Chair of Drilling and Completion Engineering

Master's Thesis

Artificial Intelligence-based Approach for Predicting Mud Pump Failures

Faraz Feizi

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AFFIDAVIT

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Faraz Feizi
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Supervisor:
Univ.-Prof. Dipl.-Ing. Dr.mont Gerhard Thonhauser
Dipl.-Ing. Asad Elmgerbi

Chair of Drilling and Completion Engineering

This research is wholeheartedly dedicated to my lovely family. A special feeling of gratitude for them because of their emotional, spiritual and financial support and many other issues. Additionally, I am grateful for those mentors and professors that have supported and inspired me through this process. I wish the bests for them and will never forget their roles in my life.

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Abstract

A significant component in the drilling operation is the circulation system. Drilling rigs have a crucial dependency on mud pumps, and a failure in the mud pumps will impose the drilling operation to stop completely; consequently, the drilling cost will increase due to the associated nonproductive time. Therefore, companies try to detect failures before occurring by implementing different techniques and strategies for improving pump operation time and efficient maintenance management to reduce or eliminate non-productive time, health, and environmental safety risks.

Different tools and techniques that support the real-time monitoring of mud pumps have been proposed in the last decade; one of them is Artificial Intelligence (AI), which has shown promising results. Therefore, the ultimate goal of this thesis is to investigate the possibility of using artificial intelligence techniques to detect specific mud pump failures by utilizing only the pump pressure and flow rate as input features.

This thesis is divided into three main parts. The first part of the thesis presents and discusses the general failure detection techniques and maintenance strategies. The second part of this work presents the common drilling mud pump failures and the impact of failures on drilling operation efficiency and HSE, and what are the state-of-the-art non-intrusive sensors that can be used to detect the pump failure signatures. The last part of the thesis elaborates on the steps of developing a conceptual approach based on artificial intelligence techniques to detect failures in drilling mud pumps. In order to validate and determine the limits of the developed tool, a case study was conducted using real historical data.

Zusammenfassung

Ein wichtiger Bestandteil des Bohrvorgangs ist das Zirkulationssystem. Bohrinseln sind in hohem Maße von Schlammpumpen abhängig, ein Ausfall der Schlammpumpen würde dazu führen, dass der Bohrbetrieb vollständig eingestellt werden muss. Daraus folgend steigen die Bohrkosten aufgrund der damit verbundenen unproduktiven Zeit. Deswegen versuchen Unternehmen, Ausfälle zu erkennen, bevor sie auftreten, indem sie verschiedene Methoden und Strategien zur Verbesserung der Betriebszeit von Pumpen und ein effizientes Instandhaltungsmanagement anwenden, um Ausfallzeiten, Gesundheits- und Umweltrisiken zu verringern oder zu beseitigen.

Unterschiedliche Instrumente und Techniken für die Echtzeit-Überwachung von Schlammpumpen wurden in den letzten zehn Jahren entwickelt. Eine von ihnen ist die Künstliche Intelligenz (KI), welche vielversprechende Ergebnisse gezeigt hat. Das Hauptziel dieser Arbeit ist es daher, die Möglichkeit zu untersuchen, mit Hilfe von Technologien der künstlichen Intelligenz bestimmte Schlammpumpenausfälle zu identifizieren, indem nur der Pumpendruck und die Durchflussrate als Eingangsmerkmale verwendet werden.

Diese Arbeit ist in drei Hauptteile gegliedert. Der erste Teil der Arbeit befasst sich mit der Vorstellung und Diskussion allgemeiner Techniken zur Fehlerdetektion und Instandhaltungsstrategien. Im zweiten Teil dieser Arbeit werden die häufigsten Ausfälle von Bohrschlammpumpen und die Auswirkungen dieser Ausfälle auf die Effizienz des Bohrbetriebs und die Gesundheit und Sicherheit am Bohrplatz vorgestellt, und weiters auch welche hochmodernen nicht-intrusiven Sensoren zur Überwachung von Pumpenausfällen eingesetzt werden können. Schließlich wird im letzten Teil der Arbeit die Entwicklung eines konzeptionellen Ansatzes auf der Grundlage von Techniken der künstlichen Intelligenz zur Detektion von Fehlern in Bohrschlammpumpen erläutert. Es wurde eine Fallstudie mit realen Vergangenheitsdaten durchgeführt, um die Grenzen des entwickelten Tools zu validieren und zu bestimmen.

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Chapter 1

Introduction

1.1 Overview

In the drilling industry, mechanical failure is one of the main reasons for downtime that have had a major impact on drilling efficiency and well expenditure. The cost of each well mainly relies on the time it takes to drill and complete it successfully. On the other hand, non-planned, unexpected events continue to plague the progress and accomplishment of drilling operations. These events are considered to create a crucial loss of time and performance, generally referred to as non-productive time. One of the NPT contributors is equipment reliability[2].

The design life of each piece of equipment needs periodic maintenance, and the most traditional maintenance approaches are reactive, corrective, or time schedule. The following pie chart illustrates (Figure 1.1) that poor maintenance strategies are the main root cause of downtimes in the drilling rig (data is based on daily maintenance reports of nine wells drilled in Olkaria). The mentioned techniques are not suitable enough for minimizing NPT and HSE risks; therefore, it is vital to move from traditional maintenance methods towards those strategies that can anticipate the occurrence of failure. Predictive maintenance strategy aims at anticipating or predicting the mechanical failure time of a system or its components based on experience, physical laws, or machine learning techniques and replacing the faulty components before failure, consequently reducing downtime[3,4].

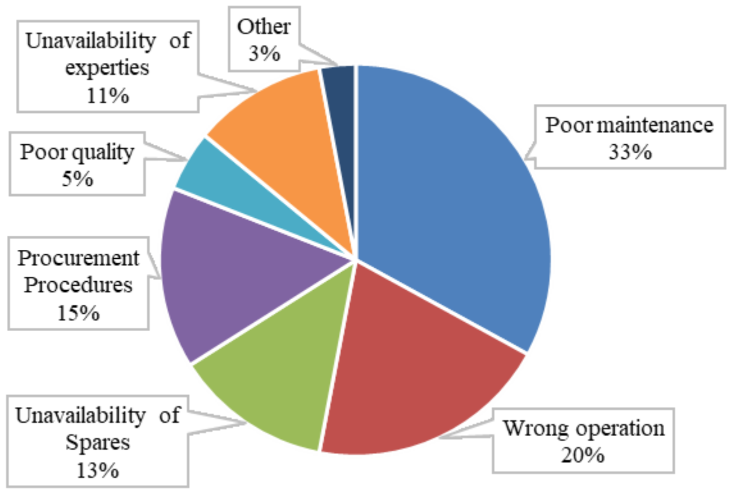


Figure 1-1. Root cause of downtime in drilling rig (P. Otieno, 2016)

A mud pump is one of the pieces of equipment known as the heart of the circulation system. This system keeps the borehole and drill bit clean provides bit lubrication and cooling and maintains sufficient hydrostatic pressure on the formation to prevent hole cave-in or blowout due to abnormal bottom hole pressures[5]. Due to these heavy-duty, the mud pump is prone to fail more frequently than the other rig equipment, especially for high-pressure, high-temperature drilling applications. Figure 1.2 compares the NPT of five rig equipment and tools. As shown in Figure 1.2, mud pump has a noticeable NPT share compared to other crucial equipment.

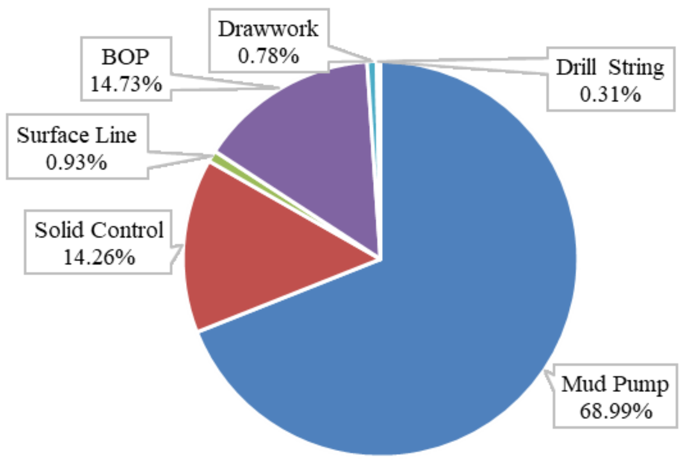


Figure 1-2. NPT% of Drilling rig equipment (A.Samuelson & W.Nirbito, 2020)

1.2 Problem Description

Non-Productive Time is the crucial reason for delays in drilling projects. There are several incidents or eventualities that cause the stoppage of drilling mud pumps as well as a marginal decrease in the development of the drilling progress. Upstream segments have been facing numerous mud pump failures and have incurred huge costs and HSE risks[6]. The most usual technical malfunctions such as seat valve failure, breaking the bearing carrier bolt, failure in the SCR which leads to increasing temperature and causes traction motor generating loads, low material quality such as the pulley, worn-out sheave grooves and damaged V-belt and so on. Different approaches and tools have supported the monitoring circulation processes as well as mud pump components. Traditional monitoring such as visual techniques and experienced crews, together with selective data acquisition have assisted crews in the monitoring process. But the gap between the time to report and the time to action leads to increase NPT. Through non-intrusive measurements and real-time monitoring companies can fill this gap with real-time data, notifications and alerts. Therefore, estimating when the mud pump or system will fail and identifying the root cause of failure create noticeable value. Artificial intelligence is one of the cutting-edge technologies that can be adapted to predict and classify the failures associated with the mud pump. Accordingly, the ultimate goal of this thesis is to develop a model based on artificial intelligence techniques that aim at detecting the symptoms of common mud pump failures by monitoring the two essential output parameters of the mud pump, mainly pressure and flow rate.

1.3 Objectives

Reducing downtime and the cost of maintenance under the premise of zero-failure manufacturing is always a crucial objective for each company. The main objective of this thesis is to develop a generic failure detection model for mud pumps. To achieve the main goal, the following stepped-objectives are defined to be the main focus of the thesis

- Review and background of existing failure detection, maintenance strategies, drilling mud pumps, pump failure, HSE, and NPT aspects of those failures
- The application of state-of-the-art technologies in predictive maintenance as well as their advantages and shortcomings
- Look at non-intrusive measurements, which can be integrated into the mud pump and can be used for anticipating failures
- Define the most applicable non-invasive measurements that can be integrated into the mud pump and can be used to detect the failures

- Creating an artificial intelligence-based model for a triplex drilling mud pump that considers the use of non-intrusive measurements and other measurements that can be read out from the pump to detect the mud pump failures in an earlier time
- Validate the developed model by using historical data

Chapter 2

Failure Detection and Maintenance Strategy

2.1 Basic Terminology

Growing demands on the safety and reliability of technical plants need early detection of process faults. At any stage in the life of a system, mechanical and electrical equipment may be poorly operated. In the drilling industry, regardless of the level of the wells construction technology, failure situations inevitably happened during drilling operations. Prompt detection of failures can noticeably reduce the nonproductive time of the well associated with the elimination of accidents consequences and costs for further materials and technical resources. Consequently, developing techniques that can support detecting failures during real-time drilling operations is essential for the petroleum industry. Techniques are developed that facilitate the earlier discovery of process faults than the customary limit and tendency monitoring based on a single process variable. These techniques include data from not just single system variables but also contain non-measurable variables as process conditions, variables, and feature quantities. Some methods require precise process models whereas others depend mostly on accessible previous process data[7].

Fault detection and fault diagnosis tasks for industrial operations are vital to prognosticate the procedure's operation time or location before a specific fault or an unusual change happens. A sustainable action like maintenance is required. Maintenance is a significant activity in the petroleum industry; with its crucial influence on costs and reliability, it is tremendously effective to a company's capability to be competitive in reasonable price, high quality, and performance. Any unexpected equipment downtime will degrade the company's core business, possibly resulting in crucial penalties and immeasurable reputation loss. Moreover, unplanned downtime can create enormous costs for offshore and onshore drilling rigs (even to 2 to 3 million dollars daily for catastrophic asset failures). Many companies still rely on obsolete techniques for fault detection and maintenance strategies, prompting several to point out data and analytics to make maintenance decisions. The following chapter presents various fault detection techniques as well as existing maintenance strategies and how they can be implemented with state-of-the-art technologies[8–10].

It is important to clearly determine terminologies used in the process monitoring field and classify those in terms of their characteristics. The following terms, such as fault, failure, and malfunction, types of fault as well as fault detection will be defined in this section.

The fault is defined as an inadmissible deviation of at least one characteristic feature of the system from the acceptable, usual, and standard conditions. Particularly, impermissible deviation shows the dissimilarity among a trigger value and fault value, and this fault may lead to a process malfunction or operation failure. It could be possible that faults already existed in the process or appear at an unknown period, and the rapidness of the emergence of faults can be various. Dependent upon the occurrence period, faults are always categorized in three groups.

As for faults classification, the first fault type is based on the faulty component, i.e., actuator faults, plant component faults, and sensor faults (Figure 2.1). The second fault type is based on the faulty form; it could be abrupt (stepwise), incipient (drift-like), or intermittent faults (with interrupts), which Figure 2.2 illustrates. The last type is an additive or multiplicative faults. This fault types appear and disappear frquently (like partially damaged in wiring). Additive faults often emerge as offsets of sensors, while the most common multiplicative faults are parameter changes through a process[7].

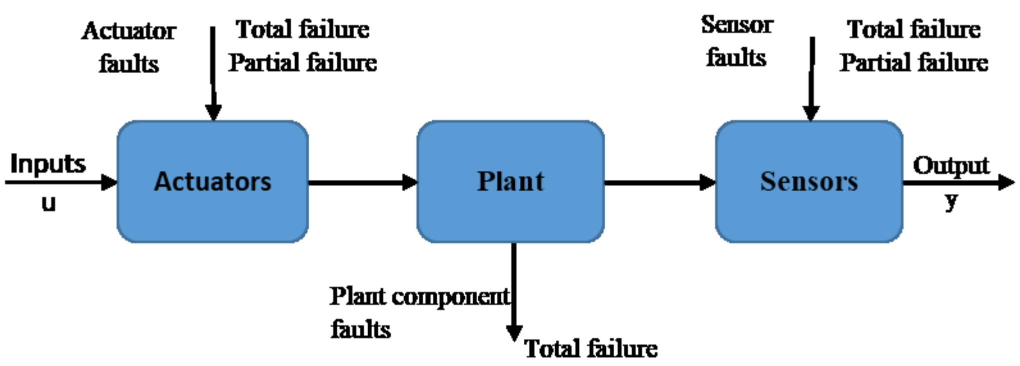


Figure 2-1. Fault models based on faulty component

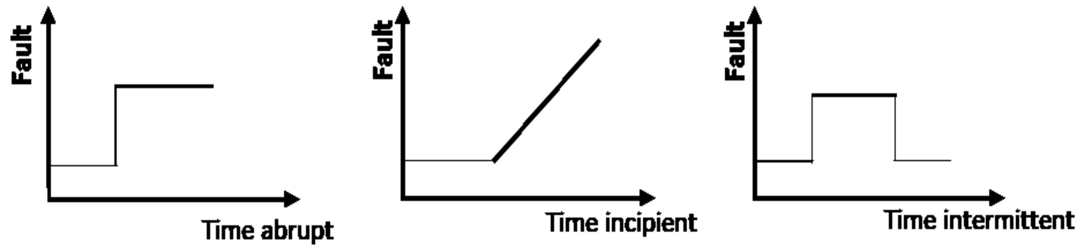


Figure 2-2. Fault models based on faulty form

Failure is a constant disruption of a system's ability to carry out an essential function under a particular operational circumstance. Based on expectedness, the types of failure can be categorized into three groups:

1) random or unpredictable failure,
2) deterministic failure, and
3) systematic or casual failure.

Malfunction is identified as a sporadic irregularity in the completion of a system's desirable function. Progression of events "failure" or "malfunction" from a fault is demonstrated in Figure 2.3[9].

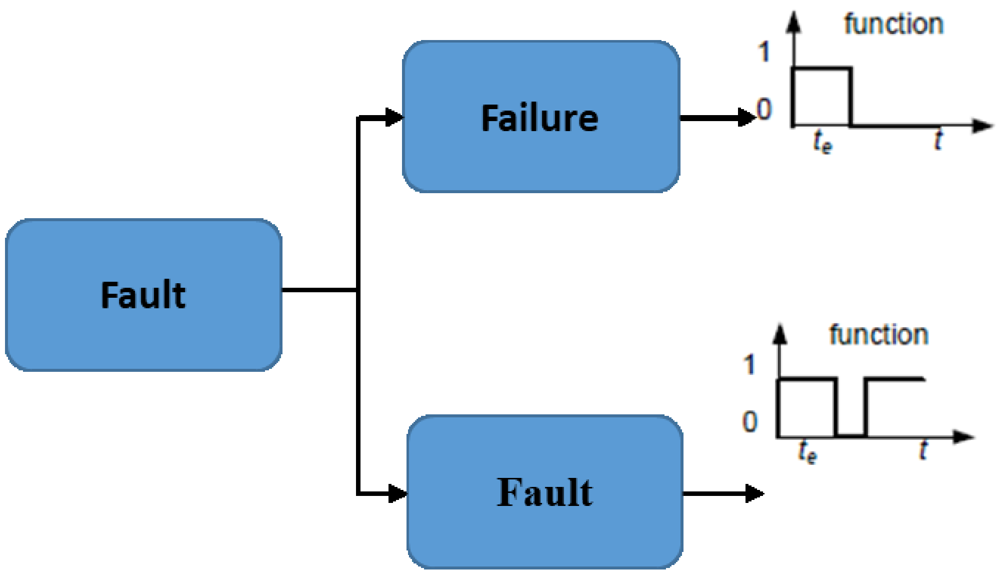


Figure 2-3. Development of fault toward failure or malfunction

2.2 Process Monitoring

A general system monitoring approach has a loop structure , which is determined by four stages and begins with detecting, isolating, identifying the fault, and recovering the process, as illustrated in Figure 2.4. Fault detection identifies the existence of a fault in the supervised system. It involves discovering faults in the system, actuators, and detectors by utilizing dependencies among various quantifiable signals. Relevant tasks are also isolating and identifying faults. Fault isolation is related to the position and the kind of fault, while fault identification is related to the scale or size of the fault. Fault isolation and fault identification are mutually indicated as fault diagnosis. The fault identification function compromises the specification of the fault, with as many elements as feasible, such as the fault size, location, and time of identification[7]. The last stage is process recovery, also known as fault correction. This step makes appropriate decisions regarding corrective actions to return to normal and safe process conditions. Since this stage is usually specific to the manufacturing process, most research generally concentrates on fault detection and fault diagnosis (FDD)[11].

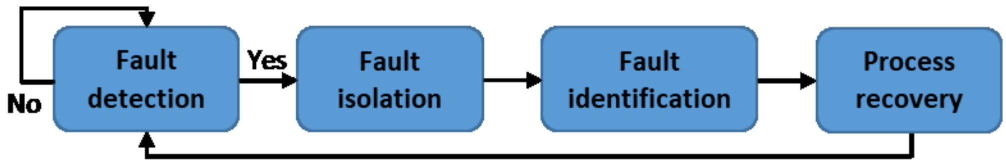


Figure 2-4. Execution procedure of a conventional process monitoring

One of the most well-known techniques for process monitoring is statistical process monitoring (SPM), also referred to as statistical process control (SPC) has been used to enhance system efficiencies in different activities. In conventional univariate SPM methods for single system variable controlling, it is supposed that the whole quantified system variables track the normal (i.e., Gaussian) distribution and are separate and individual. Nevertheless, the traditional SPC approaches have many restrictions since a supposition is often inaccurate for the data gathered from many actual industrial processes due to their fundamental characteristics, for instance multivariate, non-linearity, non-Gaussianity, and non-stationarity. As example, it is insufficient to implement a univariate monitoring chart to a multivariate system if the factors in that system include non-linearity features and cross-correlation.

To surpass the restrictions of the traditional univariate SPC techniques for controlling the dynamic industrial system, different chief multivariate statistical process monitoring (MSPM) approaches, including useful data have been created and applied for several industrial processes. Additionally, for monitoring non-measurable process variables (e.g., status, parameters, and so on.), useful prediction techniques and process-based models have been broadly investigated and widely applied. Especially, by adverting and developing sensor technology that facilitates to regularly gather data on various system factors, numerous useful system controlling and fault diagnosis (FD) techniques on the basis of multivariate statistical approaches have gained great attention[9].

2.3 Fault Detection and Diagnosis Techniques (FDD)

The FDD is a significant function in different industrial processes. It has been an active research area to confirm efficient and safe operations as well as the productivity of the process. Generally, fault detection is a task to define or indicate faults in a process or system, actuators and sensors by using dependencies between various measurable signals. The faulty process or variable should isolate next since fault diagnosis is a general responsibility to define fault type, fault size, location of the fault, occurrence time of the detected fault, and behavior of fault among a suitable evaluation of the fault. There are numerous overlapping classifications of the field. Many of them are more oriented toward the control engineering approach than mathematical, statistical, and AI techniques. Literature is abundant on process fault diagnosis ranging from analytical methods to artificial intelligence and statistical approaches, but in the following section, the most common methods can be observed[7]:

- Data-Based Methods and Signal Models
- Process Model-Based Methods
- Knowledge-Based Methods

2.3.1 Data-Based Methods and Signal Models

Data base methods are derived directly from collected process operation data and fault detection and diagnosis and exploit only available experimental (historical) data. The systematic taxonomies of different data-driven FDD methods are brought in the following sections.

2.3.1.1 Limit Checking and Trend Checking

Limit Checking, and trend checking are the most straightforward and frequently used techniques for fault detection, which directly measure variables. Thereby, calculated variables of a process are monitored as well as checking if their absolute values or trends surpass specific thresholds. Generally, two limit values, named thresholds, are preset, the highest value Y_{max} and the lowest value Y_{min}.

It means that the process is a normal condition if the monitored variable remains within a specific tolerance zone. By exceeding the thresholds, fault indicates somewhere in the process. By the side of false alarms over normal fluctuations of the variable should be prevented; on the other hand, faulty deviations should be identified early. Consequently, a trade-off between too-narrow and wide thresholds exists.

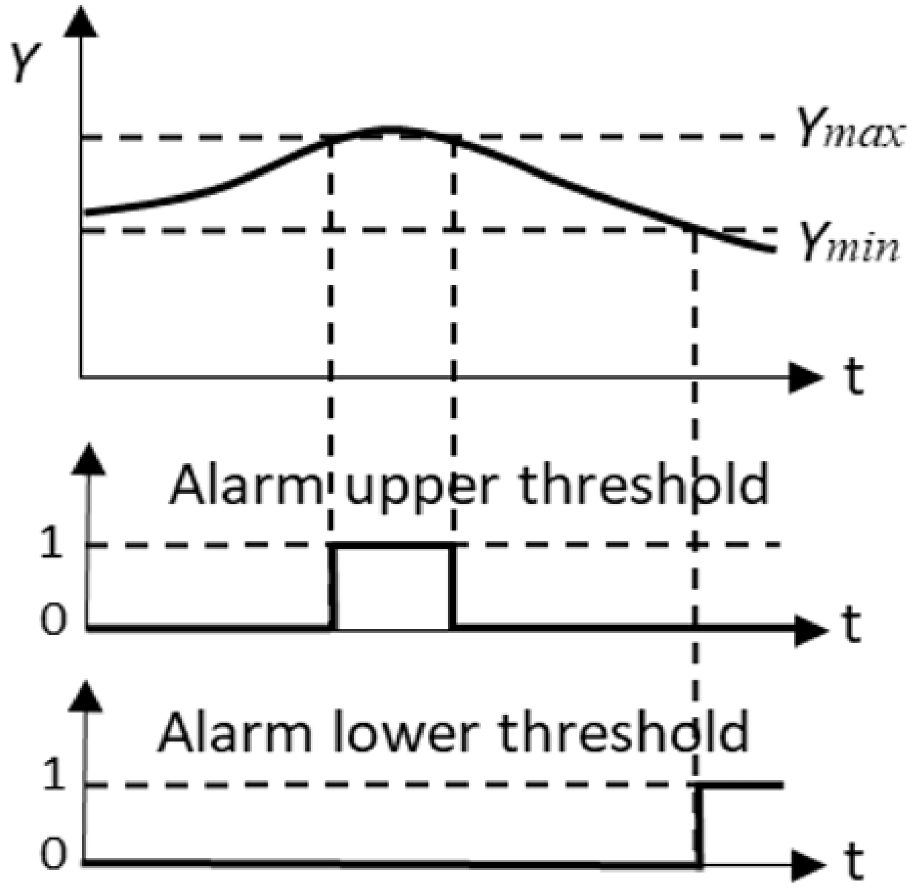


Figure 2-5. Limit checking absolute value Y(t)

The limit-checking method can also be applied to the first derivative $\dot{Y} = dY(t)/dt$, which is known as trend checking. The trend of monitored variable and to control if $\dot{Y}min < \dot{Y}(t) < \dot{Y}max$. When approximately a small threshold is selected, an alarm can be gotten earlier than for limit checking of absolute value, see Figure 2.6 The main benefit of this checking is the clarity and trustworthiness of its methods, although they are capable to react after comparatively big change of properties. The distribution of non-fault condition (normal state) information is not all the time Gaussian; for this purpose, Gaussian Mixture Patterns can be used[12].

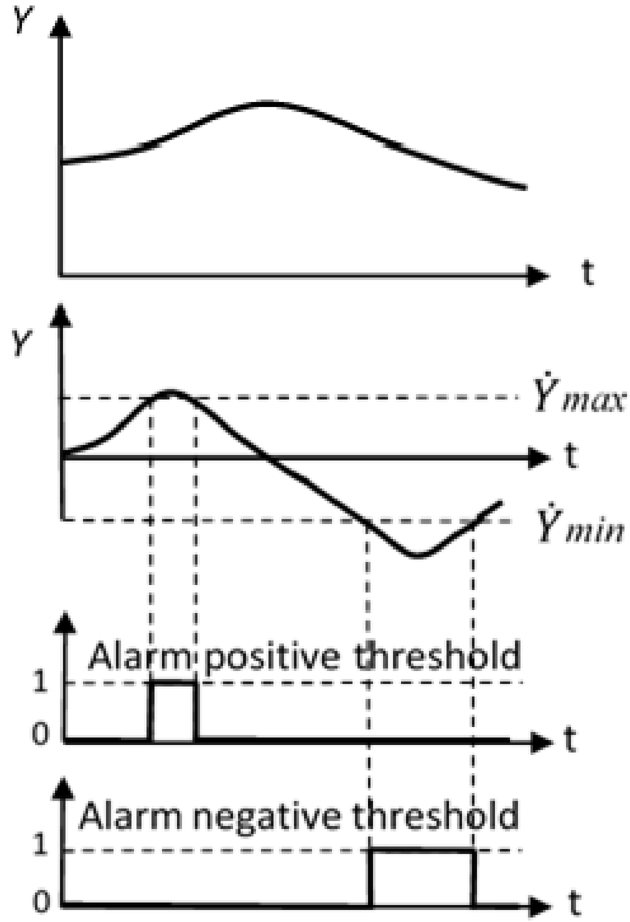


Figure 2-6. Trend checking Y ̇(t)

2.3.1.2 **Detecting Fault with Principal Component Analysis**

To increase monitoring performance, the detection of changes in the process needs a modeling technique that captures the central relations between the process variables. The principal component analysis (PCA) method is an influential MSPC (multivariate statistical process control) technique that has been broadly used to monitor such modern industrial processes. It is a reliable method for capturing variable correlation , and utilizes an uncorrelated conversion to transform a set of examination of potentially correlated variables into a set of rates of orthogonal variables known as main elements (into two orthogonal subspaces: a principal component subspace (PCS) and a residual sub-space (RS))[13].

In PCA- based monitoring, information extraction from regularly achieved data, constructed mode, residual space, and identified the control limits of both subspaces could be used. It is determined by straight conversion matrix $\mathbf{P}_{[m \times r]}$, r < m (its identification need some matrix calculation steps), that transforms matrix of entry information $\mathbf{X}_{[N \times m]}$ in a class of uncorrelated data $\mathbf{T}_{[N \times r]}$ (PCS). By analyzing a wide range of interrelated variables, PCA decreases the dimensionality of the data set, while keeping as much as possible variation in a data set. This leads monitoring and processing of large dimensional data feasible. Fault detection is implemented by using the alternation identification on transformed information **T** takes allowable means and variances into consideration (Figure 2.7)[7].

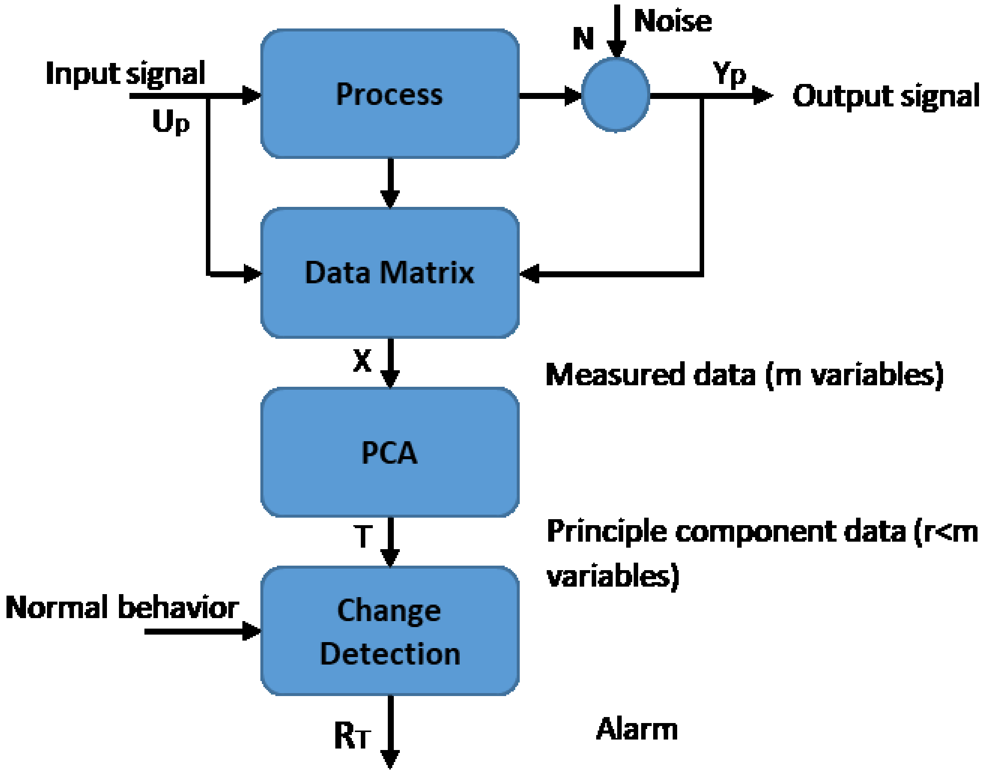


Figure 2-7. Fault detection with Principal Component Analysis

2.3.1.3 **Fault Detection with Signal Models**

Several assessed signals of processes demonstrate oscillations that are either of harmonic or random character or both. In case alternation of these signals is associated with the error in the actuators, the process, and sensors, signal model-based fault-detection methods can be applied. If the alternations in signals are corresponding to faults in a system, the signal analysis can be implemented. By considering mathematical models for the analyzed signal, relevant features can be calculated (like amplitudes, phases, and spectrum). A comparison with the observed features for normal behavior provides changes in the features that are considered analytical symptoms. The mission of the signal models approach is summarized in Figure 2.8.

The signal models can be categorized into nonparametric models, like frequency spectra or correlation functions, or parametric models, like amplitudes for distinct frequencies or autoregressive moving-average (ARMA) type models. The spectrum analysis and the parametric signal models are two practical signal analysis techniques for fault detection.[12]

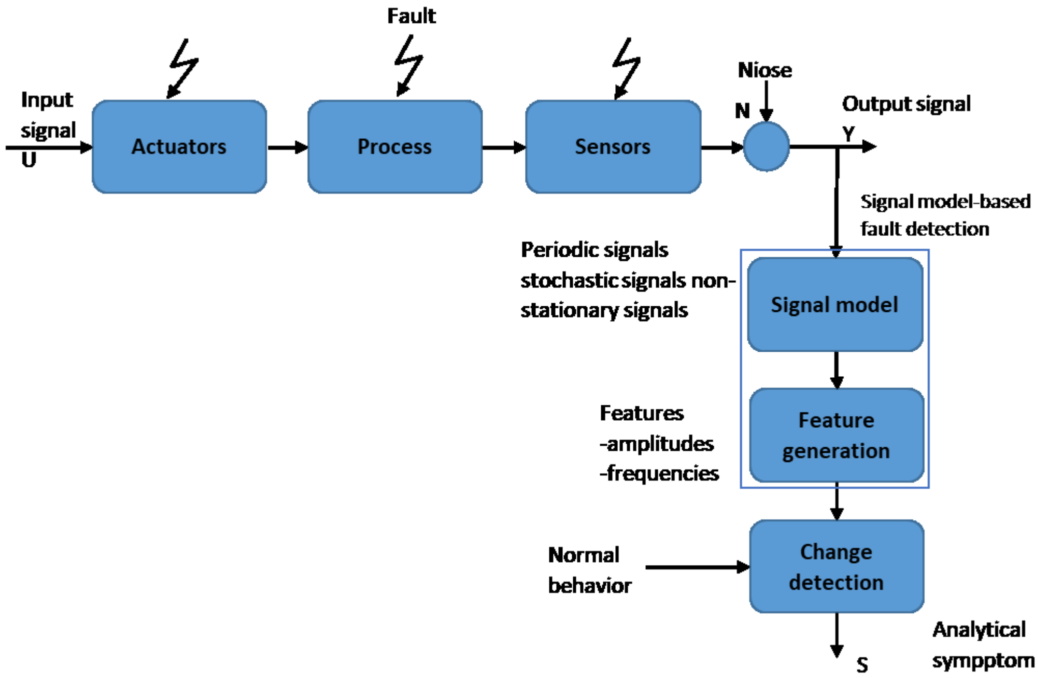


Figure 2-8. Signal Models approach

Spectrum Analysis

The extraction fault-related signal properties can be limited to the amplitudes or amplitude densities within a specific signal bandwidth. For calculating the frequency content of signal *X(t),* the algorithm Fast Fourier transform (FFT) can be used. Throughout normal operation components, A_i falls within a specific range[7] $A_i min \leq | A_i | \leq A_i max$.

Parametric signal model

Two overall linear models for parametric representation of multicomponent non-stationary signals are the time-dependent ARMA (autoregressive moving-average) process and the sum of modulated signals with time-variant amplitude and phase functions[14].

2.3.1.4 Pattern Recognition (Artificial Neural Network)

An artificial neural network is a neuron network that learns highly complicated functions through a series of nonlinear transformations. It has been successfully used for pattern identification as well as fault detection[15]. Each neural network has two feature components: Architecture, which is the pattern of connection among the neurons. The second is a learning algorithm known as a training algorithm and used for establishing the connection weights. Supervised training a feedforward network is the most regular architecture (Figure 2.9), which is usually trained with some variant of the backpropagation algorithm. Unsupervised training is needed (training data without labeled input-output pairs). Kohonen's self-organizing network is a choice, Figure 2.10. The third one is activation functions. It uses to transform the activation level of a unit (neuron) into an output signal[16].

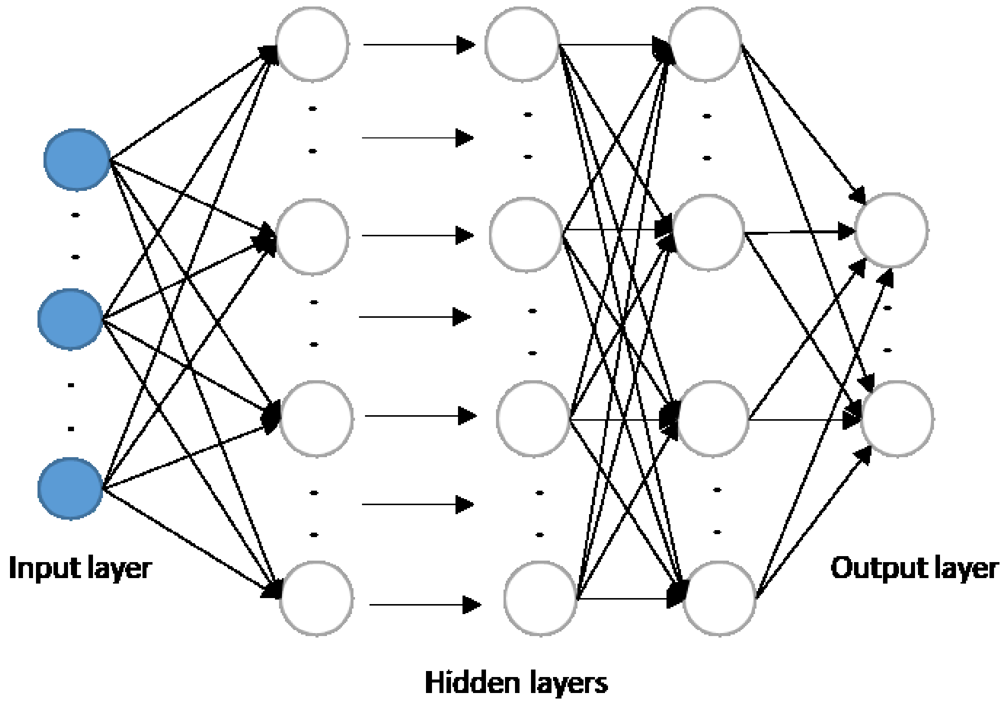


Figure 2-9. Feedforward Neutral Network

The neurons of the competitive net train to identify groups of similar input vectors in such a way that each neuron competes to react to an input vector X_t, the neuron whose value m_c is nearest to X_t get the highest net input and consequently wins the competition and outputs one, all other neurons output zero. Normal (non-fault) and fault conditions are represented as different subsets of neurons through a map. Between other statistical classifiers, the regular is the k-Nearest Neighbor rule as a nonparametric supervised classification approach.

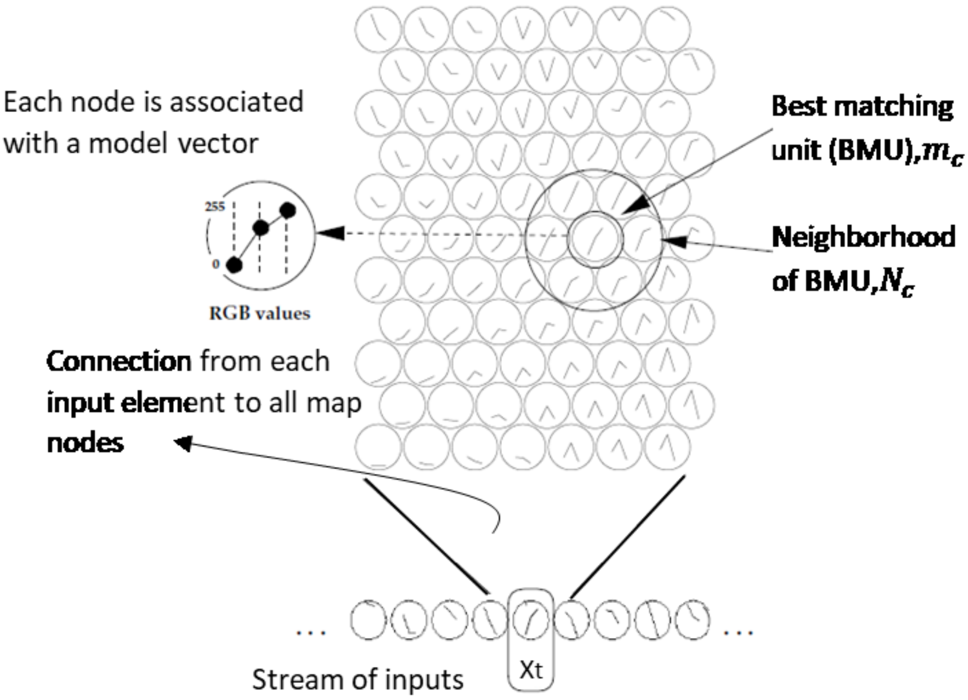


Figure 2-10. Self-organize map (SOM) (T. Kohonen, 1997)

2.3.2 Process Model-Based Methods

This technique consists of detecting faults in the processes, actuators, and sensors using the dependencies among various measurable signals. Mathematical process models present these dependencies. In this technique, the signal is first fitted into a suitable model, then this model is used for analysis, synthesis, and different other signal-processing tasks. Figure 2.11 illustrates the overall structure of model-based fault detection.

Residual assessment is implemented by threshold logic and decision function. Alongside fixed thresholds, advanced robust adaptive residual evaluators exist. According to assessed input signals U and output signals Y, the detection techniques create residuals r; factor estimates $\ddot{\Theta}$ or state estimates $\dot{x}$ that are named features. In contrast with the normal features, changes in features are discovered, leading to analytical symptoms S[17]. This technique supposes that the model's structure and parameters are exactly recognized. Faults can be represented as state variable changes. Restricting attention to linear system[7].

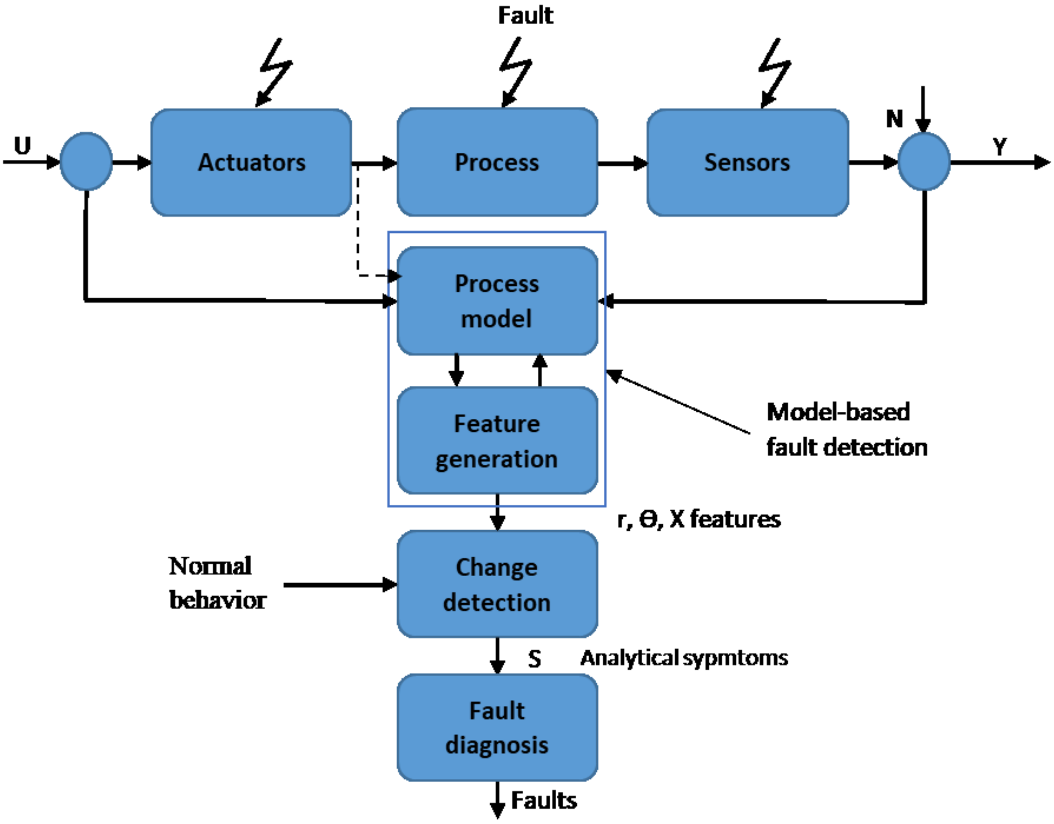


Figure 2-11. Overall scheme of process model-based FDD

2.3.2.1 Fault Detection with Parity Equations

This method is a straightforward approach that compares the process behavior with a process model describing non-faulty behavior. The variation of signals among the model and the processes are presented by residuals (Figure 2.12). Then residuals identify differences among the process and the model and check for consistency. The process is characterized by transfer function $G_P(s)$ and process model by $G_m(s)$. A simple model-based technique is to take fixed model G_M and execute it in parallel to process, therefore forming an output error or r′[12].

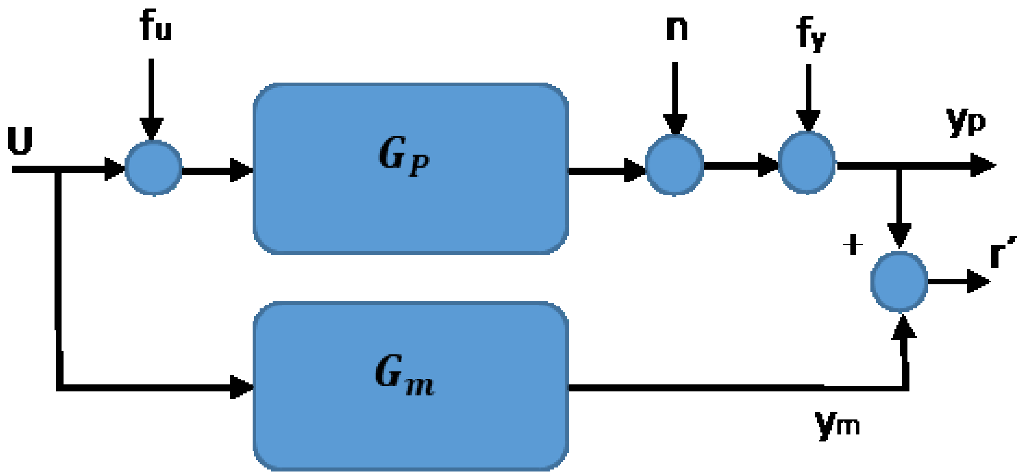


Figure 2-12. Fault detection with parity equations technique

2.3.2.2 **Fault Detection with State Observers and State Estimation**

Alternations in the input and output action of the process cause to change of output error and state variables. The main concept of the observer approach is to remodel the outputs of the system from the measurements with the help of observers using the estimation error, or innovation, as residual for the detection of the fault. Different techniques have been considered for fault detection that is based on the classical Luenberger state observer, Kalman filter and the so-called output observer[12].

State Observers Technique

This method can be implemented when the faults can be modeled as state variable changes Δx_i. The structure of the linear full-order state estimator is demonstrated in Figure 2.13. A linear-time invariant process can be presented by the state-space model, which includes a parallel process model. By the feedback (matrix H) of the prediction error (e), is used for computation of the residual, **r**, for the purpose of fault detection (by threshold logic).

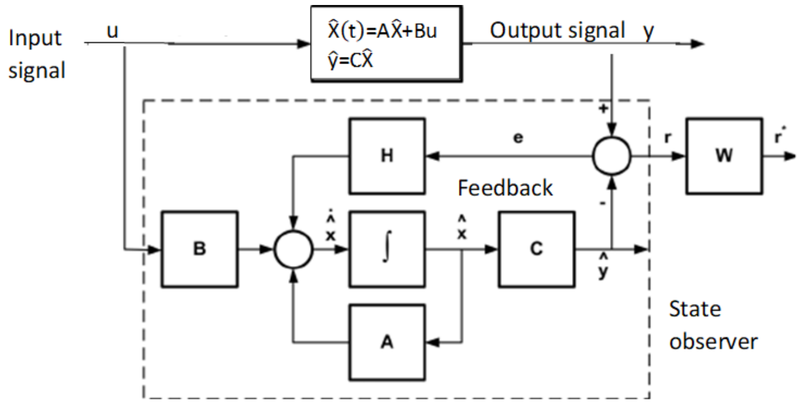


Figure 2-13. Process and state observer (D. Miljković, 2011)

Output Observers Technique

The primary purpose of state observers is to remodel the state of the process. Nonetheless, there is no such requires for a diagnostic objective. When the reconstruction of the state vector $X(t)$ is not of interest, it is feasible to use output observers. A linear transformation with matrix T_1 conducts to new state vector$\xi(t)$. Output observers remodel the outputs in order to generate redundancy[18]. The below figure illustrates this technique.

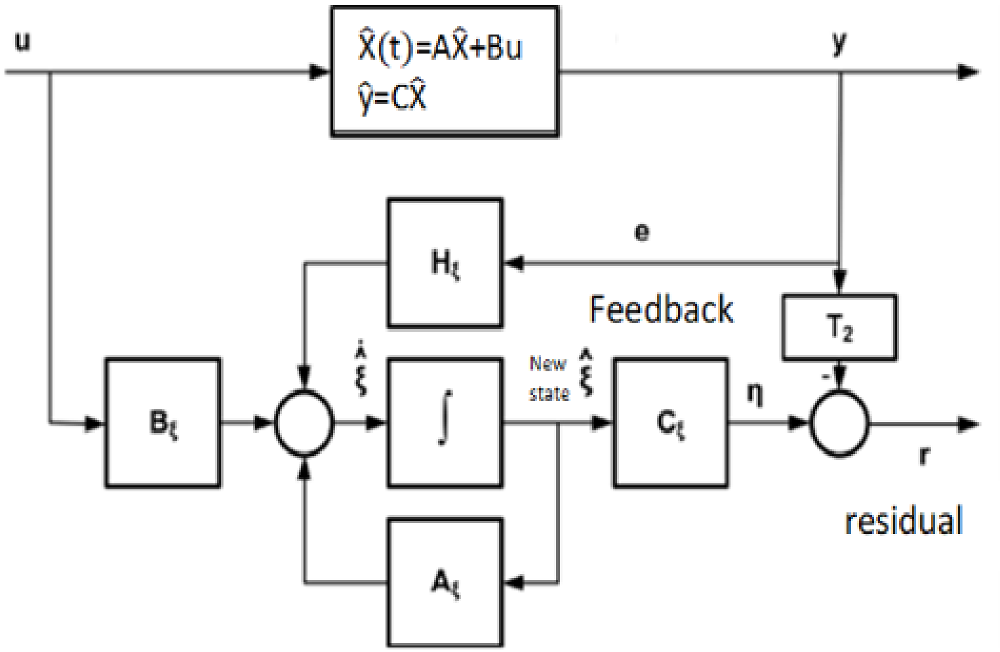


Figure 2-14. Process and output observer (D. Miljković, 2011)

2.3.2.3 Fault Detection with Parameter Estimation

This technique relies on the principle that feasible faults in the monitored process can be connected with specific parameters and states of a mathematical model of a process given in general by an input-output relation. Faults of a dynamical system are reflected in physical factors (mass, friction, resistance, capacitance, inductance, etc.). The concept of the parameter estimation technique is to identify the faults with the estimation of the parameters of the mathematical model. The basis of this technique is the combination of theoretical modeling and parameter estimation of the continuous-time model. The overall procedure to detect faults follows the steps below[19]:

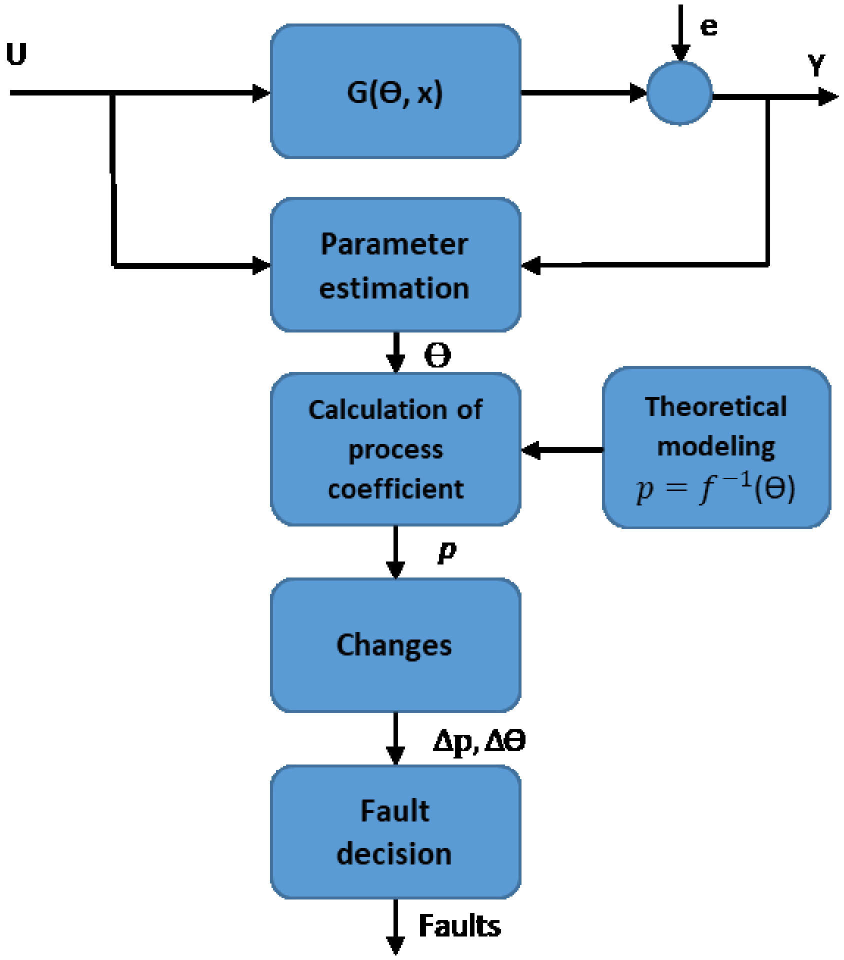


Figure 2-15. Fault detection with parameter estimation technique

1. Establishment of the numerical model of the system's non-fault behavior at this point acceptable tolerances for the system's parameter values are also defined
2. Determination of connection among the model parameters Θi and physical parameters pi, $\quad \theta = f(p)$
3. Recognition of model parameter vector θ using the input u and output y of the current system
4. Identification of physical factor vector $p = f^{-1}$
5. By taking nominal value from the nominal model, vector deviations Δp can be achieved
6. Decision on a fault by exploiting the connection between fault and changes in the physical factors Δp_i

2.3.2.4 Nonlinear Models and Neural Networks

Several technical processes are not proper to traditional modeling techniques due to the lack of accuracy, formal knowledge regarding the system, and strongly nonlinear behavior. If numerical process models G_p are not available, a nonlinear model can be applied to generate residuals (Figure 2.16). A method to create a nonlinear model $G_{NM}$is to use neural networks.

Neural networks do not need specific knowledge of process structure. They can act as black-box models of general nonlinear, multivariable static and dynamic systems.

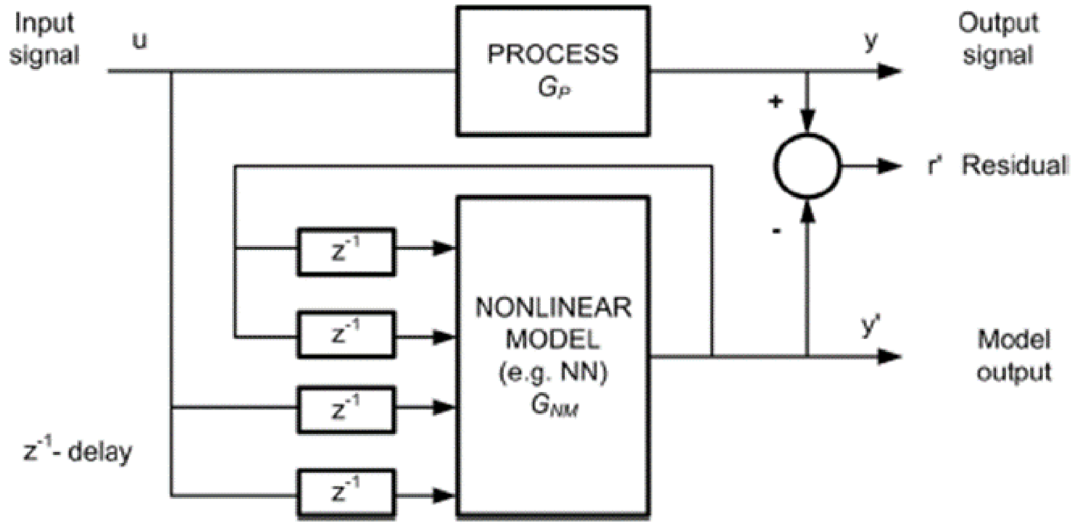


Figure 2-16. Fault detection using nonlinear model and parity equations (D. Miljković, 2011)

Neural networks consist of several factors, but these factors are basically not suitable for the physical interpretation of the modeled system. Nevertheless, once the process modeling is completed, fault detection with parity equations can be applied. Moreover, the combination of neural networks with different process models as well as using in the residual assessment is possible[7].

2.3.2.5 Fault Detection of Control Loops

The key purposes for using automatic control loops are accurate following of reference variables (setpoints), a quick response than in an open loop, compensation of all kinds of external disturbances on the controlled variable, stabilization of unstable processes, reduction of the influence of process parameter alteration with regard to the static and dynamic behavior, partial compensation of actuator and process nonlinearities, and, of course, replacement of manual control by humans[12].

Control systems have to consist of automatic supervision of closed-loop operation to find malfunctions as early as possible. For larger plants with hundreds of control loops, it is functional to have automatic fault detection for control loops. Control loop faults conduct to oscillations, therefore automatic detection of various types of oscillations is of importance. Techniques are signal-based (variance), detection of oscillations and model-based.

2.3.3 Knowledge-Based Methods

By advancement of computer technology. Modern industrial processes tend to be more automated, integrated, complex and intelligent. In real process monitoring, because of the large scale of industrial processes and complex business logic, there is a complex connection among process variables in the production process. Meanwhile, with the increasing complexity of the process, the influencing factors are gradually increasing, and multiple faults happen frequently in complex industrial systems. Although the conventional fault detection technology is mostly implemented under single fault type and simple influencing parameters, its precision is mostly reduced in the face of complex industrial processes[20].

In the current period, there is a trend towards knowledge-based and artificial intelligence approaches. The knowledge-based method does not need specific knowledge of the exact mathematical of the object. It can be mainly classified into fuzzy logic, expert system and neural network, support vector machine fault diagnosis method, and so on. These fault techniques can effectively make use of expert knowledge and experience to make judgments. In some areas, through constructing the fault ontology, the researchers would model the connection between the fault phenomenon and the cause, and then use the ontology reasoning technology to diagnose. Nevertheless, in the real fault diagnosis process, there is usually an uncertain connection between the fault phenomenon of the equipment to be inspected and the cause of the fault[21].

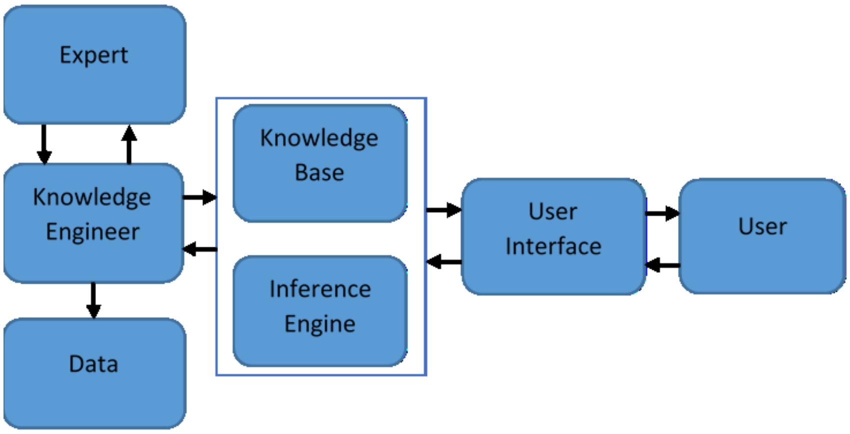


Figure 2-17. Basic structure of Knowledge Based

2.3.3.1 **Fuzzy Logic**

Fuzzy logic is a system for dealing with inexact or unreliable information. The output of the fault detection system does not require an alarm that takes two values, fault or no-fault. Instead of simple binary decision fault or no-fault, the fault severity of the system is provided to operators as the output of the fuzzy controller. It supports users to work with ambiguous or fuzzy quantities such as large or small, or data that is subject to interpretation. A linguistically comprehensible rule-based model is formed based on the available expert knowledge and measured data. The following diagram of the fuzzy logic controller is shown in Figure 2.18[22].

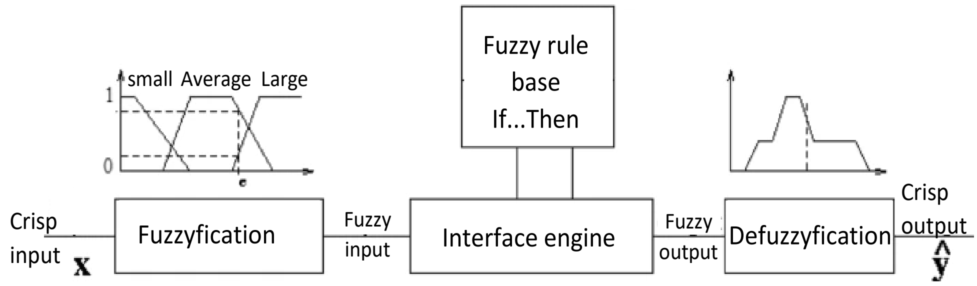


Figure 2-18. Fuzzy logic controller (M. Alakhras, 2020)

As can be seen in Fig.19, fuzzy inference process consists following steps[7]:

a) Fuzzyfication

Entry to a control unit moves during the fuzzification process utilizing membership functions. The membership function is a visual depiction of the size of involvement of each entry. The shape of some membership functions is represented in Fig. 19.

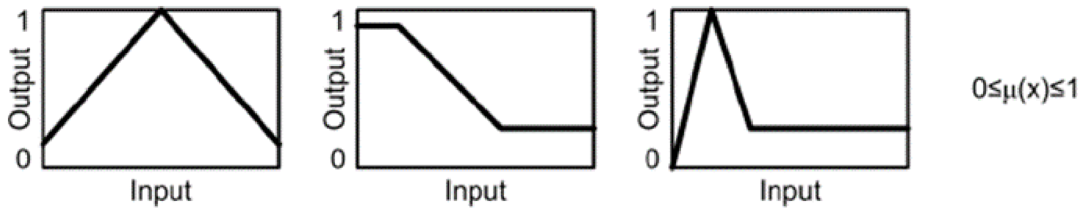


Figure 2-19 Some membership functions (D. Miljković, 2011)

b) Rule Based Inference

All rules are analyzed in parallel using fuzzy reasoning. The fuzzy inference process utilizes membership functions, logical operations, and if-then rules (Fig. 2.20).

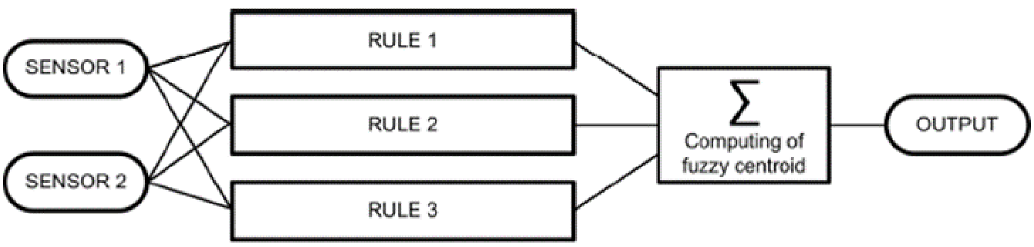


Figure 2-20 Fuzzy inference process (D. Miljković, 2011)

c) Defuzzification

Defuzzification is defined as converting the fuzzy information to crisp. It is achieved by integrating the consequence of the inference system and computing the "fuzzy centroid" of the area, x^* is defuzzified value, $\mu_i(x)$ is the accumulated membership function, x is the output variable.

2.3.3.2 Support Vector Machine-Based (SVM)

Artificial neural network (ANN) technology is superior to conventional methods in pattern recognition and categorization. Between identification algorithms, the neural network (NN), the support vector machine (SVM), and learning vector quantization are among the more outstanding smart classifiers due to their preferable effect of classification and regression. SVM is a representative nonlinear approach (can deal with large feature spaces), and it is a potentially effective method for categorizing all types of datasets (based on the structural risk minimization principle). The basic principle of SVM is to categorize the dataset into two separate classes based on the hyperplane (a decision boundary), which should have a maximum distance among support vectors in each class. Support vectors are representative data points, and their rising number may increase the difficulty of the problem[23,24].

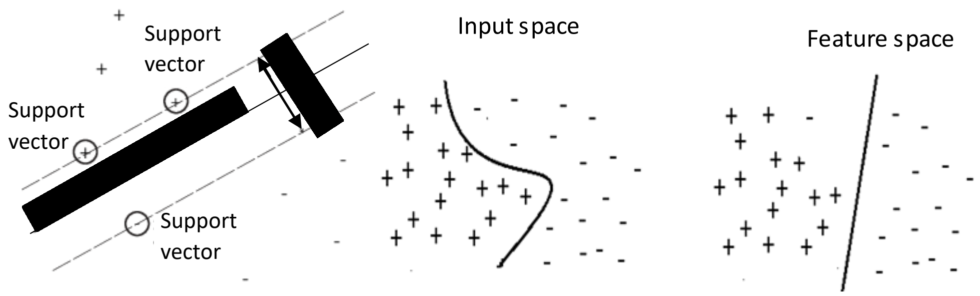


Figure 2-21. SVM concept, Non-linear to a linear transformation (MathWorks.com/svm)

2.4 Maintenance Concepts

The FDD (fault detection and diagnostics) approaches are executed in order to select various maintenance management scheduling and operations of these actions. The purpose of these activities is to perceive phenomena and operating consequently. Nonetheless, rather than realizing an incident that has emerged as a failure, it looks suitable to predict its indication and consequences in order to consequently and, as quickly as possible, resort to protective actions. As far back as parts, machines, and equipment have existed, there has been a necessity for them to be repaired and supported. Records of maintenance can be found already in ancient Egypt. In the beginning, maintenance was straightforward. It means, in case of breakdown, one simply fixed it and was known as reactive maintenance. Insufficient attention was given to the maintenance consequences had on cost or when it should happen. As time goes on, the parts and machines became more complex, maintenance strategies began to mature at the onset of

World War II. Thereafter world war, the development of formal maintenance was lead to the second generation of maintenance in the 1950s. In the late 1970s and 1980s, the third generation of maintenance was evolved when the first programmable logic controller e.g. PLC, was made. The data that developed from these maintenance notions could be analyzed to make informed decisions and initiate to estimate when maintenance should be completed (Figure 2.22). Nowadays, maintenance has existed in its fourth generation, an abundance of Internet-linked sensors, parts as well as machines can be monitored using real-time predictions[25] and EN 1306:2017 defined maintenance as the 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.

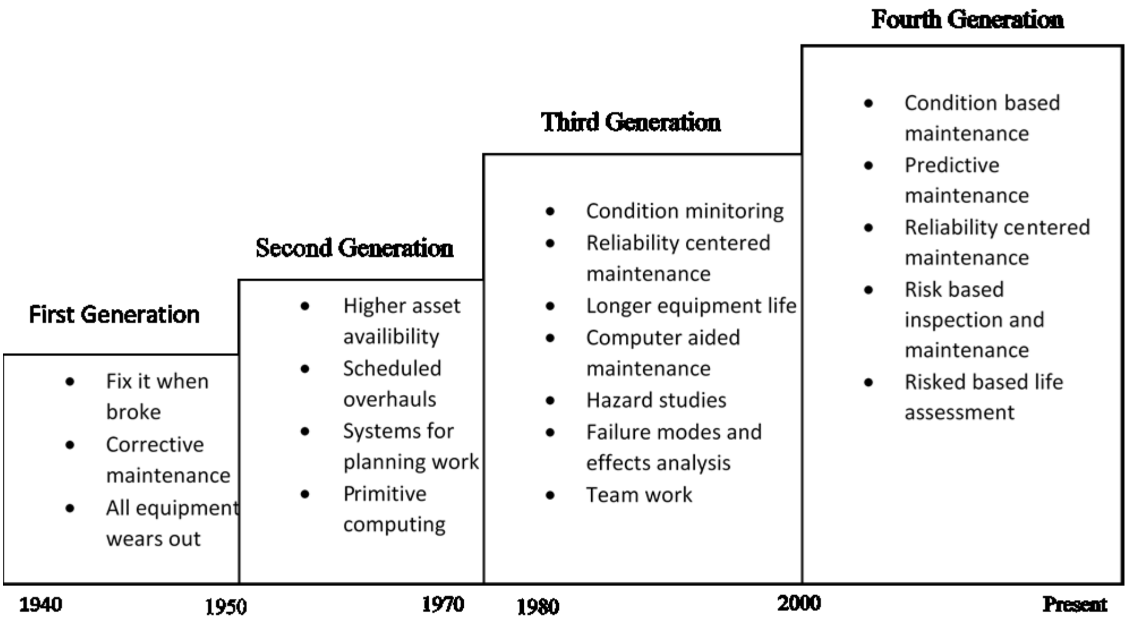


Figure 2-22. The development of maintenance expectations and methods from 1940 to Present (J. Moubray, 1997 and I.Lazakis, 2018)

Maintenance notions have a direct impact on the amortization and maintainability requirements for the design of the asset, and the operating costs of a business because some party must ultimately pay for the maintenance. In general, across all sectors, the costs of maintaining physical assets demonstrate 5%-12% of the total capital invested, up to 15% of the gross sales, and up to 10% of the production costs of an asset[26]. From management‘s point of view, there is a need to determine whether maintenance operation is planned or unplanned. Different kinds of maintenance strategies can be applied for different scenarios. BS EN 13306:2017 divided maintenance into two key groups: unplanned maintenance and planned maintenance. Each group is subdivided into several categories, Figure 2.23 illustrates it.

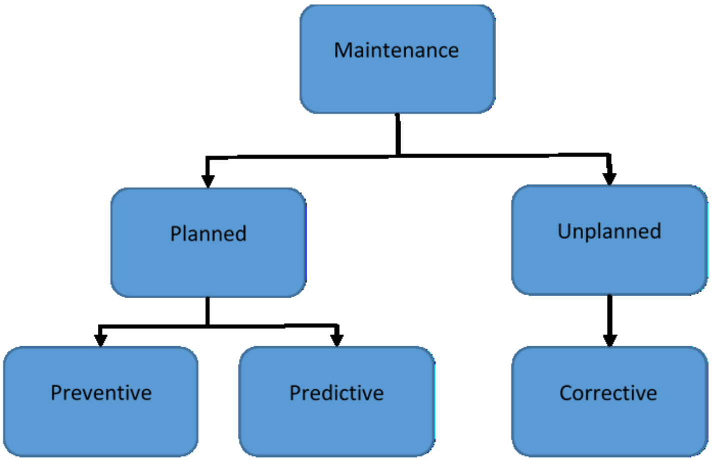


Figure 2-23. Maintenance classification overview

2.4.1 Corrective Maintenance

Corrective maintenance (CM) is also known as Run to fail (RTF) maintenance and it is the strategy to repair or replace a machine after it has broken down until the machine fails, there is no intervention. These activities include diagnostics, disassembly (repair), repair, replacement, reassembly, alignment and adjustments, and checks. The advantage of using this type of maintenance is that it can increase the proper operating time before it requires to be stopped or shut down for repair. The potential problems of this maintenance are that it includes the procure of a large number of spare parts to be ready when required (involving high costs) and needs the constant application of crisis management. The maintenance team is usually overworked and faces daily (unexpected) emergencies that may arise; moreover, a malfunction could be catastrophic, and that it continues to impart damage on other nearby components or machines[27]. A total run to failure methodology is the most expensive method of maintenance management, and drilling rigs usually perform basic preventive tasks like machine adjustments and lubrication[28].

In this type of maintenance, it is essential to follow a series of stages to fix it or restore it to its full operability. These stages involve: diagnosing the failure, isolating it, disassembling the equipment to gain access to the broken component, repairing it, and as can be seen in Figure 2.24, completing these stages is a corrective maintenance cycle. Table 1 gives more information about the pros and cons of corrective maintenance.

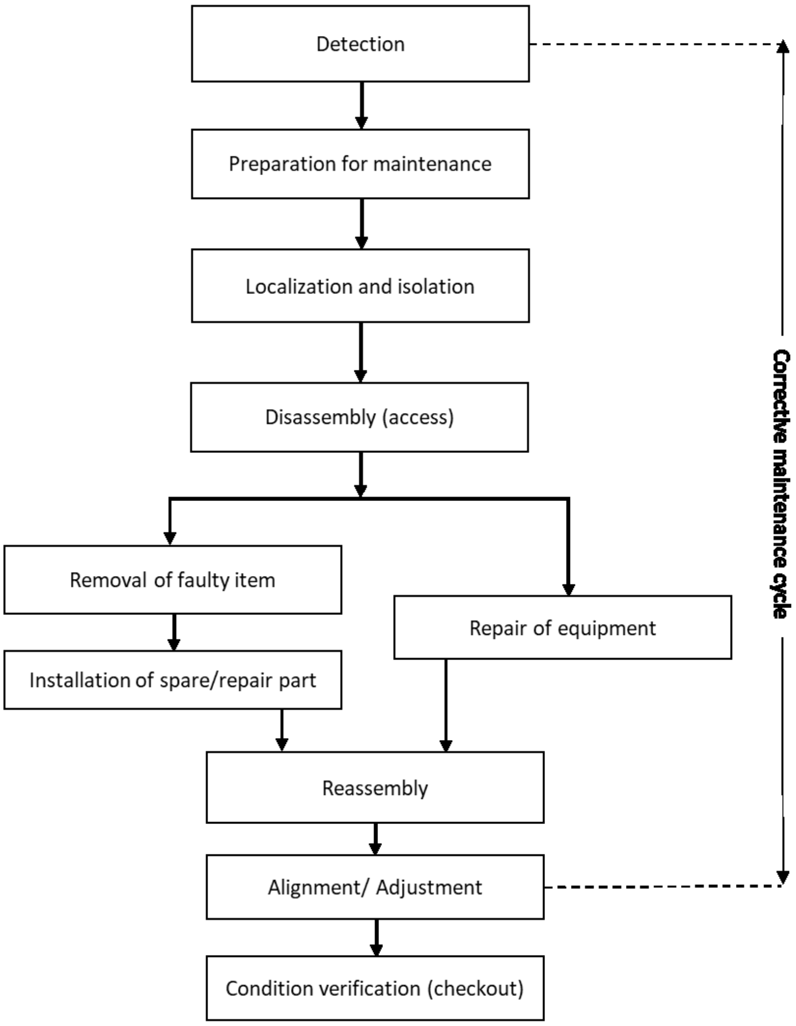


Figure 2-24. Corrective maintenance cycle

The table below gives more information about pros and cons of corrective maintenance.

Corrective Maintenance	
Advantages	Low cost
	Less staff
Disadvantages	Increased expenditure due to unplanned downtime of equipment
	Increased labor cost, especially if overtime is required
	Cost involved with repair or replacement of equipment
	Feasible secondary equipment or process damage from equipment failure
	Ineffective use of staff resources

Table 1. Corrective Maintenance pros and cons (O&M Best practice, 2010)

2.4.2 Preventive Maintenance

The preventive maintenance compromises the substitute, repair and maintenance of equipment for purpose of preventing unexpected failure through the operation. The primary objectives of PM are to reduce the failure rate or failure frequency of the equipment which leads to cost reduction, less machine or equipment downtime and increasing productivity and enhancing the quality. There are two significant types of PM techniques, maintenance in periodic cycle and maintenance dependent on equipment status. As for the maintenance based on periodic cycles could be unreasonably costly for about 92% of machine components. Machine-based maintenance replaces the components as well as interferes with the equipment only when deviations start to show up in its procedure, making it more efficient. This kind of planned maintenance is based on regular, repetitive tasks done to maintain machines or equipment in the suitable working order and to optimize its efficiency and precision. These tasks consist of frequent, regular cleaning, calibrating, lubricating, adjusting testing, and exchanging the components to prevent the breakdown[25,29,30].

All PM management techniques suppose that the equipment is going to degrade within a specified time of their individual classification. Figure 2.25 portraits the statistical life of a machine. The bathtub curve or MTTF (mean time to failure) illustrates that new equipment or machine has a great possibility of failure because of installation issues through the first few weeks of operation. Throughout this stage, the reasons for malfunctions can, for instance, be human error, low-quality control, low manufacturing quality as well as poor material and workmanship of the machine and its components.

The second period is defined as the useful life (constant failure) where the failure frequency remains stable and constant. The failures which occur in this stage are usually natural failures, undetectable failures, and human errors. The last period is called the wear-out period when the malfunction frequency increases. It could be represented as poor maintenance, corrosion, erosion, or wear from the friction of components. This stage is the last period of a machine's life. The following table gives more information about the merits and demerits of preventive maintenance[31]. Table 2 represents the advantages and disadvantages of preventive maintenance.

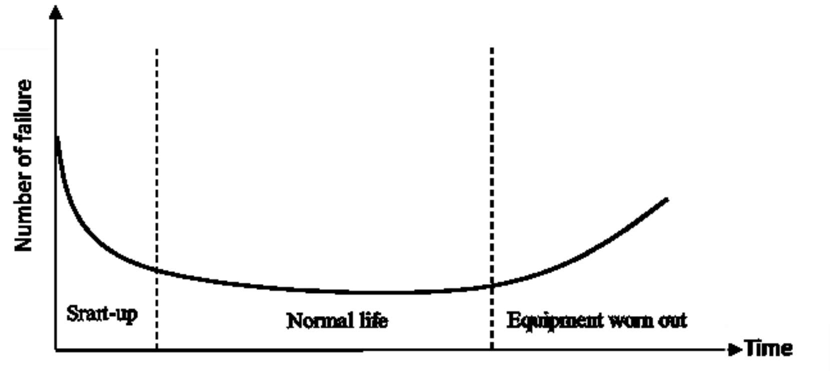


Figure 2-25. Typical bathtub curve

Preventive Maintenance	
Advantages	Cost effective in several capital-intensive processes
	Adaptability allows for the adjustment of maintenance periodicity
	Higher component life cycle
	Energy saving
	Lower machine or process failure
	Estimated 12% to 18% cost reduction over reactive maintenance approach
Disadvantages	Labor intensive
	Consists performance of unnecessary maintenance
	Potential for incidental damage to components in conducting unnecessary maintenance
	Catastrophic failures still likely to happen

Table 2. Preventive Maintenance pros and cons (O&M Best practice, 2010)

2.4.3 Predictive Maintenance

Predictive maintenance (PdM) or sometimes called “on-line monitoring”, “risk-based maintenance”, or “condition-based maintenance”, is the latest maintenance approach adopted by many industries which analyze efficiency, productivity, and remaining useful life for scheduling before occurring any breakdown in the system. There are various definitions for this type of maintenance, but the general premise of PdM is that steady monitoring of the real mechanical condition, functional efficiency, and other indicators of the working condition of machine-trained; moreover, the operating systems are going to contribute the data needed to verify the highest interval among repairs and reduce the range and cost of unscheduled breakdowns created by machine-train failures.

Performing PdM has a direct impact on the overall equipment effectiveness (OEE), by strengthening the equipment life cycle and quality, reducing human effort, maximize supply and facilitate the management of reliability and errors, losses, wastage, and costs. The physical structure of equipment and the kind of failure is associated with an evaluation of identifying unpredictable problems. Consequently, the assessment of the predictive maintenance model is based on the mathematical models that are beneficial to determine when failure arises and when to perform maintenance action. Hence, PdM supports measuring and report physical parameters continuously for evaluating and comparing data to make maintenance decisions. The convergence of PdM with preventive maintenance is only in terms of scheduling the maintenance operation in advance to prevent equipment failures. In comparison with the traditional preventive maintenance, PdM schedule operations are based on gathered data from sensors as well as trained algorithms[31–33].

In another word, the PdM is an approach or an attitude which represent the actual operating condition of plant machines and systems to optimize whole plant operation. By using the most cost-effective tools such as vibration monitoring, thermography, tribology, performance monitoring, and ultrasonic noise detection and so on, the PdM can reach the actual operating condition of critical plant systems and according to the current information schedule all maintenance activities on an as-needed basis.

The developed version of predictive maintenance is known as Condition Based Maintenance (CBM) where provoking alarms are triggered before occurring any breakdown. Contrary to dependent on mean-time-to failure (i.e., industrial or in-plant average-life statistics) to schedule maintenance operation, condition monitoring uses direct monitoring of the actual mechanical condition, system efficiency as well as other indicators to identify the current mean-time-to-failure or loss of efficiency for each equipment or machine in the operation. The various techniques and algorithms can be used to implement CBM. The predictive threshold in CBM is presumed as degradation-based failure which has to reduce to an allowable level for better efficiency. CBM plans prospective component’s health conditions by signal processing methods which provide decision support for predictive maintenance. Real-time prediction and data acquisition support to estimate a sign of likely hazards as well as prevent them from occurring[32].

In general, executing which maintenance approaches are suitable for maintenance operations are based on two parameters: the frequency of failure and the time development of failure (the below figure gives more information regarding these two factors). Occurring failure in an acceptable normal frequency Figure a, preventive maintenance in any approach can be a suitable choice as a countermeasure. When failures have development time like pattern Figure c, predictive maintenance can be a proper technique in this case. Figure d demonstrates failures without a development time might take advantage of a predetermined preventive maintenance method instead, such as time and calendar-based, in case the failures happen in a moderately regular frequency. Figure b represents the random failures occurring that a development time could possibly benefit from a PdM technique, whereas components without a development time may require to be operated by a corrective maintenance technique. But the right choice of maintenance depends on the operating context of the asset. Other points of view, such as HSE, finance, quality, also require to be taken into consideration.

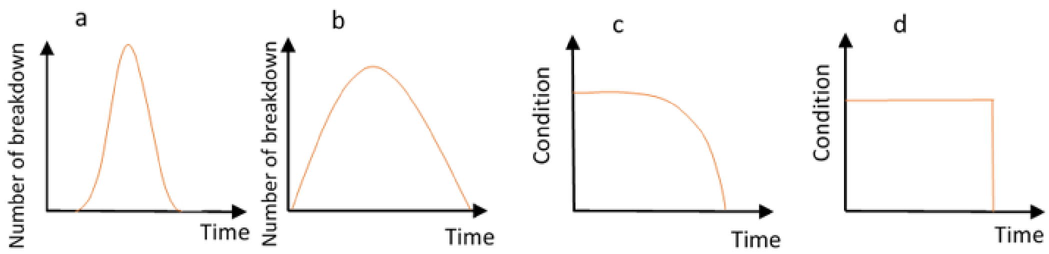


Figure 2-26. Failure frequency (a & b) and failure development time (c & d)

When the condition monitoring methods execute properly, it has a great impact on failure reduction, but if they are unsuitable they can be a very costly and sometimes caustically unsatisfying loss of time. Condition monitoring not only requires to have an acceptable pay-back period but also needs to be technically feasible. In order to achieve a feasible condition monitoring, the development time of failure importance has to exist to perform a warning period. This is sometimes referred to as a Potential failure to functional failure or p-f curve that P is identified as a measurable potential failure and f is a functional failure.

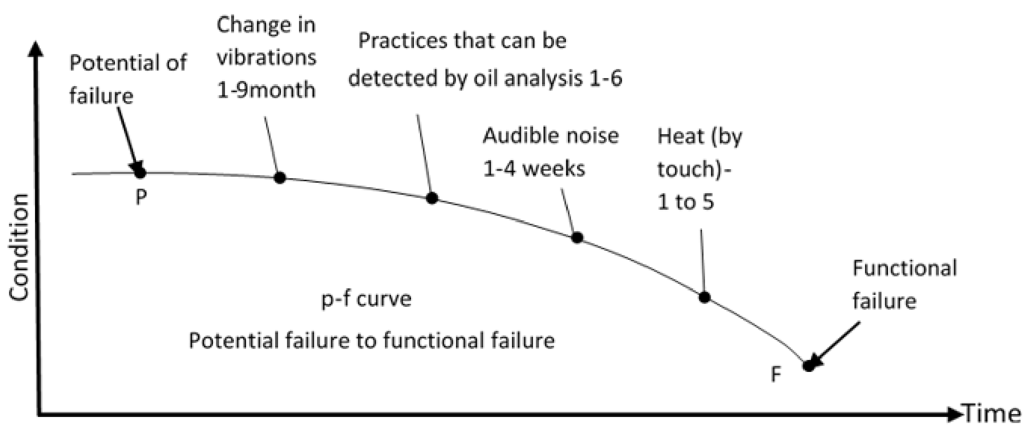


Figure 2-27. Example of a p-f curve of a ball bearing

PdM has many advantages in comparison to other maintenance strategies. A well-organized PdM program is going to minimize catastrophic machine failures from 70 to 75%, reducing downtime up to 45%, cost reduction up to 30% as well as boosting production to 25%. The following table gives more information regarding the advantages and disadvantages of the PdM technique[34]. Another significant benefit of predictive maintenance is to evaluate the RUL of a machine or a system. According to previous sections, the RUL is the time between a machine's actual condition and failure. Three different models exist to estimate RUL: survival mode, degradation model, and similarity model. Using each model depends on how much data and information are available. For instance, a survival model can be used in case data are available only from the time of failure rather than complete run to failure histories. As for using the degradation model, the data should exist between the healthy state and failure, and the safety threshold should not be exceeded in the current condition. The similarity model can be used, when data spans the whole deterioration of a machine from a healthy condition to failure. The figure below illustrates mentioned models[35]. Table 3 summarized the merits and demerits of predictive maintenance.

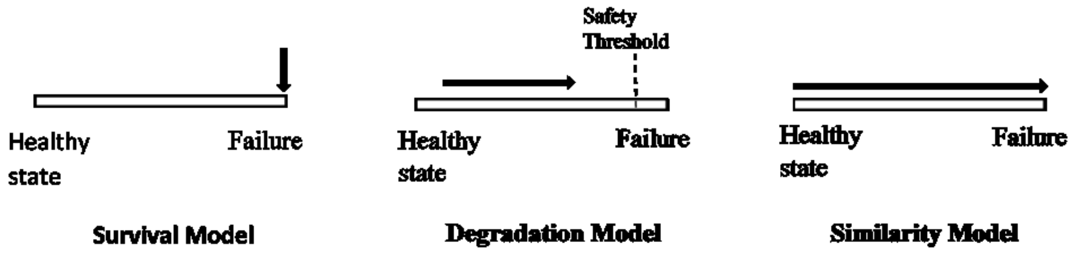


Figure 2-28. RUL estimator models

Preventive Maintenance	
Advantages	Enhanced component operational life and availability
	Provides for preventative corrective actions
	Reducing equipment or process downtime
	Reducing in expenditure for parts and labor
	Increasing product quality
	Improved HSE
	Enhanced worker morale
	Predicted from 8% to 12% cost savings over preventive maintenance technique
	Energy saving
Disadvantages	Increased investment in predictive equipment
	Require skillful operators
	Savings potential not readily seen by management

Table 3. Predictive Maintenance pros and cons (O&M Best practice, 2010)

Prediction is estimating the period of time after which a component can no longer perform its intended or expected capability to enhance system safety. The ISO 13381-1:2004 (International Standard Organization) elucidates Prognostics as the TTTF (estimated time to failure) and the risk of existence or subsequent appearance of one or more failure modes. The various researches have categorized condition-based monitoring strategies differently, but according to the section 2.3 the most common strategies which could be seen are defined as[36]:

- Data-driven
- Model-based
- Knowledge-based
- Hybrid

Data-driven approaches are originated from the configuration, operation and historical run to failure data relevant to maintenance decision-making. By informing the maintenance decision based upon the failure threshold, these methods are often used for prediction. For instance, the Wavelet packet decomposition and/or HMMs (Hidden Markov Models) techniques can be used where time-frequency properties allow more accurate results than using time-variable only. Nevertheless, the techniques result from the historical data used for estimating machine life without the foreknowledge of the physics of the formation of a component. Moreover, there are other techniques for data-driven strategies, such as PEMFC (Proton Exchange Membrane Fuel Cells), SW-ELM (Summation Wavelet-Extreme Learning Machine) and SVM (Support Vector Machine) and so on.

Model-based approach is also known as the physical-model-based technique which is related to an understanding of the physics for reliability predictions. By using physical science of components and generated empirical equations to estimate the conditions. The Crack-growth-model also can be used for prognosticating the RUL (remaining useful life) of a system affected by the fatigue failure mechanism. By evaluating such crack failure such as fatigue, wear out, and corrosion of components relevant to mathematical laws used to predict RUL. The model base strategy should be a combination of experiment, observation, geometry, and condition monitoring of data to predict any damage resulting from an individual failure system.

The knowledge-based method is a combined experience as well as computational intelligence approaches relative to collected data from domain experts and rule sets for interpretation. An expert mechanism for decision support working according to the principles of service feedback for analysis. Variables of reliability are predicted using an experience-based approach to collect data for understanding the operations of an asset. The knowledge-based approach evaluates the correlation between the actual condition and a database of previous failures and infers the life expectancy from prior occurrences using expert and fuzzy systems.

A hybrid model is a combination of one or more approaches for estimation to improve precision. This model uses non-parametric and parametric information to implement prediction as well as improving precision. The quality of data and the comprehensiveness can be inadequate for the data-driven model because they need historic data historical knowledge. Therefore, the hybrid model considered all three approaches (the experimental-based model, data-driven model and physics-based model) for estimating the RUL[36]. Consequently, predictive maintenance is showing great potential when conducted by an ML (machine learning) algorithm that works in the domain of AI and DT. The following sections are more going through the state-of-the-art technologies in PdM.

2.5 Cutting-edge Technology in PdM

The advent of the fourth industrial revolution has led to a noticeable connection between the physical and digital world, referred to as CPS (cyber-physical systems), IoT (internet of thing), IoS (internet of service), and DM (data mining). The main objective of Industry 4.0 is to initiate the interaction among a number of technological advances which is going to create additional benefits in the manufacturing process, maintenance management. In another word, it has had great advancement by associating various technologies which generate and communicate information between systems. The data achieved from different resources are interpreted and turned into useful data. Those useful data are subsequently used to control and coordinate the systems as well as subsystems to perform optimally and possibly individually. These technologies can be used in the purpose of predicting product performance degradation, and autonomously managing as well as optimizing product service needs[37].

According to the high applicability of Artificial Intelligence (AI) and Digital Twin (DT) in industrial sectors, they are among the top ten technology trends in the last years. The association of big data analytics and AI techniques with DT enables the features of real-time monitoring and digitalization for asset management. This combination is leading to evaluate the past and present condition of machines and makes predictions about the future state[38,39]. The next part of this section focuses on the application of AI and DT technologies in predictive maintenance.

2.5.1 Application of AI in PdM

Artificial Intelligence is fundamentally a computer system implemented as a replacement for the intelligent functions of human beings. It imitates techniques of solving problems and learning in human beings over data and knowledge collecting. AI is also known as computational intelligence or machine learning and consists of the following area of activities: Processing of human language, image and visual processing, intelligent robots, neural networks and expert systems.

One of the most applicable technology in the field of machine diagnosis is Expert systems. It tries to maintain the information and knowledge of experts and make identification of any irregularity of a given piece of equipment by classification, diagnosis, and prediction. Accordingly, AI can support preventive maintenance by evaluating big data collected from numerous sensors to monitor, identify, and prognosis machine failures. The application of AI frameworks can lead to significant cost savings, increasing operational performance and safety as well as raising the remaining useful life of assets, especially for identifying equipment condition and predicting when maintenance should be performed[40–42].

Machine learning techniques can be divided into three categories, unsupervised, semi-supervised, supervised, and reinforcement learning. As for unsupervised learning, the data is not going to be labeled. By means of analogies among the data points, the ML model is intended to find out the unknown patterns in the data. Therefore the algorithms should be developed in a way to discover structures and patterns in the data independently. For the semi-supervised learning approach, the input data is a combination of marked and unmarked data points. While in the supervised learning approach, the machine learning model utilized labeled information training data that the specified labels with the proper output and plans to learn a mapping of inputs to outputs. This step is iterated until the model reaches a suitable level of precision on the training data and can anticipate the outputs for the new cases. The last machine learning approach is (reinforcement one) used trial and error in an exploration versus exploitation way to find the behavior that generates the highest rewards. Moreover, condition-based maintenance is used in convergence with AI techniques for tough fault detection and diagnosis (FDD). There are several AI techniques such as neural network (K-Nearest Neighbors) and pattern recognition, fuzzy logic, support vector machine (SVM) and so on which talked in the fault detection and diagnostic section more about them[43].

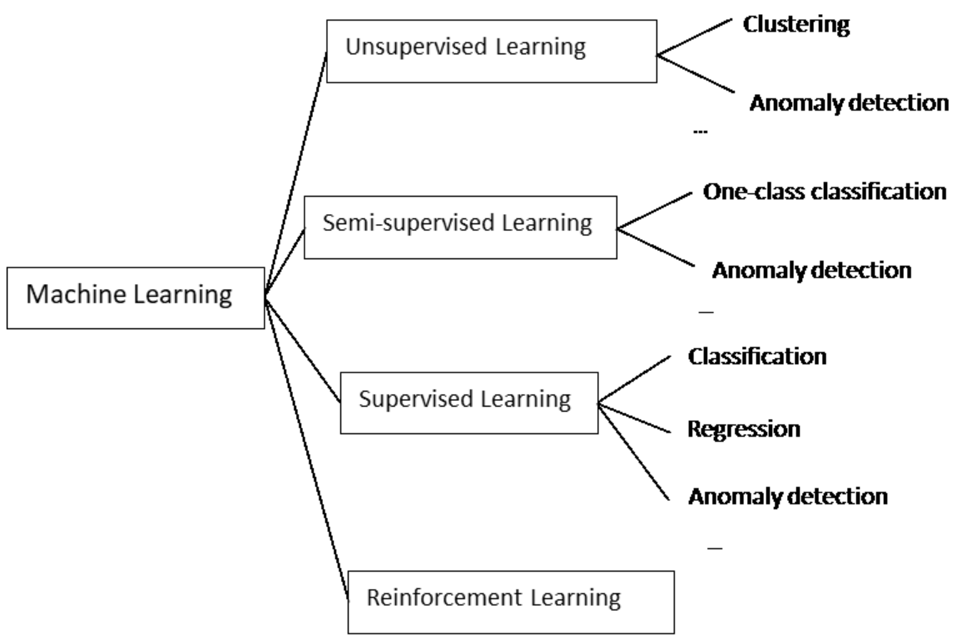


Figure 2-29. Classification of machine learning the ML tasks

One of the chief complexity of executing an AI process to maintenance data is the selection of the right workflow, therefore this section is going to explore the simple and complete framework for AI technology in PdM. A machine learning project should always initiate with the establishment of a precise and clear interpretation of the goals. Because the system implements a specific task and when a model has an unclear objective, it is not able to predict what it is intended to. The most significant step in the ML project is the capability to realize the data applied and how it is relevant to the task that wants to be solved. Choosing the algorithm should be purposeful. Because if it selects randomly, it will not be effective. Therefore, using a data set leads to acquire good results. It is essential to figure out what is going on in the data set before beginning to build a model. As for creating a machine-learning solution, the following issues must be answered:

- What problems are going to be solved?
- Does an accessible data set allows to solve these problems?
- What is the suitable approach to paraphrase the problems as a Machine Learning challenge?
- Is the accessible data set adequate to represent the problem that is going to be solved?
- Which attributes or properties have been extracted and can they lead to a correct estimation?
- How the outcome of the application of ML can be measured?
- How does achieved ML solution interact with the rest of the process?

It is important to take into consideration that the ML algorithms and techniques are only a small part of a larger process for solving a specific challenge. Because a huge amount of time is wasted on creating the complex ML solutions, while at the end it is discovered they do not solve the problem which is waiting for. Thus, the assumptions for creating the ML algorithms can be caused explicitly or implicitly. Fig 2.30 represents the machine learning workflow[44].

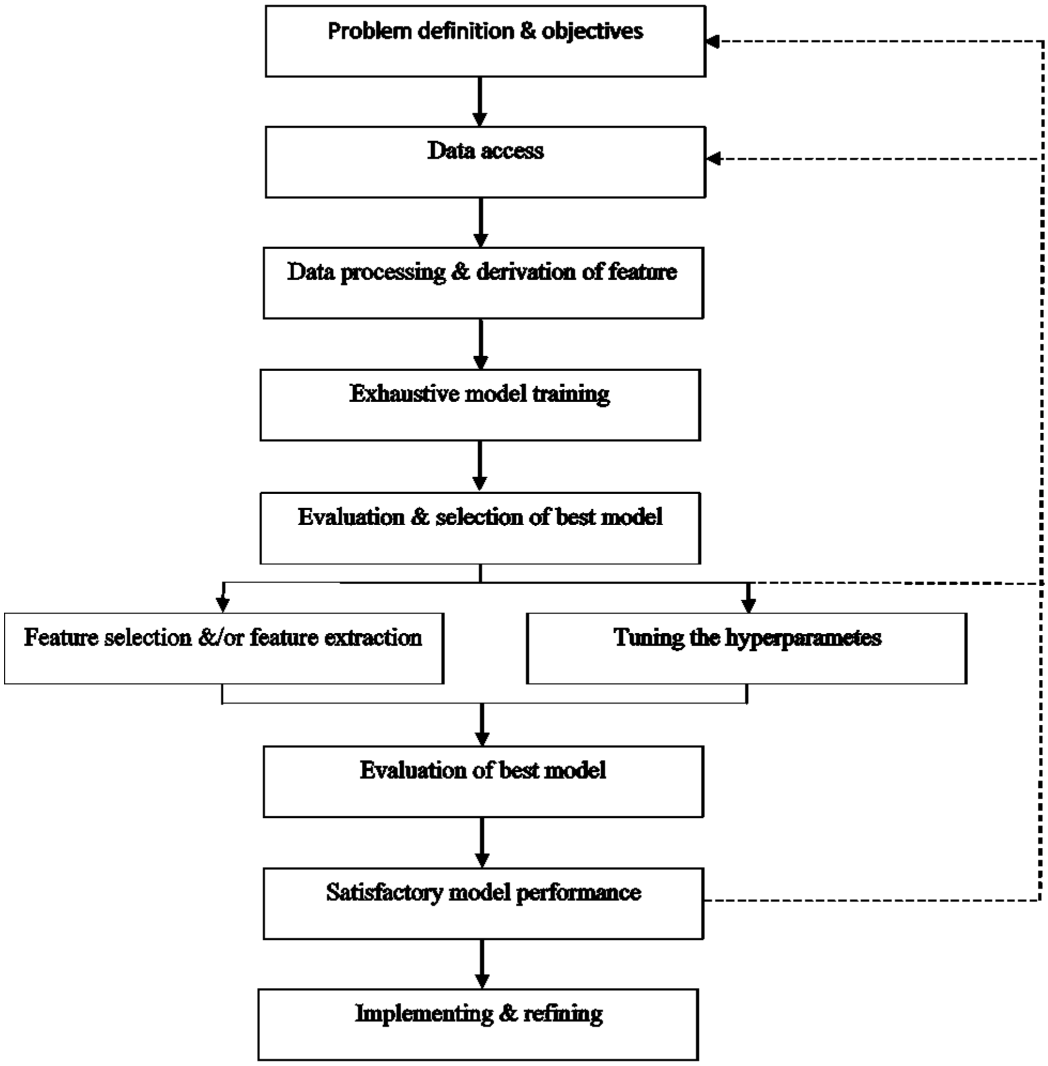


Figure 2-30. Machine Learning procedures

For evaluating the ML model different assessment techniques are apply to verify the attributes as well as the performance of simulation. In machine learning approach the regression problems and classification problems are two common types of problems. For those models which have dependent variables (continuous in nature) regression methods can be used while for those model which have categorized variable classification methods can be utilized. In further chapters, confusion matrix will be applied for classification approach in order to demonstrate the actual and predicted values. According to the following figure, the true positive section represents the positive prediction whereas the false positive one represents the values that are negative but falsely estimated as positive (named as error I). The false negative section are related to those values which are positive but falsely estimated as negative (named as error II). The last section is related to those values which are negative and estimated as negative[45].

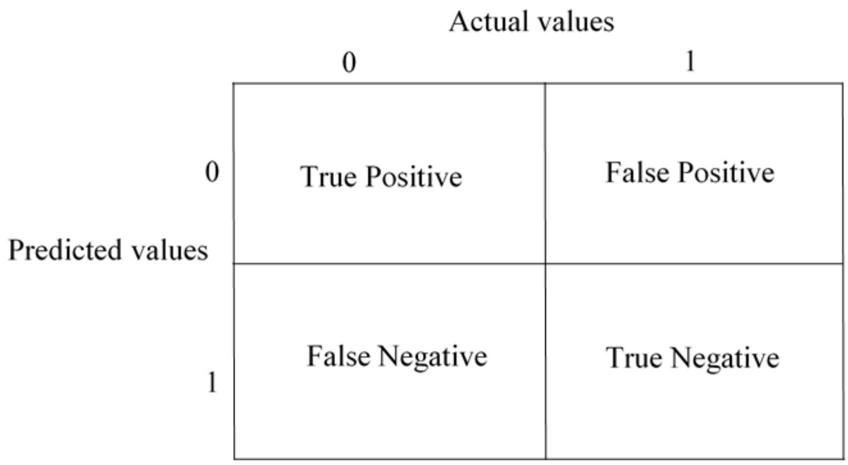


Figure 2-31. Confusion matrix for binary classification

2.5.2 Application of Digital Twin in PdM

The appearance of real-time and condition monitoring has led to the generation of a huge abundance of information that necessitates using big data analytics through a product life cycle. The key objective of big data analytics is providing personalized and precise product service and enhancing quality. The data source for big data analysis is known as PLM (product life cycle management). One of the main applications of PLM data is in the root cause analysis of a product during the integration of maintenance data.

The Digital Twin (DT)was first introduced as a PLM concept to maintain product-related information over the entire life cycle. In general, DT can create value with the virtual illustration of a physical system that is able to real-time monitoring of a product or an asset through its life cycle. DT can evaluate performance data gathered over time and under various conditions. In the PdM framework, DT can be used widely in[46]:

- Health monitoring of assets, by monitoring fatigue, abnormalities, deformation and reliability of equipment
- Digitally analyzing the life of a physical asset to anticipate its performance affected by various ambient condition
- To improve an asset intelligence with its historical and actual state

The DT requires to be fully associated with the asset and interacted with the environment as well as its physical processes. Due to the diversity of components and the close interaction among computer programs, platforms/networks and physical components, this interaction becomes more complex. Therefore, DT is not only a passive twin of the real systems, but also is an active and reactive component that can constantly analyze the actual condition of its real replica and include professional recommendations in the context of optimizing processes, forecasting and scheduling maintenance, and enhancing the design and overall performance.

The mentioned interaction in DT needs a domain understanding of the physical asset and some facilitate technologies. DT concept model is comprised of three key elements: physical modeling of the machine, virtual objects in virtual space, the interaction of data among the virtual object and real machine. The main purpose of real-time condition monitoring and updating of the digital model is to create a similar behavior of the machine.

A significant value added to DT for PdM is that a set simulation can be implemented on the digital model of the machine for purpose of exposing aspects, like component deterioration of the real asset which cannot be directly determined by using data only gathered by the real machine elements. To achieve this, a group of Virtual Sensors is used for purpose of defining the components which will be monitored throughout the simulation. This feature is led to prevent stoppages the real machine's operation during its activity for testing. Based on the DT approach, the industrial men and users are able to simulate the future condition of the machine, generate failures profiles and even plan the maintenance operations[47].

A physics-based simulation refers to solving the counter kinematics of the model by supplying position signals as well as acquires the calculated torque signals that are exerted to each machine`s element as a simulation output. The same procedures will be attributed in the reality to the simulation models directing to utilize the simulation output for the RUL calculation. The utilization of static digital models to create the required data for remaining useful life anticipation is not suggested because the real machine condition may be changed. To verify that the created information by the simulation of the digital model can be utilized for the precise anticipation of the RUL, the physics-based digital models have to be updated online by using information coming from the actual world.

In order to create the DT for the cyber-physical-system, the following procedures should be taken into consideration:

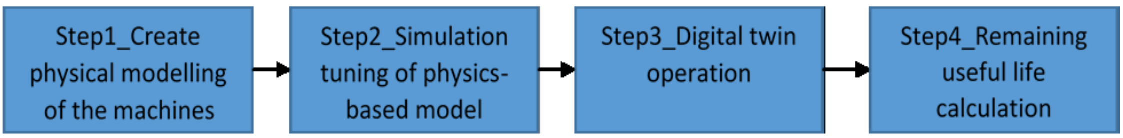


Figure 2-32. Overview of DT framework for PdM

1. Create a physical Model

The first stage is to create a 3D model of the cyber-physical system. Except for the kinematic as well as dynamic features of the equipment, a group of virtual sensors will be incorporated into the equipment simulation models. This step contains replicating physical processes and objects to digital systems with the use of CAD models that represent the kinematic and structural models of the machines. The comprehensive model of each machine includes a number of components that demonstrate the dynamic behavior of each machine's element on the basic model of the mechanical, electoral, hydraulic and other functions. For the purpose of having an effective and practical model that can be simulated in an allowable computational time, it has to be determined which elements of machine are supposed to be modeled. The number of the machine's elements are determined as black boxes (without any information of its internal operations) or as the grey boxes (utilizing theoretical information to carry out its model) or as white boxes which represent the accurate functionality and operating mechanism of the element are known.

Thereafter defining and modeling the elements, the virtual sensors of the model have to be defined for implementing the machine's simulation model. The virtual sensors are simulated as a layout of components as well as their functionality is to observe and collect information from the physics-bases models through their simulation. Thus, it is significant to have determined and specified the information to be collected from the model's simulation with the purpose of using it in the algorithm of remaining useful life predictions. The utilization of virtual sensors, at each component and application of the model, rises the computational time of the model's simulation. Finally, the modeling parameters are defined that will be utilized to upgrade the physical model, based on the sensor and controller information. These parameters are modifiable and will be linked to the synchronized simulation tuning with an objective to modify the attitude of the machine's model with its real machine.

2. **Tuning the physical model**

The second stage is to leverage two-way communication in order to synchronize the real and digital twins. While the simulation of the equipment model is applied for its RUL calculation, the equipment model must be tuned constantly to prevent feasible variation between its real and simulated functionality. The main purpose of this step is to recognize the DT of the real machines in the simulation circumstances. The most crucial stage in tuning the physical model is how the data can be monitored with the physical sensors as well as controllers. Based on the previous step, the modeling parameters constitute the base for the interpretation of these data. A data synthesis method can be used for both physical and computational reductions. Physical reduction is referred to the abundance of information that has to be synthesized (potential lack of information may happen) whereas computational reduction is referred to the computational time for the information synthesis. The purpose of the synthesized data is to tune the model by upgrading the modeling parameters.

More precisely, the current information which is collected by the machine's sensors and the controller can be used for two purposes. The first reason is to supply them as input in the digital model for the simulation of it and the second one is to compare them with the simulation's output. Consequently, a comparison between the current attitude of the robot and the anticipated one will occur. For recognizing the DT technique, the modeling parameters which already determined in step 1 are going to remove the error of this comparison had to be defined. Then periodical anticipation of the parameters modeling should be considered in the digital model. This tuning process is in accordance with the current machine's element behavior with the estimated one. These comparisons are performed with the signals. Because the model is tuned and the modeling parameters are anticipated, the variation among the current and digital machine's element performance is decreased. If this variation is less than the appropriate limit, the tuning process stops, and the new modeling parameters are achieved and given to the digital model.

Another task that should be considered in determining the priority of the online real-time machine's element tuning. Accordingly, the synchronized tuning of the simulation model is responsible for maintaining the accuracy of the DT accomplishment above 95%. On the contrary, it is not vital for all modeling parameters to be constantly upgraded.

3. **Digital twin operation**

The third stage contains the simulation of the physics-based model utilizing collected sensors and equipment controller data as input. The key intention of this step is the application of the DT. Thereafter steps 1 and 2 (modeling and tuning the machine through their operation), the next phase is allocated to simulation. The similar tasks that the actual machine has to implement are utilized as input to the simulation. These tasks are carried out virtually by the simulation software, and their results are utilized for each machine's remaining useful life computation for the RUL phase. The results of the virtually executed tasks are compared with the current result of the real machine operation and the output of this correspondence is used for the next step.

4. **Remaining useful life calculation**

The fourth stage consists of associating the simulation outcome and monitored equipment data to anticipate the equipment's remaining useful life. The reliability factors of the equipment have been merged into its simulation models[48,49]. The elements of RUL are measured by analyzing the data collected from the controller, sensors, and the simulation of the machines' physics-based models. The model's associated simulation enables the estimation of the system's performance under various operational conditions. In addition, the digital models can be utilized for the simulation of the assets in the prospective based on the determined operational plan. The essential of DT emerges from the reality that the gathered sensor data are not usually sufficient for RUL estimation. The physics-based models can only extrapolate data using virtual sensors on the basis of a mathematical model of the machine.

The supervised parameters can be associated with voltage, current, temperature, torque and power. They are collected directly by the controller, whereas the physical-based models utilized the virtual sensors as mentioned in stage 2. All these assessments are categorized and filtered for an individual time phase. The purpose of this classification and filtering is to prevent the random sudden alterations of the parameters which are not significant to the machine's condition. The result of this step provides the computation of the machines' component RUL through their operations.

The remaining useful life estimation is based on the comparison of the anticipated behavior of the machine's elements and the nominal conduct of the machine's element. This analogy is according to signal comparison, especially with torque signal one. The process to predict the RUL for a machine's element is to simulate the digital model continually, by considering the prospective operation plan of the actual machine and the degradation model of a physical phenomenon over a period of time as well as comparing the simulation result with the nominal output of the machine. Productive algorithms are utilized to handle and merge the collected information intending to provide the created data to the simulation software. These data are used as an entry for the simulation and the tuning of the simulation model[48].

There is a difference between time to failure (TTF) and RUL. The TTF is the amount of time left before a machine reaches a mechanical failure, while RUL is the amount of time remained before a machine fails to operate within allowable limits. The TTF can be computed always the feature value cross an individual value of interest known as the detection threshold. The TTF assessment is set to zero prior to the feature value cross the detection threshold. Thereafter threshold is crossed, the TTF will be achieved. The TTF calculation is the variation between the actual time step and the time of the estimated threshold crossing. The RUL calculation is also similar to TTF, but instead of a failure threshold, an upper operating limit threshold exists. The figure below depicts the differences and shows the operating threshold of RUL is lower than the failure threshold. Therefore it presents the importance of RUL, because RUL supports to repair system prior to failure[50,51]

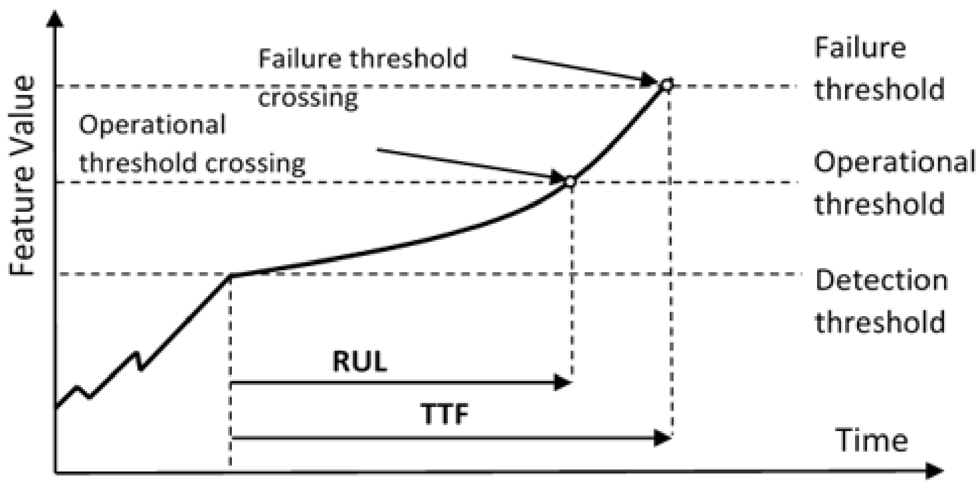


Figure 2-33. Difference between RUL and TTF

Chapter 3

Drilling Mud Pump Common Malfunctions and Maintenance Approach

3.1 Overview

Reciprocating positive displacement pumps, also known as slush pumps or power pumps are a chief component of the circulation system. They are capable to supply a continuous flow rate of fluid regardless of the pump's outlet pressure. Reciprocating pumps utilize fluid pressure to transmit power. The benefits of the reciprocating positive displacement pumps consist of the capability to pump high solid content fluids, to move the large particles, no difficulty in operation, reliability, operating during a broad range of pressures as well as flow rate by modifying the diameter of liners (compression cylinder) and pistons. These kinds of pumps are categorized into duplex and triplex pumps.

Two kinds of piston strokes exist for the reciprocating positive displacement pumps, the single-action piston stroke, and the double-action piston stroke. The single-action stroke has three cylinders known as the triplex pumps (Figure 3.1), while the double-action type (Figure 3.2) has two cylinders, known as duplex pumps. In general, two duplex pumps can perform the job efficiently for uncomplicated drilling applications; however, the triplex pump is the most efficient with complex well trajectory designs and increased pumping requirements.

Figure 3-1. A triplex mud pump (B.GUO, 2011)

Figure 3-2. A duplex mud pump (B.GUO, 2011)

Triplex pumps are more compact and lighter than duplex ones, their output pressure pulsation is not as tremendous, and they are cheaper in comparison with the duplex pumps. Accordingly, the most recent pumps being placed into operation are of the triplex design. In general, the duplex pumps can manage higher flow rates while the triplex pumps can supply with higher working pressure. On the other hand, for all of the mentioned pumps, the flow rate and working pressure can be modified by changing the sizes of the liners inside the pump. Normally, two pumps can be operated at shallow depth for high flow rates and only one can be utilized for the deeper sections. Advanced drilling rigs on the contrary have four pumps, three of them working in parallel meanwhile one is on standby. On a particular occasion, the fourth pump is also utilized as a riser booster pump, such as in offshore drilling, to support the movement of cuttings in the annulus. The pump on which this study focused is the triplex pumps. The following section is going to explain more about mud pumps components in general[6,52].

3.2 The Key Mud Pump Components

There are two main principal sections to drilling mud pumps, the power end, and the fluid end. The power end part takes the input power, generally over a driveshaft, and transforms it into the reciprocating motion required for the pistons. Furthermore, it uses a crosshead crankshaft for this transformation. The fluid end section, which consists of valves, pistons (or plungers), and liners, is the division where the actual pumping occurs. The fluid end part is in direct contact with the drilling fluid. The below figure illustrates the plan view of the triplex mud pump.

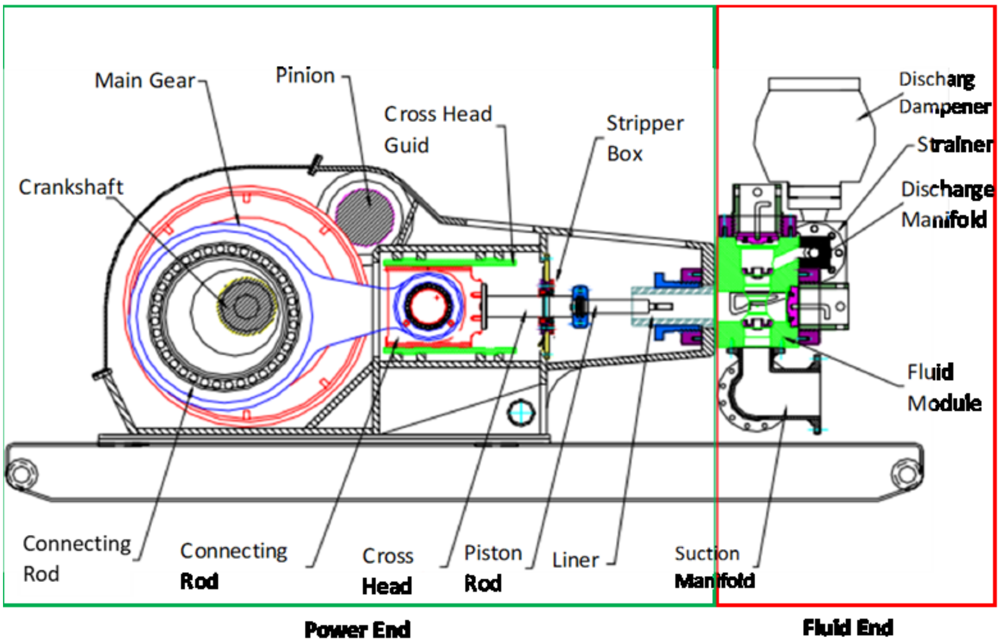


Figure 3-3. Cross-sectional view of the triplex drilling pump

3.2.1 Crankshaft

The crankshaft is a shaft driven by a crank mechanism, consisting of a series of cranks and crankpin which converts the reciprocating motion to rotational motion. Additionally, converts the energy that applies in the pivot point and distributes equally to the center point. It is made of cast alloy steel and furnished with herringbone gear. The power balance crankshaft decreases vibrations and noises and leads to extend the life of the bearings and crankshaft (Figure 3.4). It supplies the axis of rotation, or oscillation, of components like gears, pulleys, flywheels, cranks, sprockets, and the like and controls the geometry of their motion and is supported by bearings[53,54].

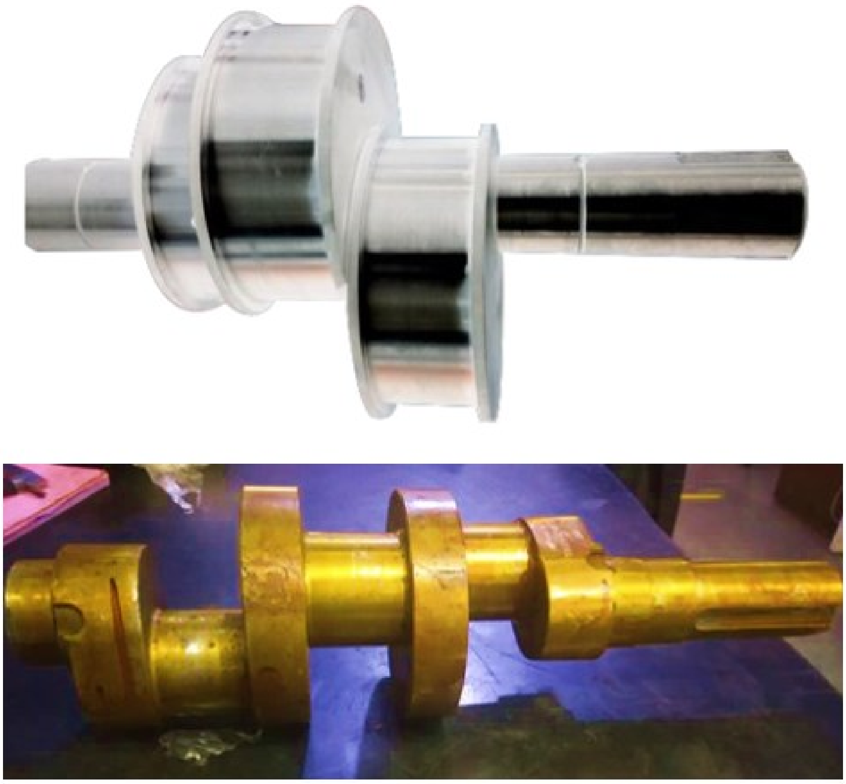


Figure 3-4. The triplex pump crankshaft (indiamart.com)

3.2.2 Fly-wheel

The fly-wheel is a big disk with teeth that act as an internal wheel. It is massive to provide energy for pistons and is mounted in the crankshaft (Figure 3.5).

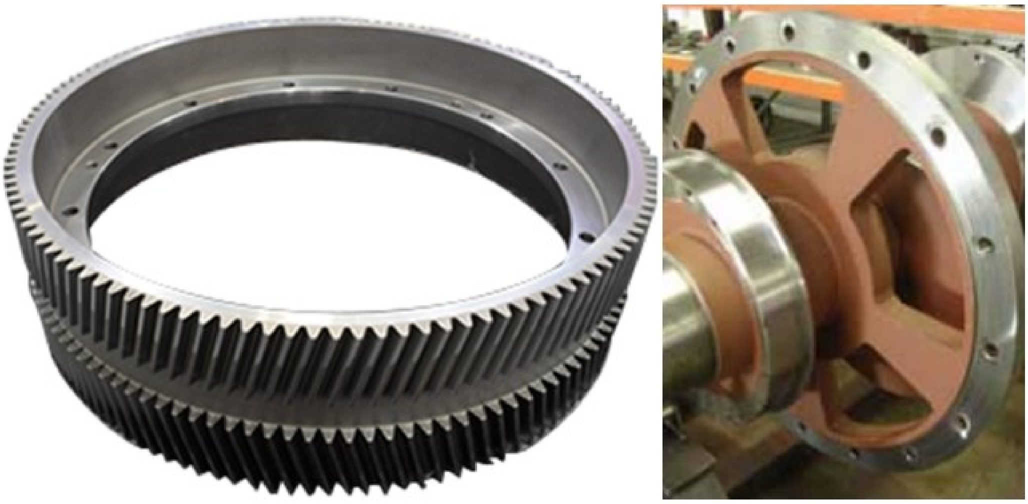


Figure 3-5. Flywheel ring and fly-wheel (Dezhou Rundong Petroleum Machinery Co., Ltd, whitestar.com)

3.2.3 Con-Rod (Connecting Rod)

The Con-Rod transfers the rotating force of the crankpin to an oscillating force on the wrist pin. In addition, it supports avoiding side forces in the cylinder and is furnished with roller or ball bearings[55].

Figure 3-6. The Connecting Rod (M.Stewart, 2019)

3.2.4 Crosshead

The crosshead which is known as X head or universal joint, is used to withstand the side forces (Figure 18). The flange bolts with pinhole fit are utilized for connecting the crosshead to the extension rod. This rigid connection secures the concentricity of the extension rod and crosshead (Figure 3.7).

Figure 3-7. Cross head assembly (Dezhou Rundong Petroleum Machinery Co., Ltd)

3.2.5 Pony Rod

The pony rod is the connecting rod that comes from the crosshead and supports to transform rotating energy to linear energy. It locates below the polished rod and is used to make a rod string of a desired length , and connected to the piston rod.

Figure 3-8. Pony rod (Hebei petroleum machinery.co)

3.2.6 Piston Rod

The Piston rod known as the piston pull rod, is the essential accessory for the connecting the power end and hydraulic end of mud pumps. The piston pull rod is a vulnerable component of the drilling pump. The bottom end (large end) of this piece, is connected with the power end of the pump within the clamp and the smaller part of it is connected to the piston that carries in a reciprocating direct line in the cylinder liner to generate pressure.

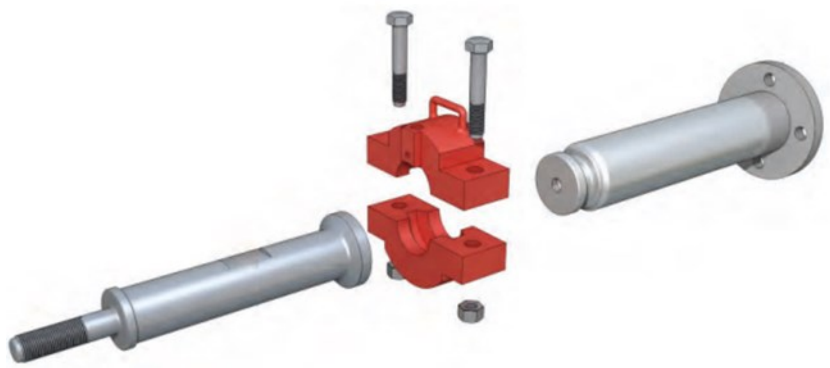


Figure 3-9. Rods assembly (texstarep.com)

3.2.7 Piston, Liner, and Valve

The piston moves forward and backward in its liner, applying a force on the cylinder chamber. Throughout the backward movement of the piston, the valve is opened and allowed the drilling fluid to be drawn into the cylinder. Thereafter the piston has completely retracted, it is pushed back into the cylinder. In the meantime, the inlet valve is closed and the exhaust valve open, letting the piston push the drilling fluid out of the cylinder under pressure. When the piston attains to its maximal depth of the cylinder, the exhaust valve closed and the process continues again and again.

Figure 3-10. Common liner types for pumps (Lakepetro.com)

Liners are always locked in place with metal contact, especially for high-pressure mud pumps. The liner packing is modified individually via set screws on a liner packing cage. In order to control the proper functioning of the packing, special tell-tail holes type can be used. In case the drilling fluid drips out of these holes the liners packing should be tightened. The middle of stroke is mostly faced with wear and it is result of the highest piston velocity in that point. The highest permissible liner wear relies on the pressure the pump has to overcome. The piston bodies have been produced with an individual tell-tale wear groove in order to support the piston wear.

Figure 3-11. The triplex mud pump pistons (texstarep.com)

Valves and seats can be categorized into three main groups. The first type is known as the full-open valve which is considered as the high performant type of valve and its seat has a fully open construction, without the support webs present at other types of valves. The pressure is equally spread on the tapered surface of the valve, therefore decreasing the appearance of valve seat wear and rising the valve assembly life. The second type is known as the Four web valve that is suitable for low and medium pressure range operations. It has center guide construction as well as provides a large bearing area for the valve that increases its operation life. The last valve type is called the Three web valve. It is the most well-known valve type in the oil sector and uses in a wide range of drilling projects. This valve type has a centered guide construction and provides support during pressure application for the valve body[56].

Figure 3-12. Valves and seats (texstarep.com)

3.2.8 Pulsation Dampeners

Since the pressure and the material are being pumped, most mud pumps can create high amount of friction and vibration. The pulsation dampener is used to create a more efficient suction process into the pump. It is filled with a little airth low pressure and has a rubber blader with air (Nitrogen gas) above it which reduces a surge in flow. It can be installed on both the suction and discharge sections of the pump. On the discharge face, it installs on the cross among the pump and the vibrator hose, that moves mud from the pump to the standpipe on the drilling mast.

Figure 3-13. Pulsation Dampener (Hebei petroleum machinery.co)

3.2.9 Vibrator Hose

The vibrator hose is a flexible hose assembly utilize to conduct high-pressure drilling fluids among two piping systems or among the mud-pump discharge outlet and the high-pressure mud piping system in order to mitigate noise, vibration, or compensating for misalignment as well as thermal expansion.

Figure 3-14. Vibrator Hose (Hebei petroleum machinery.co)

3.2.10 Pop Off Valves

The pop-off valves are designed to support against overpressure from the pump supply in the flow line. It is located over the mud pump near to discharge damper and will be opened at a preset pressure. It exists in two structures, needle and spring formats.

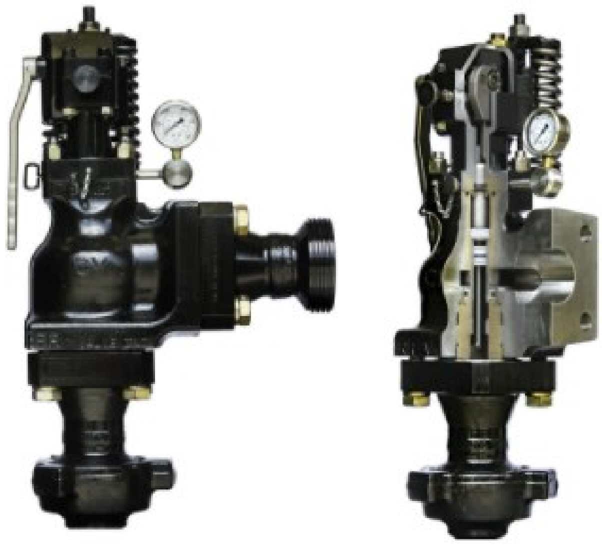


Figure 3-15. Pop off valve (rrvalve.com)

3.2.11 Pulley

The pulleys or sheaves are designed to connect pumps to diesel motors by V-belts, which transmit the required horsepower to the pump.

Figure 3-16. Pulley or sheave (Robust.com)

3.2.12 Bearings

There are four crucial bearings used in the triplex mud pumps. Main bearings (used in the crankshaft support), pinion bearings (input), wrist pin or crosshead bearing (connecting rod, small end) and eccentric bearings (connecting rod, small end). In a triplex mud pump design the load is changing in direction, while the in the single-acting type the load is consistent in one direction. Therefore in the triplex pump, two separate load zones are existed in the outer race of the connecting rod bearings, as significant connecting rod load operates in two directions.

The crankshaft main bearings are mostly the tapered roller bearing which is simple to install and perform well in tough conditions. The TDO (two-row double outer race) and spherical roller bearings are mainly used for crankshafts that in the spherical roller type a brass cage model has high strength and high durability in comparison with a steel cage. The Pinion bearings (input) are faced with the highest operating speed in the mud pumps and the spherical or roller bearing types are common bearings in for them. The next bearing model is the Crosshead bearing (connecting rod small end) which is installed on the shaft as well as in the housing in order to achieve a very low radial internal clearance in the installed position. The two-row HJ heavy-duty cylindrical bearing type is utilized as the crosshead/wrist bearings. The last bearing type in this classification is the Eccentric bearings (mounted on the connecting rod large end). They are the largest bearing in the mud pump which four-flanged locating-type cylindrical roller bearings are used in this section.

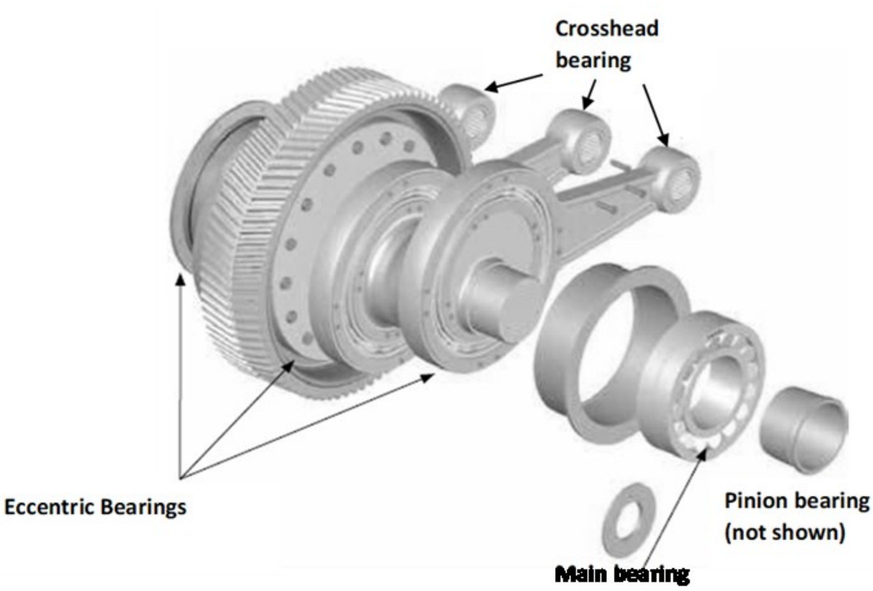


Figure 3-17. Main bearng types in mud pumps (R. Yorty, 2020)

3.3 Pump Performance Characteristics

The four fundamental parameters in pump performance are Power, Head, Flow and Efficiency. The below table represents basic terms and units in pump performance. It is commonly suitable to utilize monometric terms for the head as well as volumetric terms for flow. This is due to the fact that the same head-flow curve applies to fluids in a range of temperatures (without considering the consequence of viscosity). As for the power-flow curve, it will be changed in direct relation to the fluid density. These four fundamental quantities are achieved by this basic equation while efficiency can be measured directly[57]:

$$\frac{\text{Pump power output}}{\text{Pump power input}}$$

$$\eta = \frac{Q\rho g H}{P} \qquad (1)$$

The main parameters that have direct impact on pump performanc are given in the following table and figure 3.18 illusrates the genericperformance curve of the pumps.

Quantity	Other terms used	Symbol	Units	Other units
Flow	Volumetric flowrate, Capacity discharge, Quantity	Q	m3/s, L/s, m3/h, ML/d, Sometimes kg/s	IGPM, USGPM
Head	Total head, Total dynamic head, Generated pressure, Generated head	H	m, kPa	Bar, ft, psi
Power	Power absorbed	P	W, kW	hp
Efficiency		η	Decimal	%

Table 4. Basic terms and units in pump performance

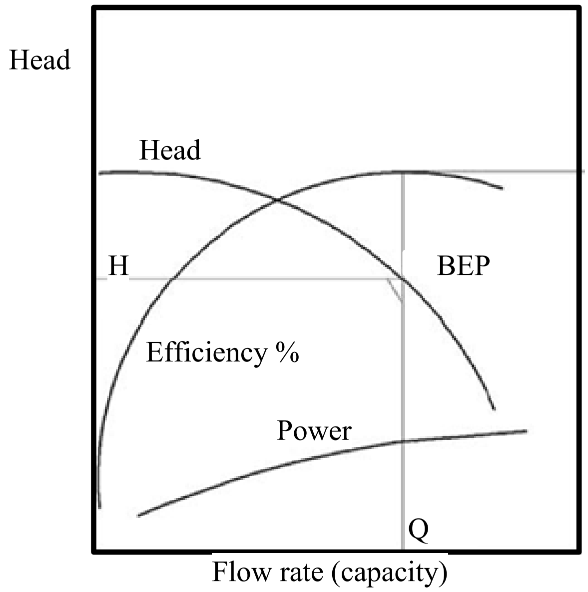


Figure 3-18. Pump performance curve (E. Shashi 2005)

One of the main features which can be measured in the condition monitoring of mud pumps is pump efficiency. Declining efficiency can represent itself through increasing cycle times; specifically machine slow down. In general, mud pump efficiency can be classified into three groups. Volumetric efficiency, mechanical or hydraulic efficiency and overall efficiency.

Volumetric efficiency is mainly dependent on the valve's condition and is defined as the measured output volume to the theoretical output volume. The theoretical flow or volume is computed by multiplying the pump's displacement per revolution by its driven speed. Deteriorating of volumetric efficiency is strongly caused by the delay in valve shutdown. During the backward plunger motion the valves are not entirely closed, as a result, the mass inertia of the valves, and some amount of drilling fluid have the possibility to flow back. By means of volumetric efficiency, the crews on the drilling rig can analyze the condition of mud pump in case of internal leakage through wear or damage. Additional reasons for decreasing this type of efficiency can be: leakage losses between piston and liner, leakage losses suction lines, gas or air absorbed in fluids and leaking in the of stuffing box[58]. The actual flow can be measured with various techniques and devices such as orifice plates, withdrawable double-tip pitot tube devices, ultrasonic flow meters. But one of the practical techniques for identifying the volumetric technique is pumping a specific amount of liquid from a tank to another and compare it via the theoretical volume measured from the number of strokes made. This process should be implemented during pumping through the well at a realistic rate to make sure the pump is delivering against pressure. The ideal time for doing this technique is when circulating prior to running casing and cementing. Generally, a triplex pump has higher volumetric efficiency in comparison with a duplex type[57].

Hydraulic/mechanical efficiency is attained from the theoretical torque needed to drive it divided by the actual torque needed to drive it. A 100% of hydraulic/mechanical efficiency means, when the pump is delivering the fluid at zero pressure, no torque or force will be needed to drive it. Instinctively, it is not feasible, because of mechanical and liquid friction. Torque is one of the crucial parameters of key performance indicators. For example, a progressive increase in a pump's torque may consequence of increasing flow to reimburse for growing leakage; an abrupt increase can be the result of a blockage downstream of the pump, whereas an abrupt decrease can indicate an upstream blockage. Torque can be measured with different tools such as dynamometer (determine torque and power required to operate a pump) and toque sensors which can provide real-time pump performance data. The torque sensors evaluate the twist in real-time and its electronics change the reading into a torque value[59]. Overall efficiency is achieved from volumetric and hydraulic/mechanical efficiency. It is utilized to measure the drive needed by a pump at a given flow and pressure. For example, if the volumetric efficiency of a triplex mud pump is 95% and hydraulic/mechanical efficiency is 91%, the overall efficiency will be 86.4% (0.95*0.91*100=86.4%).

3.4 Common Mud Pump Physical Damages

This section is allocated to the technical problems and their solutions, which directly and indirectly impact the NPT and HSE aspects of the drilling operations. This information was collected from a different maintenance and technical reports from onshore and offshore drilling rigs for the reciprocating positive displacement pumps (triplex models). The majority of accidents occur in the following main groups:

3.4.1 Failure in Pulley and Groove of Pulley

Throughout the drilling operation, when the driller observe the stork per minute (SPM) of the mud pump is decreasing and the V-belts are noisy as well as begin to stretch and slip on pulleys with making a high amount of smoke, noise and vibration. In this case, the temperature has to be checked on both electric motors (A and B) on the sprocket ends. If there is a temperature variation between A and B, that means there is a possibility of a defect on the pinion drive shaft pulley. Therefore, the side belt guard of the mud pump should be removed and controlled by supporting links of the pinion drive shaft pulley (sheave).

The reason can be originated from existing of crack or fracture on the sheave. Moreover, the crack can be developed and oversized which leads to the eccentricity and belts vibration during pump operation (Figure 3.19). Thereafter observing the failure in the pulley, the new items (pulley and V-belts) should be assembled. There are two possibilities after this maintenance. In the first one, the SPM increased and operated normally.

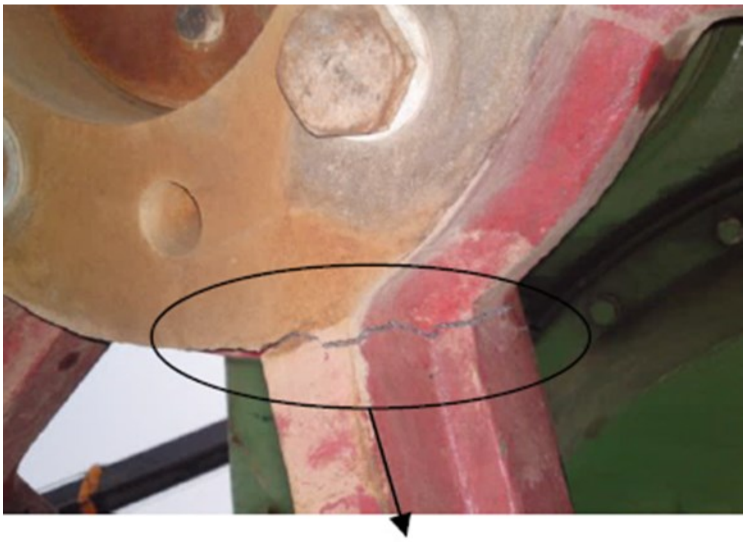


Figure 3-19. Failure in the pulley due to a developed crack (R.Khademi, M. Makvandi, 2014)

As for the second possibility, if the pulley was changed and the SPM increased at the beginning, but the V-belts started to slip, make noise and after somewhile SPM decreased again and the temperature of new pulley increased gradually. Then the maintenance team should inspect pulleys for any indication of abnormal wear (maybe there is a defect or pitting on grooves of the pulley). The main reason for these failures comes from low-quality material that used for manufacturing pump components. After replacing the new item the SPM shuold be increased and pumps operated normally.

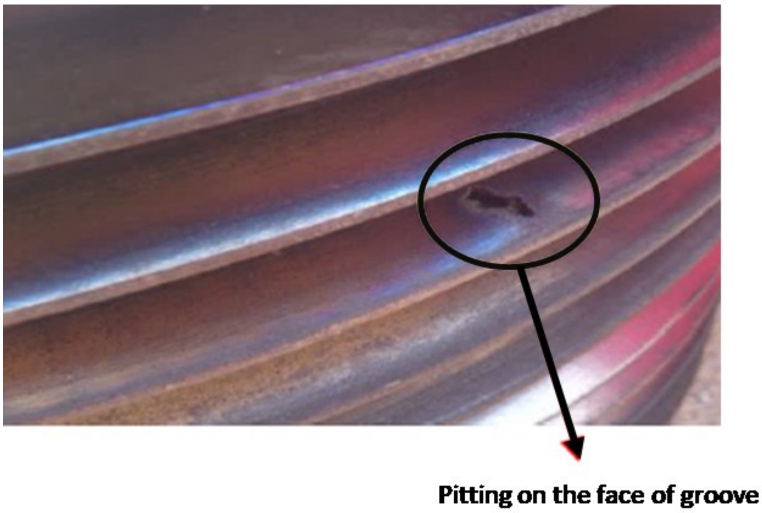


Figure 3-20. Pitting defect on the groove of pulley (R.Khademi, M. Makvandi, 2014)

In case the temperature of the new pulleys and V-belt increased with operating time, they can lead to slip and produce noise again. To avoid more damage, the drive between the mud pump and DC motors from V-belt can be changed to multi-chain drive. The replaces components consist of electric motor drive and pinion drive shaft sprockets and drive chains.

3.4.2 Failure of Bearing Carrier Bolt

Breaking or cracking the bearing carrier bolt in the crankshaft start with the loud noise. In this case, the mud pump has to be shut down instantly. Because it can damage crankshaft, main bearings, crossheads, crosshead pins. This failure‘s condition can happen in pump power end main parts involving main bearings, main bearing carrier bolts, connecting rod bearings, crankshaft, crankshaft gear as well as pinion gear.

3.4.3 Failure in SCR

The power generators used in drilling rigs are configured with the diesel-AC generators and the Silicon Controlled Rectifiers (SCR). On the DC drilling rigs, DC traction motors are controlled by SCR and the AC (alternate current) is generated by AC generators which are converted to DC (direct current) with a SCR system. The electrical controls are supported the electrical motors through variable speeds. The existence of this variable speed can assure different flow rates in drilling operations to compensate for downhole conditions and hole size. The malfunction in the SCR can increase the temperature of the motor and also caused the traction motor to generate loads that will be carried to the pump input shaft. Therefore, SCR should be replaced with the new one[5].

3.4.4 Failure in Valve

The mud pump valves are produced in various constructive forms, which have a significant effect on their wear resistance as well as their service life. Erosive wear of them have direct influence on the proper operation of the other pump components that can lead to mud pumps failure. The erosion in the valves is indicated with a delay between piston and cylinder and damages the suction and discharge valves. It is not simple to identify the appearance of wear to suction and discharge valves. They can be determined only in a final stage of deterioration, when keeping constant the discharge pressure becomes difficult. In this case, the pump should be stopped instantly and the broken valve should be replaced. Listening to the unusual noise is used as an approach (health stethoscope and mini microphones) for evaluating the valve's condition. The main reason for the erosion of valve assembly (Figure 3.21) is the high operating pressure. The abrasive drilling fluid, including solid particles and debris, is circulated at high pressures and velocities which can damage all the mud pump parts[56,60].

Figure 3-21. Valve and seat failure due to high operaating pressssure and abrasive drilling fluid (V.Ulmanu, 2016)

3.4.5 Failure in Piston

The main component of a mud pump that ensures mud circulation is the piston; however, the main reasons for failure in the fluid end section are caused by piston's wear as well as piston's sealing failure (due to the operations under complex and harsh working conditions). Therefore, the abrasive drilling fluid simply enters the kinematic pair of the cylinder liner, abrading the piston surfaces and decreasing its service life and drilling performance. As a result, it is vital to improve the contact sealing and wearing-resisting performance of the mud pump piston.

One of the solutions for increasing the sealing efficiency is using nonsmooth surface structures that can enhance the mechanical sealing performance. This sealing structure can be considered as the radial labyrinth-like or honeycomb-like surfaces which increase the performance of gap sealing. The piston with groove structure has higher sealing effiiciency in comparison with the normal one. Because machining a groove-shaped multilevel structure on the magnetic pole will prevent the magnetic fluid gradually and slow down the passing velocity, thereby creating the sealing effect. The following figure illustrates both normal piston and nonsmooth piston.

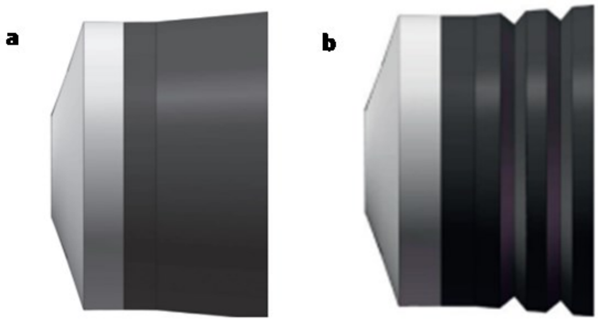


Figure 3-22. A Standard piston , B Striped piston (Q. Cong, T. Gao, 2019)

The piston assembly comprises piston core, rubber, circlip, pressure plate et cetera. The piston core is produced from 42CrMo, and the material of the piston rubber is nitrile rubber or polyurethane rubber. A specific type of piston rubbers must be used for different drilling conditions. The ideal piston rubbers must have excellent wear resistance, chemical resistance, high tensile strength, and long service life in their drilling working environment. For instance, in ordinary drilling environments pressure and temperature (below 20Mpa and 120 °C) the nitrile rubber is proper, while this nitrile rubber is not suitable for drilling operations which have pressure and temperature more than 20Mpa and 120 °C, respectively. Therefore for the pressure up to 35 Mpa, polyurethane rubber is more efficient. As for the high-pressure, high-temperature (HPHT) and high sulfur content well, the hydrogenated nitrile rubber has great performance. Because the other rubber types will damage under HPHT conditions as well as the action of hydrogen sulfide, carbon dioxide, methane, steam and acid, but hydrogenated nitrile rubber has great performance in pressure and temperature up to 75 Mpa and 150 °C[61,62].

3.4.6 Failure in Crosshead Bearing

The sign of this failure begins with smoke and knocking sound from crosshead which generated heat, smoke and unnormal noise. The reason comes from the wiper rubber's seal failure. Because when the washout wiper seal occurs, the wiper seal fails in holding the liner water from entering the pump chamber. Consequently, the oil used for the lubrication was polluted by water and it leads the lubrication to underperform. Lubrication is a significant parameter for reducing friction, dissipating heat and inhibiting corrosion on balls and raceways. Another issue that intensify this failure is the coarse materials from drilling fluid. The abrasive particles in mud can broken the wiper rubber when the screen for filtering the coarse materials from the mud fluid was not the real screen as should be based on the pump manual.

Figure 3-23. Consequce of washout wiper seal on the crosshead bearing (A.Samuelson, 2020)

The solutions for the wiper rubber seal washout are: first, using the suitable seal rubber for each specific drilling condition, i.e. Nitrile Rubber seals has good performance with a temperature range of -40 °C to 121 °C, while Nitrile rubber is caused washout in the HPHT drilling and Viton rubber seals must be used in there. The Viton rubber seal temperature range is from -23 °C to 315 °C. The second solution is taking Standard Operation Procedures (SOP) or manual of mud pump into consideration for utilizing proper and standard screen for filtering the coarse materials[63].

3.4.7 Failure in Pressure Gauge

Due to the pulsation of the effect of drilling fluid in the pipeline, the pressure gauges can be prematurely worn out. This problem impacts the accuracy of its readings. Moreover, the wrong and unprecise pressure indication, especially when the pressure increased. This issue can damage the valve couples, valve spring, pistons, the gate valves on the discharge line, failure in downhole motors well as drilling bit and so on. In order to overcome pulsation's negative effect and equalize the flow rate in the injection line, pneumatic compensators are a constructive solution. If the pressure in the pump's discharge line is higher than the pressure inside the gas, the pneumatic compensator acts like an air cap.

3.4.8 Failure in Discharge Line

The status of the discharge line from the riser to the pump outflow must be rectilinear as much as possible or even without any sharp turns, should have slopes to assure that the mud flows from the entire line when the pumps do not operate. This issue is really noticeable in low-temperature areas, due to freezing of the fluid remaining in the line can lead to its rupture when starting the pumps. As for preventing this type of failure in the discharge pipe or pump, especially in case of pressure is higher than the allowable near the pump outlet, a plate-type safety device can be used. The groove of the safety plate must be directed towards the discharge of the fluid and the drain line from the safety device conduct the fluid to the receiving tank. This type of installation excludes the workplace pollution in the pump room as well as injuries to crews from a direct impact by chemical solutions or fragments of the plate over its destruction[64].

3.4.9 Failure in Discharge/Suction Valve

The most common failures in the fluid end subunit come from leaks. If the leaks are associated with the wear of the piston-cylinder interface the sign which represents damage is the pollution of water cooling the cylinder liners. The contamination in this case, can easily observe (it is apparent even if the damage is minor), because of working in the closed circuit the water returns to the cooling water storage. But the problem arises when leaks are related to both discharge and suction valves, because these types of wash-outs are not visible. These failures can be found only in the final stage of damage when it is completely difficult to maintain a steady discharge pressure. In this situation, it is vital to stop the pump and exchange the valves. The problematic matter for replacing new valve is which valve is damaged or which of them begins to malfunction. The experienced crews tried to evaluate the condition of the valves by the ear. This technique is inaccurate, unreliable and consists of comparing acoustical effects from the individual pump subunits at 15-minute intervals. There is another solution for this type of failure, which will be discussed in the acoustic emission technique setion.

3.4.10 Failure in Lubricating System

The main parameter in the power end section is to control the lubricating oil quality as well as the frequency of replacement is the parts least subject to impairment. The failure in the lubricating system can lead to malfunction in the gear transmission system. Because the gear transmission transferring the force from the elctrical motor to the pistons. The reason for this failure is either too low pressure on the oil pump or filter blockage. In case these signs happened, the pump must be stopped instantly[65].

3.4.11 Cavitation

One of the key factors which reduced pump efficiency and caused excessive wear and damage to pump elements is cavitation. The parameters that can be related to this problem, like fluid velocity and pressure, can sometimes be assigned to an insufficient mud system design and/or the reducing performance of the mud pump’s feed system. The reasons for cavitation are related to: inappropriate sizing of the charge pump, height or elevation change and useless elbows in plumbing from mud tank to mud pump, inappropriate plumbing size from charge pump to mud pump, insufficient suction as well as discharge dampening and so on. Various solutions can be considered for cavitation's issues such as routine inspection and maintenance, using speed pressure sensors in the suction line to notify if the pressure falls below 30 psi, using accelerometers to identify minor changes in module performance and controlling the pump's oil levels[66].

3.5 Mud Pump Failure Symptoms and Roots

The Positive reciprocating pumps can usually resist more abuse and variations in system demand compared to other pumps; nevertheless, they should have a steady supply of relatively clean liquid to operate correctly. The inlet and discharge valves utilized to handle the pumping function are weak links in the mud pump's design. The most repetitive failures come from the valve's malfunctions. Most of the time, fatigue is the main reason for valve failure. The only constructive way to minimize or avoid these failures is to ensure that the right maintenance is regularly implemented on these elements. The common failure modes in the mud pumps are represented with different signs and problems such as: no liquid delivery, insufficient capacity, short packing life, high wear in fluid end and power end sections, extreme heat in the power end components, inordinate vibration and noise, strong knocking, motor trips and so on. In the following section, the main reasons for each of these indications will be mentioned[31].

3.5.1 No Liquid Delivery

- Excessive suction lift
- Non-condensables (air) in fluid
- Insufficient suction pressure
- Impediments in lines
- Supply tank is empty
- Valves, seats, liners, rods or pistons are worn out

3.5.2 Insufficient Capacity

- Broken valve springs
- Cylinders are not filling
- Excessive suction lift
- Low volumetric efficiency
- Non-condensables (air) in fluid
- Insufficient suction pressure
- One or more cylinders are not operated
- Incorrect pump speed
- Pump valves stuck open
- Leaking in relief or bypass valve

- Scored piston or rod
- Valves, seats, liners, rods or pistons are worn out

3.5.3 Short Packing Life

- Abrasives or corrosives in fluid
- Cylinders are not filling
- Improper packing selection
- Low volumetric efficiency
- Misalignment of rod or packing
- Non-condensables (air) in fluid
- Worn cross-head or guides

3.5.4 High Wear in Fluid End Section

- Abrasives or corrosives in fluid
- Broken valve springs
- Cylinders are not filling
- Valves, seats, liners, rods or pistons are worn out

3.5.5 High Wear in Power End Section

- Overloading
- Other mechanical problems such as wear, rusted and so on

3.5.6 Excessive Heat Power End

- Insufficent lubrication
- Liquid entry into power end section
- Other mechanical problems such as wear, rusted and so on
- Incorrect pump speed
- Worn cross-head or guides

3.5.7 Inordinate vibration and noise

- Broken valve springs
- Cylinders are not filling
- Drive-train problems
- Gear drive problem
- Insufficient lubrication
- Non-condensables (air) in fluid
- Impediments in lines
- Other mechanical problems such as wear, rusted and so on

3.5.8 Persistent Knocking

- Gear drive problem
- Loose cross-head pin or crankpin
- Loose piston or rod
- Other mechanical problems such as waer, rusted and so on

3.5.9 Motor Trips

- Drive-train problems
- Excessive suction lift
- Insufficient lubrication
- Misalignment of rod or packing
- Non-condensables (air) in fluid
- Impediments in lines
- Overloading
- Scored piston or rod

3.6 Mud Pump Failure Contribution in NPT

Technical failure is one of the main reasons for non-productive time , which has had a crucial consequence on drilling efficiency and well cost. By considering various NPT, drilling time analysis reports, maintenance reports, and downtime analysis reports from different dilling projects, mud pump failure has been the top NPT reasons (Figure 3.24). There is a primary difference between the productive time and the productivity of a mud pump that is used in NPT. The productive time analyzes the system is operating or not while the productivity evaluates how well the system is in operation. A mud pump which has sufficiently high productive time but unacceptably less productivity can still lose money for the company by taking longer than predicted to accomplish a drilling campaign. On the other hand, productivity identifies if the predicted amount of work gets done throughout the available productive time.

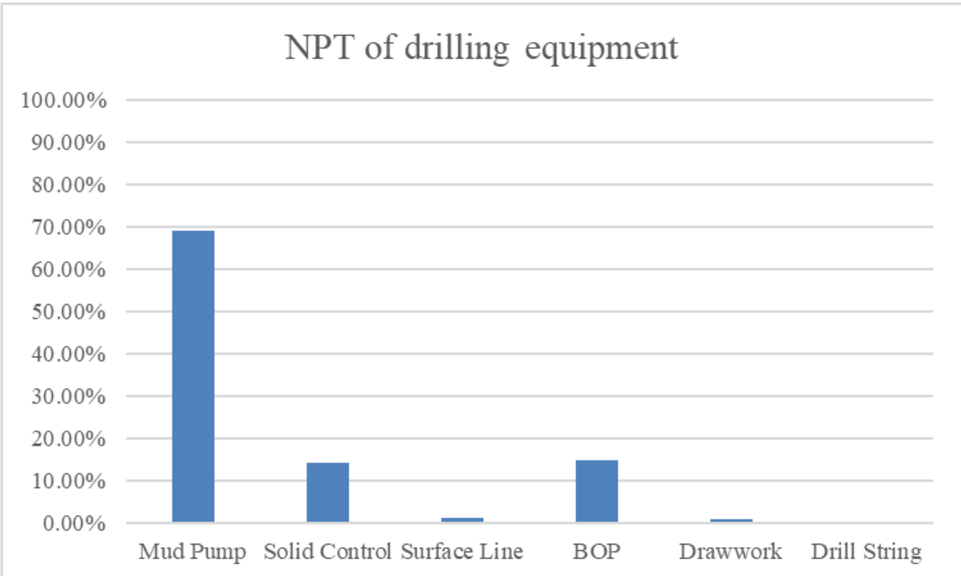


Figure 3-24. NPT of drilling equipment (A.Samuelson, 2020)

There has been another survey which also obtained data from the daily maintenance reports and drilling time analysis reports of nine wells drilled in Olkaria. In this investigation by using Pareto analysis, the root causes are discovered for downtime (the Pareto principle is a statistical technique in decision making used for the choosing of the small number of tasks that create crucial overall concequences). Figure 3.25 demonstrates that poor maintenance has a significant impact on the downtime of these nine drilled wells1,68. The following section is allocated to the root causes of mud pump downtime in detail.

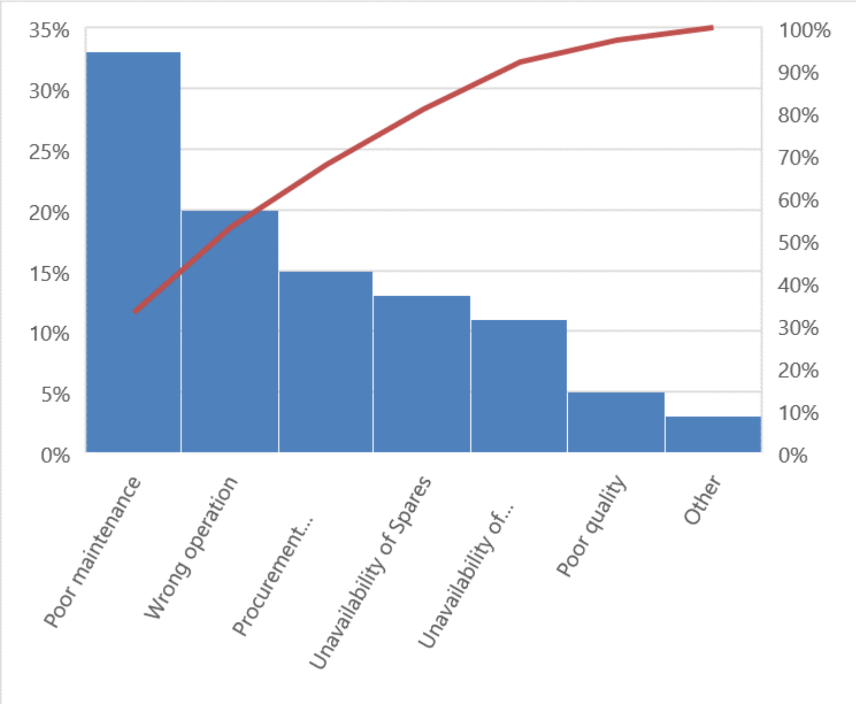


Figure 3-25. Root cause analysis of equipment downtime (O. Otieno, 2016)

3.7 HSE Risks Associated with Mud Pump Failures

Based on different investigations regarding mud pump incidents, the main reason for most of them is the inability of crews to predict, eliminate or decrease the occupational risks in advance; however, it is always better to prevent an incident than to handle the consequences. Failures in mud pumps and deviations in technical procedures can lead to catastrophic outcomes related to human life and substantial financial losses of the enterprise. Additionally, the 96% of the jobs of personnel servicing drilling rigs are harmful or dangerous; therefore minimizing the incidents which originate from mechanical failure can create additional value from the HSE point of view. Throughout the operation of mud pumps, hazardous and harmful production parameters can influence crews, which are divided into physical, chemical, psychophysiological and biological parameters, which lead to occupational risks for drilling crews. The majority of accidents happen in the following main groups of negative parameters[64,67].

The functionality of plunger pumps is based on the kinematic features that are affiliated with an uneven supply of drilling mud and the consequent pressures, which leads to shocks in the discharge line, considerable structural vibrations, weakening, and rupture of the joints and discharge line. By growing the pressure above the admissible level results in rupturing the connections and the hydraulic components of the pump such as cylinders, air cap, discharge line, valves, expansion joints, and mud hose. In case the crews are in the danger zone, such incidents can coincide with severe or fatal incidents.

The pulsation of drilling fluid in the pipeline, instrumentation (especially in pressure gauges) early wear out which has a direct impact on the precision of its readings. Flawless running of pressure gauges is one of the critical conditions for safety when mud pumps are under operation. These pulsations can increase pressure and leads to wear of the working surfaces of the valve couples of the pump, surface of plungers as well as valve spring.

In the low temperature area, there is a possibility of freezing the fluid that remained in the discharge line from the riser to the pump outflow, this issue can lead to the rapture during the starting the pump. This can break the discharge line and the pump especially when the pressure is greater than the allowable near the pump outlet.

In case the bottom hole pressure surpasses the static pressure of the fluid column in the borehole, oil and gas manifestations are feasible. Therefore, the ambient area of the pump room can be polluted by oil and gas components especially with explosive and toxic gases which can lead to the explosion and irreparable consequences.

Thruoh mud pump operation, because of the abrasive action of sand in the drilling fluid the most hydraulic components of pump wear out quickly, that leads to disruption of the normal pump operation as well as a decrease in the flow of drilling fluid to the bottom of the well. This issue can create other negative consequences for humans and environment.

There are additional issues that endanger crews in the operations is the moving parts of mud pump like pully, V-belt drive, crankschaft and the other heavy components. It may occur during hazardous operations for repairing and maintenance. For instance, when the hatches of the oil bath and chamber are not tightened, moving rotating components of the pump and during the fencing V-belt (if the belt is not too strong) there is a possiblity the belt can not withstand the load. Additionally, sometimes the crews have to tighten the stem seal of the stem with the sleeve by pressing the cover, tightening the nuts through the window of the bed. This issue can lead to incident due to pressing the crew's hand with the cutter against the gland. Another topic that can be considered for the crews is during the use of electrical motors to drive mud pumps, insulated componets of electrical equipment in case of urgency can be stimulated, touching which becomes deadly if there is no or malfunctioning protective ground connecting the metal to the ground.

The extra noise levels beyond the standards in accordance with GOST 12.1.003-83 in the pump compartment reaches up to 10 dBA, for vibrating screens (up to 18 dBA), which has a negative effect on the human body and leads to weaken the hearing sense, negative impact on the general activity of the nervous, cardiovascular and digestive system, causes fatigue, reduced functioning and slowed mental reactions. There are other technical problems that can directly and indirectly impact the human as well as environment. In section mud pumps failures and solutions more cases will take into consideration[64].

3.8 PdM Techniques Application in Mud Pumps

In predictive maintenance activities, condition-based maintenance is one of the most used techniques. It is an efficient strategy where maintenance is performed by observing particular factors or particular components of the mud pumps. The benefit of this approach is that the state of the mud pump is presented in real-time. Nevertheless, the mud pumps basically have a well-defined operational curve by the producer; depending on the drilling conditions and the operational environment, it may undergo changes, resulting in failure. According to condition-based maintenance, a broad range of factors can be monitored for predictive maintenance. Additionally, most failures already discussed in previous sections are affiliated with unacceptable vibrations, noises, temperature, lubrication issues, and corrosion problems. Therefore, a comprehensive PdM program has to include other monitoring and diagnostic methods. These methods include vibration analysis, acoustic analysis, lubrication oil analysis, thermography analysis, and ultrasonic and non-destructive testing techniques. In the following section most practical and effective analysis will be discussed.

3.8.1 Vibration Monitoring

Vibration analysis is one of the fundamental, predictive maintenance tools used for the last decades to monitor electromechanical systems. The mud pump vibration is mostly at its lowest level, if functioning at the best efficiency point (BEP), and can be doubled in magnitude as flow is decreased to 25% or so of BEP. This assumption is noticeable throughout the routine measurements as a range of vibration levels may happen although the pump internal condition is constant. In case the BEP in operation is not constantly possible, therefore a standard flow has to be considered for regular measurements, except a number of normal vibration levels in different flow rates are achieved and used as the information.

The crucial quantities for vibration measurement are displacement, velocity and acceleration. Additionally transducer is used for acquiring accurate information over the mud operation and the accelerometers are the most typical tools for handholding data collectors or analyser. According to the physic’s laws, the low frequincies are the result of large displacement and small acceleration. While the high frequencies are from low displacement and high acceleration. During all frequencies, the velocity remaines unchanged. The place where the vibration sensor is mounted is named as the reading point. The sensor can be installed in one or more directions or orientations.

In the mud pumps, the reading point should be corresponded to the entry shaft where the sprocket is placed, both on the pulley side and the opposite, and on the crankshaft, where the gearwheel is located to measure on both ends. Moreover, for evaluating and monitoring pump vibration's severity, the measurements with contact transducers are taken at bearings in vertical, horizontal (on the shaft centreline) and axial directions. In general, it can be 4 measuring points or bearing support as a minimum 2 on each shaft (8 radial measurements will be considered 4 vertical and 4 horizontal) and 2 axial measurements on each shaft. The intensity and range of vibration are always expressed in: a.The frequencies up to 10 Hz is known for the displacement of low-speed machines, b. The frequencies between 10-1000 Hz are known for velocity which the majority of machines fit here and c. The frequencies from 1000 Hz onward are for acceleration. The table below represents the velocity span limits as well as machinery classes, based on ISO-2372.

Vibration is frequently a mixture of several frequency elements of variable amplitudes. These amplitudes are essential for a more accurate diagnosis of pump faults. The vibration amplitude is represented in the time domain. The Fast Fourier Transform or FFT spectrum is a practical tool for vibration analysis. The FFT spectra supports the user to evaluate amplitudes at different component frequencies on the FFT spectrum. Utilizing the vibration spectrum provides more perceptions about the reason for vibration[57].

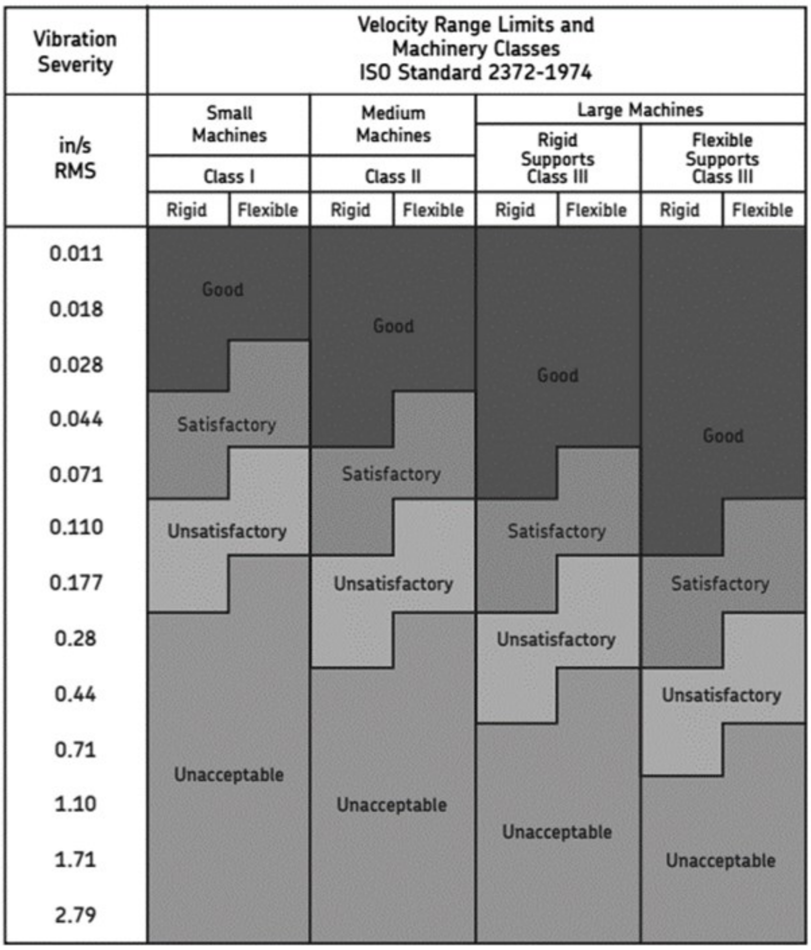


Table 5. Vibration severity range (ISO-2372)

The vibration monitoring systems identify indications associated with certain problems occurring in the entire area of the mud pump, but it is complicated to determine with certainty the specific place of origin, even more so to recognize the component itself that generates an increased level of vibrations. Therefore vibration techniques must be used along with other predictive maintenance methods.

3.8.2 Acoustic Emission Monitoring

Acoustic emission (AE) is an approach that takes transient elastic waves created by the rapid discharge of energy from a particular source of energy. High-frequency elastic waves allow users to separate other signals from in the area devices. The drilling mud pump has a different AE source. The AE technique uses the piezoelectric sensor to capture acoustic emission and transmit them to the preamplifier to intensify the signal and send it to the SAEU2S AE acquisition box. The output of this monitoring will be in the form of an amplitude chart that oscillates in different ways and is then analyzed. As already discussed, the fluid end section in the mud pump is most subject to wash out, and it is not simple to identify in the early stage. The AE approach is an efficient technique to detect wear on the fluid end part. The Piezoelectric sensors have suitable features for fault detection in the pump such as high detection distance capability (up to 300 meters), well sensitivity (20-20000 Hz and >20000Hz), less safety risks (long-distance detection as well as low voltage) and simple maintenance.The AE test can be implemented with some properties that are incorporated into a monitoring tool known as an electric audio module (EAM). EAM is worked base on the acoustic emission and compromise of Piezoelectric sensor, RCA cable, Pre-amplifier, Power supply, Driver amplifier, Loudspeaker, Jack audio 6.5 mm, Jack audio 3.5 mm and Interface cable DB25. The application of EAM is to monitor the development of waer in the fluid end part in advance with considering the safety issues.

The acoustic emission elastic waves are not restricted to the audible domain, and the effective spectral span can extend to numerous or even tens of megahertz frequency span. The extension of elastic waves in mud pumps depend on the transition and reflection of vibration modules at the phase boundaries of real objects. The reason for the effect of frequency fluctuation is the alteration in the attenuation rate; Moreover, the friction node is another factor for these frequency changes which can be caused by tear, wear and tribological processes. Therefore, it can represent relevant diagnostic data. Any impairment to the tested pump creates a change in the AE elastic wave signal.

The piezoelectric sensors are mounted in each bonnet valve module or placed in each mud pump module to find out abnormal noises. In order to minimize the scattering of elastic waves, silicon grease should be used (it acts as a coupling liquid between the sensor and mud pump housing). The installed piezoelectric sensors will identify oscillations from acoustic emissions that come out due to the drilling fluid and fluid end part in the mud pump module, thereafter it creates acoustic emission pulses in the piezoelectric and flows over the cable to the EAM. At the electric audio module, the emission pulses are regenerated into two outputs. The first output is achieved by laptop software such as sonic visualizer free (the linear programming output read on a laptop). The second one is in the kind of acoustic emission sounds which can be modified in volume and heard in headphones.

The non-linear diagnostic technique is used for AE signal analysis. The two significant issues that directly impact the non-linearity behavior are elastomers and gases. Because in the solid material structure like metals, such as metals, the phenomenon of high non-linearity is often related to degradation, the occurrence of cracks, any defect in the crystalline structure. In this case, local elasticity is various for stretching as well as compression, and associated non-linear behaviors cause rising high frequencies of the harmonics. The same issues happen in the valve unit of the mud pump. The valve unit consists of metal and elastomer. Therefore, the non-stationary and non-linear behaviors are obvious here. Based on these fluctuations, crews can diagnose the damage and its location. For instance, the following figures illustrate a comparative evaluation of the signals from the proper operating of valve unit in mud pump and early-stage valve unit failure[60,65].

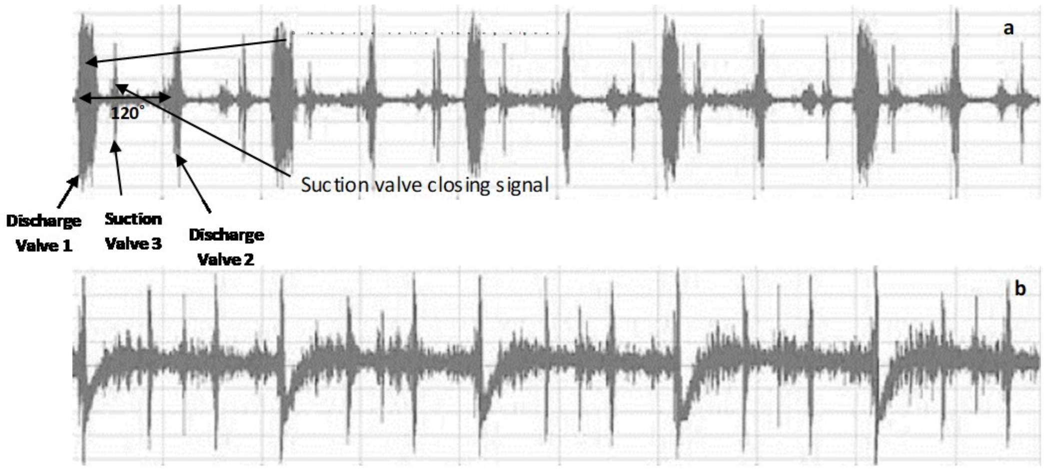


Figure 3-26. AE elastic waves comparison between the properly operating of valve unit (a) and early stage valve unit failure (b)

3.8.3 Lubrication Oil Analysis

Oil analysis provides another valuable source of data for early pump failure detection. Oil monitoring can identify oil condition degradation by defining the loss of additives or detection of contamination. Lubrication oil supports the mud pump by providing a protective layer between moving component surfaces in the power end section, to reduce friction and prevent the mating elements from seizing. Additionally, it cools the elements, prevents the corrosion of the metal component, keeps the mud pumps free of containment deposits. Alterations in the physical and chemical oil features change the properties of the lubrication oil that could lead to performance weakening. There are different lubrication oil analyses which can directly or indirectly monitor these properties. The crucial reasons for oil degradation are water contamination, oxidation and particle contamination.

As for water contamination, the viscosity of oil decreases during the combination of oil with water. This viscosity reduction can lead to oil leakage or the degradation of layers among the metal parts, generating extra wear and friction. Oxidation also has an impact on viscosity and causes the formation of wear particles which leads to damage of the mechanical system, in case they come into contact via the elements. In better words, the created wear particles can block the strainer or filter or oil holes which leads to lubricant starvation as well as mating element seizure. For the particle contamination, the metal debris due to wear and friction of parts, soot contamination and dust which can cause seizure of components (because of increasing the viscosity)[68].

There are numerous specifications and techniques for testing lubricant wear debris. The normal and abnormal classifications are the common ones. While the normal wear proceeds, the portion of particles grows. By doing one of the spectrometry analyses, the ppm (present as parts per million) of elements can be found out. The larger particles of up to 50 micrometeres in size or greater are known as abnormal wear and are beyond the range of spectroscopy. The form of debris particles is helpful in the identification and diagnosis process. The screening technique is also a valuable approach for diagnosing the wear debries. The online/offline devices and carriable testers can be applied to evaluated iron particles in the oil sample.

The acid digestion method is another technique to minimize larger particles which can implement with a patch test (combination of the microscope, ferrography and filtergrams) for purpose of facilitating larger particles to be seen. In the filtergram technique, the oil sample is taken from the pump. Then by using single-use laboratory plastic ware for passing the mixed sample over a fine filter paper, the sample oil is removed with solvent and the filter paper analyzed with a micrsocope to find out the particle's size. The automatic inspection in this case can be done with computerized atlases. The cleaner lubrication oil leads to increase the life of beatings and other parts. The ISO-4406 categorizes the cleanliness of lubricants based on three code numbers from minimum to maximum size span. The minimum code numbers consist of low concentrations of particles in the oil (4,6 and 14micrometers). For instance, ISO code 18/16/14 represents that the lubricant has 1300-2500 particles per milliliter ≥ 4 µm, for 320 to 640 particles ≥ 6µm and from 160 to 180 particles ≥ 14µm in size. The table below summarises the main techniques for oil analysis.

	Filter Inspection	**Magnetic Plug Inspection**	**Magnetic Particle Detectors**	**Spectrometric Oil Analysis**	**Ferrographic Wear Analysis**	**Filtergrams Wear Analysis**
Measurement of concentration	Good	Good-ferrous particles	Good-waer particles	Excellent	Good-ferrous particles	Good
Particle appearance	Good	Good	-	-	Excellent	Excellent
Size of distribution	-	-	Excellent	Fair	Good	Good
Identifies elements	Fair	Ferrous only	All particles	Excellent	Ferrous only	Good
Particle size range	> 2 µm	25-400µm	1-80 µm	1-80 µm (direct dilusion)	>1 µm	Widest (by choice of filter paper)
Type of analysis	In field, off line	In field, on/off line	On site, laboratory, off line	Laboratory, off line	Laboratory, off/on line, on site	Laboratory off line, in field off line

Table 6. The most common oil analysis techniques (S.Beebe, 2004)

As can be seen in table 6, each of the mentioned approaches can use in different conditions. The filter inspection can be used as a condition monitoring indicator for analysis while the magnetic plug inspection, use to identify abnormal wear. On the other hand, someones believe the screening technique is the best approach for magnetic particle detectors on site. Spectrometric oil analysis s a suitable approach to monitor normal wear. In addition to those approaches, ferrographic wear analysis is the best technique to predict incipient failures.

3.8.4 Thermographic Analysis

The use of thermography has been expanding rapidly in various sectors of the oil and gas industry. The objective of the thermographic or infrared thermal analysis is to recognize areas where extra heat is being created which can lead to failure in the mud pump. The thermal camera scans the surface of the pump and represents the temperature profile in color scales. This analysis can identify thermal variations which can indicate issues like vale leaks, hot bearing, electrical faults, determining baseline thermal signatures for future trending, identify components suffering from drive shaft misalignment problems and so on. Each color indicates different temperatures in the monitoring. The following colors are related to the specific temperatures range:

- Green color is from 10 ˚C to 25 ˚C
- Yellow color is from 25 ˚C to 40 ˚C
- Orange color is from 40 ˚C to 70 ˚C
- Red color is from 70 ˚C onwards

Figure 3.27 shows thermal imaging in the mud pump electrical cable. The right side cable does not carry the current to the mud pump and the whole current is passing through another cable, while the temperature in the left side cable is growing.

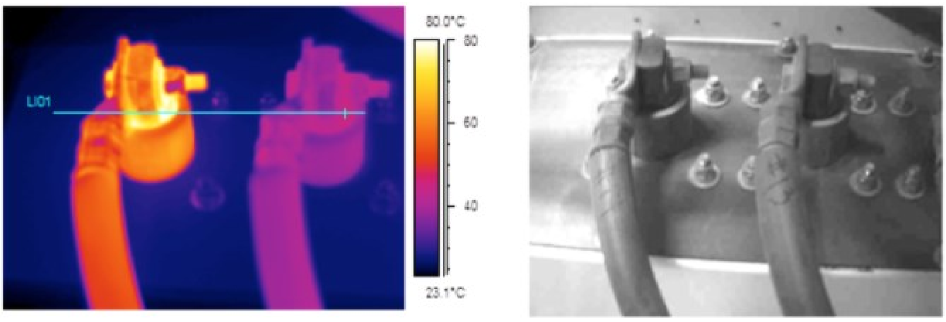


Figure 3-27. Thermal imaging of the current in the cables of mud pump (rigtech.com)

The key features that identify the performance of a modern thermal imaging camera are:

- Temperature range
- Noise equivalent temperature difference or NETD (the lowest temperature variation which can be determined by the thermal imaging camera)

- Field of view or FOV (is defined as an angle and identifies the surface which can be captured with thermal imaging camera. It strongly depends on the lenses type)
- Instantaneous Field of View or IFOV (evaluated the capability of a detector to illustrate the smallest details)
- Instantaneous Measured Field of View or IFOV meas (represent the smallest object whose temperature is still to be accurately measured by an infrared camera)[69]

3.8.5 Power Analysis and Electrical Testing

The predictive maintenance approach in power and electrical engineering can be achieved by monitoring electrical parameters as well as evaluating installation (precise assessments of the quality parameters for the received and consumed power)[69].To acquire the power absorbed by the pump, the efficiency of the motor and any gearbox or fluid coupling (from works test data) should be considered. It must be mentioned that the rate of analyzed motor current to the full load rated current does not associate directly with measured power, as no-load current should be known, e.g., 60% rated current is not 60% rated load[57]. Conventional electrical testing techniques should be used in conjunction with vibration analysis, in order to prevent the early failure of electrical motors. These investigations should consist of Resistance testing, Megger testing, HiPot testing, Impedance testing and other techniques.

By utilizing ohmmeter resistance can be measured. It measures the current instead of resistance. The rate of current supplied by the meter is too low, normally in the range of 20 to 50 microamperes. The meter functions by implementing its terminal voltage to the test point and evaluating the current in the circuit. Practically, despite resistance analysis is of limited value, several useful analysis may be applied. A resistance analysis will represent an open or close circuit. This indicates whether a break in a circuit existed or a dead short to ground existed. Resistance analysis will more frequently not identify windings that are shorted together or weak insulation and have restricted value for testing coils. It will distinguish an open coil, or a coil shorted to the ground.

Megger testing is another technique for measuring high resistances via mega-ohmmeter. The difference between this instrument and ohmmeter is that instead of measuring current to identify resistance, it measures voltage (relatively high voltage, from 500 to 2500 volts). In general, this analysis is considered as non-destructive test and used to test the integrity of the insulation. This approach will not discover shorts between windings, but it can identify higher-voltage–related issues in relation to the ground.

High potential testing or HiPot testing is a destructive test. This test is used in order to identify the integrity of the insulation. The implemented voltage level in this kind of test is twofold the rated voltage plus 1000 volts. This technique is principally used for purpose of the tool's quality assuring. It should be notified that the HiPot testing does some damage to insulation every time it is implied, because of this reason it is not recommended for field use.

Impedance test is another technique that can be used in electrical testing. It comprises two elements, a real (or resistive) element and a reactive (inductive or capacitive) element. This is a practical technique to detect serious shorting in coils, either between turns or to ground. There is no other non-intrusive approach to identify a coil that is shorted between turns[31].

Ultrasound inspection is another significant power and electrical analysis which is known as a practical non-destructive test. This technique can detect as well as isolate high-frequency sounds that are otherwise imperceptible to the human ear. It is applied to differentiate electrical discharge noises from ordinary sound patterns. Safety is enhanced in this technique due to inspection of the energized electrical equipment without having to open it up. The ideal practice is to utilize both ultrasound and infrared techniques together, because they identify various failure modes and together contribute considerable safety benefits. Infrared discovers resistance-based issues such as overheating fuses and insulation breakdown, whereas ultrasound identifies ionization-based issues such as tracking on loose and faulty connections in switchgear, tracking on transformer windings and cracked insulators[70]. There are additional techniques that can support PdM include eddy-current, motor current, signature analysis, magnetic particle, residual stress and so on that the ANST (American Society of Nondestructive Testing) has published a series of comprehensive handbooks for numerous nondestructive testing approaches.

3.8.6 Performance Analysis

Performance analysis requires performance data or replicable measurements, like pressure, temperature, flow, displacement, speed, power, and time. In this case, real-time monitoring has been facilitated the productivity and accuracy of the processes. Two significant parameters which support this technique from undesirable failures are stand pipe pressure (SPP) and flow rate. In other word, SPP is considered as the total pressure drop (because of fluid friction happened). SPP is measured by pressure sensor which is mounted at standpipe manifold. There are analogue and new generation pressure sensors. The analogue type comprises of a diaphragm, pressure transducer and hydraulic line while the new generation one consists of the strain gauge fixed to a steel plate (force summing component) for the purpose of pressure measurement at standpipe. SPP analysis can prevent liner failures in mud pumps or worn pumps packing[71].

Drilling mud pumps is worked at high speed of drilling fluid, including solid particles and debris which can cause of failure in pump components, especially in the pump valves. The flow rate is calculated based on the SPM (number of pump strokes per minutes) and the pump output per stroke which dependent on piston characteristics, therefore, flow rate analysis can leads to prevention of mud pumps failure. The flow sensor is settled close to the piston of mud pump[56].

The other condition monitoring techniques by performance analysis in positive displacement pumps can be considered of relief valve setting, crankcase return flow, capacity tests, and thermodynamic method. Relief valve setting is used for keeping the essential pressure as the pump wears and the discharge relief valve should be modified. Its setting will therefore represent pump wear, in case it is feasible to observe and record it. In this matter of variable speed pumps, as with centrifugal pumps, increased speed for standard duty points to internal wear. As for the crankcase return flow, by increasing piston ring wear, the crankcase flow will be increased. Someone believed, a container has to be inserted by hand into the oil reservoir in order to gather this flow. For the purpose of removing this possible health hazard and difficult access, a tee piece and two valves can be used. They should be mounted in a way that the flow could be diverted into a measuring container external to the reservoir.

In the capacity test, a flowmeter can be mounted in the return line between the relief valve and the return tank. The flowmeter will measure the flow rate at various pressures arranged by the relief valve's setting. For some of the heavy oil installations, a quality volumetric flowmeter is sometimes arranged, and performance tests can be implemented. For the thermodynamic method, as wear progresses, running clearances will increase. Internal leakage over clearances is a function of clearance cubed. The increased clearance is led to a power loss and converted into heat. The higher pump pressure, the greater the temperature increase for the provided pump condition and efficiency[57].

3.8.7 Smart Pumping Technique

More and more the operations, engineering, maintenance (OEMs), and operators of mud pumps apply advanced digitalization technologies to improve pumping system operation and maintenance. Among those state-of-the-art technologies, the combination of AI and DT creates a smart pumping concept. The capabilities of this combination are remote condition monitoring, diagnostics and serviceability, which leads to reducing pump downtime. Smart pumping can analyze and test optimization cases to fix operational problems as they occur and reduce them before costly breakdowns. The following points give more information regarding the smart pumping approach:

1. **Process Twin**

Digital process twins can maintain a pumping system's commissioning costs and time to the lowest level, therefore proceeding to convey value throughout its whole life cycle. Experts can perform dynamic process simulations during a diverse range of the system's features. Simulations can consist of analyzing simple input/output or signal of the pumping process's control to make sure its effectiveness, as well as logic, works correctly. Furthermore, they are capable to optimize the pumping operations and training crews with virtual commissioning simultaneously with the manufacture and other related groups to save time.

2. Plant Twin

By utilizing 3D engineering data (as-built documentation) digital plant twins can be represented as a virtual-reality viewer over a pump or pumping system's life. Experts can analyze the instrumentation control and safety system (ICSS) ahead, in case of a single or more pumping system earlier than commissioning and startup. Additionally, a digital plant twin can be changed between 2D drawings as well as 3D representations with a centralized engineering information repository that leads to improvement of cross-discipline association, spare time and minimizes the mistakes and miscommunications.

3. Intelligent Monitoring

Throughout this stage, the pumping system is activated during a web-based analytics and visualization abilities that can comprise of: physics-based analytics of pump's KPIs, checking the loop as well as alarm system operation, AI-based machine learning for monitoring and optimizing the functioning of pump system elements, periodical (daily, weekly and yearly) maintenance and operational KPIs and maintenance warnings. The real-time operational visibility and monitoring of the pump can be improved via visualization tools that represent the KPI trends, warnings and faults graphically.

4. OEM Services

Operations, engineering and maintenances of the mud pump and circulation operations bring immense experience from the design and engineering of their solutions. Despite the fact that intelligent monitoring can offer a practical intelligence derived from conditional monitoring on these pump system's KPIs, an OEM's in detail and cross awareness of their pumping instrument is still expensive. RSD or remote diagnostic services are based on an OEM's engineering support the operations by identifying emerging performance problems before unexpected downtime or disastrous failures. Using AI technology support the operators to compare KPI information, like vibration, power, and temperature and so on to reference operating signatures to discover differences that could escape notice by crews[72].

3.9 Additional Mud Pump Sensors

In addition to the monitoring techniques that have already been discussed, other non-intrusive and intrusive sensors can be used in real monitoring as well as predictive maintenance for mud pumps. The most common types used for pump real-monitoring are Flow, SPP, Tachometer (also used for temperature analysis), and Stroke sensors. The combination of these sensors can be used for comprehensive predictive maintenance. Nonetheless, this thesis will only consider flow and SPP sensors for building the fault detection model because these two sensor types can identify wide ranges of pump failures. Table 8 summarizes the most common component failure that these sensors can identify.

Sensor	**Failures**
Flow	Valves, seats, liners, rods or pistons are worn out, excessive suction lift, volumetric efficiency, impediments in lines and leaking in relief valve or bypass valve
SPP	Insufficient suction pressure, , impediments in lines, leaking in relief valve or bypass valve, valves, seats, liners and rods or pistons are worn out
SPM	Piston or rod, One or more cylinders not operating, incorrect pump speed, misalignment of rod or packing and other mechanical problems (wear, rusted, etc.)
Temperature	Insufficient lubrication, bearing problem and overloading

Table 7. Sensors for identifying the failures (R. Keith Mobley, 2002)

3.10 Summary of Mud Pump Failure Symptoms and Roots

The failures in reciprocating positive-displacement pumps can be from different sources and roots, but one of the primary reasons for most of the failures comes from inlet and discharge valve breakdown, these are the Achille's Heel of mud pumps and are caused by fatigue. It is vital to follow the manufacturer's instructions and use the most efficient maintenance strategy to minimize them[31]. Table 8 summarizes the most typical pump failure symptoms and their possible causes.

	The Issues								
The Reasons	No Liquid Delivery	Insufficient Capacity	Short Packing Life	High Wear in Fluid End Section	High Wear in Power End Section	Excessive Heat Power End	Inordinate vibration and noise	Persistent Knocking	Motor Trips
Abrasives or corrosives in fluid			•	•					
Broken Valve Springs		•		•			•		
Cylinders are not filling		•	•	•			•		
Drive-train problems							•		•
Excessive Suction Lift	•	•							
Gear Drive Problem							•	•	•
Improper Packing Selection			•						
Insufficient lubrication						•	•		•
Liquid Entry into Power End of Pump						•			
Loose Cross-Head Pin or Crank Pin								•	
Loose Piston or Rod								•	
Low Volumetric Efficiency		•	•						
Misalignment of Rod or Packing			•						•
Non-Condensables (Air) in Liquid	•	•	•				•		•
Insufficient suction pressure	•	•							
Impediments in lines	•						•		•
One or More Cylinders Not Operating		•							
Other mechanical problems (wear, rusted, etc)					•	•	•	•	
Overloading					•				•
Incorrect pump speed		•				•			
Pump Valve(s) Stuck Open		•							
Leaking in relief or bypass valve		•							
Scored piston or rod		•							•
Supply tank is empty	•								
Worn Cross-Head or Guides			•			•			
Valves, seats, liners, rods or pistons are worn out	•	•		•					

Table 8. Common mud pump failure and causes

Chapter 4

Mud Pump Failure Detection Model Development and Testing

4.1 Overview

As can be seen in the previous chapter, worn-out mud pump components, liner, packing, and valve failures are the most common breakdown reasons that can lead to other mud pump failures. This chapter will represent the approach and methodology for creating a model based on artificial intelligence techniques for detecting the symptoms of the mentioned failures at the earlier stage to avoid the total collapse of the mud pump, consequently reducing the NPT. The Methodology is built in MATLAB software environments using an integrated app , the Diagnostic feature app, and the Classification Learner app. To successfully achieve the objective of the developed model, two types of data are required: a) sensor data (SPP and Flow rate and weight on bit) before occurring of the failure and during the failure and b) the daily drilling reports (DDR), which will be used to precisely determines the time windows of the failure. The evaluation of acquired data will be based on the performance analysis point of view. Through this approach, performance data or replicable measurement sensor data are taken into consideration for training the MATLAB model. Figure 4.1 illustrates the main processes followed to develop the model.

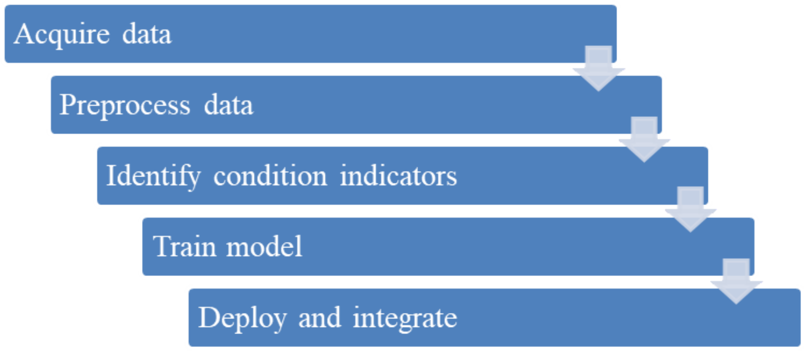


Figure 4-1. the main steps to develop AI model

The following points are going to give more information in further paragraphs regarding the methodology of simulation:

- Required Data Description
- Data Preparation
- Condition indicators Identification
- Models Training and Evaluation
- Methodology Testing
- Limitation

4.2 Required Data Description

Through this stage, collecting the pump data is vital to identify the information required to create the model. Data acquisition is one of the significant and primary steps for perceiving, sensing, and implementing any evaluation as well as interpreting mud pump failures. Because it is the process of getting signals from real monitoring or real conditions of the mud pumps and transforming them into the computerized value for further processing. The sensor data acquired from the drilling rig includes total depth, bit depth, rate of penetration, weight on bit, rotation per minute, torque, standpipe pressure, and flow rate. The sensor data represent the drilling progress and condition. Moreover, the data should illustrate the healthy and faulty condition of the mud pump. It is mandatory to use the sensor data allocated to a particular field for the same drilling rig and well configuration.

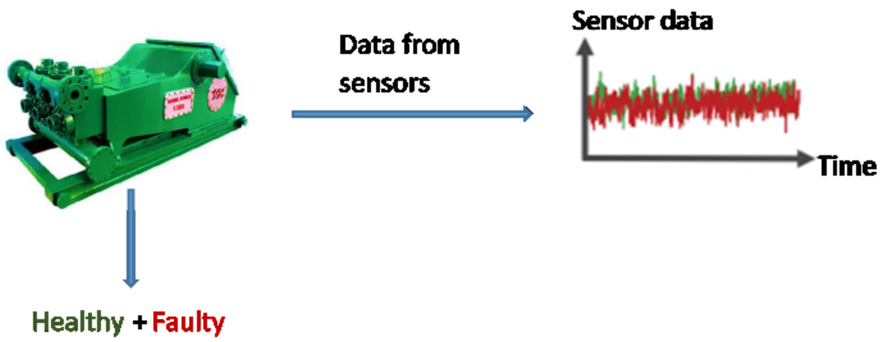


Figure 4-2. Data acquisition overview from the mud pump

Figure 4.2 demonstrates the overview of data acquisition from the mud pump. In addition to sensor data, according to the daily drilling report, the time when the pump was failed obtained and recorded, then the corresponding data window from the real-time sensor data is extracted. In the following sections, both healthy and faulty behaviors are considered. Figure 4.3 shows different variables acquired from sensors that will be used in the next stages.

Time	Tot Depth	Bit Depth	ROP	ROP ft/hr	HK Hght	WOH h	WOB	RPM	TORQU	SPP	FLWpm	MW IN	T Revol	PumpTim
0:28:30	7372.8	7372.8	1.1	56	61.7	243.3	29.9	135	6634	2787	900	8.3	29	13.19
0:28:40	7372.8	7372.8	1.1	56	61.7	244.9	28.3	135	6318	2797	905	8.3	29	13.19
0:28:50	7372.8	7372.8	1.1	56	61.7	245.5	27.7	135	6238	2781	908	8.3	29	13.19
0:29:00	7372.8	7372.8	1.1	56	61.7	247.1	26.1	135	6209	2791	911	8.3	29	13.19
0:29:10	7372.8	7372.8	1.1	56	61.7	248	25.1	135	6192	2772	910	8.3	29	13.2
0:29:20	7372.8	7372.8	1.1	56	61.7	249.9	23.3	135	6094	2778	909	8.3	29	13.2
0:29:30	7372.8	7372.8	1.1	56	61.7	252.1	21.1	135	6520	2774	908	8.3	29	13.2
0:29:40	7372.8	7372.8	1.1	56	61.7	253	20.2	135	5956	2767	901	8.3	29	13.21
0:29:50	7372.8	7372.8	1.1	56	61.7	254.2	18.9	135	6311	2794	903	8.3	29	13.21
0:30:00	7372.8	7372.8	1.1	56	61.7	255	18.1	135	6744	2774	906	8.3	29	13.21
0:30:10	7373	7373	1.1	56	61.5	255.6	17.5	135	6193	2771	907	8.3	29	13.21
0:30:20	7373	7373	6	10	61.5	252.7	20.5	135	6216	2783	906	8.3	29	13.22
0:30:30	7373.1	7373.1	6	10	61.4	252.4	20.8	135	6527	2797	907	8.3	29	13.22
0:30:40	7373.1	7373.1	6	10	61.4	251.8	21.3	135	6079	2774	905	8.3	29	13.22
0:30:50	7373.1	7373.1	6	10	61.4	251	22.1	135	6134	2766	905	8.3	29	13.22
0:31:00	7373.1	7373.1	6	10	61.4	251.4	21.8	135	6028	2773	908	8.3	29	13.23
0:31:10	7373.1	7373.1	6	10	61.4	251.6	21.6	135	5221	2768	908	8.3	29	13.23
0:31:20	7373.1	7373.1	6	10	61.4	251.4	21.8	135	5113	2803	909	8.3	29	13.23
0:31:30	7373.1	7373.1	6	10	61.4	252	21.1	135	5102	2782	908	8.3	29	13.24
0:31:40	7373.1	7373.1	6	10	61.4	252.7	20.5	135	4940	2771	908	8.3	29	13.24
0:31:50	7373.1	7373.1	6	10	61.4	253.5	19.7	135	5144	2763	907	8.3	29	13.24
0:32:00	7373.1	7373.1	6	10	61.4	253.3	19.9	135	5256	2797	902	8.3	29	13.24
0:32:10	7373.1	7373.1	6	10	61.4	253.9	19.2	135	5348	2782	900	8.3	29	13.25
0:32:20	7373.1	7373.1	6	10	61.4	254.2	19	135	5815	2784	906	8.3	29	13.25

Figure 4-3. Data acquisition from sensors

4.3 Data Preparation

During data preparation, the raw sensor data are prepared into a suitable form for further analysis and processing. Moreover, in this step, due to the possibility of uncompleted, inconsistent and imprecise (comprises outliers) information, preprocessing data is needed. As for the archived sensor data in this research, the WOB, SPP, and flow rate are the required data for simulation. Now it turns to preparing data (bringing the sensor's data into a proper form) to a format in which data can be easily extracted. Therefore in the current stage, the acquired data should be preprocessed by implementing the noise, outlier, and missing data removal techniques.

In some cases, there is essential to reveal extra data that may not be visible in the original form of the data. For instance, this adjustment may contain modification of time-domain data to frequency-domain. This stage contains both healthy and faulty conditions.

WOB	SPP	Flow	Fault
{1891×2 table}	{1891×2 table}	{1891×2 table}	0
{ 180×2 table}	{ 180×2 table}	{ 180×2 table}	1
{6570×2 table}	{6570×2 table}	{6570×2 table}	0
{8639×2 table}	{8639×2 table}	{8639×2 table}	0
{8640×2 table}	{8640×2 table}	{8640×2 table}	0
{2969×2 table}	{2969×2 table}	{2969×2 table}	0
{ 360×2 table}	{ 360×2 table}	{ 360×2 table}	1
{5310×2 table}	{5310×2 table}	{5310×2 table}	0
{2879×2 table}	{2879×2 table}	{2879×2 table}	0
{ 180×2 table}	{ 180×2 table}	{ 180×2 table}	1
{ 540×2 table}	{ 540×2 table}	{ 540×2 table}	0
{ 545×2 table}	{ 545×2 table}	{ 545×2 table}	1
{4500×2 table}	{4500×2 table}	{4500×2 table}	0
{8639×2 table}	{8639×2 table}	{8639×2 table}	0

Figure 4-4. Preprocessing data based on their healthy and faulty status

As can be seen in Figure 4.4, the data are categorized based on their operating conditions (by considering the DDR reports and the sensor data attributes). The operating condition is defined as the binary characteristic, fault 0 or 1. Fault zero represents the normal or healthy operation, whereas fault 1 is corresponded to faulty or pump failures (in this case there are four times of mud pump failure which leads to stop the mud pump operation). After that classifying the data into a useful format, the preprocessed data should be imported into the diagnostic feature app. From figure 4.5 can be observed, the selected parameters (WOB, SPP and flow rate) in this section should be changed from condition variable to signal variable type to represent the attribute of the data based on time and frequency domain. This app is able to develop properties and analyze potential condition indicators by utilizing a multi-functional graphical interface.

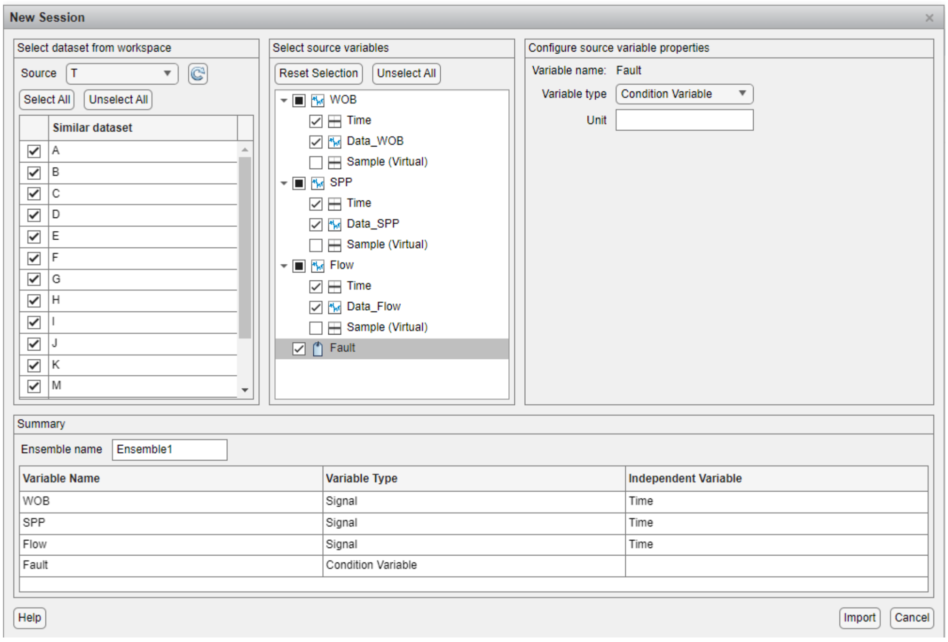


Figure 4-5. Importing the preprocessed data to diagnostic feature app

4.4 Condition Indicators Identification

In MATLAB, the PdM Toolbox lets the user create condition indicators using the model- and signal-based techniques. In this thesis, the signal-based approach has been considered. Before importing the preprocessed sensor data to the diagnostic feature app (figure 4.5), defining the faults as a condition variable item is necessary. Otherwise, the faulty operation cannot easily differentiate from the normal operation. In order to represent how the signals will change with time, signal trace diagrams should be generated. Moreover, those signals can also be demonstrated via the magnitude and phase as a function of frequency. The following figure shows the peaks in the frequency information move left as the mud pump degrades; then, the peak frequencies can be considered as condition indicators. Figure 4.6 represents the main steps of transforming the raw data to the preprocessed data type.

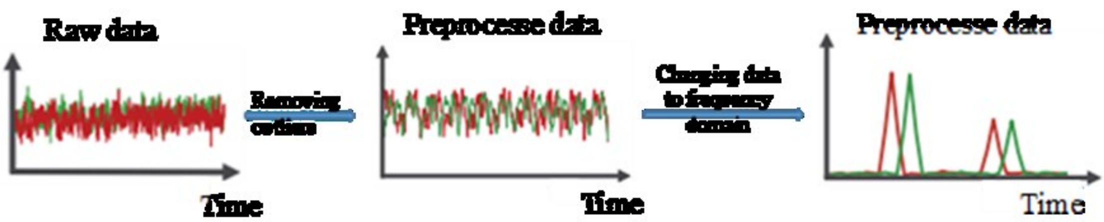


Figure 4-6. Overview of the identify condition indicators step

For the next step, the signal trace diagrams should be grouped in the diagnostic feature app according to the pump failures. This step aims to determine condition indicators, properties that attitude change in an expected way as the system degrades. These properties are utilized to distinguish between faulty and healthy operations. In order to differentiate diverse fault conditions or distinguish faulty conditions from healthy ones, features should be extracted (it is based on signal-based condition indicators). For instance, the mean value of an individual signal or its standard variation might change as system health degrades. Therefore in this stage, signal features will be extracted.

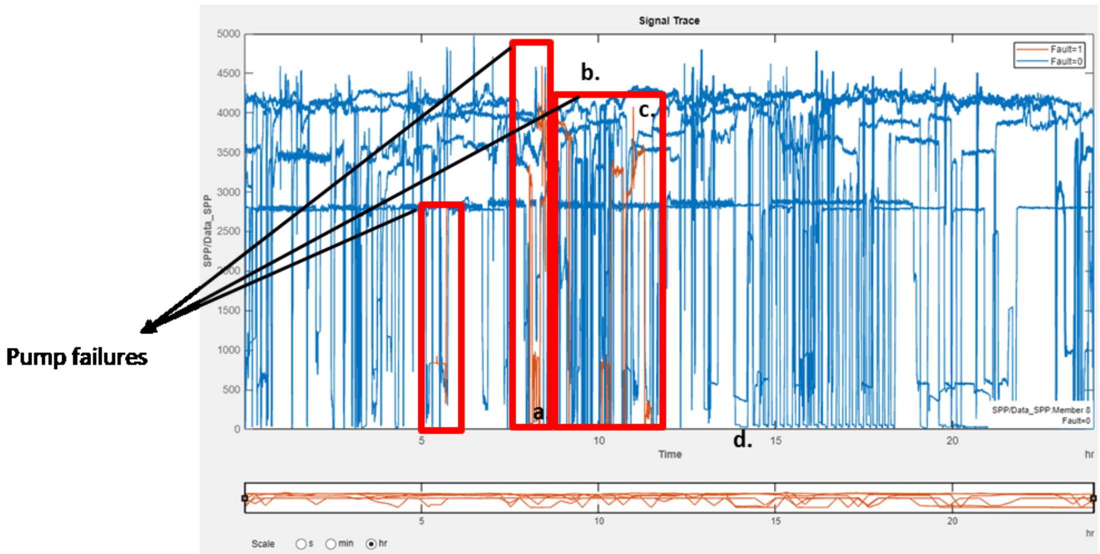


Figure 4-7. SPP signal trace diagram

Figure 4.7 and 4.8 represent the signal attributes of the mud pump for standpipe pressure and flow rate, respectively (signal trace diagrams for SPP and flow rate on 24 hours for various operational days). As can be seen in both figures, the five times pump failures are shown in the diagrams. The a. failure occurred a day at 05:15 am, and the pump was stopped for 30 minutes for repair. The b. failure is related to another day in which the mud pump was under maintenance from 08:15 am to 09:15 am. The c. and d. failures correspond to a single day, c. had been started from 08:00 am to 08:30 am, and d. had begun from 10:00 am to 11:30 am. After that, it is required to generate the time-domain diagram for further steps.

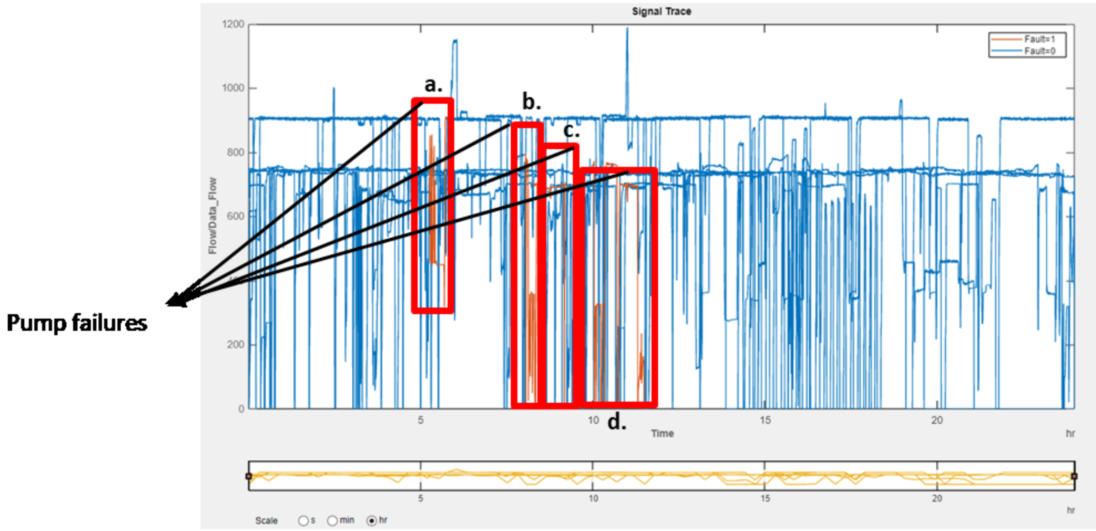


Figure 4-8. Flow rate signal trace diagram

Since the time-domain features are inadequate to perform as condition indicators, the frequency-domain feature technique can be used with time-domain features. In MATLAB, the time-domain feature is essential for creating a feature table (for the ranking feature section). The frequency-domain feature technique gives cyclic fluctuations of the pump pressure and flow graphs that give us an efficient insight into how pressure and flow signals change under various fault conditions.

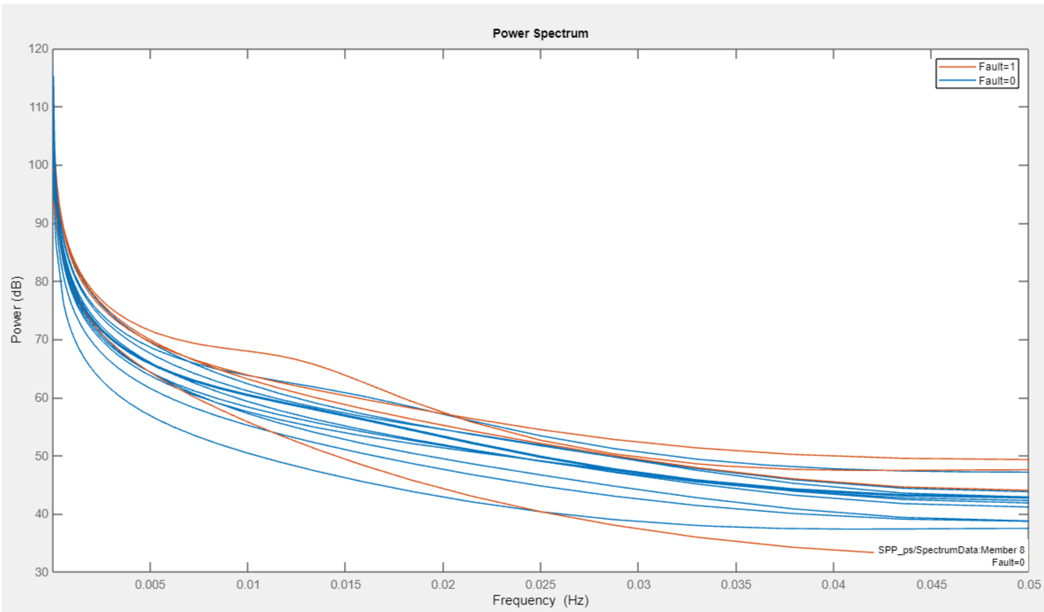


Figure 4-9. SPP power spectrum diagram

Then the results can be plotted to observe whether the features facilitate the diagnosis of different fault conditions. Signals which replicate intermittently in time are shown via a power spectrum as illustrated in Figures 4.9 and 4.10. Based on the Fourier analysis, any natural or physical signal can be converted into a value of discrete frequencies or the spectrum of the frequencies throughout the ongoing range. The frequency domain illustration of the signal is sometimes easier to evaluate than the time domain diagrams (it is also more frequent in the vibration and acoustic emission techniques). The failure attributes in both power spectrum diagrams are shown according to the previous analysis. As can be observed from power-frequency graphs the orange lines have an unusual trend which the system takes into consideration as the pump failures.

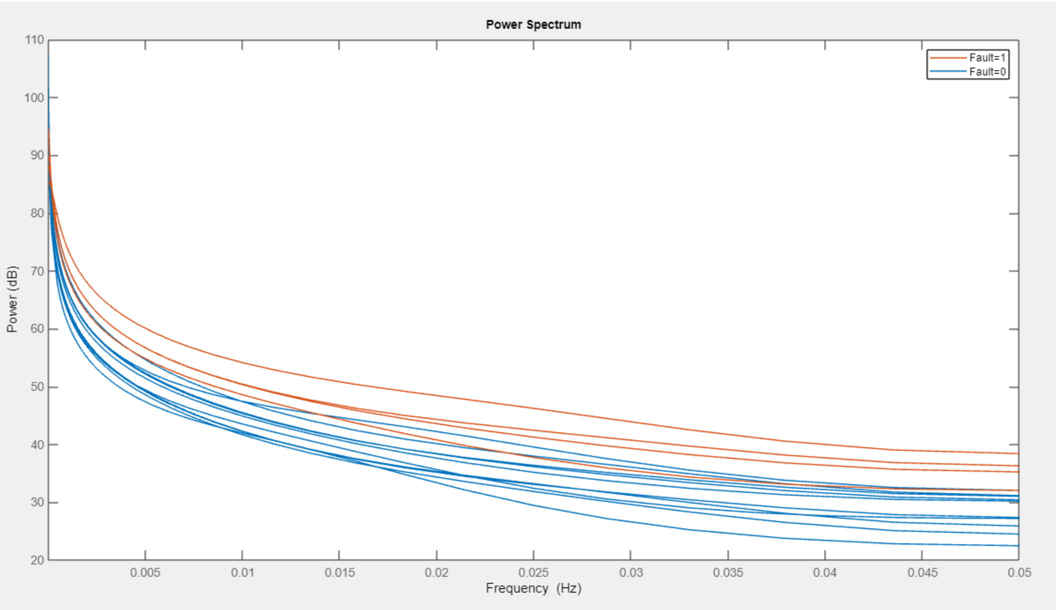
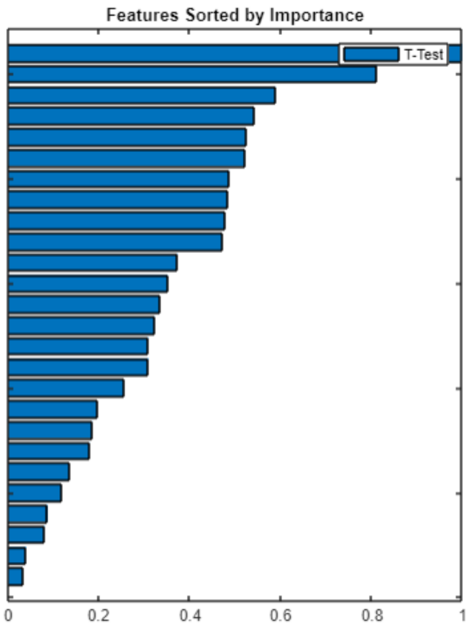


Figure 4-10. Flow rate power spectrum diagram

4.5 Models Training and Evaluation

The key purpose of this section is to train the model to identify certain types of patterns. In the following step, the whole extracted features should be transferred to a table, in order to illustrate the computed featured data. As more properties are evaluated, more columns get annexed to the table. After that, the distributions of the feature values for numerous condition variable values, in this regard, fault class, the feature table will be represented as the histogram for the different features. They are categorized by fault. The further step has to identify which properties are more valuable for fault prediction. It comprises ranking and exporting the features. The software ranks the properties according to their importance based on the metric value. For the performance analysis technique, standpipe pressure and flow rate properties are more important for the ongoing trained model. In such a case, the root means square value (RMS) for flow signals and the impulse factor for SPP are the properties that most intensely recognize various fault types from each other (diagnosed by MATLAB). Thereafter prioritizing the properties based on their importance, now is time to train the model based on these properties. Figure 4.11 represents the most notified features.



Feature	T-Test
Flow_sigstats/RMS	4.9660
Flow_sigstats/Mean	4.0325
Flow_sigstats/SNR	2.9238
Flow_sigstats/SINAD	2.6934
SPP_sigstats/ImpulseFactor	2.6023
SPP_sigstats/ClearanceF...	2.5874
SPP_sigstats/CrestFactor	2.4128
SPP_sigstats/Mean	2.3991
SPP_sigstats/RMS	2.3671
SPP_sigstats/ShapeFactor	2.3389
Flow_sigstats/PeakValue	1.8519
Flow_sigstats/Skewness	1.7473
SPP_sigstats/Skewness	1.6604
SPP_sigstats/PeakValue	1.6071
Flow_sigstats/ImpulseFactor	1.5372
Flow_sigstats/CrestFactor	1.5358
Flow_sigstats/ShapeFactor	1.2678
SPP_sigstats/SNR	0.9749
Flow_sigstats/ClearanceF...	0.9273

Figure 4-11. Ranking features histogram

Then, the top features that need classification should be selected and exported to the next stage for diagnosis of different faults (this will be done by the classification learner application). The classification learner app illustrates the scatter plot for a signal model based on the flow rate and standpipe pressure data (Figure 4.12 and Figure 4.13).

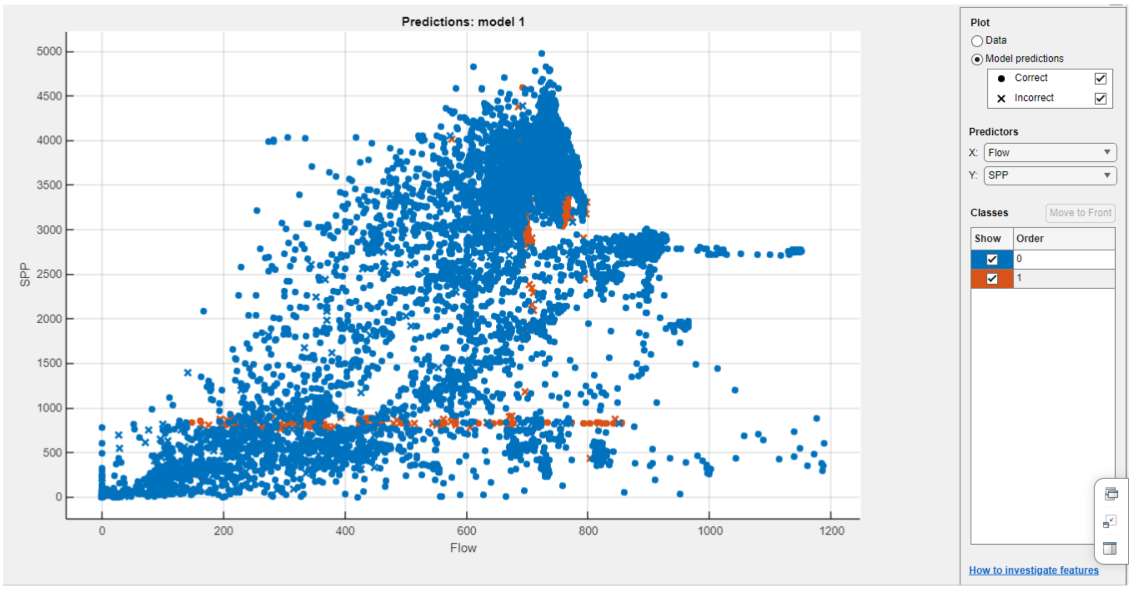


Figure 4-12 SPP-Flow prediction scatter plot

These scatter plots in classification application, are going to determine predictors that separate classes well by representing various pairs of predictors. Figures 12 and 13 demonstrate training information as well as misclassified points. In the app, the pressure and flow rate axis can be changed. The X-axis represents the actual values of SPP and flow rate and illustrates the predicted values throughout the Y-axis. The orange and blue colors show both correct and incorrect values (correct values are illustrated by bullet shape, and incorrect ones are shown with cross sign).

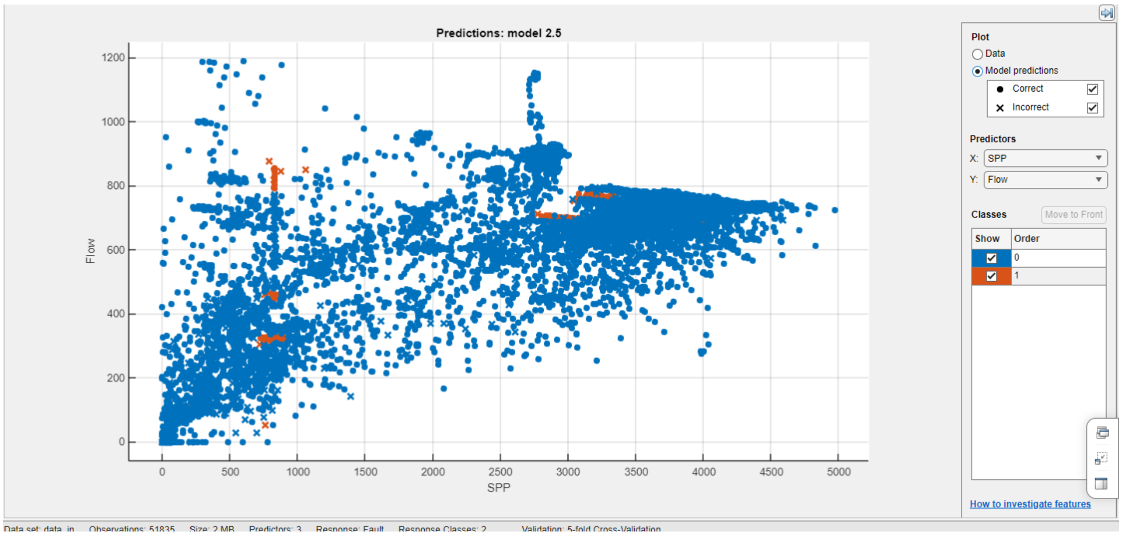


Figure 4-13 Flow-SPP prediction scatter plot

After fulfilling the training, the classification learner listed each model based on the model number, besides the model accuracy as well as represents a confusion matrix (is one of the useful performing classifiers that can be trained via extracted features to evaluate the quality or the performance of the model) for the first model. The K-Nearest Neighbor which already has discussed in the second chapter can support this classification to reach an accuracy up to 90 %. To enhance the precision of the matrix, the number of features can be increased or use various frequency peaks or adjust the bandwidth.

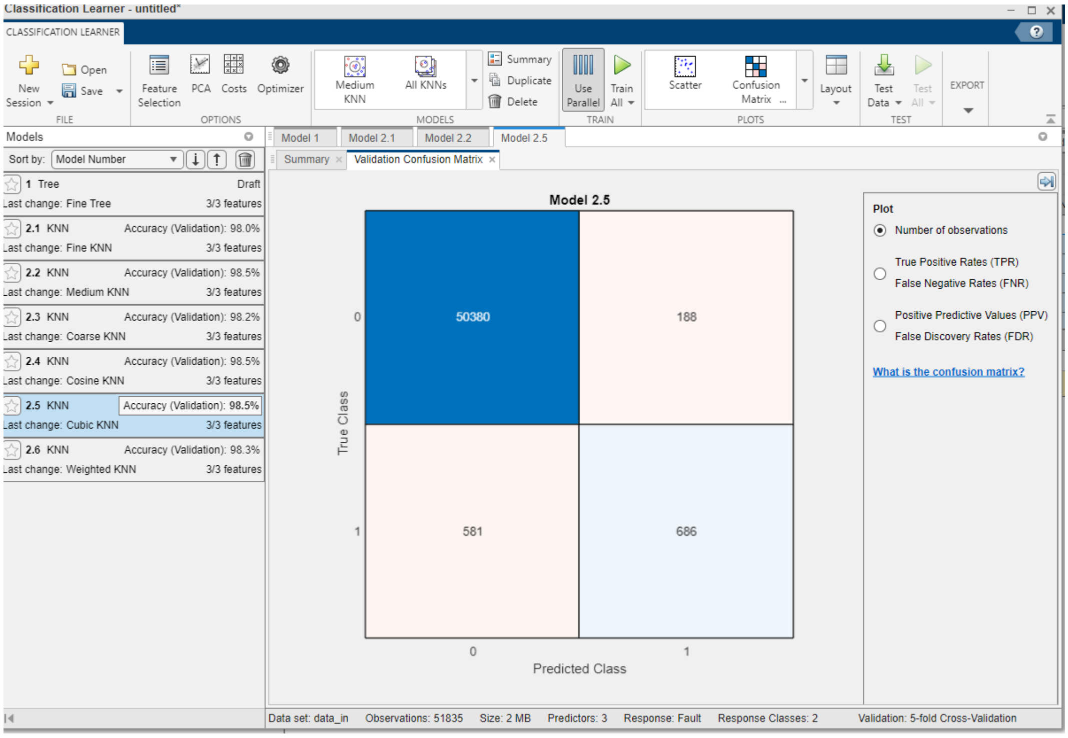


Figure 4-14. Mud pump confusion matrix for healthy and faulty conditions

By confusion matrix, the number of observations in both predicted class (row) and actual or true class (column) can be represented, or in the better word, the right and false classifications are filled into the table. Figure 4.14 facilitates the understanding of how the actual selected classifier acted in each class. Among these created models, MATLAB selected the model with highest accuracy automatically by itself and the represented confusion matrix is corresponding to the selected model. As can be seen in the confusion matrix (figure 4.14), the 50380 sensor records were predicted correctly by the model as healthy mud pump conditions. The second section shows the 188 sensor records were related to faulty conditions but wrongly predicted as normal pump operations; moreover, the 581 sensor records were related to healthy conditions, but wrongly estimated as the pump's failure. The last section is related to the 686 sensor records which were estimated correctly by the model as faulty states.

4.6 Case Study

The data used in chapter 4 is related to a drilled well in North Africa. The model is also trained with sensor data from six drilling operation days (24 hours operation) which mud pump failures occurred on three different days. During these periods four pump breakdowns happened. The other 3 operational days data are corresponding to normal drilling activities without failure. To enhance the quality and accuracy of the simulation, the operational days which do not have any failure were also taken into consideration. The healthy operational pump data trained the model for normal operation at different depths and other parameters. The healthy pump data used in this model training are related to the day before, and after failures; the reason for that is to observe the deviation from normal attributes.

The last step in this methodology is to place the trained ML model into the cloud or on the edge or end device where it can be utilized for its further purpose. In case there is no internet connection, the algorithm can be run on inserted devices that are near the mud pump. The combination of cloud and embedded devices are feasible (the preprocessed and data extraction stages are on the edge device and transferring the extracted properties to the prediction model that runs on the cloud).

In order to verify the accuracy of the model via new sensor data and validate whether the trained model works properly or not, a new data set belonging to the same drilled well should be used. For this purpose, the trained model should be exported to the new workspace (in this stage MATLAB will generate a code as well as the related prediction function for the trained model). It is required to modify the input name of the prediction function in the newly generated code and write a code to read the new sensor data for the trained model. Then the new mud pump sensor data will be imported for evaluation (the new sensor data was related to the 24 hours normal drilling operation). The following points represent the key steps in the generated MATLAB code:

- Creating an input table with the new sensor data
- Taking WOB, SPP and Flow as the predictor variables
- Response to failure
- Train a classifier (all classifier options should be specified)
- Create result struct (by predict function)
- Add additional fields to result struct
- Extract predictors and response
- Perform cross-validation
- First output, Compute validation predictions
- Second output, compute validation accuracy

Figure 4.15 represents the trained model has 98% accuracy with imported sensor data. At the end, when sensor data is run or used in the trained model, the user can observe whether the input data is healthy or faulty.

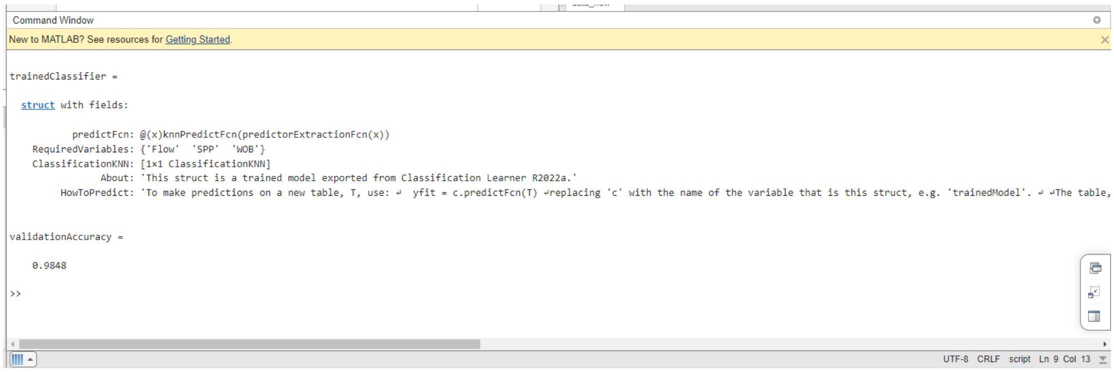


Figure 4-15. Trained model validation

4.7 Limitation

The main limitations of the developed model are summarized in the following points:

- Since the model relies on a binary classifier algorithm to differentiate between the failure and regular operation of the pump, multiple historical datasets in which the incidents occurred are required.
- Similarity must exist in the utilized data set; the data must be from the same pump, field, phase, used drilling fluid, etc; otherwise, the model will not work effectively, and false alarms will be generated.
- Training data frame selection and classification have a significant impact on the model performance, which is considered to be subjective.
- The model's current version uses the SPP as an indicator; however, the abnormality of the SPP can be caused by another issue, such as downhole drilling problems. This issue can be solved by considering additional sensors, such as vibration and temperature sensors.

Chapter 5

Conclusions

The Mud pump is one of the crucial components of drilling rigs and its operational condition plays a significant role in nonproductive time and HSE issues. Therefore it is necessary to keep it in the best condition and try to anticipate and minimize the possible failure on it. This thesis has tried to choose the most efficient fault detection and diagnosis approach in order to use it in the AI frame and created the machine learning model based on the best maintenance strategy. To sum up all the significant aspects of this thesis, the following points are summarized based on the previous chapters:

1. The most common FFD techniques are the data-based and signal-based models, process model-based, and knowledge-based techniques. In this research, data-based and signal-based technique is implemented for fault detection. The trained model is built according to the collected process operation non-intrusive sensor data, fault detection, and diagnosis and exploits only available experimental (historical) data.
2. On the other hand, by emerging the 4th industrial revolution, the advancement by connecting different technologies that create and communicate between systems has been observed. The information in these communications can be achieved from different sources which interpreted and turned into useful information. Among theis new progresse, AI technology can be used in order to anticipate mud pump performance degradation, and autonomously manage as well as optimize pump service needs.
3. Machine learning is one of the applicable and well-known techniques in AI technology to train a model according to this research objectives. One of the significant applications of the ML model is to identify unknown patterns in the mud pump's sensor data and is developing a way to discover structures and patterns in the data independently. For this purpose, associating the condition-based monitoring and machine learning approaches can create a trained model that is capable to identify drilling pump conditions.

4. Mud pumps have two key sections, power end and fluid end parts. Each of the mentioned sections has different components and subcomponents. The most common failures in mud pump elements are 1. Pulley and groove of pulley, 2.Bearing carrier bolt, 3.SCR, 4. Valves, 5.Piston, 6.Crosshead bearing, 7.Pressure gauge, 8.Discharge line, 9. Discharge/Suction valve, 10. Lubricating system and 11. Cavitation failures and so on. According to the recorded reasons for these failures each of them has specific symptoms and roots. Among these failures, valve related issues are the most common breakdown reason which can lead to failure in other components.
5. In case to boost the uptime of any component in mud pumps and minimize the NPT as well as HSE incidents, a profound and precise predictive maintenance approach is required. There are various kinds of PdM techniques for mud pump failures that most of them integrated via non-intrusive measurements like Vibration monitoring, Acoustic emission monitoring, Lubrication oil analysis, Thermographic analysis, Performance analysis, Smart pumping technique, Power analysis and Electrical testing.
6. In this thesis, the performance analysis approach has been considered for the predictive maintenance of mud pumps. This technique is based on analyzing the replicable measurements such as standpipe pressure, flow rate and weight on bit. These parameters have a direct impact on such pump failures like damaging pump components, valve breakdown, wearing liners, seats and pistons out that can be reasoned for other mud pump failures.
7. The methodology throughout this study is based on the integration of AI technology and the PdM approach which have been led to train a machine learning model. The model has been trained by real sensor data in MATLAB Classification and Diagnostic feature apps. For this purpose, the methodology is comprised of 5 key stages that have been started with acquiring sensor data, preprocessing achieved data, identifying condition indicators, training model, deploying and integrating the trained model. The main output or achievement in this methodology is the ML-trained model which has been verified by setting new sensor data to determine the pump conditions.

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Nomenclature

H	Head	[kPa]
P	Power	[Kw]
Q	Flow	[m3/s]
ppm	Part per million	[ppm]
η	Efficiency	Decimal
P	Pressure	[psi]

Abbreviations

AADE	American Association of Drilling Engineers
AE	Acoustic Emission
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASNT	American Society of Nondestructive Testing
BEP	Best Efficiency Point
CM	Condition Monitoring
CPS	Cyber-Physical Systems
DM	Data Mining
DT	Digital Twins
EAM	Electric Audio Module
NPT	Non Productive Time
HPHT	High Pressure High Temperature
HiPot	High Potential Testing
HSE	Heath Safety and Environment
HMMs	Hidden Markov Models
KPI	Key Performance Indicator
KNN	K-Nearest Neighbors
ML	Machine Learning
MSPM	Multivariate Statistical Process Monitoring
OEM	Operation, Engineering and Maintenance
OEE	Overall Equipment Effectiveness
PLM	Product Life Cycle Management
PM-FD	Process Monitoring and Fault Diagnosis
PSC	Principal Component Score
IIOT	Industrial Internet of Things

IFOV	Instantaneous Field of View
IOT	Internet of Things
FDD	Fault Detection and Diagnosis
PEMFC	Proton Exchange Membrane Fuel Cells
PCA	Principal Component Analysis
PdM	Predictive Maintenance
PM	Preventive Maintenance
ICSS	Instrumentation Control and Safety System
TDA	Two-row Double Outer race
SCR	Silicon Controlled Rectifiers
SPC	Statistical Process Control
SOP	Standard Operation Procedures
SPM	Statistical Process Monitoring
SPM	Stroke per Minute
SPP	Standpipe Pressure
SVM	Support Vector Machine
SW-ELM	Summation Wavelet-Extreme Learning Machine
TDO	Two-row Double outer race
RTF	Run to Failure
RUL	Remaining Useful Time
RDS	Remote Diagnostic Services
WOB	Weight on Bit