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Reliability–Centered Maintenance Using Reliability Parameters on Gas Compressors

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ABSTRACT

The main objective of reliability-centered maintenance is the cost-effectiveness of the maintenance strategy. These strategies, rather than the different components of reliability-centered maintenance being applied independently, are optimally integrated to take advantage of their respective strengths to optimize equipment reliability and life-cycle costs. The article uses reliability parameters to define the type of maintenance strategy and time to perform maintenance on gas compressors. This article presents a methodology using the gas compressor's reliability parameters to model reliability-centered maintenance procedure for the gas compressors. The approach is based on reliability parameters gotten from the liner regression carried out on the gas compressors. The shape parameter (β) from the Weibull linear regression shows that most components in the two gas compressors were experiencing early failure with their β < 1 and the distribution that best fits the data is the lognormal distribution, whose parameters are the shape parameter (σ') and the scale parameter (μ').

KEYWORDS

Reliability, Parameter, RCM, Predictive Maintenance, Proactive Maintenance

1. INTRODUCTION

Reliability-Centered Maintenance (RCM) is the process that is used to determine the most effective approach to maintenance. It involves identifying actions that, when taken, will reduce the probability of failure and which are the most cost effective. It integrates Preventive Maintenance (PM), Predictive, Corrective Maintenance (also called reactive maintenance), and Proactive Maintenance to increase the probability that a machine or component will function in the required manner over its design life cycle with a minimum amount of maintenance and downtime. These principal maintenance strategies, rather than being applied independently, are optimally integrated to take advantage of their respective strengths and maximize facility and equipment reliability while minimizing life-cycle costs. The goal of this approach is to reduce the Life-Cycle Cost (LCC) of a facility to a minimum while continuing to allow the facility to function as intended with required reliability and availability. (NASA, 2008).

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Sachdeva Anish et al., (2009) proposed a new modified FMECA approach to deal with the problems encountered while defining the best mix of maintenance policies. An objective weighted function based multi-criteria failure mode analysis technique using TOPSIS was proposed to find more accurate and reliable priority risk numbers for performing the criticality analysis. This enables them to obtain a ranking of failure modes / components by incorporating several types of information related to performance, safety and society. Furthermore, significant failures have occurred in service, perhaps involving safety or financial loss. To provide timely delivery of quality products, the managers and engineers have been forced to optimize the performance of all systems/subsystems involved in their flow station. The deterioration and failure of these systems/subsystems might incur high costs due to production losses and delays, unplanned intervention on the system and safety hazards. To avoid such situations, an appropriate maintenance policy strategy is necessary to repair/ replace the deteriorated system before failure. Their proposed approach forms a basis for the continuous process of reliability design and maintenance strategy decisions. Islam (2010) described the application of reliability-centered maintenance methodology to the development of maintenance plan for a steam-process plant. His methodology showed that the main time between failures for the plant equipment and the probability of sudden equipment failures are decreased. Also, his results show that the labor cost decreases from 295,200 $/year to 220,800 $/year (about 25.8% of the total labor cost) for the proposed preventive maintenance planning. Moreover, the downtime cost of the plant components was investigated. The proposed PM planning results indicated a saving of about 80% of the total downtime cost as compared with that of current maintenance. Ulhas (2022) described how ships can benefit by deploying Big Data analytics, the Internet of Things and Artificial intelligence (AI) in enhancing the value of RCM in ship maintenance and thus are indispensable for the RCM. He believes that the synergy that will be created by using big data, RCM and AI concepts will enable the creation of a maintenance business model that will eventually develop a new growth engine for the stakeholders in the shipping industry. Renan et al. (2023) proposed novel methods that effectively integrate RCM and Risk-Based Maintenance (RBM) by adapting the traditional RCM method to incorporate risk management into maintenance planning decision-making to support maintenance management. The proposed Reliability and Risk Centered Maintenance (RRCM) method allows organizations to determine maintenance plans that ensure the reliability of the physical assets while considering and prioritizing the risks associated with their potential functional failures. The results show the ability of RRCM to assist in the development and implementation of maintenance plans oriented to reliability, risk, and cost. Ismail et al. (2023) proposed a Reliability-Centered Maintenance (RCM) strategy to minimize the risk of equipment failure and improve the safety of the 15-ton overhead traveling crane and save costs. Their RCM strategy was developed using Failure Modes and Effects Analysis (FMEA) to identify the potential failure modes of the crane and their consequences. The results of their FMEA were used to develop a maintenance plan that includes preventive maintenance tasks and procedures to prevent or mitigate the identified failures. Li et al. (2021) analyzed the dynamic equipment of the alkylation unit using the RCM approach to propose a data-driven method for building the failure mode library and integrated the maintenance records and failures diagnosis of the equipment to improve the traditional RCM method. Egbe et al. (2024) presented a methodology using the Pareto analysis in conjunction with failure mode effect and criticality Analysis in maintenance resources optimization to enables an organization to set priorities towards achieving certain goals which are availability and reliability of the equipment for operational excellence Their approach was based on ensuring all failure mode criticality number are considered to obtain the significant failures mode that you should focus on as a priority. Their analysis shows that failure modes; FM5, FM 3, FM 2, FM 12, FM 7 and FM 13 are confirmation to the Pareto principle, identifying that most of the downtime of the Instrumentation Air Compressors originated from these failure modes. Furthermore, their study developed a valuable tool for the oil and gas industry that are seeking to optimize maintenance resources and improve their operational excellence with ensured safety and minimal environmental impact. Ogra et al. (2021) applied reliability-centered-maintenance

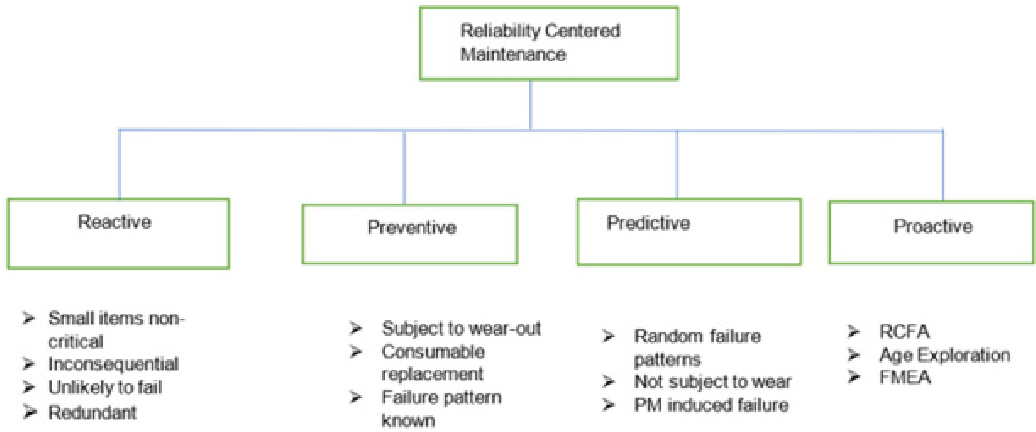
(RCM) to reduce the operational cost of heat exchanger and feed water pump in a brewery. The feed water pump and heat exchanger system were selected for RCM analysis as they both have significant impacts on the quantity and quality of the beer produced in the brewery. The results of their RCM technique applied to the brewery plant showed that the Run-To-Failure frequency has been reduced. The preventive maintenance task was made up of scheduled reliability-centered maintenance which had great impact on the routine maintenance task by recommending the tasks to be carried out monthly and six-monthly. With the proposed labor program carried out, the results show that the labor cost decreases from N108,000,000.00/year to N67,200,000.00/year for the proposed PM planning. The results also showed that about 36.19% of the annual spare parts cost are saved when proposed PM planning is adopted other than the current maintenance plan.

Afefy et al. (2019) proved that RCM theory has effectively improved the reliability of equipment operation and reduce maintenance costs. Wei et al. (2023) introduced and implemented reliability-centered maintenance (RCM) assessment of ammonia-related dynamic equipment as a key part of the integrity management of ammonia-related dynamic equipment. Through data analysis and system screening they were able to clarify the operation status, key roles, and potential risks of each ammonia-related equipment. Furthermore, they used FMEA to analyze failure mode, develop suitable risk assessment criteria and risk matrix, determine the risk level of each dynamic equipment, and develop maintenance strategy for the equipment. Moradi et al, (2024) developed a mathematical programming model to determine the annual implementation and plan the annual equipment maintenance activities, by the minimum total annual cost and total annual Risk Priority Number RPN and their effect on the failure modes of physical asset management through Reliability Centered Maintenance RCM. Mengchu et al, (2023) presented a framework of model-based RCM analysis, which is driven by functional modelling and reasoning to classify failure modes and identify maintenance significant items (MSIs). Their study focused on identifying the so-called maintenance significant items through assessment of failure consequences. Their result shown that Multilevel flow modelling (MFM) was proved competitive to identify sufficient system functions that expect maintenance to preserve. It is was also able to define failure modes and represent their interactions with system functions, which are essential to RCM. Xiuzhen et al, (2024) proposed a mission reliability-centered opportunistic maintenance optimization model for multistate manufacturing systems to realize the optimal combination of maintenance activities of multistate manufacturing systems. Their result showed that the proposed approach is superior to the conventional RCM method, ensuring the healthy operation of the manufacturing system at a low cost. Nugroho and Tedjo (2024) integrated Reliability Centered Maintenance (RCM) II and Failure Modes and Effect Analyze (FMEA) to determine which components where due for repairs, and identifying the root cause of engine failure. Their results of their analysis shown that the maintenance interval for the Electromotor component (electric motor) of 20hours, for the Lower and upper nozzle components with a maintenance interval of 181 hours. Darmein et al, (2023) Presented an optimal maintenance strategy for gas turbines using the Reliability Centered Maintenance (RCM) method related to availability, reliability, maintainability, and maintenance costs. They carried out an analysis of the causes and effects of failure using the Failure Mode and Effect Analysis (FMEA) method, with the parameters of failure frequency and consequences of failure then analyzed it using the RCM worksheet to determine an effective maintenance strategy. The application of their RCM method was able to reduce maintenance costs by up to 30.678% along with reduced downtime rates, decreased failure rates and the number of Mean Time To Repair (MTTR). Jiang et al. (2023) combined the characteristics of pumped storage unit operation and maintenance management and years of maintenance practice experience to improve and innovate the RCM technology method, forming a reliability-centered pumped storage unit maintenance strategy optimization technology method applicable to pumped storage power generation units. This technology method has been applied on the system equipment of pumped storage power generation unit. It shows that the application of their technology method has made significant contribution to optimizing equipment maintenance strategies, reducing maintenance workload and the overhaul time. Geisbush & Ariaratnam (2024) reviewed potential models for predicting the progression of distressed concrete pipe segments for use in RCM analysis and proposed a regression model operators can use to forecast when to perform maintenance activities. The results of their study suggest that RCM analyses for large diameter water pipelines can improve reliability, reduce maintenance costs, and extend the useful life of a pipeline regardless of age or material. Further, using their regression style model with gathered data can be used to forecast when specific maintenance thresholds may be reached, prompting predictive maintenance actions. Kharmanda et al. (2023) In their work, RCM technology used failure mode effect analysis (FMEA) was presented as an analytical process to determine the appropriate failure management strategies to ensure safe operations and cost-wise readiness. This technology method has been applied to a coffee maker. It shows that the application of their technology method has led to reduction in maintenance costs, improving quality, and increasing reliability. Several failure modes considering MSG-3 standard are presented to provide suitable preventive maintenance actions. The benefits of FMEA are to reduce costs, improve quality, and increase reliability. Edwardo, (2016) described the main objective of RCM is to define an equipment component maintenance policy based on several criteria, including failure, cost, reliability, and safety. RCM is a guide to support maintenance managers in making decisions about maintenance based on planning developed during RCM analysis.

Reliability analysis and planned maintenance need to be carried out to avoid loss of availability of equipment/systems which will help the flow station managers to optimize the performance of the systems and maintenance tasks as well. The problem is to predict when or if failure will occur when the equipment is used. This information can then be used to determine inspection and maintenance policies as well as warranties. It can also be used to predict costs due to maintenance and eventual failure if failure occurs while the equipment is in operation. However, when time to failure field data is analyzed using parametric analysis based on methodology that applies to time to failure data, the analysis would provide an in-depth information about the equipment and system reliability and their performance behavior over time. It is therefore necessary to carry out a reliability analysis of these equipment and systems to compute the functions of interest such as the distribution parameter that will serve as input to the reliability centered maintenance. This paper will deal with the application of reliability centered maintenance on gas compressors.

A flow station is a gathering center where primary separation/processing of the reservoir fluid takes place, these fluids are later transported to terminals for export or to the refinery, while the other products are either treated, flared or disposed (Devold, 2013). Operators of flow stations want to make as much profit as possible with ensured safety and minimum environmental impact also placing increased emphasis on the reliability of the flow station. The availability of flow station critical equipment such as Gas Compressors is the core term for maintenance activities in the flow station. Compressors are mechanical devices that are used to increase the pressure of compressible fluid such as gas or vapor and as well reduce the volume of the gas as it passes through it.

Figure 1. Components of an RCM (NASA 2008)



1.1 Common Maintenance Practices

The reliability and maintainability of equipment determine the availability of the equipment, this section will deal on overview of maintenance. Figure 1 shows the different component of reliability centered maintenance, rather than being applied independently, are optimally integrated to take advantage of their respective strengths, and maximize facility and equipment reliability while minimizing life-cycle costs. According to Kobbacy in the modern world as today, the efficient running of the society depends on the smooth operation of many complex systems. All equipment is unreliable in the sense that it degrades with ageing and fails when it no longer has capacity to deliver required services or products (Kobbacy and Murthy 2008). The consequences of failure of any critical system could be dramatic. This might immediately bring great threats on human safety, environment damage, and economic efficiency. In this sense, maintenance is introduced to ensure equipment and systems run efficiently for their designed life at least. According to Markeset et al. (2012), there are different aspects of maintenance, including safety enhancing aspects of maintenance, performance enhancing aspects, economical aspects, quality enhancing aspects, environmental aspects, life span increasing aspects, and aesthetic aspects. There are mainly four kinds of maintenance programs in use, which are corrective maintenance, preventive maintenance and predictive maintenance. By carrying out the proper planned maintenance such issues as catastrophic failure, secondary damage, additional spare parts costs, unnecessary overtime and injury to staff can be avoided (Mobius Institute 2009). As a result, the uptime of the equipment may be increased, and maintenance costs may be reduced.

Different types of companies have various ways to measure the success of the operations. In some cases, keeping machine running is essential and failure of the equipment must be avoided to prevent huge costs associated with loss of production. In other cases, for instance, for supply vessels during the operations in the arctic, it is important to be prepared and be available for "operation windows" due to weather conditions. According to (Pintelon and Puyvelde 2009) Maintenance planning varies according to the goals of the organization. There are two definitions that one has to be aware of: maintenance policy and maintenance concept. Maintenance policy represents a rule or a set of rules describing conditions for the variety of maintenance activities. Maintenance concept is a set of policies and activities planned and supported by decision structure. According to Mobius Institute there are four commonly used maintenance policies (Mobius Institute 2009):

- Corrective/Breakdown maintenance
- Preventive maintenance
- Predictive maintenance

- Precision maintenance

Ulansky and Raza (2024) Investigated various maintenance approaches, such as preventive and corrective maintenance, and evaluates their performance, considering the uncertainties introduced by imperfect inspections. By analyzing the existing literature and research findings, their survey provides valuable insights into the challenges and opportunities associated with maintenance decision making in the presence of inspection imperfections. The comparison between maintenance models with constant and non-constant probabilities of false positives and false negatives sheds light on the dynamic nature of these models, enabling a deeper understanding of their real-world applicability and effectiveness.

1.1.1 Corrective/Breakdown Maintenance

The main point of breakdown maintenance philosophy is that the machine is allowed to run until failure without preventive actions. This approach is cost-effective only for a few types of components (e.g., light bulbs) and companies. It may be done in case the repair costs exceed the costs of failure consequences. For most of the equipment related to offshore drilling industry this "Run-to-failure" philosophy may bring significant expenses. It may include secondary damage to the machine, additional spare-parts costs, overtime labor, production downtime and etc.

1.1.2 Preventive Maintenance

Preventive maintenance may be called time-based maintenance, calendar-based maintenance, planned maintenance etc. (Eti et al., 2007). The main point of this approach is to perform regular overhauls before the machine fails thus extending its lifetime. This philosophy is based on specifics periods between maintenance activities established according to the maintenance history and statistical analysis. The important part of this type of maintenance and one of the most uncertain is the balance between overhaul costs and risks associated with equipment failure. It may happen due to improper maintenance, poor lubrication, incorrect parts being installed etc. Thus, unnecessary performance of maintenance activities may often lead to higher risks of machine failure (Mobius Institute 2009). The advantages of this approach in comparison with the previous one are that the failure is often prevented, few catastrophic failures occur and there is better control over spare parts and costs.

1.1.3 Predictive Maintenance

Fortunately, the machine is able to provide to us some symptoms before failing. It could be the increased vibration in some parts of the equipment, abnormal temperature level, too many metal particles in lubrication and changes in current. All of these and other signals may predict the imminent failure of the system, and the maintenance activities could be planned according to this information. That is what the predictive maintenance approach is about. Ideally by utilizing this approach the lifetime of the machine is supposed to increase and maintenance costs - to reduce. Coanda et al. (2020) presented a state of the art of maintenance techniques, and described predictive maintenance being one of the biggest topics going forward. Predictive maintenance techniques were discussed and presented in detail creating the necessary links with nowadays industry advances: Industry 4.0. Therefore, it shows that the application of intelligent maintenance started to gain weight in applied maintenance methods due to the long-term benefits it provides. Even if the implementation of Industry 4.0 may be yet in an incipient phase, the value added by the means offered by it can provide a starting point for intelligent maintenance systems and methods which are superior to the old maintenance practices.

1.1.4 Precision/ Proactive Maintenance

Precision maintenance could be called as "Proactive Maintenance". One of the main differences between this approach and predictive maintenance is the intention to find root cause of failure and reduce the chance of problem to appear (M. Dunn 2008). Root-cause analysis (RCA) or Root-cause failure analysis (RCFA) is often considered as tool for investigating root cause of failure. It may imply the analysis of historical maintenance & condition monitoring records and performance of the specific test to identify main cause-effect relationships for the component Davies (2012). The whole point with the precision maintenance is to increase the reliability of the equipment. One of the main challenges related to precision maintenance philosophy is the implementation phase. It may take a significant amount of time before everyone in the whole company's structure will accept and understand the benefits and principles of this approach (M. Dunn 2008).

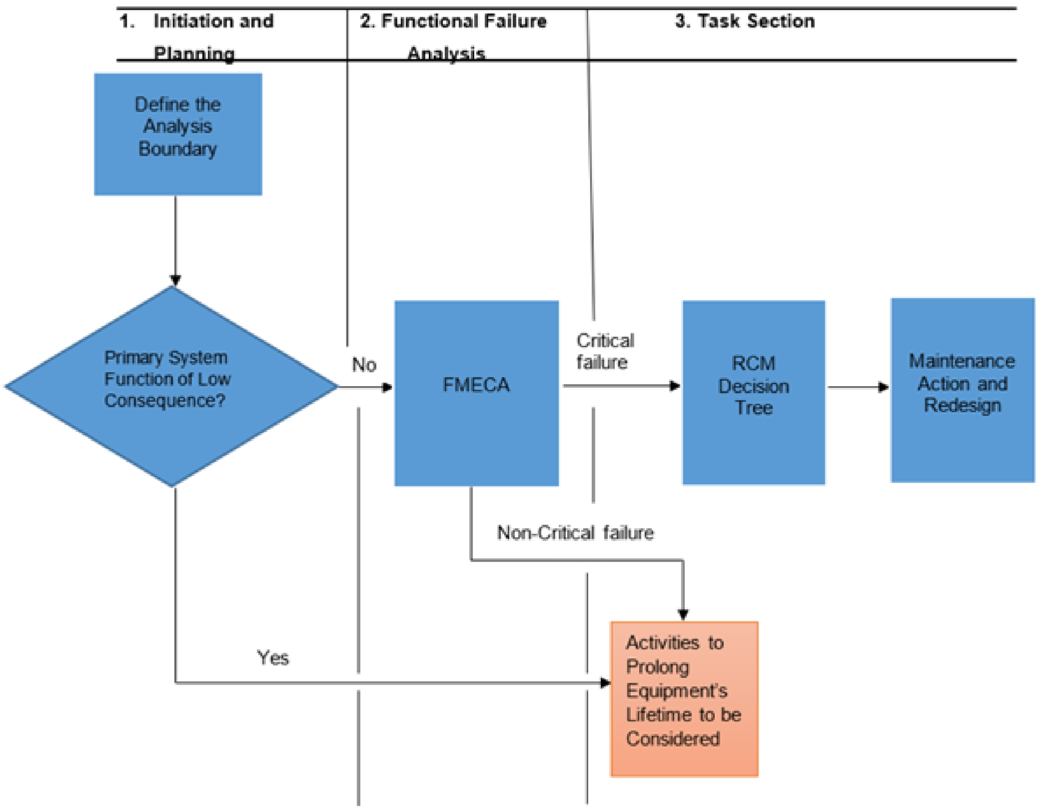
2. METHODOLOGY

In the Oil & Gas industry, there is great attention on the concepts of maintainability, reliability and safety, and many analyses are used to estimate the risk of hazards and damage to equipment to improve maintenance policies and reduce the amount and frequency of maintenance costs. The major equipment failures in a Oredo Flow Station Ologbo, Nigeria are related to Gas compressors.

Gas compressors of all types are used in every phase of petrochemical industry, production, transportation and refinery. Flow station critical equipment such as gas compressors will not remain safe, reliable and available unless it is maintained. The main challenge for maintenance engineering is that it is practically impossible to predict exactly when things will fail. In recent years, many flow stations utilize advanced methods to enhance their knowledge and understanding about the Gas compressors' performance and its impact on process behavior to provide a practical and structured approach for a satisfactory maintenance strategy.

RCM process could be arranged as shown in Figure 2. It typically follows a route of initiation and planning, functional failure analysis, and task selection according to IEC (IEC 60300-3 2011). Initiation and planning are to define the scope/ boundary of the analysis. In this phase, system function will be evaluated and criticality of consequence from single failure would be ranked. If the consequence seems to be critical, some functionality risk analysis like FMEA could be used to evaluate the severity consequence to the whole system out of single failure. With the result from the above analysis, actions could be made with consideration of both criticality and probability of occurrence. Different maintenance methods could be utilized for improving reliability or correcting mistakes.

Figure 2. RCM process



The purpose of this study is to apply reliability centered maintenance using the gas compressor's reliability parameter to analyze and define the type of maintenance strategy and time to perform each equipment maintenance procedure in both subsystems.

The data used in the study for Gas Compressor K-4000 run on a 24/7 basis.

Recording data started 1200hrs on 19th Feb 2018 and recording stop by 1300hrs on the 18th July 2020 while that of Gas Compressor K-3600 run on a 24/7 basis. Recording of data started 1200hrs on 9th March 2018 and recording stop by 1300hrs on the 18th July 2020.

2.1 Reliability Parameter Estimation

The term parameter estimation refers to the process of using sample data (in reliability engineering, usually times-to-failure or success data) to estimate the parameters of the selected distribution, we used Rank Regression (or Least Squares), method in this paper. Haven determines the best failure distribution that fit the data from the gas compressor failure data in this case Weibull distribution and Lognormal distribution. The Weibull distribution reveals the nature of the failure patterns being experienced, with the parameters; shape parameter β, the scale parameter, η and location parameter γ, but in this paper we are using 2- parameter distribution hence we will be using the shape parameter β and the scale parameter η which is the time it takes 63,2% of the failure to have occurred in other words the time take for the cumulative percentage failure to be 63.2%

$$MTTF = \eta * \Gamma\left(1 + \frac{1}{\beta}\right) \quad (1)$$

Where Γ is gamma function
When $\beta = 1.0$, MTTF = η, the useful life phase
When $\beta > 1.0$, MTTF is less than η, the wear-out life phase
When $\beta < 1.0$, MTTF is greater than η, the early life phase
When $\beta = 0.5$, MTTF=2x η

$$R(t) = e-^{\left(\frac{T}{\eta}\right)^{\beta}} \tag{2}$$

Where $R(T)$ is the Weibull distribution Reliability at time (T)

$$\lambda(T) = \frac{\beta}{\eta}\left(\frac{T}{\eta}\right)^{\beta-1} \tag{3}$$

Where $\lambda(T)$ is the Weibull distribution Failure Rate at time (T)
The lognormal distribution is a 2-parameter distribution with parameters $\boldsymbol{\mu}$'and $\boldsymbol{\sigma}$'.
$\boldsymbol{\mu}$' = the mean life or MTTF in terms of the natural logarithms of the times-to-failure, is also the scale parameter, the scale parameter defines where the bulk of the distribution lies, scale parameter (μ') which is MTTF, shows that there is a greater chance of failure occurring at that specified time
$\boldsymbol{\sigma}$'= standard deviation of the natural logarithms of the times-to-failure, is also the shape parameter

$$R(t') = 1 - \Phi\left(\frac{t' - \mu'}{\sigma'}\right) \tag{4}$$

Where $R(t')$ is the Lognormal distribution Reliability at time (t')

$$\lambda(t') = \frac{f(t')}{R((t'))} \tag{5}$$

Where $\lambda(t')$ is the Lognormal distribution Failure Rate at time (t')

$$\textbf{\textit{The proposed schedule maintenance interval}} = (\boldsymbol{\mu}' - \boldsymbol{\sigma}') \tag{6}$$

These reliability parameters will now serve as input to RCM to determine the type maintenance strategy to be used.

2.2 Case Study

This proposed methodology is presented here with a case analysis of a Gas Compressor in Oredo flow station Ologbo Benin, Edo State Nigeria. There are many critical equipment in a Oredo flow station such as the Export Pumps, Booster Pumps, Gas Compressors, Instrumentation Air Compressors and power source (Gas Generator). The current methodology is based on reliability centered maintenance (RCM) using reliability parameters on Gas Compressors, which is one of the main and most important functional units of the Oredo flow station. The equipment being studied in this research is gas compressor K-4000 and K-3600 both connected in k-out-of-n mode. Table 1 shows the Weibull data for Governor in gas compressor K- 3600. Table 2 shows Weibull linear Regression for Governor in gas compressor K- 3600 Table 3 shows Weibull Data Analysis for Governor in gas compressor K- 3600, Table 4. Shows the Lognormal Regression for Governor for Governor in gas compressor K- 3600 and Figure 3 shows the Weibull Failure Rate Chart for Governor in gas compressor K- 3600 and Figure 4 shows the Weibull Reliability R(t) Vs Time Chart for Governor in gas compressor K- 3600

Table 1. Weibull data for governor

i	Adjusted Rank(i)	t (hrs)	X = LNt	F(t) =(i-0.3)/(N+0.4)	$Y_i = LN\{-LN(1-F(t))\}$
1	1.0000	20.4	3.015534901	0.040229885	-3.192684658
2	2.0000	26.88	3.291382516	0.097701149	-2.274877577
3	3.0000	38.95	3.662278772	0.155172414	-1.780091531
4	4.0000	49.44	3.900759813	0.212643678	-1.430980590
5	5.0000	60.8	4.107589789	0.270114943	-1.155601100
6	6.0000	79.17	4.371597439	0.327586207	-0.924117873
7	7.0000	173.1	5.153869462	0.385057471	-0.721080787
8	8.0000	355.65	5.873947101	0.442528736	-0.537264880
9	9.0000	484.42	6.182952299	0.500000000	-0.366512921
10	10.0000	545.78	6.302215964	0.557471264	-0.204260615
11	11.0000	591.25	6.382238940	0.614942529	-0.046711512
12	12.0000	940.5	6.846411649	0.672413793	0.109754476
13	13.0000	1069.8	6.975226994	0.729885057	0.269192971
15	14.2500	2235.05	7.712018878	0.801724138	0.481250134
16	13.5000	4876.77	8.492238394	0.758620690	0.351632227
17	16.7500	7222.9	8.885011813	0.945402299	1.067384229

Table 2. Weibull regression for governor

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.942982348							
R Square	0.889215709							
Adjusted R Square	0.881302546							
Standard Error	0.384043295							
Observations	16							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	16.57361915	16.57362	112.3717	4.5149E-08			
Residual	14	2.064849529	0.147489					
Total	15	18.63846867						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept(a)	-3.894411895	0.321019911	-12.1314	8.13E-09	-4.58293113	-3.2058927	-4.58293113	-3.20589266
X Variable (β)	0.569968337	0.053767797	10.60055	4.51E-08	0.45464788	0.68528879	0.45464788	0.685288791

Weibull Parameters
β 0.569968
η 927.6747

Table 3. Weibull data analysis for governor

T(hrs)	$R(t) = \exp(-t/\eta)^\beta$	$\lambda = (\beta/\eta)(t/\eta)^\beta\text{-}1$
20.4	0.8926738	0.003172097
26.88	0.875584029	0.002817273
38.95	0.848622287	0.00240193
49.44	0.828581835	0.002167811
60.8	0.809315437	0.001983325
79.17	0.781983007	0.001770466
173.1	0.681067803	0.001264708
355.65	0.560456999	0.000927915
484.42	0.501320342	0.000812453
545.78	0.477552792	0.000771835
591.25	0.461362583	0.000745726
940.5	0.365000459	0.000610788
1069.8	0.338024003	0.000577874
2235.05	0.19191703	0.000420949
4876.77	0.076144888	0.000300964
7222.9	0.039905913	0.000254191

Table 4. Lognormal regression for governor

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.970492883							
R Square	0.941856437							
Adjusted R Square	0.937703325							
Standard Error	0.217155407							
Observations	16							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	10.69430083	10.6943	226.7833	4.83042E-10			
Residual	14	0.660190588	0.047156					
Total	15	11.35449142						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept(a)	-2.714877753	0.181519142	-14.9564	5.29E-10	-3.104197592	-2.325557913	-3.10419759	-2.325557913
X Variable (b)	0.457844763	0.030402738	15.05933	4.83E-10	0.392637375	0.523052151	0.392637375	0.523052151

Lognormal Parameters
σ' =1/b 2.184146
μ' = exp- (a* σ') 5.929691

Figure 3. Weibull failure rate vs time chart for governor

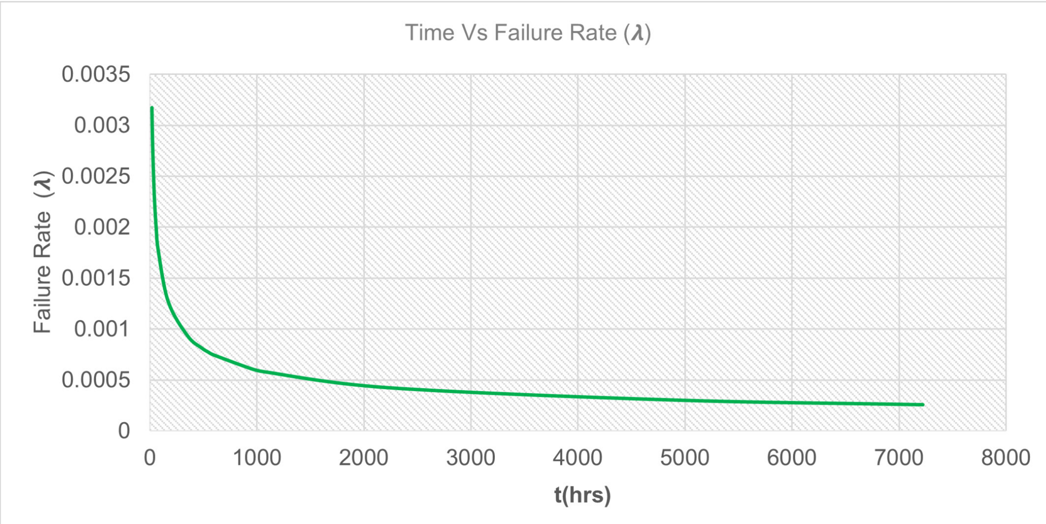


Figure 4. Weibull reliability R(t) vs time chart for governor

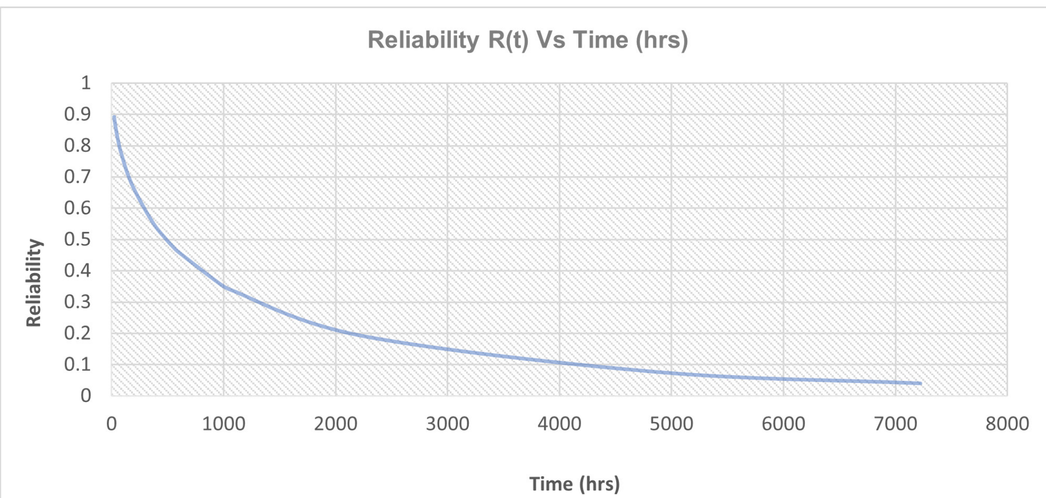


Table 5 shows the Weibull data for Engine Drive End in gas compressor K- 4000. Table 6 shows Weibull linear Regression for Engine Drive End in gas compressor K- 4000, Table 7 shows Weibull Data Analysis for Engine Drive End in gas compressor K- 4000, Table 8. Shows the Lognormal Regression for Engine Drive End in gas compressor K- 4000 and Figure 5 shows the Weibull Failure Rate Vs Time Chart for Engine Drive End in gas compressor K- 4000 and Figure 6 shows Weibull Reliability Vs Time Chart for Engine Drive End Gas Compressor K-4000

Table 5. Weibull data for engine drive end gas compressor K-4000

i	Adjusted Rank(i)	t (hrs)	X = LN(t)	F(t) =(i-0.3)/(N+0.4)	$Y_i = LN\{-LN(1-F(t))\}$
45	1.0000	4.5	1.504077397	0.015418502	-4.164427808
44	2.0000	11.8	2.468099531	0.037444934	-3.265862539
43	3.0000	22.62	3.118834471	0.059471366	-2.791760373
42	4.0000	23.65	3.163363115	0.081497797	-2.464974899
41	5.0000	24.02	3.178886817	0.103524229	-2.213805165
40	6.0000	27.07	3.298426104	0.125550661	-2.008715324
39	7.0000	28.38	3.345684672	0.147577093	-1.834630405
38	8.0000	40.17	3.693120448	0.169603524	-1.682804564
37	9.0000	41.58	3.727619282	0.191629956	-1.547706374
36	10.0000	47.05	3.851210866	0.213656388	-1.425611587
35	11.0000	50.28	3.917607384	0.235682819	-1.313890287
34	12.0000	58.53	4.069539443	0.257709251	-1.210613915
33	13.0000	59.42	4.084630870	0.279735683	-1.114323992
32	14.0000	67.14	4.206779992	0.301762115	-1.023888682
31	15.0000	68.87	4.232220670	0.323788546	-0.938409942
30	16.0000	71.53	4.270116942	0.345814978	-0.857161205
29	17.0000	72.94	4.289637185	0.367841410	-0.779544239
28	18.0000	83.53	4.425205849	0.389867841	-0.705058455
27	19.0000	85.03	4.443004135	0.411894273	-0.633278535
26	20.0000	93.8	4.541164856	0.433920705	-0.563837740
25	21.0000	128.64	4.857017805	0.455947137	-0.496415186
24	22.0000	201.07	5.303653106	0.477973568	-0.430725907
23	23.0000	212.8	5.360352757	0.500000000	-0.366512921
22	24.0000	214.1	5.366443196	0.522026432	-0.303540699
21	25.0000	216.5	5.377590547	0.544052863	-0.241589633
20	26.0000	224.29	5.412939857	0.566079295	-0.180451144
19	27.0000	239.34	5.477885135	0.588105727	-0.119923170
18	28.0000	241.71	5.487738660	0.610132159	-0.059805775
17	29.0000	257.6	5.551407994	0.632158590	0.000103380
16	30.0000	395.85	5.981035352	0.654185022	0.060013981
15	31.0000	412.19	6.021484408	0.676211454	0.120148778
14	32.0000	481.97	6.177881871	0.698237885	0.180750550
13	33.0000	593.54	6.386104609	0.720264317	0.242090999
12	34.0000	623.77	6.435781711	0.742290749	0.304482597
11	35.0000	715.51	6.572995575	0.764317181	0.368295023
10	36.0000	796.35	6.680038788	0.786343612	0.433978846
9	37.0000	870.91	6.769538642	0.808370044	0.502101123

continued on following page

Table 5. Continued

i	Adjusted Rank(i)	t (hrs)	X = LN(t)	F(t) =(i-0.3)/(N+0.4)	$Y_i = LN\{-LN(1-F(t))\}$
8	38.0000	876.81	6.776290321	0.830396476	0.573401344
7	39.0000	907.14	6.810296793	0.852422907	0.648884157
5	39.3333	1288.32	7.161094323	0.859764317	0.675202546
4	40.6667	1424.86	7.261828842	0.889134361	0.788201088
3	42.0000	1455.26	7.282939858	0.918502203	0.919158331
2	43.3333	1726.73	7.453984725	0.947870044	1.083165440
1	44.6667	2310.98	7.745426956	0.977240088	1.330452459

Table 6. Weibull linear regression for engine drive end (EDE) gas compressor K-4000

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.969944708							
R Square	0.940792736							
Adjusted R Square	0.939383039							
Standard Error	0.294563237							
Observations	44							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	57.90623641	57.90623641	667.3724143	2.09045E-27			
Residual	42	3.644235028	0.086767501					
Total	43	61.55047143						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-4.526014488	0.158236623	-28.60282532	3.63558E-29	-4.845348922	-4.206680054	-4.845348922	-4.206680054
X Variable (β)	0.772278068	0.029894382	25.8335521	2.09045E-27	0.711948763	0.832607373	0.711948763	0.832607373

β 0.772278068
a/ β -5.860602125
Ƞ = exp-(a/ β) 350.9353874

Table 7. Weibull data analysis for engine drive end gas compressor K-4000

t (hrs)	R(t) = exp(-t/η)^β	λ = (β/η)(t/η)^β-1
4.5	0.96601001	0.005934715
11.8	0.929781084	0.004764964
22.62	0.886616035	0.004108687
23.65	0.882890871	0.004067234

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Table 7. Continued

t (hrs)	$R(t) = exp(-t/\eta)^\beta$	$\lambda = (\beta/\eta)(t/\eta)^\beta-1$
24.02	0.881565577	0.004052882
27.07	0.870883438	0.003944043
28.38	0.866419642	0.003901826
40.17	0.829017013	0.003605015
41.58	0.824830274	0.003576804
47.05	0.809074395	0.00347754
50.28	0.800105699	0.003425356
58.53	0.778197304	0.003308871
59.42	0.775912898	0.003297519
67.14	0.75668067	0.003207059
68.87	0.752506192	0.003188533
71.53	0.746178204	0.003161135
72.94	0.742867113	0.003147114
83.53	0.718891096	0.003051441
85.03	0.715614784	0.003039099
93.8	0.697002937	0.002971918
128.64	0.630852932	0.002765665
201.07	0.521820638	0.002498205
212.8	0.506847484	0.002466156
214.1	0.505226256	0.002462738
216.5	0.502252661	0.002456494
224.29	0.492770961	0.002436799
239.34	0.475156129	0.002401025
241.71	0.472462984	0.002395644
257.6	0.454942108	0.00236116
395.85	0.333714164	0.002141095
412.19	0.322292996	0.002121464
481.97	0.278689414	0.002047237
593.54	0.223006691	0.001952429
623.77	0.210295817	0.001930467
715.51	0.176657848	0.001871079
796.35	0.152142557	0.001826021
870.91	0.132962671	0.001789181
876.81	0.131567545	0.001786432
907.14	0.124654802	0.001772652
1288.32	0.065212169	0.001636553
1424.86	0.052288539	0.001599439

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Table 7. Continued

t (hrs)	R(t) = exp(-t/η)^β	λ = (β/η)(t/η)^β-1
1455.26	0.049812771	0.001591768
1726.73	0.032612538	0.001530959
2310.98	0.013744824	0.001432651

Table 8. Lognormal linear regression engine drive end gas compressor K-4000

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.989125947							
R Square	0.97837014							
Adjusted R Square	0.977855143							
Standard Error	0.138931839							
Observations	44							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	36.6692766	36.6692766	1899.76014	1.34397E-36			
Residual	42	0.810686352	0.019302056					
Total	43	37.47996295						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept (a)	-3.167319574	0.074632888	-42.43865751	4.02266E-36	-3.31793484	-3.016704309	-3.31793484	-3.016704309
X Variable (b)	0.614557047	0.014099796	43.58623796	1.34397E-36	0.586102508	0.643011587	0.586102508	0.643011587

σ' =1/b 1.627188239
μ' = exp- (a* σ) 5.153825162

Figure 5. Weibull failure rate vs time chart for engine drive end gas compressor K-4000

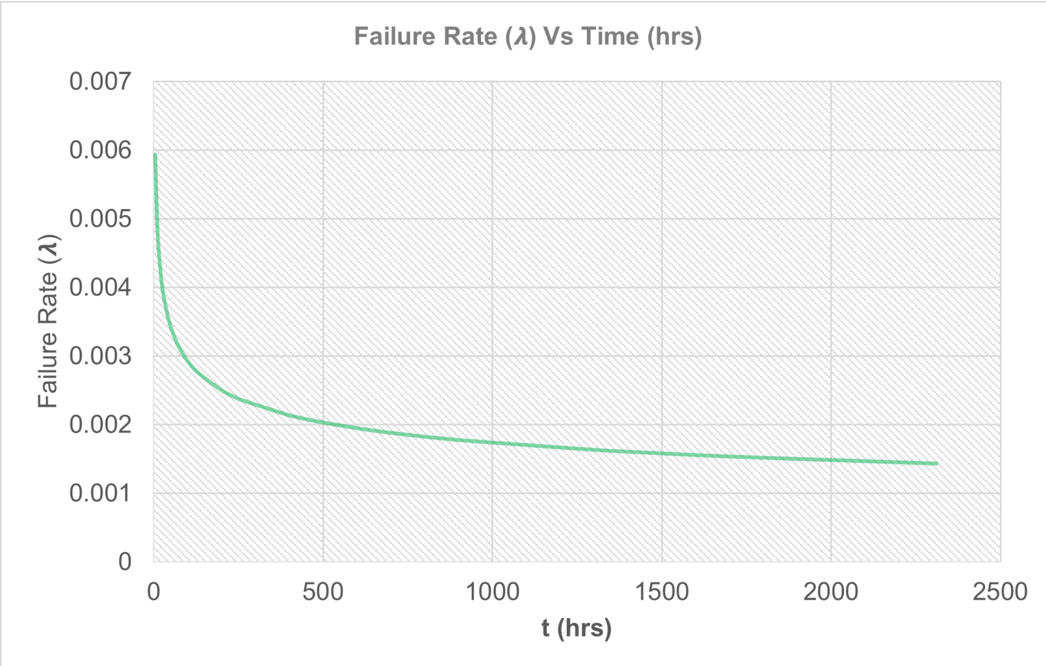
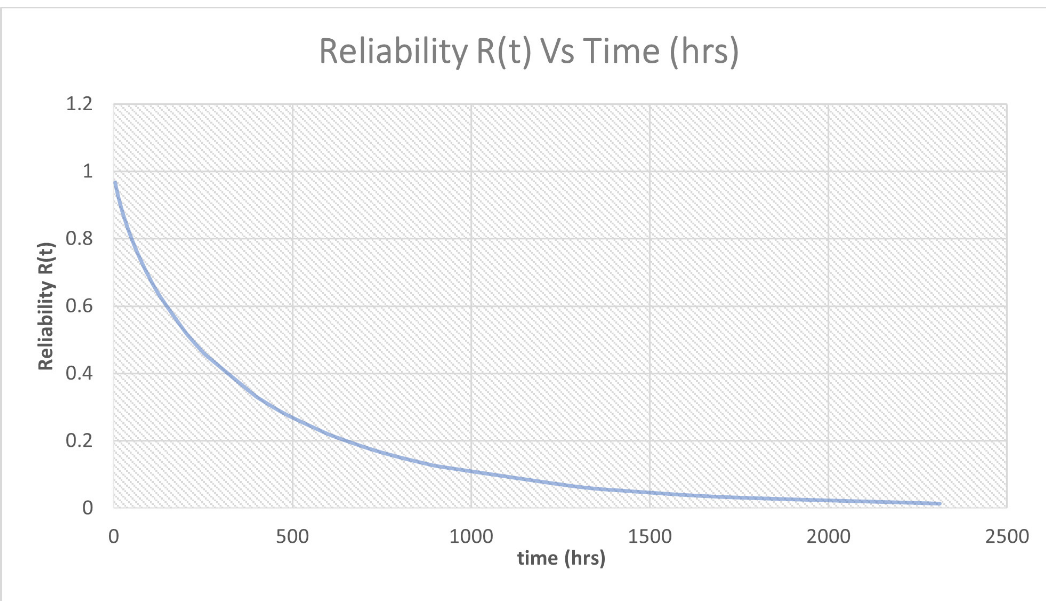


Figure 6. Weibull reliability vs time chart for engine drive end gas compressor K-4000



2.3 Abbreviation

μ' Lognormal scale parameter
FM Failure Mode
FMEA Failure Mode Effect Analysis
LCC Life Cycle Cost
MTTF Mean Time to Failure
NASA National Aeronautics and Space Administration
pdf Probability Distribution Function
PM Preventive Maintenance
RCA Root Cause Analysis
RCFA Root Cause Failure Analysis
RCM Reliability Centered Maintenance
RRCM Reliability and Risk Centered Maintenance
β Weibull shape parameter
γ Weibull location parameter
η Weibull scale parameter
σ' Lognormal shape parameter
Γ gamma function

3. RESULTS AND DISCUSSION

Determining reliability parameters; shape (β) parameter scale (η) parameter Scale (μ) parameter' and Shape (σ') parameter for both Weibull and Lognormal distribution respectively for the time to failure data using linear regression with the aid of Microsoft excel for Governor in Gas Compressor K-3600 and Engine Drive End in Gas Compressor K-4000 as show in table 2, table 4, table 6 and table 8 respectively. Equation 2 to equation 5 was used in analyzing data for both Weibull and Lognormal distribution for Governor in Gas Compressor K-3600 as show in table 1, table 4 and for Engine Drive End in Gas Compressor K-4000 as show in table 6 to table 8 respectively. Figure 3 show failure rate Vs time chart for Governor in Gas Compressor K-3600, while figure 4 shows the reliability Vs time chart for Governor in Gas Compressor K-3600, Figure 5 show failure rate Vs time chart for Engine Drive End in Gas Compressor K-4000, while figure 6 shows the reliability Vs time chart for Engine Drive End in Gas Compressor K-4000. Equation 1 and equation 6 was used to the proposed schedule maintenance interval. From our linear regression as shown in table 2 and table 4 for Governor, the Correlation coefficient (R) for Lognormal distribution with 0.97 is greater than that of Weibull of 0.94 which indicate a stronger linear relationship between the CDF and Time for Lognormal compared to that of Weibull also the P-Value for Lognormal is smaller compared to that of Weibull. The Lognormal distribution is accepted as adequately fit these times-to-failure data at 0.05 significance and that the data is from a lognormal distribution. Furthermore, as shown in table 6 and table 8 for Engine Drive End in Gas Compressor K-4000, the Correlation coefficient (R) for Lognormal distribution with 0.98 is greater than that of Weibull of 0.96 which indicate a stronger linear relationship between the CDF and Time for Lognormal compared to that of Weibull also the P-Value for Lognormal is smaller compared to that of Weibull. Figure 3 shows the Weibull Failure Rate Vs Time Chart for Governor in Gas Compressor K-3600 showing a decrease in the failure rate over a period of time, while Figure 5 shows the Weibull Failure Rate Vs Time Chart for Engine Drive End in Gas Compressor K-4000 showing a decrease in the failure rate over a period of time indicating that the components are experiencing early failure in their life cycle. The Weibull distribution shape Parameter β also tells us which of the failure family is present, in this case it is mostly early life failure for both compressors. Furthermore, figure 4 and figure 6 shows the reliability of the Governor and Engine Drive End over a period of time.

Applying reliability centered maintenance using reliability parameter method by considering all possible failure mode, gas compressor features and reliability parameters had been analyzed to define the type/class of failure and time interval to perform each components maintenance procedure in both systems. Following the procedure in figure 1 and figure 2. Table 9 shows the Reliability Centered Maintenance for Gas Compressor K-4000, while Table 10 shows the Reliability Centered Maintenance for Gas Compressor K-3600, it is possible to recognize that recommendation is related to the period and maintenance strategy. For the Engine Drive End the best pdf distribution that fit the data is lognormal as show in table 6 and table 8, the parameters are $\sigma' = 1.627188239$ and $\mu' = 5.153825162$. using equation 6

The proposed schedule maintenance interval = 5.153825162-1.627188239 = 3.5months. because in 5months there is a greater chance of failure occurring. Also, for the Governor the pdf distribution is lognormal and the parameters are $\sigma' = 2.18414642$ and $\mu' = 5.929690524$. using equation 6

The proposed schedule maintenance = 5.929690524 - 2.18414642 = 3.7months. because in 6months there is a greater chance of failure occurring. The same idea was applied to other components.

Table 9. Reliability centered maintenance for gas compressor K-4000

Component That Failed	Failure Mode	Cause of Failure	Effect of Failure	Reliability	Maintenance Strategies	Recommendations
Discharge valve	Fail open	Process impact	Shut down	Lognormal σ = 3.336562762 μ = 6.25887876	Preventive/ Proactive	Perform preventive maintenance in 3months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Engine Drive end	High engine vibration	Spark plug and air filter	Vibration	Lognormal σ = 1.627188239 μ = 5.153825162	Predictive/ Preventive	Perform preventive maintenance in 3.5 months, predictive maintenance (Monitor vibration based on sensor constantly), verify the quality of repairs and improved design may be needed
By pass Valve	Fail open	Process impact	Shut down	Lognormal σ = 2.790022283 μ = 7.455947732	Preventive/ Proactive	Perform preventive maintenance in 4.5months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow	Clogged	Reduced flow	Lognormal σ = 2.045169744 μ = 5.590325137	Predictive/ Preventive	Perform preventive maintenance in 3.5months, annual inspection for clogged, verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow	High vibration	Friction/wear	Lognormal σ = 2.045169744 μ = 5.590325137	Predictive/ Preventive	Perform preventive maintenance in 3.5months, predictive maintenance (Monitor vibration based on sensor constantly), verify the quality of repairs and improved design may be needed
Cylinder discharge valve	Trip on HiHi stage 2 discharge temp.	High temperature	Wear	Lognormal σ =1.312958599 μ = 6.467632082	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 5months, predictive maintenance (infrared thermography), perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Scrubber Dump Valve	Fail to close	Internal component damage	Process impact	Lognormal σ = 1.467561045 μ = 7.492936808	Preventive/ Proactive	Perform preventive maintenance in 6 months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed

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Table 9. Continued

Component That Failed	Failure Mode	Cause of Failure	Effect of Failure	Reliability	Maintenance Strategies	Recommendations
Sensor (Non-Drive End)	Lack of signal	High Vibration	process impact	Weibull β = 0.58412765 MTTF = 3205.994117 hrs 4.5months	Predictive/ Preventive	Perform preventive maintenance in 4months, (Monitor vibration based on sensor constantly), verify the quality of repairs and improved design may be needed
Suction strainer	Suction inline strainer failure	Plugged on strainer	Drop pressure flow	Lognormal σ = 3.889327986 μ = 7.807945084	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 4months, annual visual inspection for plugs. perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Suction strainer	Suction inline strainer failure	Plugged on strainer	Drop pressure flow	Lognormal σ = 3.889327986 μ = 7.807945084	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 4months, annual visual inspection for plugs. perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Engine Stop Switches	switch activated by excessive vibration	High vibration	Engine Shutdown	Lognormal σ = 2.790022283 μ = 7.455947732	Predictive/ Preventive	Perform preventive maintenance in 4.5months, predictive maintenance (Monitor vibration based on sensor constantly), verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow alarm	High vibration	Friction/wear	Lognormal σ = 2.045169744 μ = 5.590325137	Predictive/ Preventive	Perform preventive maintenance in 3.5months, predictive maintenance (Monitor vibration based on sensor constantly), verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow alarm	Battery	Shut down	Lognormal σ = 2.045169744 μ = 5.590325137	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 3.5months, predictive maintenance (Monitor sensor battery constantly), perform proactive maintenance (age exploration), verify the quality of repairs and improved design may be needed

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Table 9. Continued

Component That Failed	Failure Mode	Cause of Failure	Effect of Failure	Reliability	Maintenance Strategies	Recommendations
Discharge valve	Fail close	Process impact	Shut down	Lognormal σ = 3.336562762 μ = 6.25887876	Preventive/ Proactive	Perform preventive maintenance in 3months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Governor	Shutdown due to engine under speed	Abnormal governor response	Shutdown	Weibull β = 1.899824179 η = 2275.228906 MTTF = 2.7months	Preventive/ Proactive	Perform preventive maintenance in 2.5months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow	Clogged Oil Filter	Shut down	Lognormal σ = 2.045169744 μ = 5.590325137	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 3.5months perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow	High vibration	Friction/wear	Lognormal σ = 2.045169744 μ = 5.590325137	Predictive/ Preventive	Perform preventive maintenance in 3.5months, predictive maintenance (Monitor vibration based on sensor constantly), verify the quality of repairs and improved design may be needed
Scrubber Dump Valve	Fail to open	Solenoid fail to energies	Shut down	Lognormal σ = 1.467561045 μ = 7.492936808	Preventive/ Proactive	Perform preventive maintenance in 6months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow	Weak battery	Friction/wear	Lognormal σ = 2.045169744 μ = 5.590325137	Predictive/ Preventive	Perform preventive maintenance in 3.5months, predictive maintenance (Monitor sensor battery constantly), perform proactive maintenance (age exploration), verify the quality of repairs and improved design may be needed

continued on following page

Table 9. Continued

Component That Failed	Failure Mode	Cause of Failure	Effect of Failure	Reliability	Maintenance Strategies	Recommendations
Cylinders	Misfiring Engine Cylinders	Bad spark plugs	Shut down	Lognormal $\sigma = 1.930487065$ $\mu = 7.829306313$	Preventive/ Predictive/ Proactive	Perform preventive maintenance in 5.8months, perform annual predictive test, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Engine drive end	LoLo Compressor Oil Pressure	Faulty oil pressure sensors	Erratic reading	Lognormal $\sigma = 1.627188239$ $\mu = 5.153825162$	Preventive/ Proactive	Perform preventive maintenance in 3.5months, perform proactive maintenance (FRCA), regular calibration of sensors verify the quality of repairs and improved design may be needed
Lubrication System	Trip due to Low Low Lube Oil pressure	Low Engine oil level	Shut down	Weibull $\beta = 4.34765735$	Predictive/ Corrective	Carryout overhauls and perform annual inspection, verify the quality of repairs and improved design may be needed

Table 10. Reliability centered maintenance for gas compressor K-3600

Component That Failed	Failure Mode	Cause of Failure	Effect of Failure	Reliability	Maintenance Strategies	Recommendations
Sensor (Non-Drive End)	Lack of signal	High Vibration	process impact	Lognormal $\sigma = 2.566158255$ $\mu = 6.370145106$	Predictive/ Preventive	Perform preventive maintenance in 3.5months, carry out predictive analysis (Monitor vibration based on sensor constantly), verify the quality of repairs and improved design may be needed
Governor	Shutdown due to engine under speed	Abnormal governor response	Shutdown	Lognormal $\sigma = 2.18414642$ $\mu = 5.929690524$	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 4months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Engine drive end	LoLo Compressor Oil Pressure	High vibration	Drop pressure flow	Lognormal $\sigma = 1.979556276$ $\mu = 5.680072392$	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 3.7months, carry out predictive analysis (Monitor vibration based on sensor constantly), carry out Proactive maintenance (FRCA) verify the quality of repairs and improved design may be needed
Cooler Flange	Gas leak on the second stage inlet to cooler flange	High vibration	External leakage	Lognormal $\sigma = 2.72410608$ $\mu = 7.191498061$	Predictive/ Preventive	Perform preventive maintenance in 4.5months, (Monitor vibration based on sensor constantly), annual inspection, verify the quality of repairs and improved design may be needed
Sensor (Digital No Flow Timer) DNFT	lube oil no flow	Clogged	Reduced flow	Lognormal $\sigma = 2.396055394$ $\mu = 5.163992964$	Predictive/ Preventive	Perform preventive maintenance in 2.8months, quarterly inspection for clogged, verify the quality of repairs and improved design may be needed
Discharge Valve	Fail close	Internal component damage	Process impact	Lognormal $\sigma = 1.647954758$ $\mu = 7.23275065$	Preventive/ Proactive	Perform preventive maintenance in 5.6months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed

continued on following page

Table 10. Continued

Component That Failed	Failure Mode	Cause of Failure	Effect of Failure	Reliability	Maintenance Strategies	Recommendations
Engine drive end	LoLo Compressor Oil Pressure	Contamination	Drop pressure flow	Lognormal $\sigma = 1.979556276$ $\mu = 5.680072392$	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 3.7months, carry out predictive analysis (Monitor vibration based on sensor constantly), carry out Proactive maintenance (FRCA) verify the quality of repairs and improved design may be needed
Cylinder	Misfiring Engine Cylinders	Bad spark plugs	Shut down	Lognormal $\sigma = 1.686308918$ $\mu = 7.658412504$	Preventive/ Predictive/ Proactive	Perform preventive maintenance in 5.9months, perform annual predictive test, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Engine drive end	LoLo Compressor Oil Pressure	Restriction. In Engine Oil pump	cavitation and a loss of engine oil pressure	Lognormal $\sigma = 1.979556276$ $\mu = 5.680072392$	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 3.7months, carry out predictive analysis (Monitor vibration based on sensor constantly), carry out Proactive maintenance (FRCA) verify the quality of repairs and improved design may be needed
Governor	Shutdown due to engine under speed	Abnormal governor response	Shutdown	Lognormal $\sigma = 2.18414642$ $\mu = 5.929690524$	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 4months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Governor	Shutdown due to engine under speed	Abnormal governor response	Shutdown	Lognormal $\sigma = 2.18414642$ $\mu = 5.929690524$	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 4months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Engine drive end	LoLo Compressor Oil Pressure	Contamination	Drop pressure flow	Lognormal $\sigma = 1.979556276$ $\mu = 5.680072392$	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 3.7months, carry out predictive analysis (Monitor vibration based on sensor constantly), carry out Proactive maintenance (FRCA) verify the quality of repairs and improved design may be needed

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Table 10. Continued

Component That Failed	Failure Mode	Cause of Failure	Effect of Failure	Reliability	Maintenance Strategies	Recommendations
Crankcase	High Crankcase Pressure	Plugged port on the crankcase pressure sensor	Leakage of the crankshaft seal	Weibull β = 2.951254582 η = 2358.82 hrs MTTF = 2.8months	Predictive/ Preventive	Perform predictive ultrasound test in 6months and preventive maintenance in 2.5months.
Scrubber Dump Valve	Fail to close	Internal component damage	Process impact	Weibull β = 0.695493 η = 4110.773 hrs MTTF = 7.2months	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 7months, quarterly visual inspection, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Cylinder Discharge Valve	HiHi stage discharge cylinder temperature	High temperature	Wear	Lognormal σ = 1.66309259 μ = 6.805050776	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 5months, predictive maintenance (infrared thermography), perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
Governor	Shutdown due to engine under speed	Abnormal governor response	Shutdown	Lognormal σ = 2.18414642 μ = 5.929690524	Predictive/ Preventive/ Proactive	Perform preventive maintenance in 4months, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed
CAT(Seal)	Worn out	Weak seal	Leakage	Exponential $mttf$ = 5042.40λ =0.000198318	Corrective	Request for 1 year of guarantee from the CAT(Seal) supplier, perform biannual predictive test, verify the quality of repairs and improved design may be needed
CAT engine spark plugs	Fail to start on demand (Cold start)	Condensation Forms On The Spark Plugs Spark Plug	Misfire and Difficult to start	Lognormal σ = 2.72410608 μ = 7.191498061	Preventive/ Proactive	Perform preventive maintenance in 4.5months, annual inspection, perform proactive maintenance (FRCA), verify the quality of repairs and improved design may be needed

4. CONCLUSION

Appropriate maintenance planning is critical for maintenance management to contribute to increasing availability, ensuring quality requirements, reliability and operational excellence, controlling the safety and environmental risks associated with physical assets. As supporting tools for developing maintenance strategies, Reliability-Centered Maintenance (RCM) is currently used in the oil and gas sector.

The following conclusions were drawn from the study.

i. The use of reliability parameters as an analytical process to determine the appropriate maintenance strategies to ensure safe operations and cost-wise readiness in Oredo Flow station was established.
ii. The study has established a methodology for reliability centered maintenance strategy that integrates Preventive maintenance (PM), Predictive maintenance, reactive maintenance and Proactive maintenance to increase the probability that a machine or component will function in the required manner over its design life cycle with a minimum amount of maintenance and downtime
iii. The method rather than the principal maintenance strategies, being applied independently, were optimally integrated to take advantage of their respective strengths.
iv. The method maximized facility and equipment reliability while minimizing life-cycle costs in dealing with problems encountered in flow station critical equipment such as incurred high costs due to production losses and delays, unplanned intervention on the system and safety hazards.
v. The study has established that most components in the two gas compressors are in their early life cycle phase hence were experiencing early failure with their $\beta < 1$.
vi. The study has established that the distribution that best fit the data was the lognormal distribution, whose parameters are the shape parameter (σ') and scale parameter (μ') which is the MTTF, which shown that there is a greater chance of failure occurring at that specified time.
vii. The study has developed a valuable tool for the oil and gas industry that are seeking to plan their maintenance strategy and improve their operational excellence with ensured safety and minimal environmental impact.

4.1. Contributions

This study tackles the critical limitation in the extant literature on reliability centered maintenance using failure mode effect analysis and other techniques, they did not capture the reliability parameters and how they could be used to plan your maintenance strategy. To overcome these limitations, this paper has developed a mathematical model for reliability centered maintenance of critical equipment such as Gas Compressors in Oredo Flow station Nigeria.

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The authors declare no competing of interest.

DATA AVAILABILITY STATEMENT

No additional data is applicable besides the data/information already included in the manuscript.

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