DATA-CENTRIC REAL-TIME INTEGRATION OF DIAGNOSTICS, PROGNOSTICS, AND PROCESS QUALITY CONTROL: REALIZING INTELLIGENT MANUFACTURING

Ph.D. Thesis

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DISCIPLINE OF MECHANICAL ENGINEERING
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DATA-CENTRIC REAL-TIME INTEGRATION OF DIAGNOSTICS, PROGNOSTICS, AND PROCESS QUALITY CONTROL: REALIZING INTELLIGENT MANUFACTURING

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AMIT KUMAR JAIN

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **DATA-CENTRIC REAL-TIME INTEGRATION OF DIAGNOSTICS, PROGNOSTICS, AND PROCESS QUALITY CONTROL: REALIZING INTELLIGENT MANUFACTURING** in the partial fulfillment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY** and submitted in the **DISCIPLINE OF MECHANICAL ENGINEERING, INDIAN INSTITUTE OF TECHNOLOGY INDORE**, is an authentic record of my own work carried out during the time period from July 2013 to April 2018 under the supervision of Dr. Bhupesh Kumar Lad, Associate Professor, Discipline of Mechanical Engineering, Indian Institute of Technology Indore, India.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Signature of the student with date
(AMIT KUMAR JAIN)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Signature of Thesis Supervisor with date
(Dr. BHUPESH KUMAR LAD)

AMIT KUMAR JAIN has successfully given his Ph.D. Oral Examination held on **16th October 2018**.

Signature of Chairperson (OEB) Date:	Signature of External Examiner Date:	Signature of Thesis Supervisor Date:
Signature of PSPC Member #1 Date:	Signature of PSPC Member #2 Date:	Signature of Convener, DPGC Date:
Signature of Head of Discipline Date:		

PROLOGUE

The systematic and easy to use tool condition monitoring systems and integrated methods developed in this thesis are radically essential for manufacturing industries. At its most fundamental level, it enables 'data-centric real-time integration of diagnostics, prognostics, and process quality control, to realize a holistic view of intelligent manufacturing to machinists, thereby forming the basis for building an autonomous decision-support system and serves as a guide for joint consideration of critical strategic operational policies and several additional progressions in the contemporary state-of-the-art. More specifically, the thesis resulted in the following contributions:

a) A methodology for dynamic optimisation of process quality control and maintenance planning, considering the real-time health state of the system is formulated and experimentally validated.
b) Solved one of the standing and non-trivial problems of literature viz. prognostics (predicting remaining useful life) under dynamic operating profiles. The proposed generic prognostic approach encompasses all real-world industrial scenarios.
c) A novel integrated diagnostics and prognostics system based on the relationship between product quality and tool degradation is proposed and validated.

In essence, the outcomes of the research in this thesis advances the existing body of knowledge by developing an autonomous decision-support system and methods for systematic expansion of intelligent manufacturing in diverse real-world production environments.

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Amit Kumar Jain

Dedicated to my

Parents (Sunil Kumar Jain, Rajni Jain),

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LIST OF PUBLICATIONS

Peer-reviewed Journals

1. **Jain, A.K.,** and Lad, B.K., (2017), "Dynamic optimization of process quality control and maintenance planning." *IEEE Transactions on Reliability*, vol. 66, no. 2, pp. 502-517, doi: 10.1109/TR.2017.2684709, IEEE. [Impact Factor: 2.729] [Citations^: 1]

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5. **Jain, A.K.,** and Lad, B.K., (2015), "Quality control based tool condition monitoring." *In Annual Conference of the Prognostics and Health Management Society*, pp. 1-10, San Diego, California, USA. [Citations: 2]

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^ *The citations mentioned are not self-citations, and database is from Google Scholar (Dated 11-10-2018).*

^^ *Journal visibility factor, retain a similar definition as that of the impact factor.*

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

Chapter 1

V'	Cutting speed
L_i	Tool life
n'	Constant
C'	Constant

Chapter 3

W_i	Wear
T_i	Time
p_i	Predicted value
a_i	Actual value
N	Number of fitted points
F_{av}	Average force
V_{sk}	Skewness
A_{sd}	Standard deviation
R^2	R-Squared value

Chapter 4

$P_{R_{a_i}}$	Product quality in terms of average surface roughness of the i^{th} product
$\overline{P_{R_a}}$	Mean of product quality in terms of average surface roughness
T_{W_i}	Tool degradation in terms of tool wear at i^{th} cutting process
$\overline{T_W}$	Mean of tool degradation in terms of tool wear
$P_{R_{a_{R_i}}}$	Rank of the product quality in terms of average surface roughness of the i^{th} product
$T_{W_{R_i}}$	Rank of the tool degradation in terms of tool wear at i^{th} cutting process
N	Total number of cases in the analysis
R_{a_i}	Average surface roughness of the i^{th} product

L	Sampling length
$Y(x)$	Coordinate of the roughness profile curve
C	Regularization parameter
ξ_i	Slack variable
z	Label vector
α	Lagrange multiplier
k	Number of health states
F_t	Tools time-to-failure
C_{t_i}	Time from when the RUL is estimated
w	Vector of weights
x	Bias
v	Model parameter
T_P	Total number of correctly recognized true positive samples
T_N	Total number of correctly recognized true negative samples
F_P	Total number of correctly recognized false positive samples
F_N	Total number of correctly recognized false negative samples
P_A	Percentage agreement and P_C is chance agreement
RUL_{P_i}	Predicted RUL and RUL_{A_i} is the actual RUL
$\overline{RUL_A}$	Mean value of actual RUL

Chapter 5

$D_s(t)$	Sensor-based degradation signal
$\xi(t)$	Operating profile at time t
Q	Set of profiles
ω	Degradation rate function
$D_s(\xi\,(t_i))$	Degradation signal under a distinct profile
t_i	Time at i^{th} instance
L_s	Length of the degradation signal
φ_n	Discrete operating bins
$G(\xi(t))$	Jerk function

χ_{A_i}	Indicator function over the interval A_i at time instant t_i
J_{ij}	Total number of times the profile i switches over profile j from time 1 to N
$D_i(N)$	Number of visits in i
ϑ	Number of visits in first operating bin (φ_1)
$\mho$	Jerk magnitude
$Y(t)$	Aggregate of profiles transition
$\varepsilon(t)$	White noise stochastic process
F_n	Time for signal to reach F_T
LT_a	Actual lifetime

Chapter 6

F_{TD}	Failure due to tool degradation
$[OTC]_{(Q\times M)_{RT}}$	Expected total cost of dynamic and integrated process quality control and maintenance planning, considering the real-time health state of the system
$T\ [CQL]_{PF}$	Expected total cost of quality loss owing to process failure
$T\ [C_{PR}]$	Expected total cost of preventive replacement
T_E	Evaluation time
δ_{S_n}	Multi-state magnitude of process shift
δ_{S_I}	Multi-state magnitude of process shift while the tool is in stage I
$\delta_{S_{II}}$	Multi-state magnitude of process shift while the tool is in stage II
$\delta_{S_{III}}$	Multi-state magnitude of process shift while the tool is in stage III
$\beta_{\delta_{S_n}}$	Probability of Type II error
$R_{\delta_{S_n}}$	Fraction of non-conforming unit owing to the magnitude of the shift
PF_{TD}	Process failure rate owing to tool degradation
P_r	Production rate
$f(\theta,\eta)_{T_E}$	Expected number of failures due to tool degradation for a given

	evaluation time as a function of given shape parameter and scale parameter
t_1	Expected time to authenticate the assignable cause
$T[t_I]$	In-control time
t_0	Inspection time for a false alarm
S	Number of samples during in-control state with process failure rate
ARL_1	Average run length in in-control state
$T[(C_{CR})_{F_{TD}}]$	Expected cost of carrying corrective replacement for a valid alarm owing to tool degradation
M_{CR}	Mean time to perform corrective replacement
M_L	Mean life of the tool
$CRUL_i$	Cost of lost remaining life
L	Cost of labor
C_{FCR}	Fixed cost of corrective replacement
$T[T_{cycle}]$	Expected process cycle length
τ	Expected time between the event of an assignable cause and the subsequent sample
t_s	Expected time to chart a sample
$T[C_S]$	Expected cost of sampling per cycle
$T(C_{IC})$	Expected cost of rejection occurred during functioning of process in in-control
$T(C_{OC})$	Expected cost of rejection occurred during functioning of process in out-of-control
C_{FS}	Fixed cost per sample
C_{VC}	Variable cost per sample
$T[C_{FA}]$	Expected cost of assessing the false alarms
C_{FA}	Cost of false alarm
R'	Fraction of non-conforming items during in-control state
C_R	Cost of rejection per piece

$T[C_{Process}]$	Cost of process failure per cycle
t'	Time period
ARL_2	Average run length in out-of-control state
C_T	Cost of tool
C_p	Cost of lost production
M_{PR}	Mean time to perform a preventive replacement
C_{FPR}	Fixed cost of preventive replacement
$(C_{CR})_{F_{TD}}$	Cost of detecting the assignable cause owing to tool degradation

ACRONYMS

TCM	Tool Condition Monitoring
RUL	Remaining Useful Life
CNC	Computer Numerical Control
SO	Sub Objective
UCL	Upper Control Limit
LCL	Lower Control Limit
AE	Acoustic Emission
RMS	Root Mean Square
PHM	Prognostics and Health Management
AE-RMS	Acoustic Emission-Root Mean Squared
ANN	Artificial Neural Network
FFBP	Feedforward Back Propagation
LM	Levenberg Marquardt
MSE	Mean Squared Error
MAPE	Mean Absolute Percentage Error
TDI	Tool Degradation Indicator
SVM	Support Vector Machine
PCC	Pearson correlation coefficient
SCC	Spearman's Correlation Coefficient
C-SVC	C-Support Vector Classification
v-SVR	v-Support Vector Regression
RBF	Radial Basis Function
DA	Diagnostic Accuracy
SPF	Specificity
SEN	Sensitivity
P	Precision
MCC	Matthews Correlation Coefficient
ROC	Receiver Operating Characteristics
MAE	Mean Absolute Error

RAE	Relative Absolute Error
RRSE	Root Relative Squared Error
RMSE	Root Mean Squared Error
NB	Naïve Bayes
RB	Rule-based
HMM	Hidden Markov Model
DTMC	Discrete-Time Markov Chain
F	Feed
S	Cutting speed
D	Depth of cut
PA	Prediction Accuracy
FEM	Fault Estimation Model
RF	Random Forest
AFEM	Advance Fault Estimation Model
MS	Mild Steel
CR	Corrective Replacement
PR	Preventive Replacement
INR	Indian Rupees

ABSTRACT

Tool Condition Monitoring (TCM) is an essential technology enabling estimates of the health state (diagnostics) and Remaining Useful Life (RUL) (prognostics) of cutting tools. The available TCM systems do not suffice the adequacy to be viable in a real-world manufacturing environment, mainly due to complexity (viz. the high cost of embedding sensor technology into the prevailing systems), inadequate generalisation competences (viz. the vast majority of systems are strictly designed on the impression that along the entire lifespan of the cutting tool, the prevailing operating conditions or profiles are unvarying or does not affect the degradation), and applicability (viz. low accuracy, high computational time). Also, tool degradation has a significant effect on the product quality (viz. surface roughness). Along these lines, economic advantages may be obtained by developing efficient process quality control based on the real-time health state of the tool as a function of its life. For instance, a variable process quality control strategy may be economical compared to the uniform strategy throughout the life of the tool. From the TCM viewpoint, the routinely measured product quality characteristics can also serve as valuable inputs for cutting tool diagnostics and prognostics. Similarly, the operating parameters viz. cutting speed, feed and depth of cut have significant effects on tool life, product quality characteristics and in turn on shop floor operations policies.

It can be easily comprehended from the above discussion that a good understanding of interdependencies among cutting tool diagnostics, prognostics, process variables, and shop floor level operations policies (for example, process quality control) is required to comprehend the holistic view of the machining and manufacturing operations. These interdependencies, if explored and modelled appropriately, may help the manufacturing industries in striding towards their goal of intelligent manufacturing. Given that, in this thesis, these challenges are circumvented by forming the basis for building an autonomous decision-support system and integrated methods that serve as a guide for joint consideration of

diagnostics, prognostics, and process quality control in dynamic and diverse production environments.

The available TCM systems focus exclusively on the diagnostics or the prognostics tasks. Consequently, an integrated TCM system is non-existent. To overcome this bottleneck, the first advancement progressed in this thesis to the current state-of-the-art was the invention of a cognitive integrated monitoring system centred on the untapped relationship between product quality and tool degradation. This part of the research is a pioneering effort towards designing a simple, easily comprehensible monitoring system utilising minimum resources, expediting the smooth realisation of the intelligent manufacturing even in medium and small scale manufacturing industries. To do so, the first-hand design of a cost-efficient experimental strategy concerning high-speed CNC milling machining was implemented. Subsequently, a comprehensive correlation investigation was performed; revealing strong positive relationship exists between product quality and tool degradation. Mapping this untapped relationship, an integrated TCM system pertaining to diagnostics and prognostics was formulated. Herein, for the first time, the diagnostic reliability was enhanced by researching on the use of a multi-level categorisation of degradation. The prognostic competence was enhanced by formulating it explicitly for the tools critical zone as a function of tool life. The system is integrated in a manner that, whenever the degradation curve of the tool reaches the critical zone, prognostics module is triggered, and RUL is assessed instantaneously. An experimentation centred performance investigation showed that the system provides a robust problem-solving framework. In succession, the contributions carried an excellent prescience that will enrich the existing TCM systems by considering the product quality as a new element for health monitoring.

The next advancement circumvents the standing non-trivial challenge of inadequate generalization competences in the present-day state-of-the-art viz. the vast majorities of available TCM systems are strictly designed on the impression that along the entire lifespan of the cutting tool, the prevailing operating profiles are unvarying or does not affect the degradation. Thus, their applications are restricted in diverse practical manufacturing scenarios viz. batch or job production environments where the operating profiles are highly time-variant. Thus, it would be of practical value to equip the TCM systems with intelligence that allows responding to the uncertainty of time-variant operating profiles and adaptable under various real-world scenarios. Accordingly, a novel and a generic TCM system under the dynamic operating profile is invented to guarantee the expansion of intelligent manufacturing in diverse real-world scenarios viz. batch production, job production, micro to medium-scale production environments. In contrast to the existing literature, the methodology offered in this part of the work is conceptually unique, as the offered system explicitly addresses the challenges allied with time-variant operating profiles by integrating its physics capturing the uncertainty in the evolution of dynamic operating profiles, in real-time. This benefit in enriching the existing TCM systems to compute the cutting tool RULs while exploiting the prior condition-centric data, along with the future characteristics of operating profiles that the tool is likely to experience. For this, a new, adaptive, and hybrid stochastic degradation model is devised; engineered to unite strategic information viz. the evolution of the future profile, jerks owing to dynamic transitions, etc. Next, new mappings, i.e., degradation rate function, and jerk function to bring realistic characteristics are formulated. The other realistic feature is that in the model the degree of divergence in tool's degradation is related to the severeness of the in-progress profile. Subsequently, a new sorting algorithm to order the profiles with regard to their impact on the corresponding degradation rate is proposed. Also, for the first time, pioneering adaptive functioning structures are inventively designed to incite generalisation in diverse real-world scenarios viz. batch production, job production, etc. The resultant generic system approximates the degradation and delivers the RULs, in real-time. The experimental study lends significant credibility to the appropriateness of offered approach over the traditional approach under time-variant industrial scenarios. Additionally, the proposed prognostic algorithm under the dynamic operating profile is not only restricted to TCM but can be seen as a universal perspective of any prognostics research.

Further, as these advancements endow realisation of intelligent manufacturing in the diverse real-world environment, it becomes necessary to invent a new dynamic integrated policy that can unlock the potential of data-centric real-time integration of diagnostics, prognostics, and process quality control, realising a holistic view of intelligent manufacturing in a real-world environment. Despite the fact that the connection among these fields is not absent, yet research on the integration of quality and maintenance considering real-time health state of the system is still very constrained. In this regard, this part of the research presents a novel methodology for dynamic and simultaneous optimisation of process quality control and maintenance planning while considering the real-time health state of the system deteriorating with time. This will enrich the existing integrated policy by instantaneously considering machine deterioration, health state, and RUL, in real-time. On top, benefits the manufacturers to simultaneously adopt the most beneficial practice for optimising the process quality control, inventory control and maintenance planning of their industry-specific applications. First, a new and a cost-efficient TCM system is built to perform instantaneous diagnostics and prognostics tasks. Further, the existing process quality control policy is customised and extended to deal with machine deterioration with time. This is done via a proposed residual-life based evaluation and multi-state magnitude of process shift schemes. Moreover, the conventional maintenance planning model is enhanced to capture real-time remaining life information of the tool, thereby leading to optimum usage of a tool's useful life. These models are integrated and built in conjunction with the developed TCM system. As a result, the proposed dynamic integrated model evolves itself dynamically to re-evaluate the optimal values for the design parameters, i.e., sample size, the time between samples, control limit coefficient and preventive replacement interval used in the entire lifecycle of the manufacturing process. The implication results and guidelines under various real-world industrial scenarios expand the model's realism to the actual production systems. In succession, the predominant contribution brought is the dual advantage, i.e., it reduces the lost quality cost due to machine degradation and also improves the manufacturing system's reliability by protecting it against failures.

In essence, the outcomes of the research in this thesis advance the existing body of knowledge by developing an autonomous decision-support system and associated methods for systematic expansion of intelligent manufacturing in diverse real-world production environments. An added contribution lies in distinguishing suitability, stability, quality, reliability, robustness, applicability and comprehensibility of the offered methods in real-world manufacturing environments, through exhaustive performance and comparative investigations via experimental case studies. The integrated approaches developed in the current research result in significant savings in overall manufacturing cost. Wherein, the results of dynamic integrated policy and prognostics under dynamic operating profiles are a breakthrough in the field of industrial engineering, prognostics and health management, and intelligent manufacturing.

Chapter 1

Introduction

"Intelligent manufacturing is more than just a flashy catchphrase. A confluence of trends and technologies promises to reshape the way things are made".

Cornelius Baur, American Analyst

In this introductory chapter, the background, motivation, theory, gaps, objectives, methodology, and contributions of the current research are presented to highlight the challenges and significance of integrating diagnostics, prognostics, and process quality control for intelligent manufacturing. In the end, the outline of the thesis is given.

1.1 Research Background and Motivation

Innovations in manufacturing have led to improved product quality, increased flexibility, and higher productivity. Mainly these benefits are extremely reliant on the smooth functioning of several machine tool components, which go through a continuous degradation during their lifetime until a failure happens. Wherein, failures owing to cutting tool degradation are a principal source of unscheduled stoppage of a manufacturing system and are indeed expensive not simply affecting downtime, but contribute extensively to machine tool or workpiece damage (Rehorn et al., 2015). Additionally, the usage of dull or worn cutting tools directly affects the quality and the cost of the manufactured products. On that front, a few examinations and manufacturing industry statistics, direct that the extent of downtime because of cutting tool failures (both wear and breakage) on an average manufacturing system ranges from as low as seven percent (Yeo et al., 2000) to as high as twenty percent (Kurada and Bradley, 1997). Whereas, the expense of these cutting tools and their replacements grosses about three to twelve percent of the overall manufacturing cost (Malekian et al., 2009). Consequently, precisely evaluating the pending failure of an expensive cutting tool has turned into a dynamic research region since the late 1980s and early 1990s (Teti et al., 2010, Siddhpura and Paurobally, 2013). This stimulates an escalating notion of the so-called Tool Condition Monitoring (TCM). TCM is an empowering field of study comprising of innovations and strategies to investigate the reliability, foresee degradation progression, and lessen the operational risks in cutting tool life cycle. At its core, the TCM systems require systematic methods of diagnostics and prognostics. Diagnostics involves estimating the health condition, and prognostics involve assessment of the Remaining Useful Life (RUL) of the cutting tool. Studies have exhibited that if Computer Numerical Control (CNC) manufacturing systems are fortified with TCM, it can cut down seventy-five percent of the downtime, and boost throughput by ten to sixty percent, and even upraise machine availability beyond fifty percent (Rehorn et al., 2015). The conventional diagnostics and prognostics centered perspective of TCM may be sufficient if machine availability is the only concern. However, from the manufacturing operations point of view, one needs to look at various other aspects associated with tool degradation and its life. For example, tool degradation also affects product quality and in turn quality control policy for the particular machine. Similarly tool degradation rate and product quality characteristics will change with the operating conditions. Along these lines, from the shop-floor level operational polices perspective, economic advantages may be obtained by developing efficient process quality control based on the real-time health state of the tool as a function of its life. For instance, a dynamic process quality control strategy may be economical compared to the uniform strategy throughout the life of the tool. Similarly, operating conditions like speed, feed and depth of cut also affect tool life as well as process quality characteristics. It can be effectively grasped from the above discussion that a good understanding of interdependencies among cutting tool diagnostics, prognostics, process variables and shop floor level operations policies (viz. process quality control) is required to comprehend the holistic view of the machining and manufacturing operations. These interdependencies, if explored and modeled appropriately, may help the manufacturing industries in striding towards their goal of intelligent manufacturing- the next big change in manufacturing after three major revolutions brought out by the impact of mechanization, electricity, and information technology (Evans and Annunziata, 2012). As a result, the attention for new concepts and solution methodologies for real-world and integrated TCM systems has increased dramatically, not only in business management but also in the scientific community.

1.2 Problem Description

In the dynamic manufacturing environment, it is radically essential to equip the manufacturing systems with autonomous decision-support systems that are self-aware and coupled with the knowledge of how to recognize the current health state and how to relate the faults and their effects on the RUL, in real-time, to avoid sudden failure when a deviant health state has been detected. Moreover, extending this knowledge for well-organized process quality control and tool replacement is essential to make the manufcturing system intelligent. Though, in reality, the available TCM systems do not suffice the adequacy to be viable in a real-world manufacturing environment, mainly due to complexity (viz. the high cost of embedding sensor technology into the prevailing systems), inadequate generalisation competences (viz. the vast majority of systems are strictly designed on the impression that along the entire lifespan of the cutting tool, the prevailing operating conditions or profiles are unvarying or do not affect the degradation), and applicability (viz. low accuracy, high computational time). Moreover, tool degradation has a significant effect on the product quality. As follows, economic advantages may be obtained by developing efficient process quality control based on the real-time health state of the tool as a function of its life. For instance, a variable process quality control strategy may be economical compared to the uniform strategy throughout the life of the tool. From the TCM viewpoint, the routinely measured product quality characteristics can also serve as valuable inputs for tool diagnostics and prognostics. However, the operating parameters viz. cutting speed, feed and depth of cut also have significant effects on tool life, product quality characteristics and in turn on shop floor operations policies. Successively, for a holistic view of intelligent manufacturing, a good understanding of interdependency among process quality control, maintenance planning, and real-time health state of the system is required. These interdependencies, if explored and modelled appropriately, may help the manufacturing industries in striding towards their goal of intelligent manufacturing. Accordingly, the problem considered in this thesis is on a technological expansion of intelligent manufacturing to create a system capable of dynamic optimization of preventive tool replacement, process quality control, and lower manufacturing costs in diverse industrial scenarios. At its most fundamental level, the work aims to empower ‘data-centric real-time integration of diagnostics, prognostics, and process quality control, to realize a holistic view of intelligent manufacturing to operations manager, thereby forming the basis for building an autonomous decision-support system.

To explicitly formulate the problem a systematic literature review[1.1] is carried out. Critical findings and major research gaps are as follows:

Gap 1: The available TCM systems focus exclusively on the diagnostics or the prognostics or process monitoring task. Consequently, a real-time and integrated TCM system linking diagnostics and prognostics is non-existent.

Gap 2: In small and medium manufacturing industries offline quality measurement is very common. The inputs from quality measurements for diagnostics and prognostics may provide useful information, but not explored in TCM literature.

Gap 3: The vast majorities of available TCM systems are strictly designed on the impression that along the entire lifespan of the cutting tool, the prevailing operating profiles are unvarying or does not affect the degradation. Thus, their applications are restricted in diverse practical manufacturing scenarios viz. batch or job production environments where the operating profiles are highly time-variant in nature.

Gap 4: Despite the fact that the connection among diagnostics, prognostics and process quality control is not absent, the integration of quality and maintenance considering the real-time health state of the system entirely eludes literature.

1.3 Research Objective

Based on the findings from literature review the overall research objective is as follows:

Overall Objective: Development of an autonomous decision-support system and integrated methods pertaining to diagnostics, prognostics and process quality control for diverse real-world production environments.

[1.1] *The detailed literature review and research gaps are provided in chapter 2.*

The overall objective is further divided into the following Sub Objectives (SO):

SO1: Real-time integration of diagnostics and prognostics centred on the relationship between product quality and tool degradation.

SO2: Development of a generic tool condition monitoring system under dynamic operating profile.

SO3: Dynamic optimization of process quality control and maintenance planning while considering the real-time health state of the system.

1.4 Theoretical Preliminaries

Operating Profile: Relative motion is required between the cutting tool and workpiece to perform a machining operation. The primary motion is accomplished at a certain cutting speed. In addition, the cutting tool must be moved laterally across the workpiece. This is a much slower motion, called the feed. The remaining dimension of the cut is the penetration of the cutting tool below the original workpiece surface, called the depth of cut. Collectively, cutting speed, feed rate, depth of cut, etc. are called the cutting conditions or operating profile. For a machining process such as turning, cutting conditions like cutting speed, feed, depth of cut plays salient role in the efficient use of a machine tool. Also, it has been established experimentally that there is a definite relationship between the operating profile and tool life. For instance, Ojolo and Ogunkomaiya (2014) identified that the increment of spindle speed, feed rate and depth of cut value mostly will affect the tool life. Karpat and Özel (2007) showed that better tool life is obtained in lowest feed rate and lowest cutting speed combination. Most published works on metal cutting regard the cutting speed as having the greatest influence on tool wear and tool life (Kayhan and Budak, 2009). On that line, F.W. Taylor conducted extensive tool life tests based on tool wear land measurement and cutting speed, commonly referred as Taylor tool life equation as shown in Eq. (1.1) (Eker et al., 2012).

$$V'L_i^{n'} = C' \tag{1.1}$$

where V' is the cutting speed, L_i is the tool life, and n', C' are constants.

Tool Wear (Degradation): Most failures of engineering systems result from a gradual and irreversible accumulation of damage that occurs during a system's life cycle. This process is known as degradation. In case of cutting tools, the degradation occurs in the form of tool wear. Tool wear can be stated as “the change in the shape from its original shape during a cutting process by gradual loss of the tool material” (Zhong et al., 2013). Tool wear in milling occurs at higher rate as the tool becomes dull. Due to which cutting forces and temperature increases and immediate loss of sharp edges occurs. After a certain point, tool wear can cause sudden failure of the cutting tool. (Tansel and McLaughlin, 1993, Ertunc and Oysu, 2004). Tool wear affects the surface roughness of the workpiece, which is the main concern of a machining process. The power consumption from motors may also increase due to tool wear (Altintas and Yellowley, 1989, Zhang et al. 1995). Thus, it is important to monitor and prevent the tool failure during cutting to achieve high product quality and efficient production.

Surface Roughness: Surface roughness is defined as “the result of irregularities arising from the plastic flow of chips during the machining” (Lou et al., 1999). The most widely used parameters for surface roughness measurements are average surface roughness, ten point height of irregularities and maximum profile peak height (Zhong et al., 2013).

Process Quality Control: Process quality control is an important methodology for asserting standards in manufactured products by testing some samples from output against the specification. Techniques provided in quality control are methodologies to screen an on-going production process. Control charts are most essential techniques of statistical process control. “The control chart is a graphical display of a quality characteristic that has been measured from the sample versus the sample number or time” (Montgomery, 2007). The chart has a centre line that presents mean value of the quality characteristics corresponding to the in-control state. Two other horizontal lines, called the Upper Control Limit (UCL) and the Lower Control Limit (LCL). These limits are set so that if the process is in control, all of the sample points will fall between them. As long as the point plots within the control limits, the process is assumed to be in control, and no action is necessary. However, points that plot outside of the control limits is interpreted as evidence that the process is out of control, and investigation and corrective action are needed to detect and terminate the assignable cause for this behaviour.

Great significance is attributed to the work of Walter Shewhart (Shewhart, 1925) who developed the theory of control charts. Celano (2011) has presented a review of the most recent research contributions dealing with modelling the statistical process control. Traditionally, control charts have been designed with respect to statistical criteria only. This usually involves selecting the sample size and control limits. The frequency of sampling is rarely treated analytically. But the practitioners are advised to consider another factor such as a sampling frequency. Thus the selection of three parameters: (1) sample size (2) a sampling frequency or interval between samples and (3) the control limits, is usually called the design of the control charts. The design of control chart has economic consequences in which the costs of sampling and testing are associated with investigating out of control signals. Correcting the assignable causes and costs of allowing non-conforming units to reach the consumer are all affected by the choice of the control chart from an economic viewpoint. Duncan (1956) proposed the first economic model for determining the three control parameters of the X-bar control chart that minimizes the average cost when a single out-of-control state (assignable cause) exists. His cost model includes the cost of sampling and inspection, the cost of defective products, the cost of a false alarm, the cost of searching for an assignable cause, and the cost of process correction. Since then, considerable efforts have been devoted to the optimal economic determination of the three parameters of different control charts. Montgomery (1980) gave a thorough review of the literature of the economic designs of various control charts.

Tool Condition Monitoring: TCM involves investigating the reliability, foresee degradation progression, and lessen the operational risks in cutting tools life cycle. Generally, the evolution of these manifestations can be monitored using sensor technology through a process known as condition monitoring. The observed condition-based signals are known as degradation signals and are usually correlated with the underlying physical degradation process. Some examples of degradation signals include vibration signals for monitoring excessive wear in rotating machinery, acoustic emissions for monitoring crack propagation, temperature changes and oil debris for monitoring engine lubrication, and many others. Typically advanced TCM system consist of four steps: (i) collection of data from shop floor through sensors, (ii) extraction of features from the signals, (iii) classification/estimation of tool wear, (iv) development of decision making technique. At its core, the TCM systems require systematic methods of diagnostics and prognostics. Diagnostics consist of detecting the current health state of the cutting tool, and which is done after the occurrence of the fault, prognostics aim at anticipating the remaining useful life of the cutting tool, and thus is done a priori. Herein, by realizing cutting tools health sate and remaining life, support activities are arranged ahead of time.

1.5 Methodologies and Innovations

Fig. 1.1 shows the overview of the proposed methodology. The three prime innovations made in this thesis with the proposed methodologies are highlighted as follows:

A. Real-Time Integration of Diagnostics and Prognostics Centred on the Relationship between Product Quality and Tool Degradation.

First, the diagnostic reliability is enhanced by researching on the use of a multi-level categorization of wear. The prognostic competence is improved by formulating it explicitly for the tools critical zone as a function of tool life. The system is integrated in a manner that, whenever the degradation curve of the tool reaches the critical zone, prognostics module is triggered, and RUL is assessed instantaneously. Moreover, to improve the integrated TCM system performance, it is built using support vector machine with optimal training technique. The proposed methodology provides an excellent prescience that will enrich the existing TCM systems by considering the product quality as a new element for tool health monitoring. On the other hand, the information obtained from the current research results in significant savings in cost, time and improving productivity for a heavily competitive manufacturing industry. The research in this work is a pioneering effort towards designing a simple, easily comprehensible monitoring system to enable easy adaptation of the technology even in medium and small scale manufacturing industries. Moreover, experimental tests verify the viability of the system.

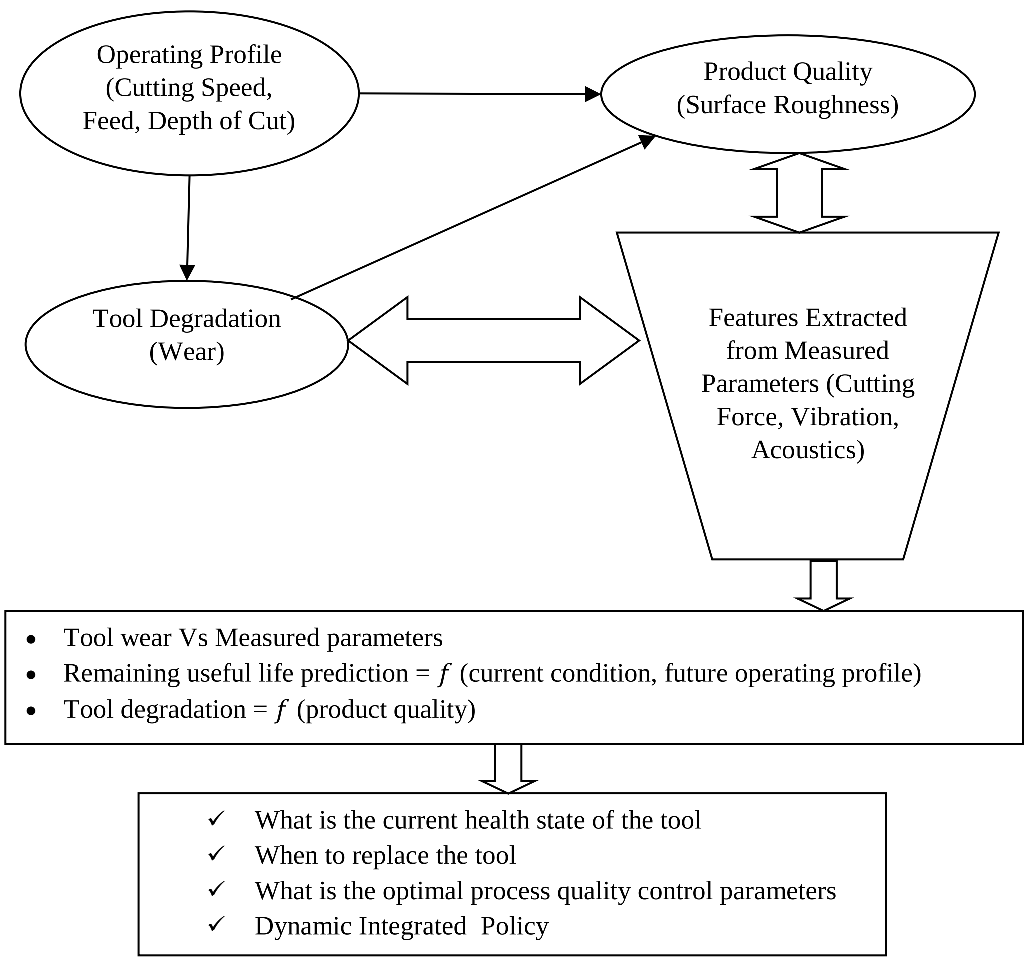

Fig. 1.1. Overview of the proposed methodology.

The novelty of this research is in the invention of an integrated TCM system by quantifying and mapping the relationship between product quality and tool degradation. This system ascertains reliable health monitoring and life prediction of the machining system at the same time with solitary experimentation. An added contribution lies in the outcomes; an exhaustive performance and comparative investigations of the proposed integrated TCM system is presented, to distinguish the suitability, stability, quality, reliability, robustness, applicability and comprehensibility in a real industrial environment.

B. A Generic Tool Condition Monitoring System under Dynamic Operating Profiles.

First, the cutting tool degradation progression is mathematically modeled via a new, adaptive, and hybrid stochastic degradation model; engineered to unite strategic information viz. the evolution of the future profile, jerks owing to dynamic transitions, etc. Next, new mappings, i.e., degradation rate function, and jerk function to bring realistic characteristics are formulated. Subsequently, the physics of evolution of dynamic profiles for various scenarios is inventively modeled. The resulting generalized system approximates the first passage time of the degradation process to a threshold and provides a precise life estimate in real-time. The proposed methodology is competent in approximating the uncertainty imposed by time-variant industrial scenarios. This aids in enriching the existing TCM systems to compute the cutting tool RULs while exploiting prior information, along with the future characteristics of operating profiles that the tool is likely to experience. Wherein, the experimental results confirmed that the offered approach delivers a generalized and a robust problem-solving structure for dynamic operating profiles. The research in this work and the promising results attained underneath dynamic operating profiles guarantee the expansion of an effective preventive maintenance plan in diverse real-world production scenarios viz. batch production, job production, micro to medium-scale production environments. On the other hand, the case study implementation lends significant credibility to the appropriateness of offered approach over the traditional approach under time-variant industrial scenarios.

The novelty of this research is three-fold. The first is the innovative design of a generic TCM system that accounts for the future characteristics of the dynamic operating profiles while prognosticating RULs. It is grounded in the physics of degradation progression and is a function of operating profiles. As a result, the fundamental advantage of utilizing the proposed system to deal with time-variant operating profiles is its proficiency to communicate the future evolution of dynamic operating profiles instantaneously. Second is the consideration of all-encompassing cases of industrial scenarios. For the first time, a complex real-world scenario of expected but fluctuating future operating profiles is well-thought-out. Third, it is not restricted to a specific machine tool, sensor, and so on; rather the system is adaptive and can be rendered as a first universal perspective to TCM and for that matter any prognostics research. An additional contribution lies in the outcomes; extensive quantitative and qualitative performance investigations are carried out. Further, in contrast to the traditional approach, the implications of the offered system under different scenarios are experimentally examined. That magnifies the robustness and applicability of the offered system in diverse real-world production environments.

C. Dynamic Optimization of Process Quality Control and Maintenance Planning while Considering the Real-Time Health State of the System.

First, the existing process quality control policy is enhanced to become dynamic and extended to deal with machine deterioration with time. This is done via the proposed residual-life based evaluation and multi-state magnitude of process shift schemes. Furthermore, the maintenance planning model is modified to capture real-time remaining life information. These models are integrated and built in conjunction with newly developed TCM system pertaining to instantaneous diagnostics and prognostics. As a result, the designed dynamic integrated model can evolve itself to re-evaluate the optimal values for the design parameters used in the entire lifecycle of the manufacturing process. The proposed methodology was proficient in capturing the interdependencies between process quality control and maintenance planning while considering the real-time health state of the system. This will enrich the existing integrated policy by instantaneously considering machine deterioration, health state, and remaining useful life. Wherein, the experimental results confirmed that the dynamic integrated policy is capable of early detection of an out-of-control process than the conventional usage of control charts. As a consequence, the information obtained from the current research results in significant cost savings in overall manufacturing cost. The implication of the proposed dynamic integrated policy under various real-world industrial scenarios revealed that this policy optimizes the inspection frequency, moderates the loss in production, consumes the optimum life of the system and delivers higher economic improvements. These implication results and guidelines expand the model’s realism to the actual production systems. This will benefit the manufacturers to adopt the most beneficial practice for optimizing the process quality control and maintenance planning of their industry-specific applications.

The novelty of this work is in the formulation of a dynamic integrated policy. Whenever a change in health state of the system is detected, the optimal design parameters of process quality control and maintenance planning are updated based on the current health state of the system as a function of its life. This dynamic integrated policy has the dual advantage, i.e., it eliminates the lost quality cost due to machine degradation and also improves the manufacturing system’s reliability by protecting it against failures. An added contribution lies in the outcomes; systematic performance and sensitivity investigation are presented. Moreover, the implication of the proposed policy in various industrial scenarios is critically analysed. This expands the model's robustness and relevance in manufacturing industries.

1.6 Contributions

The systematic and easy to use tool condition monitoring systems and integrated methods developed in this thesis are radically essential for manufacturing industries. At its most fundamental level, this work enabled ‘data-centric real-time integration of diagnostics, prognostics, and process quality control, to realize a holistic view of intelligent manufacturing to machinists, and formed the basis for building an autonomous decision-support system and serves as a guide for joint consideration of critical strategic operational policies and several additional progressions in the contemporary state-of-the-art. More specifically, the thesis resulted into following contributions:

a) A methodology for dynamic optimization of process quality control and preventive tool replacement while considering the real-time health state of the system is formulated.

b) Solved one of the standing and non-trivial problem of literature viz. prognostics (predicting remaining useful life) under dynamic operating profiles. The proposed generic prognostics approach encompasses all real-world industrial scenarios.

c) A novel integrated diagnostics and prognostics system based on the relationship between product quality and tool degradation is proposed.

An added contribution lies in the outcomes; an exhaustive performance and comparative investigations via experimental case studies are presented, to distinguish the suitability, stability, quality, reliability, robustness, applicability and comprehensibility of the offered methods in real-world manufacturing environments.

1.7 Thesis Organization

The thesis is broadly divided into seven chapters. The current chapter introduces the reader to the background of the work, outlines the research objectives and proposes the methodology with which the objectives are circumvent.

Chapter 2 presents a comprehensive review with emphasis on process quality control, maintenance planning, and TCM, in terms of the technology driving the transformation, its benefits, its challenges and its global status.

Chapter 3 presents an preliminary investigation on overall performance enhancement of data-driven prognostics framework by concentrating on amelioration of data-processing, degradation assessment, and RUL prediction steps.

Chapter 4 provide a cost efficient and cognitive integrated monitoring system to instantaneously prevent machining system performance degradation and sudden failures.

Chapter 5 equip TCM systems with intelligence that allows responding to the time-variant operating profiles and adaptable under various real-world production environments.

Chapter 6 provides a holistic view of the intelligent manufacturing, thereby forming the basis for building an autonomous decision-support system that serves as a guide for joint consideration of strategic operational policies pertaining to diagnostics, prognostics and process quality control.

Chapter 7 draws conclusions and future scope on the work.

Chapter 2

Literature Review

“The problem in this business isn’t to keep people from stealing your ideas; it's making them steal your ideas!”.

Howard H. Aiken, American physicist

To distinctly highlight the contribution of this work and its position in the available work, a systematic review of literature with emphasis on cutting tool diagnostics, prognostics, and process quality control is carried out. In the end, findings from literature review and detailed research gaps are outlined.

2.1 Introduction

A good understanding of interdependencies among cutting tool diagnostics, prognostics, process variables and shop floor level operations policies (viz. process quality control) is required to comprehend the holistic view of intelligent manufacturing. Accordingly, to evidently foreground the contribution of this research and its position in the related research, a systematic literature review with emphasis on cutting tool diagnostics, prognostics, and process quality control is carried out in the following section.

2.2 Cutting Tool Diagnostics, Prognostics and Process Quality Control

Real-time health monitoring of cutting tools helps in capturing valuable information concerning the current health state of the tool and accordingly leads to preventive maintenance activities that secure the tool more efficiently against failures. Consequently, an efficient tool condition monitoring is essential to improve machining system availability, reducing downtime cost and enhancing operating reliability. The TCM systems require systematic methods of cutting tools diagnostics and prognostics. Diagnostics involves estimating the health condition, and prognostics involve assessment of the remaining useful life of the tool. The available TCM methodologies can be broadly classified as direct and indirect methods. Direct methods are offline, such as computer vision, etc., and used for wear estimation. Indirect methods are online and correlate appropriate measurable process signals (viz. cutting forces, vibration and acoustic emission, etc.) to tool wear. Since the late 1980s, numerous investigations have been dedicated to the development of direct and indirect method based TCM systems. In particular, this review emphasizes on four fundamental aspects that have traditionally been examined separately: a) approximating the cutting tool degradation progression, b) diagnosing the health status of the cutting tool, c) predicting the RUL and d) integrating the effects of operating profiles on cutting tools deterioration.

A plethora of research focuses on approximating tool degradation progression, diagnosing the health status and foreseeing the RUL (Ambhore et al. 2015, Anusha et al. 2016). For instance, a direct method like computer vision has been pursued for over three decades now. The innovation in computer vision has directed the advancement of several vision sensors to gather data about the condition of the tool. Basically, an image of the tool is apprehended to deliver information about the behavior or level of wear. For example, Su et al. (2006) and Castejón et al. (2007) utilized this technology to formulate a wear quantifying system for drill and cutting inserts to identify the time for its replacement. Wang et al. (2005) suggested a method on sequential image scrutiny for periodic quantification of tool wear and to identify the wear area. Doukas et al. (2013) proposed a method in which microscopy measurements and photos of worn inserts have been taken during face milling operations for the assessment of the wear level. Tawade et al. (2014) proposed a tool wear measurement system for detection of micro and macro wear using imaging methods. In these works, characteristic measures from the tool image are extracted for classification of tool health state as new-worn or broke. However, these methods fail to perform under the variation of surrounding conditions, radiance of light, and the existence of chip or dust particles, thereby restricting the application in the real industrial environment. Among others, Zhang et al. (2014) proposed a novel tool wear monitoring method in ultra-precision raster milling by using cutting chips. Their proposed method works on mathematical model based on chip morphology, which makes their method difficult and less efficient in real industrial environment. On this line, Shiraishi (1988) mentioned that direct method of TCM suffers from high inaccuracies; thus, they are unreliable.

Following, the main line of research is focused on the analysis of real-time degradation signals viz. cutting forces (Muhammad et al., 2013), vibrations (Serra and Rmili, 2016), acoustic emission (Bhuiyan et al., 2016), etc. measured during cutting processes. Herein, the degradation signal derives solitary from an explicit sensor or their combinations and correlated with tool wear/state. In this, the relationship between degradation signals and tool wear/state is mapped using data driven approaches (coupled with various feature selection approaches) viz. artificial neural networks (Fuqing et al., 2013), fuzzy systems (Yadav et al., 2012), regression models, proportional hazard models (Wu and Tian, 2012), etc. For instance, Chen and Li (2009) and Rizal et al. (2013) presented tool wear prediction models by quantifying the cutting force deviations in various machining process viz. turning. Nadgir and Ozel (2000) formulated a flank wear prediction system explicitly based on force signal analysis; proficient for precise wear prediction. However, the accurateness declined as the operating conditions were altered considerably. Whereas, Zhai et al. (2010) and Huang et al. (2010) proposed a cutting force based approach for the modelling and detection of cutter degradation and surface integrity in high speed milling process. Čuš and Župerl (2011) developed an adaptive neuro fuzzy inference system based model for predicting the tool wear through cutting force signals in end-milling process. Li et al. (2009) used four approaches namely, multi regression model, back propagation neural network, radial basis function network and fuzzy neural network for ball nose end milling process. Regression based genetic algorithm technique is used for feature selection. Maximum force levels, total amplitude of cutting force, average force, standard deviation are used as the features for the wear prediction. Javed et al. (2012) used three approaches namely, improved-extreme learning machine algorithm, adaptive neuro fuzzy inference system and extreme learning machine for predicting the cutting tool condition from high speed CNC machine. Benkedjouh et al. (2013) developed a cutting force based health assessment model for cutting tools based on support vector regression. From these studies, it is observed that the cutting dynamics is governed by the deviation in the cutting force and can be related to wear. As per, Li et al. (2009) tool dynamometers are generally employed to measure cutting forces. Though, Zhong et al. (2013) in the recent study demonstrated that dynamometers are not appropriate for industrial usage, because of their higher cost, negative effect on machining framework rigidity, geometric constraints, etc. Whereas, Orhan et al. (2007) proposed a cutter wear evaluator method, through vibration data in milling process. Likewise, Bhattacharyya et al. (2007) developed multiple-linear regression based approach.

Along with, Alonso and Salgado (2008) and Wang et al. (2014a) proposed a tool wear evaluation model utilizing vibration investigation. Several characteristic measures indicative of tool wear were extracted from the processed vibration measurements and a strong relationship with tool wear is recognized. However, efficient utilization of these approaches requires placement of costly accelerometer sensors close to the tool-workpiece interface which becomes cumbersome with tools subjected to rotating motion. Consequently, Bhuiyan et al. (2012), and Ren et al. (2014) investigated aspects of Acoustic Emission (AE) in the machining process and developed new tool wear monitoring methodologies. The major issue with the application of these methods is the attenuation of the AE signal; also the AE sensor needs to be close to its source. Therefore, even with the realization of the AE methods, on its own, the evidence delivered by the AE method is not sufficient to provide a completely precise estimation of tool condition. Ambhore et al. (2015) verified that the data from the acoustic emission sensors alone is inadequate to provide an efficient wear monitoring. Accordingly, the multi-sensors fusion techniques have received tremendous applications in recent studies. Like, Vallejo et al. (2006), and Elangovan et al. (2011) developed diagnostic models using vibration and acoustic measurements for classifying the tool health conditions in different states viz. good-broke or worn-no worn or low-high blunt. Likewise, Dey and Stori (2005) presented a Bayesian-based method for diagnosing the low and high level of tool wear variations using multiple sensor metrics. Yamaguchi et al. (2007) looked into the cutting force and acoustic emission data to estimate tool life. Dimla and Lister (2000) presented a tool wear monitoring system utilizing cutting force and vibration measurements. Geramifard et al. (2012) proposed a temporal probabilistic approach based on hidden Markov model with multiple sensors fusion (force, vibration, and acoustics emission) to predict the real-valued health state metric (tool wear) instead of discrete types or stages in a CNC milling machine. Similarly, Ghosh et al. (2007), Nakai et al. (2015), and Zhang et al. (2015a) describe experimental and analytical models for TCM based on an examination of various process signals, namely cutting force, vibration, AE, and power, etc. Zhong et al. (2013)

performed statistical analyses of the force and acoustic emission signals to examine the tool condition of a milling process using multi regression model. Correlation analysis is utilized for feature selection. Eight features from force (peak, peak to peak, mean of Root Mean Square (RMS), mean, standard deviation, absolute deviation, mean of band power and mean of RMS) and eight features from AE signal (kurtosis, peak to peak, mean of RMS, standard deviation, mean of band power, standard deviation of band power, absolute deviation and count) are feed as input. Chen (2011) developed a multi-model for wear approximation using dynamometer, accelerometer, and AE data. It is observed that force data is highly sensible to cutter performance compared to vibration and acoustics data (Dan and Mathew, 1990, Ghasempoor et al., 1998). Some studies deal with the angular approaches. For example, Girardin et al. (2010) examined the angular speed occurring without delay through the spindle encoder measurements. In general, these measurements are required to be corresponded with a reference measurement, usually cutting force, to confirm their precision. Duro et al. 2016 proposed a framework using multi-sensors to enhance the reliability of monitoring under static operating profile. Though, such systems are a widespread choice amongst scientists but only effective in laboratory environments owed to the fact that these approaches work well for discrete events, for instance, breakage, wear estimation etc., however, are harder to implement for remaining useful life prediction. In addition, these approaches not only cost a substantial amount of time and money on sensor setup but also possibly contain a substantial amount of errors because of handling complexities in multi-sensors setups (Sick, 2002). Teti et al. (2010) and Siddhpura and Paurobally, (2013) carried an informed, all-inclusive review of sensors, signal processing, and executive strategies for TCM. The mainstream of these researches are focused on continuous machining viz. turning, and these methods are not assured to work adequately for a semi or fully intermittent process viz. grinding, milling, etc., as in these operations tool wear evolution is different as the tool teeth go in and out repetitively during the course of the machining. Moreover, these works are typically designed to estimate the present wear or do classification as a healthy/faulty tool based on current signal observation. As a result, such approaches are inflexible towards RUL expectation, and do not aid to the decisive function of TCM. By realizing what components need maintenance, support and replacement activities are arranged ahead of time, based upon the state of the cutting tool. Thus, goal of RUL prediction is to have the capacity to recognize approaching failure sufficiently early to take preventive replacement decisions in a convenient way.

Following that, in literature, close attention is paid to RUL prediction of cutting tools. Explicitly, degradation data from a sample of cutting tools tested are used to infer and estimate the RUL of the population by utilizing artificial intelligence or statistical theory based decision-making strategies. For instance, Sun et al. 2016 presented a method for evaluating the remaining useful life of an individual cutting tool while the tool is in process; using sensitive features extracted from force, vibration and acoustic emission signals to form characteristic matrices. Olufayo and Abou-El-Hossein (2015) studied the properties of the acoustic emission signal in the end-milling process. Based on wavelet transform, some features, including root mean square and mean, were extracted as inputs of the artificial neural network model for RUL estimation. Al-Zubaidi et al. (2014) adopted the adaptive neuro-fuzzy inference system to calculate the RUL for end milling of Ti6Al4V alloy with coated and uncoated cutting tools under dry cutting conditions. Likewise, some significant contributions are (Vallejo et al., 2008, Abellan-Nebot, and Subirón, 2010, Geramifard et al., 2012, Javed et al., 2015, Zhu et al., 2015, Javed et al., 2016). Although artificial intelligence based approaches are extensively utilized for TCM, even the utmost promising systems are not certainly adaptable in real-world scenarios (Wang et al., 2001, Dong et al., 2004, Anusha et al., 2016), principally owing to inadequate generalization competences viz. the usage is constrained to a particular operation/sensor/machine tool or solitary valid for specific industrial scenarios (principally, restricted to high volume of productions viz. mass production, where the operating profiles are time-invariant). Besides, none of these models accounts for the dynamic operating profiles and doesn’t incorporate their effects on the degradation progression. In recent years, a few probabilistic and stochastic methods are designed. For instance, Karandikar et al. 2013 demonstrated the random walk method that estimates the RUL for a selected tool based on the spindle power during machining. Tobon-Mejia et al. (2012) offered a significant aid for predicting tools RUL in a CNC center by utilizing a stochastic methodology. Lee and Whitmore (2006) compiled various stochastic degradation models gauging the failure distribution for cutting tools. Nevertheless, such frameworks address failure as a random incident and do not deliver statistics regarding the degradation progression peculiar to a tool operating in dynamic operating profiles (Noortwijk 2009). In essence, a large cross-section of these literature, assumes that the operating profile is time-invariant or have no effect on degradation processes (Roth 2010, Li, et al., 2009, Anusha et al., 2016). As a result, their applications in predicting RUL and to plan other shop floor operational policies are restricted in diverse industrial scenarios viz. batch or job production environments where the operating profiles are highly nonlinear time-variant in nature.

In distinction, the other radical of research emphases on exhibiting the effects of operating profiles on tool degradation or its manifestations. For instance, Tamizharasan et al. (2006), Palanisamy et al. (2008), and Prakash et al. (2011) predicted the wear as a function of operating parameters for instance cutting speed, etc. Kopac and Krajnik (2007) and Sivasakthivel et al., (2010) presented an analytical approach to predict, the tool wear, pertaining to operating parameters viz. helix angle, etc. Leone et al. (2011) provided an experimental technique to estimate wear as a function of the machining interval and tools rotating speed. These methods provide a good reference to model the effects of various operating profiles on tool wear. However, as these methods are not based on real-time measurements, their suitability is mainly limited to offline operating parameter optimization.

The cutting tool degradation significantly influences product quality and machine tool performance. Thus, for shop floor efficiency and effectiveness modern manufacturing industries rely on the optimum and efficient design of their shop floor operational policies; process quality control and maintenance planning are fundamental. Since the 1950s, investigation in these areas has attracted substantial attention. However, these policies are used in isolation. Montgomery (1980) presented a comprehensive review of process quality control policies, while Pierskalla and Voelker (1976) reviewed the literature on maintenance planning. It is realized that the use of these policies in isolation provides sub-optimal solutions, as they are interrelated (Ben-Daya and Duffuaa, 1995). Consequently, the integrated optimization of process quality control and maintenance planning is receiving the much needed momentum. For example, Cassady et al. (2000), Linderman et al. (2005) simultaneously optimized the process quality control and maintenance planning policy to reduce the overall cost. Zhou and Zhu (2008) suggested a method for process quality control and maintenance planning to examine the expense of the joint modeling for obtaining optimum design parameters. Panagiotidou and Nenes (2009) attempted an integration of the variable-parameter Shewhart control chart. Mehdi et al. (2010) developed a combined model designed for conforming and non-conforming items. Brief overviews of the literature dealing with these integrated models are reported in (Rahim and Ben-Daya, 2001, Budai et al., 2008, Pandey et al., 2010, and Hadidi, et al., 2012). Most of these integrated models are built on the assumption that the health state of the machine changes from working to failure with a constant failure rate. In other words, no degradation phenomenon is present except breakdown. Such assumption restricts the applicability of these integrated models for systems deteriorating with time (having an increasing failure rate), viz. cutting tools, etc. This motivated Banerjee and Rahim (1988) to extend the existing model (Duncan, 1956) to the Weibull shock model; though such extensions are passive. The active action necessary for industries is to restrict the unit from aging when the failure behaviour has an increasing failure rate. A framework that is formulated to function as a preventive maintenance program will only aid this purpose. Along these lines, Ben-Daya (1999) attempted the integration of process quality control and preventive maintenance, when the process failure follows increasing failure rate. In any case, such models are very complex than the standard process quality control policy, as it requires calculation and continuous updating of the probability that the process is in the out-of-control state, and subsequently the policy becomes tough to execute. Recently, Pandey et al. (2011) proposed a jointly optimized quality and maintenance planning policy considering increasing process failure rate in an efficient manner. Their model is built utilizing the average process failure rate for the entire planning horizon. However, in cases of deteriorating systems viz. cutting tools, the failure rate increases dynamically. Thus, the more realistic approach will be to dynamically update the process failure rate based on the current health state of the system throughout its life.

For the integrity of this widespread review of interrelated research, it is stated that scarce studies are accessible, associating degradation progression with the operating profiles. However, such studies approach the problem in a way that each time the degradation of a cutting tool is approximated, the future operating profile is assumed to be constant and equivalent to the current profile. Most recent works where operating profiles effects were considered are from Zhang and Zhang (2015), and Aramesh et al. (2016); they addressed the problem from an accelerated degradation testing perspective solely centered on the offline current observation at different operating levels. Though, they do not model the physics associated with the evolution of dynamic operating profiles. It would be of practical value to equip the TCM systems with intelligence that allows responding to the uncertainty of time-variant operating profiles and adaptable under various real-world scenarios. Moreover, many investigators (Özel and Karpat, 2005, Kaya et al., 2012, Tangjitsitcharoen et al., 2014) have perceived that there is a link between product quality and tool degradation, yet research in this area is still very constrained. Investigation of such relationship will be beneficial to the industries; as product quality is affected by tool degradation. Thus, product quality can be an important element in estimating the health condition of the tool. Lastly, it is stated that few works are available, combining process quality control with maintenance planning for deteriorating systems. However, they approach the problem typically from a quality perspective, as they solitary study quality deterioration mechanisms. The most recent work in this area is from Ben-Daya and Rahim (2000); they aim to perform integrated optimization of the process quality control and the maintenance planning of deteriorating systems. However, these works do not consider the real-time health state of the system, which can be a new element for dynamically updating the optimal design parameters of integrated policy as a function of machine's useful life.

2.3 Findings from Literature Review

It is observed that important aspects of manufacturing viz. diagnostics, prognostics and process quality control are studied in the isolation and needs to be integrated. Explicitly, based on the critical review and similar other works, following findings have been identified.

1. The available TCM approaches in the literature focus exclusively on the diagnostics or the prognostics task. In any case, integrating diagnostics information with prognostics will be of great interest to advance the TCM system. Such integrated TCM system is not reported in the relevant literature. Also, there is an immediate requirement of a reliable TCM system capable of catering to the need of the handling complexities, at the same time; it should also be convenient and adaptable enough to satisfy the financial constraints posed by the contemporary industrial practices. Moreover, performance of the TCM systems in terms of accuracy and applicability are some of the major constraints for use in real industrial applications. Therefore, many of the developed indirect or direct monitoring systems are not available yet or have not been tested in an industrial environment.
2. Available TCM systems either fit trends in the monitored parameters (cutting force, vibrations, etc.) to predict the future wear state or do classification as a healthy or a failed tool. The extension of such systems for the multi-level characterization of degradation and remaining life assessment is not researched satisfactorily in the relevant literature.
3. Many investigators have perceived that there is a link between product quality and tool degradation, yet research in this area is still very constrained.

Investigation and modelling of such relationship will be beneficial to the industries; as product quality is affected by tool degradation. Thus, product quality can be an important parameter in estimating health state of the tool. However, no specific real-time TCM system is reported mapping such relationship.

4. Traditional TCM systems are designed on the impression that along the entire lifespan of the cutting tool, the prevailing operating profiles are temporally unvarying or do not significantly affect tool degradation. Although, in reality, the operating profiles frequently fluctuate with operating mode conversions, and mostly, exert significant effects on the degradation. Still, the impact of time-variant operating profiles on life estimation has not received enough consideration. Specifically, there is a need for a system that can prognosticate tool RULs while exploiting prior information, along with the future characteristics of dynamic operating profiles under diverse real-world scenarios viz. batch, job, and mass production environments. In reality, a real-time TCM system designed for prognosticating RULs under time-variant industrial scenarios is still an open area that needs to be addressed.
5. A lot of the investigations integrating quality with maintenance are reported; such integration for machines deteriorating with time viz. cutting tools are scarcely reported. Available models aim at quality control problems concerning machine failure in terms of complete breakdown and mostly ignore the performance deterioration in relation to poor quality that results in high rejections and calls for maintenance action or change in quality control policy. The existing integrated model assumes a fixed value for the underlying design parameters. Although the initial distribution of the parameters is economically chosen at the beginning stage of the manufacturing process, no attention is given to the intermediate stages. This may be non-economical in practical situations, where one cannot assume a fixed value of control chart parameters for the entire lifecycle of the manufacturing process subjected to deterioration. For instance, cutting tools, where the health state of the tool changes due to degradation. In such cases, considering the real-time health

state of the system can be a new element as health assessment is not only a diagnostic necessity to avoid equipment failure and manufacturing loss, but also have a vital role which essentially influences the dimensional uprightness, well-functioning, and service life of the product. However, the health monitoring efficiency cannot be assessed in a significant manner without considering whether the maintenance task is satisfying the production demands or not. Accordingly, a proper understanding of this dependency between process quality control and maintenance planning, considering the real-time health state of the system will open a novel opportunity of a dynamic integrated policy, and would results in significant savings in overall manufacturing cost.

These findings are summarized in the form of specific research gaps and highlighted in section 1.2 of chapter 1.

Chapter 3*

Augmenting Data-Driven Modeling from Degradation to Remaining Useful Life Approximation: Preliminary Investigation

"In God we trust; all others must bring data".

William Edwards Deming, American Statistician

In this chapter, as a part of the preliminary investigation, a new and systematic methodology for augmenting data-driven modeling from degradation approximation to RUL approximation for distinct industrial cases is offered.

Key Highlights

Purpose: *The purpose of this investigation is to present some preliminary understanding of the key challenges in the execution of the tool condition monitoring as an enabling technology for intelligent manufacturing. Moreover, to account for such challenges, this investigation provides manufacturing industries with augmentation of data-driven modeling from degradation approximation to RUL approximation for distinct industrial cases.*

Methodology*: A trial and error approach is proposed for dominant feature identification, screening and selection. New condition-based data-centric offline, online and semi-offline models based on artificial neural network are inventively designed for degradation prediction. Herein, tool degradation (wear) was considered as the monitoring variable in addition to the measured variables viz. cutting force, vibration, etc. In succession, these models are extended from degradation approximation to RUL approximation for distinct industrial cases:*

** The preliminary investigation presented in this chapter is published in two parts. Firstly, under the title "Data driven models for prognostics of high speed milling cutters" in "International Journal of Performability Engineering", Totem Publisher, USA, Vol. 12.1, pp. 3-12, 2016. Secondly, under the title "Predicting remaining useful life of high speed milling cutters based on artificial neural network" in "International Conference on Robotics, Automation, Control and Embedded System, 2015", IEEE, doi: 10.1109/RACE.2015.7097283.*

1) When only online monitoring data are available,

2) When incidental (or planned) offline inspection data are also available.

***Findings**: These models are developed and validated based on open source experimental data. The new trial and error approach significantly aids in improving the accuracy of degradation prediction. On the other hand, the proposed approach provides over prediction at the early age of the life which reduces unnecessary disturbance of the manufacturing process when the cutting tool is new. As the tool reaches end of its life, proposed model provides accurate prediction of the impending failures thereby initiating remedial action in a timely manner. These findings encourage the development and application of data-driven models for intelligent manufacturing.*

***Practical Implications:** The accuracy of degradation prediction models so obtained in this research is better than those reported in the literature with same set of experimental data. Wherein, the most reliable semi-offline model is useful for optimizing planned shutdown intervals for the machine in real-world manufacturing environment.*

***Originality and Contribution:** The novelty of this investigation is in augmenting data-driven modeling from degradation approximation to RUL approximation. Wherein, RUL predictions is carried out for two distinct industrial scenarios viz., when only monitoring data are available and when incidental (or planned) offline inspection data are also available, using inventively designed and developed online, offline and semi-offline models. In addition, comparative studies on prediction performances of distinctive models show that the developed model is superior to different conventional models.*

***Research Limitations and Future Scope**: The preliminary investigations presented in this chapter are based on the secondary data taken from Prognostics and Health Management Society. Only a limited data set was available for model training. Moreover, various important and related dimensions of the problems could not be investigated because of the lack of data. For example, all the* *samples were collected at a constant operating condition, product quality characteristics were not recorded, etc. Study of product quality characteristics (surface roughness) with tool degradation would lead to important conclusions. Further, such characteristics can also give important features for tool failure and may help in improving prediction accuracy. Also, linking the monitored parameters with product quality characteristics would enable dynamic process quality control strategies. All the samples were collected at a constant operating condition or profile. It precludes any possibility of predicting tool RUL based on future operating profile which may be varying. These observations motivate to develop an experimental setup and develop present research methodologies reported in chapter 4-6.*

3.1 Introduction

Effectiveness of tool condition monitoring depends on precise degradation (viz. tool wear) modelling of cutting tools. Wherein, data-driven modelling is largely used for degradation approximation of cutting tools. There exist a numerous data-driven modelling frameworks for tool degradation approximation. Though, performance of these modelling frameworks in terms of robustness, reliability, accuracy and applicability are some of the major constraints for use in real-world manufacturing environment. From the comprehensive literature review (presented in chapter 2) in the area of tool degradation approximation, it is observed that the main focus of the researchers is on improving the degradation approximation accuracy of the data-driven modelling frameworks. In general, neural networks, extreme learning machine etc., based modelling frameworks are found to be more suitable for handling the nonlinearity present in the tool degradation (wear) data compared to multi regression models. It is also found that statistical feature selection plays an important role in the reduction of computational load and increasing the performance of the modelling framework. Among various feature selection methods, regression based genetic algorithm, correlation etc. are widely used. Still, there is a scope for development of an efficient feature selection method, to identify optimum set of inputs to be feed to the modelling framework for better performance with low computational load. Moreover, the available frameworks are stringently designed for tool degradation approximation and don't deliver failure time information, which does not serve the ultimate purpose of tool condition monitoring. As, the failure time prediction is not only necessary to verify whether the mission goal(s) can be accomplished but also important to aid in efficient tool replacement and operations planning decisions. Accordingly, extending the current degradation approximation modelling frameworks to instantaneous remaining useful life approximation is of high practical importance. Thus, present investigation first aims at enhancing the performance of tool degradation approximation, in terms of accuracy and applicability, via an offered feature selection approach. And then, augment's data-driven modeling from tool degradation to remaining useful life approximation for distinct industrial cases.

First, preliminary screening on different measured process variables viz. cutting force, vibration, etc. is carried out. From the screened measured process variables multiple significant statistical features are extracted. Next, a trial and error approach is proposed for dominant feature selection. Following, new condition-based data-centric offline, online and semi-offline models based on artificial neural network are inventively designed for degradation prediction. Herein, tool degradation (wear) was considered as the monitoring variable in addition to the measured variables viz. cutting force, vibration, etc. Next, these models are extended from degradation approximation to RUL approximation for distinct industrial cases 1) when only online monitoring data are available; 2) when incidental (or planned) offline inspection data are also available. These models are validated based on experimental data.

The novelty of this investigation is in augmenting data-driven modeling from degradation approximation to RUL approximation. To the best of the knowledge, so far no model has been introduced implementing the tool wear itself as a variable in the model in addition to the measured parameters, thereby being able to predict the RUL of tools based on the current tool wear value. This could be considered as the significant practical advantage of this model over the existing models, since it is capable of estimating the RUL of fielded tool, regardless of its usage history, with a simple tool wear measurement. The accuracy of degradation prediction models so obtained in this research is better than those reported in the literature with same set of experimental data.

3.2 Problem Addressed

In the present investigation open source data is used; data is taken with permission from the Prognostics and Health Management (PHM) society[3.1] (PHMS-CDC, PHMS). The data was mainly collected to estimate wear of high speed CNC milling machine cutters using cutting force, vibration and acoustic

[3.1] *PHM Society is a non-profit organization dedicated to the advancement of PHM as an engineering discipline. The milling cutter data is openly downloadable from their website (Link: https://www.phmsociety.org/competition/phm/10). Permission has been taken to use this data for the current work presented in this chapter. I acknowledge the support.*

emission data. The data is in the form of time domain signals from dynamometer, accelerometer and acoustic emission sensors. The milling process in the experiments is to create an oblique plane surface on a workpiece by ball-nose end milling operation. Description of data is given in table 3.1. Some of the most important test details are as follows: A high speed CNC milling machine and a 6 mm 3 flutes ball nose tungsten carbide cutter is used for machining stainless steel (HRC 52) workpiece, spindle speed of the cutter was 10400 RPM, feed rate was 1555 mm/min, Y depth of cut (radial) was 0.125 mm and Z depth of cut (axial) was 0.2 mm. Data was acquired at 50 KHz. Further details of the apparatus and experimental setup can be found in Li et al. (2009). The monitored data includes operational data from three different milling cutters. Each cutter data consists of time domain signals for each cut as shown in table 3.1. The cutters flank wear from three flutes of cutter was measured after a complete 27,216 mm cutting distance using a LEICA MZ12 microscopy system. Average value of cutters flank wear from three flutes is considered in this study for developing models. Each cutter data consists of total 315 cuts. In the present study data is divided into two subsets: training data (2 cutters) and test data (1 cutter). The objective of this work is to develop accurate and applicable models for wear estimation and RUL prediction. The application of the models is demonstrated using two industrial cases:

Case I: When only online monitoring data are available.

Case II: When incidental (or planned) offline inspection data are also available.

3.3 Methodology

The overall procedure of the proposed method is illustrated in Fig. 3.1. Experimentation step is discussed in section 3.2. Rest of the steps is discussed in the following sub-sections.

3.3.1 Preliminary Feature Identification and Screening

To predict the cutter wear from measured process variables, statistical features are needed to be extracted. A statistical feature transforms raw signals into more informative signatures of a system (Ding et al., 2009). Various statistical features from force-vibration-acoustic signals are used throughout the literature (Li et al., 2009, Chen and Li, 2007, Tian, 2009, Prasad et al., 2012, and Zhang et al., 2015). Table 3.2 shows the list of some of the most important statistical features.

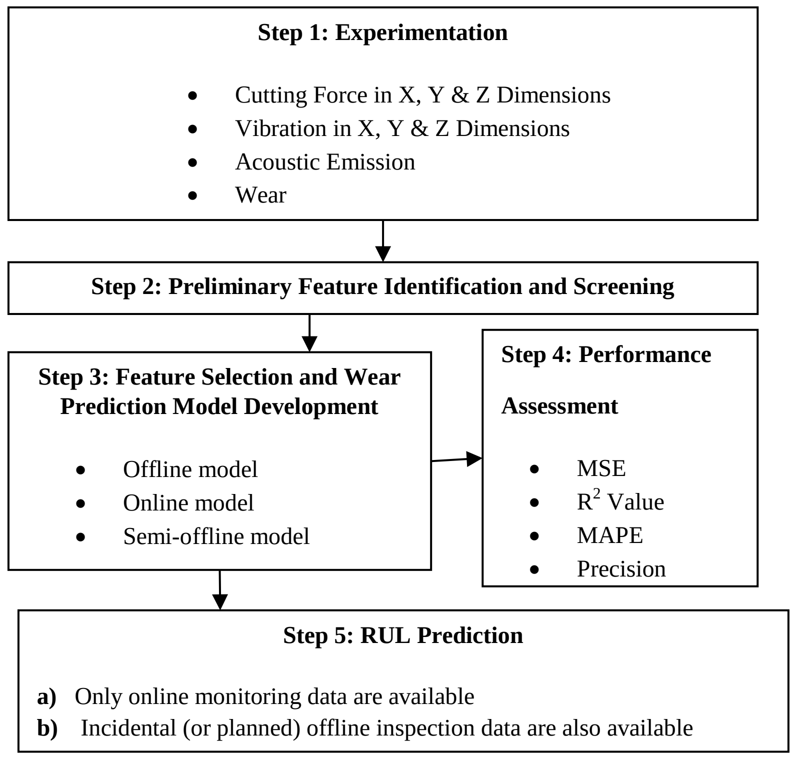

Fig. 3.1. Flow chart of the proposed method.

TABLE 3.1

DESCRIPTION OF DATA

S No.	Data
1	Force (N) in X Dimension
2	Force (N) in Y Dimension
3	Force (N) in Z Dimension
4	Vibration (g) in X Dimension
5	Vibration (g) in Y Dimension
6	Vibration (g) in Z Dimension
7	Acoustic Emission-Root Mean Squared (AE-RMS) (V)

TABLE 3.2

IMPORTANT STATISTICAL FEATURES

S. No.	Cutting Force Signal (X, Y and Z Dimension)	Vibration Signal (X, Y and Z Dimension)	AE-RMS Signal
1	Average force	Root mean square	Root mean square
2	Standard deviation	Standard deviation	Standard deviation
3	Skewness	Skewness	Skewness
4	Kurtosis	Kurtosis	Kurtosis
5	Peak of the cutting forces	Peak	Peak

Literature have shown that the cutting force in the feed direction (Y direction in this case) is the most sensitive force signature to the change in cutting conditions due to its lower damping ratio during cutting process compared to the other two axes (Zhai et al., 2010). Therefore, features in feed direction for force and vibration along with acoustics are considered for further study. Although, all of these features are statistically significant, it has been observed that beyond a certain point, involvement of all these features leads to an unsatisfactory performance (Li et al., 2009). Therefore selection of most relevant feature is necessary for efficient establishment of correlation models with acceptable computing performance.

3.3.2 Feature Selection and Wear Prediction Model Development

Following three types of wear prediction models are developed in this research based on the test data.

- Offline wear prediction model
- Online wear prediction model
- Semi-offline wear prediction model

Artificial Neural Network (ANN) has been considered to be one of the most promising approaches for modelling wear due to their adaptability, nonlinearity, and ability of arbitrary function approximation (Rajakarunakaran et al., 2008). The same is therefore used in all the above three models. Three layers (input, hidden and output) Feedforward Back Propagation (FFBP) neural network is used in this research. Fig. 3.2 shows the basic architecture of the FFBP neural network.

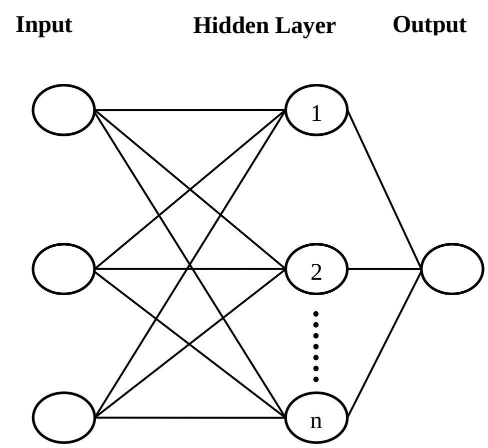

Fig. 3.2. Architecture of FFBP neural network.

A FFBP neural network is employed due to its high performance in modelling complicated processes. Network weights were adjusted by error feedbacks. By means of revising weights of the network, actual output is closer to the expected output. The output is normalized between 0 and 1, which gives same order of magnitude variables to avoid numerical instability. Levenberg Marquardt (LM) learning algorithm is used to train the network. The configuration of FFBP neural network model uses hyperbolic tangent sigmoid transfer function in its hidden and linear transfer function in its output layer.

Offline, online and semi-offline models mainly vary in terms of inputs feed to the network. Output in all the three models is the cutters flank wear (W_i). These models are explained in brief as follows:

Offline wear prediction model: Offline model is developed to model rate of change of wear. The inputs to the model are time at present (T_i) and previous (T_{i-1}) and wear at previous state (W_{i-1}).

Online wear prediction model: Force-vibration-acoustic properties of cutting process are the measurements which are monitored online (Zhai et al., 2010).

These measurements contain very useful information about the cutter wear. Various statistical features from force-vibration-acoustic are extracted as shown in table 3.2, for best performance significant features are needed to be identified. An ANN based trial and error approach is used to select the most sensitive set of features. Input to the model was time at present (T_i), previous (T_{i-1}) and force/vibration/acoustic emissions features from present and previous state. The model is tested with statistical features of the force-vibration-acoustic properties of cutting process separately and there combination (feature subset) and Mean Squared Error (MSE) is calculated. MSE is the average of the squares of the difference between the actual and predicted values. Mathematically,

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{p_i} - \mathrm{a_i})^2 \tag{3.1}$$

where p_i is the predicted value, a_i is the actual value, N is the number of fitted points.

Features or the feature subset with lowest mean squared error is most significant features to predict the cutter wear and are selected for development of online model. Most significant features identified for online wear prediction model are:

- Average force (F_{av}) from cutting force signal.
- Skewness (V_{sk}) from vibration signal
- Standard deviation (A_{sd}) from AE-RMS signal.

An online wear prediction model is developed with time, average force (F_{av}), skewness (V_{sk}) and standard deviation (A_{sd}) from its present and previous state as inputs.

Semi-offline wear prediction model: In semi-offline model apart from statistical features (as used in online model), wear in the current state (W_{i-1}) is considered as input to the model. Output is the wear in the next cut (W_i). It is identified from trial and error method that in case of semi-offline model only average force with wear gives best results in terms of MSE. Thus, from cutting force signal F_{av} with wear are used for semi-offline model development.

3.3.3 Performance Assessment

A total of 630 sets of data were selected from the total of 945 of data sets for the purpose of training FFBP neural network model. The other 315 sets were used for testing and to verify the accuracy of the predicted values of cutters wear. For accuracy assessment mean squared error, R-Squared value (R^2), Mean Absolute Percentage Error (MAPE) and precision indices are calculated. These are defined as follows:

Mean Squared Error: MSE is explained in previous sub-section and is calculated as shown in Eq. (3.1).

R-Squared Value: R^2 is the coefficient of determination that should be closer to 1. Polynomial multiple regression analysis is used to calculate it.

Mean Absolute Percentage Error: MAPE is the measure of accuracy of a method for constructing fitted time series values in statistics. It is calculated as follows.

$$\mathrm{MAPE} = \frac{100\%}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \left| \frac{\mathrm{a_i} - \mathrm{p_i}}{\mathrm{a_i}} \right| \tag{3.2}$$

Precision: This measure quantifies the dispersion of the prediction error around its mean, as shown in Eq. (3.3).

$$\mathrm{Precision} = \sqrt{\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} [(\mathrm{p_i} - \mathrm{a_i}) - \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{p_i} - \mathrm{a_i})]^2}{\mathrm{N}}} \tag{3.3}$$

To check the applicability of developed approach; computational time, that is the required time to learn dataset is also computed. Table 3.3 presents the results of developed models.

TABLE 3.3

RESULTS OF THE DEVELOPED MODELS

Model	No. of Neurons	MSE	R^2 Value	MAPE	Precision	Time (sec)
Offline	26	5.61×10^{-05}	0.96	4.60	0.008	1
Online	6	3.31×10^{-04}	0.81	11.8	0.018	1
Semi-offline	21	1.18×10^{-06}	0.96	0.70	0.001	2

Proposed models have demonstrated promising results in terms of predicting cutter wear. The accuracy of wear prediction models so obtained in this research are better than those reported in the literature with same experimental data as shown in table 3.4.

TABLE 3.4

ACCURACY OF WEAR PREDICTION MODELS REPORTED IN LITERATURE WITH SAME EXPERIMENTAL DATA

		Performance Measures	
S. No.		**MSE**	**R^2**
1	Current Approach	3.31×10^{-04} to 1.18×10^{-06}	0.81to 0.96
2	Li et al. (2009)	4.43×10^{-02} to 1.743×10^{-05}	0.58 to 0.99
3	Javed et al. (2012)	-	0.45 to 0.66

The extension and application of all the three models for RUL prediction is discussed in following section.

3.3.4 Remaining Useful Life Prediction

The main objective of prognostics of milling cutter is to predict its remaining useful life during its operation. The application of the model is demonstrated using two industrial cases:

Case I: Only online monitoring data are available: In this case the developed online model can be used. Online model gives continuous wear prediction based on process variables, but it will not give the idea of time remaining till failure. For that a wear threshold is fixed (it can be fixed with general experience, as at a particular range of tool wear it is most prone to failure); as the tool wear reaches this threshold the cutting tool is discarded. The predicted tool wear from online model, when changes significantly from the previous data point, that points could be taken as critical alarms indicating the degree of tool degradation, as shown in Fig. 3.3. Predicted wear at these points say C1 or C2 will be feed to the offline model as an input. Offline model will predict the future wear of the cutter. The predicted future wear can again be used as input for next prediction in offline model. The process will be repeated till the predicted wear reaches the threshold value. The difference of time at which threshold is reached and critical point (i.e. C1 or C2) will gives the remaining useful life of the cutter.

Case II: Incidental (or planned) offline inspection data are also available: In continuous production kinds of manufacturing setup sometimes process may be stopped due to unavailability of raw material or due to failures of machine components. At such unplanned stoppages opportunities exist to monitor the cutting tool wear and utilizing the same along with online monitored parameters, semi-offline model can be used to predict the future wear. This predicted wear from semi-offline model is than feed to the offline model as an input and the same procedure as explained above can be repeated for remaining useful life prediction. The critical points C1 or C2 at which prediction is done in semi-offline model are shown in Fig. 3.4.

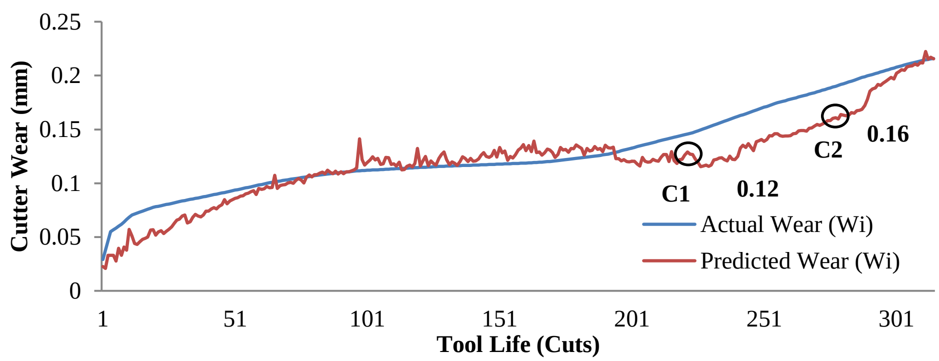

Fig. 3.3. Actual vs. predicted wear from online wear prediction model.

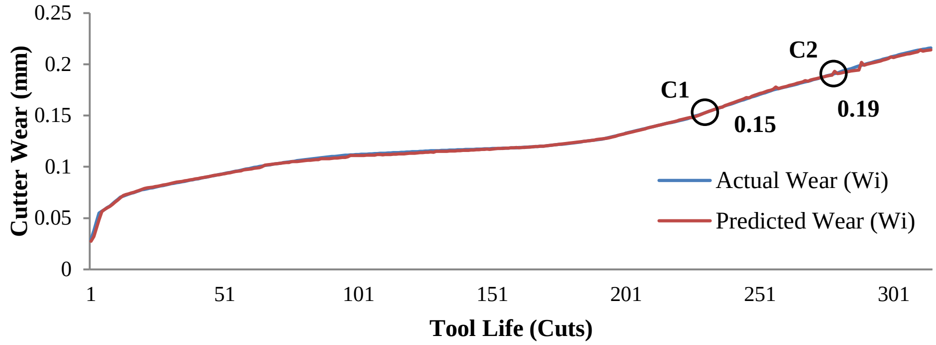

Fig. 3.4. Actual vs. predicted wear from semi-offline wear prediction model.

Such an industrial case is very common in many industries; for instance, in case of gas turbines during scheduled or incidental downtime or maintenance, offline inspection of crack growth is carried out. The offline inspected data is used for improving the performance of preventive maintenance.

Table 3.5 shows the predicted RULs in both the cases from C1 and C2 both. Threshold value was set to be 0.21 mm; the actual time to reach this point was 305 cuts. From the results it is clear that the RUL through semi-offline model is very closer to the actual RUL as compared to the online model. It is also observed that the prediction from point C2 is more accurate than the point C1. Hence, it is recommended that RUL prediction should be continuously updated with age of the cutter to increase the effectiveness of TCM policy. The developed models are accurate as well as applicable; the results from these models are not having over prediction which is very important for real industrial implementation.

3.4 Preliminary Investigation Rundown

When most of the researchers in TCM focus on wear prediction based on online monitored parameters, current investigation attempts to extend the same for RUL prediction. Also, the trial and error approach, used in the current investigation, for selecting the best set of features improves the accuracy of the wear prediction. Thus, the approach not only provides accurate estimation of cutter wear but also predicts the number of cuts cutter can make before the failure of predefined level of wear is reached. Such estimation of RUL makes it easier to plan for tool replacement and also helps the production manager in efficiently managing its operations. Second contribution of the paper is the semi-offline model that is improvement over online prediction model, based on wear measured during planned shutdown or incidental stoppage of the machine. This can be useful for setting planned shutdown interval for the machine.

TABLE 3.5

REMAINING USEFUL LIFE ASSESSMENT

	Predicted RUL	
Threshold Value set at 0.21 mm (305th cut)	From point C1 (233th cut)	From point C2 (278th cut)
Actual Remaining Useful Life	72 cuts	27 cuts
Predicted Wear from Online Model Feed to Offline Model for RUL Prediction	63 cuts	22 cuts
Predicted Wear from Semi-offline Model Feed to Offline Model for RUL Prediction	66 cuts	25 cuts

The results from this study encourage the development and application of data-driven models for intelligent condition monitoring of cutting tools. However, only limited data sets were available for model training. Moreover, various important and related dimensions of the problems could not be investigated because of the lack of data. For example, all the samples were collected at a constant operating condition, product quality characteristics were not recorded, etc. Study of product quality characteristics (surface roughness) with tool degradation would lead to important conclusions. Further, such characteristics can also give important features for tool failure and may help in improving prediction accuracy. This will be especially useful for industries that do not have costly sensors for online monitoring of the health of their machine. Also, linking the monitored parameter with product quality characteristics would enable dynamic process quality control strategies. All the samples were collected at a constant operating condition or profile. It precludes any possibility of predicting tool RUL based on future operating profile which may be varying. These observations motivate to develop the present research problem and methodology. It also motivates to develop and efficient experimental setup for collection of required data.

Chapter 4*

Real-Time Integration of Diagnostics and Prognostics, Centered on the Relationship between Product Quality and Tool Degradation

"Out of clutter, find simplicity. From discord, find harmony. In the middle of difficulty lies opportunity".

Albert Einstein, German-born Theoretical Physicist

This chapter describes the formulation of a novel integrated tool condition monitoring system pertaining to diagnostics and prognostics by quantifying and mapping the relationship between product quality and tool degradation. Moreover, based on the research gaps identified in Chapter 2, the first-hand design of a cost efficient experimental strategy, including its hardware, is described. Some new observations about association between product quality and tool degradation are given. In addition, an overall functionality and practicality of the new methodology via experimental implementation can also be obtained in this chapter.

Key Highlights

Purpose: *The purpose of this chapter is to provide manufacturing industries with a cost efficient and cognitive integrated monitoring system to instantaneously prevent machining system performance degradation and sudden failures.*

Methodology*: The diagnostic reliability is enhanced by researching on the use of a multi-level categorization of tool wear. The prognostic competence is improved by formulating it explicitly for the tools critical zone as a function of tool life. The system is integrated in a manner that, whenever the degradation curve of the tool*

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* *The work presented in this chapter is published under the title "A novel integrated tool condition monitoring system" in "Journal of Intelligent Manufacturing", Springer, doi: 10.1007/s10845-017-1334-2.*

reaches the critical zone, prognostics module is triggered, and RUL is assessed instantaneously. Moreover, to improve the integrated TCM system performance, it is built using support vector machine with optimal training technique.

***Findings**: The proposed methodology provides an excellent prescience that will enrich the existing TCM systems by considering the product quality as a new element for tool health monitoring. On the other hand, the information obtained in the current research results in significant savings in cost, time and improving productivity for heavily competitive manufacturing industry.*

***Practical Implications:** The research in this work is a pioneering effort towards designing a simple, easily comprehensible monitoring system utilizing minimum resources to enable easy adaptation of the technology even in medium and small scale manufacturing industries. Moreover, experimental tests verify the viability of the system.*

***Originality and Contribution:** The novelty of this research is in the invention of an integrated TCM system by quantifying and mapping the relationship between product quality and tool degradation. This system ascertains reliable health monitoring and life prediction of the machining system at the same time with a solitary experimentation. An added contribution lies in the outcomes; an exhaustive performance and comparative investigations of the proposed integrated TCM system is presented, to distinguish the suitability, stability, quality, reliability, robustness, applicability and comprehensibility in a real industrial environment.*

***Research Limitations and Future Scope**: The restriction in this work is that the proposed approach is only suitable for the applications in which the operating conditions are fixed. The applicability of this approach can be seen in applications with high volume of productions. The approach can be generalized by considering multiple operating conditions. The same is presented in next chapter.*

4.1 Introduction

Rendering to the discussion presented in chapter 1, that a reliable TCM system is significant for manufacturing industries for fault diagnostics and prognostics to prevent machinery performance degradation and catastrophic failures. In that line, chapter 2 expresses that, literature has devoted less attention to the criterion of integrated diagnostics and prognostics to cutting tools and has mostly ignored the interaction effect between product quality and tool degradation. In this chapter, it is aimed to bridge the gap[4.1] and make an attempt to propose a novel integrated tool condition monitoring system pertaining to diagnostics and prognostics, centered on the relationship between product quality and tool degradation.

Firstly, a new cost efficient experimental strategy concerning high-speed CNC milling machining is executed. Further, a comprehensive correlation investigation between product quality and tool degradation is performed; revealing the strong positive relationship. Mapping this relationship; a novel integrated tool condition monitoring system pertaining to diagnostics and prognostics is formulated. The diagnostic reliability is enhanced by researching on the use of a multi-level categorization of wear, and the prognostic competence is improved by formulating it explicitly for the critical zone as a function of tool life. A new Tool Degradation Indicator (TDI)[4.2] with diverse functionality is introduced as the system input. The architecture of the proposed cognitive system comprises of diagnostics and prognostics modules linked together. The diagnostics module estimates the current health state of the tool, whenever, the degradation curve of the tool reaches the critical zone, the prognostics module is triggered, and remaining useful life is assessed instantaneously. To map the desired relationship, Support Vector Machine (SVM) has been utilized. An optimal training technique is adopted based on grid search approach to advance the system performance. The developed system is validated based on the experimental data, and its performance is critically analyzed. The implementation results show that the

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[4.1] *These gaps are briefed in chapter 2, section 2.3.*
[4.2] *TDI is the set of measures (tool current age and product quality measurements) sensitive to cutting tool degradation.*

enhanced maintenance performance can be obtained, which makes the system suitable for advance asset management in manufacturing industries.

The novelty of this work is in the formulation of an integrated TCM system by quantifying and mapping the relationship between product quality and tool degradation. This system ascertains reliable health monitoring and life prediction of the machining system at the same time with a solitary experimentation. An added contribution lies in the outcomes; an exhaustive performance and comparative investigations of the proposed integrated TCM system is presented, to distinguish the suitability, stability, quality, reliability, robustness, applicability and comprehensibility in a real industrial environment. This expands the proposed system robustness and applicability in manufacturing industries.

The rest of the chapter is structured as follows. In next section, the details of the new experimental strategy are given. Section 4.3 illustrates the investigation of the relationship between product quality and tool degradation. Section 4.4 shows detailed formulation and the architecture of the integrated TCM system. Section 4.5 briefly discusses the implementation results. In section 4.6 contributions are highlighted. Lastly, section 4.7 summarizes the chapter.

4.2 New Experimental Strategy

The aim is to develop an experimental strategy which successfully attempts to provide an adaptable system in real industrial environment, at low cost and with minor changes in prevaling manufacturing system. In the exercise, testing and validation of fault diagnostics systems is anything but difficult to implement, as the faults can be easily introduced to the cutting tools. In any case, this is not true for the prognostics systems where the change in the health condition is the result of a long and slow degradation of cutting tool. Consequently, to test these strategies, it is important to create the degradation through accelerated degradation tests of cutting tool and quantify the health attributes throughout its entire life. Accordingly, in the current investigation, initially no defects are introduced in the cutting tools and degraded cutting tool may contain practically all sorts of failures (worn-out, breakage, etc.).

The complex high-speed CNC vertical milling machine (EMCO MILL E350) is utilized as the testing platform. A high-speed steel 6 mm milling cutter is utilized for the analysis. The milling process selected was face milling for generating a flat surface on the mild steel workpiece (165 x 100 mm), with fixed operating profile (feed = 300 mm/min, speed =1000 RPM, depth of cut = 0.25 mm) in the absence of coolant. Mitutoyo TM-505 Toolmakers' microscopy system at 15x eyepiece magnification and a resolution of 0.001 mm, according to ISO/IEC 17025 is used to measure the tool degradation of the tool in terms of flank wear. An HANDYSURF E-25A/B portable surface roughness device was utilized to quantify the product quality in terms of average surface roughness parameter (R_a), according to ISO'97 / JIS'01 / DIN. Run-to-failure tests with six milling cutters have been performed to investigate the degradation behavior of these tools. Two different failure types were witnessed namely tool worn-out and tool breakage. After every 1320 mm of machining distance, tool wear and average surface roughness of the finished product is measured and recorded. Current experimentation enables testing and validation of the proposed integrated TCM system. Fig. 4.1 shows the developed experimental setup. The current arrangement is cost effective, convenient and adaptable to the real industrial environment, as no sensor or fixture is utilized with the test bed. Likewise, the quantifying instruments used are not required to be installed on the test bed and are kept discretely in order to keep the machining system rigidity and avoid any sort of geometric limitations.

4.3 Experimental Investigation

Experimental tests conducted on milling cutters direct that even the exact same cutters functioned at similar operating settings demonstrate diverse wear behavior. Fig. 4.2 displays experimental wear measurements of two different failure types milling cutters. Where, Fig. 4.3 shows the average surface roughness of the finished product with different failure types cutting tool as a function of its life.

Fig. 4.3 depicts that average surface roughness value remains small and steady with small tool wear. Though, when tool wear moves towards moderate wear zone average surface roughness increases gradually, then it significantly increases as tool wear reaches the critical zone. This infers that some relationship exists between product quality and tool degradation. Experimental evidence of such relationship is missing in the relevant literature. Consequently, Pearson correlation coefficient (PCC) is employed to evaluate the strength of the relationship between the product quality and tool degradation. PCC value is in the range of −1 to 1; where value closer to 1 shows a positive correlation. The mathematical expression for PCC is given in Eq. (4.1).

$$PCC\left(P_{R_a}, T_W\right) = \frac{\sum \left(P_{R_{a_i}} - \overline{P_{R_a}}\right)\left(T_{W_i} - \overline{T_W}\right)}{\sqrt{\sum \left(P_{R_{a_i}} - \overline{P_{R_a}}\right)^2 \left(T_{W_i} - \overline{T_W}\right)^2}} \tag{4.1}$$

where $P_{R_{a_i}}$ is the product quality in terms of average surface roughness of the i^{th} product, $\overline{P_{R_a}}$ is the mean of product quality in terms of average surface roughness, T_{W_i} is tool degradation in terms of tool wear at i^{th} cutting process and $\overline{T_W}$ is the mean of tool degradation in terms of tool wear.

To better comprehend this relationship a comprehensive correlation investigation is executed. Herein, three milling cutters of each failure type have been utilized to compute the value of PCC. Fig. 4.4 shows the detailed results of correlation investigation. The results depict that the value of PCC ranges from 0.584 to 0.821 for the cutters failed owing to worn-out, while it ranges from 0.583 to 0.663 for the cutters failed owing to breakage. The average values of PCC in the case of worn-out and breakage are estimated as 0.731 and 0.628 respectively. These results clearly indicate that a strong positive correlation exists between product quality and tool degradation.

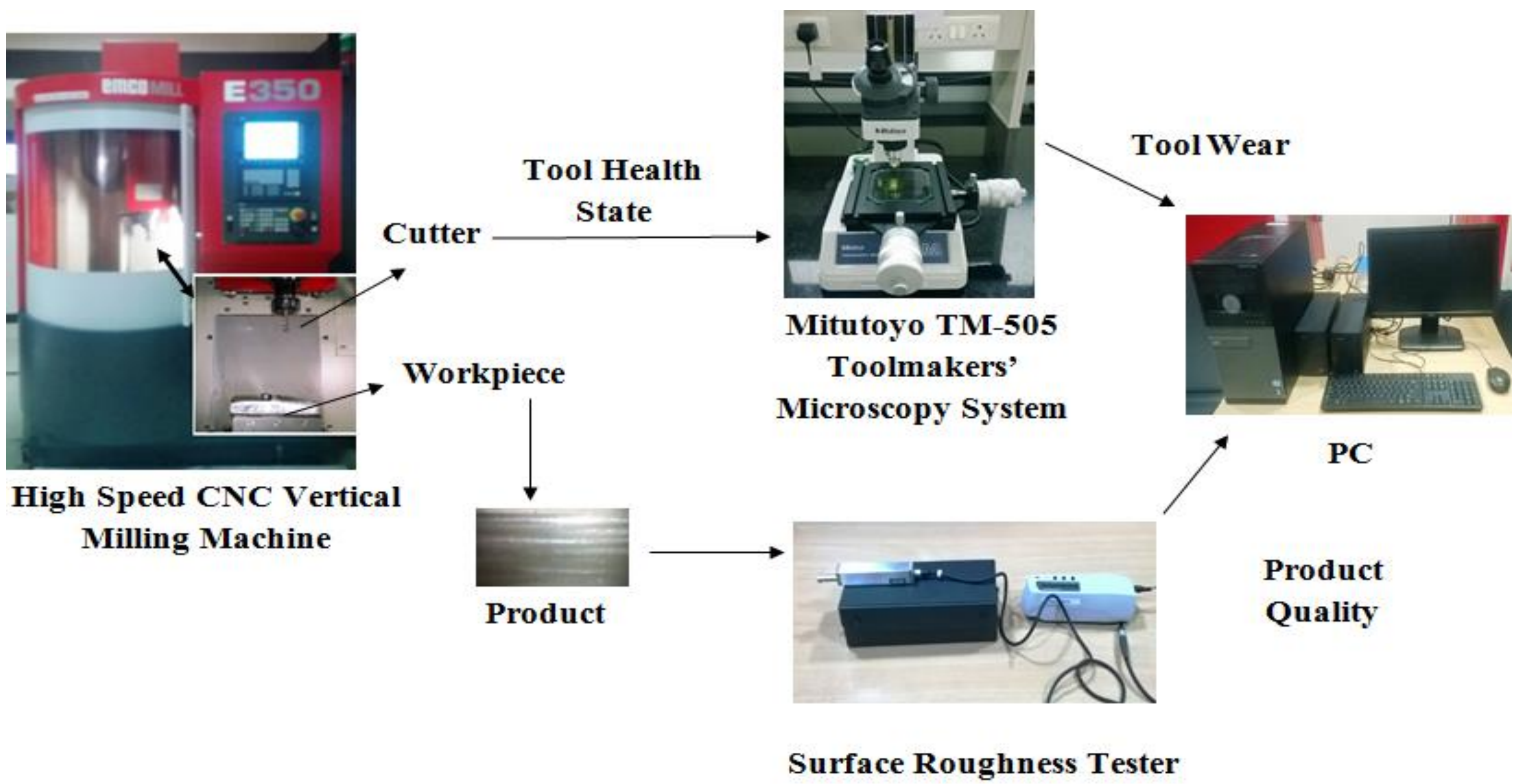

Fig. 4.1. Experimental setup.

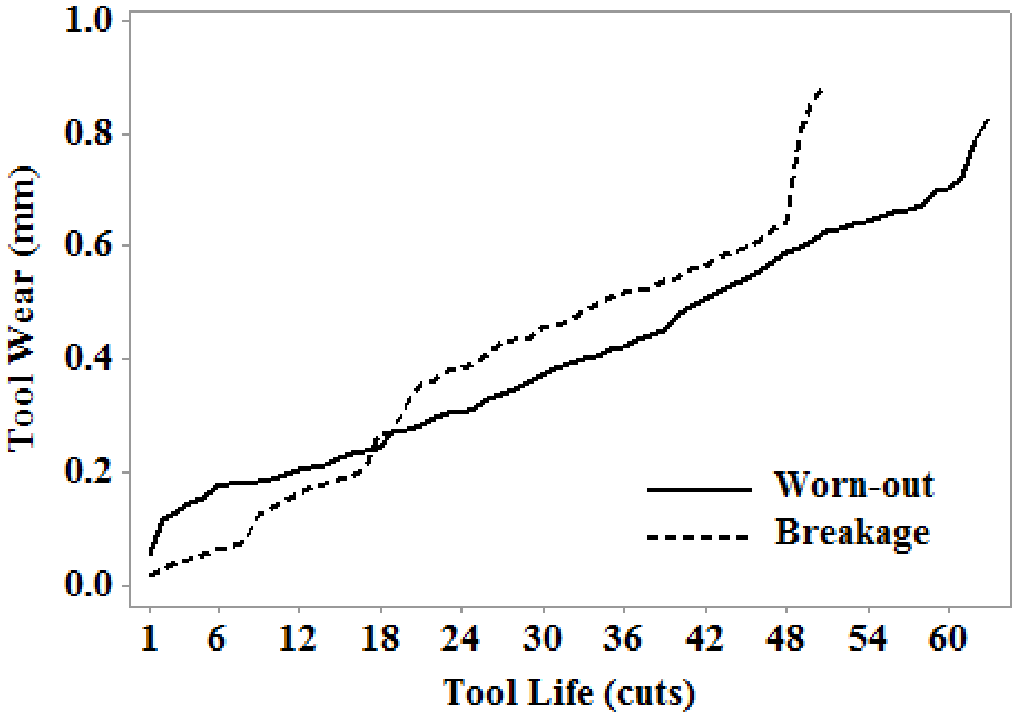

Fig. 4.2. Wear behaviour vs. tool life.

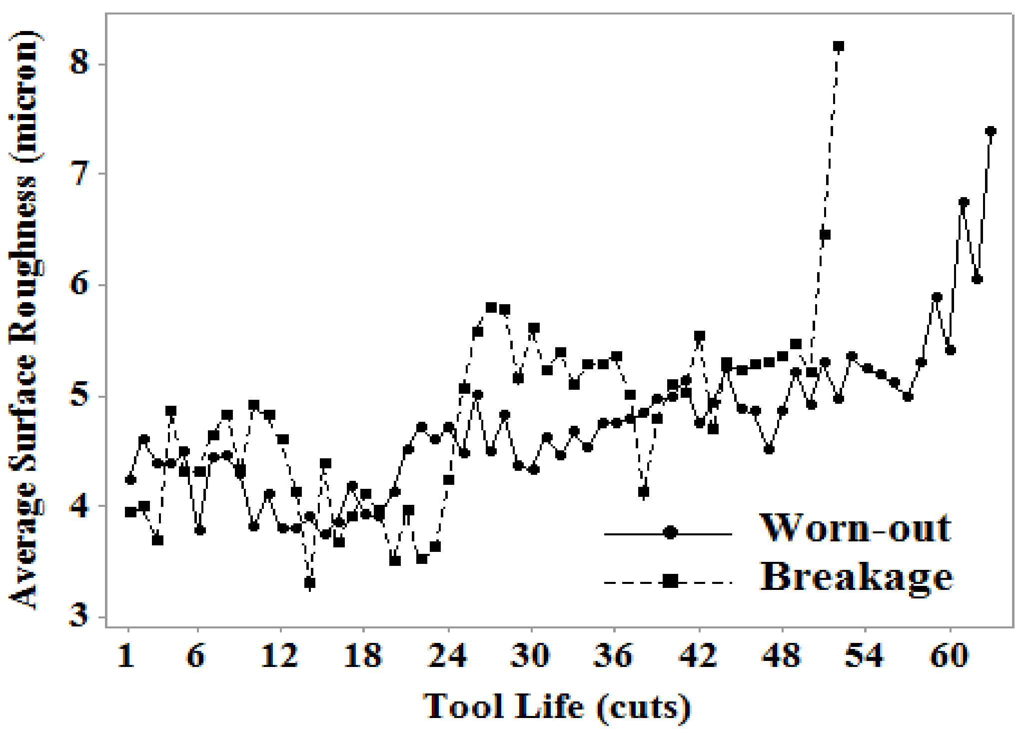

Fig. 4.3. Average surface roughness behavior vs. tool life.

To further verify these results, Spearman's Correlation Coefficient (SCC) is employed to gauge the strength of the monotonic relationship between product quality and tool degradation. It is the non-parametric version of the PCC, and its interpretation is similar to that of PCC. Eq. (4.2) shows the mathematical expression for SCC. Herein, the examination shows that the value of SCC ranges from 0.555 to 0.868 for the cutters failed owing to worn-out, while it ranges from 0.532 to 0.801 for the cutters failed owing to breakage. The average values of SCC in the case of worn-out and breakage are estimated as 0.739 and 0.658 respectively. These results confirm that even with different types of tools failure there exists a strong positive relationship between product quality and tool degradation.

Mapping this relationship will be of high significance to estimate the health condition of the tool based on product quality.

$$SCC\left(P_{R_a}, T_W\right) = 1 - \frac{6\sum(P_{R_{a_{R_i}}} - T_{W_{R_i}})^2}{N(N^2 - 1)} \tag{4.2}$$

where $P_{R_{a_{R_i}}}$ is the rank of the product quality in terms of average surface roughness of the i^{th} product, $T_{W_{R_i}}$ is the rank of the tool degradation in terms of tool wear at i^{th} cutting process and N is the total number of cases in the analysis.

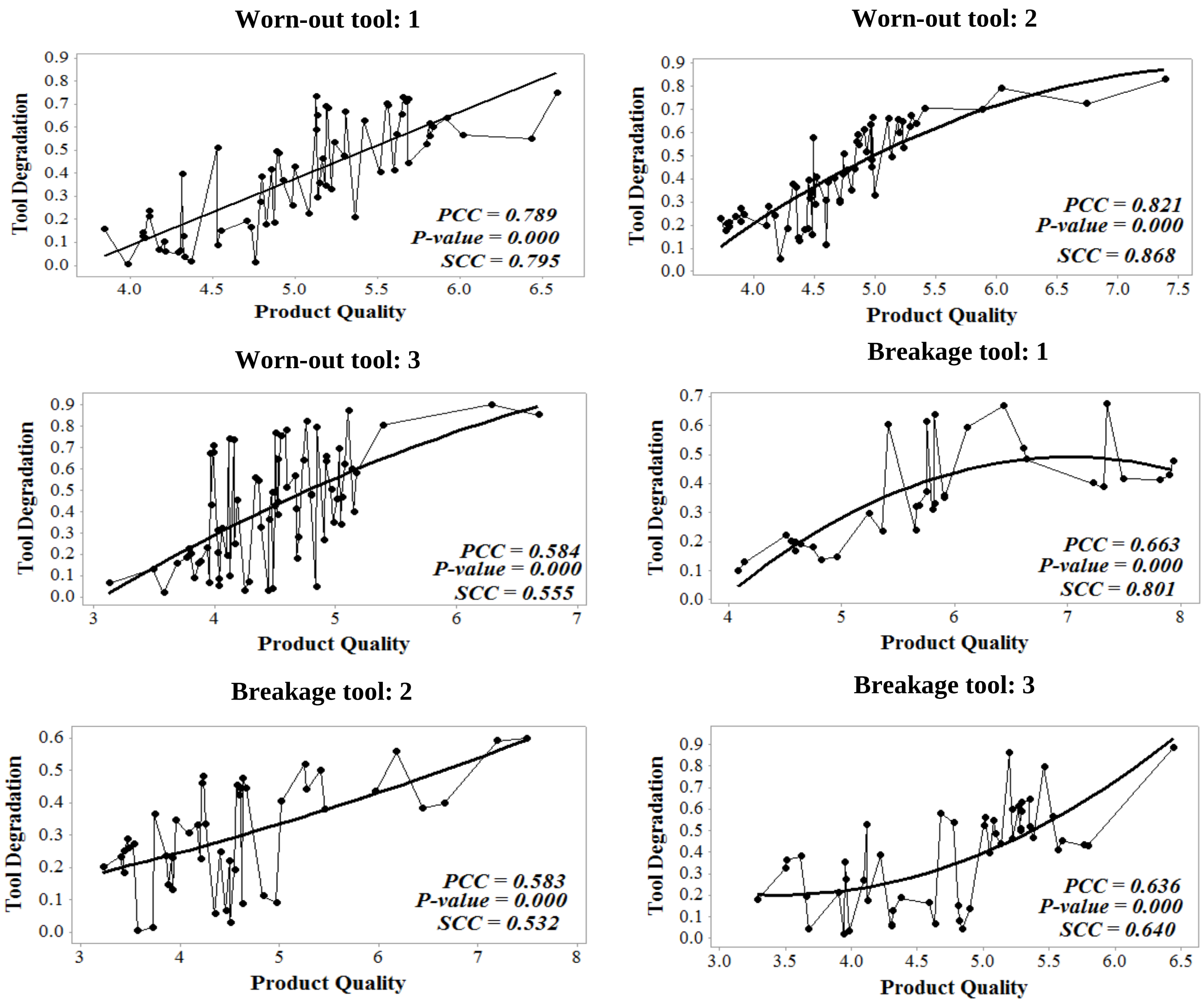

Fig. 4.4. Results of comprehensive correlation investigation.

4.4 Integrating Diagnostics and Prognostics

An integrated TCM system is scarcely studied in the relevant literature. Accordingly, an integrated TCM system based on the relationship between product quality and tool degradation is proposed. The architecture of a proposed integrated TCM system consists of two intelligent modules linked together. The first one is the diagnostics module; it is modeled to estimate the current health state of the cutting tool. Second is the prognostics module; it is formulated explicitly for the tools critical zone to predict remaining useful life. These modules are linked together to function as follows: the diagnostics module monitors the current health state of the cutting tool, whenever the degradation curve of the cutting tool reaches the critical stage the prognostics module is triggered and remaining useful life of the tool is assessed instantaneously. To model the desired mappings a supervised learning system, support vector machine is utilized. This SVM based integrated TCM system ascertains health monitoring and life prediction at the same time with a solitary experimentation. Theoretical and mathematical foundations of the developed diagnostics and prognostics modules are elaborated in following sub-sections.

4.4.1 Diagnostics Module

A significant part of the past work on tool monitoring has regarded the problem as one of figuring out if the cutting tool is worn or not worn. In reality, tool wear is a dynamic process, with tools, moving from being new to progressively greater levels of wear and possibly to breakage. On that ground, and as it provides more valuable information to machinists, the use of a multi-level categorization of wear is explored. Considering the case of cutting tools, health states of the cutting tools are categorized in three stages as a function of tool life. Fig. 4.5 demonstrates the splitting of the health states with their wear scopes. It splits the health state into three zones viz., Stage I: slight wear zone, Stage II: moderate wear zone and Stage III: critical or worn-out zone. A similar idea of quantized wear levels is also explored in Kurada and Bradley (1997) and Al-jonid et al. (2013). These literature and observation of the noticeable physical change in the surface roughness of the produced surface with tool degradation during experiments are the primary basis for selections of these wear scopes. In addition, to build the desired integrated TCM system, a new tool degradation indicator with diverse functionality as an input to represent the degradation features of the cutting tool is proposed. The TDI is a set of measures (current age and quality measurements), sensitive to cutting tool degradation. Current age (T_i) is the current age of the tool. Product quality in terms of the most widely used parameter average surface roughness is used and defined as “the result of irregularities arising from the plastic flow of chips during the machining” (Lou et al., 1999). The product quality during current and previous inspection can be defined as follows:

Current inspection;

$$R_{a_i} = \frac{1}{L}\int_0^L |Y(x)_i|\, dx \tag{4.3}$$

where the parameter L is the sampling length, and function *Y(x)* is the coordinate of the roughness profile curve.

Previous inspection;

$$R_{a_{i-1}} = \frac{1}{L}\int_0^L |Y(x)_{i-1}|\, dx \tag{4.4}$$

The proposed TDI plays a distinctive role in diagnostics module. The tool current age is important for diagnostics module in estimating the degradation of the cutting tool. While, average surface roughness measurements of the present and previous inspection are useful in representing the current health condition of the cutting tool. Herein, the TDI is normalized. The output from the diagnostics module is the current health state of the cutting tool.

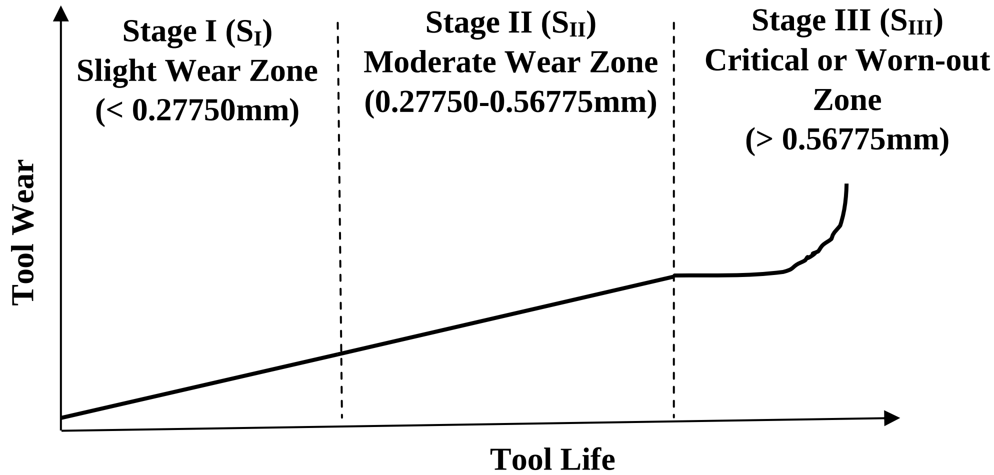

Fig. 4.5. Tool health states as a function of tool life.

Modeling of the diagnostics module should be proficient in achieving the desired input-output mapping. Consequently, C-Support Vector Classification (C-SVC) is utilized for modeling diagnostics module. Through, C-SVC, an optimum separating hyperplane is built in the higher-dimensional input space, for the classification of different health states of the milling cutter. Let the *n*-dimensional input training vectors $y_i \in \mathrm{S}^{\mathrm{n}}, i = 1, 2 \ldots, m$, (*m* is the number of samples) in two classes and a label vector $z \in \mathrm{S}^{\mathrm{m}}$, such that $z_i \in \{1, -1\}$, slack variable (ξ_i) and regularization parameter *C*. The required optimum hyperplane is established by solving a convex quadratic optimization problem (Cortes and Vapnik, 1995), given as:

$$\min_{a, b, \xi} \quad \frac{1}{2} a^T a + C \sum_{i=1}^{m} \xi_i \tag{4.5}$$

$$\text{Subject to} \quad z_i(a^T \phi(y_i) + b) \geq 1 - \xi_i,$$

$$\xi_i \geq 0, i = 1,2 \ldots, m,$$

where a is an *n*-dimensional vector and b is a scalar (utilized to decide the location of the separating hyperplane) and the function $\phi(y_i)$ maps y_i in a higher dimensional space.

The variable α is possible to have high dimensionality; thus the problem is simplified by converting into the equivalent Lagrange dual problem through Kuhn-Tucker conditions and given as:

$$\min_{\alpha} \quad \frac{1}{2}\alpha^T R\alpha - f^T\alpha \tag{4.6}$$

$$\textit{Subject to} \quad (z^T\ \alpha) = 0,\ 0 \le \alpha_i\ \le C,\ \ i = 1,2\ldots,m,$$

where α is Lagrange multiplier, $f = [1,\ldots,1]^T$ is the vector of all ones, R is an l by l positive semi definite matrix and given as:

$$R_{ij} \equiv z_i z_j K(y_i, y_j),\ K(y_i, y_j)\ \equiv\ \phi(y_i)^T\phi(y_j) \tag{4.7}$$

The kernel function ($K(y_i, y_j)$) is used to project the data into a virtual space where it might be easier to separate them. Radial Basis Function (RBF) kernel is utilized as a part of this work to shape the decision boundary, since they are not sensitive to the outliers and have no equal variance requirement for the input data. The RBF kernel takes the following form:

$$K(y_i, y_j) = \exp^{-\gamma\|y_i - y_j\|^2} \tag{4.8}$$

To increase the diagnostic reliability of the system, this work research on the use of multi-level categorization of degradation. This makes the current problem a multi-class classification problem. Accordingly, a multi-class classifier from binary C-SVC is reconstructed. According to a comparative investigation between different methods for multi-class C-SVC by Hsu and Lin (2002), it is established that the one-against-one (building and combining numerous binary classifiers) is a competitive method. Consequently, the same method for binary decomposition is employed. Herein, if k is the number of health states of the cutting tool, then $k\ ((k-1)/2)$ binary classifiers are constructed and each separates each other overlooking entire supplementary health states. Various coupling schemes are used to associate binary classifiers for the global solution of this problem. Herein, a voting strategy is used, “each binary classification is considered to be a voting where votes can be cast for all data points y, in the end a point is designated to be in a class with the maximum number of votes" (Chang and Lin, 2011). Subsequently, for the training samples of the i^{th} and the j^{th} health states, a binary classification problem given in Eq. (4.9) is solved.

$$\min_{a^{ij}, b^{ij}, \xi^{ij}} \quad \frac{1}{2}(a^{ij})^T a^{ij} + C\sum_t (\xi^{ij})_t \tag{4.9}$$

Subject to $(a^{ij})^T \phi(y_t) + b^{ij} \geq 1 - \xi_t^{ij}$, if y_t in the i^{th} class,

$(a^{ij})^T \phi(y_t) + b^{ij} \leq -1 + \xi_t^{ij}$, if y_t in the j^{th} class, $\xi_t^{ij} \geq 0$.

Here, the support vectors are lesser than the training samples making C-SVC computationally efficient. Finally, the desired optimal decision function of the proposed diagnostics module is as follows:

$$sgn(a^T \phi(y) + b) = sgn\,(\sum_{i=1}^{l} z_i \alpha_i K(y_j, x) + b) \tag{4.10}$$

This diagnostics module involves estimating the current health state of the tool; as the critical health state is detected, prognostic is needed to be involved in predicting the remaining useful life of the tool. Thus, a prognostics module is linked with the diagnostics module.

4.4.2 Prognostics Module

In most of the available work, researchers built models for future wear prediction. This does not assist in the definitive function of tool condition monitoring. On this ground, and as it will be more significant, the prognostics module is formulated to deliver information about the remaining useful life of the cutting tools. Herein, the prognostics module predicts RUL by assessing the extent of degradation from its expected state of health in its expected usage conditions. The life of the cutting tool comprises of three health states as a function of tool life. In which, the tool is most failure-prone in its third stage, as tool wear is in the critical zone. The precise knowledge of RUL, while tool wear is in critical zone, is crucial to avoid failure consequences. Thus, to improve the prognostics module competence, the module is explicitly formulated for the critical zone as a function of tool life. This explicit module will be more beneficial than developing the module for the entire life of the tool. Also, as the module is built for a specific time frame, it will reduce the error in prediction. Based on real-time RUL assessment from the prognostic module, effective actions can be taken to minimize production loss and extend tool life.

The proposed tool degradation indicator (see, Section 4.3.1) plays a diverse role in prognostics module. The TDI consists of the current age of the tool (T_i) and product quality measurements in the present (R_{a_i}) and previous ($R_{a_{i-1}}$) inspection (see, Eq. (4.3) and (4.4)). Herein, T_i is important for prognostics module in estimating the RUL of the cutting tool. Whereas, R_{a_i} and $R_{a_{i-1}}$ are useful in representing the tool's working condition. For the output of the prognostics module remaining useful life is preferred and is denoted as RUL, as shown in Eq. (4.11).

$$RUL = F_t - C_{t_i} \tag{4.11}$$

where F_t is the tools time-to-failure (the time for which the tool is in service) and C_{t_i} is the time from when the RUL is estimated (the current time at which the RUL is required).

The RUL of a cutting tool is a non-linear function. To predict it, there is a need of the powerful tool which can determine the mapping relationship between the tool degradation indicator from the cutting tool and the RUL of the tool. To achieve this, the v-Support Vector Regression (v-SVR) is proposed; as it is a very powerful tool that can determine the non-linear function of the system. v-SVR is centered on the structural risk minimization principle and therefore capable to govern the upper bound of generalization risk at the same time cutting down the module complexity (Cortes and Vapnik, 1995, Benkedjouh et al., 2013). Taking the set of input-output pairs from the tools critical zone $\{(TDI_1, RUL_1), \ldots, (TDI_n, RUL_n)\}$, the aim is to approximate the non-linear relationship between tool degradation indicator and remaining useful life of the tool given in Eq. (4.12), in a manner that $f(TDI)$ must be closer to the actual RUL and must be flat to avoid over-fitting.

$$f(TDI) = w^T \phi(TDI) + x \tag{4.12}$$

where w is the vector of weights, x is the bias and the function $\phi(TDI)$ characterizes the non-linear mapping function.

For ensuring that the $f(TDI)$ come across the aim of closeness and flatness, the primal objective is to minimize (Chang and Lin, 2011):

$$Min \qquad \frac{1}{2}\|w\|^2 + C\left\{v.\varepsilon + \frac{1}{n}\sum_{i=1}^{n}(\xi + \xi^*)\right\} \tag{4.13}$$

$$Subject\ to \qquad RUL_i - \langle w^T.\phi(TDI)\rangle - x \leq \varepsilon + \xi_i^*,$$

$$\langle w^T.\phi(TDI)\rangle + x - RUL_i \leq \varepsilon + \xi_i,$$

$$\xi_i^*, \xi_i \geq 0.$$

where parameter ε is a deviation of a function $f(TDI)$ from its actual value and ξ, ξ_i^* are supplementary slack variables.

For solving the problem in Eq. (4.13), its dual formulation is presented by building a Lagrange function (Bhatt et al., 2014); the dual optimization problem is as follows:

$$\begin{aligned} Max \quad & -\frac{1}{2}\sum_{i,j-1}^{n}(\alpha_i - \alpha_i^*).(\alpha_j - \alpha_j^*).K\left(TDI_i, TDI_j\right) \\ & + \sum_{i-1}^{n} RUL_i.(\alpha_i - \alpha_i^*) \end{aligned} \tag{4.14}$$

Subject to

$$\sum_{i-1}^{n}(\alpha_i - \alpha_i^*) = 0,$$

$$\sum_{i-1}^{n}(\alpha_i + \alpha_i^*) \leq C\ v,$$

$$\alpha_i, \alpha_i^* \in \left[o, \frac{C}{n}\right].$$

where $K(TDI_i, TDI_j)$ represents the kernel function specified by $K\left(TDI_i, TDI_j\right) = \phi(TDI_i)^T . \phi(TDI_j)$. The solution to Eq. (4.14) produces the Lagrange multipliers α, α^*.

RBF kernel with parameter gamma (γ), as given in Eq. (4.8), is selected as it supplies high precision and has less execution time. Putting w in Eq. (4.12) gives the absolute approximated function of the proposed prognostics module, given as:

$$f(TDI) = \sum_{i-1}^{n}(\alpha_i - \alpha_i^*). K(TDI_i, TDI) + x \tag{4.15}$$

This explicit prognostics module will lead to a more precise estimate of RUL of the cutting tool. Consequently, guide towards the establishment of a well-organized preventive maintenance program based on an early warning of incipient defects.

4.5 Experimental Implementation Results

This section presents an exhaustive performance investigation of the proposed integrated TCM system. The tests and verification of the system are performed by using an Intel (R) Core (TM) i7-3770 CPU 3.40GHz PC. The principal of the multi-class C-SVC and v-SVR formulations are implemented by using the WEKA (version 3.7.12).

4.5.1 Optimal Module Parameters Setting

To train the developed integrated TCM system, the module and kernel parameters are need to be specified, that play an imperative part in the performance of the system. In most work, the authors end up choosing parameter by trial and error, which is not efficient. In the diagnostics module, regularization parameter C and RBF kernel parameter γ are the tuning parameters that need to be optimized. The parameter C ranges from $0 < C \leq \infty$, and controls over-fitting of the model; a high value of C means a strict classifier that does not admit many misclassified points. The parameter γ controls the degree of non-linearity of the model, a small value of γ will lead to curved hyper planes and a high value will constrain the hyper planes to be straighter. Likewise, in the prognostics module, model parameter υ and RBF kernel parameter γ are the important tuning parameters. The value of υ lies between 0 and 1, and governs the number of support vectors and training errors; higher support vectors reduces the computational efficiency of the module.

To optimize these parameters, a potential range of these parameters with the grid space is defined. Then, all the grid points are iterated to evaluate the one contributing the higher cross-validation accuracy. Finally, the parameters with the highest accuracy are selected for training the integrated TCM system. Usually, the search becomes slower as the values of these parameters become higher, thus it is better to restrict it to an equitable range. Accordingly, in the diagnostics module, the interval for the parameter C is taken as $\{1\ 1000\ 1000\}$, this will test the regularization parameter from 1 to 1000 with 1000 steps. Likewise, in the prognostics module, the interval for the parameter υ is taken as $\{0.01\ 1\ 60\}$, this will test the parameter from 0.01 to 1 with 60 steps. The interval for the parameter γ is taken as $\{0.01\ 2\ 120\}$, this will iterate over the gamma parameter, using values from 0.01 to 2 with 120 steps. Employing this grid search technique, the optimal training parameters obtained for diagnostics module are as $C = 100$, and $\gamma = 0.344$, and for prognostics module as $\upsilon = 0.497$, and $\gamma = 0.110$

respectively. These optimal parameters are used to train the integrated TCM system to achieve the best generalization ability.

4.5.2 Performance Investigation

In-depth performance assessment of the integrated TCM system is significant to recognize the practicability of the system in a real industrial environment. Accordingly, an exhaustive performance investigation is executed to distinguish the suitability, stability, quality, reliability, robustness, applicability and comprehensibility of the proposed integrated TCM system, for advanced industry maintenance. Consequently, the performance is verified by utilizing the life data of six milling cutters consisting of 321 samples drawn from experiments. Herein, K-fold cross-validation is designated for experimentally validating the integrated TCM system. It is a widely used statistical technique to evaluate the classification and regression systems. Kohavi, (1995) has shown that 10-fold cross-validation is paramount to make sure the strength and consistency of the performance of the model; the same is employed in the current study. The investigation is carried out in two phases; in the first phase the diagnostics module is evaluated, in next phase the prognostics module is evaluated.

4.5.2.1 Experimental Validation and Assessment of Diagnostics Module

The effectiveness of the diagnostics module is distinguished as follows:

a) Suitability

The Diagnostic Accuracy (DA) is evaluated to gauge the suitability of the diagnostics module. DA is the extent of the samples correctly categorized among the total number of samples evaluated. Detailed diagnostic accuracy per health state of the tool is demonstrated in Fig. 4.6. The weighted average DA accomplished by diagnostics module is 92.84 %; higher estimation of DA puts forward the suitability of the diagnostics module for classifying tool health states. The weighted average of the diagnostic accuracy is the sum of all diagnostic accuracy; each weighted according to the number of instances with that particular class label.

$$DA = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \times 100 \tag{4.16}$$

where T_P and T_N are total number of correctly recognized true positive samples and true negative samples respectively, F_P and F_N are total number of correctly recognized false positive samples and false negative samples respectively.

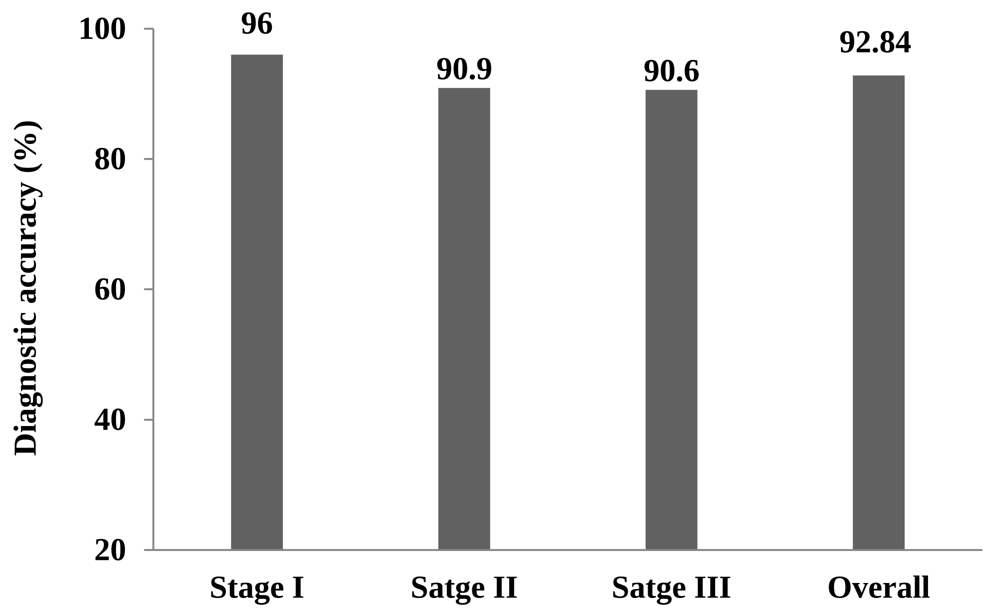

Fig. 4.6. Detailed DA for different health states of the tool.

b) Stability

To illustrate the stability of the diagnostics module, Specificity (SPF), Sensitivity (SEN) and Precision (P) are computed. SPF evaluates the extent of negatives which are correctly recognized. SEN evaluates the extent of actual positives which are correctly recognized. P is the proportion of true positives to the total number of positives recognized by the module. Their weighted average values are 95.80%, 92.80%, and 92.80%, respectively; this shows the stability of the diagnostics module, as it provides perfect predictions and lesser variance in predictions.

$$SPF = \frac{T_N}{T_N + F_P} \times 100 \tag{4.17}$$

$$SEN = \frac{T_P}{T_P + F_N} \times 100 \tag{4.18}$$

$$P = \frac{T_P}{T_P + F_P} \times 100 \tag{4.19}$$

c) Quality

For evaluating the quality of the classifications made by diagnostics module, Matthews Correlation Coefficient (MCC) and F-measure are calculated. MCC measures the quality of classifications, through the essence of correlation between the actual and predicted; its value lies between -1 and +1. Whereas F-Measure is interpreted as a weighted harmonic mean between precision and recall, its value stretches its best at 1 and its worst at 0. MCC value of 0.887 and F-Measure value of 0.928 from diagnostics module represents the good quality of predictions.

$$MCC = \frac{T_P.T_N - F_P.F_N}{\sqrt{(T_P + F_N)(T_P + F_P)(T_N + F_N)(T_N + F_P)}} \tag{4.20}$$

$$F - Measure = \frac{2 \times P \times SEN}{(P + SEN)} \tag{4.21}$$

d) Reliability

Reliability of the diagnostics module is verified through Kappa statistic; it is a chance-corrected indicator of agreement between the classified and the actual health states. Herein, the inter-class agreement is considered, making it more reliable degree. Its value lies between -1 and 1. A Kappa value of 0.888 from diagnostics module represents a reliable agreement for classification of tool health states.

$$Kappa\ Statistic = \frac{P_A - P_C}{1 - P_C} \tag{4.22}$$

where P_A is a percentage agreement and P_C is chance agreement.

e) Robustness

Robustness of the diagnostics module is evaluated by plotting the Receiver Operating Characteristics (ROC) curve. ROC curve contains a lot of information about the robustness of the modules predictive ability, as it provides an understanding of the complete spectrum of sensitivity and specificity, as all conceivable SEN / SPF sets for an individual examination are plotted. A worthy examination is one where SEN increases promptly and 1-SPF barely rises at all till SEN becomes high. Fig. 4.7 shows the ROC curve for different tool health states, it is evident that ROC curve of the diagnostics module covers a maximum area among all three stages. The weighted average ROC area is 0.943, which indicates the robustness of the diagnostics module for tool health state classification.

f) Applicability

Computational efficiency of diagnostics module is measured as 0.14 seconds in terms of the CPU time, making it computationally efficient to be applicable in real-time industrial environments.

g) Comprehensibility

Judging the comprehensibility of the diagnostics module is significant to see the performance by each health state. The best classification of a particular health state requires the specificity, sensitivity and precision values to be near to 100. Similarly, the MCC, F-Measure, and ROC area values should approach towards 1. As shown in table 4.1, the obtained specificity, sensitivity and precision values of each health state approach towards 100. Likewise, the MCC, F-Measure and ROC area values of each health state are very close to 1. These results underscore the merit of the classification performance of each health state.

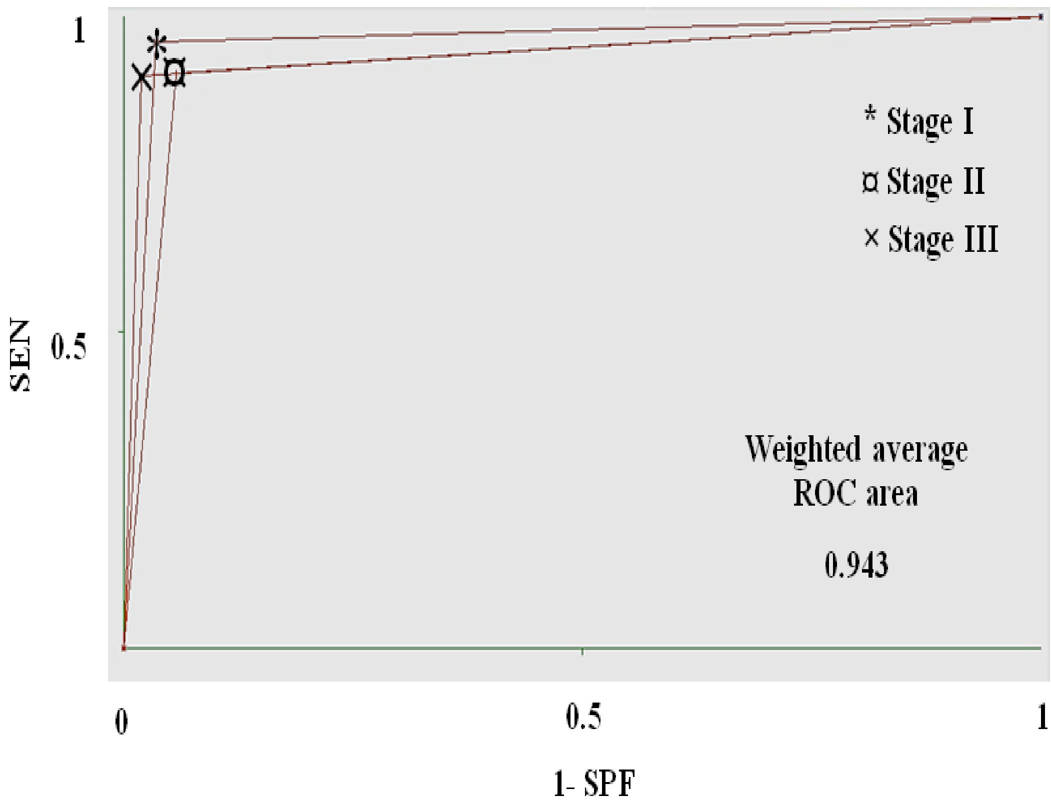

Fig. 4.7. ROC curve for different health states of the tool.

TABLE 4.1

COMPREHENSIBILITY ASSESSMENT

Health State	**Specificity (%)**	**Sensitivity (%)**	**Precision (%)**	**Matthews Correlation Coefficient**	**F-Measure**	**ROC Area**
$\mathbf{S_I}$	96.40	96.00	94.50	0.922	0.952	0.962
$\mathbf{S_{II}}$	94.20	90.90	91.60	0.852	0.913	0.925
$\mathbf{S_{III}}$	98.10	90.60	92.10	0.892	0.913	0.943
Weighted Average	95.80	92.80	92.80	0.887	0.928	0.943

These implementation results show that the diagnostics module is capable of effectively monitoring the health state of the milling cutters. This performance by the diagnostics module proves its worth for advanced industry maintenance.

4.5.2.2 Experimental Validation and Assessment of Prognostics Module

The performance of the prognostics module is distinguished in the following manner:

a) Suitability

To check the suitability of the prognostics module, Mean Absolute Error (MAE) is calculated. Herein, MAE measures how close RUL predictions are made by the module to the actual RUL. The MAE value of 1.613 from prognostics module shows predicted RUL is very close to the actual RUL, proving the suitability of the prognostics module in a real industrial environment.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|RUL_{P_i} - RUL_{A_i}\right| \tag{4.23}$$

where n is the total number of observations, RUL_{P_i} is the predicted RUL and RUL_{A_i} is the actual RUL.

b) Stability

For stability, Relative Absolute Error (RAE) and Root Relative Squared Error (RRSE) are evaluated; these are the measures of the variance in the predictions. Error rates of 39.16 % and 45.60 % represent the lesser variance in prediction and showing the stability of the module.

$$RAE = \frac{\sum_{i=1}^{n}\left|RUL_{P_i} - RUL_{A_i}\right|}{\sum_{i=1}^{n}\left|\overline{RUL_A} - RUL_{A_i}\right|} \times 100 \tag{4.24}$$

where $\overline{RUL_A}$ is the mean value of actual RUL.

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n}(RUL_{P_i} - RUL_{A_i})^2}{\sum_{i=1}^{n}(\overline{RUL_A} - RUL_{A_i})^2}} \times 100 \tag{4.25}$$

c) Quality

The quality of the prediction from the prognostics module is assessed through the goodness of fit. For which R-squared (R^2) correlation coefficient is calculated. Here, R^2 equals the square of the Pearson correlation coefficient between the actual and predicted RULs, R^2 represents how much predicted RULs are related to actual RULs. The R^2 value of 0.884 from prognostics module shows perfect linear relationship and high strength of correlation between actual and predicted RUL.

d) Reliability

Root Mean Squared Error (RMSE) is chosen to signify the reliability of the predictions from the prognostics module; it characterizes the standard deviation of the differences between predicted RULs and actual RULs. RMSE value of 2.175 represents reliable RUL predictions.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|RUL_{P_i} - RUL_{A_i}\right|} \tag{4.26}$$

e) Applicability

Computational efficiency of prognostics module is measured as 0.25 seconds in terms of the CPU time, making it computationally efficient to be applicable in real-time industrial environments.

f) **Comprehensibility**

Comprehensibility of the prognostics module is assessed by plotting the each output performance of the prognostics module, as shown in Fig. 4.8. Observation from this figure displays that each actual and predicted RUL are very close to each other. This performance shows that the prognostics module is robust in predicting the remaining useful life of the tool.

These implementation results from the prognostics module are very promising. This will ensure the development of an efficient preventive maintenance program based on an early warning of incipient failures. In addition, this will improve machining system availability, reduce downtime cost and enhance operating reliability.

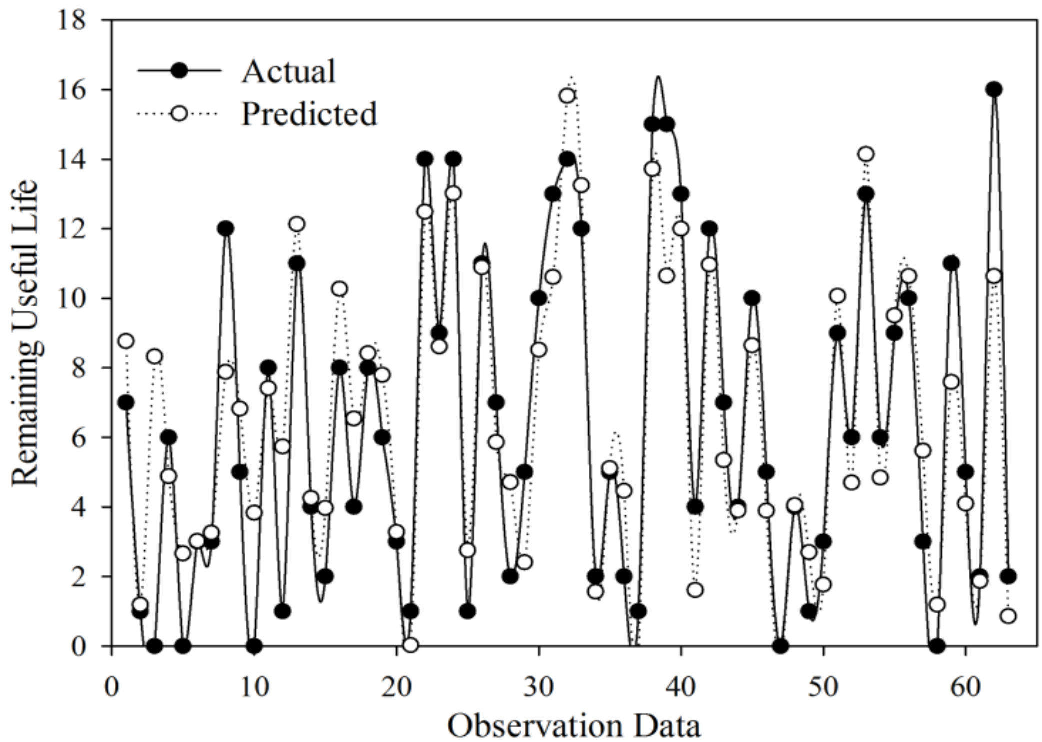

Fig. 4.8. The output performance of prognostics module.

4.5.3 Influence of Kernel Function

This section presents a comparative study on the performance of the RBF kernel with other kernels namely sigmoid kernel and polynomial kernel. Table 4.2 shows the mathematical expressions for these kernels. Herein, it is considered to judge the best kernel that yields optimal results, as no definite way is reported to decide the best kernel type. The proposed integrated TCM system is tested by comparing different kernels on the basis of accuracy and computational time using optimal kernel parameters and constant model parameters ($C = 100$ and $v = 0.497$). Table 4.2 shows the detailed comparative results. The experimental evaluations demonstrated that satisfactory results are produced by all the kernels in diagnostics module. Among which the polynomial kernel produced the lowest diagnostic accuracy. In consistency with several researches, RBF kernel yielded a higher diagnostic accuracy. In other words, RBF obtains almost 1.6 and 2.5 % better diagnostic accuracy compared with sigmoid and polynomial kernels respectively. In addition, RBF kernel shows the optimal results with respect to the fastest computational time, as it takes less training time than other kernels. Likewise, in prognostics module the results clearly show that, the RBF kernel provides lowest mean absolute error and having about 60 % improvement in accuracy over other kernels. Where, the accuracies of the sigmoid and polynomial kernels are relatively same. Moreover, the RBF kernel is found capable of taking less computational time compared to other kernels. Herein, it is worth noticing that; polynomial kernel is not suitable for remaining useful life prediction, as it takes high computational time.

On the ground of this comparative study, it can be concluded that the RBF kernel is proficient in achieving higher accuracy with the fastest computation. Consequently, the advanced performance of the integrated TCM system is the consequence of utilizing RBF kernel.

4.5.4 Comparative Analysis

In the direction of ensuring that the proposed integrated TCM system is having a robust problem-solving framework. An exhaustive comparative analysis is performed with widely used data-driven schemes build with the same set of experimental data. Herein, to verify the performance of diagnostics module it is compared with distinctive classification algorithms such as, Fuzzy system (Kaburlasos et al., 2003), Naïve Bayes (NB) (McCallum and Nigam, 1998), Rule-based (RB) (Frank and Witten, 1998), Hidden Markov Model (HMM) (Xu and Ge, 2004). Moreover, the performance of the prognostics module is verified by comparing it with the widely used ANN (Nakai et al., 2015). The detailed comparative results are shown in table 4.3. From this table, it is evident that among all HMM has shown the worst performance with 0 MCC and Kappa value representing very less agreement for classification of tool health states. The low DA from fuzzy, NB, RB and HMM classifiers shows poor suitability, as well as lower values of SEN, SPF, P shows poor stability. The lesser value of F-Measure than 0.7 shows low classification quality. The robustness of the proposed diagnostics module is evident with a highest weighted average value of ROC area among other classifiers. Furthermore, results in table 4.3 indicate that the high R^2 correlation coefficient from prognostics module shows that predicted RUL are highly related to actual RUL compared to ANN. Lower values of MSE and RMSE from prognostics module show higher accuracy in RUL prediction compared to ANN's output. Prognostics module has lesser error rate in the RAE and RRSE as it provides, the more perfect predictions and lesser variance in predictions. Moreover, the proposed prognostics module is also computationally efficient to be applicable in real-time environment.

Implementation results from this comparative study confirm that the proposed integrated TCM system is superior to other data-driven schemes and provides a robust problem-solving framework.

TABLE 4.2

PROFICIENCY OF INTEGRATED TCM SYSTEM FOR DIFFERENT KERNEL FUNCTIONS

Kernel function $K(y_i, y_j)$	Mathematical expression	Integrated TCM system					
		Diagnostics module			Prognostics module		
		Optimal parameter value	Diagnostics accuracy (%)	Computational time (s)	Optimal parameter value	Mean absolute error	Computational time (s)
Radial basis	See Eq. (4.8)	0.344	92.84	0.14	0.110	1.61	0.25
Sigmoid	$tanh(\frac{-{y_i}^T y_j}{s})$	10.869	91.28	0.17	9.091	4.11	0.40
Polynomial	$({y_i}^T y_j + 1)^p$	1st degree	90.34	6.98	2nd degree	3.63	842.50

TABLE 4.3

RESULTS OF COMPARATIVE ANALYSIS

Diagnostics Module						Prognostics Module		
Performance Measures	**Proposed Method**	**Fuzzy**	**NB**	**RB**	**HMM**	**Performance Measures**	**Proposed Method**	**ANN**
Diagnostic Accuracy (%)	92.84	75.70	64.18	76.01	38.94	**R-squared Correlation Coefficient**	0.884	0.641
Specificity (%)	95.80	75.70	64.20	76.00	38.90	**Mean Absolute Error**	1.613	2.826
Sensitivity (%)	92.80	90.20	75.10	83.50	61.10	**Root Mean Squared Error**	2.175	3.634
Precision (%)	92.80	79.60	77.50	62.40	15.20	**Relative Absolute Error (%)**	39.16	68.63
Matthews Correlation Coefficient	0.887	0.655	0.448	0.590	0	**Root Relative Squared Error (%)**	45.60	76.2
F-Measure	0.928	0.759	0.582	0.682	0.561			
Kappa Statistic	0.888	0.637	0.398	0.599	0	**Computational Time (sec)**	0.25	3.06
ROC Area	0.943	0.839	0.914	0.845	0.5			

4.6 Contributions

In this chapter, a novel integrated tool condition monitoring system was formulated by quantifying and mapping the relationship between product quality and tool degradation. The purpose was to provide manufacturing industries with an intelligent integrated monitoring system to instantaneously prevent machining system performance degradation and sudden failures. The major contributions from this chapter are highlighted as follows:

- A cost efficient experimentation strategy was implemented in an effort to create a simple, easily comprehensible monitoring system utilizing minimum resources to enable easy adaptation of the technology even in medium and small-scale machining industries. Where, mostly offline quality inspection is carried out and not much attention is given on integration of sensor system in the prevailing manufacturing system.
- A comprehensive investigation of the correlation between product quality and tool degradation was realized; revealing the strong positive relationship. Based on the investigated relationship, an integrated tool condition monitoring system based on support vector machine with optimal training technique was formulated. The architecture of the proposed system includes a linked diagnostics module with a prognostics module. Herein, the diagnostic reliability was enhanced by researching on the use of a multi-level categorization of degradation. Whereas, the prognostics competence was improved by formulating it explicitly for the tools critical zone as a function of tool life. In addition, a new tool degradation indicator with diverse functionality was introduced as an input, to represent the degradation features of the cutting tool. The function of this integrated system was to monitor the current health state of the machining system, and whenever the degradation curve of the tool reaches the critical zone, prognostics module was triggered, and remaining useful life was assessed instantaneously.
- The proposed system was thoroughly evaluated on a high-speed CNC milling machining system to recognize the practicability of the system in

a real industrial environment. Consequently, a comprehensive performance examination was performed to distinguish the suitability, stability, quality, reliability, robustness, applicability and comprehensibility of the integrated TCM system. This extreme performance assessment expands the system's robustness and applicability to the real industrial environment. The implementation results showed that the proposed system can monitor the machining system health condition effectively and improve the precision of remaining useful life prediction, thus it is pertinent to advance industrial asset management.

4.7 Closure

The proposed integrated TCM system was proficient in capturing the relationship between product quality and tool degradation and provides a robust problem-solving framework for the intelligent machining process. This will enrich the existing tool condition monitoring systems by considering the product quality as a new element for tool health monitoring. The advancement in the knowledge obtained in the current research results in significant savings in cost, time and improving productivity in the heavily competitive manufacturing industry.

The restriction in this work is that the proposed approach is only suitable for the applications in which the operating conditions are fixed. The applicability of this approach can be seen in applications with high volume of productions. Next chapter offers a generalized TCM system for a dynamic operating profile that enriches reliability of remaining useful life predictions while meliorating applicability in diverse real-world industrial scenarios.

Chapter 5*

A Generic Tool Condition Monitoring System under Dynamic Operating Profile

"*The effectiveness to be aimed at calls for the application and refinement of all conceivable prognostic techniques for adding to knowledge of the future, including those which can be effectively developed over an ever-wider time scale".*

Fred Polak, Dutch Futurist

In this chapter, the critical research gap identified in chapter 2 and the restriction of work presented in chapter 4 is circumvented by putting forward a novel and a generic TCM system capable of embracing the critical problem of remaining useful life prediction under dynamic operating profile. Succeeding, for the first time, pioneering adaptive functioning structures are formulated, to incite applicability for various real-world scenarios viz. batch production, job production, etc. In addition, the system was extensively evaluated using real-world vibration-based degradation signals from a high-speed CNC milling machining centre to substantiate the claim.

Key Highlights

Purpose: *The purpose was to equip manufacturing industries with intelligence that allows responding to the time-variant operating profiles and adaptable under various real-world production environments.*

Methodology*: The cutting tool degradation progression is mathematically modeled via a new, adaptive, and hybrid stochastic degradation model; engineered to unite strategic information viz. the evolution of the future profile, jerks owing to dynamic transitions, etc. Next, new mappings, i.e., degradation*

* *The work presented in this chapter is in review under the title "A generic tool condition monitoring system under dynamic operating profile" from September 2018 in "IEEE Transactions on Reliability", IEEE.*

rate function, and jerk function to bring realistic characteristics of any production system are formulated. Subsequently, the physics of evolution of dynamic profiles for various scenarios is inventively modeled. The resulting generalized system approximates the first passage time of the degradation process to a threshold and provides a precise life estimate in real-time.

***Findings**: The proposed methodology is competent in approximating the uncertainty imposed by real-world industrial scenarios. This aids in enriching the existing TCM systems to compute the cutting tool RULs while exploiting prior information, along with the future characteristics of operating profiles that the tool is likely to experience. Wherein, the experimental results confirmed that the offered approach delivers a generalized and a robust problem-solving structure for dynamic operating profiles.*

***Practical Implications:** The research in this work and the promising results attained underneath dynamic operating profiles guarantee the expansion of an effective preventive maintenance plan in diverse real-world production scenarios viz. batch production, job production, micro to medium-scale production environments. On the other hand, the experimental case study implementation lends significant credibility to the appropriateness of offered approach over the traditional approach under diverse industrial scenarios.*

***Originality and Contribution:** The novelty of this research is three-fold. The first is the innovative design of a generic TCM system that accounts for the future characteristics of the dynamic operating profiles while prognosticating RULs. It is grounded in the physics of degradation progression and is a function of operating profiles. As a result, the fundamental advantage of utilizing the proposed system to deal with time-variant operating profiles is its proficiency to communicate the future evolution of dynamic operating profiles instantaneously. Second is the consideration of all-encompassing cases of industrial scenarios. For the first time, a complex real-world scenario of expected but fluctuating future operating profiles is well-thought-off. Third, it is not restricted to a specific* *machine tool, sensor, and so on; rather the system is adaptive and can be rendered as a first universal perspective to TCM and for that matter any prognostics research. An additional contribution lies in the outcomes; extensive quantitative and qualitative performance investigations are carried out. Further, in contrast to the traditional approach, the implications of the offered system under different scenarios are experimentally examined. That magnifies the robustness and applicability of the offered system in diverse real-world production environments.*

Research Limitations and Future Scope*: The proposed framework consents modelling of solitary sensor, in future, for further strengthening of the prediction performance will requires extracting the information from multi-sensors.*

5.1 Introduction

Recalling chapter 1, that studies have exhibited that if CNC machining systems are fortified with tool condition monitoring, it can cut down seventy-five percent of the downtime and boost throughput by ten to sixty percent, and even upraise machine availability beyond fifty percent. Wherein, chapter 2 gives a picture that even the utmost promising TCM system is not certainly adaptable in real-world scenarios, principally owing to inadequate generalization competences viz. the vast majority of systems are strictly designed on the impression that along the entire lifespan of the cutting tool, the prevailing operating profiles[†5.1] are unvarying or does not affect the degradation. Thus, their applications are restricted in diverse practical industrial scenarios viz. batch or job production environments where the operating profiles are highly time-variant in nature. It would be of practical value to equip the TCM systems with intelligence that allows responding to the uncertainty of time-variant operating profiles and adaptable under various real-world scenarios. Accordingly, the aforementioned challenges[5.2] are addressed by offering a novel and a generic TCM system for a dynamic operating profile that enriches reliability of RUL predictions while meliorating applicability in diverse real-world industrial scenarios.

In contrast to existing literature, the methodology offered in this chapter is conceptually unique, as it explicitly address the challenges allied with time-variant operating profiles by integrating its physics capturing the uncertainty in the evolution of dynamic operating profiles, in real-time. Thus, the approximated RUL taps past as well as the future characteristics of operating profiles. Accordingly, a new, adaptive, and hybrid stochastic degradation model is devised; engineered to unite strategic information viz. the evolution of the future profile, jerks owing to dynamic transitions, etc. Next, new mappings, i.e., degradation rate function, and jerk function to bring realistic characteristics are formulated. The other realistic feature is that in the model the degree of divergence in tool's

[5.1] *Note: operating profile or profile refers to the specific combination of the levels of the operating parameters viz. speed, feed, depth of cut, etc.*
[5.2] *These challenges are briefed in chapter 2, section 2.3.*

degradation is related to the severeness of the in-progress profile. Subsequently, a new sorting algorithm is proposed to order the profiles with regard to their impact on the corresponding degradation rate. Also, pioneering adaptive functioning structures are inventively designed to incite generalization in diverse real-world industrial scenarios viz. batch production, job production, micro to medium-scale production environments. Withal, the model is correspondingly adaptive in perceiving the traditional degradation model, where the operating profiles remain same along the lifespan, appropriate for mass production environments. The resultant generalized TCM system approximates the first passage time of the degradation process of cutting tools to a failure threshold and is used to deliver the RULs, in real-time. To finish, the validation of the proposed system is demonstrated via an experimental case study employing vibration-based degradation signals from a high-speed CNC milling machining center. The verification results direct that the proposed system incisively predict the RULs in all the real-world scenarios.

The novelty of this work is three-fold. The first is the innovative design of a generic TCM system that accounts for the future characteristics of the dynamic operating profiles while prognosticating RULs. It is grounded in the physics of degradation progression and is a function of operating profiles. As a result, the fundamental advantage of utilizing the proposed system to deal with time-variant operating profiles is its proficiency to communicate the future evolution of dynamic operating profiles instantaneously. Second is the consideration of all-encompassing cases of industrial scenarios. For the first time, a complex real-world scenario of expected but fluctuating future operating profiles is well-thought-off. Third, it is not restricted to a specific machine tool, sensor, and so on; rather the system is adaptive and can be rendered as a first universal perspective to TCM and for that matter any prognostics research. An additional contribution lies in the outcomes; extensive quantitative and qualitative performance investigations are carried out. Further, in contrast to the traditional approach, the implications of the offered system under different scenarios are experimentally examined. It magnifies the robustness and applicability of the offered system in diverse real-world production environments.

The remainder of this chapter is structured as follows. In-depth formulation of the mathematical model and functioning structures are offered in section 5.2. In section 5.3, systematic and extensive performance investigations are demonstrated. In section 5.4 contributions are highlighted. Finally, section 5.5 summarises the chapter.

5.2 Methodology

The proposed methodology is targeted at prognosticating cutting tool RULs while exploiting prior information, along with the future characteristics of operating profiles, in real-time. Necessitating innovative modeling for (1) a real-time sensor-based degradation progression; (2) the physics of evolution of time-variant operating profiles under diverse real-world scenarios. Accordingly, a realistic mathematical modeling framework is devised via a new, adaptive, and hybrid stochastic degradation model, innovatively engineered to unite following critical roots of information:

- The real-time degradation signal and rate of degradation characteristics.
- The evolution of the future operating profile.
- Jerks owing to dynamic transitions.

These are discussed in details here under.

5.2.1 The Real-Time Degradation Signal and Rate of Degradation Characteristics

Fig. 5.1 displays real-life vibration-based degradation signals concerning Root Mean Square (RMS) value from three similar cutting tools functioned under various profiles viz. low, medium, and severe operating profile[5.3]. Fig. 5.1 suggests that the sensor-based degradation signals of even same tools operating under various profiles exhibit different functional forms. Following, the current

[5.3] Note that the term “low operating profile” or “medium operating profile” refers to the profile’s degradation inducing severity, which depends on the levels of a specific combination of the operating parameters viz. speed, feed, etc.

observation of degradation signal from the in-situ sensor is incorporated in the model. Also, Fig. 5.2 represents that under time-variant profile the vibration level of tool increases as it transits from lower profile to severe profile and vice-versa. It is implied that the degree of divergence in tool's degradation is related to the severeness of the in-progress profile. To induce this realistic characteristic, the model is made to capitalize the prior information from a population of same tools about the tool's rate of degradation that it will follow under a specific profile. Thus, a new degradation rate function is formulated and integrated it with the model.

At time t, $D_s(t)$ is any sensor-based degradation signal and $D_s(0)$ is deterministic current sensor-based observation. Moreover, let $\xi(t)$ be any operating profile at time t and the in-operation tool can occupy one of the profile from a set of profiles Q ($Q = \{q_1, q_2, \dots, q_r\}$, q_r is the total number of profiles in the given set and $q_r < \infty$. Herein, determining the precise number of profiles, and a meaningful ordering of the profiles in Q, are important aspects of the proposed model. Although in general total numbers of profiles in which the manufacturing system will operate are known in advance. So, it is undertaken that the value q_r is identifiable. Following that, the formulated degradation rate function is $\omega(\omega : Q \to \mathbb{R}^+)$. So, $\omega(\xi(t))$ indicates tool's degradation rate, i.e., at any time $\xi(t) = j \in Q$, the tool degrades at rate $\omega(j)$ (it is presumed that $\omega(j) > 0$ for each $j \in Q$). In this work, the formulated degradation rate function aids in approximating a trend i.e., it is the change in sensor-based degradation signal for a unit change in time along the tool life under a specific profile. Herein, the approximation of rate of degradation for any sensor-based degradation signal under a distinct profile ($\omega\big(\xi\,(t_i)\big)$) is projected from past historical data and given as follows:

$$\omega\big(\xi(t_i)\big) = \frac{(\sum D_s(\xi(t_i))(\sum {t_i}^2) - (\sum t_i)(\sum D_s\big(\xi(t_i)\big) \times t_i)}{L_s \times \left(\sum D_s\big(\xi(t_i)\big)^2\right) - \left(D_s\big(\xi(t_i)\big)^2\right)} \tag{5.1}$$

where $D_s(\xi\,(t_i))$ is the degradation signal under a distinct profile, t_i is the time at i^{th} instance ($i \in \{1, \dots, L_s\}$), and L_s is the length of the degradation signal.

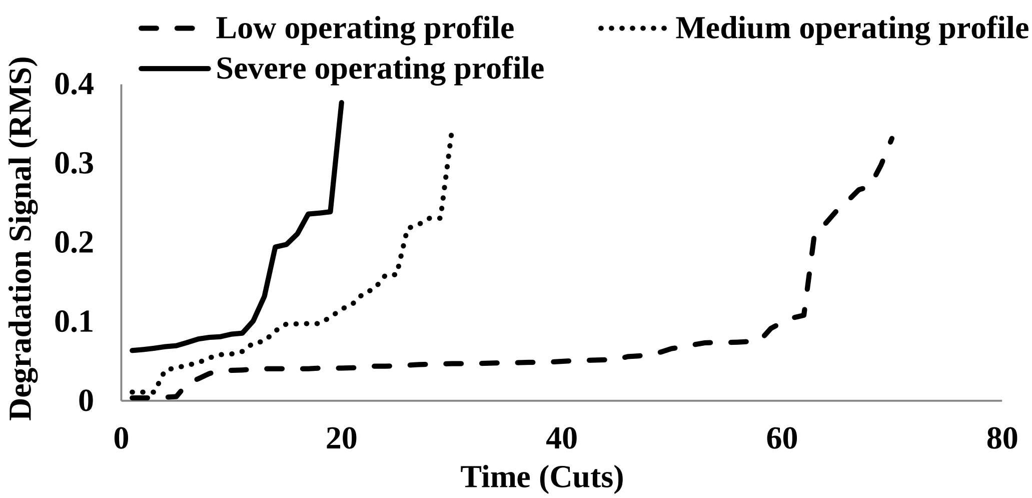

Fig. 5.1. Real-life degradation signals under various operating profiles.

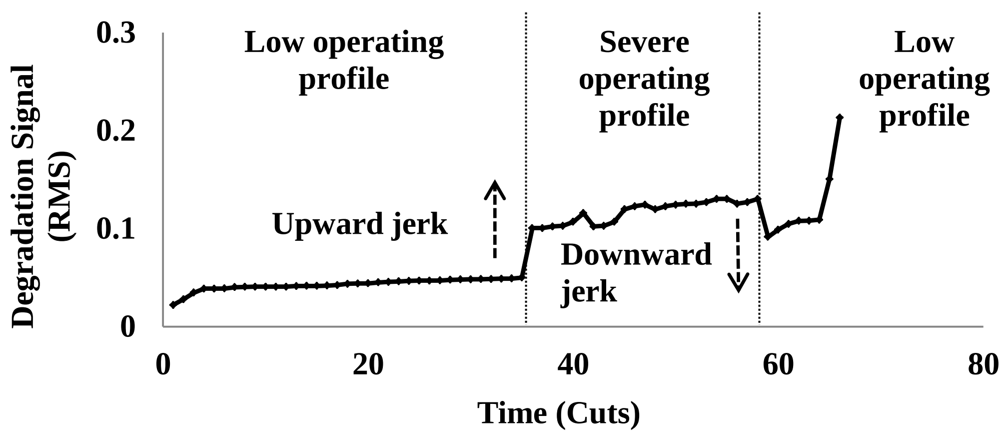

Fig. 5.2. Real-life degradation signal in time-variant operating profiles.

Next, an essential aspect of the modeling framework is described, namely determining the set of operating profiles and arranging the elements of the set Q by ordering them according to their level of severity. In general, the degradation of tools in any machining system is influenced by speed, feed, depth of cut, lubrication, etc. Though not all of the operating parameters are necessarily significant, and some of these possible combinations have a similar effect on the degradation rate. Since a vast number of profiles might raise possible computational issues; only the significant operating parameters are chosen and the profiles are ordered. Let $Z_1, Z_2, \dots, Z_{k'}$ represent k' significant parameters and $\xi(m_1, \dots, m_{k'})$ denotes the profile when Z_1 assumes level m_1, Z_2 assumes level m_2, and so forth. Now a sorting algorithm is proposed to order the profiles $\xi(m_1, \ldots, m_{k'})$ with regard to their impact on the corresponding degradation rate $\omega(m_1, \ldots, m_{k'})$. The observations from past historical data are used to perform a hypothesis test with null hypothesis being H_0: $\omega(m_1, \ldots, m_{k'}) \geq \omega(m'_1, \ldots, m'_{k'})$ against the alternate hypothesis H_1: $\omega(m_1, \ldots, m_{k'})) < \omega(m'_1, \ldots, m'_{k'})$. If there is sufficient evidence to reject the H_0 at the α level of significance, it is concluded that profile $\xi(m_1, \ldots, m_{k'})$ is less severe than the profile $\xi(m'_1, \ldots, m'_{k'})$. This comparision procedure can be applied pairwise to all profiles. So, all of the operating profiles in Q from low to high by severity can be ordered so that, for any two $i, j \in Q, i < j$ implies that profile i induces a smaller degradation rate than profile j.

5.2.2 The Evolution of the Future Operating Profile

Evident from Fig. 5.2, the transition among various profiles expressively contributes the degradation progression. Consenting that, the model is reinforced to approximate the physics of evolution of time-variant operating profiles. Accordingly, for the first time, adaptive functioning structures are formulated to incite generalization in following diverse real-world scenarios:

- Industrial Scenario I: A deterministic, dynamic operating profile.
- Industrial Scenario II: A randomly-varying dynamic operating profile.
- Industrial Scenario III: An expected but fluctuating future operating profile.

5.2.2.1 Industrial Scenario I: A Deterministic, Dynamic Operating Profile

In this scenario, dynamic operating profiles that evolve in a deterministic manner is emphasized, i.e., there is certainty about the profile transition times, see, Fig. 5.3 (a). Herein, the degradation rate changes when the tool is operated under diverse profiles, and such changes induce distinct degradation patterns that are usually significant, see Fig. 5.3 (b). Such a scenario exceedingly arises in a batch production type of environments (where the machining system runs at a particular profile to meet the requirement of a specific batch and transit to other profile based on the prior batch scheduling decisions) which belong to repetitive production. It concerns with the manufacturing of products, the quantity of which is well-known and where same goods are made in batches by the demand of consumers'. Herein, one batch of goods may not resemble with the next batch, it means that the machining system run at a particular operating profile for a certain amount of time and then the product is changed, so as the operating profile to regulate the new requirements. Consequently, the operating profile varies dynamically, but in a deterministic manner, as the distinct operating profiles operate for a specific time, as well as the time at which it transit to other profile is also known/deterministic. Such a scenario is encountered in medium and heavy engineering industry (engaged in the manufacturing of electric motors, switchgear, machine tool, etc.), as these are allied with unique seasonal demand, or there is a requirement to manufacture diverse products. To circumvent this, the impact of in-progress operating profiles on the degradation rate under this scenario is modeled, while undertaking the evolution of the future operating profile, as a finite-valued deterministic and piecewise constant function. So, let $\xi: [0, \infty) \to Q$ be an Q-valued piecewise constant function; $\xi(t_i)$ is the profile at a discrete deterministic time t_i $(i \in \{1, 2, \dots, T\})$. That is, in-operation the profiles in Q visits in a deterministic way. Following that, the finite-valued deterministic and piecewise constant function $\xi(t_i)$ is formulated as follows:

$$\xi(t_i) = \sum_{i=1}^{T} \alpha_i \chi_{A_i}(t_i) \ \ for\ all\ real\ numbers\ of\ i. \tag{5.2}$$

where α_i is a real number such that $\alpha_i \in Q$ and $\chi_{A_i}$is the indicator function over the interval A_i at time instant t_i.

$$\chi_{A_i} = \begin{cases} 1 & for\ t_i \in A_i, \\ 0 & for\ t_i \notin A_i. \end{cases}$$

In this formulation, the intervals (A_i) follows the following two properties:

a) The intervals (A_i) are pairwise disjoint set i.e. $A_i \cap A_j = \emptyset$ for $i \neq j$

b) The union of the intervals covers the whole range of positive real numbers i.e $\bigcup_{i=1}^{T} A_i = \mathbb{R}^+$.

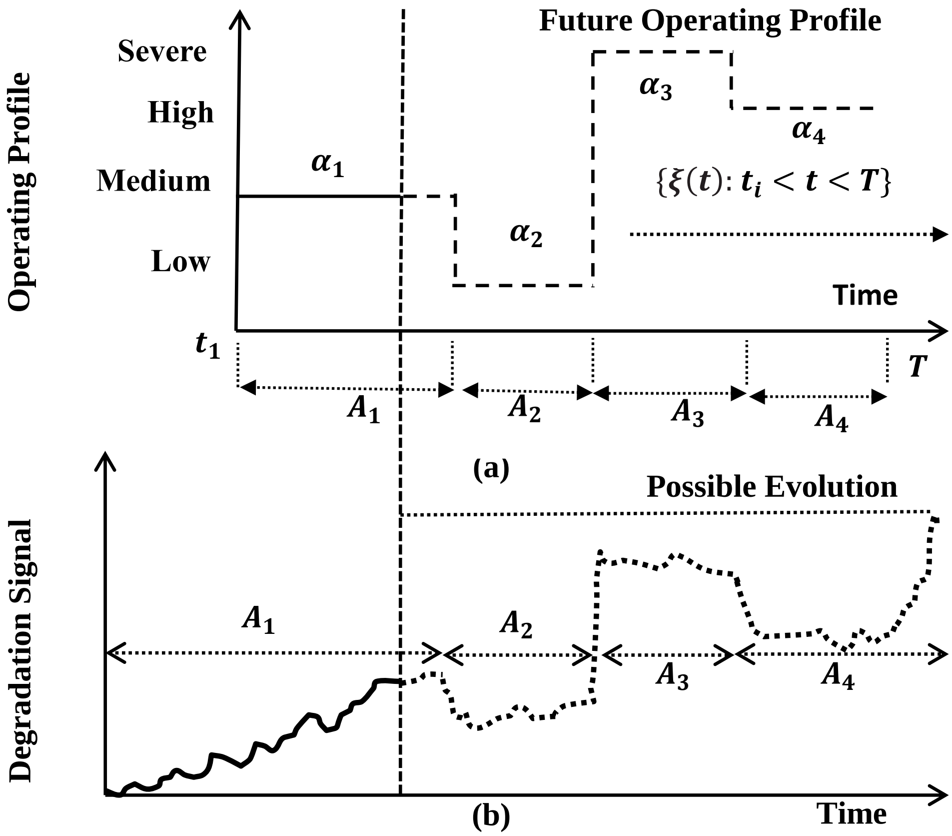

Fig. 5.3. Deterministic, dynamic operating profile.

Precisely, in accordance with Fig. 5.3, $\xi(t_i)$ is expressed as:

$$\xi(t_i) = \begin{Bmatrix} Medium\ (\alpha_1), & t_1 \in A_1 \\ Low\ (\alpha_2), & t_2 \in A_2 \\ Severe\ (\alpha_3), & t_3 \in A_3 \\ High\ (\alpha_4), & t_4 \in A_4 \end{Bmatrix}$$

Finally, on the interval $[t_i, T]$, the previously formulated rate of degradation function while undertaking the evolution of the future profile as a finite valued deterministic and piecewise constant function can be written as, $\int_{t_i}^{T} \omega(\xi\,(x))\,dx$.

5.2.2.2 Industrial Scenario II: A Randomly-Varying Dynamic Operating Profile

In this scenario, the evolution of dynamic operating profiles is uncertain. This mean that the transition times in each distinct profile is exclusively random or time-variant, see Fig. 5.4. Such a scenario is exceptionally often in job production environments, which take on the manufacturing of customized products, such as a one-time product for a specific customer or a small batch of products by clients' uncompromising demand. Herein, as each product is unique (varying in dimensions and material); it necessitates a distinct profile for machining. Thus, the operating profiles are dynamically varied in a manner to suit the uncertain requirements of a particular product. Aerospace and shipbuilding industries are recurrently lying open to such a scenario. Herein, the more prominent challenge is to generalize the functioning structure of scenario I by approximating the physics in arrears with the inherent uncertainty of randomly-varying future profiles. To circumvent this, under periodically monitored situations, it is undertaken that the randomly-varying dynamic profile progresses rendering Discrete-Time Markov Chain (DTMC). So, let $\{\xi(t): t \geq 0\}$ be the DTMC and $\xi(t)$ be the random operating profile. Herein, DTMC is for the set of operating profiles $Q = \{q_1, q_2, \dots, q_r\}$, Q is discrete and have finite number of operating profiles ($q_r < \infty$). Herein, $\{\xi(t): t \geq 0\}$ is a sequence of random operating profiles, say, $(X_1, X_2, X_3, \dots, X_N)$. As it is already mentioned, that the set of possible profiles Q of X_n (where n is the index for time) is finite and called as state space of the chain. The chain transition from one profile (say, q_i, $\forall\ i \in \{1, \dots, q_r\}$) to another profile (say, q_j, $\forall\ j \in \{1, \dots, q_r\}$) with the transition probability (say, p_{ij}) in one step, and given as:

$$p_{ij} = Pr(\ X_1 = q_j | X_0 = q_i) \tag{5.3}$$

Subjected to

$$0 \leq p_{ij} \leq 1,$$

and

$$\sum_{j=0}^{\infty} p_{ij} = 1.$$

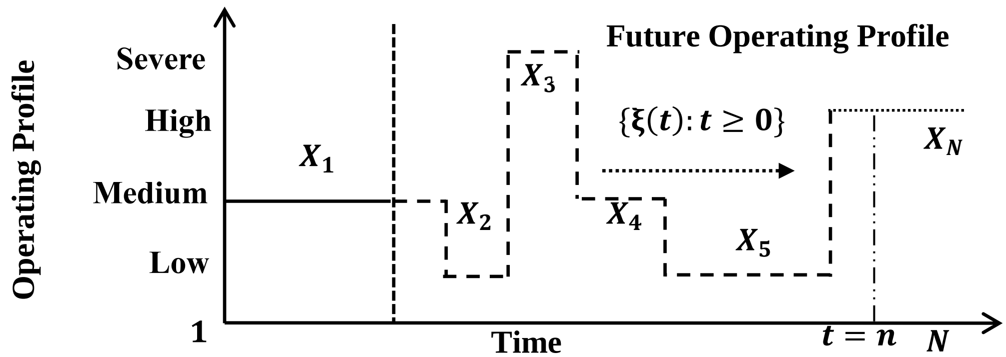

Fig. 5.4. Randomly-varying dynamic operating profiles.

Next, to represent the probability distribution of transitions from one profile to another a transition matrix (say, $\theta = (p_{ij})_{i,j,}$) is formulated. Where, θ is a square matrix of dimension $q_r \times q_r$, where each element of position (i, j) represents the transition probability p_{ij}. In most practical cases, the transition probability matrix is unknown. In view of that, a method to approximate transition probability matrix from the historical profile transition dataset is presented. Let $Y_N = (y_1, \ldots, y_N)$ is a q_r state chain with parameter to estimate being transition probability matrix and constraints being: $0 \leq p_{ij} \leq 1$ and $\sum_{j=0}^{q_r} p_{ij} = 1$. So, first the likelihood function is formulated, which is as follows:

$$p(Y_N; \theta) = p(y_n | y_{n-1}; \theta)\, p(y_{n-1} | y_{n-2}; \theta) \ldots p(y_1 | y_0; \theta)\, p(y_0; \theta) \tag{5.4}$$

Next, the log-likelihood function is formulated, as follows:

$$logp(Y_N; \theta) = \sum_{k=1}^{N} log\, p(y_k | y_{k-1}; \theta) \;\; logp(y_0; \theta) \tag{5.5}$$

Substituting the likelihood function in Eq. (5.5) and solving gives:

$$= \sum_{i=1}^{q_r} \sum_{j=1}^{q_r} J_{ij}(N)\, log p_{ij} + \sum_{i=1}^{q_r} \delta(y_0 - i)\, \pi_0(i)$$

where J_{ij} is total number of times the profile i switches over profile j from time 1 to N.

Then, subjected to constraints, taking the derivative and set it equal to zero as:

$$\frac{d}{dp_j} log p(Y_N; \theta) = 0$$

This yields the one-step transition probabilities, as follows:

$$p_{ij} = \frac{J_{ij}(N)}{\sum_{j=1}^{q_r} J_{ij}(N)} = \frac{J_{ij}(N)}{D_i(N)}$$

where, $D_i(N)$ is the number of visits in i. Hereafter, arranging one-step transition probabilities into a matrix, gives $\theta = \begin{bmatrix} p_{11} & \cdots & p_{1q_r} \\ \vdots & \ddots & \vdots \\ p_{q_r 1} & \cdots & p_{q_r q_r} \end{bmatrix}$. The complete training data is used to approximate this matrix. Finally, the randomly-varying process $\{\xi(t): t \geq 0\}$ is the future profile from time t_0 up to some future time $t = n$. The previously formulated rate of degradation function while undertaking the evolution of the future profile as a discreet time Markov chain can be formulated as, $\int_0^t \omega(\xi\,(x))\, dx$.

5.2.2.3 Industrial Scenario III: An Expected but Fluctuating Future Operating Profile

In the third scenario, the prior understanding of the expected future profile is known in advance, withal; the dynamic transitions of a profile in the future are subjected to uncertainty. For instance, consider a manufacturing system operating under two distinct profiles (say, low and high), where it is expected that along the lifespan of the cutting tool, it will operate a total forty percent of the time at a low profile, and remaining total sixty percent at the high profile. Though, there is existent uncertainty in the evolution of these standard profiles, as the future profile fluctuates randomly amongst distinct profiles along the lifespan of the cutting tool but total expected duration in a specific profile is known, see Fig. 5.5. Such a complicated scenario is prominently realistic for almost every micro to medium-scale production environments (here the demand forecasting may reveal the total expected duration under different profiles of the machining system), where products are standard with customary minimum order quantity; nevertheless, their demands are subjected to fluctuations. In this, as all the goods are standard, operating profiles to machine each product is distinct. Also, as the manufacturer sets the customary minimum order quantity, it is expected to know in advance that along the lifespan of the system for how much time it will operate in distinct operating profiles. On top, the demands from a customer for these products are uncertain. As a result, the dynamic operating profiles are expected but fluctuating. Spare-part, jig, and fixture manufacturing industries (engaged in the production of various standard spare-parts/fixtures for electronic, automobile, railway, etc.) are vastly exposed to such a scenario; as these are associated with standard parts with high variations in demands. The more significant challenge existent here than before is in bringing together the restrictions (as per the expected future profiles) while approximating the physics in arrears with the evolution of uncertain fluctuating future profiles. To circumvent this, for the first time, discrete operating bins (φ_n) are characterized for respective operating profiles and the percentage of the time the tool will function in a particular operating bin is utilized as the additional statistics fed into the proposed stochastic degradation model while accounting the future evolution of expected but the fluctuating operating profile. Herein, a restriction in the evolution of the time-variant profile based on the expected future profile is probabilistically induced. In the interior, the model is designed to compute the aggregate of transitions in respective operating profiles; the instance the expectancy of the respective operational profile is achieved, the transition distribution is updated probabilistically. The updated distribution better characterizes the standard expected future profile and further reduces uncertainty. To mathematically illustrate this in accordance with Fig. 5.5, where, a manufacturing system operating under two distinct operating profiles ($Q = \{\text{Low (1)}, \text{High (2)}\}$) with the known transition probabilities ($\theta = \begin{array}{c} \text{Low (1)} \\ \text{High (2)} \end{array} \begin{bmatrix} 0.7 & 0.3 \\ 0.5 & 0.5 \end{bmatrix}$) is considered. Whereas, it is expected that the system will operate 40% of the time in low profile and remaining 60% in high profile. So, the operating bins are set as φ_1= 40% $\xi(t)$ and φ_2= 60% $\xi(t)$ and a new set of states such as $(1, \vartheta)$ and $(2, \vartheta)$ are introduced, where, ϑ is the number of visits in first operating bin (φ_1). Subsequently, the transition probabilities of previously formulated DTMC with discrete operating bins ($\{\xi(t): t \geq 0, \varphi_n\%\}$) changes in accordance with expected future operating profiles, and as follows:

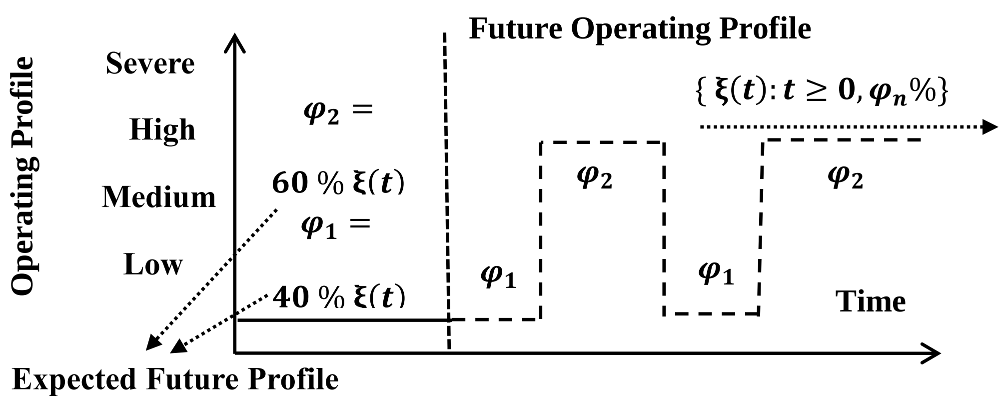

Fig. 5.5. Expected but fluctuating dynamic operating profiles.

$$Pr\big(\, \xi(t+1) = (1,\, \vartheta + 1) \,\big|\, \xi(t) = (1,\, \vartheta)\big) = 0.7, \text{ and} \tag{5.6}$$

$$Pr\big(\, \xi(t+1) = (2,\, \vartheta) \mid \xi(t) = (1,\, \vartheta)\big) = 0.3. \tag{5.7}$$

Similarly,

$$Pr\big(\, \xi(t+1) = (1,\, \vartheta + 1) \,\big|\, \xi(t) = (2,\, \vartheta)\big) = 0.5, \text{ and} \tag{5.8}$$

$$Pr\big(\, \xi(t+1) = (2,\, \vartheta) \,\big|\, \xi(t) = (2,\, \vartheta)\big) = 0.5. \tag{5.9}$$

As these transitions probabilities are formulated for the first operating bin (φ_1), ϑ $\geq$ 40. Then, it turns into:

$$Pr\big(\,\xi(t+1) = 2 \,\big|\, \vartheta > 40\big) = 1. \tag{5.10}$$

In the same manner, any number of operating profiles can be modeled. Finally, the expected, but fluctuating process $\{\xi(t): t \geq 0, \varphi_n\%\}$ is the future profile from time t_0 up to some future time t with given expected discrete operating bins (φ_n). The previously formulated rate of degradation function while undertaking the evolution of the future profile as expected, but fluctuating process can be formulated as, $\int_0^t \omega\big(\xi\,(x)\big)\,\varphi_n\%\ dx$.

In essence, the impact in cooperation with the rate of degradation in diverse functioning structures on degradation progression is characterized and united in the model.

5.2.3 Jerks Owing to Dynamic Transitions

From Fig. 5.2, it is also prevalent that the vibration signal experiences an upward/downward jerk in the magnitude when the profile of the tool transit from lower to higher or vice versa. Accordingly, for an account of reality, it is think through that transition in operating profiles might bring upward/downward jerks in the magnitude. To account for this upward/downward shift in the magnitude of degradation signal, in the model, a new mapping for jerks is formulated $G: Q \to \mathbb{R}^+$ so that $G(\xi(t))$ is a jerk function and the impact of jerks owing to dynamic transitions is captured as follows:

$$G\big(\xi(Z_j)\big) = \mho \times 1^{\tau}\big(\xi\,(t)\big). \tag{5.11}$$

where Z_j is j^{th} transition time, $\mho$ is jerk magnitude which is modeled as a uniform random variable ($\mho \sim U(0, \mathfrak{a})$, with equal probability in the range of 0 and $\mathfrak{a}$, ($\mathfrak{a}$ is the average jerk magnitude, estimated from training data), $1^{\tau}\big(\xi\,(t)\big)$ is the indicator function for jerk direction (at particular profile transition times when the jerk is upward $1^{\tau}\big(\xi\,(t)\big) = "+"$, and when the jerk is downward $1^{\tau}\big(\xi\,(t)\big) = "-"$).

In principle, this hybrid configuration of information captures and approximates degradation progression under dynamic profiles. Finally, the realistic mathematical model for sensor-based degradation signal progression approximation under dynamic operating profiles is given as follows:

$$D_s(t) = D_s(0) + \wp(\omega(\xi\,(x))) + \sum_{j=1}^{Y(t)} G(\xi\,(Z_j)) + \sum_{t=1}^{T} \varepsilon(t) \tag{5.12}$$

where $\wp\left(\omega(\xi\,(x))\right)$ is the indicator function of rate of degradation while undertaking the evolution of the future profile as per the in-operation functioning structure (for scenario I: $\wp\left(\omega(\xi\,(x))\right) = \int_{t_i}^{T} \omega(\xi\,(x))\,dx$, for scenario II: $\int_0^t \omega(\xi\,(x))\,dx$, and for scenario III: $\int_0^t \omega(\xi\,(x))\varphi_n\%\,dx$), $Y(t)$ is aggregate of profiles transition, and $\varepsilon(t)$ is white noise stochastic process.

The white noise stochastic process $\varepsilon(t) \sim \mathcal{N}(0,\,\sigma)$, is statistically independent and identically distributed at different time points. Thus, Eq. (5.12) can be re-written as:

$$D_s(t) = D_s(0) + \wp(\omega(\xi\,(x))) + \sum_{j=1}^{Y(t)} G(\xi\,(Z_j)) + \varepsilon(t) \tag{5.13}$$

Next, the method for estimating the unknown parameter (σ) of white noise stochastic process from real-life data utilizing maximum likelihood estimation technique is described. So, $\varepsilon(t)$ for different time instances is as follows:

$$\varepsilon(t) = D_s(t) - D_s(0) - \wp\left(\omega(\xi\,(x))\right) - \sum_{j=1}^{Y(t)} G\left(\xi\,(Z_j)\right) \tag{5.14}$$

Next, first concatenate $\varepsilon(t)$ for different time instances, say, $\{t_1, \ldots, t_N\}$ in a vector $\boldsymbol{\varepsilon} = \{\varepsilon(t_1), \varepsilon(t_2), \ldots, \varepsilon(t_N)\}$, and formulate the likelihood function of $\boldsymbol{\varepsilon}$, given as follows:

$$L(\boldsymbol{\varepsilon}|\sigma^2) = \frac{1}{(\sqrt{2\pi\sigma^2})^N} exp\left(-\frac{\sum_{i=1}^{N} \varepsilon^2(t_i)}{2\sigma^2}\right) \tag{5.15}$$

Taking logarithm of Eq. (5.15) gives the log-likelihood function of $\boldsymbol{\varepsilon}$**,** which can be written as:

$$lnL(\boldsymbol{\varepsilon}|\sigma^2) = \frac{N}{2} ln\frac{1}{2\pi\sigma^2} - \frac{\sum_{i=1}^{N} \varepsilon^2(t_i)}{2\sigma^2} \tag{5.16}$$

.

The maximum likelihood estimate (MLE) of σ^2 is given by:

$$\widehat{\sigma^2}_{MLE} = \underbrace{argmax}_{\sigma^2} lnL(\boldsymbol{\varepsilon}|\sigma^2) \tag{5.17}$$

Henceforth, σ^2 which maximizes log-likelihood function $lnL(\boldsymbol{\varepsilon}|\sigma^2)$ is obtain by equating the first order derivative of $lnL(\boldsymbol{\varepsilon}|\sigma^2)$ to zero. Taking the derivative of Eq. (5.16) results in:

$$\frac{\partial}{\partial\sigma^2} lnL(\boldsymbol{\varepsilon}|\sigma^2) = -\frac{N}{2\sigma^2} + \frac{\sum_{i=1}^{N} \varepsilon^2(t_i)}{2(\sigma^2)^2} \tag{5.18}$$

Equating Eq. (5.18) to zero and solving for the parameter of white noise stochastic process (σ) yields:

$$\hat{\sigma}_{MLE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \varepsilon^2(t_i)} \tag{5.19}$$

With ultimate objective being prognosticating tool RULs, the system approximates the first passage time of the degradation process to a threshold F_T, i.e., the failure time and provides a precise life estimate in real-time. Thus, at any point of time t_i, the RUL can be calculated as follows:

$$RUL(t_i) = F_n - t_i. \tag{5.20}$$

where F_n is the time for signal to reach F_T.

Nevertheless, the proposed mathematical framework is correspondingly adaptive in distinguishing the traditional degradation model, appropriate for mass production environments. Subsequently, this generic TCM system will lead to a more precise estimate of RUL of the fielded cutting tool operating under dynamic operating profile.

5.3 Results and Discussions

This section presents extensive qualitative and quantitative performance investigations of the proposed generic TCM system.

5.3.1 Experimental Case Study

An experimental case study is exhibited to demonstrate the functionality and practicality of the proposed system. The widely used vibration-based degradation signals (generated via experimental platform) are correlated with the degradation of cutting tools and were used to assess the RUL prediction performance under diverse industrial scenarios.

5.3.1.1 Experimental Platform

Fig. 5.6 illustrates the developed experimental platform. A high-speed CNC milling machine is exploited as the test bench. The cutting tool employed is a high-speed steel 6 mm diameter flat end mill cutter. The workpiece material selected is a flat bar (165 mm × 100 mm × 20 mm) of mild steel. Machining operation engaged is face milling to form a flat plane surface of the workpiece. After one horizontal cutting line along the feed direction, the cutter then retracted to another start along the left direction with the same cutting depth. In each experiment, the cutter was used to cut the workpiece surface in succession to machine an entire surface of 165 mm × 34 mm. The total length of cut for one surface (i.e., eight passes) is 165 mm × 8 = 1320 mm. All tests were performed under dry cutting conditions to accelerate the tool degradation. Kistler accelerometer is mounted on the workpiece to measure the vibrations of cutting process in the feed direction for the entire operational life of the milling cutters.

The vibration signals were acquired with a frequency range from 1 to 10 kHz and amplified via Kistler coupler. Then, the signal is acquired by National instruments DAQ card with 2,500 Hz sampling frequency. Moreover, RMS value is recorded for each cut (a complete 1320 mm of cutting distance) to record the tool degradation process. All cutters were run-to-failure, till breakage or till the RMS value reaches a pre-defined level (F_T = 0.30, as per engineering criterions based on equipment vibration, for example ISO2372). In contrast to the existing literature, the defects were not seeded instead various defects (viz. breakage, etc.) were observed under run-to-failure tests. This allowed a more realistic representation of TCM.

5.3.1.2 Design of Experiments

The L4 orthogonal array of the Taguchi method with six replications is chosen to adequately capture the rate of degradation characteristics from multiple combinations of distinct operating parameters. Specifically, three significant parameters used are feed, cutting speed and depth of cut, with two levels, see, table 5.1. Four experimental runs derived from the L4 design are shown in table 5.2 (Exp. ID 1-4). The rate of degradation characteristics of real-time vibration data throughout its life is taken as a measured response. Next, the distinct profiles are ordered according to their level of severity via. proposed sorting algorithm. The resulting ordering of distinct operating profiles from least severe to most severe is ω(F:250, S:1050, D:0.20) < ω(F:350, S:1300, D:0.20) < ω(F:350, S:1050, D:0.35) < ω(F:250, S:1300, D:0.35) (see, severity column of table 5.2, Exp. ID 1-4). This precise design helps prepare the historical data to maximize the value of rate of degradation parameter estimation for various profiles.

TABLE 5.1

PARAMETERS AND LEVELS FOR L4 ORTHOGONAL ARRAY

Parameters	Unit	Parameter Levels	
Feed (F)	mm/min	250	350
Cutting speed (S)	RPM	1050	1300
Depth of cut (D)	mm	0.20	0.35

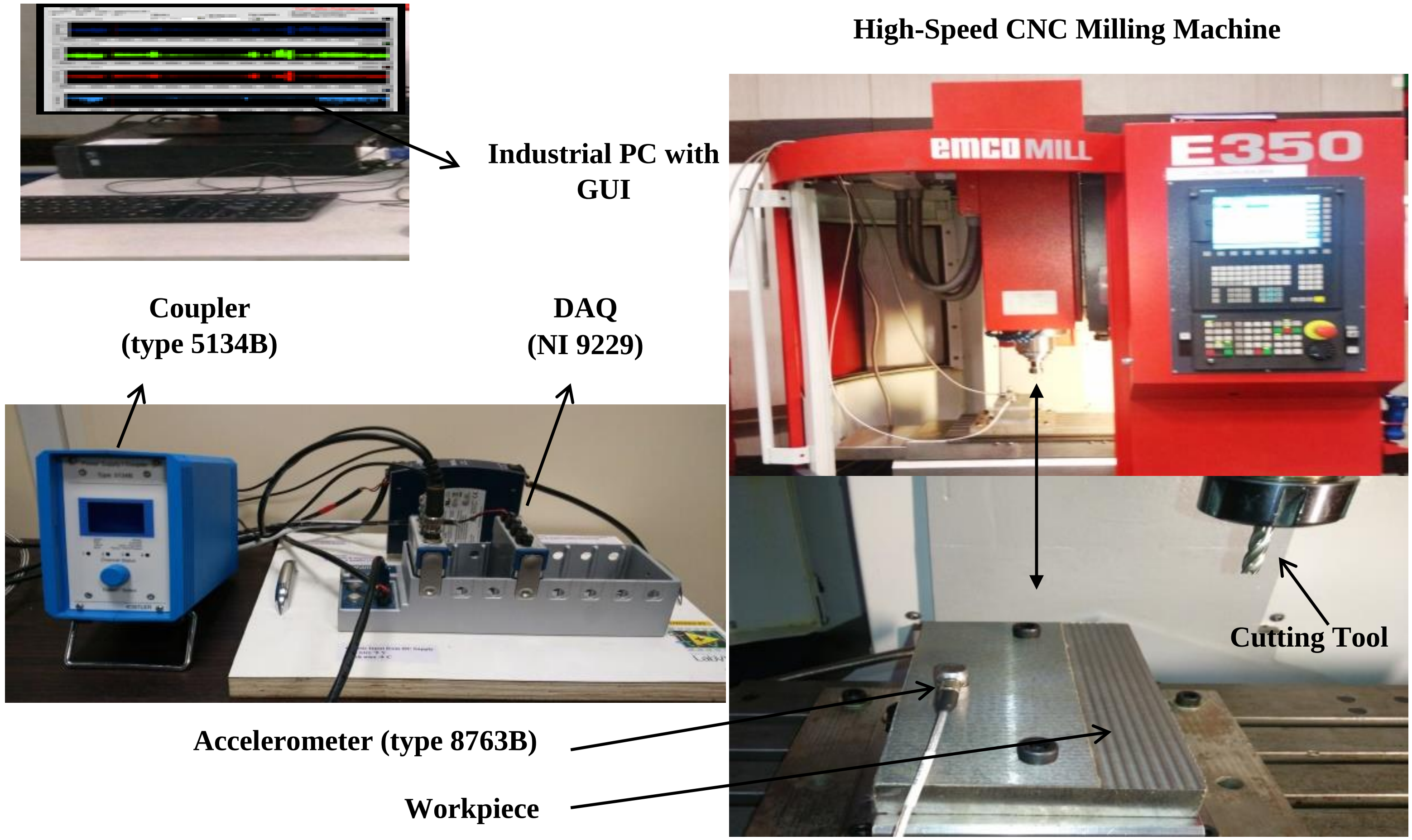

Fig. 5.6. Experimental platform.

5.3.1.3 Constructing Degradation Signals with Dynamic Operating Profiles

Degradation signals rendering different real-world industrial scenarios are constructed as follows:

a) Industrial Scenario I

For constructing the deterministic, dynamic operating profile, a manufacturing system operating under two distinct profiles (low and high), that evolves in a deterministic manner is considered. So, the operating profiles are changed among these levels at known time intervals. The cutters were initially operated at the low profile, then just after sixteen cuts, the cutter transits to high profile till twenty-six cuts, and then transmit back to lower profile till failure.

b) Industrial Scenario II

For the randomly-varying, dynamic operating profile, a manufacturing system functioning in two profiles (medium and severe), that progresses stochastically is considered. Given that, the profiles are randomly changed among these levels at uncertain time intervals. Explicitly, the cutters were primarily functioned at the severe profile, which randomly transits to medium profile, and then again randomly transits to severe profile till failure.

c) Industrial Scenario III

For the expected but fluctuating dynamic operating profiles, a manufacturing system operating under two profiles (low and severe) is considered, where it is expected that the system will operate approximately 45% of the time in low profile and remaining 55% in severe profile. So, the profile expectancy is retained and the profiles are randomly changed among these levels at uncertain time intervals. In detail, the operating bins are set as φ_1= 45% $\xi(t)$ and φ_2= 55% $\xi(t)$ and then, first the cutters were operated at the low profile, which randomly transits to severe profile, while roughly accounting the profile expectancy, the profile again randomly interchanged to low profile till failure. Note the expected standard of profile was maintained.

Following all these scenarios, two groups of accelerated life tests are further conducted (see, table 5.2, Exp. ID 5-10). In the first set Exp. ID 5-7 each cutter is operated with profiles rendering different real-world scenarios. By this set and along with the Exp. ID 1-4, the model parameters are estimated. The second set Exp. ID 8-10 is used for online validation under diverse scenarios. This design maximizes the likelihood that sufficient real-time data is collected to verify the performance under dynamic operating profiles.

TABLE 5.2

EXPERIMENTAL DESIGN MATRIX

Constant Operating Profile			
Exp. ID	**Operating Parameters**	**No. of Cutters**	**Severity (State)**
E1	(F:250, S:1050, D:0.20)	6	Low (1)
E2	(F:350, S:1300, D:0.20)	6	Medium (2)
E3	(F:350, S:1050, D:0.35)	6	High (3)
E4	(F:250, S:1300, D:0.35)	6	Severe (4)
	Dynamic Operating Profile		**Industrial Scenario**
E5	(F:250, S:1050, D:0.20)→(F:350, S:1050, D:0.35)→(F:250, S:1050, D:0.20)	2	Deterministic, dynamic operating profile
E6	(F:250, S:1300, D:0.35)→(F:350, S:1300, D:0.20)→ (F:250, S:1300, D:0.35)	2	Randomly-varying dynamic operating profile
E7	(F:250, S:1050, D:0.20)→ (F:250, S:1300, D:0.35)→ (F:250, S:1050, D:0.20)	2	Expected but fluctuating dynamic operating profile
E8	(F:250, S:1050, D:0.20)→(F:350, S:1050, D:0.35)→(F:250, S:1050, D:0.20)	1	Deterministic, dynamic operating profile
E9	(F:250, S:1300, D:0.35)→(F:350, S:1300, D:0.20)→ (F:250, S:1300, D:0.35)	1	Randomly-varying dynamic operating profile
E10	(F:250, S:1050, D:0.20)→ (F:250, S:1300, D:0.35)→ (F:250, S:1050, D:0.20)	1	Expected but fluctuating dynamic operating profile

5.3.1.4 Experimental Validation under Diverse Scenarios

For validating and assessing the performance of the system under the scenario I, data from Exp. ID 1, 3 and 5 is used for training and data from Exp. ID 8 is used for online validation. While, for scenario II, data from Exp. ID 2, 4 and 6 is used for training and data from Exp. ID 9 is used for online validation. Similarly, for scenario III, data from Exp. ID 1, 4 and 7 is used for training and data from Exp. ID 10 is used for online validation. Table 5.3 offers the entire model parameters estimated from training data. Next, to meticulously validate the performance and to investigate the influence of dynamic operating profiles on the RUL prediction results, a comprehensive qualitative and quantitative performance investigation is carried out, as follows:

a) Qualitative Performance Investigation

First, the dynamic operating profile evolution path (under uncertainty) approximated by the system for validation cutting tools (see, Fig. 5.7 and 5.8) is examined. It can be manifested that the system is competent in approximating the uncertainty imposed by time-variant industrial scenarios. More prominently, in scenario III, the system approximated evolution path is virtually matching the actual evolution path (see, Fig. 5.8); as the updated distribution better characterizes the expected future profile and eventually reduces the uncertainty. Next, the validation tools were engaged to predict the RULs under diverse scenarios at different intervals of the lifetime percentiles. The predicted RULs were estimated from ${q_i}^{th} - {q_j}^{th}$ percentiles($q_i - q_j \in \{0-30\%, 31-60\%, 61-90\%\}$). Herein, the quantity measure of performance is the lifetime prediction error (LPE).

$$LPE = \left| 1 - \frac{Current\ Observation\ Epoch + RUL_{p_i}}{LT_a} \right| \tag{5.21}$$

where RUL_{p_i} is the predicted RUL, ($Current\ Observation\ Epoch + RUL_{p_i}$) is the predicted lifetime, and LT_a is the actual lifetime.

Fig. 5.9 - 5.11 shows the prediction performance allied to a different interval of lifetime percentile under diverse scenarios. These figures revealed a significant finding that the prediction error under diverse scenarios exhibits progressive reduction as it move towards end of lifetime of the tool (i.e., as ${q_i}^{th} - {q_j}^{th}$ increases). These promising results in time-variant scenarios guarantee the expansion of an effective preventive maintenance plan.

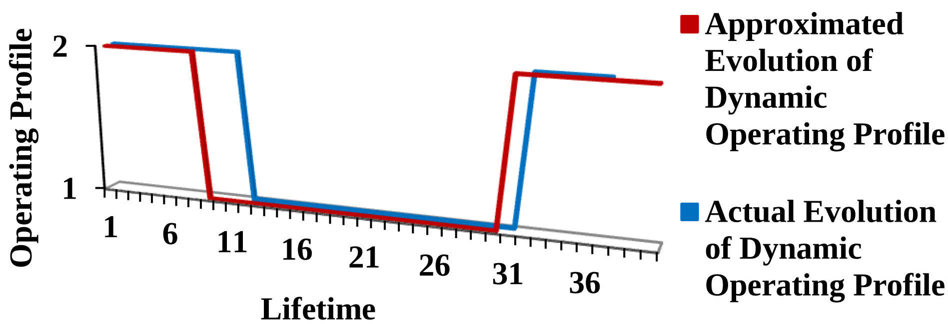

Fig. 5.7. Approximated and actual evolution path for scenario II.

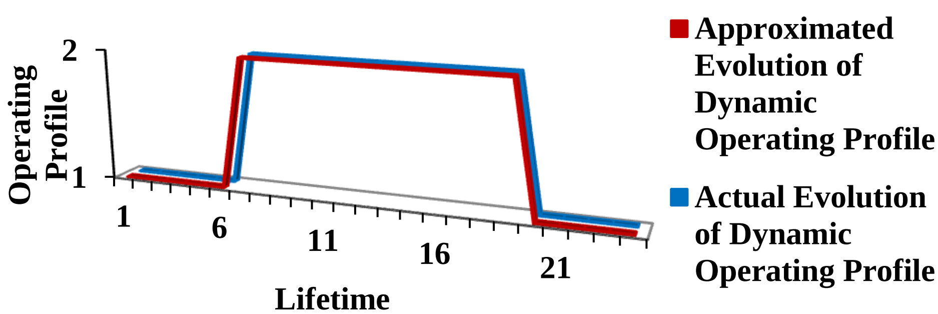

Fig. 5.8. Approximated and actual evolution path for scenario III.

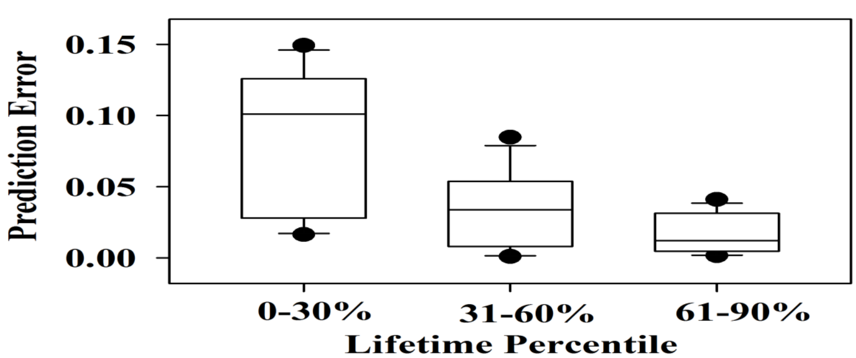

Fig. 5.9. Performance at different intervals of percentile for scenario I.

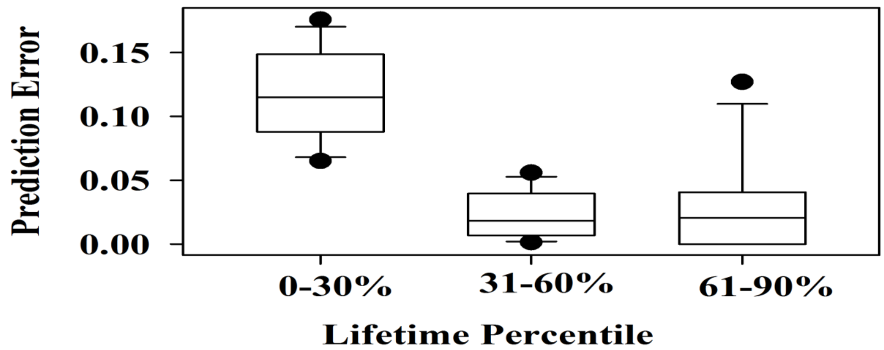

Fig. 5.10. Performance at different intervals of percentile for scenario II.

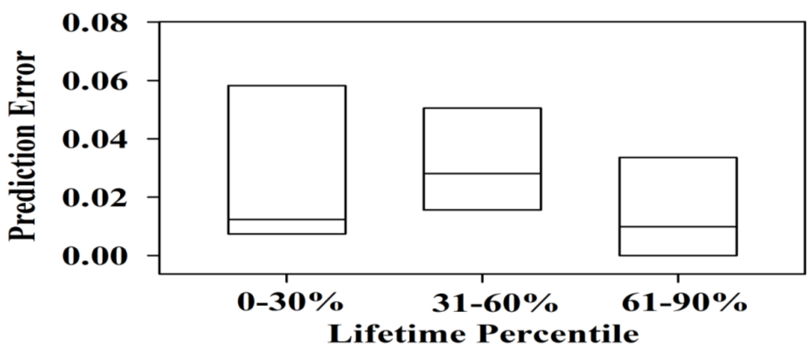

Fig. 5.11. Performance at different intervals of percentile for scenario III.

b) Comparative Analysis of Quantitative Performance

A comprehensive quantitative performance investigation in contrast to the extensively adopted traditional approach, see, table 5.4 for detailed results is carried out. In general, the traditional approach is designed on the impression that along the entire lifespan of the cutting tool, the prevailing operating profiles are unvarying. So, the proposed system is adapted to perceive the traditional approach on the same set of experimental data. This assessment is extensively distinguished as follows:

- **Accuracy**: The Prediction Accuracy (PA) is the degree of the RULs correctly predicted amongst the total number of observations assessed. The results (see, table 5.4) manifest that under all the scenarios proposed approach has shown improved performance, with PA resulting 89.60% in contrast to 79.96% from the traditional approach for scenario I. Whereas, for scenario II and III, the PA attained was more than 90% which is a significant improvement over 47.79 and 30.54 from the traditional approaches.

$$PA = \frac{1}{n}\sum_{i=1}^{n}\left[1 - \left(\frac{\left|RUL_{a_i} - RUL_{p_i}\right|}{RUL_{a_i}}\right)\right] \times 100 \tag{5.22}$$

where n is the total number of observations, and RUL_{a_i} is the actual RUL.

- **Suitability**: For this, mean absolute error is calculated. MAE measures how the system makes close RUL predictions to the actual RUL; lower MAE is better, a perfect model would score zero MAE. The MAE values acquired from traditional approach is found to be about three times higher than the values attained from the proposed approach. Lower MAE values from the offered approach prove the suitability of the system under time-variant industrial scenarios by predicting the RULs closer to the actual RULs.

- **Stability**: For this, relative absolute error and root relative squared error are evaluated; these are the measures of the variance in the predictions. The lower RAE and RRSE values from offered approach signify the stability of the system under diverse industrial scenarios. For instance, in scenario II these errors are 76.15 and 69.96% lower than that attained from the traditional approach.

- **Quality**: This is assessed through the goodness of fit. For which R-squared (R^2) correlation coefficient is calculated. The high R^2 correlation coefficient from proposed approach displays that anticipated RULs are greatly associated to actual RULs in contrast to traditional approach, showcasing better quality predictions from offered approach.

- **Reliability**: Root mean squared error is selected to indicate the reliability of the predictions; it illustrates the standard deviation of the differences between predicted and actual RULs; RMSE closer to zero indicates greater reliability. The higher reliability of RUL predictions under time-variant scenarios from the proposed approach is apparent, as RMSE values are two times lesser than the traditional approach.

- **Robustness**: The robustness is visualized by plotting the confidence or error bounds. Herein, the bounds for the RUL estimates are 25% deviations from the actual RULs in either direction. Lesser the deviations from the actual RULs, better is the performance. As a result, error bounds make it easier to interpret the robustness of the approach. It can be observed from Fig. 5.12 – 5.14 that under different scenarios, from beginning to end of operational life of tools almost all values of the estimated RULs from the proposed approach lie within the specified error bounds. Whereas, estimated RULs from the traditional approach in the beginning mostly lies outside the error bounds and only lies within the bounds at the end of operational life. It can be summarized that the proposed approach offers accurate prediction even in the early operation life. This is highly desirable for planning maintenance at the early stage of the life. This performance suggests that the proposed approach makes reasonably robust estimates of the RUL under dynamic operating profiles at all times.

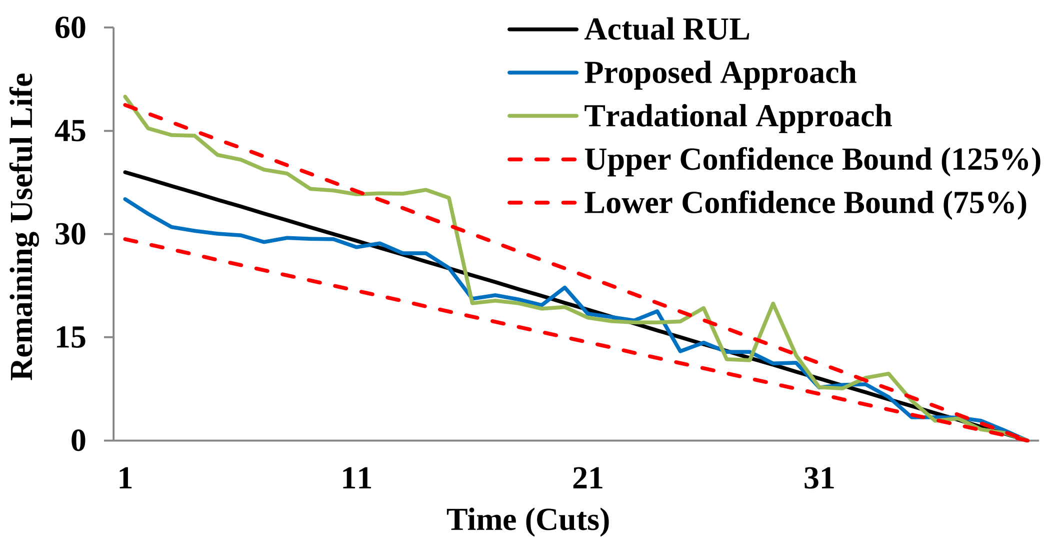

Fig. 5.12. Comparison with confidence bounds on the actual and predicted output under the scenario I.

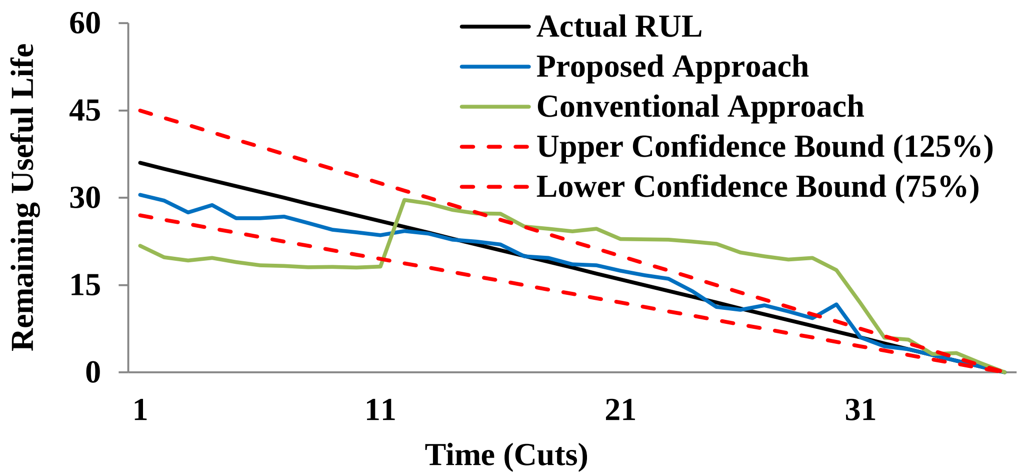

Fig. 5.13. Comparison with confidence bounds on the actual and predicted output under the scenario II.

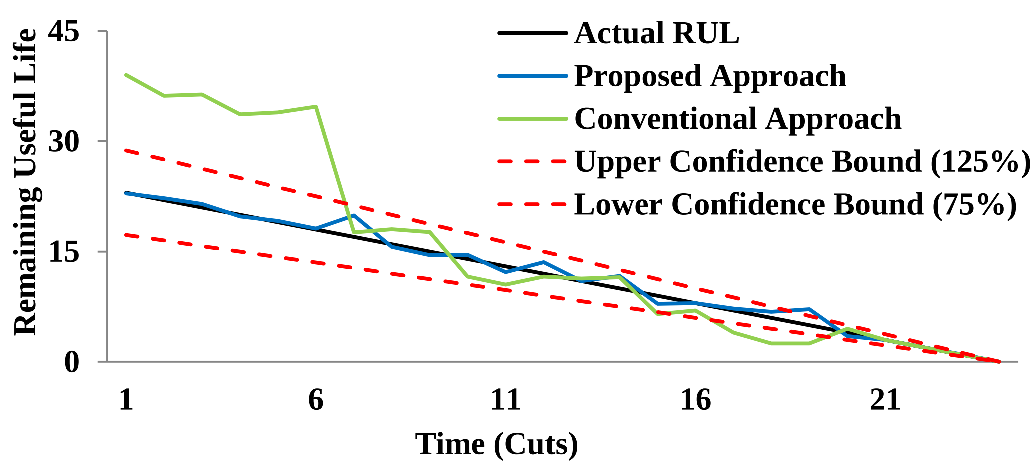

Fig. 5.14. Comparison with confidence bounds on the actual and predicted output under the scenario III.

- **Comprehensibility**: For this, the squares of the deviations around the RULs allied with these approaches are computed. The progressing trails of the squared deviation at each observation for both approaches under diverse scenarios are shown in Fig. 5.15 - 5.17. As the offered approach effusively exploits the future characteristics of dynamic operating profiles, the squared deviation of the RUL approximation is maintained in a reasonably low level in contrast to traditional approach under all scenarios and approaches a lowermost mean squared deviation than the traditional approach. Also, the proposed approach throughout circumvents the unexpected variation of squared deviation happening in all scenarios as the offered approach effusively exploits the future characteristics of dynamic operating profiles. Additionally, the total squared deviation (sum of all the squared deviation over the lifespan) of the offered and traditional approach are 226.20, 1119.83 under the scenario I, 263.29, 2917.10 for scenario II and 22.30, 1440.96 for scenario III. Apparently, the offered approach has the least total mean-squared deviation and thus has a better RUL estimation under dynamic operating profiles than the traditional approach.

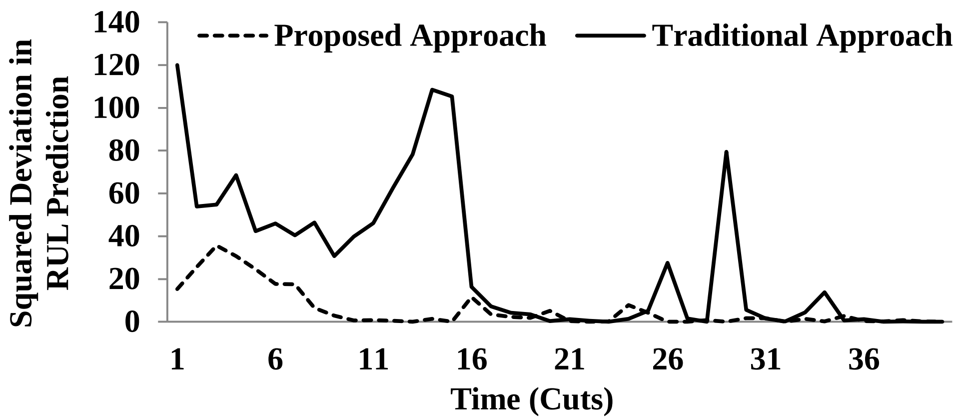

Fig. 5.15. Comparative results of squared deviation in the scenario I.

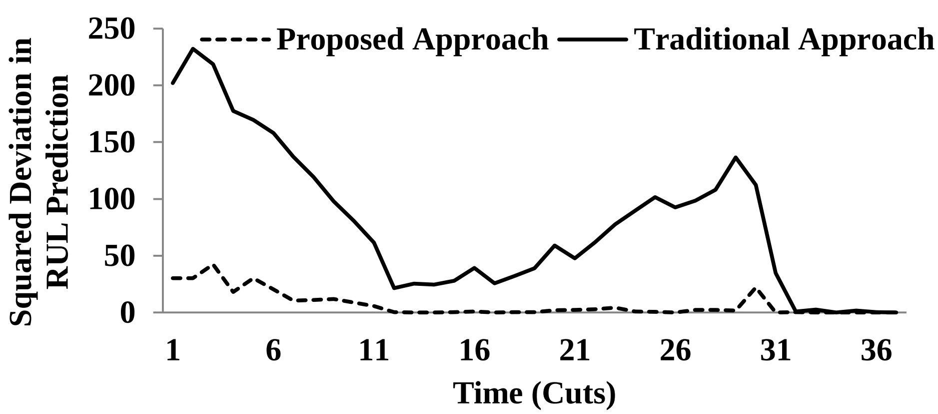

Fig. 5.16. Comparative results of squared deviation in the scenario II.

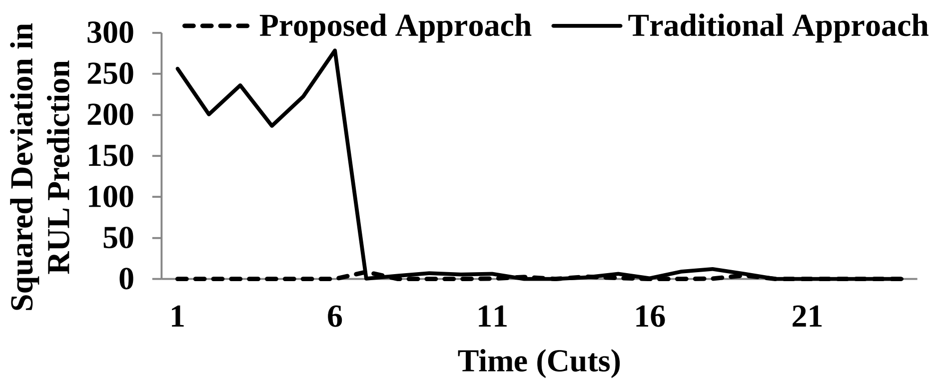

Fig. 5.17. Comparative results of squared deviation in the scenario III.

- **Applicability**: In real-world applications, it is always desired to foresee failures early than late. Hence, to deliver a more valued and overall valuation of prediction performance an asymmetric score metric (see, Eq. (5.23)) is computed. This score stresses substantial penalties on late prediction than early prediction, and the penalty propagates exponentially with increasing error. It is evident from Fig. 5.18 that the offered approach outperforms the traditional approach in all scenarios by prompting lower score. Implying, higher over/under predictions attained from the traditional approach, because while prognosticating RULs the prevailing operating profiles are considered to be unvarying along the entire lifespan of the cutting tool. For instance, in scenario II, initially the tool is operating in severe operating profile and from those points when a prediction is made the approach provide a higher under prediction, this can be visualized from Fig. 5.13. Whereas in scenario III, initially, the tool is operating in low operating profile and from those points when a prediction is made the approach provides a higher over prediction, this can be visualized from Fig. 5.14. This is because in these scenarios the operating profiles are dynamically chaining along the lifespan of the tool from severe to low or vice versa. Though, while prognosticating RULs from those points via the proposed approach the asymmetric score in contrast to traditional approach got reduced by 82% and 92% respectively for scenario II and III.

$$Asymmetric\ Score = \begin{cases} \sum_{i=1}^{n} e^{\left(\frac{RUL_{p_i} - RUL_{a_i}}{10}\right)} - 1 & for\ (RUL_{p_i} - RUL_{a_i}) < 0 \\ \sum_{i=1}^{n} e^{\left(\frac{RUL_{p_i} - RUL_{a_i}}{13}\right)} - 1 & for\ (RUL_{p_i} - RUL_{a_i}) \geq 0 \end{cases} \tag{5.23}$$

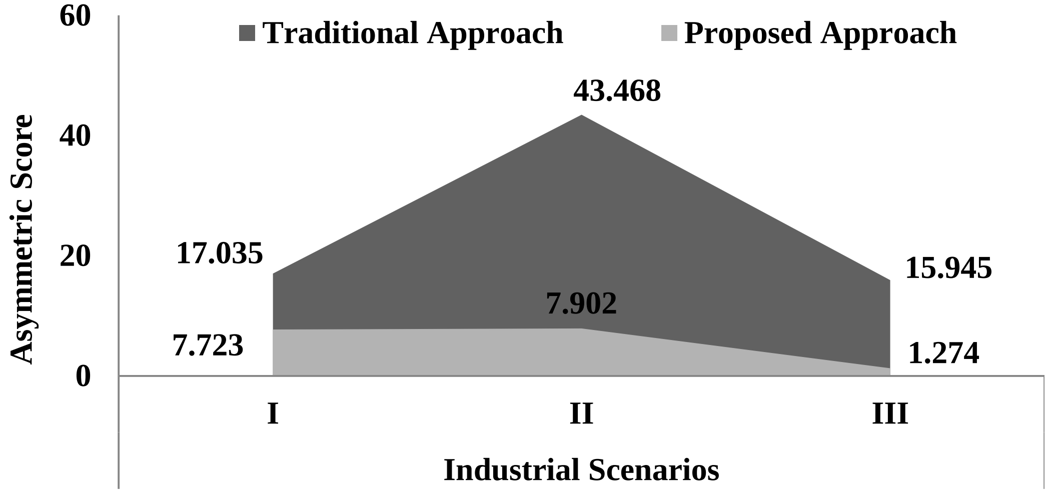

Fig. 5.18. Asymmetric score comparison under diverse scenarios.

In essence, all these implementation results lend significant credibility to the appropriateness of proposed approach over the traditional approach under time-variant industrial scenarios.

TABLE 5.3

ESTIMATED MODEL PARAMETERS FROM TRAINING DATA

Industrial Scenario I		**Industrial Scenario II**		**Industrial Scenario III**	
Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
$\boldsymbol{Q}$	$\{\text{Low (1)}, \text{High (2)}\}$	Q	$\{\text{Medium (1)}, \text{Severe (2)}\}$	Q	$\{\text{Low (1)}, \text{Severe (2)}\}$
$\boldsymbol{\xi}((\boldsymbol{t_i}))$	$\begin{Bmatrix} Low, & 0 \le t < 16 \\ High, & 16 \le t < 26 \\ Low, & 26 \ge t \end{Bmatrix}$	$\{\xi(t): t \ge 0\}; \theta$	$\begin{array}{c} \text{Severe (1)} \\ \text{Medium (2)} \end{array} \begin{bmatrix} 0.95 & 0.05 \\ 0.06 & 0.94 \end{bmatrix}$	$\{\xi(t): t \ge 0, \varphi_1 = 45\%, \varphi_2 = 55\%\}; \theta$	$\begin{array}{c} \text{Low (1)} \\ \text{Severe (2)} \end{array} \begin{bmatrix} 0.90 & 0.11 \\ 0.08 & 0.92 \end{bmatrix}$
$\boldsymbol{\omega}\left(\boldsymbol{\xi}\left(\textbf{Low (1)}\right)\right)$	7.28×10^{-3}	$\omega\left(\xi\left(\text{Medium (1)}\right)\right)$	8.97×10^{-3}	$\omega\left(\xi\left(\text{Low (1)}\right)\right)$	7.28×10^{-3}
$\boldsymbol{\omega}\left(\boldsymbol{\xi}\left(\textbf{High (2)}\right)\right)$	1.23×10^{-2}	$\omega\left(\xi\left(\text{Severe (2)}\right)\right)$	1.39×10^{-2}	$\omega\left(\xi\left(\text{Severe (2)}\right)\right)$	1.39×10^{-2}
$\boldsymbol{\sigma}$	3.15×10^{-2}	σ	0.019 1.90×10^{-2}	σ	3.59×10^{-2}
$\boldsymbol{\alpha}$	1.54×10^{-2}	α	3.00×10^{-2}	α	3.00×10^{-2}

TABLE 5.4

RESULTS OF COMPARATIVE ANALYSIS

Industrial Scenarios		I		II		III	
Performance Metric		**Proposed Approach**	**Traditional Approach**	**Proposed Approach**	**Traditional Approach**	**Proposed Approach**	**Traditional Approach**
Accuracy	PA (%)	89.60	79.96	90.23	47.79	93.31	30.54
Suitability	MAE	1.691	4.033	1.864	7.821	0.604	4.843
Stability	RAE (%)	16.91	40.33	20.18	84.61	10.07	80.71
	RRSE (%)	20.60	45.84	24.98	83.16	13.92	111.94
Quality	R^2	0.976	0.947	0.965	0.333	0.983	0.878
Reliability	RMSE	1.300	2.008	1.365	2.797	0.777	2.201
Applicability	Computation time (s)	0.440	0.425	0.312	0.225	0.455	0.446

5. 4 Contributions

The research presented in this chapter progresses the existing body of knowledge by formulating a novel and generic TCM system for dynamic operating profiles. The purpose was to equip manufacturing industries with intelligence that allows responding to the time-variant operating profiles and adaptable under various real-world industrial scenarios. The main contributions made are highlighted as follows:

- A realistic mathematical framework via a new, adaptive, and hybrid stochastic degradation model is offered, that inventively models sensor-based degradation signal of cutting tools functioning under dynamic operating profile, to prognosticate the RULs under diverse industrial scenarios.
- To precisely approximate the degradation under dynamic profiles the framework uniquely leverages strategic information viz. viz. 1) the real-time degradation signal characteristics from the sensor; 2) the rate of degradation characteristics from historical data; 3) the evolution of the future operating profile; 4) jerks owing to dynamic transitions.
- To take along realistic characteristics, new mappings, i.e., degradation rate function and jerk function are formulated. As well, as an essential aspect of the framework, a first-hand sorting algorithm to order the operating profiles with regard to their impact on the corresponding degradation rate is offered.
- For the first time, the physics of evolution of dynamic profiles to incite generalization in diverse real-world scenarios viz. batch production, job production, micro to medium-scale production environments is innovatively modeled.
- A real-life experimental case study is exhibited to validate the system's qualitative and quantitative performance meticulously and to comprehensively investigate the influence of dynamic operating profiles on the RUL prediction results, showcasing an excellent agreement.
- To further evaluate the performance, a series of validation experiments are conducted in contrast to the traditional approach. Wherein, the experimental

results confirmed that the offered approach delivers a robust problem-solving structure for dynamic operating profiles.

5.5 Closure

In real manufacturing environment, machining systems are often subject to time-variant operating profiles, the effect of which, if not properly considered, may greatly reduce the accuracy of RUL predictions. In view of that, the proposed framework inventively compute the cutting tool RULs while exploiting prior information, along with the future characteristics of operating profiles that the cutting tool is likely to experience, in real-time. This will enrich the existing tool condition monitoring systems by considering the effects of the operating profiles on cutting tool degradation, as well, render a first universal perspective to TCM. The promising results attained under time-variant industrial scenarios guarantee the expansion of an effective preventive maintenance plan in diverse real-world industrial scenarios viz. batch production, job production, micro to medium-scale production environments.

The proposed framework consents modelling of solitary sensor, in future, for further strengthening of the prediction performance will requires extracting the information from multi-sensors.

Chapter 6*

Dynamic Optimization of Process Quality Control and Maintenance Planning

"Others dream of things that were, and ask 'Why?' I dream of things that never were, and ask 'Why not?".

Cardinal Saint-Saens, French Composer

Chapter 2 facilitated recognizing that the integration of quality and maintenance considering real-time health state of the system entirely eludes literature. Thus, this chapter intends to invent a dynamic integrated policy, so that the existent machining systems can be augmented with collective knowledge, and yield better performance. Accordingly, a novel methodology for dynamic optimization of process quality control and maintenance planning whilst considering the real-time health state of the system is proposed. Moreover, for one of the research deliverables, case studies in various industrial scenarios are implemented to demonstrate the practical feasibility of the offered policy.

Key Highlights

Purpose: *The purpose was to equip industries with a holistic view of the intelligent manufacturing, thereby forming the basis for building an autonomous decision-making system that serves as a guide for joint consideration of operational policies pertaining to diagnostics, prognostics and process quality control.*

Methodology*: The existing process quality control policy is enhanced to become dynamic and extended to deal with machine deterioration with time. This is done via the proposed residual-life based evaluation and multi-state magnitude of*

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* *The work presented in this chapter is published in two parts. Firstly, under the title "Quality control based tool condition monitoring" in "Annual Conference of the Prognostics and Health Management Society, 2015", California, USA, Vol. 6, pp. 1-10. Secondly, under the title "Dynamic optimization of process quality control and maintenance planning" in "IEEE Transactions on Reliability", IEEE, doi: 10.1109/TR.2017.2684709.*

process shift schemes. Furthermore, the maintenance planning model is modified to capture real-time remaining life information. These models are integrated and built in conjunction with newly developed TCM system pertaining to instantaneous diagnostics and prognostics. As a result, the designed dynamic integrated model can evolve itself to re-evaluate the optimal values for the design parameters used in the entire lifecycle of the manufacturing process.

***Findings**: The proposed methodology was proficient in capturing the interdependencies between process quality control and maintenance planning whilst considering the real-time health state of the system. This will enrich the existing integrated policy by instantaneously considering machine deterioration, health state, and remaining useful life. Wherein, the experimental results confirmed that the dynamic integrated policy is capable for early detection of out-of-control process than conventional usage of control charts. As a consequence, the information obtained in the current research results in significant cost savings in overall manufacturing cost.*

***Practical Implications:** The implication of the proposed dynamic integrated policy under various real-world industrial scenarios revealed that this policy optimizes the inspection frequency, moderates the loss in production, consumes the optimum life of the system and delivers higher economic improvements. This will benefit the manufacturers to adopt the most beneficial practice for optimizing the process quality control and maintenance planning of their industry specific applications.*

***Originality and Contribution:** The novelty of this work is in the formulation of a dynamic integrated policy. Whenever a change in health state of the system is detected, the optimal design parameters of process quality control and maintenance planning are updated based on current health state of the system as a function of its life. This dynamic integrated policy has the dual advantage, i.e. it eliminates the lost quality cost due to machine degradation and also improves the manufacturing system's reliability by protecting it against failures. An added* *contribution lies in the outcomes; systematic performance and sensitivity investigation are presented. Moreover, the implication of the proposed policy in various industrial scenarios is critically analysed. This expands the model's robustness and relevance in manufacturing industries.*

Research Limitations and Future Scope*: In the present work, the machine is considered to be made up of a single component i.e. cutting tool, the failure of the components of the machine tools also have similar effects on process quality. Thus, extending this analysis for other components of machine will further lead to more significant cost benefits to the industries.*

6.1 Introduction

Recalling the discussion from chapter 1 and 2, in today's progressive manufacturing environment, achieving operational excellence is a challenge. Thus, shop floor efficiency and effectiveness have become a high priority for manufacturing industries. Process quality control and maintenance planning are the key shop floor operational policies. These policies are interrelated, for example, the efficacy and quality of the machine output are influenced by maintenance (Ollila and Malmipuro, 1999). Whereas unnecessary maintenance leads to excessive costs, delaying the maintenance might increase the process variability viz., increase in rejections. Lad and Kulkarni (2008) showed that if the failure of a machine arises, it may not stop the machine immediately, but may also adversely affect the quality of the goods being produced on the machine. According to Kurada and Bradley (1997), cutting tool failures usually takes around 20% of the downtime of a manufacturing system. Whereas Malekian et al. (2009) found that tool degradation has a direct impact on the quality of the product produced, and the expense of tools and their replacement accounts up to 12% of the overall manufacturing cost. Thus, real-time detection of tool failure becomes essential to enhance the process quality control and the ability to prepare and perform tool replacement. To manage higher shop floor effectiveness, a good understanding of interdependency among process quality control, maintenance planning, and real-time health state of the system is therefore lucrative. Though, chapter 2 unveils that despite the fact that the connection among these fields is not absent, further examination is required in this course. However, the integration of quality and maintenance decisions considering real-time health state of the system entirely eludes literature[6.1], hence offers an excellent opportunity for investigation. In this regard, the aim of this chapter is to present a novel methodology for dynamic and simultaneous optimization of process quality control and maintenance planning whilst considering the real-time health state of the system deteriorating with time.

[6.1] *The gaps are briefed in section 2.3 of chapter 2.*

To begin with, a joint methodology pertaining to diagnostics and statistical process quality control is proposed as part of a preliminary investigation. The main contribution of which is in an attempt to explore a methodology for joint consideration of statistical process quality control and tool condition monitoring. The promising outcomes from this investigation encouraged and empowered instituting an autonomous decision making system pertaining to data-centric real-time integration of diagnostics, prognostics, and economic process quality control for real-world manufacturing environments. Herein, first, a new tool condition monitoring system is built to perform instantaneous diagnostic and prognostic tasks. Further, the existing process quality control policy is customized and extended to deal with machine deterioration with time. This is done via a proposed residual-life based evaluation and multi-state magnitude of process shift schemes. Moreover, the conventional maintenance planning model is enhanced to capture real-time remaining life information of the tool, thereby leading to optimum usage of a tool’s useful life. These models are integrated and built in conjunction with the developed TCM system. As a result, the proposed dynamic integrated model evolves itself dynamically to re-evaluate the optimal values for the design parameters, i.e. sample size, the time between samples, control limit coefficient and preventive replacement interval used in the entire lifecycle of the manufacturing process. An experimental case study is presented to demonstrate the practicability of the developed method. An extensive performance investigation revealed substantial economic benefits are achieved through proposed policy over conventional independent policies.

The novelty of this work is in the formulation of a dynamic integrated policy. Whenever a change in health state of the system is detected, the optimal design parameters of process quality control and maintenance planning are updated based on current health state of the system as a function of its life. This dynamic integrated policy has the dual advantage, i.e. it eliminates the lost quality cost due to machine degradation and also improves the manufacturing system’s reliability by protecting it against failures. An added contribution lies in the outcomes; systematic performance and sensitivity investigation are presented. Moreover, the implication of the proposed policy in various industrial scenarios is critically analysed. This expands the model's robustness and relevance in manufacturing industries.

The rest of the chapter is systematized as follows. In the next section, a preliminary investigation on development of a joint methodology is thoroughly illustrated. Section 6.3 briefs the development of the proposed dynamic integrated policy. Section 6.4 illustrates results from the experimental case study and other investigations. In section 6.5 contributions are highlighted. The last section concludes the chapter.

6.2 Preliminary Investigation: Quality Control based Tool Condition Monitoring

Quality control and tool condition monitoring are important part of machining process. Thus, developing a joint methodology, that not only maintains the quality but also performs tool condition monitoring, will be a highly profitable option. Herein, the key finding[6.2] from chapter 4 pertaining to the relationship between product quality and tool degradation is an integral part of this study. As it helps in getting rid of measurable signal monitoring system (sensors) and its associated expenses, the only expense associated will be the cost of quality control. The results from such relationship are used to provide guidelines for efficient process monitoring and dynamic process quality control. Thus, in a single expense, both the purpose of quality control and tool condition monitoring will be accomplished. Such type of methodology is not reported in the existing literature of current research. Consequently, the development of a methodology for joint consideration of statistical process quality control and tool condition monitoring will be a stepping stone in the direction of realizing a holistic view of intelligent manufacturing to machinists and will lead to greater cost savings in overall manufacturing cost.

[6.2] *The key finding pertaining to the relationship between product quality and tool degradation is appraised in section 4.3 under the heading experimental investigation of chapter 4.*

6.2.1 Joint Methodology

Details of the proposed joint methodology coupled with experimental implementation results are given in following sub-sections.

6.2.1.1 Fault Estimation Model

As already established in chapter 3, tool degradation (wear) is the major cause of tool failure, identification and estimation of cutting tool health state is very important in the machining process, so that it can be replaced on timely manner. Also, the relationship between product quality (surface roughness) and tool degradation is of great interest. Accordingly, a new Fault Estimation Model (FEM) is developed to link one or more of the product quality parameters like R_a, R_z and R_p with the health state of the tool. Input to this fault estimation model will be quality parameters and output will be the current health state (stage I, stage II or stage III) of the tool. The prediction of current health stage will help in tool replacement decisions.

To develop an efficient fault estimation model, an ensemble classifier is needed. As a result, Random Forest (RF) is used to develop the fault estimation model. RF is utilized because of its high performance in modeling complex processes, unbiased estimate of the generalization error, high accuracy and fast build time (Liaw and Wiener, 2002). Originally proposed by Breiman (2001), the method adds an extra layer of randomness to the original bagging algorithm. It is more user friendly, intuitive, and is based on two parameters (the number of variables in the random subset at each node and the number of trees in the forest) only. Further, in contrast to most algorithms in literature viz. discriminant analysis, it is dependent on the data values and is less sensitive to the values of the two parameters (Liaw and Wiener, 2002). Consequently, it is perfectly aligned to current needs, thus, this method is used to formulate the fault estimation model for cutting tools. In RF classifier each tree is constructed using the following methodology: Firstly, N number of training cases and M number of variables are taken in the classifier. m number of input variables are used to take decision at the node of the tree, here, *m* is kept lesser than *M*. A training set is selected for this tree by choosing *n* times with replacement from all *N* available training cases. Rests of the cases are used to estimate the error of the tree, by predicting their classes. For each node of the tree, randomly *m* variables are selected, on which to base the decision at that node. Then, the best split based on these *m* variables in the training set is calculated. Each tree is fully grown and not pruned. For prediction, a new sample is pushed down the tree. It is assigned the label of the training sample in the terminal node it ends up in. This procedure is iterated over all trees in the ensemble, and the average vote of all trees is reported as random forest prediction.

For the current study, random forest of 100 trees, each constructed while considering 1 random feature is used. The life data used here is drawn from experiments[6.3] conducted on five milling cutters. Health states of the milling cutters are classified in three stages (see, Fig. 4.5 in chapter 4). The 10-fold cross-validation method was chosen (Stone, 1974) in this study. For performance assessment, accuracy of the testing results is calculated. Accuracy of a classification model is calculated as, the proportion of the total number of predictions that were correct (Wang et al., 2014). To check the applicability of developed model; computational time, that is the required time to learn and test the dataset is also computed. Moreover, to improve relevance and accuracy of prediction, an Advance Fault Estimation Model (AFEM) is also developed. In the advance model, with average surface roughness value (as in FEM) two more parameters (R_z and R_p) are given as input. This advance fault estimation model can be used in the presence of extra information in terms of R_z and R_p in place of the fault estimation model to update the accuracy of the prediction. Table 6.1 shows the performance of both the developed models.

The results from developed fault estimation models are promising and show potential to be practically applied under industrial constraints in reasonable computational time.

[6.3] *The details of experiments are given in section 4.2 under the heading new experimental strategy of chapter 4.*

TABLE 6.1

PERFORMANCE OF FAULT ESTIMATION MODELS

Model	Accuracy (%)	Time (s)
Fault Estimation Model	70	0.13
Advance Fault Estimation Model	82	0.17

6.2.1.2 Process Monitoring and Statistical Quality Control Policy

A CNC milling process is used for Mild Steel (MS) plate manufacturing with fixed dimensions (165x100x20mm). Average surface roughness (Ra) of the plate in horizontal direction is an important quality characteristic. The average surface roughness value is in micron. A statistical control of the average surface roughness of the plate in this process using $\bar{x}$ and R control charts is need to be established. This will require setting of control charts limits. This is explained as follows:

a) Setting of $\bar{x}$ and R Charts

In order to get statistical control limits for $\bar{x}$ and R charts, common approach is to take some initial samples from the process considering the process was in control. In the current experiments, all the process related variables are kept constant, for example the operating conditions are kept constant throughout the process to achieve the desired dimensions. Similarly machine tool, workpiece material and the work environment etc. are same throughout the process. The only variable which changes periodically is the cutting tool, as it degrades with the time and eventually fails, thus it is to be replaced periodically. In order to get safe statistical control limit for $\bar{x}$ and R charts for future use, data from in control process are required. In the current manufacturing scenario cutting tool is the only variable in the whole process which changes periodically (because of failures). The current study revealed that different failure modes of the cutting tools have significant effect on the product produced from them (see, Fig. 4.2 and Fig. 4.3 in chapter 4). This behaviour of different failure modes on the product quality is very important to be considered while setting the control charts. As in production process, the tool will vary timely, and will fail from different failure modes. Thus, initial samples taken for control chart setting are to be selected from different tools failed with multiple failure modes. With the help of developed experimental setup six milling cutters are run till failure, the life data generated from the experimental setup is important in the sense that they correspond to “normally” degraded milling cutters. This means that the defects were not initially initiated on the cutters and that each degraded cutter contains almost all the types of defects (worn-out and breakage). Three cutters from both the failure modes (worn-out and breakage) are observed.

Twenty five initial samples, each of size five; have been taken from six milling cutters samples with different failure modes, when the cutter was operating in its healthy stage (considering the process was in control). The interval of time between samples is one hour. These samples are used for setting the $\bar{x}$ and R charts. When setting up the control charts, it is recommended to start with the R chart. Because the control limits on the $\bar{x}$ chart depend on the process variability, unless process variability is in control, these limits will not have much meaning (Montgomery, 2008). Using the initial samples from different cutting tools, the center line for the R chart is found as shown in Eq. (6.1).

$$\bar{R} = \frac{\sum_{i=1}^{n} R_i}{n} \tag{6.1}$$

$$\bar{R} = \frac{\sum_{i=1}^{25} R_i}{25} = \frac{20.034}{25} = 0.801$$

where n = total number of samples, R_i = Range of the i^{th} sample.

The control limits of the R chart are calculated as follows:

$$UCL = D_4\bar{R} \tag{6.2}$$

$$UCL = D_4\bar{R} = (0.3251)0.801 = 1.694$$

$$LCL = D_3\bar{R} \tag{6.3}$$

$$LCL = D_3\bar{R} = (0)0.801 = 0$$

where the constants D_3 and D_4 are tabulated based on sample size (for sample size of 5, $D_3 = 0$ and $D_4 = 0.3251$) (Montgomery, 2008).

Since, the R chart indicates that the process variability is in control (see, Fig. 6.1); now construct the $\bar{x}$ chart. The center line is calculated as shown in Eq. (6.4).

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{n} \bar{x}_i}{n} \tag{6.4}$$

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{25} \bar{x}_i}{25} = \frac{105.441}{25} = 4.218$$

where $\bar{x}_i$ = Mean of the i^{th} sample.

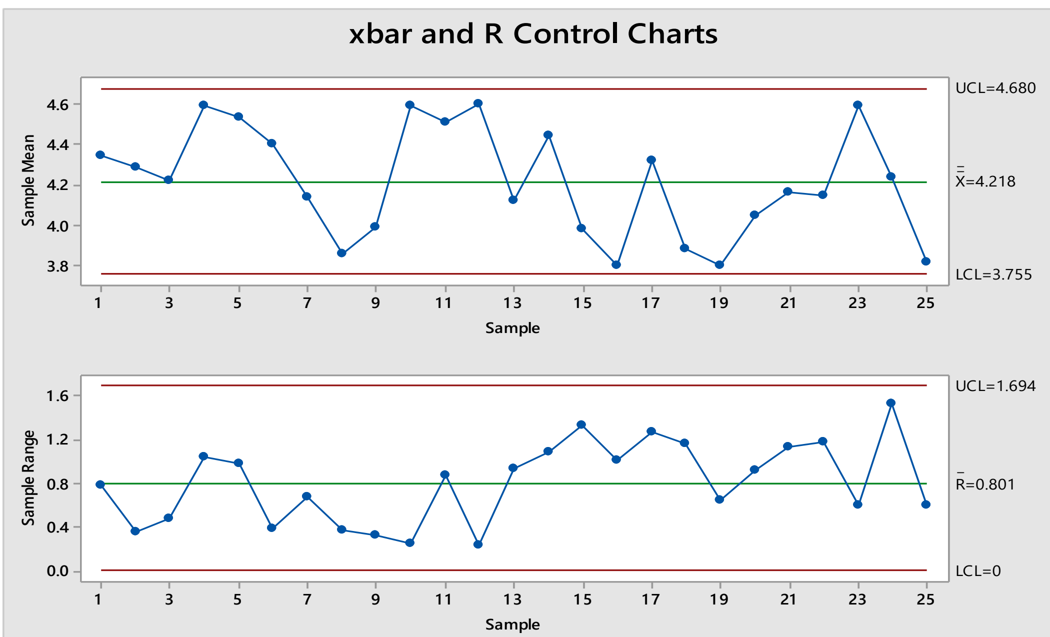

Fig. 6.1. $\bar{x}$ and R charts.

The control limits of the $\bar{x}$ chart can be found out as follows:

$$UCL = \bar{\bar{x}} + A_2\bar{R} \tag{6.5}$$

$$UCL = 4.218 + (0.577)(0.801) = 4.680$$

$$LCL = \bar{\bar{x}} - A_2\bar{R} \tag{6.6}$$

$$LCL = 4.218 - (0.577)(0.801) = 3.755$$

where, the constant A_2 is tabulated based on sample size (for sample size of 5, $A_2 = 0.577$) (Montgomery, 2008).

When the preliminary sample means are plotted on this chart as shown in Fig. 6.1, all the points are inside the control limits. Since, both the $\bar{x}$ and R charts depict control, it means that the process is in control under stated levels. This set of safe control limits are adopted for monitoring future production. This completes the setting of $\bar{x}$ and R charts limits for future use. The control charts shown here are made using Minitab (Version: 17.2.1). Next, the conventional usage of the $\bar{x}$ and R control charts is explained.

b) Conventional Process Monitoring and Quality Control Policy

Once a set of safe control limit is established, the conventional way is to use the control charts for monitoring future production. Fig. 6.2 (a) illustrates the working of conventional process monitoring and quality control policy. Additional samples from the process, each of sample size five from the process (with a new cutting tool) were collected after the control charts were established and the sample values of $\bar{x}$ and R are plotted on the control charts with sampling frequency of one hour. The control chart detected out of control process at 6th sample. As the control chart shows an out of control process, it means that an assignable cause has occurred at that time. Conventionally, the operator is directed to check process variables viz. cutting tool, process settings, calibration etc. and then make the adjustments in an effort to bring the process back into state of control. This conventional usage of control chart will only detect occurrence of assignable causes, also fixed sampling frequency or sample size were used throughout the monitoring. It will be of great interest to detect the reason for assignable cause and simultaneously able to vary the sampling frequency or sample size while monitoring the process for early detection of out of control process. Accordingly, for early detection of out of control process, fault estimation model based process monitoring and dynamic quality control policy is proposed next.

c) Fault Estimation Model based Process Monitoring and Dynamic Quality Control Policy

In this process, the mean surface roughness is monitored with a $\bar{x}$ control chart, and the process variability is monitored by R chart. Notice that if the R chart displays an out of control point, operating personnel are coordinated to contact process engineering instantly. The current manufacturing process is having only one controllable variable, cutting tool. In this scenario, the high chance of assignable cause may be tool health. Thus, the developed fault estimation model is linked with the control chart in such a way; the sample quality data is fed as input to the fault estimation model to know the current health state of the tool without stopping the production. The fault estimation model can give three types of indication about the health of cutting tool:

- Tool is in stage I (Safe Zone)
- Tool is in stage II (Partial Safe Zone)
- Tool is in stage III (Worn-out Zone).

Based on the output from fault estimation model some guidelines are proposed for each health stage of the cutting tool for process monitoring and dynamic quality control. When the health state of the cutting tool is identified as stage I (the stage I of the cutting tool indicates only slight wear have been occurred in the tool, and the tool is in safe zone), the process monitoring is continued with initial sampling frequency or sample size. As the fault estimation model indicate the shift in the health state of cutting tool from stage I to stage II, it means that moderate wear is now present in the tool and this can be the reason of assignable cause in near future. Being in partial safe zone, it’s not wise to discard the tool, here the decision on varying the sampling frequency or sample size is needed to be taken for early detection of out of control process in future. As the tool health state is identified as stage III (tool is now in worn-out zone), this indicate that tool wear will soon can cause out of control process, thus here further decision on varying the sampling frequency or sample size can be made for very early detection of out of control process. Also, as the tool is reached to its failure zone, tool replacement decision can be taken in a timely manner, and this will also eliminate the faulty product development and reduce losses because of tool failure viz. power consumption etc. Based on these guidelines smart decisions on quality improvement (cost of inspection can be managed efficiently), and timely tool replacement can be taken efficiently before tool failure.

Fig. 6.2 (b) illustrates the working of fault estimation model based process monitoring and quality control policy, applied on the same process data as used for conventional process monitoring and quality control policy. Additional samples from the process, each of sample size five from the process are fed as input to the fault estimation model to know the current health state of the cutting tool. From the results of fault estimation model it is identified that the current health state of the cutting tool is reached to stage II at third sample. According to the proposed guidelines, the decision on varying the sampling frequency is taken for future monitoring. Sampling frequency from the fourth sample is changed to half an hour from one hour for early detection of out of control process. With this change the control chart is now able to detect the out of control process early. The control chart detected out of control process at fourth sample. Table 6.2 shows the performance of fault estimation model based usage of control chart.

TABLE 6.2

FAULT ESTIMATION MODEL BASED USAGE OF CONTROL CHART

Sampling frequency	**1 hour**	
	Input	**Output**
Fault estimation model	1^{st} sample	Stage I
	2^{nd} sample	Stage I
	3^{rd} sample	Stage II
Decision on change in sample frequency from 4^{th} sample onwards		
New Sampling frequency	1/2 hour	
Out of control process detection	4^{th} sample	

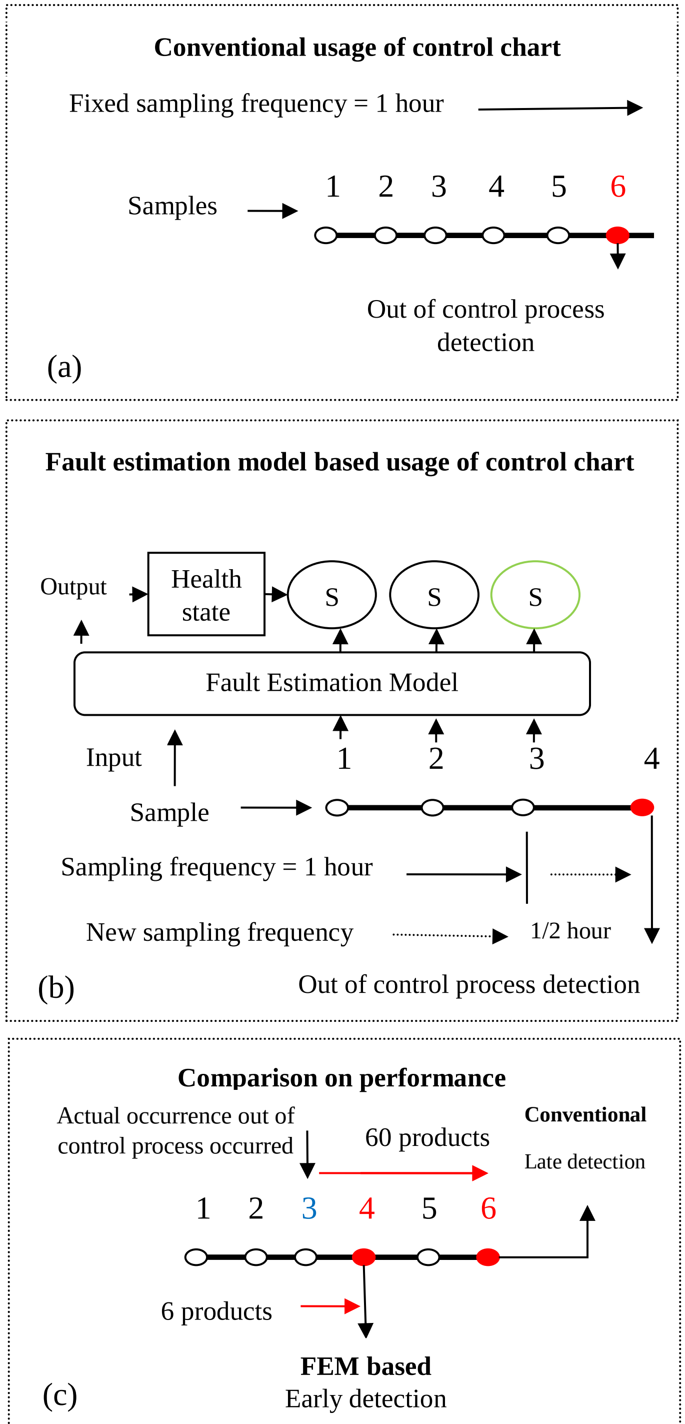

Fig. 6.2. Illustration of conventional and fault estimation based process monitoring and quality control polices.

d) Comparison of Conventional and Fault Estimation Model based Process Monitoring and Quality Control Policy

Table 6.3 and Fig. 6.2 (c) shows the comparison of performance of conventional and fault estimation model based control chart policy in terms of product produced till detection of the out of control process. Till actual occurrence of out of control process twenty nine products were produced. Whereas, in conventional usage of control chart, total sixty products were produced from the process till the detection of out of control process. However, only thirty five products were produced from the process till the detection of out of control process through fault estimation model based usage of control chart. It is clear that the fault estimation model based process monitoring and dynamic quality control policy is capable of detecting out of control process very early than conventional policy. With the help of fault estimation model based control chart usage, the number of faulty product development gets reduced. As the difference between the products produced before the detection of out of control process is thirty one from conventional policy with actual occurrence, this is considerably high. Consequently, only six products were produced till the detection of out of control process from the fault estimation model based usage of control chart.

TABLE 6.3

COMPARISON OF PERFORMANCE OF CONVENTIONAL AND FAULT ESTIMATION MODEL BASED USAGE OF CONTROL CHART

	Actual occurrence of out of control process	**Conventional way of usage of control chart**	**Fault estimation model based usage of control chart**
Products produced till out of control process detection	29	60	35

In essence, this joint methodology forms the basis of a quality control based intelligent predictive monitoring system to estimate the useful life of the tools and detect the surface degradation prior to costly failure and damage to high valued workpieces. As a consequence, lead to online monitoring of the production process as well as serve the purpose of tool condition monitoring.

6.2.2 Preliminary Investigation's Rundown

This preliminary investigation explores the interdependency between diagnostics and statistical process quality control and utilizes the same for dynamic quality control and efficient tool replacement decisions; this is of high importance for manufacturing industries in improving the performance of their machining process as well as reducing the overall manufacturing cost. The major contributions of this investigation are as follows:

- An ensemble (random forest) based fault estimation models are developed to map the relationship between surface roughness and tool wear.
- Guidelines for process monitoring and quality control based on the results of fault estimation model are proposed. These guidelines lead to efficient quality improvement as well as timely tool replacement decisions.
- The fault estimation model based process monitoring and dynamic quality control policy is capable for early detection of out of control process than conventional usage of control charts.

The encouraging results from this study promote the establishment of an autonomous decision-making system capable of dynamic optimization of preventive replacement, process quality control, spare parts inventory management, and lower manufacturing costs in real-world manufacturing environment. The next section outspreads this preliminary investigation in the direction of an autonomous decision-making system development.

6.3 An Autonomous Decision-Support System: Dynamic Integrated Policy Pertaining to Diagnostics, Prognostics, and Economic Process Quality Control

The developed autonomous decision-support system is briefly discussed in subsequent sub-sections.

6.3.1 New Tool Condition Monitoring System: Instantaneous Diagnostics and Prognostics

A new tool condition monitoring system for instantaneous diagnostic and prognostic is proposed. Wherein, diagnostic information helps gauge the current health state of the tool, while the prognostic information provides the RUL of the tool. This ascertains health monitoring and life prediction instantaneously with a solitary experimentation. Theoretical and mathematical foundation of the developed TCM system is elaborated from next paragraph onwards.

As previously recognized in chapter 4, that a significant part of the past work on tool monitoring has regarded the problem of figuring out whether the tool has been worn-out or not. In reality, tool wear is a dynamic process, with tools, moving from being new to continuously higher levels of wear. On that ground, and as it provides more valuable information to machinists; in chapter 3 as well in the preliminary investigation of this chapter multi-level categorization of wear is well explored. Now, the use of a multi-level categorization of tool life is introduced. Yet again, considering the case of cutting tools, its life is divided into three health states as a function of tool life (see Fig. 6.3, splitting the health states as Stage 1: slight wear zone, Stage 2: moderate wear zone and Stage 3: critical or worn-out zone; with their life scopes). As such no specific method or technique is available to decide life scopes. Based on the literature (Wang et al., 2014) and observation of the noticeable physical change in the surface roughness of the produced surface with tool degradation during experiments are the primary basis for selection of these life scopes. Multi-class classification algorithms viz. support vector classification, etc. are used for such diagnostic problems; this requires an independent classification model (as seen in chapter 4). However, to make the current TCM system capable of performing instantaneous diagnostics and prognostics tasks, the TCM system is built to provide information about remaining useful life of cutting tools; by assessing the extent of degradation from its expected state of health in its expected usage conditions. Herein, the TCM system will predict the RUL of the tool, based on the RUL and multi-level categorization of tool life; one can easily diagnose the current health state. Furthermore, guide towards the establishment of an efficient preventive maintenance program.

To build the desired TCM system, the tool degradation indicator proposed in chapter 4 is used. The TDI is a set of measures, sensitive to cutting tool degradation. TDI comprises of tool current age and product quality measurements. Tool current age (T_i) is the current age of the tool. Product quality measurement in terms of surface roughness is "the result of irregularities arising from the plastic flow of chips during the machining (Lou et al, 1998)." Extensively used average surface roughness (R_a) parameter is used to define the surface roughness of the machined product. The product quality during current and previous inspection can be defined as follows:

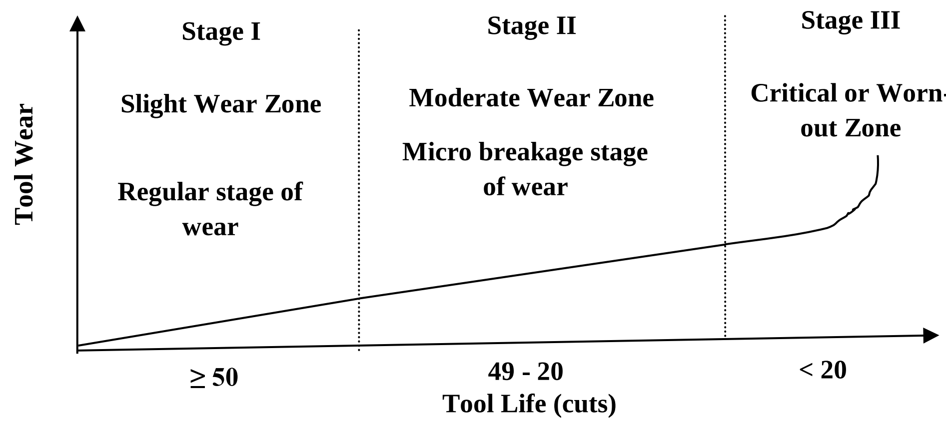

Fig. 6.3. Health states as a function of tool life.

Current inspection;

$$R_{a_i} = \frac{1}{L}\int_0^L |Y(x)_i|\, dx \tag{6.7}$$

where, the parameter L is sampling length, and function *Y(x)* is the coordinate of the roughness profile curve.

Previous inspection;

$$R_{a_{i-1}} = \frac{1}{L}\int_0^L |Y(x)_{i-1}|\, dx \tag{6.8}$$

The proposed tool degradation indicator has a characteristic function in the modeling of the new TCM system. Herein, the tool current age is important in estimating the RUL of the cutting tool. Product quality measurements in the present and previous inspections are useful in representing the tool's current health condition. In most of the available work, current wear is the preferred output of the TCM system. However, just wear estimation will not assist the end goal of tool condition monitoring. Accordingly, in this work for output, the remaining useful life of the tool is preferred and is denoted as RUL_i, as shown in Eq. (6.3).

$$RUL_i = T_F - T_{c_i} \tag{6.9}$$

where, T_F is the time to failure of cutting tool, T_{c_i} is the current inspection time.

Modeling of the TCM system should be proficient in achieving the desired input-output mapping. Consequently, v-Support Vector Regression is employed to model the TCM system. v-SVR works with the structural risk minimization principle (Cortes and Vapnik, 1995). Considering given input-output sample pairs as $\{(TDI_1, RUL_1), \dots, (TDI_m, RUL_m)\}$. Herein, the objective is to model the nonlinear relationship between tool degradation indicator and remaining useful life of the tool ($f(TDI)$, see Eq. (6.10)), such that $f(TDI)$ is close to the output RUL and must be flat to eliminate over-fitting.

$$f(TDI) = w^T \phi(TDI) + x \tag{6.10}$$

where, w is the weight vector, $\phi(TDI)$ is the non-linear mapping function and x is the bias.

To make sure that $f(TDI)$ meets the goal of closeness and flatness, a dual expression is presented by building a Lagrange function (Bhatt et al., 2012). Maximizing the Lagrange function gives w and provides the dual optimization problem, given as follows:

$$Max \qquad (-1/2)\sum_{i,j-1}^{m}(\alpha_i-\alpha_i^*).(\alpha_j-\alpha_j^*).K\big(TDI_i,TDI_j\big) + \sum_{i-1}^{m} RUL_i.(\alpha_i-\alpha_i^*) \tag{6.11}$$

Subject to

$$\sum_{i-1}^{m}(\alpha_i-\alpha_i^*)=0,$$

$$\sum_{i-1}^{m}(\alpha_i+\alpha_i^*)\le Cv,$$

$$\alpha_i,\alpha_i^*\in[o,C/m].$$

where, $\alpha,\alpha^*$are Lagrange multipliers, $K(TDI_i,TDI_j)$ is the kernel function given by $K\big(TDI_i,TDI_j\big)=\phi(TDI_i)^T.\phi(TDI_j)$, C is the regularization parameter, and v is the higher bound on the function of margin errors in the data.

Substituting w in Eq. (6.10), the final approximated function is given as follows:

$$f(TDI)=\sum_{i-1}^{m}(\alpha_i-\alpha_i^*).K(TDI_i,TDI)+x \tag{6.12}$$

Radial basis function kernel with parameter gamma (γ) is utilized as a part of this work as it provides high precision and low execution time. A Karush-Kuhn-Tucker condition (Kuhn and Tucker, 1951) to identify bias is utilized. For given input-output training data, the developed TCM system ascertains the Lagrange multipliers α, α^* and x. Once the model parameters (v, etc.) are selected, the TCM system can foresee the RUL of the tool at any point of time using corresponding tool degradation indicator through Eq. (6.12). One can refer the work of (Chang and Lin, 2011) for advance particulars and mathematics related to v-SVR.

The complete life data of five milling cutters consisting of 321 samples drawn from experiments were used for training. To train the build TCM system, model and kernel parameters are need to be specified, that play a crucial role in the performance of the method. In most work, the authors end up choosing parameter by trial and error, which is not efficient (Fasshauer and Zhang, 2007). In this work v and γ are the most significant tuning parameters that need to be optimized. Accordingly, a feasible range of v and γ with the grid space is supplied. Subsequently, the entire grid points are attempted to get the one imparting the maximum cross validation accuracy. Usually, the search becomes slower as the values of these parameters become higher, thus it is better to restrict it to an equitable range. Accordingly, the interval for the parameter v is taken as $\{0.01\ 1\ 10\}$, this will test the parameter from 0.01 to 1 with 10 steps. Likewise, the interval for the parameter γ is taken as $\{0.01\ 0.1\ 10\}$, this will test the gamma parameter from 0.01 to 0.1 with 10 steps. Using this grid search approach, the optimal parameters are found as $v = 0.67$ and $\gamma = 0.09$. Ten-fold cross-validation is chosen to make certain the reliability and stability of the performance of the system. The performance of the TCM system is measured with widely used imperative measures. For evaluating the goodness of fit of the TCM system, R-Squared correlation coefficient (R^2) is calculated. Here, R^2 equals the square of the Pearson correlation coefficient between the actual and predicted RULs, R^2 represents how much predicted values are related to actual values. The R^2 value of 0.849 from TCM system shows the perfect linear relationship and high strength of correlation between actual and predicted RUL. To check the suitability of the model, mean absolute error is used. MAE measures how close predictions are made by a model to the actual values. The MAE value of 7.447 from TCM system shows predicted RUL is close to the actual RUL, showing the suitability. In addition to this, root mean squared error is also evaluated; it is the standard deviation of the differences between predicted and actual RULs. RMSE value of 9.135 represents good accuracy in predicting RUL. For stability, relative absolute error and root relative squared error are evaluated; these are the measures for the variance in the predictions. Error rates of 50.67 % and 52.62 % represent the lesser variance in prediction and showing the stability of the model. Moreover, computational efficiency of TCM system is measured as 0.07 seconds in terms of the CPU time, making it computationally efficient to be applicable in a real industrial environment. This performance shows that the proposed TCM system is reliable, robust and applicable for fault diagnostic and prognostics to prevent tool performance degradation and catastrophic failures. The tests and verification of TCM system are performed using an Intel (R) Core (TM) i7-3770 CPU 3.40GHz PC. The core of the v-SVR is implemented using WEKA (version 3.7.12).

6.3.2 Dynamic and Simultaneous Optimization of Economic Process Quality Control and Maintenance Planning Model

A dynamic policy for integrated optimization of process quality control and maintenance planning, considering the real-time health state of the system, is proposed. The model is dynamic because of its ability to re-evaluate the optimal values for the design parameters of process quality control and maintenance planning used in the entire lifecycle of the manufacturing process. Whenever a change in the current health state of the system is detected the initial optimal design parameters are updated as a function of life. As a result, the model can evolve itself based on the real-time knowledge of the actual health state of the system. This is more viable in practical environments, where a system is subjected to degradation. The additional functionality is discussed from next paragraph onwards.

Consider a manufacturing system; comprising of cutting tool as a single component machine with time-to-failure following Weibull distribution. Herein, failure is considered in terms of tool degradation (F_{TD}) due to wear. Tool degradation is identified with a time lag by control chart. It is assumed that at any time if failure is discovered, Corrective Replacement (CR) is performed, resulting in an expected CR cost. Degradation also influences the functionality of the tool, which reduces the process quality control; leading to increased rejection rate, till it is identified. This incurs the extra cost of lost quality. Accordingly, Preventive Replacement (PR) of the tool is performed to reduce the probability of tool failure and cost of lost quality. However, PR requires extra time and capitals. Thus, PR optimization is carried out to trade-off the failure and PR cost.

Considering that quality can be judged by assessing critical to a quality characteristic of the produced goods (say, 'Q_c'). Assuming Q_c is a normal random variable with process mean (μ) and standard deviation (σ); μ is at its target value during in-control state. It can shift instantly, owing to tool degradation. Herein, the control chart mechanism is followed to examine Q_c, as degradation cannot be detected directly. Thus, detection time relies upon the power of control chart. The design parameters of control chart are sample size (n), time (in hours) between samples (h), and the number of standard deviations of the sample distribution between the center line of the control chart and the control limits (k). Thus, the resulting Upper Control Limit (UCL) and Lower Control Limit (LCL) for the $\bar{x}$ chart are $UCL = \mu + k\frac{\sigma}{\sqrt{n}},\ LCL = \mu - k\frac{\sigma}{\sqrt{n}}$ (Pandey et al. 2011). All the process values (sample mean) are plotted on the chart. If the process values fall within the upper and lower control limits, the process is referred to as in-control. If the process values plotted fall outside the control limits, the process is referred to as out-of-control (Duncan, 1956). Control chart design involves several costs, viz. costs of sampling, false alarm, process shift, etc. Therefore, an economic design of the control chart is carried out to attain the economically optimal design parameters.

It was obvious from the previous discussion that, machine degradation and maintenance affects the process quality. Thus, the control chart design and PR optimization must be done simultaneously. The optimal values of design parameters of process control and preventive replacement are updated based on the real-time knowledge of the health state of the system throughout the manufacturing process. To exhibit the benefits of integrating process control with maintenance planning, considering the real-time health state of the system, a cost model is formulated by capturing the several costs related to the manufacturing process; those are influenced by process quality control policy and PR planning. In this work Duncan's model (Duncan, 1956) for economic design of $\bar{x}$ control chart is customized for capturing the cost of lost quality because of degradation, and built in conjunction with developed TCM system. The decision variables in current problem are n, k, h, and T_R. The parameter T_R is the optimal time for preventive replacement.

6.3.2.1 Dynamic Integrated Cost Model

The expected total cost per unit time of dynamic and integrated process quality control and maintenance planning, considering the real-time health state of the system ($[OTC]_{(Q\times M)_{RT}}$) is the ratio of the summation of the expected total costs of quality loss owing to process failure ($T\,[CQL]_{PF}$) and preventive replacement $T\,[C_{PR}]$ to the evaluation time (T_E). It is written as follows:

$$[OTC]_{(Q\times M)_{RT}} = (T\,[CQL]_{PF} + T\,[C_{PR}])/T_E \tag{6.13}$$

Theoretical and mathematical models of constituent costs in $[OTC]_{(Q\times M)_{RT}}$ are detailed in following sub-sections.

a) Dynamic Economic Process Quality Control Model

Current work customizes the existing Duncan's model (Duncan, 1956) for capturing the cost of lost quality due to degradation and makes it dynamic with the real-time health state of the system. Major modifications over existing model are highlighted as follows:

- Duncan's and most of the available models consider a fixed design approach for the design of the control chart. Where, the initially obtained optimal design parameters are kept constant for the entire life of the manufacturing process. Such fixed design approach is not considered economical for machines deteriorating with time viz. cutting tools. As any change in quality characteristic from its target value due to the machine degradation is an indirect loss to the customers. However, considering the real-time health state of the system with the economic design of control chart will be more economical. Accordingly, the proposed economic control chart design is formulated considering the real-time health state of the system derived from the developed TCM system. As a consequence, whenever the change in health state of the system will occur, the designed control chart will be able to evolve itself to re-evaluate the optimal values for the design parameters of process quality control used in the entire lifecycle of the manufacturing process as a function of life. This will lead to dynamic quality control policy.

- Most of the available work evaluates optimal design parameters for the entire life of the manufacturing process. Whereas, the time-to-failure is a random variable; it is observed from the experiments that even the identical cutting tools fail at different times because of the inherent design variations. At any point of time, the tool failure probability depends on the current health condition of the machine. Thus, despite considering constant optimal design parameters for the entire life of the manufacturing process it will be more economical to update and re-evaluate the optimal design parameters as a function of tool life. Accordingly, residual-life based evaluation scheme is proposed. Herein, at the initial stage of control chart design the optimal parameters are evaluated based on the mean life of the tool; estimated based on past failure history. As soon as the first sample as per initial optimal time between samples (h) from the process is taken. This is fed as input to the developed TCM system to predict the real-time RUL of the tool based on the current health condition. Consequently, the evaluation time (T_E) is updated as the residual-life of the tool and the optimal design parameters are re-evaluated as a function of tool life.

- The optimal sample size (n) is principally influenced by the magnitude of the shift (δ). In practice, the δ value is taken as constant (generally mean shift) for the entire process. Whereas, it is always better to design a control chart to function practically well over a range of shifts than a specific level of shift. Accordingly, a multi-state magnitude of process shift (δ_{S_n}) scheme is proposed; to handle the vibrant nature of tool degradation more efficiently, and making the control chart design more convenient and powerful enough to detect a wide range of shifts as a function of tool life. Along these lines, regardless of the sole magnitude of process shift for the entire lifecycle of the manufacturing process, the magnitude of process shift is foreseen from multiple health states of the tool as a function of tool life. Herein, assuming that at the initial stage of control chart design the tool belongs to stage I of its life. Herein, the multi-state magnitude of shift (δ_{S_n}) will be taken as average shift while the tool was in stage I (δ_{S_I})

estimated based on the past data. The developed TCM system will provide the information about a change in the current health state of the tool. As soon as stage II is detected the shift will be updated as the average value of the shift while tool belongs to stage II ($\delta_{S_{II}}$). Likewise, the shift will be further updated to average shift for stage III ($\delta_{S_{III}}$) of the tool. As a result, the multi-state magnitude of process shift scheme will accommodate the dynamic nature of tool degradation; by means of dynamically updating the magnitude of process shift as soon as significant progressions in tool wear is detected. Accordingly, the probability of Type II error ($\beta_{\delta_{S_n}}$) and the fraction of non-conforming unit owing to the magnitude of the shift ($R_{\delta_{S_n}}$) is considered in the following manner:

$$\beta_{\delta_{S_n}} = F\left(k - \delta_{S_n}\sqrt{n}\right) - F\left(-k - \delta_{S_n}\sqrt{n}\right) \tag{6.14}$$

$$\mathrm{R}_{\delta_{S_n}} = 1 - F\left(3 - \delta_{S_n}\right) - F\left(-3 - \delta_{S_n}\right) \tag{6.15}$$

where, F denotes normal cumulative distribution function.

- In this work, it is considered that tool failure affects the performance of the tool (i.e. the tool operates with degraded functionality), which prompts to a fall in quality by changing the process mean. As a consequence, F_{TD} causes process failure, and it is sensed after a time lag. Duncan's model (Duncan, 1956) is built on an assumption that the process failure follows a probability distribution with constant failure rate. Such assumption is not valid with machines subjected to increasing failure rate, viz. cutting tools, where degradation is a dynamic process, with tool moving from being new to progressively greater levels of wear. As per recent literature (Muller et al., 2008) is concerned, it is presented that tool wear follows a Weibull distribution. To verify this, multiple goodness of fit test is performed using the maximum likelihood estimation method to determine the best distribution among exponential, normal, lognormal, logistics, loglogistics and Weibull. This investigation on experimental data verified that tool wear obeys Weibull distribution; same has been chosen to model process failure rate. Herein, inspired by the work of Pandey et al. (2011), process failure rate owing to tool degradation (PF_{TD}, see (6.16)) is modeled as the ratio of the expected number of failures due to tool degradation in a given evaluation time as a function of Weibull distribution parameters to the given evaluation time (T_E).

$$PF_{TD} = f(\theta,\eta)_{T_E}/T_E \tag{6.16}$$

where, $f(\theta,\eta)_{T_E}$ is the expected number of failures due to tool degradation for a given evaluation time as a function of given shape parameter (θ) and scale parameter (η).

- The existing models are built on the assumption that period of the in-control state has a negative exponential distribution (Pandey et al., 2011). However, the period of in-control state is modelled following Weibull distribution, having an increasing failure rate. Thus, the in-control time ($T[t_I]$) comprises of the time before failure plus the inspection time for false alarm.

$$T[t_I] = [(1 - f\left(\theta,\eta)_{T_E}\right) \times T_E] + t_0 \times (S/ARL_1) \tag{6.17}$$

where, t_0 is the inspection time for a false alarm, S is the number of samples during in-control state with PF_{TD} ($S = e^{-PF_{TD}.\mathrm{h}}/(1 - e^{-PF_{TD}.\mathrm{h}})$) (Lorenzen and Vance, 1986), and ARL_1 is the average run length in the in-control state ($ARL_1 = 1/\alpha$), α represents the probability of Type I error ($\alpha = 2F(-k)$).

In this work, expected numbers of failures are estimated through a simulation-based method utilizing BlockSim (version 10). One can refer the pioneering work of Kajima (1989) for a brief overview of the simulation-based method.

- Assuming process is ceased throughout the examination and replacement. Considering $(C_{CR})_{F_{TD}}$as the cost of detecting the assignable cause owing to tool degradation including the downtime cost. Accordingly, the expected cost of carrying corrective replacement for a valid alarm owing to tool degradation ($T[(C_{CR})_{F_{TD}}]$) is considered as follows:

$$T[(C_{CR})_{F_{TD}}] = \{M_{CR} \times [P_r \times C_p + L] + C_{FCR}\} \times f(\theta,\eta)_{T_E} \tag{6.18}$$

where, M_{CR} is mean time to perform the corrective replacement (hours), P_r is production rate (products/hours), C_p is cost of lost production, L is the cost of the labor (INR/hours), C_{FCR} is fixed cost of corrective replacement (including the cost of tool replacement).

The dynamic process quality control model is explained in following subsections.

I. Expected Process Cycle Length ($\mathbf{T[T_{cycle}]}$)

It is the summation of in-control time (see, Eq. (6.17)), out-of-control time and process restoration time. The out-of-control time comprises of the expected time of these actions: time between the event of an assignable cause and the subsequent sample ($\tau = \frac{h}{2} - \frac{(PF_{TD} \times h^2)}{12}$) (Montgomery, 2008), activate an out-of-control indication, chart a sample (t_s), authenticate the assignable cause (t_1).

$$\begin{aligned} T[T_{cycle}] = [(1 - f(\theta,\eta)_{T_E}) \times T_E] + t_0 \times (S/ARL_1) + ((h \times ARL_2) \\ - \tau + n \times t_s + t_1) + M_{CR} \end{aligned} \tag{6.19}$$

where, ARL_2 is the average run length in out-of-control state ($ARL_2 = 1/(1 - \beta_{\delta_{S_n}})$) (Pandey et al., 2011).

II. Process Quality Control Cost

It is comprised of the expected cost of rejection occurred during functioning of process in in-control ($T(\mathrm{C_{IC}})$) (see, Eq. (6.20)) and out-of-control ($T(C_{OC})$) states (see, Eq. (6.21)), the expected cost of sampling per cycle ($T[C_S]$) (It is the summation of the fixed ($\mathrm{C_{FS}}$) and variable ($\mathrm{C_{VC}}$) cost per sample, see, Eq. (6.22)), the expected cost of assessing the false alarms ($T[\mathrm{C_{FA}}]$) (Taking the $\mathrm{C_{FA}}$ as the cost of false alarm, which consist of cost of examining and testing for the false and assignable cause, see, Eq. (6.23)) and the expected cost of restoration of the process due to machine degradation ($T[(C_{CR})_{F_{TD}}]$) (see, Eq. (6.18)).

$$T(\mathrm{C_{IC}}) = (R' \times P_r \times C_R) \times [(1 - f(\theta,\eta)_{T_E}) \times T_E] + t_0 \times (S/ARL_1) \qquad (6.20)$$

where, R' is the fraction of non-conforming items during in-control state ($R' = 1 - F(k) - F(-k)$ (Pandey et al., 2011, Montgomery, 2008), C_R is the cost of rejection per piece.

$$T(C_{OC}) = \left((P_r \times \mathrm{R}_{\delta_{S_n}} \times C_R)/(1 - \beta_{\delta_{S_n}})\right) \times ((h \times ARL_2) - \tau + t_1 + n \times t_s)) \qquad (6.21)$$

$$T[C_S] = [(\mathrm{C_{FS}} + \mathrm{C_{VC}} \times \mathrm{n}) \times ([(1 - f(\theta,\eta)_{T_E}) \times T_E] + t_0 \times (S/ARL_1) + (h \times ARL_2) - \tau + n \times t_s)]/h \qquad (6.22)$$

$$T[\mathrm{C_{FA}}] = \mathrm{C_{FA}} \times (\mathrm{S/ARL_1}) \times t_0 \qquad (6.23)$$

Adding Eq. (6.18), Eq. (6.20), Eq. (6.21), Eq. (6.22), and Eq. (6.23) provides the cost of process failure per cycle ($T[C_{Process}]$); therefore, T $[\mathrm{CQL}]_{\mathrm{PF}}$ is given as:

$$T[C_{Process}] = \mathrm{T}\ [\mathrm{CQL}]_{\mathrm{PF}} = T[(C_{CR})_{F_{TD}}] + T(\mathrm{C_{IC}}) + T(C_{OC}) + T[C_S] + T[\mathrm{C_{FA}}] \qquad (6.24)$$

b) Cost per Preventive Replacement

In most of the wok, cost per preventive replacement of the tool is modeled to include the downtime cost owing to replacement, labor and tool cost. In reality, the replaced tools always have some useful remaining life, which is mostly not considered in PR cost. An exhaustive model, including the effect of lost remaining life in overall PR cost, will be more significant. Thus, in this work, the effect of tools lost a remaining life is also modeled in PR cost. This will lead to optimum usage of the tool life. Remaining life is the residual life of the equipment after a certain time period (t′). As per literature, remaining life is estimated as the Mean Residual Life (MRL) (Ebeling, 2004) and given as:

$$MRL(t') = (1/(e^{-(t'/\eta)^{\theta}})) \times \int_{t'}^{\infty} e^{-(t/\eta)^{\theta}} dt \qquad (6.25)$$

Herein, this model is modified to capture the real-time remaining life with the help of the developed TCM system. Thus, despite taking mean residual life from Eq. (6.25), the real-time RUL of the tool is considered. Herein, the cost of lost remaining life ($CRUL_i$) in relation to mean life cost is considered. It is assumed that the tool cost is uniformly distributed over the lifetime of the tool; the cost of lost remaining life is given as:

$$RUL_i = (C_T/M_L) \times RUL_i \tag{6.26}$$

where, C_T is cost of tool (INR), M_L is the mean life of the tool (see, Eq. (6.27)), RUL_i is the remaining useful life of the tool in hours at a given time, and it is obtained in real-time using TCM system.

$$M_L = \int_0^{\infty} e^{-(t/\eta)^{\theta}} dt \tag{6.27}$$

Thus, the total cost per preventive replacement is expressed as follows:

$$T\,[C_{PR}] = \{M_{PR} \times \left[P_r \times C_p + L\right] + C_{FPR} + CRUL_i\} \tag{6.28}$$

where, M_{PR} is mean time to perform preventive replacement (hours), C_{FPR} is fixed cost of preventive replacement (INR).

Consequently, the preventive replacement decision will be evaluated. Herein, for assessing the optimal preventive replacement decision, a balance is made between the cost of lost remaining life of the tool with maintenance and lost quality costs. The sum of both the costs, i.e. total expected cost ($[\mathrm{OTC}]_{(\mathrm{Q}\times\mathrm{M})_{\mathrm{RT}}}$) is calculated for each cut to be made by the tool, and corresponding to minimum cost; optimal preventive replacement decision along with optimal design parameters of quality control are obtained.

At beginning of the production process, the dynamic integrated model is provided with three inputs (δ_{S_I}, T_E and cost parameters, provided in next section), and $[\mathrm{OTC}]_{(\mathrm{Q}\times\mathrm{M})_{\mathrm{RT}}}$ is minimized to obtain the initial optimal process quality control design parameters (*n*, *k*, *h*) and initial optimal time for preventive replacement (T_R). Fig. 6.4 illustrates the flow chart of the proposed methodology. Current work uses “@ RISK” optimizing tool (version 6.1.1) to solve the optimization problem.

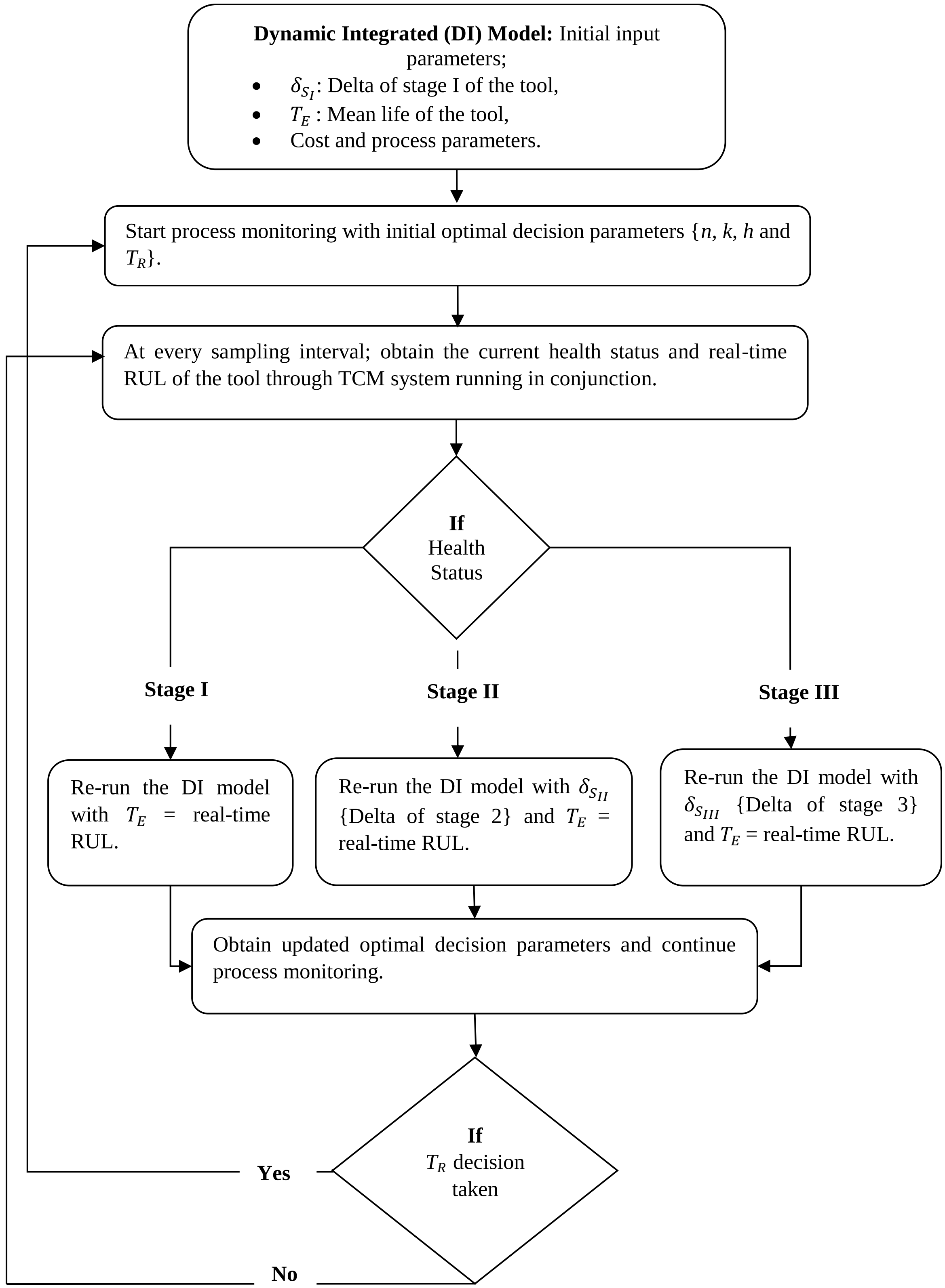

Fig. 6.4. Flow chart of the proposed methodology.

6.4 Experimental Case Study Implementation Results

To demonstrate the functionality and practicality of the developed methodology, an experimental case study is exhibited. A manufacturing system comprising of milling cutter as a single component machine producing MS plates (165 mm × 100 mm × 20 mm) is considered. Average surface roughness in micrometer of the product in the horizontal direction is critical to the quality characteristic, and should be monitored. The cost of milling cutter (C_T) utilized in the process is 2000 INR. Time-to-failure of milling cutter is modeled using two parameter Weibull distribution with shape parameter (θ) = 5.51 and characteristic life (η) = 4.44 (hours). The process is characterized by process mean and standard deviation of μ = 4.22 and σ = 0.27. Past tool health state examination data portrays that the multi-state magnitude of shift (δ_{S_n}) is approximately 1.05 standard deviations for stage I (δ_{S_I}), 1.42 for stage II ($\delta_{S_{II}}$) and 1.91 for stage III ($\delta_{S_{III}}$) respectively. Likewise, the mean life of the tool is captured through past failure data, and given as 55 cuts (4.03 hours).

Considering an examination of quality control expert salaries and the expenses of the testing gear, the underlying values of the initial parameters are specified in table 6.4. The cost of the product is 600 INR per piece and the profit is 50 INR per piece. In any case, identification of fault at client end will cost more to the manufacturer in perspective of returning of the whole batch. Which is higher than the expense of good quality item, along these lines the cost of rejection (C_R) is considered as 1500 INR per piece. According to maintenance records, the mean time to carry out corrective (M_{CR}) and preventive (M_{PR}) replacement actions are 0.5 hours individually. The fixed cost of corrective (C_{FCR}) and preventive (C_{FPR}) replacement is 2000 INR separately.

TABLE 6.4

PARAMETERS UTILIZED IN THE EXPERIMENTAL CASE STUDY

Parameter	P_r **(Product/h)**	C_p **(INR/product)**	L **(INR/h)**	t_0 **(h)**	t_s **(h)**	t_1 **(h)**	C_{FA} **(INR)**	C_{FS} **(INR)**	C_{VC} **(INR)**
Value	10	50	600	0.5	0.2	0.5	1300	50	20

At commencing of the production process, the dynamic integrated model is designed; with δ_{S_I} and T_E = 4.03. Initially obtained optimal design parameters are as follows: n = 7, k =1.6, h = 2.5 h, and T_R = 49 cuts. Designed dynamic integrated model in conjunction with TCM system is initiated to monitor the production process and manufacturing system simultaneously. As per initial sampling plan (h = 2.5), samples from the process are taken and monitored through the designed control chart. Likewise, the TDI from the manufacturing system is fed to the TCM system, to ascertain the current health state and life prediction of the milling cutter. TDI is evaluated as per optimal sampling plan, ensuring optimized health monitoring interval. After two and half hours of operation, the TCM system diagnosed a change in the health state of the tool from stage I to stage II; and RUL is predicted as 46 cuts (3.37h). Herein, as soon as stage II is diagnosed; the optimal design parameters are updated for further monitoring of the production process. With $\delta_{S_{II}}$ and T_E = 3.37h, the updated design parameters are as follows: n = 5, k = 1.9, h = 1.4 and T_R = 24 cuts. The updated parameters are followed for further monitoring, and preventive tool replacement is made after the 24 cuts of the tool. In this course of action the total cost $[\mathrm{OTC}]_{(\mathrm{Q}\times\mathrm{M})_{\mathrm{RT}}}$ is 1433.18 INR. Herein, the tool is replaced preventively before the process would have been gone out-of-control. Consequently, total 49 healthy products were produced in the complete process. This leads to defect free production. To better comprehend the performance of the proposed policy over conventional policy, an exhaustive comparative analysis is presented next.

6.4.1 Comparative Analysis

To gauge the efficacy and performance of the dynamic integrated policy, an exhaustive comparative analysis with widely used conventional independent policies is performed. The conventional process quality control policy (Duncan, 1956) and conventional maintenance planning policy (Pandey et al., 2011) ignores quality deterioration owing to equipment degradation and simply planned maintenance is assumed. For the two conventional independent policies, fixed magnitude of shift as 1.5 standard deviations and the equivalent values of the related parameters as utilized in the previous section are allocated. Table 5.4 presents the detailed results of the comparative analysis. The total expected cost from conventional independent quality control and maintenance planning policies is obtained as 1586.20 INR. The dynamic integrated policy shows 9.65 % of improvement compared to conventional independent policies; showing substantial economic benefits. Furthermore, a comprehensive assessment is performed to see the robustness of the dynamic integrated policy. To do so, both the approach was applied to the experimental data. By observing the experimental data, the actual out-of-control was originated after the production of 50 products. Through this course of action, it was found that with the proposed approach 49 healthy products were manufactured. This result is in contrast to the conventional approach where only 40 healthy products were obtained. From these figures, it can be seen that updating design parameter with real-time health monitoring enables efficient process monitoring. In the complete process monitoring, and through the proposed approach, only eleven products were measured for their quality characteristics. On the other hand, the conventional approach needed a total of twelve products to be measured for their quality characteristics; leading to a higher sampling cost and time. Moreover, with proposed approach loss of only 1 healthy product incurred, whereas the conventional approach, incurred the loss of 10 healthy products. These insights specify that dynamic integrated policy is superior to the conventional independent policies, and can lead to a resultant rise in the improved production process and manufacturing system monitoring.

6.4.2 Sensitivity Analysis

In practice, the estimation of relevant process and cost parameters subject to inaccuracies. Thus, it is essential to recognize the impact of errors on the nature of the result acquired from the model. Herein, systematic sensitivity analysis utilizing important model parameters is conducted, see table 6.6. The base level is taken as used in the experimental case study, and four other levels of these parameters at ± 10 and ± 20% of the base value. The range of the optimal parameters and obtained cost are presented in table 6.6 and 6.7. Fig. 6.5 shows that $[OTC]_{(Q\times M)_{RT}}$ is more sensitive to the cost of rejection and fixed cost of preventive replacement; and less susceptible to the variable cost of sampling, etc. Thus, estimation of the cost of rejection and fixed cost of preventive replacement should be done accurately.

TABLE 6.5

DETAILED RESULTS OF COMPARATIVE ANALYSIS

Policy		Optimal Parameters				Independent Cost (INR)	Total Cost (INR)	Healthy Products Produced	Products Measured	Loss of Healthy Products
		n	k	h	T_R					
Proposed policy	**Initial**	**7**	**1.6**	**2.5**	**49**	**-**	**1433.18**	**49**	**11**	**1**
	Updated	**5**	**1.9**	**1.4**	**24**					
Conventional policies in isolation	Quality	4	1.8	1.1	-	770.75	1586.20	40	12	10
	Maintenance	-	-	-	40	815.45				

TABLE 6.6

SYSTEMATIC SENSITIVITY ANALYSIS

Parameter	Base Level	-20%	-10%	+10%	+20%	$[OTC]_{(Q\times M)_{RT}}$ Base Level	-20%	-10%	+10%	+20%	Range
$\mathbf{t_0}$	0.5	0.4	0.45	0.55	0.6	1429.83	1408.73	1420.29	1438.00	1445.74	1408.73 - 1445.74
$\mathbf{C_{VC}}$	20	16	18	22	24	1429.83	1412.04	1421.13	1438.00	1444.97	1412.04 - 1444.97
$\mathbf{C_R}$	1500	1200	1350	1650	1800	1429.83	1351.12	1391.14	1467.49	1503.57	1351.12 - 1503.57
$\mathbf{C_{FPR}}$	2000	1600	1800	2200	2400	1429.83	1330.66	1380.24	1479.42	1529.00	1330.66 - 1529.00
$\mathbf{C_{FS}}$	50	40	45	55	60	1429.83	1423.64	1426.77	1432.76	1435.70	1423.64 - 1435.70
$\mathbf{C_{FA}}$	1300	1040	1170	1430	1560	1429.83	1410.03	1420.88	1437.53	1444.85	1410.03 - 1444.85
$\mathbf{C_p}$	50	40	45	55	60	1429.83	1414.09	1421.96	1437.70	1445.57	1414.09 - 1445.57
$\mathbf{C_{FCR}}$	2000	1600	1800	2200	2400	1429.83	1399.62	1415.92	1442.35	1453.46	1399.62 - 1453.46
$\mathbf{t_1}$	0.5	0.4	0.45	0.55	0.6	1429.83	1418.85	1424.38	1435.23	1440.63	1418.85 - 1440.63
$\mathbf{C_T}$	2000	1600	1800	2200	2400	1429.83	1418.13	1424.40	1434.65	1438.75	1418.13 - 1438.75
L	600	480	540	660	720	1429.83	1410.94	1420.39	1439.27	1448.68	1410.94 - 1448.68

TABLE 6.7

RANGE OF OPTIMAL DESIGN PARAMETERS ACQUIRED THROUGH SENSITIVITY ANALYSIS

Design Parameters	***n***	***k***	***h***	T_R
Range	6-7	1.5-1.7	2.2-2.6	47-52

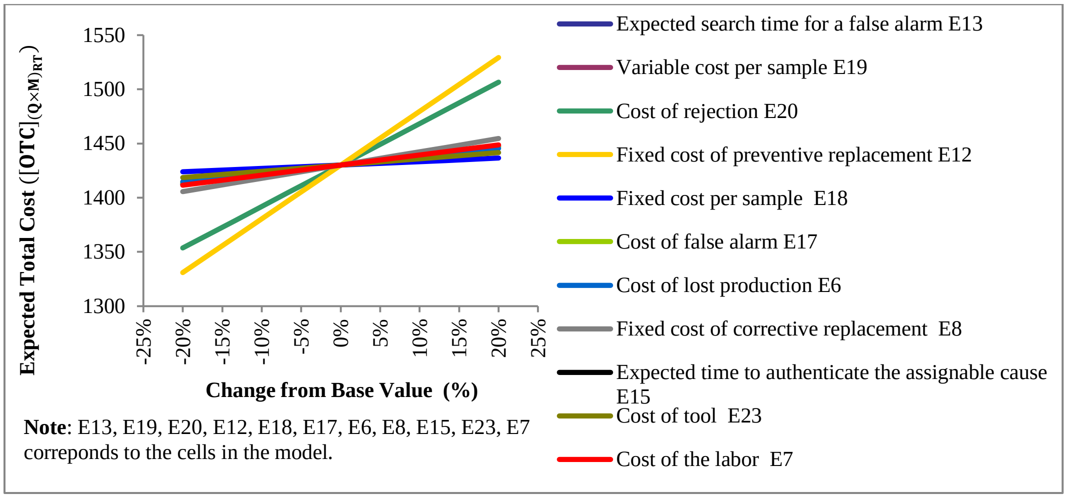

Fig. 6.5. Expected total cost vs. percentage change of the model parameters.

6.4.3 Implication in Various Industrial Scenarios

This section presents the implication of the proposed dynamic integrated policy for various industrial scenarios. Moreover, to critically analyze the efficacy of the proposed policy in different scenarios, the results obtained based on the experimental data from the proposed policy with the conventional independent policies are compared.

- **Scenario I:** Consider a production system producing very costly products where the cost of rejection, as well as the cost of the tool, is very high. Such type of production systems is common for manufacturing of the parts for aviation, automobile industries, etc. In such industrial scenarios, the focus is on minimizing the product rejections at the same time utilizing the optimum life of the costly tools. Accordingly, the cost of rejection and the cost of the tool are taken as high as 10,000 INR each and fixed costs of corrective and preventive replacement are considered as per the cost of the tool. All other process parameters are kept same as used in the experimental case study.

- **Scenario II:** Consider the production system where the cost of rejection is significant compared to the cost of the tool. Such type of production system is common in the manufacturing of general industrial products viz. gears, bearings, etc. In such scenarios, the focus is only on reducing the product rejections. Accordingly, the cost of rejection is considered as 10,000 INR and the nominal cost of the tool as 2000 INR.

- **Scenario III:** Consider a production system where the cost of rejection is less significant compared to the cost of the tool. Such type of production system is common in batch and continuous manufacturing systems. In such scenarios, the main focus is to utilize the optimum life of the tool. So the cost of the tool is taken as high as 10,000 INR and the nominal cost of rejection as 2000 INR.

The proposed policy and conventional independent policies are applied for these scenarios to realize the performance. It can be seen from Fig. 6.6 that the proposed dynamic integrated policy always gives better performance in terms of total cost (4 to 28 % economic improvement) compared to the conventional independent policies. In addition, from table 6.8 it can be seen that conventional policy for process quality control and maintenance planning is biased towards quality rejections. It always focuses on minimizing the cost of rejection, as it produces zero rejected products. However, the conventional policy incurs an excessive cost in terms of lost production. This directly implies that the optimum life of the costly tool is not utilized, which reduces the overall effectiveness of the approach. This effect is more in scenarios where the tool is expensive, as evident from the results of scenario III in Fig. 6.6. Moreover, in case of scenario II where the cost of rejection is high, the conventional policy tries to implement over inspection. Therefore, it results in high inspection cost, as apparent from Fig. 6.7, where the inspection cost is almost 50 % higher compared to the proposed policy. Therefore, conventional policy leads to zero rejections. Though, the overall cost in conventional policy is higher than the proposed policy because of higher loss in production. However, the proposed policy offers superior performance even with lesser inspections. These improvements are owing to the fact that the proposed policy is considered the criterion of dynamically updating the optimal design parameters based on the current health state of the cutting tool. Thereby, the proposed dynamic integrated policy optimizes the inspection frequency, moderates the loss in production, consumes the optimum life of the system and delivers higher economic improvements.

One of the other significant observations from this study can be seen by observing the optimal design parameters in table 6.9. In scenario I, it is seen that the process quality control and preventive replacement parameters obtained at the initial state of the tool was updated significantly throughout the life of the tool. For instance, at the initial state T_R obtained was 51 cuts with evaluation time (T_E) as 55 cuts, which was later updated to 41 cuts with T_E at 58 cuts, and it was further re-updated to 26 cuts. This was done during the intermediate stage of the tool. This implies that in such scenarios the process quality control and preventive maintenance parameters should be continuously evaluated from the initial state of the tool and updated at intermediate stages. As a result, in such industrial scenarios, the proposed policy should be used in the same manner as illustrated in Fig. 6.4. Whereas, for scenario II, the optimal design parameters obtained in this implementation are also summarized in table 6.9. The optimal design parameters of process quality control are updated from the initial state of the tool. For instance, the time between samples (h) was 1.1 hours at the initial state, which was updated to 0.9 hours, and then re-updated to 0.6 hours at the intermediate stage. However, at the initial state, the preventive replacement decision obtained was 55 cuts with evaluation time as 55 cuts. This was updated to 60 cuts with evaluation time as 60 cuts. Then the decision was re-updated at the intermediate stage of the tool as 42 cuts with evaluation time as 42 cuts. Herein, it is evident that the preventive replacement decision is always coming at the end of the tool life. This distinctly implies that the preventive replacement decision is insignificant in the initial or the intermediate stage. However, it is important at the end stage of the tool to avoid sudden failures. For that reason, in such industrial scenarios, the proposed policy can be modified as follows; at the initial and intermediate stages, only the process quality control parameters should be evaluated. As soon as the third or end stage is detected the preventive replacement decision should also be assessed with process quality control parameters. While, for scenario III, the preventive replacement decision obtained at the initial state was 45 cuts with evaluation time as 55 cuts (see, table 6.9). It was realized that this decision is not updated in between till the intermediate stage. At the intermediate stage, the decision was updated significantly as 23 cuts with evaluation time as 40 cuts. This implies that in such scenarios the tool preventive replacement decision is not significant at the initial state of the tool. Though, the preventive replacement decision at the intermediate stage is significantly important. This ensures the utilization of optimum life of the costly tools. Consequently, for such industrial scenarios, the proposed policy can be modified in the following manner; at the initial state, only the process quality control parameters should be evaluated. As soon as the tool reaches the intermediate stage, the preventive replacement decision should also be evaluated with process quality control parameters and so on.

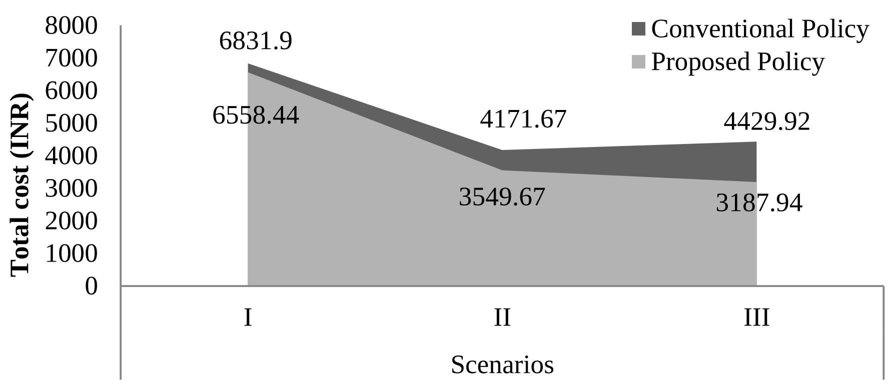

Fig. 6.6. Total cost of operation.

TABLE 6.8

OUTPUT PERFORMANCE OBTAINED FOR VARIOUS INDUSTRIAL SCENARIOS

Scenarios	**Product rejection**		**Lost production**	
	Conventional Policy	**Proposed Policy**	**Conventional Policy**	**Proposed Policy**
I	0	2	9	0
II	0	3	10	0
III	0	0	9	5

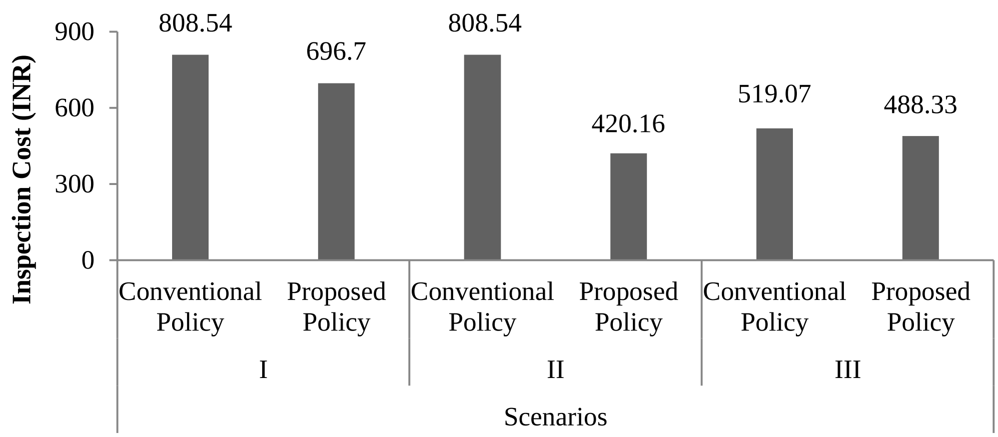

Fig. 6.7. Inspection cost.

TABLE 6.9

OPTIMAL DESIGN PARAMETERS OBTAINED FOR VARIOUS INDUSTRIAL SCENARIOS

Scenarios		**Optimal Design Parameters**			
		n	***k***	***h***	T_R
I	Initial	4	1	1.3	51
	Updated	4	1.1	1.3	58
	Re-updated	3	1.3	0.7	26
II	Initial	4	1	1.1	55
	Updated	4	1	0.9	60
	Re-updated	2	1	0.6	42
III	Initial	7	1.7	2.2	45
	Updated	5	2	1.2	23

These implication results and guidelines expand the model's realism to the actual production systems. This will benefit the manufacturers to adopt the most beneficial practice for optimizing the process quality control and maintenance planning of their industry specific applications.

6.5 Contributions

The research in this chapter advances the existing body of knowledge by developing a novel methodology for dynamic optimization of process quality control and maintenance planning whilst considering the real-time health state of the system; whose main contributions are highlighted as follows:

1. A cost-cutting experimental strategy was implemented that successfully attempted to improvise existing setups by removing their drawbacks like system rigidity, geometric limitations, etc. The experimental setup was made free from exclusive sensors, fixtures, jigs, etc., which made it cost effective, convenient and adaptable for the real-time industrial environment.

2. The missing experimental proof of the relationship between product quality and tool degradation was recognized through a rigorous correlation investigation, revealing a strong positive relationship. Based on the investigated relationship, a new monitoring system was formulated for instantaneous diagnostic and prognostic. The TCM system reliability was enhanced by investigating the use of a multi-level categorization of tool life. The system is validated based on experimental data. The proposed system was found efficient in distinguishing the change from regular wear to the critical zone of wear, which is of high significance to the industries.

3. The existing process quality control model was customized and extended to deal with machine deterioration with time. This was done via the proposed residual-life based evaluation and multi-state magnitude of process shift schemes. Furthermore, the maintenance planning model was modified to capture real-time remaining life information. These models were integrated and build in conjunction with the developed TCM system. As a result, the proposed dynamic integrated model evolves itself dynamically to re-evaluate

the optimal values for the design parameters (n, k, h and T_R) used in the entire lifecycle of the manufacturing process.

4. An experimental case study was exhibited to check the viability of the developed policy; substantial economic benefits were obtained over conventional independent policies. This was further complimented with a systematic sensitivity analysis.

5. Furthermore, implications of the proposed policy for various industrial scenarios are critically analyzed. All these expanded the model's robustness and relevance in the real manufacturing environments.

6.6 Closure

In essence, the proposed methodology was proficient in capturing the interdependencies between process quality control and maintenance planning whilst considering the real-time health state of the system. This will enrich the existing integrated policy by instantaneously considering machine deterioration, health state, and remaining useful life. The information obtained in the current course of action results in significant cost savings in overall manufacturing cost. Though in the present work, the machine is considered to be made up of a single component i.e. cutting tool, the failure of the components of the machine tools also have similar effects on process quality. Thus, extending this analysis for other components of machine will further lead to more significant cost benefits to the industries.

Chapter 7

Conclusion

“Technological change is like an axe in the hands of a pathological criminal”.

Albert Einstein, German-born Theoretical Physicist

Objective of this chapter is to provide a summary of the work reported in this thesis in terms of industrial and technological context, research contributions, and utility of the research. In the end, limitation and future scope of the study are given.

7.1 Summary

The outcomes of the research in this work advances the existing body of knowledge by developing an autonomous decision-support system and methods for systematic expansion of intelligent manufacturing in dynamic and diverse real-world production environments. In general this research work can be assessed as following:

7.1.1 Industrial and Technological Context

Present research adds following innovative technical outcomes to the body of knowledge which would be very important from the industrial context.

A. Augmenting Data-Driven Modeling from Degradation to Remaining Useful Life Approximation.

The accuracy of degradation prediction models so obtained in this research is better than those reported in the literature with same set of experimental data. Wherein, the most reliable semi-offline model together with offline model is useful for optimizing planned shutdown intervals for the machine in real-world manufacturing environment. Herein, the novelty is in augmenting data-driven modeling from degradation approximation to RUL approximation. Wherein, RUL predictions is carried out for two distinct industrial scenarios viz., when only monitoring data are available and when incidental (or planned) offline inspection data are also available, using inventively designed and developed online, offline and semi-offline models. In addition, comparative studies on prediction performances of distinctive models show that the developed model is superior to different conventional models.

B. Real-Time Integration of Diagnostics and Prognostics Centred on the Relationship between Product Quality and Tool Degradation.

The research in this work is a pioneering effort towards designing a simple, easily comprehensible monitoring system utilizing minimum resources (as the proposed system does not require any additional sensors) to enable easy adaptation of the technology even in medium and small scale manufacturing industries. In this, the novelty is in the invention of an integrated TCM system by quantifying and mapping the relationship between product quality and tool degradation. This system ascertains reliable health monitoring and life prediction of the machining system at the same time with solitary experimentation. An added contribution lies in the outcomes; an exhaustive performance and comparative investigations of the proposed integrated TCM system is presented, to distinguish the suitability, stability, quality, reliability, robustness, applicability and comprehensibility in a real industrial environment.

C. A Generic Tool Condition Monitoring System under Dynamic Operating Profiles.

The research in this work and the promising results attained underneath dynamic operating profiles guarantee the expansion of an effective preventive maintenance plan in diverse real-world production scenarios viz. batch production, job production, micro to medium-scale production environments. On the other hand, the case study implementation lends significant credibility to the appropriateness of offered approach over the traditional approach under time-variant industrial scenarios. The novelty of this research is three-fold. The first is the innovative design of a generic TCM system that accounts for the future characteristics of the dynamic operating profiles while prognosticating RULs. It is grounded in the physics of degradation progression and is a function of operating profiles. As a result, the fundamental advantage of utilizing the proposed system to deal with time-variant operating profiles is its proficiency to communicate the future evolution of dynamic operating profiles instantaneously. Second is the consideration of all-encompassing cases of industrial scenarios. For the frist time, a complex real-world scenario of expected but fluctuating future operating profiles is well-thought-off. Third, it is not restricted to a specific machine tool, sensor, and so on; rather the system is adaptive and can be rendered as a first universal perspective to TCM and for that matter any prognostics research. An additional contribution lies in the outcomes; extensive quantitative and qualitative performance investigations are carried out. Further, in contrast to the traditional approach, the implications of the offered system under different scenarios are experimentally examined. That magnifies the robustness and applicability of the offered system in diverse real-world production environments.

More importantly, this can help in effciently planning shop floor operations based on cutting tool degradation and remaining life. Moreover, this will equip manufacturing industries with intelligence that allows responding to the time-variant operating profiles; reliazing intelligent manufacturing under various real-world production environments. In addition, the proposed approach may be seen as an genric perspective to prognostics and can be applied to any other filed also.

D. Dynamic Optimization of Process Quality Control and Maintenance Planning while Considering the Real-Time Health State of the System.

The implication of the proposed dynamic integrated policy under various real-world industrial scenarios revealed that this policy optimizes the inspection frequency, moderates the loss in production, consumes the optimum life of the system and delivers higher economic improvements. This will benefit the manufacturers to adopt the most beneficial practice for optimizing the process quality control and maintenance planning of their industry specific applications. The novelty of this work is in the formulation of a dynamic integrated policy. Whenever a change in health state of the system is detected, the optimal design parameters of process quality control and maintenance planning are updated based on the current health state of the system as a function of its life. This dynamic integrated policy has the dual advantage, i.e., it eliminates the lost quality cost due to machine degradation and also improves the manufacturing system’s reliability by protecting it against failures. An added contribution lies in the outcomes; systematic performance and sensitivity investigation are presented. Moreover, the implication of the proposed policy in various industrial scenarios is critically analysed. This expands the model's robustness and relevance in manufacturing industries. Fundamentally, this work helps reliaze a holistic view of the intelligent manufacturing by dyanmically capturing the interdependencies between process quality control and maintenance planning whilst considering the real-time health state of the system.

7.1.2 Research Contributions

The present study resulted in a number of contributions which can be summarized as follows:

1. A methodology for dynamic optimisation of process quality control and maintenance planning while considering the health state of the system is formulated.
2. Solved one of the standing and non-trivial problem of literature viz. prognostics (predicting remaining useful life) under dynamic operating profiles. The proposed generic prognostics approach encompasses all real-world industrial scenarios.
3. Invention of a cost-efficient and cognitive integrated monitoring system centred on the untapped relationship between product quality and tool degradation.
4. Robust, reliable and applicable condition-based data-centric offline, online and semi-offline models are inventively designed for degradation approximation and remaining useful life prediction.
5. Introduction to a new tool degradation indicator with diverse functionality, to represent the degradation features of the cutting tool.
6. Experimental case studies are implemented to demonstrate the practical feasibility of the developed methodologies.
7. The decision-support systems and integrated approaches results in substantial economic benefits in overall manufacturing cost.
8. The results of dynamic integrated policy and prognostics under dynamic operating profiles are breakthrough in the field of industrial engineering, prognostics and health management, and intelligent manufacturing.

In essence, this work forms the basis for building an centralized autonomous decision-support system for joint consideration of several other critical strategic operational policies viz. production planning, supply chain planning, etc. under dynamic and diverse operating environments; realizing a holistic view of intelligent manufacturing to machinists.

7.1.3 Utility of the Research Work

The systematic and easy to use decision-support system and integrated methods developed will help manufacturing industries in the following manner:

1. Provide manufacturing industries with augmentation of data-driven modeling from degradation approximation to RUL approximation for distinct industrial cases.
2. Provide manufacturing industries with a cost efficient and cognitive integrated monitoring system to instantaneously prevent machining system performance degradation and sudden failures.
3. Equip manufacturing industries with intelligence that allows responding to the time-variant operating profiles and adaptable under various real-world production environments.
4. Lastly, equip manufacturing industries with a holistic view of the intelligent manufacturing, thereby forming the basis for building an autonomous decision-making system that serves as a guide for joint consideration of strategic operational policies pertaining to diagnostics, prognostics and process quality control.

Moreover, the implications of the proposed methods in various industrial scenarios are critically analysed (see table 7.1). This expands the model's robustness and relevance in manufacturing industries.

TABLE 7.1

INDUSTRIAL RELEVANCE

Chapter Number	Scenarios	Possible Industrial Case	Model/Methods
3	When only online monitoring data are available.	Common in manufacturing industries where the cost of cutting tool and workpiece is huge, and generally the process is not stopped for any offline inspection, due to even higher downtime cost viz. aerospace manufacturing industries.	Online model coupled with offline model is developed to predict RUL under this scenario.
	When incidental (or planned) offline inspection data are also available.	In continuous production kinds of manufacturing setup sometimes process may be stopped due to unavailability of raw material or due to failures of machine components. Such an industrial case is very common in many industries; for instance, in case of gas turbines.	Semi-offline model coupled with offline model is developed to predict RUL under this scenario.
4	An industrial scenario in which the operating profiles are fixed. Also, where quality inspections are frequent.	For instance, mass production environment, where the operating profiles are time-invariant. Generally, while manufacturing a similar product in a huge quantity the operating condition are not changed and are fixed for the entire manufacturing process. Also, in small and medium manufacturing industries is quality measurement is common.	An integrated TCM system pertaining to diagnostics and prognostics is built using support vector machine with optimal training technique.

5	A deterministic, dynamic operating profile.	Such a scenario exceedingly arises in a batch production type of environments (where the machining system runs at a particular profile to meet the requirement of a specific batch and transit to other profile based on the prior batch scheduling decisions).	To circumvent this, the impact of in-progress operating profiles on the degradation rate under this scenario is modeled, while undertaking the evolution of the future operating profile, as a finite-valued deterministic and piecewise constant function.
	A randomly-varying dynamic operating profile.	Such a scenario is exceptionally often in job production environments, which take on the manufacturing of customized products, such as a one-time product for a specific customer or a small batch of products by clients' uncompromising demand.	To circumvent this, under periodically monitored situations, it is undertaken that the randomly-varying dynamic profile progresses rendering discrete-time Markov chain.
	An expected but fluctuating future operating profile.	Such a scenario is prominently realistic for almost every micro to medium-scale production environments (here the demand forecasting may reveal the total expected duration under different profiles of the machining system).	To circumvent this, for the first time, discrete operating bins for respective operating profiles are characterized and the percentage of the time the tool will function in a particular operating bin is utilized as the additional statistics fed into the proposed stochastic degradation model.
6	Production system where the cost of rejection, as well as the cost of the tool, is very high.	Such type of production systems is common for manufacturing of the parts for aviation, automobile industries, etc. In such industrial scenarios, the focus is on minimizing the product rejections at the same time utilizing the optimum life of the costly tools.	The existing process quality control policy is enhanced to become dynamic and extended to deal with machine deterioration with time. This is done via the proposed residual-life based evaluation and multi-state magnitude of process shift schemes. Furthermore, the maintenance planning model is

	Production system where the cost of rejection is significant compared to the cost of the tool.	Such type of production system is common in the manufacturing of general industrial products viz. gears, bearings, etc. In such scenarios, the focus is only on reducing the product rejections.	modified to capture real-time remaining life information. These models are integrated and built in conjunction with newly developed TCM system pertaining to instantaneous diagnostics and prognostics. As a result, the designed dynamic integrated model can evolve itself to re-evaluate the optimal values for the design parameters used in the entire lifecycle of the manufacturing process.
	Production system where the cost of rejection is less significant compared to the cost of the tool.	Such type of production system is common in batch and continuous manufacturing systems. In such scenarios, the main focus is to utilize the optimum life of the tool.	

7.2 Limitation and Future Scope of the Study

- In the present work, the main focus is on TCM, from the machine tool point of view, it is equivalent of considering that the machine tool is made up of a single component i.e. cutting tool, the failure of the components of the machine tools also have similar effects on process quality. Thus, extending this analysis for other components of machine tool will further lead to more significant cost benefits to the industries.
- On the other hand, the proposed generic TCM system under dynamic operating profile, consents modelling of solitary sensor, further strengthening of the prediction performance will requires extracting the information from multi-sensors.
- Exploring the use of proposed generic prognostics under dynamic operating profiles for other systems like gas turbine, wind turbines etc. may be give more significance to such approaches.
- In future, such work can be utilized to developed intelligent digital twins of machine tools for Industry 4.0 or Smart Manufacturing.

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