B. TECH. PROJECT REPORT

On

Design and Development of an Experimental Setup for Cyber Twin

BY

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DISCIPLINE OF MECHANICAL ENGINEERING

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Design and Development of an Experimental Setup for Cyber Twin

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degrees

of

BACHELOR OF TECHNOLOGY

in

MECHANICAL ENGINEERING

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INDIAN INSTITUTE OF TECHNOLOGY INDORE

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CANDIDATE'S DECLARATION

We hereby declare that the project entitled "**Design and Development of an Experimental Setup for Cyber Twin**" submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Mechanical Engineering' completed under the supervision of **Dr. B.K. Lad, Associate Professor, Department of Mechanical Engineering**, IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Signature and name of the student(s) with date

<u>CERTIFICATE by BTP Guide</u>

It is certified that the above statement made by the students is correct to the best of my knowledge.

Signature of BTP Guide with date and their designation

Preface

This report on "Design and Development of an Experimental Setup for a Cyber Twin" is prepared under the guidance of Dr. B.K. Lad.

Preface

This report on “Design and Development of an Experimental Setup for a Cyber Twin” is prepared under the guidance of Dr. B.K. Lad.

Through this report I have tried to provide a simulated environment for converting the existing manufacturing units into smarter units. Besides, a real-time validation is presented which is performed in a manufacturing industry.

I have tried to the best of my abilities and knowledge to explain the content in a lucid manner. We have added figures and snapshots to make it more illustrative.

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Without the support from people, mentioned above, the completion of project and report would not have been possible.

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Abstract

In this project, a Cyber Twin has been proposed that can be applied anywhere in the manufacturing industries and possibly, other industries as well. In order to develop the system, literature has been reviewed extensively for identifying most appropriate degradation indicators and for developing models. These models collectively are referred to as Cyber Twin of the actual machines. Using the cyber twin, machines can be simulated to study its behaviour in the near future. In order to make the models dynamic, algorithms have been developed for updating the models with real field data.

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List of Abbreviations

SW/HW	- Software/Hardware
DT	- Digital/Cyber Twin
CAD	- Computer Aided Design
VR	- Virtual Reality
AR	- Augmented Reality
QR	- Quick Response
IoT	- Internet of Things
CNC	- Computer Numerical Control
DC	- Direct Current
DAQ	- Data Acquisition
PC	- Personal Computer
NI	- National Instruments
TCM	- Tool Condition Monitoring
AE	- Acoustic Emission
RUL	- Remaining Useful Life
SVM	- Support Vector Machine
MCU	- MicroComputing Unit
HMM	- Hidden Markov Model

Chapter 1

Introduction

Contents:

1.1 Smart Manufacturing:

Smart manufacturing is a broad category of manufacturing that employs computer-integrated manufacturing, high levels of adaptability and rapid design changes, digital information technology, and more flexible technical workforce training. Other goals sometimes include fast changes in production levels based on demand, optimization of the supply chain, efficient production and recyclability. In this concept, as smart factory has interoperable systems, multi-scale dynamic modelling and simulation, intelligent automation, strong cyber security, and networked sensors.

Smart manufacturing utilizes big data analytics, to refine complicated processes and manage supply chains. Big data analytics refers to a method for gathering and understanding large data sets in terms of what are known as the three V's, velocity, variety and volume. Velocity informs the frequency of data acquisition, which can be concurrent with the application of previous data. Variety describes the different types of data that may be handled. Volume represents the amount of data. Big data analytics allows an enterprise to use smart manufacturing to predict demand and the need for design changes rather than reacting to orders placed.

Smart manufacturing can also be attributed to surveying workplace inefficiencies and assisting in worker safety. Efficiency optimization is a huge focus for adopters of "smart" systems, which is done through data research and intelligent learning automation. For instance operators can be given personal access cards with inbuilt Wi-Fi and Bluetooth, which can connect to the machines and a Cloud platform to determine which operator is working on which machine in real time. An intelligent, interconnected 'smart' system can be established to set a performance target, determine if the target is attainable, and identify inefficiencies through failed or delayed performance targets. In general, automation may alleviate inefficiencies due to human error. And in general, evolving AI eliminates the inefficiencies of its predecessors.

Smart manufacturing has been inspired by the concepts largely developed in the realm of computing. Though manufacturing will continue to benefit from these concepts and other ideas that will emerge (e.g. quantum computing could be a major disruptor), it has its own identity captured in six pillars that are discussed next (see Figure 1). They are neither exhaustive nor stationary. The ultimate pillars will be defined by the research, technology development and applications that will emerge in the future. The ultimate pillars could be formally defined in a number of ways, including clustering of the research papers, industrial reports and information about new technology with text and data mining algorithms.

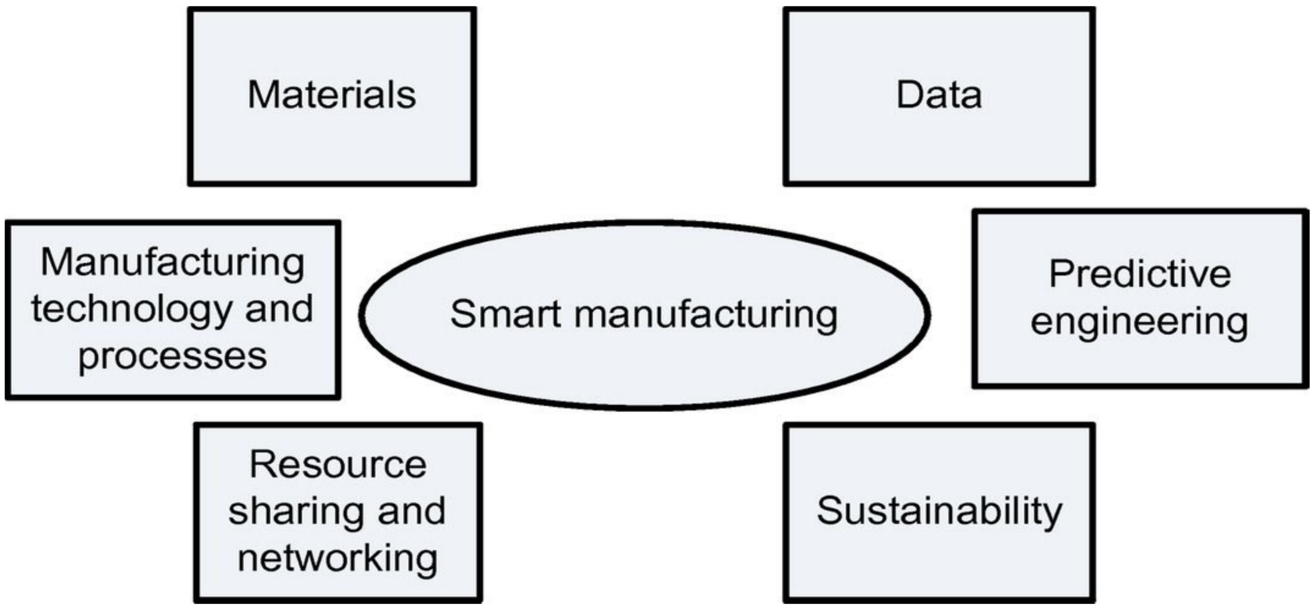

Figure 1. Six pillars of Smart Manufacturing

The six pillars of smart manufacturing are manufacturing technology and processes, materials, data, predictive engineering, sustainability and resource sharing and networking. The names and the degree of importance of these six pillars have been changing, however, they have been around manufacturing throughout its history. For example, data has been an integral part of manufacturing. In the era of smart manufacturing it has become big data. Production planning and forecasting have preceded predictive engineering versed in data science of today.

***Pillar* 1: Manufacturing technology and processes**

The emergence of manufacturing technologies and processes are expected in future years. New materials, components and products will emerge (Kusiak 2016a). Additive manufacturing can serve as an example of a new technology that has prompted the development of new materials, impacted the design and manufacture of products and opened doors to new applications such as biomanufacturing. Manufacturing tools have been designed to integrate various operations, e.g. machines that are capable of horizontal and vertical milling as well as drilling (a machining centre). New hybrid processes will emerge, e.g. hybrids of traditional and additive processes, laser and net-shape manufacturing. Greater integration of processes will occur, e.g. integration of new materials, product design, manufacturing processes, such as discovery of a chemical compound leading to design of a new medication and a delivery device, as well as the manufacture of medication and the device. Big and small area additive manufacturing will expand its prominence in the factories. New generation of low cost robots will enhance factory automation. Sensors and software capabilities will make the new manufacturing equipment smarter and amenable to factory and beyond communication.

***Pillar* 2: Materials**

Smart manufacturing does not make a special call for the development of smart materials, e.g. shape memory alloys or functionally graded materials. It may well be that smart materials and smart products will follow their own development paths. Smart manufacturing is open to all types of materials, including organic-based materials and biomaterials, needed to produce future products. The significance of recovering materials from products at the end of their lifecycle will increase. It is conceivable that landfills will become new mines of various materials. Some new materials will require novel processes that must be developed and incorporated in smart manufacturing. Additive manufacturing alone will be a great contributor to the search for new materials and their mixes.

***Pillar* 3: Data**

We are witnessing the renaissance of data in manufacturing. Some of it has been triggered by deployment of sensors, wireless technology and the progress in data analytics. Greater collection of data from diverse sources, ranging from material properties and process parameters to customers and suppliers has begun. The data will be used to power any application to be envisioned, including building predictive models. Moreover, it will be the best source for preserving and extraction of past and new knowledge related to manufacturing.

***Pillar* 4: Predictive engineering**

Predictive engineering is one of the latest additions to the space of manufacturing solutions that will lead to an anticipatory rather than reactive enterprise. Traditionally, the manufacturing industry has focused on using data for analysis, monitoring and control, e.g. productivity analysis, process monitoring and quality control. Six sigma and other data-analysis concepts have had tremendous impact on advances in the quality of manufactured products and services. However, for the most part, traditional efforts have emphasised the past over the future states of manufacturing processes and systems. Predictive engineering offers a new paradigm of constructing high-fidelity models (digital representations) of the phenomena of interest. Such models will allow exploring future spaces, some within the realm of the existing technology and others that have not been seen previously. In the future, today's models will be enriched with both limited-scope models (e.g. behaviour of a supply chain) and those that involve multiple systems (e.g. models that integrate productivity, product quality, energy and transport) to support decisions concerning future production and market conditions. Such wide-scope models may contribute to restructuring the manufacturing industry. It is conceivable that some manufacturing will become highly distributed and some may be centralised. For example, products that are sensitive to the transportation cost, time-to-market and customisation could be produced at locations in proximity to the customers.

***Pillar* 5: Sustainability**

Sustainability will be of paramount importance in manufacturing. The goals of sustainability efforts will be materials, manufacturing processes, energy and pollutants attributed to manufacturing. The entry points of any major sustainability effort are the product and the market. There is no doubt that the greatest sustainability gains are accomplished when the development of products and processes is guided by the sustainability criteria. Examples of possible scenarios include: (i) sustainable product design will drive manufacturing, (ii) sustainable manufacturing processes will impact the design of products and (iii) simultaneous development of sustainable materials, products and processes will take place. Additive manufacturing represents the second scenario in which a process has resulted in new designs of components and products.

Sustainability is not about what is manufactured but how it is performed. It is the main force behind providing equal footing for remanufacturing, reconditioning and reuse with manufacturing. Because of sustainability, the line between manufacturing and service will remain blurry. For example, reconditioning a used product is not a traditional manufacturing activity, however, it may enter the new manufacturing dictionary.

***Pillar* 6: Resource sharing and networking**

As manufacturing is becoming digital and virtual, much of the creative and decision-making activities will take place in the digital space. While at some level the digital space may be highly transparent, the physical manufacturing assets with their know-how will be protected. This digital-physical separation will allow for shared use of resources across businesses, including the ones that compete.

1.2 Cyber Twin:

The vision of the *Cyber Twin* itself refers to a comprehensive physical and functional description of a component, product or system, which includes more or less all information which could be useful in all—the current and subsequent—lifecycle phases. In this chapter we focus on the simulation aspects of the *Cyber Twin*. Today, modelling and simulation is a standard process in system development, e.g. to support design tasks or to validate system properties. During operation and for service first simulation-based solutions are realized for optimized operations and failure prediction. In this sense, simulation merges the physical and virtual world in all life cycle phases. Current practice already enables the users (designer, SW/HW developers, test engineers, operators, maintenance personnel, etc) to master the complexity of mechatronic systems.

As shown in Figure 2, given an existing physical product, in general, it takes six steps to create a fully functional digital twin. It should be made explicit though, in practice, manufacturers may not strictly follow the sequence to build DTs. It is also possible that these steps can be carried out concurrently.

Step (1): Build the virtual representation of the physical product:

The enabling technologies of this step are computer-aided design (CAD) and 3D modelling. Both are commonly used technologies in product design. The virtual product includes three aspects: elements, behaviours, and rules. At the level of elements, the virtual product model mainly includes the geometric model and physical model of the product, user and environment, etc. At the level of behaviour, the authors not only analyse the behaviour of products and users, but also focus on the analysis of the product and user interaction generated by the behaviour and modelling. At the rules level, it mainly includes the evaluation, optimisation and forecasting models established following the law of product operation.

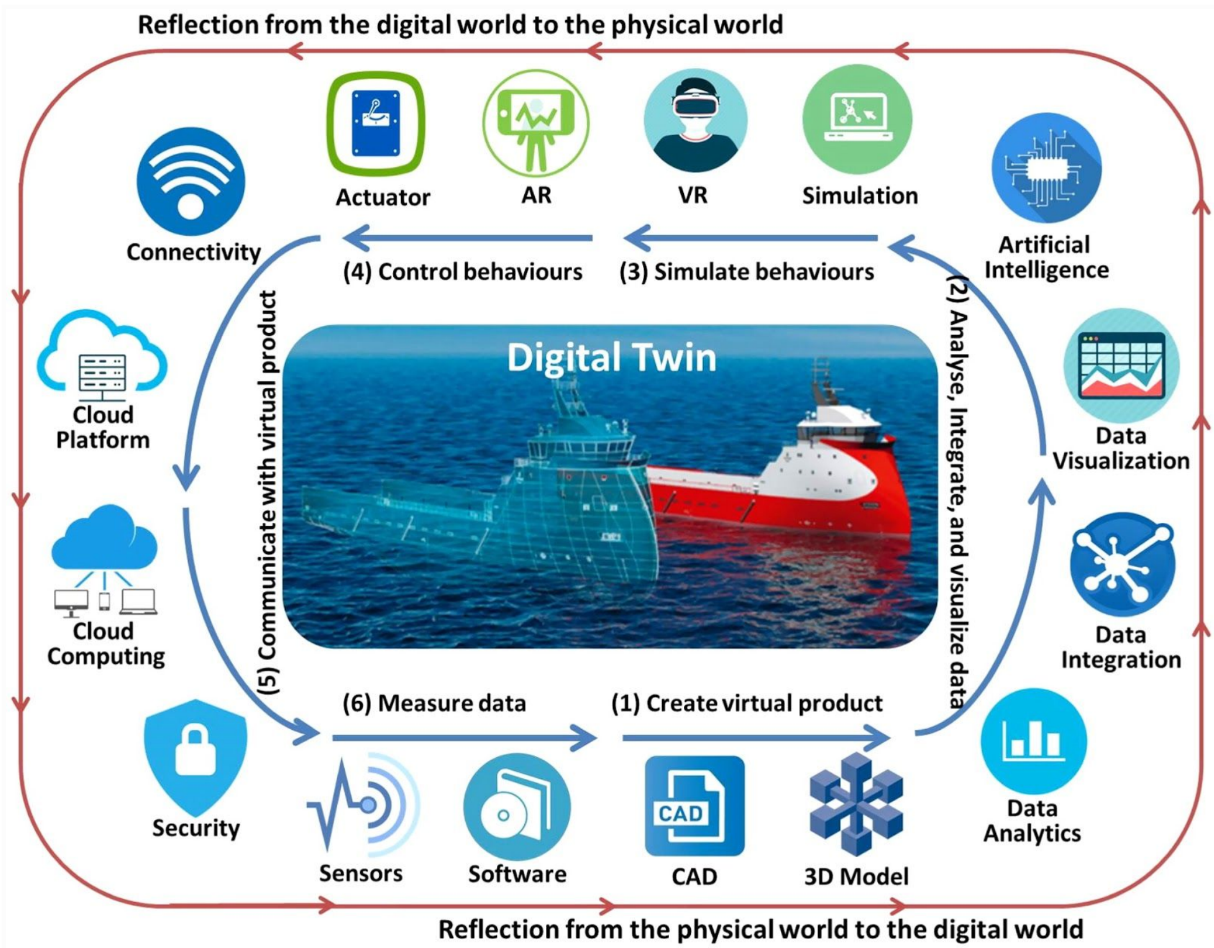

Figure 2. Enabling Technology of Cyber Twin

Step (2): Process data to facilitate design decision-making:

Data collected from different sources (i.e. mainly from the physical product, and also from the Internet) are analysed, integrated and visualised. Firstly, data analytics is necessary to convert data into more concrete information that can be directly queried by designers for decision-making. Secondly, since product data are collected from diverse sources, data integration is useful for discovering the hidden patterns that cannot be uncovered based on a single data source. Thirdly, data visualisation technologies are incorporated to present data in a more explicit fashion. Finally, advanced artificial intelligence techniques can be incorporated to enhance a DT's cognitive ability (e.g. reasoning, problem solving and knowledge representation), so that certain relatively simple recommendations can be made automatically.

Step (3): Simulate product behaviours in the virtual environment:

The enabling technologies of this step include simulation and virtual reality (VR). The former is used to simulate key functions and behaviours of the physical product in the virtual world. In the past, simulation technologies are widely used in product design. On the other hand, virtual reality (VR) technologies play the role of involving designers and even users to 'directly' interact with the virtual product in the simulated environment. Recently, VR technologies are increasingly employed to support virtual prototyping and product design. Many readily available VR hardware devices can be directly adopted for digital twin.

Step (4): Command the physical product to perform recommended behaviours

Based on the recommendations of DT, the physical product is equipped with a capability, by means of various actuators, to adaptively adjust its function, behaviour and structure in the physical world. Sensors and actuators are the two technological backbones of a digital twin. The former plays the role in sensing the external world, whereas the latter plays the role in executing the desirable adjustments requested by DT. In practice, the commonly used actuators that are suitable for consumer products include, for example, hydraulic, pneumatic, electric, and mechanical actuators. In addition, augmented reality (AR) technologies can be used to reflect some parts of the virtual product back to the physical world. For example, AR enables end users to view the real-time state of their products. Recently, AR technologies are increasingly applied in the factory domain production engineering.

Step (5): Establish real-time, two-way, and secure connections between physical and virtual product

The connections are enabled using a number of technologies, such as network communication, cloud computing and network security. Firstly, networking technologies enable the product to send its ongoing data to the 'cloud' to power the virtual product. The feasible networking technologies for consumer products include, for example, Bluetooth, QR code, barcode, Wi-Fi, Z-Wave, etc. Secondly, cloud computing enables the virtual product to be developed, deployed and maintained completely in the 'cloud', so that it can be conveniently accessed by both designers and users from anywhere with an Internet access. Lastly, since product data are directly and indirectly concerning user-product interactions, it is critical to guarantee the security of connections. In light of the Internet of Things, much effort has been devoted to connecting the physical and virtual product, which can be adapted for the DT research.

Step (6): Collect all kinds of product-related data from different sources

Generally speaking, there are three types of product-related data that should be processed by DT. For ordinary products, physical product data is usually divided into product data, environmental data, customer data and interactive data. Product data contains customer comments, viewing and download records. Interactive data consist of user-product-environment interaction, such as stress, vibration, etc. Using the sensor technology and IoT technology can collect some of the above data in real time, and analyse from the product manual, web page customer browsing records, download records, evaluation feedback, etc.can obtain the rest of the data. The collected data are fed to the Step (1) in order to close the loop towards building more functional virtual product.

Chapter 2

Experimental Setup

Contents:

2.1 Tabletop CNC Machine(Milling):

Computer numerical control (CNC) has been incorporated into a variety of new technologies and machinery. Perhaps the most common type of machine that is used in this realm is known as a CNC mill.

CNC milling is a certain type of CNC machining. Milling is a process that is quite similar to drilling or cutting, and milling can perform these processes for a variety of production needs. Milling utilizes a cylindrical cutting tool that can rotate in various directions. Unlike traditional drilling, a milling cutter can move along multiple axes. It also has the capability to create a wide array of shapes, slots, holes, and other necessary impressions. Plus, the work piece of a CNC mill can be moved across the milling tool in specific directions. A drill is only able to achieve a single axis motion, which limits its overall production capability.

Figure 3. Tabletop CNC machine used in the Setup

Specifications of the Tabletop CNC Machine(VPL-CNC-2010) used:

1. Travel:
   a. X-axis: 229mm
   b. Y-axis: 178 mm
   c. Z-axis: 137 mm
2. Spindle motor voltage: 90V DC
3. Spindle RPM range: 90-2800 rpm
4. Spindle Nose Thread: 3/4-16 T.P.I

2.2 Data Acquisition System:

Data acquisition (DAQ) is the process of measuring an electrical or physical phenomenon such as voltage, current, temperature, pressure, or sound with a computer. A DAQ system consists of sensors, DAQ measurement hardware, and a computer with programmable software. Compared to traditional measurement systems, PC-based DAQ systems exploit the processing power, productivity, display, and connectivity capabilities of industry-standard computers providing a more powerful, flexible, and cost-effective measurement solution.

Such a Data Acquisition System is desirable which can sample signals over a wide range of sampling rate and must be easily programmable.

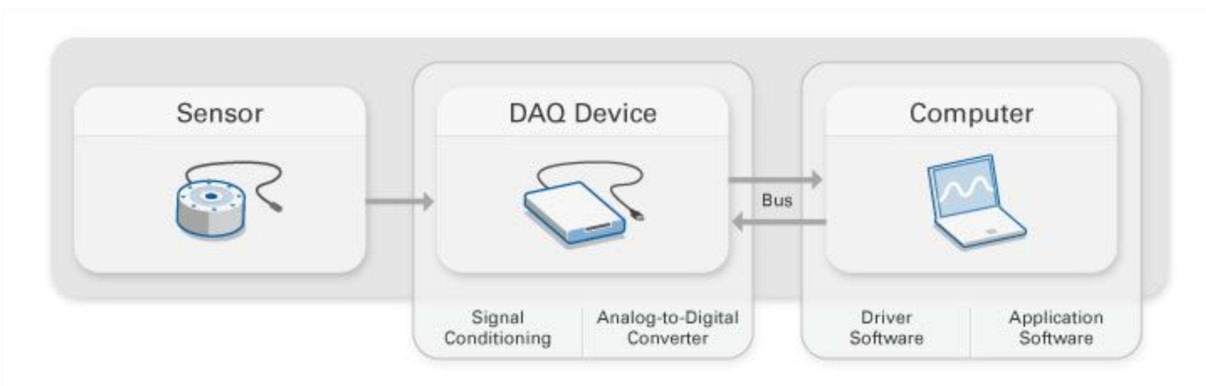

Figure 4. Parts of a DAQ system

The DAQ system used for the experimental setup is NI DAQ(cDAQ-9188XT). The drivers are easily available and also, its Python library is open source so it is easily programmable. The only downside is that the library is poorly documented.

2.3 Sensor Selection:

2.3.1 Literature Review:

Real-time health monitoring of cutting tools help 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 machine system availability, reducing downtime costs 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.

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 signal and tool wear/state is mapped using data driven approaches(coupled with various feature selection approaches) viz. Artificial neural networks and regression models. For instance, Chen and Li(2009) and Rizal et al.(2013) presented tool wear prediction models by quantifying the cutting forces deviations in various machining processes. Nadgir and Ozel(2000) formulated a flank wear prediction system explicitly based on force signal analysis. 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 recognised. However, efficient utilization of these approaches require s placement of costly accelerometers 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 in the machining process and developed new tool wear monitoring methods. 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.

However, in the experimental setup employed, we have used only vibration sensor as AE sensor did not show any significant change in amplitude of signals with progression of tool wear. Also, there was no significant change in power consumption by the spindle motor. In Figure 5, placement of sensors and other devices is shown.

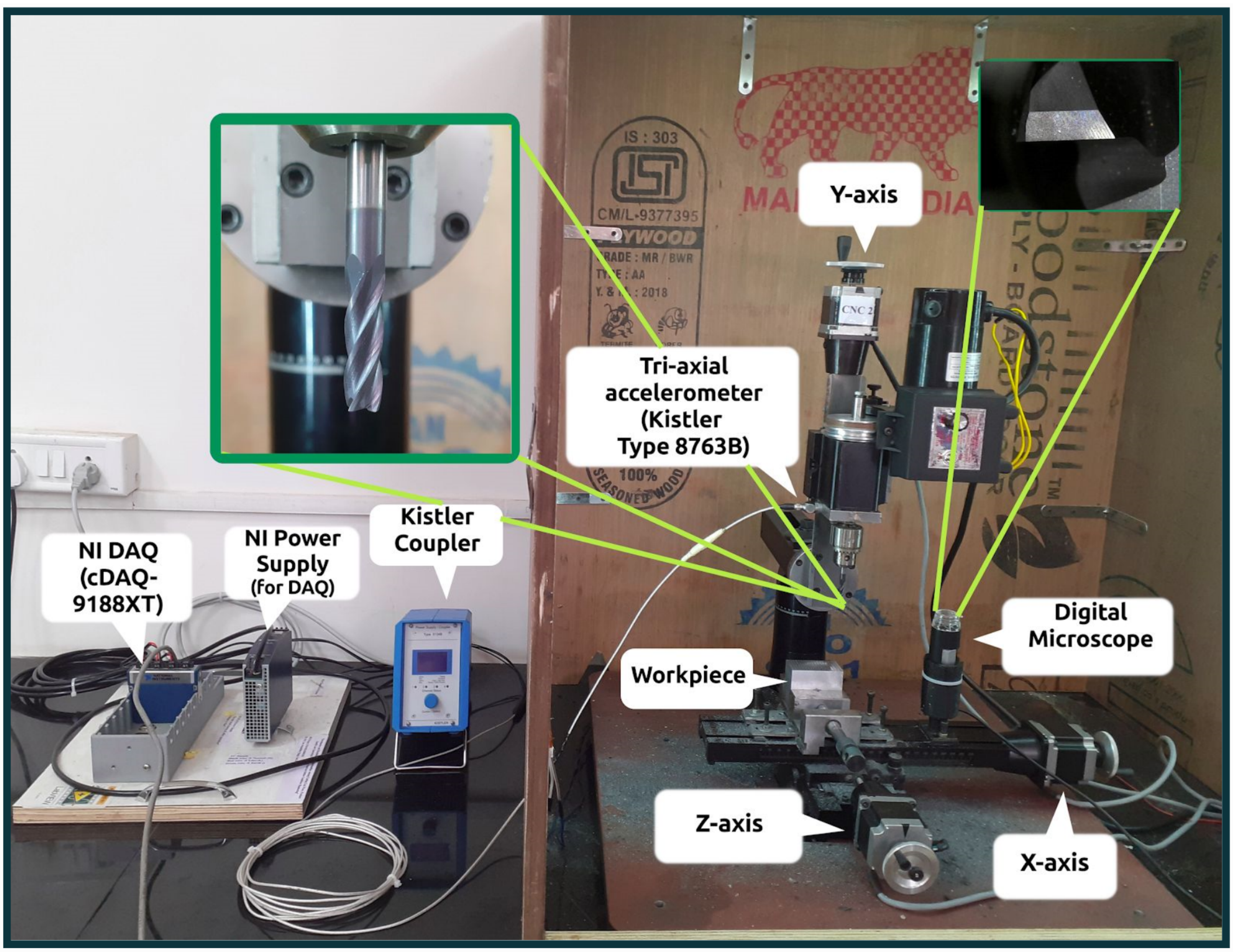

Figure 5. Experimental Setup

2.4 Roughness Measurement Setup:

Surface roughness often shortened to roughness, is a component of surface texture. It is quantified by the deviations in the direction of the normal vector of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small the surface is smooth. In surface metrology, roughness is typically considered to be the high-frequency, short-wavelength component of a measured surface. However, in practice it is often necessary to know both the amplitude and frequency to ensure that a surface is fit for a purpose.

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. Figure 6 shows the setup for measuring surface roughness.

$$Ra = \frac{1}{n}\sum_{i=1}^{n}|y_i|$$

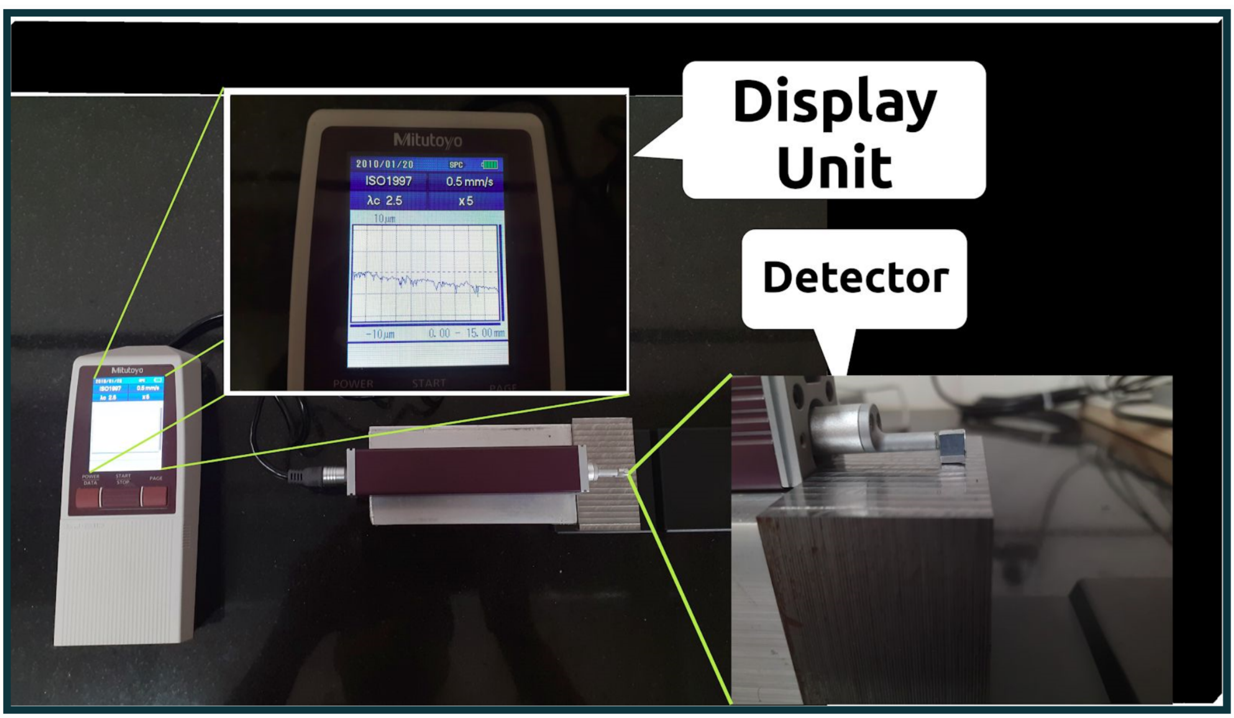

Figure 6. Surface Roughness Measurement Setup

Chapter 3

Diagnostic and Prognostic Models

Contents:

3.1 Machine Learning Algorithms:

3.1.1 Logistic Regression:

Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable, although many more complex extensions exist. In regression analysis, logistic regression (or logit regression) is estimating the parameters of a logistic model (a form of binary regression). Mathematically, a binary logistic model has a dependent variable with two possible values, such as pass/fail which is represented by an indicator variable, where the two values are labeled "0" and "1". In the logistic model, the log-odds (the logarithm of the odds) for the value labeled "1" is a linear combination of one or more independent variables ("predictors"); the independent variables can each be a binary variable (two classes, coded by an indicator variable) or a continuous variable (any real value). The corresponding probability of the value labeled "1" can vary between 0 (certainly the value "0") and 1 (certainly the value "1"), hence the labeling; the function that converts log-odds to probability is the logistic function, hence the name. The unit of measurement for the log-odds scale is called a logit, from logistic unit, hence the alternative names. Analogous models with a different sigmoid function instead of the logistic function can also be used, such as the probit model; the defining characteristic of the logistic model is that increasing one of the independent variables multiplicatively scales the odds of the given outcome at a constant rate, with each independent variable having its own parameter; for a binary dependent variable this generalizes the odds ratio.

3.1.2 Random Forest:

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct for decision trees' habit of overfitting to their training set.

An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark (as of 2019, owned by Minitab, Inc.). The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho and later independently by Amit and Geman in order to construct a collection of decision trees with controlled variance.

3.1.3 Support Vector Machine:

In machine learning, support-vector machines (SVMs, also support-vector networks[1]) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on the side of the gap on which they fall.

3.1.4 Decision Tree:

In statistics, Decision tree learning uses a decision tree (as a predictive model) to go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). It is one of the predictive modeling approaches used in statistics, data mining and machine learning. Tree models where the target variable can take a discrete set of values are called classification trees; in these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees.

3.1.5 K-Nearest Neighbours:

In statistics, Decision tree learning uses a decision tree (as a predictive model) to go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). It is one of the predictive modeling approaches used in statistics, data mining and machine learning. Tree models where the target variable can take a discrete set of values are called classification trees; in these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees.

3.1.6 Gaussian Naive Bayes:

Naïve Bayes has been studied extensively since the 1960s. It was introduced (though not under that name) into the text retrieval community in the early 1960s, and remains a popular (baseline) method for text categorization, the problem of judging documents as belonging to one category or the other (such as spam or legitimate, sports or politics, etc.) with word frequencies as the features. With appropriate pre-processing, it is competitive in this domain with more advanced methods including support vector machines. It also finds application in automatic medical diagnosis.

Naïve Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers.

3.2 Selection of Features:

In machine learning and pattern recognition, a feature is an individual measurable property or characteristic of a phenomenon being observed. Choosing informative, discriminating and independent features is a crucial step for effective algorithms in pattern recognition, classification and regression. Features are usually numeric, but structural features such as strings and graphs are used in syntactic pattern recognition. The concept of "feature" is related to that of explanatory variables used in statistical techniques such as linear regression.

The initial set of raw features can be redundant and too large to be managed. Therefore, a preliminary step in many applications of machine learning and pattern recognition consists of selecting a subset of features, or constructing a new and reduced set of features to facilitate learning, and to improve generalization and interpretability.

Pre-processing of data was performed by converting raw signals into more informative features or parameters. In specific, 31 statistical features were extracted by each MCU. This was followed by the feature screening. In this work, Pearson correlation methodology was applied for feature screening. It helps in identifying highly correlated features. Correlation value near -1 and 1 considered as strongly correlated and value near to 0 was considered as unrelated features. It was inferred that highly correlated features give the same information about the system. Therefore, it helps in eliminating redundant features. In this way, 18 features for force MCU, 16 features for vibration MCU and 11 features for acoustic emission MCU were retained for further analysis. Three methods viz. logistic regression, random forest classifier, and decision tree classifiers are applied for identifying most relevant features. Accuracy of the results was calculated for each method (refer Table 1). Top 5 features based on the most accurate method for a particular MCU are then used for further diagnostics and prognostics. These features are listed in Table 2.

	Force MCU	**Vibration MCU**	**AE MCU**
Logistic Regression	88.33%	88.60%	86.82%
Random Forest	84.39%	81.40%	84.08%
Decision Tree	89.65%	79.82%	89.55%

Table 1. Accuracy Predicted for all MCUs(for feature selection)

Force MCU	**Vibration MCU**	**AE MCU**
Mean	Crest Factor	Kurtosis
Median	Skewness	Crest Factor
RMS	Range of Values	Coefficient of Variance
Entropy	K-factor	Energy Operator
Kurtosis	Mode	Residual Kurtosis

Table 2. Selected Features for Modelling

3.3 Diagnostic Models:

To diagnose the health-state of the tool machine learning classification algorithms have been trained on the acquired data using selected features. Accuracies of different classifiers have been reported in Table 3.

	Force	Vibration	AE	ALL
Logistic Regression	74.47%	70.21%	57.45%	63.83%
Random Forest	76.6%	70.21%	59.57%	74.47%
Support Vector	74.47%	68.09%	55.32%	55.32%
Decision Tree	78.72%	70.21%	59.57%	72.34%
K-neighbours	80.85%	53.19%	51.06%	65.96%

Table 3. Diagnostic Models Accuracy

3.4 Prognostic Models:

To predict the RUL of the end milling cutter used in the experiment machine learning regression models have been trained and tested using selected features. Accuracies of different regression models have been reported in Table 4.

	Force	Vibration	AE	ALL
Random Forest	5.66	3.82	6.99	4.15
Support Vector	14.76	15.42	18.97	19.04
Decision Tree	13.12	9.486	12.2	11.87
K-neighbours	11.05	12.96	18.29	17.06

Table 4. Prognostics Models Accuracy

3.5 Hidden Markov Model:

Hidden Markov Model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobservable (i.e. hidden) states. In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters, while in the hidden Markov model, the state is not directly visible, but the output (in the form of data or "token" in the following), dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore, the sequence of tokens generated by an HMM gives some information about the sequence of states; this is also known as pattern theory, a topic of grammar induction.

The adjective hidden refers to the state sequence through which the model passes, not to the parameters of the model; the model is still referred to as a hidden Markov model even if these parameters are known exactly.

Consider a system with states S_i. Since these states are not directly observable, they need to be identified or detected using indirect measurement. This can be done by using sensors to monitor parameters that can indicate the state of the system. These parameters are called observations. Let these observations be O_j. One step transition probability table can be used to calculate the probability of the system being in a particular state after 'N' cuts or time steps. Similarly, Conditional probability transition table can be used to find probabilities of discrete states given an observation.

t+1->	**S1**	**S2**	**S3**	**S4**
S1	0.96	0.04	0	0
S2	0	0.91	0.029	0.057
S3	0	0	0.94	0.059
S4	0	0	0	1

Table 5. One Step Transition Probability Table

	O1	O2	O3	O4	O5
S1	0.19	0.69	0.12	0	0
S2	0	0.59	0.29	0.085	0.034
S3	0	0.06	0.76	0.18	0

Table 6. Conditional probability transition table

Chapter 4

Integration in Cyber Twin

Contents:

4.1 The Concept:

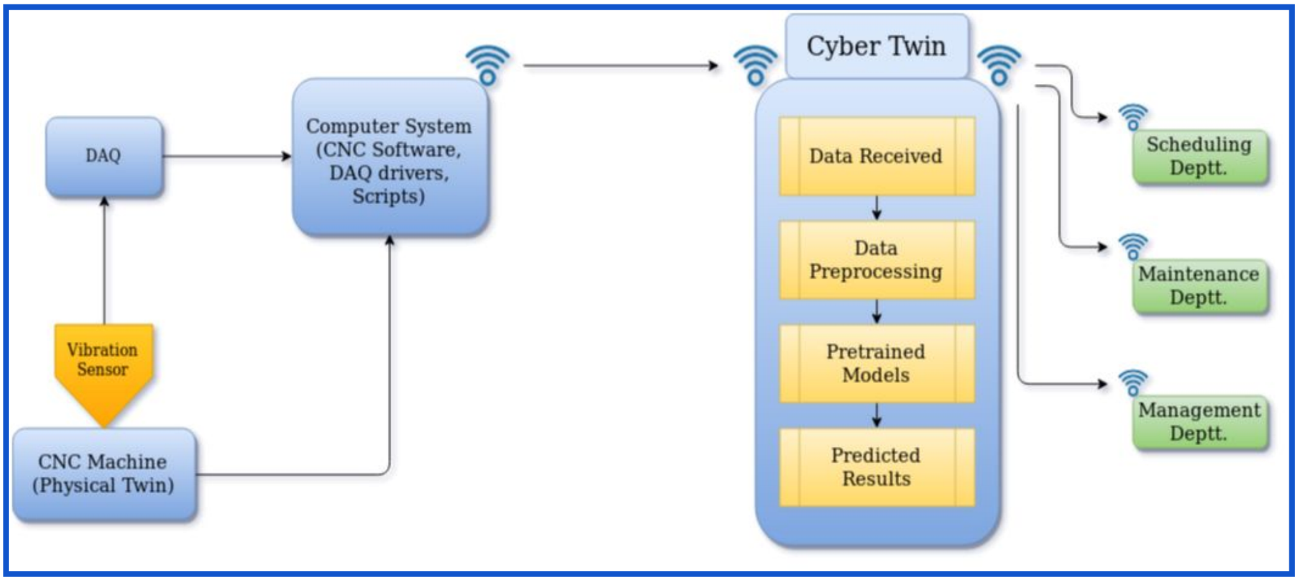

Figure 7. Final Implementation

Figure 7 shows the final implementation concept of the proposed setup for Cyber Twin. The pretrained models reside on the central server that predicts the current state of the tool. Digital twins integrate internet of things, artificial intelligence, machine learning and software analytics with spatial network graphs to create living digital simulation models that update and change as their physical counterparts change. A digital twin continuously learns and updates itself from multiple sources to represent its near real-time status, working condition or position. This learning system, learns from itself, using sensor data that conveys various aspects of its operating condition; from human experts, such as engineers with deep and relevant industry domain knowledge; from other similar machines; from other similar fleets of machines; and from the larger systems and environment in which it may be a part of. A digital twin also integrates historical data from past machine usage to factor into its digital model. In various industrial sectors, twins are being used to optimize the operation and maintenance of physical assets, systems and manufacturing processes. They are a formative technology for the Industrial Internet of Things, where physical objects can live and interact with other machines and people virtually.

4.2 Features:

The proposed Cyber Twin setup will have following features:

1. Showing current machining parameters.
2. Showing the current health state and RUL.
3. Communication with other machines in a manufacturing environment.
4. Optimizing Process Quality control parameters
5. Optimizing quality of the finished jobs.
6. Predicting the RUL to help in maintenance planning.
7. The data and current health state that can be accessed locally or remotely.
8. Making process parameters and current health state available to other departments as well.

Chapter 5

Conclusion and Future Work

Contents:

5.1 Multi-State Fault Diagnosis and Prognosis:

There are two main tasks, namely diagnosis and prognosis, dichotomized the prediction process in TCM system. The previous studies have mostly focused on either diagnosis or prognosis in TCM. Diagnosis is to estimate what the current health state is. Prognosis is to predict what will happen next. Prognostics is the study as to show how the tool condition degrades and to estimate the remaining useful life (RUL) of the tool. With effective and reliable estimation of RUL, TCM can reduce overall downtime of the manufacturing processes. Although prognosis plays an important role in TCM, it still a lukewarm research area with few reported studies. In a TCM system, the tool wear estimation forms the basis of tool RUL estimation. In this paper, we would like to focus on tool state estimation as the main diagnostics task and tool wear estimation as the main prognosis task. The performance of prognosis can be improved based on more accurate current health state estimation. Because the degradation trends of the system/components may be different based on different current health states, the results of diagnostics and prognosis are tightly related with the overall performance of the TCM system. Since the distribution of data in different health states are naturally multifarious, any single model is quite hard to handle them. We consider that multi-state diagnosis and prognosis framework distinguishes health states in finer details, that allows us to apply different models according to the diagnostic data attributes. We have a good reason to believe that such multimodal approach offers better performance.

In the experimental setup prepared, other faults can also be introduced carefully and then vibration signals be investigated to find the signature of the fault introduced artificially. Furthermore, Machine Learning and Deep Learning models can be trained on the acquired data to predict the introduced faults, which then, further, can be integrated in Cyber Twin to facilitate scheduling of jobs and maintenance of the machine.

Also, the prognosis of motors and bearings can be done in order to prepare a closely simulated Cyber Twin of the CNC machine. Other sensors can also be introduced at different places on machine for more accurate modelling and to include as many faults and failures possible to detect and predict possible. Definitely, it will help in a much sophisticated design of Cyber Twin and it will be most helpful in job scheduling and maintenance planning.

5.2 Dynamic Optimization of Process Quality Control:

In today's progressive industrial 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. Whereas unnecessary maintenance leads to excessive costs, delaying the maintenance might increase the process variability viz., increase in rejections. Lad and Kulkarni 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. Although, the integration of quality with maintenance has been investigated in the literature, one that integrates for machines deteriorating with time, viz., cutting tools is missing. According to Kurada and Bradley, cutting tool failures usually takes around 20% of the downtime of a manufacturing system. To manage higher shop floor effectiveness, a good understanding of interdependence among process quality control, maintenance planning, and real-time health state of the system is therefore lucrative. 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 considering real-time health state of the system eludes literature, and hence offers an excellent opportunity for investigation. In this regard, the aim of this work is to present a novel methodology for dynamic and simultaneous optimization of process quality control and maintenance planning while considering the real-time health state of the system deteriorating with time. 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 presented a comprehensive review of process quality control policies, while Pierskalla and Voelker reviewed the literature on maintenance planning. It is realized that the use of these policies in isolation provides suboptimal solutions, as they are interrelated . Consequently, the integrated optimization of process quality control and maintenance planning is receiving the much needed momentum. For example, Cassady et al., Linderman et al. simultaneously optimized the process quality control and maintenance planning policy to reduce the overall cost. Zhou and Zhu 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 attempted an integration of the variable-parameter Shewhart control chart. Mehdi et al. developed a combined model designed for conforming and nonconforming items.. 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. However, many times machine may degrade to an undesirable working condition before failure. Such assumption restricts the applicability of these integrated models for systems deteriorating with time (having an increasing failure rate), viz., cutting tools, etc. where the failure rate increases over time due to degradation.

5.3 Conclusion:

The project concluded in the development of a system for converting the CNC machine into intelligent systems supported with external intelligence in the form of a cyber twin. This system has the capability to extract using data from the machine is through the data acquisition interface. The data obtained can be analyzed by the models in the form of distributions represented by a set of parameters.The Cyber Twin has the capability to update the models by updating the parameter values using the new data received by the system.This makes the system dynamic and responsive in nature. 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. The accuracy of degradation prediction models so obtained in this research is better than those reported in the literature. In addition, comparative studies on prediction performances of distinctive models show that the developed model is superior to different conventional models. The study solved one of the standing and non-trivial problems of literature viz., prognosis under dynamic operating profiles. The proposed generic prognostics approach encompasses all real-world industrial scenarios.

The research work done in this project can equip manufacturing industries with intelligence that allows responding to the time-variant operating profiles and adaptable under various real-world production environments.

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