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Ecole Nationale Polytechnique

Mechanical Engineering Department
Laboratory of Green and Mechanical Development

Thesis

Doctoral
Mechanical Engineering

BAZI Rabah

Diagnosis and Prognosis of cutting tools based on Blind Sources Separation - Application to milling-

Presented and publicly defended on ***(24/05/2022)*** *In front of the jury composed of:*

Chairman :	*Mr. Arezki SMAILI*	*Professor. ENP*
Supervisor:	*Mr. Said RECHAK*	*Professor. ENP*
Co-supervisor	*Mr. Tarak BENKEDJOUH*	*MCA. EMP*
Examiners :	*Mr. Yacine BELKACEMI*	*MCA. ENP*
	Mr. Mouloud BOUMAHDI	*MCA Univ Medea*
	Mr. Moussa HADDAD	*Professor. EMP*
	Mr. Taha CHETTIBI	*MCA. Univ Blida*
Guest:	*Mr. Youcef ATMANI*	*MCB. ENST*

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Laboratory of Green and Mechanical Development

Thèse

Doctorat

Génie mécanique

BAZI Rabah

Diagnostic et Pronostic Des Outils De Coupe basés sur la séparation aveugle des sources - Application au fraisage-

*Présenté et soutenue publiquement le (**24/05/2022**) Devant le jury composé de :*

Président :	*Mr. Arezki SMAILI*	*Professeur. ENP*
Directeur :	*Mr. Said RECHAK*	*Professeur. ENP*
Co-Directeur :	*Mr. Tarak BENKEDJOUH*	*MCA. EMP*
Examinateurs :	*Mr. Yacine BELKACEMI*	*MCA. ENP*
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	Mr. Taha CHETTIBI	*MCA. Univ Blida*
Invité :	*Mr. Youcef ATMANI*	*MCB. ENST*

ENP 2022

ملخص:

في هذه الدراسة، قمنا بتطوير نموذجين جديدين للمراقبة التلقائية للحالة الصحية لأدوات القطع. تتكون هذه الطريقة من التقدير؛ التحقق من صحة الحياة المتبقية وحسابها (RUL). تستخدم الطريقة بيانات المراقبة التي توفرها أجهزة الاستشعار (القوة، والتسارع، انبعاث صوتي) ، وتستند إلى مرحلتين رئيسيتين: المرحلة الأولى عبر الإتصال والمرحلة الثانية دون اتصال. في النموذج الأول، تتم معالجة الإشارات الأولية التي توفرها أجهزة الاستشعار أولاً لاستخراج المعلومات المفيدة من خلال استخدام التحويل المويجي المستمر (CWT) ، وفصل المصدر "SCA" ونظام تاجيتشي- محال أنوبيس. (MTS)؛ وفي النموذج الثاني، تم تطبيق التقسيم الوضعي المتغير (VMD) و (CNN-BLSTM). تعد معالجة البيانات بعد فصل المصدر موضوع تطوير مؤشر الصحة. يسمح التنبؤ بالحياة المتبقية بتحديد الدقة والمعايير المختلفة للتشخيص مثل RMSE، والتي تسمح بتصنيف والتحقق من قوة هذا النموذج.

يمكن تنفيذ الطريقة المقترحة على بيانات حقيقية من أجل تحديد مدى تآكل أدوات القطع أثناء عملية تصنيع المواد المختلفة.

الكلمات الدالة: مراقبة التآكل الأدوات، التشخيص، هندسة التكهنات، المتبقي، التقسيم الى الوضع المتغير، التحويل التمويجي المستمر، تعلم عميق، تعلم أقصى.

Résumé:

Dans cette étude nous avons élaboré deux nouveaux modèles pour la surveillance automatique de l'état de santé des outils de coupe. Cette méthode consiste d'estimer ; de valider et de calculer leur durée de vie résiduelle (RUL). La méthode utilise des données de surveillance fournies par des capteurs (Force, Accélération et AE), et s'appuie sur deux étapes principales : la première étape en ligne et la deuxième étape hors ligne.

Dans la premier model, les signaux brutes fournies par les capteurs sont d'abord traitées pour extraire des informations utiles grâce à l'utilisation de transformation en ondelettes continues (CWT), de la séparation de sources "SCA" et du système Tagichi-Mahal-Anubis (MTS); et dans le deuxième model, la décomposition en mode variable (VMD) et (l'apprentissage profond) ont été appliqué. Le traitement des données après la séparation de sources est fait l'objet de développement de l'indicateur de santé. La prédiction de la durée de vie résiduelle permet la détermination de l'accuracy et les différents paramètres du pronostic comme le RMSE, qui permettent de classer et de valider la robustesse de ce modèle. La méthode proposée peut être mise en œuvre sur des données réelles pour but de déterminer l'usure des outils de coupe lors du procédé d'usinage des différents matériaux.

Mots clés: Surveillance de l'Usure d'Outil, Extraction et Réduction des Données, Diagnostic, Pronostics, Indicateur de Santé, Durée de Vie Utile Apprentissage profond, Apprentissage maximal, Transformation continue en ondelettes, partitionnement en mode variable

Abstract :

In this study we have developed two new models for the automatic monitoring of the state of health of cutting tools. This method consists of estimating; validate and calculate their residual life (RUL). The method uses monitoring data provided by sensors (Force, Acceleration AND AE), and is based on two main stages: the first stage online and the second stage offline.

In the first model, the raw signals provided by the sensors are first processed to extract useful information through the use of continuous wavelet transform (CWT), source separation "SCA" and the Tagichi-Mahal system. -Anubis (MTS); and in the second model, variational mode decomposition (VMD) and (CNN-BLSTM) were applied. Data processing after source separation is the subject of the development of the health indicator. The prediction of the residual life allows the determination of the accuracy and the various parameters of the prognosis like the RMSE, which allow to classify and validate the robustness of this model.

The proposed method can be implemented on real data in order to determine the wear of the cutting tools during the machining process of the different materials.

Key words: Tool Wear Monitoring, Data Extraction and Reduction, Diagnostics, Prognostics, Health Indicator, Remaining useful Life, Deep Learning, Extreme Learning, Continuous Wavelet Transform, Variable Mode decomposition.

DEDICATION

In memory of the martyrs of the struggle for national liberation;

In memory of the martyrs of national duty;

In memory of my mother;

In memory of my father;

To my little family;

To my brothers and sisters and their families;

To my wife's family.

ACKNOWLEDGMENTS

First , I want to give thanks to God who guided me on the right path.

In thus ending my thesis, here are a few words for all those who have been close to me during this period.

I would like to thank Prof: Said Rechak and MCA: Tarak Benkedjouh, for the trust they placed in me throughout the preparation of this thesis. I also express my gratitude to them for their many advice and their availability.

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I do not forget either the support of Prof. Noureddine Zerhouni and his acceptance to participate in the preparation of this work and to present his fair opinion whenever we ask him.

My thanks also go to Professor Mr. A. SMAILI who did me the honor of agreeing to chair the Jury of this thesis.

My acknowledge then go to the members of the jury who have done me the honor of participate in my defense. I sincerely thank Mr. Y.BELKACEMI, Mr. M.BOUMAHDI, Mr. M. HADDAD and Mr. T.CHETTIBI for agreeing to evaluate my work as a examiners. My thanks also go to Mr.Y.ATMANI for his participation in the jury.

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SYMBOLS

LIST OF SYMBOLS

Symbols	Symbols
t_c: The current moment	t_D: Moment of degradation
t_f: Moment of failure	N: Number of system
D_i: Distance between the planned and actual instants of failure	D_0 : Normalization constant
σ_0 : Normalization factor	R_0: Normalization factor
R_i: confidence interval of the prediction for experiment i	m: Discrete measurements
Q: Matrix of n modal coordinates	(S):Underlying sources
A: Mixing matrix	W: Un-mixing matrix
l_1:Sparsity or norm solution	$x(k)$: Instantaneous mixing model
$f(t)$: Wide-band random input force	$\aleph$: Set of ordered pairs of doublets
m_i: Mean	S_i: Standard deviation
S_β: Sum of squares due to slope	V_e: Error variance
u_k: Decomposition modes	res : Residual signal after optimization
ω_k: Center frequencies	$\delta(t)$: impulse function
α: Quadratic penalty factor	λ : Lagrange multiplier
τ: Noise tolerance	ρ: Correlation coefficient
ε: Convergence error	σ : Standard deviation
φ: Activation function	$\sigma(x)$: Logistic sigmoid

ABBREVIATIONS

LIST OF ACRONYMS AND ABBREVIATIONS

Abbreviations	Abbreviations
PHM : Prognostics and Health Management	RUL : Remaining Useful Life
CM : Condition Monitoring	MOC : Maintenance in Operational Conditions
CM : Corrective Maintenance	PM : Preventive Maintenance
CBM : Condition Based Maintenance	ISO : International for Standardization Organization
EoL : End-of-Life	MAD : Mean Absolute Deviation
POF : Physics of failure	$FMEA$: Failure Modes and Effects Analysis
PDF : Probability Density Function	URM : Uncertainty Representation and Management
AI : Artificial Intelligence	ANN : Artificial Neural Networks
HMM : Hidden Markov Models	$IBLM$: Instance Based Learning methods
FT : Failure Threshold	PH : Prognostic Horizon
ALM : Accelerated Life Model	TCM : Tool Condition Monitoring
CNC : Computer Numerical Control	AE : Acoustic Emission
DIP : digital image processing	SF : Signal Feature
FFT : Fast Fourier Transform	$UVAM$: Ultrasonic Vibration Assisted Milling
$TWCR$: Tool-Workpiece Contact Rate	$STFT$: Short-Time Fourier Transform

Abbreviations	Abbreviations
$EEMD$: Ensemble Empirical Mode Decomposition	$SFLA$: Shuffled Frog-Leaping Algorithm
ELM : Extreme Learning Machine	SNN : Spiking Neural Network
$ANFIS$: Adaptive Neuro-Fuzzy Inference System	$DENFIS$: Dynamic Evolving Neuro-Fuzzy
$TWNFIS$: Transductive Weighted Neuro-Fuzzy	FL : Fuzzy Logics
$FNNs$: Fuzzy Neural Networks	SOM : Self-Organizing Map
GA : Genetic Algorithm	SVM : Support Vector Machine
$SVMG$: Support Vector Machine Genetic	$FPGA$: Field Programmable Gate Array
PID : Proportional Integral Derivative	BSS : Blind Source Separation
OMA : Operational Modal Analysis	ICA : Independent Component Analysis
OD : Over Determined	UD : Under Determined
DOF : Degrees-Of-Freedom	FIR : Finite Impulse Response
TS : Time Synchronization	MTS : Mahalanobis Taguchi System
SCA : Sparse Components Analysis	CWT : Continuous Wavelet Transform
RMS : Root Mean Square	WPT : Wavelet Packet Transform
$EEMD$: Ensemble Empirical Mode Decomposition	$BPNN$: back-Propagation Neural Network
DWT : Discrete Wavelet Transform	$SFLA$: Shuffled Frog-Leaping Algorithm
DNN : Deep Neural Network	DBN : Deep Belief Network
$FNNs$: Fuzzy Neural Networks	$PARAFAC$: Parallel Factor
SSI : Stochastic Subspace Iteration	MS : Mahalanobis Space
ED : Euclidean Distance	OA : Orthogonal Array
SNR : Signal to Noise Ratio	HMI : Human-Machine Interface
HI : Health Indicator	$LSSVM$: Least Squares Support Vector Machine
$RMSE$: Root-Mean-Square Error	CNN : Convolutional Neural Networks
VMD : Variational Mode Decomposition	$BiLSTM$: Bi-Directional Long-Term Memory
IMF : Intrinsic Mode functions	PCA : Principal Component Analysis
ML : Machine learning	DL :Deep Learning
$RNNs$: Recurrent Neural Networks	$SAEs$: Sparse Auto Encoders
DBN :Deep Belief Network	RBM : Restricted Boltzmann Machines
$GASF$: Gramian Angular Summation Fields	SVR : Support Vector Regression

General Introduction

GENERAL INTRODUCTION

Machining process by material removal become a very hot point in the manufacturing industry with the development of systems and CNC machine [1, 2]. There is a growing need for rapid, direct and mass production of important products from super alloys in aerospace, automotive, biomedical and military applications. Reliability analysis of industrial equipment are extremely important for machining process. Remaining Useful life estimation and health assessment can reduce the maintenance downtime of machining equipment, improve production safety and reduce production costs [3]. Generally, several sensing techniques have been proposed and evaluated within the literature for tool wear estimation indirectly including vibrations, force, spindle current and acoustic emission [4] or using sensor fusion [5, 6]. However, no research has been investigated on the feasibility of moni-toring using sparse components analysis and Mahalanobis distance for tool wear conditions monitoring.

Several signal processing methods for failure prognostic is closely related to features extraction from collected signals [7]. Many of these methods analyzing the signal in time domain, frequency, and time-frequency domains [8]. Lauro et al. [9] present a discussion for the first steps involved in choosing and defining various techniques that may be used to monitor machining processes. The limitation of these methods are sensitive to the cutting conditions, and cannot be used to estimate the current state of the wear in the presence of different cutting conditions throughout the process [10]. The force signal is the most widely used measurement in TCM. Due to the differences in the nature of sensors, each can extract different information from the machine. Moreover, it has been shown that time-frequency analyses such as Continuous Wavelet analysis or Wavelet Packet Decomposition can provide valuable information about the health state of the tool in different machining operations [11]. The different signals collected by sensors (vibrations, forces and Acoustic Emission) for TCM are define the combination of vibration energy produced by different components (spindle, cutting tool, electric motor, workpiece...etc.) in addition to the noise. In this mixture of signal measurements it is difficult to obtain reliable monitoring criteria to identify in situ tool failure during machining process because the collected sensor signals are usually contaminated with a great deal of noise. However, developing degradation signals from component sensors is an important issue to estimating the RUL.

Several research utilizing MTS to determine values similarities from known and unknown samples. However, little are available to compare the use of MTS to predict the prognostics methodologies such as neural networks or support vector machines. The main objective of MTS is to make accurate predictions in multidimensional systems by constructing a measurement scale. MTS is a powerful in solving a wide range of problems including medical diagnosis, manufacturing ,face recognition and has recently popularized a new set of multivariate techniques, as tools for diagnosis, classification and variable selection [12]. Chinnam, et al. [13] applied MTS in detecting the ageing of cutting tools and used MTS to determine the key parameters in the ageing of cutting tools, so as to replace them promptly and save cost and time. . Therefore, it is important to develop a robust filtering scheme for improving the signal and features extraction. A blind source separation (BSS) proposed for recovering the various independent sources exciting a system given only the measurements of the outputs of that system [14]. BSS has become an appealing field of research with many technological applications areas such as medical, image processing, communications ...etc. Lately, it was applied to condition monitoring of rotating machinery [15]. However, little has been investigated with the application of the BSS for tool wear condition monitoring. Shao et al. [16] developed blind sources separation (BSS) technique to separate those source signals in milling process. A single-channel BSS method based on wavelet transform and independent component analysis (ICA) is used, and source signals related to a milling cutters and spindle are separated from a single-channel power signal. Zhu et al. [17] introduces a Fast ICA algorithm as a preprocessor to provide noise-free forces for later correlation to tool flank wear. It was identified that there exist both Gaussian and non-Gaussian noises. It applies the Fast ICA for these blind sources separation and then discards the separated noise components. The BSS process is treated as signal denoising in this approach. Shi et al. [18] proposed an approach based on empirical mode decomposition and independent component analysis is presented to deal with the blind source separation problem of cutting sound signals in face milling with the objective of separating cutting oriented sound signals from those background noises.

The approach to study in the first work, presented in the third chapter; it is a new approach to failure prognosis based on the Mahalanobis-Taguchi system (MTS). The purpose of this research is focused on the separation of dependent sources and propose an algorithm combining CWT and BSS. The CWT is used to reduce the computational cost of covariance estimation. The method consists of three processing stages. In the first s tage, t he sensor signal collected from milling cutters decomposed into several groups of signals based on CWT. In the next stage, the BSS algorithm is used to deal with these CW signal, and hence to complete the separation process. The proposed data-driven scheme used the Mahalanobis distance values over time. When the degradation started, the prognostics scheme, which monitors the progression of the MD values, is initiated. Finally, using a linear approximation, time to failure is estimated. The performance of the approach has been validated via experiments performed on cutting tool inside the (CNC) machine experimental setup. The cutting tool have been instrumented with force, vibration and acoustic emission sensors and experiments involving healthy and various types of faulty operating conditions have been performed. The experiments show that the proposed approach renders satisfactory results for tool wear condition monitoring. Overall, the proposed solution provides a re-liable multivariate analysis thus reducing analysis overhead. In addition, the MTS-based approach is a robust methodology that is insensitive to variations in multidimensional systems. The implementation of MTS based approach requires limited knowledge of statistics. A single-channel BSS method based on wavelet transform and independent component analysis (ICA) is developed, and source signals related to a cutter and spindle are separated from a single-channel power signal; experiments with different tool conditions illustrate that the separation strategy is robust and promising for the cutting process monitoring [19].

Subsequently, the UBSS algorithm is used to process these CWT signals and consequently to terminate the separation process. In addition, the application of the MTS algorithm with these functionalized processes the signals of the multi- channel transformation. Finally, the state of health of the cutting tools was identified by calculating the state of health of the cutting tools, a health indicator obtained by calculating the energy of the independent signal (RMS). The objectives of this survey are to propose a new approach based on CWT, BSS and MTS for diagnosis and prognosis, as well as; to optimize the parameters of the model, in order to verify the robustness and the meaning of this mathematical model. The CWT based on the UBSS method is developed and the source signals associated with a milling cutter and a machine are separated. The MTS method based on CWT and UBSS is applied to predict the RUL of cutting tools, and experimental results have shown that the predictive model formed by CWT, UBSS and MTS is very accurate, as well as experiments with different cutting tools show that the separation strategy is robust and promising for monitoring the cutting process.

An approach to tool wear classification by means of sensory data imaging and deep learning. The GASF encoding keeps the temporal correlations for each flute, which is an advantage over classification methods that are based on statistical features, where the features of a particular flute are lost. Experimental results show the ability of the CNN to capture and learn the features on the raw data to correctly classify tool wear condition. Overall, the percentage of accurately classified cases on the test set is high, achieving in most cases above 80% when testing in a new cutter. The moment prior to the transition from critical wear to failure is in most cases correctly identified, and the cases where it is incorrectly classified were generally labelled as a failure, which from an application standpoint means the replacement of the tool would still be enacted. These results show the importance of using a training sample set that can represent all of the input space. In this case, the training set needs to be enriched with samples from multiple cutters to ensure the successful detection of the transition period from severe to failure. The application of this work will allow for the extension of the remaining useful life of the tool, improve cut quality and ensure machining elements are replaced before failure[20].

In the second work Recently, a new processing technique called VMD has enriched the signal denoising method. [21] proposed a new method for level estimation based on LSTM and multi-mode decomposition. Compared with other decomposition technique such as the Empirical Modes Decomposition (EMD), VMD successfully avoids mode aliasing and border effects, and has better noise and sample rate robustness. Lahmiri et al. [22] proposed a method for signal denoising based on VMD and discrete wavelet transform. LSTM has been successful because of their performance in several fields of research such as, speech recognition, medicine, maintenance, etc. this part is dedicate to expose some frameworks based on LSTM network in maintenance field.Weili et al. [23] proposed a hybrid model based on LSTM for tool wear monitoring, The feature extraction from raw data by using the designed stacked LSTM. Then, the feature selection was fed in model for regression to predict the tool wear. Xia et al. [24] propose an ensemble framework for predicting turbofans RUL,CNN-BLSTM is proposed and applied as the base model which has high level of prediction accuracy and speed computation. Jianjing et al. [25] proposed a method based on BiLSTM for tool wear condition monitoring, this deep network allows from statistical features to predict the life of cutting tool and compared with traditional technique to show its effectiveness. Wang et al. [26] proposed a new condition awareness technique by the combination of two powerful structures of deep learning using CNN and LSTM. The proposed model is able to extract and learn simultaneously both spatial and temporal features.

In the second work, a new driven approach is proposed to predict cutter RUL. Firstly, the signal distribution obtained using the Variational Mode Decomposition allows modeling random degradation tools. The signals construction are used also for Health indicator construction. Secondly, using convolution neural network to extract useful information's from Variational Mode Decomposition, then deep learning to track degradation during cut-ter's life. Finally, the validation of the eectiveness of the proposed approach based on experimental dataset [27] of cutter's degradation. The thesis document is divided into 5 chapters, where: Chapter 01: Is devoted to the emergence of prognostic activity in main-tenance strategies. We present the new industrial challenges which have made the maintenance function evolve, as well as the major role of prognosis. The concept of prognosis as well as a state of the art of prognosis approaches are also presented. The purpose of this chapter is to define the prediction of the state of a cutting tool which degrades progressively, and for which no a priori knowledge on its degradation law. Chapter 02: Provides a literature review of tool wear characterization. It describes the fundamentals of direct and indirect measurements, as well as successful and unsuccessful efforts over the years. The move to multiple sensing of processes is described, as well as efforts to automate the analysis of the tool wear state, with Artificial Intelligence (AI). Chapter03: This chapter presents a data-driven approach for estimating tool wear using the Mahalanobis Taguchi (MTS) system, based on Continuous Wavelet Transformation (CWT) and Sparse Component Analysis (SCA). The MTS distance values are then fitted with a regression to obtain the model for estimating the remaining useful life (RUL). In addition, this chapter discusses several relevant challenges, such as determining the failure threshold during anomaly detection and RUL estimation, by developing adaptive thresholds.

Chapter04: This chapter proposes a new data-driven approach using Variational Mode Decomposition (VMD) and deep learning. Two deep learning machines used in this study, Convolutional Neural Networks (CNN) and Bi-Directional Long-Term Memory (BiLSTM) to perform collaborative data mining on (VMD) and to improve modeling accuracy . In a general conclusion, we reposition all of our developments with regard to the initial objective of the study: "Diagnosis and Prognosis of Cutting Tools by Blind Source Separation "Application to Milling"". We summarize the main results of our work and end up with a discussion of the work perspectives that flow from this thesis.

Chapter I:

Prognostics and Health Management approach for cutting tools

CHAPTER 01

PROGNOSTICS AND HEALTH MANAGEMENT APPROACH FOR CUTTING TOOLS

2.1 Introduction

The incorporation of online monitoring systems for monitoring the wear of cutting tools in the machining process has become an unavoidable requirement in order to complete the automation chain of mechanical production systems. Also, in order to perform this task, several reliable techniques for online monitoring, supervision and monitoring of cutting tool wear have been developed. In this context, the wear of the cutting tool is one of the major factors most determining the maximization of production and the guarantee of the quality of machined products.

Prognostics and Health Management (PHM) aims at extending the life cycle of engineering assets, while reducing exploitation and maintenance costs. For this reason, prognostics is considered as a key process with future capabilities. Indeed, accurate estimates of the Remaining Useful Life (RUL) of an equipment enable dining further plan of actions to increase safety, minimize downtime, ensure mission completion and efficient production. Recent advances show that data-driven approaches (mainly based on machine learning methods) are increasingly applied for fault prognostics. They can be seen as black-box models that learn system behavior directly from Condition Monitoring (CM) data, use that knowledge to in-fer its current state and predict future progression of failure. However, approximating the behavior of critical machinery is a challenging task that can result in poor prognostics[28].

2.2 Taxonomy of maintenance policies

Long seen as a necessary evil, maintenance has become a real concern in industry. It has established itself as a real competitive issue, both in terms of ensuring the availability performance of existing equipment and in terms of safety, quality and costs, for example. We also note the inclusion of new concerns such as environmental aspects through the reduc-tion of polluting waste emissions or the recycling of end-of-life systems. Today, it is seen as an industrial process in its own right when it is not identified as one of the main activities of industrial exploitation. We are thinking here in particular of an industrial activity such as nuclear or wind energy production, for example, for which maintenance costs should evolve from 30% of the overall operating budget during the operating phase in 2012. This taking into account results in a more global vision with the highlighting of the various interactions with traditional processes and the development of new processes such as "main-tenance logistics". Thus, this evolution positions the objectives of the maintenance manager at a strategic decision-making level while ensuring the business objectives of the company.

2.2.1 Definition of maintenance

According to standard NF EN 13306 (2001), maintenance can be defined as the set of all technical, administrative and management actions during the life cycle of an asset, intended to maintain it or restore it to a good condition. in which it can perform the required func-tion [29]. It thus includes a series of troubleshooting, repair, control and verification actions for material equipment, and should contribute to the improvement of industrial processes. In the traditional view, the maintenance function makes it possible to guarantee the op-erational safety characteristics of equipment, in particular availability. It therefore aims globally to apprehend the failure phenomena and to act accordingly, in order to ensure that the system (the asset) is able to fulfill the function for which it was designed (Maintenance in Operational Conditions, MCO). However, the missions of the maintenance function are no longer limited to the implementation of the means to ensure the "service of goods". Quality, safety and cost requirements have arisen, and the challenges and prerogatives of the maintenance function have evolved over the past twenty years. [30].

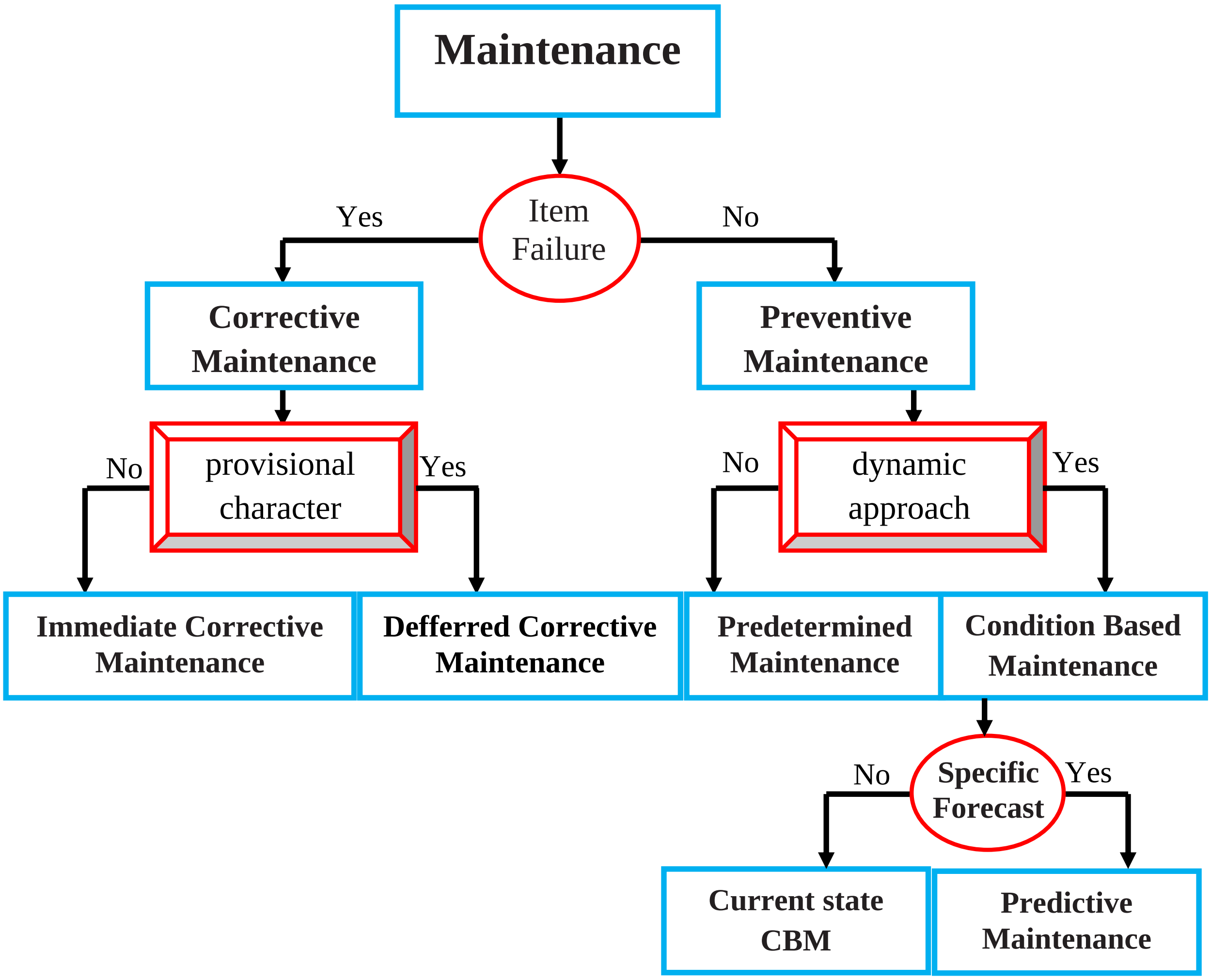


Figure 2.1: Classification of maintenance policies. [30]

2.2.2 Maintenance policies

Maintenance strategies can be classified into two broad categories: Corrective maintenance (MC) and preventive maintenance (PM) (Figure2.1). Corrective maintenance is the intervention following a failure in a system [28, 31].

Corrective maintenance

Corrective maintenance is an earliest form of maintenance that is unplanned (or reactive) and is undertaken after machinery breakdown. A failed item is repaired or replaced with a new one to store functional capabilities. This type of maintenance can be further categorized as immediate corrective maintenance or deferred corrective maintenance [31].

However, such maintenance is suitable for non-critical engineering assets, where failure consequences are slight and no immediate safety risks are involved. In other words, it should be used when there are no serious consequences of unscheduled downtime [28].

Preventive maintenance

Preventive maintenance is a planned (or proactive) strategy for maintaining machinery that was introduced in 1950s [32]. The main objective was to increase availability of machinery as compared to corrective maintenance. This type of maintenance is triggered according to a schedule (working hours, kilometers worked, etc.) and results in the periodic replacement of parts, without prior checking and whatever the state of deterioration of the goods, it is possible to avoid certain breakdowns. , sometimes catastrophic, to occur. On the other hand, it can also lead to over-maintenance, that is to say to an excess of unnecessary interventions, and therefore to financial waste for the company and uncontrolled production stoppages[28]. To remedy this, two other preventive maintenance policies have emerged: predetermined maintenance and Condition Based Maintenance (CBM).

a- Predetermined maintenance

With predetermined maintenance repairs are performed on the basis of predefined schedule (or fixed intervals). Maintenance tasks are carried periodically (like lubrication, calibration, refurbishing, checking and inspecting machinery) after fixed time intervals to decrease the deterioration phenomena [33]. However, the maintenance procedures do not involve evaluation of current state in particular. Although predetermined maintenance can be a simple approach to maintain equipment, it can be costly due to unnecessary stoppages or replacements of operating machinery. Another problem of this approach is that failures are assumed to occur in well defined intervals.

b- Condition-based maintenance

Condition-based maintenance is defined as "preventive maintenance based on monitoring the operation of the asset and / or significant parameters of this operation including the resulting actions" (Figure2.1). This maintenance strategy is thus based on the analysis of real-time data from industrial equipment (for example, vibrations, temperature, etc.). It aims to detect anomalies in the functioning of industrial machines: the discovery of changes in their characteristics foreshadows in the short term a failure to come. Condition-based maintenance makes it possible to take better account of the conditions of use of an equipment than traditional systematic maintenance. However, it does not allow the maintenance policies to be dimensioned with certainty: the date of occurrence of the failure remains uncertain [30]. Forecast / predictive maintenance aims to compensate for this lack of knowledge. It is defined as " Condition-based maintenance carried out by following extrapolated forecasts from the analysis and evaluation of significant parameters of the degradation of the asset". The underlying idea is to project the current state of the asset into the future, in order to estimate the uptime before failure. Predictive maintenance is thus more dynamic. It takes into account the current conditions of the equipment and tries to predict the evolution over time of the condition of the assets. As maintenance interventions are planned with greater precision, predictive maintenance should lead to substantial savings and has been the subject of increasing attention in recent years. The expected benefits are indeed numerous:

- reduction in the number of breakdowns;
- production reliability;
- improvement of personnel safety and the image of the company;
- reduction of equipment downtime (costly);
- increase in business performance.

The implementation of a predictive maintenance policy is based on the deployment of a key process aimed at determining the future states of the monitored system: that of the “industrial prognosis”. The following section is devoted to it[30].

2.3 Diagnostic and prognostic framework

2.3.1 Definitions

The term prognostic founds its origin in the Greek word “prognôstikos”, which means “to know in advance”. Prognostic is well used in medical domain, where doctors try to make predictions about the health of a patient by taking into account the actual diagnosis of a disease and its evolution compared with other similar observed cases. This reasoning can be transposed into the industrial domain where the patient is a machine, an industrial system or a component[34].

Several definitions have been given in the literature about industrial prognostic, where three main points are highlighted: the system’s actual state, the projection (or extrapolation) of this latter, and the estimation of the remaining time before failure. These definitions are then normalized by the ISO13381-1 standard [35] in which prognostic is defined as the estimation of the operating time before failure and the risk of future existence or appearance of one or several failure modes. This standard defines the outlines of prognostic, identifies the data needed to perform prognostic and sets the alarm thresholds and the limits of system's reset (total shutdown). The main steps to perform prognostic, as defined in the standard, are summarized in Fig. 1. The first step consists of monitoring the system by a set of sensors or inspections achieved by operators. The monitored data are then pre-processed to be used by the diagnostic module. The output of this module is an identification of the actual operating mode (more details on failure diagnostic can be found in [36]. This mode is then projected in the future, by using adequate tools, in order to predict the system's future state. The intersection point between the value of each projected parameter or feature and its corresponding alarm threshold permits to estimate the RUL.

Finally, appropriate maintenance actions can be taken depending on the estimated RUL. These actions may aim at eliminating the origin of the failure, which can lead the system to evolve to any critical failure mode, delaying the instant of a failure by some maintenance actions or simply stopping the system if this is judged necessary[36].

Diagnostics is the act of tracing back the evidence of anomaly behavior to their respective causes, i.e., their faults. In particular, taking inspiration from [36, 37], defines a fault as "an unmerited deviation of at least one characteristic property or parameter of the system from the acceptable condition" (or baseline). Usually, diagnostics is performed after the machine has experienced a breakdown, i.e., it has been conceived as a posterior analysis. Therefore, in the context of PHM, it is more appropriate to think of the diagnosis phase as the diagnosis of early fault signs [36], which basically is needed to trigger the prognostic module. While monitoring translates into a comparison between baseline and current machine data, diagnostics translates into a comparison between current operating data and a faults database. From a more technical perspective, diagnostics is a pattern recognition and classification problem:

+ **Pattern recognition** because the data set collected with a faulty machine are used to search for patterns among the extracted features, to be able to distinguish among the different faults. It is worthy to elaborate a bit on this statement. Pattern recognition is a preliminary phase, which comes before classification, only when supervised learning algorithms are used. In this case, a training dataset with already recognized faults is needed. When using unsupervised learning algorithms, pattern recognition is called clustering [38]. Unsupervised learning algorithms are useful for detecting new faults. For instance, faults that could not be inferred neither in the preliminary analysis nor analyzing the training dataset. The event in which a technician did not fix correctly a screw while reassembling the asset and this caused unexpected machine vibrations can be considered as a realistic example. These issues could even happen when the faults contained in the recorded data are not known a priori that demonstrates that there is a very limited knowledge of the system;

+ **Classification** because, once the fault database has been built, the current machine data have to be classified to decide which faults are affecting the system. Several algorithms can be used for pattern recognition and classification. A review of their application to the diagnostics problem . See [39] for a table which sums up the strengths and shortcomings of the main diagnostic algorithms today available. As for monitoring, the feature selection step is crucial. There are currently two methods for diagnostic feature selection [40]:

* **Filter-based method**, which ranks the features based on a pre-selected criterion. One of the most used index for feature ranking is Fisher score;

* **Wrapper-based method**, which selects the best features by using the chosen classification algorithm along with search methods as for instance forward and backward search [40]. Basically, the feature set which yields the best classification results is elected as the diagnostic feature set [41].

2.3.2 Relation between diagnostics and prognostics

Like prognosis, diagnosis is also an important element of PHM cycle. In literature, there is a little disagreement, that prognostics is related to and highly dependent upon diagnostics. Mainly, diagnostics involves fault / failure detection, isolation and identification of damage that has occurred, while prognostics is concerned with RUL estimation and associated confidence interval (Figure6.2). Therefore, in terms of relation between diagnostics and prognostics, diagnostics process detects and identifies a fault / failure that has caused degradation, where prognostics process generates a rational estimation of RUL until complete failure [42, 28]. However, in general, diagnostics is a reactive process that is per-formed after the occurrence of fault / failure and cannot stop cutting tool downtime in, where a prognostic is a predict to prevent behavior [39]. It should be noted that there is a difference between /fault diagnostics" and /failure diagnosis". The terminology of fault diagnostics implies that, the cutting tool under observation is still operational, however, cannot continue operating indefinitely without any

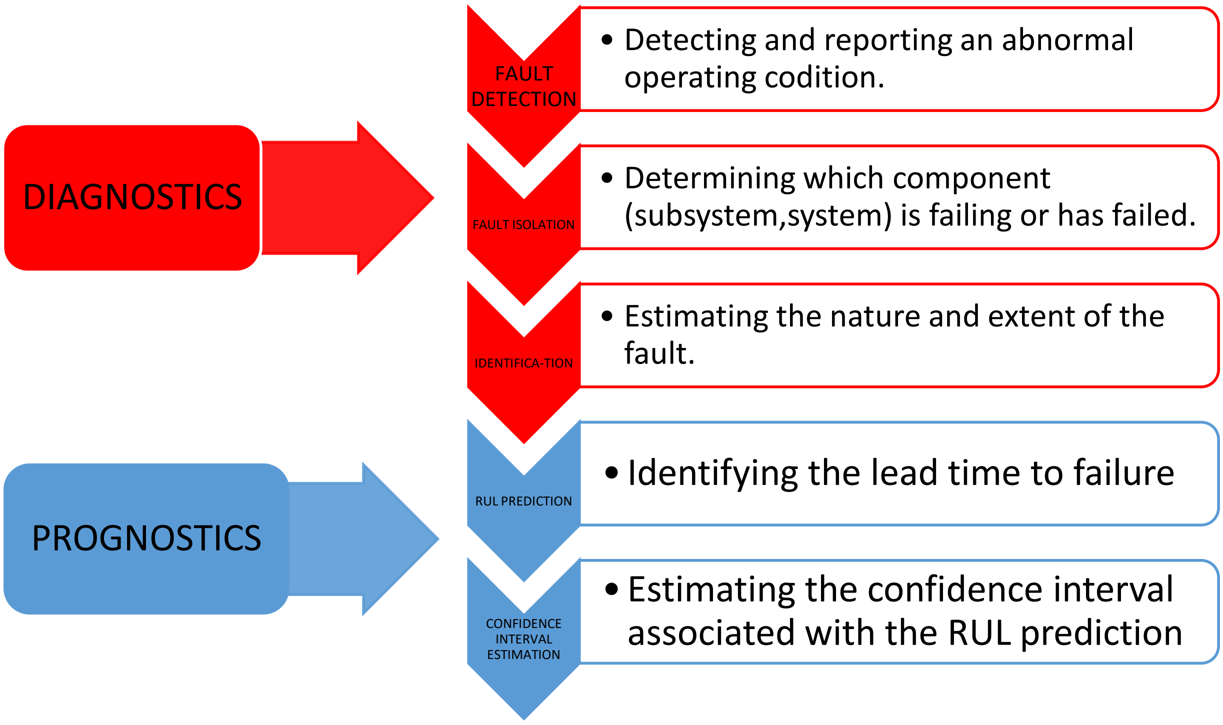


Figure 2.2: Steps of prognosis results and relation to diagnoses. [42]

maintenance intervention. Where, failure diagnosis is performed on machinery that has ceased to perform its functionality [43]. As compared to prognostic, diagnosis domain is well developed and has several applications in industry.

2.3.3 Prognosis and Estimation of Remaining Useful Life (RUL)

Therefore, rely on evaluation criteria whose limits depend on the monitoring system and the performance objectives. Formulated differently, the prognosis implies not only to be able to project the behavior of a system over time [30], but also to know how to identify its state at any time, taking into account the mission criteria chosen. Therefore, there is no one set of evaluation metrics suitable for all prognostic applications [44]. Two classes of measures can however be distinguished.

Prognostic measures

The main objective of the prognosis is to provide the information enabling good decisions to be made. Thus, a first set of metrics is that which makes it possible to quantify the risks incurred by the monitored system. This type of metric corresponds to prognostic measurements, the main one of which is the residual time before failure T_0: $Time-to-Failure(TTF)-or-[Remaining\ Useful\ Life.(RUL)]$ [30]. A confidence measure must also be constructed to indicate the degree of certainty of the RUL. By way of illustration, let us consider the left part of (Figure2.3) in which, for the sake of simplicity, the degradation is considered as a one-dimensional quantity. The RUL can be defined as the time between the current instant t_c (after detection of the degradation; t_D), and the instant when the degradation will reach the failure threshold t_f:

$$RUL = t_f - t_c.[30] \tag{2.1}$$

Performance measures of the prognosis system

It is also necessary to be able to judge the quality of the prognosis in order to decide on adequate actions. In this sense, several indicators can be constructed: the performance measures of the prognosis system. The main measures put forward in the literature are Timeliness, Precision and Accuracy. These are distance measurements between a set of RUL estimates and exact RUL values (Figure2.3) [30]. The definition of a set of appropriate metrics for prognostic applications is the subject of work by researchers as well as industrialists working in the field of [30] CBM. Several measures emerge from the literature and are presented below. At least two classes of metrics are of interest:

1- The main objective of the prognosis is to provide the information allowing good decisions to be made, ie the choice of maintenance actions. Thus, a first set of metrics is that which makes it possible to quantify the risks incurred by the monitored system. This type of metric corresponds to prognostic measurements [34];

2- Given that the prognosis is in essence an uncertain process, it is interesting to be able to judge its quality in order to imagine more adequate actions. In this sense, several indicators can be constructed. These are the performance measures of the prognosis system.

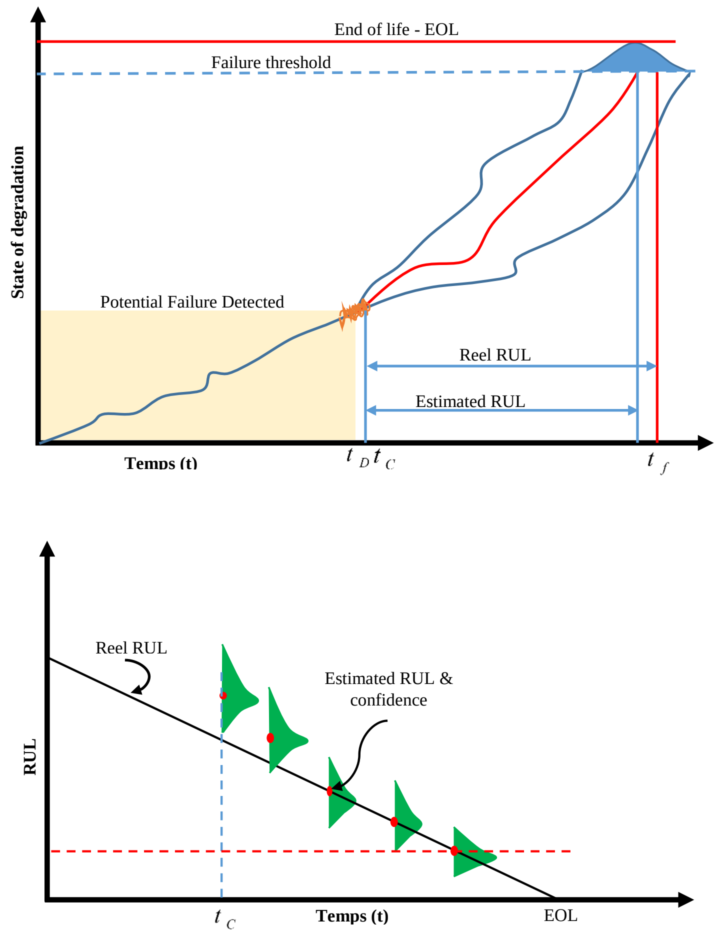


Figure 2.3: Illustration of prognostics and RUL estimates. [30]

a- Accuracy

Measures how close the expected failure date is to the actual failure date. The calculation of this metric represents a critical point in the prognosis process. The calculation of this quantity is based on the existence of historical data on several components which have broken down as a result of stresses undergone throughout a known period of time, which is not always possible (single equipment). If a set of N systems have failed (with associated prognoses).

$$Accuracy = \frac{1}{N}\sum_{i=1}^{N} e^{\frac{D_i}{D_0}}.[45] \tag{2.2}$$

With $D_i = \left|\hat{t}_{fail}(i) - t_{fail}(i)\right|$ the distance between the planned and actual instants of failure; D_0 a normalization constant whose value is based on the importance of the actual value in the application. The exponential function is used here to give a smooth monotonically decreasing curve. The value of $e^{\frac{D_i}{D_0}}$ represents the decrease in accuracy. In other words, the accuracy is great (close to 1) when the predicted value is the same as the actual value and decreases when the predicted value deviates from the actual value. The exponential function also has the greatest decay rate when D_0 is close to 0.

b- Precision

Precision is a measure of the dispersion of predictions. It evaluates how the predicted values are grouped around the interval in which the failure occurs. Precision is highly dependent on the level of confidence and the distribution of predictions. The precision equation is as follows:

$$Precision = \left(\frac{1}{N}\sum_{i=1}^{N} e^{-\frac{R_i}{R_0}}\right) e^{\frac{\sigma^2}{\sigma_0}}.[45] \tag{2.3}$$

With

- $E_i = \hat{t}_{fail}(i) - t_{fail}(i)$;

- $\bar{E} = \frac{1}{N}\sum_{i=1}^{N} E_i$ and $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}\left(E_i - \bar{E}\right)^2$;

- σ_0 and R_0 are the normalization factors, and the confidence interval of the prediction for experiment i.

Likewise, an exponential function is used here to define the relationships between the standard deviation of the prediction, the confidence interval and the precision. The precision has a value between 1 and 0 (1 indicating the highest precision and 0 the lowest).

c- Timeliness

The timeliness is the relative position of the probability density function (pdf: probability density function) of the prognostic model with respect to the occurrence of the failure event. This measure changes as data becomes available and helps to judge the right time to perform maintenance. [34] recommends defining limits at the earliest and at the latest beyond which the predicted value must be considered unacceptable from a performance point of view. These two limits are the consequence of the fact that the prediction error is not systematically centered with respect to zero (where the error is defined as the difference between the real remaining life and the estimated remaining life). For example, if the prediction is (too early), the resulting alarm requests intervention too early to check the potential for a failure to occur, to monitor the various process variables and to perform a recovery mode. In the other case, if the failure is expected (too late), this error reduces [34].

Definition of Prognostic Indicators

The efficacy of a prognostic method relies on the representativeness of the prognostic indicators chosen. A number of desirable characteristics are expected to be look at in the choice [46]:

- **Monotonicity:** The indicators are wished to present an overall positive or negative trend in time, excluding possible self-healing situations;

- **Prognosability:** The distribution of the final value that an indicator takes at failure is wished to be 'peaked', i.e. not too wide-spread;

- **Trendability:** The entire histories of evolution of the indicator towards failure are wished to have quite similar underlying shapes, describable with a common underlying functional form.

Other characteristics may be desirable. For any characteristic sought, a metric must be introduced to allow comparing the different potential prognostic indicators on the different characteristics. A detailed list of possible metrics, and their meaning, is given in [44] with the distinction among accuracy-based, precision-based and robustness-based metrics. Furthermore, in the manipulation of prognostic indicators for the tasks of state estimation and prediction it is often convenient to reduce the multivariate problem into a single-variable one, by opportunely combining the multiple indicators, e.g. by weighted average. Multiob-jective optimization problems may arise from these issues.

2.3.4 Prognostics and Health Management (PHM)

With aging, machinery or its components are more vulnerable to failures. Availability and maintainability of such machinery are of great concern to ensure smooth functioning and to avoid unwanted situations. Also, the optimization of service and the minimization of life cycle costs / risks require continuous monitoring of deterioration process, and reliable prediction of life time at which machinery will be unable to perform desired functionality. The barriers of traditional condition-based maintenance (CBM) for widespread application, are as follows [28]:

* Inability to continually monitor a machine and / or a cutting tool;

* Inability to accurately and reliably predict the Remaining Useful Life (RUL);

* Inability of maintenance systems to learn and identify impending failures and recommend what action should be taken.

Mainly, acronym PHM consists of two elements [46].

+ Prognostics refers to a prediction / forecasting / extrapolation process by modeling fault progression, based on current state assessment and future operating conditions;

+ Health Management refers to a decision making capability to intelligently perform maintenance and logistics activities on the basis of diagnostics / prognostics information.

That is why, PHM is a key enabler to facilitate different industries to meet their desired goals e.g. process industry, power energy, manufacturing, aviation, automotive, defense, etc. Some of the key benefits of PHM can be highlighted as follows:

= Increase availability and reduce operational costs to optimized maintenance;

= Improve system safety (predict to prevent negative outcomes);

= Improve decision making to prolong life time of a machinery [28].

Prognostics and Health Management architecture

1- Prognostics and Health Management modules

PHM is a process consisting of seven modules, as shown in (Figure6.4)

- **Data acquisition:** consists of measuring physical quantities such as acoustic emission, acceleration, temperature, etc. using sensors, software and human observations. This data is obtained through an acquisition system that collects and preprocesses data to be sent to other modules and to be stored in a reliable and secure database;

- **Signal / data processing:** analyzes and interprets the signals in order to extract information characterizing the behavior of the system, either in the time and / or frequency domain;

- **The evaluation of the current state:** will be obtained from these characteristics and will allow the nominal behavior aid to detect the various possible anomalies;

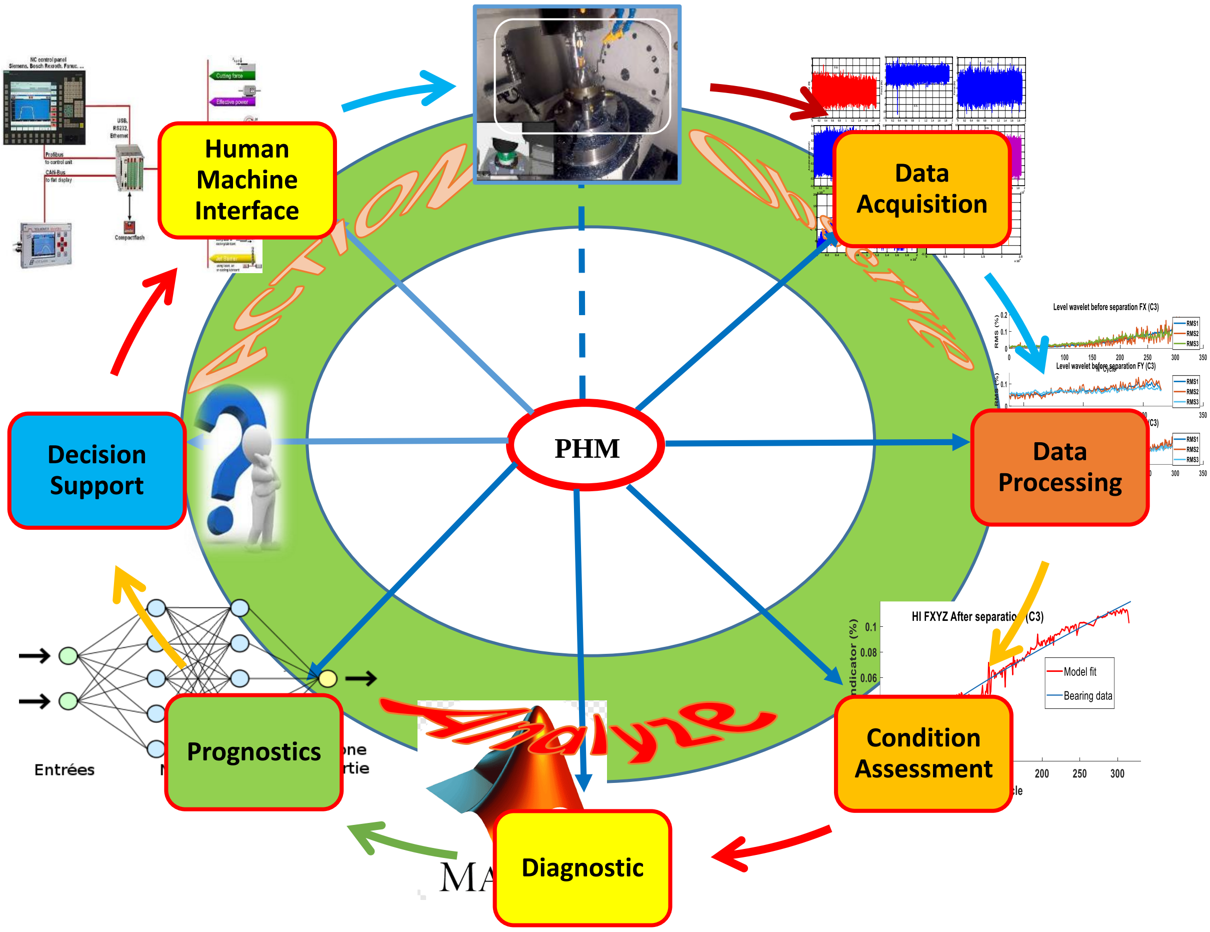


Figure 2.4: Prognostics and Health Management cycle. [47]

- **Diagnostics:** corresponds to the location and identification of the causes of anomalies or failures;

- **Prognostics:** Based on the current state of the system and the outcome of detection and / or diagnosis to predict life to failure;

- **Decision support:** concerning the maintenance strategies to be implemented to keep the system in good condition. This module is based on all the information obtained (current state of the system, RUL, knowledge of the context, etc.);

- **The human-machine interface:** provides a means of presenting and storing useful information in different forms [28].

2- Prognostics and Health Management phases

PHM makes use of past, present and future information of an equipment in order to assess its degradation, diagnose faults, predict and manage its failures. Considering such activities, PHM is usually described as the combination of 7 layers adapted from Open System Architecture for CBM [28, 46], that all together enable linking failure mechanisms with life management (Figure2.4). we can divided these layers into three main phases 1) observe, 2) analyze and 3) act (Table6.1).

Table 2.1: Prognostics and Health Management phases. [28]

Observe	1 Data acquisition: gather useful condition monitoring (CM) data records using digitized sensors. 2 Data processing: perform data cleaning, denoising, relevant features extraction and selection.
Analyze	3 Condition assessment: assess current condition of monitored machinery, and degradation level. 4 Diagnostics: perform diagnostics to detect, isolate and identify faults . 5 Prognostics: perform prognostics to project current health of degrading machinery onto future to estimate RUL and associate a confidence interval.
Action	6 Decision support: (off-line) recommend actions for maintenance / logistic, and (on-line) system configuration (safety actions). 7 Human Machine Interface: interact with different layers, e.g. prognostics, decision support and display warnings etc

2.3.5 Prognostics approaches

Many failure prognosis tools and methods have been proposed during the last decade. The prognosis methods generally differ by the type of application considered, while the tools implemented depend mainly on the nature of the data and knowledge available to build a model of the behavior of the real system including the phenomenon of degradation. Also,

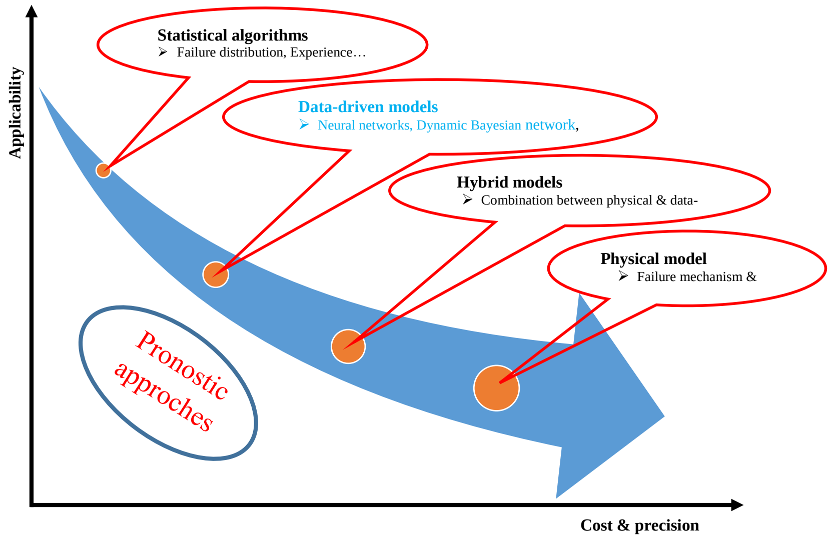


Figure 2.5: prognostics approaches. [48]

these methods and tools can be grouped into a limited number of approaches. The first classification of prognostic approaches was proposed by. In their paper, the authors suggest a three-level pyramid classification of prognostic approaches (Figure2.5): experience-based approaches, data-driven approaches, and model-based approaches. To dissociate these three types of approaches, the following criteria are considered: the cost and complexity of implementation, the precision of the results obtained, and the applicability of the approaches. In 2006, proposed a new taxonomy of prognostic methods, distinguishing two main categories of methods. The first groups together the methods relating to the esti-mation of the future state of the component, subsystem, or system (estimation of the RUL or TTF), and the second category concerns the methods allowing to determine the RUL while integrating the context system operation (maintenance actions and operating conditions). Recently, proposed a new classification based on the three approaches suggested by [47] to which has been added a fourth class qualified as integrated.

Table 2.2: Prognostic approaches and type of information. [49]

	Approaches		
	Model-based	Data-driven	Reliability based prognostics
System model	Necessary	Useful Not	necessary
Failure history	Useful	Not necessary	Necessary
Past conditions	Necessary	Not necessary	Useful
Current conditions	Necessary	Necessary	Useful
Failure recognition methods	Necessary	Necessary	Not necessary
Maintenance history	Useful	Not necessary	Useful
Sensors and model	Yes	Yes	No

The authors therefore suggest considering prognostic approaches depending on the type of data and knowledge avail-able. With regard to the first type of approach, they propose to group together the methods which use experience feedback data. The second type of approach corresponds to methods which employ surveillance data (mainly those provided by sensors installed on the system) as input information for prognostic algorithms.

These methods can be divided into two subcategories, those based on mathematical models and those using monitoring data exclusively. The last type of approach corresponds to methods combining reliability and monitoring data. The classification of prognostic approaches is not an end in itself and it appears that the pyramidal vision [47] is the reference today. We therefore choose for the following to distinguish approaches based on a physical model, approaches guided by data, and approaches based on experience.

From an application point of view, the information required to deploy prognostic approaches is of a diverse nature: engineering models, data, failure histories, system stresses, operating conditions, etc. [28] gives a generalization of what could be the set of inputs and outputs of a prognosis model. The main inputs and their interest in each of the for prognosis approaches can be schematized as proposed in (Table2.2) [28]. Of course, the expected outputs are essentially those making it possible to judge the future state of the system.

Physics based prognostics

The physics based or model based approaches for prognostics use explicit mathematical representation (or white-box model) to formalize physical understanding of a degrading system [50]. RUL estimates with such approaches are achieved on the basis of acquired knowledge of the process that affects normal machine operation and can cause failure. They are based on the principle that failure occurs from fundamental processes: mechanical, electrical, chemical, thermal, radiation. Common approaches of physics based modeling include material level models like spall progression models, crack-growth models or gas path models for turbine engines [42]. To identify potential failure mechanisms, such methods utilize knowledge like loading conditions, geometry, and material properties of a system [50]. To predict the behavior of the system, such methods require detailed knowledge and through understanding of the process and mechanisms that cause failure. In other words, failure criteria are created by using physics of failure (POF) analysis and historic data information about failed equipment [51]. Implementation of physics based approach has to go through number of steps that include, failure modes and effects analysis (FMEA), feature extraction, and RUL estimation [50]. It should be noted that in literature, different works categorize physics based (or model based) prognostics as POF and system modeling ap-proach [52]. However, because system modeling approaches are dependent on data-driven methods to tune parameters of physics based model and should be classified as hybrid approach for prognostics.

In general, physics based approaches are application specific. They assume that system behavior can be described analytically and accurately. Physics based methods are suitable for a situation where accuracy outweighs other factors, such as the case of air vehicles. POF models are usually applied at component or material level [53]. However, for most industrial applications physics based methods might not be a proper choice, because fault types can vary from one component to another and are difficult to identify without interrupting operating machinery. In addition, system specific knowledge like material composition, geometry may not be always available. Besides that, future loading conditions also affect fault propagation. Therefore, in a dynamic operating environment, the model may not be accurate due to assumptions, errors and uncertainty in the application [53, 28]. In such cases POF models are combined with data-driven methods to update model parameters in an on-line manner, which turns into a hybrid approach.

Data-driven prognostics

Data-driven prognostics approaches are black box models that learn equipment behavior directly from CM data (to fit changing observations). They are low cost approaches and have the advantage of better applicability. They require data to gain knowledge internally, instead of detailed external knowledge from experts. Several studies are performed to classify data-driven approaches. [54] grouped data-driven approaches as machine learning and statistical approaches. [55] classified data-driven approaches as artificial intelligence (AI) techniques and statistical techniques. A survey on AI approaches, where data-driven ap-proaches were grouped as machine learning and conventional numerical methods. classi-fied data-driven methods as machine learning/ AI, evolutionary and state estimation tech-niques. According to literature, we classify data-driven approaches as machine learning and statistical learning approaches and also elaborate their close links.

a- Machine learning approaches

The branch of AI that attempt to learn by examples and are capable to capture complex relationships among collected data that are hard to describe. They have the advantage of low implementation cost and can be deployed quickly. Also, they can give system-wide scope. Depending on the type of data, learning with such data-driven methods can be performed in different ways[54]. 1) Supervised learning can be applied to labeled data, i.e., inputs and the desired output is known; 2) Unsupervised learning is applied to unlabeled data,

i.e., only inputs; 3) Semi-supervised learning that involves both labeled and unlabeled data (see Fig. 9). Machine learning approaches are categorized as follows with examples[54].

b- Connectionist methods

1. Artificial neural networks (ANN) [56];
2. Neuro-Fuzzy systems [56].

c- Bayesian methods

1. Markov Models and variants, e.g., Hidden Markov Models (HMM);
2. State estimation methods, e.g., kalman Filter, particle -lter and variants [42].

d- Instance Based Learning methods (IBL)

1. K-nearest neighbor algorithm [57];
2. Case-based reasoning [54].

e- Combination methods

1. Connectionist and state estimation techniques [58];
2. Connectionist and clustering methods [59];
3. Ensemble to quantify uncertainty/ robust mod- els [60].

Statistical learning approaches

RUL is achieved by fitting the empirical model (a function) as close as possible to the collected data and extrapolating the fitted curve to failure criteria. Such models can be regression methods for trend extrapolation for e.g linear, exponential and logarithmic functions. Like machine learning approaches they are simple to conduct. Also they require sufficient data to learn behavior of degrading equipment. [61] Presented a review of statistical methods, where the taxonomy was mainly based on nature of CM data. From this systematic review paper, some commonly known prognostics approaches are: stochastic filtering (or state estimation) methods like kalman filters, particle filters and variants, hid-den Markov models and variants etc. The details about this taxonomy are given in [61]. Note that, Bayesian techniques mentioned just above can also be called as machine learn-ing approaches. Other methods in this group can be classical time series approaches like auto-regressive moving average and variants [42]. Lastly, this category also include combination models for example using a particle filter to tune the parameters of the empirical model (i.e., exponential/ logarithmic, etc.,).

2.3.6 Application perspective

Data-driven approaches encounter a common criticism that they need more data as compared to physics based modeling, which is not surprising. Obviously sufficient run-to-failure data are necessary to train data-driven models and to capture complex relations among data. According to [42], sufficient quantity means that data have been observed for all fault modes of interest. The machine learning prognostics could be performed with an ANN [56] to recursively predict the continuous state of degradation, until it reaches the defined FT. Bayesian techniques can be applied to manage prognostics uncertainty [62], but, again RUL estimation rely on FT. In contrast, instance based learning does not require FT and can estimate RUL directly by matching similarity among saved examples and new test instances [57]. They are also known as experience based approaches [54]. A combination of different machine learning methods can be an appropriate choice to overcome the drawbacks of an individual method [59]. But, whatever approach is considered for prognostics modeling, it is necessary to integrate operating conditions and actual usage environment. Lastly, in some cases the statistical learning approaches for prognostics do not consider operating conditions, failure mechanism and actual usage environment [54].

Experience-based prognostics

The experience-based prognosis approaches are based on the formalization of the failure mechanisms of systems by probabilistic models (lifetime law, Markovian or non-Markovian processes) constructed by prior knowledge, by experience feedback or by expert judgment. The main advantage of this type of approach is that it does not require in-depth knowledge of the physical degradation mechanisms. Also, they are relatively simple to implement and inexpensive. This method is mainly used in the situation where there is no knowledge available on the physical nature of the system and where no device for monitoring the state of degradation is operational [28]. The main limitations of experience-based approaches are as follows: - There is frequently a gap between the models developed (single-component with 2 states) and industrial reality (multi-component multi-state system), - It is difficult to have a history of past experience representative of all the conditions of use of the systems [28].

The experience-based approaches are mainly derived from traditional abilist modeling and treatment methods. The prognosis is in this sense assimilated to a study of predictive ability, the objective being to identify the parameters of a random distribution describing the phenomenon of degradation or failure (Poisson's law, exponential law, Weibull's law , log-normal distribution). In this set, weibull's law remains the most widespread [34]. In addition, the use of an evolutionary abilist model such as ALM (Accelerated Life Model), PHM (Proportional Hazard Model), or the implementation of a Bayesian approach allowing to update the parameters of the law of degradation with each new information available can also represent a solution. Monte Carlo simulation makes it possible to combine different random phenomena but is confronted with the problem of explosion of simulation time [34].

- **Applications**

Among the recent works in the field of experience-based prognosis, we can mention the following. proposed the EXAKT software to optimize the replacement of critical equipment (turbine, valve, motor, etc.). The proposed methodology combines the monitoring of the failure rate obtained by a Weibull model and the forecasting of the evolution of covariates following a discrete non-homogeneous Markovian process. proposed EDF's IBTV software suite by integrating an original prognosis methodology where the maintenance strategy is based on triggering interventions following the detection of component aging (valve, electrical relay, mechanical structure, for example). The approach is based on a

Bayesian approach with a priori modeling of the behavior of the failure rate (exponential law / Weibull composition). In addition, the e ciency of maintenance actions is taken into account according to the expert opinion. optimized the frequency of preventive interventions on ventilators. modeled the service life of concrete bridges to improve their maintenance and replacement cost. [34] calculated the average availability of a compressed air circuit breaker subjected to two failure modes.

Hybrid prognostics

A hybrid prognosis method is the integration of a physical model of behavior and a data-driven approach. Two classes of hybrid prognosis are generally distinguished. When a physical (even empirical) model can be established, a data driven approach is used to estimate and predict the unobservable parameters of the model. We then speak of series approaches [63, 30]. A so-called "parallel" (or "fusion") approach consists in combining the output of a physical model with that of a data-oriented tool to reconstruct the overall output. In such cases, the data-oriented tool is generally used to estimate and predict unexplained and therefore non-modeled phenomena [64, 30]. Hybrid approaches exhibit good estimation and prediction performance. They also allow good modeling of uncertainties. On the other hand, they can be very costly in computing resources, and are limited by the need for physical modeling of degradation phenomena. Hybrid modeling can be performed in two ways: 1) series approach, and 2) parallel approach.

- **Series prognostics**

In PHM discipline, series approach is also known as system modeling approach that combines physics based approach having prior knowledge about the process being modeled, and a data-driven approach that serves as a state estimator of unmeasured process parameters which are hard to model by first principles. Several works in recent literature address series approach as model based prognostics [64, 28, 54]. However it cannot be regarded as model based, because, physics based model is dependent on a data-driven approach to tune its parameters (Figure6.6). In brief, the representation (or modeling) of an engineering asset is made with mathematical functions or mappings, like differential equations. Statistical estimation methods based on residuals and parity relations (i.e., difference of predictions from a model and system observations) are applied to detect, isolate and predict degradation to estimate the RUL [30]. Practically, even if the model of process is known, RUL estimates might be hard to achieve, where the state of the degrading machinery may not be

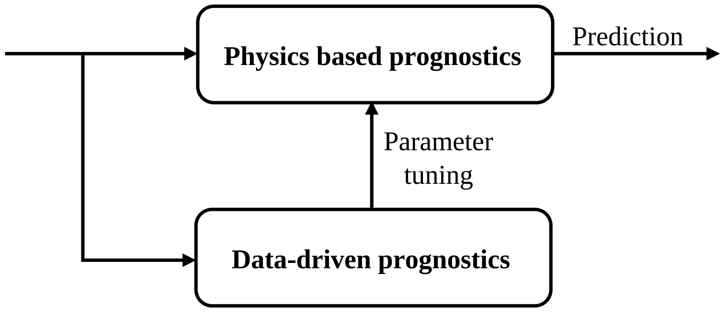


Figure 2.6: Series prognostics for hybrid prognostics model. [64]

observable directly or measurements may be affected by noise [64]. In this case, a mathematical model is integrated with on-line parameter estimation methods to infer degrading state and furnish reliable quantification of u ncertainty. State estimation techniques can be Bayesian methods like Kalman filter, Particle filter and variant [42], that update the predic-tion upon collection of new data.

As for example from recent literature, [30] developed a physics based model relying on particle filtering to predict the RUL of turbine b lades. An approach to RUL estimation of power MOSFETs (metal oxide field effect transistor), which used an extended Kalman filter and a particle filter to accomplish prognostics m odels. An unscented Kalman filter based approach was applied for prognostics of PEMFC (polymer electrolyte membrane fuel cell)[65]. Recently, another interesting application on prognostics PEMFC was presented by [30], using particle filter that enabled to include non-observable states into physical models. Proposed a particle filter b ased a pproach t o t rack s pall p ropagation r ate a nd t o update predictions. A Matlab-based tutorial presentation that combines a physical model for crack growth and a particle filter, which uses observed data to identify model p arameters. [60] Proposed a serial approach to predicting the RUL of a creeping turbine blade.

- **Parallel prognostics**

Physics based approaches make use of system specific k nowledge, w hile d ata-driven approaches utilize in situ monitoring data for prognostics. Both approaches can have their own limitations and advantages. A parallel combination can benefit f rom a dvantages of physics based and data-driven approach, such that the output from resulting hybrid model is more accurate (Figure2.7). According to literature, with parallel approach, the datadriven models are trained to predict the residuals not explained by the first principle model [64].

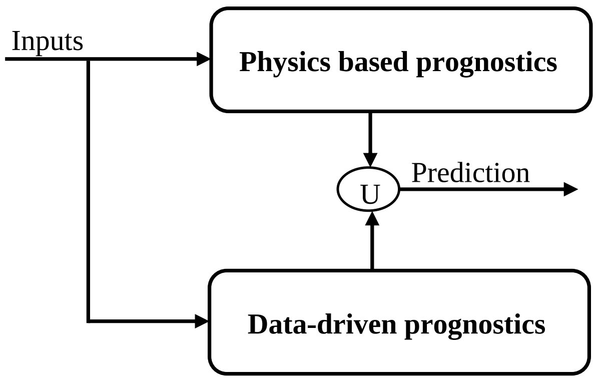


Figure 2.7: Parallel prognostics for hybrid prognostics model. [64]

In PHM discipline still different terminologies are being used for such modeling. Called it as parallel hybrid approach, to build a model by combining a data-driven ensemble to POF model for an application of choke valve. In some works, such a combination of physics based and data-driven approaches is also called as fusion prognostics, that also requires an accurate mathematical model to represent a system for POF, and data for the data-driven approach [66]. As for some examples, [64] presented a fusion approach for prognostics of multilayer ceramic capacitors. A fusion methodology for electronics products. A case study was performed on computer by considering environmental and operational loads that a system is exposed to throughout its life cycle. presented a road map for information and electronics-rich systems, where the proposed fusion approach was illustrated on an application of printed circuit card assembly. A hybrid approach to fuse outputs from model-based and data-driven approaches was proposed by [28].

= **Application point of view**

Series approach for hybrid prognostics requires detailed knowledge of degrading process. However, for the complex systems in a dynamic industrial environment, it's hard to achieve accurate mathematical models. Also, it is important to precisely have FTs to estimate the RUL.

The need for implementation of parallel hybrid prognostics model lies in the limitation of building a prognostics model with an individual approach i.e., data-driven or model based approach. There fore, accuracy of parallel approach should be higher. However, implementation of such models include several steps, which can limit their applicability in real-time for some cases, due to computational complexity factor [66]. For example, the main steps to achieve RUL estimates by a parallel hybrid approach can be, parameter identification and monitoring, feature extraction and healthy baseline creation, anomaly detection, parameter isolation, POF models, failure definition, parameter trending and RUL estimation [30]. Finally, parallel hybrid prognostics approach has higher complexity than series hybrid approach.

2.4 Conclusion

Maintaining industrial systems in operational condition at a lower cost has become a critical factor in the performance of companies and the traditional concepts of preventive and corrective maintenance are gradually being supplemented by a more reactive and proactive consideration of failures. With this in mind, Prognostics and Health Management has received increasing attention over the past twenty years. Its overall principle is to transform a set of raw data collected on the monitored equipment into one or more health indicators whose extrapolation over time makes it possible to define adequate and above all detailed reaction policies (decision support: control, maintenance). In this, seven subprocesses are generally distinguished as the founder of the PHM. In addition to this position-ing of the PHM with regard to the maintenance activity.

The acquisition of data representative of the initiation and progression of degradations in the system, where a generic approach to obtain reliable and exploitable monitoring data for a PHM application is proposed. This is based on:

- Identification of critical components;
- The definition of the physical quantities to be monitored;
- The choice of sensors to be installed;
- Specification of the data acquisition and storage system.

Chapter II:

Tool wear conditions monitoring

CHAPTER 02

TOOL WEAR CONDITIONS MONITORING

3.1 Introduction

Machining as a manufacturing technology has invariably played a significant r ole i n the manufacturing processes of many enterprises. It is estimated [67] that expenditure on machining account for approximately 5% of the GDP in the developed countries. Therefore, machining technology is constantly evolving. It results from numerous research concerning i.e. the accuracy of the machined parts, or the stability of the high-speed machining process [68].

Despite a number of research and innovations regarding technologically advanced cutting tools, or more demanding materials to be machined, further striving to increase productivity and quality decreasing total costs at the same time, requires search for innovative solutions, including those of an optimizing character. Therefore, recently, the number of scientific research in the field of machining is gr owing. They concern advanced processing of collected measurement data coming from diagnostic and monitoring systems of technological machines. On the one hand, this is the result of the rapid development of measurement and analytical techniques [69], and the growing importance of broadly understood durability and reliability.

On the other hand, it is the result of expectations related to the implementation of solutions based on the idea of Industry 4.0. Machine to machine communication, smart technologies, or the need to develop cyber-physical systems (CPS), taking into account the broadly understood principle of sustainable development, pose a number of new research challenges.

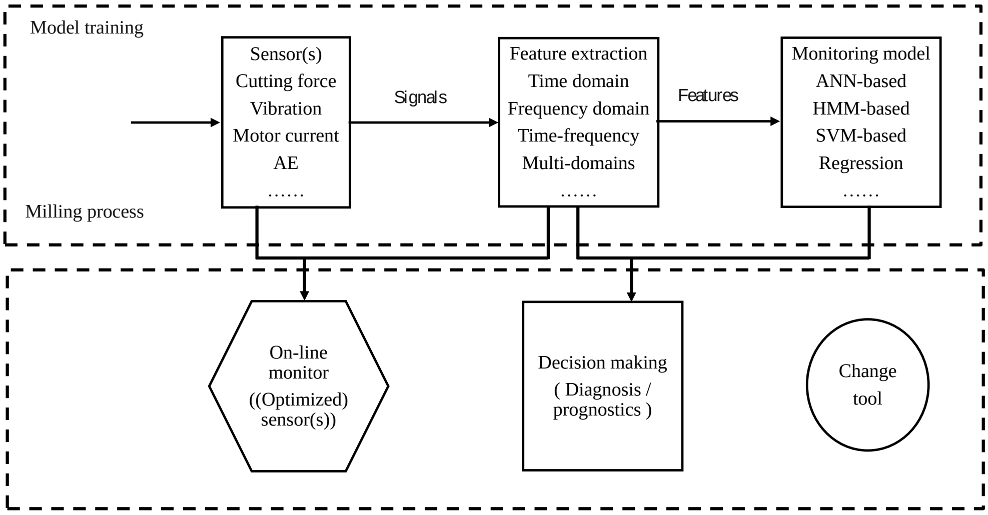
According to Lee at al. [70], recent advances in manufacturing industry have paved way for a systematical deployment of CPS systems, within which information from all related perspectives is closely monitored and synchronized between the physical factory floor and the cyber computational space. This requires advanced information analytics for networked machines, which finally will be able to perform more efficiently and collaboratively.

Currently available advanced technological solutions in measurement sensors and data collection and processing systems as well as widespread use of industrial computer networks open up an opportunity for potential future smart factories. However, the increasing amount of collected data **requires** effective analytical tools [68, 71]

3.2 Advanced analysis in terms of tool wear condition monitoring

Over many years, there has been a number of evaluations undertaken on the state-of-the-art of research internationally, in a keynote paper, detailed the activities of the CIRP (International Academy for Production Engineering) Tool Condition Monitoring; gave an overview of the research being undertaken, however, only in Korea, into machining process monitoring; published another state-of-the-art paper within CIRP and at this point investigations were very active in the field. Many of the process parameters being sensed are the same now as in the 1970s. What has changed dramatically in the intervening years is the com-puter processing power, memory storage and data acquisition speeds. If one accepts the prediction of Moore's Law in terms of computing capacity doubling every 18 months, then it is easy to also accept that the available computing tools are dramatically different now to the ones that the early TCM pioneers had at their disposal (Figure3.1).

In that light, [73] keynote paper, being the most recent overview paper and issued more or less in the era when Big Data analysis is possible, offers the most relevant insight into the advantages and the limitations of the various methodologies that had been investigated. The sensed parameters are unlikely to change any more and, while the sensors may undergo further improvement, it is tempting to believe the state-of-the-art is now ripe for working TCM systems (Figure7.2). For this reason, an area of particular interest to this researcher in that paper, although not part of the research presented in this thesis, was in the usage of artificial intelligence (in the form of Neural Network's and pattern matching) to inter-pret the data, and ultimately to use the data and the networks' understanding of this to



[Figure 3.1: Basic process flow of tool condition monitoring (TCM) in milling processes. 72]

make decisions. To properly accomplish TCM tasks, a great amount of the TCM models

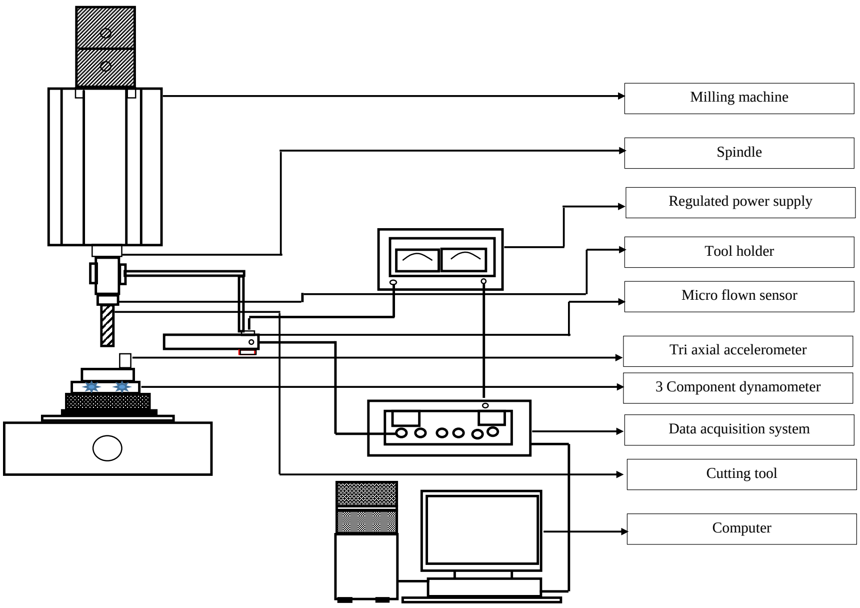


Figure 3.2: Layout for online tool condition monitoring system. [4]

published recently are focused on empirical analysis [74], or sensory data-driven methods such as cutting forces [74, 75], spindle current, vibration [76, 77], and acoustic emission (AE). The related studies have been summarized in several comprehensive reviews.

Typically, the TCM system employs sensing systems to monitor the process, and then extract most relevant information from the sensory signals to identify and classify the tool conditions, to reduce the cost increased by tool failure. As sensing technology continues to mature and advance, how to extract the most relevant information has become a vital issue for TCM. However, discontinuous cutting is one of the remarkable features of the milling process, and this would result in non stationary sensory signals. The commonly-used time-domain statistical features, frequency-domain features [78, 79] are sensitive to the variation of cutting conditions [75] in milling; this would limit the applications of the proposed TCM systems. Wavelet analysis has strong time-frequency analysis capability to analyze non stationary signals effectively [74].

Singularity analysis is applied and is observed in sensory signals collected in the machining process, particularly during tool tilting and breaking. Fourier transform and wavelet analysis are commonly used singularity analysis tools, but wavelets can provide a better time-frequency localization property. Singularity analysis based on wavelet transform to deal with TCM in machining, wavelet coefficient standard and statistical characteristics of AE signals were selected as data samples to classify tool conditions in turning. Fractal property is one of the important attributes of singularity analysis; it was also employed to classify the variation of tool conditions in turning, they established are current neural network to connect the fractal features of machining dynamics with flank w ear. The introduction of the singularity probability density functions estimated from the cutting force in micro-milling is done to correlate with different tool conditions, and insensitivity to cut-ting conditions such as part material, federation, depth of cut, etc. has been verified by experimental studies [80]. In summary, the recent TCM studies with singularity analysis [80] were focusing on cutting force, AE in turning or micro-milling process experimentally or theoretically. As a result of the non-stationary and the sophistication of the vibration signal of the milling process, the TCM approaches based on singularity analysis of vibration signals are rarely established[74].

3.3 Cutting tool health

Automated Tool condition monitoring is critical in intelligent manufacturing to improve both productivity and sustainability of manufacturing operations. Estimation of tool wear in real-time for critical machining operations can improve part quality and reduce scrap rates. Tool wear monitoring is an important factor to ensure a high quality in the manufacturing process and an efficient operation. Moreover, the early detection of damage in cutting tools and end mills represents the opportunity to avoid furtive costs due to down-time, quality issues or even injuries [81, 82, 83]. Therefore, different challenges and research questions are addressed to monitor CNC 5 milling machines [84, 85]. Nowadays, CNC milling machines are optimized towards Industry 4.0 and able to measure internal signals like spindle speed and feed rate. Those signals can be evaluated to characterize the tool condition [86] and the remaining tool life. While Industry 4.0 is closely related to the latest sensing technologies and network connectivity [87], the vast majority of the existing machines and tooling in the industry do not have any of those capabilities. A key factor towards a swift transition into Industry 4.0 resides on the feasibility to retrofit conventional machinery to meet the current technological needs [88]. The purpose of this work is to demonstrate the process of retrofitting machines of middle (10 years) to long production lives (30 years and above). One focus will be given to implement the existing, low-budget, all in one sensing technologies, which enable collecting, exchanging and making information available through a so-called cloud server. Based on the acquired data, the application of artificial neural networks (ANN) will be demonstrated in order to classify the tool state.

CNC technology has evolved to the point where, in some cases at least, finish tolerances of low single microns are now possible, which places a demand on the CNC operator and on the CNC manufacturing companies. This is all the more so, when the material being machined is challenging [89]. A typical example in biomedical devices would be austenitic stainless steels and titanium (and its alloys), which have been widely used for bio-materials, such as artificial hip joints and dental implants and in the aerospace industry. A specific biomedical example that is very challenging is Ti–6Al–4V, one of the most often used bio materials. It is well known for its poor machinability, due to its low thermal conductivity that causes high temperature on the tool face and strong chemical affinity with most tool materials, thereby leading to premature tool failure. Moreover, its inhomogeneous deformation makes the cutting force fluctuate and further aggravates tool-wear. In practice, the solution in industry to this challenging machinability is to limit the cutting speed to less than 60 m/min [89].

Another challenge is that as tool wear increases, the hardness of the material increases also due to the work hardening process while machining [90].

The negative impact of tool wear is usually only detected at the end of the machine cycle. In most commercial deployments, errors associated with tool wear remain uncompensated for and once an error is spotted, the product is usually only of scrap value. For example, the author is an engineering manager at the Schivo CNC facility, where scrap at is estimated to be 2%of turnover and costs the company about €300,000 per year. Analysis of this figure has shown that over 50% of the scrap generated is attributed to worn or broken tooling. If real time TCM were in place, then machining parameters could be adjusted to compensate for tool wear, tools could be replaced in proper time when they approach their tool life, and not prematurely (or posthumously) as they are now. Machines could also be scheduled for down time and surface finish and dimensional stability would be increased [89].

3.4 A Technology Update

Direct monitoring of the machining results (e.g. machined surface) is one of the traditional approaches to TCM. Another approach, which is widely applied, is the exchange of the tool after a predetermined machining time, which must be much smaller than the real tool life, to avoid machining with a blunt tool and thereby not assuring the desired product quality. Even more damaging is the possibility of catastrophic tool failure, which can happen when the tool wear is too high. TCM research is driven on by the need for higher quality, stimulated by growing demands for process automation and reduction of human supervision requirements.

The illustration of many inputs and outputs from the machining operation that have been investigated as possible sources of information related to the effectiveness of the process [89]. This illustration outlines many of the physical emissions from the CNC process that could be monitored and indeed have been evaluated through the years of research.

One of the early innovations in terms of in-situ evaluation was the development by Renishaw of the touch trigger probe in the early 1970's, which is now widely used in machine tools to provide location and measurement information on both the tools and the work-pieces.

In terms of CNC machine development, there are ongoing attempts by the two largest CNC machining manufacturers to develop systems to offer feedback on machine process stability. Yamazaki Mazak have developed a number of systems such as IBA (Intelligent Balance Analyser), ITS (Intelligent thermal shield), IPS (Intelligent performance spindle), IMS (Intelligent Maintenance Support) and AVC (Active Vibration Control). These systems are all useful for monitoring a specific element of the m achine. H owever, at the t ime of writing, there is no fusion of the information and, overall, a general machining performance status is not available. Mori-Seiki has developed the Mori-Net system, which allows remote monitoring of the machine.

Table 3.1: Commercial products and their limitations. [89]

Technology	Use	Limitations
Probes	Quantify tool wear	Poor accuracy, not related to product quality, doesn't measure efficiency of process
Machine Vision	Machine Vision	Processing lag time, poor accuracy, inability to determine surface roughness; doesn't measure process efficiency
Individual Sensors	Process efficiency	Not robust, Not accurate, limited capabilities, requires experience to analyze

However, the only real advantage of Mori's offering is that monitoring that takes place at the machine can now be undertaken remotely. The Mori-Seiki Company presented their vision of next generation CNC machine technology at the 2015 CIRP winter meetings [89].

Other companies have developed systems, which enable some degree of monitoring of the performance of the machine. However, like the developments offered by the big CNC machining manufacturers, these do not have the resolution to give the required level of performance information. For example, the OMAT vibration control monitor system does indicate when there has been a change to the monitored state of the machine, but will not provide any indication as to the cause or effect of the detected change. Inevitably it seems that it will improve, but most commercially available systems apply "one process – one signal feature (SF)" strategies.

Shows the current technologies available to industrial precision engineering firms and their associated limitations. Suprock Technologies is one of the more recent additions to the market and have developed a tool tip which incorporates torque, vibration, and tem-perature sensors into it. However, this system experiences problems with channel fading and disruption of signal in the machining environment, particularly at high spindle speeds and is limited by its design to particular machining processes (rotating cutting and end-milling). This product also does not have an integrated artificial neural network and soft-ware designed to combine various sensory data into one simple graphical output and also requires significant operator knowledge to operate the system effectively [89].

In the laboratory, there has also been extensive investigation of tool condition monitoring. The most often used of the available signals and variables, are the cutting force components; acoustic emission (AE) and vibration [91].

Machine vision systems based on digital image processing (DIP) offer great promise, when applied for measurement of tool wear. Two approaches are taken in DIP: observation of the outline of a tool or observation of flank wear [92]. Use of information on the state of tools from the camera in conjunction with information from sensors: cutting forces, acoustic emission or vibration, can increase the effectiveness of monitoring system (X, 2002).

Despite many sensors and sensor techniques available, it is generally acknowledged that reliable tool wear evaluation based on one signal feature (SF) is impossible, because the measured feature depends not only on the tool wear but also on variety of other process parameters of random nature. It makes the relationship between tool wear and measured values very complex and it has a statistical rather than strict, predictable nature.

3.4.1 Patented technology pertaining to TCM

To gain an understanding of the attempts that have been made to commercialize different methodologies or systems, the author decided that a review of successful patent applications relating to systems or devices that claim to monitor and measure tool breakage, would be of benefit. A patent has been filed on a device on a device, which used as its signal input, the cutting tool motor forces. A blunt tool has greater overall interaction with the work piece material, so motor forces tend to increase as a tool wears. The patent application proposed a system whereby continuous monitoring was employed on the ratio of one of spindle force or power, or low frequency vibration energy compared to high frequency vibration energy during the cutting process. The patent application does suggest some methodologies, such as motor power, that have since been found to be challenging in overall effectiveness in terms of their ability to provide useful, real-time information on the cutting tool condition. However, the patent application also saw great merit in the effectiveness of accelerometers. The use of motor current as an indicator of cutting performance has also been patented. The basis of their device is the use of measurement of the active power being absorbed by the spindle motor and the comparison of this power to known power data for good cutting conditions, which had been detected, for example, during the first cutting operation of the tool. In theory, the application is feasible, assuming the motor information is valuable. However, (as discussed in the broader literature review) the use of motor power and currents can be challenging in monitoring the performance of the cutting tool, for example, due to transmission losses and excessive signal-to-noise ratios in the measured parameters [89].

An application had been made by for a similar system, which again used a reference signal, detected during the first operation of the tool. This signal is assumed to be a known good set of information and compared that signal against the current signal being obtained from sensors providing information on the tool profile and cutting conditions. Again, the application goes into detail on the sensor signal analysis, but the main sensor application is an eddy current sensor, which would be unlikely to be accurate enough for today's high-precision applications . The Howatt proposal also claimed improvements that its system would have over a previous patent filed [89]. Hamilton proposed the use of a distance comparison arrangement, where the degree of wear of the tool would be monitored using sensing device(s), to measure the distance to an area of the cutting surface of the tool and a non-cutting surface of the same tool. The logic being that as the tool wears, the distance to the cutting surface increases, while the distance to the non-cutting surface remain the same, in a manner similar to some of ultrasonic TCM research. The application details the electronics involved and it is particularly this element of the application that Howatt felt he had improved. However, neither system would be sufficiently accurate for a modern application based on their platform technologies. Thompson proposed using a probe on the tool holder to probe the distance to the freshly cut metal, as an indication of tool wear. As the freshly cut metal surface comes closer to the probe, this is an indication that there is wear on the nose of the tool[89]. The systems proposed for use, in order of preference were, air gauging, capacitance gauging, inductance gauging, optical and contact gauging. The measuring probe would be mounted just after the tool for the measurement of the distance to the cut metal surface. The obvious issue with this configuration is that their system is expected to perform distance measurements in an extremely harsh environment, where cutting fluid and swarf are interference factors. Their system provides some alleviation for this, by using a mean of the readings to determine the overall distance. However, overall their system would not produce the required accuracy and would not give more valuable information on the process, such as surface finish and chatter, which are both also caused by tool wear, but do not necessarily affect the depth of the tool cut [89]. A patent application, which employed the use of resistance to determine the wear of a tool, was successfully filed. Their system used a resistor applied directly to the tool, the resistance of which varied according to the level of wear being experienced by the tool. Overall, the patent application seemed speculative and lacking in detail and seemed to be an attempt to patent the use of resistance as a tool condition monitoring method rather than detailing the application. For example, the ideal location of the sensor was not identified, with multiple sites instead being suggested.

Moreover, the benefit is further clouded by not specifying the cutting operation, as the application states that overall the invention relates broadly to the use of electrical resistance in tool condition monitoring. A similarly vague (in this author's opinion) patent application was submitted by, which employed a plurality of sensors for monitoring of the tool condition. Their patent application is more concerned with the monitoring and understanding system that is being proposed, rather than the actual acquisition methods for the raw process data. In stating that, if suitable sensors were applied, theirs is a good initial expert system for the prediction of tool wear. While the application claims to be a system and method for the use of an expert system for tool life prediction and tool wear analysis, the actual patent claims relate more to the expert system than to the tool wear monitor method, in the opinion of this author. More recently a system was developed, which was using work process data for the tools, rather than actual real-time condition information.[93] patented the system, "Tool Sentinel". Their system in essence used sensors to detect the machine cycles in which the tooling is being used and extrapolated a tool condition by comparing that data against the predicted tool life for that tool. The system can be used on multiple machines and with multiple tooling once all the prediction information has been entered for the tooling types and operation cycles. The obvious drawback is the fact that their system was theoretical rather than actually realized and would not detect issues such as unusual tool degradation (from a material fault in a tool or a workpiece material), or a catastrophic event (tool breakage). Another considerable drawback is the fact that the tool life is just an estimation and if the initial estimation of the tool life is conservative, then the system will declare a tool worn, when it may still have considerable cutting life left. Overall the patents that have been applied for in relation to the area of tool wear and associated monitoring systems seem vague and many appear to be an attempt to get a patent on a particular tool condition monitoring methodology, while the validation of the system is not yet completed, and the fundamentals of the applied technology have not been practically proven [89]. Some of the most relevant patented technology in this field is summarised in (table 3.2).

3.5 Tool condition monitoring sensors

A number of sensors have been employed in TCM to obtain signals for tool condition monitoring. The sensor configuration can be divided according to the types of sensors employed into two categories: single sensor and multi-sensor configurations.

Table 3.2: Patented technology pertaining to TCM. [89]

Patent Name	Patent Number	Date Filed	Expired
Tool Wear and/or Breakage Control Device for a Machine Tool	US2004/0217873	6th Feb 2004	No
Production of Tool Wear Detector	4120196	25th Mar 1978	Yes
Apparatus for Directly Measuring Tool Wear	4176396	23rd Sep 1977	Yes
In-Process Cutting Tool Condition Compensation and Part Inspection	4620281	15th Feb 1984	Yes
Cutting Tool Wear Detection Apparatus and Method	4831365	5th Feb 1988	Yes
Tool Wear Detector	5000036	23rd Mar 1990	Yes
System and Method Utilizing a Real Time Expert System For Tool Life Prediction and Tool Wear Diagnosis	5251144	18th Apr 1991	Yes

In terms of single-sensor configurations. While other types of single sensors have been employed for TCM in milling processes, such as sound [94] and temperature [72] sensors, these sensors are rarely adopted alone because they are significantly affected by environmental conditions. Therefore, they are generally employed in conjunction with other sensors in multi-sensor configurations.

Sensors for process monitoring must meet the following requirements:

- Accurately measure the sensed parameter and correctly convey that measurement the TCM processor;
- Cause no reduction in the static and dynamic stiffness of the machine tool;
- Cause no restriction of working space and cutting parameters;
- Should be wear- and maintenance-free, easily changed, and low cost;
- Be resistant to external influences, e.g. dirt/chips/fluid, mechanical, electromagnetic and thermal stress;
- Function independently of tool or workpiece;
- Display adequate metrological characteristics and afford reliable signal transmission.

3.5.1 Intelligent Sensors

Generally, intelligent sensors have a much greater functionality than conventional sensors because they must respond to the special needs of the machine tool or process they are monitoring. An intelligent sensor may be best described as one driven based on self-decision making as opposed to predetermined commands [95]. In addition to sensor feedback of the machining process the intelligent machine can utilize experience accumulated during past operations, accumulates knowledge through learning and can accommodate ambiguous in-puts.

Intelligent sensors should be able to do some or all of the following:

- Self-calibration;
- Signal processing;
- Decision making;
- Dusion ability;
- Dearning capability.

Signal processing in this case means that the sensor has the capability to do feature extraction from the measurement vector, so that a data stream comes out of the sensor, not just the sensed signal. Decision making as part of the sensor system enables it to do such things itself not relying on the controller or other processors to do this. Sensor fusion describes the ability to combine or add the output of other sensors to provide a more robust decision on the process state. A very important aspect of the sensor is that it should be able to learn from past information using a neural network or other knowledge representa-tion scheme, in order to continuously increase its reliability and robustness. An intelligent sensor is, thus, more or less a combination of conventional sensors, signal processing and feature extraction methods, as well as implementation strategies that are integrated in the sensor or sensor system [95].

3.5.2 Energy monitoring

To reduce power consumption in machine tool operation, the major causes are investigated and three cases are studied with following findings:

1- Power consumption can be reduced for drilling and face/end milling by setting the cutting conditions high yet within a value range which does not compromise tool life, surface finish, thereby shortening of machining time;

2- Power consumption for deep hole machining can be reduced with an adaptive pecking cycle, which executes pecking as needed by sensing cutting load;

3- Power consumption can be reduced further by synchronizing the spindle acceleration/deceleration with the feed system at rapid traverse stage.[96]

Analyzing the overall efficiency of manufacturing systems by combining electricity consumption data with additional facility level or process level information has been investigated by many researchers with promising results, however, there is scant attention given to the challenge of choosing the correct power metering solution within the literature. Choosing the correct metering device for the required analysis is a challenging task that requires an understanding of both the meter characteristics such as measurement resolution, sam-pling rate, and accuracy and also the characteristics of the electrical event including spectral content and duration. This paper gives an overview of the current state of the art in electrical energy metering. Three classifications of meter are proposed and the functionality associated with each class is investigated; an indication of price is also given. A state of the art in industry review is also included and this illustrates the different options available from different meter suppliers. Considering the fact that power metering within industrial facilities is a process that has only recently become popular due to its ability to fault find and facilitate energy efficient optimizations, it is safe to assume that the industrial power metering industry is one that will continue to expand over the next decade [97].

3.5.3 Visual and optical systems

An early, good overall evaluation of the state of- the-art of different sensing techniques has been provided. As a foundation for the discussion on vision sensor applications an overview of the basics of machine tool wearing is discussed, along with a general discussion on direct sensoring (proximity, vision) and indirect sensoring (force, vibration, AE). The vision based tool condition monitoring systems comprises of three major components; illumination, cameras and image digitization. Two camera types are commonly used in vision tool condition monitoring. Videocon cameras, which use an electron beam to provide image data onto a photosensitive surface, have been used, but have been found to suffer from image drift and geometric distortions. More recently CCD cameras have been employed in these types of systems, which offer high resolution and are also available in high speed.

The image digitization comprises of the following block sequence: The paper includes a state-of-the-art description on tool wear monitoring using vision systems. It discusses in broad terms the contribution made to the field, but makes no real claims as to the validity or worth of any of the various methods discussed. However, a second in a further detailed paper discussed in depth a specific application of vision systems in this area and discounted the general worth of the method [89].

Another proposal of a method to visually monitor the cutting face of a tool using two lighting configurations and one camera position to record wear from both the flank and rake faces. The images were segmented into 10-pixel wide strips and for each of the strips, the degree of wear was determined by comparing the average grey level for the worn and unworn regions of the tool. Although this approach was novel at that time and formed the basis in some respects for the more recent experimentation into the use of vision system examination, it was clearly constrained by the available technology.

The cutting tool tip has been illuminated with a 0.8mm beam diameter laser and captured the reflected pattern with a camera located perpendicularly to the flank fa ce. A contour of the wear region of the tool was produced using a series of signal processing steps. The system was found to be accurate to within 0.1mm of the traditional tool microscope limits and was found to have very high processing speed of 1.7 seconds. the accuracy of 0.1mm is really not good enough for modern applications [89].

3.5.4 Ultrasonic analysis

Through the years there were a number of advances in the field, all of which were based on the application of high energy and high frequency ultrasound waves at the cutting interface. provided a state-of-the-art review of the research into this area of machining, which made good observations in conclusion on the optimum conditions and configurations that would be required to achieve maximum efficiency from an ultrasonic machining process.

However, while the research and industrial development into the use of ultrasonically assisted machining was further pursued, the use of this energy for the monitoring of the performance of the cutting operation was also being researched.

In ultrasonic CNC research, there are two significant experimental attempts, by Hamm

(2006) and also by, that have practically demonstrated that there is theoretical merit in the suggestion that ultrasonic analysis and monitoring of a cutting operation is viable.

The two practical investigations both demonstrated the merits of ultrasonic energy as a monitoring methodology, to determine tool wear in machining. However, both encountered similar experimental difficulties, in terms of transmission pathways and the overall practicality of the use of this medium.

A further discussion of the wider research, briefly t ouched o n a t t he b eginning o f this section, which has been undertaken into ultrasonic applications at the cutting interface, would also demonstrate that researchers in this area have encountered similar difficulties in their research. However, the primary challenges and benefits h ave b een t eased o ut here, in covering the two papers and deeper analysis is outside the scope of this research [89].

A theoretical model for calculating TWCR r in UVAM process was proposed, which was helpful to understand intermittent machining mechanism in UVAM. The influence of machining parameters on TWCR in UVAM was also studied in detail. Since machining parameters are closely related to the TWCR, this work experimentally studied the effect of cutting and vibration parameters on machining performance in UVAM of titanium alloy Ti-6Al-4V. According to the analytical model and experiment results, following conclusions can be drawn [98].

The experimental setup mainly consists of a CNC machining center, an ultrasonic vibration system, a data acquisition system and an on-line monitoring system. The ultrasonic vibration system mainly includes an ultrasonic generator, an ultrasonic transducer, an ultrasonic horn and a resonant block. An online monitoring system used to monitor vibration characteristics of the workpiece mainly consists of a laser displacement sensor, a controller, a high-speed acquisition card and a PC Figure(3.3).

- According to the analytical model of TWCR r in UVAM, the nominal cutting speed nu_c, ultrasonic frequency f, ultrasonic amplitude a and cutting angle phi are four key machining parameters affecting TWCR. And the relationship between TWCR r and the four machining parameters were expressed in graphical;

- The analysis of cutting force signal in UVAM and CM demonstrated the oscillation characteristics and amplitude reduction characteristics in UVAM original force signal. Both low and high frequency components existed in FFT spectrum in UVAM force signal while only low frequency components appeared in FFT spectrum in CM;

- The experiment results showed that the cutting force components Fx and Fy in UVAM

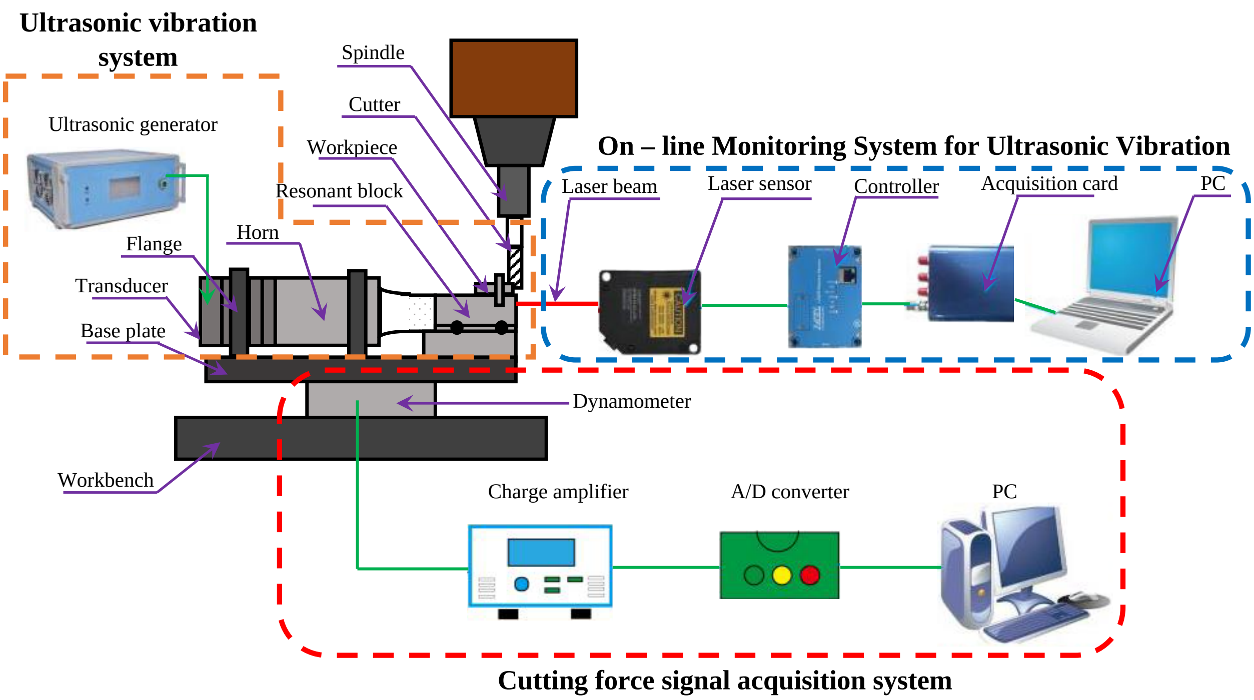


Figure 3.3: Schematic diagram of a complete UVAM system. [98]

were respectively reduced by 21,5–37,24% and 31,02–46,30% compared with that in CM. And the cutting force Fx and Fy in UVAM decreased with the increase of vibration amplitude;

- The comparison of surface morphology between UVAM and CM showed machining defects, such as tool path marks and bulges, had an excellent improvement in UVAM. It could be observed that uniform vibration pattern appeared on the finished surface in UVAM. The finished surface roughness Ra using UVAM were lower than that using CM method. And the maximum improvement of surface roughness Ra was 48.3% at a cutting speed of 17m/min and the minimum improvement was 25.9% at a cutting speed of 5m/min. In addition, the excessive vibration amplitude had a negative influence on the machined surface quality;

- The experimental results also verified the technical advantages of UVAM method in burr suppression and uniform chip formation. Burr phenomenon in titanium alloy machining had been improved obviously because of the intermittent machining mechanism in UVAM, which could greatly reduce cutting force. In UVAM, the short, thin and uniform chips were produced because of the reduction of dynamic cutting thickness. And uniform ultrasonic vibration texture appeared on chips morphology in UVAM process. The experimental results showed that the sizes of chips tended to decrease with the increase of vibration amplitude [98].

3.5.5 Acoustic emission

Acoustic emission (AE) signals are measured using an acoustic emission transducer or microphone. This is a prevalent method among TCM techniques. AE signals consist of acoustic (elastic) waves, which are generated when the workpiece is exposed to plastic deformation after the cutting tool penetrates the workpiece during machining. They occur due to the rapid release of energy within a material as a result of plastic deformation [99, 100].

According to [101] and, AE signals are divided into continuous and transient signals, which have different characteristics. If the AE signal is continuous, it comes from the cutting tool and indicates tool wear. However, if the AE signal is transient, it indicates that the cutting tool is broken.

Another work has been developed intensively on an AE-based TCM method Ṫhey benefited from AE signals used to predict tool wear and chip formation generated during face milling. During an analysis, AE signals and the size of the cutting tool flank wear were measured at a fixed interval, and at the same time, chips were also collected synchronously for monitoring the tool wear and chip formation. Furthermore, Marinescu and Axinte conducted a study on the monitoring and detection of both tool failure and surface defects during the milling process using AE signals. In this study, AE signals obtained during the milling are transformed from the time domain into the time-frequency domain using the STFT method to identify tool and workpiece malfunctions. The time-frequency domain represents a spectrogram of AE signals. Here, the cutting time (Tc) for each tool was first determined. Then, STFT transformation was applied to the obtained time-series graphs for each tool, resulting in time-frequency matrices called spectrograms. A sample spectrogram obtained after an STFT transformation. In this spectrogram, the pattern of the STFT area representing each tooth engagement is extracted and combined on a dense spectrogram for further inference [99].

3.5.6 Cutting force

As soon as the tool starts cutting, due to the relative motion between the tool and workpiece, various wear modes become active and the tool starts becoming blunt. Worn tool requires more force to remove the same amount of material than the sharp tool. So, the cutting force increases with increasing wear and is thus considered as one of the parameters that can be measured easily to monitor tool wear. The nonlinear relationship was observed between friction force, friction coefficient, and tool wear (Figure3.4). The cutting force measurement techniques have been used by many researchers for tool wear monitoring, Dan and Mathew [101] have reviewed various force measurement techniques and proposed that although the force measurement techniques is one of the most commonly used techniques in detecting tool wear, due to the complex relationship between cutting forces and mechanisms causing tool wear and failure, the results of various research are quantitatively different and cannot be used even empirically.

Dimla carried out another detailed review of tool condition monitoring techniques, and various force measurement techniques for tool wear monitoring were discussed. As the static cutting force is prone to fluctuations due to joints and couplings of machine tools and minute changes in cutting conditions and can lead to chatter, it is necessary to know the dynamic cutting forces in order to obtain an indication of system fluctuation. It was emphasized that the measurement of static as well as dynamic cutting forces is vital in order to develop a reliable TCMS.

It was proposed that forces are the most important process parameters related to tool wear but as not only the wear but also changes of variable cutting conditions have a significant influence on the force signals, the force sensing method can only make sense if used in combination with a force normalizing method.

In their recent publication presenting an update of the literature on tool condition monitoring, Teti [73] carried out an up-to-date comprehensive survey on sensor technologies, signal processing, and decision-making strategies for the monitoring of machining operations. The force measurement techniques used for flank wear monitoring Scheffer and Heyns [102] have been reviewed by them along with many recent publications. It was concluded that the systems developed so far were only tested in the laboratories in industry like environment but not on the actual shop floor.

Developed a model-based methodology capable of operating under varying cutting conditions for the online flank wear estimation based on cutting force measurements. The proposed system could estimate the flank wear for varying conditions with the limitation that the cutting variables must vary one at a time in a step wise and constant manner which is not feasible in practice. Developed an analytical model relating flank wear to cutting forces. Cutting forces were reconstructed from the accelerometer signals and experimentally determined dynamic model of a lathe.

The low-frequency system response obtained through the model correlated well with experimental data. Choudhury used the ratio of feed force to the cutting force to develop a mathematical model for flank wear. The experiments were carried out to measure the forces during turning, and the measured values were used to calibrate the regression equation for flank wear. The force ratio monitored the flank wear reliably.

Chungchoo and Saini [103] developed a quantitative model based on a correlation between increases in feed and radial forces and the average width of flank wear. Sikdar measured three-dimensional cutting forces and three-dimensional flank wear surface area and observed an increase in the cutting force with increasing flank wear. It was concluded that the greater value of flank wear results in increased area of contact at the flank–workpiece interface increasing the friction between them and resulting in a higher value of the cutting force. Cakir and Isik [101] carried out tool wear and breakage detection tests and found that among various methods available for TCM, the force measurements were more sensitive to chipping and breakage than vibration and motor current. It was concluded that the success rate obtained with the developed TCMS was low and can be improved by measuring vibration signals along with the force signals. Luo et al. [104] developed a flank wear rate model combining the cutting mechanics simulation and an empirical model to predict the flank wear width. Experiments were carried out for the force measurement, and a good agreement was observed between predicted and measured tool flank wear land width. Oraby et al. [101] developed a tool wear diagnostic approach based on the hid-den correlation between instantaneous tool wear state and the corresponding variations in the stochastic component of the dynamic cutting force. Autoregressive moving average (ARMA) analysis was used to obtain significant models of tool wear at various levels from the cutting force signals. The approach can accurately detect the onset of the plastic defor-mation zone and can be utilized as an integrated monitoring and control system. Thangavel et al. [101] used force measurement results along with response surface methodology to develop the mathematical model for the flank wear prediction, and the results obtained using the mathematical model were found to be in good agreement with experimental results.

Chen [105] monitored force and vibration signals during turning to carry out tool condition monitoring. The combination of force and vibration features extracted from the frequency domain correlated well with tool wear. Sharma and Gajate carried out cutting force, vibration, and AE measurement in order to develop flank wear monitoring system. The neuron-fuzzy techniques used for constructing flank wear monitoring systems -

provided satisfactory results with the cutting parameters for which the models were trained. Calamaz [106] measured cutting forces, and from experimental results, it was found that feed force increases with flank wear. The numerical cutting model was developed to understand the evolution of feed force with tool wear.

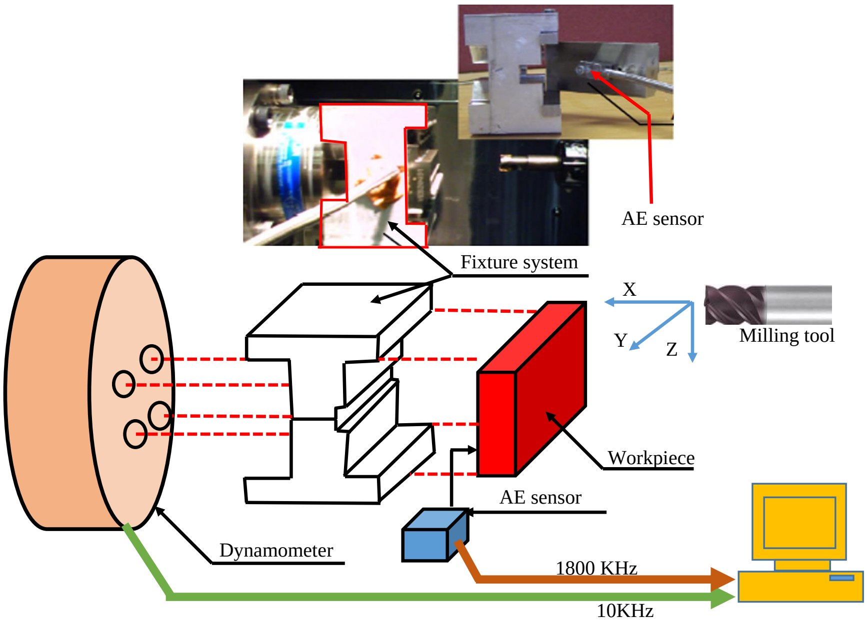


Figure 3.4: TCM method using an AE sensor and a dynamometer. [107]

Al-Habaibeh [108] used force and AE signals in a feature fusion model to predict tool wear during turning. An automated signal and signal processing selection system was used to automatically detect the features sensitive to the tool wear. The system was able to pre-dict tool wear successfully. Ren [109] considered cutting force measurement as the most reliable and accurate sensing method for online tool wear monitoring and used force mea-surements in a Takagi–Sugeno–Kang (TSK) fuzzy approach for tool wear monitoring. It was observed that such models were difficult in estimating the error of approximation and needed development to capture the uncertainty during turning process. Fang. [101] also carried out force and vibration measurement during turning to analyze the relationship between cutting tool wear and these signals. Apart from flank wear, the cutting forces are also sensitive to other parameters and can vary with cutting speed, depth of cut, and work hardness, making correlation with wear more complicated.

3.5.7 Vibration

Vibration sensors are widely employed in TCM because they are inexpensive, easy to install, and provide a similar periodic signal shape to that of the cutting force [72]. Besmir et al. [110] established that low levels of vibration are generated with sharp cutting tools, while the levels of vibration increase with increasing deterioration in the tool condition. Numerous studies have demonstrated the feasibility of adopting vibration signals for TCM in milling processes [111]. For example, Hsieh et al. [112] demonstrated that the spindle vibration acceleration signal can distinguish different tool conditions during micro-milling when used in conjunction with appropriate feature extraction and classifiers. Madhusudana et al. [113] installed a tri-axial integrated electronic piezoelectric (IEPE) accelerometer on the spindle housing to capture the spindle vibration acceleration signal during face milling. Gao [113] achieved positive tool condition diagnostic accuracy by adopting a laser vibrometer to acquire the vibration displacement of a tool holder. However, the characteristics of milling processes limit the accuracy of TCM employing vibration signals. First, vibrations are generated during machine operation even when the tool is not engaged in cutting, as during an air-cut operation. In fact, efectively distinguishing between entitycut and air-cut operations remains an open challenge. Second, vibration signals are difficult to filter, and are therefore prone to providing erroneous data [110]. Finally, the position of sensor installation and the use of cutting fluid can affect the vibration signal [72].

3.5.8 Motor current

Because the cutting force increases with increasing tool wear, the current drawn by the machine motor undergoes a corresponding increase. Motor current sensors are considered to be more suitable for manufacturing settings than cutting force sensors due to their relatively simple application and lack of installation effects on machining operations. Ghosh demonstrated that current sensors provide TCM results that are fairly comparable to that of cutting force sensors in actual industrial TCM applications. Stavropoulos [114] demonstrated that motor current signals correlate more strongly with tool wear than do vibration signals, and the motor current signal suffers less sensitivity to environmental noise, resulting in more accurate tool condition diagnoses. Ammouri [72] established a TCM index based on the measured current values of the spindle and drive motors of a machine tool. However, use of the motor current signal for TCM also has a few disadvantages.

First, motor current signals contain a considerable amount of noise, obstructing the detection of small fluctuations in the cutting force, and high-frequency components are lost by filtering [115]. Second, the motor current signal is significantly influenced by the viscous damping of the feed system and friction in the mechanical system [72]. Finally, experiments conducted by Lee et al. [116] demonstrated that the motor current is not sensitive to changes in the cutting force at high motor frequencies, which means that the motor current signal is not suitable for TCM conducted at high spindle speeds.

3.5.9 Audible sound energy

To the author's surprise, at the outset of this research, there has not been a huge body or work undertaken to correlate the perceived ability of experienced machinists to "hear" the CNC machine process degrade through tool wear.

Lazarus [117] was one of the first w orks e ncountered p ursuing t his t heme. I n the Lazarus investigation, although the phenomenon is referred to as "acoustic emissions", which includes a large range of frequencies that are outside the frequency range of hearing for humans, it was in fact audible sound energy that was being assessed during the exper-iment. In any event the experimentation lacked a degree of sophistication, but ultimately concluded that humans can hear tools wear over time. Teti proved with a greater degree of sophistication that there clearly is a correlation between tool wear and the sound energy from a CNC machine in the 2-20kHz range. This was further demonstrated by the authors own paper in the Journal Wear, Downey, O'Leary [117]. The big challenge faced by any investigation into audible sound energy is external interference from other noise sources, transmission paths transmission media.

3.5.10 Temperature

In metal cutting, temperature is another considerable outcome due to friction between the tool and the workpiece. As the cutting progresses, with the increase in cutting temperature, the chemical dissolution of the tool material increases. Thus, there is a good relationship between the mechanical abrasion/friction, tool wear, chemical dissolution, and cutting temperature, which can be established by developing mathematical models [118]. The models may be able to estimate wear rate and temperature, but it is hard to predict the wear length and requires a database of thermochemical properties of specific tool-workpiece combina-tion.

In order to measure the cutting temperature, as reviewed by this author in [119], researchers investigate several techniques including the tool-work thermocouple, the inserted thermocouple, the spectral radiation thermography, and the recently proposed thin film thermal sensor. The tool tip is a very small zone (usually, 0.5-2 mm depending on parame-ters), where the maximum temperature is produced. It is hard to place a sensor in this tiny zone. The other techniques need special arrangement. Due to this, the measurement of ac-tual temperature from the active zone is almost impossible. The data or signals received by the above stated techniques are calibrated to estimate the flank wear land over cutting time. However, these techniques cannot provide any information about tool chipping, breakage and catastrophic failure, and tool life. Thus, the temperature data acquisition method is not useful for a TCMS in manufacturing production systems [120].

3.6 Signal processing tools

The development of a robust and reliable tool condition monitoring system requires the application of the most meaningful TCM signal features (SFs), which best describe the tool wear [121]. Therefore, the key issue in a TCM system is calculating a sufficient number of SFs related to tool and/or process conditions. There has been much work carried out on signal feature extraction of various different signals for various applications. Each of these signal feature extraction methods works, with varying success, with different sen-sor signals. Many of the various sensors used in tool condition monitoring (TCM) require individual feature extraction methods for optimal function. Feature extraction methods in-clude; general purpose time domain features, acoustic emission time domain features, time series modelling, Principal Component Analysis, Singular Spectrum Analysis, Permuta-tion Entropy (time domain), Fast Fourier transform, Wavelet transform and Hilbert–Huang transform (frequency and time–frequency domain). Each of these signal processing meth-ods has advantages and disadvantages when used with different sensors and it is likely that for a multiple sensor configuration a number of these methods will need to be employed. It is impossible to predict in advance which SFs will be useful for tool and process condition monitoring in a particular application. Therefore, efficient methods to evaluate automat-ically their usability usually need to be applied. A robust TCM system should be able to combine signal feature extraction methodsand use robust methods to process multiple sensors, without any intervention by, or even knowledge of, the machine tool operator[89].

Signal processing and their subsequent analyzes depend of course on the nature of the sig-nal; distinguishes three classes:

- Scalar values (one dimension);
- Functions (two dimensions);
- Multidimensional, for example imaging in the visible domain, ionizing radiation (UV, X) or even infrared (infrared thermography).

The concept of signal processing particularly affects the last two. It should be noted that some techniques for processing two-dimensional functions can also produce graphical indicators, for example time-frequency analysis. This is why it is common to categorize analyzes into three according to the domains of representation: time, frequency and time-frequency[122].

In temporal analysis based on the study of the evolution of a quantity over time, the statistical quantities such as: the average value, the peak or peak-to-peak value, the RMS value and the Kurtosis appear first. . Another method in this family is also the time synchronous average. Statistical modeling is still used, for example auto-regressive moving average models (ARMA). Finally, some nonlinear methods such as principal component analysis or pseudo phase portrait are classified in this category.

For the approaches relating to the frequency domain, the oldest is spectral analysis by the FOURIER transformation (FFT) from which various techniques have been derived (power spectral density, frequency filters, envelope analysis or HILBERT transform).

The CEPSTRE represents another tool making it possible to process signals either of pulse type or of modulated type.

High order spectra, such as bi-spectrum or tri-spectrum, should also be mentioned. Some researchers to solve particular problems have also applied the notion of holo-spectrum.

The analyzes in the time-frequency domain make it possible to represent non-stationary signals in these two spaces. In this category, apart from the sliding window Fourier transform (STFT), operation from which the spectrogram is determined, the energy distribution of WIGNER-VILLE constitutes an analysis method that is widely used in signal processing. With the distribution of CHOI-WILLIAMS, the latter fits into the class of bilinear transformations. Finally, the wavelet decomposition or time-scale analysis, largely developed here, appears in this third category[122].

3.6.1 Time domain analyzes

For force signals, the features are usually extracted in the time domain. The features usually considered are the magnitude of the signal, RMS level, and force ratio. Jong-Jin and Ulsoy [101], Balazinski et al. [123], used time domain analysis for force signals. It was found that the time domain features of force signals correlated well with tool wear.Reddy used the time domain features of AE and surface roughness signals, and these features correlated well with progressing tool wear. Jemielniak [124] carried out multifeature fusion by extracting time domain, frequency domain, and time–frequency domain features from force, vibration, and AE signals [101].

Wang [101] used time domain features from surface roughness data and found good correlation with tool wear. Time domain features offer a great deal of simplicity in terms of extraction, but they are susceptible to disturbances so they need to be supplemented with features from other domains.

The signal in the time domain can be measured by parameters. Of these, kurtosis and RMS are the most effective. The shock pulse method has also gained wide industrial acceptance.

Root Mean Square (RMS) [125]

$$\sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n)]^2} \tag{7.1}$$

Crest factor (Cf) [125]

$$\frac{\sup|x(n)|}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n)]^2}} \tag{7.2}$$

Peak [125]

$$\sup|x(n)| \tag{7.3}$$

K factor [125]

$$\sup|x(n)|\sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n)]^2} \tag{7.4}$$

Kurtosis [125]

$$\int_{-X}^{-X}\frac{\left(X-\bar{X}\right)^4}{\sigma^4}P(x)\,dX \tag{7.5}$$

Shape factor [125]

$$\frac{RMS}{\frac{1}{N}\sum_{N=1}^{N}|a_N|} \tag{7.6}$$

Impulse factor [125]

$$\frac{Peak}{\frac{1}{N}\sum_{n=1}^{N}|a_n|} \tag{7.7}$$

3.6.2 Frequency domain analysis

Features of the vibration and sound signals are often extracted using the frequency domain. To extract the signal features in the frequency domain, fast Fourier transform (FFT) is often used. Siddhpura [101] used the energy variation of sound signals in the frequency domain. It used the spectral density plots for vibration signals. The data-dependent system methodology developed isolated the mode of vibration most sensitive to tool wear and gave power contribution extracted from the frequency domain which showed a specific trend with tool wear.They used noise spectrum for AE signals. The level of noise emitted due to the rubbing action of the tool and workpiece in the frequency range 2.75 – 3.50 kHz increased with increasing tool wear.It used frequency spectra for the force signals. In the dynamic force spectrum, there was a distinct characteristic peak around 2 – 5 kHz. The amplitude of characteristic frequency signals was found to increase monotonically with tool wear and fall sharply at the point of entry to the tertiary wear zone. Al-Habaibeh [108] used a FFT program to obtain the power spectrum representation of time domain signals. The frequency domain features obtained using FFT correlated well with tool wear. It carried out a frequency domain analysis of AE signals. The lowfrequency AE signals were strongly dependent on the tool– workpiece and tool–chip interfacial contact conditions while the high-frequency AE signals were associated with cracking occurring at and below the tool surface. Kamarthi carried out experiments to compare frequency (FFT) and time–frequency (fast wavelet transform-FWT) domain features. The FFT-based method was more suitable for vibration signals while FWT models were recommended for the force signals.

They carried out a time domain and frequency domain analysis of force and vibration signals, respectively, and found good correlation with tool wear. They used frequency domain features for force, vibration, sound, and AE signals. used frequency domain features for sound signals and found that early prediction of tool wear was possible based on the sound signals. Silva [126] obtained energy in the frequency bands 2.2 – 2.4 and 4.4 – 4.6

kHz for force, vibration, and sound signals from the power spectrum. The features extracted were adequate and generated enormous amount of information. Haddadi [101] used frequency domain features for surface roughness and vibration signals. The energy of the signal spectrum in the range of $0 - 3.5$ kHz was a good indicator for tool wear, and wearing of the tool was accompanied by an increase in the spectrum amplitude in $0 - 3.5$ kHz frequency range. It is not always easy to identify the spectral bands which are sensitive to tool wear, and it is difficult to understand why certain frequencies are influenced by tool wear. Also, it is necessary to understand the dynamics of measurement hardware in order

to fully utilize the benefits offered by this method.

3.6.3 Time-frequency domain analyzes

This domain is used to extract features from non-stationary signals. It is performed mainly based on wavelet transforms that can provide useful information about singularity (i.e., localization) of a signal in both the time and the frequency domains at the same time. Wavelet transforms can be of three types – continuous, discrete, and stationary. One or more are applied to extract tool condition features of machining signals including force, vibration [120] AE. As the metal cutting is a dynamic phenomenon, it is important to identify the most stationary part of the signals originating from neighbor sources. In their study, Scheffer observed that the time–frequency analysis with spectrograms can detect the most stationary parts of force signals.Found that the extracted features from discrete wavelet coefficients along with HMM can accurately predict the tool wear. In their review of various applications of wavelet analysis in TCMSs, Zhu [120] concluded that, due to its sparsity and localization properties, this analysis method is very effective in accurately analyzing non-stationary machining sensor signals than any other time–frequency methods. This method requires less processing time, but it is difficult to determine exact contribution of a specific frequency at a given time because of time variant nature of wavelet transforms. Overall, this method offers much better performance in TCM as compared to individual time or frequency domains. Although wavelet transform in the time-frequency domain has great potential for TCM, more efforts are needed to prove its superiority among all other techniques. Many researches are published to justify the appropriate domain for specific requirements in machining systems as presented in (table7.3).

Table 3.3: Data/signal processing methods and their TCMS applications. [120]

Extractors	Till 1989	1990–1999	2000–2009	2010–2019	Applicability and key factors	Limitations
Time (43)	02	15	17	09	Suitable with force, AE and surface roughness data	Prone to disturbances. Limited analyses on power and vibration data
Frequency (49)	10	9	14	16	Suitable with vibration, sound, force, AE, and roughness signals. Good prediction accuracy.	Difficult to identify the characteristic spectral bands
Wavelet (19)		2	6	11	Vibration, force, AE signals. High prediction accuracy, Less processing time.	Limited study. Hard to estimate exact contribution of specific frequencies.
Statistical (38)	6	6	16	10	Vibration, sound, force, AE, wear image, surface roughness. Good to estimate wear rate. Fairly high accuracy, less computation efforts	Hard to identify the random tool wear features. Model-based detection

3.6.4 Statistical domain

In the statistical domain, the signals are considered as the output from a random process and features are extracted. This includes the features which describe the probability dis-tribution of the random process such as mean, variance, skew, kurtosis, and standard deviation and coefficients of time series signals such as auto-regression (AR), moving average (MA), and ARMA.

Leslie and Lorenz [101] analyzed the wear behavior of two grades of carbide tools using multiple regression analysis in order to determine the effects of interrelated variables. If used correctly, the multiple regression comparison method can provide valuable information regarding interrelationship of the variables and the degree of the interrelationship which affects the resulting estimating equations. It considered variance, skew, and kurtosis for AE signals from a turning process.

They used an AR series model for processing signals along with the power spectrum amplitude. The AR coefficient matrices were used as the parameters which characterize the state of the cutting tool. The application of the AR parameters with an artificial neural network (ANN) structure can effectively detect the tool wear.It carried out nonlinear regression to develop mathematical tool wear model using measured force data. The developed mathematical models were more appropriate in estimating the gradual wear levels only within the region of constant wear rate and the random disturbances such as chipping and fracture were not detectable. Ravindra [101] used regression models to develop an online tool wear monitoring strategy. The developed models held good at higher cutting velocities and depth of cuts as they closely resembled the measured values.

It used mean and standard deviation for the optical analysis of the image. A quite good correlation was found between the standard deviation parameter and tool wear. used absolute deviation, mean, skew, and kurtosis for sound and vibration signals. It was observed that these parameters exhibited little correlation with flank wear. But applications of neural networks along with all the parameters and Taylor's tool life model led to a closer prediction of tool wear.

Choudhury and Srinivas [127] developed a tool wear model as a function of cutting velocity, feed, depth of cut, variation of normal load with respect to flank wear, wear coef-ficient, hardness of cutting tool, and the index of the diffusion coefficient. The regression equation was developed and experiments were carried out to obtain regression coefficients. The method of least squares was used to find the unknown parameters of the regression equation. It was found that the flank wear was significantly affected by the cutting velocity and the index of diffusion coefficient.

Oraby used ARMA models for an online monitoring technique to reflect dynamic characteristic variation due to the tool wear. The post processing of these models was carried out using Green's function in order to extract information about dynamic behavior at various tool wear states. The ARMA models were adequate to represent the cutting process with reasonable accuracy. Özel and Karpat used analysis of variance (ANOVA) for feature extraction from surface roughness signals. The extracted features were used to train neural network models, and the developed prediction system was found to be capable of accurate surface roughness and tool wear prediction for the range it was trained. Thangavel used regression analysis to calculate the coefficients of the polynomial equation model developed using process parameters. Chelladurai processed the force and vibration signals through ANOVA to check the effect of machining parameters on them. The empirical models were developed by performing statistical analysis of the experimental data. The multiple regression model developed was in good agreement with experimental results. Deiab used neural network and polynomial classifiers (PC) t o p redict a nd c lassify different t ool w ear states based on statistical features extracted from cutting force and AE signals. The signals ob-tained from force and AE sensors correlated well with the tool wear. Dureja [128] analyzed the effect of machining parameters such as speed, feed, depth of cut on surface finish, and tool wear by ANOVA. The feed rate, depth of cut, and workpiece hardness had a statistically significant effect on the flank wear, whereas feed rate and workpiece hardness significantly affected the surface roughness [101].

Elangovan [129] used statistical features such as mean, standard error, median, standard deviation, sample variance, kurtosis, skewness, range, minimum, maximum, and sum for the vibration signals to develop a Bayes classifier-based condition monitoring system for the cutting tool. Statistical features were compared with histogram features, and it was found that the statistical features yielded more accurate results when compared to the histogram features. Ghani [101] developed a regression model based on the integrated kurtosis based algorithm for z-filter (I-kaz) t o c arry o ut o nline t ool w ear m onitoring. T he s ystem pro-vided satisfactory results in terms of predicted flank wear, and it was possible to determine maximum permissible flank wear.

This technique largely reduces the computational costs. But some of the statistical do-main features largely depend upon the sample size and so can provide misleading results if correct sample size is not selected.

3.7 Conclusion

As can be seen in the earlier sections, there has been a long desire to develop a system or methodology for the accurate monitoring and reporting on the performance of the CNC machining process. Many avenues have been explored and there is no phenomenon within or around the cutting process the viability of which has not been evaluated in detail. For the past number of years the conclusion has been reached that it is only a combination of the available phenomena (in a sensor fusion) coupled with sophisticated data mining and analysis techniques, that will result in accurate and reliable monitoring of this process. Neural networks, coupled with data from multiple sensors, are the technique that holds most promise at the moment.

A neural network with input from multiple sensors mimics the cognitive ability of the human body, where the brain is the ANN, and sensors are the 5 senses. And we anecdotally know that experienced machine operators appear able to detect wearing tools through sound, vibration, touch and other variables. It is clear from the literature review that since the commencement of investigation into the potential to use physical phenomena from the CNC operation to interpret the performance of the operation 40 years ago the available technology has become so advanced that TCM systems are now inevitable. Early efforts as outlined earlier relied on piezo-electric sensors and analogue oscilloscopes as the sensor-interpretation circuit. Today we have extremely sophisticated sensors, deployed in fusion, with well-developed signal conditioning techniques. And this information is being interpreted by complex Neural Network computing systems.

In spite of previous technological shortfalls, for many years patents have been lodged outlining a tool condition monitoring system. As discussed earlier, these have proven largely speculative and without substance in terms of the key interpretative process that they will employ and have relied on vague descriptions of the hardware configuration. However, the key to intelligent tool condition monitoring systems now is in the sensor configuration (fusion) and subsequent signal interrogation. It is this sensor fusion and the interrogation of the signals that this research intends to address. The experimentation that will be outlined in the coming pages will investigate the worth of each of the identified sensor sources against the next, across a number of machines, a number of cutting configurations, and a number of materials.

Chapter III:
Condition monitoring based on Blind Sources

CHAPTER 03

CONDITION MONITORING BASED ON BLIND SOURCES SEPARATION

4.1 Introduction

The automation of machine condition monitoring are gaining popularity due to advancements made in sensing technologies and computing algorithms.This paper presents a data-driven approaches for Tool wear estimation using Mahalanobis Taguchi System (MTS), based on Continuous wavelet Transform (CWT) and Sparse Components Analysis (SCA). CWT is one of the most powerful time frequency analysis and has been widely applied in TCM. The CWT used to transform one set of one-dimensional series into multiple sets of one dimensional series for preprocessing.

SCA method used to separate CWT series of one-dimensional time series into independent time series. The health indicator based on the MTS is proposed based on distance computing between the normal and faulty state of cutting tools. The MTS distance used to estimate the health between the differents degradation levels. The MTS distance values are then fitted to a regression to obtain the model for Remaining Useful Life (RUL) estimation. In addition, this paper addresses several pertinent challenges, such as failure threshold determination during anomaly detection and RUL estimation, by developing adaptive thresholds. The results demonstrate the efficacy of the proposed framework compared to state-of-the-art methods in terms of the accuracy and convergence of the RUL estimation of cutting tools. The method is applied on real world cutting tool degradations. Experimental results show that the proposed method can reflect effectively the performance degradation of tool wear condition monitoring. In this chapter, a novel MTS-based data driven approach is presented. The purpose of this research is focused on the separation of dependent sources by combining CWT and BSS and applied MTS for severity evaluation and life prediction. The proposed technique consists of three processing stages. In the first stage, the signal collected from milling cutters decomposed into several coefficients of signals based on CWT. In the next stage, the BSS algorithm is used to complete the separation coefficients obtained by CWT. When the degradation started, the prognostics approach, which monitors the progression of the MTS values, is initiated. And finally, using a linear approximation, time to failure is predicted. The performance of the approach has been validated via experiments performed on CNC machining process.

The cutter has been instrumented with force, vibration and acoustic emission transducers and experiments involving healthy and numerous types of faulty operating conditions have been achieved. The experiments show that the proposed method renders acceptable results for TCM. Overall, the proposed approach provides a reliable multivariate analysis thus reducing analysis overhead. In addition, the MTS-based approach is a robust approach that is insensitive to differences in multidimensional systems. The experiments with different tool conditions illustrate that the separation strategy is robust and promising for cutting process monitoring [19]. Subsequently, the BSS algorithm is used to process these CWT signals coefficients series and consequently to terminate the separation process. In addition, the application of the MTS algorithm with these functionality processes the signals of the multichannel transformation. Finally, the health state of the cutter was identified by cal-culating the state of health of the cutting tools, a health indicator obtained by calculating the energy of the independent signal (RMS). The objectives of this survey are: to propose a new approach based on CWT, BSS and MTS for diagnosis and prognosis, as well as; to optimize the parameters of the model, in order to verify the robustness and the meaning of this mathematical model. The CWT based on the SCA method is developed and the source signals associated with a milling cutter and a machine are separated. The MTS method based on CWT and SCA is applied to predict the RUL of cutting tools, and experimental results have shown that the predictive model formed by CWT, SCA and MTS is very accurate, as well as experiments with different cutting tools show that the separation strategy is robust and promising for monitoring the cutting process.

4.2 Artificial intelligence methods and applications

The AI is the system that thinks and acts like a human being. It can also imitate human behavior. It is majorly concerned with the development of a computer's ability to engage in human-like thought processes like learning, reasoning and self-correction. In the last decade, there has been a growing need in AI to solve the problems of engineering. Earlier, these problems were considered hard to be solved analytically or by using mathematical modelling and needed human intelligence [130].

Nowadays, there is an increased demand for advanced AE analysis tools. This chapter shows that many scholars have studied the detection and diagnostic of several faults by using the AE methods in AET and signal analysis. The AI techniques as mentioned earlier have also been extensively used in the field of engineering.

Fault diagnosis combining fault mechanism and detection techniques; it is a subject based on the theory of signal processing and pattern recognition. Various algorithms based on computational intelligence for fault and wear of cutting tools diagnosis are presented in this section. (Figure4.1) [131] shows the taxonomy of the computational intelligence techniques used as classifiers for machinery fault diagnosis.

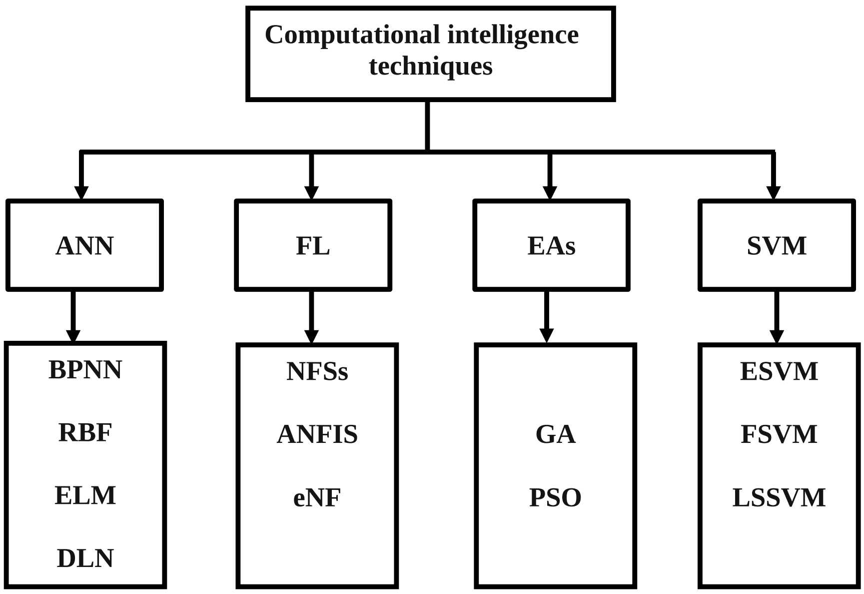


Figure 4.1: Taxonomy of computational intelligence. [131]

4.2.1 Artificial Neural Network (ANN)

ANN is a special case of neural computation, which is inspired by the human brain. This neural network is a mathematical model that can achieve distributed parallel information processing. ANN can adjust the interconnections among internal nodes to achieve information processing of a complex system.

Diagnostic inference can be interpreted as a solution of a problem based on the specific mapping relationship between fault symptoms and fault causes. For complex mechanical systems, the mapping relationship is generally nonlinear. Therefore, ANN has been widely used in fault diagnosis because it can effectively approximate various mapping relations. At present, most of fault classification methods utilize time-frequency analysis methods as the early feature extraction, and ANN or its optimized forms are then employed for fault classification. [131], wavelet packet transform (WPT) and ANN were integrated to diagnose fault in internal combustion engine, in which WPT was used to extract the fault characteristics, and generalized recurrent neural network (RNN) was proposed to classify various fault conditions. Lei [132], proposed an intelligent diagnosis method based on ensemble empirical mode decomposition (EEMD) and wavelet neural network. EEMD was used to extract the characteristics of time and frequency domains from the sensitive intrinsic mode functions (IMFs). Wavelet neural network was adopted to complete the pattern recognition. WPT and empirical mode decomposition (EMD) were utilized to preprocess and extract features, and ANN was used to diagnose early fault in rotating machinery. Cui, proposed a new back-propagation neural network (BPNN) based on the coefficient entropy of wavelet packet decomposition to realize quantitative diagnosis of fault severity trend of rolling bearings. Saravanan, presented a new hybrid method based on discrete wavelet transform (DWT) and ANN to diagnose various faults of spur bevel gearbox. Zhao [133], utilized BPNN and improved shuffled frog-leaping algorithm (SFLA) to perform fault classification. The accurate selection of suitable features that reflect the running status of equipment in practical application of fault diagnosis is the key point of research. Therefore, fault feature selection based on ANN is an important research direction [131].

Fault diagnosis of mechanical system based on ANN has some limitations. First, extraction and selection of features depend largely on the prior knowledge of signal-processing technique and diagnosis experience, and generalization is weak. Second, ANN adopts a shallow structure, which also limits ANN to learn complex nonlinear structures in fault diagnosis [134]. Deep neural network (DNN) is developed based on deep learning theory, which can enhance the accuracy of big data classification and effectively overcome the preceding shortcomings. Deep learning was first introduced into the field of fault diagnosis by Tran, who applied deep belief network (DBN) based on Teager energy operator to achieve fault diagnosis of reciprocating compressor valves. A multi-sensor health diagnosis method based on the DBN, which classified the sensor signals collected from a damaged structure. Guo, developed a hierarchical adaptive deep convolutional neural network for bearing fault diagnosis. [134], used DNN for intelligence fault diagnosis in rotating machinery, especially in the case when the vibration data were massive. ELM has been extensively applied and popularized in the fault diagnosis of mechanical system in recent years. Yang, proposed a multilayer ELM based on representational learning for fault diagnosis. The effectiveness of this method was successfully verified by applying a wind turbine system. Wei, proposed a method based on local mean decomposition to identify the different fault types of gearbox, combining permutation entropy and ELM. More references on the applications of ELM in machine fault diagnostics [131].

4.2.2 Spiking neural network

Recently, spiking neural network (SNN) is the third-generation neural network (Figure8.2) and has gained a lot of interest in the scientific community . The SNNs became famous before the introduction of the sigmoidal or the perceptron neuron [130]. It was observed that the SNNs were very suitable for the parallel implementation in the digital hardware and in the analogue hardware [130].

The earlier generations of the neural networks used the analogue signals for conveying the data from one neuron to the next. This communication between the neurons in the SNNs used spikes, which was similar to the system used in the actual human neurons. The spikes could be recognized only at those instances when they had occurred. With the help of the weighted sum of the analogue input value, the earlier neuron estimated the value using the sum-specific non-linear function. The value helped in determining the delay in the spike output, which was aimed for the succeeding neuron. Generally, the spiking neuron was viewed as the leaky integrator because the target neuron integrated the spikes for a period of time and accepted the resultant integrated values used as the membrane potential. When the membrane potential value approached a specific threshold value, then, the neuron was seen to send a spike; thereafter, the membrane potential v alue was reset [130].

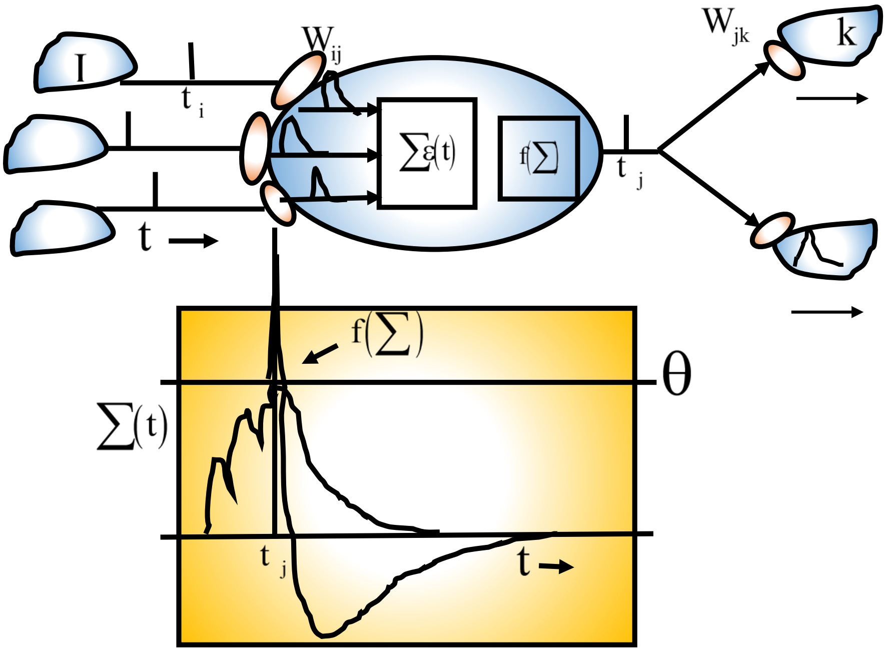


Figure 4.2: Spiking neural network. [135]

An increased knowledge in the information processing of the biological neurons helped in explaining many additional parameters (like the gene and the protein expression) that needed to be taken into consideration for the neurons to spike. The additional parameters included the different physical properties of the connections, the likelihood of the spikes being accepted at the synapse and the emitted neurotransmitters or the open-ion channels [136]. Several of the properties were modelled mathematically and were used for studying the biological neuronal system. The SNNs were made of the artificial neurons that communicated using the trains that were considered as the pulse-coded data [137]. The SNN was biologically acceptable, and it was seen to offer a means for the representation of the frequency, time, phase and such other features for the information processing. Moreover, the SNN possessed the ability for training the neurons for converting their spatial-temporal data to spikes (their properties include the spiking rates and spiking time). When one was selecting the neuronal model for an SNN, one needed to consider the computational efficacy and the biological credibility [137]. If it was seen that the computational efficacy was better than the biological plausibility, then the leaky integrate and-fire (LIF) model needed to be adopted due to its cost effectiveness.

In their study, [130] depicted the applications of the prototype decision support system for monitoring the tool wear depending on the SNN technique. This system consisted of six different components, that is, collection of data, feature extraction, multisensor integration, pattern recognition, tool wear estimation and the outlier detection. Their proposed architecture consisted of one built-in self-organizing neural architecture part that was based on the SNN. Their study showed that the modelling process was very efficient for classifying the tool wear level of the tool inserts with the help of the apparent weak features. Their method showed the effectiveness of using the SNN model for the tool condition monitoring, thus implying that the approach was feasible for many industrial applications, wherein a lot of noisy data are obtained. This researcher was the only one who used SNN in condition monitoring; the result showed the capability of spiking neuron networks for tool condition monitoring [130].

4.2.3 Neuro-fuzzy

Neuro-fuzzy inference techniques, also known as fuzzy neural networks (FNNs), combine the models of neural networks and fuzzy logic systems. They aim to take benefits of both the techniques by achieving the simplicity of modeling from NNs and by providing structured knowledge for complex system behavior offered by fuzzy logic systems [120]. Sharma et al. developed an adaptive neuro-fuzzy inference system (ANFIS) for predicting tool wear from the measured signals by force, vibration, and AE sensors during turning. The overall accuracy was estimated to be 82.9%. Different neuro-fuzzy approaches are attempted for TCM system development in [120], which include ANFIS, dynamic evolving neuro-fuzzy inference system (DENFIS), and transductive weighted neuro-fuzzy inference system (TWNFIS). Experiments show that the transductive methods are better than the inductive methods, because incremental online learning with data updates the knowledge in model [120].

The FNN techniques are comparatively new since 2000s; thus, a very few studies are performed so far. For tool wear estimation, researchers paid more attentions rather to realize the advantage of FNN techniques over both NN and fuzzy logics (FL). With processing force signals, concluded that the tool wear prediction accuracy is almost the same by these three classifiers. However, FNN perform better, while NNs are more time-consuming model with the training duration and FL system models require some degree of skill and expert knowledge. Also studied comparison between NN, FL, and FNN classifiers for tool wear prediction with radial cutting force. They concluded that FNN can estimate better results than the other two techniques, but argued that the Kohonen's SOM and FL could be applied for shop floors due to an advantage of less processing time. With vibration signals, [112] compared these three techniques, and concluded that FNN technique is the best in accuracy $\left(R^2 = 99.2\%\right)$, followed by NN $\left(R^2 = 98.5\%\right)$, while FL is the least $\left(R^2 = 73.7\%\right)$.

In summary, although the average tool wear and the error prediction accuracy offered by NNs is highly acceptable, the training duration was found to be higher. Due to this, practical application of NNs in production floors is a bit difficult. The processing time with fuzzy logic system is lower. However, practical use of FL system needs expertise of the operator to analyze and correlate the wear and the input signals. Neuro-fuzzy (FNN) techniques proved to be more effective due to their better or at least the same wear prediction ability by avoiding the burdens of less processing time and expertise. A drawback is that the calibrated model in FNN techniques can predict tool wear only for the specific cutting parameters for which it is trained. So, if the parameters are modified, the model has to be retrained. Though FNN techniques are suggested to be more viable, only a few researches are done [120]. Morever, they are only based on cutting forces, thus not that practical in the factory floors. However, a recent effort by this author in [81] suggest that, due to close prediction accuracy, the force data are replaceable with power data, which can be received from the spindle motor directly from the outside of the machine tools. Thus, FNN approaches should be further tested and confirmed for such viable signal options, like spindle power, AE, vibration, or insitu wear image signals in order to implement in unmanned or semi-automatic production floors [120].

4.2.4 Genetic algorithm-based fault diagnosis

GA created by John Holland in the 1970s is an evolutionary algorithm which is part of the field of artificial intelligence. A genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next gener-ation. Over successive generations, the population "evolves" towards an optimal solution [130].

As originally proposed, a simple GA mainly consists of three processes: selection, genetic operation and replacement. The population composed of a group of chromosomes, which were the candidates for the solution. The fitness values of all chromosomes were evaluated by an objective function (performance criteria or a system's behaviour) in a decoded form (phenotype). A particular group of parents was selected from the population for generating offspring on the basis of the defined genetic operations of crossover and mutation[130].

The fitness of all offsprings was then evaluated using the same criterion. The chromosomes in the current population were then replaced by their offspring on the basis of a certain replacement strategy. Such a GA cycle was repeated until the termination criterion was reached. Using ANNs utilised a simple problem of a roller with health monitoring to illustrate the effectiveness of GA in AE feature selection for fault classification. It re-vealed that utilising Gas to select an optimal feature set for a classification application of ANNs was a very powerful technique. Ming applies the AE technique for bearing condition monitoring and fault diagnosis. Scales for continuous wavelet transform, wavelet-based waveform parameter selection and optimisation on the basis of genetic algorithm were the proposed selection methods.

The AE was monitored by utilising a data acquisition system during the process of conducting the mechanical tests on several materials. Two of the sensors were positioned directly on the specimen. AE signals were thought to be pattern vectors described by a number of writers. In this chapter, "model" data sets were generated to become closer to AE signals that were recorded during the tests. This chapter presented and validated a genetic algorithm based approach to cluster the AE signals. Its superiority over the k-means algorithm was highlighted by the study of different "model" data sets. The genetic strategy can be characterized by a high stability and a high performance especially to cluster data sets consisting of a minority class, a cluster with signals of extreme features or a set of clusters with very different sizes [130].

4.2.5 Support vector machine

SVM is a classifier which classifies the input data into one of two possible classes. Sun [101] considered manufacturing losses due to under-prediction and over prediction of tool wear and utilized SVM to carry out tool condition identification. The developed SVM approach which utilized the effective feature set extracted from AE signals as inputs and fivefold cross-validation for parameter tuning could reliably identify the tool flank wear and reduce the overdue prediction of worn tool condition and its relative losses. Yiqiu used support vector machine with a genetic algorithm along with surface texture analysis to predict the tool wear. The SVM with genetic algorithm (SVMG)-based predictive model was constructed by learning the correlation between extracted texture features and actual tool wear. It was found that SVMG implemented the principle of structural risk minimization instead of experimental risk minimization, and this has excellent generalization ability in the situation of small sample. The SVMG presented a good estimation error when the training data set was reduced and a greater capability of generalization when compared with the ANN [101]. It is evident from the above discussions that failure detection and flank wear monitoring is very crucial in order to achieve production targets in today's demanding and competitive market scenario. In the research discussed, the signal acquisition and signal processing have been carried out separately. Although the field of sensorics is very old and research in the direction of efficient and reliable sensor developments is ever-growing, there still exists a need to develop sensors or fusion of sensors which are capable to carry out both signal acquisition and signal processing and show the results online or, in other words, smart sensors. For a critical application like flank wear monitoring, if smart sensors can be utilized, the tool change can be done over a shorter time. Future trends of sensors and actuators and their technologies were discussed emphasizing the fast growing technologies of 1990s like microsystems, smart materials, and integrated circuit technologies. It developed a smart tool based on the combination of advanced coating techniques with an efficient sensor and micro-electromechanical systems (MEMS) technology which enabled online control of the cutting conditions measured directly at the cutting edges and wear detection. The smart sensor was tested for various cutting conditions, and very satisfactory results were obtained. Ulrich [138] also emphasized the need for development of multifunctional tool coatings in order to optimize tribological applications like tool wear detection. Trejo-Hernandez [139] developed a fused smart sensor based on field programmable gate array (FPGA) for the quantitative estimation of flank wear area in inserts for CNC turning. The vibration signals obtained from a three-axial accelerometer and feed motor current signals measured by a current sensor were fused together and analyzed using FPGA-based hardware signal processing unit. The experimental results confirmed that this approach made it possible to obtain three times better accuracy in flank wear area estimation when compared with the accuracy obtained from processing both the signals separately. Des-forges [101] proposed a design methodology for smart actuator service for machine tool control and monitoring. The proposed smart actuators enable functions of monitoring, diagnosing, and adapting to be carried out and can accommodate the indirect type of flank wear monitoring technique.

Although the smart drive design methodology seems promis-ing in the field of smart sensing and overall monitoring of machine tools, it has been on the virtual lathe only and needs to be tested in an actual industry environment.

4.2.6 Fuzzy logic classifier

Fuzzy modeling has the capability to model complex system behavior in such a qualitative way that the model is more effective and versatile in capturing the behavior of ill-defined systems with fuzziness or a fully defined system with realistic approximation [] [66]. When compared with neural networks, fuzzy systems can directly encode structured knowledge in a numerical framework and can estimate the functions of systems with even a partial system behavior description as described by Scheffer [101].

It carried out force measurement to compare neural network, fuzzy logic, and neuro-fuzzy classifiers b ased o n a ccuracy o f t he r esults a s w ell a s p ractical u sability. T he feed forward back propagation neural networks, a fuzzy decision support system, and a neural network-based fuzzy inference system were used. All three artificial intelligence methods were able to estimate tool wear with almost the same accuracy, but the fuzzy logic approach was a bit difficult for practical use. This is due to the fact that the operator needs to analyze the dependence of tool wear on the cutting force while this was not the case for the other two, but the training time was a bit high in the case of neural network approach. It also followed this approach and carried out experiments to compare neural network, fuzzy logic, and neurofuzzy classifiers by monitoring the radial force to predict tool w ear. They used self-organizing maps for the neural network approach, triangular fuzzy membership for the fuzzy logic approach, and triangular fuzzy membership along with back propagation networks for the neurofuzzy technique. The fuzzy logic approach helped in generating linguistic rules, and among the three, neurofuzzy techniques proved to be more effective.

Bojja [140] developed a neural network-based proportional integral derivative (PID) controller and fuzzy logic-based PID controller and compared them with a PI controller and observed that the neural network and fuzzy logic controllers were superior. Chen [105] used fuzzy vertical clustering to carry out feature extraction from the force and vibration signals. The proposed method can extract information from a large number of objective characteristics for effective feature without expertise. Lan proposed a parameter optimization approach using the fuzzy Taguchi deduction optimization method. The proposed method can satisfactorily carry out the parameter optimization and improve tool wear performance.

Ren [101, 105] proposed a TSK fuzzy model for tool wear condition monitoring using force signals. The proposed model was effective for tool wear monitoring, but such models still lack the ability to estimate the error of approximation. The decision making in fuzzy system is fast due to its simplicity, but it suffers from the difficulties in selecting suitable membership functions for the target system.

4.3 Blind source separation methods (BSS)

Blind Source Separation (BSS) emerged in the 90s as a powerful signal processing tool for de-mixing audio sources from recordings, e.g., see [141]. BSS is often described using the cocktail party problem, where the basic objective is to identify individual speakers (sources) from a simultaneous recording (together called mixing) of multiple speakers. In this signal separation problem, unknown individual signals and contributions in the resulting mixtures are defined as the sources and mixing matrix, respectively. The problem is called separation if all the sources are identified simultaneously, or called extraction if only a subset of sources are sequentially separated. In their work, demonstrated the use of BSS in structural dynamics, however without explicitly considering the connection between the modal expansion theorem and the BSS models used in OMA. In the following papers [142], the mathematical equivalence with the problem of structural dynamics, namely modal superposition using normal modes for lightly damped systems, was established. In this relation-ship, the sources are nothing but the modal responses and the mixing matrix contains the amplitudes, or the arbitrarily scaled mode shapes (it is well-known fact that only un-scaled mode shapes can be obtained in OMA) of the system. Even though scaling and permutation ambiguities exist in the resulting sources, it can be circumvented using, say an ordering scheme based on the frequencies of hidden sources. In OMA, a simple ordering according to natural frequencies is deemed sufficient. The mathematical analogy (i.e., measured response equals the mixing matrix times the source components; physical response equals the modal matrix times the modal responses) only provides a necessary condition for application of BSS to OMA; the sufficient condition requires a relationship to exist between the identified sources and modal responses, for example the correlation structure of amplitude modulated sinusoids [143, 141]. Recently [144] showed how least action principles can be used to provide physical insights into the mechanism of BSS within the context of modal expansion theorem.

4.3.1 Theory of Blind Sources Separation (BSS)

A detailed description of fundamental principles of BSS can be found in the following references [141] presented an excellent summary of various BSS methods with special emphasis on statistics-based source separation and showed the intra-relationship amongst various methods using information theory.

BSS models in the literature fall into two classes depending on the mixing structure for the sources:

- static or instantaneous;
- dynamic or convolutive. BSS for modal identification generally employ discrete linear static mixing models (convolutive mixtures, which are less common, are described later).

For example, consider m discrete time-domain measurements (x) comprising instantaneous mixtures of n underlying sources (s) as follows [141]:

$$\left.\begin{aligned} &x_1(k) = a_{11}s_1(k) + a_{12}s_2(k) + \ldots + a_{1n}s_n(k) \\ &x_2(k) = a_{21}s_1(k) + a_{22}s_2(k) + \ldots + a_{2n}s_n(k) \\ &. \\ &. \\ &. \\ &x_m(k) = a_{m1}s_1(k) + a_{m2}s_2(k) + \ldots + a_{mn}s_n(k) \end{aligned}\right\}[141] \tag{4.1}$$

Where a_{ij} are the un-known real or complex valued mixing coefficients of the mixing matrix A BSS starts with the problem where both s and A are unknown (i.e., blind); hence, they are determined based on x exclusively. The following reference [141] elegantly summarizes the basic mathematical formulation of blind identification. First, it is important to recognize that solving the algebraic equations for s_j using least-squares by assuming an arbitrary matrix A' (containing a'_{ij} elements) with the same column rank of the original matrix A (a_{ij} elements) is meaningless. This is because such a process will yield little resemblance to s_j in both the shape and statistical properties. The authors then describe an equivalence relation $\mathfrak{R}$ defined as a set of ordered pairs of doublets (A, s) and (A', s') such that they are equivalent to each other to the extent that they differ only by a scalar multiplier and/or a permutation transformation. Such an equivalence preserves not only the shape of the sources, but also the statistical properties of s and the algebraic properties of A Readers are referred to this reference [141] for a more in-depth discussion on the mathematical foundations of blind identification.

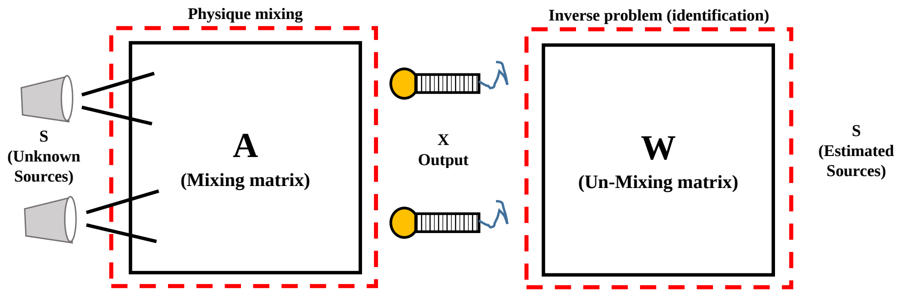


Figure 4.3: Illustration of BSS. [141]

Fundamental to solving (Eq4.1) is the assumption regarding the statistical nature of the sources and one of the most popular tools, called independent component analysis (ICA) [145], assumes that the sources are statistically independent. Restrictions other than independence on the nature of the sources such as spatially uncorrelated sources (but, temporally correlated) have found widespread use in dealing with time-domain vibration data and modal identification problems. These methods have commonly been referred to in the literature as second-order methods [146].

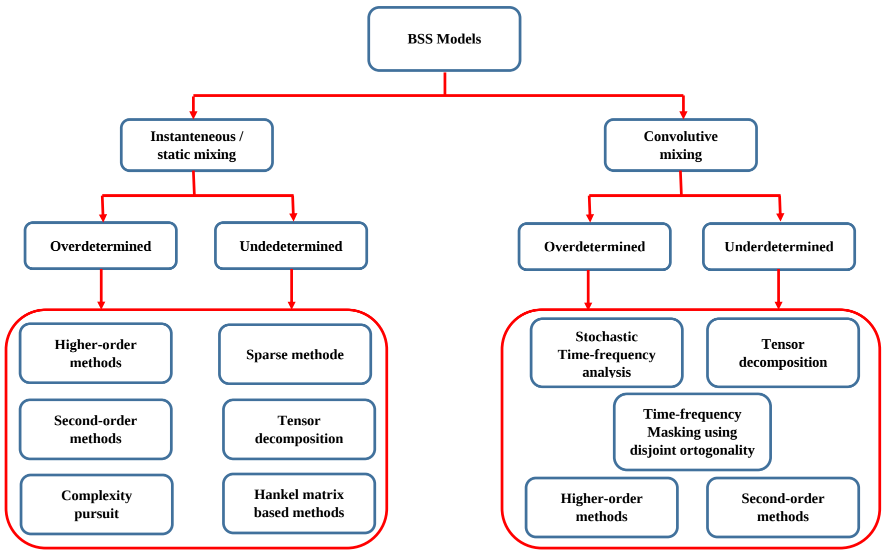


Figure 3.4: BSS flowchart. [141]

BSS problem is best described using the schematic shown in (Figure8.3). By utilizing either statistical, temporal and/or structural information of the signal, an un-mixing matrix W and the sources can be estimated. For the case of over-determined mixtures (i.e. $m > n$), the problem admits least-squa res type solution, however the matrix $A^{-1} = W$ is unknown. The components of the un-mixing matrix W can be estimated, for example using ICA, by maximizing the independence (as quantified by measures of non-Gaussianity such as kur-tosis and information-theoretic criteria) of the resulting sources. In second order methods, the components of the mixing matrix are determined using matrix diagonalization methods, for example, joint approximate diagonalization (JAD) [146].

When $m < n$ (under-determined mixtures), estimating W cannot be undertaken in the separation space (i.e. A^{-1} does not exist), but rather both A and s have to be estimated directly in the mixing space [147]. This estimation process typically consists of estimating A first, followed by estimating s, where concepts such as sparsity or norm solution [141] and tensor based decomposition under multiple time lags [148] have been used effectively.

A flowchart describing various modeling and solution approaches in BSS is shown in (Figure8.4). It will be shown later that both of these methods can be classified into two sub-classes – over determined (OD) and underdetermined (UD) – depending on the availability of sensor measurements compared to the number of target sources. These methods are primarily based on the statistics (either higher order or second order statistical information), and data structure (i.e., sparsity or higher dimensional form) of the signal.

Instantaneous mixing

The instantaneous mixing model is the most rudimentary model where the sources are assumed to arrive instantaneously at the sensors with differing intensities and is expressed in (Eq4.2) as:

$$x(k) = As(k) + b(k)[149] \tag{4.2}$$

where b denotes the measurement noise vector. Comparing (Eq4.2) with the problem of modal superposition, it was shown for linear lightly damped systems that operational modal analysis can be cast using a static mixing model where the mixing matrix is equivalent to the normal mode shape vectors and the sources are the modal responses. Consider a linear, classically damped and lumped-mass n degrees-of-freedom (DOF) dynamic system, subjected to a wide-band random input force,$f(t)$:

$$M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = F(t)[141] \tag{4.3}$$

where, $x(t)$ is a vector of displacement coordinates at the DOF. The solution to (Eq4.3) for the case of broad-band $F(t)$ can be written in terms of an expansion of vibration modes:

$$x = \Psi Q[141] \tag{4.4}$$

where $x \in \Re^{n\times N}$ the trajectory matrix is composed of the sampled components of x at m measurement locations, and $Q \in \Re^{n\times N}$ is a matrix of the corresponding n modal coordinates and W, the modal transformation matrix. (Eq4.4) is analogous to classical instantaneous mixing model as shown in (Eq8.2) and provides the basic equivalence model for using BSS as a modal identification tool. Under certain special circumstances, the modal coordinates can be regarded as the most independent sources (termed as virtual sources) [142]. The modal coordinates Q can be regarded as a special case of the general sources s with time structure, and W the mixing matrix A. It is important to note that when the spectral contents of the sources are nearly disjoint as is the case with lightly damped and well separated modes, the sources are nearly uncorrelated. Hence, both the methods based on independence as well as second-order correlation measures have been demonstrated to be successful for OMA. Once the sources and the mixing matrix are recovered using BSS tools (described later), the natural frequencies can be identified either through observation of the cycles in the time series, or using the Fourier spectrum, and the damping can be estimated using the logarithmic decrement method, or the half-power bandwidth method provided the recovered sources are mono-component [141].

When sufficient number of vibration measurements are available, the modal identification problem becomes an over determined static mixing problem. On the other hand, the underdetermined static mixing model can be used to solve modal identification when a lim-ited number of sensor measurements are used. Various BSS solution approaches for static mixing addressing over determined and underdetermined modal identification problems will be discussed later [141].

Convolutive mixing

Static instantaneous mixture models are not capable of modeling time delays, i.e. if the sources (s) do not arrive simultaneously or the mixing matrix coefficients (i.e. A) are time-varying. For a majority of OMA problems, this issue has been less of a concern since the modal superposition model widely used and accepted in the field is an equivalent static mixture model. However, during the last decade, the validity of static mixtures model has been questioned in dealing with data acquired using wireless sensors, where data from multiple locations do not arrive simultaneously [150]. To separate sources mixed in a convolutive fashion, a technique called convolutive BSS was developed by treating signal mixing as a convolution allowing time delays to be accounted for in the modeling. For solution purposes, this model is then converted into an equivalent static mixing problem in a transformed domain using time-frequency transformation [151, 152]. *A* convolutive model can be of two types: echoic or anechoic. An echoic convolutive mixture can be expressed as:

$$x_i(t) = \sum_{j=1}^{n} \left(\int_{\infty}^{\infty} a_{ij}(\tau) s_j(t-\tau) d\tau \right) [153] \tag{4.5}$$

Table 4.1: Linear operator and mixing parameters of different types of BSS mixing. [154]

Mixing	Linear operation	Mathematical model	Mixing coefficient
Instantaneous	Matrix multiplication	$x(t) = As(t)$	$a_{kj}\delta(t)$
Anechoic	Delay	$x(t) = A * s(t)$	$a_{kj}\delta\left(t-\tau_{kj}\right)$
Echoic	Convolution	$x(t) = A * s(t)$	$\sum_{l}^{L} a^{l}{}_{kj}\delta\left(t-\tau^{l}{}_{kj}\right)$

where i and j are the measurement and source indices, respectively. (Eq4.5) represents a dynamic problem where the sources and the outputs have well defined time properties and the coefficients of the un-mixing system are essentially the coefficients of a deconvolution filter (e.g. finite impulse response (FIR) filter). From a structural dynamics standpoint, this means that the mixing system is characterized by a transfer function with its attendant dynamics. The instantaneous mixing model is a special case of the convolutive model where the filter coefficients are constrained to be proportional to the delta function; $a_{ij}(t) = a_{ij}\,\delta$ (t). Compared to the echoic model, an anechoic mixture model assumes a linear combination of time-shifted and scaled versions of the sources, without permitting multiple occurrences of the same source in the mixture. These models are equivalent to convolutive models in

that the filter coefficients are constrained to the form, $a_{ij}(t) = a_{ij}\delta\left(t-\tau_{ij}\right)$ [151] resulting in the equation:

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_{ij}\left(t-\tau_{ij}\right) [141] \tag{4.6}$$

Unlike the static mixtures model, this model now allows for the non-concurrent arrival of the source signals, as modeled using the shifted delay terms. The anechoic model provides more flexibility in terms of modeling time delays, e .g. time-synchronization (TS) errors in wireless sensors [155], compared to an instantaneous model.

It is relatively straight-forward to convert an anechoic model to an instantaneous form. Fourier transformation on both sides of (Eq4.6) yields:

$$X_i(\omega) = \sum_{j=1}^{n} a_{ij} e^{-i\omega\tau_{ij}} S_j(\omega) \Leftrightarrow X(\omega) = A(\omega) S(\omega)[141] \tag{4.7}$$

which is an instantaneous mixing model in the frequency domain. Similar to instantaneous mixing, convolutive mixing also has two types: underdetermined and overdeter-mined, depending on the number of available sensors. Studies have shown that modal frequencies and damping ratios are not influenced by random time delays in the measurements; however, the quality of structural modeshapes obtained using such data can be affected [156]. The issue of synchronization errors has been investigated in the field of OMA. For example, Nagayama et al. proposed a resampling technique using lowpass filtering and curve fitting to minimize TS error. In [157], the authors related the presence of TS er-rors on modeshape reconstruction and showed that the resulting errors are proportional to the time delays and modal frequencies. A modified approach using complex modeshapes was proposed [158] to reduce TS error in modal identification.

Specific to BSS, in [159], the authors formulated the problem of time-delays present in non-concurrent measurements and showed that modal superposition under TS errors is analogous to an anechoic mixing problem. In this study, the timedomain signals were converted into an instantaneous mixing model in the frequency domain and then complex ICA was employed to undertake source separation. The resulting complex sources in the frequency domain were then transformed back into the time-domain through inverse Fourier transform. With recent advances in wireless technology, the TS errors in vibration measure-ments have been significantly reduced for low sample rates, which means that the instantaneous mixing model is generally satisfactory for most applications in OMA. A summary of various linear operators and mixing matrix components specific to the different types of BSS models is presented in (Table8.1).

4.3.2 Current challenges and future research directions

As evidenced from the review of BSS methods applied to OMA, it is clear that there is significant interest in utilizing BSS for a variety of structural and mechanical engineering applications. The most appealing aspect of BSS based algorithms stems from the relatively simple underlying mathematical structure, which can be manipulated to yield results in a wide range of situations related to OMA. While it is true that over hundred articles have appeared specifically looking into various aspects and applications of OMA, there are areas in which their application is yet to mature. Here is a short summary of the gaps and the proposed research directions where BSS methods can be used to further the field and our understanding of OMA.

- In the current literature, nearly all BSS-based modal identification methods are operated offline, or in a batch-mode. While this approach works adequately standard OMA applications, it is not suitable for control applications. There is a considerable amount of literature in the area of blind signal extraction, which can be leveraged to undertake online OMA. This would also enable automating the process of modal parameter identification;

- While the main advantage of a wide class of BSS tools have relatively few tunable parameters (which is the major advantage), tensor decomposition based methods involve the user selection of tunable parameters (i.e., rank order selection and lag parameters), whose choice is not obvious and depends on the data and problem at hand. A formal process to tune such control parameters and minimize user intervention still need to be studied and developed;

- While the work on overdetermined mixtures has matured considerably, the same cannot be said regarding underdetermined problems. Sparse BSS methods including tensor decomposition methods and Hankel matrix-based methods are only potential approaches and there is considerable potential to develop new and more efficient methods to undertake underdetermined BSS. Methods based on Hankel matrices have also been shown to perform relatively better compared to PARAFAC;

- The current suite of BSS algorithms are heavily focused on linear normal mode identification and there is virtually no literature on nonlinear mode identification. This could provide a valuable opportunity for furthering the field of BSS applied to structural dynamics;

- Latency issues related to decentralized wireless sensors require careful consideration through convolutive BSS methods, especially for high data rate applications where such issues may govern the quality of identified results;

- The discrimination of physical and numerical modes which arise in many BSS algorithms (and in sub-space methods such as SSI), still remains unsolved. Moreover, very little work related to the effect of measurement noise on OMA results has been undertaken, especially when the measurement noise does not satisfy the statistical properties envisioned in standard BSS algorithms being widely used [141].

8.4 Mahalanobis–Taguchi system (MTS)

8.4.1 Mahalanobis Distance (MD)

Mahalanobis distance (MD) is a measure of distance, which is based on correlations between variables and the different patterns that can be identified and analyzed in respect to the reference population. This reference population is identified as Mahalanobis space (MS). On the other hand, the measure of distance is commonly identified as Mahalanobis scale. It aids the discriminant analysis approach in assessing the level of abnormality of datasets against MS. In addition, MD is different from Euclidean distance (ED), in a sense that the latter does not take correlations among variables of the data points into account. MD is defined as in (Eq8.8) [160]:

$$MD_j = D_j^2 = \frac{1}{k} Z_{ij}^T A^{-1} Z_{ij}[160] \tag{4.8}$$

with $Z_{ij} = \frac{x_{ij} - m_i}{s_i}$

Based on the equation(Eq4.8),k is the total number of variables, i represents the numbers of variables ($i = 1, 2, ..., k$); j represent the number of samples ($j = 1, 2, ..., n$); Z_{ij} is the standardized vector of the normalized characteristics of x_{ij}. On the other hand, x_{ij} is the value of the ith characteristic in the jth observation; m_i represents the mean of the ith characteristic; s_i is the standard deviation of the ith characteristics; T represents the transpose of the vector. Last but not least, A^{-1} is the inversion of the correlation matrix [160].

MD has been well deployed into a broad range of applications [161]. This is mainly because of its effectiveness in tracking intervariable correlations of data. Furthermore, the Mahalanobis scale offers a statistical measure in order to distinguish between unknown sample conditions and known sample conditions. It also provides information in order to make predictions for future concerns.

In MTS, Taguchi extended MD methodology with his "robust engineering" concepts. With these concepts, his methodology has become an efficient and effective strategy for the prediction and forecasting in multidimensional system. Moreover, compared to all pattern recognition systems, an efficient system would require less computational time while maintaining the same or better level of effectiveness. Therefore, the reduction in system variables has become a prime concern. As for optimization, orthogonal array (OA) was introduced as an approach utilized for feature selection mechanism, which is coupled with signal to noise ratio (SNR). SNR is used as an assessment metric for a significant extraction of feature, in order to achieve the objectives. Lastly, MTS methodology involves four fundamental stages [160],

- **Stage 1: Construction of a measurement scale** In order to construct a measurement scale, a homogeneous dataset representing normal observations needs to be collected. The collection of these data will build a reference group, which is identified as "normal group". This is used as a base or reference point of the scale. Furthermore, the collected normal datasets need to be standardized in order to obtain a dimensionless unit vector. This is followed by MD computation using equation (1). Practically, the MD used for an unknown data is interpreted as the nearness to the mean of the normal group. In terms of countercheck, it is necessary that the average value for the MDs of the normal group is always close to unity. Therefore, they are identified as the unit space or Mahalanobis space (MS);

- **Stage 2: Assessment of measurement scales**In order to evaluate measurement scales, observations outside of MS or abnormal datasets will be used. Besides, the same mathematical calculation is repeated in order to produce the same goal (MD value) using abnormal sample data. However, the abnormal data is normalized based on the mean and the standard deviation of the normal group. Additionally, the inverse correlation matrix of the normal data will also be used during abnormal MD computations. It should also be noted that a good measurement scale demonstrates a significant discriminant ability of MDs used to distinguish between normal and abnormal observations;

- **Stage 3: Identify significant variables** In the third stage of MTS methodology, the system is optimized. This step is for the extraction and selection of useful features as important variables. Furthermore, this is where the OA and SNR approaches are applied. Moreover, the variables are assigned to two levels of orthogonal array experimental run. In this experimental run, Level 1 is labelled as 'used', while Level 2 is labelled as 'not used'. Following that, the computation of MD for each experiment needs to be repeated for all the related variables on each abnormal sample. Then the MD value is again tabulated under the same experiment format. Therefore, the SNR for each experiment is then computed.

In MTS, only two types of SNR are used, which consist of the larger SNR, and the SNR with better dynamic. However, dynamic SNR is always recommended. Meanwhile, in the context of MTS, SNR is used as a metric in order to assess the significance of the contribution given by each variable in the system. This contribution is for the discriminant ability to distinguish between the normal and abnormal observations. (Eq8.9) shows the ratio of the dynamic SNR:

$$SN = 10\log\left(\frac{\frac{1}{r}\left(S_\beta - V_e\right)}{V_e}\right)^2 [160] \tag{4.9}$$

Based on the equation (Eq4.9), r represents the sum of squares due to input signal; S_β is the sum of squares due to slope, and V_e represents the error variance. For further details on the formulation [162]. For each variable x_i, SNR^1 represents the average SNR of the 2nd level of x_i, while SNR^2 represents the average SNR of the 2nd level of xi throughout the vertical columns of OA. Therefore, the positive gains from (Eq4.10) constitute useful variables, while the negative gains from the same equation constitute otherwise:

$$\text{Gain} = \text{SNR}^1 - \text{SNR}^2 [162] \tag{4.10}$$

- **Stage 4: Future deployment of MTS, with significant variables** The optimized system should be re-evaluated using abnormal samples to validate the effectiveness of the system, which is done through an assessment on the discriminant power. Once confirmed, the optimized system is used for future applications of diagnosis, classification, or forecasting purposes [160].

4.4.2 Review on Current MTS Literatures

The reduced pattern recognition model, which is obtained via MTS, is considered robust. This is because the S/N ratio identifies the useful variables that are least sensitive to noise or variations. Furthermore, the variables that are cost efficient are also identified, as they

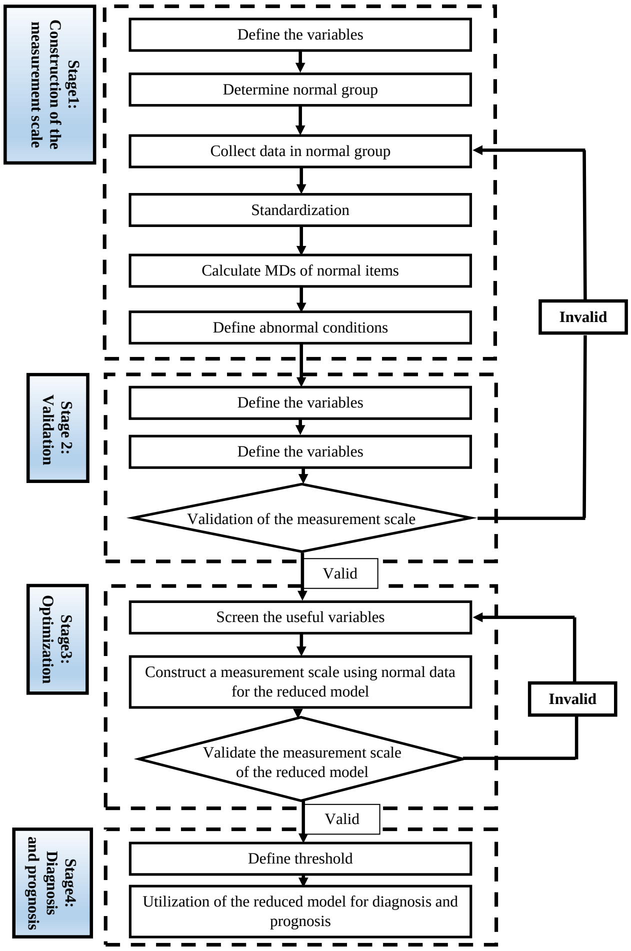


Figure 4.5: Mechanism of MTS. [12]

constitute the smaller number of attributes for the same of higher level of performance's effectiveness. These reasons have drawn tremendous amount of interests from various scholars around the globe across different continents (majority in Asian region) to use MTS. This method is useful, in terms of solving variety of pattern recognition problems, which are based on the number of papers produced regarding MTS studies (Figure4.6); (Figure4.7)[160].

4.4.3 Conventional MTS application

Japan is the pioneering country in deploying MTS methodology to its vast industrial spectrum for more than 20 years. However, the objective of this paper is to generally review the studies regarding conventional MTS under various industrial case studies outside Japan.

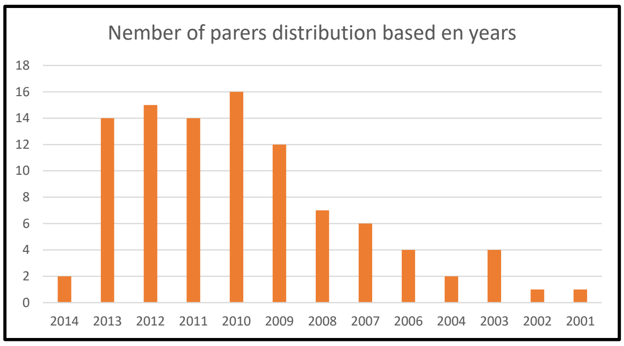


Figure 4.6: The number of studies conducted on MTS since 2001. [160]

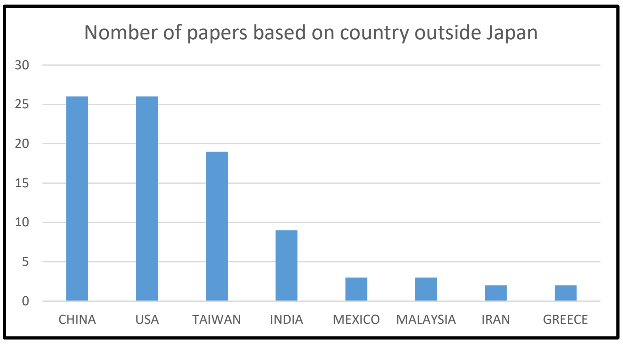


Figure 4.7: Distribution of papers on MTS studies based on country of origin. [160]

The word 'conventional MTS' refers to the application of MTS deployment, which merely involves the four fundamental stages mentioned above.

In automotive industry, conventional MTS strategy has been demonstrated by Chen and Phillips for Engine Control Module (ECU) software abnormal detections [163]. Furthermore, significant work performed by Cudney et al . was r ecorded using MTS. The record was made in order to predict customers' satisfaction rating when driving a new vehicle. It is also for the prediction of the warranty cost of car components [164].

In electronics industry, Su and Hsio attempted to use MTS for the analysis on the radio frequency (RF)'s functional inspection process of dual band mobile phone manufacturing [165]. Meanwhile, Yang and Cheng used MTS in order to optimize the measurement of stud bump height area [166]. Moreover, Riho et al. deployed MTS in order to investigate the root cause of failure in CCD production process. This investigation is for the improvement of production rate.

As for the maintenance of machinery health screening, significant case studies have been conducted in order to diagnose any faults within the screening. The maintenance is also for the assessment on the health of bearings [167] and the prognosis of cooling fans and motors in rotating machinery [168].

In the electrical power industry, the study on the development of the remaining duration of service provided by the diagnostic technology of phenol insulators for circuit breakers has drawn Miki et al. to utilize the MTS approach in their research [169]. Several attempts have been recorded during the study on circuit breakers using MTS for the same industry from [170], which took place in the following years.

In the finance sector, [171] attempted to predict the status of the financial crisis occurred in Taiwan's electronics companies. Meanwhile [160], conducted similar studies that took place in Malaysia. On the other hand, demonstrated the use of MTS in creating the criteria of decisions made for financial creditors.

In addition, pattern recognition is considered as important in the security sector. The subjects that are mostly involved in pattern recognition are (among others) the face [160], thumb and finger print, retina (eye), and voices. Pattern recognition with the involvement of face, which is through MTS approach, was first proposed by [160]. Mitsuyoshi et al. further analyzed face recognition under a more complex condition, which was created by adding noise (variation due to different lighting luminance) in the given condition [160].

The application of conventional MTS could also be seen in aerospace, SMT , environmental corrosion, software industry [172], medical science [173], ICT management, aviation industry, building construction, manufacturing process, project management, and aquaculture [160].

A summary on the application of MTS in industrial sector as the manufacturing sector (i.e., automotive, electronics, electrical appliances, software, manufacturing processes), is shown in the figure below. On the other hand, service industry (i.e., medical and healthcare, finance, corporate management, ICT), as well as machinery and equipment health surveillance sector had higher demands of MTS in order to improve the respective system performances [160].

4.5 Prognostic and health management PHM for TCM

PHM is a contemporary maintenance strategy that can help equipment sellers, integrator or operators to dynamically maintain their critical engineering assets[28]. In view of its importance in automation, modernization, sustainability, cost reduction and control of manufacturing processes, extensive research has been carried out in the area of Tool Condition monitoring (TCM) It is a new engineering approach that allows a real-time health assessment of the state of a tool and its future state (Figure8.8) the acronym PHM mainly comprises two elements.

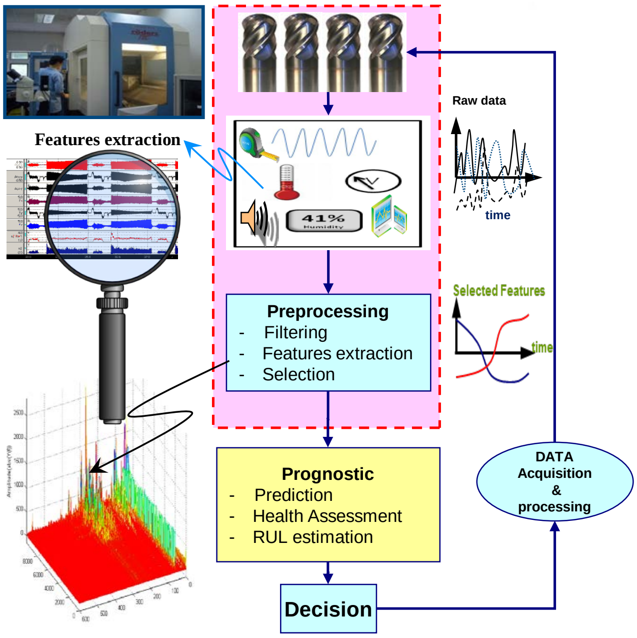


Figure 4.8: PHM cycle.

1- Prognosis refers to a prediction, forecast and extrapolation process by modeling the progression of faults, based on the assessment of the current state and future operating conditions;

2- Health management refers to a decision-making capacity to intelligently carry out maintenance and logistics activities based on diagnostic / prognostic information.

It is described as the combination of 7 modules [28]: data acquisition, manipulation, condition assessment, diagnostic, prognostics, decision making and human-machine interface (HMI) (Figure4.8). The 7 modules can be divided into three main phases 1) observe, 2) analyze and 3) act. In the analysis phase, prognosis is considered a key task with future capabilities, which should be performed effectively for successful decision support in order to recommend actions for maintenance.

8.6 Methodology

The proposed MTS based approach used Mahalanobis distance for tool wear condition monitoring in order to estimate the RUl s into different working cycle. The scheme also utilizes the values progression of the MD over machining cycle in order to facilitate prognosis of time to failure for cutting tool (Figure8.9). In (Figure8.9), the proposed mathematical

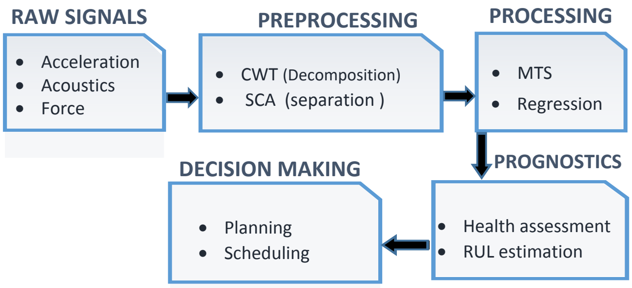


Figure 4.9: Framework of the proposed method.

model of four steps to be followed in the MCT process are: The data acquisition step is to collect data related to the health of the system; Data preprocessing consists of analyzing the acquired signals, including centering and filtering, in order to remove the offset in the measured signals. The proposed approach used the progression of the MD values over time in order to facilitate the prognostics of time to failure for cutting tool. The details of the proposed approach are presented in the rest of the section.

4.7 Mahalanobis Taguchi System for RUL estimation

MTS uses Mahalannobis Distance to discriminate areas and identifies the pattern of data from multiple dimension data. Firstly, it introduces only one measurement scale in any multi-dimensional space by using the Mahalannobis Distance in any subset of the selected space as uniform one and calculating the distance from the norm against the distance of other members. Secondly, it uses the SN ratio to evaluate the quality of measurement. Finally, it optimizes all of the information to improve the SN ratio with an orthogonal array. MTS begin with data collection on normal conditions. Then, the MD is calculated using independent coefficients series obtained by SCA and CWT. The mathematical model pro-posed based on combining (CWT) and (SCA) for computing the MTS. In this context the coefficients series obtained by CWT considered as a mixture of source derived from the observed signal, and then MTS used to compute the health indicator between the good and degraded conditions shown in (Figure8.9) the variables collected on each element to determine its "healthiness" as $V_i, i = 1, 2, ..., p$. The observation of the ith variable on the jth item $i = 1, 2, ..., p, j = 1, 2, ..., m$. Thus, the $p \times 1$ data vectors for the normal group are designated $v_j, j = 1, 2, ..., m$ [174]

Each individual variable in each data vector is standardized by subtracting the mean of the variable and dividing by its standard deviation, with both statistics calculated using data on the variable in the normal group. We thus obtain the standardized values.

$$Z_{ij} = \frac{\left(V_{ij} - \bar{V}_i\right)}{S_i}, i = 1, 2, ..., p, j = 1, 2, ..., m[160] \tag{4.11}$$

Where

$\bar{V}_i = \sum_{j=1}^{m} \frac{V_{IJ}}{m}$

and

$S_i = \sqrt{\frac{\sum_{j=1}^{m}\left(V_{ij} - \bar{V}_i\right)^2}{m-1}}$

Next, the values of the MDs, MDj, $j = 1, 2, ..., m$, are calculated for the normal items using

$$-10 \log\left[\left(\frac{1}{t}\right)\sum_{j=m+1}^{m+t}\left(\frac{1}{MDj}\right)^2\right][160] \tag{4.12}$$

Where

$z_J^T = \left[z_{1j}, z_{2j}, ..., z_{pj}\right]$ and S is the sample correlation matrix calculated as:

$$S = \frac{1}{m-1}\sum_{j=1}^{m} z_j z_J^T [160] \tag{4.13}$$

The MDj values in shown in (Eq8.12) have an average value of unity. For this reason, a unitary space used for referenced the Mahalanobis distance. In step 2, the selected abnormal items and not incorporated the uncertainty into the MTS showing the status of each item utilized for determining the MTS scale measurement. In step 3, OAs and $\frac{S}{N}$ ratios are used for the identification of the most useful variables set. An OA is a matrix design that contains the levels of some factors in the experiment runs for investigating the variables effects on the interest response. Each experiment factor assigned to a column of the OA, and the matrix rows correspond to the experimental runs. The MTS has p factors in the experiment. The level of a factor signifies the inclusion or exclusion of a variable in the MTS analysis. The p factors are assigned to the first p columns of the OA, with the other columns ignored. Thus the OA selected must initially have at least p columns. The MD values are then used to calculate the value of a $\frac{S}{N}$ ratio, which becomes the response for the run. Different $\frac{S}{N}$ ratios are utilized in Taguchi's analysis of experiments designed. These are defined in such a way that larger $\frac{S}{N}$ ratio values are preferred. One option mentioned in the MTS is to use Taguchi's larger-is-better $\frac{S}{N}$ ratio (Eq4.12)

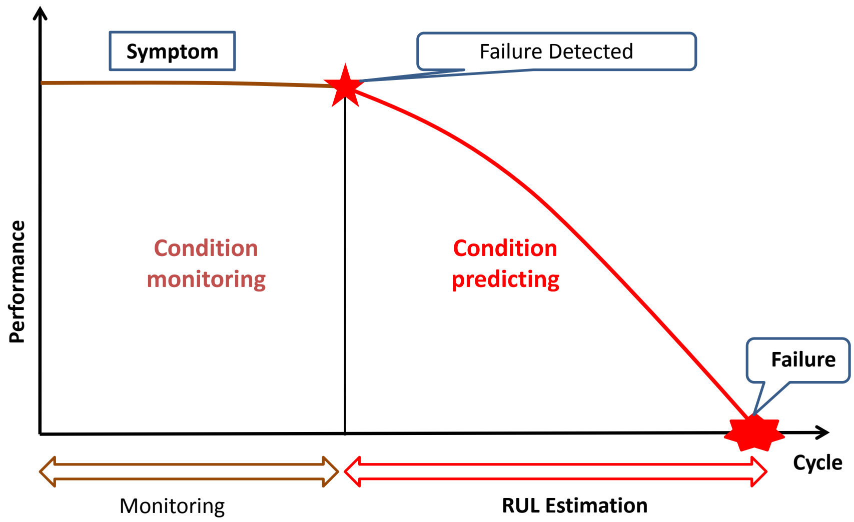


Figure 4.10: Illustration of remaining useful life. [48]

PHM aims to assess the state of the current physical system and predict its RUL before the failure. The objective is to maximize the operational safety and availability of the Cutting tool, and better health management. An illustration of a RUL is given in (Figure4.10).

Finally the Health indicator (HI) is determined by this equation:

$$HI = -10\log\left[\left(\frac{1}{t}\right)\sum_{j=m+1}^{m+t}\left(\frac{1}{MD_J}\right)^2\right][160] \tag{4.14}$$

The predicted RUL can be obtained by estimating the time between the current time t_c and the time t_f related to the wear threshold. Therefore; the equation of the RUL is given by:

4.8 Results and discussion

4.8.1 Experimental setup

To evaluate the effectiveness of the proposed approach, the tool wear task prediction conducted on a high-speed CNC machine tool (Figure4.11). The machining experiments were carried out on a Roder CNC machining center. The work piece is made of Inconel 718 which is a hard material to be cut and whose thermal and mechanical properties are of interest in the aeronautical field [27]. The piece used in the experiments is of square trapezoidal

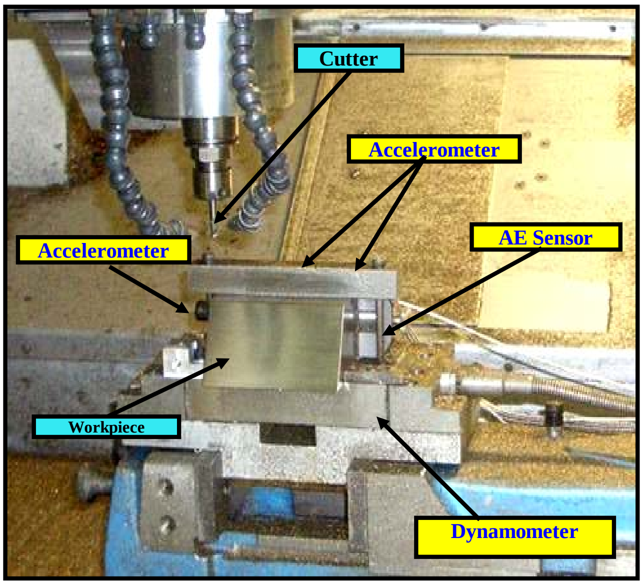


Figure 4.11: Experimental setup. [27]

shape with a width of 112.5mm and a high of 78 mm. The cutting tools are six in number. They are made of tungsten carbide, round nose and have three cutting edges. They operate at a speed of 10360 rpm, and with an advance of 1.555 m / min. The passes made are 0.125mm wide and 0.25mm deep. The data acquisition files for different signals (force in XYZ dimensions, acceleration in XYZ dimensions and acoustic emission) (Figure8.11) are in .csv format, with seven columns.

8.8.2 Health assessment and RUL estimation

The different steps involved in the proposed method are given in (Figure8.12). The estimation of RUL is done in two main phases, as shown in (Figure8.12) a learning phase and a testing phase . A cutting tool is planned for training and a new one for testing. The learning phase aims to extract the dominant characteristics contained in the collected force signals. The CWT, in particular at the seven levels, is used to break down the strength signals. The RMS of the actual ratio and the image coefficients for each frequency band are considered to be tools wear monitoring functions. These characteristics are then fed by SCA learning algorithms to establish the most appropriate data driven prognosis model (learning model) describing the evolution of wear on the cutting tools.

The next step is the test phase where a new cutter is taken. During this phase, the extracted entities are injected continuously into the model learned using MTS. The health indicator have been represented by the output result which is used to assess the current state of health and predict the RUL of cutting tools with identical previous operating conditions used in the offline phase. Several techniques for extracting parameters exist in the literature [4].

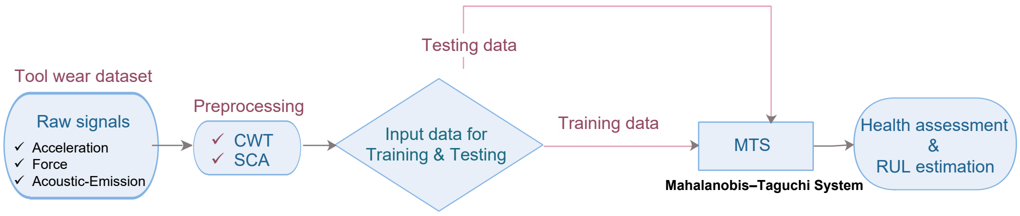


Figure 4.12: System framework for tool health prognostics.

In this study, we use wavelet transforms, it is a signal analysis tool; Compared to normal wavelet analysis, it has special capabilities to achieve higher discrimination by analyzing the higher frequency ranges of a signal. The frequency domains separated by the wavelet can be easily selected and classified according to the characteristics of the signal analyzed. CWT considered a tree; the top is the original signal. The next level of the tree is the result of a step in the wavelet transformation. The following levels are built recursively by applying the wavelet transform, the low-pass and high-pass filters of the previous wavelet. Then, when the transformation process is complete, the energy in different frequency bands can be calculated and considered as a characteristic. In this study, Daubechies "db4" wavelets were used to break down the cutting forces into six levels. The different frequency bands represent the force coming from different levels of wear. In the signal analysis process, the CWT is used first to decompose the raw cut signal by CWT and obtain the coefficients. By the CWT decomposition, the coefficients are obtained. (Figure4.13,Figure4.14) shows the coefficients extracted from the collected signals in all three directions force; and AE. (Figure4.15, and (Figure4.16) show the sensors measurements of the first and last cycle of machining for different sensors (Force, Acceleration and AE) respectively. The RMS calculation and the continuous wavelet transformation of the signals (force, vibration and AE), represent three different regions. In the first region, we observe that the energy dissipation increases very quickly, which means the sudden entry of the tool into the material (wear). The second region represents the stability of the cutting tool,

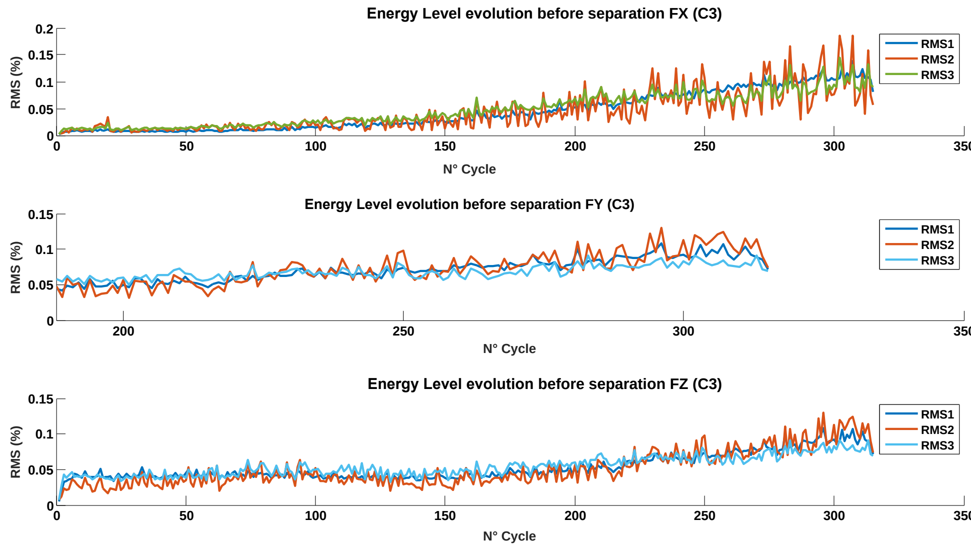


Figure 4.13 : Energy coefficients of the force signal before separation (C3).

which implies an almost constant dissipation rate (stabilized wear) at the end of operations. Finally, the energy loss increases very quickly, the tool becomes unstable due to wear faults resulting from the progressive contact between the tool and the material (accelerated wear). The proposed CWT-BSS-MTS algorithm can separate the signals correctly. To compare the different algorithms of the SRS according to the statistical performance criteria. In order to verify the benefit of the CWT-BSS method, signal processing with the SRS has

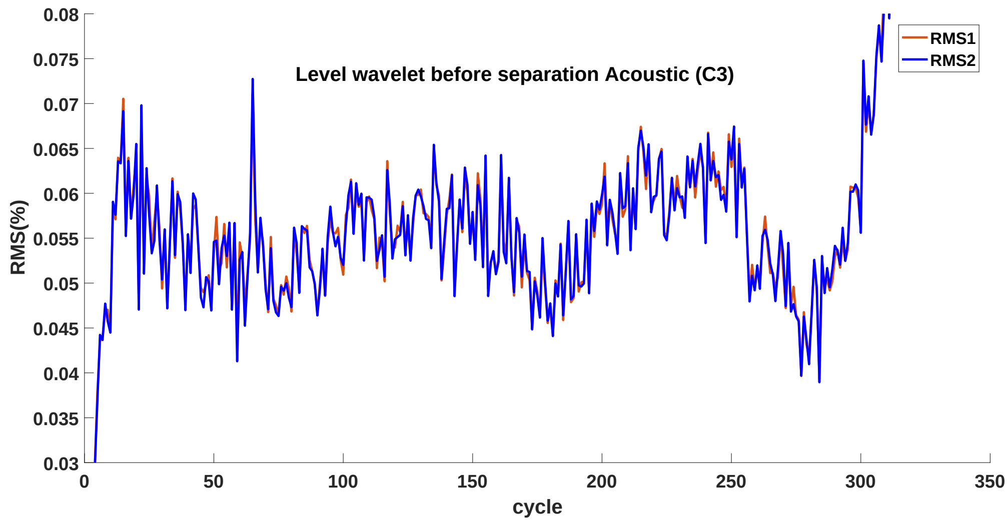


Figure 4.14: Energy coefficients for the Acoustic-Emission signal (C3).

only been performed in [48]. The signal collected in the grinding process was collected

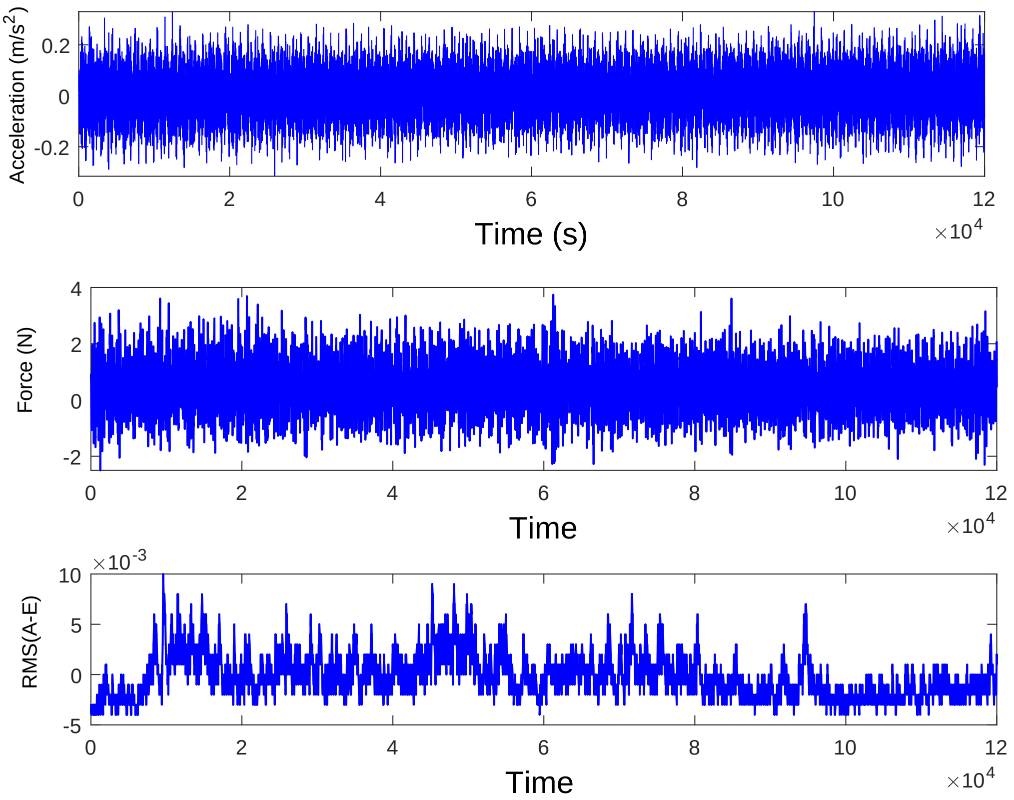


Figure 4.15: Sensors measurement for the force, acceleration and AE signals (First cycle).

using three sensors (vibration and force) (Figure8.17,Figure8.18). The observed signals obtained by computing the wavelet coefficients were selected as mixtures for the BSS only. The application of (CWT-SCA) source separation allows the information to condense in a well-determined energy coefficient in order to keep the Monotonicity, Prognosability and trendability; (Figure8.17) in this database indicate that the strength is the best performing to determine the health indicator and the RUL; In order to validate the robustness of this model.

4.8.3 Cutting Tool and Health Indicator

The application of MTS allows the extraction of the health indicator; the latter is the best approach to increase the effectiveness of tool wear monitoring. In this work, the health indicators of the tools (C3) rely mainly on the signals of force and vibration (Figure4.19,Figure4.20). The use of temporal domain features is allowed as health indicators for tools. The predicted and real HI for the cutter C3, is shown in (Figure4.21). It can be seen that the predicted HI is close to the real which is suitable for interventions before the occurrence of a failure.

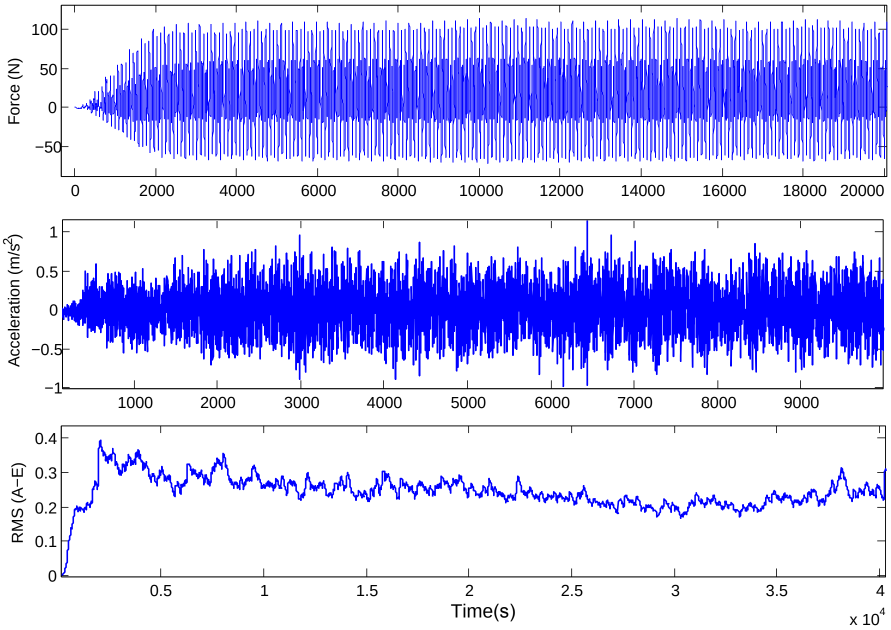


Figure 4.16: Sensors measurement for the force, acceleration and AE signals (Last cycle) (C3).

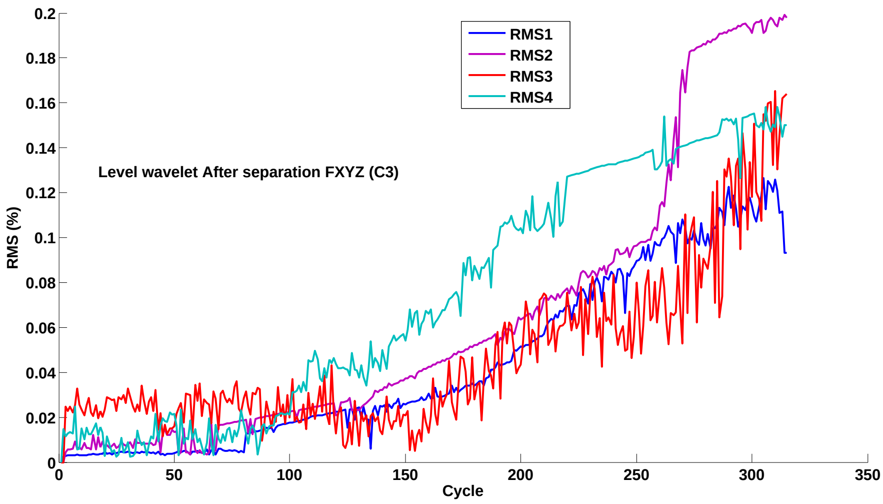


Figure 4.17: Energy coefficients evolution from force signal after separation.

8.8.4 Statistical independence

In order to confirm the validity of the proposed method CWT-SCA . The source correlation values of different sources obtained by CWT coefficients are shown in (Table4.2) for the vibrations signal in Z dimension at the cycle 160. Separated signals based on SCA are highly dependent for the cutter C3. The proposed CWT-SCA algorithm can separate the

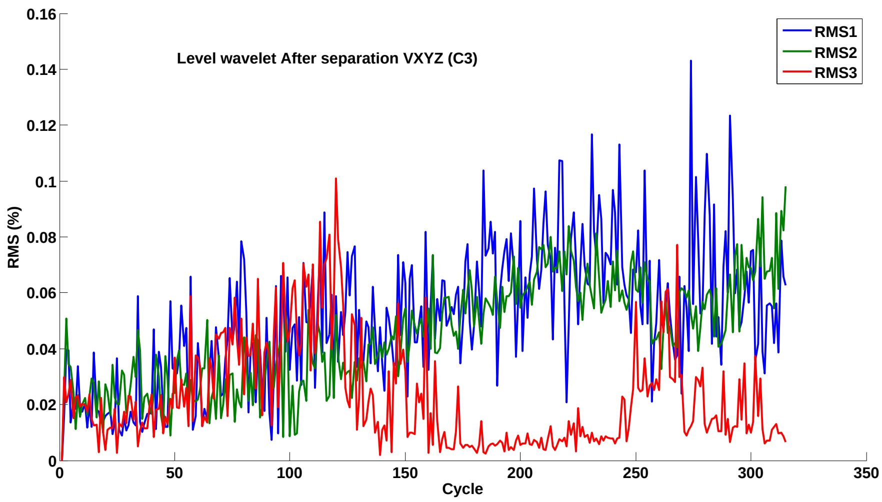


Figure 4.18: Energy coefficients evolution from vibration signal after separation.

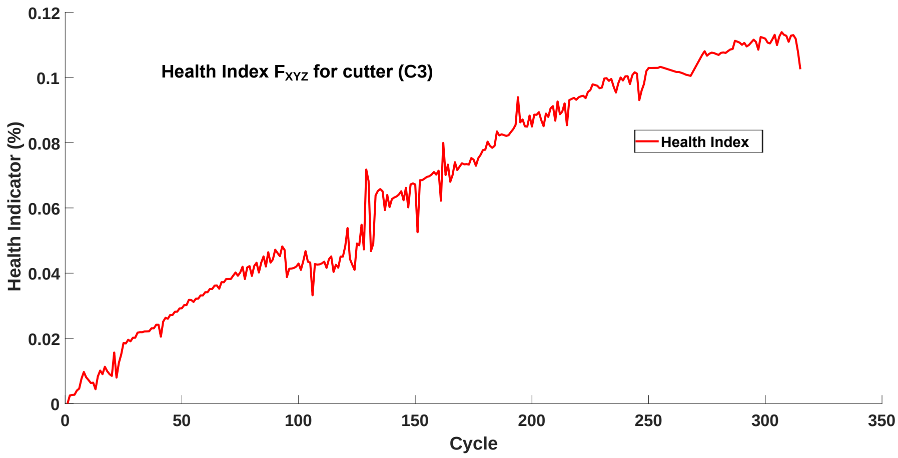


Figure 4.19: Health indicator obtained from the force signal after separation (C3).

Table 4.2: The Correlation Values Between Sources.

	source 1	source 2	source 3	source 4	source 5
$\hat{S}_1$	0,9998	0,0037	0,0242	-0,0164	-0,0058
$\hat{S}_2$	0,0442	0,9994	-0,0473	-0,0404	0,0265
$\hat{S}_3$	0,0130	-0,0237	0,9922	-0,1248	0,0970
$\hat{S}_4$	0,0032	-0,0062	-0,1048	0,9847	0,0278
$\hat{S}_5$	0,0235	-0,0177	-0,0929	-0,0250	0,9918

signals properly shown in (Table8.2).

4.8.5 RUL estimation

The estimated RUL obtained from MTS, real RUL and the failure threshold for the tested cutter C3, is shown in (Figure8.22). According to the gradually increasing trends of tool wear width with the development of wear severity, the tool wear processes contain three degradation stages, start by initial wear stage, moderate wear stage and severe wear stage. For the performances evaluation, to further reveal the advantage of proposed method Back propagation Neural Networks (BPNN) [175], LSSVM [176] are also used to predict tool wear. The comparison results of the proposed approach for three datasets are shown in (Table8.2). It is found that CWT-SCA based MTS can more accurately track the tool wear process than other existing methods [48]. The results between LSSVM, BPNN and our proposed methods indicate that our proposed approach still can achieve higher predic-

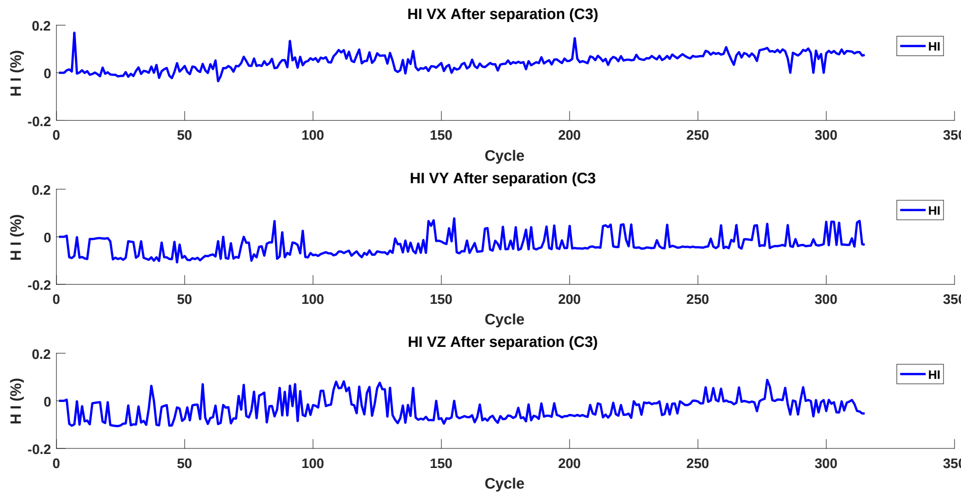


Figure 4.20: Health indicator obtained from the acceleration signal after separation (C3).

tion accuracy. The performance evaluation of the three prediction datasets are given by: $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{predict} - y_{real}\right)^2}$

The goal of this method is to analyze prediction capabilities by using CWT-SCA based MTS for tool wear estimation. A comparative study between some techniques in litterateurs on reliability performance analysis was summarized in (Table8.1). The wear evolution of three flutes for the cutter C1 are given in (Figure4.23). the first step is to use the data for selected three cutters (C1, C4 and C6) to build up a reference model which can be used

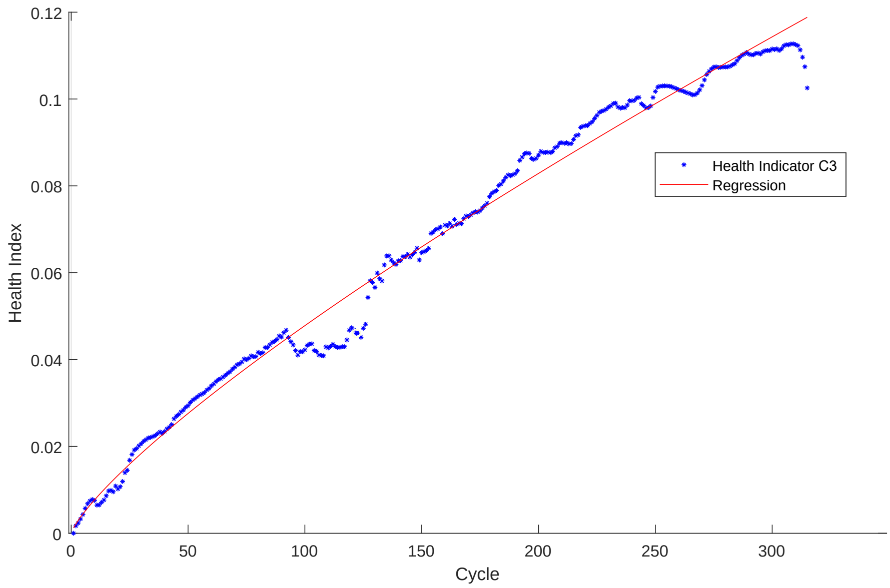


Figure 4.21: Tool Wear prediction from the force signal after separation (C3).

to predict tool wear for the cutter (C2,C3 and C5), the second step by using the model to predict tool life for another three cutters (data not used in model development) and check the model accuracy. The output wear values shown in (Figure8.24), (Figure8.25) and(Figure8.26) of the three flutes were provided (in 10-3 m m). the training cutters (C1, C4 and C6) were used for estimating the wear for the cutter (C2,C3 and C5). The value of the wear was predicted by the optimal input parameters of separation and the level of decomposition (L=7)and the signal from three dimension.

Table 4.3: Comparison results of eight approaches for three datasets.

Method	C1	C4	C6
	RMSE	RMSE	RMSE
[175]	28.74	25.80	24.81
[176]	19.79	20.86	22.08
CWT-SCA based MTS	**13.86**	**14.75**	**16.53**

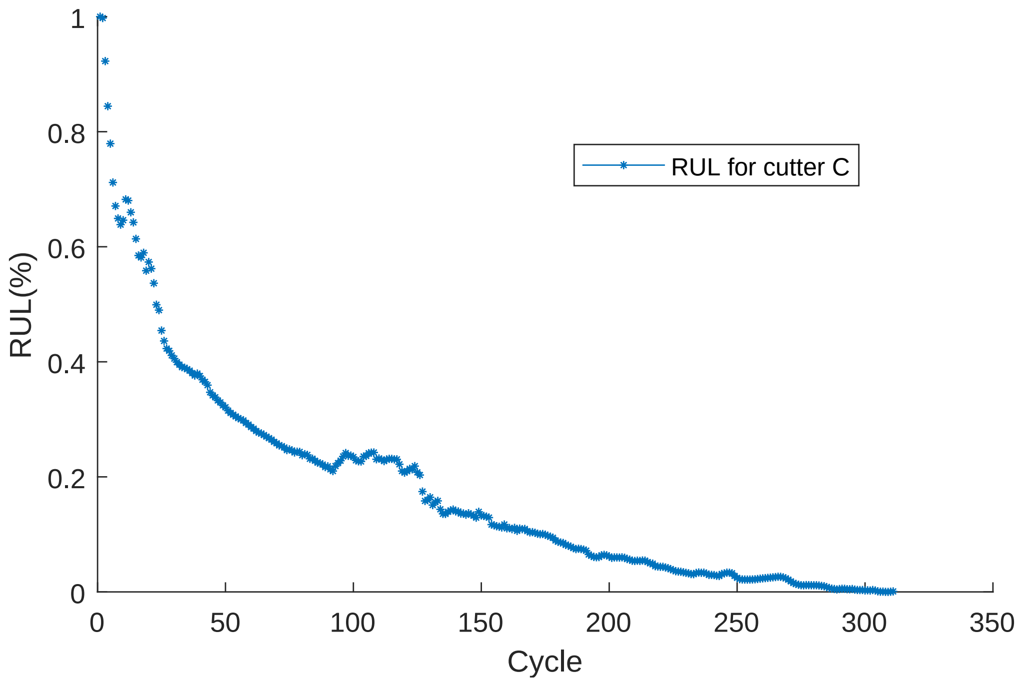


Figure 4.22: RUL evolution obtained for cutter C3.

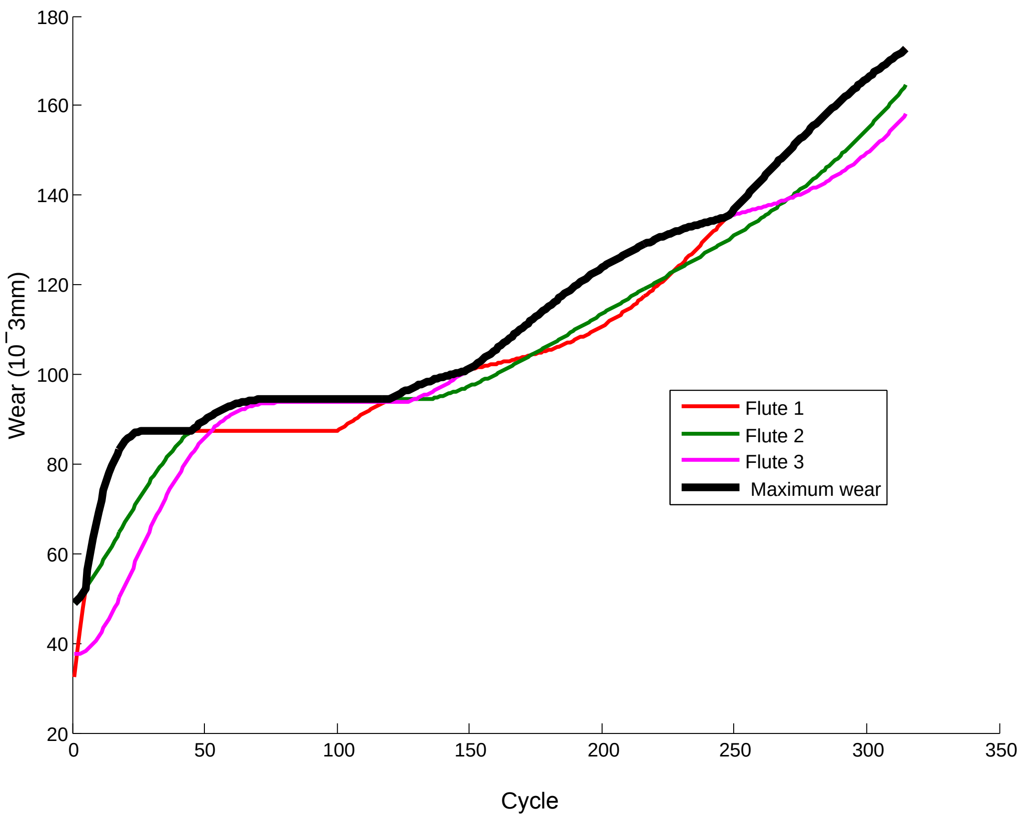


Figure 4.23: Wear of three flutes for the cutter C3.

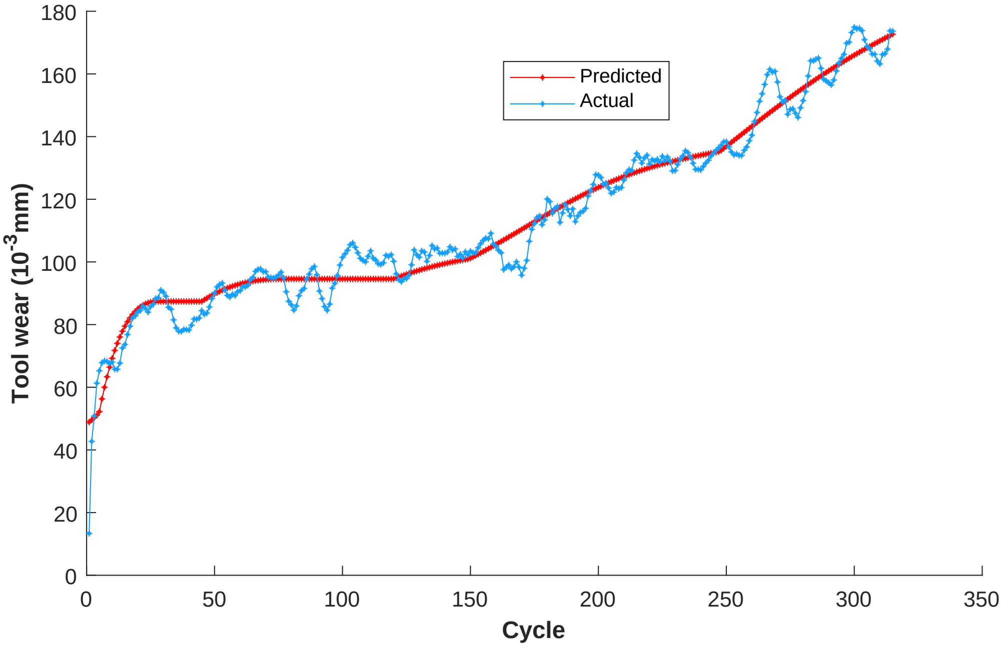


Figure 4.24: Tool Wear prediction for the cutter C1.

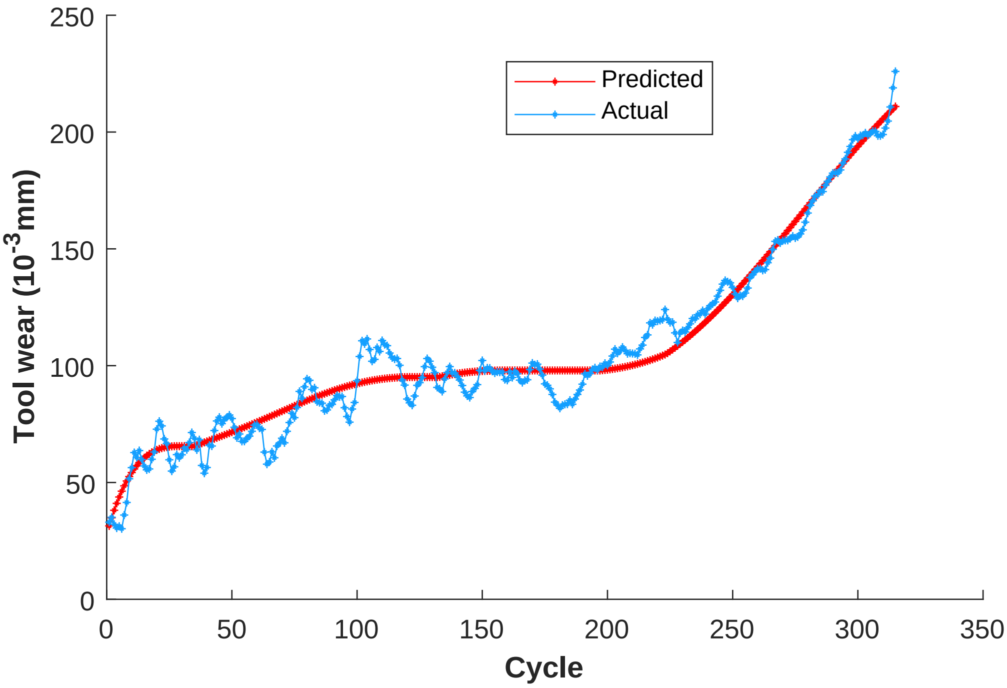


Figure 4.25: Tool Wear prediction for the cutter C4.

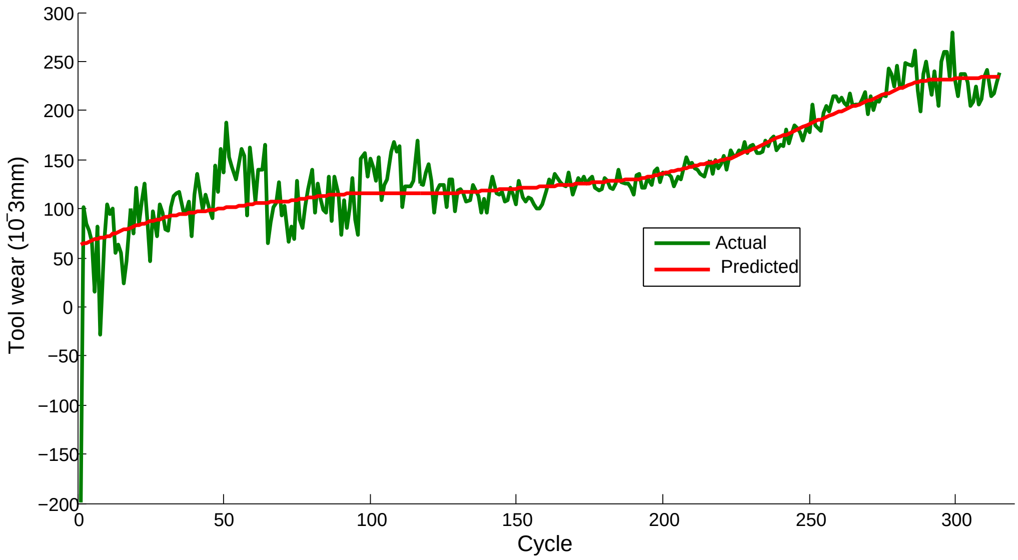


Figure 4.26: Tool Wear prediction for the cutter C6.

8.9 Conclusion

In this paper, a new scheme for tool wear condition monitoring has been proposed based on continuous wavelet transform, Sparse Components Analysis (SCA) and Mahalanobis Taguchi System (MTS). The method was applied starting from real data during several cuts of 06 CNC milling tools. For improving the computational capability, the relevant features from the force and acceleration signals were extracted by the CWT, particularly at the seven levels of the (Daubechies) wavelet. The RMS of the image coefficients for six levels was carried out. The extracted features are then reduced to set up energy coefficients By using SCA, the separated coefficients which are used as inputs in learning MTS for generating the model that represents the wear's behavior. Based on the obtained model, the online phase leads to estimate the current health state and predict the RUL of the cutting tools. From the obtained results, it is expected that the proposed approach gave higher forecasting accuracy of RUL estimation than other existing approaches. Therefore, the proposed approach is very promising to the success of smart manufacturing operations for intelligent decision making. In the future scope, the other prediction methods will be applied in different wear degradation stages and the proposed approach will be extended and improved to other mechanical components.

Chapter IV:
Condition monitoring based on deep learning

CHAPTER 04

CONDITION MONITORING BASED ON DEEP LEARNING

5.1 Introduction

Tool Condition Monitoring (TCM) has become essential to achieve high quality machining as well as profitable production. Identifying the condition of the cutting tool during machining before it reaches its failure stage is critical. With deep learning techniques combined with the development of Industry 4.0 technology, it is important to reduce maintenance costs and ensure the safety of the machining process. The degradation of the cutting tool can lead to economic losses and significant risks for the users of the machine. To overcome these difficulties, a new approach developed in the application of deep learning to estimate tool wear during the milling process. The proposed methodology is based on the data-driven approach using variational mode decomposition (VMD) and deep learning. Two deep learning machines used in this study, Convolutional Neural Networks (CNN) and Bi-Directional Long-Term Memory (BiLSTM) to perform collaborative data mining on (VMD) and to improve modeling accuracy . VMD is a new decomposition technique used to decompose the signal into time subseries called intrinsic mode functions (IMF). However, the VMD performances depend specifically on the constraint parameters which must be predetermined for the VMD method, in particular the number of modes. Model development based on 1D-CNN and BiLSTM is selected using MFIs as inputs. The performance of the proposed approach is further improved using the combined method. In addition, the universal method can also be applied to other prognosis systems. Comparisons with traditional learning techniques and adopted in previous work highlight the superiority of the proposed prognostic method. Among all models, the VMD-CNN-BiLSTM achieves the best modeling performance in terms of efficiency and effectiveness.

5.2 Variational Mode Decomposition (VMD)

As above-mentioned in the state of the art review, signal processing is the step of choice to handle the issue of acquired signals corrupted by noise and harmonics. This is particularly the case of vibration signals related to mechanical components generating low amplitudes pulses [177]. Signal processing techniques are therefore used to isolate these components [178, 179]. The VMD technique has been introduced to improve the EMD and become a technique for the analysis choice of nonlinear data for detection in a wide range applications [180]. VMD has the advantageous ability to decompose complex signals into several stationary signals, regardless of their origin, using Wiener filter [181].

$$x_n(t) = \sum_{i=1}^{k} u_k(t) + res(t).[177]. \tag{5.1}$$

Where x_n is the acquired signal, $\{u_k\} = \{u_1, u_2, ..., u_n\}$ are decomposition modes, and is the residual signal after optimization. the decomposition process lies in solving an optimization problem formulated as:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) . u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} [].[179]. \tag{5.2}$$

subject to $\sum_k u_k = f$ Where f is the original signal, $\{\omega_k\}$ center frequencies of each $\{u_k\}$, $\delta(t)$ is an impulse function, and k is modal component number. The new formulation of the variational constrained problem is an augmented Lagrangian equation formulated as follows [181]:

$$\begin{aligned} L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) . u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \end{aligned} .[179]. \tag{5.3}$$

where α is quadratic penalty factor and λ is Lagrange multiplier. Resolution is done by iterative techniques allows estimating modes u_k and their central frequencies ω_k as well as the Lagrangian operator $\lambda(t)$, formulated iteratively in(Eq5.4, Eq5.5, Eq5.6), respectively [182]

$$\hat{u}_k^{n+1}(\omega) \leftarrow \frac{\hat{f}(\omega) \sum_{i\langle k} \hat{u}_k^{n+1}(\omega) - \sum_{i\rangle k} \hat{u}_k^n(\omega) + \frac{\lambda^n(\omega)}{2}}{1 + 2\alpha\left(\omega - \omega_k^n\right)^2}.[182] \tag{5.4}$$

$$\omega_k^{n=1} \leftarrow \frac{\int_0^\infty \omega \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega}.[182] \tag{5.5}$$

Where, $\hat{u}_k^{n+1}$ are obtained by Wiener filtering.

$$\lambda^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau \left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega) \right).[182] \tag{5.6}$$

The stopping criterion is formulated as follows:

$$\sum_k \frac{\left\| \hat{u}_k^{n+1} - \hat{u}_k^n \right\|_2^2}{\left\| \hat{u}_k^n \right\|_2^2} \langle \varepsilon.[182] \tag{5.7}$$

Where, τ is noise tolerance, and ε is convergence error.

9.2.1 Pearson Correlation Coefficient

Correlation between two signals A and B of size is the measure of their linear dependence. It is positively or negatively assessed if the correlation coefficient is close to 1 or -1, respectively [183]. Pearson correlation coefficient is calculated as:

$$\rho(A,B) = \frac{1}{N-1} \sum_{i=1}^{N} \left(\frac{A_i - \mu_A}{\sigma_A} \right) \left(\frac{B_i - \mu_B}{\sigma_B} \right).[183]. \tag{5.8}$$

where μ_A , μ_B , σ_A and σ_B are mean and standard deviations of A and B, respectively.

5.3 Deep learning

The conventional ML models are typically shallow. In ANNs, the conventional neural networks (NNs) usually have a maximum of two hidden layers with limited data processing capability in their raw form. In many applications, analyzing big or high-dimensional data with conventional NNs requires feature engineering as a priori. Data are usually processed through dimensionality reduction methods such as principal component analysis (PCA) or data mapping methods like SOM [184]. Thus, two or more models should be linked together to form a hybrid intelligent system capable of analyzing complex data. While the term deep learning refers to employing numerous hidden layers in the structure of an ANN, it is mainly different from the traditional ML models in how representations are learned from the raw data. A deep model learns representations of data with multiple levels of abstraction. In other words, the learning process yields a high-level meaning in data through employing a high-level data abstraction [185]. DL models have more hidden layers than ML ones; however, what makes DL unique and different from traditional ML is the high-level feature engineering capabilities of deep models, where complex feature construction and abstraction are performed in the model structure during the learning process.

The high-level abstract representation and feature engineering capabilities make DL models robust to data variation [186]. Also, the deep networks' hierarchical structure enables them to model the complex nonlinear relationship in big data. On the other hand, ML models typically face difficulty in analyzing very big and high-dimensional datasets. Thus, feature selection serves as a dimensionality reduction approach enabling MLs to process big datasets. The challenge is those big datasets acquired in real industrial applications are typically polluted by noises and include outliers and different types of anomalies, making the feature selection a challenging task. Table 2 compares the typical characteristics of ML and DL models [187].The most commonly used DL networks in intelligent manufacturing are autoencoders and their variants, deep belief networks (DBNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) [186].

5.3.1 Auto encoder

Auto encoders (AEs) are unsupervised feed-forward neural networks, where their output tries to return the input data (Figure9.1). It comprises encoder and decoder steps, in which the former transport the input data into a latent representation, and the latter reconstructs the input from this representation. Gradient-descent-based algorithms are usually employed to tune the model's hyper parameters by minimizing the reconstruction error. The main variants of AE are de-noising and sparse auto encoders (SAEs) [186, 187].

5.3.2 Deep Belief Network

Deep Belief Network (DBN) comprises a stacking of multiple restricted Boltzmann machines (RBMs) [188]. There is a connection between the layers in DBN but not between the neurons within a layer. The layer-by-layer structure of the network provides a hierarchical feature representation, which is used to construct a high-level representation of input data. During the unsupervised training process, the DBN reconstructs its input through learn-

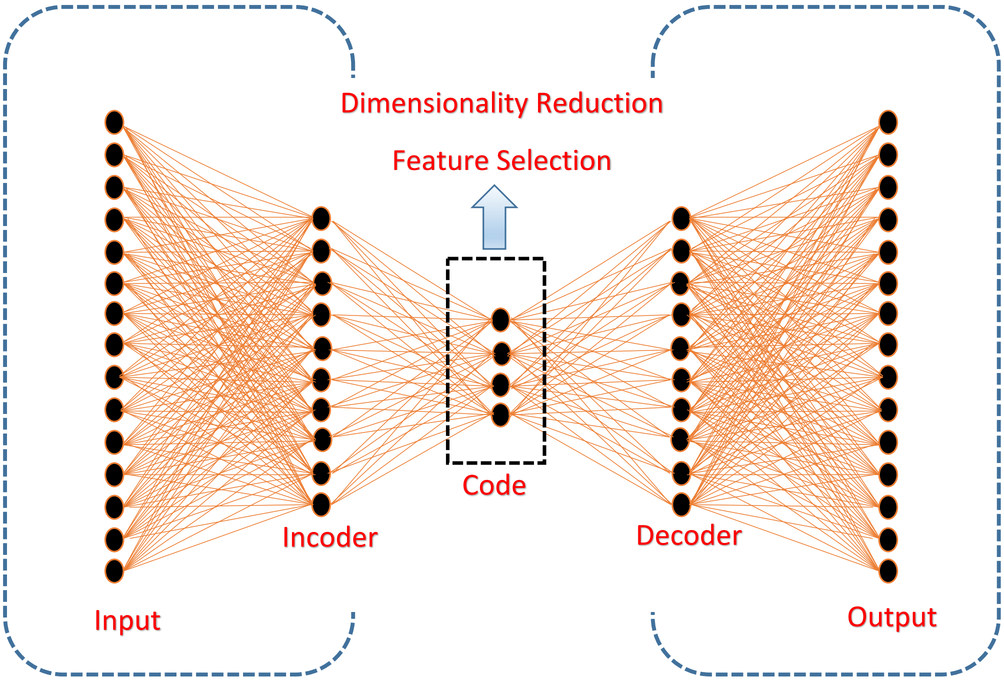


Figure 5.1: Schematic of an autoencoder network showing the encoder, decoder, and code layer used for dimensionality reduction and feature selection. [186]

ing a probability distribution. RBM is a generative stochastic feed-forward ANN that is an effective tool for feature engineering. Training a DBN includes training multiple RBMs, where the hidden layer of the lower RBM is deemed the model training data, and the RBM output is used as the training data of the upper RBM. After training all RBMs, fine-tuning process is performed by applying a back propagation algorithm with the training data as output [187].

5.3.3 Recurrent neural network

Recurrent neural network (RNN) is a class of feed-forward ANNs, with the capacity to update the current state based on the current input data and past states. Thus, it is ideal for dealing with sequential and time-series data or unsegmented signals through capturing information stored in sequence in the previous elements. RNNs benefit from supervised learning, and model training is performed using Back propagation.

5.3.4 1D-Convolutional neural networks

The design of CNN is mainly based on the inputs convolution with filters to generate more discriminating features output, and will be used as inputs in the next layer. Pooling layers (Mean,Max,L2-norm or Average) allow information complexity reduction [189], in addition to overfitting control ensuring a better learning [190]. Typical CNN consists of Convolutional Layers, Pooling Layers, Activation Layers, and Fully-Connected Layers As can be seen from (Figure5.2) At present, CNNs have the architecture characteristics of fast training speed and high accuracy. Convolution between input features u and Kernel filters k is provided by:

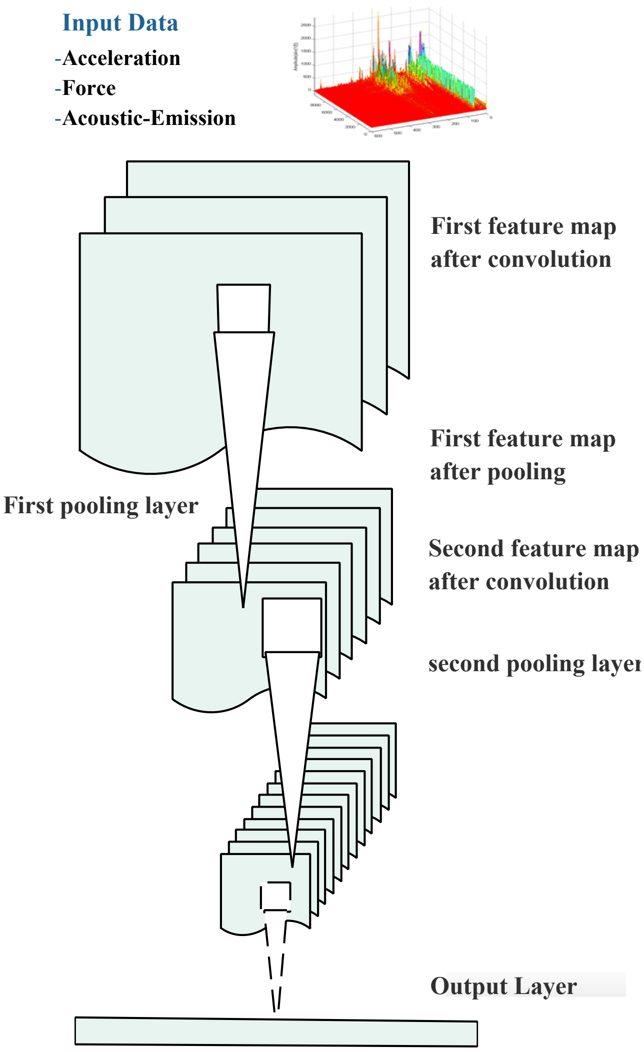


Figure 5.2: Convolutional Neural Network (CNN) structure diagram. [190]

$$f = \varphi(u * k + b).[191] \tag{5.9}$$

Where f represents the obtained new features, $*$ denotes the convolution operator, b is the bias, and φ is the activation function [191]. Feature extraction convolution and pooling layers are followed by feature learning layers (fully connected layers), which are traditional neural networks with an input, hidden layer, and classification layers [190]. The 1DCNN model used in this study enhances the model's learning ability by adding conventional ReLU activation functions to the convolution and Fully- Connected Layers [192].

9.3.5 Bidirectional long short-term memory networks

The architecture of LSTM node is shown in (Figure8.9), and equations managing the flow of information within are formulated from (Eq5.10) to (Eq5.15):

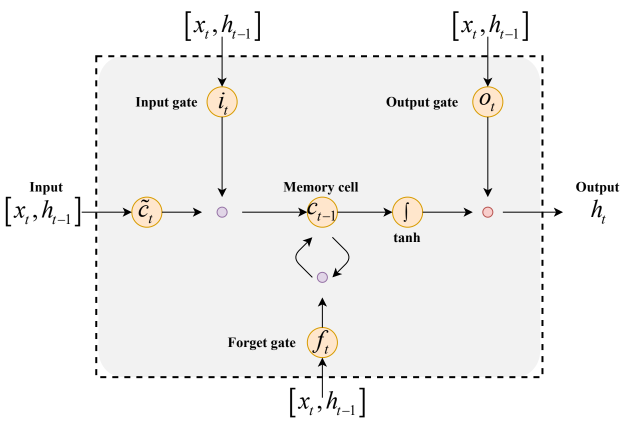


Figure 5.3: LSTM bloc. [193]

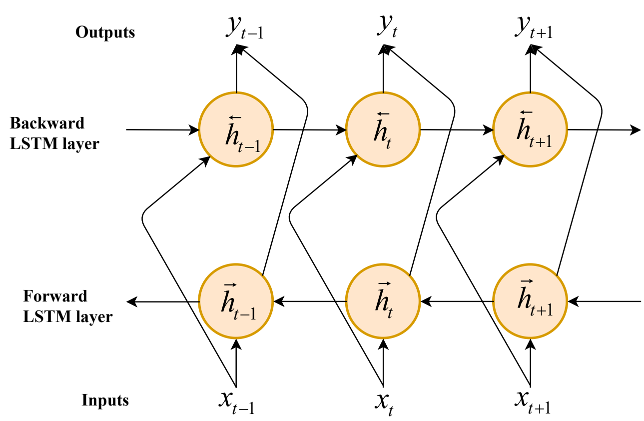


Figure 5.4: Bidirectional process. [193]

Input gate

$$i^t = \sigma(W_I x_t + U_i h_{t-1} + b_i) \tag{5.10}$$

Forget gate

$$f^t = \sigma\left(W_f x_t + U_i h_{t-1} + b_i\right). \tag{5.11}$$

Output gate

$$o^t = \sigma(W_o x_t + U_o h_{t-1} + b_o). \tag{5.12}$$

Candidate state of the memory unit

$$\tilde{c}_t = \tanh(W_o x_t + U_c h_{t-1} + b_c) \tag{5.13}$$

Updated internal state

$$c_t = f_t o c_{t-1} + i_t o \tilde{c}_t . zheng2017long[24] \tag{5.14}$$

LSTM unit's final output

$$h_t = o_t o \tanh(c_t) . zheng2017long \tag{5.15}$$

Where W , U , and b represent the network parameters to be learned, o is Hadamard product, and two types of activation function were used, $\sigma(x)$ as logistic sigmoid and $g(x)$, $h(x)$ as hyperbolic tangent.

In the same context of improving time-series monitoring, a new variant of LSTM named BiLSTM, the first one ensures the dependency from the past towards the future, but BiLSTM network ensures a double dependency of the past towards the future and the inverse, as in (Figure8.10), by keeping the same architecture as unidirectional LSTM with a difference in the flow of information in the layer.

The equations are presented in the following for describing this aspect[24]:

$$\overrightarrow{h}_t = LSTM\left(x_t, \overrightarrow{h}_{t-1}\right) \tag{5.16}$$

$$\overleftarrow{h}_t = LSTM\left(x_t, \overleftarrow{h}_{t+1}\right).[24] \tag{5.17}$$

$$y_t = W_{\overrightarrow{h}y} \overrightarrow{h}_t + W_{\overleftarrow{h}y} \overleftarrow{h}_t + b_y .[24] \tag{5.18}$$

Knowing that $\overrightarrow{h}_t$ and $\overleftarrow{h}_t$ represent forward and backward hidden state respectively, LSTM is the application of equations from (Eq5.5) to (Eq5.3), and represent forward and backward LSTM weights.

5.4 Applications of deep learning in machining and Tools monitoring

The applications of DL in machine health monitoring are rapidly growing [194]. It can be seen that the majority of researches focused on monitoring the tool wear condition and prediction of the flank wear and the remaining useful life (RUL) of the tool. Few studies have also been performed on employing DL for chatter detection and surface roughness monitoring.

5.4.1 Autoencoders

An unsupervised condition monitoring approach using AE is to define a nd e mploy an anomaly threshold using the AE reconstruction error. This monitoring technique's core concept is that the reconstruction error can reveal whether the tool condition is changing or not. In this case, the AE is trained with reference data indicating the base condition (the typically stable situation with no damage and anomaly), and the reconstruction error is calculated. In the monitoring phase, the same AE is fed with new observations, and the reconstruction error is computed again. The basic assumption is that as long as the system condition is not experiencing a major change, the reconstruction error should be stable and small. However, if the reconstruction error goes beyond a defined threshold, then the state of the tool is changing, and it may experience damage such as tool wear. Dou et al. [195] used this approach for tool wear monitoring using the vibration and force signals in the milling process. They directly fed the segments of signals to the SAE model and showed that as tool wear increased, the reconstruction error became more unstable. They could identify four tool wear states using the proposed monitoring model. When more than two states are to be monitored, each state should be used as a base condition to train an AE and define another threshold to show the next state's border. For example, three thresholds should be defined to identify the borders between the healthy, initial wear, steady wear, and extreme wear states. Kim et al. [196] also used the AE thres holding based method to differentiate the new and used tool using the cutting force and current sensors. However, instead of directly using the signal segments, they manually extracted 36 features from the signals. AE was trained using 80 samples collected from machining with a new tool. The testing data included 20 samples corresponding to the new tool and 218 samples associated with the used tool. Kim et al. [196, 187] showed that the code size and the network architecture impacted the classification performance.

A unique characteristic of an autoencoder is that the neurons in its code layer can be used as a low-dimensional representation of the data. Thus, the feature selection can be achieved through dimensionality reduction in the model. The challenge with employing autoencoder for feature selection is finding the optimal model architecture (number of hidden layers and neurons), especially when dealing with big data. Moldovan et al. [198] de-termined the state of the tool wear using extracted features from the tool image having an input vector with a dimension of 11,844. The dataset was combined with an autoencoder, and it was shown that the model testing success rate increased by 60% when increasing the number of neurons in the 1st hidden layer to 150.

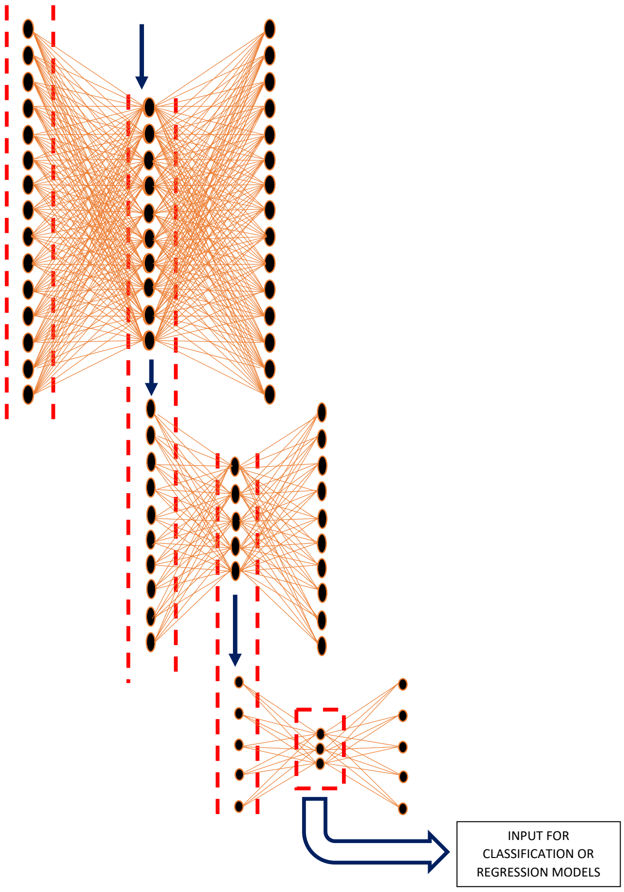


Figure 5.5: A sample architecture of stacked AEs for data reduction and feature selection. In this approach, the neurons in each autoencoder code layer are used as the next encoder's input layer. The last code layer could be linked to a softmax or regression layer for machin-ing and tool condition monitoring . [197]

Fine-tuning the autoencoder structures can be challenging and may require trial and error or grid-search techniques for optimizing the model hyper parameters. An approach for feature selection by dimensionality reduc-tion is using stacked AE. In this method, the dimensionality reduction is achieved using stacked autoencoders, in which the code layer of each autoencoder forms the input layer of the subsequent encoder (Figure9.5). Ocha et al. [199] used stacked sparse autoencoders (SSAEs) for tool wear classification in the milling process of aluminum using force, vibra-tion, and acoustic emission sensors. The study considered four classes of tool conditions, and the input dataset comprised a total of 441 sensory data. In this study, seven sensory features were extracted from the signals as the input of data. Thus, the SSAE did not directly analyze the high-dimensional raw signal.

Proteau et al. [200] discussed that AE is effective for dimensionality reduction and 2D visualization of data and showed a better dimension reduction capability compared to PCA for cutting state monitoring using vi-bration and current signals. AEs have also been used for tool wear monitoring in milling using the current signals [201] and yielded higher monitoring accuracy than methods such as ANN, SVM, or KNN. Ou et al. [202, 187] showed that introducing noise and using a stacked denoising autoencoder improved tool condition monitoring performance. Figure 12 shows their adopted methodology for AE-based tool wear monitoring using. The AE concept can be integrated with feature fusion to better extract the meaningful features of signals. Shi et al.[187] employed this approach for flank wear prediction using the vibration data acquired during the milling process of aluminum and stainless steel. The sensory data can be augmented using the Fourier and/or wavelet transforms. The time, frequency, and time-frequency data were then separately fed into SAE for feature selection. The selected features in different single domains were then combined and fed into a final AE to yield the input of a nonlinear regression model for tool wear prediction. It was shown that such a model outperformed the conventional machine learning models, however, at the expense of more training and testing time. When a series of AEs are stacked, other than feature transfer learning, weight transfer can also be performed between the AEs to enhance the model performance by improving the weight initialization process. Sun et al.[203] investigated deep transfer learning based on sparse AE for the tool's remaining useful life prediction. AE combined with a hybrid clustering method was used for chatter detection [204, 187].

5.4.2 Deep belief neural networks

Yu and Liu [205] employed DBN combined with symbol and classification rules for surface roughness prediction and showed that DBNs effectively model complex nonlinear relationships between the machining process variables. DBN was successfully employed to build a feature space for cutting state monitoring (idling, stable cutting, and chatter) using the vibration data collected during the end milling process. The vibration signals were seg-mented into signals with a dimension of 256. Besides, manual feature extraction was em-ployed in the frequency (12 features) and wavelet (2 features) domains. The performance of DBN was compared with those obtained from ANN, SVM, and k-means clustering. It was shown that while feature reduction generally improved the performance of ANN and SVM, DBN was more robust to the manual feature extraction and yielded lower error than other models. It was also revealed that comparing to the PCA, the output of DBN could better separate the three monitoring states with a relatively large margin and thus capable than PCA in feature engineering from the sensory data [205].

Chen et al. used DBN for tool wear prediction during the high-speed CNC milling process using the cutting force, accelerometer, and acoustic emission signals. Maximum, minimum, average, standard deviation, and the time stamp indicating the tool wear evolution and wear rate were chosen as the sensory features and were fed into the DBN. Four DBN layers were used, and for simplicity, every hidden layer was set with the same number of hidden neurons ranging from 10 to 15. The DBN was compared with the support vector regression (SVR) and MLP NN. They showed that while there was no significant difference between the three studied models' performance in terms of coefficient of determination (R2), ANNs and DBNs required 60% shorter prediction time than the SVR model. Moreover, while the performance of ANN was fluctuating with changing the number of hidden neurons, epochs, etc., DBN was more robust to hyperparameter variation, which thus outperformed the other models[187].

5.4.3 Convolutional neural networks

Compared to the autoencoders and DBNs, more research has been conducted on CNNs for intelligent machining, focusing on tool wear monitoring [206]. It has also been used for chatter detection [207] and surface roughness prediction [187, 208]. CNNs are ideal for handling image-based data; however, time-series data or extracted sensory features can be directly fed to 1D CNN. Xu et al. [209] employed a 1D CNN to extract features from the vibration data for tool wear monitoring. Lee et al. [210] also used a 1D CNN for tool condition monitoring in the grinding process using sound signals. The authors identified the most critical frequency range of the signals (using Fourier transform analysis) and trained the 1D CNN using the audio signals in the time domain, preserving the critical frequency segment. During the machining process, the acquired sensory data can be combined with the experience and physics-based features from the process to build low-cost models for process monitoring. Li et al. [187, 211] developed a model, which relies on physical analysis to extract useful features to establish a reliable health indicator for tool condition monitoring utilizing the vibration and acoustic signals. Then, they developed a deep CNN model using 20 low-cost processes and cut variables to replace the physics based model.

The manually extracted features from different signal channels can be combined to form a multi-domain feature matrix. Huang et al. [212] extracted nine features from force and vibration signals in three directions to form a multi-domain feature matrix for wear prediction in the milling process using CNN.

Thus, for each sample data, a total of 54 multi-domain features were extracted to form a column of the original feature matrix. Zhang et al. [213] showed that feature optimization (using recursive feature elimination and cross-validation (RFECV)–based and Isomap-based methods) on themanually extracted features enhanced the performance of CNN for tool wear prediction.Motivated by the similarity between the pixel matrix of high-dimensional image and the raw data matrix of multisensory time-series signal, Huang et al. [214] introduced a reshaped time series stage to represent the multisensory raw signals. Accordingly, the multi-sensory raw signal data were re-shaped and then fed into CNN for tool wear prediction. The method based on reshaped time series convolutional neural network (RTSCNN) was shown to outperform some of the other advanced ML and DL models for tool wear prediction. In many applications, the time series sensory data were used to construct image-based input data before training the CNN.

Reformatting time-series features as images would let the model learn the temporal dependencies on data. Cao et al. [215] discussed that compared to the 1D CNN, the 2-D signal matrix retains more information than a single reconstructed sub-signal. Its associated CNN resulted in higher accuracy than 1D CNN for tool wear state identification. Thus, some research emphasized training CNN using constructed images from the time series sensory data [215, 216]. Song et al. [217] used the spindle current clutter signal for tool wear state identification using CNN. They used the Fourier series and the least square method to fit and remove the signal components corresponding to the cutting parameter and extracted the current clutter signal with little dependency on the processing conditions that could best reflect the tool wear condition. Then, they applied image binarization and used the image of the signals as the input of the DL model. Other researchers used mathematical techniques such as Gramian Angular Summation Fields (GASF) to convert the sensory into image data [214]. Martınez-Arellano et al. [20] applied time series imaging on 3-channel force signals using GASF and fed the obtained images to CNN for tool wear classification and achieved classification accuracy above 90% .
Another approach to obtain image-based dataset from time series sensory data is through time-frequency analysis and imaging using techniques such as the wavelet transform. Zheng and Lin [218] constructed an image from the 1D force signals using the wavelet and short-time Fourier transform. They designed a CNN using the obtained images and discussed

that higher network accuracy was obtained when using wavelet transform for image construction from the force signals. Tran et al.[207] utilized continuous wavelet transform (CWT) on the force signals for chatter detection in the milling process. They applied CWT to the segments of force signals acquired during the stable, transitive, and unstable cutting states. The time-frequency images obtained using CWT were used to train the CNN, and classification accuracy of 99.97% was achieved. Wavelet packet decomposition [216] and Hilbert envelope analysis [215] have also been used to convert the 1-D signal into a 2-D signal matrix. The general finding is that folding the 1-D spectra into 2-D spectral maps enhances the learning ability of the 2-D CNN [216].

Another approach to train CNN is by directly feeding the machining processes. Images of machined surface textures were successfully trained CNNs for chatter detection and surface roughness prediction [208]. Tool wear imaging was also used to train CNN for automatic wear state identification in the face milling process. The network model was pretrained using an automated convolutional encoder (ACE), and its output was set as the initial value of the CNN parameters for tool breakage identification.

5.4.4 Recurrent neural networks

There has been increasing attention to using RNNs, specifically LSTMs, for TCM during machining processes [7, 219]. Recently, LSTM was used for chatter detection [220] and surface roughness prediction [221]. For tool wear classification, the hidden state in the model that is the learned representation of input data can be connected to a softmax layer. In contrast, for tool wear prediction or remaining useful life (RUL), prediction regression layers can be linked to the RNNs. Zhao et al. [222] used a deep LSTM network using three-layer LSTMs with dropout on raw signal and obtained a higher performance for tool wear prediction using deep LSTMs comparing to a basic LSTM. They showed that the prediction accuracy is sensitive to the LSTM architectures, which should be defined by trial and error. They also discussed that when better task-specific LSTMs are desired, the acquired signals can be processed using the wavelet transformation method to obtain better meaningful or noise-free signals to be fed into the model. Aghazadeh et al. [223] employed wavelet transformation on the sensory data and fed the extracted features from the time-frequency domain to LSTM for tool wear prediction. They reported that LSTM outperformed MLP with above 10% in prediction accuracy. Cai et al. [23] developed deep LSTMs for tool wear prediction in milling. They combined the temporal features extracted by LSTMs with the process information to form a new input vector. Examples of process information are the material, feed, depth of cut, etc. [210].

They discussed that having the process information combined with the collected sensory data can significantly improve the prediction accuracy when the machining process runs under various operating conditions. They also reported a higher prediction accuracy using deep LSTMs compared to SVR, MLP, and CNN. Combining the process information (working conditions) with the sensory signals was practiced by Zhou et al. [224] for RUL prediction. Int J Adv Manuf Technol Hybrid and novel RRN-based networks have been designed to better extract the meaningful feature for process health and condition monitoring. For example, Gugulothu et al. developed an RNN based autoencoder to learn more robust embeddings from the multivariate input time series. Yu et al. [225] applied bidirectional RNNs to the RNN-based autoencoder network for RUL prediction in the milling process and showed the competitiveness of the proposed method. Vashisht and Peng [220] showed that using a low-cost current sensor and LSTM, chatter detection can be achieved with an accuracy of 98%. LSTM was also used to predict the surface roughness in the grinding process using the grinding force, vibration, and acoustic emission signals [221, 187].

5.4.5 LSTM-CNN

It has been discussed that while LSTMcaptures the long-term dependency in sequential data, its feature extraction capability is still lower thanCNN [226, 227]. This may be an obstacle for LSTM to directly analyze the raw time series data polluted by noise. Xu et al. [228] discussed that, unlike the CNNs, the inherent structure of LSTM does not consider spatial correlation. On the other hand, CNN does not consider the sequential and temporal dependency [228].

Therefore, to overcome the mentioned challenge, combined CNN-LSTM networks were used [229, 230]. In these models, the CNN was used for local feature extraction from the original sequential sensory data. The combined CNN-LSTM model was shown to yield superior performance than many other baseline models for tool wear monitoring [231]. An et al. [226][127] combined CNN with a stacked bidirectional LSTM (BLSTM) and unidirectional LSTM (ULSTM) for RUL prediction in the milling process.

CNN was first used for local feature extraction and dimension reduction from raw data. Then two layers of BLSTM and one-layer ULSTM were employed to encode the temporal information. The output of LSTM was connected to regression layers and predicted the RUL with an average prediction accuracy of up to 90%. Such a hybrid model could obtain more in-depth feature engineering with minimal need for expert knowledge for feature selection. A similar approach has been practiced for RUL and tool wear prediction [232, 233]. Niu et al. [232] used a 1D-CNN LSTM network architecture for RUL prediction.

The sensory data were decomposed using discrete wavelet transform for denoising, and statistical features were extracted from each sample. It was then fed into the 1D CNN-LSTM network for feature engineering, connected to a fully connected and dropout layer for RUL prediction. Zhao et al. [233] also showed that the performance of RNNs is improved when combined with CNN for local feature extraction. Different network architectures can be

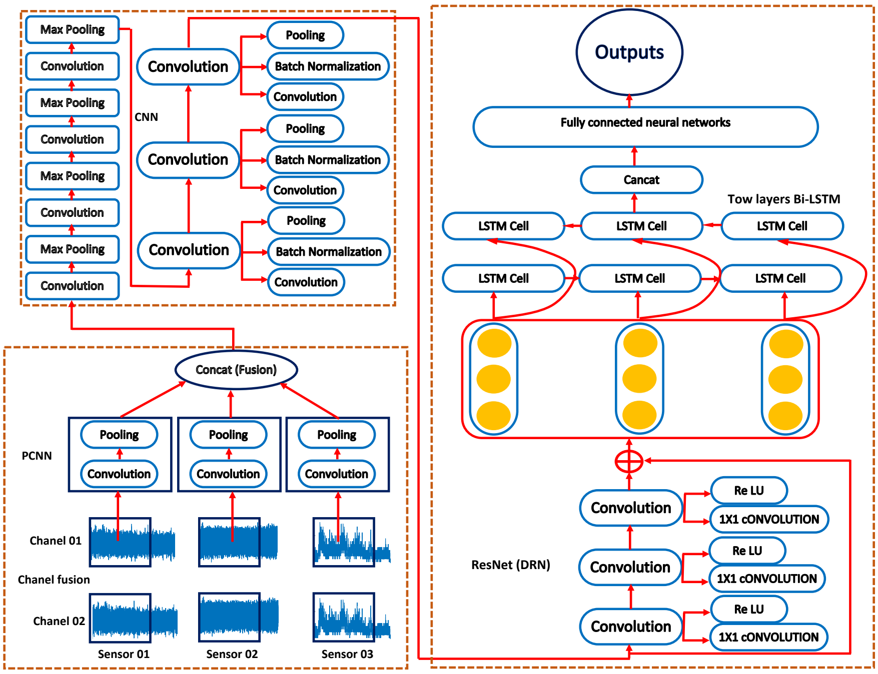


Figure 5.6: A feature-fusion-based CNN-LSTM model for flank wear prediction. [228]

disigned to address the process complexity and extract more meaningful features for process and tool monitoring. Qiao et al. [231] discussed that the features learned by lower layers of a deep learning model are the general features, while the features learned by higher lay-ers are more task-specific and more suitable for tasks such as TCM. Accordingly, they built a BLSTM network on top of a multi-scale convolutional long short-term memory model (MCLSTM) to further extract features related to the tool wear prediction tasks. It should be noted that the input data frommulti-sensors encompasses multi-scale features, which can-not be captured by the traditional LSTM or traditional CNN due to their lack of multiscale feature extraction ability [231, 234, 235]. To address that, Qiao et al. [231] employed a multiscale convolutional long short-term memory model that consisted of different parallel CNN layers. Xu et al. [228] designed a feature fusion- based deep model for flank wear prediction. Accordingly, they converted the signals from multiple sensors to images with multi-channels as the model input data. The input data were then fed into different CNNs to extract features in parallel from the multi-source data. The extracted features were then concatenated for multi-sensor information fusion (Figure9.6). The outpour of this process was then linked into BLSTMs and fully connected layers for tool wear prediction.

5.5 Proposed prognostics methodology

Prognostics and Health Management is an important task for maintenance cost reducing, equipment reliability increasing and dynamically maintain their critical engineering assets [236]. In (Figure9.7), the proposed methodology contains three key components: (1) sensors measurements, (2) feature extraction and selection, and (3) monitoring models for the health states classification in the decision-making step. A new engineering approach allows a real-time health assessment of the state of a tool and its future state (Figure9.7). The acronym PHM mainly comprises two elements [83].

1- Prognosis refers to health prediction by modeling the progression of faults severity, based on current state assessment and the future operating conditions;

2- Health management provide remote decision-making support for operators in unattended conditions and refers the capacity to intelligently carry out maintenance based on diagnostic / prognostic information.

Recently, several researches have been developed the deep learning approaches for PHM due to their great potentials applications [237] . Generally, the traditional applications of PHM have a fairly high practical barrier, as they need always human expertise in statistical analysis, signal processing, etc. The most important task for deep learning compared with traditional techniques is the automation of feature selection without extraction manually. This task reduces the height of the technical barrier of PHM applications and extract automatically the most representative features. The proposed approach is part of the PHM activities by using deep learning, more precisely the monitoring of cutting tool health status for RUL estimation. Based on data-driven approach and health indicator to provide a decision support tool for the industry.

In this study, an original prognostic approach is proposed based on PHM steps sequence, starting by signal acquisition. These latter are exploited to extract necessary information's, by the construction of HI on one side, and on the other signals processing to extract information related to degradation using VMD. Finally, design an expert system to learn and automatic assess tool health state based on 1D-CNN and BiLSTM network , and finally as shown in (Figure9.7).

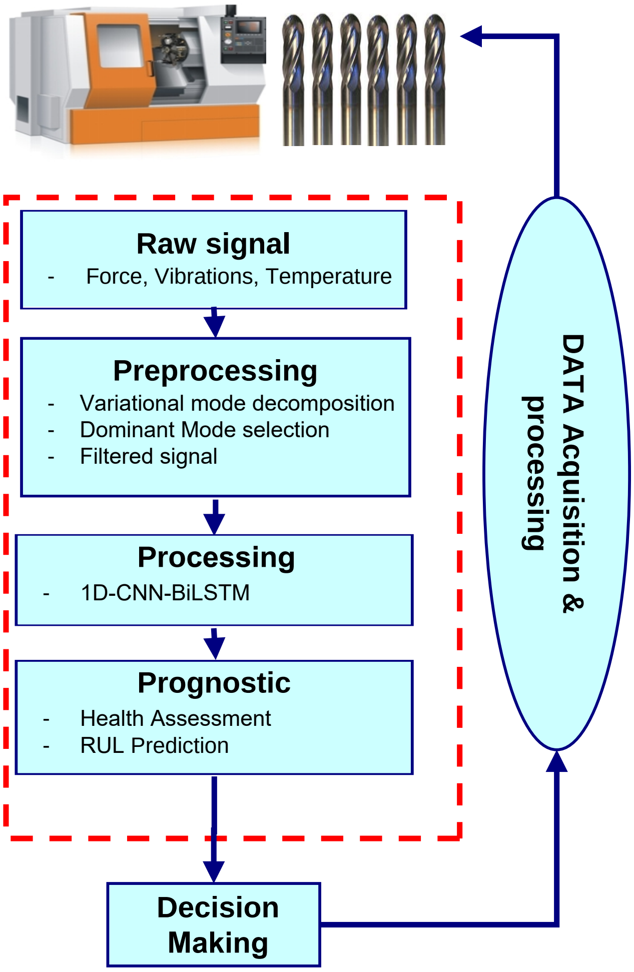


Figure 5.7: Proposed methodology.

In (Figure9.7), the proposed methodology contain four steps in the monitoring of machining process; The data acquisition step for data collection; preprocessing step consists of acquired and analyzing the collected signals. The processing step used the VMD values over time in order to facilitate the prognostics of time to failure for cutting tool. In the last step, englobing the RUL estimation with the proposed methodology based on the useful variables of VMD. (Figure5.8) shows this rough phenomenon of the degradation component's performance as it reaches entire failure point. Point t_P is the start of a component degradation where it is observed in the data. And point t_{EoL} or the End Of Life (EOL) indicates a complete failure of component. The time between when the failure is detected and the complete failure of components is the hole life of component.

PHM aims the assessment of the current state of physical system and predict its RUL before the failure. The objective is to maximize the operational safety and availability of the Cutting tool, and improved health management. An illustration of a remaining useful life is shown in (Figure9.8).

The predicted RUL can be obtained by estimating the time between the current time tc and the time tf related to the wear threshold. Therefore; the equation of the RUL is given by:

$$RUL(t) = 1 - HI^{-1}(t) \tag{5.19}$$

After this step, the proposed network can be trained to estimate HI, after, RUL can be calculated with a simple temporal inversion as in (Eq.5.19), unfortunately, the obtained results contain several fluctuations that do not have a physical meaning and can be reduced with a simple smoothing using moving average window. In the end, a comparison with traditional methods using average accuracy.

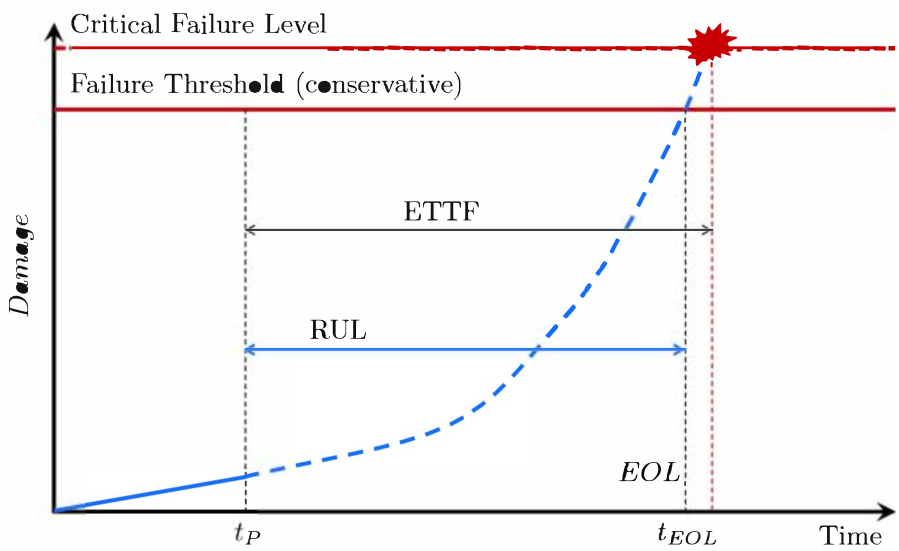


Figure 5.8: Illustration of remaining useful life.

5.6 Results and discussion

5.6.1 Description of NASA Ames milling data set

The data conducted on a milling machine under different operating conditions, including 16 cases, the description of the experimental conditions are shown in (Figure5.9) and (Table5.1). [238] The signals collected during the milling of cast-iron and stainless steel under

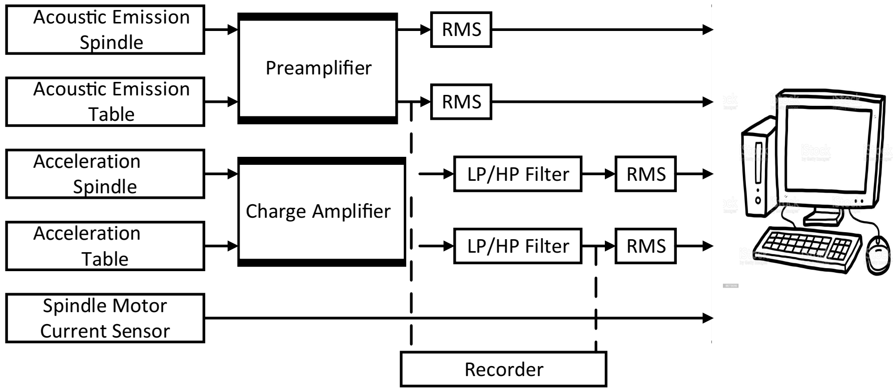


Figure 5.9: experimental setup for NASA Ames milling data set. [238]

the spindle speed of 826 rpm using the Matsuura MC-510 V machining center. Vibration, Acoustic emission and current sensors are mounted in the table and spindle. Sixteen cases with varying number of runs.
Taking the vibrations data of spindle and table as an example for the first and last machining cycle, the decomposition results are shown in (Figure9.10). The original signal is decomposed into 5 subseries with their corresponding frequencies, which are named from IMF1 to IMF5 with increasing frequency. The lowest frequency of the series IMF1 reflects the variation trend of original signal, while the highest frequency signal in IMF5.

5.6.2 Results for NASA Ames data set

igure.(5.11a).Figure(5.11b).Figure(5.11c) and Figure(5.11d) shown the predicted value and the actual value of the health index tool wears using the proposed approach for four tests of cutting tools from the good state of cutter up to the end of life of cutter wear values.

The results of different methods for NASA Ames milling machine runs under various operating conditions are shown in (Table5.2).

Table 5.1: Description of milling data set. [238]

Case	Depth of cut	Feed	Material
1	1.5	0.5	1-cast iron
2	0.75	0.5	1-cast iron
3	0.75	0.25	1-cast iron
4	1.5	0.25	1-cast iron
5	1.5	0.5	2-steel
6	1.5	0.25	2-steel
7	0.75	0.25	2-steel
8	0.75	0.5	2-steel
9	1.5	0.5	1-cast iron
10	1.5	0.25	1-cast iron
11	0.75	0.25	1-cast iron
12	0.75	0.5	1-cast iron
13	0.75	0.25	2-steel
14	0.75	0.5	2-steel
15	1.5	0.25	2-steel
16	1.5	0.5	2-steel

The proposed approach achieves the best performance. To illustrate the effectiveness, a difference between the proposed model and other methods are shown in (Table5.2), which shows that our proposed model is capable of predicting the tool wear with a reasonable prediction value and with a small error.

(Table9.2) Shown the results and the performances evaluation of tool wear estimation for different methods. Based on the results, the proposed approach has the highest average accuracy and with minimum of RMSE. It can be observed that relatively big difference between the accuracy of the other methods and the proposed approach by processing the signals using VMD method.

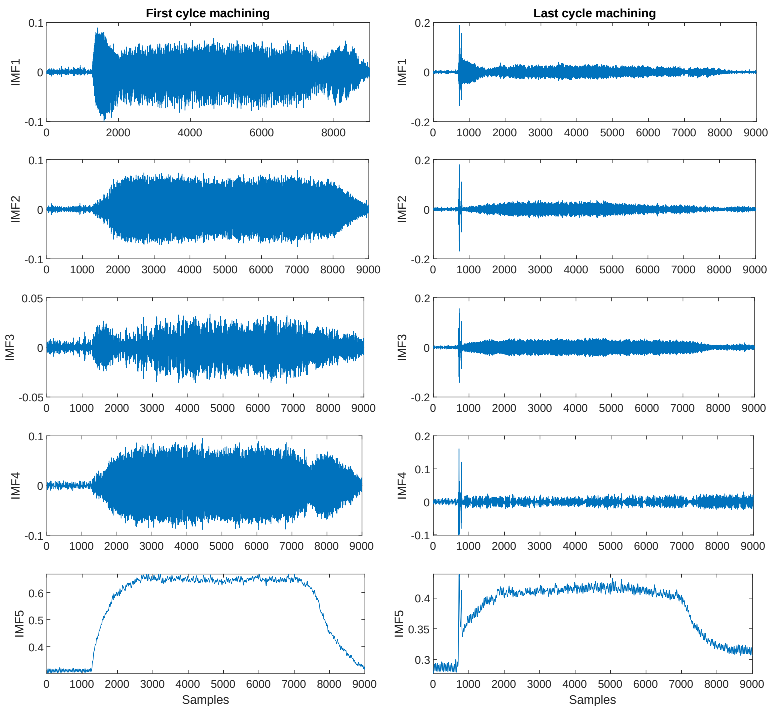


Figure 5.10: Variational mode decomposition of vibration spindle (left) and table (right).

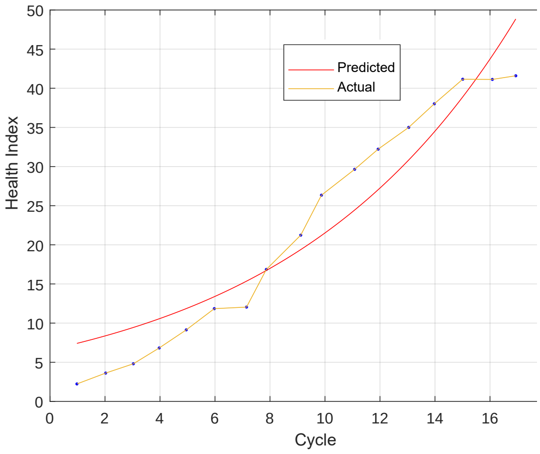
5.6.3 Description of 2010 PHM Data set

The evaluation of the proposed approach, tool wear task prediction conducted on a high-speed CNC machine tool Figure(5.13). The milling process experiments were carried out on a Roder CNC machining centre. The work piece is made of a hard material (Inconel 718) [242].

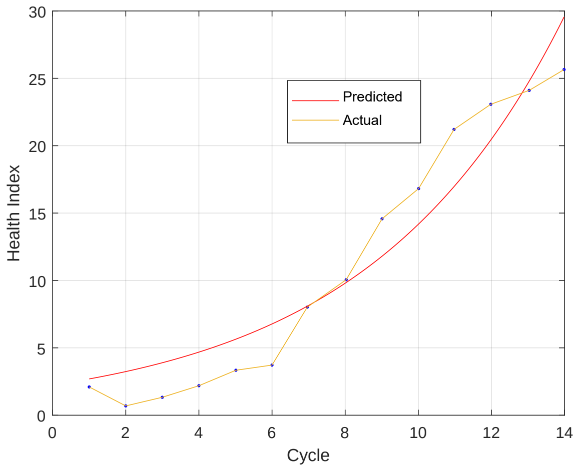
The piece used in this study is of square shape with a width a dimension of (112.5×78 mm). The number cutters are six made of tungsten carbide, round nose and with three cutting edges. They cutter speed is 10360 rpm, and with an advance of 1.555 m / min. The passes made are 0.125mm wide and 0.25mm deep. The signals collected (force in XYZ dimensions, acceleration in XYZ dimensions and acoustic emission) Figure(5.13). In this study 315 cuts were achieved using the cutting tools C1, C4 and C6, respectively. The cutter C4 taking as an example for learning.

5.6.4 RUL estimation for PHM data challenge

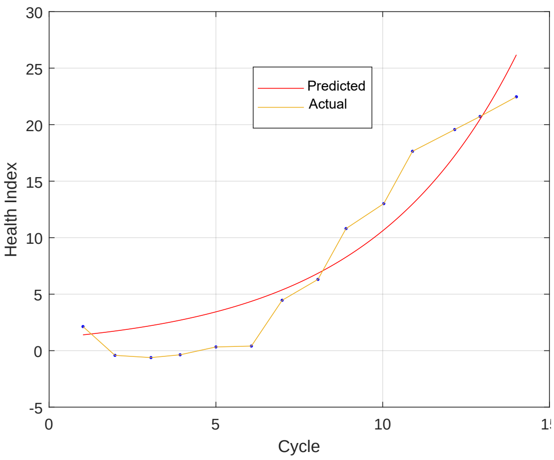
In this study, tool wear prediction method of cutting tool based on the structure of 1DCNN-LSTM is proposed. Firstly, the information's data is obtained by 1D convolution network. Then the temporal information of data is obtained by BiLSTM, which fully used the features



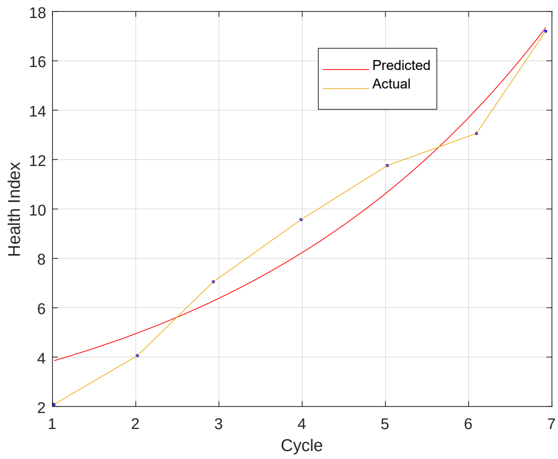
(a) Health indicator for case 1



(b) Health indicator for case 2



(c) Health indicator for case 3



(d) Health indicator for case 4

Figure 5.11: Health Indicator Prediction.

space-time of VMD shown in Figure(5.14).

The framework of the proposed approach for RUL prediction based on the VMD process is illustrated in Figure(5.14), and includes the training phase model and RUL phase prediction. Here, the parameters of the VMD model are determined in the model training phase in conjunction with a tool wear degradation process training dataset, while the RUL value and 95% confidence interval for the cutting tool are predicted in the RUL prediction phase.

At this stage, it's necessary to use signal processing technique allowing to appear useful information's, this framework propose to use VMD. Now, move to the construction of the health indicator, by the use of RMS as a statistical indicator, which is often used in prognosis frameworks, given that it is sensitive to degradation.

Table 5.2: Performance comparison (NASA Ames data set).

Methods	Average accuracy				RMSE			
	case 1	case 2	case 3	case 4	case 1	case 2	case 3	case 4
LSTM [23]	0.8512	0.9050	0.9108	0.9045	0.1512	0.1050	0.1108	0.1045
CNN [239]	0.9319	0.9733	0.8982	0.8820	0.2319	0.0733	0.0982	0.0820
IELM [240]	0.8853	0.8652	0.8731	0.8619	0.2147	0.1152	0.1068	0.0954
TCN [241]	0.9158	0.9249	0.9144	0.8891	0.1958	0.0749	0.1144	0.0891
Proposed	**0.9567**	**0.9747**	**0.9611**	**0.9432**	**0.1141**	**0.0564**	**0.0718**	0.0521

To show more the evolution over time, Figure(5.15) present different samples of degraded cutter, and makes it possible to conclude that this signal processing technique can provides useful information about the evolution of degradation.

To handle the extraction of useful features for the tracking of tool degradation, the proposed methodology uses CNN. This network uses two convolution filters of different sizes 64×5 and 32×5 to display features that evolve with degradation. Another type of layer is called Max Pooling with pooling size equal to 4, to compresses the information in the vector.

In the activity of prognosis, we often manipulate time-series, which represents a dependency in time and requires the use of deep neural networks with memory effect, which justifies the use of BiLSTM network, to benefit from the double temporal dependency. The proposed network in (Figure9.3), consists of input layer stacked with two layers of BiLSTM with 200 and 150 nodes respectively, and separated by two dropout layers with a rate of 0.2 to avoid overfitting, and finalized by two fully connected layers of 135 nodes each one, followed by a regression layer for RUL estimation.

By arriving at this step, HI can be predicted by training the proposed network and specify training options, in this paper, Adam optimizer is used, with a learning rate of 0.00001, minibatch size of 12, and using GPU execution, given at the end, a good learning progress-ing without overfitting.

After the training of the proposed model, the obtained results are shown in Figure(5.17), Figure(5.20), and Figure(5.22) for the prediction of HI, remarkably, the two curves are almost pasted, which shows the performance of the proposed methodology.

The wear evolution of the cutter C1 are shown in Figure(5.16). Firstly, the using data for cutters selected in this study (C1, C4 and C6) to build up a reference which can be utilized for tool wear prediction for cutters (C2,C3 and C5). Finally, the proposed model based on

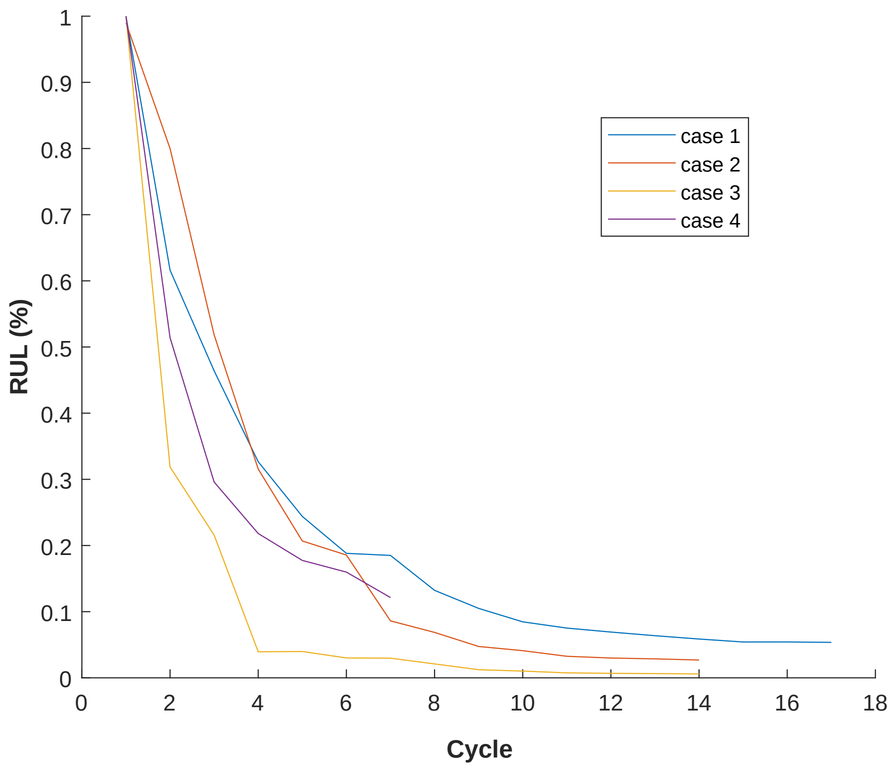


Figure 5.12: Remaining useful life estimation (NASA Ames data set).

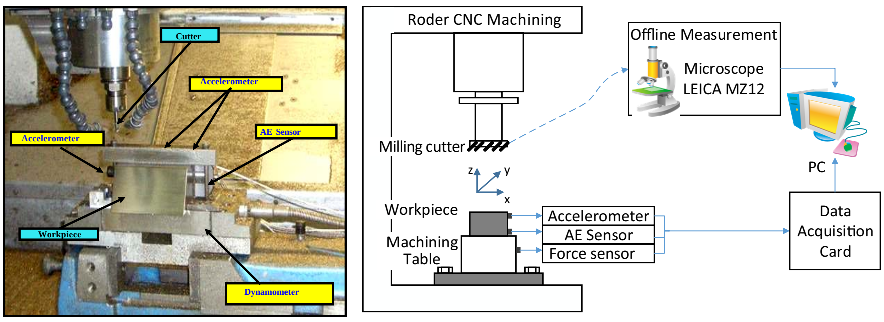


Figure 5.13: Experimental setup (2010 PHM Data set). [242]

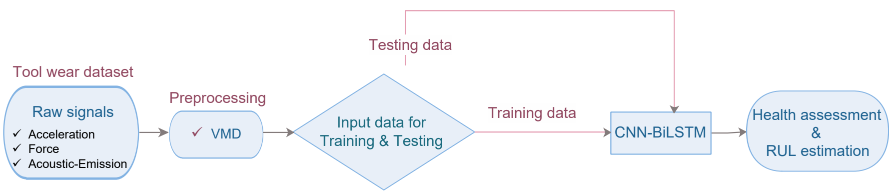


Figure 5.14: Flowchart of the proposed approach.

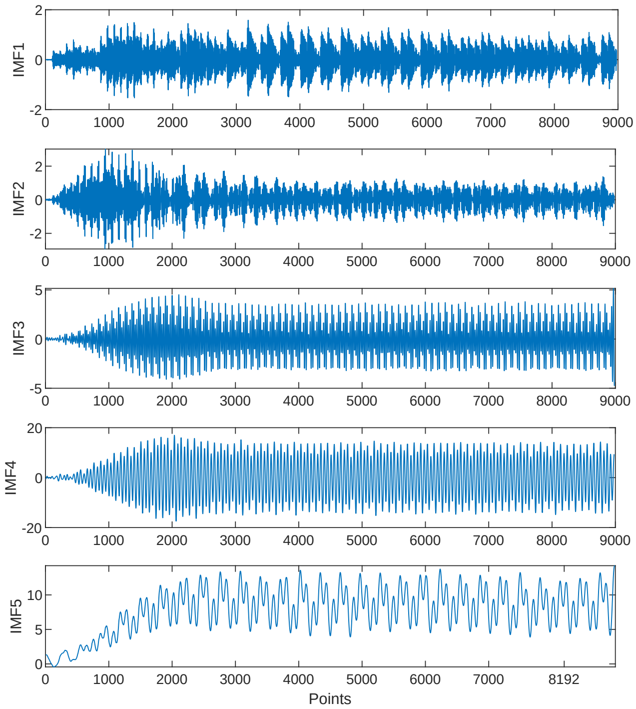


Figure 5.15: Variational mode decomposition of vibration signal (Cycle N∘ 150) (2010 PHM Data set) .

VMD-1DCNN-BiLSTM used to predict the tool wear and check the accuracy of each cutter.

The flank wear of three flutes shown in Figure(5.16) was measured in the experiment for each cut. The flank wears of the cutting tool C1 are shown in Figure(5.16). The recommendation of the ISO 8688–2 (1989), the cutter life limit is obtained by the mean wear of three flutes.

The output wear values shown in Figure(5.17), Figure(5.20) and Figure(5.22) of the three flutes w ere p rovided (in 1 0-3 m m). t he t raining c utters (C1, C 4 a nd C 6) w ere u sed for estimating the wear for the cutter (C2,C3 and C5). The value of the wear was predicted by the optimal input parameters of separation and the level of decomposition (L=7)and the signal from three dimension.

By a temporal projection, allows to estimate RUL in Figure(5.17), Figure(5.20), and Figure(5.22) from HI in Figure(5.17), Figure(5.19) and Figure(5.21), which present true and predicted values. Figure(5.17), Figure(5.19) and Figure(5.21), shows that the prediction have a tendency very close to the actual RUL.

In tool conditions monitoring in milling process, the threshold of wear depth in cutting tool is defined i n ISO8668 - 2 : 1 989 a s a c riterion o f t he h ealth i ndex o r e quivalent i n this

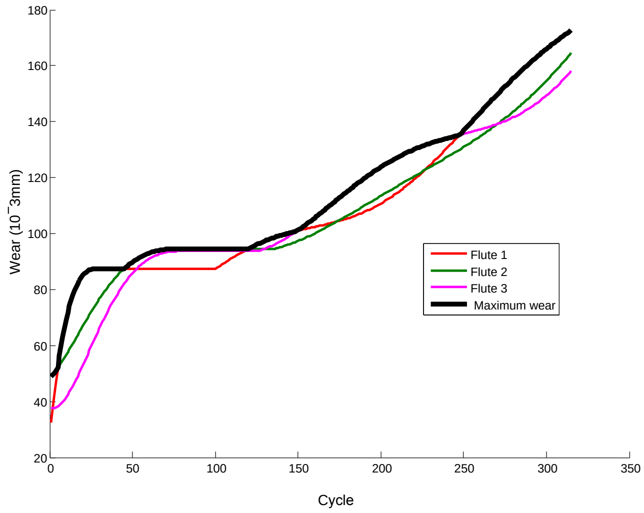


Figure 5.16: Three flutes wear for the cutter C1.

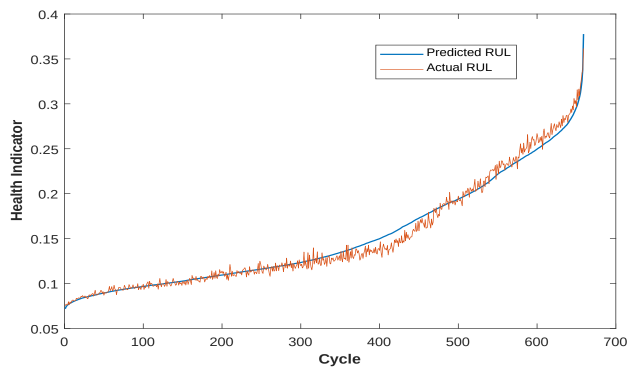


Figure 5.17: Health Index for cutter C1.

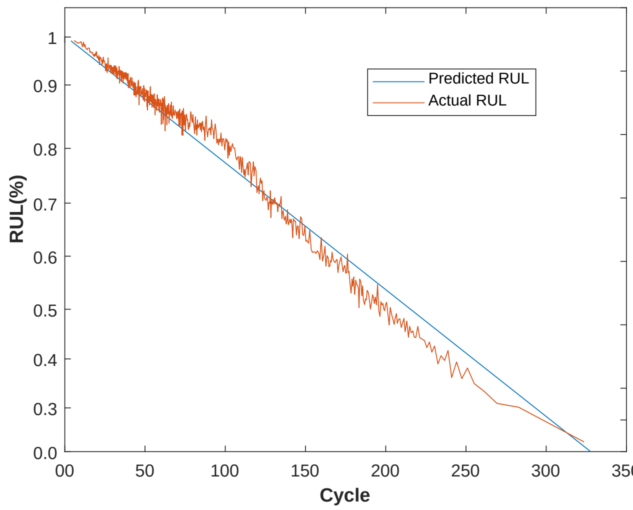


Figure 5.18: RUL prediction for cutter C1.

study of (0.4mm).

When selecting the models for the proposed approach, another important step is the model's complexity. The ResNet 50 architecture given a high level accuracy by comparing with other networks architectures (Alexnet and SqueezeNet). The proposed approach were chosen based on their regression performances tasks shown in (Table5.3).

5.6.5 Comparison of prediction performance with other methods

In this study three criteria are adopted for the performance evaluation of the proposed approach: The average accuracy, with an average length of 95% confidence interval. Here, The

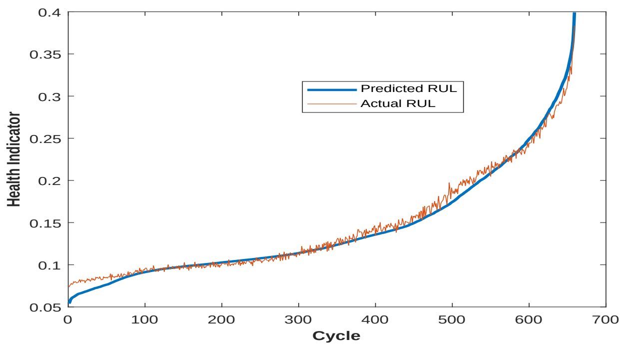


Figure 5.19: Health Index for cutter c4.

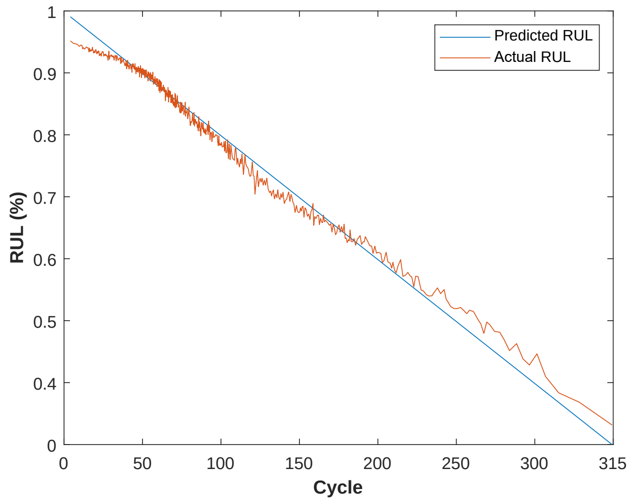


Figure 5.20: RUL prediction of cutter C4.

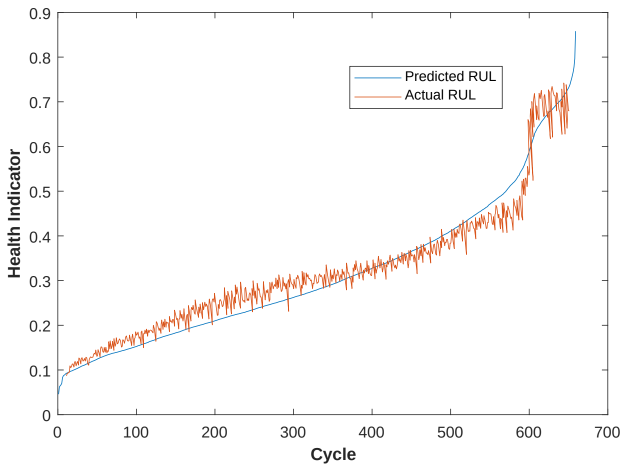


Figure 5.21: Health Index for cutter c6.

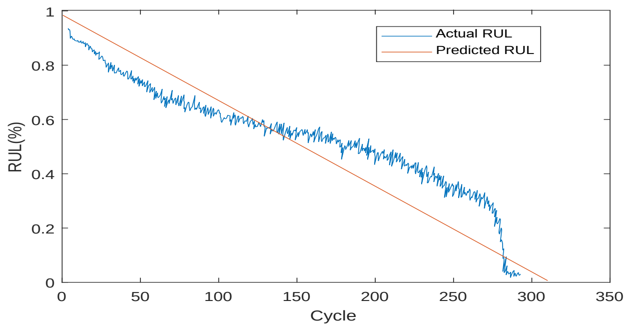


Figure 5.22: RUL prediction cutter C6.

indicators used to evaluate quantitatively the prediction quality was shown in (Table5.3). The calculations are given by the equation (Eq.5.20)

$$\bar{A} = \frac{1}{m}\sum_{i=1}^{m}\frac{\left|\hat{y}_i - y_i\right|}{\bar{y}} \tag{5.20}$$

In the end, the average accuracy were used to compare the performance of the proposed model with other machine learning methods, like BPNN, SVR, LSSVM, MLP. As shown in (Table5.3), the proposed model outperforms the aforementioned ML techniques in terms of all metrics by achieving the smallest values of average accuracy.

The training errors (Average accuracy) of the proposed model are calculated under different numbers of wear states. The results are shown in (Table5.3).When the number of wear states reaches 6, the training error decreases slowly. When the number of wear states

Table 5.3: Performance and comparison.

Algorithm	Average accuracy		
	c1	c4	c6
BPNN [175]	0.7872	0.8441	0.8975
LSSVM[176]	0.8522	0.7302	0.9201
SVR [243]	0.9136	0.7539	0.8046
LSTM [23]	0.7800	0.6847	0.8083
VMD-CNN-BiLSTM	**0.9188**	**0.9281**	**0.9221**

is too large, the sample points in each wear state will also decrease.

Therefore, the least tool wear state is selected within the allowable error range. From this, it is determined that the number of tool wear states is 6. The failure threshold of VB wear is set to 150 μm in this study. Firstly, using the tools 1 and 2 as the training set, the tool 3 as the test is set to predict the RUL sequence of the tool at the current moment. The prediction results of the proposed model are validated using cross validation method verifies the average accuracy of the above models.

In the view of all results of health indicator evolution shown in Figure(5.17), Figure(5.19), Figure(5.21), the average accuracy of the dataset presents significant improvement by comparing with traditional techniques shown in (Table5.3), and it illustrates the RUL of milling cutter's prediction has the potential and higher performance.

5.7 Conclusion

In this chapter a new hybrid deep learning approach for laser RUL estimation have been proposed. The proposed approach is coupled via fusion and a fully connected neural network to improve the performance based on the integration of a deep CNN LSTM model. A prediction method using data-driven approach of tool wear monitoring built by the structure of 1DCNN-BiLSTM is proposed in this study. At first, the VMD information of cutting tool is extracted by 1DCNN, and then the temporal information of tool wear is used to fed BiLSTM, which fully used the space-time features of cutting tool. The results obtained by this experiment show that the prediction value obtained by the proposed approach adopted in this paper has a small error and high average accuracy. VMD for signal processing and

1D-CNN-BiLSTM for learning dependencies of the degradation process. This proposed methodology is based on the steps of PHM, starting with signals from an experimental dataset of Intelligent Maintenance Systems, after the construction of the Health Indicator expressing the degraded state of the cutter and on the other hand, signal processing by the use of VMD, to be able after training an expert system using BiLSTM, in the end, to make this framework useful, different metrics evaluation are used to estimate the quality of prediction and compare with other traditional techniques.

From the obtained results, it is expected that the proposed approach gave higher prediction accuracy of RUL estimation than other existing approaches. Therefore, the proposed approach is very promising to the success of smart manufacturing operations for intelligent decision making. In the future scope, the other prediction methods

Conclusion & future scope

CONCLUSION & FUTURE SCOPE

6 Conclusion

The 4th Industrial Revolution (Industry 4.0) necessitates implementing the prognostics and health management (PHM) practices in manufacturing processes. The traditional machine learning approach has well assisted the PHM practices within the same data distributions. However, when a high noise environment, versatile operating conditions, and cross-domain machining is considered, it still lacks key steps of generalizing unknown tool faults. In an attempt to address PHM practices under such domains, a generic Deep Learning-based scheme is gaining significant a ttention. In this thesis, an inclusive review is presented in order to provide an insight into the application of DL in tool condition monitoring (TCM), particularly in milling. Commonly used DL algorithms and their applications toward TCM are initially discussed and number of illustrative DL models applied for TCM is presented. Later, emergent DL themes and their computational techniques are summarized with an intention to provide framework for domain generalization. Finally, challenges in further exploration and futuristic trends in TCM are discussed.

As size of data increases the performance of models using classical artificial intelligence increases. There are many machine learning approaches available for tool condition monitoring for milling process. The shortcomings of machine learning are accuracy, speed, ro-bustness etc. These are overcome with deep learning approach. The comparative study of different deep learning techniques are rigorously discussed. Depending of the nature of signals one can select appropriate technique for tool condition monitoring. The software and hardware are listed for deep learning. The comparison of different software used for deep learning is discussed. The comprehensive review shows that to meet emergent demands to successfully implement industry 4.0 deep learning approach plays an important role which overcomes the shortcomings offered by machine learning approach at some extent.

Data-driven prognosis has transformed machining monitoring by adopting machine learning and deep learning techniques to develop intelligent systems for monitoring the health and condition of cutting tools. Machine learning, in general, and deep learning, in particular, have had a significant impact on feature engineering and expert decision making by enabling automated feature selection, big data management and of large dimension, and avoiding the redundancy of the sensors. It also facilitates optimal data fusion and development of intelligent hybrid models that can be used for descriptive analysis for changing cutting tools before failure to inspect product quality. Despite its enormous opportunities, a data-driven industrial approach still faces challenges, particularly with regard to the size and quality of the data acquired. The concept of deep learning, its opportunities and limitations should be further investigated and compared to traditional machine learning models.

Comparative studies between different basic deep models and more complex hybrid models should be carried out. Small data challenges should be investigated by practicing data fusion methods and comparative studies between machine learning and deep learning. The concept of fusion at different sensor, functionality and decision levels needs to be evaluated and compared. The discrepancy between laboratory-scale results and real-world conditions should be emphasized by studying process uncertainty and applying cloud computing. Incremental and transfer learning can play a crucial role in bridging the gap between lab and industry. To fully understand the power of data-driven methods, smart machining must focus on big data acquisition. Additionally, the crucial role of feature engineering should be recognized in developing an attitude that incorporates feature selection and expert decision making to better uncover hidden patterns in data for intelligent monitoring.

This proposed research method based on data fusion enhanced deep learning to estimate tool wear value under different cutting conditions. Firstly, the original signals are decomposed and transformed to obtain high-dimensional feature series set through EMD, VMD and wavelet packet decomposition, and then CNN is employed to select useful features and Prediction results of LSTM and RNN and SVR Vibration signal Tool Spindle reduce the feature dimension, in order to reduce operational burden and improve the accuracy of regression.

Finally, these selected feature series are input into bidirectional LSTM network to estimate tool wear value. Hence, applications of the proposed method to milling TCM experiments demonstrate it outperforms significantly SVR- based and RNN- based methods under different cutting conditions.

Data-driven methods have transitioned machining monitoring into embracing machine learning and deep learning techniques for developing intelligent systems for process health and condition monitoring. Machine learning, in general, and deep learning, in particular, have significantly impacted feature engineering and expert decision making by allowing for automated feature selection, handling big and high-dimensional data, and avoiding sensor redundancy. It also facilitates optimal data fusion and the development of intelligent hybrid models that can be used for descriptive analytics for product quality inspection, diagnostic analytics for fault assessment, and predictive analytics for defect prognosis. Despite its huge opportunities, there are still challenges facing a data-driven industrial approach, especially concerning the size and quality of the acquired data. The deep learning concept and its opportunities and limitation should be further investigated and compared with the traditional machine learning models. Comparative studies among different basic deep models and more complex hybrid models should be performed. Small data challenges should be studied by practicing data fusion methods and comparative studies among machine learning versus deep learning. The fusion concept at different levels of sensor, feature, and decision should be assessed and compared. The gap between the laboratory scale results and real-life conditions should be emphasized by investigating the process uncertainty and applying cloud computing. Incremental and transfer learning can play a crucial role in bridging the gap from the laboratory to the industry. To fully comprehend the power of data-driven methods, intelligent machining should focus on big data acquisition. Also, the crucial role of feature engineering should be acknowledged by developing an attitude that integrates feature selection and expert decision-making to better unveil the hidden patterns in data for intelligent monitoring.

Annexes

ANNEXES

ANNEXES

A-Extreme learning 2010 PHM Data set:

CWT before separation (Force signal):

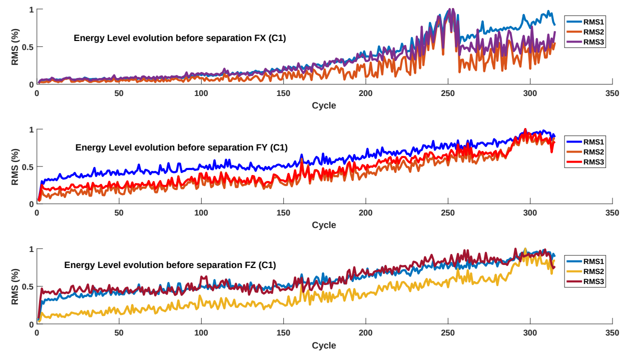


Figure 7.1: Energy Level evolution before separation Fxyz (C1)

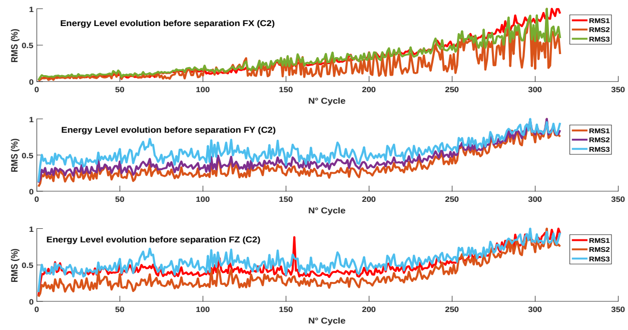


Figure 7.2: Energy Level evolution before separation Fxyz (C2)

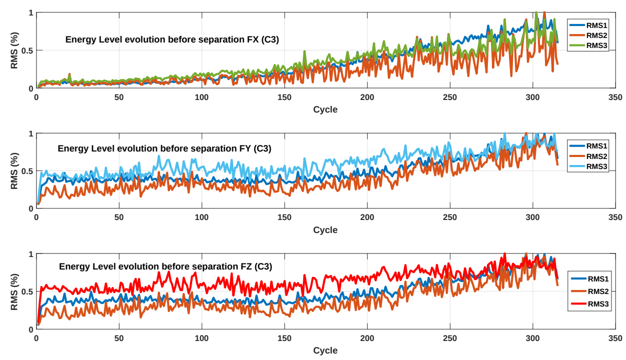


Figure 7.3: Energy Level evolution before separation Fxyz (C3)

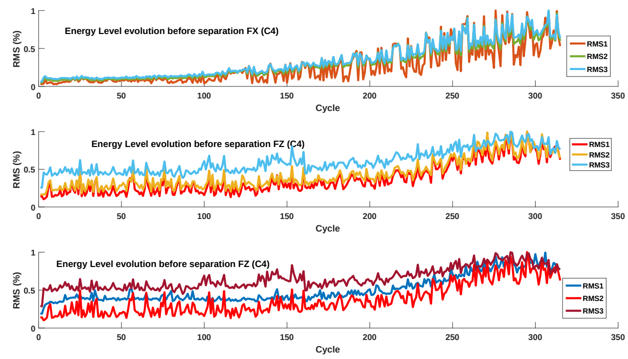


Figure 7.4: Energy Level evolution before separation Fxyz (C4)

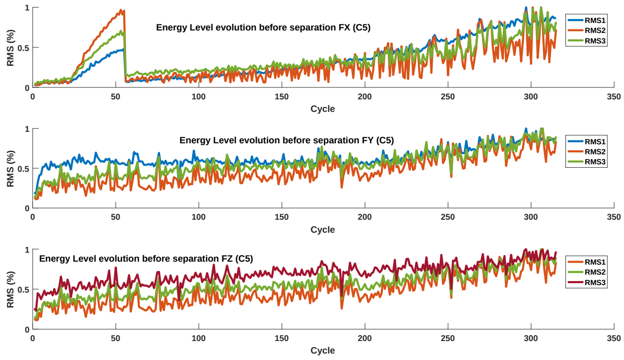


Figure 7.5: Energy Level evolution before separation Fxyz (C5)

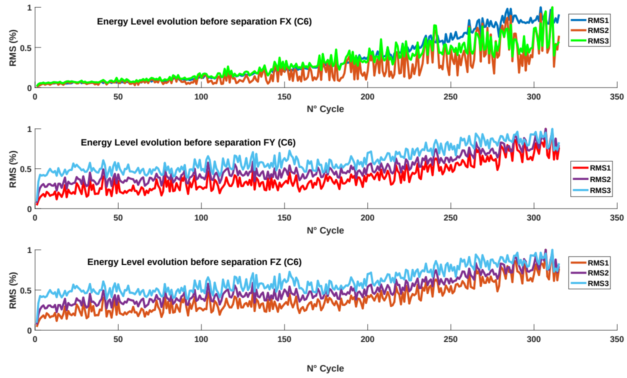


Figure 7.6: Energy Level evolution before separation Fxyz (C6)

CWT after separation (Force signal):

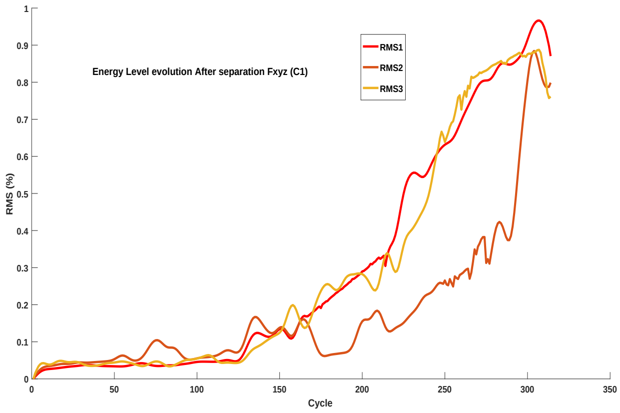


Figure 7.7: Energy Level evolution After separation Fxyz (C1)

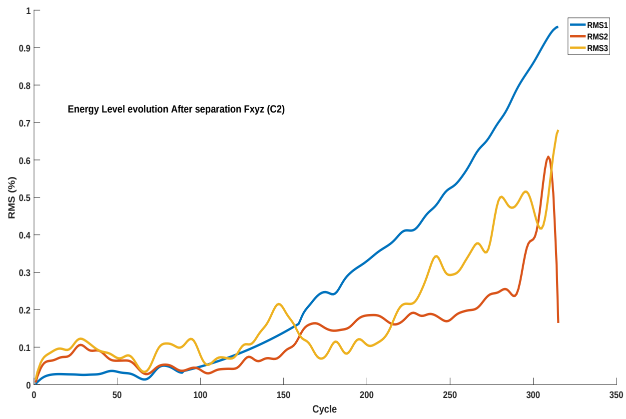


Figure 7.8: Energy Level evolution After separation Fxyz (C2)

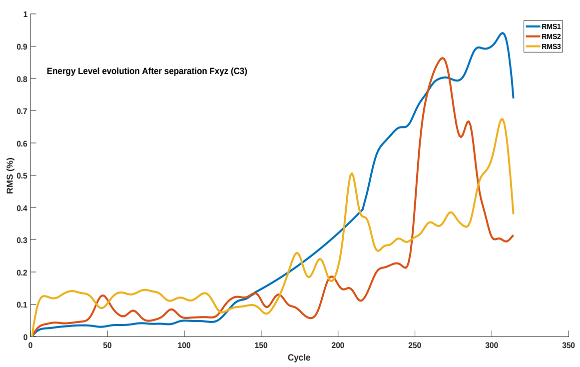


Figure 7.9: Energy Level evolution After separation Fxyz (C3)

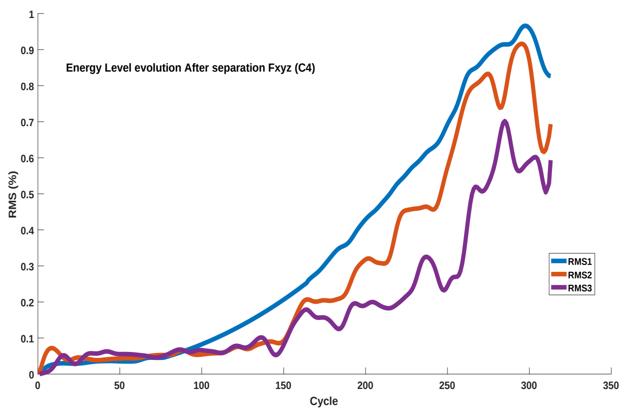


Figure 7.10: Energy Level evolution After separation Fxyz (C4)

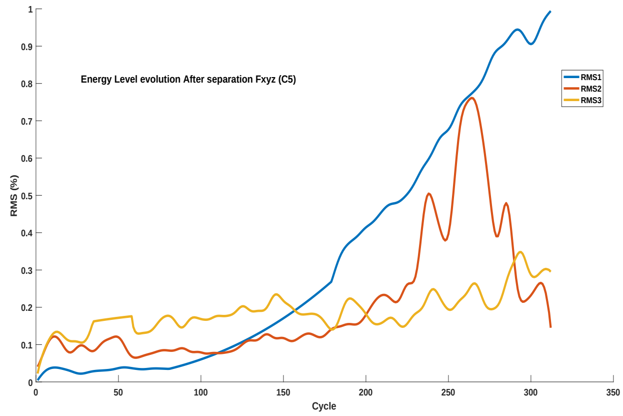


Figure 7.11: Energy Level evolution After separation Fxyz (C5)

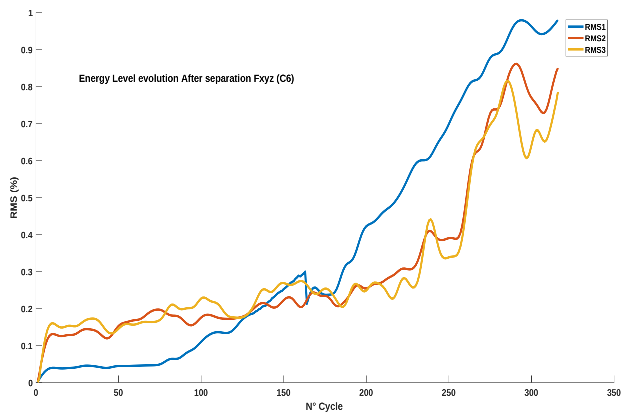


Figure 7.12: Energy Level evolution After separation Fxyz (C6)

Health Indicator (Force signal):

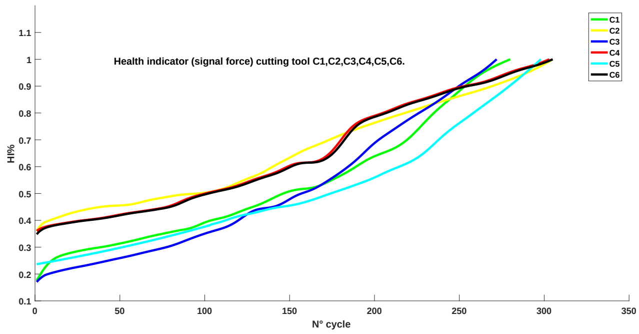


Figure 7.13: Health indicator (signal force) cutting tool C1,C2,C3,C4,C5,C6.

RUL (Force signal):

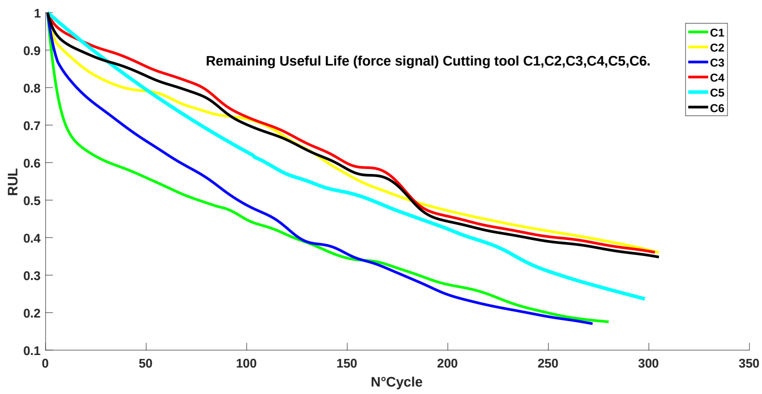


Figure 7.14: Remaining Useful Life (signal force) cutting tool C1,C2,C3,C4,C5,C6.

CWT before separation (Acceleration signal):

CWT after separation (Acceleration signal):

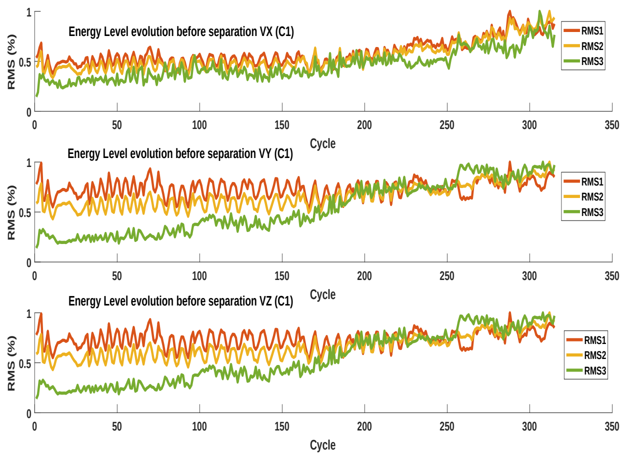


Figure 7.15: Energy Level evolution before separation Vxyz (C1)

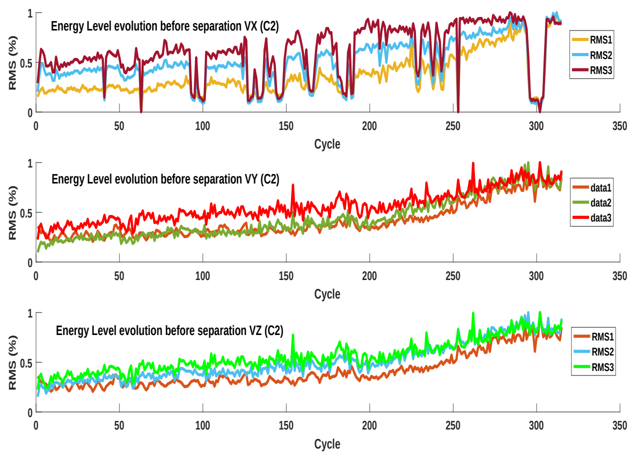


Figure 7.16: Energy Level evolution before separation Vxyz (C2)

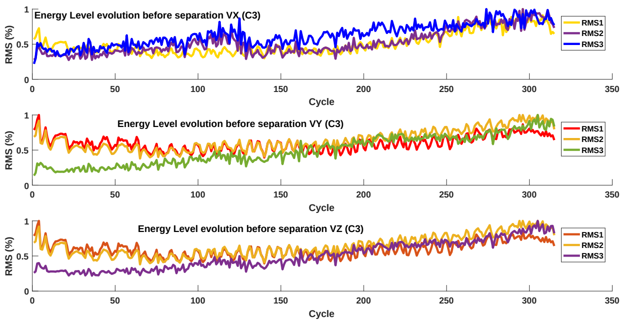


Figure 7.17: Energy Level evolution before separation Vxyz (C3)

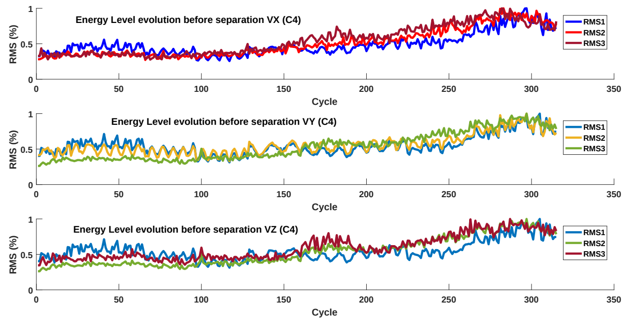


Figure 7.18: Energy Level evolution before separation Vxyz (C4)

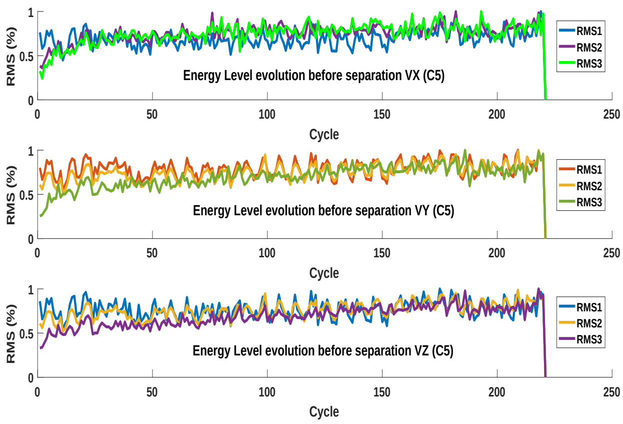


Figure 7.19: Energy Level evolution before separation Vxyz (C5)

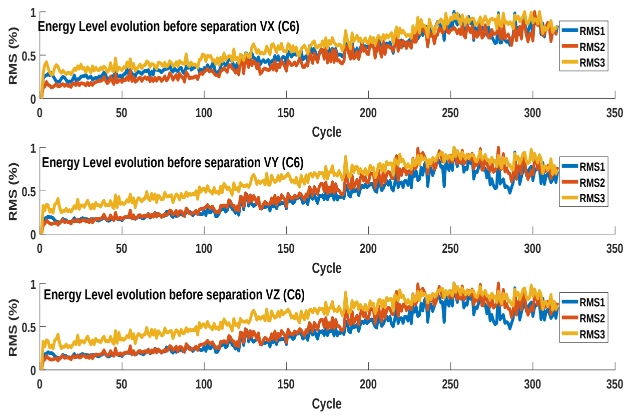


Figure 7.20: Energy Level evolution before separation Vxyz (C6)

Health Indicator (Acceleration signal): RUL (Acceleration signal):

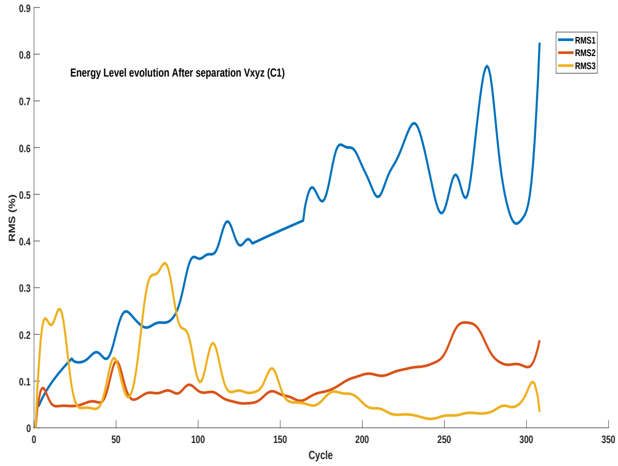


Figure 7.21: Energy Level evolution After separation Vxyz (C1)

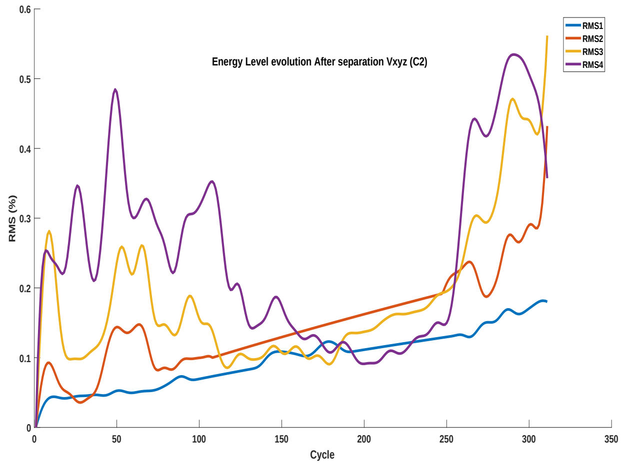


Figure 7.22: Energy Level evolution After separation Vxyz (C2)

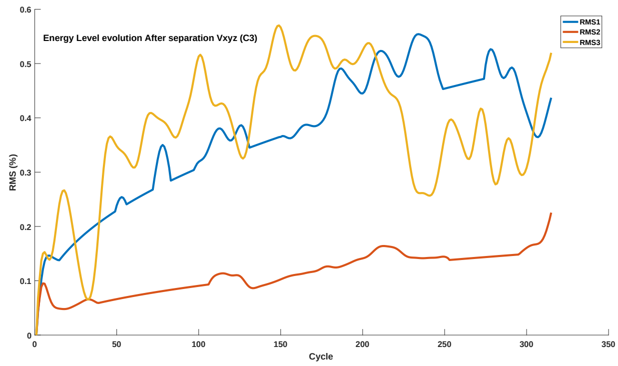


Figure 7.23: Energy Level evolution After separation Vxyz (C3)

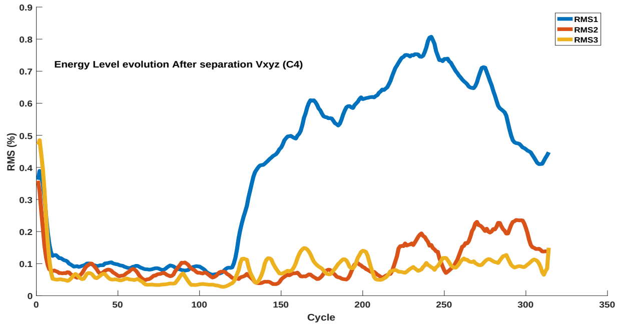


Figure 7.24: Energy Level evolution After separation Vxyz (C4)

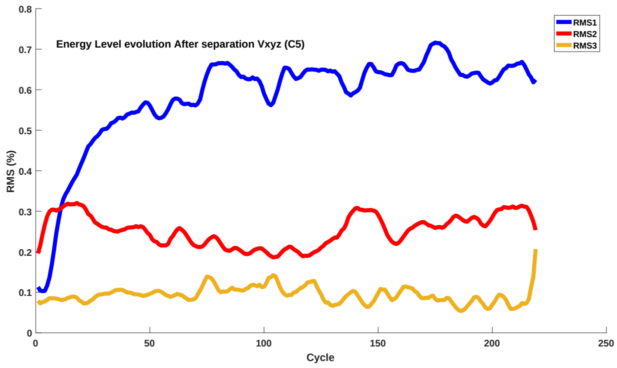


Figure 7.25: Energy Level evolution After separation Vxyz (C5)

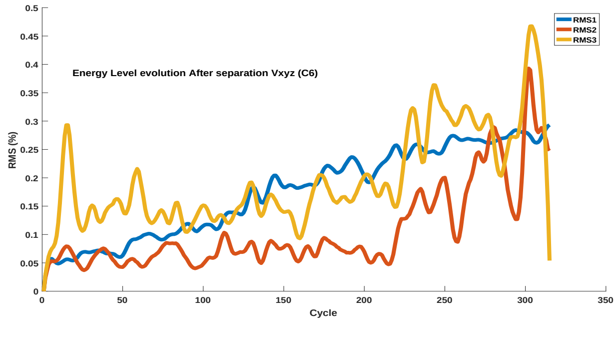


Figure 7.26: Energy Level evolution After separation Vxyz (C6)

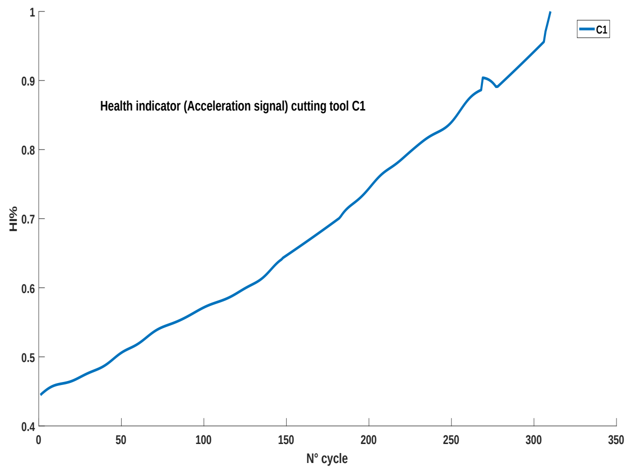


Figure 7.27: Health indicator (Acceleration signal) cutting tool C1

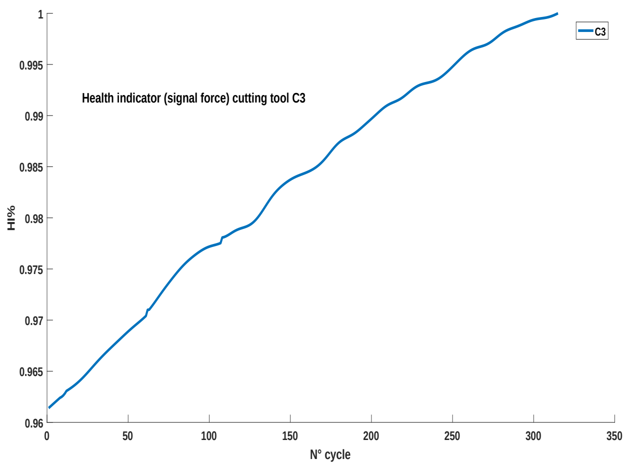


Figure 7.28: Health indicator (Acceleration signal) cutting tool C3

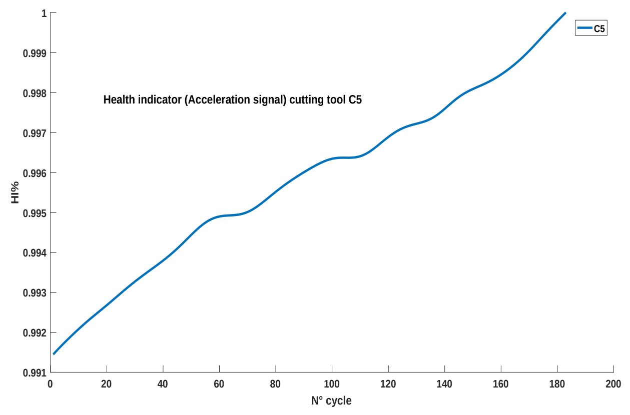


Figure 7.29: Health indicator (Acceleration signal) cutting tool C5

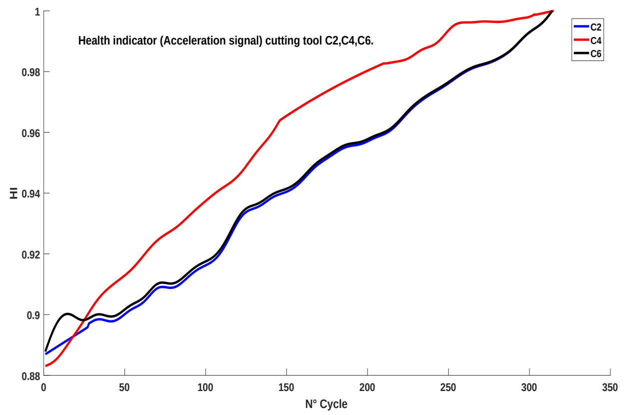


Figure 7.30: Health indicator (Acceleration signal) cutting tool C246

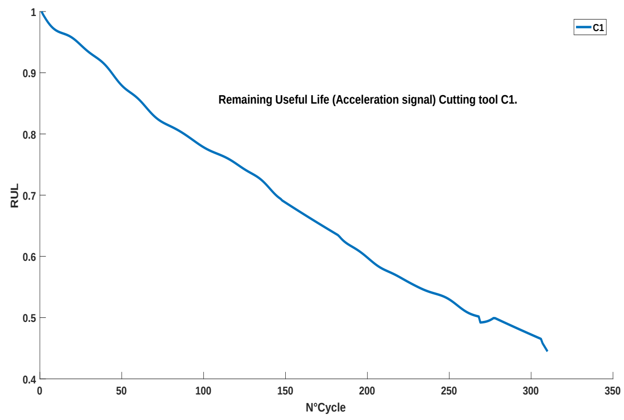


Figure 7.31: Remaining Useful Life (Acceleration signal) cutting tool C1

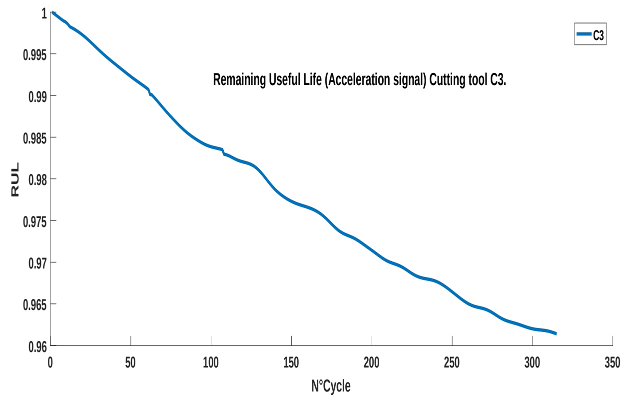


Figure 7.32: Remaining Useful Life (Acceleration signal) cutting tool C3

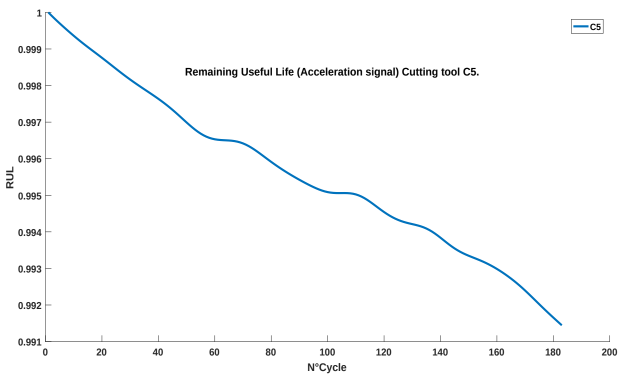


Figure 7.33: Remaining Useful Life (Acceleration signal) cutting tool C5

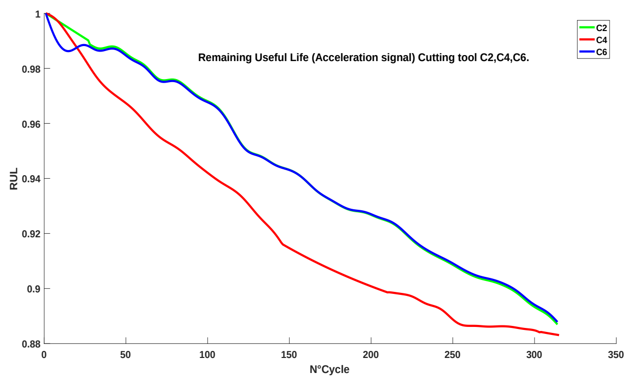


Figure 7.34: Remaining Useful Life (Acceleration signal) cutting tool C246

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