using the processed and analysed vibration signal. This approach is a data-driven approach that incorporates advanced sensors for signal capturing, cyber-physical technology brought about by the IoT devices, gateway, and cloud computing which makes remote access to the signals possible. This TWCM system implies that production can be improved based on the prior knowledge of the product quality requirement and the real-time condition monitoring system available for updating the machining operation trend. With the application of tolerance, the smart turning operation can be optimized at any machining station by using the tool to the end of its useful life.

The nature of the challenges involved in the turning operation have made it a daunting task which has necessitated developing techniques and procedures to accurately monitor the tool and workpiece condition during operation. Most of the available techniques have adopted an indirect method of tool or workpiece condition measurement due to the fact that the region of operation is obstructed during operation. While some indirect methods have demonstrated a good outcome in terms of accuracy, the disadvantages caused by downtime due to intermittently stopping the process for condition measurement has made the approach inefficient. Several attempts have been made to detect failure of the cutting tool through monitoring and analysis of different operating parameters, and using different sensor types to capture data from the region of operation. Amongst other types of sensor data captured, acoustic data, vibration and temperature have been widely used as discussed in Chapter 2. However, due to the fact that the region of operation is obstructed during turning, some signal types have been shown to be inaccurate at isolating the conditions of the cutting tool or the workpiece during operation. For example, it requires a great deal of effort in data processing to filter out acoustic emissions that emanate from the reaction between the tool and the workpiece during operation due to the noise produced by the machine tool during operation as earlier discussed in Chapter 2. Similarly, measuring the temperature of the cutting zone during operation is a daunting task due to the constantly rotating workpiece and sometimes the introduction of coolants under extreme conditions may affect the accuracy of the measurement. An example found in the reviewed literature and discussed earlier is where the tool is bored and a temperature sensor inserted to measure the temperature close to the cutting zone but this process still experiences some major setbacks such as those caused by variations in the tool type used in the turning operation, a fracture along the bored region of the cutting tool, the non-scalability of the approach as it requires that all cutting tools be bored for the deployment of the temperature sensor, and lastly, inconsistencies in the measured result due to varying conditions of machining in cases where coolants are introduced. These setbacks are a major deterrent to using this parameter for evaluating the condition of the cutting tool during operation. Furthermore, vibration signals captured in the region of the turning operation may only produce a fair reflection of the power generated due to the interaction between the cutting tool and the workpiece during operation. In addition, the signal type has a drawback due to the varying low contribution in the signals due to the alignment of the accelerometer (vibration sensor) to the gravitational field. In this research work, an attempt was made to capture the thermal image of the region of the cutting operation for the purpose of monitoring the condition of the cutting tool and the workpiece during operation. However, this approach failed because the region of turning is obstructed during operation. Alternatively, the thermal image could be captured intermittently, which is not consistent with Objective Three which was to develop a non-obstructive TWCM system for optimising turning operation. Therefore, of the three widely used parameters, the vibration parameter remains the parameter with the most accuracy in capturing the conditions reflecting the region between the cutting tool and the workpiece during operation. In this research, the vibration parameter was used as the processed signal for extracting features for optimising the turning operation by classifying the condition of the tool and workpiece during operation. The First Objective of the study, which was to analytically determine the workpiece surface roughness parameters that correlated with the cutting tool condition for a turning operation, has been described in Section 5.2.1 of Chapter 5. Of the measured surface profile parameters captured from the workpiece and cutting tool, six (6) parameters were used to develop the knowledge base of the classes of tools and the workpiece condition during machining operation. The Second Objective of the study was to analytically determine the range of surface profile parameter data values for each class of tool and workpiece condition monitoring. The Third Objective of the study was to adaptively design and capture real-time signals for tool and workpiece surface conditions using a non-obstructive hardware with characteristic industrial application and advanced signal analysis. This objective was achieved and was discussed both in Section 3.11 in the design of the TWCM system and also in Section 5.2.3 that explains the implementation procedures and outcome. The Fourth Objective of the study was to compute and derive features vectors of instantaneous physical properties from raw signals using advanced signal processing techniques capable of discriminating and classifying different tool and workpiece conditions during turning operation in real time. This was discussed and achieved in Section 5.3.2 of Chapter 5, with 12 features computed from the processed signals. All these features might be used; however, parameter optimization for the selection of important features for the ML algorithm was implemented using GA as explained in section 5.3.3, which addressed the Fifth Objective of the research, which was to determine the optimal features through hyperparameter optimization for selection of important features for the ML algorithm. Hyperparameter optimization of the fitted KNN8 model was performed with the objective function being the error loss and the constraints in the distance metrics. The objective function of the model after hyperparameter optimisation specified 'cityblock' distance metrics using the '*kdtree*' neighbour searcher method to perform optimally with the fitted model, hence 'cityblock' distance was therefore used as the distance metrics for the trained model which was the Sixth objective of the study which was addressed and achieved in Section 5.3.3 of Chapter 5. The last objective was to optimize the ML models developed for tool and workpiece condition classification by applying different ML algorithms with k-fold cross-validation techniques as discussed in Section 5.4 of Chapter 5. Five-fold (5-fold) and 10-fold cross-validation techniques were applied on both the SVM and KNN models to determine which of the models gave the better performance in terms of accuracy by evaluating the error loss of each of the models and comparing the results. The achievement of all the objectives invariably reduced the downtime during machining process due to system shutdown for tool and workpiece condition monitoring, hence achieving the aim of the study.

Tool failure and condition monitoring has been widely researched with much attention given to different sensor data and analytical approaches, and with fair consideration being given to workpiece surface quality output. In cases where the major focus was on the workpiece, less consideration was given to the cutting tool. Tool condition plays a major role in the machining of any part during turning operation. A worn tool invariably produces a poor-quality output which may not meet the product quality requirement. Furthermore, due to varying product quality requirements, the tool may still be within its useful life if it meets the surface quality of the product. It is therefore important to optimise the turning operation by considering the product quality requirement and the tool condition for an operation. This implies that if the product quality requirement to produce a particular product requires high precision manufacturing for utmost product surface quality, even a good tool within its useful life may fail to perform the function satisfactorily in this instance while a new tool that meets such requirements may during the turning process gradually degenerate and also fail to perform the machining process function satisfactorily. However, if the product quality requirement changes, that is, if a new machining operation is to be carried out to produce a product with a level of surface quality that does not require high surface quality precision, the used good tool would function satisfactorily. Hence, this becomes a real challenge in determining the tool condition and the corresponding workpiece quality output for meeting the production quality requirement. Therefore, extracted parameters that capture the variation in the tool conditions and the corresponding workpiece surface quality output were evaluated using MANOVA analysis, which addresses Objective Two as explained in Chapter 4, Section 4.4. and Chapter 5, Section 5.2.1. The surface/edge roughness parameters for different conditions of cutting tools were measured and the corresponding surface quality output of the workpiece machined with the tool was measured as well. Parameters that were significant for measuring the variation due to the condition of the cutting tool were estimated using multiple anova (MANOVA) analysis. Six (6) prominent parameters were estimated to give significant variations due to the conditions and the range of classes of measured values of each cutting tool and the workpiece quality output was determined. This was the Second Objective of the study and it was discussed in Chapter 5, Section 5.2.2. The classes for the classification of condition form the knowledge base for the output class for the classification algorithm used for the TWCM system for optimising turning operation.

In addition, the accuracy of any tool condition monitoring technique relies on the strength of the signal analysis. Due to the obstructive nature of most of the machining operation, it is challenging to capture the signals reflecting the tool or workpiece condition. Therefore, the accuracy of any method replies on the application of robust data processing and advanced signal analysis to filter out the signals that reflect the threshold generated from mainly the component/s that are of concern to the research. In this research advanced signal processing functions and tools were used in extracting feature vectors from signal buffers captured by the IoT cyber-physical systems for further classification using the artificial intelligent approach.

Furthermore, the vibration signals captured during the machining operation cannot be directly used in analysing the conditions of the tool and workpiece as the signal is in time series. Therefore, advanced processing techniques are needed to extract the instantaneous physical features from the signals. The EMD method was applied to the captured vibration signal to decompose the signal into real and imaginary components, which are IMFs and Residuals respectively. HHT was then applied to the IMFs to compute the instantaneous physical properties such as the instantaneous energy, amplitude and frequency of the signal. Twelve (12) feature vectors were computed from the signals which addressed the Fourth Objective as highlighted in Section 5.3.2 of Chapter 5. To reduce the computational cost and the processing time of the classification model, the feature selection method using GA was applied. The prominent pertinent features that significantly and accurately discriminated between the condition of the cutting tool and workpiece during operation were extracted from the computed signals using parameter optimization with GA. Four (4) features were selected from the twelve (12) features computed from the signals, hence addressing the Fifth Objective of the study as explained in section 5.3.3 of Chapter 5. Hyperparameter optimization was also performed on the fitted KNN8 model and the objective function of the model after hyperparameter optimisation specified 'cityblock' distance metrics using the '*kdtree*' neighbour searcher method to perform optimally with the fitted model, hence 'cityblock' distance was therefore used as the distance metric for the trained model. This addressed the Sixth Objective as explained in Section 5.3.3 of Chapter 5. Classifying the cutting tool and workpiece condition during turning operations from the extracted features requires more than statistical tools to evaluate accurately (Painuli, Elangovan and Sugumaran 2014). Hence, most tool condition monitoring uses the artificial neural network machine learning approach (Silva *et al.* 1998; Ambhore *et al.* 2015; Abubakr *et al.* 2021). There are quite a few neural network types that can be used for classifying the condition of the tool and workpiece for turning operation optimisation; however, a feed forward neural network with SCG algorithm was used for classifying the conditions of the Tool and Workpiece Conditions into four (4) as explained earlier. Only one hidden layer was used in the network with eighteen (18) nodes and four (4) output classes. The result showed that the classification algorithm would perform at a confidence level of about 89.8% as explained in Section 5.4 of Chapter 5. Other ML algorithms such as SVM and KNN were also used for classifying the condition of the tool and workpiece during operation. The models were optimised using the k-fold cross-validation technique with the KNN algorithm performing better than the SVM. All the features were deployed for training the classification algorithm to compare the performance to when feature selection was applied. The KNN8 model performed the best in terms of error loss in the classification of the model, which addressed the Sixth Objective of the study.

In conclusion, even though digital filters have been widely used in many research studies to eliminate low varying contribution to the vibration signals, the EMD method with HHT is a preferred approach in vibration signal processing. The physical properties of the signal were derived by applying HHT on the IMFs of the decomposed signals as the features for training ML algorithms. Furthermore, KNN was shown to be a better algorithm than SVM and Feed Forward Backprop with SCG in modelling the classification of Tools and Workpiece conditions from the study based on the classification error loss.

6.3 Recommendations

Generally, the advent of 4IR has enabled endless divergent applications and systems capable of performing and implementing smart and intelligent decisions across several systems and processes. The endless possibilities of IoT devices have enabled systems, devices, machines and humans to communicate and exchange information and commands at different levels, executing tasks and instructions with fewer limitation of space and presence. Advancement in the development of smart IoT devices has further improved and enhanced the numerous possibilities of smart systems and processes compared to the early days of 4IR. Stand-alone industrial wireless sensors capable of transmitting signals under varying conditions have been developed which have increased the application of smart system development and integration to applications. Furthermore, the transition from a 2G to a 4G and now to a 5G network has enhanced data transmission to and from the cloud. This has changed the dimension of how Internet of Things (IoT) devices communicate and exchange data and information across different online platforms, thereby creating a new communications possibility between machines and humans known as cyber-physical systems. It has also brought about a revolution in the world of automation as automated systems can be programmed with intelligent IoT enabled controllers that interpret signals from sensors, process them and send instructions to the actuators for self-adjustment or re-configuration. Output information may even sometimes be presented to the operator through HMI for decision making.

The research took advantage of advanced smart IoT devices and cloud computing to build a cyber-physical system capable of capturing signals from a turning operation and sending them through a gateway to a remote online cloud for data processing and decision making. The cloud platform is capable of sending a feedback instruction on the platform and works with any stand-alone third-party online platform/software. The cloud server can connect up to one hundred (100) sensors, transmit data, save and execute instructions as it is programmed to do, which makes it a robust application for both industrial application and research purposes. The shortcoming of the gateway connection, however, is that it involves quite a few steps and requires advanced knowledge to configure and run the connection between the sensors, gateway configuration and the cloud platform, or server communication. The integration of the three components for smart systems should be improved to accommodate people with limited knowledge of networking. The gateway also requires server configuration but, however, does not work efficiently on a public server or domain, which may be a challenge when the only available server is a public one.

In most industries where precision manufacturing is undertaken, it is very important that product requirements be adhered to. To achieve this, high running costs are incurred due to under-utilization of the cutting tool to the end of its useful life and the increased number of scrapped workpieces due to poor product quality output produced from the machining station. To overcome this challenge, there is a need to optimise the turning operation by monitoring the condition of the tool and workpiece based on a robust, developed, advanced signal analysis and machine learning algorithm that can predict the class of tool and workpiece condition during turning operation. This approach could also be used by monitoring several more examples of tool and workpiece conditions non-obstructively by establishing more additional classes with the threshold of the parameters for the range of the classes being considered. The signals are captured and analysed, and features are extracted and trained for the classification of different tool conditions using the machine learning algorithm. This could be used for a particular application to optimise the production during operation without intermittently stopping the process for monitoring.

Lastly, the TWCM system could also be deployed for varying machine operating parameters such as the feed rate and the spindle speed during a turning operation. This would require more data and signals to be captured for a more robust and accurately trained network. The inclusion of the operating parameters would imply that more output classes could be considered while the feature extraction procedures remained the same and the parameters were varied one at a time. Hence, with a constant spindle speed, and with the feed rate varied, and a label used for the resulting outcome of the tool condition, the workpiece surface quality output, and the resulting vibration signal could be generated during the turning process. Thereafter, the feed rate could be varied at constant spindle speed, and the same procedure followed for the turning operation experiment except that a different label would be used for representing the resulting classes from the operation. The same procedure could be used for varying the spindle speed at a constant feed rate and a different label used to represent the output class resulting from the tool and workpiece based on the resulting signals captured during the manufacturing process. Hence the result of this more robust system is that the outcome and the extracted features can be trained using the deep learning approach that uses multiple hidden layers and a backpropagation neural network. The recommendations may therefore be summarized as follows:

- A more robust TWCM system may be developed to incorporate the varying operating parameters of the machine, such as the spindle speed and the feed rate. This may require that more tool and workpiece classes may need to be created to accommodate the various conditions and ultimately the corresponding condition output.
- Another factor that may need to be considered is the machine tool condition during operation as it has the potential to alter the significance of the signals captured during operation. The TWCM system could also be developed to identify potential damage initiation with the machine tool.
- A high precision TWCM system may be implemented by further breaking down the classes for TWC classification to less than four classes. This would imply that the range of classification of both the tool and workpiece would likely have a smaller range of threshold.

6.4 Future Research

Smart manufacturing requires that products are manufactured using cutting edge technology to bring about an improved production rate and improved quality at a reduced production cost, and in optimal time. This can be achieved using smart intelligent devices, cyber-physical systems through cloud computing, IoT devices and the machine learning approach. With the emergence of these smart devices and technologies, manufacturing has been pushed to the brink and efficient systems have emerged with more safety considerations due to less involvement of humans in a hazardous work environment. Remote monitoring and control for process operation and for decision making has reduced the level of exposure to industrial risk while also enhancing the level of productivity of the manufacturing facility.

The developed TWCM system optimizes the turning operation by classifying the extracted features from a new signal buffer captured during the turning operation process into the classes of existing conditions trained by the network. The heartbeat of the sensor and gateway is re-set to 30 seconds after training the network, which means the data is captured after every 30 seconds and classified by the TWCM system. This therefore implies that the condition can be monitored to check that the classification is within the recommended range. Further future research on this research area can be done in the area of integrating the system so as to give feedback to the controller of the CNC lathe machine for prompt attention in case the monitored condition is severe. The system could also be developed to consider the input as the product requirement before commencement of the turning operation. In this regard, the system is automated as the decision is intelligently taken by the controller of the machine tool and notification for change of cutting tool is requested if the threshold would exceed the input values of the product at the commencement of the turning operation. This would incorporate production optimization into the numerically controlled machine for smart manufacturing.

6.5 Conclusion

This research has optimized tool wear and workpiece condition monitoring by developing a tool and workpiece monitoring system capable of classifying the condition of the cutting tool and workpiece surface/edge roughness during a turning operation without intermittently stopping the machine. The system monitors the turning operation by classifying the condition of the tool and workpiece with regard to determining the product's output based on requirement while optimally utilizing the tool. If the product quality requirement is known before commencing the operation, the signal captured can be used to optimise production by determining the range of class the signal must indicate all through the operation. Once the signal is classified close to the required threshold class, the system can be shut down and the tool changed for optimal productivity. Therefore, the system reduces the number of scrap workpieces while increasing product output. It also allows for maximum utilization of a cutting tool as the tool is fully utilized based on the product quality requirement. Furthermore, the cost of reworking or scrapping the product resulting from tool damage directly affecting the workpiece is also reduced.

In addition, since the parameters indicating the range of values for the output classes and their corresponding product surface output is known per each of the classes, tool surface/edge roughness parameters can be measured to provide confidence for the range of product quality required from the production, and the system can invariably classify the class during operation to monitor changing tool conditions during the turning operation for the purpose of checking that the quality requirement of the product has not been compromised. This implies that when the edge/surface wear parameters of the cutting tool are measured before commencing turning, the workpiece quality output can be determined accurately, and the condition of the machine can be determined during operation. Even though the measurement of the tool condition and the workpiece roughness parameters during operation is daunting and almost impracticable, the TWCM system developed has accurately captured the condition from the indirect method of analysing and processing signals using advanced signal processing techniques that firstly adopt smart devices such as industrial IoT, gateway, and cloud computing to capture vibration signals, and applying advanced signal techniques for signal processing. The features that can discriminate between the varying classes of tools and workpiece are extracted from the analysed signal and a neural network classification feedforward algorithm is used for classifying the features, and hence the condition of the tool and workpiece.

In conclusion, if there is a signal that captures the power generated from the reaction between the cutting tool and the workpiece during turning operation despite the nature of the operation, then the signal can be analysed using some advanced algorithm for signal analysis and features extracted from the analysed signal and classified using AI algorithm. In summary, the developed TWCM system optimises tool and workpiece wear condition monitoring by classifying the extracted features from the processed signals and classifies the condition using a neural network algorithm.

Therefore, the approach in this study has focused on advanced signal processing and analysis and feature extraction, selection, and classification to determine the condition of the cutting tool during the machining operation without intermittent stoppage of the machining operation. In this study, the cutting tool was first classified into four classes using ISO 3685:1993 based on the flank wear (VB) of the cutting tool. The captured vibration signals were first decomposed using the EMD method to obtain the corresponding IMFs and residuals of the signals. To derive the feature vectors of the signals with instantaneous properties capable of classifying the tool classes, HHT function was applied to the IMFs. It could be observed that 12 features were obtained after applying the Hilbert transform to the IMFs. So as to reduce the computational burden and time, feature selection was performed with GA. After applying three ML models for classifying the tool condition with 5-fold and 10-fold cross-validation, the following observations were noted:

1. Four classes of tool and workpiece surface parameter condition classification were developed. The parameters considered the correlated surface profile parameters such as R_a, R_z, R_y R_t , R_{max} and R_q for evaluating the flank wear of the cutting tool and the surface profile condition of the workpiece during operation. This approach is unique to this study.

2. Neural network feedforward backprop with the SCG ML model was first adopted for classifying the tool classes with a fair error of 0.102. A better model has been observed to provide better performance.

3. SVM and KNN were applied for feature classification with both 5-fold and 10-fold cross-validation and the effectiveness of the models was evaluated by determining the error loss of both models.

4. The lowest error loss of 0.4752 was observed with the SVM model when 5-fold cross-validation was implemented, whereas, with the KNN model, the lowest error loss was observed as 0.0166 when 5-fold cross-validation was implemented. In this case, feature selection using GA was implemented before ML classification.

5. The lowest error loss of 0.4881 was observed with the SVM model when 10-fold cross-validation was implemented, whereas with the KNN model the lowest error loss was observed as 0.0109 when 10-fold cross-validation was implemented. Similarly, feature selection using GA was implemented before ML classification.

6. When all the features were used (with no feature selection done), the lowest error loss of 0.1170 was observed for the SVM model when 10-fold cross-validation was implemented, whereas with the KNN model the lowest error loss was observed as 0.1606 when 10-fold cross-validation was implemented.

7. Also, when all the features were used (with no feature selection done), the lowest error loss of 0.1021 was observed for the SVM model when 5-fold cross-validation was implemented, whereas with the KNN model the lowest error loss was observed as 0.1870 when 5-fold cross-validation was implemented.

8. Of the two models, KNN performed better in classifying the tool classes during the machining operation when the decomposition method with HHT was applied to the vibration signals captured during the operation.

9. SVM models performed better when all the features extracted from the vibration signals were considered compared to when feature selection was implemented, whereas for the KNN model the performance was better when feature selection was implemented.

10. Hyperparameter optimization was implemented on the fitted KNN8 model and the objective function of the model after hyperparameter optimisation specified '*cityblock*' distance metrics using the '*kdtree*' neighbour searcher method to perform optimally with the fitted model, hence 'cityblock' distance was therefore used as the distance metric for the trained model. The estimated objective function value was 0.01416 while the observed objective function value was 0.014.

11. The methodology developed based on tool classification using advanced signal processing techniques can be used to classify product quality output based on work requirements in terms of the correlated roughness parameters.

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APPENDIX

MATLAB Codes and Functions

```
% data1 = xlsread('DataMonitoring.xlsx');
data = xlsread('ResearchData.xlsx');
z = size(data);
vib = data;
% [acc, actid, actlabels, t, fs] = getRawAcceleration('subjectId', 1, 'Acc
Type', 'total', 'component', 'X');
% x = 3; y = 0.001; z = 100;
% acc(:, 1) = x - y *rand(1, z) + y;
% acc(:, 2) = 1.0:1:z;
%t = acc(:, 2);

NewTool = find(data(:, 3) == 1);
goodTool = find(data(:, 3) == 2);
rough = find(data(:,3)== 3);
WornTool = find(data(:,3)==4);




% plotAccelerationColouredByActivity(t, acc, actid, ('vertical
acceleration'))
%
============================================================================
figure;
plot(vib(1:230, 2), vib(1:230, 1), 'g', 'MarkerSize', 7)
hold on
plot(vib(721:800, 2), vib(721:800, 1),'g', 'MarkerSize', 7)
hold on
plot(vib(911:925, 2), vib(911:925, 1), 'g', 'MarkerSize', 7)
hold on
plot(vib(231:550, 2), vib(231:550, 1), 'b', 'MarkerSize', 7)
hold on
plot(vib(801:890, 2), vib(801:890, 1), 'b', 'MarkerSize', 7)
hold on
plot(vib(551:676, 2), vib(551:676, 1), 'y', 'MarkerSize', 7)
hold on
plot(vib(891:910, 2), vib(891:910, 1), 'y', 'MarkerSize', 7)
hold on
plot(vib(677:720, 2), vib(677:720, 1), 'r', 'MarkerSize', 7)
hold on
plot(vib(926:1000, 2), vib(926:1000, 1), 'r', 'MarkerSize', 7)

hold off
grid on
xlabel('Time in Minutes');
ylabel('Vibration of the TailStock');
title('Vibration of the Tailstock by Color Specification of Tool Condition');

legend('--b NewTool', '-r WornTool', '-y roughTool', '-goodTool');

% xlabel('Time in minutes');
```

```
% ylabel('Wear Measurement');

fprintf('Program paused. Press enter to continue.\n');
pause

%============================================================================
=
% Tocheck the statistics of the signal we may plot the histogram
%% To plot the data without indicating the varying classes of signals
figure(2)
plot(data(:, 2), data(:, 1))

xlabel('Time in Minutes');
ylabel('Vibration of the TailStock');
title('Vibration of the Tailstock vs Time');



%%
% The objective of the filter design is to get rid of the varying low
contribution due to the allignment
% of the accelerometer to the gravitational(rotational) field. (We view the
infant response and step response to visualize the performance)
%%
fhp = FilterAcc;

% Decouple the acceleration due to the operation dynamics to gravity
ab = filter(fhp, data);

% Plot the filtered acceleration by the activity or class colour
figure(3);

plot(vib((1:230), 2), ab((1:230), 1), 'LineWidth', 1, 'MarkerSize', 7)
hold on
plot(vib((721:800), 2), ab((721:800), 1),'LineWidth', 1, 'MarkerSize', 7)
hold on
plot(vib((911:925), 2), ab((911:925), 1), 'LineWidth', 1, 'MarkerSize', 7)
hold on
plot(vib((231:550), 2), ab((231:550), 1), 'b', 'MarkerSize', 7)
hold on
plot(vib((801:890), 2), ab((801:890), 1), 'b', 'MarkerSize', 7)
hold on
plot(vib((551:676), 2), ab((551:676), 1), 'y', 'MarkerSize', 7)
hold on
plot(vib((891:910), 2), ab((891:910), 1), 'y', 'MarkerSize', 7)
hold on
plot(vib((677:720), 2), ab((677:720), 1), 'r', 'MarkerSize', 7)
hold on
plot(vib((926:1000), 2), ab((926:1000), 1), 'r', 'MarkerSize', 7)

hold off
grid on
xlabel('Time in Minutes');
ylabel('Vibration of the TailStock');
title('Vibration of the Tailstock by Color Specification of Tool Condition');
```

```
legend('--b NewTool', '-r WornTool', '-y roughTool', '-goodTool');

hold off

xlabel('Time in seconds');
ylabel('Vibration of the TailStock');

%%
fhp = FilterAcc;

% Decouple the acceleration due to the operation dynamics to gravity
ab = filter(fhp, data);

% Plot the filtered acceleration by the activity or class colour
figure(3);

plot(ab((1:230), 2), ab((1:230), 1), 'LineWidth', 1, 'MarkerSize', 7)
hold on
plot(ab((721:800), 2), ab((721:800), 1),'LineWidth', 1, 'MarkerSize', 7)
hold on
plot(ab((911:925), 2), ab((911:925), 1), 'LineWidth', 1, 'MarkerSize', 7)
hold on
plot(ab((231:550), 2), ab((231:550), 1), 'b', 'MarkerSize', 7)
hold on
plot(ab((801:890), 2), ab((801:890), 1), 'b', 'MarkerSize', 7)
hold on
plot(ab((551:676), 2), ab((551:676), 1), 'y', 'MarkerSize', 7)
hold on
plot(ab((891:910), 2), ab((891:910), 1), 'y', 'MarkerSize', 7)
hold on
plot(ab((677:720), 2), ab((677:720), 1), 'r', 'MarkerSize', 7)
hold on
plot(ab((926:1000), 2), ab((926:1000), 1), 'r', 'MarkerSize', 7)

hold off
grid on
xlabel('Time in Minutes');
ylabel('Vibration of the TailStock');
title('vibration of the tailstock by color specification of Tool condition');

legend('--b NewTool', '-r WornTool', '-y roughTool', '-goodTool');

hold off

%% isolate filtered signals for good tools
sel = vib(:, 2)< 280 & vib(:, 3)==2;
% Those are signals for good tool
tgTool = vib(sel, 2);
abw = ab(sel, 1);
figure(5)
plot(tgTool, abw, 'b','MarkerSize', 7)
grid on
xlabel('Time in Minutes');
ylabel('Vibration of the TailStock');
```

```
title('vibration of the tailstock with good Tool condition');


function EMD = empirical

%% vibration analysis
data = xlsread('ResearchData(vib, Time & Label).xlsx');
z = size(data);
vib = data;
figure

plot(vib(:,2), vib(:,1),'Markersize', 3);
grid on
xlabel('time')
ylabel('vibrations')
title('vib of the tailstock vs time')
rng(10);

[imf, res] = emd(vib(:,1));

figure
set(gcf,'color','w','units','normalized','Position',[0.1, 0.15, 0.8 0.5]);
tiledlayout(size(imf, 2)+1, 1);
for i = 1: size(imf, 2)
    nexttile
    plot(vib(:,2), squeeze(imf(:, i)),'MarkerSize', 3);
    title(strcat(num2str(i),'IMF'),'interpreter','latex');
    xlabel('$t$','interpreter','Latex');
    % xlim([0 stopTime_plot])
    ax = gca;
    ax.FontSize = 12;
end

nexttile
plot(vib(:,2), res, 'MarkerSize', 3)
title('residual','interpreter','latex');
xlabel('$t$','interpreter','latex');
ylabel('Feq.','interpreter', 'latex');
% xlim([0 stopTime_plot])
ax = gca;
ax.FontSize = 12;

fs = 20;
figure
set(gcf,'color','w','units','normalized','Position',[0.1, 0.15, 0.8 0.5]);
tiledlayout(size(imf, 2)+1, 1);
for i = 1: size(imf, 2)
    nexttile
    hht(imf(:, i), fs);
    title(strcat(num2str(i),'IMF'),'interpreter','latex');
    xlabel('$t$','interpreter','Latex');
    % xlim([0 stopTime_plot])
    % ylim([0 30])
    ax = gca;
    ax.FontSize = 12;
```

```
end
% Extracting features from hilbert transform
[hs, f, t, imfinsf, imfinse] = hht(imf, fs);
% f, imfinsf, imfinse to a single matrix features
feat = [imfinsf imfinse];
xlswrite('HilbertFeatures.xlsx',feat);
yFeatLabel = vib(:, 3);




%% classification using Neural network
%classification through neural network
XX = sFeat';
Y = (vib(:, 3));

%xx = [0.5 0.2; 0.1 0.15;0.7 2.1; 1.5 2.4;0.2 0.3;0.9 1.8;1.35 2.6;1.56
2.5;0.8 1.5;0.3 0.45];
% XX =xx';
% Y =[1;1;2;3;1;2;3;3;2;1];

tgt = dummyvar(Y)';

rng default;

net = patternnet(18);

net = train(net, XX, tgt);
%% Test run the classification
% M = fitcknn(sFeat, 'var$');
% crossmodel = crossval(M);
% Using 5 KFold crossvalidation and then SVM and KNN model

k = 10;
%NsFeat = size(a,1);
ssFeat = sFeat; % sFeat;

Y = (vib(:, 3));
YY = dummyvar(Y);

%SVM_M = zeros(k);
%KNN_M = zeros(k);
LKnn = zeros(k);
LSvm = zeros(k);
ErrorVal = zeros(k, 2);
size(sFeat)
size(Y)

rng(10);
c = cvpartition(1000, 'KFold', 10)
% m = fitcsvm(ssFeat, Y, 'standardize',true);
% m = fitcecoc(ssFeat, Y);
% crosmodel = crossval(m,'cvpartition', c);
training(c, 1);
```

```
sum(training(c, 1))
% KNN_M = fitcknn(ssFeat(idxTrain, :), Y(idxTrain));


for i = 1:k

    idxTrain = training(c, i);
    idxTest = test(c, i);
    SVM_M = fitcecoc(sFeat(idxTrain, :), Y(idxTrain));
    %SVM_M(i) = fitcsvm(ssFeat(:, idxTrain), YY(idxTrain));

    KNN_M = fitcknn(sFeat(idxTrain, :), Y(idxTrain), 'NumNeighbors', 4,
'Standardize',1);

    % to predict with the model
    svmPred = predict(SVM_M, sFeat(idxTest,:));
    knnPred = predict(KNN_M, sFeat(idxTest,:));

    % calculating the loss of each model
    LKnn = loss(KNN_M, sFeat(idxTest, :), Y(idxTest));
    LSvm = loss(SVM_M, sFeat(idxTest, :), Y(idxTest));

    ErrorVal(i,:) = [LSvm LKnn];

end

noNeib = KNN_M.NumNeighbors;

y = ErrorVal;

yError = mean(y)
errorSize = size(y);
figure
grid on
bar(y)
xlabel('5-Fold Cross-validation Model')
ylabel('Model Error Loss')
title('SVM vs KNN Model Error')
legend(' SVM Model', ' KNN Model')

xlswrite('ModelPrediction.xls', y);


%% ==============================================================
sFeat = xlsread('selectedFeat.xlsx');
sFeat;
rng(10);
YN = (vib(:,3));
% validate the test set for new data
c = cvpartition(1000, 'KFold', 10);
idxTrain = training(c,9);
idxTest = test(c, 9);
KNN_M8 = fitcknn(sFeat(idxTrain,:), YN(idxTrain), 'NumNeighbors',4,
'Standardize',1);
```

```
noNewN = KNN_M8.NumNeighbors;


%%
dataNew = xlsread('Validatn.xlsx');
vibNew = dataNew(:, 1);
yNew = dataNew(:,3);
fs = 20;
rng(10);

[imfN, resN] = emd(vibNew);
% Extracting features from hilbert transform
[hn, l, t, imfinsfN, imfinseN] = hht(imfN, fs);
% f, imfinsf, imfinse to a single matrix features
featN = [imfinsfN imfinseN];

% xlswrite('HilbertFeatures.xlsx',feat);
%yFeatLabel = vibNew(:, 3);
%%
sFeat = xlsread('selectedFeat.xlsx');
feat = xlsread('HilbertFeatures.xlsx');
data = xlsread('ResearchData(vib, Time & Label).xlsx');
vib = data;
YN = vib(:,3);
rng(10)
KNN_MOO = fitcknn(sFeat,
YN,'NumNeighbors',4,'OptimizeHyperparameters','auto','HyperparameterOptimizat
ionOptions',struct('AcquisitionFunctionName','expected-improvement-plus'));
% VariableDescriptions = hyperparameters('fitcknn',feat,YN);

%%
KNN_MOO

%featVal = featN(:, [1 2 3 4]);
%%
% predict the classsification of the
% KNN_8.NumNeighbors = 3;
[label, score, cost] = predict(KNN_M8, sFeat(idxTest));
LossKnn_8 = loss(KNN_M8, sFeat(idxTest, :), YN(idxTest));

LossKnn_8








%%
atx = vib(:, 1);

ntest = 500;
idx = 500+1*(0:500-1)+1;
for k = 1:ntest
```

```
    ax = atx(idx(k), :);
end

%plot acceleration components
 plot(ax, t);

 % extract features

 Xnew = [X; ax];
 nFeat = OnefeaturesBuffer(Xnew, 50);
 NewFeat = nFeat';
 class = net(NewFeat);
%%
XX = xFeat';
Y = (vib(:, 3));

[trainIn, ValIn, testSet] = dividerand(size(XX, 2), 0.7, 0.15, 0.15);
xtest = XX(:, testSet);
pp = Y';
ytest = pp(:,testSet);
tgttest = dummyvar(pp);
scoretest = net(xtest);

figure
plotconfusion(tgttest, scoretest);


%% try some data generated
fs = 500;
dt = 1/fs;
stopTime = 5; % length of signal
t = (0:dt:stopTime-dt);
stopTime_plot = 2; %limit the time axis for improved visualization
F_1 = 20;
F_2 = 5;
A_1 = 4;
A_2 = 7;
data1 = A_1*sin(2*pi*F_1*t) + A_2*sin(2*pi*F_2*t);
figure
set(gcf, 'color', 'w', 'units', 'normalized','Position',[0.1, 0.2, 0.8,
0.5]);
plot(t, data1, 'LineWidth', 2);
xlabel('str', 'interpreter','latex')
ylabel('Eg(t)s', 'interpreter', 'latex');
xlim([0 stopTime_plot]);
ax = gca;
ax.FontSize = 16;
% Saveas(gcf, Strcat(Documents/All Desktop Folder/PhD Folder/PhD Examiner's
Review/, 'inputData.png'));

[imfs, res] = emd(data1);
figure
set(gcf,'color','w','units','normalized','Position',[0.1, 0.15, 0.8 0.5]);
tiledlayout(size(imfs, 2)+1, 1);
for i = 1: size(imfs, 2)
```

```
    nexttile
    plot(t, squeeze(imfs(:, i)),'LineWidth', 1.5);
    title(strcat(num2str(i),'IMF'),'interpreter','latex');
    xlabel('$t$','interpreter','Latex');
    xlim([0 stopTime_plot])
    ax = gca;
    ax.FontSize = 12;
end

nexttile
plot(t, res, 'LineWidth', 1.5)
title('residual','interpreter','latex');
xlabel('$t$','interpreter','latex');
xlim([0 stopTime_plot])
ax = gca;
ax.FontSize = 12;

figure
hht(imfs(:,1), fs)

figure
set(gcf,'color','w','units','normalized','Position',[0.1, 0.15, 0.8 0.5]);
tiledlayout(size(imfs, 2)+1, 1);
for i = 1: size(imfs, 2)
    nexttile
    hht(imfs(:, i), fs);
    title(strcat(num2str(i),'IMF'),'interpreter','latex');
    xlabel('$t$','interpreter','Latex');
    % xlim([0 stopTime_plot])
    ylim([0 30])
    ax = gca;
    ax.FontSize = 12;
end

xx = hht(imfs, fs);




end
%% Genetic Algorithm (version 1)
clc,
% Load the features

newFeatures = xlsread('HilbertFeatures.xlsx');
vib = xlsread('ResearchData(vib, Time & Label).xlsx');
label = vib(:,3);
feat = newFeatures;
% testing the model
dataNew = xlsread('Validatn.xlsx');
vibNew = dataNew(:, 1);
yNew = dataNew(:,3);
% Benchmark data set
%
load ionosphere.mat;
% Set 20% data as validation set
```

```
ho = 0.2;
% Hold-out method
HO = cvpartition(label,'HoldOut',ho,'Stratify',false);
% Parameter setting
N        = 10;
max_Iter = 100;
CR       = 0.8;
MR       = 0.3;
% Genetic Algorithm
[sFeat,Sf,Nf,curve] = jGA1(feat,label,N,max_Iter,CR,MR,HO);
%[sFeatN, nSF, Nfn] = jGA1(vibNew,yNew,N,max_Iter,CR,MR,HO);
% Plot convergence curve
figure;
plot(1:max_Iter,curve);
xlabel('Number of generations');
ylabel('Fitness Value');
title('GA'); grid on;
xlswrite('selectedFeat.xlsx',sFeat)
```