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Application of Linear Regression Maintenance Models on Rotodynamic Systems

***Elijah, P.T. and Obaseki, M.**

Applied Mechanics and Design/Production Research Group, Department of Mechanical Engineering, Nigeria Maritime University, Okerenkoko, Delta State, Nigeria.
*paul.elijah@nmu.edu.ng

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ABSTRACT

This paper presents a maintenance model as well as its analysis for minimizing unexpected breakdowns, decrease in productivity and high maintenance cost, associated with rotodynamic systems failures. This work presented a case study of a gas compressing systems and integrates linear regression models derived from Weibull's exponential distribution in determining the frequency of failure and the mean time between failures (MTBF) of the gas compressing systems. Results obtained showed that the gas compressing system's frequency of failure and the mean time between failures were 0.00052% and 4.12 years respectively. The result presented established the comparison of the proposed maintenance model with the existing one at the case study to indicate a significant improvement.

1. INTRODUCTION

Rotodynamic systems like every other industrial systems are subject to repair actions when failures occur. The useful lifetime of an of an asset is influenced by both the intrinsic ageing rate of the system and the effectiveness of the repair action. A better understanding of these two features is necessary in optimizing maintenance activities (Hussin and Hashim 2011). Rotodynamic system maintenance is crucial for safe and efficient operations of rotodynamic systems and thus refineries spend significant portion of their operational costs for maintenance.

Consequently, several techniques have been proposed to deal with the menace of breakdowns and interruptions due to failures and maintenance issues. These include the use of predictive, preventive and reactive maintenance paradigms. Predictive maintenance is concerned with determining when a single component could fail and maintenance task carried out on it. Preventive maintenance is concerned with determining when to carry out a comprehensive maintenance overhaul on the facilities, while reactive maintenance waits and sees when a facility fails and then acts on it. However, predictive maintenance is an easy option to take and does not require upfront cost unlike preventive maintenance. The preventive maintenance reduces the risk of catastrophic damage and reduced labour and inventory cost (Lacey *et al.*, 2019).

Due to the peculiarity of the oil and gas industry, the application of reactive maintenance could subject a system to frequent shutdowns leading to losses. Though several mathematical models have been applied in the modeling of failure pattern in the oil and gas industry, many of these are concerned with the timing of the failures using concept such as mean time to fail (MTTF) and mean time between failure (MTBF). These models pay less attention to maintenance cost as a function of time and as such are suitable for systems where the time of failures are known. This would result in better planning for future failing assuming costing is of no importance. The failure rate modeling of actual systems has been modeled using Weibull function which involves determination of the shape parameter and the scale parameters from obtained sample data and determination of the failure rate function. The reality is that the higher the rate of maintenance at a specific average cost, the higher the overall cost of maintenance on any system. Thus, one needs to balance the frequency of maintenance and the maintenance cost. The reviews from authors are thus: loss of production, unexpected failures, and downtimes linked with such failures and higher maintenance cost remains a critical problem in any industrial system (Krishnasamy *et al.*, 2005); Jardine and Banjevic (1999) developed an optimal maintenance program based on vibration monitoring of critical bearings on machinery in the food processing industry. Desphande and Modak (2002) applied the concept of reliability centered maintenance (RCM) to a medium scale steel melting shop industry. Rao and Naikan (2006) proposed a condition-based preventive maintenance policy for continuously functional devices whose condition worsens with time in service. Bukowski (2001) presented a methodology that integrated repairs and periodic inspections which are known with certainty into existing an industrial system Markov model. Chen *et al.* (2003) carried out an optimal preventive maintenance for multi-state deteriorating industrial systems with several stages of performance reduction before failure. Rahmoune *et al.* (2017) proposed solutions to a real-time reliability model, applied to an industrial pump. A new model for reliability centered maintenance (RCM) in petroleum refineries was proposed by Deepak and Jagathy, (2013). Wen *et al.* (2018) employed universal generating function (UGF), a reliability estimation method which has shown significant result in multi-state systems, and Praks *et al.* (2007) developed a reliability model for a compression station and a surrounding transit gas pipeline network located in Czech Republic.

This study is intended to show the relevance of maintenance management in gas compressing systems (using a refinery gas compressing system as a case study) and aimed at developing a reliability maintenance model for gas compressing system as well as validating the results with existing plant data in order to demonstrate the accuracy and applicability of the model.

2. METHODOLOGY

2.1. System Description

A standard gas compressing system, as shown in Figure 1, is composed of a high, medium and low-pressure compression train, with different stages. Each stage takes gas from a suitable pressure level from the separators and from previous stages in the compression train. A typical stage has a heat exchanger, a scrubber and a compressor. The heat exchanger is used to cool the gas, as a lower temperature in the gas requires less energy to compress this gas. The scrubber is used to remove small fractions of liquid from the gas (either water or hydrocarbon), as liquid droplets entering the compressor will contribute to the erosion of the compressor's blades. The division in several trains is aimed at improving the maintainability and availability of the system, as well as improving the capacity of the system.

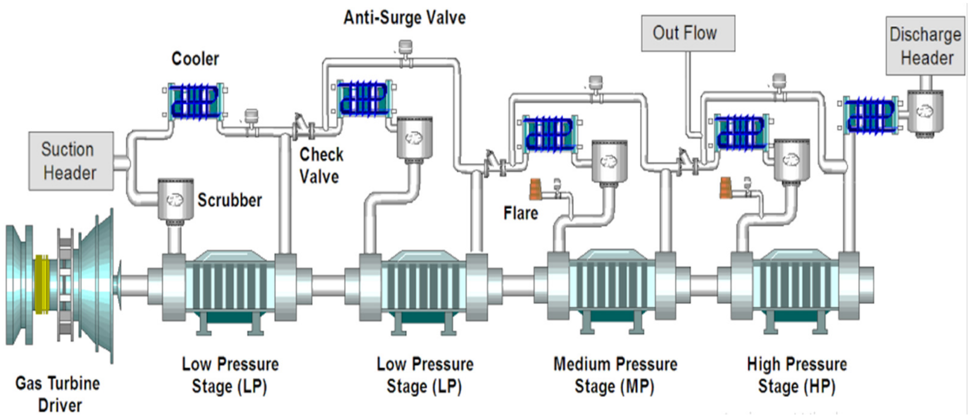

Figure 1: Gas compressing system

Gas from the high-pressure compressor suction manifold (at 30 °C) is separated within the first stage high-pressure compressor suction scrubber, with liquids returned to the closed drain system. This separated gas is then compressed in two parallel throws of a reciprocating compressor, from 11.3 bar to 30.6 bar (gauge). The vapor discharge, along with the condensate return from the third stage high-pressure compressor suction scrubber is cooled in the second stage compressor suction cooler to a temperature of 30 °C. The gas/liquid from the second stage high-pressure compressor suction cooler is separated within the second stage high pressure suction scrubber, with liquids returned to the high-pressure compressor common suction scrubber. The separated gas is then compressed in two parallel throws of the reciprocating compressor, from 29.9 bar to 79.2 bar (gauge). The vapor discharge along with the condensate returned from the fourth stage high pressure compressor suction scrubber to a temperature of 35 °C.

The higher temperature is to avoid hydrates in the liquid recycle line from the third stage high pressure compressor suction scrubber. Figure 2 shows that gas from the third stage high pressure compressor suction cooler is separated within the third stage high pressure suction scrubber, with condensate/water returned to the second stage high pressure compressor suction cooler.

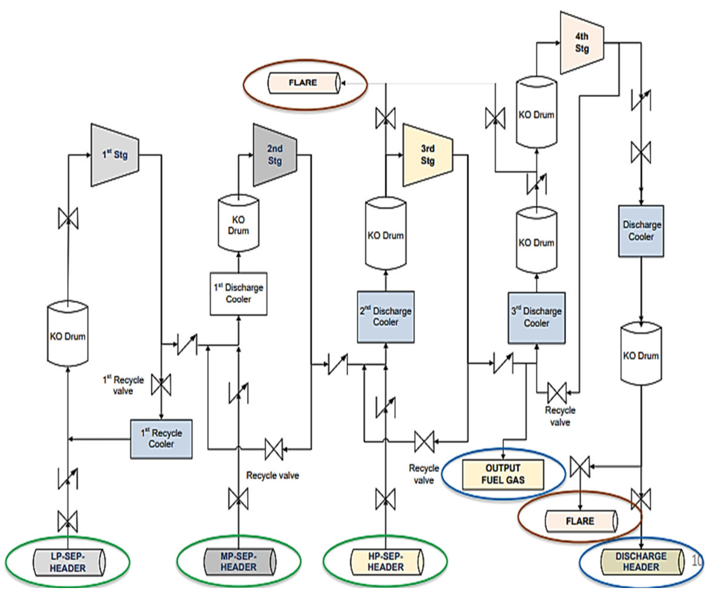

Figure 2: Detailed gas compressing system

The separated gas is the compressed in a single throw of the reciprocating compressor, from 78.5 bar to 170.9 bar (gauge). The vapor discharge is cooled in the fourth stage high pressure compressor suction cooler to a temperature of 30 °C. The gas from the fourth stage high pressure compressor suction cooler is separated within the fourth stage high pressure compressor suction scrubber, with water (low flow rates) returned to the third stage high pressure compressor suction cooler. The separated gas is then compressed in a single throw of the reciprocating compressor, from 169.9 bar to either 352 bar, or the back pressure exerted by the gas reinjection reservoir (typically 300 bar). The vapor discharge is then routed to the high-pressure fuel gas system or the gas reinjection pipeline, depending upon which supply is required. The final discharge temperature is kept below 65 °C in accordance with the design basis.

The compression trains have four stages and each first stage is composed of a reciprocating compressor and a scrubber while the second to fourth stages are composed of a cooler, a reciprocating compressor and a scrubber. To control the process, there are level, temperature and pressure transmitters, as well as control valves.

2.2. Existing Maintenance Model

The existing maintenance response for preventing failures has always been to have a predictive maintenance (PdM) program that has both condition-based tasks and time-driven tasks. Condition-based tasks are derived mainly from vibration analysis while time-driven tasks typically arise out of equipment manufacturer recommendations and are conventionally referred to as preventive maintenance (PM) plans. In addition to the PM and PdM plans, firms that employ this maintenance model like that of the refinery in the case study also employ root cause failure analysis (RCFA) program in the case of compressing system breakdown, so as to determine the actual cause of failure. The whole process ensures that a preliminary level of reliability assurance is achieved in these systems. As shown in Figure 3, the gas compressing system undergoes preventive maintenance regularly, to reduce the likelihood of component failure, which would have adverse effect on the system. Predictive maintenance is also carried, to predict future failure of the system's components so that they can be replaced before it fails. Criticality analysis implies that key components are rated based on their potential risk, giving rise to predictive maintenance. And in the case of system failure, a root cause of failure analysis is carried out to determine the actual cause of failure in the system and corrective maintenance employed.

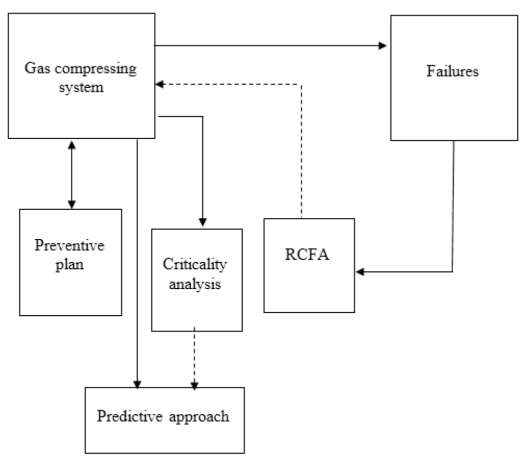

Figure 3: Existing maintenance model

2.3. Proposed Reliability Centered Maintenance Model

A major issue related to the existing model is that it is a static model. Once a preventive maintenance or predictive maintenance plan has been generated, the actions do not change automatically, based on the observed performance of the program. Also, while a root cause failure analysis program does generate failure causes, this only results in the upgradation of the equipment or replacement of an inferior component by a superior component. The existing model does address core issues with reliability, but has the following limitations: carrying out failure mode and effect analysis (FMEA) is rare, as it often relies on conventional root cause failure analysis for corrective actions. Its preventive and predictive maintenance programs do not vary with time, and it treats all equipment alike, decides on preventive and predictive maintenance based on a onetime criticality analysis. These limitations result in a condition whereby, after some time of distinct reliability improvement, the organization encounters insignificant or no improvement in reliability (as measured by the MTBF).

The proposed reliability centered maintenance (RCM) model focuses on utilizing the company's preventive maintenance schedule, predictive maintenance and failure analysis record. The use of these failure analysis outcomes will greatly aid in establishing likelihood of occurrence of failure modes. As shown in Figure 4, in addition to the integration of the existing maintenance model, the proposed reliability centered maintenance model (RCM), carries out a failure mode and effect analysis based on the failure pattern of key components and the mean time between component failures over the years. The root cause failure analysis was carried out using fault tree analysis (FTA), a top-down, deductive failure analysis, in which an undesired state of a system is analyzed using Boolean logic to combine a series of basic events. Based on these analyses and those of the existing model, the proposed reliability maintenance model is designed.

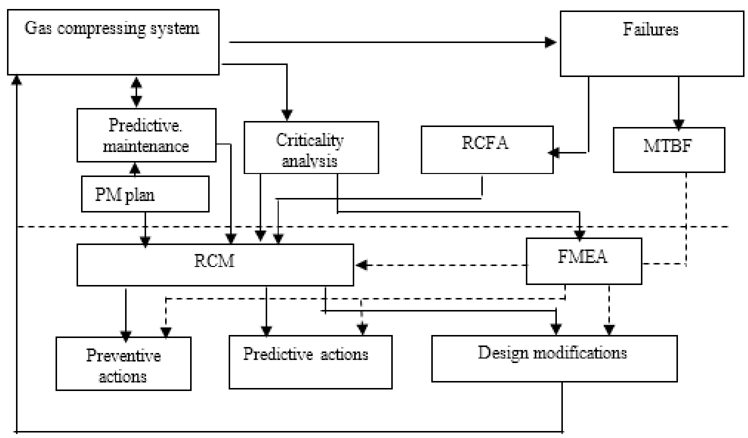

Figure 4: Proposed maintenance model

2.4. System Failure Mode and Effect Analysis

In this work, a failure mode and effect analysis was carried out on the gas compressing systems of the case study. As seen from Table 1, the failure mode and effect analysis is made of the following scope:

i. Failure mode: The failure mode is manner in which the gas compressing system fails to perform its required function. A failure may have one or more failure mechanism.
ii. Failure mechanism: It is a physical, chemical or other process which may lead to failure. Examples of failure mechanisms are corrosion, fatigue, wear, etc.
iii. Effect of failure: It is the immediate consequence of a failure i.e., what happens to the system or process if the failure mode takes effect?
iv. Failure cause: It is the circumstance during specification, design, manufacturing, installation, use or maintenance that results in failure i.e., the underlying reason that caused a failure to occur.

Table 1: Gas compressing system failure mode and effect analysis

Process function	Failure mode	Effect of failure	Failure mechanism	Cause of failure
Gas compression	Abnormal instrument reading	Compressing system shut down due to bearing failures	Faulty signal/indicator/alarm	Instrument failure, vibration, software failure, short circuit
Gas compression	Abnormal instrument reading	Compressing system shut down due to bearing failures	Vibration	
Gas compression	Breakdown	Compressing system shut down due to breakage of mechanical components	General mechanical failure	Vibration, wear, wrongly assembled skids
Gas compression	Breakdown	Compressing system shut down due to surge	General instrument failure	Vibration, software failure, open or short circuit
Gas compression	Breakdown	Foreign objects in compressing system causes it to shutdown	External influence	Wrongly assembled components
Gas compression	Breakdown	Compressing system shutdown due to bearing failure	Vibration	Bearing failure
Containment	External leakage - process medium	Unsafe operation due to the release of hydrocarbons	Corrosion	Chemical reaction
Containment	External leakage - process medium	Unsafe operation due to seals and/or gasket failure	General material failure	Wear
Gas compression	External leakage - utility medium	Unsafe operation due to seals and/or gasket failure	Alignment and/or clearance failure	Vibration, wear, wrong assembly
Gas compression	External leakage - process medium	Unsafe operation due to seals and/or gasket failure	Leakage	Material failure
Gas compression	Failed to stop on demand	Compressing system unsafe to operate	Combined causes	Instrument failure, mechanical failure
Gas compression	Failed to stop on demand	Compressing system unsafe to operate	General instrument failure	Software failure, vibration, open circuit, short circuit

2.5. Weibull Distribution and Linear Regression Model for the System

Weibull distribution was employed to determine the reliability and failure rate function of the gas compressing system. Weibull's method was chosen because, it produces a more accurate value for mean time between failure, considering the large number of suspended values which are put into the failure distribution to produce a cumulative distribution function (CDF) that is correctly calculated for the statistical parameters. The introduction of linear regression into this model, stems from the fact that the logarithm of the failure rate function of the Weibull exponential reliability model is a linear function of the system's failure times, and is also the best method for estimating shape, slope parameters and mean time between failure.

To analyze the probability of failure of the system using Weibull distribution, the following parameters are obtained (Ahmad *et al.*, 2009).

The survivor function (or reliability function) of the gas compressing system is defined as:

$$R(t) = 1 - F(t) = P(T > t), \mathrm{t} > 0 \tag{1}$$

Rewriting Equation (1) yields:

$$R(t) = 1 - \int_0^t f(u)du = \int_t^\infty f(u)du \tag{2}$$

$$R(t) = e^{-(\frac{t}{\alpha})\beta} \tag{3}$$

where: R(t) denotes the reliability of the system, F(t) denotes the probability that the item fails within the time interval (0, t), α is the shape parameter, β is the scale parameter, and f(u) is the probability density function.

$$f(t) = \frac{d}{dt}F(t) \tag{4}$$

The failure rate function is given as:

$$\lambda(t) = \alpha\beta e^{-\beta t} \tag{5}$$

The mean time between failures according to Akuno et al., (2016) is given by:

$$\mathrm{MTBF} = \alpha\Gamma(1 + \frac{1}{\beta}) \tag{6}$$

Equation (6) can be rewritten as:

$$MTBF \approx \frac{1}{\lambda(t)} = \frac{1}{\alpha\beta e^{-\beta t}} \tag{7}$$

where: t is the failure time.

Taking the logarithm of both sides of Equation (7) yields:

$$\ln(\mathrm{MTBF}) = -\ln(\alpha\beta) + \beta\mathrm{t} \tag{8}$$

$$\text{Let } F = \ln(MTBF)\,;\ -\ln(\alpha\beta) = \mathrm{a} \tag{9}$$

$$\beta = b \tag{10}$$

$$F(t) = a + bt \tag{11}$$

Applying the method of least squares to the linear regression model of Equation (11), the least square estimator for parameters a and b in Equation (12), are obtained thus:

$$a = \frac{\sum_{i=1}^n t \sum_{i=1}^n Ft - \frac{1}{n} * \sum_{i=1}^n F \sum_{i=1}^n t^2}{\left(\sum_{i=1}^n t\right)^2 - n * \sum_{i=1}^n t^2} \tag{12}$$

$$b = \frac{\sum_{i=1}^n t_i F_i - \frac{1}{n} * \sum_{i=1}^n t_i \sum_{i=1}^n F_i}{\sum_{i=1}^n {t_i}^2 - \frac{1}{n} * \sum_{i=1}^n (t_i)^2} \tag{13}$$

From Equations (8) and (11), the shape and scale parameters are obtained as:

$$\alpha = \frac{e^{-a}}{b} \tag{14}$$

$$\beta = b \tag{15}$$

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The mean time between failure for known shape and scale parameter is given as:

$$MTBF = (\alpha\beta)^{-1}e^{\beta t} \quad (16)$$

Reliability and maintenance data for the gas compressing system were obtained from the case study.

3. RESULTS AND DISCUSSION

In determining the shape and scale parameters, failure rate function and the mean time between failures of the gas compressing system, the linear regression model derived from Weibull's exponential distribution was employed. Table 2 shows the linear regression analysis at various test situations. In Table 2, points 1A – 4V denotes the points at which vibration reading were taken, when the gas compressing system was operating in the axial, horizontal and vertical directions. In order to obtain the scale (α) and shape (β) parameters, which are crucial components in determining the failure rate and mean time between failure of the system, the mean reading at each of the four points were substituted into the regression model in Equation 11 in order to obtain the constants a and b as shown in Equations 12 and 13 respectively. Upon obtaining the constants a, and b, the scale (α) and shape (β) parameters were obtained, and in turn, the performance indicators (failure rate and mean time between failure as shown in Table 3).

Table 2: Linear regression analysis

Sample points	N	$\sum Ft$	$(\sum Ft)^2$	$\sum (t)^2$	a	B	α	β
1A	64	2099.2	4406641	89440	0.000578	-3.0608	43.01	0.0226
1H	64	215.2	46311.04	63				
1V	64	6634.5	44016590	2099.2				
2A	64	149.8	22440.04	215.2				
2H	64	4559.8	20791776	6634.5				
2V	64	30.5	930.25	149.8				
3A	64	1001.7	1003403	4559.8				
3H	64	186.7	34856.89	30.5				
3V	64	3448.6	46958.89	420.1				
4A	64	1185.1	1404462	89440				
4H	64	977.5	170238.3	216.7				
4V	64	718.24	132080	26.8				

Table 3 shows the failure rate as well as the mean time between failure of the gas compressing system. The failure rate (λ) which is the frequency of failure of the gas compressing system at any given time during its operational time was 0.00016%, which implies that the probability of failure of the system at any given point in time during its 7200 hours of operation is 0.00052%, estimated at 1 failure/year. Lastly, the mean time between failures of the system is one of the best performance indicators applied to repairable systems. The average length of operating time without failure between one failure and the next failure was 4.12 years, which implies that based on the current number of hours the system is operated; it may likely fail in four years' time.

The mean time between failures which is a key reliability indicator for repairable systems, indicates the robustness of the system measured in the past and predicts the rate of failure in the near future based on that measurement. Table 3, the mean time between failure of 4.12 years indicates that from previous root cause of failure analysis and predictive maintenances carried out, the gas compressing system at case study refinery may likely fail in 4 years-time. This means that the number of preventive and reactive maintenances carried out all through the 7200 hours in which the system is available, should be minimized. This would save cost associated with frequent preventive and reactive maintenances since the system will not fail in the next four years.

Table 3: Gas compressing system indicators

Parameter	Value
Failure rate function	0.00052%
Mean time between failure	4.12 years

Figure 5 shows the failure rate of the compressing system. The failure rate is the frequency at which the system fails at any given point in time during its operating period. From Figure 5, it can be seen that as the time interval in which the system is operating increases, the failure rate also increases. This implies that an increase in the operating time results in a higher probability that the system may fail at any point. Also, at 7200 hours, which is the average number of hours the system is operated at the case study refinery, the failure rate was obtained as 0.00024%, which is equivalent to an estimate of 1 failure/year.

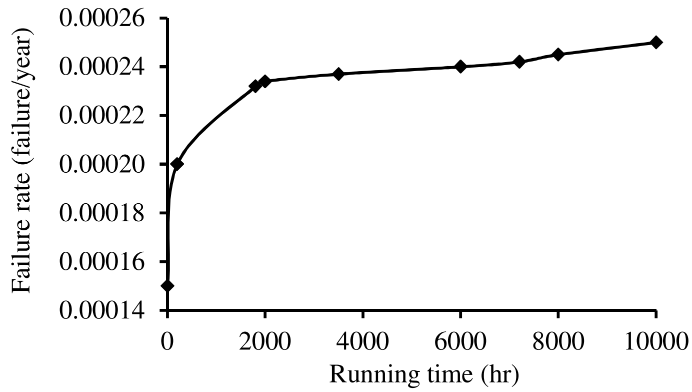

Figure 5: The failure rate of the gas compressing system

Figure 6 shows the frequency of failure of the gas compressing system at any given point in time, during its 7200 hours of operation. As seen in the proposed and existing model, as the number of operating hours increases, the probability that the system will fail at any time, also increases. The failure rate of the existing model was greater than that of the proposed reliability maintenance model at same operating time. At 7200 hours, the failure rate was 0.00016% (4 failures/year estimation) and 0.00052% (1 failure/year estimation) for the existing model and the proposed reliability maintenance models respectively. This also confirms that the proposed model brings significant improvement when compared to the existing model.

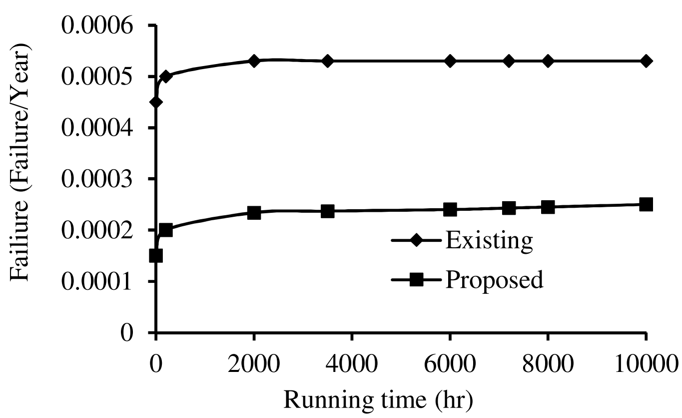

Figure 6: Existing frequency of component failure versus proposed

4. CONCLUSION

This work shows that the application linear regression models derived from Weibull's distribution, for gas compressing systems, results in substantial improvement when compared to the existing model at case study refinery. Hence, this model can be used in place of technical and computationally advanced mathematical models to solve the problem of complex system reliability, associated risk and high maintenance cost. A mean time between failures of 4.12 years indicates that the gas compressing system may likely fail in 4 years' time. Hence, the number of preventive and reactive maintenances carried out on the system yearly, should be reduced, so as to save cost arising from maintaining functional components since the system will not result in functional failure in the next 4 years. It is recommended that the methodology applied in this work be adopted for effective and efficient operations Also, future work should focus on cost indicators, in order to measure improvements on the gas compressing system, brought by the application of the proposed reliability centered maintenance approach.

5. ACKNOWLEDGMENT

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6. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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