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Building a Simple Smart Factory

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BUILDING A SIMPLE SMART FACTORY

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This thesis is submitted in partial fulfilment of the requirements for the degree of Master of Science in Mechanical Engineering

Under the Supervision of Dr. Sangarappillai Sivaloganathan

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Declaration of Original Work

I, Iman Abdulwaheed, the undersigned, a graduate student at the United Arab Emirates University (UAEU), and the author of this thesis entitled "*Building a Simple Smart Factory*", hereby, solemnly declare that this thesis is my own original research work that has been done and prepared by me under the supervision of Dr. Sangarappillai Sivaloganathan, in the College of Engineering at UAEU. This work has not previously been presented or published, or formed the basis for the award of any academic degree, diploma or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my thesis have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation and/or publication of this thesis.

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Abstract

This thesis describes (a) the search and findings of smart factories and their enabling technologies (b) the methodology to build or retrofit a smart factory and (c) the building and operation of a simple smart factory using the methodology. A factory is an industrial site with large buildings and collection of machines which are operated by persons to manufacture goods and services. These factories are made smart by incorporating sensing, processing and autonomous responding capabilities.

Developments in four main areas (a) sensor capabilities (b) communication capabilities (c) storing and processing huge amount of data and (d) better utilization of technology in management and further development have contributed significantly for this incorporation of smartness to factories. There is a flurry of literature in each of the above four topics and their combinations. The findings from the literature can be summarized in the following way. Sensors detect or measure a physical property and records, indicates, or otherwise responds to it. In real-time they can make very large amount of observations. Internet is a global computer network providing a variety of information and communication facilities and the internet of things, IoT, is the interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data. Big data handling and provision of data services are achieved through cloud computing. Due to the availability of computing power the big data can be handled and analysed under different classifications using several different analytics. The results from these analytics can be used to trigger autonomous responsive actions that make the factory smart.

Having thus comprehended the literature a seven stepped methodology for building or retrofitting a smart factory was established. The seven steps are (a) situation analysis where the condition of the current technology is studied (b) breakdown prevention analysis (c) sensor selection (d) data transmission and storage selection (e) data processing and analytics (f) autonomous action network and (g) integration with the plant units.

Experience in a cement factory highlighted the wear in a journal bearing causes plant stoppages and thus warrant a smart system to monitor and make decisions. The experience was used to develop a laboratory-scale smart factory monitoring the wear of a half-journal bearing. To mimic a plant unit a load carrying shaft supported by two half-journal bearings were chosen and to mimic a factory with two plant units, two such shafts were chosen. Thus there were four half-journal bearings to monitor. USB Logitech C920 webcam that operates in full-HD 1080 pixels was used to take pictures at specified intervals. These pictures are then analysed to study the wear at these intervals. After the preliminary analysis wear versus time data for all four bearings are available. Now the 'making smart activity' begins.

Autonomous activities are based on various analyses. The wear time data are analysed under different classifications. Remaining life, wear coefficient specific to the bearings, weekly variation in wear and condition of adjacent bearings are some of the characteristics that can be obtained from the analytics. These can then be used to send a message to the maintenance and supplies division alerting them on the need for a replacement shortly. They can also be alerted about other bearings reaching their maturity to plan a major overhaul if needed.

Keywords: Smart factories, autonomous, IoT (Internet of Things), big data, cloud computing, journal bearing.

Title and Abstract (in Arabic)

صناعة المصنع الذكي

الملخص

تتناول هذه الأطروحة (أ) البحث والتطرق لنتائج المصانع الذكية والتقنيات التمكينية الخاصة بهم , (ب) منهجية بناء أو تعديل المصنع الذكي و (ج) بناء وتشغيل مصنع ذكي بسيط باستخدام المنهجية المستخدمة في الأطروحة. المصنع عبارة عن موقع صناعي به مباني كبيرة ومجموعة من الآلات التي يقوم بالعمل عليها أشخاص لتصنيع السلع والخدمات. لقد أصبحت هذه المصانع ذكية من خلال دمج قدرات الاستشعار عن بعد ,المعالجة والاستجابة الذاتية.

تجري التطورات في أربعة مجالات رئيسية (أ) القدرات الاستشعارية (ب) قدرات الاتصالات (ج) تخزين ومعالجة كمية هائلة من البيانات و (د) الاستخدام الأفضل للتقنيات الحديثة في الإدارة ومواصلة التطوير و هي عوامل ساهمت بشكل كبير في دمج هذا الذكاء للمصانع. هناك دراسات عديدة أُجريت على الموضوعات الأربعة المذكورة أعلاه منفردة ومترابطة مع بعضها البعض. يمكن تلخيص نتائج الدراسات السابقة بالطريقة التالية. تقوم المستشعرات باكتشاف أو قياس إحدى الخواص ماديًا وتسجيلها أو الإشارة إليها أو الرد والتفاعل معها بطريقة أخرى. حاليًا، يمكن عمل عدد كبير جدًا من الملاحظات بناءً على ما سبق. الإنترنت عبارة عن شبكة كمبيوتر عالمية تُوفر مجموعة متنوعة من مرافق المعلومات والاتصالات. IoT، هو الربط البيني عبر شبكة الاتصالات لأجهزة الحوسبة المضمنة في الأجهزة المستخدمة يوميًا، مما يُتيح لها إرسال البيانات وتلقيها. يتم تحقيق معالجة البيانات الكبيرة وتوفير خدمات البيانات من خلال الحوسبة السحابية. نظرًا لقوة الحوسبة المتوفرة، يمكن معالجة البيانات الضخمة وتحليلها في ظل تصنيفات مختلفة باستخدام تحليلات مختلفة. يمكن استخدام نتائج هذه التحليلات لتحريك إجراءات الاستجابة الذاتية والتي تجعل المصنع ذكيًا.

بعد مراجعة عميقة للدراسات السابقة، تم إنشاء منهجية ذات سبع خطوات لبناء أو تعديل مصنع ذكي. الخطوات السبع هي (أ) تحليل الحالة حيث تتم دراسة حالة التقنية المستخدمة حاليًا (ب) تحليل منع التوقف (ج) اختيار المستشعر (د) نقل البيانات واختيار نوعية التخزين المستخدمة (هـ) معالجة البيانات والتحليلات (و) شبكة العمل المستقلة (ز) التكامل مع وحدات المصنع الأخرى.

سلّطت التجربة في مصنع للأسمنت الضوء على التآكل الذي يحدث في مُرتكز عمود التحمل والذي يؤدي بالضرورة إلى توقف المصنع وبالتالي الحاجة لوجود نظام ذكي لمراقبة واتخاذ القرارات. تم استخدام التجربة لتطوير مصنع ذكي على نطاق المختبر لمراقبة تآكل نصف مُرتكز عمود التحمل. لمُحاكاة وحدة المصنع، تم اختيار عمود مُثقل بأوزان مدعوم بنصفي مرتكز عمود التحمل، ولمحاكاة مصنع ضم وحدتين تشغيليتين، تم اختيار اثنين من هذه الأعمدة. وبالتالي كان هناك أربعة من مرتكز أعمدة التحمل للرصد. تم استخدام كاميرا الويب USB Logitech C920 التي تعمل بدقة 1080 بكسل عالية الدقة لالتقاط الصور على فترات زمنية محددة. ثم يتم تحليل هذه الصور لدراسة التآكل في هذه الفواصل الزمنية. بعد التحليل الأولي، تتوفر بيانات تُظهر العلاقة بين التآكل و الزمن لمرتكزات أعمدة التحمل الأربعة. والآن يبدأ "صنع نشاط ذكي".

وتستند الأنشطة الذاتية التحليلات المختلفة. يتم تحليل بيانات التآكل مع الزمن تحت تصنيفات مختلفة. ويُعتبر العمر الافتراضي المُتبقي، ومُعامل التآكل المُحدّد للمرتكزات، والتباين الأسبوعي في التآكل وحالة المرتكزات المجاورة من بعض الخصائص التي يمكن الحصول عليها من التحليلات. يمكن بعد ذلك استخدامها لإرسال رسالة إلى قسم الصيانة والإمدادات لتنبيههم إلى الحاجة إلى استبدالها قريبًا. يمكن أيضًا تنبيههم بشأن مرتكزات أعمدة التحمل الأخرى التي تصل إلى مرحلة النضج (نهاية العمر الافتراضي) للتخطيط لإجراء إصلاحات كبيرة إذا لزم الأمر.

مفاهيم البحث الرئيسية: المصانع الذكية، الاستقلال بالتحكم الذاتي، انترنت الأشياء، البيانات الكبيرة، والحوسبة السحابية، مُرتكز عمود التحمل.

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My sincere thanks goes to Engineer AbdulRahman for helping in the manufacturing of the frame and offering valuable advice and inspiring discussions, which got me interested and excited about doing my thesis.

Last, but certainly not least, I express my eternal appreciation and gratitude to my beloved parents and family who have always been there for me no matter where I am, for their unconditional love, support and patience. I thank them for always believing in me and letting me find my own way.

Dedication

To my beloved parents and family

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List of Abbreviations

AR	Augmented Reality
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CAx	Computer Aided Technologies
CPPS	Cyber Physical Production System
CPS	Cyber-Physical Systems
GPS	Global Positioning System
IaaS	Infrastructure as Service
IIoT	Industrial Internet of Things
IoT	Internet of Things
MTTF	Mean Time To Failure
PaaS	Platform as a Service
RFID	Radio Frequency Identification
SaaS	Software as Service
VR	Virtual Reality

Chapter 1: Introduction

1.1 Overview

A factory, with its origin during the 18th century, is an industrial site, consisting of buildings and large collection of machinery, where workers operate machines to manufacture goods. The technologies employed were continuously improved with continued new developments in science and technology. Factories manufacturing chemicals are often called plants and have most of their equipment, consisting of blowers and ducts, pumps and piping, tanks, pressure vessels and chemical reactors, located outdoors and operated by personnel in control rooms. Such a plant will have several machine units made up as an assemblage of several components that get worn-out and eventually break. Maintenance in these factories consists of actions necessary for retaining or restoring a piece of equipment, machine, or system to the specified operable condition. This is often achieved by replacing components, that have reached the near-end-of-life condition or broken down completely, during an overhaul.

Traditional maintenance assumes that the operation of a population of devices can be viewed, as shown in Figure 1, comprising 3 distinct periods:

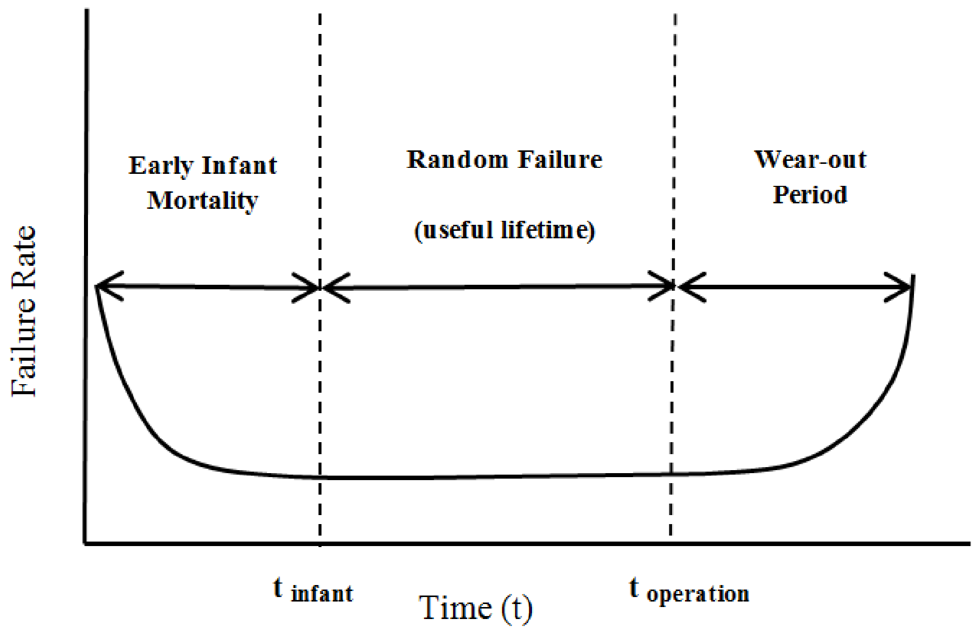


Figure 1: Cumulative Operating Time Versus Failure Rate

a) an ‘early failure’ (burn-in) period, where the chance of failure is high at the beginning and decreasing rapidly over time

b) a ‘random failure’ (useful life) period, where the chance of failure remains constantly low over time and

c) a ‘wear-out’ period, where the chance of failure increases over time

Historical data are collected in the form of time to failure or mean time to failure (MTTF) and components are assumed to reach the ‘wear-out’ period when their time in operation approaches the MTTF. During a shutdown of a plant for maintenance, it is customary to replace such components that are in the wear-out period to increase the reliability of the plant. However, these components will often have some useful life left in them. Thus a traditional factory can be considered as an assemblage of components which are kept in operating state optimally by (a) replacing and restoring components guided by the MTTF and (b) keeping components and personnel in stand-by for rectifying breakdowns.

On the other hand science and technology worldwide has advanced in several dimensions and the final report of the Industrie 4.0 Working Group [1] states that "the introduction of the internet of Things, IoT and Services, into the manufacturing environment is ushering in a fourth industrial revolution. In the manufacturing environment, these Cyber-Physical Systems, CPSs, comprise smart machines, storage systems and production facilities capable of autonomously exchanging information, triggering actions and controlling each other independently. This facilitates fundamental improvements to the industrial processes involved in manufacturing, engineering, material usage and supply chain and life cycle management". The factories that employ these approaches and technologies are called smart factories. Within a CPS, the combination of cyber and physical elements can transform a product into a smart product. A smart product is a product that can perform a much more useful function with the empowerment provided by the Internet of Things [2].

In this context a smart factory can be described as a factory with the empowerment provided by the data, connectivity and processing capabilities of the components (and their additional accessories) of a factory which enable them to function autonomously or semi-autonomously thereby increasing the capability of the factory.

This thesis describes designing and building a simple smart factory as an assemblage of two sets of loaded shafts running on half journal bearings which were empowered by a computer vision system that continuously monitor the wear in them and communicate to a computer which analyzes the data and initiate cross communication between the components and with some modifications in the future work it can trigger remedial actions. The main aim is to understand the constituents and the method of their integration to form a smart factory. The required knowledge in different areas for a smart factory is described in chapter 2. It also includes facts about the ways of measuring wear in journal bearings. Chapter 3 provides details about the proposed methodology for retrofitting an existing factory into a smart factory. Chapter 4 discusses the implementation of the proposed methodology .The results are presented and discussed in chapter 5. Finally, chapter 6 concludes the outcomes of this thesis work and provides an insight to future works.

1.2 Statement of the Problem

There is a tremendous worldwide effort underway to incorporate technological developments described later in chapter 2 to address a multitude of industrial problems under the broad heading Industry 4. Smart factories are the principal structures in Industry 4. However the literature shows limited guidelines on 'how to build or retrofit a smart factory'. To get the knowledge and experience on 'how to build or retrofit a smart factory addressing specific issues', a simple smart factory, made up of basic building blocks and addressing a single issue using the principles of smart factory outlined above is needed. Wear in journal bearings is an issue encountered in many industries and this is chosen as the single issue to be addressed in this effort to build a simple smart factory.

1.3 Aim and Objectives

The research aims to "Design and build a simple smart factory as an assemblage of two sets of loaded shafts running on half journal bearings to monitor the wear characteristics and use the principles of smart factory to empower the bearings to function autonomously".

This objectives of this research are as follows:

1. To conduct a detailed literature survey and comprehend the concept of smart factories and their constituents
2. Establish a methodology to retrofit an existing factory into a smart factory
3. Design and build a laboratory-scale factory consisting the two sets of loaded shafts running on half journal bearings.
4. Design and build a computer vision based 'sensing system'to continuously monitor and record wear in bearings.
5. Design and implement algorithms and analytics to process wear data.

1.4 Salient Achievements and Findings from the Research

This research has five main achievements. They are:

a. Collecting, comprehending and summarizing the constitution and constituents of a smart factory and establishing a method for retrofitting.
b. Designing and building a laboratory-scale smart factory with four half journal bearings as the elements.
c. Designing and building a vision monitoring system for monitoring wear in individual bearings.
d. Developing a MATLAB based software for analyzing and obtaining wear characteristics for individual bearings.
e. Observing and measuring the variation of wear factor so that autonomous remedial actions can be taken to make the system more robust .
f. Estimating the remaining life which results in removing uncertainties in conventional factories.

Chapter 2: Literature Survey

A great worldwide endeavour is underway, to use the Internet of Things (IoT) and smart analytics in technologies in the manufacturing industries and, consequently, to improve the overall performance, quality, and controllability of manufacturing processes. Smart factory may be described as the incorporation of latest technologies in its development to have self-x capabilities, where x stands for characteristics such as description, awareness, management, organizing, controlling, directing, healing, correction, auto-discovery, re-configuration, predicting, comparing, maintaining, organizing etc., which in turn makes manufacturing reliable, safer, economical, sustainable and high quality. The integration of all IoT technological advances in computer networks, data combination and analytics to the manufacturing factory is referred to as a smart factory [3]. It is a fully connected and flexible system that can use a constant stream of data from connected operations and production systems to learn and adapt to new demands [4]. ‘Smart Factory’ can be defined as a factory of connected and intelligent machines, where waste, defect, and downtime are almost equal to zero. These highly productive factories move materials more efficiently across the factory floor, made possible in part by data seamlessly moving from sensors on machines to servers to services [5]. Smart factory is seen as the panacea for all the difficulties and limitations of conventional factories.

Smart factory is a disruptive development to the existing factory system, and as such the first step of this review considers the ‘advances in science and technology’ that make the smart factories appropriate for the present time (sensors, IoT, storing and processing a huge amount of data and data analytics). In the second step the descriptions of smart factories (definitions) are collated and analyzed and in the third step the constituents, governing design principles as identified from the literature are collected, analyzed and categorized. Then the prevailing factory system and its weaknesses are identified to elicit the benefits that are offered by smart factory systems. It then paves the way for a methodology to implement retrofitting or designing new facility so that it will be a smart factory. It can be said that this research is aimed at reviewing the published literature to identify (a) why smart factory is the appropriate development now, for the factory system of manufacture (b) what are the constituents of a smart factory and (c) how retrofitting or developing a new factory has to be handled.

2.1 Technological Developments

This section describes the advanced technological developments that are the key contributors for the desired disruptive development for the present factory system. They are identified and grouped as the following for easy comprehension:

a. New opportunities to generate large amount of data (sensors)

b. Opportunities provided by communication capabilities and IoT

c. Opportunities for storing and processing huge amount of data

d. Opportunity for new and better management

The following sub-sections describe them.

2.1.1 New Opportunities to Generate Data (Sensors)

Sensor is a device that detects events or changes in the environment, and transforms signals from different energy domains (such as radiant, mechanical and thermal) to the electrical domain and provides a corresponding output [6]. It detects or measures a physical property and records, indicates, or otherwise responds to it. Sensors are used in high precision manufacturing equipment like CNC machine tools and industrial robots to provide feedback signals to the controller that uses them to precisely move the drives. Sensors and instrumentation are considered as the central driving forces for innovation for all megatrends that are described with the adjective smart, e.g. smart factory, smart production, smart mobility, smart home, or smart city [7]. Kanoun and Tränkler [8] state that sensors and sensor systems achieve their function through an interlocked interaction of sensor structure, manufacturing technology, and signal processing algorithms. It consists of a sensor element that changes its output depending on the magnitude if the measured quantity and a pre-processing unit where the sensor signal is transformed into an adequately amplified and filtered signal. There are a variety of sensors including temperature sensor, proximity sensor, accelerometer, infrared sensor, pressure sensor, optical sensor and ultrasonic sensor. With such a vast choice, non-destructive online sensors have become easily available at affordable prices. Multi-sensor systems have become affordable where a phenomenon is measured by more than one sensor for applications that require high level of reliability like applications involving fire and passenger transportation.

In 2004 Kanoun and Tränkler [7] anticipated the following two areas of development:

a) Maintenance-free sensors with long life expectancy and low electric power consumption.

b) Increased use of multisensory and wireless systems and miniaturization.

In 2018 Schütze, Helwig and Schneider [8] report of smart sensors, which generate the data and allow further functionality from self-monitoring and self-configuration to condition monitoring of complex processes. In short sensor technology of today has become advanced to provide sensors to (a) continuously generate data for every aspect of the manufacturing process (b) track real-time movements and locations of raw materials, work-in-progress and finished goods, and high-value tooling (c) be placed on equipment to drive predictive and cognitive maintenance analytics and (d) geofence dangerous equipment from operating in close proximity to personnel. In this context geofence is a virtual geographic boundary, defined by GPS (Global Positioning System) or RFID (Radio-frequency Identification) technology that enables software to trigger a response when a mobile device enters or leaves a particular area.

2.1.2 Opportunities Provided by Communication Capabilities and IoT

Internet, as known to everyone, is a global computer network providing a variety of information and communication facilities. The internet of things, IoT, is the interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data. This is a revolutionizing development that has the potential to change the way factories operate and people conduct their day-to-day lives. In other words this can be part of the disruptive technology desired for developing smart factories.

Patel and Patel [9] express the vision of IoT in the following way: Internet of Things (IoT) is a concept and a paradigm that considers pervasive presence in the environment of a variety of things/objects that through wireless and wired connections and unique addressing schemes, are able to interact with each other and cooperate with other things/objects to create new applications/services and reach common goals. In the context of a factory the things/objects can be blowers and ducts, pumps and piping, tanks, pressure vessels, chemical reactors, and their constituent components like shafts and bearings. With the latest development of RFID technology, IoT has been paid more and more attention because it could provide a promising opportunity to build powerful industrial systems and applications. This is achieved by leveraging the growing ubiquity of RFID, wireless, mobile and sensor devices embedded in the object, logic object and internet-based information infrastructure. The Internet of Things (IoT) is a significant element of Industry 4.0 that creates comprehensive network infrastructure to create virtual systems and physical objects using the internet [10] leading to operations that can be performed more efficiently, accurately and intelligently [11].

Two remarkable developments that are worth mentioning here are (a) Internet of Services (IoS) and (b) Cyber physical systems (CPS).

Internet of Services (IoS): The internet of services enables service vendors to offer their services via the internet. The IoS consists of participants, an infrastructure for services, business models and the services themselves. Services are offered and, combined to value-added services, by various suppliers; they are communicated to users as well as consumers and are accessed by them via various channels [12]. In the context of a factory this can mean for example the two-way communications originated by a component between the maintenance team or supplies division and itself about its approaching end-of-life condition. It is possible that this concept can be transferred from single factories to entire value added networks. Factories may go one step further and offer special production technologies instead of just production types. These production technologies could be offered over the IoS and can be used to manufacture products or compensate production capacities. Within the Internet of Services, large amounts of data can be processed autonomously in order to provide better and more useful services: Smart services. Examples of these Smart Services include predictive and preventive maintenance made possible by processing large amounts of data collected from running product or machines [13].

Cyber Physical Systems: A cyber physical system (CPS) can be described as a physical system that is controlled or monitored by computer-based algorithms and tightly integrated with the Internet and its users. The industry of developed countries in Europe and North America are based on the use of cyber-physical systems based on the integration of wireless control system, wireless systems, machine learning and production based sensors [14]. Such industries are developing a national platform for new production systems. In other words, it is a new generation of systems that integrate computer and physical capabilities. Through the ability to interact and use the expansion capabilities of the physical world using computing power, communication technologies and control mechanisms of the physical world, cyber physical systems allow feedback loops, improving production processes and optimum support of people in their decision making processes [15]. By using the corresponding sensor technology, cyber physical systems are able to receive direct physical data and convert them into digital signal. They can share this information and access the available data that connect it to digital networks, thereby forming an Internet of Things [16].The real value of the IoT comes by using the cyber elements in order to make an object, a machine or a plant perform better. Within a CPS, the combination of cyber and physical elements can transform a product into a smart product. A smart product is a product that can perform a much more useful function with the empowerment provided by the internet of things [13].

2.1.3 Opportunities for Storing and Processing Huge Amount of Data

Advancement in sensor technology has opened the floodgates for the influx of huge amounts of industrial data. Industrial data is growing twice as fast as any other sector. Yet today, less than 3% of the data is tagged and used in a meaningful fashion [17]. With the use of advanced sensor technologies modern manufacturing systems increase the complexity in generating huge amounts of continuously generated data. This data contain valuable information useful for several use cases such as knowledge generation, optimization of key performance indicators (KPI), diagnosis, prediction, and feedback to design or decision support [18]. Technology for storing and handling this data also is developing faster. Big data is the concept of data where it is hard to collect, manage and process by traditional tools and technologies [12]. One of the focuses of smart manufacturing is to create manufacturing intelligence from large amount of real-time data to support accurate and timely decision-making. Therefore, big data analytics is expected to contribute significantly to the advancement of smart manufacturing [13]. Big data analytics tools are the suitable solutions to provide ease in cleaning, formatting and transforming industrial data [12].

Cloud computing is a complete new technology to provide services in storing and processing huge amount of data. To users, cloud computing is a Pay-per-Use-On-Demand mode that can conveniently access shared IT resources through the Internet where the IT resources include network, server, storage, application, service and so on and they can be deployed with much quick and easy manner and least management and also interactions with service providers. It is the development of parallel computing, distributed computing grid computing, and is the combination and evolution of virtualization, utility computing, Infrastructure-as-a-Service (IaaS), Software-as-a-Service (SaaS), and Platform-as-a-Service (PaaS). Cloud is a metaphor to describe web as a space where computing has been pre-installed and exist as a service; data, operating systems, applications, storage and processing power exist on the web ready to be shared [14]. IoT cloud computing architecture plays a great role in the IoT data. IoT data and applications are stored in the cloud to make it easy to get from anywhere with any web browser or client software. Industry 4.0 appreciates the cloud computing architecture for their centralized control available by different users including managers, customers, operators and programmers [12].

2.1.4 Fundamental Deviation in Data Processing and Use of Data

In order to figure out huge data and its impact imagine a journal bearing carrying a running shaft in a factory. The wear in the bearing is the parameter that tells whether it is in the operable condition or is reaching the wear-out period. When no continuous data is available, as in the conventional factory, routine change of lubricant and the MTTF from the historical data are the two things to rely upon. Imagine a condition where the wear is taken twice every hour. This is a large amount of data about a single component. But this provides opportunities to decide the daily wear rate reflecting the condition of lubrication providing a better way to manage than the routine oil change. The measurement of wear permits the estimation of the remaining life. This can facilitate to plan the spare part and bring the maintenance team in time to minimize the downtime. But this needs two things: (a) availability of large data and (b) processing capability or analytics to compute different monitoring constructs to assist efficient operation. In other words, a fundamental deviation in collecting data and processing data is required.

Collection of continuous data provides opportunities for viewing single and subsets of data under different classifications. In this context classification can be seen as a systematic arrangement of data. For example, the continuously collected data from the journal bearing above can be used to calculate (a) the average wear per week (b) overall wear rate per day to estimate the life available (c) the impact of the environmental change (say the dusty condition) by considering the data during the period (d) the requirement of lubricant change indicated by increased wear on the daily and weekly basis and so on. It is worth noting here that a single item of data can belong to several different groups under different classifications. The classification of data for different constructs results in establishing different analytics. Making the journal bearing smart may include it sending a photograph of itself to the maintenance team when it is entering the 'end-of-life' stage of its life. Thus the data processing and use of data has to be part of the disruptive technology and undergo a fundamental deviation. It should adopt the processing techniques highlighted earlier in section 2.1.3 about 'Opportunities for storing and processing huge amount of Data'.

2.1.5 Opportunity for Better Management

Groover [15] identifies that production systems have two constituents namely (a) facilities and (b) manufacturing management systems. Facilities consist of the factory, production machines and tooling, material handling equipment, inspection equipment and computer systems that control the manufacturing operations.

Manufacturing Management Systems are the procedures and systems used by the firm to manage production and solve the technical and logistics problems associated with designing the product, planning the processes, ordering materials, controlling the work-in-process as it moves through the plant, and delivering the product to customers. Four functions are performed in this category: business functions, product design, manufacturing planning, and manufacturing control. Collection of huge amount of data and associated analytics greatly enhance the ability to utilize the facilities to the full and seamlessly integrate the manufacturing management systems to assist production and minimizing waste and downtime while maximizing sustainability.

2.2 What is a smart factory?

Smart factory can be described as the incorporation of latest technologies described in section 2.1 in its development to have the self-x capabilities, where x stands for characteristics such as description, awareness, management, organizing, controlling, directing, healing, correction, auto-discovery, re-configuration, predicting, comparing, maintaining, organizing etc., which in turn makes manufacturing reliable, safer, economical, sustainable and high quality. This follows the technology transfer model Research → Development → Design → Production as proposed by Ramanathan [16]. In this model research findings are first developed sufficiently for incorporation into design of goods and services. Then the design phase starts which leads to commercial production. Smart factory concept is between the development and design phases and hence the definition of it in terms of constituents and the level of their incorporation in designs are fuzzy. Another important aspect about technology transfer identified by Bennet and Vaidya [19] is the ‘basic knowledge in science and technology of the recipients’. The nature of smart factory requires competence in what is traditionally called multi-disciplinary. The level of competence of the implementers thus has a significant influence on the constituents of any specific implementation of smart factories. The following sub sections explore the description of smart factory by different authors, constituents of smart factories and design principles of smart factories.

2.2.1 Description of Smart Factories by Authors

The literature has listed many descriptions for ‘smart factory’. When reading through them one could immediately realize that they are goal oriented descriptions answering the ‘what’ question than the ‘how’ question. Table 1 shows some of these descriptions.

Table 1: Description of Smart Factory by Authors

Author	Description of Smart Factory
Jay Lee [3]	The combination of all new IoT technological advances in computer networks, data integration and analytics to bring transparency to all manufacturing factories
Elvis Hozdic [20]	Integrating between the numerous industrial and non-industrial partners who build virtual organizations resulting in an effective and flexible production solution.
Radziwon et al. [21]	A manufacturing solution that is related to automation, known as a combination of software, hardware and mechanics, which should lead to optimization of manufacturing resulting in reduction of unnecessary labor and waste of resource.
Deloitte Development [4]	A self-optimizing performance across a broader network, self-adapt to and learn from new conditions in real or near real time and autonomously run entire production processes

2.2.2 Constituents of Smart Factories

According to Deloitte Development LLC [4] the components needed to enable a successful smart factory are largely universal, and each one is important: data, technology, process, people, and security. Following this five clusters were formed.

1) Data:

Data is the lifeblood of the smart factory. Through the power of algorithmic analyses, data drive all processes, detect operational errors and provide user feedback. When gathered in enough scale and scope, it can be used to predict operational and asset inefficiencies or fluctuations in sourcing and demand. Combining and processing the resulting data actions are what make them valuable. To power the smart factory, manufacturers should have the means to create and collect on-going streams of data, manage and store massive loads of information generated [4].

2) Technology:

For a smart factory to function, assets defined as plant equipment such as material handling systems, tooling, pumps, and valves should be able to communicate with each other and with a central control system. The control system can take the form of a manufacturing execution system, which is an integrated, layered hub that functions as a single point of entry for data from across the smart factory and the broader digital supply network, aggregating and combining information to drive decisions. Organizations have to consider other technologies including transaction and enterprise resource planning systems, IoT and analytics platforms, and requirements for edge processing and cloud storage.

3) Process and Governance:

One of the most valuable features of the smart factory is its ability to self-optimize, self-adapt, and autonomously run production processes which can fundamentally alter traditional processes and governance models. An autonomous system can make and execute many decisions without human intervention, shifting decision-making responsibilities from human to machine in many cases, or concentrating decisions in the hands of fewer individuals. The connectivity of the smart factory may extend beyond its four walls to include increased integration with suppliers, customers, and other factories.

4) People:

In a smart factory people are expected to still be key to operations. However there can be profound changes in the operations and IT/OT organizations, resulting in a realignment of roles to support new processes and capabilities. Some roles may no longer be necessary as they may be replaced by robotics (physical and logical), process automation, and AI. Other roles might be augmented with new capabilities such as virtual augmented reality and data visualization. Organizational change in management could play an important role in the adoption of any smart factory solution.

5) Cybersecurity:

By its nature, the smart factory is connected and thus cybersecurity risk presents a greater concern in the smart factory than in the traditional manufacturing facility and should be addressed as part of the overall smart factory architecture. In a fully connected environment, cyber-attacks can have a more widespread impact and may be more difficult to protect against, given the multitude of connection points.

2.2.3 Terminologies used in Smart Factory Descriptions

It was observed that existing technologies and terminologies were given specific features and meanings when they were applied in smart factory applications. Therefore, the existing terminologies towards smart factories have been reviewed. With their additional features and meanings they have become the active constituents of smart manufacturing. They could be clustered into the above five constituents.

Table 2: Technology/Terminology and References

Technology/Terminology	Reference
Intelligent	[22-25]
Energy saving efficiency	[24, 26-30]
Cybersecurity	[24-26, 31]
Real time Communication	[24, 34, 35]
CPS/CPPS	[24, 26, 34-36]
Virtual Reality and Augmented Reality	[26, 37, 38]
IoT/IIoT	[24, 26, 39, 40]
Data analytics/big data analytics	[29, 41-46]
Data visualization	[47, 48]
Operation Planning	[49]
IT-based production management	[24]
Smart Materials	[27, 50, 51]
Advanced manufacturing	[52, 53, 57, 29]

Table 2 illustrates a collection of these technologies and terminologies, which were found in the references accompanying them. For example, one terminology is intelligent technology which means the ability to change its action based on its own experience. Another term is energy saving efficiency which is a technology where the energy necessary to provide a product or service can be reduced. Cyber security is one of the five constituents as discussed earlier in section 2.2.2, it is when data should be secured from cyber threats. In addition real-time communication is a technology, which enables users to exchange data with systems in real-time and this, can be put with the technology cluster. CPS/CPPS (Cyber Physical Systems /Cyber Physical Production System) are technologies used to solve and work with physical mechanisms or components. This is placed under the process and governance cluster. Virtual Reality (VR) creates 3D images using a computer and the interaction in that space with the help of electronic devices, for the user to feel as if he or she has been immersed in a synthetized environment. Augmented Reality (AR) is a technology that can superimpose a computer-generated 3D numerical format in the real world but not interact with it. VR and AR are categorized under the people cluster because there are changes in the operations supporting new processes and abilities. IoT/IIoT (Internet of Things /Industrial Internet of Things) enables communication between the physical and internet-enabled devices, which can be used to improve the existing manufacturing systems. IoT/IIoT is also placed under the process and governance cluster.

Additional terminologies such as big data is a technology that can analyze large sets including real-time data that are difficult to analyze by traditional methods. Data analytics is dealing with data into actions and insights within a manufacturing system. This terminology is clustered under the data cluster. Indeed, big data can be understood as being part of this technology which also makes it under the data constituent cluster. Data visualization represents data with the help of graphs and other visual representations which can lead to graph patterns to analyze the data. The authors agreed that data visualization should be in the process and govenance cluster. Furthermore, operation planning is when all the activities of the organization is planned to achieve the final objective. In other words, connecting everything happening within the organization through the help of IT. This terminology can also be placed on the process and governance cluster. The IT-based production management includes computer-aided design (CAD), computer-aided manufacturing (CAM), computer aided technology (CAx) etc. These are the tools that allow to design, analyze and facilitate the design and production. Therefore, the CAx tools are included in the technology cluster. Smart materials can sense the change in environment with the help of sensors and take the corrective actions using actuators, as well as they provide data for analysis as well, which may lead to improved part design.

Smart materials can sense the change in environment and operations with the help of sensors and can take corrective actions using actuators and they can also provide data for analysis as well which results in an improved part design. Since smart materials require the use of sensors and actuators they should be considered in the data cluster. Finally, advanced manufacturing terminology which is for instance additive manufacturing that is a technology that can print a 3D image into an object with the help of laser beam, electron beam which is a technology cluster .

In summary, the clustering has been done according to my subjective judgment by determining the most suitable cluster because there are some items that could have been possibly placed in another cluster; nevertheless, they are placed in a specific cluster. However, it is fully acknowledged that one might argue that the respective items might fit into another cluster as well based on the individual background and experience.

2.2.4 Design Principles of Smart Factories

Various authors identified six design principles that would help designers to build new smart factories or upgrade existing ones [12, 55-57]. The five constituents are data, technology, process, people, and security that are identified from section 2.2.2 are aimed to act as the capabilities to enable smart manufacturing together with these design principles. These design principles are:

1) Interoperability: Being able to allow communication through interfaces between the components/sub-systems of a manufacturing system, allowing it to work with or use parts of another components of subsystems.

2) Virtualization: Creating an artificial factory environment with CPS similar to the actual environment and to being able to monitor and simulate physical processes. Such environment can be created by the information transparency in CPS and the aggregation of sensor data [58] .

3) Decentralization: is the ability of smart manufacturing systems and technologies to make decisions on their own and to perform their tasks autonomously including global production goals [58].

4) Real-time capability or Responsiveness: is the ability to automatically and in real-time collect manufacturing system data via a network of sensors such as IoT and immediately provide the derived understandings [59].

5) Service orientation: Manufacturing industries and organizations focus on profit from selling the service rather than selling the product [57]. Cloud computing plays an important role in enabling the on-demand provision of services [60].

6) Modularity: is the design of the system components. It is when system components are combined and separated easily and quickly. It allows the system to respond to changing customer requirements and to avoid the internal system malfunctions [61].

After understanding (a) the technological advancements that make the smart factory as an appropriate contemporary development (b) the definitions of a smart factory and its five constituents (c) the terminologies that describe smart factory systems and (d) the design principles guiding the design of smart factories, it is time to introduce the issue encountered in this thesis which is wear in journal bearings. This is done by discussing some general assessment of wear failure and ways of measuring wear of journal bearings in industry.

Journal bearings are used to provide support and to enable the relative motion between rotor systems.The bearing failures are generally complex and can be recognized to several failure modes which combine to cause a failure.The journal bearings are smaller in nature and relatively cheaper than the components of an engine or machine.The failure of a machine bearing leads to serious problems including the need for a complete overhaul.The bearing damage that frequently occurs in journal bearings includes scratching,wiping,wear and fatigue.The most common cause for journal bearing failures are related to inadequate lubrication, faulty assembly, improperly machined components, misalignment and overloading.

When the journal bearings are lubricated properly,they do no exhibit signs of wear.The wear takes place on the bearing when the speed of the shaft is too low to produce sufficient fluid pressure to support the bearing sufaces on a lubricant film.

2.3 Fundamentals of Wear Failure

Wear is a critical concern in many types of machine components; in fact, it is often a major factor in defining or limiting the suitable lifetime of a component. An important example is the wear of dies and molds. Wear generally is manifested by a change in appearance and profile of a surface. Wear results from contact between a surface and a body or substance that is moving relative to it. Wear is progressive in that it increases with usage or increasing amounts of motion, and it ultimately results in the loss of material from a surface or the transfer of material between surfaces. Wear failures occur because of the sensitivity of a material or system to the surface changes caused by wear. Typically, it is the geometrical or profile aspects of these changes, such as a dimensional change, a change in shape, or residual thickness of a coating, that cause failure. However, a change in appearance and the nature of the wear damage also can be causes for failure. An example of the former would be situations where marring is a concern, such as with optical scanner windows, lens, and decorative finishes. Examples of the latter include valves, which can fail because of galling, and structural components, where cracks caused by wear can reduce fatigue life [62, 63]. In addition to these differences, the same amount or degree of wear may or may not cause a wear failure; it is a function of the application. For example, dimensional changes in the range of several centimeters may not cause wear failure on excavator bucket teeth, but wear of a few micrometers might cause failure in some electromechanical devices. As a consequence of these differences, there is no universal wear condition that can be used to define failure. The specific nature of the failure condition generally is a significant factor in resolving or avoiding wear failures. It can affect not only the solutions to a wear problem but also the details of the approaches used to obtain a solution. While this is the case, there are some general considerations and approaches that can be of use in resolving or avoiding wear problems.

2.3.1 Ways of Measuring Wear

There are several techniques have been used for measuring wear in journal bearings where out-of-roundness was found to be the most reliable method for measuring small wear quantities in journal bearings.Wear measurement methods can be categorized in three groups based on change in weight, change in geometry and change in wear debris quantity. To achieve high accuracy in measurements it is preferred that the amount of wear is significant so that the measurement error is small too. Measurement of wear by recording the change in geometry of the component itself is also a useful wear measuring method and directly useful in estimating the life of tribo-pairs such as brakes and clutches [64]. The three wear measurement methods can be summarized as follows:

a) Weight loss: weight loss in bearing as well as in shaft.

Weight loss is one of the direct evidence of wear losses and also one of the most trusted approaches of measuring the wear in machine components. It was recorded for the bearing as well as sleeve specimens.

b) Change in wear debris quantity: particle count and debris weight.

Change in wear debris quantity is considered to be a reliable method for monitoring wear in machine components. There are two methods of quantifying the wear debris: the particle count and the aggregate weight of the wear debris.

c) Change in geometry: out-of-roundness, radial clearance, surface roughness, maximum wear depth.

The change in radii of the bearing as well as in the shaft gives the correct measure of the change in radial clearance of the bearing. The change in radial clearance directly relates to the load carrying capacity of a journal bearing. A relationship between the drop in load carrying capacity and the useful life of a bearing can be successfully derived analysing the effect of change in radial clearance on minimum oil film thickness similar to that of Chu and Kay [65].

The following section evaluates the evolvement of conventional factories and their methods of operation. This vision would create the foundation for smart factory implementation.

2.4 Conventional Factory

A conventional factory can be seen as a collection of physically connected and non-connected units. An industrial blower driven by a motor is a typical example for such a connection. The motor will be totally unaware of the condition of the impellor vanes or the supporting bearings of the blower, even though they are physically connected. External monitoring and human intervention are the means to make this connection in a conventional factory. Routine inspections and observation of noise and current levels are the principal means employed to handle deficiencies. Preventive maintenance based on historical data and routine inspection, are the two main methods for keeping a conventional factory in the functional state. Increasing the reliability of key plant units and scheduled maintenance activities including replacement of partially worn-out units in key plants are some of the steps taken to keep the conventional factories operational.

2.4.1 Limitations of Conventional Factory

Operation of a conventional factory can be regarded as an endeavour to maximize the state of functioning (Sofu) and minimize the state of failure (Sofa) of the plant in the safest possible manner. Every activity, including resource allocation and data collection, is tailored to minimize 'Sofa'. Maintenance was classified as (a) breakdown maintenance (b) preventive maintenance and (c) planned maintenance for general work and condition based maintenance for special units. Maintenance personnel called the 'running maintenance team' were kept on 'stand-by' to attend breakdowns. Preventive maintenance routinely checked the plant and changed the lubricants routinely to prevent breakdowns. Based on historic data planned maintenance works were carried out to refurbish or replace worn-out components nearing their life expectancy derived from crude measurements and historic data. Historic data itself was collected as aggregate parameters like the time to failure (which is used to estimate the mean life of a component) rather than the large amount of data about each component at short time intervals. Spare units of critical components also were kept in waiting for replacement during break down maintenance or planned maintenance. This approach has stabilized the operation and maintenance and, efficiency levels were established as targets to represent good performance (for example more than 330-340 days of operation of a cement plant in an year). The limitations can be summarized as follows:

a) Organization of the maintenance as breakdown, preventive and planned maintenance.

b) Running maintenance team waiting as stand-by.

c) Spare components waiting as stand by.

d) Shortage of spare units and emergency purchases.

e) Data collection in summary form which lacks continuous analysis of data and optimization.

f) Limited opportunities to detailed data analysis for finding root causes, due to summary format of data collection.

g) Bulk of the maintenance work is post-event.

The problem is further exacerbated by the rapid obsolescence of products and the emergence of new products, high quality standards, short delivery and decreasing costs [20]. Conventional factories and their supply chains face challenges in keeping up with ever-shifting fashion. Conventional factories have the safety, environmental and sustainability issues [4]. 'Fixed Routing' is a major limitation where the production line is fixed except when manually reconfigured by people with system power down. There is no communication among machines, products, information systems and people and the field devices are separated from the upper information systems. In the current thinking this is considered as a major drawback. Another major limitation is due to the fact that 'any malfunction of a single device will break the full operation since every machine is preprogramed to perform the assigned functions only' [66].

2.4.2 Analysis

The situation in the conventional factories needs some disruptive development that will destroy the existing methodologies and procedures and introduce better and autonomous new ones based on advanced technologies that make very much reduced waste, defect, and downtime. New developments based on advanced technologies namely (a) sensors to generate more operational data (b) Internet of Things (IoT) for effective communication (c) cloud and dedicated computing to handle huge amount of data (d) deviation from traditional processing and (e) integrated management, should be considered for incorporation. Non-invasive online condition monitoring and appropriate autonomous corrective actions are the way forward for these factories. Analysis of the literature about the methodology for retrofitting and implementing smart factories revealed seven main steps underlying a successful smart factory implementation which are discussed in chapter 3 and 4.

Chapter 3: The Methodology

Chapter 2 concluded that non-invasive online condition monitoring and appropriate autonomous corrective actions are the way forward for these factories. A conventional factory can be visualized as a collection of elements of which some are physically connected to ensure functionality. Figure 2 shows a factory as an assemblage of physically connected elements. Depending on the nature of the elements they need some components in them refurbished or replaced. Data about these elements are collected routinely at very large intervals of time and there is no possibility for any inter-element communication. If it is a process plant operating round the clock the endeavour is to maximize its state of functioning and minimize its state of failure. The traditional approach is to monitor the key elements and replace or refurbish them during a planned shut down or an unplanned breakdown.

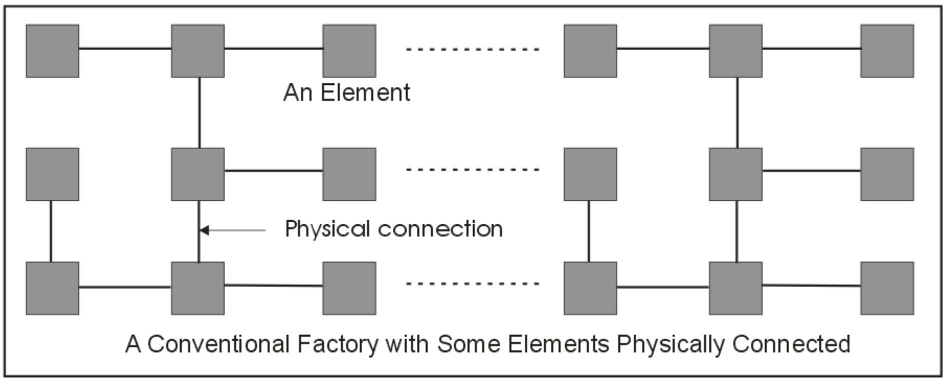


Figure 2: A Factory as an Assemblage of Physically Connected Elements

The objective of the proposed methodology is to make the conventional factory into a smart factory by including smart technologies in the appropriate plant units. In a smart factory the elements are physically connected to ensure functionality as in the conventional factory and the key elements are fitted with accessories and sensors which continuously monitor them and communicate the condition to controllers which store and analyze the data with or without the help of backup cloud computing. The controller then communicate with the accessories to effect changes based on the results of the analyses. This ability to monitor and control provides autonomous capabilities to the element and the factory. Figure 3 shows the schematic of a smart factory as an addition of accessories and sensors to the elements shown in the conventional factory to make it smart.

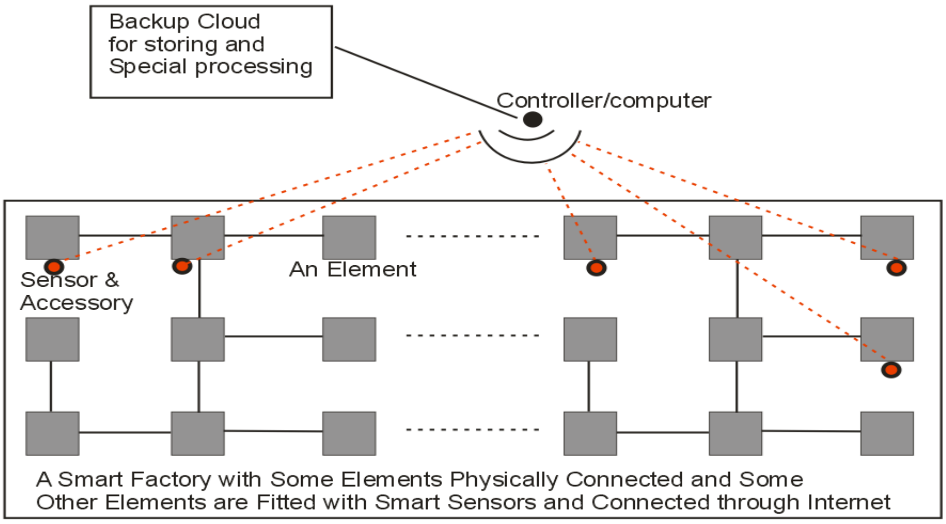


Figure 3: Schematic of a Smart Factory

This chapter proposes a methodology for installing the online condition monitoring and appropriate autonomous corrective actions. The proposed methodology has seven stages (a) situation analysis (b) breakdown prevention analysis (c) sensor selection (d) data transmission and storage selection (e) data processing and analytics (f) autonomous action network (g) integration with the physical plant units. The methodology is schematically shown in Figure 4. The following sections describe these seven stages.

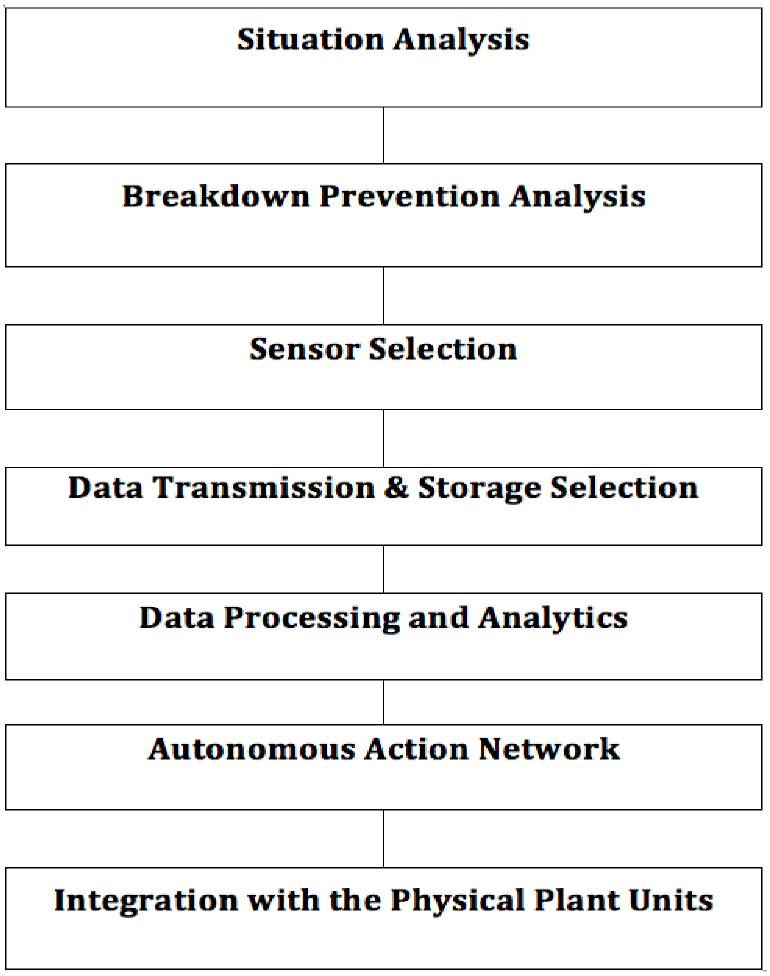


Figure 4: Methodology for Building a Smart Factory

3.1 Situation Analysis

Situation analysis starts with the process description with the associated plant units. Then historical data of these units could be appraised through performance analysis of the plant units. This would identify the units that have robust performance and need little change, and the vulnerable units that can be subjected to process improvement. A 'Pareto Analysis' can easily identify the units that frequently breakdown and thus need enhancement [67].

3.2 Breakdown Prevention Analysis

In the next breakdown prevention analysis the vulnerable units identified earlier are investigated for rectifying their vulnerability. It may be that the particular unit is breaking down because of the failure of a particular part. Then monitoring the condition of this part and taking remedial action at the right moment is the way forward in making them robust. This needs the identification of the needed self-x characteristics. This self-x characteristic for example may be the notification of the remaining life of a journal bearing. At the end of this stage a ‘list of vulnerable units and the needed self-x characteristics’ can be produced as the output of this stage.

3.3 Sensor Selection

The next stage is to establish the monitoring needed to incorporate the specific self-x characteristics. Suitable sensors have to be selected for this monitoring. There are a variety of sensors including temperature sensor, proximity sensor, accelerometer, infrared sensor, pressure sensor, optical sensor and ultrasonic sensor. With such a vast choice, non-destructive online sensors have become easily available at affordable prices. The chosen sensor should easily measure the required characteristic or parameter amongst the various noises such as vibration, dusty condition and bad lighting that can prevail in the factory.

3.4 Data Transmission and Storage Selection

The data generated by the measurements made by sensors should be transmitted and stored for analysis. Estimation of the amount of data that would be generated and the choice of the communicating method are crucial at this stage.There are a variety of communicating technologies that support the specific networking functionality needed in an IoT system in contrast to a standard uniform, network of common systems. The major enabling technologies of IoT are RFID, NFC, low energy bluetooth, low energy wireless, low energy radio protocols, LTE-A and Wi-Fi-Direct [68]. The following subsections describes them.

3.4.1 NFC and RFID

RFID (radio-frequency identification) and NFC (near-field communication) provide simple, low energy, and useful options to identity and access tokens, connection bootstrapping, and payments etc. RFID technology uses two-way radio transmitter-receivers to identify and track tags associated with objects. However, NFC consists of communication protocols for electronic devices, typically a mobile device and a standard device [69].

3.4.2 Low-Energy Bluetooth

This technology supports the low-power, long-use need of IoT function while exploiting a standard technology with native support across systems. Bluetooth technology allows connection to a variety of different electronic devices wirelessly to a system for the transfer and sharing of data and this is the main function of bluetooth. Bluetooth technology uses radio waves to communicate between devices. Most of these radio waves have a range of 15 to 50 feet. Cell phones are connected to hands-free earpieces, wireless keyboard, mouse and mic to laptops with the help of bluetooth as it transmits information from one device to other device. Bluetooth technology has many functions, and it is used most commonly in wireless communications' market [69].

3.4.3 Low-Energy Wireless

This technology replaces the most power hungry aspect of an IoT system. Though sensors and other elements can power down over long periods, wireless communication links must remain in listening mode. Low-energy wireless not only reduces consumption, nevertheless also extends the life of the device through less use [69].

3.4.4 Radio Protocols

ZigBee, Z-Wave, and Thread are radio protocols for creating low-rate private area networks. These technologies are low-power, but offer high throughput unlike many similar options. This increases the power of small local device networks without the typical costs [69].

3.4.5 LTE-A

LTE-A, or LTE Advanced, delivers an important upgrade to LTE technology by increasing not only its coverage, but also reducing its latency and raising its throughput. It gives IoT a great power through expanding its range, with its most significant applications being vehicle, UAV, and similar communication [69].

3.4.6 WiFi-Direct

WiFi-Direct allows P2P (peer-to-peer) connections with the speed of WiFi, but with lower latency therefore it eliminates the need for an access point. Although, WiFi-Direct eliminates an element of a network that often bogs it down, and it does not compromise on speed or throughput [69].

3.5 Data Processing and Analytics

The important next stage is where the generated large amount of data is arranged in suitable classes (data processing) and subjected to various analyses. Evaluation of the analyses would reveal conditions where remedial or reactive actions are needed to keep the unit operational or to minimize the downtime and safety risks. This activity may require services from 'Cloud Computing'. Most cloud computing services fall into four broad categories which are infrastructure as service (IaaS), platform as a service (PaaS), server less, and software as a service (SaaS) [70]. These are called cloud computing stack because they build on top of one another.

3.5.1 Infrastructure as a Service (IaaS)

This is the most basic category of cloud computing services. With IaaS, the IT infrastructure servers and virtual machines, storage, networks, operating systems form a cloud provider on as you go basis [71].

3.5.2 Platform as a Service (PaaS)

This is another cloud computing service that supply an on-demand environment for developing, testing, delivering, and managing software applications. PaaS is designed to make it easier for developers to quickly create web or mobile apps without worrying about setting up or managing the underlying infrastructure of servers, storage, network, and databases needed for development. However, serverless computing which is considered as the overlapping of PaaS focuses on building app functionality without spending time continually managing the servers and infrastructure required to do so. The cloud provider handles the setup, capacity planning, and server management for you. Server less architectures are highly scalable and event-driven only using resources when a specific function or trigger occurs [72].

3.5.3 Software as a Service (SaaS)

This is a method for delivering software applications over the internet, on demand and typically on a subscription basis. With SaaS, cloud providers host and manage the software application and underlying infrastructure and handle any maintenance like software upgrades and security patching. Users connect to the application over the Internet, usually with a web browser on their phone, tablet or PC [72].

3.6 Autonomous Action Network

Time has now come to take remedial action autonomously. This needs the controlling network for transmitting controlling information to accessories fitted in the originating plant unit or to other units or seek human intervention. The control action may include shutting down the plant, sections of the plant, units in sections or slowing down operational rates. This is the establishment of autonomous or self-acting network of activities.

3.7 Integration with Physical Plant Units

Once the network of activities or actions described in section 3.6 is established the last stage is to integrate the process with plant units. It may include fitting new accessories in various plant units or totally replacing the unit itself with a better one. This will make the vulnerable units in the conventional plant more robust due to self-monitoring and autonomous remedial action. As a closing remark it can be said that the methodology proposed is based on the findings from literature review and the limited experience with plant units. The methodology needs testing to prove its validity.

Chapter 4: The Implementation

Chapter 3 established a methodology for retrofitting an existing factory into a smart factory or building a new smart factory. Implementing the methodology therefore needs a factory in the first place. A laboratory-scale factory was built for this purpose. The methodology was then applied to make it smarter. This chapter describes the building of the factory and implementation of the methodology to make it smart. As explained in Chapter 3, a factory is considered as an assemblage of some physically connected elements, which function together in harmony to form the factory.

4.1 The Laboratory-Scale Factory

This section explains the conceptualization and designing of the laboratory scale factory which was built and tested. There are very many mechanical elements and the factories housing them that can be chosen for investigation. The main aim here as stated earlier is ‘To get the knowledge and experience on ‘how to build or retrofit a smart factory addressing specific issues’, a simple smart factory, made up of basic building blocks and addressing a single issue using the principles of smart factory outlined earlier’. Based on the experience the main supervisor Dr Sivaloganathan had in a cement factory wear in journal bearings, an issue encountered in many industries, is chosen as the single issue to be addressed.

4.1.1 Requirements

In order to build the laboratory-scale factory its requirements were identified as follows:

a. It should reflect some real-life situation and involve elements that are widely used in factories.

b. These elements should have behavioral characteristics that make them vulnerable due to random failure.

c. The characteristic or characteristics should be easily monitored in a continuous manner.

d. Analysis of the measured data of the characteristic under consideration should lead to some behavior that could be explained using established principles of engineering.

e. The analysis should point towards some remedial actions to improve the performance of the factory.

4.1.2 Triggering Problem and Conceptual Design

An experience by the main supervisor Dr Sivaloganathan in a cement factory triggered the basis for the laboratory-scale factory. The experience can be described in the following way: The drive of the grate cooler attached to the kiln was connected to the drive through a journal bearing. The bearing gets worn out in short intervals. When the wear increases beyond a certain limit the play in the bearing creates a ‘knock’, which shakes the cooler plate assembly. This and the resulting vibrations loosen the bolts that fix the cooler plates to the chassis and the cooler plates got dislodged causing a breakdown stopping the kiln.

The experience identified journal bearing as the candidate for observation and wear of the bearing as the characteristic for continuous monitoring. The wear caused the failure and it is affected by various factors such as the ambient temperature, dusty condition of the air, condition of lubrication etc. Cameras were chosen to monitor the wear on a continuous basis. A single bearing can be considered as an element in the factory and two of them when connected to carry a shaft can form a connected unit. But there should be more than one such unit. In the end the laboratory-scale factory was conceptualized to have two shaft assemblies, each carried by two journal bearings. But getting a clear view from the camera to monitor wear, proved difficult. It was observed that 'Goods Wagons' in railways use half-bearings as shown in Figure 5. Following this pattern the shafts were carried by half journal bearings. This enabled clear vision of the 'top part' of the lower-half bearing.

Figure 5: Bearings in Railway Goods Wagons [73]

To initiate wear the shaft has to be loaded. To load the rotating shaft a pulley supported by a ball bearing was installed at the center of the shaft. The conceptual design of the setup is shown in Figure 6. The conceptual design consists of two motors, two gear boxes, two loaded shafts and four half journal bearings. Out of these, the four half journal bearings, are the key elements that are vulnerable for failure due to wear. To make the factory smart these bearings have to be monitored continuously. A vision system has been developed to monitor these bearings. Four webcam cameras were employed for this purpose.

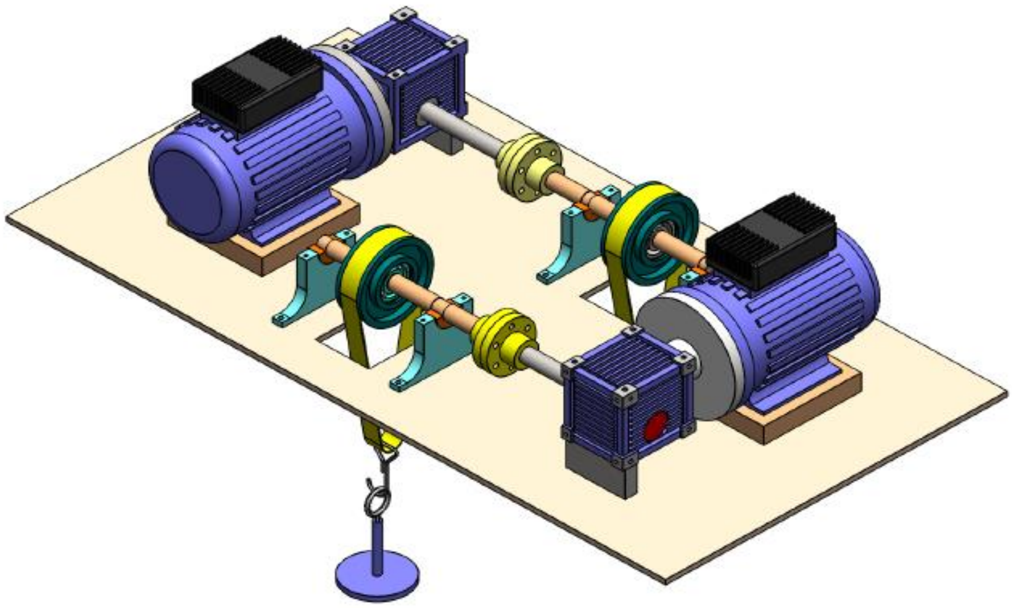


Figure 6: Conceptual Design of the Laboratory-Scale Factory

4.1.3 Completed Laboratory-Scale Factory

The detailed design of the factory was completed using SolidWorks software as shown in Figure 7. The 'Production Drawings' are given in Appendix A.

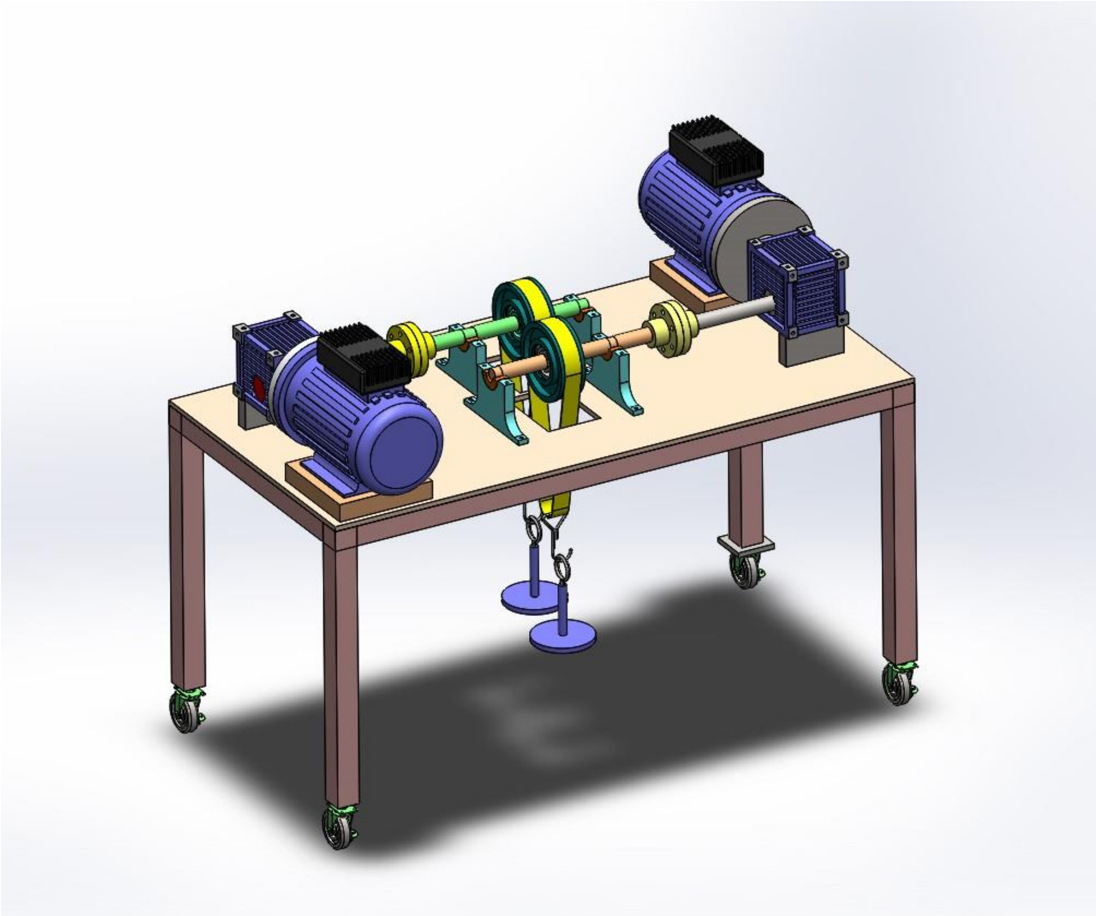


Figure 7: Motor and Shaft Assembly without the stand

4.1.4 Stand for the Cameras

Proper measurements require clear pictures and they should be at a constant location to yield accurate calculations. The cameras should not be fixed to the factory frame because the vibrations could shake the camera while pictures are being taken. To prevent this a frame to mount the four cameras was designed and fabricated as shown in Figure 8. The fabricated factory and the camera stand are shown in Figure 9.

Figure 8: Framework for Carrying the Cameras

Figure 9: The Fabricated Laboratory-Scale Factory

4.1.5 Functional Description of the Factory

Two motors each were connected to a flexible coupling (universal joint) and then to a shaft formed the drive units.The flexible coupling was used to fix any misalignment between the gearbox and the shaft. A 316 L AISI stainless steel shaft was loaded by a ball bearing fixed inside the pulley holding a load of 7.5 kg and the half journal bearings were mounted on bearing housings to carry the shaft.The housing of the journal bearing was made from aluminium alloy (Al Zn 6 Mg Cu) whereas the bushing of the journal bearing was made from bronze (Cu Sn 7 Pb 6

Zn 4). The bill of materials table is shown in Appendix C. Each journal bearing had a camera sensor to monitor its wear. Operating the journal bearing with the load in a harsh condition to get the maximum amount of wear and monitoring and making this failing bearing smart were the purposes of this factory. Furthermore, the design allows for relatively simple assembly and disassembly requiring 2 persons (complete removal and disassembly of the setup requires less than 4 hours).Having thus seen the description of the laboratory-scale factory the seven-stepped methodology for making it smart can be applied.

4.2 Situation Analysis

Since this laboratory scale factory is built to monitor the journal bearings there is no need for a situation analysis.

4.3 Breakdown Prevention Analysis

To prevent the breakdown there are some self-x characteristics needed. The vulnerable unit in the cement factory was the journal bearing which has been chosen as a candidate component for making the factory smart. Monitoring the condition of the journal bearing and taking remedial actions at the right moment is the way forward for making it robust. The needed self-x characteristics for making the frequently failing journal bearing smart is (a) The notification of the remaining life of the journal bearing can be calculated from the historic data 'wear value to breakdown'.(b) The average K is the combination of K, and the coefficient of friction f_s called the 'wear factor' and is determined by experiments for different materials.This value for the specific bearing can be calculated where the K value can be used to trigger a lubricant flush.

Other vulnerable units can exist and accordingly a list of self-x characteristics can be generated.

4.4 Sensor Selection

The monitoring needed to incorporate the self-x characteristics is done using a sensor. There are several sensors available in literature but in this work the sensor selected was the USB Logitech C920 webcam. It operates in full-HD 1080 pixels. It comes with a photo quality of 15 Mega pixels and a video quality of 1920x1080.It has a full-HD glass lens. The frame rate of the cameras is 30 frame per second. Logitech C920 produces brighter images because it is equipped with automatic HD light correction, the C920 fine tunes to your lighting conditions to produce bright, well-contrasted images even if you're in a dim setting [74].The camera was placed at a constant distance of 7 centimetres away from the journal bearing. Figure 10 shows the C920 Logitech USB Webcam.

Figure 10: A C920 USB Logitech Webcam

4.5 Data Transmission and Storage Collection

The data generated by the measurements made by the sensor selected (Logitech C920) in section 4.4 should be transmitted and stored for analysis. Estimation of the amount of data that would be generated and the choice of the communicating method are crucial at this stage. There are several communication methods that can be used such as ethernet, low energy wireless, low energy radio protocols, LTE-A and Wi-Fi-Direct. In this thesis ethernet communication has been used for data transmission and storage collection where the devices were connected through a wired local area network. MATLAB image processing toolbox and the USB webcam package has been installed to the PC using Ethernet communication (wired communication). The Image Processing Toolbox is a collection of functions that extend the capability of the MATLAB numeric computing environment [75]. The toolbox supports a wide range of image processing operations. MATLAB Image processing toolbox has been used to measure and process the wear of half journal bearing. At specific time intervals a Logitech webcam camera takes an image or picture of the shown journal bearing assembly, which is stored in the computer memory. The vision software then analyzes the image of the region ABCD shown in Figure 11 and estimates by how much the edge AD has moved from the first image. This is the wear. The wear is written to a file together with the lapsed time. The process continues with the image-acquiring and wear-calculating activities. The measured wear is then analyzed to monitor the wear rate, remaining life etc. They can be used to trigger messages to the maintenance, supplies and other necessary parties.

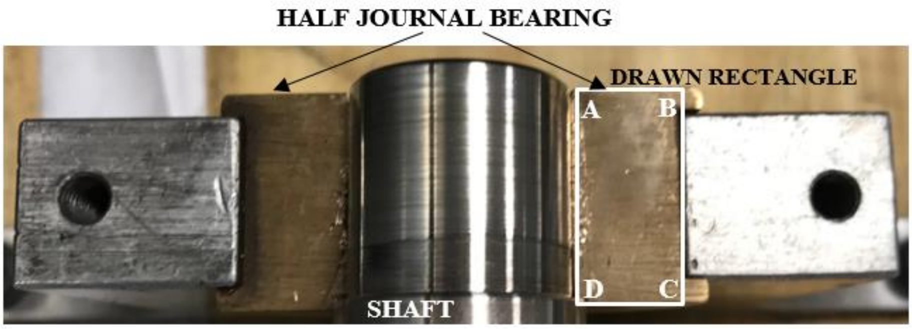
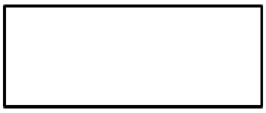
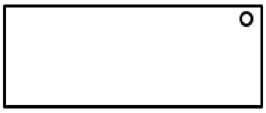
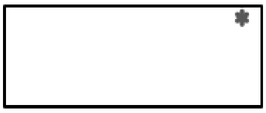


Figure 11: The Half Journal Bearing under Investigation

Diagrams and images are considered more communicative as compared to text. Therefore, Jackson Structured Programming Diagrams [76] has been used to illustrate the code. JSP is basically a program design procedure that applies on systems with well-defined inputs and outputs. This design technique is language independent and can be used for any structured programming language. Table 3 shows the JSP symbols and description.

Table 3: JSP Symbols and Description

JSP Symbols	Description
	**Sequence** A component that has two or more parts occurring once each, and in order
	**Selection** It is a composite task and consists of one or more parts, only one of them is executed
	**Iteration** It is a composite task that repeats zero or more times

The Methodology of measuring the wear consists of three parts:

1. Image acquisition
2. Creating the mask with first unworn image and
3. Obtaining the measurement of the wear and getting the wear versus time values table.

The following subsection describe the process done in each one of them.

4.5.1 Image Acquisition

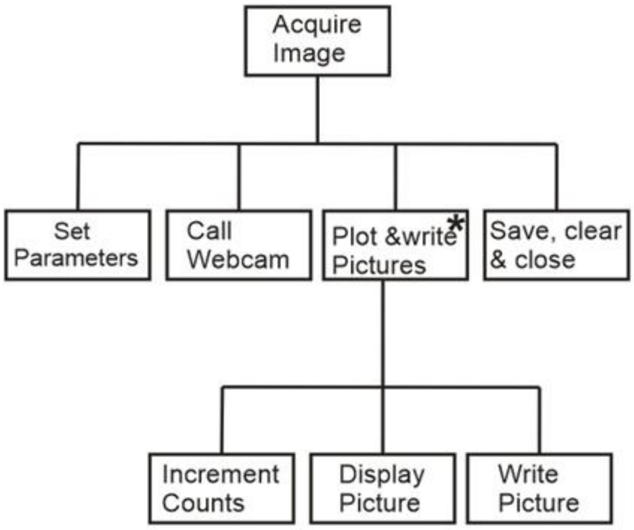


Figure 12: Software for Acquiring the Image

This is the process of taking pictures at a specified interval over a specified period of time, display the image on the computer screen, and write the picture in a file. For the process reported here the images were obtained for a period of three hours and the pictures were taken at 50 seconds interval so that with processing time one picture is taken every minute that is a total of 180 pictures for each trial. To see significant amount of wear no lubricants were introduced between the journal and the bearing. The software to execute this activity is written as a function in MATLAB whose structure is shown in Figure 12. The function starts with setting up maximum time, pause time, resolution, file name and other similar variables under the title ‘set parameters’. The camera, which is connected to form part of the image processing system, is then called to take pictures. The camera in turn takes pictures in cycles. The picture taken is transferred to the computer, which displays the picture in the screen and writes it in the file present in the computer hardware during every cycle.

The process is repeated until the specified maximum time is reached. Appendix B shows the code structure of the 'acquire image function'.

4.5.2 Masking the Region of Interest

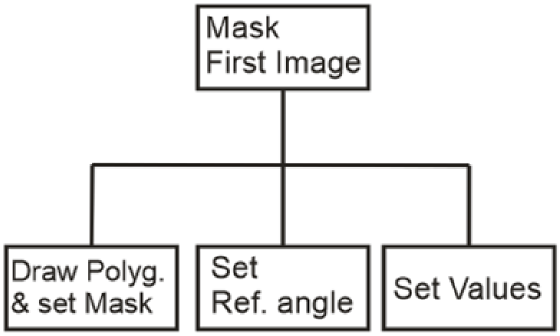


Figure 13: Software for Masking the Region of Interest

The picture covers a relatively large area in comparison to the bearings area of interest, which is marked by the reference rectangle ABCD shown earlier in Figure 11. This step is done only once on the first image in each set since the camera does not move and its position is constant for the same set. The process starts by drawing the rectangle ABCD (called polygon in Figure 11) and setting this rectangle as the mask. Then the reference angle is set as one equal to the arc tan of y divided by the x values. The values of the drawn rectangle and the distance are set. Figure 13 shows the program structure of the masking .These values are saved for use in the next program where the wear is measured.

4.5.3 Algorithm for Measuring Wear

This section discusses the process of processing the wear, where the mask done in the previous step is loaded and initialized first. Then a for loop is written to split the pictures into jpg format and numbers to make it easy in handling and manipulation.

Then the pixels and depth of wear is initialized to start obtaining wear continuously. Before obtaining the wear some preprocessing is done to prepare the region of interest to be calculated. Then setting the angular position to fix the inclination after cropping. This results in some black edges appearing on the edges. The black edges are removed and the image is grayscaled, filtered and binarized. Moreover, the pixel versus rows is plotted to see the distance from the first edge to the other edge by detecting the maximum peaks. To remove the error it has been subtracted and then the plot of wear versus time is obtained. Figure 14 shows the algorithm for measuring the wear. Figure 15 shows the whole process for measuring the wear. The detailed process with pictures is shown in chapter 5.

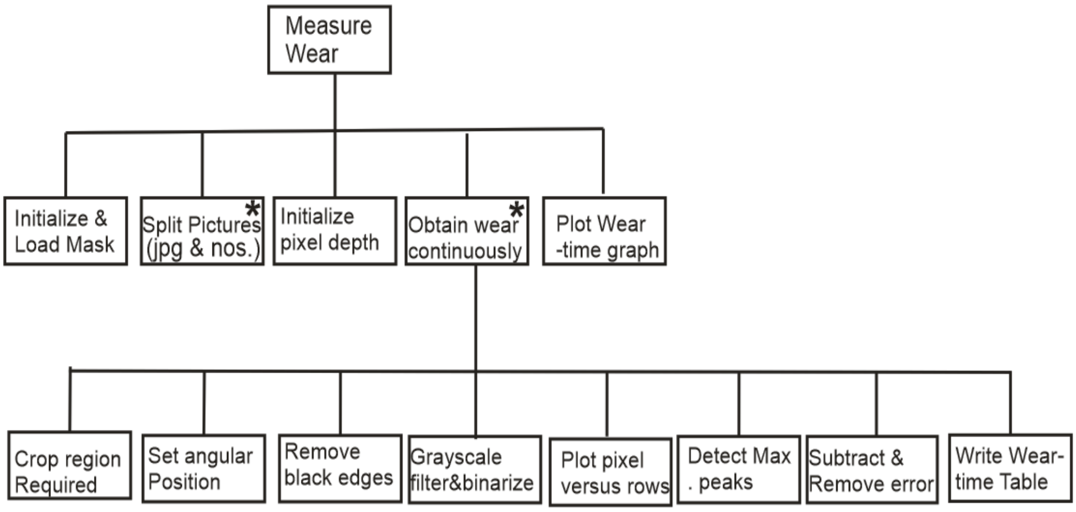


Figure 14: Software for Measuring Wear

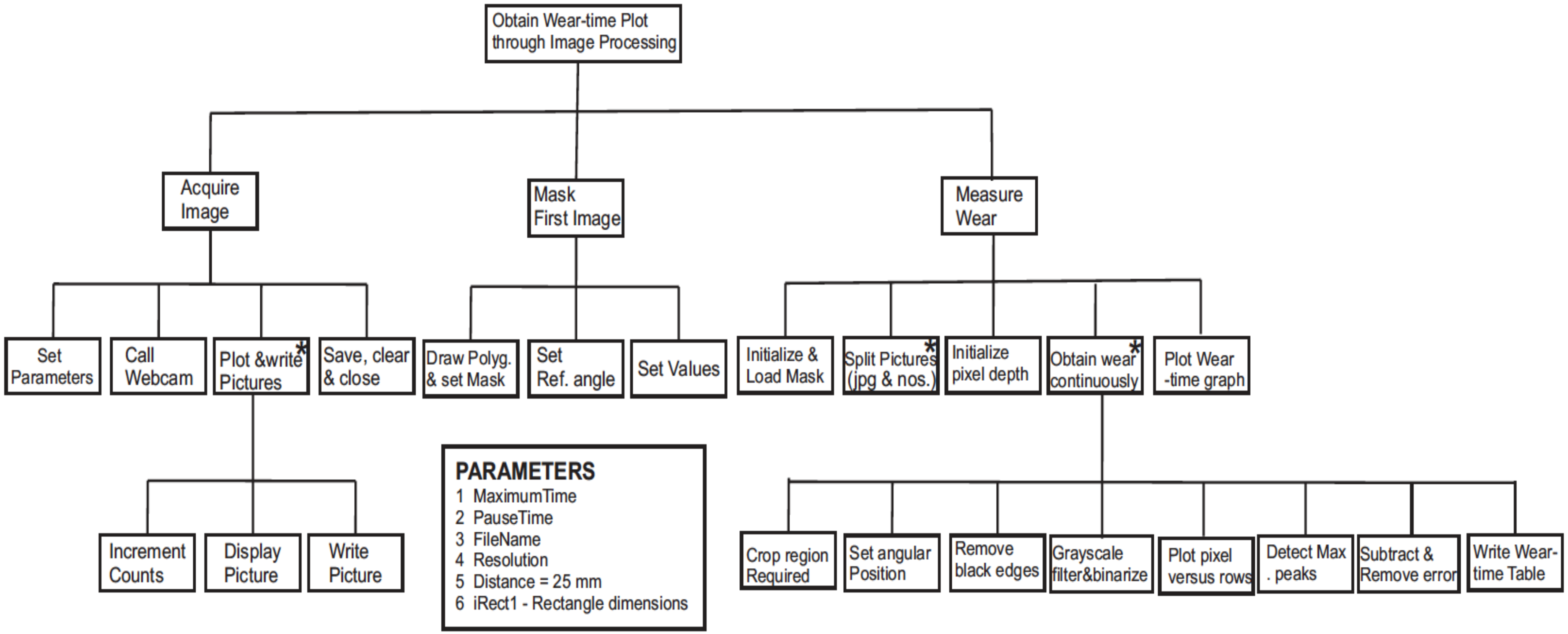


Figure 15: Structure of the Complete Program

4.5.4 Details of Processing and Preprocessing the Wear

The procedure for preprocessing and calculating wear is described in this chapter.The required region is masked as shown in Figure 16(i) and cropped as in Figure 16(ii) and then the cropped image is rotated as in Figure 16(iii) this results in adding more zeros, or in other words black edges around the image. The zeros are removed by taking row-wise and column-wise sum of the pixel values, and considering the first nonzero sum as the beginning and the end of each summed lines and the result of this step is shown in Figure 16(iv). The RGB image is converted to grayscale, after that a range filter is used to enhance only the important aspects like contour of wear. The filtered image is then binarized using a predefined threshold to capture much of the contour that indicates wear. Figure 16(v) shows the binarized image showing the boundaries of the bearing. Figure 16(a) shows the unworn journal bearing 1 and Figure 16(b) shows the same steps for processing a worn journal bearing 1. Figure 17,18 and 19 shows the same process for the the other three journal bearings.

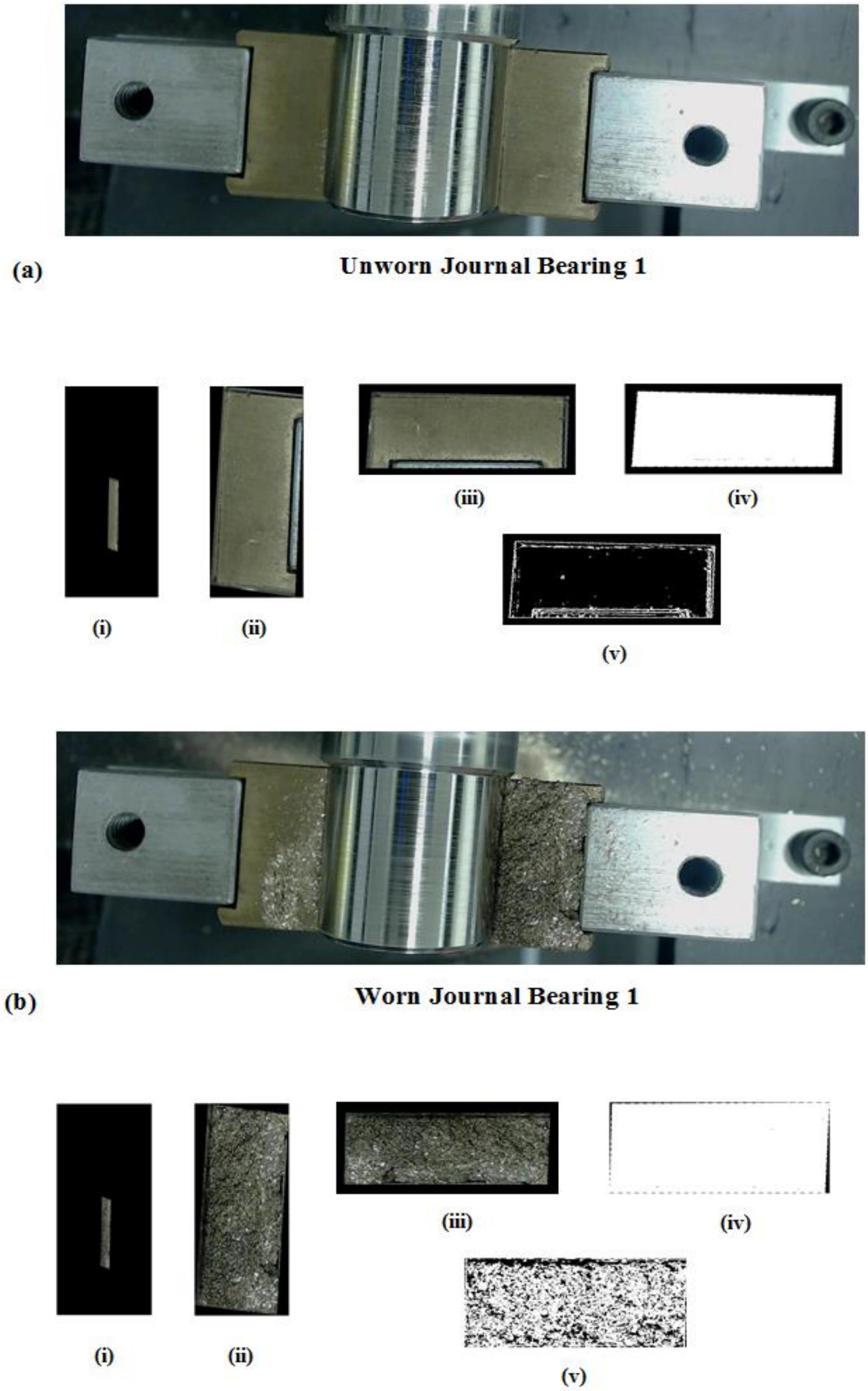


Figure 16: Processing the Images (a) Unworn Journal Bearing 1 (b) Worn Journal Bearing 1

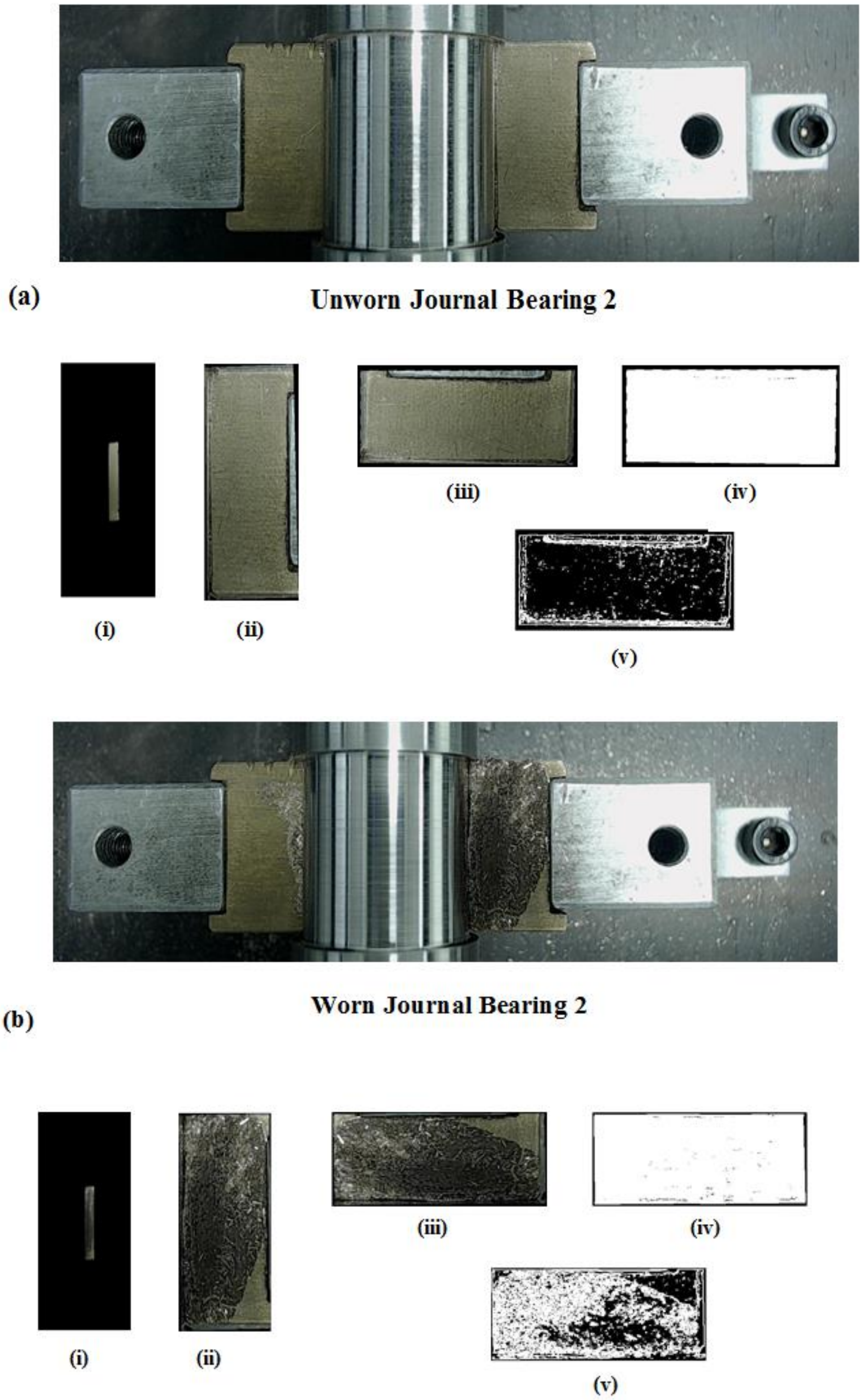


Figure 17: Processing the Images (a) Unworn Journal Bearing 2 (b) Worn Journal Bearing 2

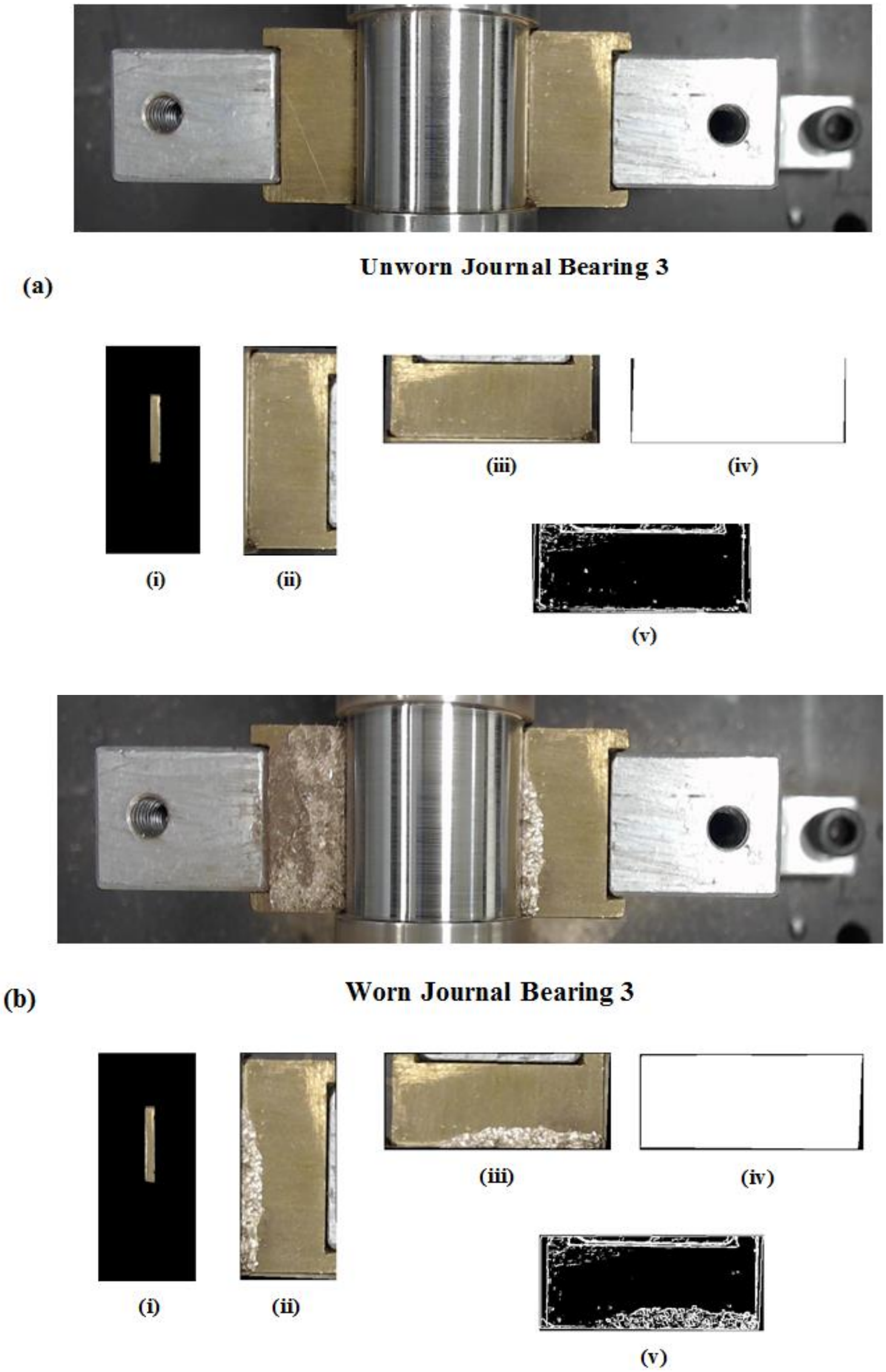


Figure 18: Processing the Images (a) Unworn Journal Bearing 3 (b) Worn Journal Bearing 3

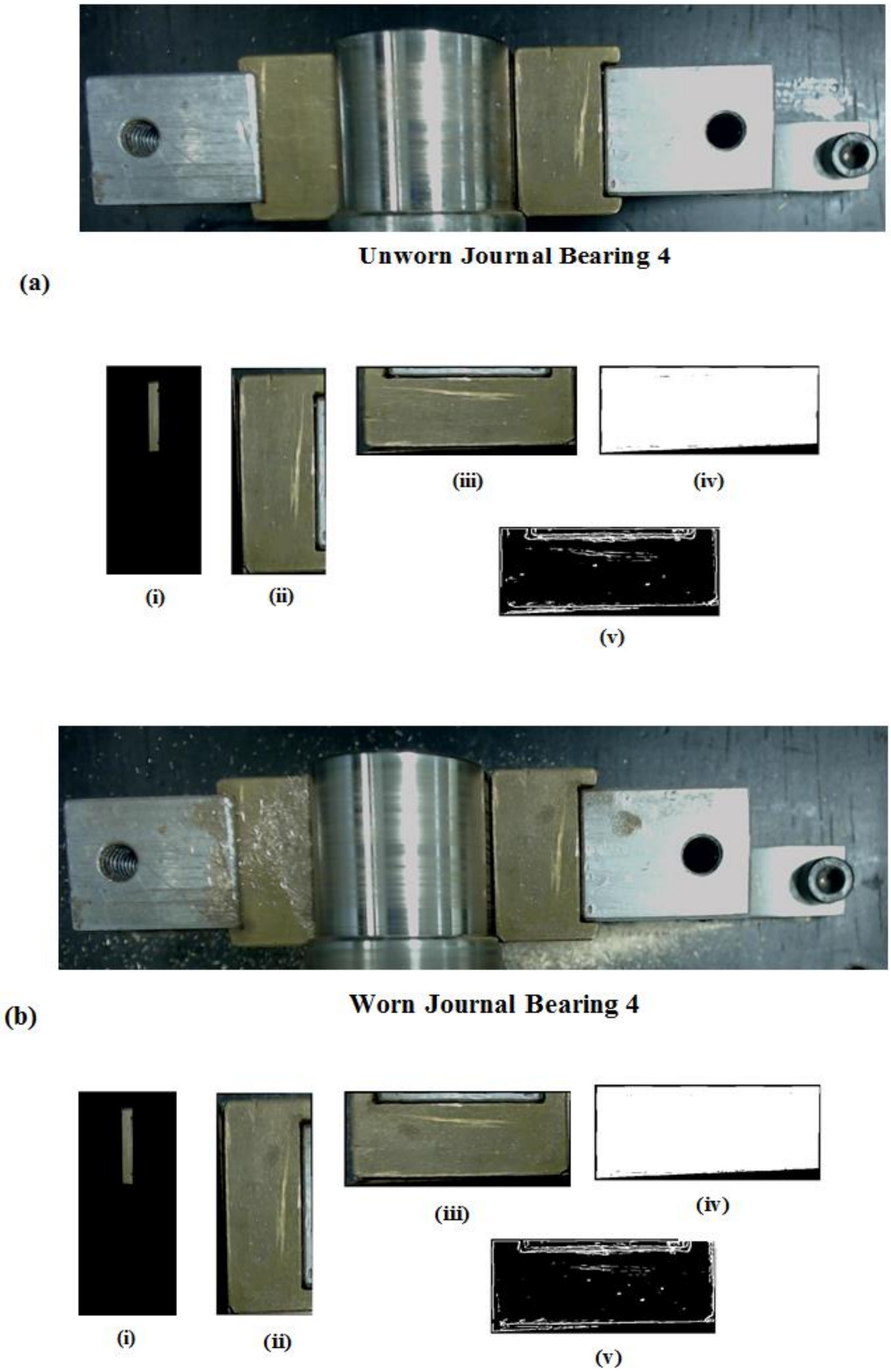


Figure 19: Processing the Images (a) Unworn Journal Bearing 4 (b) Worn Journal Bearing 4

Then this binarized image is used to get the pixels' values versus rows graph. The highest peaks are detected by using differentiation command so that the boundaries of the region of interest are clearly shown. Figure 20 shows a typical 'pixel sum' versus 'Row' graph where the actual length is represented by the gap between the peaks. Every picture taken by the camera at specified time intervals will be having a similar graph from which the actual size of AB represented by this gap can be calculated during the processing of that picture. The difference between the reference size (from the first picture) and the current size is the cumulative wear.

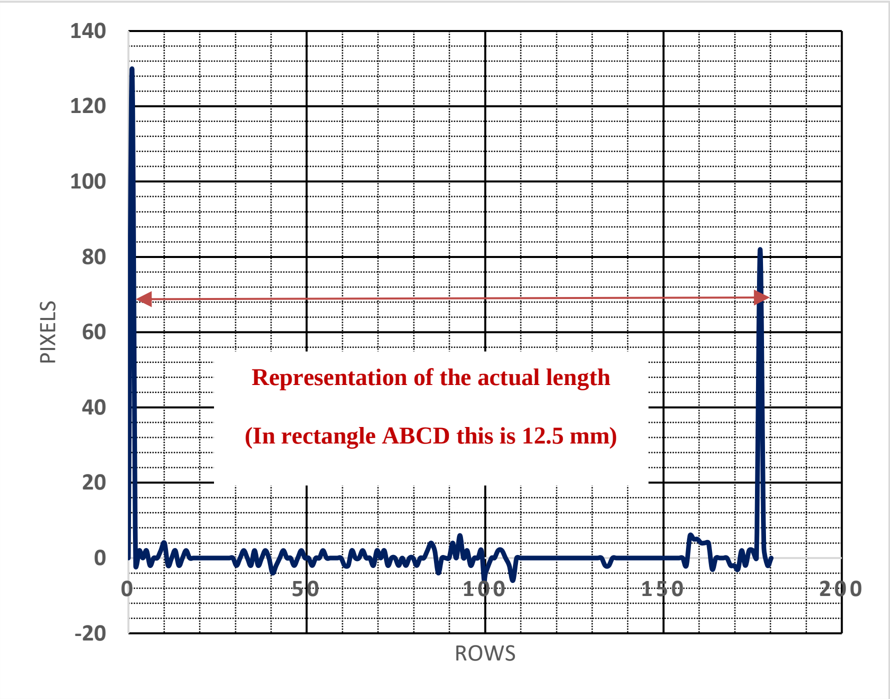


Figure 20: Pixel Sum Versus Row Number

4.6 Data Processing and Analytics

The important next stage is where the generated large amount of data is arranged in suitable classes (data processing) and subjected to various analyses. Evaluation of the analyses would reveal conditions where remedial or reactive actions are needed to keep the unit operational or to minimize the downtime and safety risks. This activity may require services from ‘cloud computing’ such as IaaS, PaaS or SaaS. In this work they were however not needed. Evaluation of the analyses would reveal conditions where remedial or reactive actions are needed to keep the unit operational or to minimize the downtime and safety risks.

The processed data has a huge impact in the management of a journal bearing carrying a running shaft in a factory. The wear in the bearing is the parameter that tells whether it is in the operable condition or is reaching the wear-out period.

A large amount of data about a single component can be classified in several ways. For example the condition of the wear rate when lubrication is provided and the wear rate when no lubrication is provided (harsh condition).This data provide a better way to manage than the routine change done in the MTTF from the historical data.

The measurement of wear permits the estimation of the remaining life. This can facilitate to plan the spare part and bring the maintenance team in time to minimize the downtime. But this needs two things: (a) availability of large data and (b) processing capability or analytics to compute different monitoring constructs to assist efficient operation.

4.7 Autonomous Action Network

Time has now come to take remedial action autonomously. The proposed smart system communicates with a cloud server on the internet through the ethernet network of the factory. The maintenance personnel check the status of the bearings through a web application. Thus, this facilitates a condition based maintenance instead of the preventive maintenance. This facilitates the decision making process in which different stake holders could access the data and take required actions such as shutting the plant, or triggering the supplies for a spare part etc. This can be shown in Figure 21.

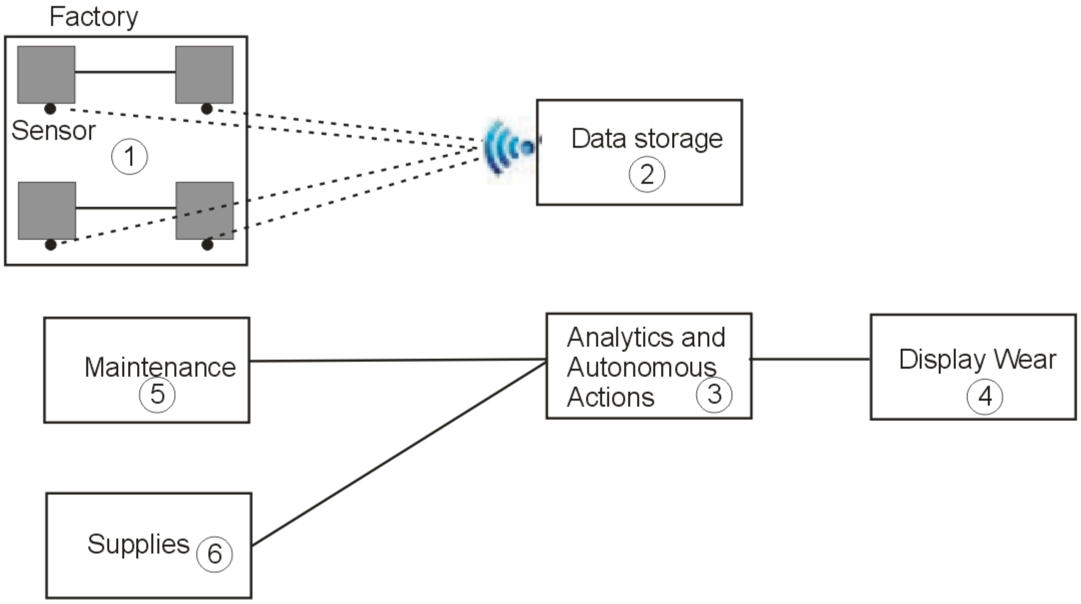


Figure 21: Schematic of the Developed Smart Factory

The analysis section of the project analyses these images and obtain the wear characteristics. The wear characteristics are plotted and displayed as a graph showing wear versus time. Another part of analysis calculates the following:

a. The wear constant
b. Any variation in wear rate
c. Remaining life

The findings from the analyses autonomously trigger alerts to the maintenance and supplies divisions to get ready with spares and maintenance team for corrective maintenance. However, this part has not been done in this thesis.

The network system is composed of the following components:

- Networked Factory (Wired or Wireless)
- Cloud Server
- Web Application

4.8 Integration with the Physical Plant Units

Once the network of activities or actions described in section 4.7 is established the last stage is to integrate the process with plant units. It may include fitting new accessories in various plant units or totally replacing the unit itself with a better one. This will make the vulnerable units in the conventional plant more robust due to self-monitoring and autonomous remedial action.

Chapter 5: Results and Discussion

In this chapter, the results of the implementation done in the previous chapter is illustrated.The four graphs of the four journal bearings are presented .As described earlier the entire system has been implemented in MATLAB using the Image Processing Toolbox.

5.1 Analysis of the Results – Graphs

Figure 22 shows the wear-time curve of the first journal bearing. The right part of the journal bearing has been masked as the region of interest. It can be seen that the wear is increasing rapidly because no lubricant was introduced. Initially, the curve shows a rapid change in wear (0 to 20 minutes) up to 0.15 mm. The slope started to be less steep after the 20 minutes. From 40 to 139 minutes the wear increased gradually to reach a value of 0.45 mm at 140 minutes.

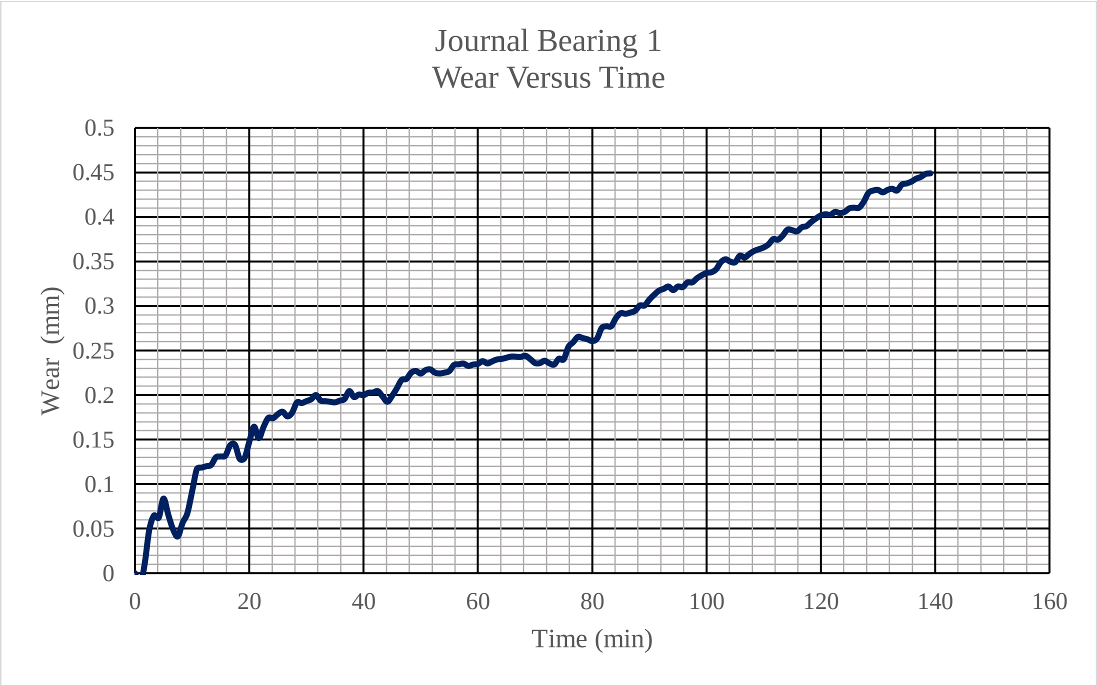


Figure 22: Wear versus Time Plot of Journal Bearing 1

Figure 23 shows the wear-time curve of the second journal bearing. Initially, the curve shows a rapid change in wear (0 to 10 minutes) where the wear reached 0.06 mm. The wear started to increase gradually to reach a value of 0.17 mm at 140 minutes.

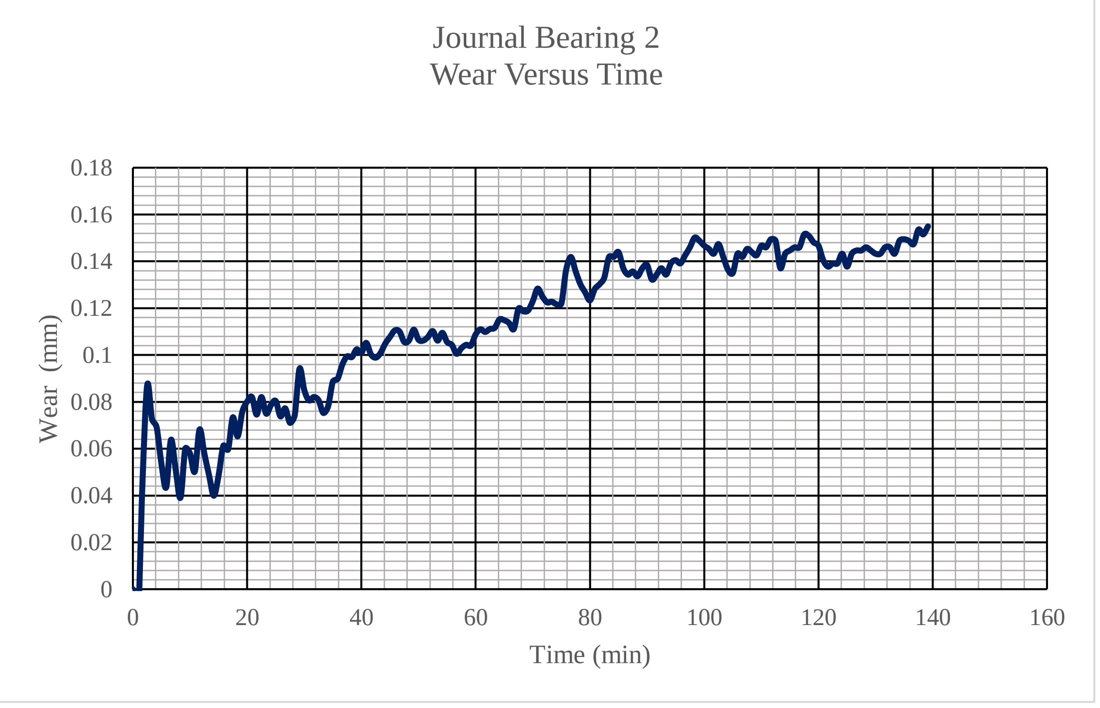


Figure 23: Wear versus Time Plot of Journal Bearing 2

Figure 24 shows the wear-time curve of the third journal bearing. Initially, the curve shows a high peak wear value of 0.06 mm in the beginning and then it decreased to reach 0.02 mm.This can be an error because of the detection or the illumination. Then it shows a representative response of wear increasing gradually until to reach a value of approximately 0.2 mm.

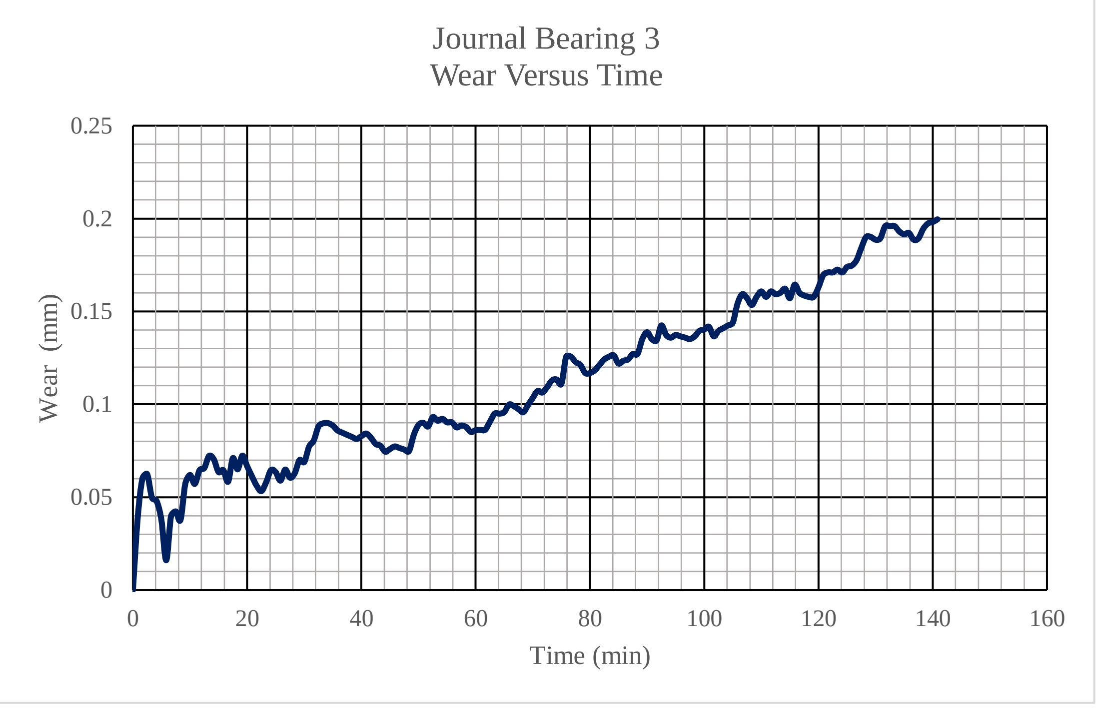


Figure 24: Wear versus Time Plot of Journal Bearing 3

Figure 25 shows the wear-time curve of the fourth journal bearing. Initially, the curve shows a rapid change in wear (0 to 5 minutes) where the wear reached 0.3 mm. The wear started to increase slightly to reach a value of 0.45 mm at 140 minutes.

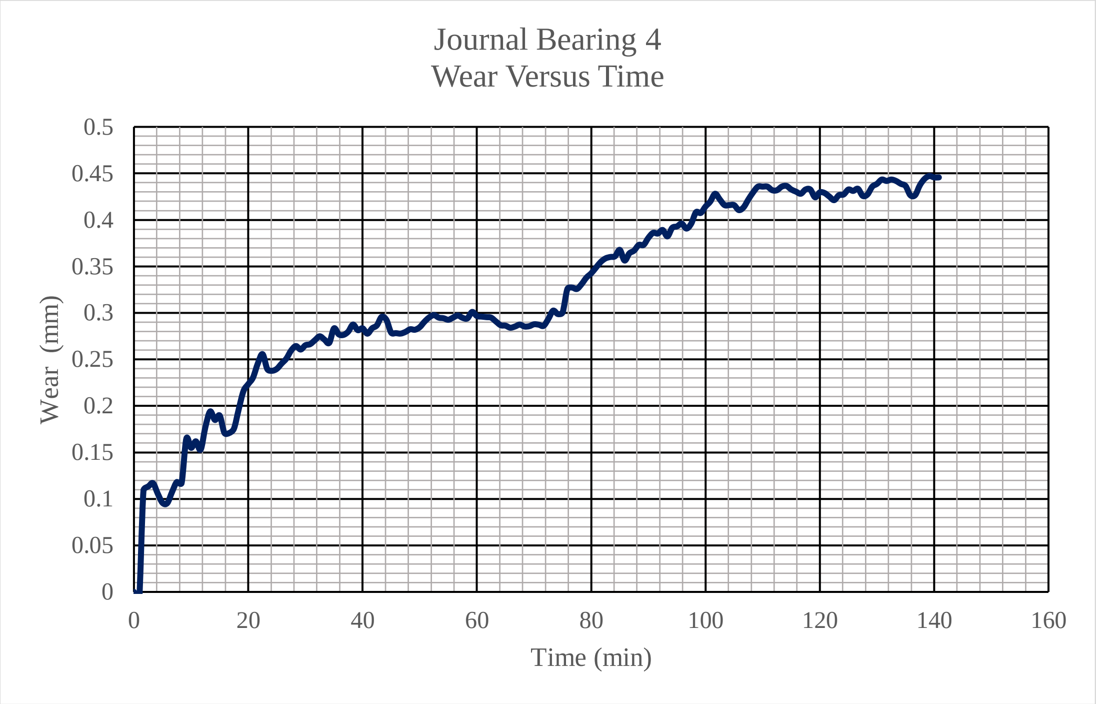


Figure 25: Wear versus Time Plot of Journal Bearing 4

5.2 Analysis of the Results – Analytics

The graph in Figure 22 has been analyzed where the estimation of K and the remaining life of the journal bearing has been calculated from the wear-time table. Table 4 shows the time and wear extracted from the Figure 22 plot. Table 4 can be used for getting the analytics.

Table 4: Wear-Time Table

Time	Wear
0	0
10.833	0.11684
20	0.14733
30	0.19316
40	0.19985
50	0.22416
60	0.23496
70	0.23595
80	0.26065
90	0.30723
100	0.33717
110	0.36578
120	0.40171
130	0.43033
140	0.4492

5.2.1 Analysis of the Wear

Budyanas and Nisbett in Shigley's Mechanical Engineering Design [77] explains the wear in the following way.

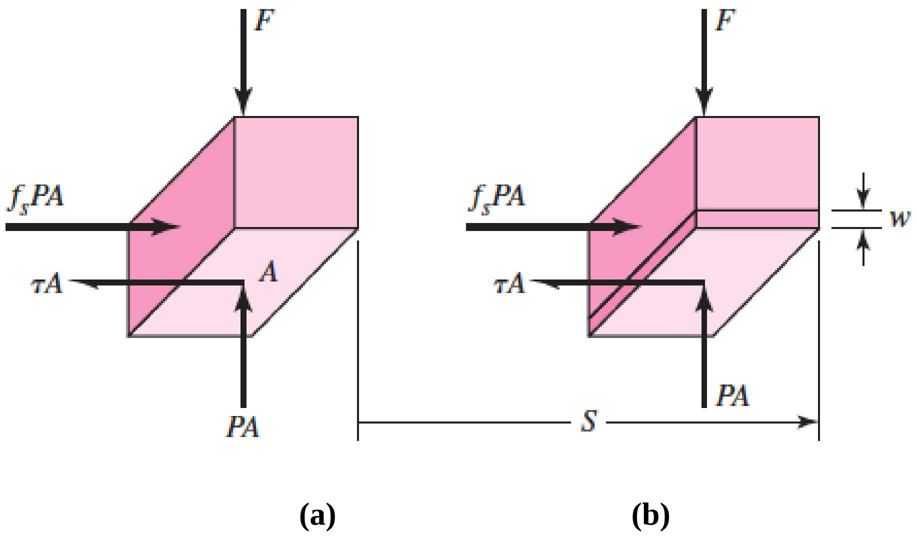


Figure 26: Sliding Block Subjected to Wear (Adapted from [77])

Consider the block of cross sectional area A shown in Figure 26 (a) sliding through a distance S and reaches the position as shown in Figure 26 (b). In the process it undergoes a wear w as shown. Let the pressure on the wearing surface be P and the coefficient of friction be f_s.

The frictional force,

$$f_s PA \text{ Newtons} \tag{1}$$

Work done in moving by a distance S is,

$$f_s PAS \tag{2}$$

But the work done is proportional to the volume of material removed. The material removed is,

$$wA \text{ mm}^3 \tag{3}$$

Therefore,

$$f_s PAS \propto wA \tag{4}$$

This leads to

$$w = K_1 f_s PS \text{ mm} \tag{5}$$

Also,

$$S = Vt \tag{6}$$

This leads to

$$w = KPVt \text{ mm} \tag{7}$$

Where K is the combination of K_1 and f_s, called the 'Wear Factor' and is determined by experiments for different materials.

A journal bearing works satisfactorily until the wear reaches a limit at which point the sloppiness would increase vibrations and create damage to the rest of the plant units. Normally maintenance units replace the worn-out bearings. Continuous monitoring as described above would permit the estimation of the wear factor at frequent intervals for the specific bearing. This can give the following benefits:

5.2.2 Estimation of the Exact Value of K for the Given Bearing

Consider the bearing in the test rig. The motor has a speed of 1400 rpm and the gearbox has a reduction of 50. This leaves the speed of the shaft be 28 rpm. The shaft diameter is 25 mm. Hence the peripheral velocity of rubbing equals,

$$(\pi \times 25) \times \left(\frac{28}{60}\right) \times 10^{-3} = 0.037 \text{ m/sec} \tag{8}$$

The load at the center is 7.5 kg. This can be considered as 75 Newtons. The length of the bearing is 25 mm. Hence the,

$$\text{Average pressure} = \frac{75}{2 \times 25 \times 25} = 0.06 \text{ MPa} \tag{9}$$

Thus in general for this bearing the wear $w = K \times 0.06 \times 0.037 \times 10^3 \times t$

Now if the wear during the first 10 minutes is considered

$$0.11684 = \mathrm{K} \times 0.06 \times 0.037 \times 10^3 \times 10.8333 \times 60 \tag{10}$$

Hence,

$$\mathrm{K} = \frac{0.11684}{0.06 \times 0.037 \times 10^3 \times 10.833 \times 60} = 8.0973 \times 10^{-5} \tag{11}$$

Now if the 30 minutes' interval from 20 minutes to 50 minutes is considered.

$$\text{Wear } w = 0.22416 - 0.1473 = K \times 0.06 \times 0.037 \times 10^3 \times 30 \times 60 \tag{12}$$

Hence,

$$K = \frac{0.07686}{0.06 \times 0.037 \times 10^3 \times 30 \times 60} = 1.9234 \times 10^{-5} \tag{13}$$

This tells that the K value under normal operations is much lower than the initial value. The initial K was high till the peaks and valleys in the two mating surfaces smooth themselves out. The variation of K values in 20 minutes' intervals is given in Table 5.

Table 5: Variation of K in 20 Minutes Interval

Time(min)	Wear (mm)	K
0	0	
20	0.14733	5.530×10^{-5}
40	0.19985	3.751×10^{-5}
60	0.23496	3.940×10^{-5}
80	0.26065	2.446×10^{-5}
100	0.33717	2.531×10^{-5}
120	0.40171	2.513×10^{-5}
140	0.4492	2.409×10^{-5}

Monitoring the K value can give an indication about the lubrication and environmental condition such as dust. It also is a reflection of the materials of the shaft and the bearing. Any increase in the value would indicate the need for checking the environment and lubrication instead of depending on Preventive maintenance.

5.2.3 Estimation of Remaining Life

Estimation of remaining life based on specific measured values would be more reliable than those figures based on historical data. For the given setup let the permissible wear be 3 mm. If an average value of 7.2×10^{-5} is assumed for K the total life can be calculated as,

$$\text{Total life} = \frac{\text{Permissible wear}}{\text{K}\times 0.06\times 0.037\times 10^{3}} = \frac{3}{7.2\times 10^{-5}\times 0.06\times 0.037\times 10^{3}} = 312.8\ \text{Mins} \tag{14}$$

As can be seen the estimated total life is 312.8 minutes. This value will change with the change in the K value. But it can be used as a more reliable estimate. Using this for example at the end of 140 minutes the remaining life can be estimated as:

$$\text{Remaining life} = (312.8 - 140) = 172.8\ mins \tag{15}$$

Chapter 6: Discussion, Areas for Future Work and Conclusion

This thesis and the laboratory-scale factory are the results of the maiden effort in the department on smart factories and digital manufacturing. Since this topic is current and many researchers are actively involved in the research the number of publications in the public domain is very high. Common terminologies in English language had different specific meanings in this digital formation. It was therefore a huge effort to carry out a representative literature survey.

6.1 Discussion

The findings from the survey prompted the question ‘How can one retrofit or build a smart factory?’. The survey and the methodology proposed were summarized and published in the International Journal of Advance Research, Ideas and Innovations in Technology under the title ‘Smart Factory: A methodology for adaptation’. This defined the smart factory for us and the methodology to build one. In the next step we used the methodology to build a laboratory-scale smart factory. The journal bearings were chosen as the single issue for investigation. The biggest problem was finding the right sensor and the method of using it for condition monitoring. Several alternatives were considered and abandoned due to their high cost. Logitech Webcam C920 was chosen and Image Processing Toolbox from MATLAB were used for carrying out the functions. It required substantial command in programming. A program was formulated and written using Jackson’s Structured Programming methodology, JSP. This was written as a paper for the Computing Conference 2019 under the title ‘Vision monitoring of half journal bearings’. This was the first attempt to monitor a single bearing. It was thought that monitoring all four bearings simultaneously could be done easily. Though monitoring was achieved the process was far from easy and complete. It needed the IoT platform. At this point it was decided that this phase would conclude here, showing how the data collected could be used to make the factory smart rather than implementing it. Chapter 5 showed that the following could be done using the data collected during the continuous monitoring (a) observing and measuring the variation of wear factor k so that autonomous actions can be taken to make the system more robust (b) estimating the remaining life which results in removing uncertainties in conventional factories.

6.2 Future Work – IoT Platform

An IoT platform bridges the gap between device sensors and data network. It is a set of components that allows developers to spread out the applications, remotely collect data, secure connectivity, and execute sensor management. It connects different components, ensuring uninterrupted flow of communication between the devices. In a factory there can be several plant units that require routine replacement after certain time is elapsed. Coordinating them and replacing them during a single planned shutdown is a major task in conventional factory maintenance. With continuous monitoring and facility for the estimation of remaining lives of several units the plant units can communicate among themselves and plan an optimal time for a shutdown. In addition to, journal bearings can communicate with voice commands illustrating the remaining live left in them and send a request to the supplies department for replacing the journal bearings.

6.3 Conclusions

This research has provided several insights into smart factories. The following can be said as conclusions from this research:

1. In the first instance it carried out an extensive survey on ‘Smart Factory’ and identified and understood the enabling technologies on which smart factories are and can be built. Developments in four main areas (a) sensor capabilities (b) communication capabilities (c) storing and processing huge amount of data and (d) better utilization of technology in management and further development are these enabling technologies and practices.
2. The research proposed a methodology to retrofit an existing factory into a smart factory and for formulating the development of a new smart factory. It outlines a systematic approach for the introduction of ‘Smartness’ in the operation of a smart factory.
3. In the research a factory at the laboratory-scale has been built. It identified the route cause or shortcoming of existing factories (wear in journal bearings) and used the enabling technologies to make it smart.
4. The laboratory-scale factory used the vision-based sensing system in a novel way to study the wear characteristics of half journal bearings.The maximum wear value was 0.45mm for journal bearing 1 and 2.
5. Finally algorithms and analytics have been developed to process the data to get results that can be used to make applications of journal bearings ‘Smart’.

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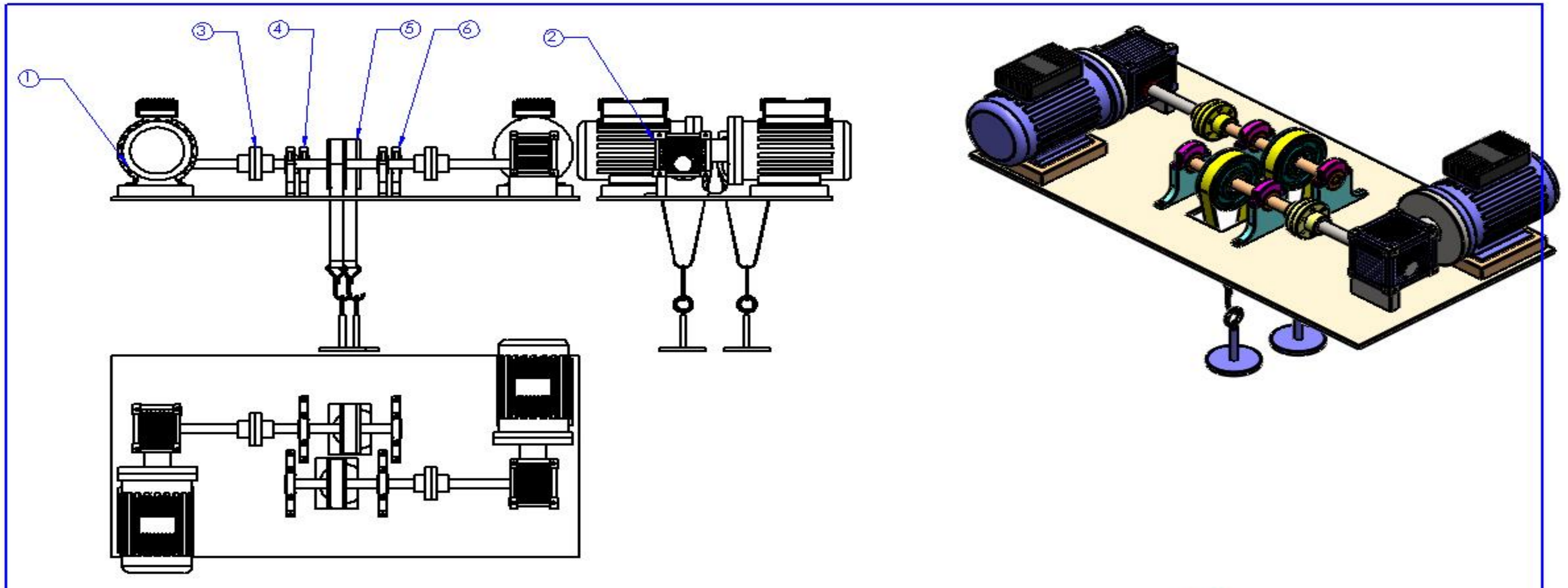
List of Publications

Iman AbdulWaheed, Sangarapillai Sivaloganathan and Khalifa Harib. *Intelligent Computing - Proceedings of the 2019 Computing Conference*, Paper ID #425.

Iman AbdulWaheed, Sangarapillai Sivaloganathan and Khalifa Harib; “Smart Factory: A methodology for adaptation”*International Journal of Advance Research, Ideas and Innovations in Technology”*, vol.5, no.1, pp.281-288, January-February 2019.

Appendix A



NOTE:
1. ALL THE DIMENSIONS ARE IN MM
2. DO NOT SCALE THE DRAWING
IF ANY DOUBTS PLEASE ASK

SR. NO.	DESCRIPTION
1	MOTOR
2	WHEEL GEAR BOX
3	UNIVERSAL JOINT
4	HALF JOURNAL BEARING
5	FLY WHEEL
6	HALF JOURNAL BEARING
7	WEIGHT HOLDER

TOLERENCE SYSTEM	
25	±0.1
25.0	±0.05
25.00	±0.01
25.000	±0.005

REVISIONS | DATE | REMARKS

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SHRINKAGE:-
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DESIGNED
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APPROVED

TITLE:
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DATE: 02-07-18

A3

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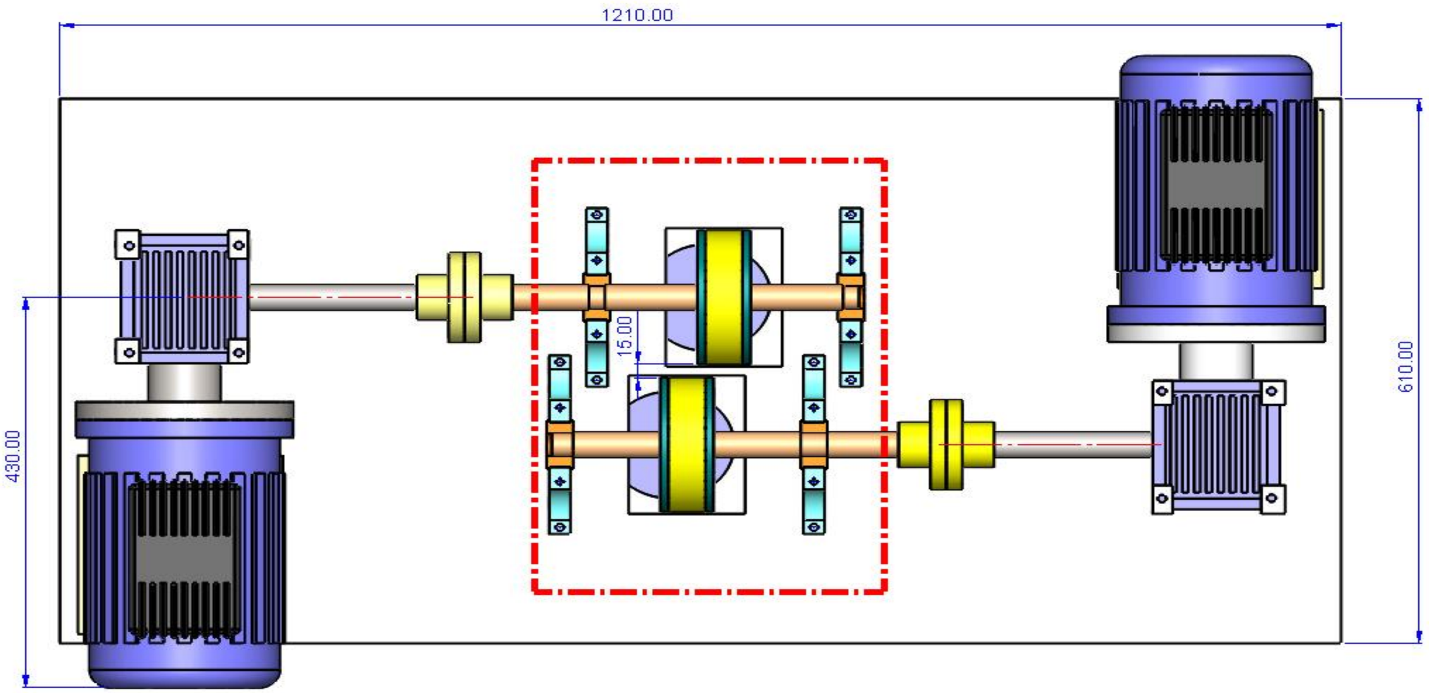
DRAWING NO.

REV.NO. 01

SHEET NO 1 OF 1



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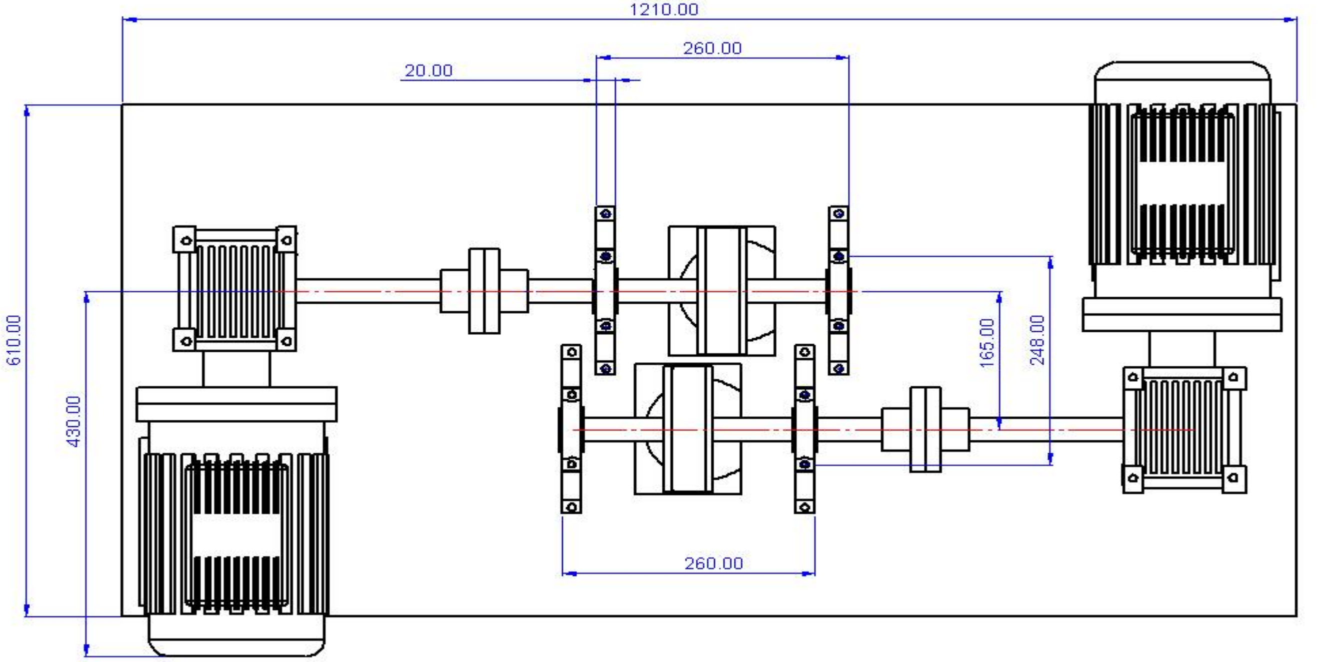

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IF ANY DOUBTS PLEASE ASK

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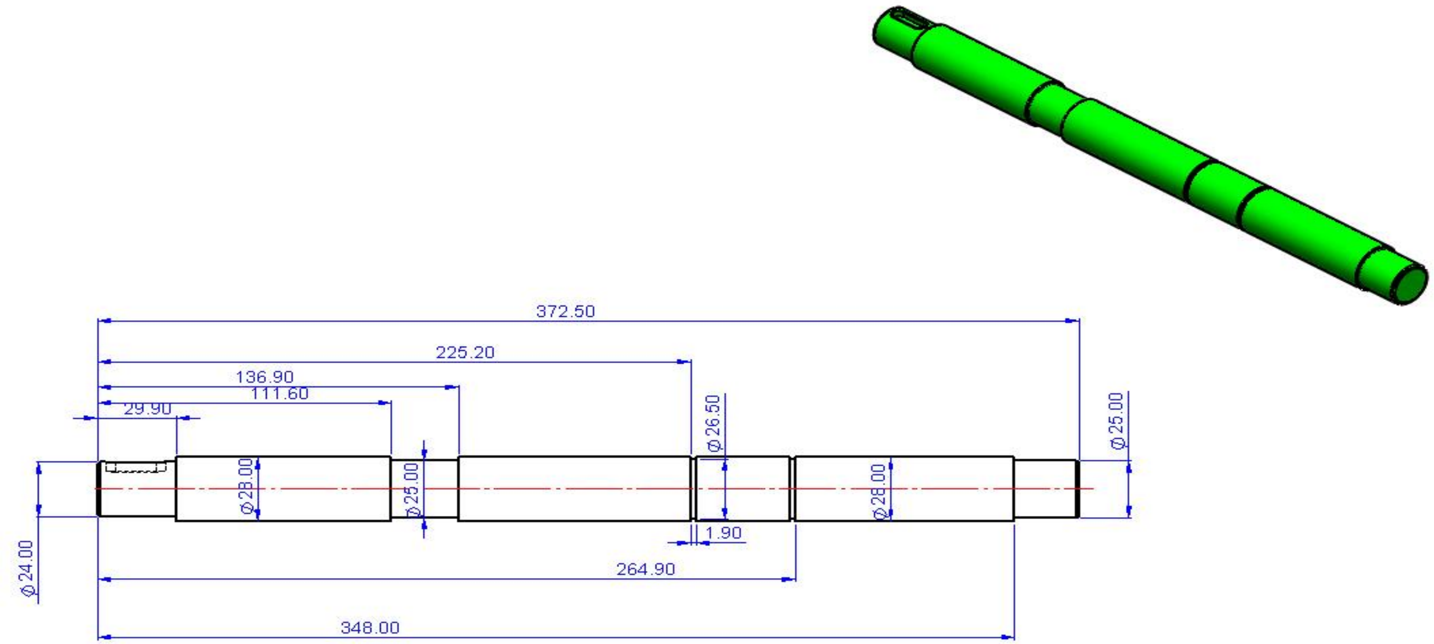

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IF ANY DOUBTS PLEASE ASK

TOLERENCE SYSTEM	
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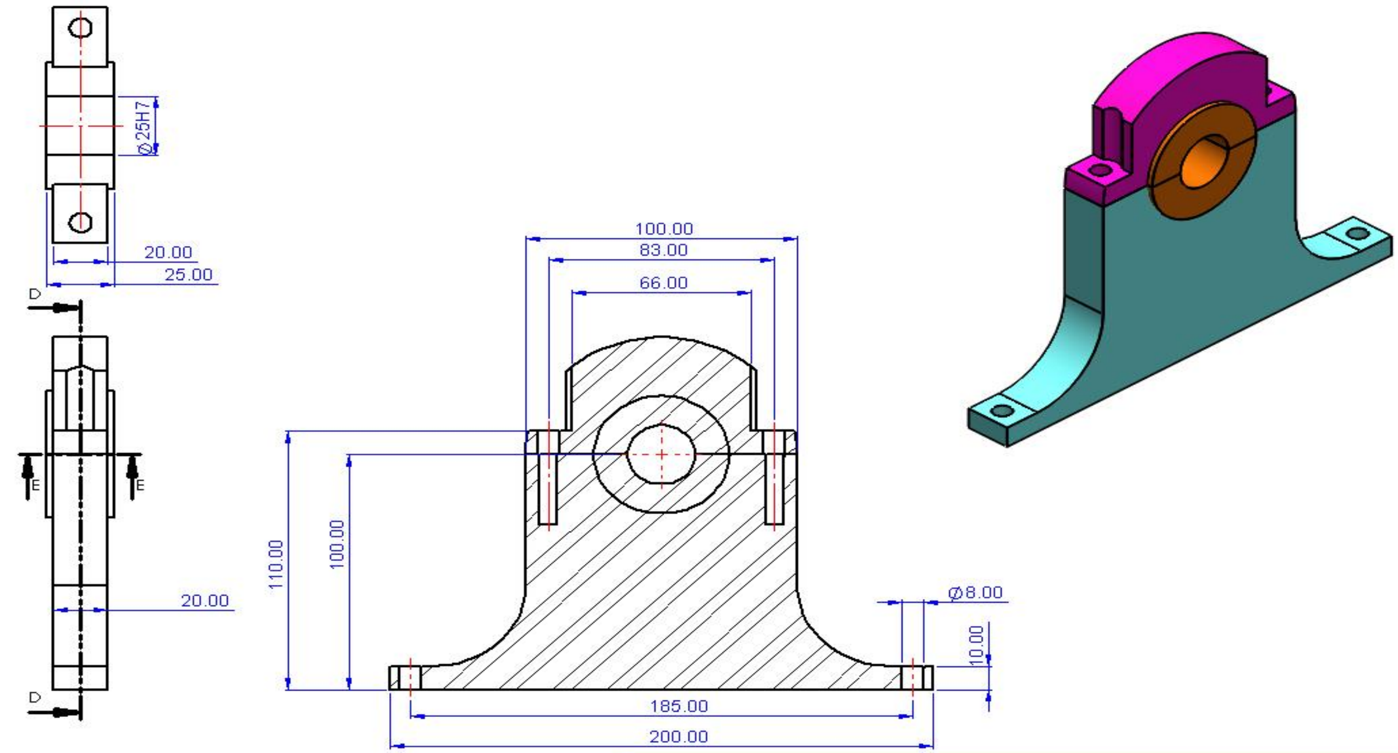

SECTION D-D
SCALE 1 : 1.5

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IF ANY DOUBTS PLEASE ASK

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REVISIONS	DATE	REMARKS

MATERIAL:-	
SHRINKAGE:-	
DRAWN	
DESIGNED	
CHECKED	
APPROVED	
SCALE	NTS
TITLE:	TEST RIG ASSEMBLY HALF JOURNAL BEARING
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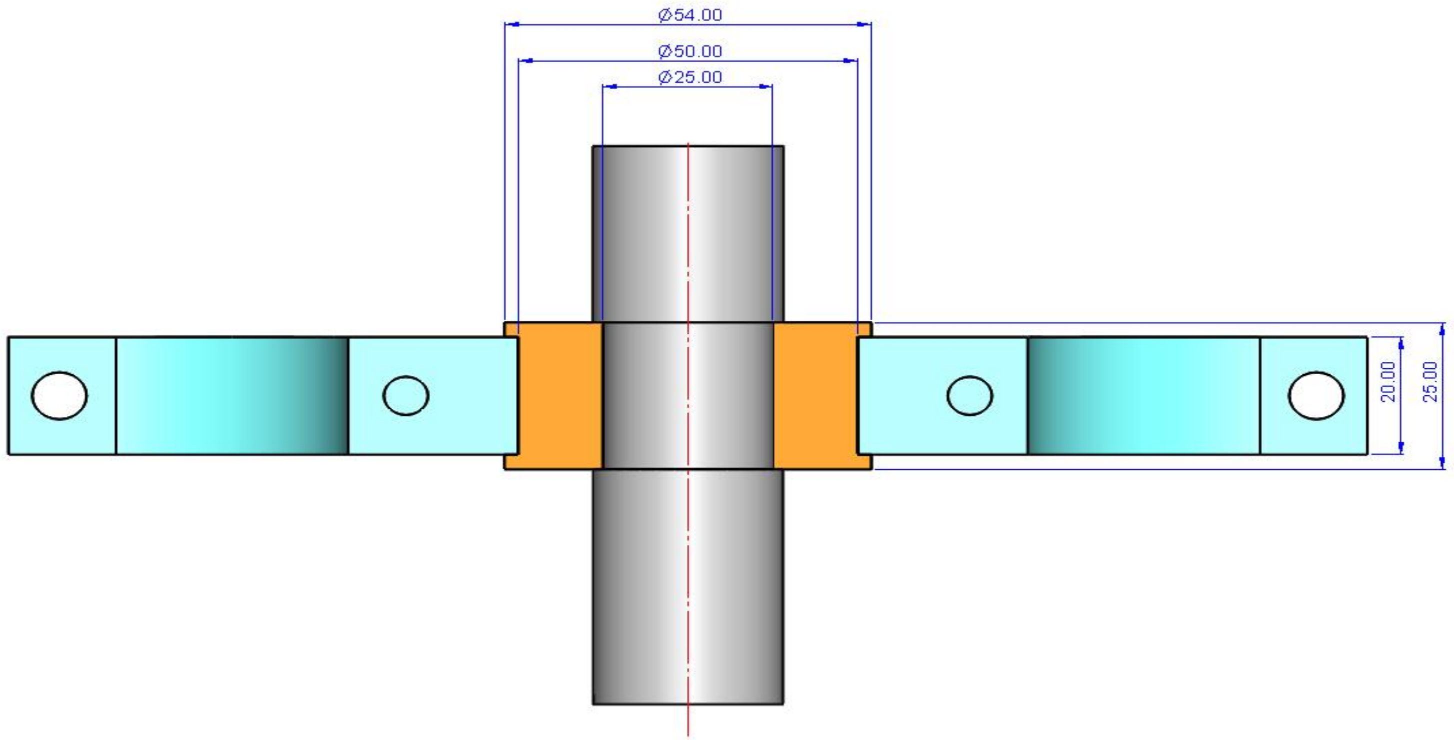
DRAWING NO.	
REV.NO	01
SHEET NO	1 OF 1



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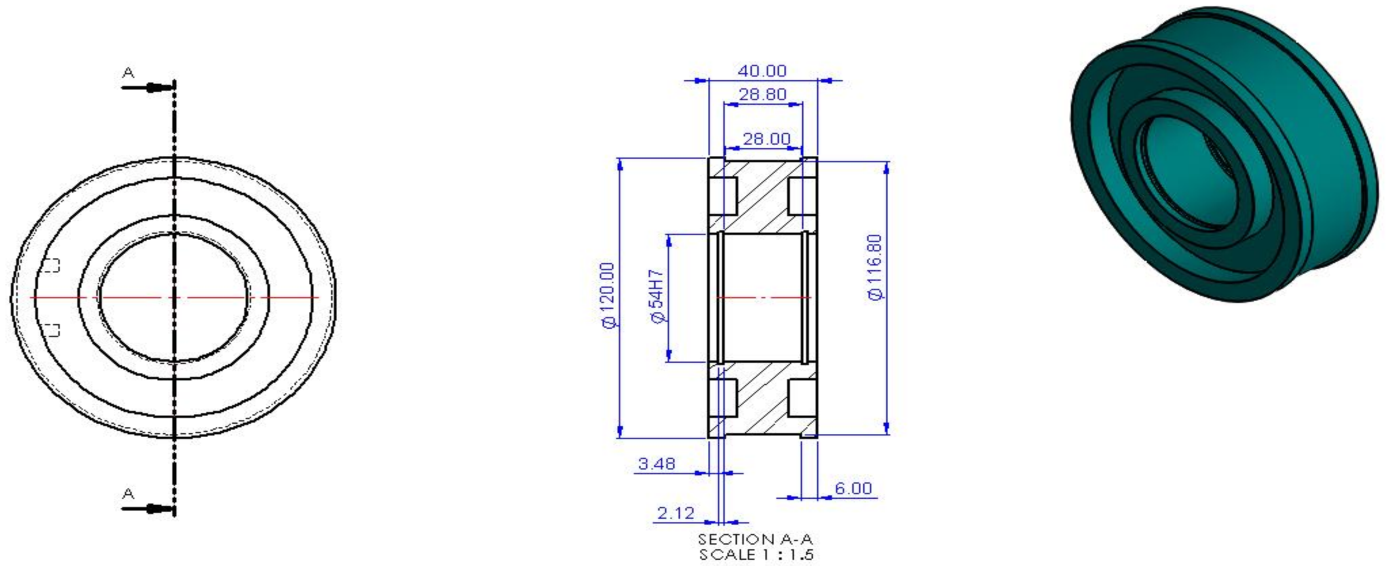

NOTE:
1. ALL THE DIMENSIONS ARE IN MM
2. DO NOT SCALE THE DRAWING
IF ANY DOUBTS PLEASE ASK

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25.0	±0.05				APPROVED		WORK ORDER NO.:		
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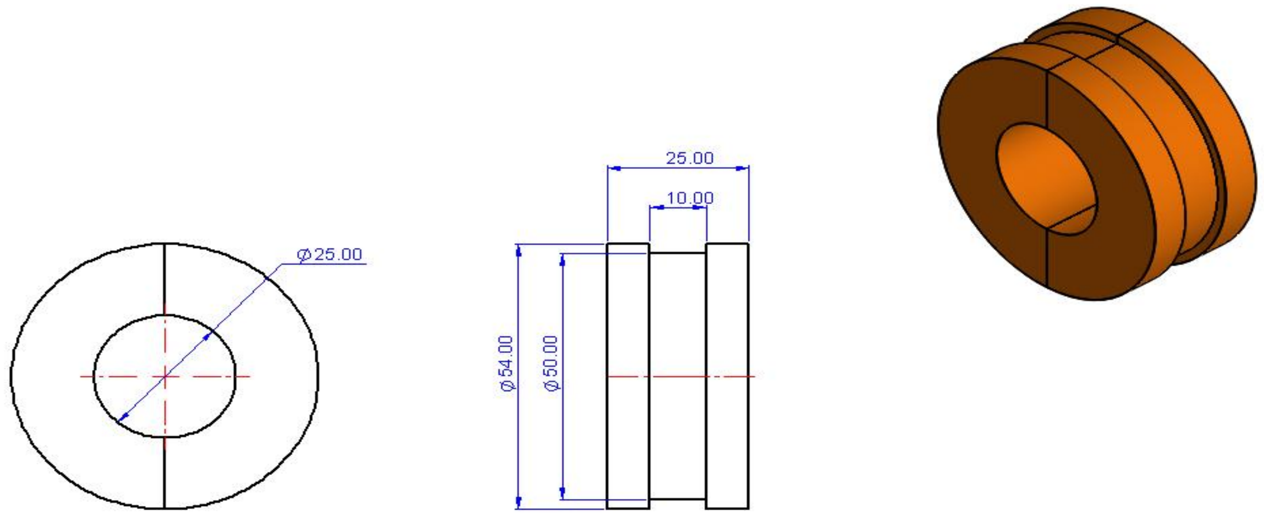
25.000	±0.005	REVISIONS	DATE	REMARKS		NTS		01	1 OF 1



NOTE:
1. ALL THE DIMENSIONS ARE IN MM
2. DO NOT SCALE THE DRAWING
IF ANY DOUBTS PLEASE ASK

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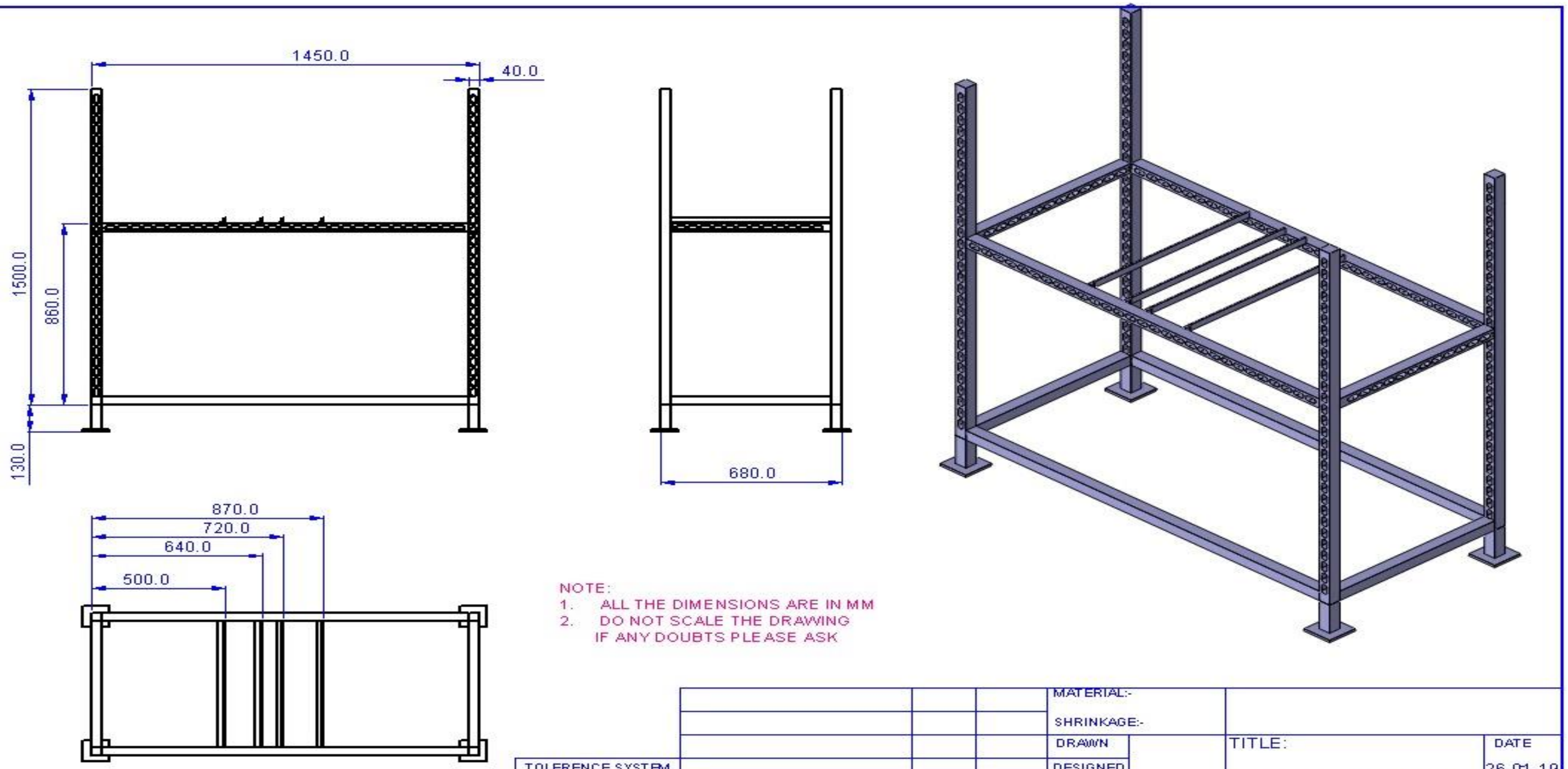
25	±0.1			CHECKED				A3	
25.0	±0.05			APPROVED		WORK ORDER NO.:			
25.00	±0.01				SCALE	DRAWING NO.	REV.NO.	SHEET NO	
25.000	±0.005	REVISIONS	DATE	REMARKS	NTS		01	1 OF 1	



NOTE:
1. ALL THE DIMENSIONS ARE IN MM
2. DO NOT SCALE THE DRAWING
IF ANY DOUBTS PLEASE ASK

TOLERENCE SYSTEM					
25	±0.1	MATERIAL:-			
25.0	±0.05	SHRINKAGE:-			
25.00	±0.01	DRAWN	TITLE: VISION SYSTEM FRAME	DATE	26-01-19
25.000	±0.005	DESIGNED			A4
REVISIONS	DATE	REMARKS	CHECKED		
		APPROVED	WORK ORDER NO.:		
		SCALE NTS	DRAWING NO.	REV.NO.	SHEET NO. 1 OF 1

Appendix B

Image Acquistion

```
clear
maxTime = 240; %in minutes
Fname =[num2str(maxTime),' minute']; % just any name for the folder
pauseTime = 60; %in seconds
cams = webcamlist; % call the webcam connected
camera1 = webcam(1);
resolution = '1920x1080';
% camera=webcam('Logitech HD Pro Webcam C920');%Connect to the
camera
camera1.Resolution = resolution;%change this but try to keep 4:3
standard
pause(10);%ensure setting of resolutions
% picture1=camera1.snapshot;
% subplot(1,2,1);image(picture1);
% path = ('Photos\');
cnts = 0;
maxTime = maxTime *60 + 10;
mkdir(strcat('C:\Users\user\Pictures\Logitech Webcam\Saved
Photos\',Fname));
presentTime = 0;
while (presentTime < maxTime)
    tic
    cnts = cnts + 1;
%     picture=camera.snapshot;
%     image(picture);title(['image ',num2str(cnts)])
    picture1=camera1.snapshot;
    subplot(1,2,1);image(picture1);title(['cam1_',num2str(cnts)])
    drawnow;
    path1=strcat('C:\Users\user\Pictures\Logitech Webcam\Saved
Photos\',Fname,'\cam1_',num2str(cnts),'.jpg');
    imwrite(picture1,path1)
    pause(pauseTime)
    presentTime = presentTime + toc;
end

clc
fprintf('Done !\n')
```

Cropping the ROI

```
clc
clear
close all

fldName = 'C:\Users\user\Pictures\Logitech Webcam\Saved Photos\180
minute\';

fname1 = 'cam1_1.jpg';


RGB1 = imread([fldName,fname1]);
imshow(RGB1)
h_good = impoly();
xy1 = h_good.getPosition;
x = floor(min(xy1(:,1)));
y = floor(min(xy1(:,2)));
w = ceil(range(xy1(:,1)));
h = ceil(range(xy1(:,2)));
theta1 = rad2deg(atan((xy1(2:end,2) - xy1(1:end-1,2)) ./
(xy1(2:end,1) - xy1(1:end-1,1))));

iRect1 = [x y w h];
iMask1 = h_good.createMask();
dist = 25;%mm

save('DistanceMask_cam1.mat','iMask1','iRect1','theta1')
```

Getting Wear

```
clc

clear
close all
load DistanceMask.mat
fldName ='C:\Users\user\Pictures\Logitech Webcam\Saved Photos\180
minute_cam2\';


folder = dir(fldName);
folder_not_a_directory = folder((~[folder.isdir]));
[filenames1]=deal({});
[index1] = deal([]);
for ii=1:length(folder_not_a_directory)
    nn = folder_not_a_directory(ii).name;
    TextSplit = strsplit(nn,{'_','.'});
    filenames1{end+1} = nn;
    index1 = [index1 str2double(TextSplit{2})];

end
if exist('theta1','var')
    theta = theta1;
end
if ~exist('dist','var')
    dist = 12.5;
end
[~,x1] = sort(index1);
```

```
filenames1 = filenames1(x1);

[pixels1,depth1] = deal([]);
for itr = 1:length(filenames1)
    filename1 = filenames1{itr};
    RGB1 = imread([fldName,filename1]);
    rgb1 = RGB1;
    rgb1(repmat(~iMask1,1,1,3)) = 0;
    rgb1 = imcrop(rgb1,iRect1);
    image1 = imrotate(rgb1,theta(2));
    VectorSum = sum(image1,3);
    yF = find(sum(VectorSum,2),1,'first');
    yL = find(sum(VectorSum,2),1,'last');
    xF = find(sum(VectorSum,1),1,'first');
    xL = find(sum(VectorSum,1),1,'last');
    image1 = image1(yF:yL,xF:xL,:);
    binaryimage1 = imbinarize(rgb2gray(rangefilt(image1)),0.15);
    Pixels_versus_row_Plot = sum(binaryimage1,2);

    if itr == 1
        pop=binaryimage1;
        [a,b]=findpeaks(diff(-Pixels_versus_row_Plot));
        [~,idx] = max(a);
        PeakStart = b(idx)+2;
        [c,d]=findpeaks(diff(Pixels_versus_row_Plot));
        [~,idx] = max(c);
        PeakStop = d(idx)-2;
        depth = 0;
        h2 = Pixels_versus_row_Plot(PeakStart:PeakStop);
        h1 = h2;
    else
        h2 = Pixels_versus_row_Plot(PeakStart:PeakStop);
        h = h2 - h1;
        [pks,locs] = findpeaks(h);
        bottomOfWear = locs(end-5);
        if isempty(bottomOfWear), bottomOfWear = 0; end
        depth =bottomOfWear/(PeakStop-PeakStart+1)*dist;
        depth=12.5-depth;
    end
    pixels1 = [pixels1 h2];
    depth1 = [depth1 depth];
    fprintf('CAM1:done %3g of %3g \n',itr,length(filenames1))
end
depth_of_wear1 = movmean(depth1,[100,0]);
depth_of_wear1= depth_of_wear1-depth_of_wear1(1);
depth_of_wear1(1)=[];
no_of_pictures1 = length(depth_of_wear1);
time1 = (0:no_of_pictures1-1)*50; %seconds
depth_of_wear1=depth_of_wear1(10:end)-depth_of_wear1(10);
time1=time1(10:end)
figure('Name','cam1')
plot(time1/60,smooth(depth_of_wear1),'o');
xlabel('Time, mins')
ylabel('Wear depth, mm')
grid on
```

Appendix C

s/n	Vendor Name	Item name	Specification
1	Bearings World Auto Spare Parts Trading L.L.C	63/28 Bearings	28 cm diameter shaft
2	SKIDAUTO.COM	Universal Joint	Borgeson Steering 1in.48 x 1DD diameter
3	ACE Al Futtaim Trading Co LLC	HOME WORKS FOLD WORKBENCH WROL	Wooden Workshop table
4	GUANGLU MOTOR FZCO	2 motors 50:1 Gearbox ratio	1400 rpm and 1hp motor 50:1 Gearbox ratio
5	SOUQ.COM	4 Logitech C920	1080p Full HD Webcam