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Abstract

The transformation from Industry 3.0 to Industry 4.0 is rapidly increasing in several industrial sectors where the automated production systems have become more as a cyber-physical and advanced production system. Internet of things (IoT), cyber-physical system, computational intelligence, cognitive capabilities and other disruptive technologies are the key enabling technologies for Industry 4.0. Recent developments in data acquisition techniques i.e. smart sensors has made it possible to initiate changes from the bottom level of complex physical systems. Cyber-physical systems have become smart enough to interconnect physical and digital world. Cognitive and computational intelligence capabilities of digital systems have been utilized to control physical equipment with minimum or zero human interference.

The transformation into industry 4.0 vision is quite demanding for several industrial sectors. Transforming the automated asset into a cyber-physical asset is a complex task since the operators need to ensure that their asset is first smart and then develop smart operations in terms of managing the maintenance and executing the required tasks. Smart asset means that the asset e.g. machine should be able to provide/share data about its behavior. Smart maintenance management operations mean that the asset data will be stored, processed, visualized in an automated and cognitive manner by utilizing several disruptive technologies related to automation of work processes e.g. predictive maintenance, artificial intelligence.

From an operator point of view, the computerized enterprise resource planning (ERP) and maintenance management systems (CMMS) e.g. SAP are the most important parts of the entire digital transformation since most of the other systems can be provided by service providers e.g. algorithms, cloud platforms. However, the operators need to deal with ERP and CMMS on daily bases and almost all acquired data from the asset will be stored and presented via those systems. CMMS is the core interface between the operator and entire digitalized production system. Thus, the operators shall be enabled to assess which CMMS (as several commercial systems are available) is most cost-effective for their applications, support the completeness of industry 4.0 vision and provide capabilities to be customized.

Concerning these needs, the purpose of this thesis is to determine the key acceptance criteria of selecting CMMS and customization aspects that are required to develop cost-effective CMMS for a specific application.

By keeping in view about requirements, a case study on an electromechanical system has been selected for this thesis where a predictive maintenance program and associated CMMS are developed. Based on this development, the key acceptance criteria and customization aspects for developing cost-effective CMMS are extracted. Moreover, industry 4.0 framework has been applied to upgrade the equipment to meet advanced manufacturing requirements. Research work is carried out on a critical processing equipment named single retention time (SRT) freezing tunnel at Gate Gourmet, United Kingdom. Systems analysis approach has been used to demonstrate case study work.

- I have used systems analysis to analyze how the selected physical system can be retrofitted to be smarter.
- I have developed a Predictive maintenance (PdM) programme for the selected system based on intelligent maintenance layers.
- I have developed a CMMS to support the PdM programme.
- I have extracted the key acceptance criteria of selecting CMMS and customization aspects that are required to develop cost-effective CMMS.

Chapter four provides a clear result of using systems analysis, which is an effective methodology to extract the failure modes, symptoms, and potential process parameters that can be monitored to detect abnormalities. The applied systems analysis of the selected physical system is an effective methodology to extract the failure modes, symptoms (required for health monitoring), and potential process parameters (required for data-driven approach) that can be monitored to detect abnormalities.

The systems analysis of the potential predictive maintenance program highlights the complexity due to the compliance with industry 4.0 requirements of the cyber-physical system at different layers (7 layers). The integrity and work process automation are main requirements to develop effective predictive maintenance program. Moreover, the developed predictive maintenance program clearly expands the expected functionality of the associated CMMS. It requires CMMS to be smarter (not just a database) by being as user interface integrator between assets (physical machines, human operations) and cyber systems (analytics, transmissions).

The systems analysis of CMMS resulted in identifying the technical functionalities and stakeholders needs with the key acceptance criteria to assess the commercial CMMS and to customize them toward the specific stakeholder's needs. The key acceptance criteria are mainly related to functionality toward increasing data volumes, velocities, veracities, and varieties, visualization, accessibility, privacy, security, interoperability with other systems, usability, scalability, affordability, and completeness to vision.

This thesis can serve as a fundamental guideline of how to analyze your physical systems to identify the requirements for developing smarter assets, predictive maintenance program, and CMMS. The extracted key acceptance criteria for selecting CMMS is significantly important to either select the best commercial option or to customize the existing CMMS solution.

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Abbreviation

SRT	Single retention time
CMMS	Computerized maintenance management system
EAM	Enterprise asset management
PM	Preventive maintenance
CM	Corrective maintenance
CBM	Condition based maintenance
PLC	Programmable logic controller
HMI	Human-machine interface
I/O	Input/output
CPS	Cyber-physical system
IoT	Internet of things
IIoT	Industrial internet of things
PEHD	High-density polyethylene
ML	Machine learning
ANN	Artificial neural networks

Preface

I am very thankful to my Idriss El-Thalji, associate professor at University of Stavanger, Norway. His passion for maintenance systems has always pushed me to think innovative and out of the box. He has always been a source of inspiration for me. I appreciate his personal support and effort to encourage me to work for my thesis outside the country.

I would also thank my mentor Christopher Styles, head of facilities and fleet UK & Ireland, Gate Gourmet for his support, endless help and generous advice during the research period.

“Finally, I want to acknowledge the support, and love of my family – my parents and siblings. They all kept me going and this work was not possible without their support”.

Author

Waqas Ashraf

1. Introduction

This chapter highlights the thesis background, problem description, scope and its structure.

1.1. Background

Industry 4.0 is a German government initiative, aimed to transform future manufacturing industry in Europe by increasing digitalization and interconnection between products, processes and business models. The transformation from automated and robotic systems (Industry 3.0) to cyber-physical systems is digitally restructuring the whole manufacturing process and value chain (Klitou, Conrads, and Rasmussen, 2017). Cyber-physical systems interconnect physical and digital world. With the cognitive capabilities of the digital world, we can develop smart assets and smart operations to manage advanced manufacturing systems. Smart assets have the functionality of interconnected machines, while smart operations use operational data for artificial intelligence and predictive analytics to improve decision making.

Transformation of automated assets into cyber-physical assets is a complex task. As highlighted in the report of European commission "Germany: Industrie 4.0", shop floor level involvement is a key barrier in the transformation process (Klitou, Conrads and Rasmussen, 2017). This digital transformation of smart assets and smart operations will be impossible without the implementation of smart computerized maintenance management system (CMMS), being the critical part of maintenance management system. As cyber-physical systems transform work processes from bottom level and minimize human dependency in the system. Therefore, **typical database system** and operator-based CMMS systems are not much effective to manage smart systems. It demands to shift maintenance from preventive to predictive approach, where machine failure could be prevented before it happens. This transformation could be carried out by the data-driven approach, in which data collected by smart sensors could be analyzed and utilized for maintenance planning and scheduling. It needs to develop computational and cognitive capabilities in CMMS to use real-time data for maintenance decision making.

1.2. Problem formulation

As per ISO 9000 quality standards, food product quality is very critical control parameter in FMCG industry. Perishable food products quality decrease with increase in temperature. It is very important to maintain, monitor and control food products temperature during the whole supply chain process (harvesting, processing, storage, and delivery). To store food products for a longer period, they need to deep freeze (reduce product temperature below -25 C°) quickly after harvesting.

This deep-freezing process is carried through single retention time (SRT) freezing tunnel which can quickly freeze food products such as fish, shrimp, meat, ice cream, dairy within 2-3-hours cycle. An unscheduled breakdown in processing phase will result in loss of production, loss of quality, labor cost, and spare parts cost. it is very critical to **maintain the asset** and **identify the failure** in advance. Another important factor to consider is to carry out repair work inside the freezing tunnel at a temperature below -25 C° is very challenging. It demands maintenance with minimum human involvement. Thus, the purpose of this thesis "is to answer the following research question" (Ekwaro-Osire, Carlos, and Alemayehu, 2018):

How can CMMS system be assessed and customized for the food industry to comply with Industry 4.0 requirements?

In fact, this question leads to three developmental issues: develop smarter assets, smarter predictive maintenance program, and smarter CMMS.

1.3. Limitation/Delimitation

Gate Gourmet is a part of Gate group; one of the world's largest food processing, airline catering, retail, hospitality, and logistics company. It is operating in four continents and has a worldwide presence with global operations in 60 countries and 160 national & international airports. The company has a total number of 28,000 employees with a net worth of 3.1B CHF. We have selected London Heathrow west production facilities of Gate Gourmet, United Kingdom.

Since this thesis is handling the development as system-level i.e. providing system architecture of PdM program, the detailed technical analyses are not considered. The case study was delimited for only SRT freezing tunnel (within the whole food catering process) in order to manage to demonstrate full case within the limited time (5 months) and resources (available data from vendors and design engineers).

1.4. Structure of the thesis

This thesis has been organized according to guideline provided by the University of Stavanger. The thesis has been divided into five chapters. Chapter 1 highlights the problem, its background, and problem statement. Chapter 2 presents theories related to Industry 4.0, IoT, predictive analytics, and CMMS. Chapter 3 highlights case company, its production facilities, and selected critical system. In chapter 4, I have carried out system analysis of physical systems and CMMS system. In the end, chapter 5 presents discussion and conclusion of the thesis.

2. Literature review and theoretical framework

This chapter highlights theory and concepts related to proposed solution for the problem. It also demonstrates key technologies related to Industry 4.0 vision.

2.1. Industry 4.0

The term Industry 4.0 (fourth industrial revolution) was first demonstrated in Hannover Fair, Germany which emphasis on the transformation of traditional manufacturing systems (Wang and Wang, 2017). In other parts of the world, similar research work is known by different names like smart manufacturing (United States, China) and intelligent manufacturing systems in (Norway, Sweden, and Finland) (Wang and Wang, 2017).

Industry 4.0 is "the extension of traditional manufacturing systems to full integration of physical, emboldened IT system including the internet" (Wang and Wang, 2017). **Figure 1** illustrates various stages of industrial evolution from Industry 1.0 to Industry 4.0; transformation from first industrial revolution to fourth industrial revolution (Varghese and Tandur, 2014). It can be seen from the figure that fundamental concepts that lead to the growth in each generation are strongly connected with the critical ideas of automation, self-configuration and self-sufficient systems which have gradually improved over time (Trappey et al., 2016).

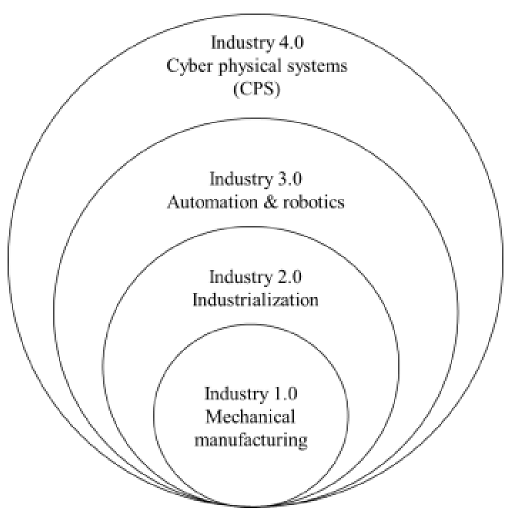

Figure 1: Industrial evolution graph. (Trappey et al., 2016)

Industry 4.0 is based on the concept of digitalization of entire value chain; an end to end digital integration of engineering systems and processes (Kagermann, Wahlster, and Helbig, 2013). It develops a networked manufacturing system by using ICT, internet connectivity and communication between devices i.e. machine to machine (M2M) and machines to the computer (M2C) (Wang and Wang, 2017). There are four key components of Industry 4.0.

- Cyber-physical systems (CPS)
- Internet of things (IoT)
- Big data
- Predicative analytics

All of these are interconnected and overlapping with each other. Internet & connectivity are the key enablers for implementation of Industry 4.0. (Wang, 2016)

2.1.2. Cyber-physical systems

Cyber-physical system (CPS) was introduced in the US in 2006. CPS is the integration of physical processes and computational systems. CPS can be considered as a basic building block in the system, which interconnects physical component of a machine (i.e. moving at high speed) with digital systems (smart sensors). Parameters monitoring of a physical process (temperature, pressure, flow, force) is a fundamental requirement in digital transformation. Advancement in the embedded system has helped to increase the functionality of sensors i.e. RFID, smart technology, nanotechnology. Radio-frequency identifications (RFID) sensors have the advantage of non-contact reading and writing capabilities. An RFID sensing system consists of “device (tag), tag reader with an Antenna and transceiver and host system” (for data storage) (Wang and Wang, 2017).

Device tag monitors and stores physical component reading, tag reader communicates the data to host system by non-contact medium (radio wave, microwave). Real-time data acquisition (**Information**) is the heart of CPS system with integration of communication, computation, and control of physical systems (Wang and Wang, 2017). **Figure 2** illustrates key elements of cyber-physical systems.

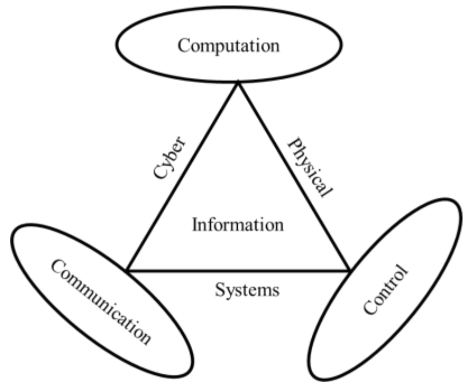

Figure 2: Cyber-physical systems (Trappey et al., 2016)

RFID technology is suitable for real-time sensing of operating parameters of a machine. It can transmit and receive data for distance up to 12 meters. It has been reported that by 2020, almost **20.8 Billion devices** will be using RFID technology for data transmission and communication (Lund et al., 2014).

CPS focuses on the digital part of the manufacturing system. CPS consists of two major functions, (1) real-time data acquisition, interaction, and communication between physical and digital world; (2) translate intelligent computations and cognitive decision (carried out in the digital world) to the physical world. **Figure 3** highlights interaction between physical and digital systems.

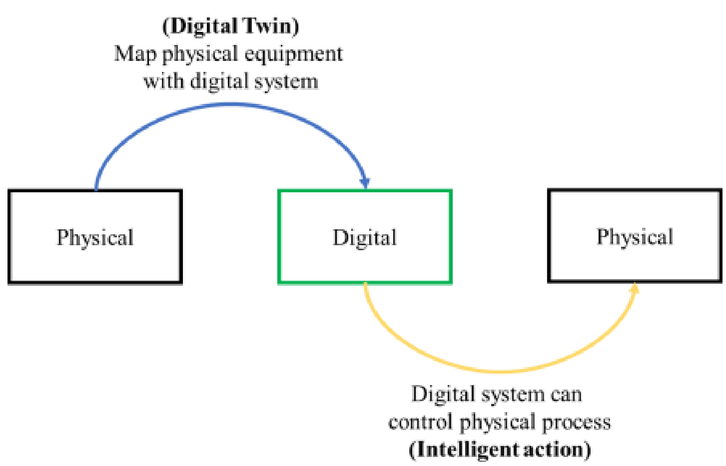

Figure 3: Physical and digital system interaction (Mueller, Chen and Riedel, 2017)

2.1.3. Internet of things (IoT)

"The term internet of things (IoT) was first coined by the MIT Auto-ID center" (Sethi, Arkko and Keranen, 2012) by Kevin Ashton. It refers to wireless communication between sensors and computing devices through the internet. "IoT can be understood from two perspectives, which are internet-oriented and things-oriented" (Wang and Wang, 2017).; The former one, internet or IP connecting a large number of devices and latter one presents a large number of things (devices). Each device (things) can be identified with a unique IP address and able to communicate over the internet through a standard communication protocol (Wang and Wang, 2017). With the invention of IPv6, 4.3 Billion devices will be able to connect over the internet with unique IP addresses. The Internet is the major key enabler of IoT concept.

As stated in National Compliance Management Services (NCMS) report that "there is a consensus that linking factory devices to the Internet will become the backbone technology for future manufacturing" (Wu et al., 2015). "IoT is key to improving automation in the manufacturing process" (Wang and Wang, 2018). For example, remote monitoring and control of process equipment and machines. Through cyber-physical systems, IoT allows human and machine to be connected in a whole manufacturing system.

IoT allows distributed cyber-physical systems (RFID sensors) to connect virtually through the internet. It works on the principle of computing concept, in which each physical component can present itself as a digital system and can able to connect, communicate through the internet. It could also identify other devices as well (Auty, 2016). Machine to machine (M2M) and machine to computer (M2C) communications of Smart sensors, wireless sensors, RFID sensors are few examples (Techopedia.com, 2018).

Generic IoT model can be represented by 4C's, connection, communication, computation, and control. Connection and communication parts are illustrated by cyber-physical systems while computation and control are distinguishing features of IoT. IoT is the technical architecture of cyber-physical systems. In this research work, advanced IoT architecture has been applied which consists of seven layers to implement IoT model in the manufacturing industry. **Figure 4** represents the seven layers of IoT and their key functions. It highlights that IoT is a bottom-up approach and systematic deployment architecture for smart manufacturing systems. The function of seven layers of IoT has been explained as under:

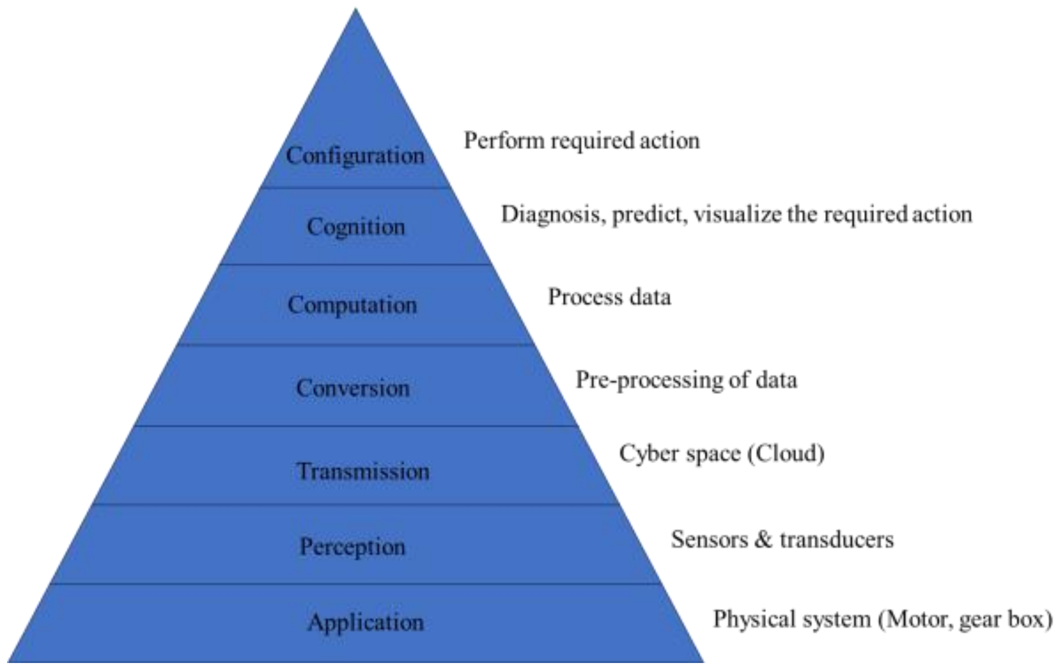

Figure 4: IoT layers architecture (Trappey et al., 2016)

Application layer: It consists of physical systems and their components such as; motors, gearbox, conveyors, rotary system.

Perception layer: It consists of measurement sensors and transducers for physical parameters monitoring. These sensors detect a change in different parameters, quantities, and events. These signals are transmitted to PLC system for control and monitoring (Trappey et al., 2016).

Connection/Transmission layer: In this layer, data from sensors is transmitted to data storage service (Trappey et al., 2016). This transmission of data could be wired or wireless. Data is usually stored on cloud servers or on-premises storage facilities.

Conversion layer: Data received from perception layer is not ready for analytics. It needs to be cleaned and processed for better decision making. In conversion layer, data from perception layers devices is converted into the desired format (structured data) and then it is ready to use for analytics in computation layer. In this step, various types of interfaces are made between different types of data sources (Trappey et al., 2016). For example, integrating archived and real-time data for specific measurement sensor. **Figure 5** illustrates data conversion layer stages. This step carries out pre-processing of data and reduces processing time in computation layer. Data conversion is very critical for real-time applications.

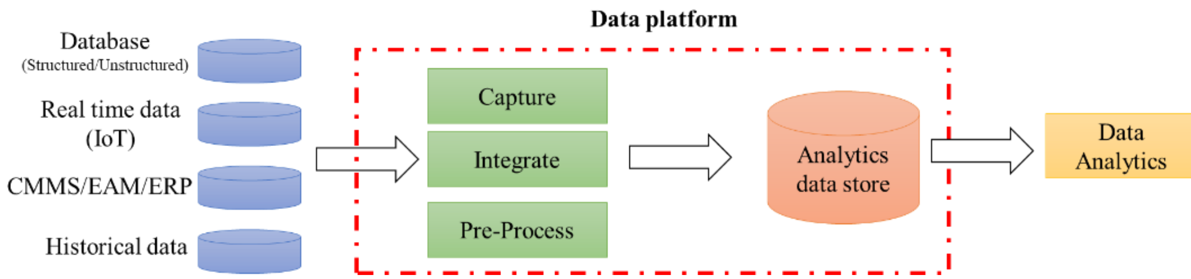

Figure 5: Conversion layer steps. (Trappey et al., 2016)

Computation layer: Computation layer uses machine learning algorithms to analyze the current state of equipment and make future predictions about the condition and behavior of the machine (Trappey et al., 2016).

Cognition layer: “Cognition presents the knowledge gathered in the higher layers for decision support” (Trappey et al., 2016). In cognition layer, computational data is used for monitoring and optimization of process parameters (Trappey et al., 2016).

Configuration layer: “Configuration is the transformation of the intelligence into action (movement from cyberspace to physical space)” (Trappey et al., 2016).

We can utilize the data acquisition, computational and cognitive capabilities of IoT layers for automation of maintenance decision making. For this purpose, an IoT based framework has been presented in **Figure 6** for intelligent maintenance system. This framework uses functionalities of the cyber-physical system and IoT architecture for automation of maintenance work process. These 8 layered structures could be divided into three major sections. The application layer, IIoT layer and cognition, and configuration layer. Application layer interconnects physical world with the digital world. Industrial internet of things uses computational capabilities of digital world data computation and analytics. While cognition and configuration, layers transform intelligent decision into the physical world.

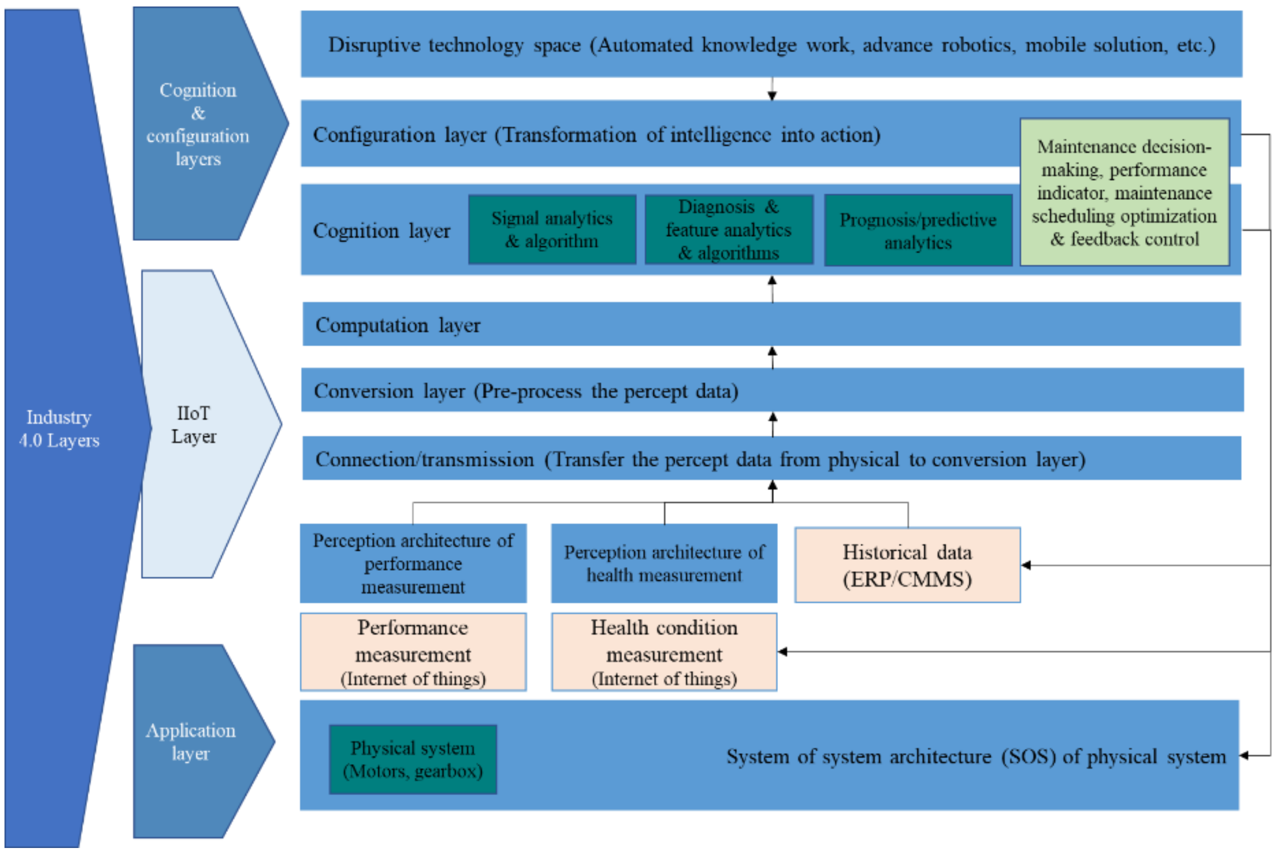

Figure 6: A Proposed framework for intelligent maintenance system (Trappey et al., 2016; El-Thalji, 2018)

2.1.4. Cloud computing

Cloud technology has been emerged as high performance, low-cost distributed network alternative. It provides hardware virtualization solutions, “virtualization: is a technology that abstracts away the details of physical hardware and provides virtualized resources for high-level applications” (Sakr et al., 2011). It provides high-speed data access and complex computing power for large-scale engineering problems through the internet. The Internet is the backbone of cloud technology (Wang and Wang, 2017).

National Institute of Standards and Technology (NIST) has defined cloud technology as "*cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction*" (NIST, 2011).

With cloud technology, an enterprise does not need to own expensive hardware and processors (GPU) to solve complex engineering problems. Instead, they can buy cloud access and high-performance computing as service, "hardware as a service (HaaS) and software as a service (SaaS)" (Kumar, 2018). Cloud computing includes hardware storage, cloud computing platform which includes operating systems, program execution environment, database, application development, testing, deployment platform. Famous IT service provider which offer cloud service are Microsoft, Google, and Amazon (Wang and Wang, 2017).

2.1.5. Big data

In manufacturing systems, a huge amount of data is generated by enterprise resources like real-time data from smart and RFID sensors, production system, automation, and control system and ERP/CMMS systems. Through internet connectivity, each component of a physical system could have the ability to connect and communicate on M2M (machine to machine) and M2C (machine to computer) level. This data can be characterized by the 3V's (volume, velocity, and variety) (Zhang, 2016).

Figure 7 highlights big data sources in maintenance systems. As shown in the figure, the high volume presents data from direct maintenance activities such as; maintenance plans, work orders, condition monitoring data. High velocity indicates high-speed data generated by smart sensors and transducers in real time. High variety represents data from multiple sources with different types and varieties.

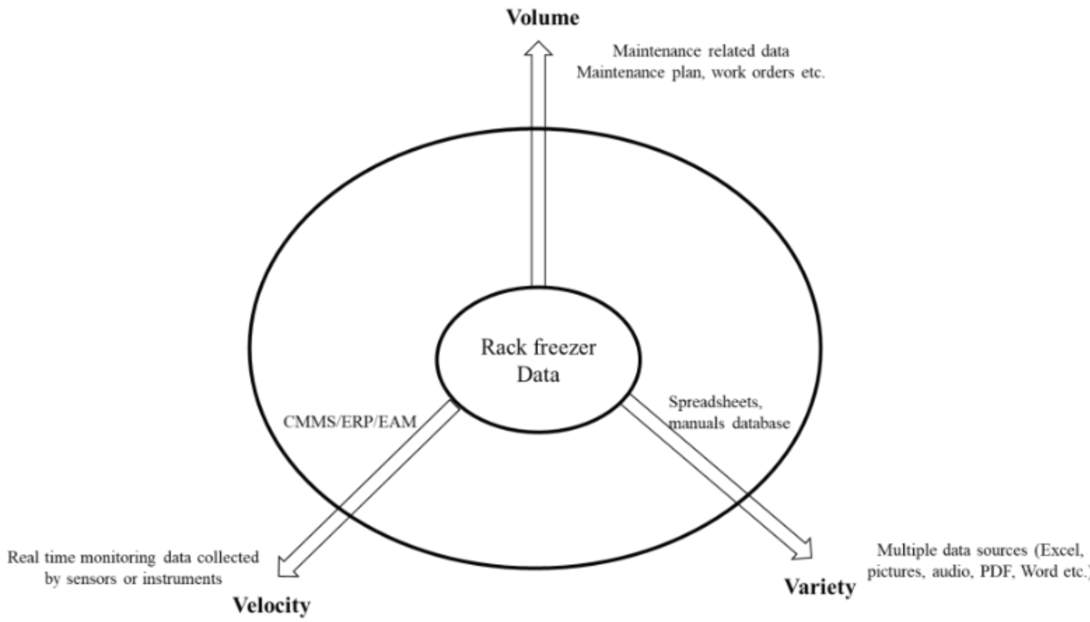

Figure 7: Big data sources in maintenance system (Zhang, 2016)

Data from all these sources is huge and heterogeneous, generating from a variety of sources in real time and high speed. This data has characteristics of being complex, decentralized and fast moving. This large amount of data is stored on Cloud servers. With limited human analytical capabilities, it is not possible to analyze the big volume of data.

2.2. Predicative analytics (Big data analytics)

Advancement in high-speed internet, high-performance processors (GPU) and cloud computing capabilities have made possible to store, process and analyze a large amount of data. Such as data received from condition monitoring sensors which could be used for processing, storage, and analysis for fault diagnosis and prognosis. Big data analytics is also known as predictive analytics. In simple words, predictive analytics is an effective approach to convert insignificant large amount data to meaningful data, which can be used by management for decision making (Wang and Wang, 2017).

Big data analytics is a computational technique for data analysis. It combines historical and real-time data to discover hidden patterns in data sets. It uses **machine learning algorithms** to discovers patterns, correlations between various data sources and make a prediction for future events and help in decision making and planning (Wang, 2016).

2.2.1. Machine learning

"Machine learning is a sub-field of artificial intelligence" (Bhandari, 2018) which teaches a machine to learn 'how to solve a problem'. Arthur Samuel (1959) has described machine learning as a "computer's ability to learn without being explicitly programmed" (Insights, 2018). Machine learning is different from classical modeling approach. **Figure 8** highlights difference between classical & machine learning modeling approach. In machine learning, input (data) and desired outputs (labels) are known and we develop a model by using machine learning algorithm to optimize the outcome.

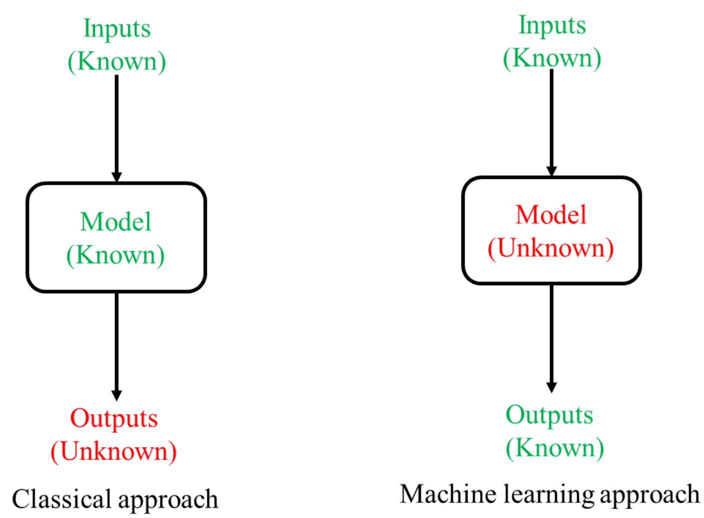

Figure 8: Classical modeling & machine learning approach. (Tegtmeyer, 2018)

The data is used by the computer to solve a given problem and make future predictions about the event that could be happening in real time (Uz et al., 2018). "Machine learning uses programmed algorithms that receive and analyse input data to predict output values within an acceptable range. As new data is fed to these algorithms, they learn and optimise their operations to improve performance, developing 'intelligence' over time" (Wakefield, 2018).

2.2.1.1. Machine learning types

Machine learning can be divided into two major categories; supervised and unsupervised machine learning.

a) **Supervised Learning:**

Supervised machine learning is analogous to the traditional education system, in which a teacher guides student for the learning process. In supervised learning, inputs (data) and outputs (labels) are known. An algorithm is supposed to find a way to reach to outputs. The algorithm analyzes the data, identify patterns in data, learn from observations.

Supervised machine learning process has been summarized in **Figure 9**. Algorithms are trained by labeled examples. Training data set guides the algorithm to reach on desired output (Khan, 2018). “This process continues until algorithm achieves a high level of accuracy” (Wakefield, 2018). The supervisor could be a human, who reviews the accuracy of output. For better accuracy of results, large data sets are required for labeled training data-set.

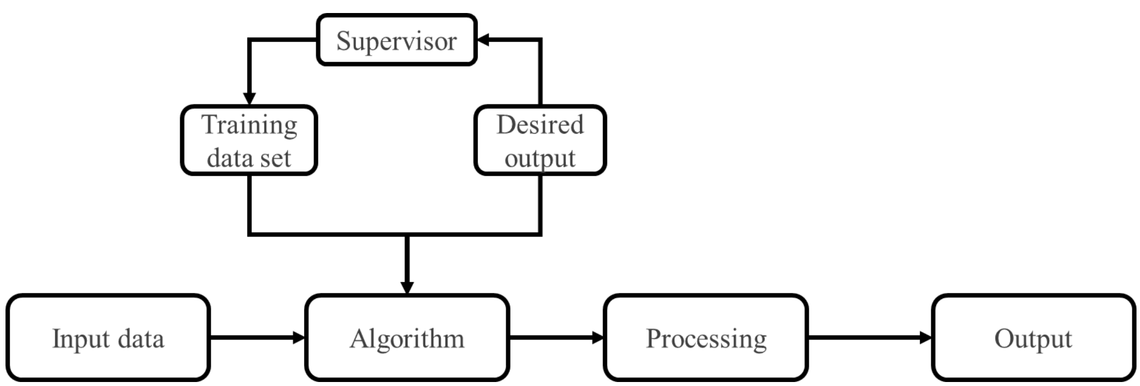

Figure 9: Supervised machine learning (Van Loon, 2018)

Supervised machine learning can be further classified into three major categories as **classification**, **regression,** and **forecasting** (Nawrocki et al., 2018). In classification, machine learning algorithm classifies input data into categories i.e. Normal and abnormal machine conditions. In regression, machine learning algorithm estimates the relationship between multiple variables and their dependencies. It is very useful to “predict the remaining useful life of the equipment in real time” (Zhicai, Dongfeng and Xinfa, 2014). In forecasting, future predictions are made on the bases of past and present data. It is very useful for trends analysis.

Figure 10 illustrates supervised machine learning process for predictive maintenance analytics process using supervised learning. Predictive maintenance uses machine learning algorithms to discover hidden patterns and correlation in real time and historical data. A supervised machine learning approach is used to train the model (McDonald, 2018). This model is deployed to predict the failures in the equipment.

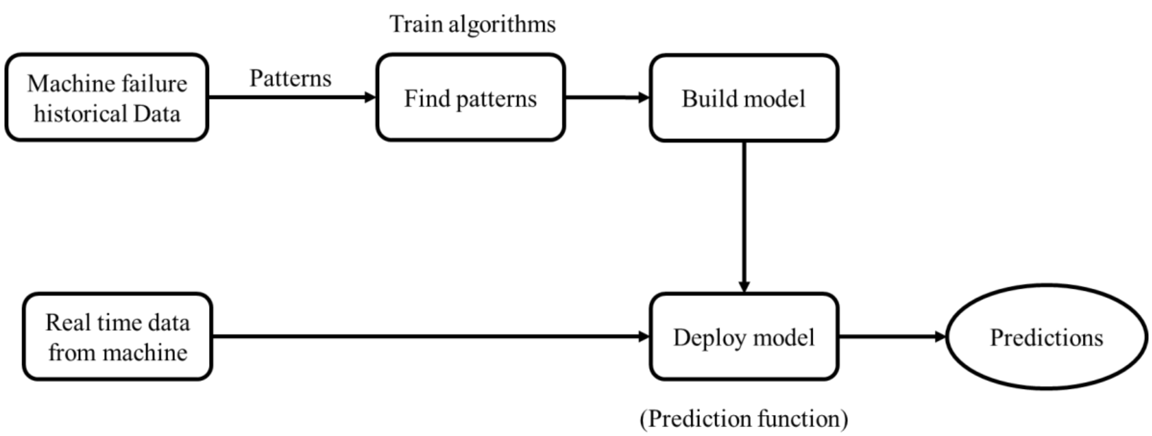

Figure 10: Predictive maintenance analytics process. (McDonald, 2018)

b) Unsupervised learning

In unsupervised machine learning, “algorithm studies data to identify patterns” (Wakefield, 2018). “There is no answer key or human operator to provide instruction. Instead, the machine determines the correlations and relationships by analysing available data. In an unsupervised learning process, the machine learning algorithm is left to interpret large data sets and address that data accordingly” (Wakefield, 2018).

“The algorithm tries to organise that data in some way to describe its structure. This might mean grouping the data into clusters or arrange it in a way that looks more organised” (Wakefield, 2018). “As it assesses more data, its ability to make decisions on that data gradually improves and becomes more refined" (Wakefield, 2018). Unsupervised learning is very useful to categorize data and Time series anomalies detection applications. **Figure 11** has summarized unsupervised machine learning process.

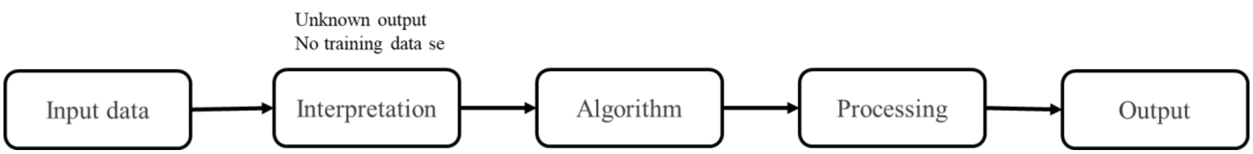

Figure 11: Unsupervised machine learning process. (Van Loon, 2018)

2.2.1.2. Algorithm selection criteria

There are large numbers of the licensed and open source machine learning algorithms available. Depending on nature of the problem, different types of machine learning algorithm are used. It is important to note that different algorithms have different characteristics, inputs, processing capacity and output accuracy. A single machine learning algorithm cannot solve all types of problems. We may need multiple algorithms to solve different types of problems. Selection of machine learning algorithm is mainly based on **business needs and objective** includes prediction requirements, accuracy requirements, time and investment resources (GPU: a graphical processing unit for data computation) available for algorithm training. **Size and quality of data** is another selection criterion for machine learning algorithm.

Selection of algorithm is often a trial and error method to reach desired output. There are two common methods to verify the algorithms. (1) Using know or recommended algorithms which are already tested to provide the desired output. (2) Using operational data from a process for 3-6 months and fine-tune the algorithm model by using supervised learning. In case of unsupervised machine learning, this duration could be increased like (6-12 months) (Wright, 2018).

2.2.1.3. Artificial neural networks

Artificial neural networks (ANN) are analogous to biological neural networks (neurons). It defines a "non-linear functional relationship between input and output data" (Graña et al., 2018), a non-linear function is used to make the relationship between inputs and outputs (Ragab et al., 2016). **Figure 12** illustrates general configuration of the artificial neural network. As shown in the figure, "it consists of three layers: the input layer, the hidden layer, and output layer" (Ragab et al., 2016). Input features are linked with an input layer, hidden layer is associated with neuron functions and output (Cerrada et al., 2015). In data-driven models, neural networks are most common algorithms to estimate remaining useful life of a component (Wang and Wang, 2017). It uses supervised learning approach to train a model.

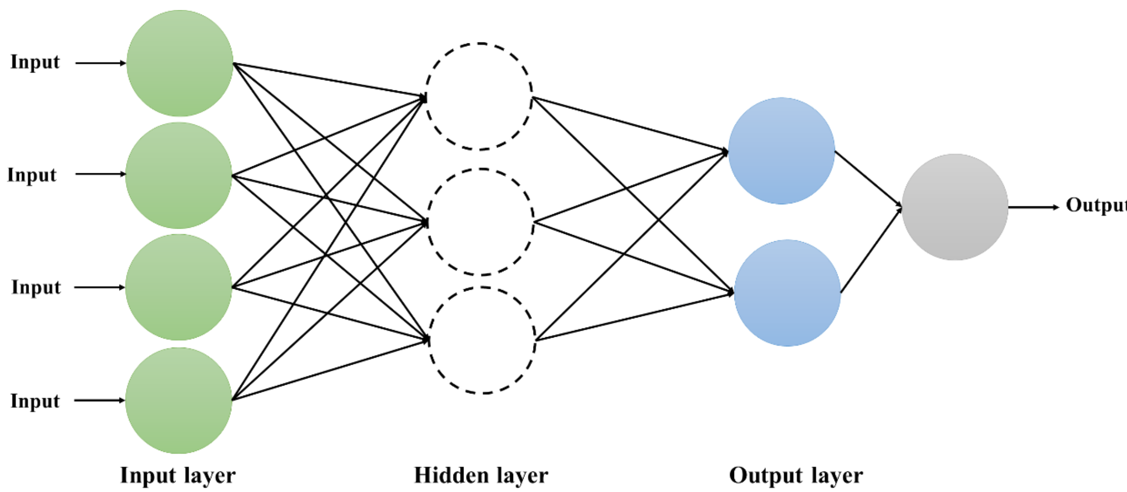

Figure 12: Generic model of artificial neural networks (ANN). (Dymczyk, 2018)

2.3. Predictive maintenance

Predictive maintenance is the industrial application of predictive analytics. Real-time monitoring capability of predictive analytics can help to detect the failure on early stage. It significantly reduces unscheduled maintenance and cost on the equipment. Predictive maintenance helps to predict equipment failure (diagnosis), forecast energy needs, improve operational performance, reduce maintenance cost and improve the reliability of an asset. For example, an irregular pattern in sensor signals can help to predict the failure pattern of an equipment. Any deviation from normal signal behavior can be categorized as a failure (Uk.mathworks.com, 2018).

Predictive maintenance uses cognitive reasoning and makes optimal decisions without human interface. It can provide a future prediction about the failure on very early stage. In predictive analytics, the health of an asset is determined based on operating conditions and maintenance recommendations based on future failure forecasting. A properly implemented predictive analytics maintenance system "can significantly reduce maintenance cost by reducing unnecessary maintenance" (Jardine, Lin, and Banjevic, 2006) activities and carry out maintenance when it is required. By eliminating unwanted maintenance can reduce asset life cycle cost, unscheduled downtime (Zhang, 2016). **Figure 13** highlights the ISO standard procedure for equipment condition monitoring process. It starts with a cost-benefit analysis to implement condition monitoring system. In the first step, critical components, failure modes, and measurement parameters are identified. Followed by fault diagnosis and prognosis.

"Diagnosis is to detect the failure that has occurred in a component (or subsystem) and isolate and identify the root of the failure, based on the data collected by the embedded sensors. Prognosis is to estimate the time at which a component will fail to operate at its stated specifications based on its current condition as well as the future load and environmental exposure, i.e., the prediction of the remaining useful life (RUL) of the component. RUL is a commonly used parameter to assess the reliability (or reusability) of a used component" (Nee, 2015).

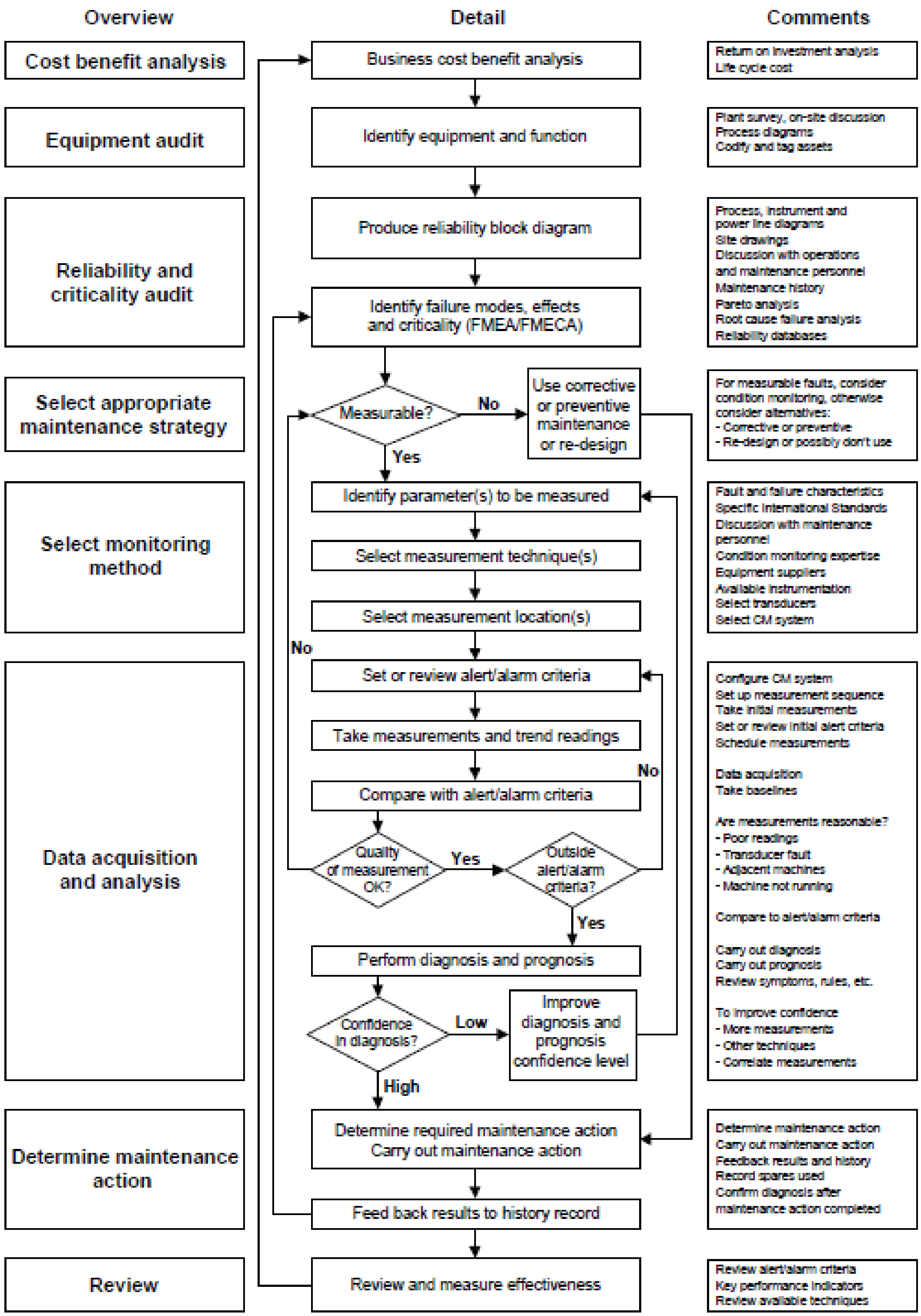

Figure 13: Condition monitoring procedure flowchart (ISO 17359:2011(E))

2.3.1. Predictive maintenance and performance measurement model

Using IoT based intelligent maintenance and predictive analytics capabilities of maintenance system. A predictive maintenance and performance measurement model have been illustrated in **Figure 14**. As shown in the figure, there are five major modules of intelligent predictive maintenance model. (1) Data acquisition, (2) Data manipulation, (3) Diagnostics and Prognostics, (4) Key performance indicators and (5) Optimization (Wang, 2016; El-Thalji, 2018).

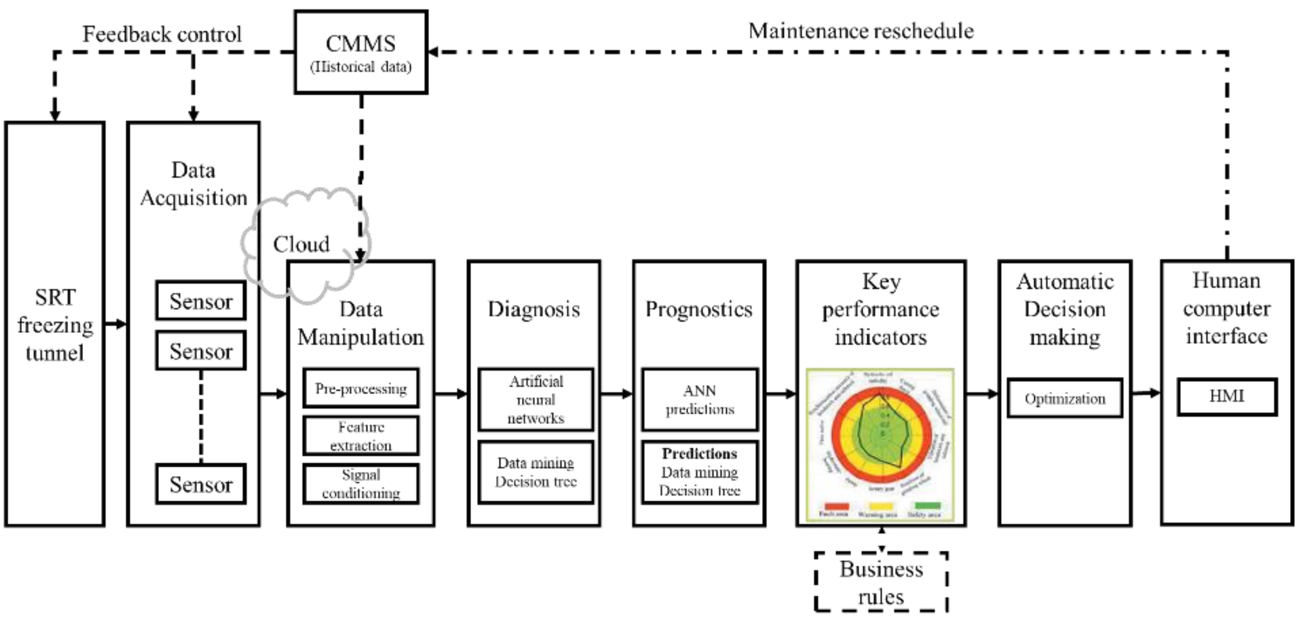

Figure 14: Intelligent predictive maintenance model (Wang, 2016; El-Thalji, 2018)

a) Data acquisition

Data acquisition is the first step in the implementation of intelligent predictive maintenance. In this step, appropriate sensors are selected, installed on the machine at a suitable location where optimal output signal can be generated for the condition of the equipment. This data is collected in real time and stored in a cloud server. Then, this data is transformed to a domain which contains maximum information about the condition of the equipment (Wang, 2016).

b) Data manipulation

Data collected from multiple sensors are not readily available for analytics, it has some missing features such as noise, redundant data, incorrect sensors readings. Therefore, it is necessary to sort, filter and prioritize the raw data before processing (Lee et al., 2014). In data manipulation module, two steps are carried out. (1) **Pre-processing and conditioning** and (2) **feature extraction**. In pre-processing and signal conditioning: signal characteristics and quality are improved. Various techniques are used for this purpose like filtration, amplification, data compression, de-noising; to remove noise from the signal to improve the signal-to-noise ratio. In features extraction: important features from the pre-processed signal are extracted which highlight incipient failure (Wang, 2016). Generally, there are three domains, from which we can "extract features time domain, frequency domain, and time-frequency domain" (Ahmed, Banaee and Loutfi, 2013). Selection of domain depends on equipment system analysis (Wang, 2016).

c) Diagnostics and prognostics

Signal identified in data manipulation section is used to identify faults of equipment. "Diagnostics focuses on detection, isolation, and identification of fault" (Wang, 2016) while prognostics focuses on the prediction of occurring of a fault (in future). Various types of fault diagnosis and equipment condition assessment models are available which could be selected based on system analysis. Selection of model is based on the availability of historical data and learning techniques; supervised and unsupervised (Uk.mathworks.com, 2018). **Figure 15** highlights method for fault diagnostics and prognostics.

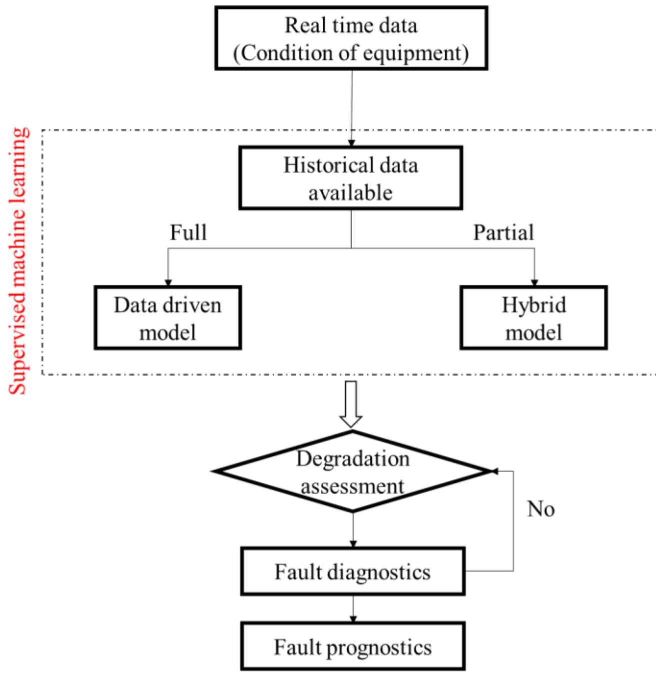

Figure 15: Fault diagnostics and prognostics model (Wang, 2016)

Time is a critical factor in prognosis. Remaining time to failure of a component ("how much time is left before a failure occurs" (Wang, 2016) is calculated. It is also called remaining useful life (RUL) of a component or machine. Intelligent predictive maintenance system calculates the remaining useful life of a component based on the data-driven model. It also analyzes the relationship between remaining useful life (RUL) and condition of the component or machine (Wang, 2016).

d) Key performance indicators

Degradation of components is graphically presented by using a radar chart/spider chart or risk chart. Key performance indicators are scaled on the basis of severity, criticality, business rules and safety. These charts help operators to visualize condition of the components graphically.

e) Optimization

It is possible to design a highly reliable equipment, but it may not be economical for industrial use. As high reliability comes up with a high cost. It is important to choose an optimal solution between failure, cost, and reliability of equipment. Similarly, in intelligent predictive maintenance, it is possible to set maintenance diagnosis and prognosis rules and limits with respect to failure, cost or reliability. Each factor has its own consequences, high-reliability results in low equipment failure but high maintenance cost.

The best approach is to make a trade-off between equipment failure, reliability, and maintenance cost. **Maintenance rescheduling** should be carried out at an optimal interval where lowest cost results in low equipment failure and high performance and reliability. A conceptual idea has been presented in **Figure 16** to highlight the relationship between failure, reliability and maintenance cost.

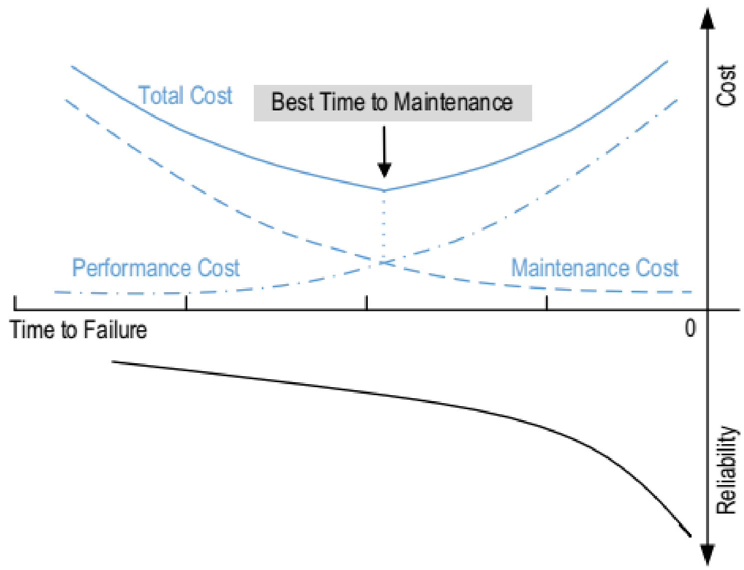

Figure 16: Relationship between failure time, reliability, and maintenance cost (Wang et al., 2015)

2.4. Computerized maintenance management system (CMMS)

"A computer-managed maintenance system is an integrated set of computer programs and data files designed to provide its user with a cost-effective means of managing massive amounts of maintenance, inventory control, and purchasing data" (Cato and Mobley, 2002). It is important to note that "the CMMS is a tool used to improve maintenance and related activities", "it does not manage the maintenance operations" (Cato and Mobley, 2002). It is also referred to as enterprise asset management software (EAM).

Computerized maintenance management system (CMMS) is a major part of the maintenance information management system (en.wikipedia.org, 2018). It's a software platform for maintenance system management. It helps in systematic planning, execution, and control of maintenance activities. It provides a cost-effective way to manage human and capital resources (Cato and Mobley, 2002). **Figure 17** highlights the resources which need to be managed in an enterprise. It can be seen from the figure that maintenance is the sub-part of enterprise and production system. Maintenance systems have high importance as both depend on it. CMMS software helps to manage resources such as labor, spares, tools, information, cost and out-sourced repair activities. These inputs result in production output, availability, maintainability and the safety of assets.

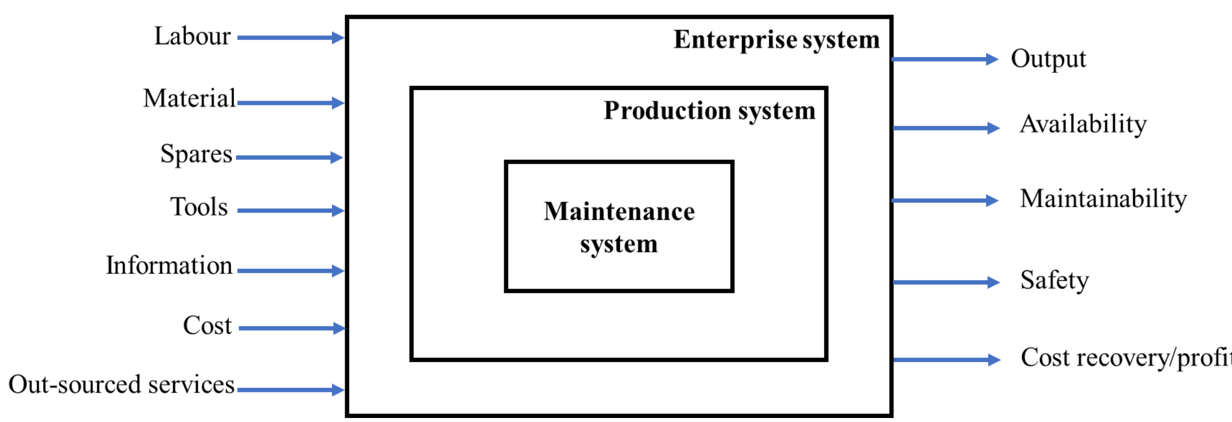

Figure 17: Input and output model for an enterprise. (Al-Turki, 2009)

CMMS is a transformation from a paper-based working environment to a computerized digital storage. It helps to eliminate traceability and recording of paperwork. Table 1 summarizes the key benefits of CMMS. CMMS helps to manage track maintenance activities such as percentage of PM work completed and backlog work order management.

Table 1: Benefits of CMMS (Ahmed Soliman, 2015)

Computerized maintenance management system (CMMS)	
• Reduce maintenance backlog • Reduce maintenance cost • Reduce overtime • Reduce follow up a time to repairs • Reduce outsourced contract maintenance work	• Improve maintenance planning and scheduling • Improve maintenance service tracking • Improve technician and service engineer performance • Improve technician and supervisor planning • Very helpful in various certifications (ISO/food/BRC)

Based on the functionality of CMMS, the software package is "grouped into subsystem or modules for specific acidity set. These subsystems may include but are not limited to" (Cato and Mobley, 2002).

- Equipment/asset register
- Preventive maintenance (PM) planning
- Work order management
- Human resource management
- Inventory management

Equipment/asset register is a database of all the equipment in the plant. All maintenance activities are linked to an asset. So, it is linked to all other databases such as PM planning, inventory, and purchase. Preventive maintenance (PM) planning module contains PM plan for the registered assets/ equipment based on maintenance checklist and frequency. The work order is the backbone of CMMS system. (Cato and Mobley, 2002). A work order can be generated by planned PM or unplanned maintenance activity. As shown in **Figure 18**; work order is the heart of CMMS system. All modules are connected and updated through a work order. Human resources include personnel and technician who carry out maintenance work activity. Inventory management includes warehousing, purchase, and ordering of spare parts (Cato and Mobley, 2002).

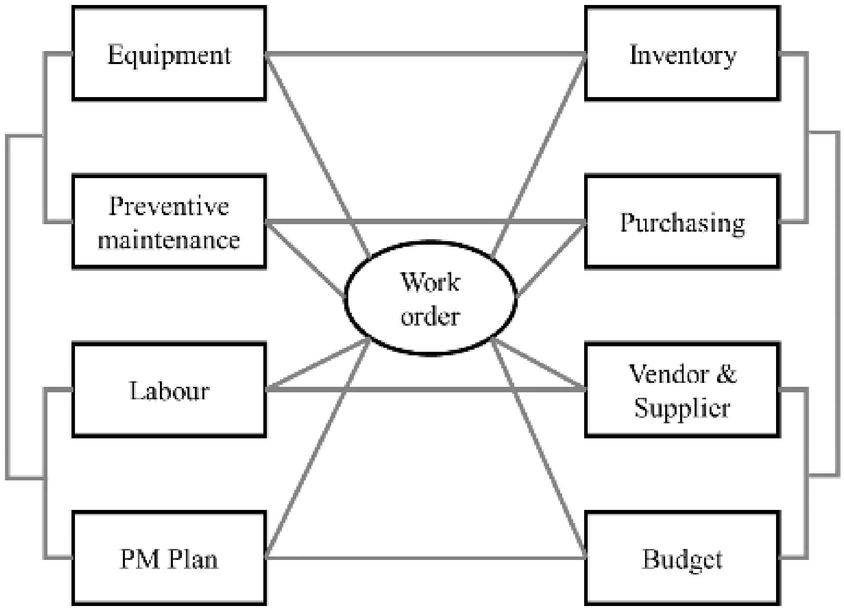

Figure 18: Integration of various CMMS modules. (Ahmed Soliman, 2015)

CMMS software is available in a variety of cost-effective models such as LAN-based or licensed software or web-based or software as-as service (SaaS) model. The LAN-based software is purchased by the company and all the data is stored on the company servers, major maintenance of parts is carried out by company IT staff or with the help of service vendor. Web-based software is available through monthly or yearly subscription. Data is stored in cloud storage and all maintenance activates are carried out by the software provider. In next decade, LAN-based CMMS software will be preferred by large organizations while the small organization will prefer SaaS-based solution. (Steenstrup and Analyst, 2017).

With the significant improvements in ICT system and high-speed internet. Focus on tradition CMMS just as the database is reducing. Instead, it's shifting toward automation of decision making using analytic tools. Based on current and future market trends, innovation and addressing customer needs (Steenstrup and Analyst, 2017), New trends in CMMS or enterprise asset management industry are (Khan, 2018)

- Industrial internet of things (IIoT)
- Cloud computing
- Big data and advanced analytics

- Blockchain
- Mobility and SaaS

Industrial internet of things (IIoT) uses industrial Ethernet for connected devices concept. Cloud computing and big data analytics include processing of a large amount of data for predictive analytics using machine learning algorithms. Blockchain technology is helping asset management to capture all transactions and change in the state of the equipment (Venkataraman et al., 2017).

CMMS software vendors can be categorized into two major groups tier 1 and tier 2. Tier 1 CMMS software includes SAP, IBM Maximo, Infor LN and IFS. While tier 2 CMMS can be named such as Avantis (Schneider Electric), Ellipse (ABB), Oracle, Mainsaver, eMaint, Fiix etc. There are many CMMS software vendors who are working to introduce new technicities in asset management industry. **Figure 19** highlights the Gartner 2017 report, which has scaled famous CMMS software such as Infor, IBM, SAP, and IFS based on their vision and ability to execute the changing market condition (Steenstrup and Analyst, 2017).

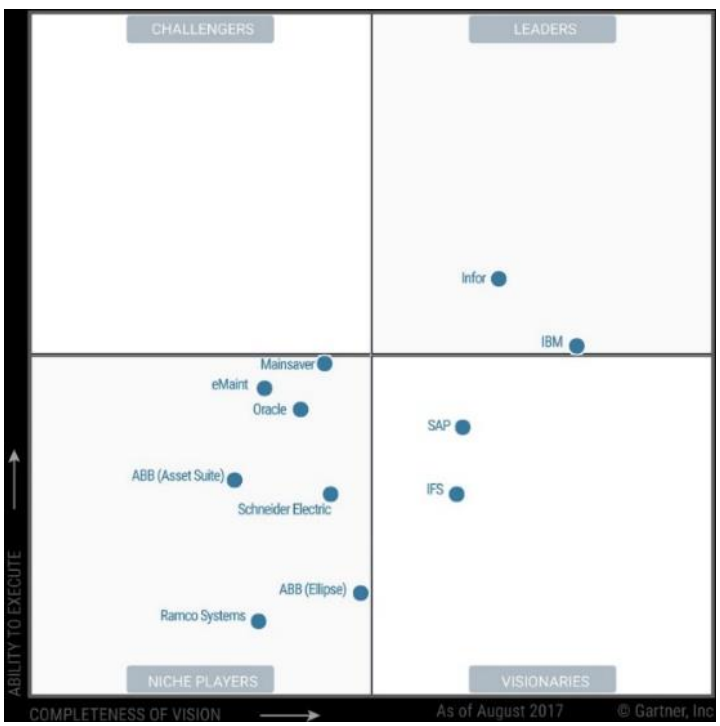

Figure 19: Magic quadrant of enterprise asset management software. (Steenstrup and Analyst, 2017)

2.4.1. Needs, requirements and acceptance criteria for CMMS system

To identify CMMS system needs and requirements, I have carried out the interview with maintenance manager, production manager, maintenance supervisors and technicians in the company. I have used a template sheet to record customer response. This sheet is attached in **Annex A**. Feedback received from the management have been summarized in Table 2.

Table 2: Customers' needs and requirements

Stakeholder	Needs	Requirements
Maintenance	The company needs a maintenance management system to solve their business needs	The system should be able to capture maintenance data for all assets.
Maintenance	The system should record all the maintenance information of asset, stakeholders, and shareholders and the strong relations with company other software.	The system should work with a central focus to obtain all information to maintenance managers.
Maintenance	The system should be able to recognize equipment problems and report them in a timely manner.	The system should be able to detect errors, failure, and correct equipment problems.
Maintenance	Software should have the latest information about the condition of the equipment.	Software should have access from real-time data from machine sensors.
	Equipment and software should be able to send and receive information.	Machine condition data should be stored in such a way that software can access it.
Maintenance	The information should be sent to software automatically.	The software should make data processing, (data received from sensors). The system should be able to transfer important data from the equipment quickly.
Maintenance	The system should be able to detect all sensors.	The software should be able to collect data from multiple data sources, types and formats. The system should be able to store and process a large amount of data.
Maintenance	The system should work without human interaction.	The software should work in automatic mode.
Maintenance	All technician should be able to use the system.	There should be enough number of the user account in the software.

		All technician should be trained to use the software.
Maintenance	The output from the software should be understandable.	The output data should be presented in an in comprehensive and summarized way.
Maintenance	The system should ensure data privacy.	The system should be secure to operate and use.

From stakeholder needs and requirements, we can deduce following acceptance criteria's. The CMMS software should be capable to handle maintenance data from various **sources** e.g. online, offline, real-time sensor data, equipment current condition data, equipment failure historical data. It should be able to receive **real-time data** from the equipment sensors. The software should be able to store **big data**. Which could be achieved using **cloud** storage of on-premise data storage. For automatic operations, we need to implement **predictive analytics** approach for automatic decision making without human interface. It should be able to support **intelligent predictive maintenance and performance measurement** (PdM). The output of CMMS should be presented and **visualized** in a summarized way, reports, charts and real-time alarms.

3. Case study and data collection

This chapter elaborates the summary of fieldwork carried out at case company. Its highlights its production, operational facilities, and analysis of the critical physical system.

3.1. Case company

Gate Gourmet is one of the world largest food processing, airline catering and food provisioning services company established in 1992 and currently operating is four continents viz. Europe, America, Australia, Asia. Gate Gourmet has a worldwide presence with global operations in 60 countries and 160 national & international airports. The company is specialized in food processing and catering service for airplane flights with a total number of 28,000 employees with a net worth of 3.1B CHF. The companies main headquarter are located in Zurich, Switzerland. The company provides 250 Million meals per year to more than 260 airline companies at 120 local and international airports (Airline Suppliers, 2018).

In the airline industry, food supply-demand is continuously changing due to new ticket booking, cancelation, and delay in flight schedule. The company uses SCALA software to manage its food supply demands. More than 250 airlines companies scan interact with Gate Gourmet through SCALA system. They can easily request desired on of meals, modify and update their food demand even some hours before the flight (Coursehero.com, 2018). **Figure 20** represents Gate Gourmet supply chain process. It consists of a complete set of activities from the purchase of raw materials, processing, freezing, and delivery of end product to the consumers.

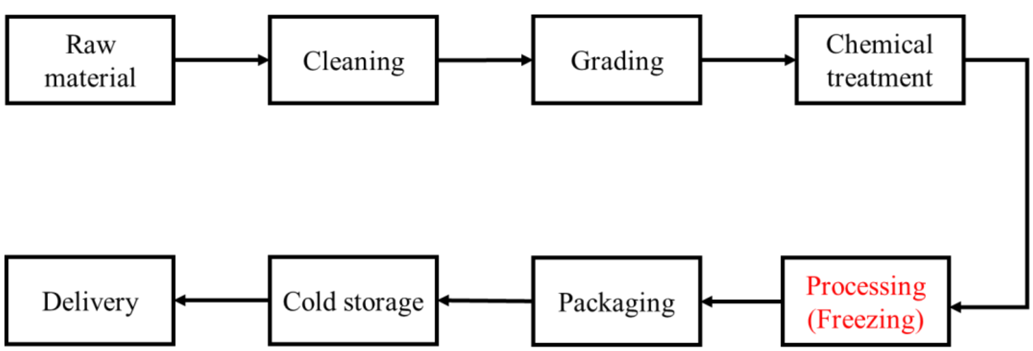

Figure 20: Processing plant - Supply chain process

Raw material receiving involves the purchase of raw material of aquaculture products (shrimps, fish) and meat. This material is cleaned and washed and sorted according to size and quality of materials. Later, these materials are treated with SMBS (Sodium metabisulfite) to increase the shelf life of the product. The product is quickly freezing to achieve a core temperature of -18 C to protect from bacterial growth. Finally, this is packaged and stored in cold storage.

3.2. Production facilities

Gate Gourmet production facility is located near to London Heathrow airport and it provides services to airline companies at Heathrow airport, the 7th busiest airport in the world (en.wikipedia.org, 2018). It has large food processing plant with several production and process sections. Raw material receiving area, processing areas, freezing system, packing stations, cold storage and shipping areas. Freezing systems consists of three large-scale freezers, SRT freezing tunnel 1, SRT freezing tunnel 2 and an individual quick (IQF) freezer; which freeze the product individually. SRT freezing tunnel freezes products in a minimum of one kg box, which is called slab. Such low temperature is achieved by using Ammonia gas for the refrigeration cycle. A separate refrigeration plant is installed close to the processing plant to supply chilled air.

3.2.1. Operating facilities

Gate Gourmet day to day operations is managed by four main departments, production, quality, process control and maintenance dept. Production dept. deals with production requirements and production targets as per sales demand. Quality dept. look after all the products are produced as per SOP's quality requirements. Hygiene and sanitation are responsible to maintain hygienic conditions in the processing facility. Process control dept. keeps an eye on process parameters for temperatures, chemical ratios etc. Maintenance department takes care of all equipment operations, maintenance, and repair. **Figure 21** highlights Gate Gourmet production facilities.

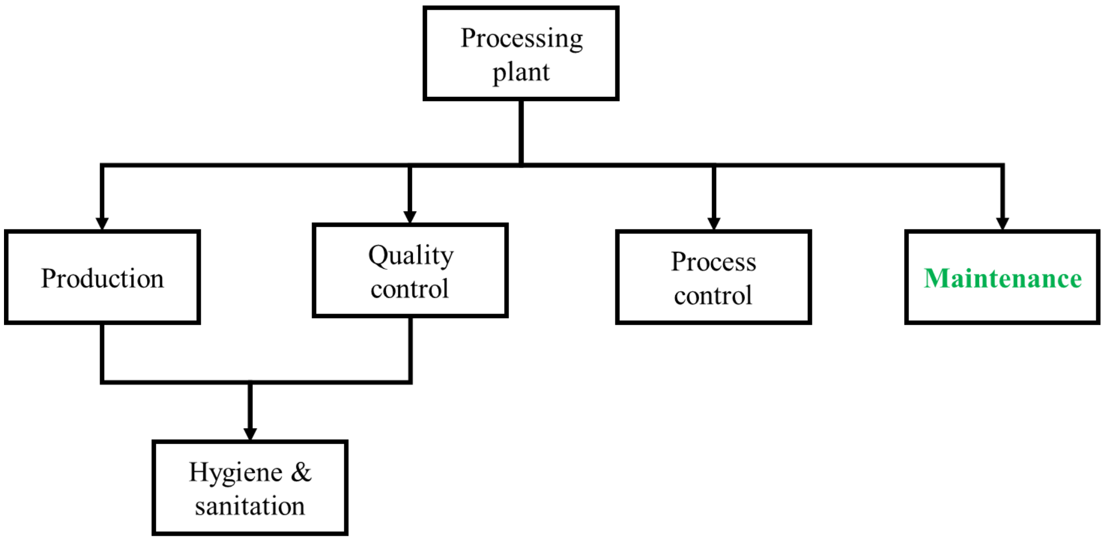

Figure 21: Gate Gourmet – operational facility

3.3. Selected critical physical system

SRT freezing tunnel is designed, developed and manufactured by Hense Jensen Engineering, Denmark. Freezing tunnel/Rack freezer is a large-scale industrial freezer which is used to quickly freeze bulk quantity food products (shrimps, fish, meat, dairy ice cream etc.). The freezing tunnel is a critical equipment is food processing industry. It works on the principle of single retention time (SRT). Retention time is the amount of time a product spends in the freezer once it has been injected into the freezer. This time varies with respect to product size, thinness, and shape. For example, the retention time for large products (fish) is different from small ones (shrimp).

Figure 22 illustrates overall system view SRT freezing tunnel. As shown in the figure, it consists of infeed system, rack system, and outfeed system. Infeed system consists of infeed conveyor, infeed pusher, and buffer plate. Rack system consists of 216 racks, chain tension station. The outfeed system consists of outfeed buffer plate, pusher, and outfeed conveyor. It also consists of electromechanical and refrigeration system.

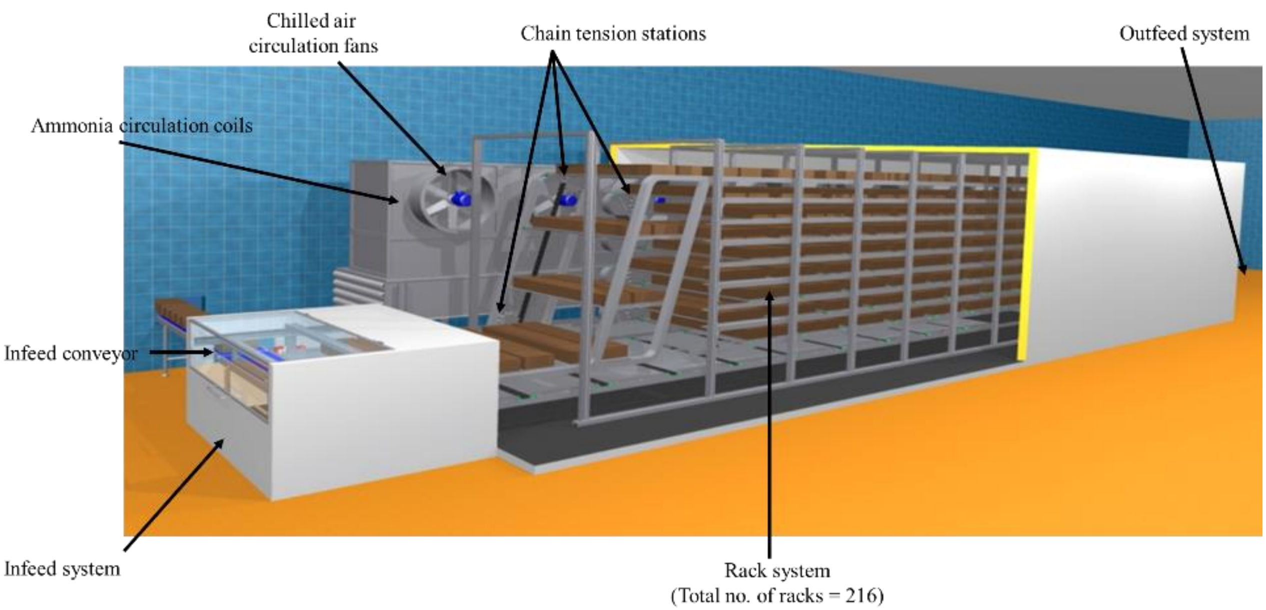

Figure 22: Single retention time (SRT) Freezing tunnel (Hans Jensen Engineering, 2018)

The SRT freezing tunnel "freezes the same product at a time as the tunnel operates with 'First IN – First OUT', which means the products get the same retention time. This tunnel is for small to large quantities of products per hour" (Hans Jensen Engineering, 2018). SRT freezing tunnel has a production capacity of 5.1 tons in one complete cycle. A complete cycle lasts for 2-3 hours, depending on the size of the product. Large products need higher freezing time to achieve core temperature. Table 3 presets production capacity calculation for SRT freezing tunnel.

Table 3: SRT freezing tunnel production capacity calculations

SRT freezing tunnel production capacity		
1 slab weight	1 kg	
No of slabs on a rack	24	(8 slabs in a row x 3 row on one rack)
Total Product weight on one rack	24 kg	
Total no. of racks	216	
Total product processed in one cycle	5184 kg	(24 x 216)
Processing capacity (1 Batch)	5.1 Ton/cycle*	*one cycle is approx. 2-3 hours
Freezing tunnel Processing capacity	40 Ton/Day	

4. System analysis and results

This chapter demonstrates applied system analysis approach to prose solution for the selected physical system and CMMS systems.

4.1. System analysis for selected physical system

4.1.1. Lifecycle processes

SRT freezing tunnel has eight life cycle processes which are listed in Table 4. Stakeholders on lifecycle phases are distributed between vendor and customer. Hans Jensen Engineering, Denmark is the vendor which have designed and manufacture the system. Gate Gourmet was the customer to purchase the equipment and responsible for the operation and maintenance of the equipment.

Table 4: Freezing tunnel lifecycle process

Sr. #	Lifecycle process	Stakeholder	
		Vendors: Hans Jensen Engineering	**Customer: Gate Gourmet**
1	Research & development	✓	-
2	Manufacture	✓	-
3	Logistics & supply	✓	✓
4	Installation & Commissioning	✓	✓
5	Training	✓	✓
6	Operation & Maintenance	-	✓
7	Upgradation & modification	✓	✓
8	Disposal & retirement	✓	✓

4.1.1.1. Key stakeholders

There are three major stakeholders of SRT freezing tunnel, production, maintenance and quality department. The production department is responsible for utilization of freezing tunnel. The maintenance department is responsible for daily operations and maintenance of freezing tunnel while the quality department is responsible to ensure that product processed in SRT freezing tunnel is as per company quality requirements.

4.1.2. System context

SRT freezing tunnel consists of three major parts, infeed, rack system and outfeed system. It also consists of mechanical, refrigeration and electrical system. **Figure 23** illustrates system context of SRT freezing tunnel.

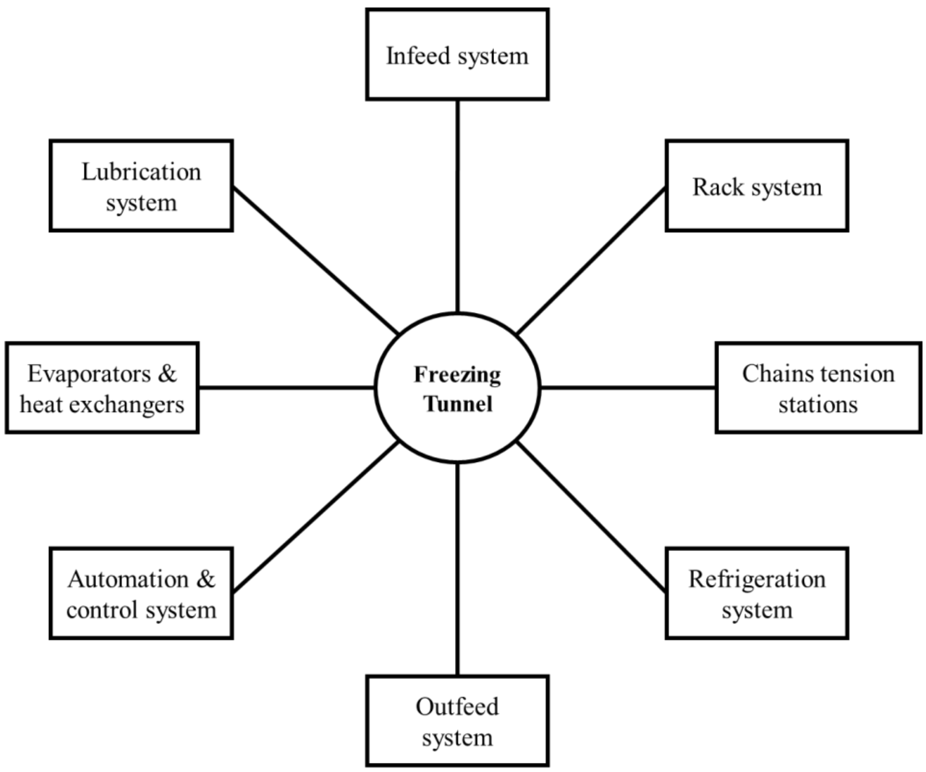

Figure 23: System context of Freezing tunnel (Hans Jensen Engineering, 2018)

4.1.3. System breakdown

SRT Freezing tunnel consists of three major systems, (1) **Infeed system**, (2) **Rack system** and (3) **Outfeed system**. Infeed system consists of 2 infeed conveyors, photo sensor, buffer plate, slabs pusher (wiper) Safety glass cover. Photosensor counts 8 product slabs and stops the conveyor. Product slabs are moved from the conveyor to racks by means of the automatic pusher (sweeper). Slabs pusher moves the 8 slabs to buffer plate (from infeed conveyor). When buffer plate and rack are on the same level, slabs pusher moves 8 product slabs to racks. **Figure 24** presents SRT freezing tunnel infeed system.

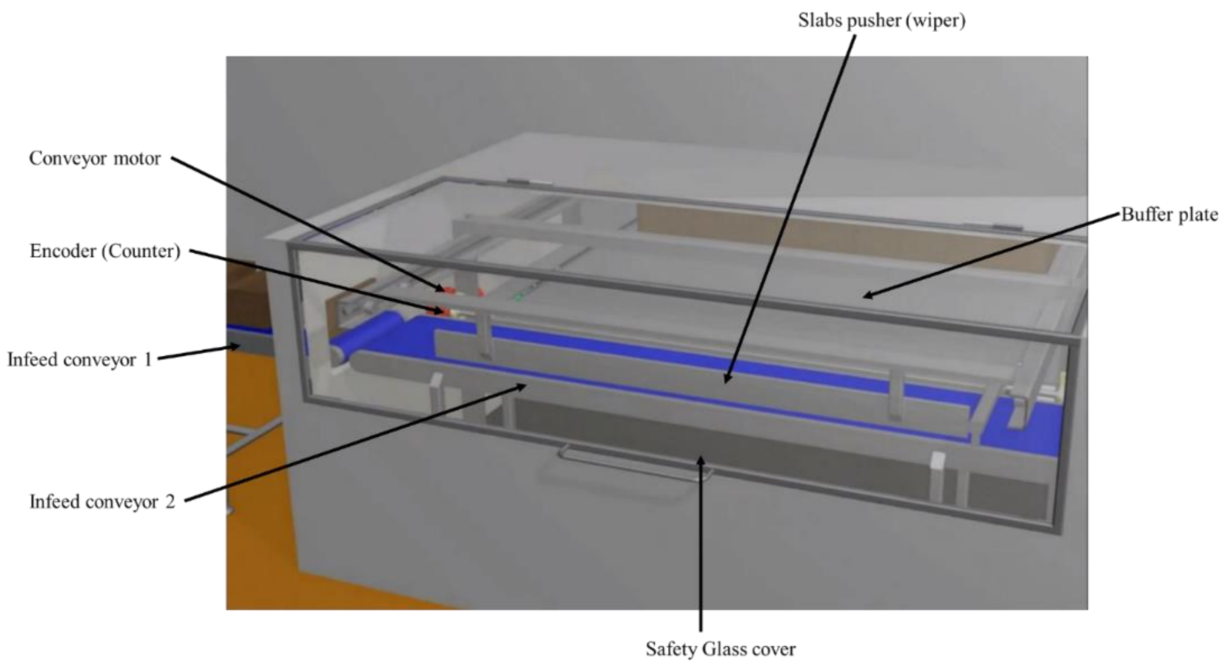

Figure 24: Infeed system - SRT freezing tunnel. (Hans Jensen Engineering, 2018)

Rack system consists of racks, main chain, and two drive motors, chain tension stations (lower, middle and top), bearings, wheels and refrigeration system (chilled air circulation fans, evaporators and defrost system). Racks are driven by two main chains, which are installed on each side of racks. Size of each chain is 3 inch (thickness). Racks are connected with a chain through chain pins. Broken chain pins can cause a breakdown. Racks are turned through PEHD wheels and always kept in the horizontal direction. **Figure 25** highlights inside view of SRT freezing tunnel.

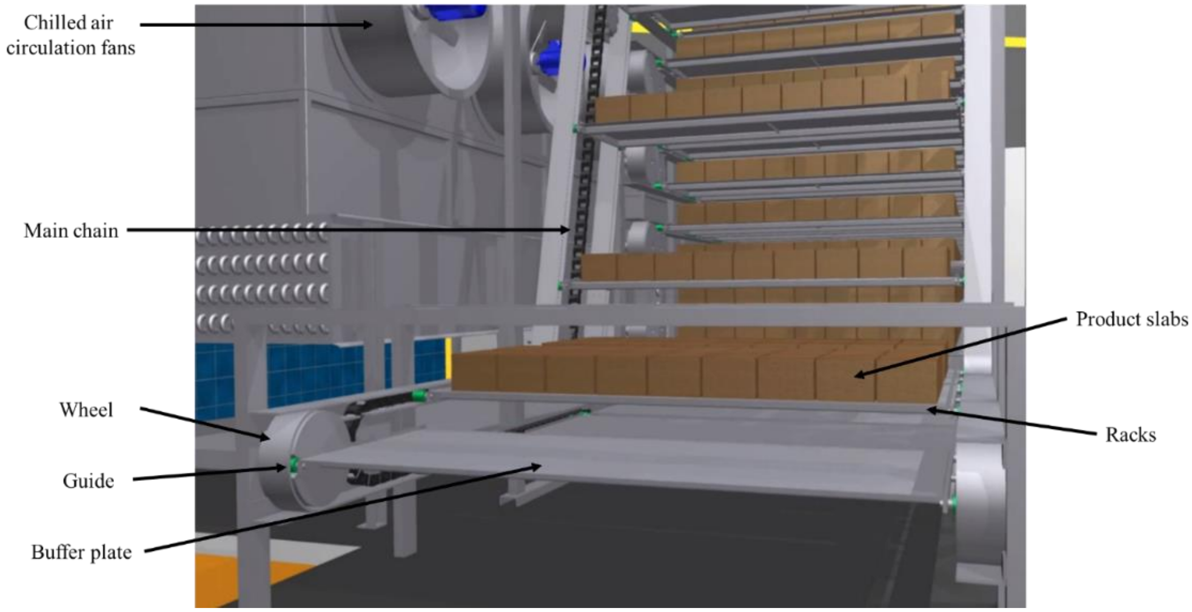

Figure 25: Inside view - SRT freezing tunnel. (Hans Jensen Engineering, 2018)

There are 216 racks in the freezing tunnel. Each rack holds three rows of product cartons and in each row contains eight slabs/carton of product. These slabs move on racks for almost 2 – 3 hours, unless core temperature of the product is achieved (-18 ^{o}C). **Figure 26** highlights rack system of SRT freezing tunnel.

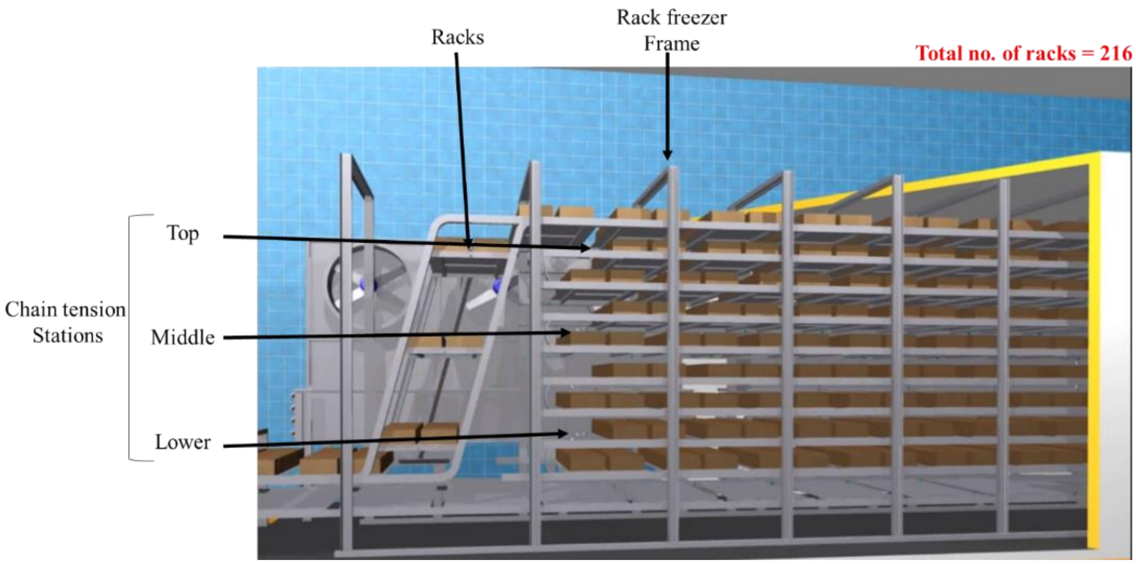

Figure 26: Racks system - Freezing tunnel. (Hans Jensen Engineering, 2018)

Outfeed system is a mirror (replica) of infeed system. It consists of the outlet, buffer plate, Outlet conveyor. At offloading station, product slabs are moved from racks to the outfeed conveyor by means of the automatic pusher (sweeper).

4.1.4. Automation & control system

Automation and control system for SRT freezing tunnels of following devices (1) Sensors, transducers and instruments (2) Programmable logic controller (PLC) and (3) Human-machine interface (HMI).

4.1.4.1. Sensors

Various types of sensors have been installed on SRT freezing tunnel, for example, position, distance, counting, temperature etc. Table 5 provide type and quantity of sensors installed in SRT freezing tunnel.

Table 5: Sensors installed on SRT freezing tunnel. (Møller, 2008)

Sensor	Type	Function	Quantity
Inductive proximity sensors	Digital	Metal detection	36
Proximity sensors	Digital	Object detection	46
Photosensors	Digital	Presence/absence of an object	12
Photosensors (retro-reflective type)	Digital	Presence/absence of an object	6
PT-100	Analog	Temperature sensors	3
Encoder (Counter)	Digital	Count no. of slabs	4
Encoder (Position detection)	Digital	Rack positioning system	3

4.1.4.2. Programmable logic controller (PLC)

PLC are industrial computers which are used to automate the production process. Sensors transmit measurement of process variables (temp, speed, position, distance etc.) to PLC system. This data is time series. SRT freezing tunnel have Siemens s7 – Micro-master 400 Programmable logic controller (PLC) system. **Figure 27** presents system context of PLC system.

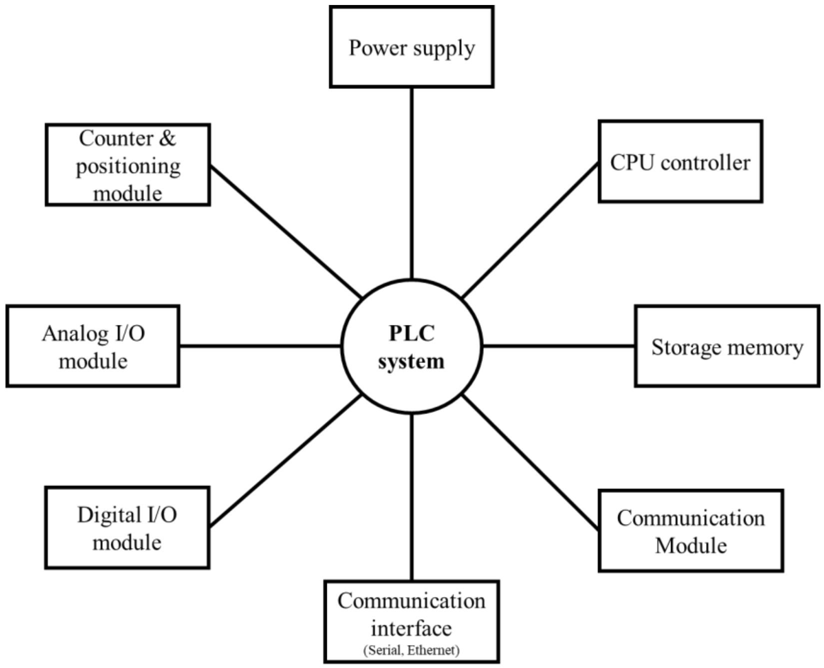

Figure 27: PLC system context (Wang, 2016)

Programmable logic controller (PLC), consist of major components microprocessors, storage memory, communication interface, timer and counter modules, inputs and output modules. Inputs are either digital (5V/12V/24) or analog (4-20 mA). **Figure 28** demonstrates PLC system installation and wiring circuit installed in a control panel.

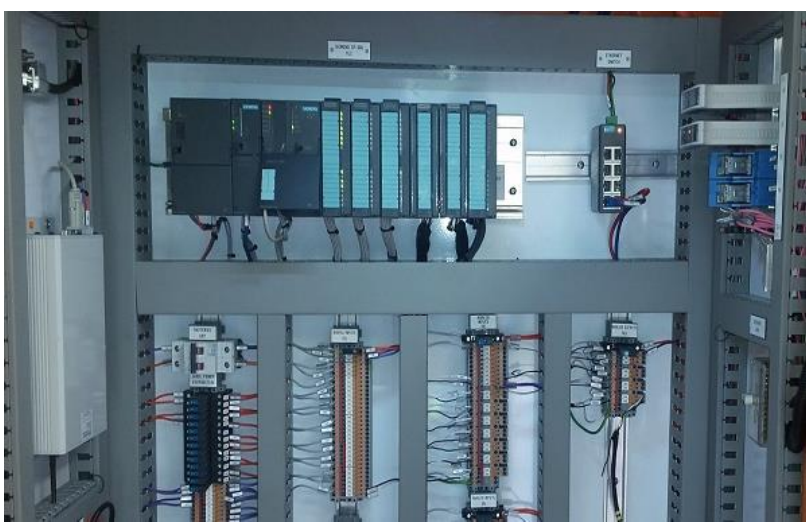

Figure 28: Siemens Sematic S7 400 – PLC. (Wagtec.com, 2018)

4.1.4.3. Human-machine interface (HMI)

"Siemens Sematic Touch" HMI has been used to provide interface between PLC and operator. It provides graphical user interface between process parameters and process monitoring system. Operator can easily interact with HMI to give instruction to the equipment and can see output, errors and alarms (Pcmag.com, 2018). **Figure 29** represents main screen of HMI. It can be seen from the figure that there are options to select different mode of operations, functionality of sensors, status of various components (infeed conveyors, buffer plates, outfeed conveyors).

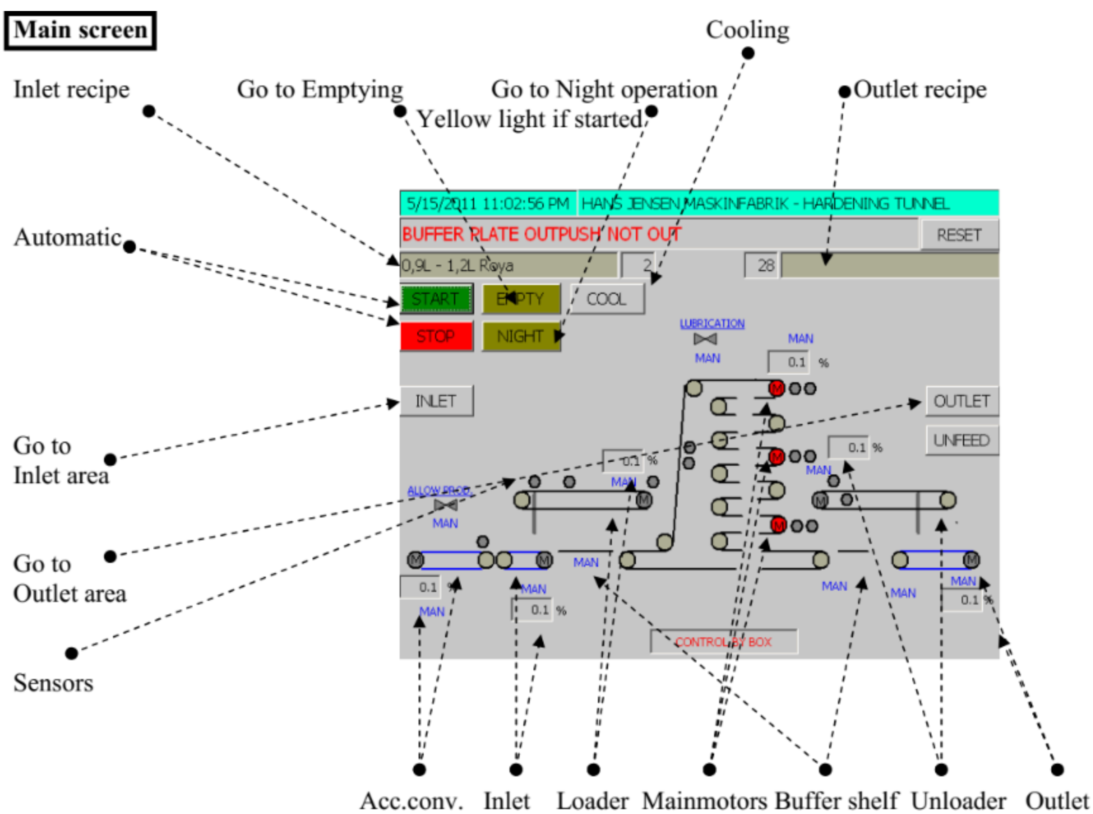

Figure 29: HMI screen of SRT freezing tunnel. (Møller, 2008)

4.1.4.4. Communication interface

Profibus (Process Field Bus) has been used for communication between various field instruments, sensors, controller. Profibus is standard communication protocol for process automation. **Figure 30** highlights communication interface for PLC and HMI.

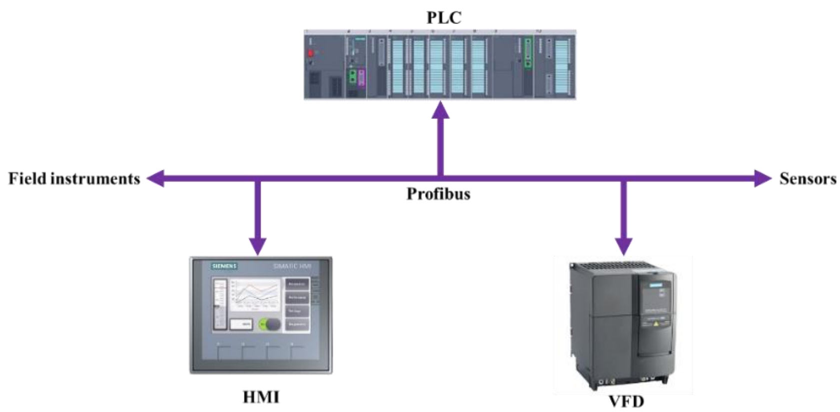

Figure 30: Profibus configuration (Kumbhar, 2018; Industrial et al., 2018; Conrad.com, 2018)

4.1.5. Refrigeration system

Figure 31 represents Ammonia refrigeration cycle. Compression and expensing capabilities of Ammonia are used to generate very low temperature (-27 C^o). Ammonia refrigeration system “consists of the following major components: compressor, condenser, expansion valve and evaporator” (Tananda, 2014). Compressor is used to compress the Ammonia gas, excessive heat is removed, and high-pressure vapors are condensed to liquid Ammonia. Which passes through expansion valve to reduce the temperature of liquid (Brain and Elliott, 2018) Sometimes due to extensive cooling, ice is frosted on Ammonia coils, an automated defrost system is installed to remove the ice from the coil.

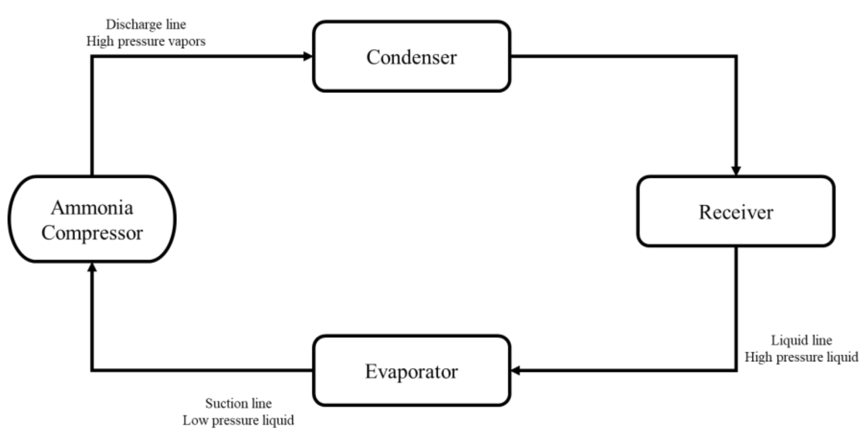

Figure 31: Ammonia refrigeration cycle (Berg Chilling Systems Inc., 2018)

Figure 32 shows chilled air circulations fans installed inside SRT freezing tunnel. These fans circulate chilled inside the freezing tunnel. A defrost system is installed at the bottom of each fan to remove accumulated ice on the Ammonia pipes.

Figure 32: Chiller air circulation fans (Gate Gourmet)

4.1.6. System of system (SOS)

Figure 33 represents system of system context of SRT freezing tunnel. The whole system has been divided into four major categories; enterprise level, system level, sub-system level and component level. From the figure, we can see that on enterprise level, selected critical system is part of processing plant. On system level, it is part of freezing system. On sub-component level, it has infeed systems, rack system and outfeed system. On component level, motors bearing (conveyors), sensors are major part of the system. SRT freezing tunnel system has been broke down into major components using system of system approach.

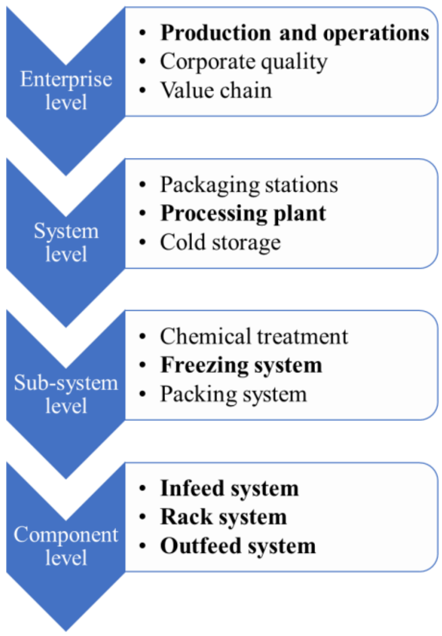

Figure 33: SRT freezing tunnel system breakdown. (Møller, 2008)

4.1.7. System operations

Freezing tunnel has two main mode of operations, Automatic mode and manual mode. Automatic mode of operation could also be divided into three sub-categories; fully automatic mode, night mode and emptying mode. In manual mode of operation, two functions are available; start-stop mode and jogging mode. Operational modes have been summarized in **Figure 34**. It is important to note that only one function can be selected at a time.

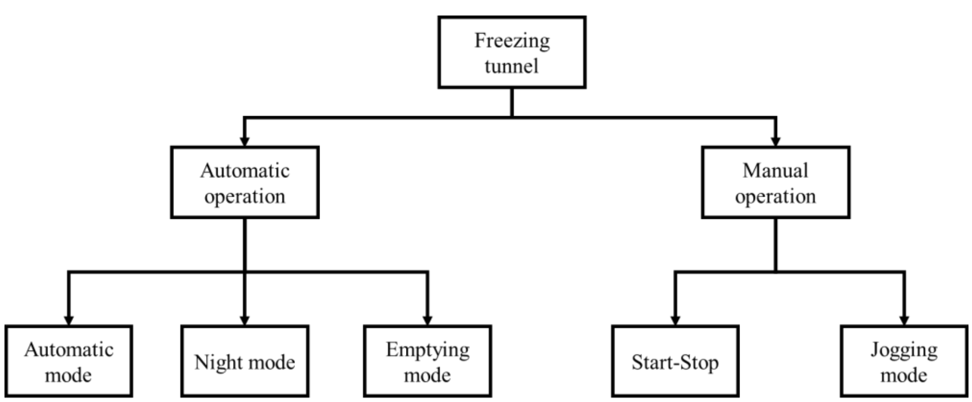

Figure 34: Freezing tunnel - Operational modes. (Møller, 2008)

4.1.7.1. Operational use case scenario

a) Automatic mode - use case scenario

Figure 35 presents SRT freezing tunnel automatic mode use case sequential diagram. Automatic mode is an interaction between operator, HMI screen and freezing tunnel. After selecting desired parameters for recipe and cycle duration, operator can start automatic mode by HMI screen. All position sensors are moved to zero position and refrigeration operators are started. It takes almost half an hour to achieve desired temperature. Soon after the system meet temperature requirements, infeed of product can be started.

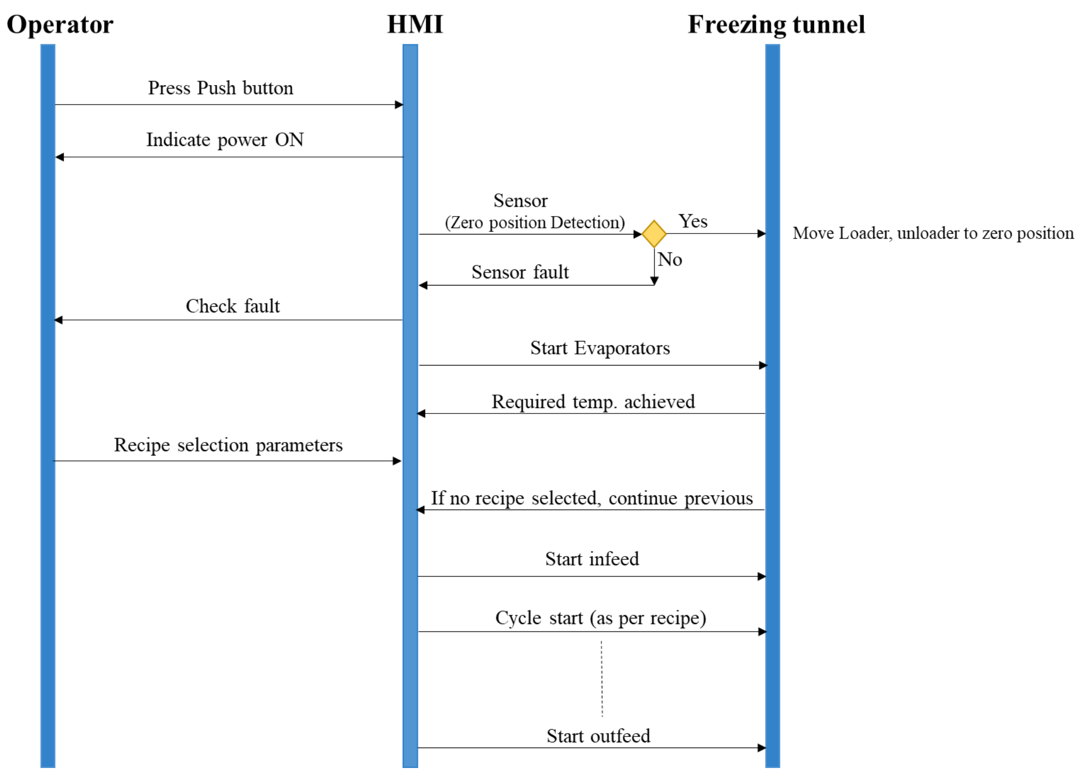

Figure 35: Freezing tunnel automatic mode - use case sequential diagram. (Møller, 2008)

In night mode, there is no infeed or outfeed, just rack system cycle continues to run. This is used when there is no intermediate production duty shift available. But it is necessary to keeping running the chain, as with such low temperature chain k stuck and become difficult to operate. In emptying mode, there is no infeed of material, just cycle continues and outfeed/unloading of material is working to remove the material from the freezer.

b) Manual operations - use case scenario

Figure 36 presents manual mode use case scenario diagram. Manual mode is normally used to test the operation of various equipment. It is also used to bring a rack to zero position, if there is a breakdown in automatic mode.

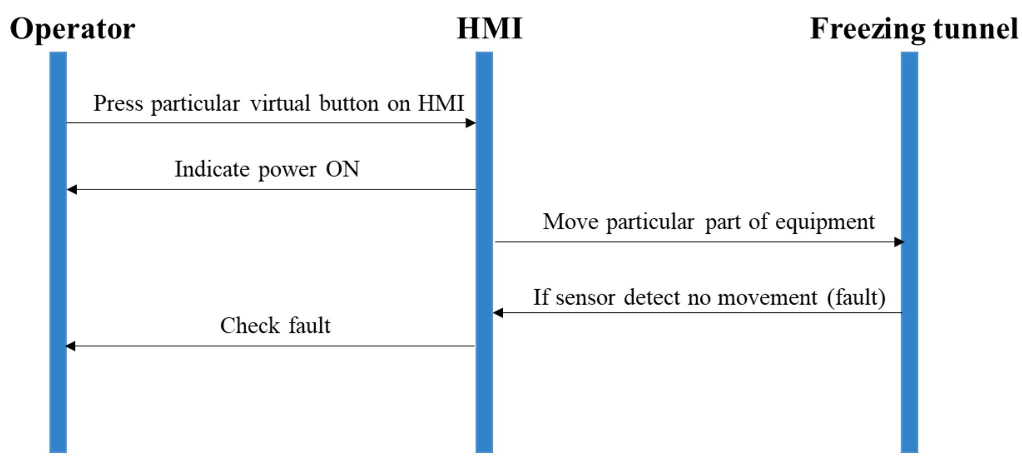

Figure 36: Freezing tunnel manual mode - use case sequential diagram. (Møller, 2008)

4.1.8. Maintenance scenarios

SRT freezing tunnel has multiple maintenance strategies, ranging from daily operational checks to yearly maintenance. Table 6 details the maintenance strategies with their frequencies and responsible persons.

Table 6: Freezing tunnel maintenance strategy. (Møller, 2008)

Maintenance strategy	Maintenance frequency	Responsibility
Corrective maintenance	• Breakdown maintenance	Maintenance technician Maintenance supervisor
Preventive maintenance	• Maintenance checks & inspections • Weekly	Maintenance technician Maintenance supervisor

	• Monthly • Quarterly • Semi annual • Annual	
First line maintenance	• Daily operations • Troubleshooting • Failure/error alarms • Product recipe change	Maintenance operator
Condition based maintenance	• Vibration analysis for the Main motor • Thermography for electrical and control panels	Third party - Outsourced maintenance service

4.1.8.1. Maintenance use case scenario

i. Corrective maintenance – use case scenario

Figure 37 illustrates presents corrective maintenance use case sequence diagram. When a failure is reported by operator or production staff, depending on the nature of failure, corrective maintenance troubleshooting is carried out to identify and rectify the failure.

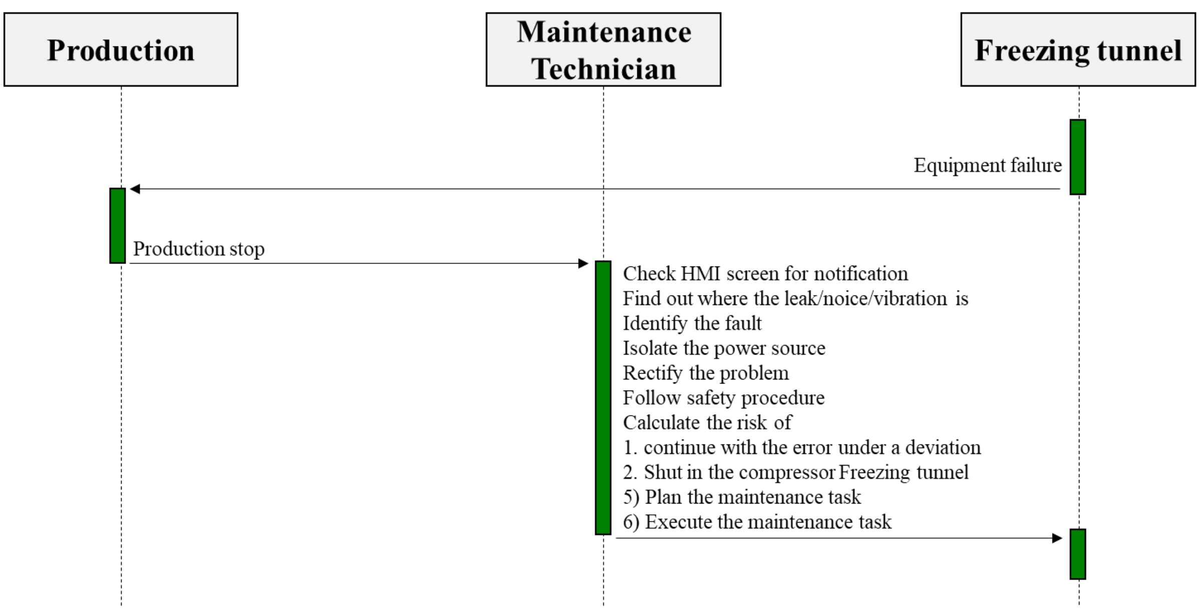

Figure 37: Corrective maintenance use case scenario (Møller, 2008)

ii. Preventive maintenance – use case scenario

Figure 38 illustrates preventive maintenance use case sequence diagram. Preventive maintenance use case is interlinked between CMMS software, maintenance planner, technician, freezing tunnel and production schedule. Maintenance planner generates PM work order, check the availability of equipment and arrange necessary spare parts and tools for execution of maintenance job. Maintenance work is carried out by technician and verified by production staff for proper operation of the equipment. SRT freezing tunnel preventive maintenance checklist has been presented in **Annex B**.

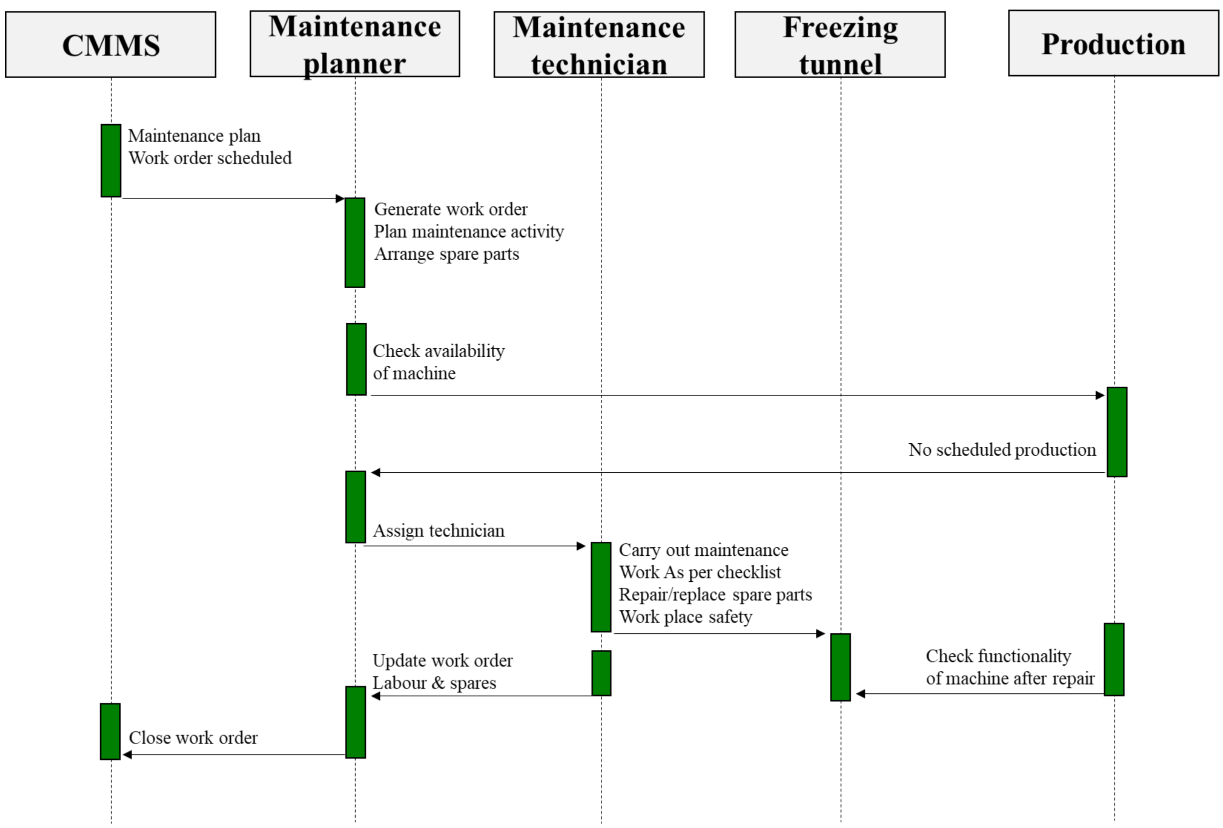

Figure 38: Preventive maintenance use case scenario (Møller, 2008)

iii. First line maintenance – use case scenario

First line maintenance includes daily inspections, monitoring, troubleshooting and minor repairs activities related to equipment operations. Most of first line maintenance activities can be controlled by HMI. Change in production recipe is also responsibility of first line maintenance operator. **Figure 39** presents first line maintenance use case sequence diagram. As shown in the figure, first line maintenance activities are interlinked between production, operator and freezing tunnel. Production plan and schedule is issued by production supervisor. Operator need to ensure that freezing tunnel is running in automatic mode with core temperature before start of production.

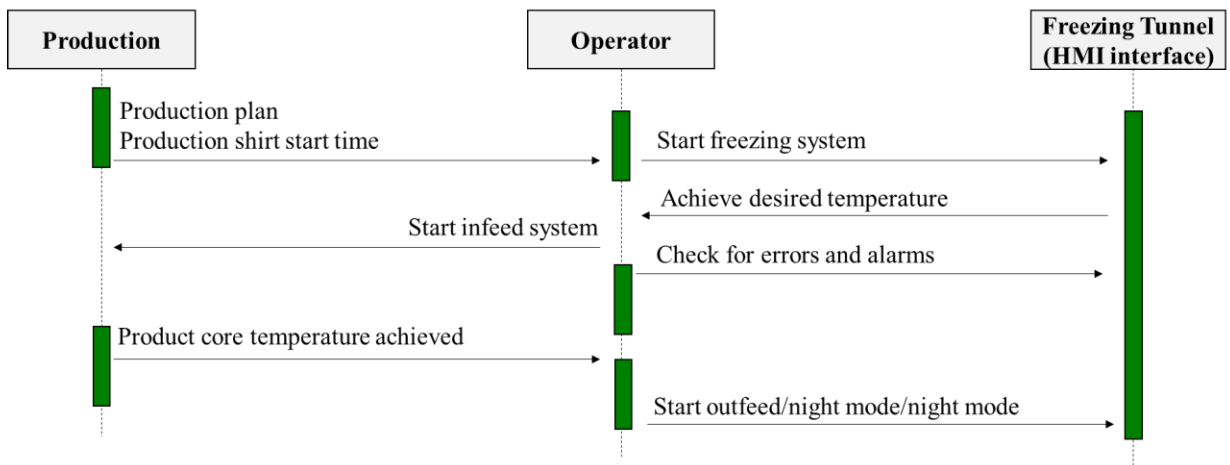

Figure 39: First line maintenance use case scenario (Møller, 2008)

iv. Condition based maintenance – use case scenario

Condition-based maintenance is carried out by the third-party service provider. Gate Gourmet take this maintenance as outsourced service. The frequency of condition monitoring inspection is usually semi-annually or on maintenance manager request.

4.1.9. Maintenance checklist

Preventive maintenance activities are carried out as per checklist recommended by the original equipment manufacturer (OEM). Which is scheduled on the weekly, monthly, quarterly, semi-annually and annually. A sample preventive maintenance checklist is attached in **Annex. B**.

4.1.10. Failures modes and mechanisms

Fault Tree Analysis: Figure 40 illustrates the fault tree analysis of SRT freezing tunnel. As we can see from the figure that chain, rack and tunnel stoppage are the main failure to SRT freezing tunnel.

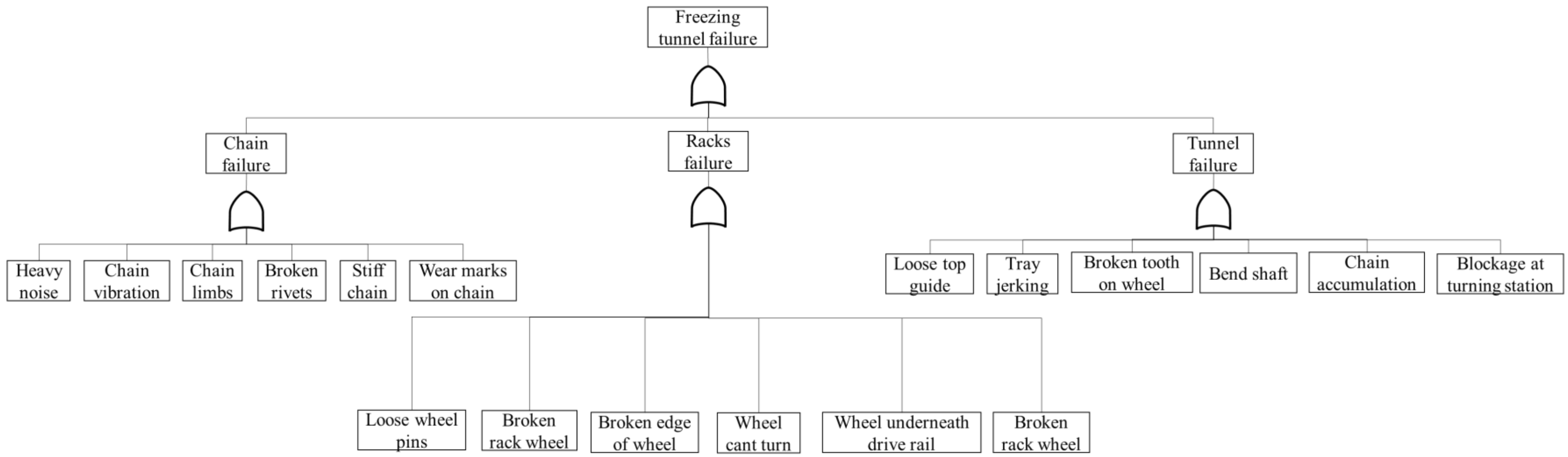

Figure 40: Fault tree analysis - SRT freezing tunnel (Møller, 2008)

FMECA: Failure mode effects and criticality analysis of SRT freezing tunnel and CMMS system has been summarized in Table 7. As we can see from the table that protentional cause of failure, failure modes symptoms and critical components (motor, bearing, racks, chain,

Table 7: Failure Mode Effect Criticality Analysis (FMECA). (Møller, 2008)

#	Part	Function or requirements	Protentional Failure mode	Potential cause of failure	Occurrence	Severity	Probability	RPN	Required action
1	Main motor	Drive rack trays	Racks stop	Short circuit	1	2	2	4	Isolate and repair
				Ground short	1	2	3	6	Isolate and repair
				Low gear oil	1	2	1	2	Top-up oil replace parts
				Gear box teeth broken	1	2	1	2	Replace
				Voltage drop	1	2	3	6	Isolate and repair
				Overload tripping	2	3	3	18	Isolate and repair
				Cables hardening	1	2	2	4	Replace and repair
2	Bearings	Enable rotation	Rack or conveyors stop	Insufficient lubrication	2	3	2	12	Grease
				Overheating/Temp. limit exceeds	1	2	1	2	Replace spares
				fatigue	2	3	2	12	Replace spares
				Imbalance	2	2	2	8	Check and repair
3	Racks	Transport slabs	Freezer stops Shaft Broken roller	Misalignment	2	3	2	12	Check and repair
				Speed is high	2	3	2	12	Reduce speed
4	Chain	Transmission	Freezer stop	Chain tension	1	3	3	9	Check and fix
				Insufficient lubrication	2	1	2	4	Lubricate the chain
				Chain wheel fault	1	1	1	1	Check alignment
				Debris on chain	2	2	3	12	Clean
				vibration	2	3	3	18	Check chain tension
5	Wheel	Rotation	Wheel stuck Broken tooth	Insufficient lubrication	2	2	2	8	Lubricate properly
				Overload	1	2	3	6	Check and fix

and sensors) have been listed in the table. The probability of each failure and nature of the desired action has also be mentioned in the table. From FMECA table, motor, bearing, and shaft are identified as critical components.

4.2. System analysis for a protentional predictive maintenance program

4.2.1. Predictive health and performance program

In this section, predictive maintenance concepts (as shown in section 2.3) have been applied on SRT freezing tunnel to detect fault and anomalies in the machine components. In the first step, SRT freezing tunnel has been divided into major sections: infeed, rack, and outfeed system. As shown in **Figure 41**, critical components related to each section has been highlighted (in yellow color), motor, gearbox, bearing, shaft, pump bearing. These critical components have been identified with respect to their critical functionality in the system.

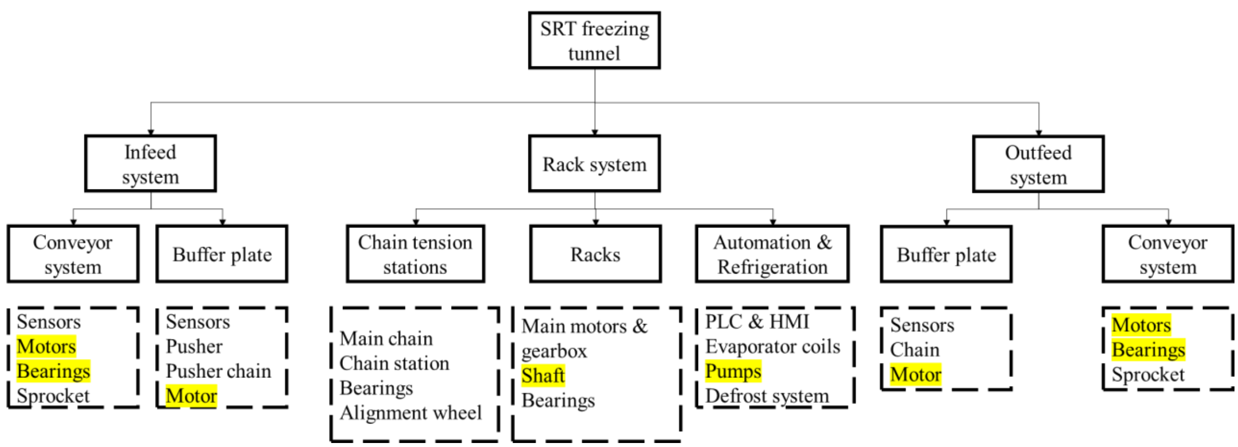

Figure 41: Breakdown and critical components identification of SRT freezing tunnel. (Møller, 2008)

In the second step, measurement sensors (such as a triaxial accelerometer, a current transducer, magnetic oil debris sensors, piezoelectric sensors) have been selected to measure the real-time condition of the critical components (Motor, bearing, shaft, pump). These sensors are the most critical part of the system, as they generate data from the current condition of the components and communicate it to data server/cloud storage. This data is transferred by connection /transmission layer network of IoT based architecture. "These sensors translate physical actions" (Coleman et al., 2017) from physical components "into digital signals that communicate variables such as" (Coleman et al., 2017) vibration, temperature, acoustic emissions etc. In Table 8, SRT freezing tunnel's critical components, their potential failure parts, condition monitoring technique and appropriate sensors to measure the condition of the component have also been presented.

Table 8: Measurement sensors, technique and algorithm for SRT freezing tunnel. (Lee et al., 2014)

Component	Potential failure	Measurement technique	Measurement sensor	Algorithm
Bearing	Outer race, inner race, roller, cage	Vibration, oil debris, acoustics emission	Triaxial accelerometer, magnetic oil debris sensors, piezoelectric sensor	Neural networks
Gearbox	Missing tooth, fatigue, crack, wear	Vibration, temperature, oil debris, acoustics emission	Accelerometer, temperature sensor, magnetic oil debris sensors, piezoelectric sensor	Neural networks
Shaft	Misalignment, Unbalance, mechanical looseness	Vibration	Accelerometer	Neural networks
Pump	Piston, bearing, crank problem	Vibration, pressure, acoustics emission	Accelerometer, piezoelectric sensor	Neural networks
Motor alternator	Rotor/stator fault, electric fault	Stator current and voltage, vibration	Current transducer, accelerometer	Neural networks

I have selected an electric motor with gearbox and having a rotational speed of 1420 RPM, a triaxial accelerometer was mounted on the outer surface of bearing case. Four fault conditions were listed such as "slightly worn, medium worn, broken teeth and faulty bearing" (Rafiee et al., 2007). Data manipulation was carried out using wavelet packet coefficient to extract the features of the signal (Rafiee et al., 2007).

As shown in **Figure 42**, data received from sensors such as a triaxial accelerometer, magnetic oil debris sensors, the piezoelectric sensor is not readily available for analytics, it needs data manipulation to make it ready from fault diagnosis. In data manipulation section, two processes are carried out; signal pre-processing and features extractions. Depending on the nature and quality of the signal, processing can be carried out in the time domain or frequency domain. In the time domain, the principal component analysis is carried out while in frequency domain fast

Fourier transform is performed on the signal. Time-frequency domain can be used to extract significant features from the signal. Time-frequency domain uses wavelet transform (Segreto et al., 2017).

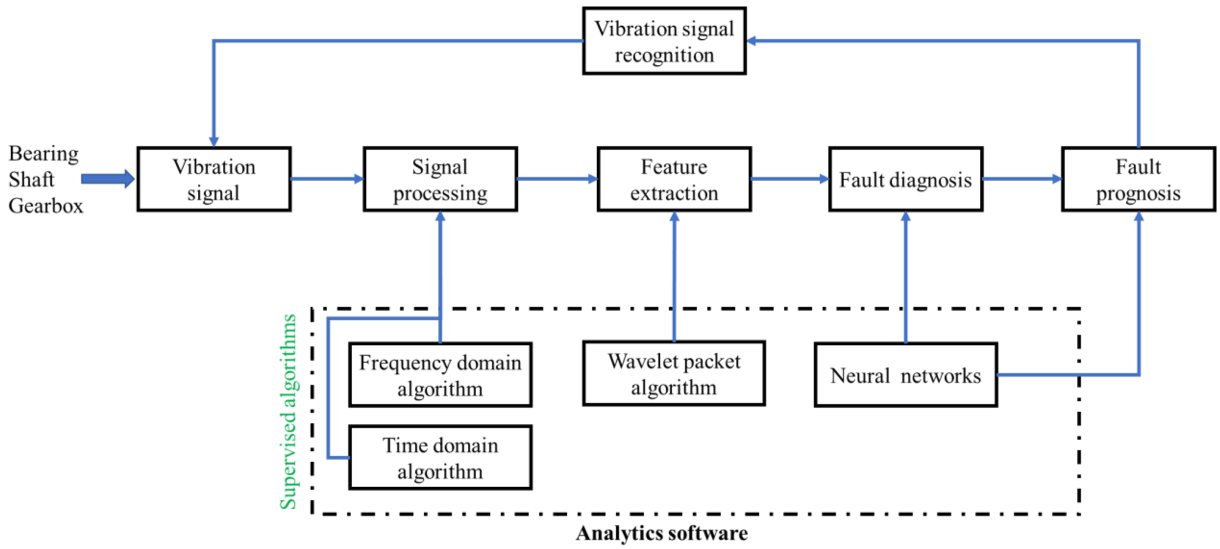

Figure 42: Vibration signal predictive health monitoring

Vibration data is a time-varying signal (non-stationary signal) which changes in amplitude and statistical properties. In some cases, it is the identification of faults in the time domain is a bit difficult, as a type of fault is not clearly identified in the time domain. "Vibration signal generated by a certain bearing has relatively low amplitude" (Ragab et al., 2016) and high noise problem. To identify the faulty signal and failure mode, the signal is subjected to the frequency domain. In which abnormal noise signals are more visible and highlighted (Ragab et al., 2016).

As shown in **Figure 43**, wavelet analysis algorithm is very useful for removing noise and decomposition of signal in non-rotating signals such as motor gearbox (Rafiee et al., 2007). "wavelet transform (WT) gives good time and poor frequency resolution at high frequencies and good frequency and poor time resolution at low frequencies" (Rafiee et al., 2007). In wavelet analysis, the original signal is broke-down in to shifted and scaled up signals. Decomposition is carried out using one high-frequency component and one low-frequency component. "Wavelet transform is a function of both time and frequency" (Ragab et al., 2016). A wavelet filter is applied to decompose the signal into a hierarchical structure. Original signal was divided into equal position and wavelet transform was applied to extract signal coefficients. In **Figure 43**, wavelet packet coefficients and associated standard deviations are shown for a medium-worn fault.

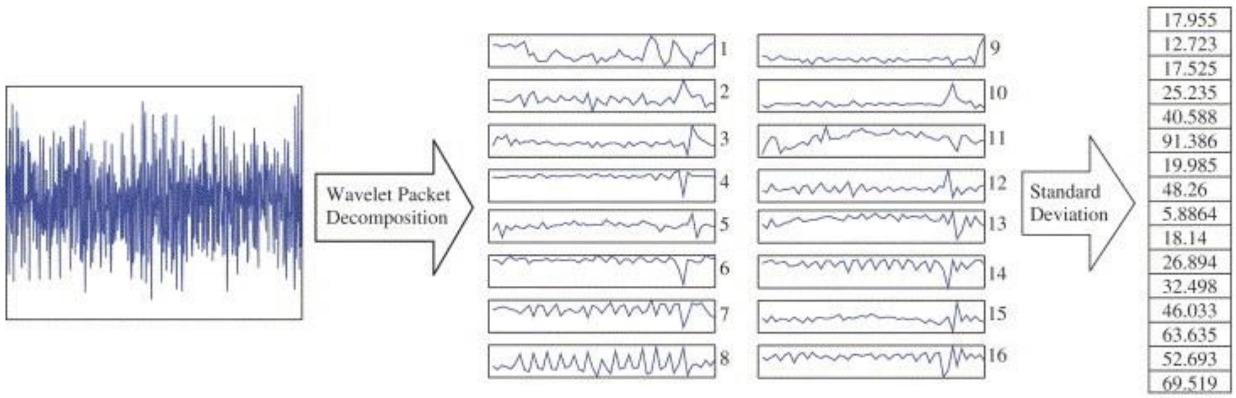

Figure 43: Calculation of standard deviation for wavelet package coefficient. (Rafiee et al., 2007).

For diagnosis of fault, feed-forward multi-layer perception algorithm has been used. Multi-layer perception algorithm is very useful for fault diagnosis in rotating machines. The algorithm has been trained using back-propagation algorithm (supervised learning) (Rafiee et al., 2007). I have used two-layer neural network configuration for fault detection (input, hidden and output layers). It helps to achieve a good level of accuracy and reduce development expenses. The neural network has been trained by wavelet feature vector, which is commonly used in fault detection of rotating mechanical equipment. As shown in **Figure 44**, three output neurons have been used to identify faulty gear. Three fault bearing conditions are used for one output neuron and for the no-fault condition, one output neuron has been used (Rafiee et al., 2007). The accuracy of the algorithm increases with time. Similarly, continuous wavelet decomposition implementation over the period of time can help for prognoses such as degradation and remaining useful life of the bearing.

Neural networks can be **optimized** in two ways; forward and backward propagation. Backward propagation is most famous for optimization. “In the forward phase, it is calculated a response provided by the network for a given input pattern. In the backward phase, the deviation (error) between the desired response (target) and the response provided by the ANN is used to adjust the weights of the connections" (Teixeira Júnior et al., 2018).

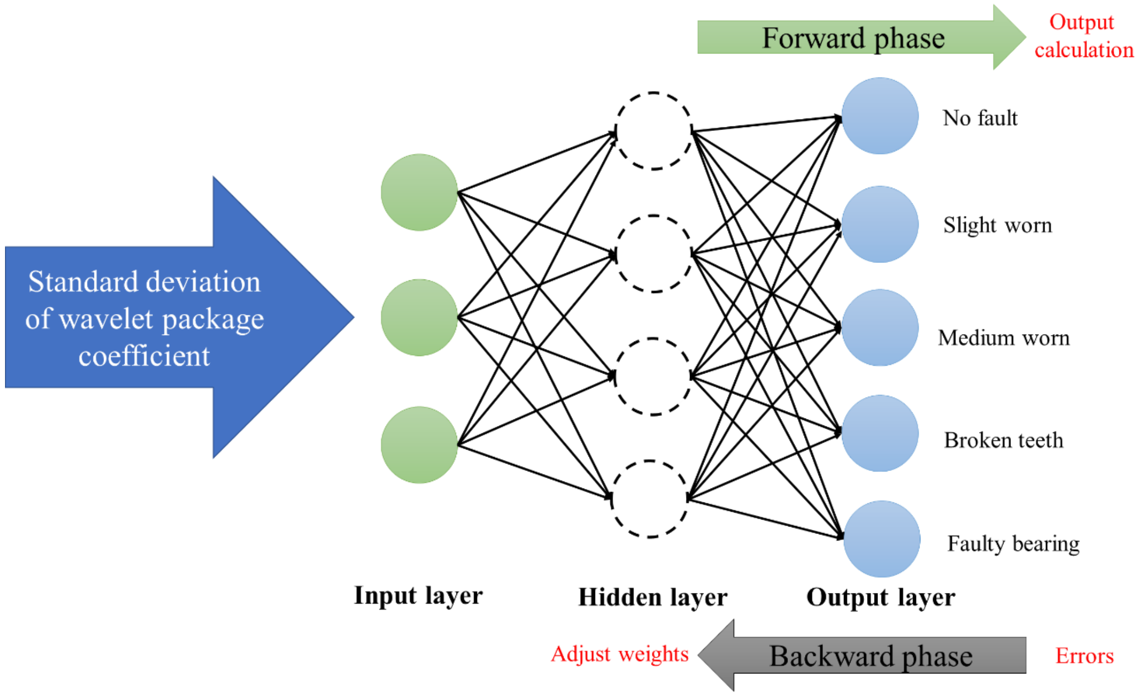

Figure 44: Feed-forward neural networks to identify faults in vibration signal (Rafiee et al., 2007).

4.2.2. The overall intelligent predictive maintenance system

Functional architecture of intelligent predictive maintenance system has been summarized in **Figure 45**. As shown in the figure; in the first step, real-time data is received from two sources sensors and PLC system. In the second step, this data is stored into data server or cloud storage platform. In the third step, unwanted signals are removed and required features are extracted from the signal. In the fourth step, a machine learning algorithm is used to diagnose the faults. In the fifth step, optimization of measurement frequency and opportunistic time interval for maintenance work is carried out. In the last step, most optimum maintenance decision is translated into maintenance action.

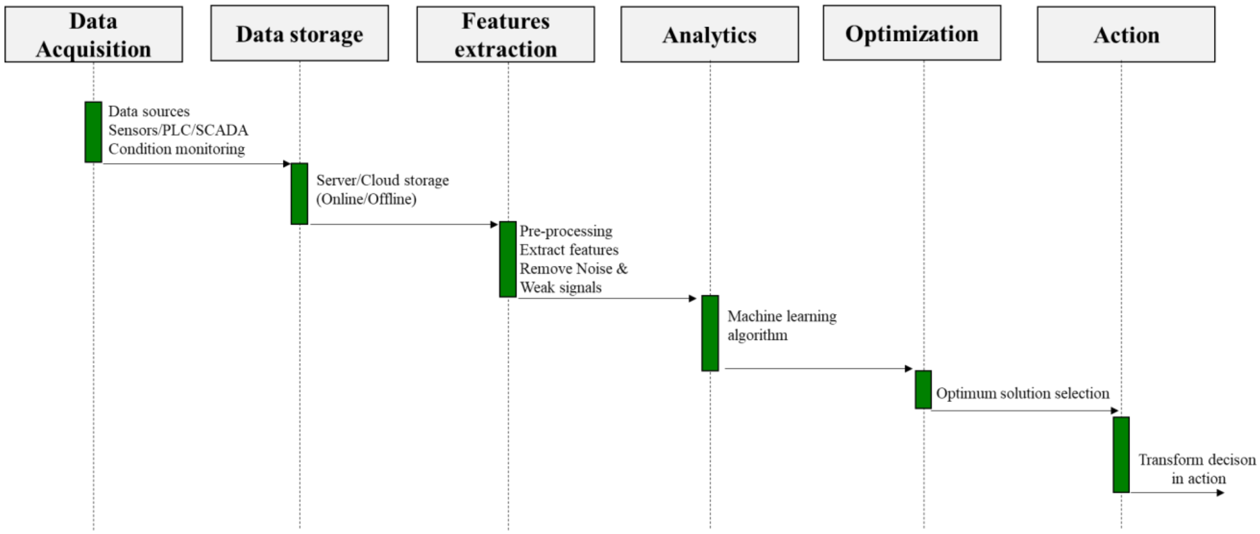

Figure 45: functional architecture of intelligent predictive maintenance. (Morozov, 2016; Santos et al., 2015)

Figure 46 illustrates physical architecture of intelligent predictive maintenance, which includes sensors and transducers, data storage service or cloud, predictive analytics software and computerized maintenance management software.

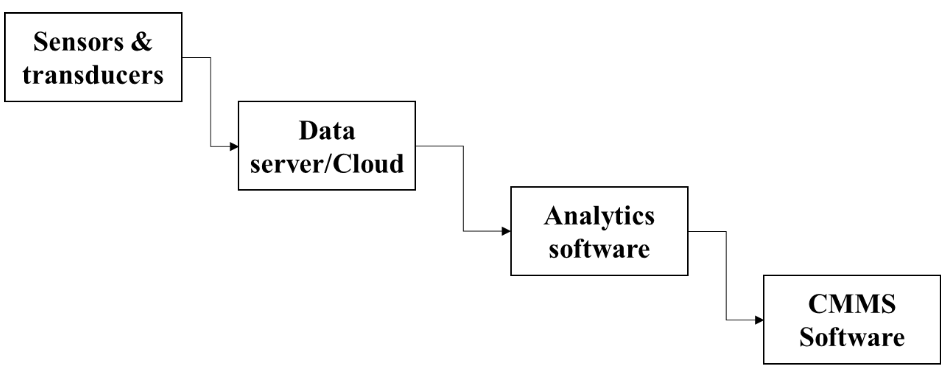

Figure 46: Physical architecture of intelligent predictive maintenance. (Morozov, 2016; Santos et al., 2015)

In **Figure 47**, inputs, outputs, resources and control functions for intelligent predictive maintenance has been summarized. As shown in the figure, inputs sources are sensors, PLC data, historical data from data server/cloud. These inputs are transformed into outputs such as; fault diagnosis, prognosis, maintenance optimization and automated decision support system. Resources for intelligent predictive maintenance are data processing tool, machine learning algorithms, computational and analytics software. Control parameters are system-defined specifications, standards, limits, supervision, rules and key performance indicators.

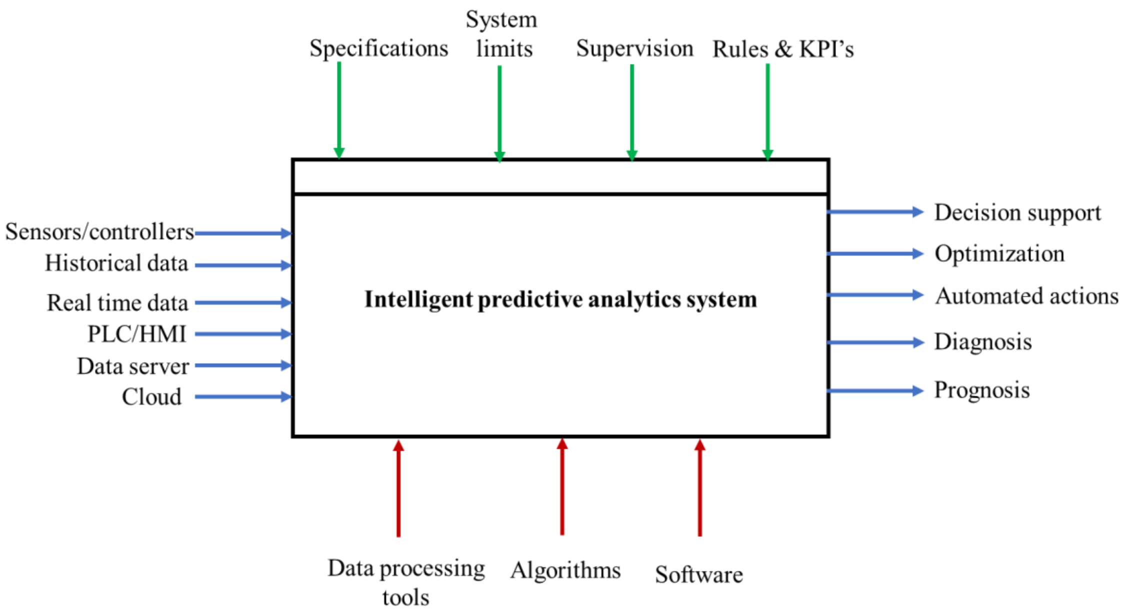

Figure 47: Inputs and output function of intelligent predictive maintenance (IDEF 0 diagram). (Morozov, 2016; Santos et al., 2015)

4.3. System analysis for computerized maintenance management system (CMMS)

4.3.1. CMMS system context

Computerized maintenance management system is a modular software, which consists of various modules such as; asset register, work order, preventive maintenance planning, inventory management, budgets planning and maintenance reports. Major modules of CMMS software have been summarized in **Figure 48**. Details of each module has been elaborated as under.

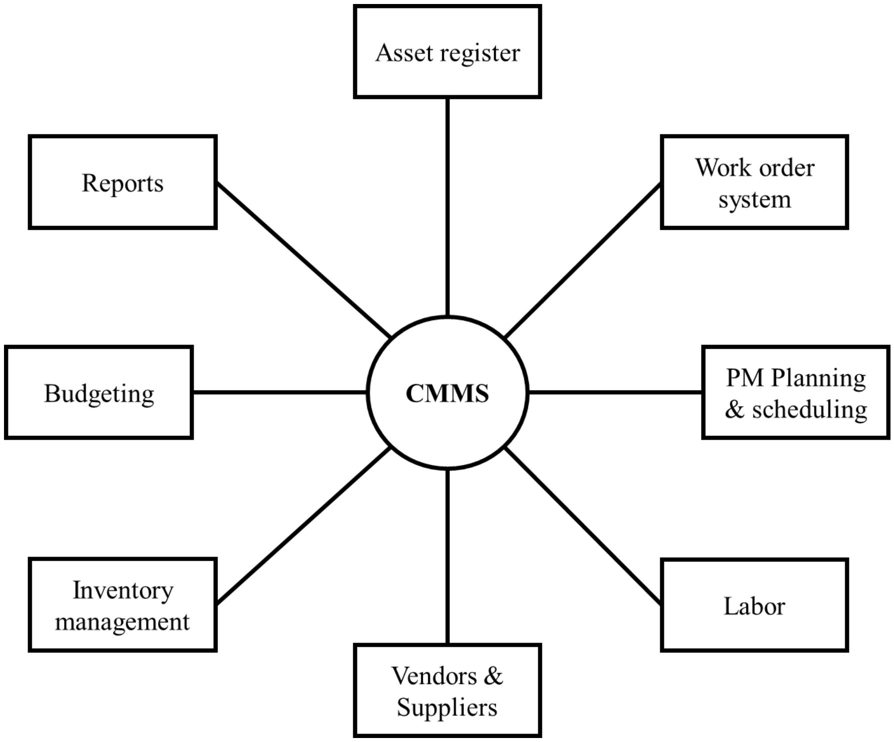

Figure 48: CMMS system modules. (Ahmed Soliman, 2015)

4.3.2. Asset register

Equipment asset hierarchy or equipment master list consists of all equipments in the plant. **Figure 49** illustrates inputs, output, resources and control functions for asset register module. Input parameters includes equipment type, identification details, model number, installation, warranty and criticality ranking etc. These input s are transformed into outputs such as equipment reliability, availability, useful life estimation, work order and repair cost. Resources of mechanisms available for PM planning are OEM maintenance manual, CMMS software, equipment failure history and operator feedback for equipment maintenance needs. Control include inspection, management supervision and quality.

In asset register, each equipment is represented by item number (4000578601) and serial number (NP-FA-FRF-001). Which is unique for each equipment. Equipments of similar type should be grouped under one item number subpart.

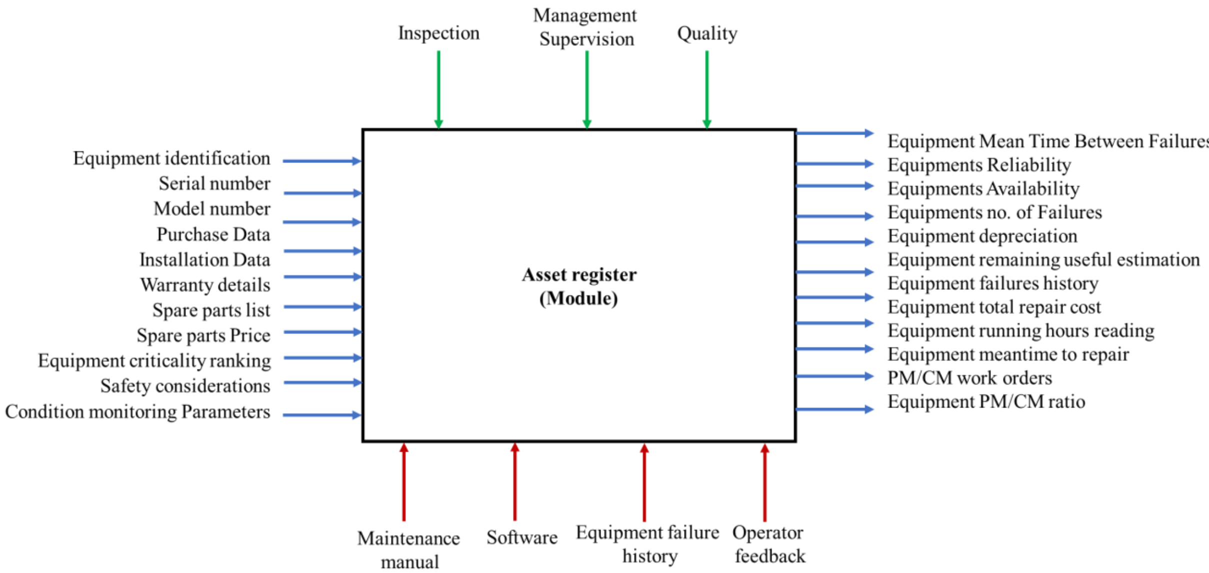

Figure 49: CMMS - Inputs and outputs functions for asset register. (Ahmed Soliman, 2015)

Equipment are registered in asset register by the systematic method, either by equipment nature or maintenance requirements. Well-structured coding system for asset register is asset **parent-child configuration** (nodes). In which sub-assets are grouped under a major asset. Table 9 highlights identification code of SRT freezing tunnel in CMMS software. Equipment identification code consists of item number and serial number.

Table 9: Example of asset registration code for freezing tunnel (INFOR LN, 2015)

Item Number	Serial Number
400 05 786 01	NP-FA-FRF-001
400 = Processing plant 05 = Electro mechanical system 786 = Freezing tunnel 01 = Equipment serial number	NP= New processing plant FA = Freezing area FRF = Rack freezer 001 = Freezer serial number

4.3.3. Work order

"The work order system is the heart of any maintenance control system, and it is a necessary tool for effective planning and scheduling" (Duffuaa and Raouf, 2015). Each maintenance job is represented by a unique work order number. As we can see from **Figure 50**, work process starts with maintenance request by the machine operator or production staff. Work request could be received by CMMS or by email. This work request is approved by maintenance supervisor. Equipment inspection, the arrangement of spare parts, availability of machine (from production) is carried out by maintenance planner. Repair work is carried out by a maintenance technician, labor and spares are punched into the software. This work is reviewed by supervisor/maintenance planner. Finally, a work order is costed and closed with the approval of equipment owner (production).

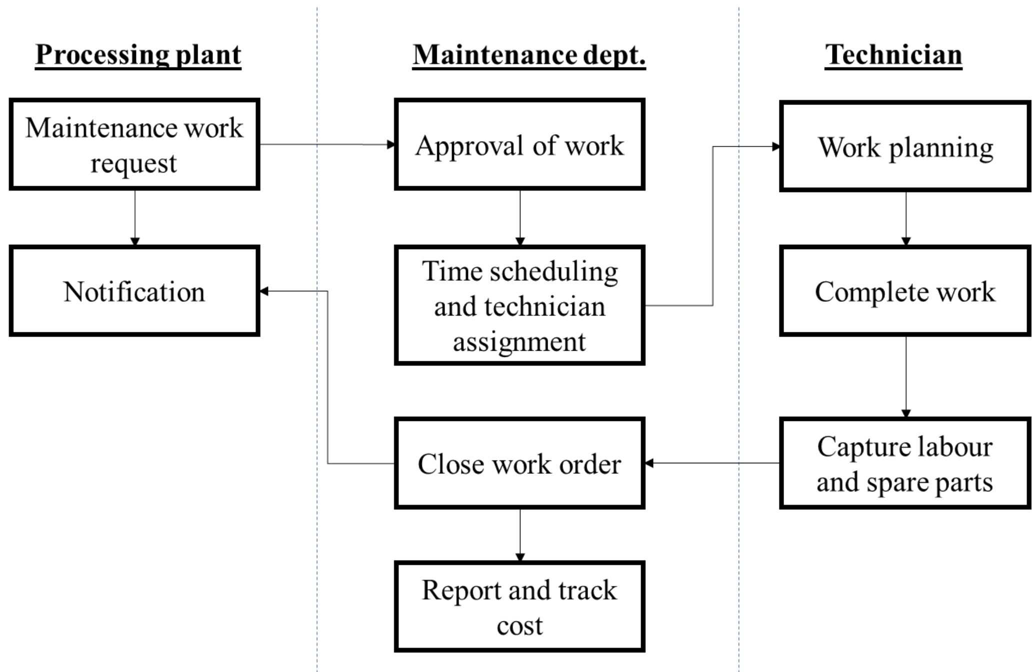

Figure 50: Typical work order process. (Holland, 2005)

A sample work order dashboard (CMMS software screen) has been shown in **Annex C**.

a) Work order types

In line with maintenance strategies, “maintenance work can be divided into two broad categories: planned and unplanned work” (Duffuaa and Raouf, 2015). Planned work orders are grouped under preventive maintenance (PM) while unscheduled breakdown is grouped under corrective maintenance (CM) and emergency work. Additional types may also include in CMMS such as CAP (capital project) and proactive maintenance.

b) Work order status

Work order status highlights the current state of execution of work order. Initially, a work order is in a free state which is converted to planned status when it is scheduled on a specific date, time and assigned to a specific technician. After the completion of the job, a work order is completed and closed by supervisor.

c) Work order text

Work order text provides information about the problem which is named as order text. For future root cause analysis, activity and solution text are also included to provide insight into what was the problem and how the problem was addressed. An alternate solution to creates failure codes in CMMS to identify equipment failures. It does not require to write long details in the text box. A list of common failure codes has been shown in **Annex D**.

4.3.4. Preventive maintenance planning

Preventive maintenance planning is a most important function of CMMS software. For each equipment in asset register, PM plan is generated for the at least one-year duration. A total number of planned work orders is based on PM frequency. For example, SRT freezing tunnel has a maintenance plan for every week, so the system will generate 52 planned work orders for a one-year duration. Later, this PM plan is scheduled on particular dates (w.r.t production plan and availability of asset) and converted to work orders every week. Planning is what needs to be done, how it would be done while scheduling is about when and where it will be done. In PM planning module, Maintenance activities (checklist) and procedures are linked with asset register based on following factors.

- Preventive maintenance checklist
- Preventive maintenance frequency

- Required spares parts and tools to carry out maintenance activity

Figure 51 illustrates inputs, output, resources and control functions for preventive maintenance planning module. Inputs include maintenance activities, PM frequency, labor hours, spare parts and tools. These inputs are transformed into outputs such as PM plan, schedule, the required number of spare parts, tools and labor hours. Resources of mechanisms available for PM planning are OEM maintenance manual, CMMS software, equipment failure history and operator feedback for equipment maintenance needs. Control include inspection, management supervision, and quality.

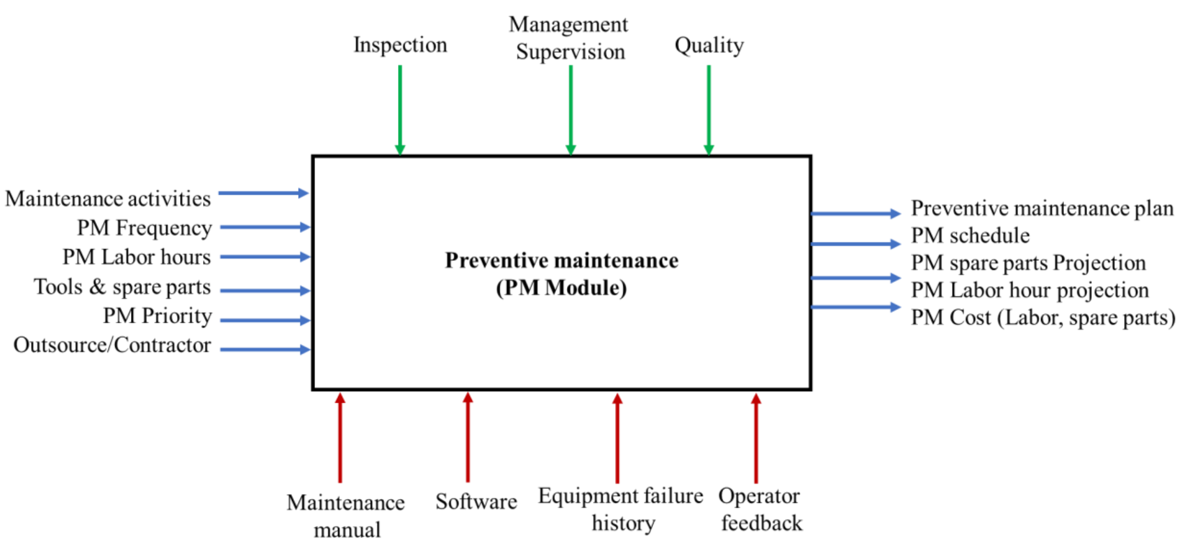

Figure 51: Inputs and outputs functions for preventive maintenance module (Ahmed Soliman, 2015)

a) Human resource (Labour hours)

Maintenance engineers, technicians and operators are registered in CMMS with their unique Employment ID, Name, department, normal working hours, overtime working hours, skillset, hourly rate (which is charged to production dept) and contact details. Typically, 160 working hours are available for the technician (5 working days X 8 working hours in a day). A total number of hours worked by technical represents his performance.

4.3.5. Inventory management

Inventory management module consists of three parts; warehouse, purchase requisition, purchase orders. The warehouse module shows available stock of spare parts in the warehouse storage with their quantities and location. Purchase requisition module shows spare part request for purchase from vendors. List of approved vendors is also made available in the CMMS software. Purchase order module shows approved purchase requisitions for purchase for spare parts.

4.3.6. Budgeting and planning

CMMS system is a very useful tool for maintenance budget tracking and cost management. Maintenance cost is divided into two parts, operational expenditures (OPEX) and capital expenditures (CAPEX). OPEX budget is allocated for operational expenditures which include salaries for maintenance department staff, spare parts purchase, purchase of tools for repair and outsourced maintenance service. CAPEX is reserved for new equipment purchase and installations of projects. OPEX

4.3.7. Maintenance reports

CMMS has very strong reporting features of maintenance management system. These reports can be generated with the flexibility of time, duration (day, month year), location, equipment wise, employees. Table 10 presents various reports from the CMMS modules.

Table 10: CMMS reports

CMMS module	Reports
Asset register	• Asset master list report • Number of assets at a specific location
Work order	• PM work order reports • CM work orders reports • PM/CM ratio report • PM compliance report
Preventive maintenance	• Preventive maintenance plan report • PM schedule report
Inventory management	• Spare parts consumption reports

	• Warehouse stock report • Inventory purchase reports • Inventory ordering report
Budgeting and planning	• Maintenance cost reports • OPEX/CAPEX reports • Budget Vs cost report • Budget variance report

A sample maintenance report has been summarized in **Figure 52**. The Figure highlights the number of service order, total cost, labor hours, labor cost and spares cost of four plants in the company.

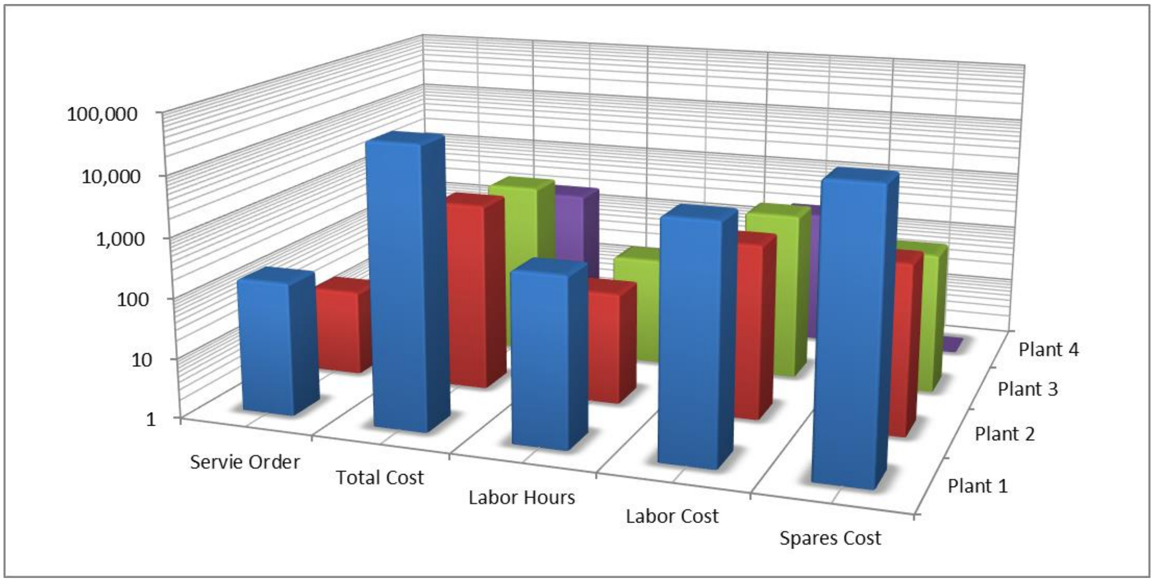

Figure 52: Maintenance reports (INFOR LN, 2015)

4.4. System analysis of potential CMMS system

4.4.1. CMMS assessment criteria

To define new features of CMMS, the first step was an analysis of commercially available software solution. By reviewing the best practices highlighted in literature and functionalities of major CMMS software. I developed an assessment criterion for CMMS system analysis. This assessment criteria were based on four key features: **user**, **functionality**, **financial** and **business** requirements. A detailed summary of CMMS assessment criteria is listed in Table 11. As shown in the table, **Software User** requirements specifications include a number of user accounts, interface. It also includes the need for additional staff for administration, operations, and user training requirements to use the software. **Functionality** is the most important feature in CMMS software, assessment features include work order, preventive maintenance, inventory management, fault diagnosis and prognosis etc. **Financial** assessment features include licensing, implementation, software annual maintenance and troubleshooting cost. **Business** requirements specifications include software already deployed in similar industry, integration with other software in the company.

Table 11: CMMS assessment criteria

(PROJECT MEMORANDUM 1.2.2 COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM ASSESSMENT, 2015; wikiHow, 2018)

Stakeholder	**Assessment criteria**
User	• Number of users account support • Ease of access • User-friendly graphical interface • Training requirements • Recruitment for additional staff in IT.
Functionality	• Preventive maintenance planning • Preventive maintenance scheduling • Tracking of maintenance work activities • Inventory management (warehousing, purchase, consumption, and suppliers) • Documentation and record keeping • Maintenance history • Out-sourced maintenance work (contractors) • Maintenance reports • Cloud services (On-premise or external cloud storage) • Data security • Mobility • Web-based software interface • Internet of things (IoT) • Fault diagnostics • Condition-based maintenance • Predictive health maintenance (PdM) and performance measurement • Machine learning algorithms • Fault prognostics

Financial	• Software licensing agreement • Modules based licensing • Software implementation • Annual software maintenance cost • Software up-gradation cost • Troubleshooting tickets cost • Software integration cost with other software (ERP/EAM/Production)
Business	• Food industry experience • Integration with production planning software (SCALA) • Project implementation timescale • Integration with production planning and ERP software

4.4.2. CMMS software alternatives

Based on assessment criteria for CMMS system, I prepared a **request for information (RFI)** documents and consulted with maintenance manager. In RFI documents, I explained the company background, a summary of requirements for functionality, hardware, scalability, integration requirements, project timeline and estimated cost for licensing, implementation and after-sales service (wikiHow, 2018). I contacted technical and commercial representatives of the CMMS software vendors (locally and internationally). This communication was carried out through email and telephonic conversations. Later, I evaluated the response and the solution presented by the vendors. I presented the solution to the maintenance manager and after discussion, we shortlisted four vendors for their CMMS system analysis, (1) SAP, (2) IFS, (3) IBM Maximo and (4) Infor LN.

4.4.2.1. SAP

SAP have both on-premise and cloud computing capabilities. There is different pricing structure for both solutions (SAP, 2018). To develop on-premise data storage and analytics capability, company (Gate Gourmet) must arrange high-performance GPU's for solving complex computational algorithms. With API support function, company production system software can be integrated with SAP system and customized mobile applications can be developed for maintenance and production staff. SAP provides data security and privacy for company database system (employees, applications, customer, suppliers). It has customer support team for troubleshooting.

4.4.2.2. IFS

Industrial and financial system (IFS) is Sweden based private organization which provides ERP and asset management services since 1983. It does not support a web-based application. It has major modules such as asset management, work order management, inventory Management, mobile device support, preventative maintenance planning and scheduling. IFS use Oracle database. It does not support condition or predictive maintenance function (Satell, and Padro, 2014). IFS is currently working with **Microsoft Azure** to develop predictive analytics capability in CMMS software.

4.4.2.3. IBM Maximo

MRO Maximo software was acquired by IBM in 2006. It has been extensively used in Medium scale manufacturing industries. It has web-based service architecture. It has six basic modules includes; "asset management, work management, service management, contract management, inventory management, and procurement management" (www-356.ibm.com, 2018). It has a wide range of functionality, customization and integration options. It has strong integration flexibility with other software. IBM Maximo is currently working with **IBM Watson** to develop predictive analytics capability in CMMS software. There are some cons associated with IBM Maximo, such as complexity, difficulties in implementation phase (need extra time for testing and validation) and overall system cost. It has strong customers association in the United States but limited European market exposure (PROJECT MEMORANDUM 1.2.2 COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM ASSESSMENT, 2015).

4.4.2.4. INFOR LN

BAAN was acquired by INFOR in 2002, it is available in the market with the software Infor EAM. Its architecture is web-based and supports Java platform. It has two database options, Microsoft SQL and Oracle database. Infor EAM has extensive functionality and integration options. It has on-premise cloud storage option: Infor cloud Site. To include basic modules like service order, preventive maintenance, mobile application, condition-based maintenance. It has GIS support for distributed assets. It has integration difficulty with real-time parameters e.g. PLC and SCADA systems. Boeing aircraft is a distinguished customer of Infor LN (PROJECT MEMORANDUM 1.2.2 COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM ASSESSMENT, 2015).

4.5. Customization of potential CMMS system

From Table 2 (needs and requirements) we have concluded following key acceptance criteria for desired CMMS system. Which are real-time monitoring, big data, cloud storage, predictive analytics and intelligent predictive maintenance, performance measurement. A CMMS software should be able to visualize these output in an understandable manner.

From an operator point of view, computerized maintenance management systems (CMMS) is the most important parts of the entire digital transformation, since most of the other systems can be provided by out-sourced from external vendors such as machine learning algorithms and cloud platforms. The operator needs to deal with CMMS on daily bases and almost all acquired data from the SRT freezing tunnel will be stored and presented via CMMS system. CMMS is the core interface between operator and entire digitalized maintenance management system. Thus, the operators shall be enabled assess which CMMS (SAP, IFS, IBM Maximo and Infor LN) is the most cost-effective for their applications, support the completeness of industry 4.0 vision and provide capabilities to be customized. From above discussion, it can be summarized that predictive maintenance and performance measurement are key customization aspects that are required to develop cost-effective CMMS.

a) Solution alternative 1

Taking predictive maintenance and CMMS from two different vendors causes integration problems (different data types). Instead, predictive maintenance system can be integrated with CMMS using an open source integration platform such as "Machinery Information Management Open Systems Alliance (**MIMOSA**)" (Avin et al., 2006). MIMOSA uses open source architecture-enterprise application integration (**OSA-EAI**) for data exchange standard between physical assets and CMMS. MIMOSA have two types of architectures; processing architecture (OSA-CBM) and information architecture (OSA-EAI). In MIMOSA OSA-CBM; physical parameters measurements, condition monitoring and diagnosis activities are carried out. MIMOSA information architecture consists of CMMS and EAM. **Figure 53** highlights the MIMOSA open architecture for process and information standards.

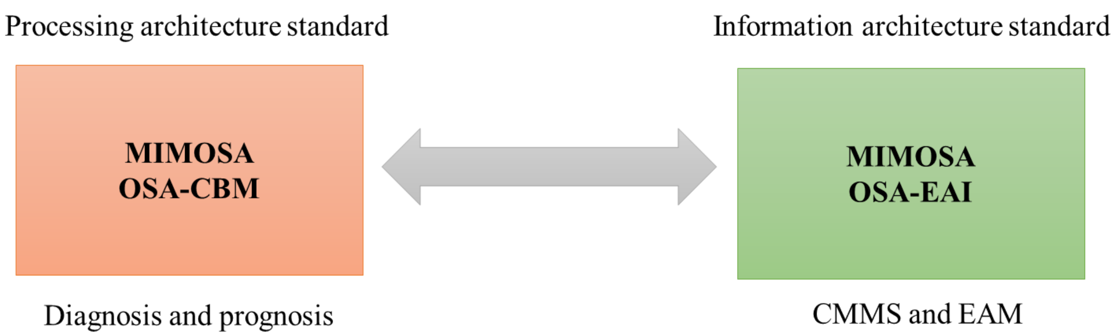

Figure 53: MIMOSA open architecture

Due to low-cost and high-reliability features, an organization like **ISO** and **SAP** have joined OSA-EAI and OSA-CBM for asset management integration solutions (Avin et al., 2006; Johnston, 2016). MIMOSA open system architecture for condition-based maintenance and enterprise application integration are ISO compliant for ISO based condition monitoring system (As shown in Figure 13) (Bever, 2008). As per ISO 13374 standard, "Published standard for open software specifications which will allow machine condition monitoring data and information to be processed, communicated and displayed by various software packages without platform-specific, vendor-specific, or hardware-specific protocols" (Bever, 2008).

Functionalities of MIMOSA-OSA-EAI are based upon Common Conceptual Object Model (CCOM)

- Asset register
- Work management systems
- Condition monitoring system
  - Fault diagnostic and health assessment systems
  - Vibration, sound, thermography
- Process data historian systems

- Test and measurement systems
- Reliability database systems

It can transfer achieved data which is stored in database (Bever, 2008). MIMOSA OSA-EAI have web-based CMMS function (XML-web) as well (Bever, 2008).

According to (Avin et al., 2006) Intelligent predictive maintenance model and open source architecture (OSA-EAI) can be integrated. A proposed predictive maintenance framework has been presented in **Figure 54**. As shown in the figure, proposed predictive maintenance process has five major steps. (1) data is acquired using smart sensors. (2) This data is utilized for anomaly detection and fault diagnosis, (3) fault prognosis is carried out using machine learning algorithms (as explained in section 4.2.1), (4) issue maintenance work order (5) update maintenance system (CMMS).

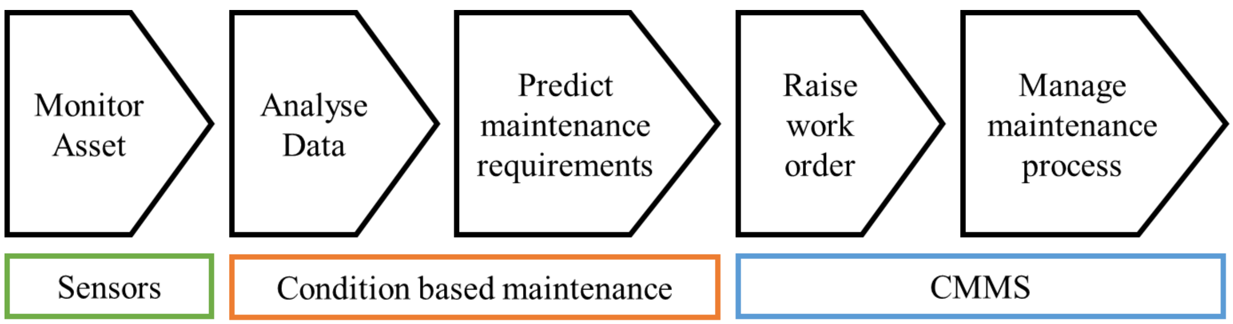

Figure 54: Prosed predictive maintenance process (Avin et al., 2006)

Figure 55 illustrates the relationship between intelligent predictive maintenance model and CMMS system. From the figure, it can be seen that each module of intelligent predictive maintenance model has direct access to database servers. Maintenance decision support module interacts with CMMS through OSA-CBM provides OSA0-CBM monitors the condition of the component and provide real-time interrogation to maintenance support module. Maintenance decision support module interacts with CMMS to raise work order.

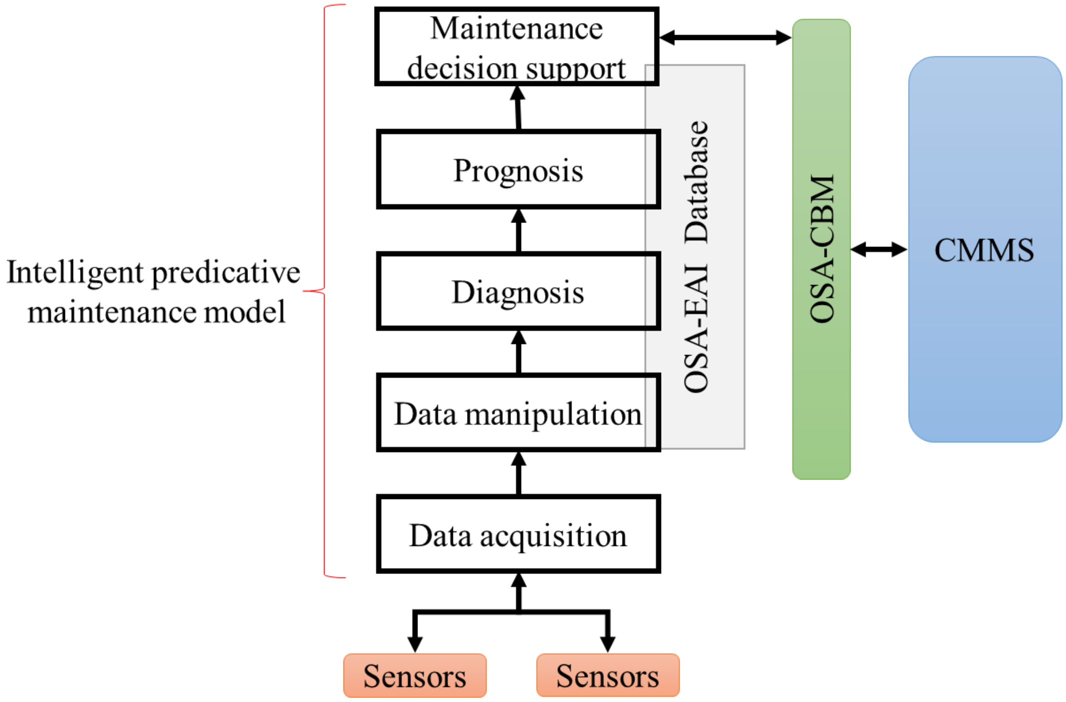

Figure 55: Smart CMMS using intelligent maintenance model (Avin et al., 2006)

b) Solution alternative 2

Table 12 highlights multi-criteria decision matrix (MCDM) for evaluation of CMMS system. All influencing factors for user, functionality, financial and business have been numbered with respect to vendor evaluation. Additionally, weight criteria are also added to grade each factor with respect to its weight in the evaluation process.

Table 12: Multi-criteria decision matrix for CMMS evaluation

(PROJECT MEMORANDUM 1.2.2 COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM ASSESSMENT, 2015)]

	Features assessment	**Weightage**	**SAP**	**IFS**	**IBM Maximo**	**Infor LN**
User	Number of users support	x1	3	3	3	3
	Ease of access	x2	3	2	2	2
	User friendly graphical interface	x2	3	3	3	3
	Training requirements	x1	2	2	3	2
	Recruitment for additional staff in IT dept.	x2	2	2	3	2

Functionality	Preventive maintenance planning and scheduling	x3	3	3	3	3
	Tracking of maintenance work activities	x3	3	3	3	3
	Inventory management (warehousing, purchase, consumption and suppliers)	x3	3	3	3	3
	Documentation and record keeping	x1	3	3	3	3
	Maintenance history	x2	3	3	3	3
	Out-sourced maintenance work (contractors)	x2	3	3	3	3
	Maintenance reports	x3	3	3	3	3
	Cloud services (On-premise or external cloud storage)	x1	3	3	3	3
	Data security	x3	3	3	2	3
	Mobility	x1	3	3	3	3
	Web-based software interface	x1	3	3	1	3
	Internet of things (IoT)	x1	3	3	1	2
	Fault diagnostics	x1	3	1	1	2
	Condition-based maintenance	x1	3	1	1	2
	Predictive health maintenance (PdM) and performance measurement	x1	3	1	1	2
	Machine leaning algorithms	x1	3	1	1	2
	Fault prognostics	x1	3	1	1	2
Financial	Software licensing agreement	x3	2	2	2	2
	Modules based licensing	x2	2	2	2	2
	Software implementation	x3	2	2	2	2
	Annual software maintenance cost	x1	2	2	2	2
	Software up-gradation cost	x1	2	2	2	3
	Troubleshooting tickets cost	x2	3	3	3	3
	Software integration cost with other software (ERP/EAM/Production)	x2	2	2	2	3
Business	Food industry experience	x1	2	2	2	2
	Catering service	x1	2	2	2	2
	Integration with production planning software SCALA/ERP	x1	3	3	3	3
	Project implementation timescale	x1	3	2	3	3
Total Score			**89**	**77**	**75**	**84**

All four software solutions have been evaluated using multi-criteria decision matrix (MCDM). Based on the weight given to each requirement, evaluation of each functional feature and impact factors (cost, time scale), **SAP** has been identified as a best possible solution for implementation in Gate Gourmet. Important features like Intelligent maintenance, predictive health maintenance (PdM), fault diagnosis, prognosis, European market experience, local after-sales support are additional leading factors in the selection of SAP software solution.

The estimated cost for SAP software licensing and implementation have been summarized in Table 13. Software license includes CMMS modules such as work order, preventive maintenance, inventory management, mobile access. It also includes software access permitted to total a number of users in the company. Software implementation includes integration of software with the physical assets of the company. It includes configuration, testing, and training of operators to use the software functions. Moreover, frequent troubleshooting and maintenance of software are charged cumulatively under an annual maintenance contract.

Table 13: SAP cost estimation

(PROJECT MEMORANDUM 1.2.2 COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM ASSESSMENT, 2015)

Cost component	**Cost estimate (USD)**	**Description**
Software license	40,000 – 200,000	*Core CMMS function, work order, asset, PM, inventory management, Mobile access, 60 specific user accounts and 30 concurrent user accounts
Software implementation	50,000 – 300,000	Implementation of core CMMS function, work order, asset, PM, inventory management, Mobile access. Software installation and configuration, testing and training.
Estimated total cost for Year 1	**90,000 – 500,000**	
Annual maintenance cost for software	15,000 – 150,000	Troubleshooting tickets, up-gradation, and annual maintenance.
Software integration cost	75,000 – 300,000	Integration with SCALA and ERP system Additional business process integration
Total estimated cost for Year 2	**90,000 – 450,000**	
*Price depends on licensing and implementation of a required number of functional modules.		

5. Discussion and conclusion

Unreliable, out-of-date data are the famous complaints made by maintenance managers about reports generated by CMMS. Managers do not rely much on CMMS reports for decision making (Reeve, 2010). The reason behind is, maintenance data is manually punched into work orders by data entry operators or technicians into CMMS system (rubbish input, rubbish output). A similar case is true for preventive maintenance plans (weekly, monthly quarterly etc.), which were injected into CMMS software based on OEM recommendations without considering important factors like current equipment condition, equipment breakdown history, and failure patterns. This data was later converted into work orders, updated by data entry operators and accumulated to generate maintenance performance reports. Unfortunately, traditional CMMS had become database only, which did not reflect the real-time analysis of shop floor activities. Organizations fail to optimize the utilization of CMMS.

The systems analysis of CMMS resulted in identifying the technical functionalities and the key acceptance criteria to assess and customize them toward the specific stakeholder's needs for the commercial CMMS. Assessment criteria for CMMS software were divided into four categories: user, functionality, financial and business requirement specifications. Most important system functionality includes work order system, preventive maintenance planning, condition-based maintenance, cloud storage support, predictive maintenance (PdM), diagnosis, prognosis and intelligent maintenance support (machine learning). Based on above-mentioned criteria, four markets famous CMMS vendors software were assessed including SAP, IFS, IBM Maximo and Infor LN.

Keeping in view stakeholder’s needs and requirements for CMMS system, the challenge was to adopt a CMMS system which can comply with predictive health maintenance, performance measurements, and intelligent maintenance system support. Based on agreed acceptance criteria ford intelligent predictive maintenance model, two solution alternatives were proposed (1) using open source architecture for integration between predictive maintenance and CMMS. (2) SAP. Recommendation of SAP asset management solution was carried out using multi-criteria decision method (MCDM).

To comply with Industry 4.0 vision, commercial CMMS software needs to consider smart assets and smart maintenance management operations. Important features for customization in CMMS includes cognitive capabilities, artificial intelligence, predictive analytics using machine learning algorithms, automation and optimization of maintenance decision making. Compliance with intelligent asset management functions will open new dimensions of innovation for CMMS vendors.

The selected critical **physical system** analysis depicted that SRT freezing tunnel was a typical example of an industry 3.0 automated, PLC & HMI based machine. The industry 4.0 vision was applied in order to develop smart assets and smart maintenance management operations for cyber-physical system approach and IoT framework. Smart assets up-gradation process was carried out in three major steps, (1) physical to digital world transformation (2) utilization of computational and cognitive capabilities of the digital world and (3) translation of cognitive decision making into the physical world.

In the first step, measurement sensors and communication interface were upgraded. To measure real-time data smart sensors were used for the determination of physical parameters such as vibration, piezoelectric, magnetic oil debris. This real-time, high speed, velocity, and variety of data were transmitted to data storage server using Ethernet TCP/IP protocol.

In the second step, IoT intelligent maintenance framework was used to develop predictive maintenance and performance measurement (PdM). Smart maintenance management operations include processing, analysis, and visualization of asset data. The keys steps in fault diagnosis and prognosis were data pre-processing, feature extractions and machine learning algorithm. Data was processed, analyzed and visualized in the automated and cognitive manner by utilizing several disruptive technologies related to automation of work processes e.g. predictive maintenance, artificial intelligence. In the final step, the optimum decision makes in the digital world are translated asset for maintenance action.

Asset integrity and work process automation were key requirements to develop predictive maintenance (PdM) and performance measurement program. Moreover, the developed predictive maintenance program (PdM) clearly expands the expected functionality of the associated CMMS. It required CMMS to be smarter (not just a database) as user interface integrator between assets (physical machines, human operations) and cyber systems (analytics, transmissions).

The study was thus helpful to analyze physical systems to identify the requirements for developing smarter assets, predictive maintenance program, and CMMS. It was concluded that key acceptance criteria for selecting CMMS are significantly important to either select the best commercial option or to customize the existing CMMS solution for industry 4.0.

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Annex. A

(Template sheet to identify customer needs)

Table 14 presents a template sheet which I had used a part of an interview with department managers, supervisors and technician to assess their needs for computerized maintenance management systems.

Table 14: Assessment sheet to identify customer needs (energy.gov, 2018)

Question	Answer	Comments
• How do you track maintenance activities carried out in the plant? • How do you check the quality and efficiency of maintenance work carried out? • What is the notification function for the completion of work? • Are you able to trace historical maintenance activities carried out in last twelve months?		
• How do you develop a maintenance plan for SRT freezing tunnel? • How do you distribute maintenance schedule over the year? • How do you plan your desired number of maintenance hours?		
• How do you manage and control spare parts inventories? • How do you control excess inventories ordering? • How long must you wait to receive spare parts?		
• How do you store and track maintenance documentation electronically? • (Maintenance work orders, maintenance procedures, maintenance manuals. Warranty information)		
• How do you track maintenance hours carried out by a technician? • How is technician informed about the potential hazard? • How do you ensure technician have appropriate safety gears to carry out maintenance work? • How is maintenance staff informed about the required tools for the maintenance work?		
• How do you prepare maintenance reports for PM compliance?		
• Does maintenance systems have failure analysis system to stop happening it in future?		

Annex. B

(SRT freezing tunnel Preventive maintenance checklist)

Table 15 highlights preventive maintenance checklist for SRT freezing tunnel. Preventive maintenance is distributed from day to day inspections to monthly, quarterly, semi-annual and annual maintenance, repair and replacement activities.

Table 15: Preventive maintenance checklist

Maintenance frequency	**Maintenance checklist**
Daily inspections	• Check Inspection overall system • Observe suspected/abnormal noise • Check for HMI alarms and carry out rectification
Weekly	• Lubricate racks chain system • Check chain tension system • Check conveyor belt • Check the bearings • Check the chain pins • Check sensors, photosensor functionality
Monthly	• Check conveyor motor • Check conveyor belt • Check bearings • Check sprockets • Check chain pins
Quarterly	• Check rack system bearings • Replace suspected bearing • Check electrical & control panel • Check conveyor belt • Check conveyor bearings (grease if required)
Semi-Annual	• Check main motor bearing • Check electrical & control panel
Annual	• Check main motor bearing • Replace conveyor bearing

Annex. C

(Work order screenshot taken from CMMS software)

Figure 56 highlight a screenshot taken from CMMS software in case company. It can be seen from the figure that work orders have been organized with respect to date, time, type (PM/CM), service technician, job start time (planned and actual start time), Duration (number of hours spent on a job) and cluster (equipment owner, production is equipment owner in most of the time).

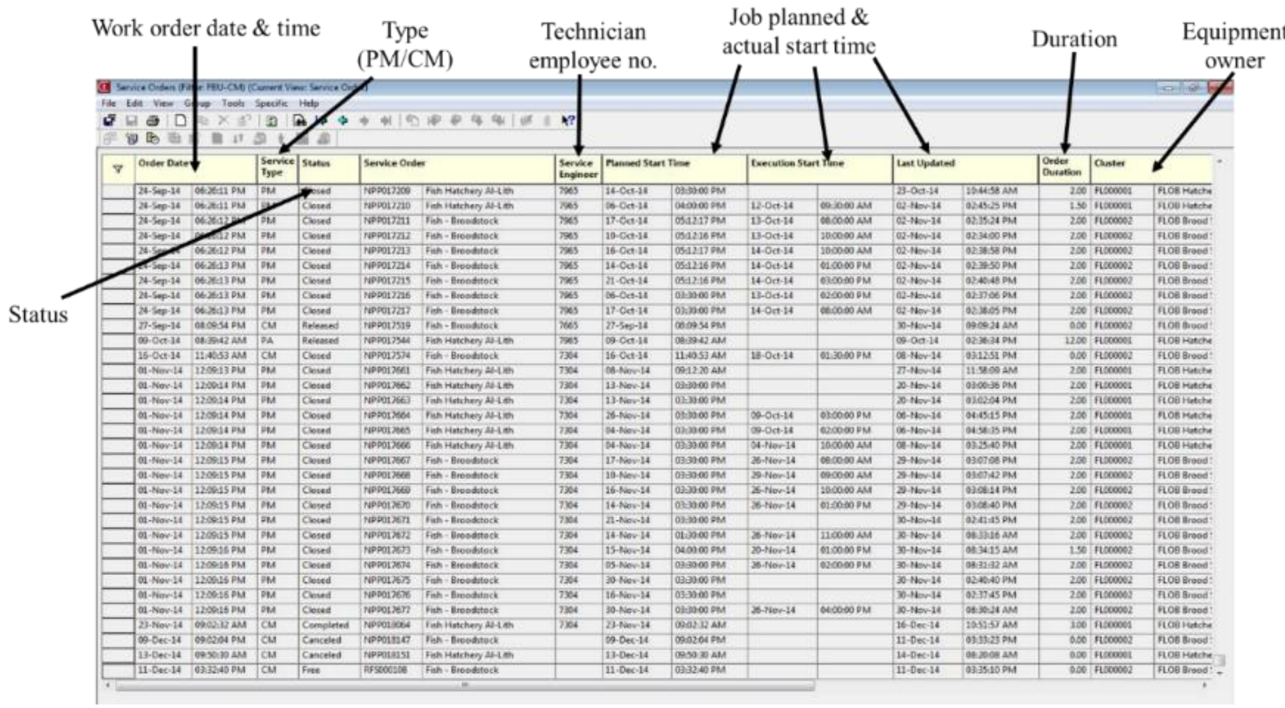

Figure 56: Work orders screenshot from software (Infor LN, 2006)

Annex. D

(Equipment failure codes in CMMS)

Table 16 lists common equipment failure codes used in CMMS software. With the help of failure code, the technician does not need to write details of the problem. Instead, the system can pick it from the prepared template.

Table 16: CMMS failure codes. (ISO, 14224)

Serial Number	Failure code	Description
001	LTA	Low-temperature alarm
002	CTA	Chain tension alarm
003	RAA	Rack alignment alarm
004	OLA	Oil leakage
005	ZPE	Zero position error alarm
006	OHA	Overheating or smoking
007	CAL	Calibration problem
008	BNA	Bearing problem
009	EFF	Evaporator fan fault
010	SRA	Sensor alarm