

Quantifying Maintenance system efficiency of a lobe blower in a maize mill

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Abstract

This study aims to assist maintenance managers in identifying the need for predictive maintenance on a specific machine. The endeavour is to provide justification for condition monitoring implementation and outline the need for technological progress. Generally, industries are reluctant to change existing systems, and it takes feasibility studies and convincing data for the capital expense. Maintenance strategies are not set in stone and can vary from one facility to another and from one machine to another in a specific facility. The current maintenance management system can be modelled using plant data from a computerised maintenance management system (CMMS). With a low-budget intermediate condition monitoring technique, existing data or data from the literature, predictive maintenance strategies can be compared using the MatLab model created in the study. The model is used in a case study on a maize mill blower from which relevant conclusions are taken regarding the feasibility of a predictive maintenance strategy for the specific machine. The model can show a direct comparison of cost and time between the existing maintenance system and that of a condition-based maintenance system.

Keywords

Maintenance strategy, predictive maintenance, preventative maintenance, condition monitoring, maintenance modelling, SimEvents, StateFlow,

List of abbreviations

AI - Artificial Intelligence

CBM – Condition Based Maintenance

CMMS – Computerised Maintenance Management System

CNC – Computer Numerical Control

GUI – Graphic User Interface

ICT – Information & Communication Technology

IIoT – Industrial Internet of Things

IoT - Internet of Things

FFT – Fast Fourier Transform

MCSA – Motor Current Stator Analysis

PDF – Probability Density Function

PdM – Predictive Maintenance

PLC – Programmable Logic Controller

PM – Preventative Maintenance

RMS – Root Mean Square

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1 INTRODUCTION

[1] describes the maintenance process as a "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function".

Maintenance is considered part of the operational process and is planned into many industries' manufacturing operations. Therefore, maintenance is required to be as economically effective and efficient as possible. There are many different maintenance management strategies, some more effective than others. In 2002 it was estimated that the total cost of maintenance in the food manufacturing industry was around 15 % of the total manufacturing cost. Industries with harsher environments, such as steel and iron, were around 60% [2]. The introduction of Computerised Maintenance Management Systems (CMMS) has helped to deal with the complexity and a large amount of information to manage maintenance effectively [3]. The introduction of ISO 55000 has assisted in asset management and the creation of an effective system for asset management [4]. These "tools" have created the opportunity to investigate maintenance systems for efficiency. CMMS data is readily available, and research into alternative maintenance strategies could create effectivity studies. With these studies, it is possible to assess the efficiency of current maintenance strategies, and managers can then use the data to evaluate whether changes to the systems are necessary.

In the milling industry, the same applies. The milling industry is a large industry providing staple foods such as wheat flour and maize flour. The milling industry also provides the first process for value-added foodstuffs such as bread, pasta, or instant porridge. The milling process has several steps, each with its unique process and definition as set out in [5].

- Grain Storage
- Cleaning/pre-cleaning
- Conditioning
- Degermination
- Milling and sifting
- Fortification
- Fine milling
- Packaging



FIGURE 1 MILLING PROCESS [6]

The milling process utilises several mechanisms of conveying, mainly distinguished by mechanical conveying and pneumatic conveying. Mechanical conveying using machinery such as:

- conveyor belts
- chain conveyors
- bucket elevators

Pneumatic conveying is also distinguished between positive pressure (blowing) and negative pressure (suction). The suction systems are primarily used in the milling process itself to re-lift the product within the building to be milled further for a finer product. Positive pressure conveying is mainly used to convey the different products (different granulation, protein contents, fat contents, and by-products) to their designated storage bins for packaging. The mill uses a lobe blower as the conveying mechanism. A rotary feeder separates the equipment above the blow line to ensure the product is delivered evenly to the blow line and conveyed to the intended storage bin or packaging line. The typical scenario is depicted in figure 2.

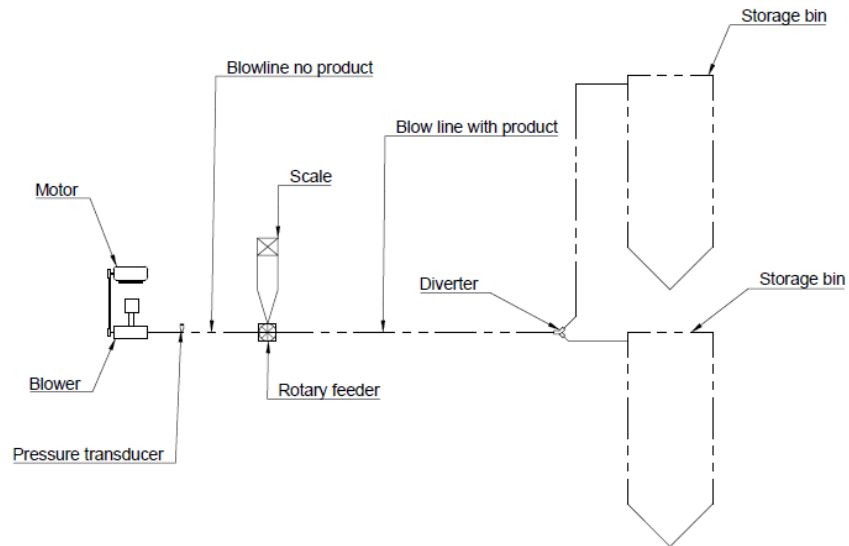


FIGURE 2 TYPICAL BLOW LINE CONFIGURATION

It is now clear where the lobe blower fits into the milling process. It is also seen in the process that the lobe blower is a critical machine in the milling process and requires the most efficient maintenance. The site for this study utilises 22 lobe blowers for various products, multiple mills, and packaging lines. With this many machines, the lobe blower's most efficient maintenance system is sought after.



FIGURE 3 INTERNALS OF A LOBE BLOWER [7]

Lobe blowers operate at various speeds depending on the airflow demand. These speeds are primarily around 3000 rpm, driven by induction motors directly or via belts. The belts are the most vulnerable part of this system, with the blower and motor relatively robust. Therefore, besides the regular oil check, there should not be much maintenance on these machines. However, this is risky since the lack of early fault detection could be fatal to the machine and result in high production losses.



FIGURE 4 MOTOR AND BLOWER DRIVEN BY BELTS

There is no doubt that any machine requires regular inspection. Efficiently doing this is what any facility strives to do. Therefore, it is no longer necessary to rely on a person's judgement to assess machinery, considering the available maintenance technology. Most importantly, it is also unnecessary to stop the machine for routine inspection to determine its condition. Various condition monitoring techniques can determine the condition of a machine, whether maintenance is necessary or not, and the urgency thereof.

The fourth industrial revolution has made it possible to take this further. The fourth industrial revolution uses the Industrial Internet of Things (IIoT), also known as Industry 4.0, to enhance the efficiency of condition monitoring by making multiple real-time condition monitoring systems available on one platform [8]. The instantaneous access to information can assist in resource management, decision making and future planning. In addition, the data collected can be directly incorporated into the CMMS that is already available.

The question, however, is whether this IIoT-based condition monitoring technology is truly economically beneficial and if it can improve the efficiency of maintenance systems. A statement in [3] mentions that a reduction of up to 20% in production losses can be seen. The reduction involves an improvement in quality and spare part inventory. In [9], a study on medical devices stated that up to 36% cost saving regarding device services could be made. However, the study in [9] utilises a statistical method to determine this value and is not device-specific using the generic term medical devices. The problem many industries face is that the data in the literature often refers to generic equipment such as "medical devices". There needs to be a clear indication of which machinery in a specific process has the efficiency-improving effect. There is now the conundrum of needing to implement a system to prove whether it has positive effects.

The authors in [10] extensively reviewed condition monitoring in the wind turbine industry. One of their conclusions is that condition monitoring can have a positive cost effect on the maintenance of wind turbines. They also mention a trend in the wind turbine industry to implement machines in remote areas such as offshore. In that industry and in such conditions, condition monitoring is a viable solution to sustainability. However, in the milling industry, where machinery is not exposed to harsh conditions and is mostly under operator supervision, the question remains, does condition monitoring provide an efficient and cost-effective maintenance strategy? Not all facilities can afford the research and development done in the wind turbine industry. Implementing a condition-based maintenance system to prove that it is viable seems like an unorthodox business strategy. However, maintenance management differs from other business ventures where sales volumes and margins can calculate a return on investment. Many variables are unknown concerning condition monitoring deployments. The severity of repairs should be low when using a condition monitoring system, but the chances of significant repairs are never eliminated. The existing maintenance system (whatever it may be) has been built up so well over the years that it has proven maximally efficient. It needs to be considered that there is an existing maintenance strategy for each machine. Therefore, an accurate comparison must be made before any decisions are made. However, machine specific studies are scarce, proprietary knowledge makes these types of results unattainable.

The complexity of plants makes the maintenance just as complex. Many maintenance strategies suit a facility perfectly. When trying to improve an existing maintenance strategy on either a specific machine or plant-wide, it is often the case that the unknowns are so significant as to derail the process from the onset. This applies especially to condition monitoring. For example, consider a machine for which the service intervals are only generically specified. This could lead to unnecessary stoppages, part replacements, or other maintenance expenses. However, it appears that the only way to know whether maintenance is unnecessary is by continually evaluating the machine's condition or letting it run past its service interval, possibly to failure. The latter is somewhat irresponsible and likely impossible in active plants. Experiments as such should be done in a laboratory or by modelling, as in [11], where the authors built a model and test rig. They managed to evaluate the effects of additional loads typically influencing the expected lifetime of a machine, suggesting that the run-to-failure procedure is not necessary for active plants. With this said, it should be remembered that such experiments are created in controlled environments that rarely reflect true conditions. Therefore, tests such as in [11] can only be used as guidelines to create maintenance strategies.

In [12], it was found that with the use of ultrasound, the specific facility started using 24% less lubricant and detected bearing anomalies at an early stage. The lifetime of the specific machine has increased fivefold with the implementation of this condition monitoring technique. These findings would only have been known by implementing their condition monitoring technique. However, these types of "blind" deployments are costly experiments. The results could just as easily have been that the existing methods were already maximally efficient. One way of addressing this issue is through real-time condition monitoring.

It is often only after implementation that the actual worth of condition monitoring is noticed. However, this contradicts good business strategies without being able to either quantify the benefits or calculate a return on investment. A detailed machine-level evaluation would also be required to determine which machinery could benefit from condition monitoring which is highly plant and machinery specific.

Convincing management to shift to predictive maintenance strategies requires evidence of feasibility. It requires a visual representation of the potential benefits. Condition monitoring has the potential, as previously mentioned, to reduce production losses by up to 20% [3]. Given the significant variations between industries and equipment, tangibly demonstrating condition monitoring value prior to deployment is a complex task.

Generally, investments are made based on certain feasibility studies' potential short-term and long-term benefits. Maintenance strategy changes that require expenditure should follow the same process. However, without the data of a previously implemented system, it is not easy to put these types of feasibility figures on the table. Some in the industry trust technological advancements and have implemented predictive maintenance strategies. For example, the energy sector shows evidence of vibration monitoring as early as the 1970s [13]. Steam turbines, a critical part of the electricity generating system, were subject to vibration analysis as a condition monitoring tool.

1.1 Problem Statement

However, some companies are reluctant to the implementation of condition monitoring. Partial reasoning could be that they are stuck in the old ways and do not want to change something that works. Another reason is that there needs to be convincing data to show the benefits condition monitoring could bring, leaving the question; how does one justify the change to predictive maintenance without a fully implemented system?

1.2 Objective

Literature shows how to implement predictive maintenance, what to use when to use it and outlines the possible benefits. The aim of this study is to develop a methodology that can assist in evaluating the possible benefits of predictive maintenance prior to complete implementation. By analysing existing maintenance management information and comparing it to predictive maintenance schemes the feasibility can be determined. We use the existing failure/maintenance information on a plant to evaluate the possible effects predictive maintenance can have.

1. Considering the above, the primary objective of this study is to show, on a machine level, the effect a condition-based maintenance system could have on the different aspects of maintenance.

A model-based approach that can present the current maintenance system with a comparative model that shows the results and aid in deciding whether condition-based maintenance would benefit that specific machine. The model should utilise the historic data of the machine to show the effect condition-based maintenance could have. Additionally, the model should be able to include existing condition monitoring data if intermediate data exists.

2. Create a cost benefit analysis to showcase the results in comparison to the direct maintenance cost and the operational influence condition monitoring could have. The cost benefit analysis must be based on the modelled results.
3. A Seeing that this study is rather machine specific, it would be beneficial if the model is compiled so that it can accommodate a variety of machines and condition monitoring methods. In addition, it would mean that the model could be used throughout various facilities and different types of machinery.

B The procedure or model should be easily implemented on a machine level that can be incorporated for any facility. In addition, the main attributes involved in maintenance should be easily identified compared to current maintenance strategies' historical data derived from a CMMS.
4. Since the model should be able to compare the existing maintenance system to that of proposed condition-based systems, there would be the possibility to amend the existing maintenance system and verify the results thereof. Therefore, an additional sub-objective could be that the model should be used not only to compare a completely new maintenance system, but also as a tool to make small adjustments to the existing maintenance system (such as a time interval between services) to improve its efficiency.

1.3 Methodology

A literature study will be conducted to show the types of maintenance systems. Predictive maintenance will be discussed together with some of its applications. A discussion on existing maintenance models will also be made.

A comparison between existing maintenance and predictive maintenance needs is required without fully implementing condition monitoring. Most maintenance systems have historical data that can be used. A predictive maintenance model will be built, comparing the basic condition monitoring data with a machine's historical data to verify the possible benefits. A model of the existing maintenance system will be used to verify the correspondence between the historical data and the model.

With the basic methodology set out above, some details will need to be resolved. These are outlined below:

- Procurement of accelerometers
- Procurement of data logger
- Acquiring maintenance procedures for the machinery
- Acquiring historical maintenance data of the machinery
- Taking vibration readings on the machine (live recordings and stand-alone recordings for playback)
- Analyse the vibration data to have an overall quantifiable condition of the machine
- Analyse historic machine data to be used for the model
- Build a model to be used as described in the objective

1.4 Summary

It has been established that a lobe blower is a critical machine used in the milling process. Used for pneumatic conveying, the lobe blower requires efficient maintenance to ensure run time and cost-effectiveness. In seeking economical and efficient maintenance, it has been realised that the maintenance processes of the specific facility might have been sub-optimal or outdated. Stagnation regarding resources, technology and maintenance decision-making, an investigation is justified. However, the need for machine-specific data has risen. The problem concerning the actual value added from condition monitoring was mentioned. Gathering evidence of the possible benefits of condition monitoring is the challenge. Machine-specific data is required to evaluate the existing maintenance and determine its efficiency. Herein lies the identified problem of demonstrating the possible value-added without a costly system integration.

The study's objectives are outlined to develop a process to evaluate the possible benefits of predictive maintenance. A brief methodology of the intended process of development is given. This included the procurement of equipment, data analysis and system development.

2 LITERATURE

This literature study discusses the lobe blower's functionality and typical machine failure modes. In addition, the study will mention types of maintenance management systems and several studies on the applications of condition monitoring. Finally, the literature study will also discuss maintenance modelling.

2.1 Lobe Blower

As mentioned in chapter one, a lobe blower is a component found in a mill and is typically used as part of pneumatic conveying. Rotary lobe blowers are positive displacement machines like that of a screw compressor. Refer to Figures 5 and 6 in the text.

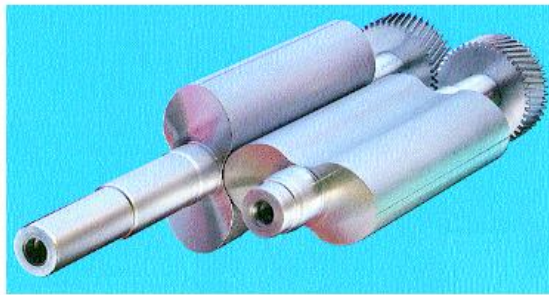


FIGURE 5 LOBE BLOWER [14]



FIGURE 6 LOBE BLOWER

The components of a lobe blower are sealed by o-ring seals matched with machined grooves to provide sufficient leak protection. This ensures optimal performance as well as machine longevity. The seals separate the conveyed air, external factors and the lubricant, ensuring the lubricant is not contaminated during operation. Regarding failures, bearings are the critical components of the machine; therefore, oil checks are a vital aspect of the maintenance process. In [14], Aerzen, the manufacturer of the machine in the study, prescribes oil changes every 4000 running hours after the first, which is required after 500 hours. The bearings should be able to last 60 000 hours at full load.

In the case of this study, where the blower is driven by an induction motor via v-belts, as shown in figure 7, it is also critical that the v-belt condition is checked regularly. The checks include v-belt tension and pulley alignment.

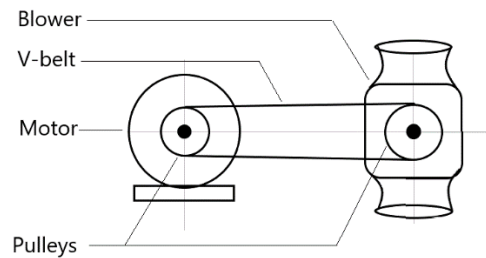


FIGURE 7 MOTOR BLOWER SCHEMATIC

Considering that the induction motor has rotating elements, the condition of the motor's components needs verification to prevent unscheduled downtime. There is a list of components that require conditional checks, namely:

- Motor
 - Bearing at the drive end (where the pulley is)
 - Bearing at the non-drive end (back end of the motor)
 - Stator windings
 - Rotor bars not scrapping on the stator
- V-Belts
 - Belt tension
 - Cracks on belts
 - Wear on both pulleys (belt not touching the bottom of the grooves)
 - Pulley alignment
- Blower
 - Oil level
 - Air filter
 - Bearings (drive and non-drive)
 - Internal gears
 - Lobe conditions

The typical maintenance process for this type of machinery would be preventative and utilise check sheets to manage inspections, oil changes, and filter changes. After a predetermined run time, the machine would be out of operation to replace the bearings and seals. In case of breakdowns, the machine would need replacement and sent to a specialised workshop for repairs.

The machine's rotors are dynamically balanced, meaning minimal noise and vibration transfer should occur. However, compression pulsations can occur at higher pressures indicating that the machine is operating above its intended working limits.

The lobe blower should be a low-maintenance machine when considering the manufacturer's recommendations. Doing the basics, such as ensuring sufficient lubricant, uncontaminated lubricant and ensuring no external vibration factors, should keep the machine running for a considerable lifetime.

2.2 Maintenance Management

The primary purpose of maintenance management is maintaining machinery for optimum operating conditions and managing maintenance resources to keep a facility running at its highest efficiency with minimal downtime and cost. However, record keeping of machine data is a critical aspect of maintenance management to ensure informed decision-making.

The manufacturing industry's most common types of maintenance systems include run-to-failure, preventative, reliability centred maintenance, and condition-based maintenance, also known as predictive maintenance [15]. With the integration of a computerised Maintenance management system (CMMS), the large amount of information that needs to be processed for a complex plant can easily be stored, processed, and assessed for decision-making. As a result, activities are easily managed, and resources are effectively utilised to ensure actions are executed timeously [3].

2.2.1 Run To Failure

Run to failure as a maintenance system is relatively self-explanatory. Besides some essential maintenance, such as lubrication, the machine is left to run until a part breaks down, forcing the company to keep a high spare inventory if they want effective and reliable production. There is no prolonging of a machine's life, meaning complete part replacements are necessary when the machine breaks down [2]. This highly reactive maintenance management strategy does not ensure high plant reliability. The costs of spare parts and breakdowns cause low reliability of the plant and make this an undesirable maintenance management strategy without considering the higher labour costs (overtime) involved and higher production losses.

2.2.2 Preventative Maintenance system

Preventative maintenance is a time-based maintenance strategy, meaning any task (besides breakdowns) is time-based, operating hours, monthly or yearly. This strategy's implementation varies from basic lubrication checks, adjustment or replacement of wear parts to highly detailed and specific part replacement and even machine rebuilds. However, everything is scheduled according to relative elapsed time. Preventative maintenance follows a mean time-to-failure strategy, which states that at the beginning of a machine's life, it is expected to require a lot of attention until most of the commissioning problems and settings are dealt with. After this, the machine will likely operate with a generally low frequency of breakdowns if the correct preventative maintenance scheme is followed. However, as the machine approaches the end of its operating lifetime, the frequency of breakdowns increases. At this

stage, major parts or machine replacements need to be considered. This is commonly described as the bathtub curve [2] and is depicted in figure 8.

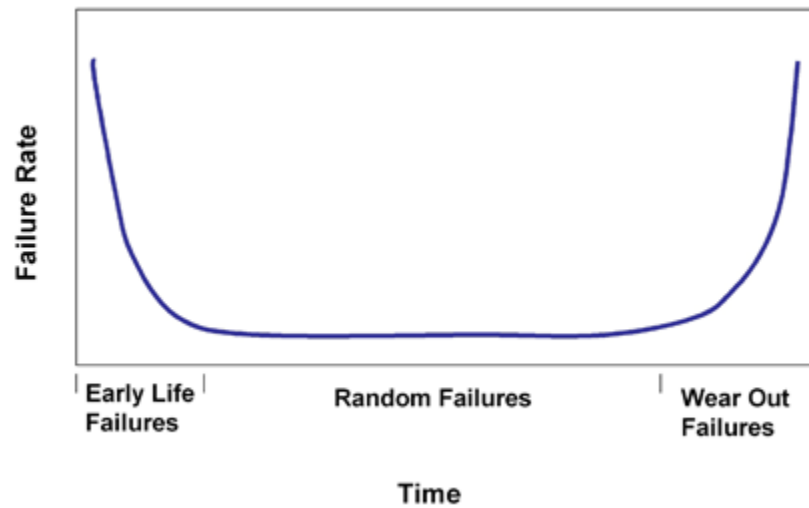


FIGURE 8 BATHTUB CURVE

Since preventative maintenance strategies are time-based, the actual condition of the machine has yet to be discovered. Although the schedules (primarily based on failure statistics or historical data) show that a machine requires a bearing replacement, it does not necessarily imply that the bearing is on the verge of failing. Furthermore, this suggests that the machine was potentially unnecessarily opened, which poses a risk of errors from the artisan or operator, and a technician replaced the bearing unnecessarily. These actions result in pointless spares, downtime, and labour costs. Additionally, the time-based schedule does not consider any additional factors. A machine that is operated at idle and near overload is treated similarly.

2.2.3 Predictive Maintenance System

The primary concept of predictive maintenance is to utilise available elements to predict failures and to schedule interventions to restore the machine to an optimal operational state. The factors mentioned can vary and can be categorised in different domains according to [16]:

- Physical – measuring physical elements (condition monitoring)
- Knowledge based – rely on expert knowledge and/or fuzzy logic
- Data driven – statistical interpretation, implementation of artificial intelligence or machine learning is also applicable
- Combined – the combination of different domains

[16] mentions that there has been an increased number of combined concepts being developed. An example is shown in figure 9 where the physical and the data drive domains are used for machine prognostics.

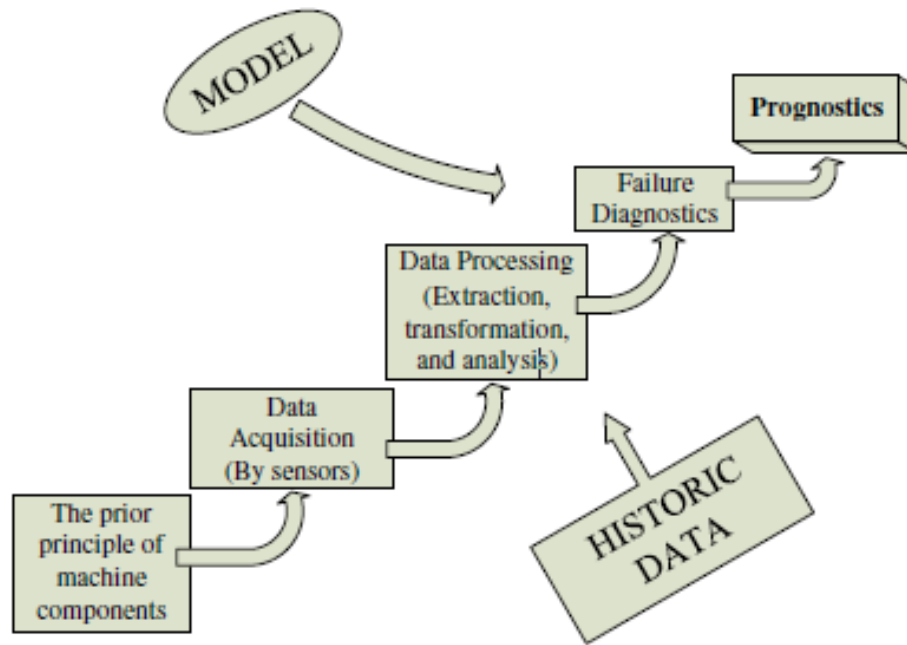


FIGURE 9 COMBINATION OF PREDICTIVE MAINTENANCE DOMAINS [16]

In figure 9, it is clear that predictive maintenance's main aim is to create a prognosis of a machine's condition. The machine condition is then used for maintenance decision-making to either react soon or extend maintenance activities.

2.3 Condition Monitoring (CM)

There are many condition monitoring methods to incorporate into a predictive maintenance management system, with some being more effective than others. Several conditions must be evaluated when choosing the most effective manner for a specific plant, manufacturing industry, or machine type. Some of the conditions are:

- Machine position, is the machine easily accessed
- Type of machine
- What is its energy source
- Components

The type of CM being used must also be cost-effective, and potential improvement in maintenance efficiency must be evident. The maintenance efficiency is quantified with more than just downtime. Labour and spare part costs should also be taken into consideration. Some of the existing CM methods are briefly discussed below.

2.3.1 Vibration Analysis

A vibration can be described as a repetitive motion over a specific interval. The time interval is known as the period (T), and the frequency of a vibration is the inverse of that period $\frac{T}{1} = f \text{ (Hz)}$. Figure 10 shows a theoretical vibration signal from an oscillating pendulum; however, a signal from a machine is much more complex.

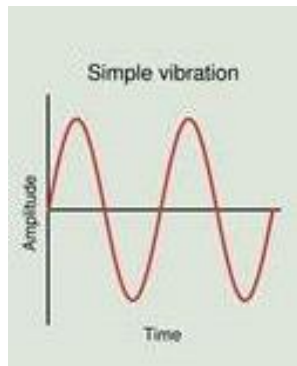


FIGURE 10 SIMPLE OSCILLATION

All mechanical machinery generates a vibration signal when in motion. The motion mentioned does not necessarily need to be rotary. Any movement of a mechanical part provides a vibration signal. This signal needs to be analysed according to the type of movement and machine application. At frequencies below 10 Hz, specialised low-frequency sensors are required. Hence for vibration analysis to be accurate, applications running at more than 60 rpm are needed [2].

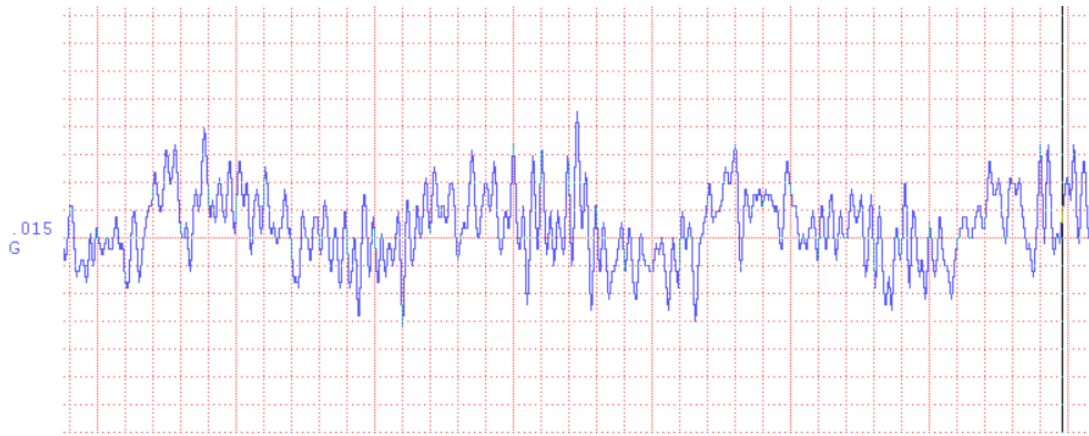


FIGURE 11 VIBRATION SIGNAL OF AN INDUCTION MOTOR MEASURED IN G (DRIVE SIDE BEARING) (0.002s GRID SPACING 10kHz)

Figure 11 shows a vibration signal generated from an induction motor drive bearing. Here we can see the complexity of several harmonics present. Figure 11 shows the complexity that vibration analysis can present. These signals cause constructive or deconstructive interferences depending on whether they are in or out of phase. The principle is depicted in figure 12.

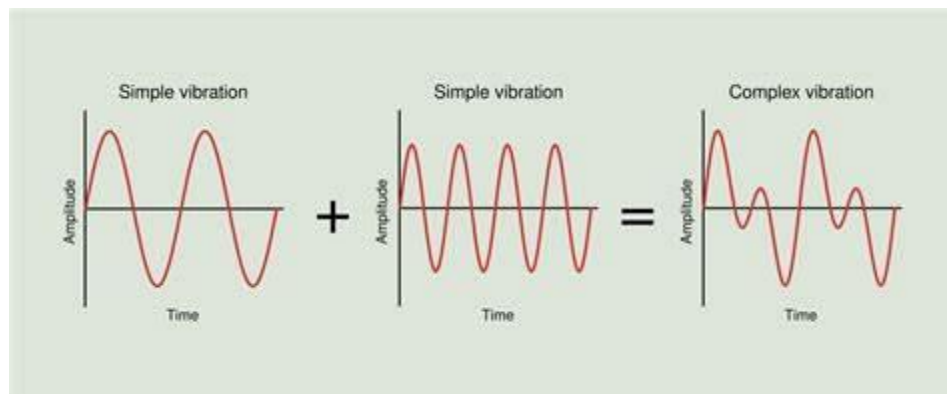


FIGURE 12 TWO SIMPLE SIGNALS TOGETHER CREATING A COMPLEX SIGNAL

A signal, as in figure 11, already helps to recognise a trend. For example, a gradual increase in amplitude could suggest that the machine is no longer in the condition it was at startup. However, the exact defect of the machine has yet to be discovered. First, the signal must be transformed to its frequency domain using a Fast Fourier Transform (FFT). The FFT decomposes the signal into a frequency spectrum. From this, we determine what frequencies run at larger amplitudes.

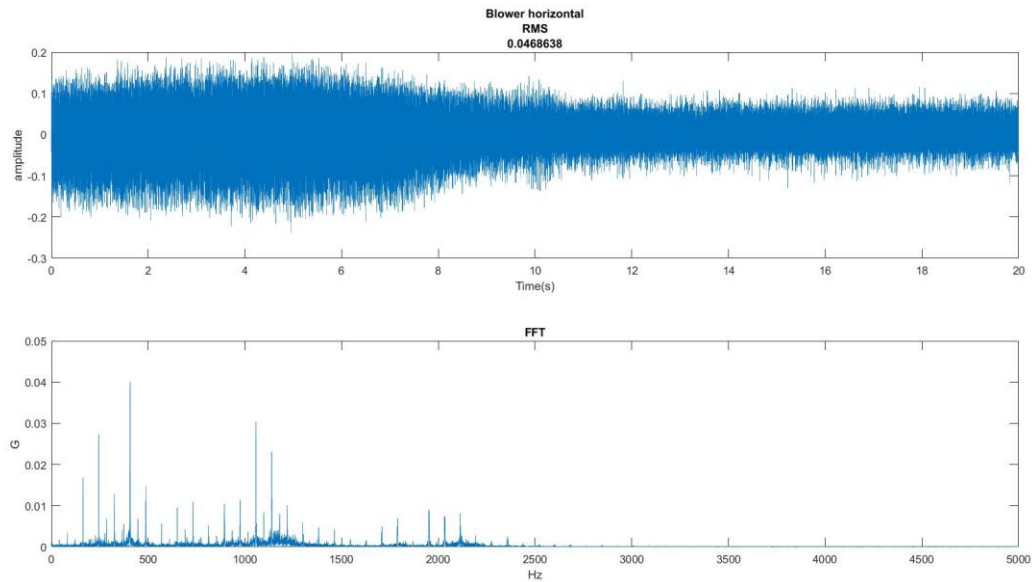


FIGURE 13 SIGNAL IN THE FREQUENCY DOMAIN (FFT PERFORMED)

From figure 13, we can see the amplitudes at different vibration frequencies. The spectrums' peak frequency, the machines' operating frequency and the machine's parts (bearings, gears etc.) are evaluated. Thereby a technician can make several deductions. Figure 14 demonstrates this with an example of angular or parallel misalignment. Note that the position of the measurement is also different for the two. For parallel misalignment, we will need to measure the bearing housing in a radial direction, and for angular misalignment, we will need to measure in the axial direction.

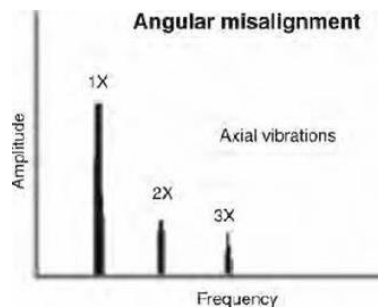


FIGURE 14 PARALLEL AND ANGULAR ALIGNMENT [17]

Numerous deductions can be made with the frequency spectrum:

- Unbalance (in fans, turbines etc)
- Misalignment (between bearings, between gearbox and motor etc)
- Bent shafts
- Eccentricity
- Looseness (loos motor base)

- Resonance (excessive vibration due to resonance – can be detrimental to structures and machinery)
- Cocked bearing
- Rotor rub (in induction motors)
- Cavitation (in pumps)

The peak of the amplitude in the FFT or the RMS value of the signal needs to be considered to determine the severity of the found defect. Usually, the overall vibration is used in mm/s to assess the severity of the machine relative to its power size. An ISO standard shown in the figure 15 can be used to evaluate the vibration severity.

VIBRATION SEVERITY PER ISO 10816					
Machine		Class I small machines	Class II medium machines	Class III large rigid foundation	Class IV large soft foundation
in/s	mm/s				
Vibration Velocity Vrms	0.01	0.28			
	0.02	0.45			
	0.03	0.71	good		
	0.04	1.12			
	0.07	1.80			
	0.11	2.80	satisfactory		
	0.18	4.50			
	0.28	7.10	unsatisfactory		
	0.44	11.2			
	0.70	18.0			
	0.71	28.0	unacceptable		
	1.10	45.0			

FIGURE 15 ISO SEVERITY CHART 10816 [17]

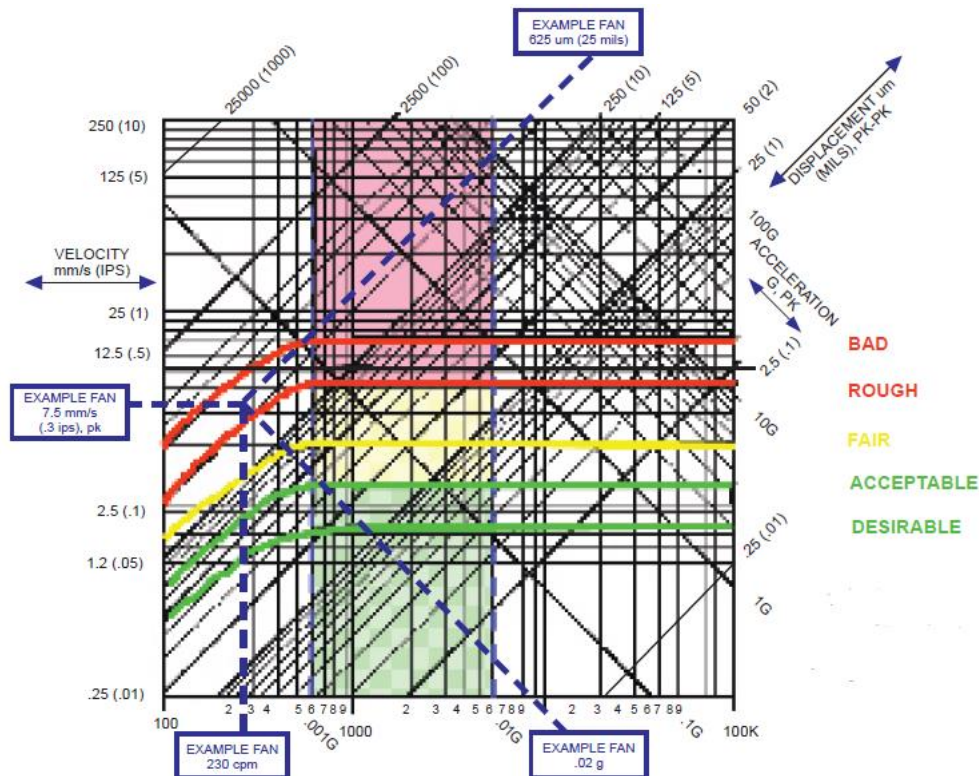


FIGURE 16 ISO SEVERITY CHART 10816 SHOWING VELOCITY AND ACCELERATION [17]

Conversion calculations from [17] can be made between displacement, velocity, and acceleration.

Equation1: $g = 0.641Vf$

Where:

- g = acceleration (m/s^2)
- v = velocity (m/s)
- f = machine running frequency (Hz)

Vibration based condition monitoring has developed tremendously in recent years and has been around for a long time. It is one of the most common and reliable forms of condition monitoring but requires relatively large computational capabilities.

2.3.2 Thermography

Thermography is a CM technique that uses infrared emissions. The operating condition of a machine can be determined by monitoring thermal anomalies. Infrared emission can only be detected using special instrumentation. Infrared is the radiation of heat from a surface. This heat can be generated by the object itself, reflected from a surface or transmitted by the object. Using thermography as a condition monitoring method, only the energy emitted by a specific object or machine is measured [2]. For thermography to

have a useful function, the reading should be taken when the machine is running under its usual conditions. Thermography is often used in electrical appliances to view the state of electrical connections, fuses, motor condition, overheating cables etc. For example, in [18], a proposed method used thermal imaging to determine whether porcelain insulators on high-voltage lines were faulty.



FIGURE 17 PORCELAIN INSULATION MONITORED BY INFRARED IMAGING

Mechanical applications such bearings on an induction motor can also be monitored as done by [19].

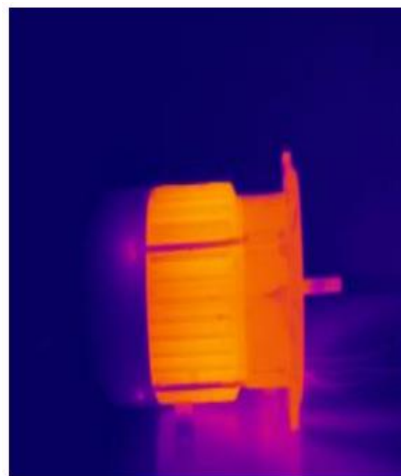


FIGURE 18 INDUCTION MOTOR MONITORED BY THERMAL IMAGING

2.3.3 Ultrasound

Ultrasonic condition monitoring bases its principle on high-frequency sound generation. It is related to vibration monitoring but focuses on higher frequencies. Ultrasound is a sound that is not detected by the human ear, typically above 20kHz.

The main condition monitoring application for ultrasound is for airborne noise, leak detection and material detection. [2]. Leak detection uses the principle of turbulent air flowing through an orifice, creating a high-frequency signal (leak). This method can detect leakages in pipes, valves, steam traps, pressure vessels and processing equipment [20].



FIGURE 19 LEAK DETECTION WITH ULTRASONIC CONDITION MONITORING [21]

Ultrasonics can also identify types of material or determine the integrity of a specific material. For example, by striking a material with a hammer, and if the material is known, a machine can monitor the response to determine the material's thickness. Also, if the thickness is known, the response time is used to determine the type of material and whether there is a crack in a workpiece [2].

2.3.4 Motor Current Signature Analysis (MCSA)

MCSA is a condition monitoring method used in induction motors. The process, as its name suggests, measures the current through the stator to determine the condition of the motor. This technique originated from nuclear power plants where equipment was widely inaccessible due to harsh conditions [22]. MCSA is a condition monitoring system that measures the live current readings of an induction motor and, through this, can detect many motor faults without any interference before catastrophic failure.

MCSA can also be used in other electrical machineries, such as generators and transformers. According to [23] MCSA can be used to detect faults such as:

- Broken rotor bars
- Abnormal levels of air gap
- Eccentricity
- Shortened turns in stator windings
- Limited mechanical problems such as bearing failure

2.3.5 CM Summary

Referring to the discussion on the basics of a lobe blower and its maintenance, a benefit could be seen in using a predictive maintenance strategy with its condition-based tools. Considering that an induction motor runs the lobe blower, MCSA can be suggested as a condition-monitoring technique. In addition, ultrasound could be helpful on the lobe blower system to ensure efficient operation with no leakages. The predominant condition-based strategy would be vibration monitoring. With this bearing and gear health can be confirmed, with the two elements in good condition, the machine would pose minimal risk of failure.

One of the problems identified in the literature on condition monitoring is the amount of data processing and storage used. In facilities with a large amount of machinery that requires condition monitoring, this could become a problem if managed with stand-alone systems. A possible solution would be to investigate the developments on the Internet of Things.

2.4 Internet of Things (IoT)

The interpretation of “the internet of things” has not been set into a clear definition. Many have given it their definition; [24] *defines it as:*

“The Internet of Things is the network of physical devices embedded with software, sensors, actuators, and network connectivity that enables these objects to collect and exchange data.”

The internet of things is critical to the fourth industrial revolution, Industry 4.0. Although the mechanical and electrical transformation of manufacturing processes formed the first two industrial revolutions, the increase in information technology and automation is referred to as the third and the fourth revolution slowly taking over our industrial processes.

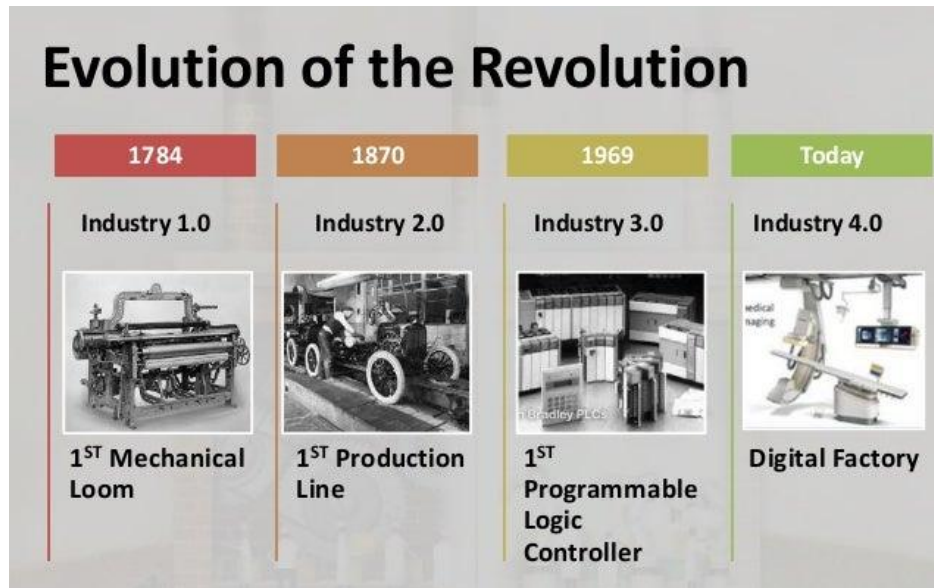


FIGURE 20 EVOLUTION OF INDUSTRY [25]

Industry 4.0 refers to the integration of cyber physical systems into our manufacturing and logistics processes, whereby IoT is the baseline of the revolution [26]. IoT is the beginning and drives behind the idea of smart factories.

Since its creation, the internet has expanded drastically and affected industry and our daily lives. Furthermore, the internet is starting to impact the physical world as well by being able to capture information from physical elements and using that information to affect another material object, as mentioned by [27].

The internet of things comprises four main components, software, hardware, network, and external systems. [27]. For maintenance, we can use IoT to integrate condition monitoring data.

The basic concepts for IoT are Cyber-Physical Systems (CPS), Cloud Computing and Machine Learning/AI [28]. These concepts enable us to monitor manufacturing systems and create a dynamic decentralised support system for the end user. This support system can be integrated to provide services for the producer and increase production capabilities through improved maintenance or quality control. Furthermore, IoT provides the possibility to increase efficiency in terms of accuracy and consistency for data management. Data is collected with IoT through sensors connected to machines. This data, in return, is processed and interpreted with analytical tools to have helpful information which can be used for decision-making, planning and the general increase in performance.



FIGURE 21 IOT STRUCTURE, PHYSICAL LAYER TO THE CLOUD [29]

One of the critical components of the further development of IoT is cloud computing. The cloud computing process can be described as storing and retrieving data, programs, tools, applications, etc., over the internet. It is a cost-benefit by avoiding the set-up of servers and requiring an in-depth ICT infrastructure in-house [28]. Where the infrastructure such as servers is not available cloud computing could be used to further enable IIoT. This is depicted by [28] in an experimental setup.

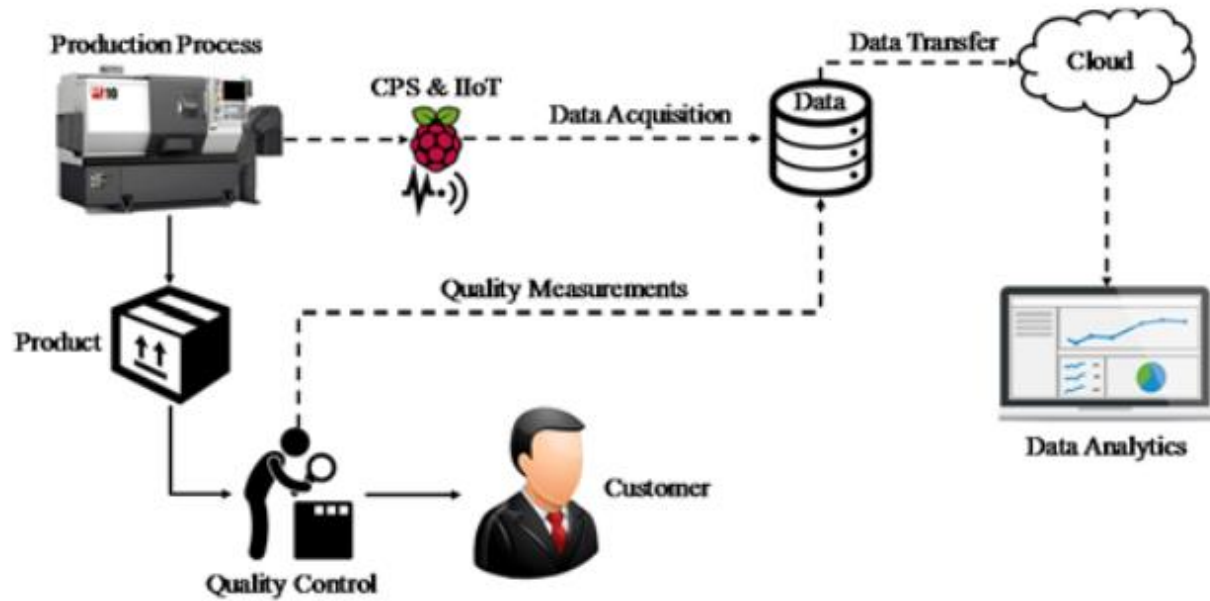


FIGURE 22 EXPERIMENTAL IOT SETUP WITH CLOUD COMPUTING [28]

IoT can be a tool to enhance predictive maintenance further. IoT is also an excellent mechanism for integrating control systems and IT functions, thereby bridging to the maintenance systems (CMMS). Control systems that are integrated allow maintenance to use data from control systems as an alarming mechanism for better maintenance decision-making or even enhancing production systems without significant improvements to the running systems. However, since IoT is only an enabler of PdM, the analysis of it will be limited in this work.

2.5 Modernised Maintenance through IoT

For maintenance management, we can use the IoT to connect physical devices (machinery), the operator and the artisan on one platform to exchange data regarding the machine's condition. The physical instrument will be able to connect with the operator, deliver information regarding its current operating condition, and have the software perform analysis. The analysis can determine whether the machine is healthy, if intervention is required, and to what extent and urgency. The process streamlines decision-making by using modern condition-based systems connected over IoT.

With all these monitoring systems, we face the problem of processing the data gathered and capturing the volume of live data. Furthermore, with new complex manufacturing systems, maintenance could also take advantage of creating an intelligent maintenance strategy [28].

The concept of a smart maintenance system has been introduced previously, and [28] discusses the subject. The Authors proposed using IoT as a predictive maintenance method, making it cost-effective for

small manufacturing enterprises. Their concept was based on a CNC machine measuring the temperature and vibration, storing the data, and running a regression tree model for predicting rejected products based on quality, indicating the machine condition (excessive vibration, tool bits being blunt etc.).

In the study done by [30], a smart system was used to determine the frequency of maintenance tasks on forklifts. The service provider was determined to keep the machines running and, in that needed to determine where the highest risk of failure was. By classifying the forklifts by age and the number of working hours, they managed to model a system that can predict which machinery is at higher risk of failure and determine the required maintenance interval.

[30] assessed the risks of failure on medical equipment to prevent long waiting periods on spare parts. The assessment assisted with deciding which machinery should be repaired in-house instead of returned to the manufacturer. A similar study by [31] incorporated Vibration analysis to forecast the failure of a machine to assist with the timely ordering of parts and determining the type of repairs required.

Incorporating the internet of things and maintenance opens the possibility of integrating artificial intelligence. For example, a paper on the development of predictive maintenance and the implementation of machine learning algorithms shows that such systems can effectively reduce downtime and unforeseen failures [32].

The studies mentioned are intelligent tools that can assist with maintenance management around condition-based decision-making. The added benefit of IoT for maintenance management is that any information gathered at any point can be reused for future analysis and trending and can be real-time data. Furthermore, decision-making is assisted with analysed data, giving support regarding maintenance activities, their intervals, and spare parts. IoT enables us to do this under one platform with easy future expansion.

There are studies regarding the overall maintenance improvement and efficacy of maintenance strategies. Some implementations of condition-based maintenance were mentioned in this literature chapter. However, these need to address the problem identified in chapter 1. In all these examples, the effects were only quantifiable after implementation. As per the introductory chapter, this is not sustainable for existing larger-scale process plants. The next section presents a representation of studies that use different modelling tools to address aspects of the problem gave.

2.6 Maintenance Modelling

As mentioned, the study aims to outline the challenges of presenting the benefits of condition-based maintenance without actual implementation. The challenge is that each facility is unique, and each company has procedures to manage their asset.

Maintenance modelling can have different approaches and is dependent on what the results would need to conclude. However, models can assist in resource management, determining the criticality of machines and machinery effectiveness. This study aims to assess the efficacy of current maintenance systems and to run a comparison with predictive maintenance.

In [33], a study regarding the criticality of maintenance strategy and its relevant assets discusses the need to verify maintenance strategies to keep up with the business model and ensure that the strategy aligns with business objectives. Considering business objectives is critical when trying to change traditional and working systems. In [33] a process of working with a model that can assist management in using a criticality analysis tool is outlined. The study mentions that such a criticality analysis should assist management in deciding which assets have higher priority within the maintenance system. This type of model could be used to justify the need to adjust maintenance strategies. A model such as this can be used to identify assets that require a change in maintenance strategy because it has a low criticality rate or high criticality rate. The criticality rate in this study factors in the type of affect and frequency a failure of an asset may have.

The model in [33], is essential to maintain a maintenance strategy and keep it effective. The authors mention that a cost -risk-benefit analysis may lead to discarding certain predictive maintenance implementations, being identified as redundant. It can also be as a coach to the identification that additional maintenance is required. On lower levelled (going into more technical detail) analysis, the question resulting from such a study would be, "What type of maintenance strategy needs to be implemented, and what will the effect thereof be?". The model creates a hierarchy of assets determining the criticality of the machines. This model is an iterative model during the operational period of a machine or plant to keep the maintenance strategies effective [33]. As an effective tool, the model's data can show that some maintenance can be eliminated or replaced. It does, however, not show what the effects of the changes could be. It is also difficult to say whether such a method can gather the necessary machine-specific information.

Keeping maintenance strategies effective is an essential part of a facility's business success. The importance of this is mentioned several times in the literature, namely [1], [33] and [34]. Determining the correct strategy plays an important role as well. An evaluation should be done for every functional part of a facility [1]. The concept of maintenance strategy selection is applied and, selecting the correct maintenance system can become complex in large facilities. Maintenance planners should have an in-

depth knowledge of the production systems, machinery, product, and production planning must be known to do this effectively [1]. This is where models can have an enormous effect.

In determining maintenance's efficacy, the cost of maintenance is primarily reviewed. However, the total maintenance cost should consider the actual maintenance cost and the failure cost. This is mentioned in [35], where mathematical models are utilised with the following key objectives:

- To estimate the effect of maintenance on the current age of the system
- Optimal preventive maintenance schedule to maximize uptime and minimize maintenance cost.
- Predictive maintenance model to predict failure behaviour.

The model focuses on creating an optimal maintenance schedule for the machinery in its state at its implementation [35].

As mentioned previously, IoT and predictive maintenance have merged in recent years and drawn attention to the manufacturing industry. In [8], a study conducted to evaluate the effect predictive maintenance has on maintenance strategies suggests that predictive maintenance becomes truly feasible with AI (Artificial Intelligence) and IoT. The impacts between aspects of predictive maintenance and preventative maintenance are evaluated. The authors in [8] mention that the accuracy of the prediction is an essential aspect of the efficacy of predictive maintenance. It is elaborated that high prediction accuracy can reduce maintenance intervals and unnecessary failures. [8] found that the cost between preventative and predictive maintenance was roughly the same. The study relies on the assumption that losses follow the Weibull distribution. This is the general distribution used to evaluate failure rates used in the simulations [8]. Statistical variations determined failure rates; it was found that the failure frequency rate had less effect on predictive maintenance than the preventative maintenance systems. A statistical method of evaluating predictive maintenance was created simply because failures are predicated in the PdM system.

[8] is the closest to a solution to the problem stated. The models mentioned can show the effects between different maintenance strategies, but not necessarily on a machine level and not as a comparison between an existing maintenance strategy and that of a possible predictive maintenance strategy. These models also do not concern themselves in detail with the type of prediction maintenance implemented. A machine/component level maintenance comparison needs to be achieved, after which a decision can be made on whether a change in strategy is necessary for the specific type of asset.

2.7 Maintenance Simulation

[8] mentions statistical analysis, specifically referring to the Weibull distribution for failure rate analysis. The authors in [36] concluded that three statistical distributions could be used for service life prediction, namely:

- Weibull
- Lognormal
- Gamma

[36] used a Monte Carlo simulation to evaluate the service life of a building. Even though this is not based on a machine, the statistical approach in using the distributions can become helpful.

Discrete event simulation has also been used as an alternative for maintenance modelling. One specific simulation is the Ultra-Reliable Aircraft Model (URAM) [37]. A model such as the URAM is based on the entirety of an aircraft. In [37] a model revolving around Maintenance Free Operating Periods (MFOP) is discussed. The type of discrete event simulation focuses on identifying the potentially liable area, building redundancy into a system, task prioritisation, planning and fault diagnostics and isolation. According to the authors in [37], this tool could be generalised for railway networks and ships. However, it missed the machine specifically and the lower-level analysis required for the problem presented in Chapter 1.

KPI's are a vital aspect for industries to measure the efficiency of business models. The same applies to maintenance. Maintenance also has standard matrices that are measured in the industry. Most of these revolve around the available machinery hours and scheduled maintenance vs unplanned maintenance costs. This follows the concept of calculating the overall equipment effectiveness (OEE), the mean time between failures etc. [38]. These statistics use historical data such as downtime, number of jobs per machine, and number of breakdowns to evaluate the effectiveness of maintenance and are based on a machine's historical data. Effective maintenance is measured by a few main areas: machine availability and cost. Any comparison model should include at least these two main aspects.

There are some aspects that the modelling methods mentioned in this chapter have in common. First, they all use some form of mathematical computation. Statistics from historical data is a prevalent method used to predict what might happen. Evaluating the criticality of the machine requires one to compute the risks and probability of failure. With the risks of failures, the costs that a failure can incur are also evaluated, this being production losses and machine replacement costs. These are then compared to the cost of ongoing maintenance and the effects thereof. Building these types of comparisons into a model can assist in the decision-making about what maintenance strategy is optimal for a specific machine or plant. Even systems that make use of machine learning make use of historical data in the decision-making matrix. Neural networks are based on statistics from that specific machine

or similar machines. Implying that there is a need for historical data to build a maintenance model for comparative reasons.

2.8 Summary

In this literature study, we have reviewed and identified different aspects of maintenance. The maintenance management strategies that exist, up to the different condition monitoring methods. The integrations of IoT with condition monitoring have been discussed, giving some examples where small systems have been integrated with machinery. The power of data usage with IoT was noticed, meaning IoT and CBM can be powerful enablers regarding maintenance efficiency.

Quantifying the efficacy of maintenance systems is the primary objective of this document. From the studies in this literature review, few to none of the systems provide figures that can provide such an analysis. The lack of cost, time, and resource comparisons between conventional maintenance and newer modern methods might be why some parties in the industry are reluctant to modernise their maintenance strategies, even though newer condition-based systems are highly spoken of. Modelling maintenance systems should be able to give the end user helpful information in terms of the pros and cons when adopting a new approach. These should provide ease of mind when adopting modern strategies or staying with conventional systems. The KPIs mentioned in the previous chapter need to be considered to make a valid comparison between an existing system and a model. The literature also showed a clear distinction between planned and unplanned maintenance, which must be considered when evaluating maintenance.

3 THE MAINTENANCE MODEL

In the literature review, one study revealed a discrete event simulation which closely resembles what is required in this study. Therefore, the model built will follow the principle of a discrete event simulation. A Simulink model is used to quantify the possible effects a predictive maintenance model can have compared to a preventative maintenance system. The model needs to compare an existing maintenance system with a condition-based one as mentioned in the objectives. From that, a possible evaluation can be made on whether an improvement on efficacy is possible. There are many aspects that can be used to evaluate the efficacy of maintenance:

- Downtime
- Cost
- Spare parts inventory
- Resource management
- Number of jobs required

For this study, the quantifiable aspects that will be used are the machine downtime due to maintenance and the cost of maintenance. In addition, the number of jobs required will also be used as a measuring unit since condition monitoring needs to address the problem of unnecessary work is being done on machinery when following a preventative maintenance system.

The measurable aspects that this model needs to generate, and compare are scheduled jobs and unscheduled jobs. Knowing this and considering the two quantifiable entities of the jobs that are required, the model needs to be able generate the two different maintenance (scheduled, unscheduled) aspects with their relevant entities (cost, hours).

Since the model needs to be able to present a comparison between an existing maintenance system and that of a simulated one, historical data representation is required. Therefore, the user must be able to enter the historical data to be processed and presented to compare with the proposed predictive maintenance model.

3.1 Maintenance System Process

Before structuring the model, the process flow needs to be evaluated and specified. This process flow will determine the required model blocks and define the simulation process with the desired outputs (cost, hours, number of jobs).

3.1.1 Preventative Maintenance

In a maintenance process, several events take place regardless of the type of maintenance strategy. Any maintenance system requires interaction between the operational environment and the maintenance environment. Operational variables would be a determining factor in triggering a maintenance event, including machine run time, operator involvement (asking for changes), machine breakdown etc. In preventative maintenance systems, we know that this event trigger is time. Time intervals between maintenance events are fixed in a preventive maintenance system, being running hours or a specified time interval, for example, a monthly maintenance schedule.

The maintenance event then occurs and once completed returns the machine to a fully operational state. This maintenance event requires resources from the maintenance department, which is recorded by the artisan that performed the tasks. The information is then processed on a computerised maintenance management system (CMMS) for record keeping. The flow of scheduled maintenance is graphically shown in figure 23—the shapes and colours used to differentiate between the steps in the process.

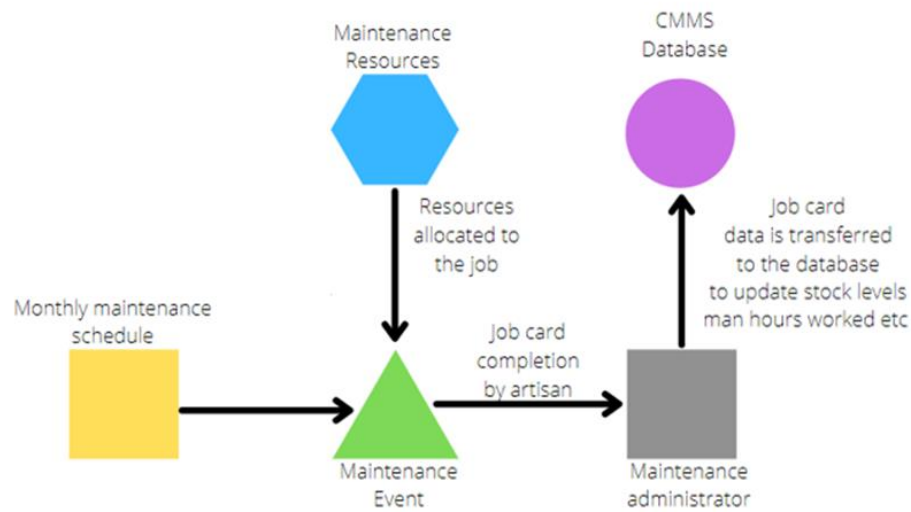


FIGURE 23 SCHEDULED MAINTENANCE FLOW CHART

As mentioned previously, the trigger for a maintenance event can be numerous. There are two distinctions between the Maintenance events, scheduled maintenance, and unscheduled maintenance, referred to as repairs. The repair jobs are events that are triggered by any other of the variables. For example, the operator might want changes, breakdowns, inefficiency, or a deficiency noticed. These random events are not at all linked to the scheduled events. This means that this job needs to trigger different events and have a unique identifier on the CMMS database. In the process flow depicted in figure 24, this other entity can be identified by the red square showing the creation of a repair job card. The repair job card includes any unscheduled job that required downtime in the facility.

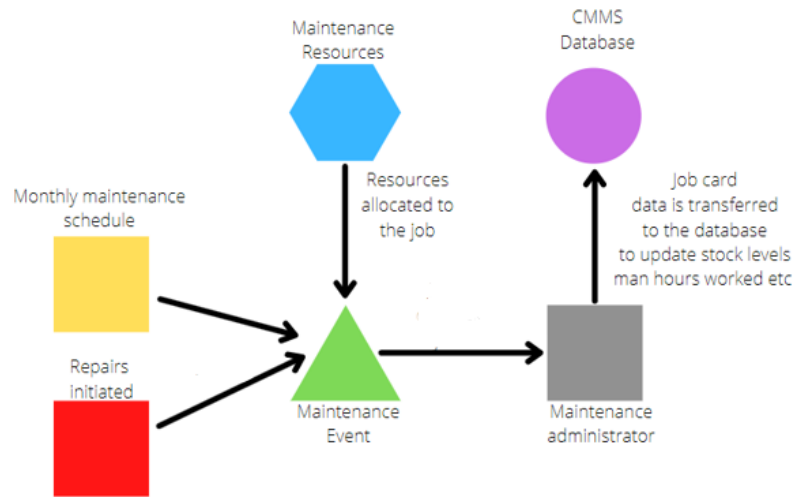


FIGURE 24 PREVENTATIVE MAINTENANCE

3.1.2 Predictive Maintenance

For predictive maintenance, the procedure is very similar, the main difference being the consideration of the machine's condition to trigger the maintenance event. Instead of having a schedule for jobs or having an operator request a job, the machine condition would determine whether maintenance jobs would be necessary. Figure 25 shows the process flow, replacing the scheduled and repair jobs by the machine condition.

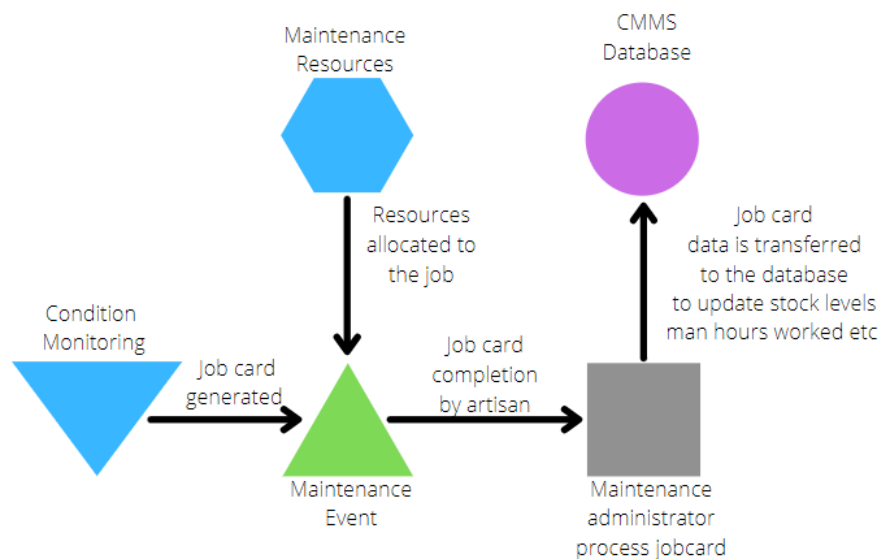


FIGURE 25 PREDICTIVE MAINTENANCE FLOW

In effect, the scheduled maintenance and repair job card triggers are replaced by condition monitoring. Depending on the condition monitoring, it is possible to determine the criticality of the machine's condition and, if critical, intervention is required, indicating what type of maintenance event is required. For example, a minor event could lead to only an inspection or minor intervention, whereas a severe condition should trigger a repair that needs to be scheduled.

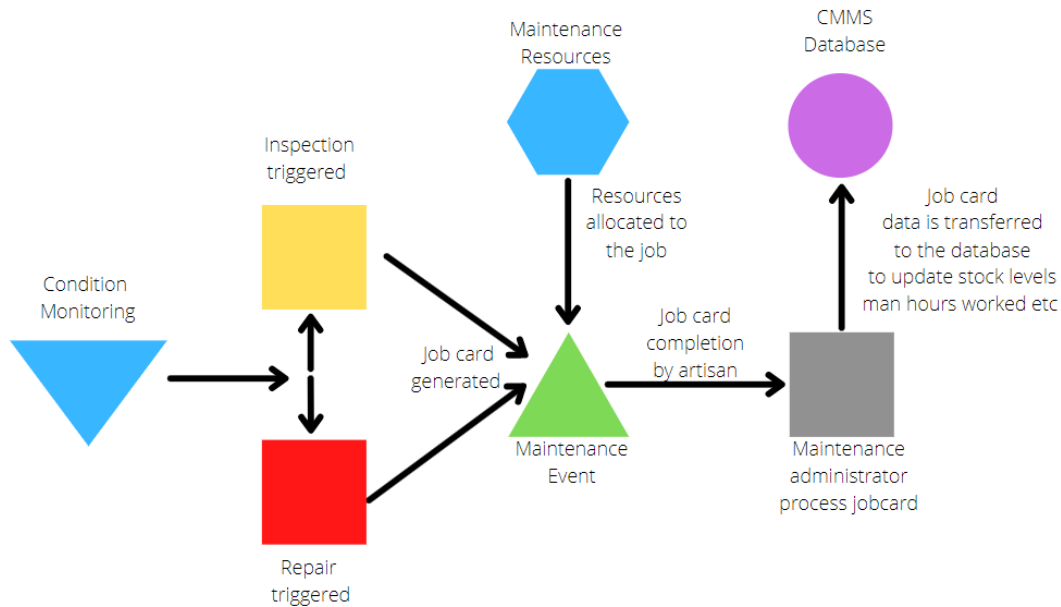


FIGURE 26 PREDICTIVE MAINTENANCE - INSPECTION AND REPAIR

Considering the literature review, one of the conclusions made was to compare an existing maintenance system and a model; a maintenance system's KPIs needs to be considered. These KPIs can show whether a maintenance system can improve or not. The main factors involved are costs, downtime, and the number of jobs.

Comparing preventative and predictive maintenance, the decision-making between the two has changed. The two systems each have two separately identified types of jobs, after which the processing remains the same. However, the initiation of these jobs is different.

Figures 24 and 26 represent the two flows, the fundamental difference being the condition monitoring in the predictive maintenance and the type of job generated. These two figures are the basic processes used to build the model.

3.2 Model Blocks

With the two process flows defined in figure 24 and figure 26, it is possible to make more explicit decisions regarding the building blocks of the model. The model blocks are based explicitly on the preventative and predictive maintenance flow charts.

3.2.1 Preventative Maintenance

For preventative maintenance, it is evident from the flow chart (figure 24) that each type of job needs to trigger an event. Within SimEvents, the Entity Generator is the function block enabling us to start an event. As per the block definition in figure 27, the time-based entity generator can fulfil the requirements to create the scheduled job.

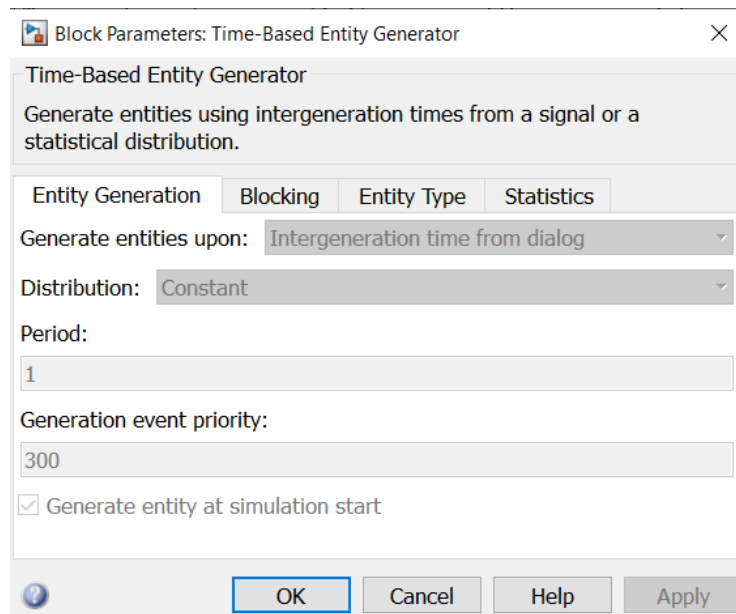


FIGURE 27 TIME-BASED ENTITY GENERATOR

The time-based entity generator allows the user to select different types of distributions and the necessary parameters required for the distribution type chosen. These statistical configurations will be discussed later in this section when discussing the detail use of each block. Using the entity generator for the scheduled job card, enables the model to generate the job on a specified time interval. However, this job still needs to be quantified. The required measurable data (hours and cost) must be linked to the job created. For this, the set attribute block is used.

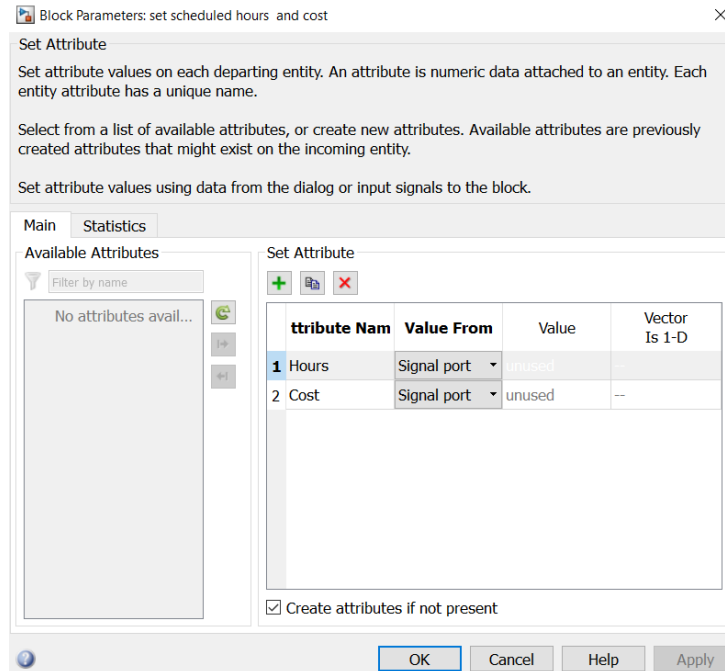


FIGURE 28 SET ATTRIBUTE BLOCK

As per the description in figure 28, the set attribute block allows the user to add defined data (hours and cost) to an entity (job). It quantifies the time-based entity (scheduled job) by adding the machine downtime due to maintenance and the costs allocated to it. The set attribute block can quantify an attribute (Hours and Cost) by either a static value or an input signal. Since a job's hours and cost attributes are never the same, the feature will need to be quantified by an input signal. The model flow for this is depicted in figure 29.

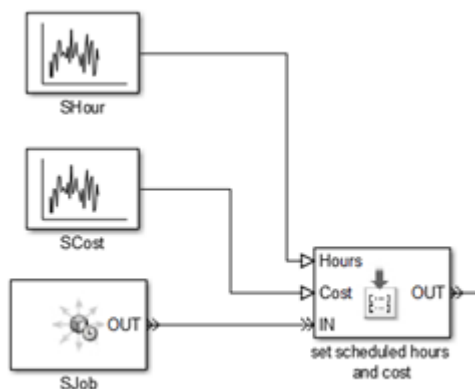


FIGURE 29 JOB CREATION AND QUANTIFICATION IN THE SIMEVENTS MODEL

The blocks in figure 29 show the following:

- SJob – Scheduled job hours attribute. An event Based random number generator
- SCost – Scheduled job cost. An event Based random number generator
- SJob – The block generating the simulated job. The time-based entity generator
- Set scheduled hours and cost – set attribute block. Adding the defined variable to the job card.

The attribute (cost and hours) signal generators require a quantifiable definition. Therefore, an event-based random number generator is used to assign the value to the attribute.

The screenshot shows a dialog box titled "Block Parameters: SHour". Inside, there is a section for "Event-Based Random Number" with the instruction "Generate random numbers from the specified distribution, parameters, and initial seed." Below this, the "Parameters" section includes a "Distribution" dropdown menu set to "Beta". The "Minimum" field is labeled "PMSHourMin", the "Maximum" field is labeled "PMSHourMax", the "Shape parameter a:" field is labeled "PMSHoura", and the "Shape parameter b:" field is labeled "PMSHourb". The "Initial seed:" field is set to "41684". At the bottom, there are four buttons: "OK", "Cancel", "Help", and "Apply".

FIGURE 30 EVENT-BASED RANDOM NUMBER GENERATOR

As the definition in figure 30, the event-based number generator will generate a number upon an event (job card) based on the distribution and input values set. The input parameters vary according to the distribution selected. Figure 31 shows the available distributions.

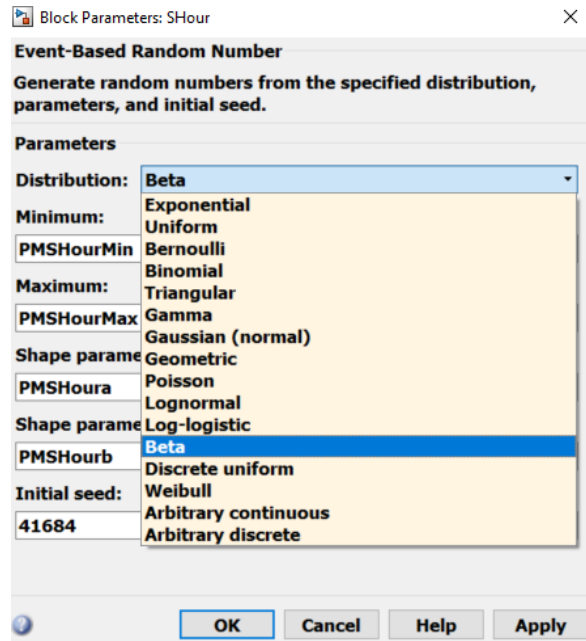


FIGURE 31 PROBABILITY DISTRIBUTIONS AVAILABLE FOR EVENT BASED RANDOM NUMBER GENERATOR

The three SimEvents blocks described in Figures 27, 28 and 30 are the primary blocks for this simulation. The blocks are used to create the simulated job card and define its variable (hours and costs). Following the blocks, as shown in figure 32 in the scheduled preventative maintenance model, are blocks that are used to make the simulation data available to the end user. The total scheduled maintenance model is shown in figure 32.

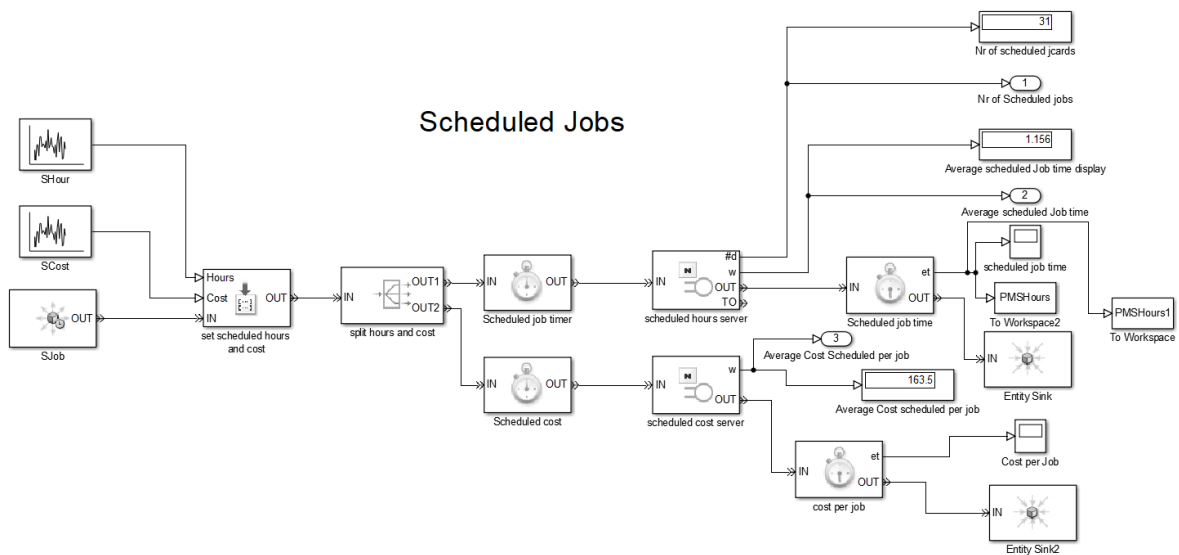


FIGURE 32 SCHEDULED MAINTENANCE MODEL

From the flow charts in figures 24 and 26, the preventative maintenance model requires a scheduled entity and a repair entity. The model is set up to depict the repairs and scheduled maintenance as a separate entity, where the repairs include any type of job that requires an unscheduled stop. Therefore, the repair model will replicate the scheduled maintenance model. The repairs simulation in the preventative maintenance model also uses a time-based entity generator to create the repair job card; however, instead of having a constant interval, historical CMMS data is used to evaluate the frequency of repairs. The time-based entity generator allows a selection between, constant, uniform, and exponential distributions. Given that the machine can be at any point in its lifetime, based on the bathtub curve, it is not clear that the frequency of repairs follows an exponential distribution. The user should be allowed the most flexibility to “recreate” the accurate frequency of repairs as per the CMMS data. When set to a uniform distribution, the time-based entity Generator requires a maximum and minimum time between events. This is depicted in figure 33. The user must use the CMMS data to the maximum period between repairs and the minimum period between repairs.

The screenshot shows a software dialog box titled "Block Parameters: RJob". It has a close button (X) in the top right corner. The main title is "Time-Based Entity Generator". Below the title is a description: "Generate entities using intergeneration times from a signal or a statistical distribution." There are four tabs: "Entity Generation" (selected), "Blocking", "Entity Type", and "Statistics". Under the "Entity Generation" tab, there are several settings: "Generate entities upon:" is set to "Intergeneration time from dialog" (dropdown); "Distribution:" is set to "Uniform" (dropdown); "Initial seed:" is a text field containing "35621"; "Minimum:" is a text field containing "PMRIntMin"; "Maximum:" is a text field containing "PMRIntMax"; "Generation event priority:" is a text field containing "300"; and a checkbox labeled "Generate entity at simulation start" which is currently unchecked. At the bottom of the dialog are four buttons: "OK", "Cancel", "Help", and "Apply".

FIGURE 33 UNIFORM DISTRIBUTION - TIME-BASED ENTITY GENERATOR

With this setting, the model can use CMMS data to create the repair job cards in the intervals as the machine's historical data suggests. Therefore, entity generation is the only difference between the scheduled and the repair systems in the preventative maintenance model. The scheduled jobs are created at constant intervals, and the repairs are intermittent, as defined by the machine's historical data. The modelled data can be verified by comparing the jobs generated within the preventative model with the historical information retrieved from the CMMS.

3.2.2 Predictive Maintenance

In figures 24 and 26, the flow charts from which the models are derived can be seen. Figure 26 is used to build the predictive maintenance model. The model blocks and setup should be similar to the preventative maintenance model. The significant difference is that the entity generation does not rely on a schedule or other external factors but rather on the machine's condition. To achieve this, the model does not use the time-based entity generator. Instead, the model will use an Event-based entity generator because the change in machine condition can be seen as an event that takes place. This block makes use of an external signal to generate an entity.

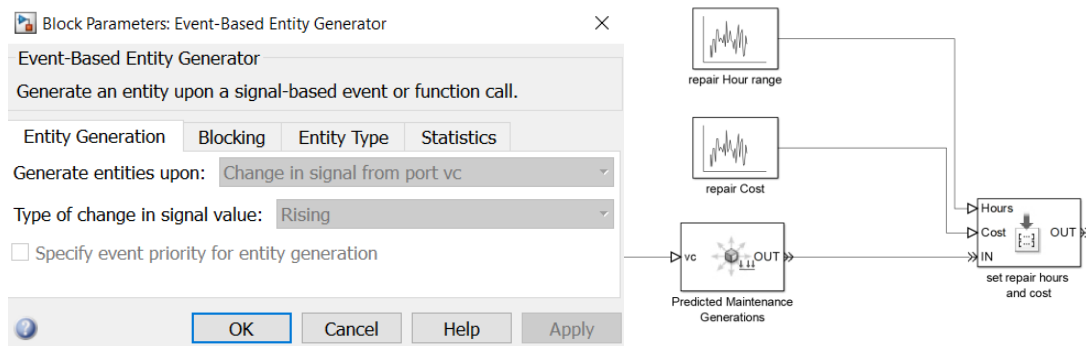


FIGURE 34 EVENT-BASED ENTITY GENERATOR

As we advance, the model is identical to the preventative maintenance model. The costs and hours are determined by the same statistical methods used in the preventive maintenance model. However, the model uses a signal to generate a maintenance event. This signal is based on the condition of the machine. Therefore, a machine condition needs to be defined. This is done with the same type of blocks used to generate a job card, time-based entity generator, event-based random number generator and the set attribute block. The time-based entity generator is used to simulate the event of condition monitoring being done. The intervals of the condition monitoring can be defined with this block. Finally, the machine's condition needs to be quantified by setting the attribute/value similarly to how the hours and costs were done previously. In this model, the condition is determined by the RMS vibration value. Hence the term RMS value. The machine condition that model is based on can be from literature on similar machines, from historical breakdown data of the specific machine or from intermittent condition monitoring data. For the case study in chapter 4 intermittent vibration readings are taken to determine the overall machine condition.

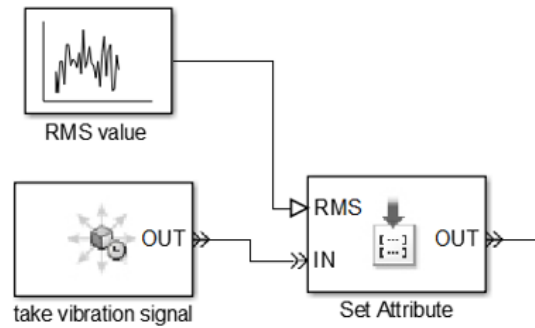


FIGURE 35 RMS SIGNAL GENERATOR

The model now generates an RMS value for the machine condition. This value determines whether a job card needs to be created or not. However, the modelled machine condition will only represent a machine condition statistically specified through the selected distribution. It is known that events can occur randomly, which induces changes in machine conditions. These are the unforeseen events that can put a machine in critical condition. These conditions need to be introduced to the machine condition model. Again, a time-based event generator and a set attribute block are used to generate this type of critical event. This random event is used to amplify the generated RMS value into a condition that triggers a maintenance event in the model.

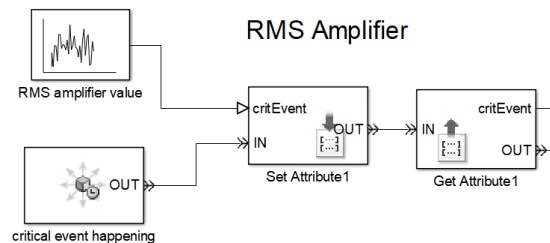


FIGURE 36 CRITICAL EVENT GENERATION

A state flow chart identifies this critical event, and the RMS value generated is amplified. The model now needs to identify that the RMS value has increased and send that signal to the event-based entity generator in the predictive maintenance model. As per figure 26, the flow charts show the predictive maintenance model needs to be able to identify between different health levels of the machine. This evaluation is based on the RMS value, and a state flow chart is used to evaluate this.

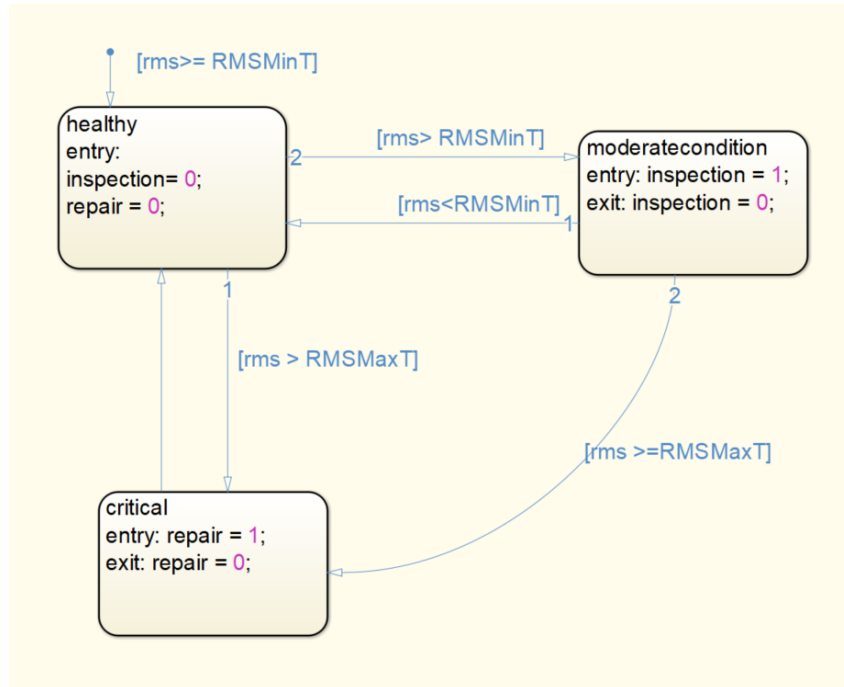


FIGURE 37 JOB STATE IDENTIFICATION

Figure 37 shows the state flow chart that evaluates the machine's condition. The condition value (RMS value) determines whether the machine is healthy, moderate, or critical, as is depicted by the logic below.

- If the machine condition (rms) is between a minimum (RMSMinT) and maximum (RMSMaxT) threshold, the machine is in a moderate condition.
- If the condition is above the maximum threshold, the machine is critical.
- If the machine's condition is below the minimum threshold, the machine is in a healthy state.
- An inspection will be initiated if the machine is in moderate condition.
- If the machine is critical, a repair will be initiated.

In the Stateflow chart, the model can identify between healthy, moderate, and critical conditions. Therefore, the model will generate a maintenance event according to the logic described in the bullets above. The RMS value generator and the job card generations are set in their respective subsystems, as depicted below.

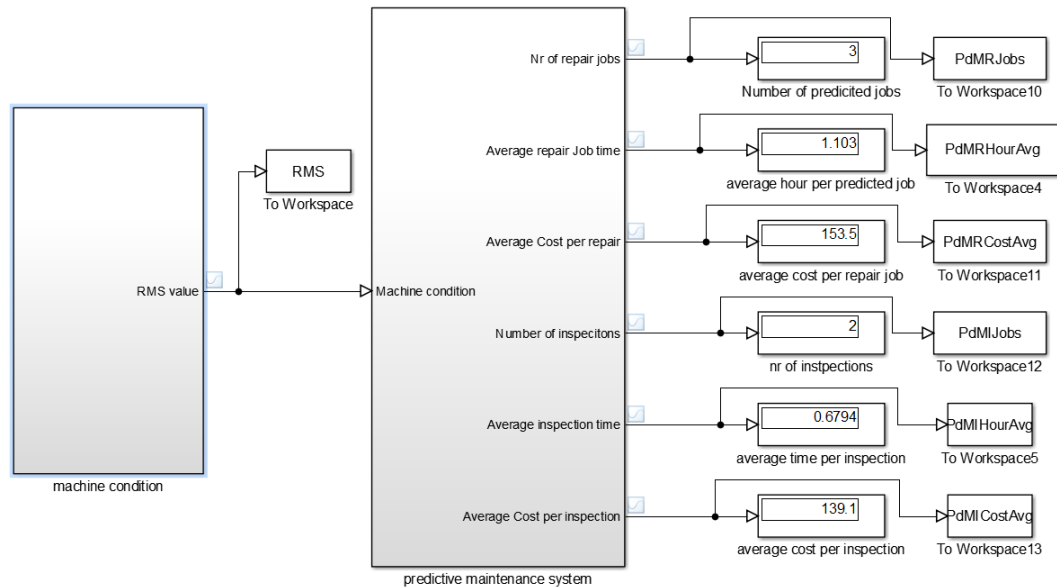


FIGURE 38 PREDICTIVE MAINTENANCE MODEL SUBSYSTEMS

The SimEvents model can be relatively complex to navigate. Given this situation, a graphical user interface is built for easy navigation and access to the necessary variables. In addition, the desired model outputs are displayed on this interface for quick and easy interpretation. The interface can be seen in figure 39 and will be discussed in more detail in the next chapter.

Maintenance Model
Preventative vs Predictive

Run Sim

Simulation period

915

Randomise Seeds

Preventative Maintenance

scheduled maintenance interval

30

Min period before Repair

100

(All Periods set in days)

Max period before Repair

180

Scheduled Hours

Scheduled Cost

Repairs Hours

Repairs Cost

Predictive Maintenance

Condition monitoring Interval

1

Min period before critical event

100

Machine Condition critical setpoint

0

Max period before critical event

180

Machine Condition moderate setpoint

0

Inspection Hours

Inspection Cost

Repairs Hours

Repairs Cost

Condition Monitoring

Critical variable

FIGURE 39 MODEL GRAPHIC USER INTERFACE

3.2.3 Model Workflow

A graphical user interface is built for ease of use, allowing users to interact and access the necessary variables. The model's first variables require the preventative maintenance system since this is used as the comparative baseline. The preventative model will be used to verify the model against the actual historical data and to compare it against the simulated predictive maintenance model. Figure 39 shows the user interface for the preventative and predictive maintenance models.

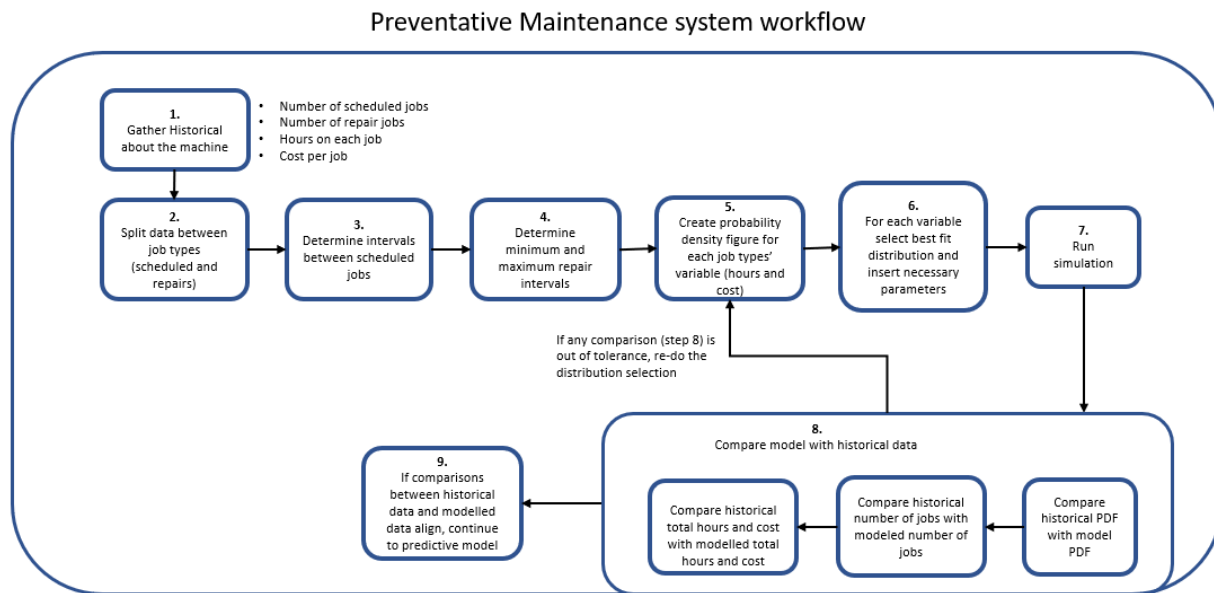
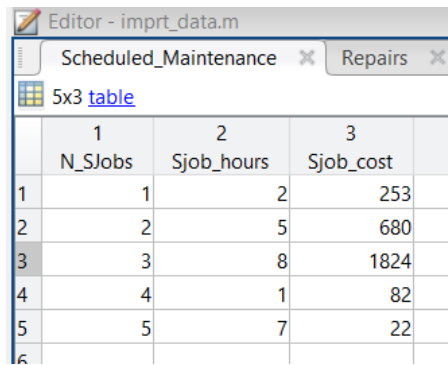


FIGURE 40 PREVENTATIVE MAINTENANCE MODEL WORKFLOW

The main objective of this study is to be able to run a comparative model between an existing maintenance system and that of a predictive maintenance system. With this, the basis of the model relies on existing machine data.

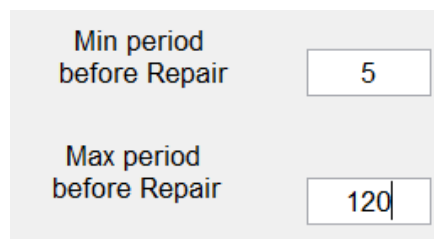
1. The flow chart in figure 24 shows the two job types (scheduled and repairs) with their attributes (hours and cost). This is the required historical data. Next, these values need to be imported into MATLAB for further processing. Figure 41 shows a typical table within MATLAB.



	1	2	3
	N_SJobs	Sjob_hours	Sjob_cost
1	1	2	253
2	2	5	680
3	3	8	1824
4	4	1	82
5	5	7	22

FIGURE 41 SCHEDULED MAINTENANCE TABLE (EXAMPLE IN MATLAB)

2. The model needs to differentiate between repair jobs and the scheduled maintenance. For this reason, the historical data needs to be evaluated as such.
3. Scheduled maintenance is determined by a certain time interval. Enter this value into the model text box marked “Scheduled Maintenance Interval”, as seen in figure 39.
4. The repairs, based on the time-based entity generator, as seen in figure 33. A uniform distribution is used, allowing the user to enter the minimum period between which a repair can happen, this depicting the frequency of required repairs. For the model, the user will enter the minimum time until a repair is initiated and the maximum time before a repair is initiated. For example, if the history of the machine shows that the shortest time between repairs is five days and the most prolonged period between repairs is 120 days, the user will enter the values as shown in figure 42.



Min period before Repair	5
Max period before Repair	120

FIGURE 42 REPAIR INTERVALS

5. The model uses the probability density function (pdf) of the historic job's variable (cost & time) to run the preventative maintenance model. The pdf of the historical data determines the cost and hours for the modelled jobs. Matlab has a built-in function to fit pdf figures according to an existing dataset. This tool within Matlab, is used to generate the PDF's for each attribute. Generating several PDF's for a single date set (eg. Job cost) will allow the user to select the most viable PDF based on the covariance and the “wellness of fit”. The datasets (CMMS data) were imported/entered into Matlab in step 1 and split into scheduled and repairs in step 2.

The literature read that three distribution functions are commonly used in reliability contexts. These are:

- Weibull
- Lognormal
- Gamma

A typical example of a pdf figure based on historical data is shown in figure 44 where the histogram (figure 43) shows the CMMS data and the curve shows the generated PDF.

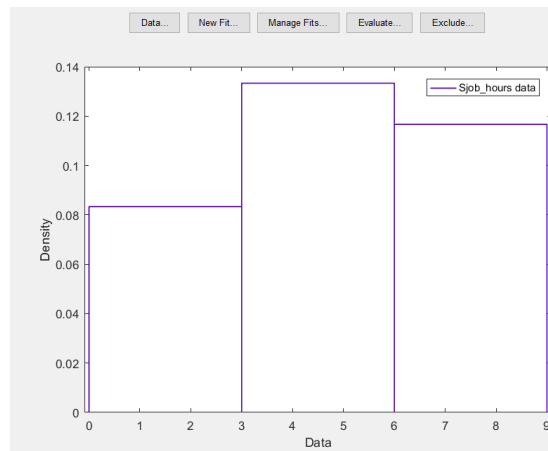


FIGURE 43 HISTORIC DATA HISTOGRAM

The histogram seen in figure 43 is then used to determine the best-fit distribution type that can be used in the model. Using the new fit function in the distribution fitting tool, the three distribution types mentioned fit against the histogram. See an example in figure 44.

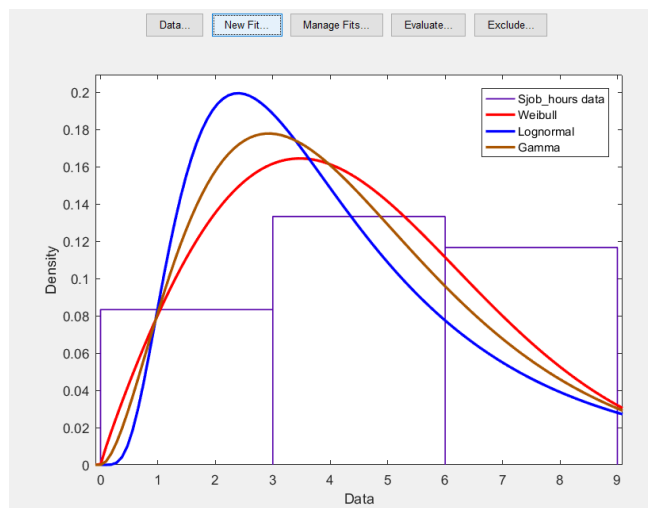


FIGURE 44 DISTRIBUTION FIT AGAINST HISTORICAL DATA

This process is repeated for each attribute in the preventative maintenance system

- Scheduled job hours
- Scheduled job cost
- Repair job hours
- Repair job cost

The model will use the PDF fitment tool within Matlab to evaluate the dataset (hours, costs for scheduled and repair jobs. The fitment tool evaluates the data to present the mean, and the variance. The tool also generates the parameters for the selected PDF to generate. The necessary parameters of the selected distributions can be accessed through the fit manager in the distribution fitter app. Finally, the data is displayed as shown in figure 45.

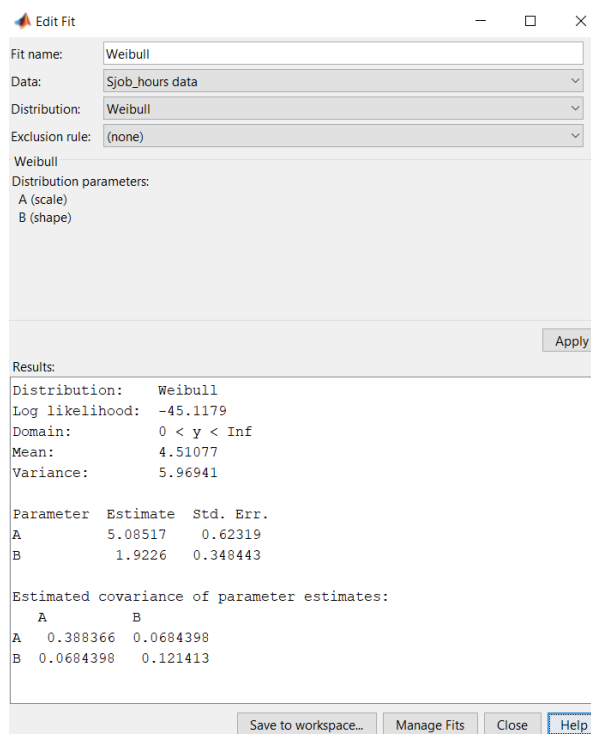


FIGURE 45 DISTRIBUTION PARAMETERS

The selection of the PDF to be used is based on the covariance as seen in figure 45. The array of the estimated covariance with the closest values to 1 will give the most accurate representation of the actual figures and hence should be the most viable PDF.

6. For each of the above bullets (attributes) the model allows the user to access the model block directly by clicking on the attributes button, see figure 46.

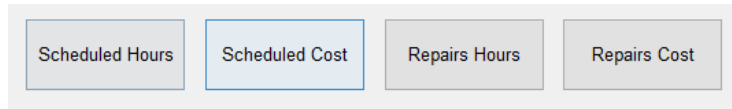


FIGURE 46 SCHEDULED MAINTENANCE ATTRIBUTE BUTTONS

By Accessing the model block the user can select the best fit distribution determined in step 5 and enter the parameters required. These are also available from step 5 in figure 45 und parameters. For each attribute, the block parameters need to be defined. The example values entered in the block can be seen in figure 47

FIGURE 47 ATTRIBUTE DISTRIBUTION SELECTED WITH PARAMETERS

The selection of the distribution can be guided by evaluating the estimated covariance of the estimated parameters as seen in figure 45. The selected fit must first visually suit the histogram after which the verification can be made using the covariance seen in figure 45. Each value in the covariance matrix of the pdf as seen in figure 45 should be as close to 1 as possible. A covariance of 1 resembles a perfect fit.

7. The preventative maintenance simulation is ready when all the attribute distributions are selected, and their parameters entered. The model will initiate its first iteration by clicking the run simulation button. The results will show in the sim results pane shown in figure 48. Use the random seeds button to be able to run an additional iteration of the model with the same parameters. The random seeds button re-initialises the random number generators.
8. Step 8 combines all the model verification before continuing to the predictive maintenance model. Here we compare the model data with the historical data to verify that the model is set up correctly. Use several iterations of the simulation for the comparative analysis. The data points that are compared are the following:
 - Histograms of attributes (hours, costs) for each job type (scheduled, repair)

- Number of scheduled job cards
- Number of repair job cards
- Total maintenance hours
- Total maintenance cost

These Results will be seen in the simulation results tab, as can be seen in figure 48.

Simulation Results	
Preventative Maintenance	
Nr of SJobs	182
Nr of RJobs	28
Avg time per S job	8.04254
Avg time per R job	4.61356
Avg cost per S job	1.12526
Avg cost per R job	1.22738
Total Maintenance Hours	1592.92
Total Maintenance Cost	239.164

FIGURE 48 SIMULATION RESULTS TAB

The results are also shown graphically to represent a timeline of the machine, as seen in figure 49, showing the repair and scheduled job jobs.

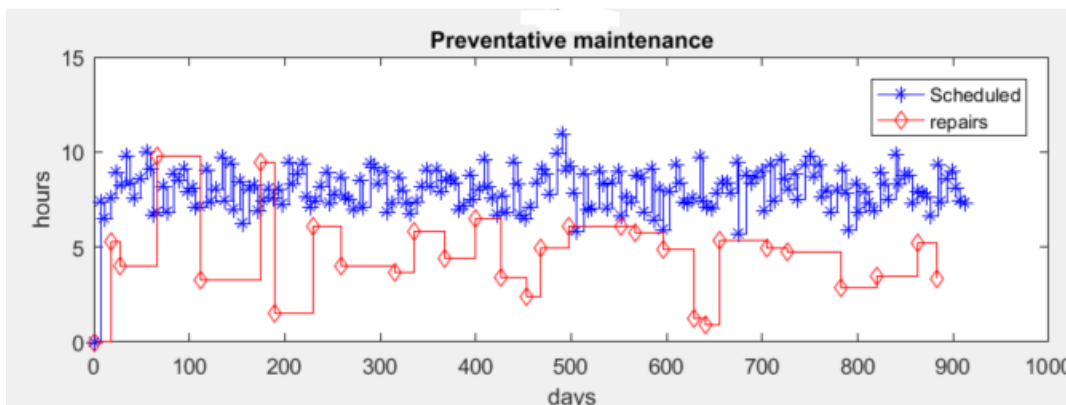


FIGURE 49 GRAPHICAL PREVENTATIVE MAINTENANCE TIMELINE

If the simulation results do not reflect the DATA from the CMMS, the root cause needs to be identified between the CMMS data input or the PDF selected.. For example, figure 50 shows where an incorrect distribution was selected and did not reflect the data from the CMMS.

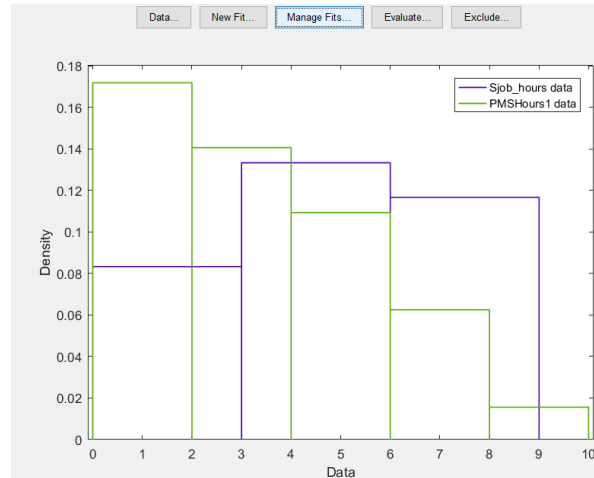


FIGURE 50 COMPARATIVE HISTOGRAM WITH INCORRECT DISTRIBUTION

In such a case as in figure 50 the distribution selection needs to be repeated.

With the preventative maintenance system ready and accurate, the predictive maintenance system can also be configured. The workflow of the predictive maintenance system can be seen in figure 51.

Predictive Maintenance system workflow

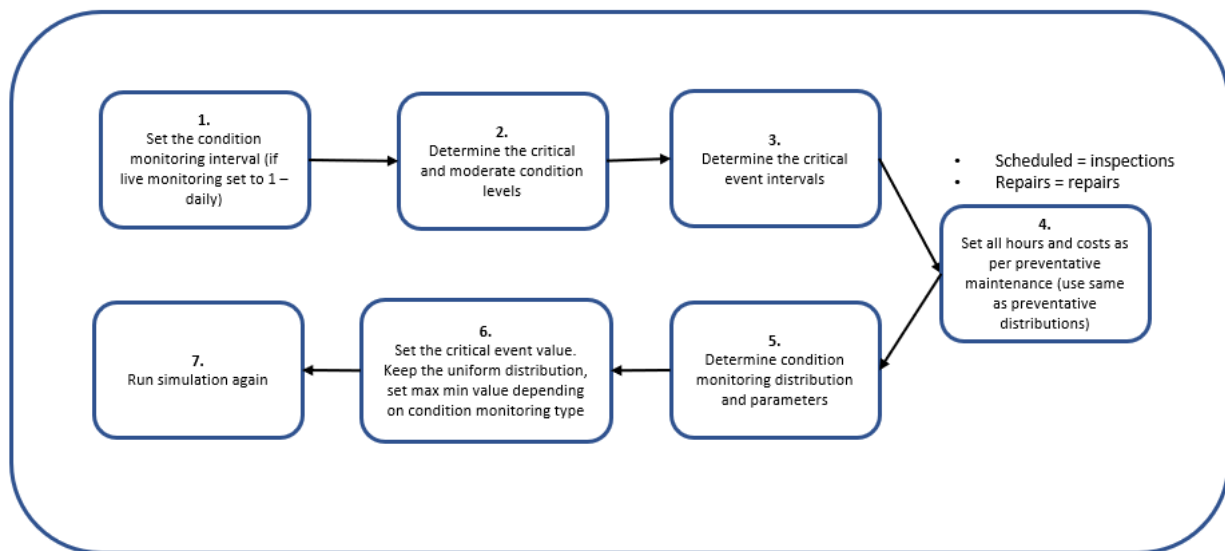


FIGURE 51 PREDICTIVE MAINTENANCE WORKFLOW

The predictive maintenance workflow is like that of the preventative maintenance system. There are only a few points that need to be additionally addressed; these are the condition monitoring parameters. The details of the workflow are being handled step by step below.

1. The predictive maintenance model allows the user to set the condition monitoring parameters. The first step is to determine the intervals of the condition monitoring. Note that all model intervals are set in days. Therefore, the set point for daily or live condition monitoring would be 1.
2. Depending on the type of condition monitoring, the user needs to set the thresholds at which a machine is in a moderate condition where an inspection would be required and a critical point where immediate repairs need to be initiated.
3. There is no doubt that any machine can have a random critical event. The critical event intervals field can set this. If there are certain jobs in the CMMS data that will not be identified by the condition monitoring type the event must be added to the critical event timeframe. Meaning that a critical event will happen since it cannot be identified by the condition monitoring. Using the root cause of a repair from the CMMS data it can be evaluated if a certain repair could have been prevented through condition monitoring. If not, that repair period should be included here in the same manner as the repairs done on the preventative model.

Predictive Maintenance	
Condition monitoring Interval	1
Machine Condition critical setpoint	0.3
Machine Condition moderate setpoint	0.022
Min period before critical event	100
Max period before critical event	180

FIGURE 52 INPUTS FOR STEPS 1-3 IN THE PREDICTIVE MAINTENANCE SYSTEM

4. The predictive maintenance model attributes (hours and cost) are based on historical data. Since historical data is the only reference to the specific machine's costs and hours for jobs, the configuration can be set to identical distributions and parameters as that of the preventative maintenance system. The schedules determine the inspections and the repairs are the same between the preventative and predictive systems.
5. The predictive model is dependent on the condition monitoring parameters. This is the block that determines the machine condition and, in turn, determines the number of jobs the model will present for the predictive maintenance system. Therefore, the system required condition monitoring data. The model block determining the machine condition is also an event-based random number generator. The event is the actual condition monitoring being done as set in step 1. The machine condition parameters can be determined by condition monitoring, data from the literature for the same type of machine or in cases where no other data exists, the historical data can be interpreted to predict the machine's condition by using the repairs and breakdown figures.

6. The critical event parameter simulates breakdowns or sudden critical conditions, as explained in step 3. The value used here depends on the type of condition monitoring, and care needs to be taken to use parameters in the uniform distribution to depict values above the range of moderate (minimum) and above the critical thresholds as set in step 2.

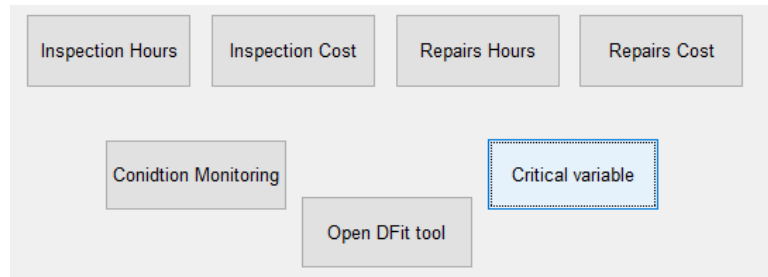


FIGURE 53 BUTTONS TO OPEN ATTRIBUTE MODEL BLOCKS FOR STEPS 4-6

7. The last step is to run the simulation. The model is built to run several iterations of the same parameters. By clicking on the randomise seeds button, the random number generators' starting values are different, thereby creating a further iteration of the same model. For an accurate interpretation, the model will need to be run several times to achieve a good average of results.

3.2.4 Machine Condition

One of the aspects of the model that might seem somewhat contradictory is the condition monitoring configuration in the predictive maintenance system. The problem statement in chapter 1 mentions that the implementation of condition monitoring before knowing its effects can be unpopular and might be a reason for companies to reject the implementation of condition monitoring. This is still the case; however, this model allows users to find alternative condition monitoring data. The model also provides an inexpensive method to test the hypothesis of condition monitoring reducing maintenance costs and time. With the model, an affordable condition monitoring system can be bought that can be modular and moved around to different machines, providing a more extensive scope than only one machine.

In this study, condition monitoring was done using vibration. The vibration was deemed the most common for rotating machines in the literature. Intermittent analysis was done with no specified interval. The equipment required is as below:

- A data logger
- Vibration sensor

The equipment can be inexpensive for a small-scale implementation compared to complete live condition monitoring. Regarding analysis, Matlab provides tools to analyse signals and run FFTs. For vibration

analysis, the overall condition can be determined by the vibration signal's RMS value (overall vibration). This is relatively easily achieved in MATLAB. In figure 54, an example of an evaluation done in Matlab can be seen. It needs to be stressed that this study will not dive into the detailed relationship between the spectrum shape and the machine failures.

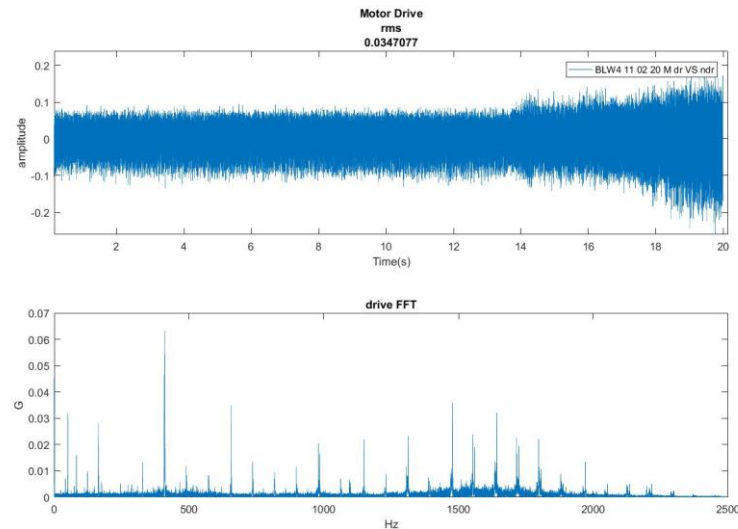


FIGURE 54 SIGNAL ANALYSIS DONE IN MATLAB

Some loggers have FFT and other computational functions built in to achieve the desired values.

The costs of the system used for this study can be seen in table 1.

TABLE 1 CONDITION MONITORING EQUIPMENT COST

Instrumentation cost summery			
Description	Unit cost	Quantity	Cost
AC102 Accelerometer	N\$2122.56	2	N\$4245.12
DATAQ logger DI-2108	US\$478 –N\$7279.94	1	N\$7279.94
		Total	N\$11 525.06

The model uses the overall condition of the machine to evaluate whether the machine requires any attention. Therefore, no detailed analysis of the peaks is necessary. Using the ISO severity chart as in Figure 15 the overall vibration is used to determine the machines condition.

The condition monitoring process and equipment explained in this chapter provides a cost-effective method to evaluate the general machine condition by means of vibration. Condition monitoring can be done in much more detail for a machine such as a blower. For example, vibration monitoring on a blower can be used to detect:

- Bearing faults on the blower and the motor
- Misalignment, parallel or angular

- Bent shafts on the motor or blower
- Motor and blower base looseness
- Eccentricity of the motor's rotor or stator or the pulleys on the shafts
- Eccentricity on the blower gears
- Shaft rub – when the shaft or other rotating component comes into contact with a stationary object
- Flow turbulence due to variations in pressure – this could detect blockages
- Lobe or gear damage on the blower

The above symptoms are specifically for blowers, there are other symptoms that can be identified when applied to other types of machinery, such as:

- Cavitation in pumps
- Structural defects or potential resonance
- Blade or vane faults in pumps and fans
- Blade or vane pass in pumps and fans
- Loose pillow or plumber block bearing housing

The wide range of mechanical defects that can be detected by vibration analysis makes it an ideal condition monitoring method for blowers and many other machines covering almost all possible failures besides electrical failures. However, the detailed analysis of the vibration analysis is not part of the scope of this study. The reason for the implementation of condition monitoring in this study has the primary purpose of supplying a general condition value of a machine. This is done by using the RMS acceleration value measured by the experimental setup described in this sub chapter. The tools for this condition monitoring were chosen to show that condition monitoring can also be achieved with cost effective equipment.

3.3 Summary

This chapter's discussion started with the primary flow between two maintenance systems, preventative maintenance, and predictive maintenance. The flow charts can be seen in figures 24 and 26. From this, one differentiation can be noticed: the preventative system's maintenance initiation is primarily based on a schedule, whereas the predictive maintenance is based on the machine's condition.

Using figures 24 and 26 the model flow is also seen. The fundamental blocks used in the model are defined.

- Time-based entity generator
 - Create scheduled job cards (fixed interval)
 - Repair job cards (generate job card within a time interval)
 - Condition monitoring initiation (fixed interval, set to 1 or daily to simulate live monitoring)
 - Critical event initiation to simulate breakdowns or random events in the predictive simulation

- Event-based entity generator
 - Create a job card based on the machine's condition
- Event-based random number generator
 - Give each event definition by linking a value to the event (hours, cost, machine condition)

The model requires some form of machine condition information. This can be from machine condition monitoring, trends from literature or other similar machinery. In addition, the model has a built-in verification process. The preventative model is built to reflect the historical data, the preventative model and the historical data should be similar. In such a case it would prove that the model configuration is correct. The configuration of the preventative system is then used to process the predictive system with the inclusion of the machine condition. The steps set out in the model are strictly derived to fulfil the objectives set out in chapter 1.

The primary objective states that the model should be able compare a predictive maintenance system to the current system implemented of a specific machine. Given that the model is built to simulate the historical machine data and that of a proposed predictive system, this objective is covered and the model should be able to assist in a decision-making process whether to amend the maintenance system or not. Part of the decision making would be the secondary objective which is to be able to do a cost benefit analysis on the implementation of the proposed condition monitoring. The data for the cost benefit analysis is derived from the information provided by the simulation.

The model is not limited to specific machines and can be implemented for any type of machine or facility that has historical machine data. Thereby complying to objectives 3.a and 3.b. For this study the model is used to compare predictive and preventative maintenance. The preventative model can be adapted to reflect a different schedule to compare historical data and the effect of a possible new service schedule.

The model has the functionality as set out by the objectives. In chapter 4 a case study is done to show the findings when following the procedure set out in this chapter.

4 CASE STUDY

The workflow provides a step-by-step guide of the model. In this chapter it will be demonstrated in detail by means of a case study. The machine in question as mentioned in chapter 1 is a lobe blower. This lobe blower is used to convey finished product from a maize mill into a finished product bin.



FIGURE 55 BLOWER AND MOTOR

4.1 Preventative Maintenance

The maintenance system currently in place is a preventative maintenance system. The job card with its relevant tasks is listed below.

MONTHLY

When machine stopped:

1. Clean filter
2. Check oil level
3. Remove v-belts and turn motor by hand to listen/feel the bearing, replace if necessary
4. Re-adjust v-belt tension
5. Inspect bell on Blow off valve for uneven wear (not damaged)
6. Make sure pressure relieve valve moves freely (Lift and Release)
7. Write date next to the week that work was done
8. Inspect motor base for loose linkages when running

Week _____

Week _____

Week _____

Week _____

Week _____

Infestation free YES NO

(Make a circle around your answer)

NOTE ANY ABNORMALITIES THAT CAN'T BE RECTIFIED IMMEDIATELY

All the necessary information is then recorded on a CMMS, which holds a record and generates the next job card as per predefined schedule.

The CMMS data that can then be generated can be seen in figure 56. Complete CMMS data for the machine is in the Annexure.

VM502-08 - Maintenance Hours and Costs per Equipment											
Parameter	From	To									
Date:	01/04/2019	14/10/2021									
Sites:	WK-MAIZ	WK-MAIZ									
Model:	BLOW	BLOW									
Equipment:	M2BLOW5	M2BLOW4									
Detail:		Yes									
Show costs larger		0.00									
Type of Jobs Shown		All									

Job Number	Date Entered	Problem Description	Type of Job	Work Done by	Number of Jobs	Hours worked	Ave per Job	Projected Labour cost (Rands)	Sub Contractor	Job Charge	Spares Cost	Non-stock parts cost	Total Cost
Windhoek													
S00028601	17/04/2019		Mechanical Overtime	Assistant		0.50			0.00	0.00	0.00	0.00	
S00029001	08/05/2019		Mechanical Double Overtime	Josef David		0.50			0.00	0.00	0.00	0.00	
R00023310	03/06/2019		Mechanical Double Overtime	Assistant		0.75			0.00	0.00	0.00	0.00	
S00029601	18/07/2019		Mechanical Double Overtime	Assistant		2.00			0.00	0.00	242.41	0.00	
S00030078	31/07/2019		Mechanical Double Overtime	Rudolf Kamenje		1.00			0.00	0.00	0.00	0.00	
S00030391	27/08/2019		Mechanical Overtime	Rudolf Kamenje		1.50			0.00	0.00	0.00	0.00	
S00030891	01/10/2019		Mechanical Overtime	Assistant		1.00			0.00	0.00	0.00	0.00	
S00031028	01/10/2019		Mechanical Overtime	Assistant		1.50			0.00	0.00	0.00	0.00	
R00025000	02/10/2019	Check pressure & flow restriction as per NVC report. M:	Mechanical	Eben Hudivall		3.00			0.00	30.00	854.00	0.00	
S00031475	06/11/2019		Mechanical Overtime	Carl Cupido		1.25			0.00	0.00	0.00	0.00	
S00031936	04/12/2019		Mechanical	Eben Hudivall		3.00			0.00	0.00	0.00	0.00	
S00032475	20/01/2020		Mechanical Overtime	Assistant		1.50			0.00	0.00	1,945.89	0.00	
S00032961	19/02/2020		Mechanical Double Overtime	Assistant		1.00			0.00	0.00	0.00	0.00	
S00033446	03/03/2020		Mechanical	Assistant		1.00			0.00	0.00	0.00	0.00	
S00033945	08/04/2020		Mechanical Double Overtime	Assistant		0.50			0.00	0.00	0.00	0.00	
S00034454	15/05/2020		Mechanical Double Overtime	Rudolf Kamenje		1.00			0.00	0.00	0.00	0.00	
S00034617	19/06/2020		Mechanical Double Overtime	Assistant		0.25			0.00	0.00	0.00	0.00	

FIGURE 56 CMMS DATA REPORT

For the use of the model the following information will be looked at

- Job card number,
- Job type, this is distinguished by the first letter of the job number (S – scheduled, R – repairs)
- Hours taken for the job
- All relevant costs allocated to the job

With this information the steps set out in the model workflow as seen in figure 40, can be followed.

1. Gather historical data

The historical data can be seen in figure 56, this has been extracted from the CMMS by means of a report. The historical data is taken from the 1st April 2019 until 14th of October 2021 giving a total time of 31 months or 924 days.

2. Split data between scheduled and repairs

The data extracted from the CMMS has been processed and imported into MATLAB to give the two relevant table. In figure 57 the repairs job table as it is in Matlab is depicted. The table shows only four repair job entries.

M2BLW4_RJobs							
4x8 table							
	1	2	3	4	5	6	7
	RJObnr	RjobdateEntered	Var3	Var4	Var5	Var6	M2BLW4_RHours
							M2BLW4_RCost
1	'R00023310'	'06/05/2019'	'M...	'D...	'A...	'	0.7500
2	'R00025000'	'15/11/2019'	'M...	'	'E...	'C...	3
3	'R00027815'	'15/06/2020'	'El...	'	'A...	'c...	1
4	'R00029259'	'20/10/2020'	'M...	'O...	'Jo...	'R...	1

FIGURE 57 REPAIR JOBS

The scheduled table shows 31 entries over the period of the study.

31x7 table						
	1	2	3	4	5	6
	JobcardNr	DateEntered	jobType	Overtime	Artisan	M2BLW4_SHours
						M2BLW4_SCost
1	'S00028601'	'08/03/2019'	'Mechanic...	'Overtime'	'Assistant'	0.5000
2	'S00029001'	'01/04/2019'	'Mechanic...	'Double'	'Josef Da...	0.5000
3	'S00029601'	'03/06/2019'	'Mechanic...	'Double'	'Assistant'	2
4	'S00030078'	'08/07/2019'	'Mechanic...	'Double'	'Rudolf K...	1
5	'S00030391'	'02/08/2019'	'Mechanic...	'Overtime'	'Rudlof K...	1.5000
6	'S00030891'	'06/09/2019'	'Mechanic...	'Overtime'	'Assistant'	1
7	'S00031028'	'06/09/2019'	'Mechanic...	'Overtime'	'Assistant'	1.5000
8	'S00031475'	'02/10/2019'	'Mechanic...	'Overtime'	'Carl Cupi...	1.2500
9	'S00031936'	'04/11/2019'	'Mechanic...	'	'Eben Hu...	3
10	'S00032475'	'06/12/2019'	'Mechanic...	'Overtime'	'Assistant'	1.5000
11	'S00032981'	'10/01/2020'	'Mechanic...	'Double'	'Assistant'	1
12	'S00033446'	'07/02/2020'	'Mechanic...	'	'Assistant'	1
13	'S00033945'	'09/03/2020'	'Mechanic...	'Double'	'Assistant'	0.5000
14	'S00034454'	'08/04/2020'	'Mechanic...	'Double'	'Rudolf K...	1
15	'S00034937'	'08/05/2020'	'Mechanic...	'Double'	'Assistant'	0.2500
16	'S00035435'	'09/06/2020'	'Mechanic...	'	'Assistant'	0.5000
17	'S00035887'	'08/07/2020'	'Mechanic...	'Overtime'	'Assistant'	1

FIGURE 58 SCHEDULED JOBS

3. Determine intervals between scheduled jobs

As the job card states, this job is performed every month. This is also seen in figure 58. Therefore, this entry will be 30 (every 30 days).

4. Determine minimum and maximum repair intervals

Using the dates from the CMMS data the shortest period between repairs is 172 days and the longest is 210 days. These values are entered as shown in figure 59

The screenshot shows a software interface for simulation. At the top left is a blue button labeled "Run Sim". To its right is a "Simulation period" input field with the value "924" and a "Randomise Seeds" button below it. Below this is a section titled "Preventative Maintenance". It contains two rows of input fields. The first row has "scheduled maintenance interval" set to "30" and "Min period before Repair" set to "175". The second row has "Max period before Repair" set to "210". Below these fields is the text "(All Periods set in days)".

FIGURE 59 SIMULATION PERIODS

5. Create probability density figure for each job type of variable (hours and cost)

The PDFs will be shown one by one. Note that the bin rules in the fitment tool is as per the matlab default.

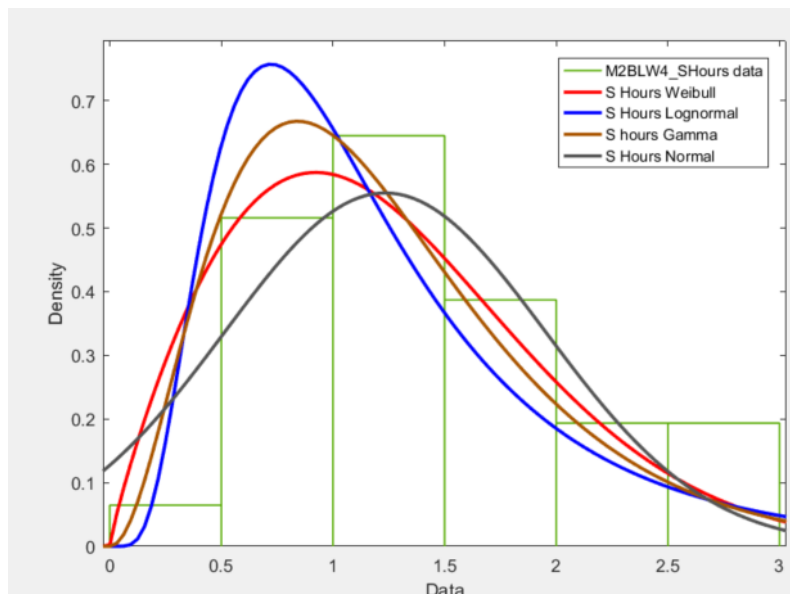


FIGURE 60 SCHEDULED HOURS PDF

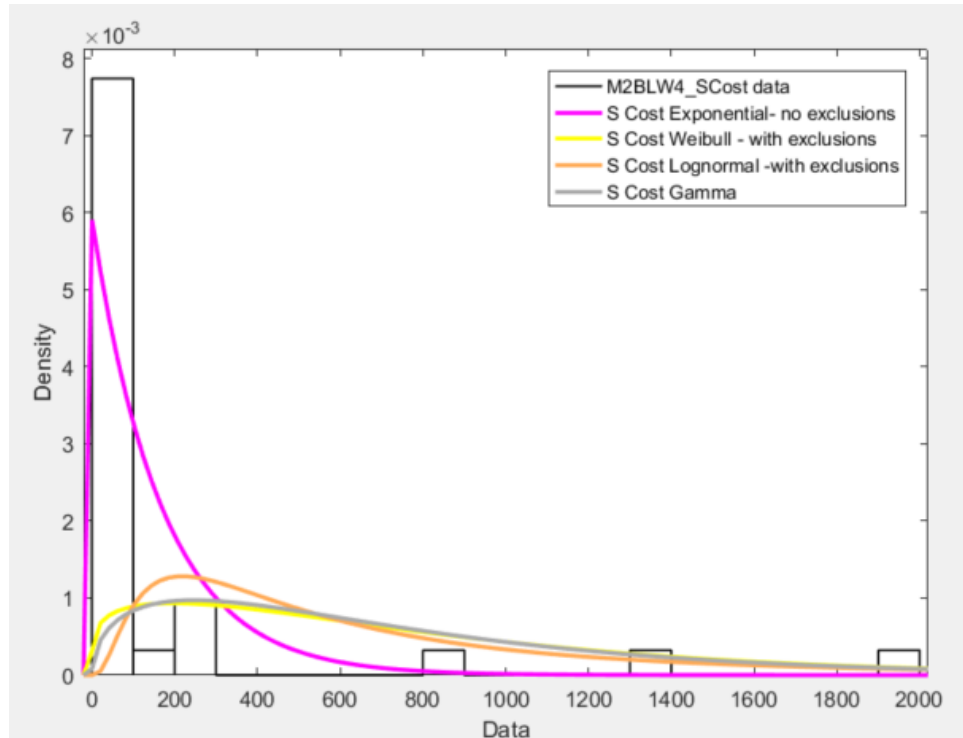


FIGURE 61 SCHEDULED COST PDF

The scheduled cost PDF was challenged because the fitment tool could not derive a fit with the data as it was. Therefore, a rule was written that the fitment tool needs to exclude the zeros values which dominated the dataset. The effect can be seen in figure 61, where the histogram of the dataset shows dominance in the first bin. As a result, only one PDF could fit into the original data, namely the exponential PDF.

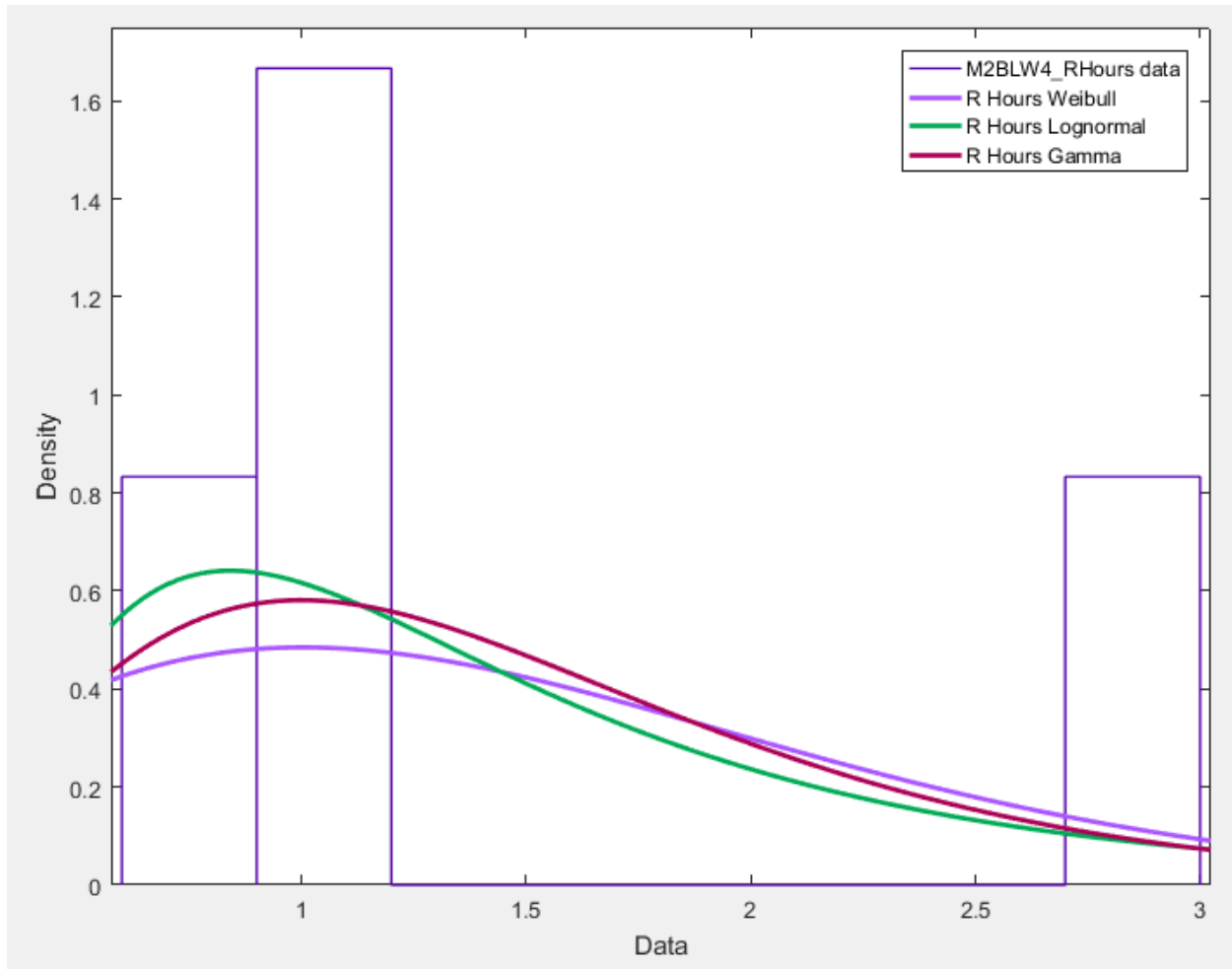


FIGURE 62 REPAIR HOURS PDF

Given the small dataset the fitment tool derived some representative PDF's. Other simulation data will need to be used to compare the results closer.

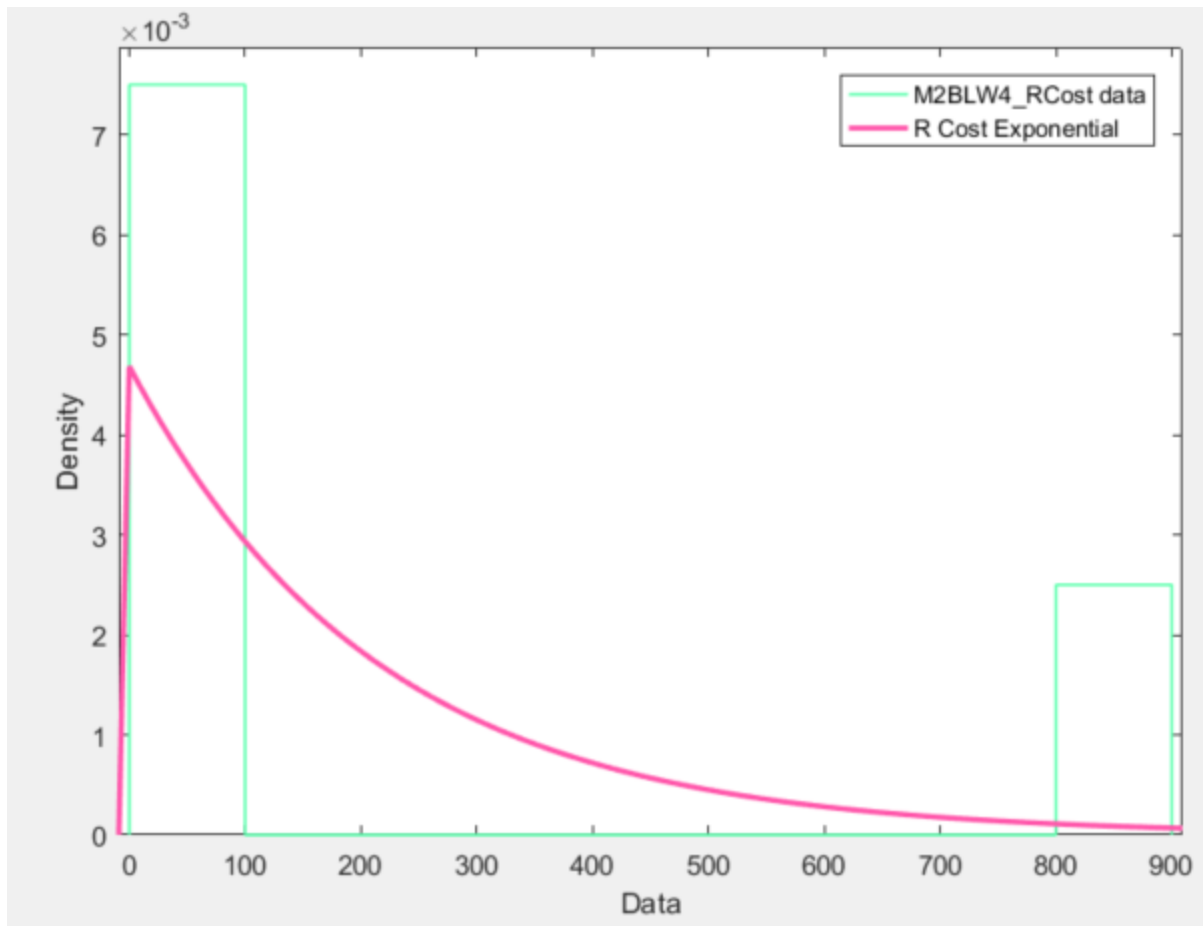


FIGURE 63 R COST PDF

The fitment tool only provided one positive figure for the PDF.

6. For each variable select the best fit distribution and insert the necessary parameters

The selections done are based on the figures 60 to 63. Table 2 is a summary of the selections.

TABLE 2 PDF SELECTION SUMMARY

PDF selection summary			
Job type and attribute	PDF selection	Parameters	Covariance
Scheduled Hours	Normal	Mu (Mean) = 1.2339 Sigma (standard dev) = 0.7186	Estimated covariance of parameter estimates: mu sigma mu 0.016658 0 sigma 0 0.00875251
Scheduled Cost	Lognormal	Mu = 6.24469 Sigma = 0.927024	Estimated covariance of parameter estimates: mu sigma mu 0.122768 -1.13996e-16 sigma -1.13996e-16 0.0781248
Repair Hours	Gamma	a = 3.27888 b = 0.438411	Estimated covariance of parameter estimates: a b a 4.88738 -0.65348 b -0.65348 0.10203
Repair Cost	Exponential	Mu = 213.5	Estimated covariance of parameter estimates: mu mu 11395.6

The selection was done according to the fitments done in figures 60 to 63. The covariance of each fit was evaluated, and the best covariance array was the deciding element for each fitment set. The fitments with the best covariance was selected (perfect fit would have a covariance of 1). The values of each attribute will be evaluated after the simulation is run.

7. Run Simulation
8. Compare model with historical data

The simulation is run several times (use randomise seeds to generate new values). Table 3 shows the comparative data for the preventative maintenance model versus the historical CMMS data.

TABLE 3 PREVENTATIVE MODEL COMPARISON

Preventative maintenance CMMS data vs Preventative Maintenance Model							
	CMMS X_{cmms}	Run1	Run2	Run3	Run4	Simulation Average X_{ave}	Accuracy percentage $P_{accuracy}$
Total S Jobs	31	31	31	31	31	31	100%
Total R Jobs	4	5	4	4	4	4.25	94%
Average time for S job	1.2339	1.3535	1.37	1.2296	1.4	1.34	91%
Average time for R job	1.4375	1.158	0.269	0.5794	0.169	0.54	38%
Average cost for S job	168.67	322	414.7	209	373.02	329.68	4.5%
Average cost for R job	213.50	174	142.8	157	273.957	186.94	88%
Total Hours	44	47	43	40	44	43.50	99%
Total Cost	6082.80	10876	13427	7111	12659	11018.25	19%

The accuracy percentage is derived between the historical data and the average of the simulations. The accuracy percentage shows the “closeness” between the CMMS data and the simulation average.

$$\text{Equation 2: } P_{\text{accuracy}} = \frac{x_{\text{cmms}} - \text{ABS}(x_{\text{cmms}} - x_{\text{ave}})}{x_{\text{cmms}}} * 100$$

The table shows that there are some entries that need re-evaluation. These are:

- The repairs jobs time
- Scheduled cost
- Total cost (this is due to very low scheduled cost accuracy)

The simulation results of the repairs are almost half the time of the historical data whereas the scheduled cost was almost double. Concerns were expressed for both the repairs hours and scheduled costs in step 5 where the figures 61 and 62 show the irregularities in the PDF fit made. The lack of data points makes the evaluation difficult however figures 61 and 62 show multiple PDF's therefore the selection criteria can be applied to another PDF.

- Scheduled cost PDF to Exponential as in figure 61
 - Parameter mu = 168
- Repair hours PDF to the Lognormal as in figure 62
 - Mu = 0.202733
 - Sigma = 0.612456

The simulation is run again giving the summary table 4.

TABLE 4 SIMULATION SUMMARY TABLE REV2

Preventative maintenance model REV 2							
	CMMS	Run1	Run2	Run3	Run4	Simulation Average	Accuracy percentage
Total S Jobs	31	31	31	31	31	31	100%
Total R Jobs	4	4	4	4	4	4	100%
Average time for S job	1.2339	1.52	1.3323	1.29518	1.20383	1.33784	92%
Average time for R job	1.4375	1.24	2.4627	1.222	1.91042	1.708798	81%
Average cost for S job	168.67	147.73	157.10	96.21	122.36	130.8518	78%
Average cost for R job	213.50	219.06	278.94	137.11	189.77	206.221	97%
Total Hours	44	52	51	41.9	45	47.475	92%
Total Cost	6082.80	5455	5986.	3531	4552.11	4881.048	80%

With these changes the overall accuracy of the model has increase from 77% to 90%. This is evaluated by the average accuracy of all model outputs. This is a good achievement showing that the model reflects the real-world situation of this machine. This concludes the preventative maintenance model allowing the study to move on to the predictive maintenance system.

4.2 Predictive Maintenance

As mentioned in the predictive maintenance workflow, the model relies on a machine condition input. This can be historical data or data from literature on a similar machine. For this study, a cost-effective condition monitoring process was used. Using a logger and four vibration sensors actual intermittent condition monitoring could be done. The vibration measurement is done at 10kHz and is measured in G. The figure used for the evolution is the overall vibration which is the rms value of the signal. Figure 64 shows two sensors marked by the red circles.



FIGURE 64 SENSORS ATTACHED TO MOTOR AND BLOWER DIVE END



FIGURE 65 BLOWER CONDITION MONITORING WITH COMPUTER

Using the workflow set out in figure 51 the predictive maintenance system can be configured.

1. Set condition monitoring interval

The goal of the study is to develop a system that can compare the efficiency of the current maintenance system against a predictive maintenance system. Therefore, the simulation will be done to simulate live condition monitoring, meaning a setpoint of 1

2. Determine critical and moderate condition levels

Using vibration monitoring, the machine's overall vibration will be used to determine the condition. A vibration signal was taken from the motor and the blower, each with an accelerometer over the end bearing housings (drive end, non-drive end). The critical levels are determined by the ISO standard mentioned in the literature. By studying equation 1, the machine running frequency is required to determine the critical and moderate values. The electrical motor is a 2-pole motor running at 3000 rpm. The pulleys on the machine have a 1-to-1 ratio meaning the blower has the same running speed. The machine is a 30kW machine and is there for classified as a class 2 machine[17]. The figure shows the vibration values for velocity. The measurements taken in the acceleration domain, therefore, figure 66 needs to be interpreted accordingly.

VIBRATION SEVERITY PER ISO 10816					
Machine		Class I small machines	Class II medium machines	Class III large rigid foundation	Class IV large soft foundation
	in/s mm/s				
Vibration Velocity Vrms	0.01 0.28				
	0.02 0.45				
	0.03 0.71		good		
	0.04 1.12				
	0.07 1.80				
	0.11 2.80		satisfactory		
	0.18 4.50				
	0.28 7.10		unsatisfactory		
	0.44 11.2				
	0.70 18.0				
	0.71 28.0		unacceptable		
	1.10 45.0				

FIGURE 66 VIBRATION SEVERITY CHART

Using the formula from [17]:

equation 1: $g = 0.641Vf$

Where:

- g = acceleration (m/s^2)
- v = velocity (m/s)
- f = machine running frequency (50Hz or 3000/60 rpm)

The values for the transition to an unsatisfactory condition and unacceptable condition can be calculated. Using figure 66 we can see that the transition to a moderate (satisfactory to unsatisfactory) condition is at 2.8 mm/s and a critical (unsatisfactory to unacceptable) condition is at 7.1mm/s. The machine operates at 3000 RPM which is converted to 50Hz. Using equation 1 we can determine that:

- moderate condition = $0.641 * 0.0028 * 50 = 0.08974g$
- critical condition = $0.641 * 0.0071 * 50 = 0.227g$

3. Determine critical event intervals

The critical events are driven by the breakdowns and repairs of the historical data. From the CMMS data available there is no clear route cause for any of the repairs. Therefore, no critical event can be excluded from the simulation meaning the minimum and maximum periods need to be the same as in the preventative model. This is interpreted as a breakdown which is not detectable by the condition monitoring.

- Minimum period 175 days
- Maximum period 210 days

4. Set all hours and costs as per preventative maintenance

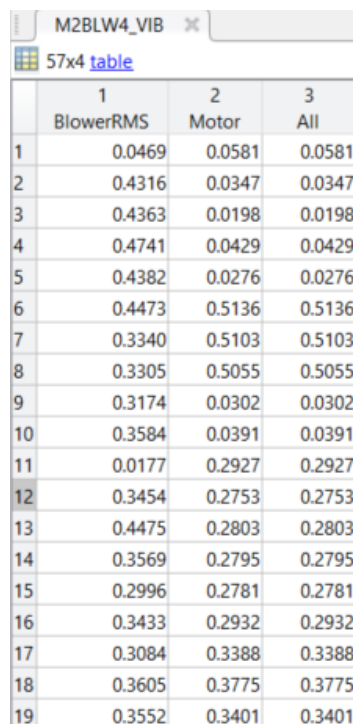
The setpoints for the hours and the costs for each job type in the predictive maintenance is the same as for the preventative system.

- Scheduled = inspections
- Repairs = repairs

5. Determine condition monitoring distribution parameters

In this case study condition monitoring data was taken with the purpose of providing an overall machine condition. The model does not provide for the interpretation of the relationship between a type of machine fault such as a bearing failure and the vibration data taken. Any defect will increase the overall machine condition value.

The data is evaluated similarly as the costs and hours. Using the PDF fit tool the distribution of the machine condition can be determined. Since either the motor or blower condition is monitored, the vibration of both are used in this evaluation. Figure 67 shows the imported data. The imported data is of the vibration monitoring done on blower 4 with the experimental equipment described in chapter 3.2.4 – Condition Monitoring. The vibration measurement is done in G at a sampling rate of 10kHz. The three columns are the blower condition, motor condition, all the vibration put into one column.



	1 BlowerRMS	2 Motor	3 All
1	0.0469	0.0581	0.0581
2	0.4316	0.0347	0.0347
3	0.4363	0.0198	0.0198
4	0.4741	0.0429	0.0429
5	0.4382	0.0276	0.0276
6	0.4473	0.5136	0.5136
7	0.3340	0.5103	0.5103
8	0.3305	0.5055	0.5055
9	0.3174	0.0302	0.0302
10	0.3584	0.0391	0.0391
11	0.0177	0.2927	0.2927
12	0.3454	0.2753	0.2753
13	0.4475	0.2803	0.2803
14	0.3569	0.2795	0.2795
15	0.2996	0.2781	0.2781
16	0.3433	0.2932	0.2932
17	0.3084	0.3388	0.3388
18	0.3605	0.3775	0.3775
19	0.3552	0.3401	0.3401

FIGURE 67 MACHINE VIBRATION TABLE IN MATLAB

The combined blower and motor data in column three is used as the dataset in the fitment tool to derive the fitments as seen in figure 68.

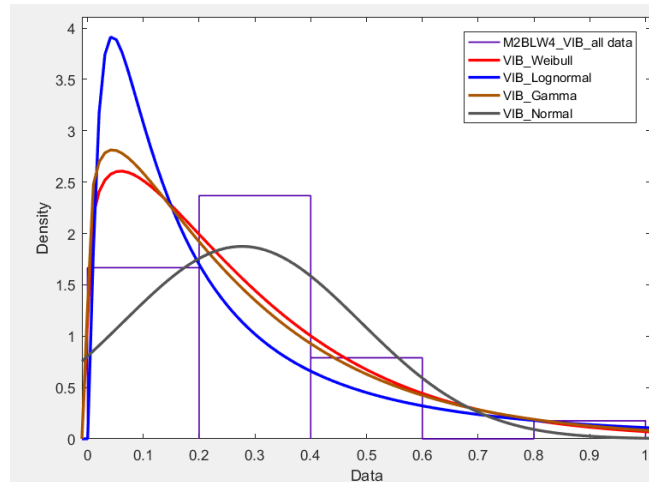


FIGURE 68 VIBRATION DATA PDF FIT

Viewing figure 68 the normal distribution seems to be the best viable PDF. This will be used for the simulation with the parameters as follows:

- $\mu = 0.276818$
- $\sigma = 0.0453101$

Figure 71 shows the evaluated covariance thereby justifying the selection.

Estimated covariance of parameter estimates:		
	μ	σ
μ	0.000794914	2.79866e-19
σ	2.79866e-19	0.000408199

FIGURE 69 VIBRATION NORMAL DISTRIBUTION COVARIANCE

6. Set critical event value

The critical event generates a value multiplied by the modelled machine condition to simulate a breakdown per historical data statistics. One sees that we need to escalate this value to above 0.08974 and that the average machine condition is 0.276. From this we can see that there must be an error in one of our evaluations, for the purpose of generating data for further evaluation a critical multiple as 1 is selected.

As mentioned in chapter 3.2.4, condition monitoring data can either be by research done on the specific machine, historical machine data or as in this case a form of condition monitoring.

7. Run the simulation

Running the simulation several times with the current setpoints, an error prevents the simulation from finishing. There error received is from the inspection hours model block. With the standard deviation and the mean hours being close to one another the simulated hours run into a negative value at some time

point during the simulation. The error is shown in figure 70. This is caused by the normal distribution that will in this case simulate negative values which are not allowed.

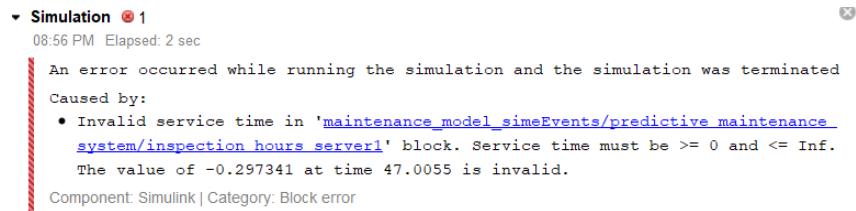


FIGURE 70 SIMULATION ERROR

The error can be eliminated by choosing a different PDF fit from figure 60. By choosing a different PDF for the scheduled and inspection hours the scheduled data needs to be verified again. Choosing a lognormal PDF with parameters

- $\mu = 0.0426737$
- $\sigma = 0.606694$

the simulation is run again.

TABLE 5 NEW DISTRIBUTION SELECTION RESULT

Scheduled hours with lognormal distribution							
	CMMS	Run1	Run2	Run3	Run4	Simulation Average	Accuracy percentage
Schedule hours	1.2339	1.4115	1.2448	1.37202	1.139	1.2918	95%

With the changed hours distribution, the simulation accuracy improves slightly and allows the simulation to complete.

The full simulations results can be seen in figure 71.

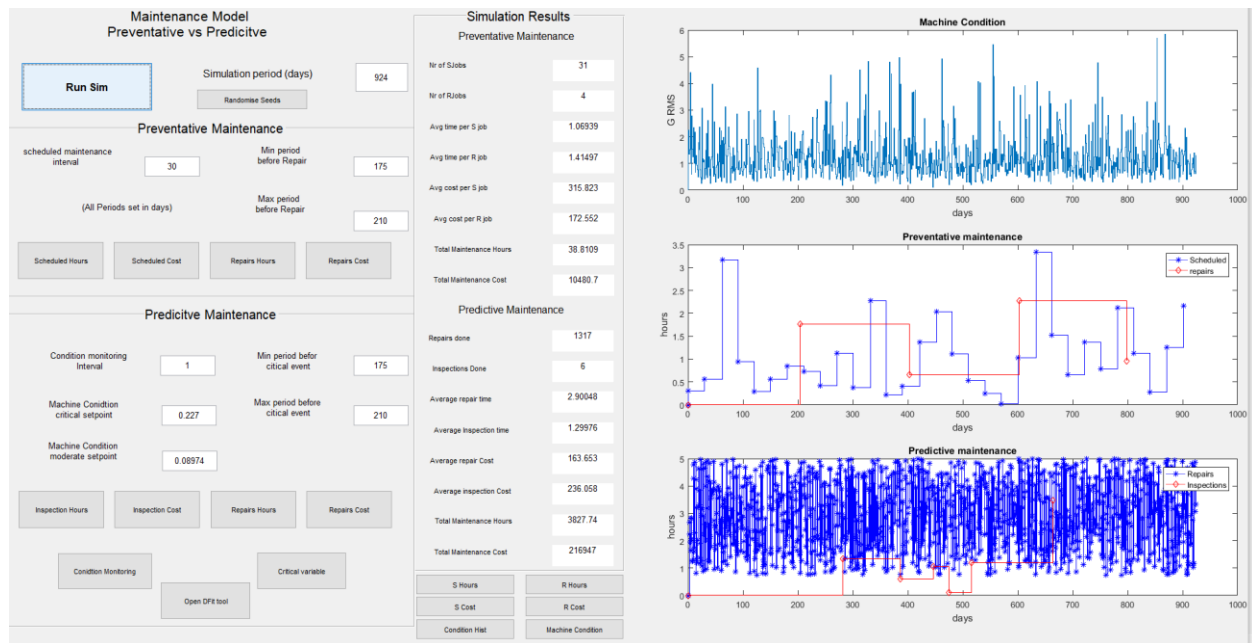


FIGURE 71 FULL SIMULATION RESULT

The results show an increase in jobs to up to 1300 jobs over the simulated period of 924 days. This is more than daily. Since the number of jobs for the predictive model is driven by the machine condition, an investigation into the vibration data is required.

4.3 Fault and rectification

Many of the vibration data taken exceed the healthy machine conditions set in step 2. This is the reason that over 1300 jobs are simulated. The historical data shows no excessive sign of machine breakages. With the moderate machine condition setpoint at 0.08974, the machine condition is expected to be below this value since no major breakdowns were experienced over the period. However, the mean RMS G value is 0.2768G, already above the critical machine condition resulting in a surprising number of simulated jobs.

An error in the condition monitoring data was found. The Windaq data logger used has two methods of logging data. One is a stand-alone unit where the logger is set up with a flash drive and a 220V power supply. The other is over a computer via the Windaq software using the computer USB outlet as the power supply and communication. The readings from the two methods vary drastically. The stand-alone method amplifies the readings by a factor of at least ten without having any sensors connected. A dominant frequency of 50Hz is also seen, which is also the motor running speed; however, the amplitude is not realistic, which means that the data taken is distorted, and the 220V power supply is identified as the problem. A comparison between the logged signals via the PC and the stand-alone application can be seen in figures 72 and 73.

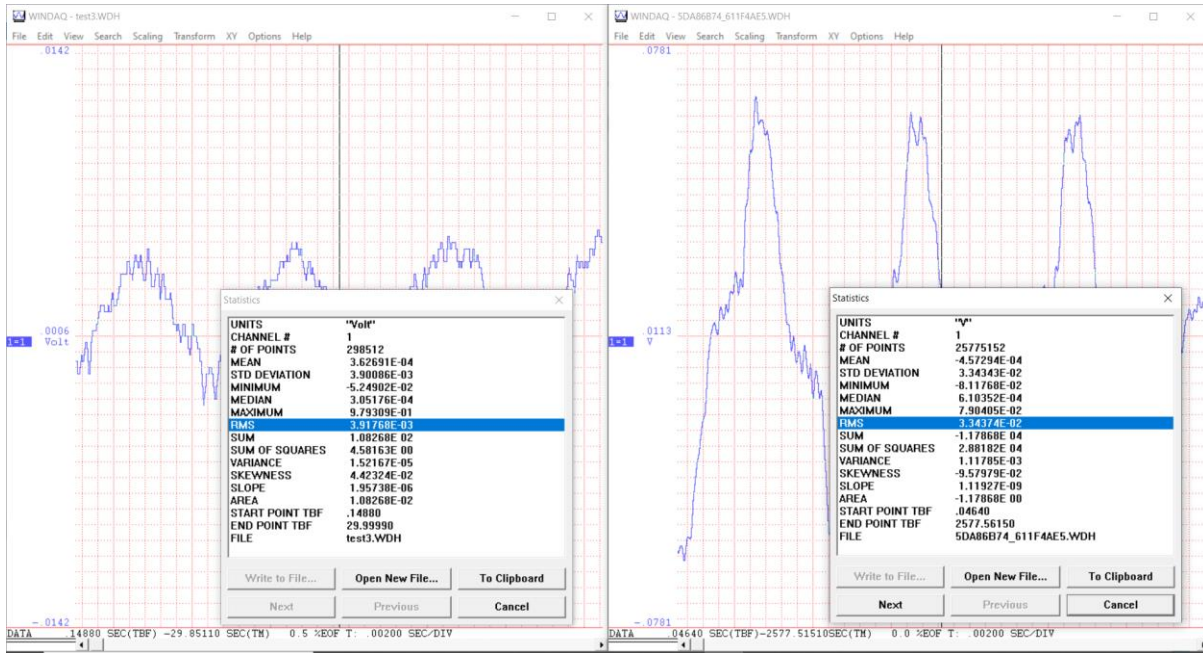


FIGURE 72 DATA LOGGED VIA PC

FIGURE 73 DATA LOGGED WITH STAND-ALONE APPLICATION

It is important to note that in figures 72 and 73, the data logger is connected to the sensor, but it is not applied to a machine. The RMS values are 3.917×10^{-3} and 3.34×10^{-2} respectively. Using a second test signal and the same conditions, the signal is compressed to give figure 74.

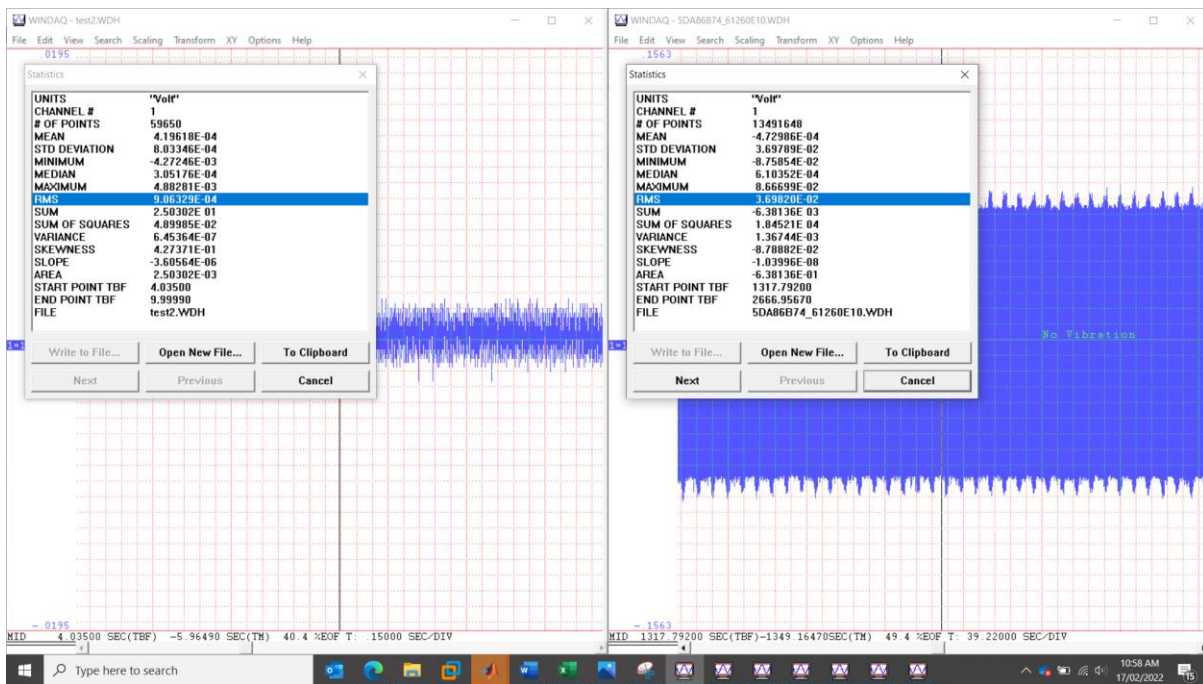


FIGURE 74 SECOND TEST SIGNAL FULL COMPRESSION (SIGNAL COMPARISON)

In figure 74, the RMS value for the full signals are 9.06×10^{-4} and 3.69×10^{-2} respectively. Also, the signal taken via stand-alone application has a dominant 50Hz cycle as previously mentioned whereas the signal taken over the computer does not. This is verified by analysing the signal in matlab as seen in figure 75.

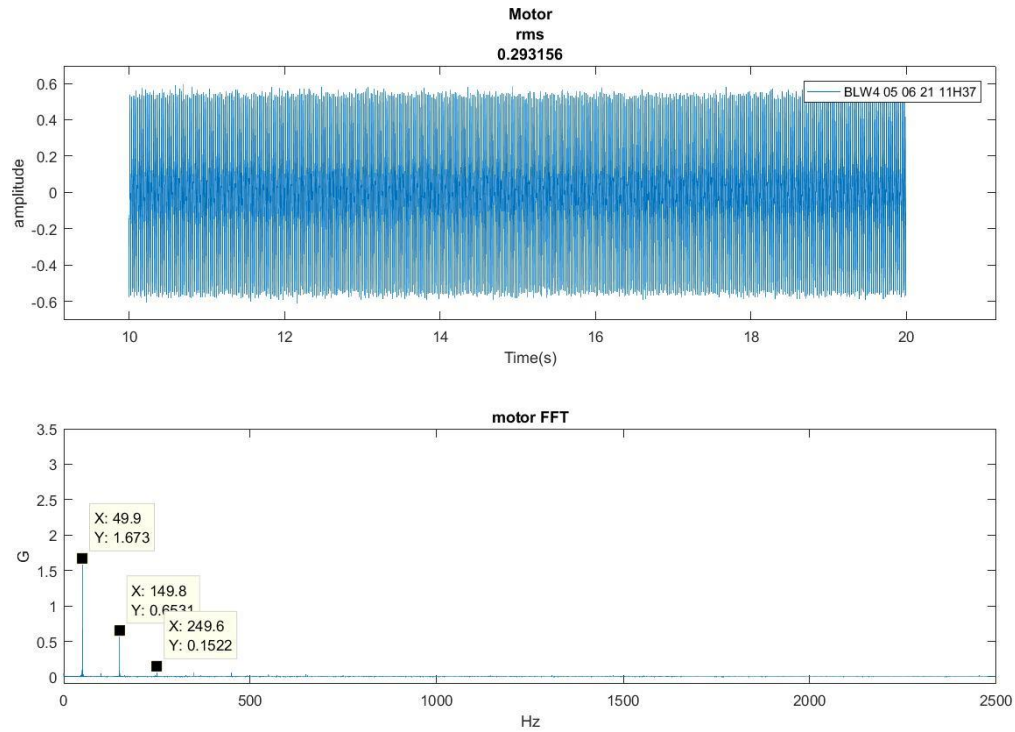


FIGURE 75 FFT SHOWS DOMINANT 50Hz FREQUENCY (COMPUTED IN MATLAB)

The dominant 50Hz frequency is expected from the true signal since the motor is running at 3000 rpm (50Hz). However, at a magnitude of 1.673G the machine would not be in a operational condition.

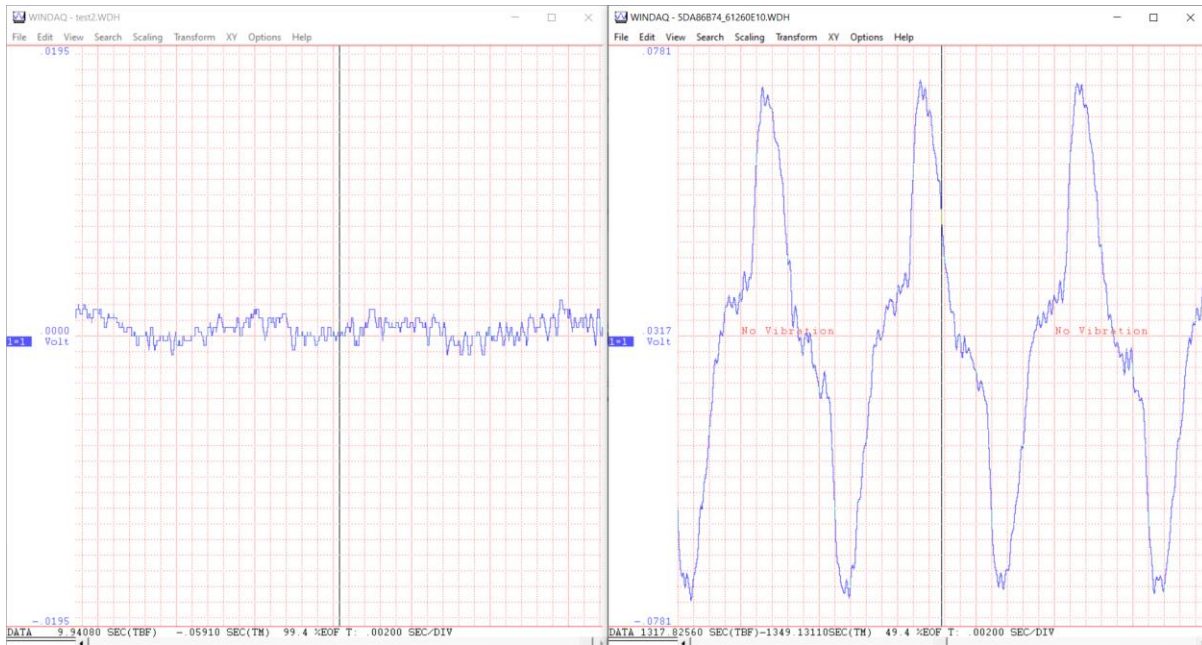


FIGURE 76 SIGNAL COMPARISON

In figure 76 a comparison between the two signals taken under the same conditions can be seen. The accelerometer is connected but is not placed on a machine. The signal from the stand-alone application is amplified with the small amount of noise visible as can be seen in figure 76. In figure 77 a compressed signal taken via the logger and computer is seen with its calculated FFT.

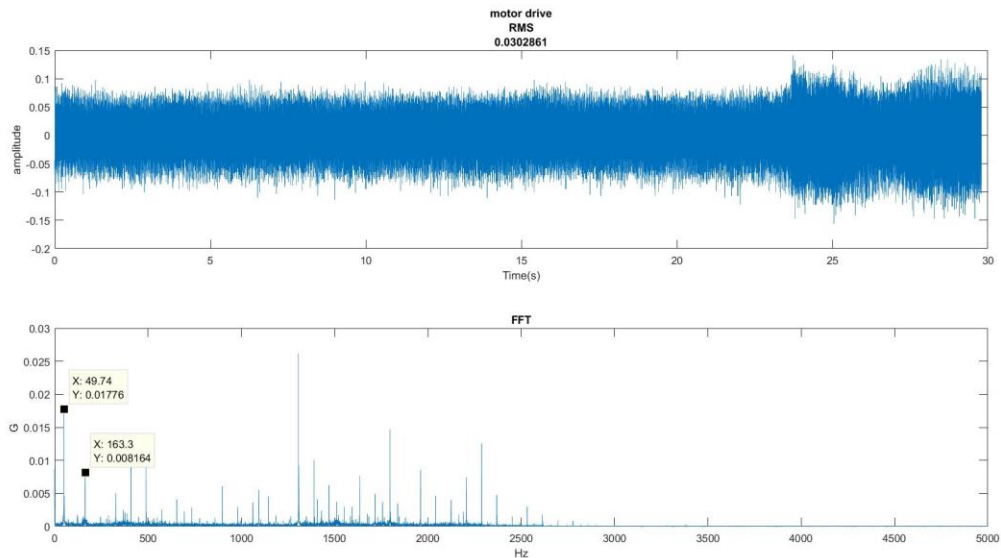


FIGURE 77 TRUE SIGNAL FFT

In figure 77 the peak at 50Hz (running speed) is also seen however, the higher frequencies which are the bearing and gear contacts are also seen. This is expected with all rotating machinery where acceleration is measured at high frequencies.

Taking this into consideration and eliminating the corrupted data there are less data points to use. However, completing step 5 the new PDF fit can be seen.

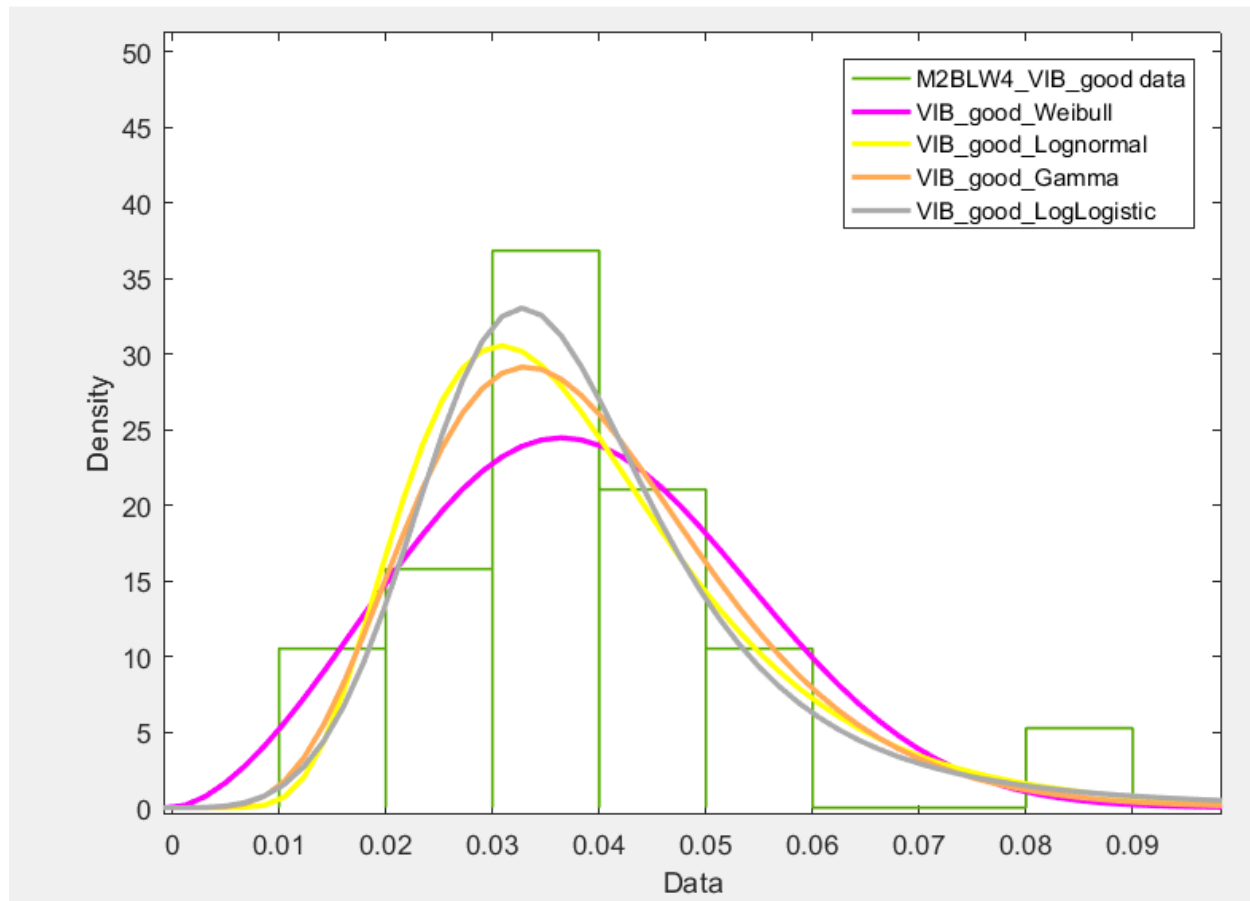


FIGURE 78 CLEANED VIBRATION DATA PDF

Figure 78 shows that the Weibull distribution fits best according to the new cleaned data.

Running the model with the new PDF (Log-Logistic) with the new parameters

- Parameter A = -3.31976
- Parameter B = 0.219642

the simulation shows much better results as seen in figure 79. Figure 79 represents the full simulation results, the preventative maintenance block showing the results simulated for the preventative maintenance, these results should reflect the CMMS data closely. The Predictive Maintenance block showing the predictive maintenance simulation. The critical set point to force the simulation into a critical event (breakdown) is set to multiply the average machine condition (0.037 G) to above the critical condition. The model interprets this as a non-healthy condition to simulate the necessity of a repair, as determined by the historic data. Hence critical variable is set above 6.

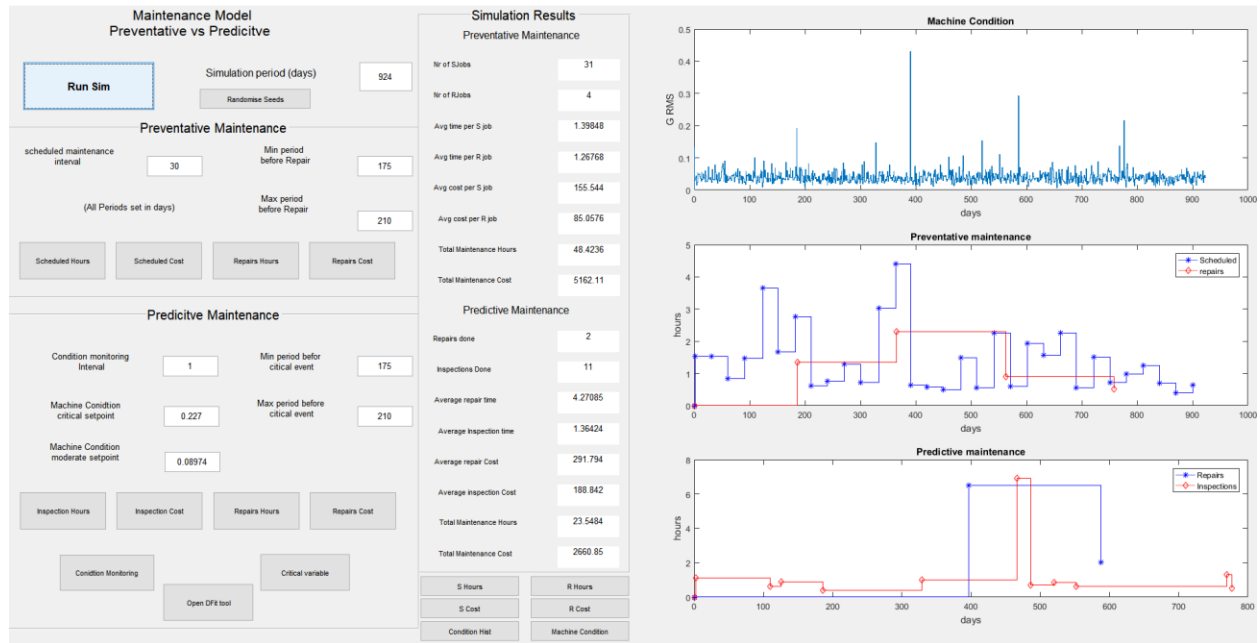


FIGURE 79 SIMULATION RESULTS WITH CLEANED VIBRATION DATA

In figure 79, a good machine condition is visible, more consistent and within the expected tolerance. The peaks are also seen which are a simulation of the critical events that take place. The model being able to have different results within the set parameters, several runs were made, and the results shown in table 6. The comparison being done with the CMMS data.

TABLE 6 CMMS DATA VS MODEL DATA

Preventative maintenance CMMS data vs Predictive Maintenance Model							
	CMMS	Run1	Run2	Run3	Run4	Simulation Average	% Deviation
Schedules vs Inspections	31	11	11	13	18	13.3	57%
Number of Repairs	4	2	3	1	1	1.8	56%
Total Hours	44	20.4	22.15	18.6	22.8	21.0	52%
Total Cost	6082.80	1877.90	2011.43	3701.66	5363.26	3238.6	47%

In table 6 the last column shows the % deviation that is simulated between the CMMS data and the modelled predictive maintenance. There is an approximate 60% reduction in number of jobs. This is also directly noticed in the total hours and total costs. The model suggests a 52% reduction in maintenance hours and a 47% cost reduction.

4.4 Cost benefit

The last simulation showed the results after the incorrect vibration data was filtered out. This clean data represents useful information to do a cost benefit calculation. The cost benefit calculation can be seen from two different aspects. The one being the direct impact condition monitoring could have on the cost of maintenance due to its increase in efficiency. The other would be the potential cost saving due to less maintenance and repair hours. The cost benefit analysis showing the later is taken directly from the simulated data using the reduction of scheduled stops.

For the cost benefit calculation to be represented consistently in terms of the simulation, some assumptions need to be outlined. These assumptions are:

- The work done on maintenance and repairs are done in overtime hours
- Overtime rates are estimated at N\$250 per hour
- Spares cost saving given by the simulation are accurate and used for the calculation
- Cost benefit of return on investment calculation is done for a complete condition monitoring system for a blower as in the case study
- Cost saving is calculated for the simulation period.
- All repairs in the simulation can be picked up with vibration analysis
- The condition monitoring is accurate

Firstly, the direct cost benefit is the comparison on what the savings would be using the simulation data directly. The cost on spares based on table 6 would be N\$ 2 844.20. The simulation suggests that there would be less maintenance hours required, mainly due to a decrease in scheduled stops for maintenance. Comparing the historical data to the simulated predictive model there would be a total of 23 hours of less stoppage time due to maintenance. The CMMS data shows 44 working hours whereas the predictive maintenance model shows 21 working hours giving a decrease of 23 maintenance hours. With the assumptions mentioned above (N\$ 250/hour labour cost) the total cost would be N\$ 5 750. This results in a total of N\$8 594.20 saved over the simulation period when live condition monitoring is implemented.

The saving of N\$ 8 594.20 does however not represent the total effect predictive maintenance could have on a facility. The 23 hours of less maintenance time could potentially have a much greater effect on the operational aspect for the facility. In respect to the specific machine in the case study, the facility would have 23 hours of additional production time. Given that the specific mill estimates a N\$ 80 000 loss per hour downtime, the potential cost benefit is escalated to N\$ 1 840 000. Usually there are certain start-up delays on a facility where no product is produced. With the mill used in this case study and refereeing to the blowers, this is generally not the case since the mill is highly automated. However, for other cases this extra time where production losses occur can be added to the cost benefit calculation. This is however not data that the model can provide. The model can only provide the maintenance hours and costs.

TABLE 7 COST BENEFIT ANALYSIS

Cost benefit analysis			
Item	Units saved	Unit Cost	Total Cost
Maintenance Hours saved	23 hours	250/hour	N\$ 5 750
Spares Saving	N\$2844.20	N\$2844.20	N\$2 844.20
Operation hours	23 hours	N\$ 80 000	N\$ 1 840 000
Total cost benefit			N\$ 1 848 594.20

The figures in table 7 assume that all hours saved were potential production hours. This is not true in practice, there are always opportunities to push maintenance work and there are also scheduled stops. To calculate a return on investment the cost for condition monitoring must be known. An estimated budget can be seen in table 9. The device mentioned in table 9 is the vibration analysis machine that only requires minor setting up such as motor speed and bearing size, with basic machine knowledge this can be achieved. It is also assumed that a facility of such a magnitude has the skills of an electrician, millwright, or instrumentation technician available to do the installation. This is the IFM VSE153 model. Further requirements are only the sensors and a power supply. If it is required to have the device accessible remotely additional networking is required.

TABLE 8 CONDITION MONITORING BUDGET

Condition monitoring budget			
Item	Quantity	Unit cost	
Accelerometers	4	N\$ 3500	N\$ 14 000
Screened cable for accelerometers	4	N\$ 1 500	N\$ 6 000
Speed sensor (inductive sensor)	1	N\$ 1 400	N\$ 1 400
Vibration monitoring device (analysis tool)	1	N\$18 000	N\$ 18 000
Power supply for unit	1	N\$ 500	N\$ 500
Panel and internal cabling	1	N\$ 1 500	N\$ 1 500
Ethernet connection to local Network	1	N\$ 1 500	N\$ 1 500
		Total Cost	N\$ 42 900

The cost estimate seen in table 8 is based on the conditions and requirements of the machine in this case study. The costs are also based on a quotation received from a local supplier.

Table 7 shows potential cost saving over 924 days (approximately 2.5 years).

$$\text{Equation 2: } \textit{payback period} = \frac{\textit{investment cost}}{\textit{yearly investement gain}}$$

As we can see from the above formula the calculation needs to be done based on yearly savings.

$1\,848\,594.20 / 2.5 = 739\,439.68$ saving annually

$$\text{Payback period} = \frac{42\,900}{1\,848\,594.20}$$

$$= 0.058 \text{ years}$$

Approximately 21 days.

A Payback period seems rather unrealistic. However, seeing the one hour of downtime can result in a financial loss of approximately N\$80 000 per hours it clear that only half an hour of downtime saved can pay for one complete condition monitoring set. Based in the simulation, there is a potential of saving approximately 9 hours a year. This concludes that even if the simulation has a low accuracy, it still provides enough evidence of a potential increase in maintenance efficiency and reduction in overall production cost.

5 VALIDATION AND VERIFICATION

In Chapter 1, specific objectives were outlined for the model. The model requires verification that these objectives are met. For this, the model is subjected to two machines of similar make. The machines are blowers and serve the same function. However, they convey wheat flour instead of maize flour and are situated on different sites. The maintenance system on these machines includes the same procedures as with the blower done in the case study.

The model has a built-in verification feature. The comparison between the historical data and the preventative model is considered a direct verification that the model works as expected since the preventative model is a direct simulation of historical data. The predictive model is based on the same foundations as the preventative model. Therefore, if the preventative maintenance model is accurate, the predictive models' results are a realistic representation of what can be expected when condition monitoring is implemented.

Together with the preventative maintenance system subjected to the blower, a time-based condition monitoring system (done by an external party) is in place, which will be used to verify the results of the model. A trend of the blowers' overall condition can be taken from the external contractor's condition monitoring. This condition monitoring is done approximately every three months.

The machines were not subjected to individual condition monitoring during the validation process. For the two blowers used in this chapter, the assumption was made that their condition is similar. The following points can support these assumptions.

- The blowers are of same make and type
- The drive system is the of the same type (via belts)
- The blowers convey the same type of product at similar rates
- The blowers are subjected to the same type of maintenance system
- The blowers are on the same site with similar conditions

This assumption allows the system to use the same condition monitoring data as statistical use for the blowers in this chapter. Two blowers will be used to verify the model's outcomes, blower 1 and blower 8. The machine selection was based on the machine similarities in the previous paragraph.

5.1 Blower 1

Flowing the workflow blow 1 is subjected to the simulation process.

Preventative Maintenance

scheduled maintenance interval	30	Min period before Repair	12
(All Periods set in days)		Max period before Repair	150

FIGURE 80 PREVENTATIVE MAINTENANCE INTERVALS

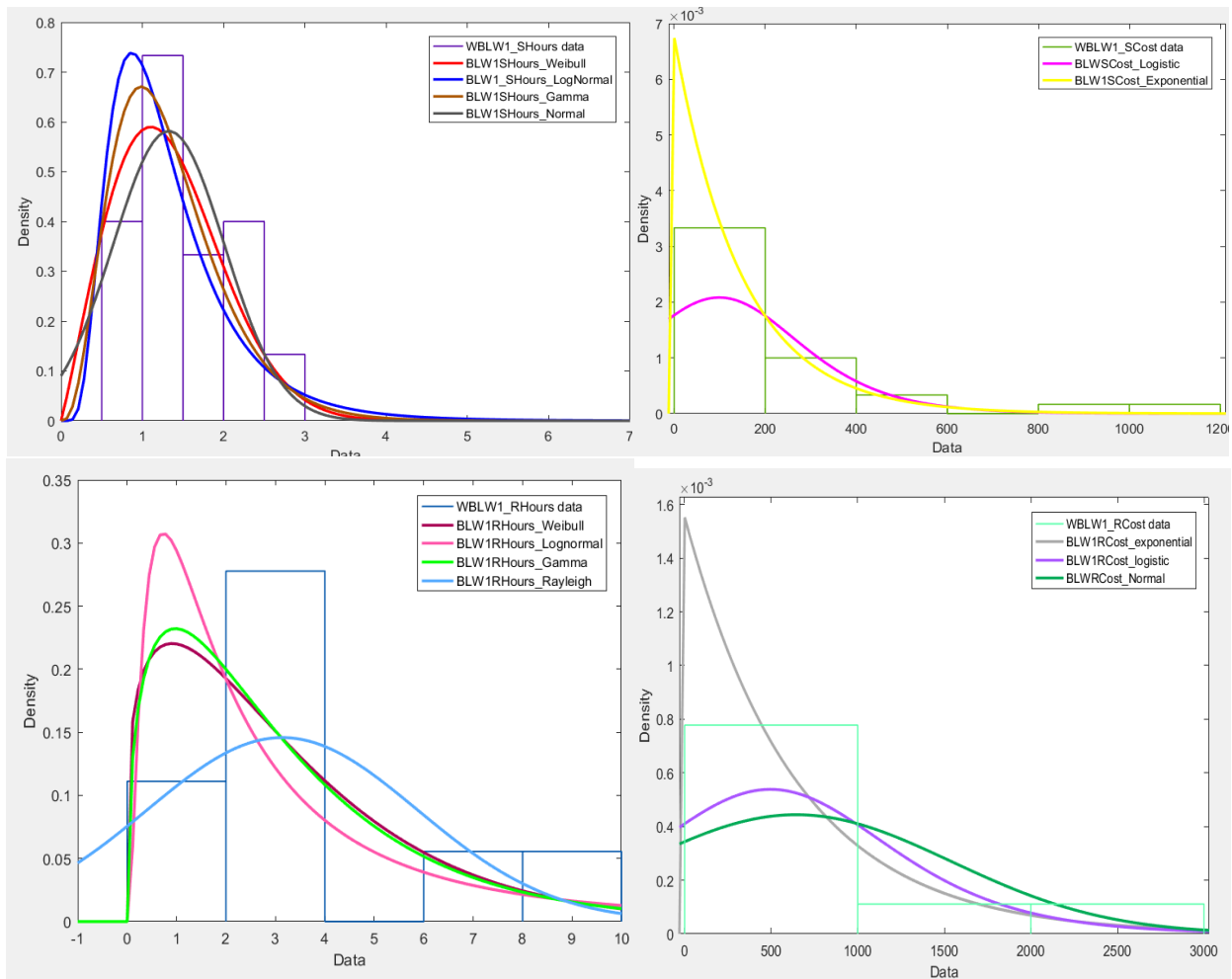


FIGURE 81 BLOWER 1 PDF FIGURES

From the above PDF's the selection summary can be seen in table 9.

TABLE 9 BLOWER 1 SETPOINTS

PDF selection summary			
Job type and attribute	PDF selection	Parameters	Covariance
Scheduled Hours	Lognormal	Mu = 0.148256 Sigma = 0.537931	Estimated covariance of parameter estimates: mu sigma mu 0.00964568 -5.26049e-19 sigma -5.26049e-19 0.00507667
Scheduled Cost	Exponential	Mu = 147.997	Estimated covariance of parameter estimates: mu mu 730.107
Repair Hours	Lognormal	Mu = 0.761243 Sigma = 1.0365	Estimated covariance of parameter estimates: mu sigma mu 0.119374 7.06839e-18 sigma 7.06839e-18 0.0716246
Repair Cost	Exponential	Mu = 643.7	Estimated covariance of parameter estimates: mu mu 46038.9

Running the simulation with these parameters the preventative model results comparison can be seen in table 10.

TABLE 10 BLOWER 1 PREVENTATIVE SYSTEM SUMMARY

	CMMS	Run1	Run2	Run3	Run4	Simulation Average	Accuracy percentage
Total S Jobs	30	31	31	31	31	31	97%
Total R Jobs	9	12	13	11	10	11.5	72%
Average time for S job	1.325	1.44	1.37	1.467	1.211	1.372	96%
Average time for R job	3.139	3.4375	2.99	2.31	1.879	2.654125	85%
Average cost for S job	147.99	135	124.96	137.76	103.88	125.4	85%
Average cost for R job	643.7	485	308.41	258.3	566.65	404.59	63%
Total Hours	68	86	81	70	56.34	73.335	92%
Total Cost	10233	10038.6	7883.09	7112.68	8886.86	8480.308	83%

The overall accuracy percentage is 84%. The lower accuracy can be seen in the average repair job costs. The significant deviation between the historical repair job costs can explain the lower accuracy for the average repair jobs. In figure 81, the repair job cost simulation cannot accurately resemble the historical

data, hence the 63% accuracy. However, seeing the total cost still has an accuracy of 83%, the preventative model can be said to represent accurate historical data. Meaning the predictive maintenance simulation can be analysed.

TABLE 11 BLOWER 1 PREDICTIVE SYSTEM RESULTS

	CMMS	Run1	Run2	Run3	Run4	Simulation Average	% Deviation
Schedules vs Inspections	30	21	20	20	20	20.25	33%
Number of Repairs	9	3	3	3	3	3	67%
Total Hours	68	57.3	30	30.0	30	36.825	46%
Total Cost	10233	3773	2676	1918.98	2676	2760.995	73%

In table 11 the summary of the predictive maintenance model results can be seen. Like the case study, this model also suggests a reduction in maintenance and cost for this machine. The model simulates a 46% reduction in maintenance time and a 73% reduction in maintenance cost. This machine requires generally more attention than the one in the case study. This means even with condition monitoring in place the machine would still require more since the faults will still be picked up however, the scheduled maintenance can be significantly reduced due to the implementation of condition monitoring.

5.2 Blower 8

The same process is done for blower 8.

Preventative Maintenance

scheduled maintenance interval

30

(All Periods set in days)

Min period before Repair

65

Max period before Repair

595

FIGURE 82 BLOWER 8 MAINTENANCE INTERVALS

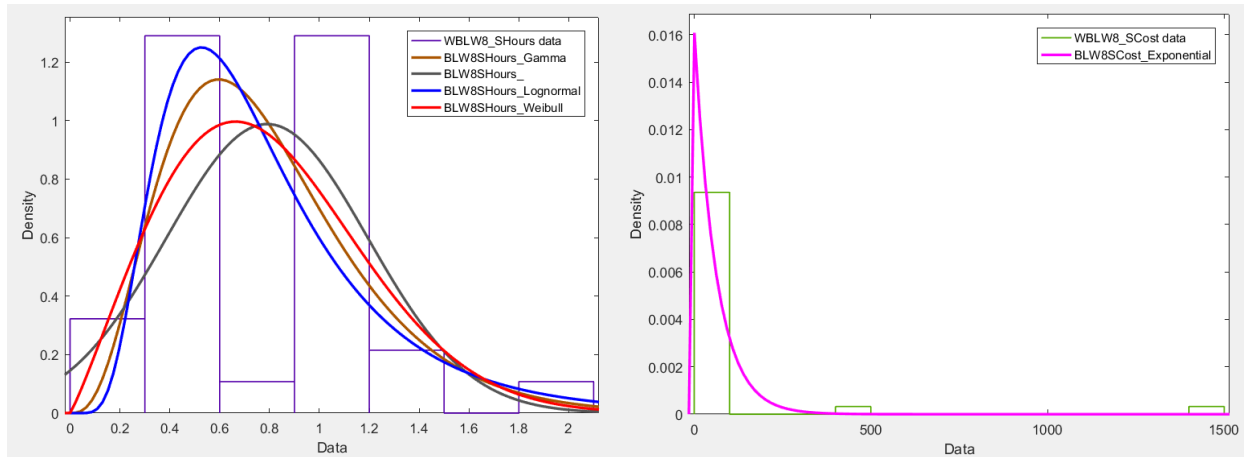


FIGURE 83 BLOWER 8 PDF'S

For blower 8, the repairs are a unique challenge because there are only two repairs over the period. With only two, it is impossible to create a PDF. In figure 83 there are no PDFs for the repairs, the reason as stated that no PDF can be made using a dataset of 2 values. Based on the historical data of the repairs, therefore a uniform distribution needs to be selected with the minimum and maximum set out according to the two data points available. Table 12 shows the selection summary for blower 8.

TABLE 12 BLOWER 8 PDF SELECTION

PDF selection summary			
Job type and attribute	PDF selection	Parameters	Covariance
Scheduled Hours	Lognormal	Mu = -0.363234 Sigma = 0.527029	Estimated covariance of parameter estimates: mu sigma mu 0.00895998 -2.69765e-19 sigma -2.69765e-19 0.00470779
Scheduled Cost	Exponential	Mu = 61.72	Estimated covariance of parameter estimates: mu mu 122.907
Repair Hours	Uniform	Minimum = 0.75 Maximum = 5	Uniform cannot be used in the fitment tool
Repair Cost	Uniform	Minimum = 0 Maximum = 4514.60	Uniform cannot be used in the fitment tool

Table 13 shows the simulation results for blower 8.

TABLE 13 BLOWER 8 PREVENTATIVE SYSTEM RESULTS

Blower 8 CMMC vs Preventative system							
	CMMS	Run1	Run2	Run3	Run4	Simulation Average	Accuracy percentage
Total S Jobs	31	31	31	31	31	31	100%
Total R Jobs	2	4	4	3	3	3.5	25%
Average time for S job	0.79	0.869	0.818	0.887	0.98	0.8885	88%
Average time for R job	2.63	3.148	3.43	3.04	3.5	3.2795	75%
Average cost for S job	61.73	42.95	67.4	44.78	69.1	56.0575	91%
Average cost for R job	2257.29	0	16.183	218.22	0	58.60075	3%
Total Hours	29.75	39.5	39.08	36.6	40.96	39.035	69%
Total Cost	6428.08	1331.54	2155.28	2043.13	2142.69	1918.16	30%

From table 13, the overall simulation represents the available data well. Excluding the repair jobs, the model can be deemed 88% accurate. The repair cost having such a significant deviation (one job going at zero cost the other 4514.60), it is not surprising that there is only an accuracy of 3%. However, the number of jobs and hours can be used to some extent since the deviation is small. Knowing that the repairs are difficult to represent for this model, the simulation continues to the predictive simulation.

TABLE 14 BLOWER 8 PREDICTIVE MAINTENANCE RESULTS

CMMS vs predictive maintenance							
	CMMS	Run1	Run2	Run3	Run4	Simulation Average	% Deviation
Schedules vs Inspections	31	24	23	16	16	19.75	36%
Number of Repairs	2	0	1	1	1	0.75	63%
Total Hours	29.75	18.	22.4	14.46	14.65	17.3775	42%
Total Cost	6428.08	1366.31	995	1123.68	1102	1146.748	82%

The simulation results tell the same story as that of the case study and the blower 1 simulation. A reduction in jobs, cost, and time. When eliminating the repairs, the model suggests that there can still be an improvement with a reduction of maintenance intervals. The schedules can either be reduced or predictive maintenance could be introduced to increase the efficiency cost and time management.

5.3 Machine Condition Validation

The machines in this study also undergo a three-monthly condition analysis by an external contractor. From this analysis, the client receives a progress report which depicts the overall machine condition and a detailed report if a machine is in an abnormal condition. The vibration analysis is based on ISO 10816, as discussed in the literature, and is categorised as seen in table 15.

TABLE 15 MACHINE CONDITION

Machine Status	
1	CRITICAL
2	ALARM
3	ALERT
4	NORMAL
5	Operation not steady
0	No data recorded

The progress report for machine one is seen in table 16

TABLE 16 BLOWER 1 PROGRESS REPORT

	WHEAT BLOWER ROOM	Machine	Location	06/17	10/17	04/18	02/19	07/19	10/19	02/20	06/20	09/20	02/21	07/21	02/22
39	Blower no.1 GM25	Motor	NDE Bearing	4	4	4	4	4	4	4	4	4	4	4	4
			DE Bearing	4	4	4	4	4	4	4	3	4	4	4	4
		Blower Input	DE Bearing	4	4	4	4	4	4	4	4	2	2	2	4
			NDE Bearing	4	4	4	4	4	4	4	4	2	2	2	4
		Blower Output	DE Bearing	4	4	4	4	4	4	4	3	3	3	3	4
			NDE Bearing	3	4	4	4	4	4	4	4	4	4	4	4

From this it can be seen that the machine has been in a relatively good condition over the timespan the intermediate condition monitoring was done. The same can be said for blower 8 in table 17.

TABLE 17 BLOWER 8 PROGRESS REPORT

	WHEAT BLOWER ROOM	Machine	Location	06/17	10/17	04/18	02/19	07/19	10/19	02/20	06/20	09/20	02/21	07/21	02/22
46	Blower no.8 GM10S	Motor	NDE Bearing					4	4	4	4	4	4	4	4
			DE Bearing					4	4	4	4	4	4	4	4
		Blower Input	DE Bearing					4	4	4	4	4	4	4	4
			NDE Bearing					4	4	4	4	4	4	4	4
		Blower Output	DE Bearing					4	4	4	4	4	4	4	4
			NDE Bearing					4	4	4	4	4	4	4	4

Tables 16 and 17 represent the data seen in our model as well. There are less repairs necessary on blower 1 than on blower 8. It can also be assumed that blower 1 is older than blower 8 seeing that there is less historical data for blower 8 than 1, being the possible reason for the lower number of repairs.

The machine used in the case study was blower 4 in the facility, its progress report can be seen in table 18.

TABLE 18 BLOWER 4 PROGRESS REPORT

PLANT BLOWERS	Machine	Location	10/19	02/20	06/20	09/20	02/21	07/21	02/22	10/22
Plant Blower no.4	Motor	NDE Bearing	4	3	4	4	4	4	4	4
		DE Bearing	4	4	4	4	4	4	4	3
	Blower Input	DE Bearing	4	4	4	4	3	4	4	4
		NDE Bearing	4	4	4	4	4	4	4	4
	Blower Output	DE Bearing	3	3	4	4	4	4	4	4
		NDE Bearing	3	3	4	4	4	4	4	4

Over the period of October 2019 and October 2022 it is seen that the external contractor has at times measured a moderate state for blower 4. From the CMMS data there is one job card to address the problem raised in October 2019 and another addressing the problem raised in February 2021. No other job correlation is visible. The experimental set up produced similar progress given no values above the moderate condition of 0.08974G rms. These values are only the true values after the faulty data was eliminated as per chapter 4.3 Fault and Rectification.

The progress report in table 18 shows that there are cases where blower 4 is in a moderate condition. Although the machine is in a critical condition, the work that was required could be planned as a repair. Although this not part of the scheduled maintenance, none of the machine broke down unexpectedly and the repairs could be planned in conjunction with the production planning.

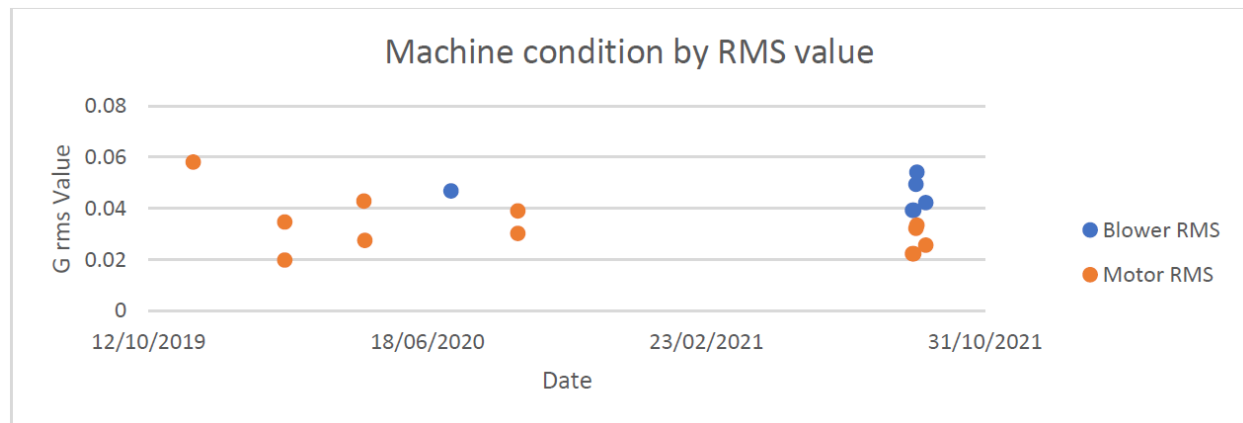


FIGURE 84 EXPERIMENTAL VIBRATION RESULTS

The results show a similar overall machine condition compared to the contractor. The FFT done by the contractor for the condition of the blower in October 2020 can be seen in figure 85.

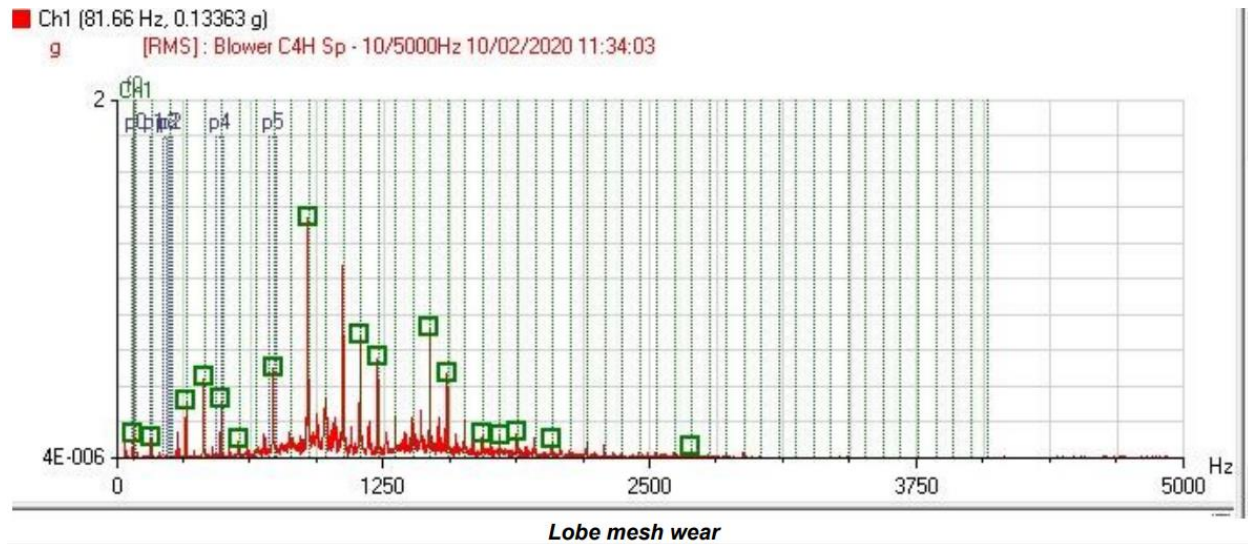


FIGURE 85 FFT FROM CONTRACTOR (SAMPLE TAKEN OCTOBER 2020)

Reviewing the FFT in figure 85 and comparing it to the FFT in figure 86 which was done by the experimental set up, the spectrums seem to be similar. It is expected that the two spectrums will reflect different amplitudes since they were taken at different times and states. The spectrum in figure 85 was taken in February 2020 and we can see in table 18 that blower was not in a healthy state at the time. Explaining the elevated amplitudes in comparison to figure 86.

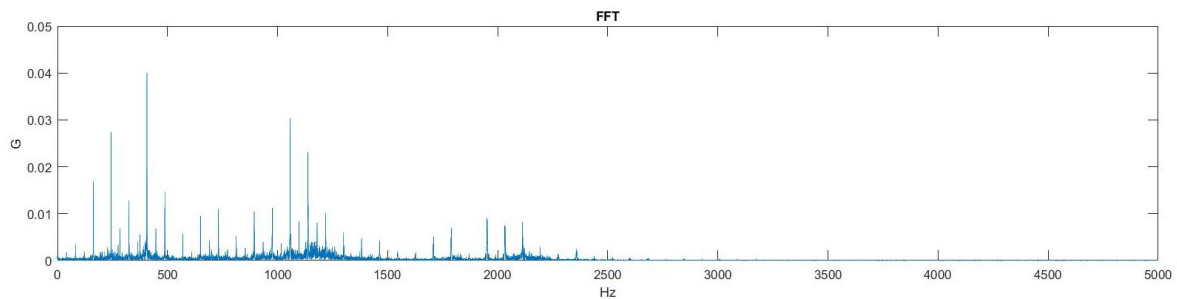


FIGURE 86 FFT BY EXPERIMENTAL SETUP (SAMPLE TAKEN NOVEMBER 2020)

Given the collective data between the similar spectrum and the condition results represent mostly the same condition over the studies period, it can be verified that the experimental setup can be used for the purpose of a study such as this to complete the objectives set out in chapter 1.

5.4 Summary

The model presents a reduction in job cards for blower 1 and blower 8. There is a direct correlation between the number of jobs done, the hours worked and the costs. This reduction in these aspects satisfies the primary objective of this study. The model clearly shows how condition monitoring can affect a specific machine. The model presents a digital twin of the existing maintenance system, with a simulation of a predictive maintenance system. The primary objective of this study is met.

The model relies on historical data and can be done for any machine. The model can be used for any individual machine if there is historical data. Condition monitoring data can be used to improve the data provided by the model. The condition data can either be from the literature on similar machines or cost-effective intermittent data, as done in this study. The model allows users to enter the MatLab PDF fitment tool with a button click. From there, the necessary data can be entered for PDF fitments. It was noticed that with the normal distribution the simulation can run into an error. The cause is that a normal distribution can generate negative values. This is not valid and will result in an error. A complete understanding of statistical analysis is not required however, careful attention should be applied to the fitments where the simulation could generate negative values. The tool provides the parameters needed for each selected fitment. This makes the model easy to use and understand.

The results of the simulations tell the same story. This is verified by the historical condition monitoring data taken by the external contractor.

6 CONCLUSION AND RECOMMENDATIONS

In essence, the model is a digital twin of the current maintenance system with the addition of a comparative simulation for condition-based maintenance.

The objectives given in chapter 1 are the guidelines for this study. Objective 1 states that a comparative tool should be made that can be used to compare a preventative maintenance system (with historic data) to that of a predictive maintenance system. With the validation done in chapter 5 on blower 1 and blower 8 as an extension to the case study, this objective is met.

The second objective is to be able to complete a cost benefit analysis based on the modelled data, this can be seen in chapter 4.4 and concludes objective nr 2. The third objective is to be able to use the model for a variety of machinery and facilities. Given the nature of the model the only requirement for the model is historical data to base the model on. There are no machine or facility type restrictions thereby meeting the third objective. The final objective was to be able to make amendments to the preventative model to compare possible scheduled maintenance changes to the historical data. For this final objective further studies are required to ensure the accuracy when the model is used in such a way.

The low-cost condition monitoring used in this study had its challenge due to the electrical harmonics. However, once the error was identified the experimental proved to be of values and showed that cost effective condition monitoring can be done but requires more attention. By comparing the historical data and the condition monitoring data one can also conclude that live condition monitoring results in better oversight and condition monitoring results.

Despite the error during the condition monitoring, the model shows that it can effectively indicate whether an improvement to a machine's maintenance strategy could be made. It is also clear that the accuracy of the condition data plays an enormous role in the model's validity. However, it needs to be stressed that if there is no condition monitoring data available, the historic data or researched data can be used for the model. With the results shown in the case study, the conclusion is that predictive maintenance would be a sensible maintenance strategy for the lobe blower. When interpreting the simulation results, the accuracy of the used condition monitoring techniques should be taken into consideration. If the model would suggest a 40% increase in maintenance efficiency the answer is clear however, if only a 2 or 3% improvement is suggested, the choice would still be difficult. With the case study made, the option is rather clear since the possible improvements are significant compared to the historical data.

Although, this study included a component of condition monitoring (by means of vibration analysis) the main reason for the inclusion of this was not to achieve live condition monitoring or to analyse the details thereof. The industry currently makes use of periodic vibration measurements as can be seen in tables 16, 17 and 18 (with an associated time delay in terms of processing and feedback). This time delay is sufficiently long that the utility of these measurements is markedly reduced. Inclusion of a low-cost alternative to these vibration studies was a precursor to indicate that expert-based analysis is not necessarily better than low-cost alternatives, this being done by means of the experimental setup referenced to in table 1. The condition monitoring was not the main scope of this case study and therefore did not dive into the details of accuracy and the detectable defects and breakdown through the vibration analysis implemented. Although sufficient details are given in the literature on the topic. Additionally, the low-cost solution could be deployed at a fraction of the cost of commercial condition monitoring solutions (neither of which had a proven track record in this given use case). It could thus be argued that the proposed methodology in this work could be deployed without incurring any capital outlay in terms of a predictive maintenance system by only making use of historic performance data. The effect of any additional real-time data into the model could only improve the performance of predictive maintenance process (dependent on the accuracy of the condition monitoring of course). This, however, would not limit the utility of the proposed methodology in determining the possible advantages that predictive maintenance could provide for a certain use case.

The CMMS data compared with the predictive maintenance simulation shows a significant difference could be made with the implementation of predictive maintenance. The model suggests a reduction of maintenance hours of approximately 52% and a reduction in costs of approximately 47%. Over 2.5 years, 23 hours of labour (in the case study) might not seem much; however, considering that the facility has 22 of these blowers on site, it mounts up to an estimated 506 hours of labour, or 17 hours of total downtime a month. Furthermore, these machines are not always available, and maintenance is done mostly over weekends. With the implementation of predictive maintenance, the simulation suggests that a service interval would be reduced by up to 52%.

Considering the literature, specifically the bathtub curve used as a generical measure of machine reliability and useful lifetime, all machines in this study are still reliable and have a long lifetime. The literature also suggests that there are specific distributions that are more effective when studying reliability. These are

- Weibull
- Lognormal
- Gamma

In this study, this was not the case. The probability density functions used to determine the attributes of the maintenance systems in this study did not follow a specific trend and tended to be somewhat random. It needs to be remembered that this study was not conducted over the lifetime of the machines. The study assessed the machines' condition over a smaller period, only considering the state the machine was in during the 2.5 years of the assessment. This would be the reason for the seeming random distributions used in the simulations. Even the condition monitoring distribution did not follow the expected reliability

distribution but rather a log-logistic distribution. One of the challenges seen is that there is a possibility that there is not sufficient data to create an accurate PDF. If one has multiple machines of similar type, one could run an overall model interpretation including all maintenance data for all the machines. This would create a simulation involving all the machines, in essence an average for the type of machine for the specific facility. This could be included to future work on the model. However, this would contradict the objectives set which states that the model should be based on a specific machine, by using an average of the same type of machine in the plant it removes the behaviour of the individual machine under investigation. Additional research can be done on this aspect in order to investigate the validity of using the historical data of one or more of the same type of machine.

In the validation and verification chapter, the condition monitoring of an external contractor is also used to validate the model results. The model results suggest that live condition monitoring would be beneficial. The current maintenance strategy on the blower is preventative, with condition monitoring done approximately every three months. The reports in Tables 16 and 17 show that blowers 1 and 8 are generally in excellent condition, supporting the data read from the model, further validating that one could rely more on a predictive maintenance strategy for a lobe blower to reduce the schedule maintenance intervals. However, the risks of the long intervals between condition monitoring (as done by the external contractor) needs to be considered. The best practice would be to introduce live condition monitoring, as the predictive maintenance model suggests. This can be an expensive practice but could be justified using this study's model. The experimental setup has proven that inexpensive methodologies can also be used.

After successful use of the model and a predictive maintenance strategy is deployed, a long-term study can be done to compare the simulated results with the actual condition-based maintenance. The study could include the trends of the condition monitoring. The types of breakdowns could be compared with the condition monitoring type for more accurate interpretation when re-doing the model for other or similar machinery. This could possibly show whether the simulation predicted a maintenance free run time correctly with the trend of the condition monitoring showing the possible gradual decrease in machine condition and eventually triggering a scheduled stop which would have been a repair job.

The model created can be based on a variety of machinery with a variety of condition-monitoring techniques that quantifies the machine's condition. In the industry, very few facilities would not have historical data on their machinery, making this model easy to use. A cost-effective condition monitoring method, available data from literature or historical data can be used to complete the predictive maintenance model to simulate the possible effects. It must be clear that certain preventative aspects of maintenance can only partially be replaced. These include checking oil and other lubrication, machine settings such as v-belt tension, housekeeping etc. are standard practices that always require resources. However, with a predictive maintenance strategy, it would be easy to pick up if the machine condition decreases due to a lack of attention to the abovementioned aspects, thereby preventing catastrophic failure.

The model can also be developed further for real-time plant implementation. One of the upgrades could be to auto populate the PDF parameters that are derived from the PDF fit tool. The predictive maintenance model is set up to receive condition monitoring data and process it to evaluate necessary maintenance action. With further development, the model could assess the real-time data and alert maintenance personnel when intervention is required. Larger scale use of the model has the potential for more machinery or even an entire facility. This would require the model to be replicated for each machine in place. This has the potential to model a whole facility's maintenance system allowing management to simulate specific effects that selected changes, such as service intervals, could have on an overall maintenance strategy. In doing so, effective resource management could also be investigated, ensuring that personnel and other resources can be allocated efficiently.

Besides the potential for further development, the model could be used readily in the industry. The tools Matlab provides in the model allow the user to implement it quickly. The user does not need intricate knowledge of statistics since the statistical representations can be used and compared graphically. Many condition monitoring methods can provide a quantified value without an in-depth understanding of the condition monitoring and analysis thereof. The only knowledge required and should be relatively available within a facility is the maintenance strategy in place and the historical data. If a CMMS is in place, it should be no problem; even if not, the user can collect data over time to compare the condition monitoring and the current system in place. The model can be used to simulate shorter or longer periods which can also assist in the necessary feasibility study to justify a change in strategy. The information in the model can be used to calculate the payback to implement condition monitoring.

The unique flexibility allows the further development of the model and its ease to use, separating the study from the maintenance evaluation methods in the literature. The literature depicts mathematical methods that are not easily implemented in the industry. Keeping in mind that this study's focus was to show what the effects of predictive maintenance could have, and the efficacy compared to the existing maintenance, users need to understand what is done and have a visual representation of these effects.

Interpreting the simulation data further can show that there is a true financial benefit to adding condition monitoring. Potentially saving 23 hours of unscheduled downtime at a cost of N\$80 000 per hour, the conclusion can be made that not only could condition monitoring increase the efficiency of a maintenance team but also have a positive financial incentive for a facility. Through this conclusion the model has achieved the outcome of being able to assist in the decision making of maintenance management.

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Annexures

Blower 4 (case study) CMMS data



VM502-08 - Maintenance Hours and Costs per Equipment

Parameter	From	To
Date:	01/04/2019	14/10/2021
Sites:	WK-MAIZ	WK-MAIZ
Model:	BLOW	BLOW
Equipment:	M2BLOW5	M2BLOW4
Detail:	Yes	
Show costs larger	0.00	
Type of Jobs Shown	All	

Job Number	Date Entered	Problem Description	Type of Job	Work Done by	Number of Jobs	Hours worked	Ave per Job	Projected Labour cost (Rands)	Sub Contract	Job Charge	Spares Cost	Non-stock parts cost	Total Cost
Windhoek													
S00028601	17/04/2019		Mechanical Overtime	Assistant		0.50			0.00	0.00	0.00	0.00	
S00029001	08/05/2019		Aechanical Double Overtime	Josef David		0.50			0.00	0.00	0.00	0.00	
R00023310	03/06/2019		Aechanical Double Overtime	Assistant		0.75			0.00	0.00	0.00	0.00	
S00029601	18/07/2019		Aechanical Double Overtime	Assistant		2.00			0.00	0.00	242.41	0.00	
S00030078	31/07/2019		Aechanical Double Overtime	Rudolf Kamenje		1.00			0.00	0.00	0.00	0.00	
S00030391	27/08/2019		Mechanical Overtime	Rudolf Kamenje		1.50			0.00	0.00	0.00	0.00	
S00030891	01/10/2019		Mechanical Overtime	Assistant		1.00			0.00	0.00	0.00	0.00	
S00031028	01/10/2019		Mechanical Overtime	Assistant		1.50			0.00	0.00	0.00	0.00	
R00025000	02/10/2019	Check pressure & flow restriction as per NVC report: M:	Mechanical	Eben Hudvali		3.00			0.00	30.00	854.00	0.00	
S00031475	06/11/2019		Mechanical Overtime	Carl Cupido		1.25			0.00	0.00	0.00	0.00	
S00031936	04/12/2019		Mechanical	Eben Hudvali		3.00			0.00	0.00	0.00	0.00	
S00032475	20/01/2020		Mechanical Overtime	Assistant		1.50			0.00	0.00	1,945.89	0.00	
S00032981	10/02/2020		Aechanical Double Overtime	Assistant		1.00			0.00	0.00	0.00	0.00	
S00033446	03/03/2020		Mechanical	Assistant		1.00			0.00	0.00	0.00	0.00	
S00033945	08/04/2020		Aechanical Double Overtime	Assistant		0.50			0.00	0.00	0.00	0.00	
S00034454	15/05/2020		Aechanical Double Overtime	Rudolf Kamenje		1.00			0.00	0.00	0.00	0.00	
S00034937	10/06/2020		Aechanical Double Overtime	Assistant		0.25			0.00	0.00	0.00	0.00	
S00035435	06/07/2020		Mechanical	Assistant		0.50			0.00	0.00	0.00	0.00	
R00027815	08/09/2020	check pressure switch: M2BLOW4	Electrical	Attie Brendell		1.00			0.00	30.00	0.00	0.00	
S00035887	06/09/2020		Mechanical Overtime	Assistant		1.00			0.00	0.00	299.85	0.00	
S00036385	02/09/2020		Mechanical Overtime	Assistant		1.00			0.00	0.00	0.00	0.00	
S00036870	07/10/2020		Mechanical Overtime	Assistant		2.50			0.00	0.00	0.00	0.00	
S00037043	22/09/2020		Mechanical Overtime	Assistant		1.50			0.00	0.00	0.00	0.00	
S00037418	02/11/2020		Aechanical Double Overtime	Assistant		2.00			0.00	0.00	0.00	0.00	
R00029259	02/11/2020	Repair safty valve on M2BLOW4	Mechanical Overtime	Josef David		1.00			0.00	30.00	0.00	0.00	
S00037935	16/12/2020		Aechanical Double Overtime	Assistant		1.00			0.00	0.00	0.00	0.00	
S00038461	12/01/2021		Aechanical Double Overtime	Assistant		2.00			0.00	0.00	853.05	0.00	
S00039044	08/02/2021		Aechanical Double Overtime	Assistant		1.50			0.00	0.00	0.00	0.00	
S00039544	10/03/2021		Aechanical Double Overtime	Assistant		1.50			0.00	0.00	299.85	0.00	
S00040089	29/03/2021		Aechanical Double Overtime	Assistant		0.75			0.00	0.00	0.00	0.00	
S00040504	28/04/2021		Aechanical Double Overtime	Assistant		0.50			0.00	0.00	0.00	0.00	
S00041017	27/07/2021		Aechanical Double Overtime	Assistant		0.50			0.00	0.00	190.81	0.00	
S00041590	23/07/2021		Aechanical Double Overtime	Assistant		1.00			0.00	0.00	1,396.94	0.00	
S00042425	02/09/2021	August 2021	Aechanical Double Overtime	Rudolf Kamenje		0.50			0.00	0.00	0.00	0.00	

Page 1 of 2

Job Number	Date Entered	Problem Description	Type of Job	Work Done by	Number of Jobs	Hours worked	Ave per Job	Projected Labour cost (Rands)	Sub Contract	Job Charge	Spares Cost	Non-stock parts cost	Total Cost
S00042832	06/10/2021	Maintenance Worksheet WSH006798 for 2021/9	Aechanical Double Overtime	Rudolf Kamenje		3.00			0.00	0.00	0.00	0.00	
M2BLOW4		Blowers			35	44.00	1.26	0.00	0.00	90.00	6,082.80	0.00	6,172.80
WINDHOEK-MAIZE					35								
					35	44.00		0.00	0.00	90.00	6,082.80		6,172.80

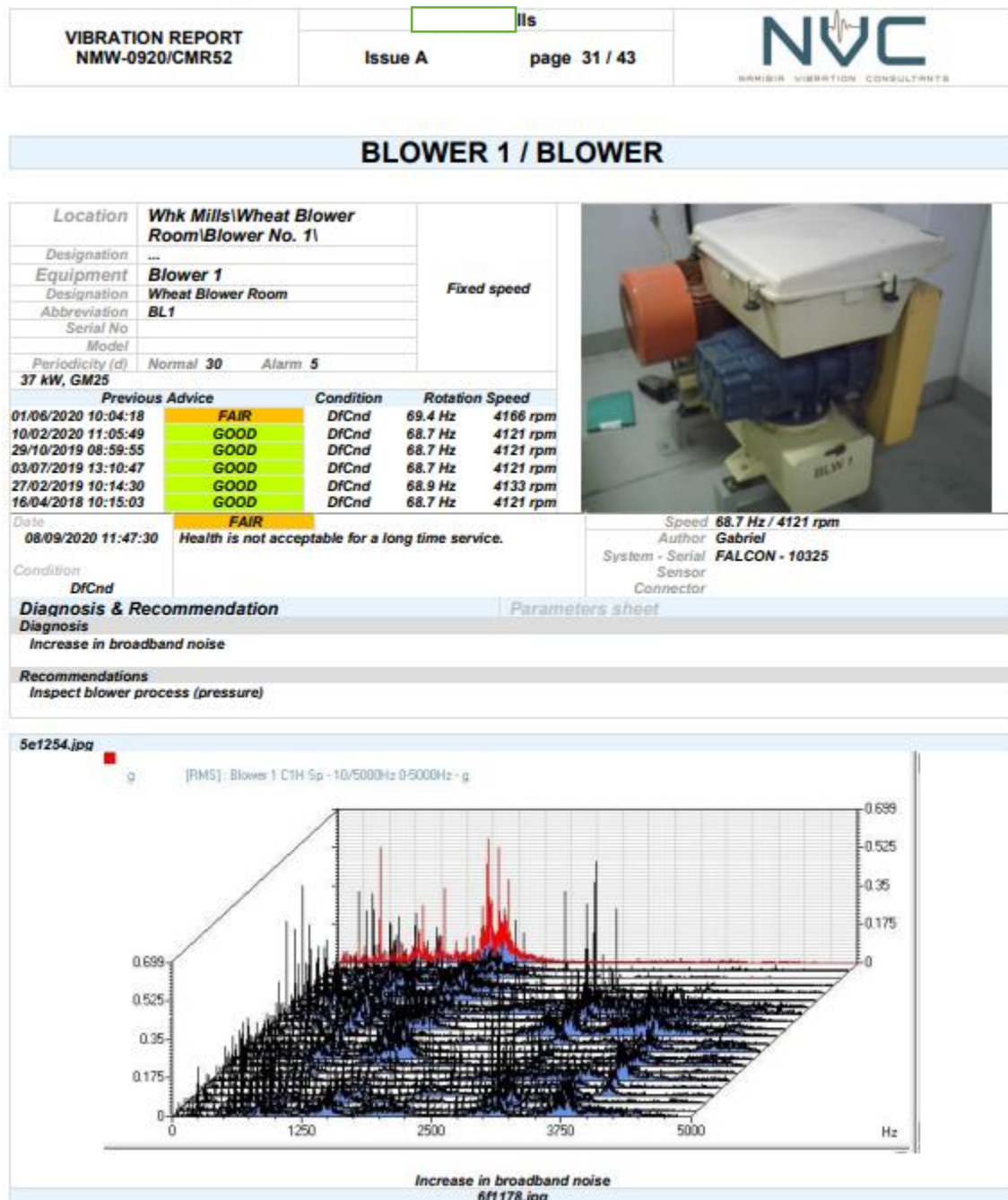
CMMS data Blower 1

Job Number	Date Entered	Work Done by	Hours	Spares
R00023350	05/06/2019	Rudolf Kamenje Windhoek - Fitter SS	0.25	390.42
R00024053	12/07/2019	Josef David Windhoek - Mechanical	2.00	277.68
R00024356	05/08/2019	Rudolf Kamenje Windhoek - Fitter SS	1.00	0.00
R00025142	11/11/2019	Attie Brendell Pasta - Electrician	3.50	2,530.84
R00025143	11/11/2019	Attie Brendell Pasta - Electrician	2.50	0.00
R00026434	09/04/2020	Amon Mbinga Pasta - Electrician	2.00	0.00
R00027418	27/05/2020	Steve Bester Windhoek - Mechanical	2.00	990.00
R00027706	08/06/2020	Rudolf Kamenje Windhoek - Fitter SS	9.00	0.00
R00029162	23/10/2020	Olavi Amupolo Windhoek - Mechanical	6.00	1,604.36
S00028642	17/04/2019	Assistant	0.50	0.00
S00029039	08/05/2019	Assistant	1.00	0.00
S00029643	18/07/2019	Assistant	0.50	0.00
S00030121	31/07/2019	Rudolf Kamenje Windhoek - Fitter SS	0.50	0.00
S00030431	27/08/2019	Rudolf Kamenje Windhoek - Fitter SS	2.00	0.00
S00030931	01/10/2019	Assistant	1.50	0.00
S00031515	06/11/2019	Assistant	1.25	0.00
S00031779	25/10/2019	Assistant	2.00	402.89
S00031977	04/12/2019	Josef David Windhoek - Mechanical	1.00	0.00
S00032514	20/01/2020	Assistant	1.50	297.78
S00033020	11/02/2020	Assistant	1.00	0.00
S00033489	03/03/2020	Assistant	1.00	0.00
S00033988	09/04/2020	Assistant	1.50	362.65
S00034497	15/05/2020	Rudolf Kamenje Windhoek - Fitter SS	1.00	816.24
S00034981	10/06/2020	Josef David Windhoek - Mechanical	3.00	277.08
S00035476	06/07/2020	Assistant	1.00	0.00
S00035928	07/08/2020	Assistant	0.50	30.14
S00036425	02/09/2020	Assistant	2.00	409.83
S00036929	12/10/2020	Assistant	2.00	0.00
S00037460	02/11/2020	Assistant	3.00	0.00
S00037746	20/10/2020	Assistant	1.50	1,041.66
S00037977	08/12/2020	Assistant	1.00	0.00
S00038503	07/01/2021	Assistant	1.00	0.00
S00039249	09/02/2021	Assistant	2.00	67.42
S00039759	11/03/2021	Assistant	1.50	0.00
S00040256	31/03/2021	Assistant	0.50	269.67
S00040729	27/04/2021	Assistant	1.00	232.28
S00041233	04/06/2021	Rudolf Kamenje Windhoek - Fitter SS	1.00	0.00
S00041755	23/07/2021	Assistant	2.00	0.00
S00042485	02/09/2021	Rudolf Kamenje Windhoek - Fitter SS	0.50	232.28

CMMS data Blower 8

Job Number	Date Entered		Hours worked	Spares Cost
R00023347	05/06/2019	Assistant	0.75	0.00
R00030022	20/01/2021	Steve Bester Mechanical Windhoek -	4.50	4,514.57
S00028638	17/04/2019	Assistant	0.50	0.00
S00029036	08/05/2019	Assistant	1.00	0.00
S00029640	18/07/2019	Assistant	0.50	0.00
S00030116	31/07/2019	Rudolf Kamenje Windhoek - Fitter SS	0.50	0.00
S00030428	27/08/2019	Rudolf Kamenje Windhoek - Fitter SS	1.00	0.00
S00030928	01/10/2019	Assistant	1.00	0.00
S00031512	06/11/2019	Assistant	0.25	0.00
S00031691	06/11/2019	Assistant	1.50	0.00
S00031974	04/12/2019	Josef David Mechanical Windhoek -	0.50	0.00
S00032511	13/01/2020	Assistant	0.50	0.00
S00033017	10/02/2020	Assistant	0.50	0.00
S00033484	03/03/2020	Assistant	1.00	0.00
S00033983	09/04/2020	Assistant	0.75	0.00
S00034492	15/05/2020	Rudolf Kamenje Windhoek - Fitter SS	0.50	0.00
S00034976	10/06/2020	Assistant	0.25	0.00
S00035472	06/07/2020	Assistant	0.50	0.00
S00035924	07/08/2020	Assistant	0.50	0.00
S00036420	02/09/2020	Assistant	1.00	0.00
S00036925	12/10/2020	Assistant	1.00	0.00
S00037455	03/11/2020	Assistant	2.00	416.67
S00037644	12/10/2020	Assistant	1.00	0.00
S00037972	08/12/2020	Assistant	0.50	0.00
S00038498	08/01/2021	Assistant	1.00	0.00
S00039153	09/02/2021	Assistant	1.00	0.00
S00039739	10/03/2021	Steve Bester Mechanical Windhoek -	0.50	0.00
S00040236	31/03/2021	Assistant	0.25	1,485.90
S00040619	27/04/2021	Assistant	1.00	0.00
S00041213	04/06/2021	Rudolf Kamenje Windhoek - Fitter SS	1.00	0.00
S00041735	23/07/2021	Rudolf Kamenje Windhoek - Fitter SS	1.00	10.94
S00042530	02/09/2021	Olavi Amupolo Mechanical Windhoek -	0.50	0.00
S00042982	11/10/2021	Rudolf Kamenje Windhoek - Fitter SS	1.50	0.00

Blower 1 detailed Vibration report (by external contractor)



Note that the detail report is only available for machinery that show defects.

Matlab script to import CMMS data

```
FFT.m x run_sim.m x Maintenance_model.m x run_samples.m x imprt_data.m x gui_mainfcn.m x +
1 -   clc
2 -   % Import tables and create arrays
3 -   M2BLW4_SJobs = readtable('D:\Blower 4\M2BLW4_Sjobs.xlsx');
4 -   M2BLW4_RJobs = readtable('D:\Blower 4\M2BLW4_Rjobs.xlsx');
5 -   M2BLW4_VIB = readtable('D:\Blower 4\M2BLW4_VIB.xlsx');
6 -   M2BLW4_SHours = table2array(M2BLW4_SJobs(1:31,6));
7 -   M2BLW4_SCost = table2array(M2BLW4_SJobs(1:31,7));
8 -   M2BLW4_RHours = table2array(M2BLW4_RJobs(1:4,7));
9 -   M2BLW4_RCost = table2array(M2BLW4_RJobs(1:4,8));
10 -   M2BLW4_ALLCost = cat(1,M2BLW4_SCost,M2BLW4_RCost);
11 -   M2BLW4_ALLHours = cat(1,M2BLW4_SHours,M2BLW4_RHours);
12 -   M2BLW4_VIB_BLW = table2array(M2BLW4_VIB(1:27,1));
13 -   M2BLW4_VIB_MTR = table2array(M2BLW4_VIB(1:32,2));
14 -   M2BLW4_VIB_all = table2array(M2BLW4_VIB(1:57,3));
15 -   M2BLW4_VIB_good = table2array(M2BLW4_VIB(1:21,4));
16
17   %Average per type and attribute
18
19 -   Sjob_hour_mean = mean(M2BLW4_SHours);
20 -   Sjob_cost_mean = mean(M2BLW4_SCost);
21 -   Rjob_hour_mean = mean(M2BLW4_RHours);
22 -   Rjob_cost_mean = mean(M2BLW4_RCost);
23
24   % Total Maintenance Hours and cost
25 -   job_hour_sum = sum(M2BLW4_ALLHours);
26 -   job_cost_sum = sum(M2BLW4_ALLCost);
27
```

Note that the purple script is the path to the excel File.

Script To Import Vibration data

```
Editor - D:\MATLAB\bin\run_samples.m
1 | FFT.m x run_sim.m x Maintenance_model.m x run_samples.m x imprt_data.m x gui_mainfcn.m x FFT_function.m x +
2 | % nov 2019
3 | % BLW4_211119bd160 = readtable('E:\Blower 4\processed\21_11_19_bd160');
4 | % BLW4_211119bnd160 = readtable('E:\Blower 4\processed\21_11_19_bnd160');
5 | % BLW4_211119mnd160 = readtable('E:\Blower 4\processed\21_11_19_mnd160');
6 | % BLW4_211119md160 = readtable('E:\Blower 4\processed\21_11_19_md160');
7 | % BLW4vs13_22_11_19_80kHz = readtable('E:\Blower 4\processed\22_11_19_13VS4_80kHz');
8 | % feb2020
9 | % BLW4_110220M_drVSndr = readtable('E:\Blower 4\processed\11_02_20_Mdrv_Mndr_10kHz');
10 | % April2020
11 | % motor_22042020 = readtable('E:\Blower 4\processed\22_04_20_motor');
12 | % July 20
13 | % BLW4_09_07_20_BLWHoriVert10kHz = readtable('E:\Blower 4\processed\09_07_20_BLWHoriVert10kHz');
14 | % mot_19_07_20_motordrive = readtable('E:\Blower 4\processed\19072009H33_motor');
15 | % blower_070920dr_ndr = readtable('E:\Blower 4\processed\07_09_20_blower_dr_ndr');
16 | % motor_070920dr_ndr = readtable('E:\Blower 4\processed\07_09_20_motor_dr_ndr');
17 | % May2021
18 | % BLW4_0505211021 = readtable('D:\Blower 4\processed\05_05_21_10H21');
19 | % BLW4_0505211400 = readtable('E:\Blower 4\processed\05_05_21_14H00');
20 | % BLW4_0605210812 = readtable('E:\Blower 4\processed\06_05_21_08H12');
21 | % BLW4_0605211236 = readtable('E:\Blower 4\processed\06_05_21_12H36');
22 | % BLW4_0705211139 = readtable('E:\Blower 4\processed\07_05_21_11H39');
23 | % BLW4_1805210719 = readtable('E:\Blower 4\processed\18_05_21_07H19');
24 | % BLW4_1805211745 = readtable('E:\Blower 4\processed\18_05_21_17H45');
25 | % BLW4_2005210813 = readtable('E:\Blower 4\processed\20_05_21_08H13');
26 | % BLW4_2005210907 = readtable('E:\Blower 4\processed\20_05_21_09H07');
27 | % BLW4_2005211209 = readtable('E:\Blower 4\processed\20_05_21_12H09');
28 | % June 2021
29 | % BLW4_0506210948 = readtable('E:\Blower 4\processed\05_06_21_09H48');
30 | % BLW4_0506211137 = readtable('E:\Blower 4\processed\05_06_21_11H37');
31 | % BLW4_1706210852 = readtable('E:\Blower 4\processed\17_06_21_08H52');
32 | % BLW4_2106211524 = readtable('E:\Blower 4\processed\21_06_21_15H24');
33 | % BLW4_2106211636 = readtable('E:\Blower 4\processed\21_06_21_16H36');
34 | % August 2021
35 | % BLW4_1608211232 = readtable('E:\Blower 4\processed\16_08_21_12H32');
36 | % BLW4_1708210916 = readtable('E:\Blower 4\processed\17_08_21_09H16');
```

Signals were converted to CSV file from the logger.

Remove “%” to uncomment script for use.

Perform FFT

```

FFT.m x run_sim.m x Maintenance_model.m x run_samples.m x imprt_data.m x gui_mainfcn.m x
7 % set new signals, insert array of signals
8 - signals = {BLW4_2005210907 'BLW4 20 05 21 09H07';...
9   BLW4_2005211209 'BLW4 20 05 21 12H09'};
10 %sampling time
11 - FS = {10000;10000;10000;10000;10000}; % set sampling time for each signal
12 - T_s = 100000; % determine starting data point for FFT
13 - T_sn =200001; % determine length of signal for FFT (number of data points)
14 - t = T_sn - T_s+1; % calc sample time
15 %calc nfft
16 - P = 2^nextpow2(t);
17 - nfft = P;
18 - nfft_2 = (nfft/2 +1) ;
19 %set array sizes
20 - y = length(signals);
21 - ST= zeros(y,1);
22 - T = zeros(y,t);
23 - x_m = zeros(y,t);
24 - x_b = zeros(y,t);
25 - X_m = zeros(y,nfft);
26 - X_b = zeros(y,nfft);
27 - mx_m = zeros(y,nfft);
28 - mx_b = zeros(y,nfft);
29 - f =zeros(y,nfft);
30 - rms_m = zeros(y,1);
31 - rms_b = zeros(y,1);
32
33 - for i = 1:y;
34   %signal time
35   ST(i,:) = (T_sn + 1 - T_s)/FS{i,1};
36   % time and G tables
37   T(i,:) = signals{i,1}.sec(T_s:T_sn);
38   x_m(i,:) = signals{i,1}.G_M(T_s:T_sn);
39   x_b(i,:) = signals{i,1}.G_B(T_s:T_sn);
40   rms_m(i,:) = rms(x_m(i,:)); % calc RMS value for motor
41   rms_b(i,:) = rms(x_b(i,:)); % calc RMS value for Blower
42   % perform FFT / divide by Fs to normalize
43   X_m(i,:) = fft(x_m(i,:),nfft)/FS{i,1};
44   X_b(i,:) = fft(x_b(i,:),nfft)/FS{i,1};
45   %absolute values of spectrum
46   mx_m(i,:) = abs(X_m(i,:));
47   mx_b(i,:) = abs(X_b(i,:));
48   %define frequency domain according t sample frequency
49   f(i,:) = (0:nfft-1)*FS{i,:}/nfft;
50 - end
51
52

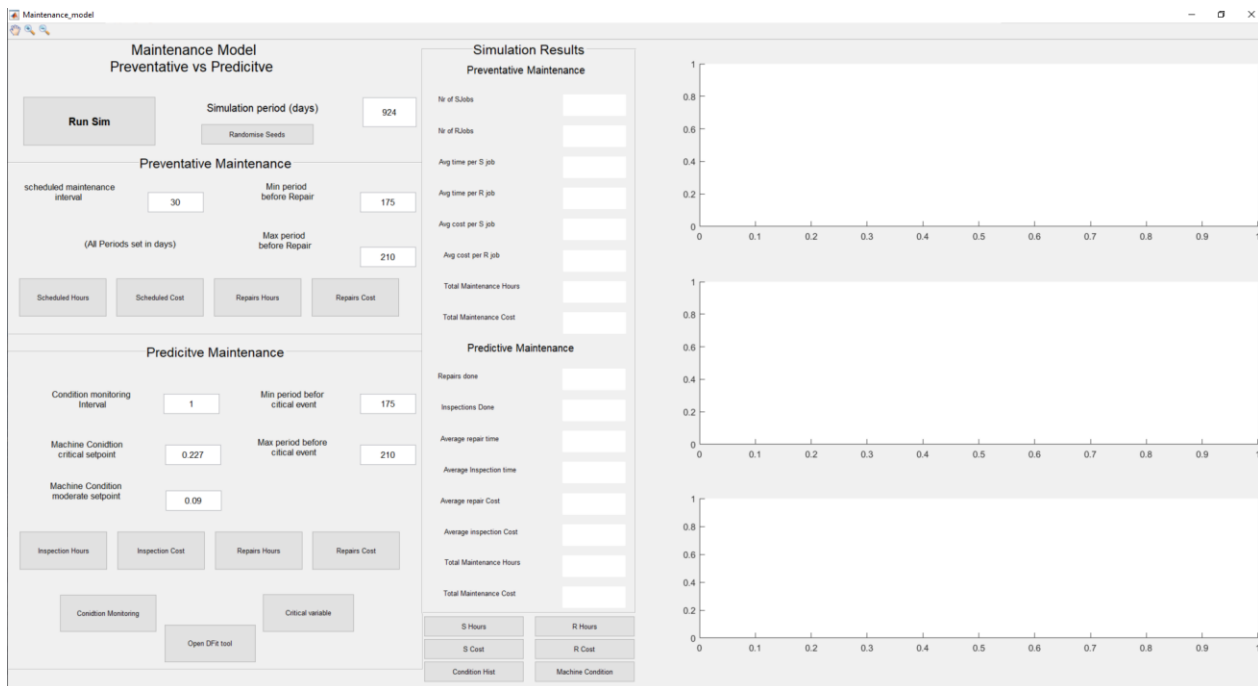
```

Create Plots for FFT

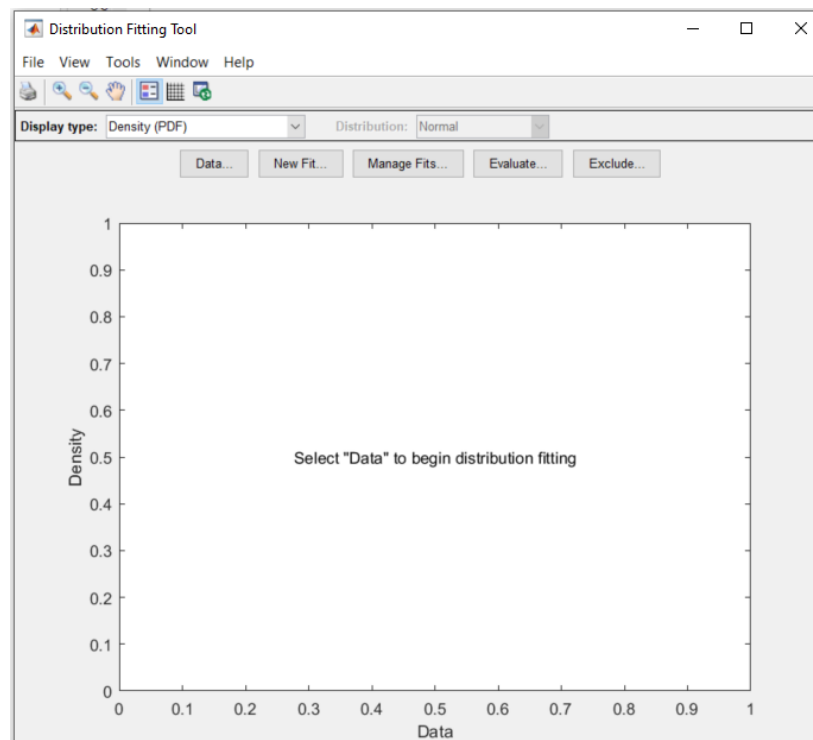
```
52     %plot motor signals
53 -   for n =1:i
54 -       figure('name',signals{n,2});
55 -
56 -       subplot(2,1,1);
57 -
58 -       plot(T(n,:),x_m(n,:));
59 -       title({'Motor';'rms';rms_m(n,:)});
60 -       xlabel('Time(s)');
61 -       legend(signals{n,2});
62 -       ylabel('amplitude');
63 -
64 -       subplot(2,1,2);
65 -       plot(f(n,:),mx_m(n,:));
66 -       title('motor FFT');
67 -       xlabel('Hz');
68 -       xlim([0, 2500]);
69 -       ylabel('G');
70 -       ylim([-0.1 3.5])
71 -       set(gcf,'position',[100,50,1100,700]);
72 -
73 -   end
74 -
75     %plot blower signals
76 -   for m =1:i
77 -       figure('name',signals{m,2});
78 -
79 -       subplot(2,1,1);
80 -       plot(T(m,:),x_b(m,:));
81 -       title({'Blower';'rms';rms_b(m,:)});
82 -       xlabel('Time(s)');
83 -       legend(signals{m,2});
84 -       ylabel('amplitude');
85 -
```

```
86 - subplot(2,1,2);
87 - plot(f(m,:),mx_b(m,:));
88 - title('blower FFT');
89 - xlabel('Hz');
90 - xlim([0, 2500]);
91 - ylabel('G');
92 - ylim([-0.1 3.5])
93
94
95 - set(gcf,'position',[100,50,1100,700]);
96
97 - end
98
```

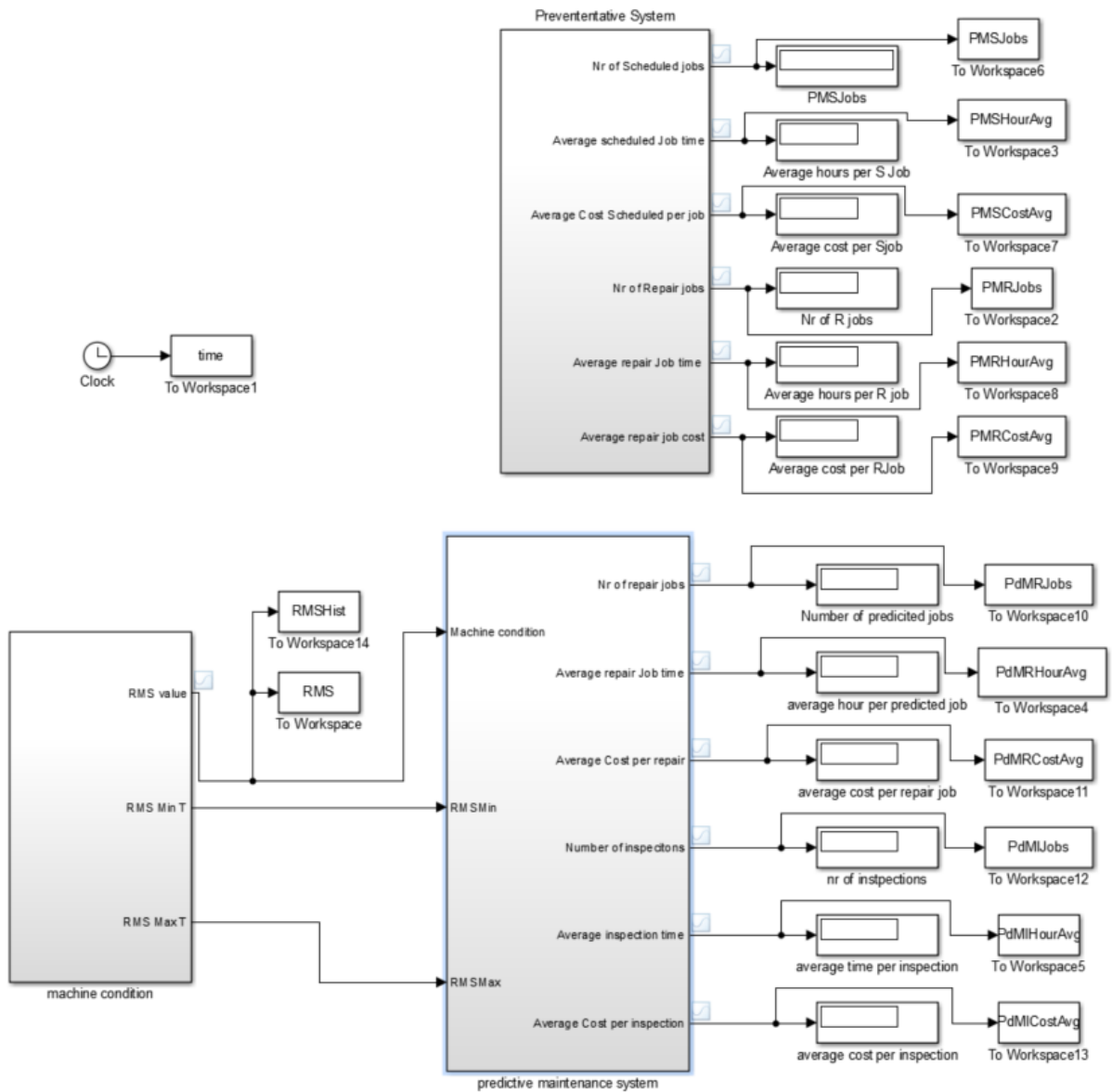
Graphic user interface (GUI)



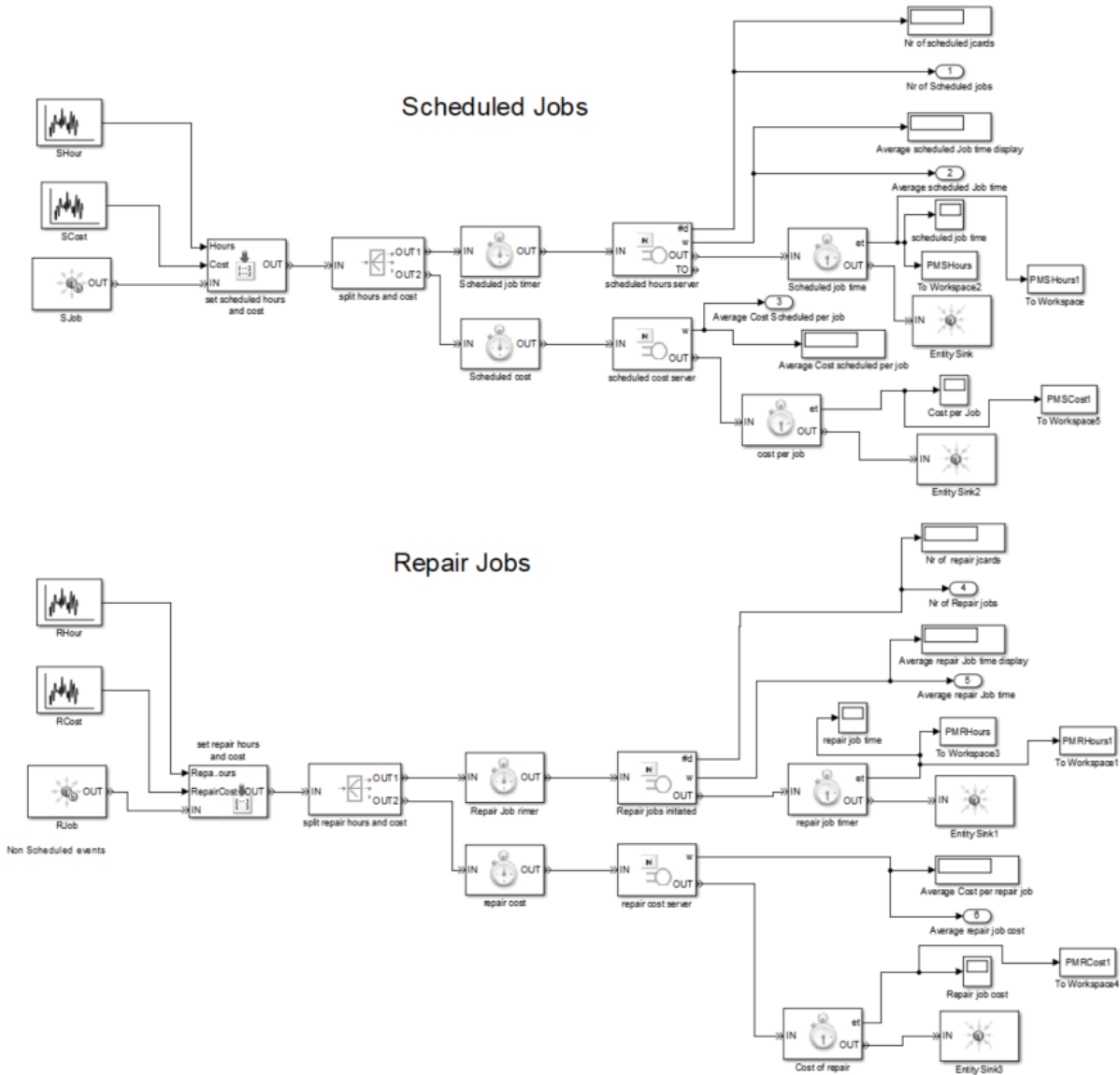
Distribution Fitting tool



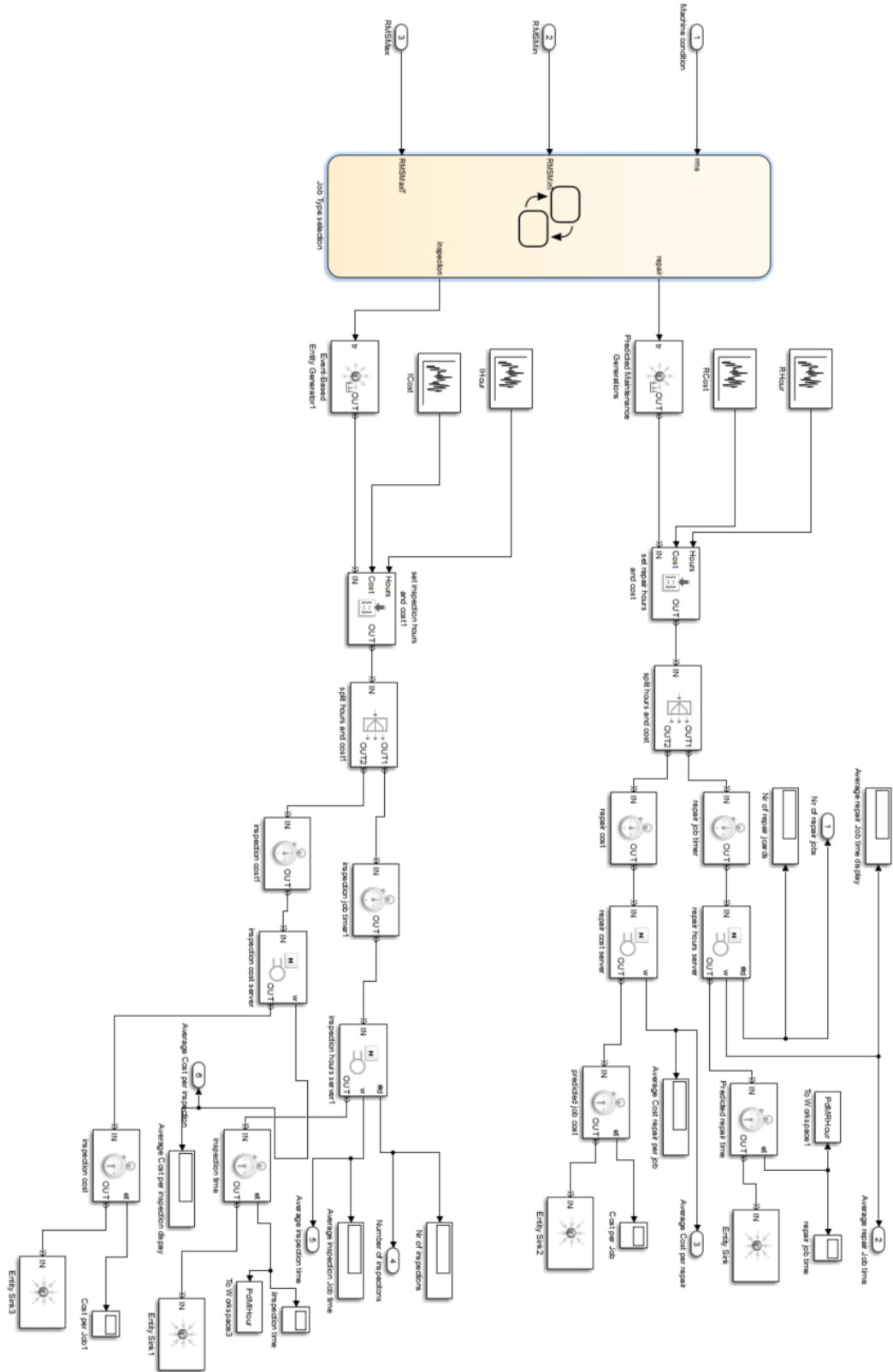
Simulink Model upper Layer, Preventative maintenance, predicitive maintenance and machine condition



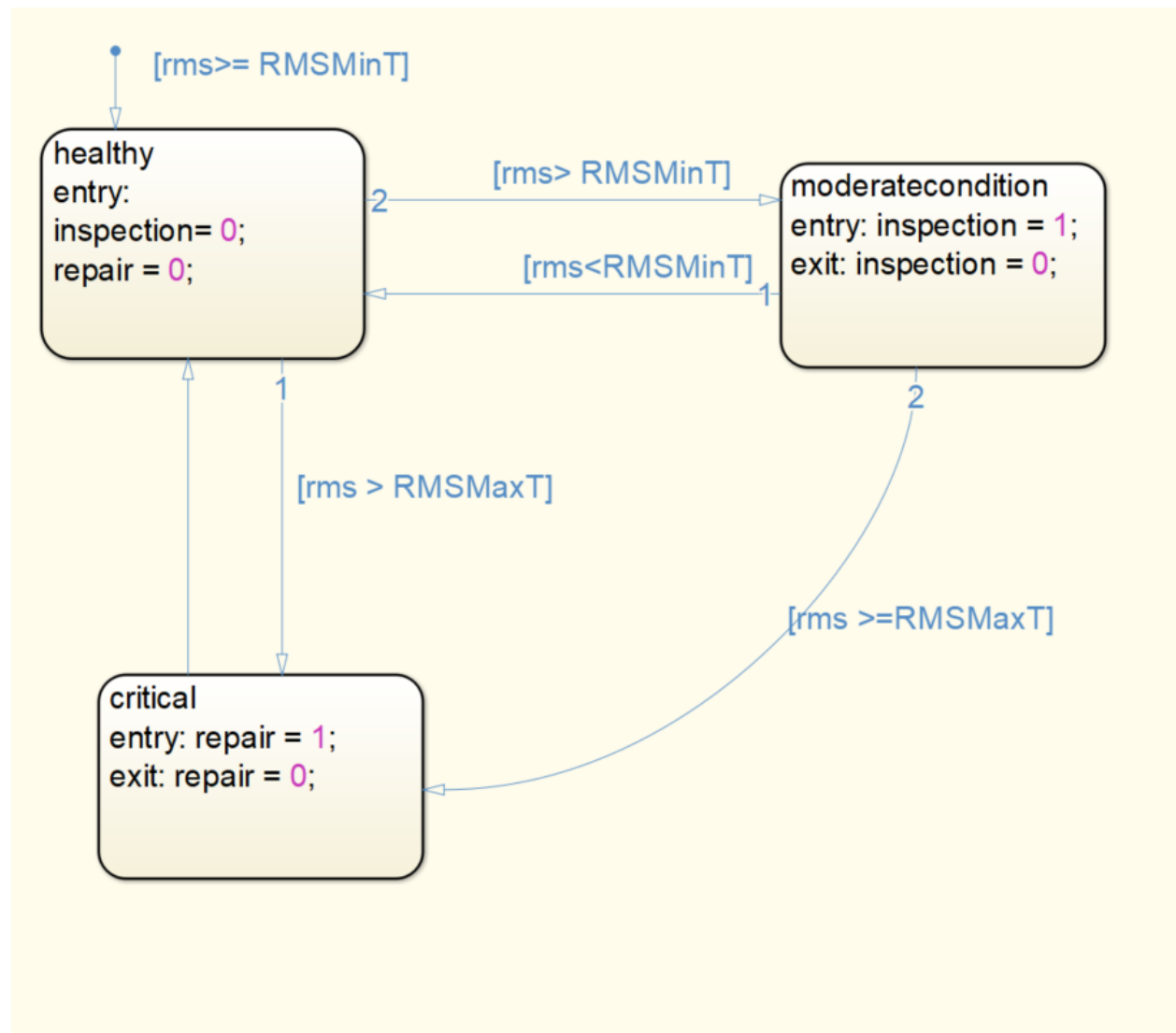
Simulink model Preventative Maintenance Model



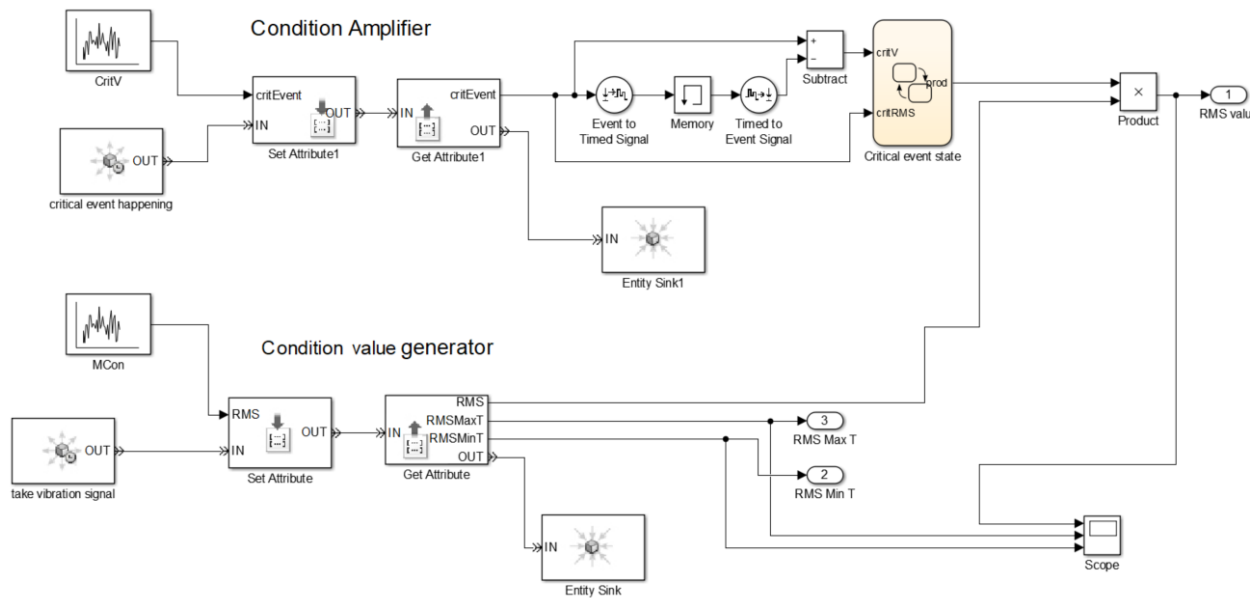
Simulink Model Predictive maintenance



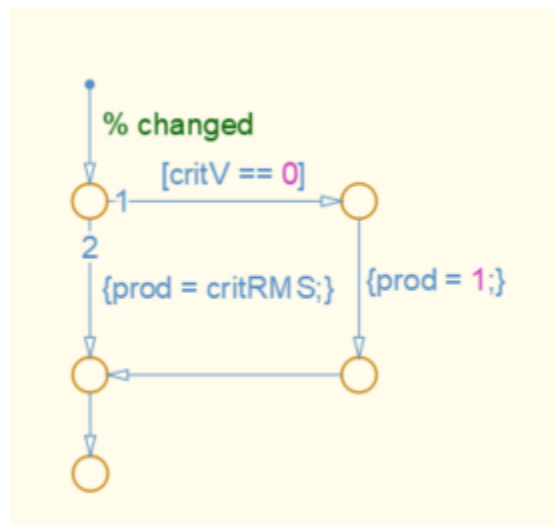
Predictive maintenance job type selection



Machine Condition



Critical Event state



Function used to link a push button from GUI to script

```
% --- Executes on button press in RUN_SIM_pbtn.
function RUN_SIM_pbtn_Callback(hObject, eventdata, handles)
% hObject    handle to RUN_SIM_pbtn (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
clc
%add path to GUI
addpath('D:\Matlab projects\GUI');
```

Assigning variable to the workspace and to the GUI. These variables are those used in the simulink model.

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%assign global variables to workspace
% Schedules
global SPeriod PMSJobs SHoursSeed
global PMSHourAvg PMSCostAvg
global PMSHours
global SimT
global PMSHours1
global PMSCost1

assignin('base','PMSCost1',PMSCost1)
assignin('base','PMSHours',PMSHours)
assignin('base','SPeriod',SPeriod)
assignin('base','PMSJobs',PMSJobs )
assignin('base','SHoursSeed',SHoursSeed)
assignin('base','PMSCostAvg',PMSCostAvg)
assignin('base','PMSHourAvg',PMSHourAvg)
assignin('base','SimT',SimT)
assignin('base','PMSHours1',PMSHours1)
```

Code to run simulation from script (by pressing button) and writing data to GUI

```
%simulate
sim('D:\Matlab projects\maintenance_model_simeEvents.slx');

axes(handles.RMS_axes);
plot(RMS)
title('Machine Condition')
xlabel('days')
ylabel('G RMS')

%set values to Guide
% preventative
PMSJobsnr = PMSJobs(end);
set(handles.PMSJobs_txt, 'string', PMSJobsnr);

PMRJobsnr = PMRJobs(end);
set(handles.PMRJobs_txt, 'string', PMRJobsnr);

PMSHourAvgnr = PMSHourAvg(end);
set(handles.PMSHourAvg_txt, 'string', PMSHourAvgnr);

PMSCostAvgnr = PMSCostAvg(end);
set(handles.PMSCostAvg_txt, 'string', PMSCostAvgnr);

PMRHourAvgnr = PMRHourAvg(end);
set(handles.PMRHourAvg_txt, 'string', PMRHourAvgnr);

PMRCostAvgnr = PMRCostAvg(end);
set(handles.PMRCostAvg_txt, 'string', PMRCostAvgnr);

PMTHours = (PMSJobsnr*PMSHourAvgnr) + (PMRJobsnr*PMRHourAvgnr);
set(handles.PMTHours_txt, 'string', PMTHours);

PMTCost = (PMSJobsnr*PMSCostAvgnr) + (PMRJobsnr*PMRCostAvgnr);
set(handles.PMTCost_txt, 'string', PMTCost);
```

Only some variable are shown as an example. This script is in the “run sim” push button function.