Original Research Article

Application of analytical hierarchical process in equipment maintenance scheduling and decision-making process in Oil/Gas

Abstract

This paper provides a novel approach for prioritizing critical equipment maintenance activities using Analytical Hierarchical Process (AH). A family of Weibull distribution function is used to define five parameters (criteria) namely the Weibull Continuous Distribution Function (CDF), Weibull Probability Density Function, Reliability function, failure rate and equipment availability. To validate the use of AHP method, data from Nine (9) critical equipment from a pump station in Port-Harcourt, Nigeria was used to prioritize maintenance activities. The slope shape parameter values of $\gamma \epsilon \{0.5,1,2\}$ are considered, which affects the shape of the distribution functions. The results show multi-criterion approach is very effective in scheduling maintenance activities based on previous history and quality of criteria applied.

Key word: Analytical Hierarchical Process; Equipment maintenance; Risk-based approach; Mean-time Between Failure (MTBF); Weibull distribution functions.

1. INTRODUCTION

Maintenance, an essential aspect of Oil/Gas operations, is a set of activities that aim at preserving the condition of equipment to reduce the probability of failure and increase operating life cycle. Over the years, Oil/Gas industry has developed and adopted different maintenance strategies to reduce the cost of maintenance while adhering to best practices. With growing instability and falling in the global oil prices, companies are subjected to severe budget cuts and cost reduction measures of some operational activities. These led to re-think on maintenance strategies and the need for establish risk-based approach that prioritized equipment maintenance activities consequence of budget constrained.

Corrective maintenance policies were predominately used in the 1940s which were based on an attempt to repair a system when there is the total breakdown. Economic considerations shifted practice towards preventive maintenance which dominated the era between the 1970s and 1990s (Igbal et al., 2016; Nnadi et al., 2007); later with improved inspection techniques and environmental regulations, predictive and proactive or risk-based maintenance (RBM) policies were developed and successfully applied in pipeline maintenance (Dey et al., 2004; Igbal et al., 2016 Usman and Ngene, 2012). Risks assessment in pipeline maintenance is a difficult task to carry out, and there are a variety of systems in place to identify, analyze failure likelihood, evaluate failure consequences and estimate the risk values for proper approach (quantitative or qualitative) to be applied (Ambituuni et al., 2015). Condition-based maintenance (CBM) and proactive maintenance as effective maintenance strategies in Oil and Gas provides a dynamic view of equipment while in use as well as predicting failure in mechanical systems through fault diagnosis (Telford et al., 2011).

The general conception of the function of maintenance is to prevent the occurrence of failure, which is correct to some extent. However, to identify the role of maintenance, considerations to the reasons of failure, which might include faulty design, abuse of equipment by the operator and as a sequence of poor maintenance planning should be analyzed (Mohammed and Saad, 2016). Therefore, the role of maintenance is to create a programme that utilizes the equipment productivity, to minimize the interruption to the production line and within the least spending. Timed-base maintenance policy requires that replacement or repair is carried out at a fixed time after the installation of a facility, which is generally independent of its condition. The period used to construct a maintenance schedule can be either calendar time or component running time (Ahmad et al. 2011). This mode of maintenance is costly and time consuming depending on the time interval.

Building equipment reliability through effective maintenance practices has a reasonably long history starting from the early days of corrective maintenance policies. These policies allow equipment to continue to operate until it fails before maintenance intervention on that equipment. This type of maintenance practices has a significant impact on production and life span of the equipment (Mili et al., 2009). Several maintenance strategies have been used and reported in connection with adequate maintenance of equipment at an industrial scale. In this section, these maintenance strategies are reviewed.

Maintenance process and planning are an essential and integral aspect of industrial activities, and they take center stage in operational activities. Maintenance refers to all technical and administrative action aimed at improving the equipment life cycle (Mili et al., 2009). Earlier maintenance practices were based on corrective actions where equipment or systems are given attention only when there is a failure (Mili et al., 2009). This type of maintenance action significantly affects production and lead to poor product quality, loss of productivity, loss of availability, negative impact on equipment yield, increase maintenance cost, and results to tight delivery timelines (Kolte and Dabade, 2017; Mili et al., 2009). As knowledge of maintenance evolve, and the increase in a high level of sophisticated machines to achieve higher production throughput with improved quality, the need for a different maintenance approach led to the concept of prevention. Preventive maintenance provides a strategy that helps to prevent breakdown and minimize failure rate of equipment in a process plant. This involves developing a pre-define maintenance plan based on the equipment conditions, cost, number of running hours and spare parts availability (Mili et al., 2009).

Variants of preventive maintenance have been developed to optimize resources allocation and improve overall maintenance efficiency (Higgins and Mobley, 2001). This is one of the industrial practices of increasing operational availability of existing equipment to increase productivity (Kolte and Dabade, 2017). Time-based and condition-based maintenance were among the most reviewed topics (Ahmed and Kamaruddin, 2012; Yang et al., 2018; Kezunovic and Natti, 2006). In time-based maintenance, which happens to be a traditional maintenance method, decisions are based on failure time analysis. This maintenance scheme assumes that the failure time is predictable and can be derived from the equipment life cycle, as shown in figure 1(Ahmed and Kamaruddin, 2012).

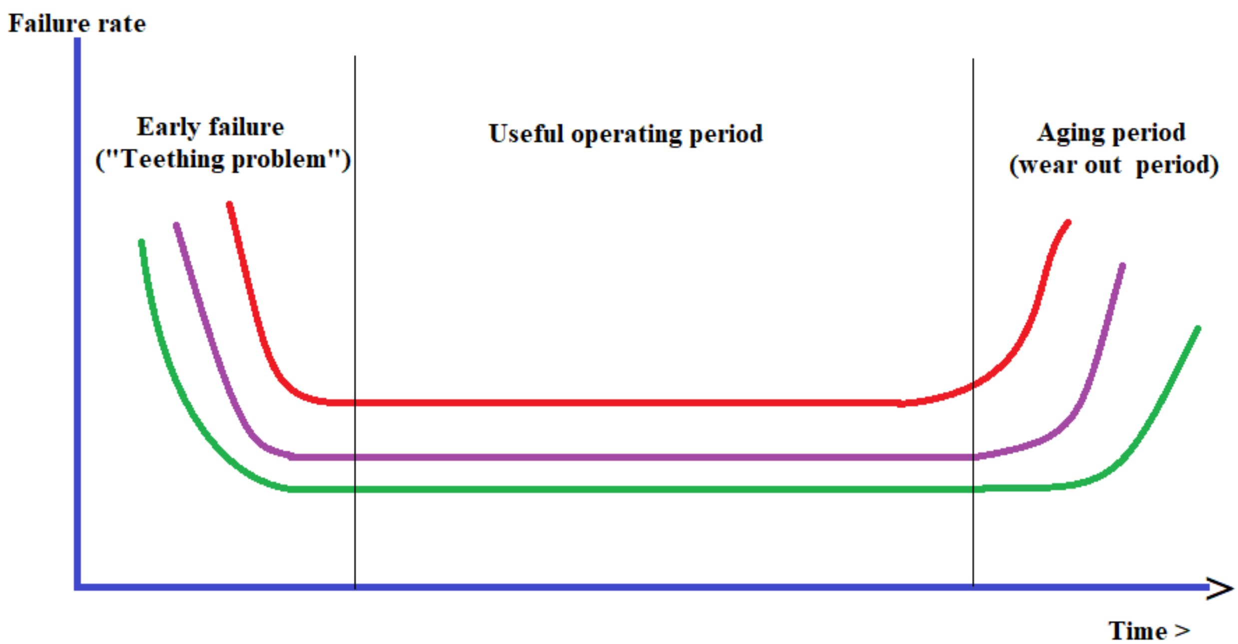

Figure 1. Equipment life-cycle curve

Figure 1. shows a typical curve for the equipment life cycle. The cycle can be divided into burn-in, useful life, and wear-out (Ebeling, 1997). At the burn-in stage, the equipment experiences a teething problem, and this failure decreases early in the equipment life-cycle. The curve is flattened over the useful operating period. This implies that the failure is nearly constant. After a reasonable period, ageing begins to affect the equipment and failure rate increases exponentially, as shown in figure 2. To begin time-based maintenance, data analysis of the failure trend is carried out to statistically investigate the failure characteristics of the equipment (Ahmed and Kamaruddin, 2012). Once a set of failure time data has been gathered, then the analysis is carried out through statistical/reliability modelling to identify the failure characteristics of the equipment, including mean time to failure (MTTF) estimation and the trend of the equipment failure rate based on bathtub curve process (Ahmed and Kamaruddin, 2012). Statistical/reliability modelling can be carried out using various statistical tools, the most popular of which is through reliability theory using the Weibull distribution model (Ghodrati, 2005; Joz'wiak, 1997). The Weibull distribution model has been widely used to model the failures of many materials and in numerous other applications due to its ability to model various ageing classes of life distributions, including increasing, decreasing, or constant failure rates (Bebbington et al., 2007).

Time-based maintenance practices in pipeline operations are challenging. Gathering sufficient amount of failure data is difficult and time-consuming and is not always available. Furthermore, incorrect or wrong data alter the results of the analysis, which makes time-based maintenance practice not very useful in complicated and broad industrial plants. Thus, in search of an effective maintenance practice due to increasing automation and cost of critical equipment, many industries are moving toward condition-based maintenance (de Jonge et al., 2017).

Condition-based maintenance (CBM) relies on parameters that indicate operating conditions of equipment. The condition-based maintenance (CBM) process requires technologies, people skills, and communication to integrate all available equipment condition data, such as diagnostic and performance data; maintenance histories; operator logs; and design data, to make timely decisions about the maintenance requirements of major/critical equipment. Condition-based maintenance assumes that all equipment will deteriorate and that partial or complete loss of function will occur. CBM monitors the condition or performance of plant equipment through various technologies. The data is collected, analyzed, trended, and used to project equipment failures. Once the timing of equipment failure is known, action can be taken to prevent or delay failure. In this way, the reliability of the equipment can remain high. Condition-based maintenance uses various process parameters (e.g. pressure, temperature, vibration, flow) and material samples (e.g. oil and air) to monitor conditions. With these parameters and samples, condition-based maintenance obtains indications of system and equipment health, performance, integrity (strength) and provides information for scheduling timely correction action.

As experience grows with the fundamentals of a robust condition-based maintenance program, users can use proactive maintenance (PAM) concepts to make continuous improvements to the program and maintenance activities in general. Proactive maintenance is a concept for 'learning from experience' of maintenance work, preventive maintenance and condition-based maintenance.

2. Related works

A risk-based maintenance strategy is established based on set theory, probability random process and optimization to aid maintenance decision making. The probability theory provides the means to rationally model, analyze and solve problems where future events cannot be foreseen with certainty. Probability can be viewed from both objective and subjective conception (Stone, 2008).

Risk-based maintenance process approaches maintenance practice by identifying hazards associated equipment or systems and estimating risks (Arunraj 2007**)**. In other words, risk management is the comprehension of processes, identification, appraisal, and prioritization of risks accompanied by organized technical or economic resources to reduce, supervise, and control the likelihood and impact of uncertainty and maximize the unexpected opportunity (Ogunwolu et al., 2015).

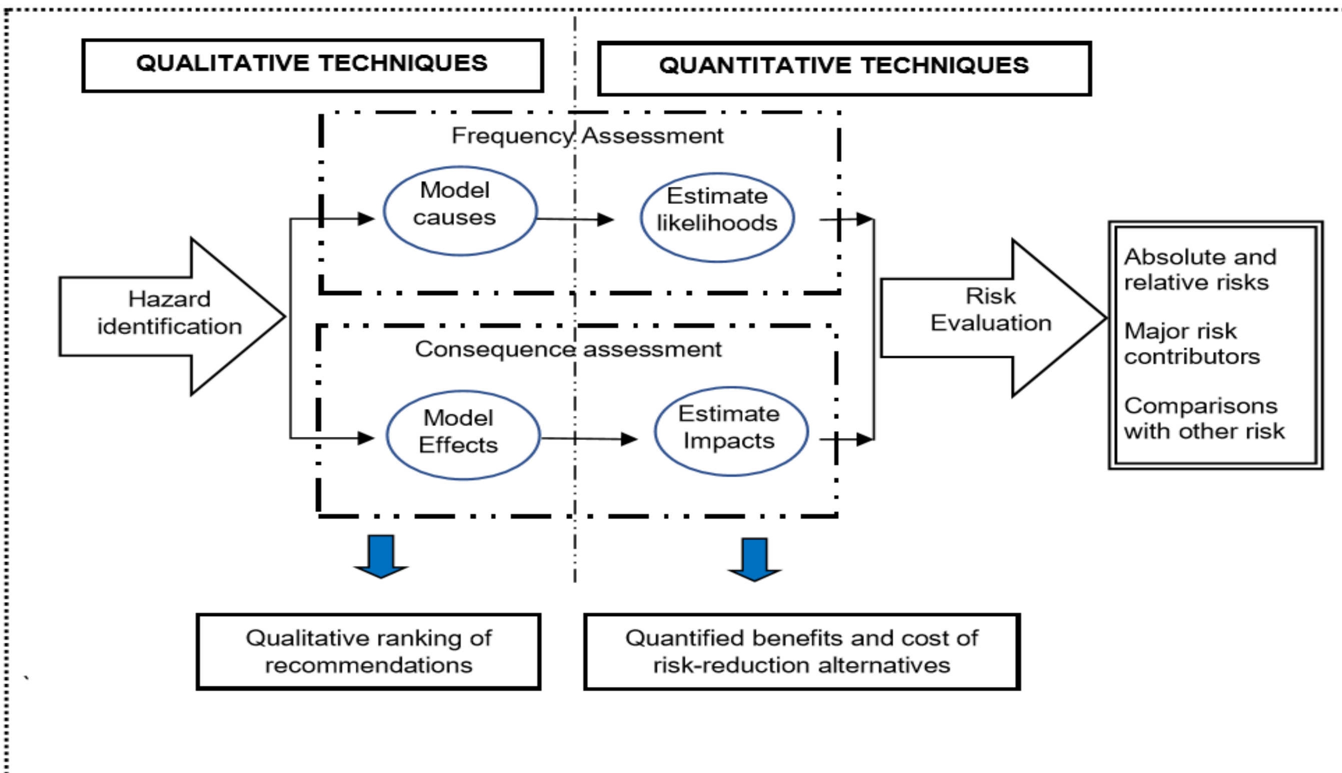

Figure 2. Process in Risk assessment (Godians and Ramachandra, 2018)

Overall equipment effectiveness can be measured using criteria (Godians and Ramachandra, 2018).

$$Availability = \frac{PPT - DT}{PPT} \text{x}100 \tag{1}$$

$$Performance\ rate = \frac{DCT * PA}{ART} \text{x}100 \tag{2}$$

$$Quality\ rate = \frac{PA - DA}{PA} \text{x}100 \tag{3}$$

where

PPT: Planed production time
DT: Down time
DCT: Design cycle time
PA: Production amount
ART: Actual running time
DA: Defect amount

The standard quantitative method employed to arrive at an appropriate decision involving risk, in practice, is well-known. The probabilities (pi) associated with possible outcomes (ci) are multiplied, and these products are summed to arrive at a value, referred to as the expected value (Vivian, 2013).

Several models have been developed to calculate, assess and quantify risks for risk-based maintenance to reduce the cost of maintenance in condition-based and time-based maintenance policies. Bayesian method was used to optimize maintenance schedules in Natural gas regulating and metering stations (Leoni et al., 2018). Bayesian network, a mathematical procedure for computing probabilities, is used to model the risks and uncertainties, which was classified as minor, major and catastrophic risks (Leoni et al., 2018). Figure 3 shows a pictorial representation of the algorithm for risk-based maintenance using the Bayesian network.

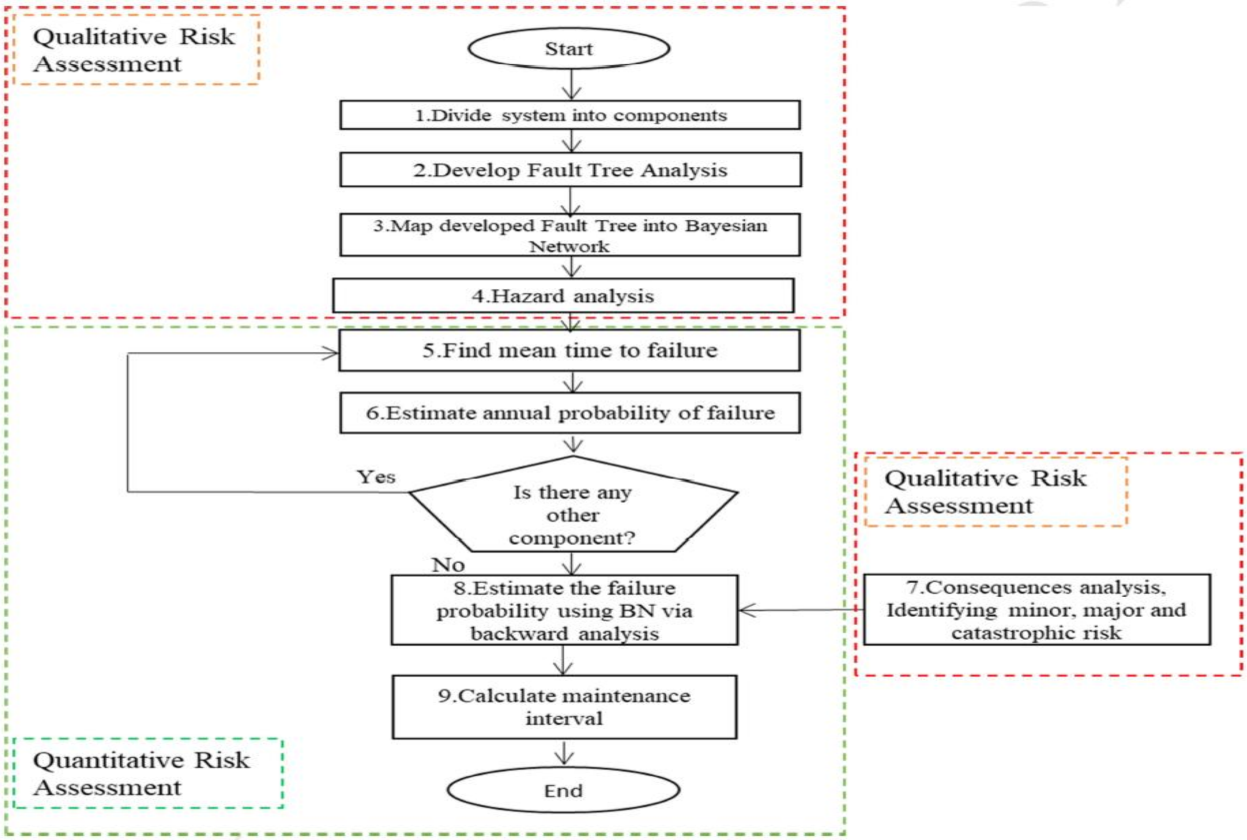

Figure 3. Bayesian Network for modeling risk and uncertainty in risk-based maintenance in Gas pipelines and metering station (Leoni et al., 2018).

Quantitative maintenance methodology based on Bayesian network was used to optimize maintenance time interval, increase the reliability of equipment and reduce the cost of maintenance (Abbassi et al., 2016). Computational frameworks for maintenance risk planning of inspections and repairs using discrete Bayesian Network were developed for Offshore Oil and Gas infrastructures (Nielsen and Sorensen, 2018). This framework, based on decision rules, is used to compute the total life cycle cost of a component by classifying decisions into simple decision rule and advance decision rules. Ratnayake and Antosz (2017) stated that ranking and classification of potential failure is the right strategy that takes into consideration maintenance interval, availability of spare parts, and choice of maintenance policy to be applied. Using the concept of membership, rule-based systems and statistical inference, Fuzzy logic based on Mamdani-type was used in developing risk matrix in risk-based maintenance practice. The use of fuzzy logic is to assist in risk ranking by taking into accounts the number of breakdowns, time to failure eliminations, personal safety, and percentage of non-conforming products (Ratnayake and Antosz, 2017). Figure 4. shows the assessment of probabilities of failure using Fuzzy RBM.

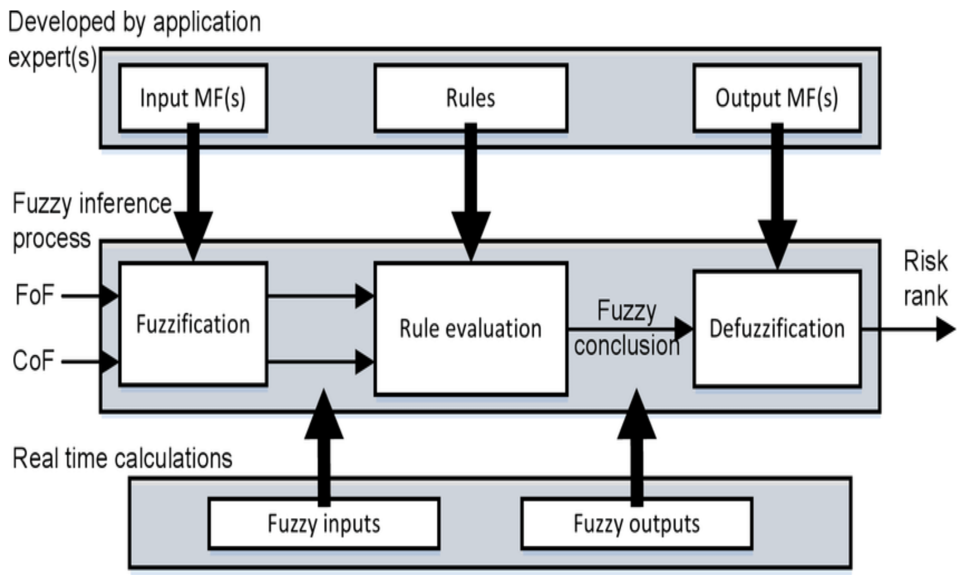

Figure 4. Overall view of Fuzzy RBM assessment process (Ratnayake and Antosz, 2017).

Risk-based maintenance model has been applied to high voltage circuits and cables to optimize maintenance schedule time (Liao et al., 2019). Indices or rank was used to classify the condition of a circuit as "**critical**", "**Importan**t", “**caution**” and “**normal**” as shown in figure 5.

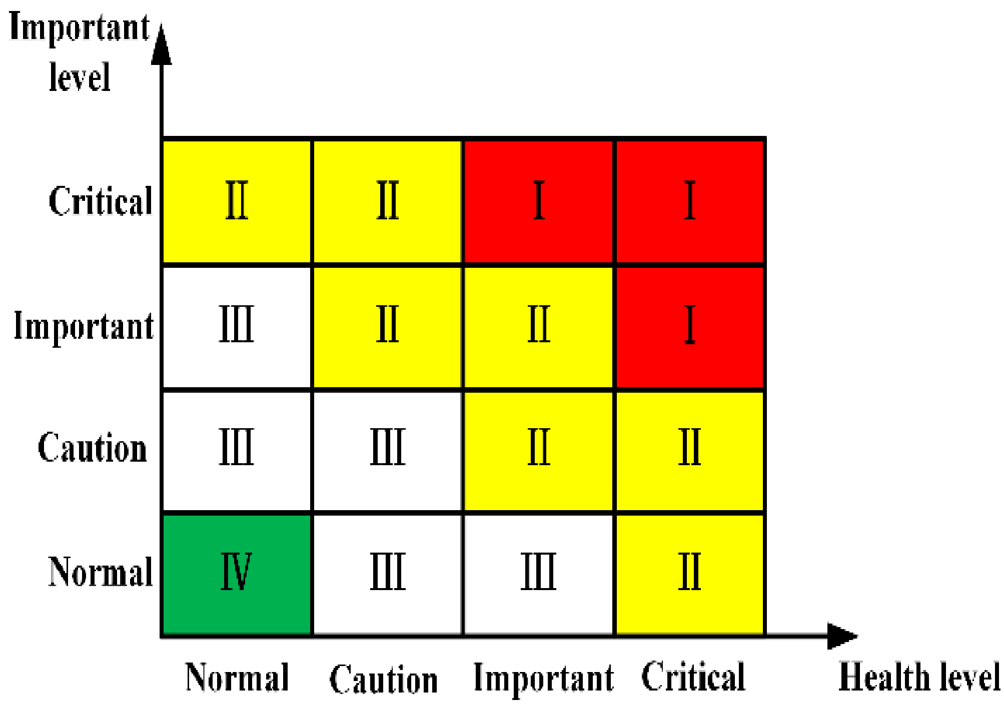

Figure 5. Cable critically index matrix (Liao et al., 2019).

In critical areas such as wind farms, risk-based maintenance strategy is highly regarded in optimizing operations and maintenance of wind turbine (Florian and Sorensen, 2017). In this study, the focus was on the turbine wind blade to ascertain the risk of failure and ensure reliability.

3. Materials and methods

In this work, we demonstrated the effectiveness of AHP as a very powerful quantitative procedure to schedule and prioritize maintenance activities. AHP is a method that is commonly used in the field of management science where multiple criteria are required to make an informed decision (Bernasconi et al., 2010). The goal of AHP is to provide a multivariate method of solving and simplifying decision making process involving more than one alternative. This method reduces complex multicriteria process into a simple comprehensible hierarchical structure (Sadiq and Tesfamariam, 2009). The technique was developed by Saaty (1977, 1986, 1994, 2006), which is a methodology of measurement of alternatives through pairwise comparisons and relies on the judgement of the expert to derive priority scales. Table 1 shows the fundamental scale developed by Saaty to derive the priority vector or matrix between different alternatives and criteria.

Table 1. The fundamental scale of importance (Saaty.,1980)

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgement slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
A reciprocal of above	If activity i has one of the above non-zero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	A reasonable assumption
1.1-1.9	If the activities are very close	May be difficult to assign the best value, but when compared with other contrasting activities, the size of the small numbers would not be too noticeable. However, they can still indicate the relative importance of the activities.

AHP reduce complex decision process by considering a set of evaluation criteria and a set of an alternative option. It works by pairwise comparison of objects. Figure 6 shows an algorithm for computing AHP using Saaty scale.

Let n be the number of items or objects. The total number pairwise comparison for n objects as

$$N = \frac{n(n-1)}{2} \tag{4}$$

The pairwise matrix is given as;

$$A = N\text{x}N \tag{5}$$

Let the element of the matrix A be a_{ij} where i and j are rows and column, respectively.

The sum of elements in each column of length, *k*, of the matrix A,

$$s_j = \sum_{i=1}^{K} a_{kj} \tag{6}$$

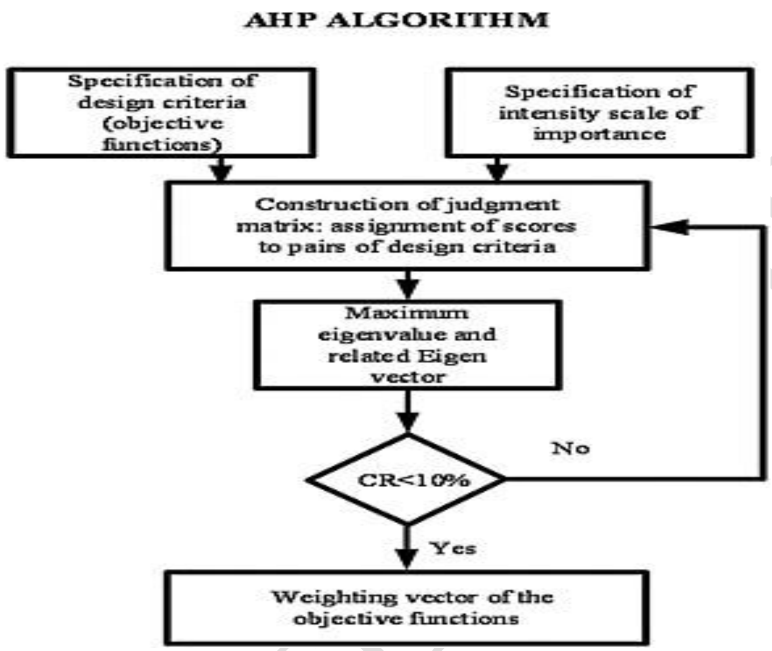

Figure 6. Algorithm for computing AHP rank score**.**

The normalized relative weigh is obtained by dividing the elements of each column by its corresponding sum as indicated by equation (3.3).

$$\overline{a_{ij}} = \frac{a_{kj}}{\sum_{i=1}^{K} a_{kj}} = \frac{a_{kj}}{s_j} \tag{7}$$

Thus, the normalized relative weight matrix is given as:

$$\bar{A} = \{\overline{a_{ij}}\} \tag{8}$$

The priority vector is obtained by summing each row of the matrix of equation (8).

$$W = \left(\frac{1}{N}\sum_{l=1}^{j}\overline{a_{jl}}\right) \tag{9}$$

The priority vector, when sorted, gives the probability that an object is preferred.

When studying the intangible properties of elements within the hierarchical structure, it is usually difficult or impossible to quantify them because such qualitative data are not known in absolute values (Triantaphyllou and Mann, 1995). It is within this context that the theory of relative methodology finds its application to assign values to each criterion. The pairwise comparison approach simply compares a criterion to another criterion. The decision-maker has to make comparisons between pairs of criteria to determine their relative importance by expressing an opinion on the relative importance of the paired criteria at a time. In pairwise comparisons, the choice of the decision-maker is expressed first as a linguistic phrase such as *"X is more important than Y"* or *"X is as important as Y"*. The main problem with the pairwise comparisons is how to quantify the linguistic choices selected by the decision-maker during their evaluation thus, making it the most crucial step in pairwise comparison based decision-making process (Triantaphyllou and Mann, 1995). The pairwise comparison in the decision-making process has in its virtue "*simplicity*". It can simultaneously allow the decision-maker to take multiple factors with the same degree of importance at the same time (Kawa, 2016).

The decision-maker rates the pairwise comparisons such as scaled in table 1 developed by Saaty (1980), and then the pairwise comparisons of various criteria are organized into a square matrix.

4. Results and discussions

4.1. Decision making criteria

In this section, we apply AHP to develop an effective means of prioritizing critical equipment maintenance subject to budget constrained. The decision process is validated using data obtained from a pipelines and storage facilities in Port Harcourt pump station, Nigeria. Nine critical equipment were selected and information from their maintenance records covering the period of January to December 2019 were expunged to calculate failure rate, mean-time between failure, reliability and operational. Table 2 shows the list of critical maintenance equipment and their common faults. The goal is to prioritize maintenance activities quantitatively using multi-criteria analytical hierarchical process.

Table 2. Critical equipment list

Equipment types and code	Commonly failure and replaceable parts
2E- Electric Mainline pump (EMLP01)	Mechanical seal leak, sleeve bearing, DE and NDE ball bearings.
2E-Diesel Mainline pump (DMLP01)	Mechanical seal leak, sleeve bearing, DE and NDE ball bearings.
2EX- Electric Mainline pump (EMLP02)	Pump gaskets and lobe Oil pump.
2EX-Diesel Mainline pump (DMLP02)	Pump gaskets.
Booster pump A (Old Refinery)-BPA	Mechanical seal leak and Contactor failure.
Booster pump B (Old Refinery)-BPB	Mechanical seal leak and Contactor failure.
Booster pump 55P01A (New Refinery)	Mechanical seal leak and Contactor failure.
Booster pump 55P01B (New Refinery)	Mechanical seal leak and Contactor failure.
Booster pump 55P01C (New Refinery)	Mechanical seal leak and Contactor failure.

Each equipment in the prioritization list in table 2 establishes one-to-many relationship with all the five selected evaluating criteria as shown in figure 7. Using Weibull class of distribution functions, we defined the following functions:

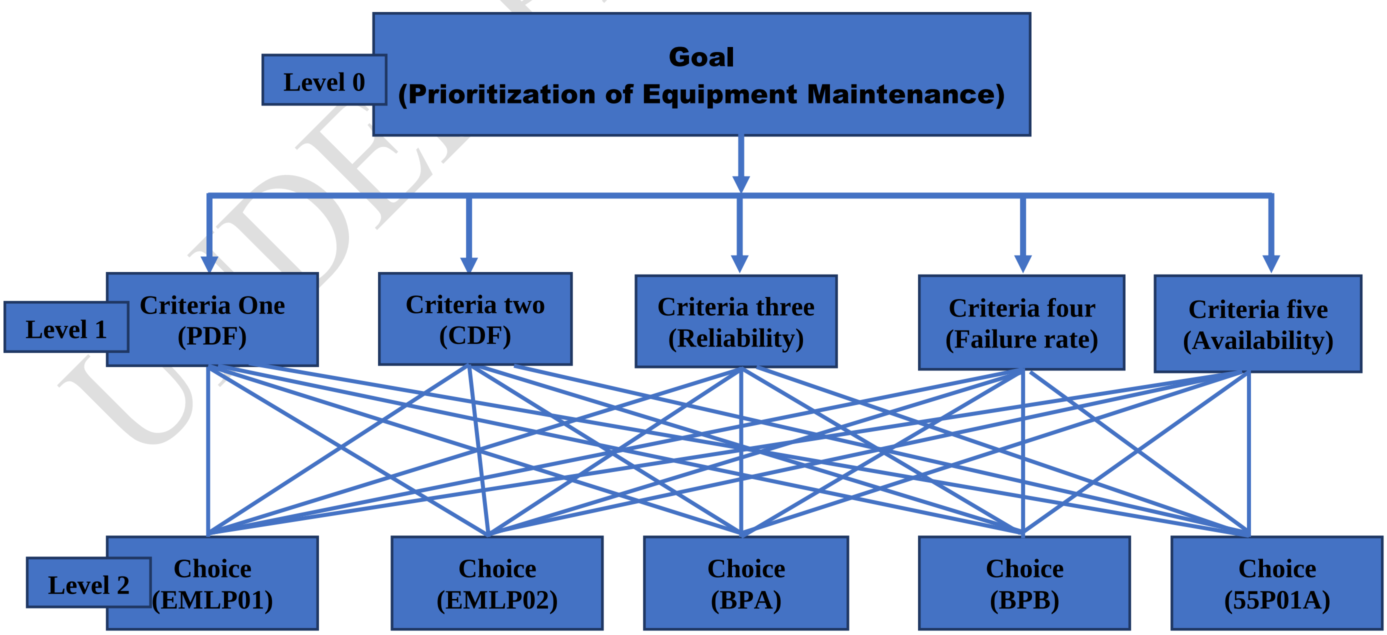

Figure 7. Criteria mapping in maintenance prioritization using AHP.

The **probability density function** is defined as;

$$f(t;\gamma;\alpha) = \frac{\gamma}{t}\left(\frac{t}{\alpha}\right)^{\gamma} e^{-\left(\frac{t}{\alpha}\right)^{\gamma}} \quad (10)$$

The **cumulative density function** defines the unreliability function of the distribution as;

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\gamma}} \quad (11)$$

The two-parameter Weibull reliability, which defines the probability of equipment to perform its functions as intended under specific condition is given as;

$$R(t) = e^{-\left(\frac{t}{\alpha}\right)^{\gamma}} \quad (12)$$

The mean time before failure (MTBF) of equipment is defined as;

$$\text{MTBF} = \text{Mean life} = \frac{\text{Total Time}}{\text{No. of Failures}} = \frac{1}{\lambda} \quad (13)$$

where λ is the failure rate of equipment or component.

Mean time to repair (MTTR) of equipment is given as;

$$\text{MTTR} = \frac{\text{Maintenance Time}}{\text{No. of Repairs}} \quad (14)$$

The availability of equipment is given as

$$\text{Availability} = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} = \frac{\text{Uptime}}{\text{Uptime} + \text{down time}} \quad (15)$$

MTBF and MTTR were estimated from the data obtained to determine equipment availability and Weibull distribution functions.

Table 3. Critical equipment maintenance record from January to October 2019

S/N	EQUIPMENT	Operating time (hr.)	No. of Failures	Total downtime due to Repairs (hrs.)
1	EMLP01	2000	4	112
2	DMLP01	-	-	-
3	EMLP02	700	2	32
4	DMLP02	-	-	-
5	BPA	1500	2	80
6	BPB	700	1	40
7	55P01A	1000	1	8
8	55P01B	-	-	-
9	55P01C	N/A	-	-

Table 4. MTBF and failure rate of the critical equipment

S/N	EQUIPMENT	MTBF (hr.)	Failure Rate (/hr.)	Availability (%)
1	EMLP01	500	$2x10^{-3}$	94.00
2	DMLP01	-	-	-
3	EMLP02	350	$2.857x10^{-3}$	95.63
4	DMLP02	-	-	-
5	BPA	750	$1.33x10^{-3}$	94.94
6	BPB	700	$1.429x10^{-3}$	94.60
7	55P01A	1000	$1x10^{-3}$	99.21
8	55P01B	-	-	-
9	55P01C	-	-	-

The records under operating period from January to October 2019 for each of the selected equipment are represented in table 3. The dash line indicate that the record is not available for that equipment.

Using table 3 and equations (13) to (15), MTBF, failure rate and availability were calculated as shown in table 4, and are inputted as decision parameters for prioritizing critical equipment maintenance activities. We develop Weibull table for the class of distribution function for each of the selected critical equipment using data in tables 2-4.

Table 5. Weibull distribution function for each of the selected equipment

S/N	EQUIPMENT	Weibull distribution (PDF)	Weibull distribution (CDF)	Reliability
1	EMLP01	$f(t;\gamma;\alpha) = \frac{\gamma}{t}\left(\frac{t}{500}\right)^{\gamma} e^{-\left(\frac{t}{500}\right)^{\gamma}}$	$F(t) = 1 - e^{-\left(\frac{t}{500}\right)^{\gamma}}$	$R(t) = e^{-\left(\frac{t}{500}\right)^{\gamma}}$
2	DMLP01	-	-	-
3	EMLP02	$f(t;\gamma;\alpha) = \frac{\gamma}{t}\left(\frac{t}{350}\right)^{\gamma} e^{-\left(\frac{t}{350}\right)^{\gamma}}$	$F(t) = 1 - e^{-\left(\frac{t}{350}\right)^{\gamma}}$	$R(t) = e^{-\left(\frac{t}{350}\right)^{\gamma}}$
4	DMLP02	-	-	-
5	BPA	$f(t;\gamma;\alpha) = \frac{\gamma}{t}\left(\frac{t}{750}\right)^{\gamma} e^{-\left(\frac{t}{750}\right)^{\gamma}}$	$F(t) = 1 - e^{-\left(\frac{t}{750}\right)^{\gamma}}$	$R(t) = e^{-\left(\frac{t}{750}\right)^{\gamma}}$
6	BPB	$f(t;\gamma;\alpha) = \frac{\gamma}{t}\left(\frac{t}{700}\right)^{\gamma} e^{-\left(\frac{t}{700}\right)^{\gamma}}$	$F(t) = 1 - e^{-\left(\frac{t}{700}\right)^{\gamma}}$	$R(t) = e^{-\left(\frac{t}{700}\right)^{\gamma}}$
7	55P01A	$f(t;\gamma;\alpha) = \frac{\gamma}{t}\left(\frac{t}{1000}\right)^{\gamma} e^{-\left(\frac{t}{1000}\right)^{\gamma}}$	$F(t) = 1 - e^{-\left(\frac{t}{1000}\right)^{\gamma}}$	$R(t) = e^{-\left(\frac{t}{1000}\right)^{\gamma}}$
8	55P01B	-	-	-
9	55P01C	-	-	-

The two Weibull distribution parameters in the equations are shape parameter, γ, and the characteristic life, α. The shape parameter is estimated to fit the distribution data. The characteristic life parameter is known as MTBF. To study the effect of the shape parameters on the equipment characteristics, $\gamma = 0.5, 1 \text{ and } 2$ were chosen. Figures 9-11 show the plots of Weibull cumulative distribution function. This is an increasing function where an equipment with the least MTBF has the highest values. MTBF is shown to be inversely proportional to the CDF. Figure 12-14 show the plots of Weibull probability density function (PDF). In figure 12 and 13, the plots decay with increasing time while in figure 14, the function increases to a maximum value before decreasing with increase in time. In each case of the PDF, the lower the MTBF, the higher the distribution function and vice versa.

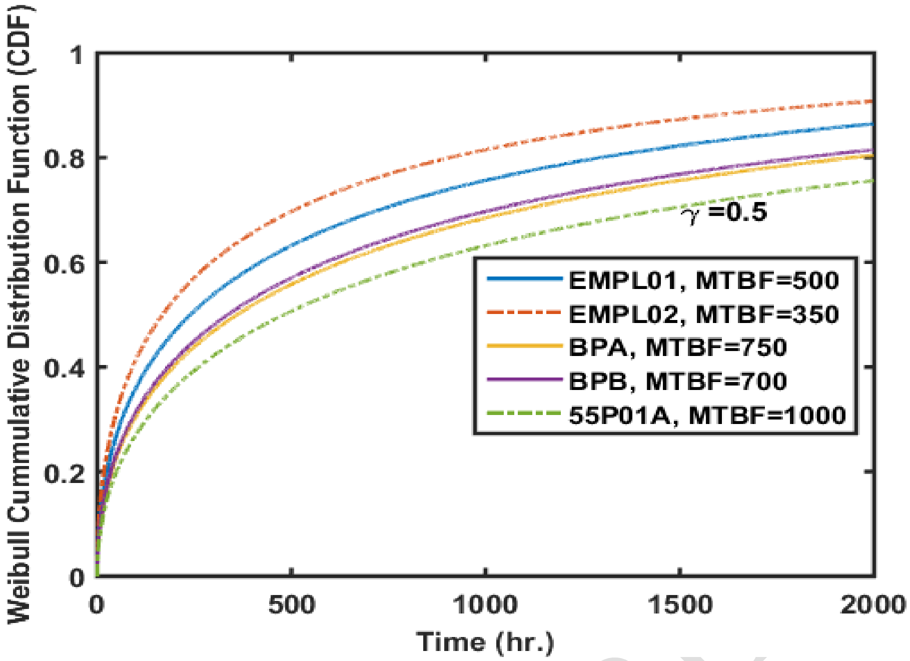

Figure 8. CDF of selected equipment as a function of time at $\gamma = 0.5$

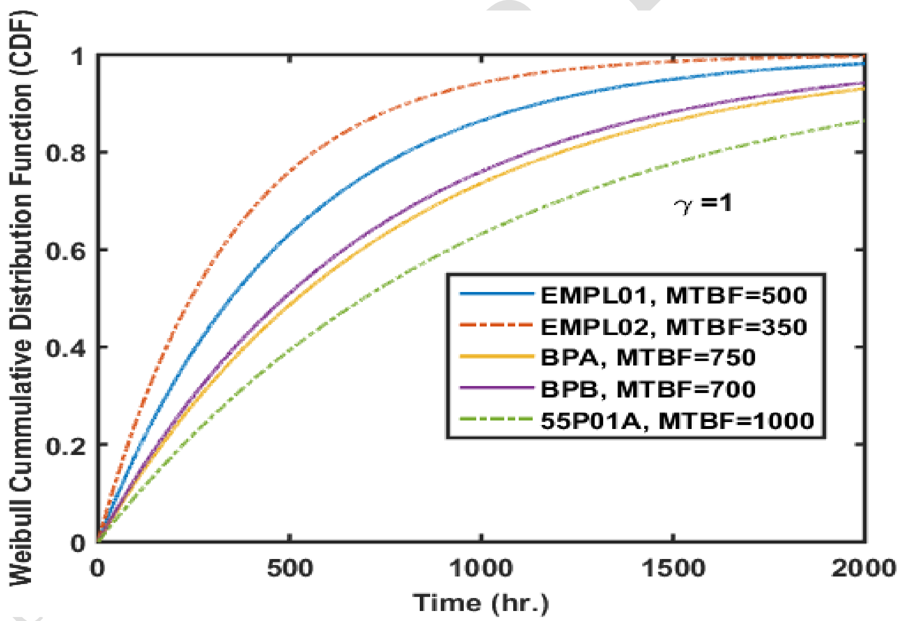

Figure 9. CDF of selected equipment as a function of time at $\gamma = 1$

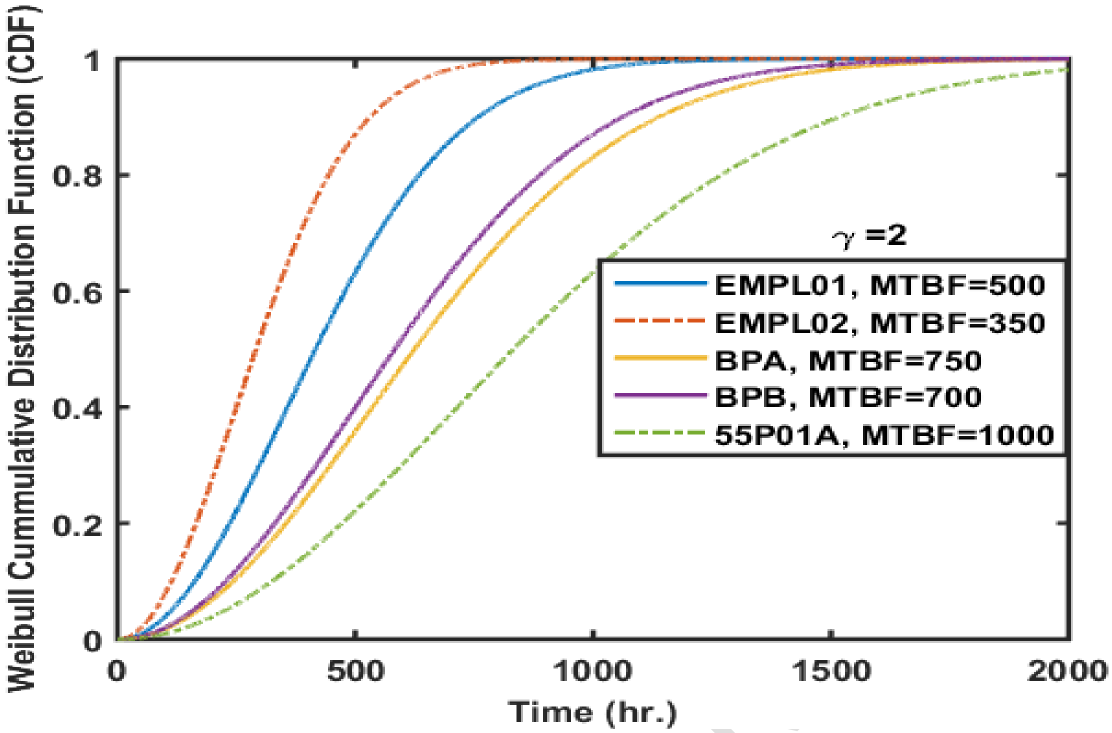

Figure 10. CDF of selected equipment as a function of time at $\gamma = 2$

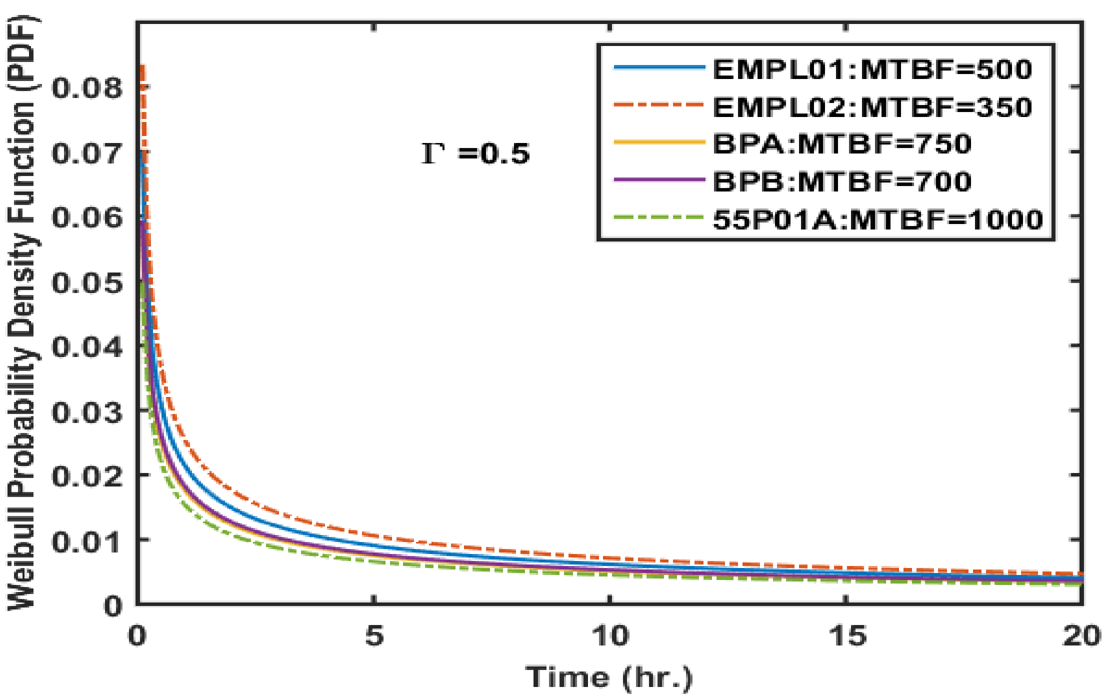

Figure 11. PDF of selected equipment as a function of time at $\Gamma = 0.5$

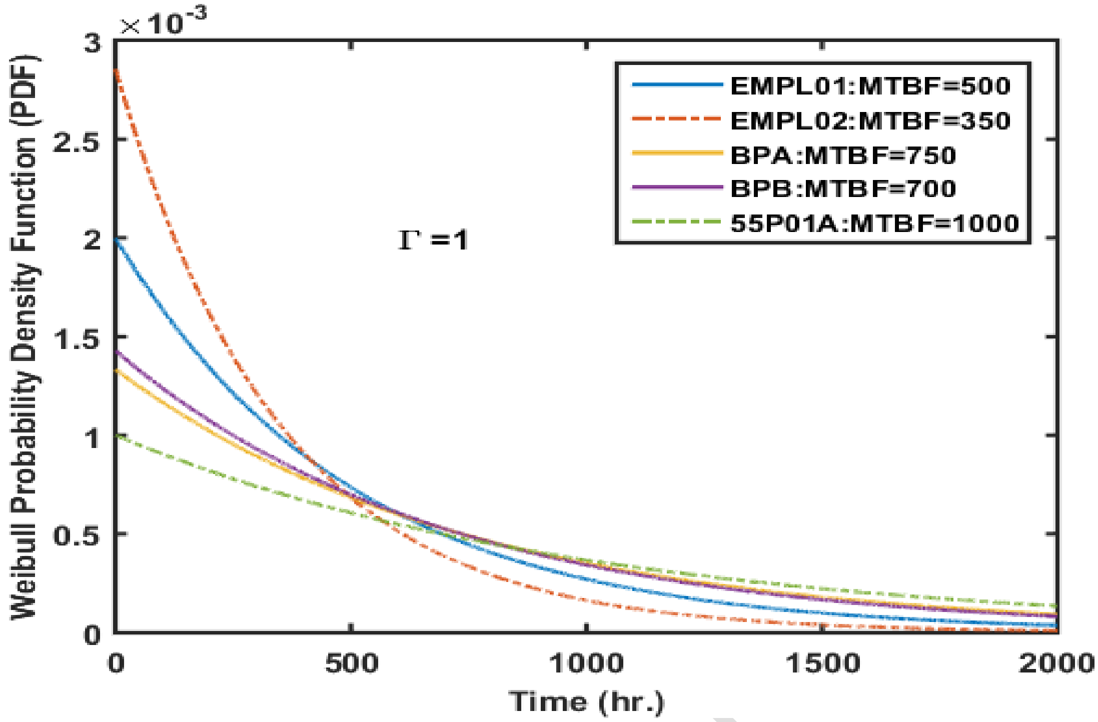

Figure 12. PDF of selected equipment as a function of time at $\Gamma = 1$

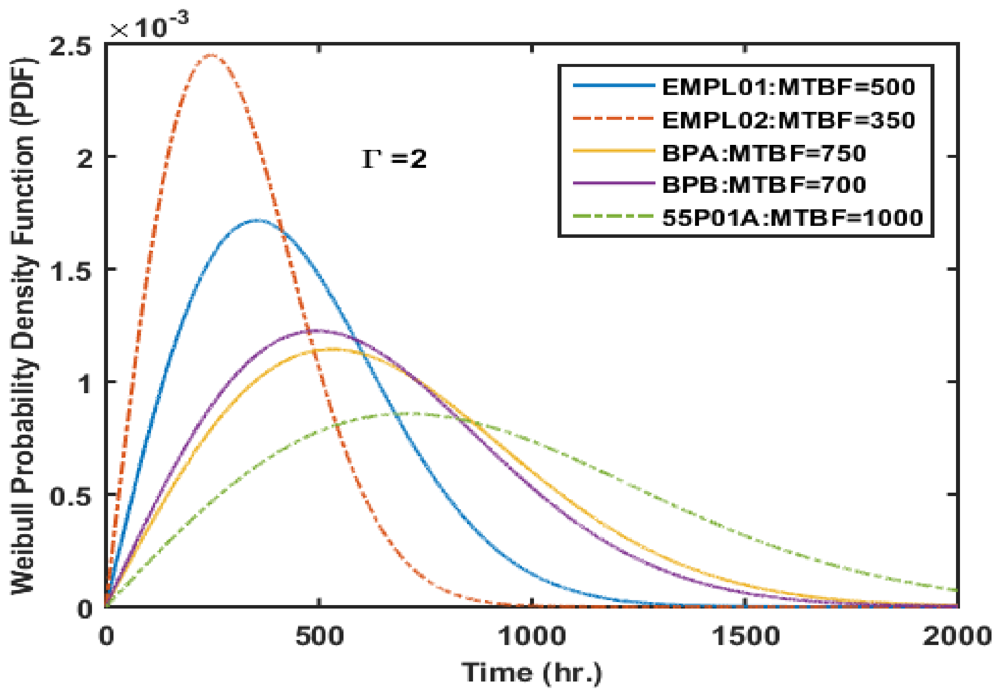

Figure 13. PDF of selected equipment as a function of time at $\Gamma = 2$

Figures 14 -15 show the plots of equipment reliability function at different values of gamma shape parameter. The plots validate the fact that the higher the MTBF of an equipment, the higher the reliability. The reliability curve decays gradually with increase in time with MTBF =1000 hrs. having the highest reliability function value at any given time.

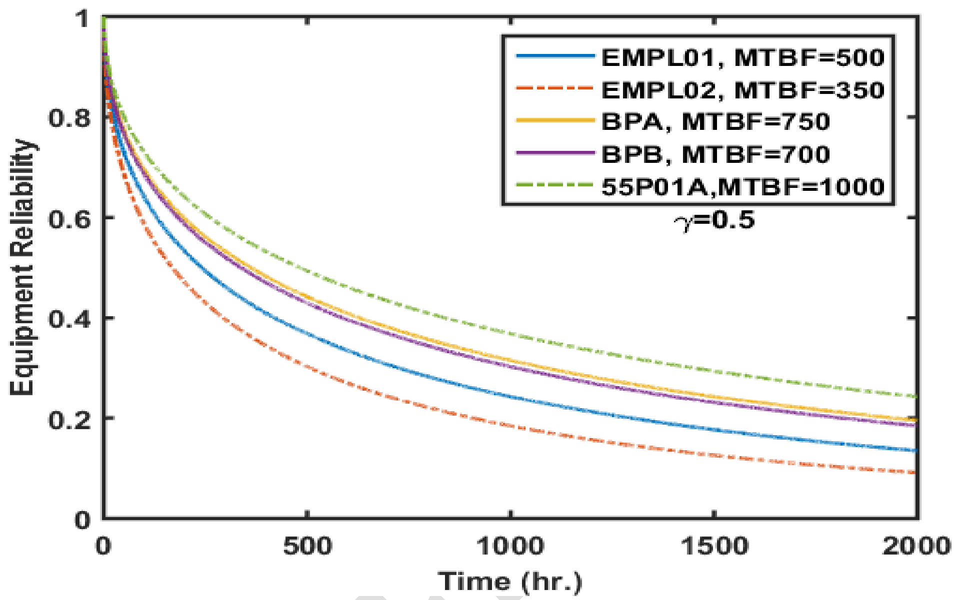

Figure 14. Equipment reliability of selected equipment as a function of time at $\gamma = 0.5$

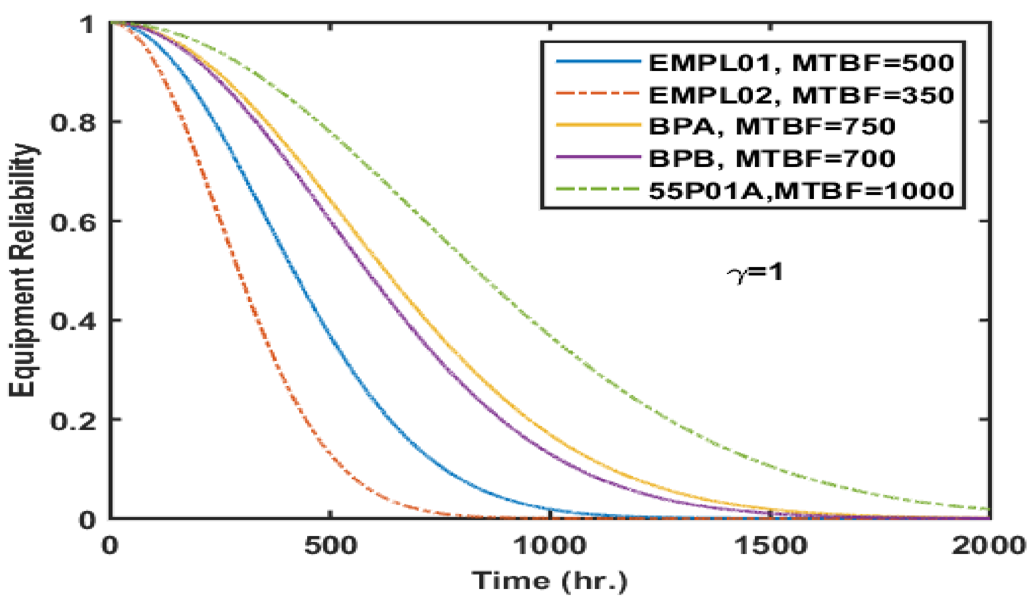

Figure 15. Equipment reliability of selected equipment as a function of time at $\gamma = 1$

4.2.Priority vector for equipment selection

The criteria established in the previous section form the basis for constructing a priority vector for the equipment. To build the vector, we chose the values of CDF, PDF, reliability, failure rate and availability at 1000 operating hours and at $= 1$.

Table 6. Criteria values at 1000 hrs. and at $\gamma = 1$

Equipment	PDF	CDF	Reliability	Failure rate	Availability
EMLP01	**0.30**	**0.83**	**0.15**	**$2x10^{-3}$**	**0.94**
EMLP02	**0.20**	**0.90**	**0.05**	**$2.86x10^{-3}$**	**0.9563**
BPA	**0.43**	**0.70**	**0.30**	**$1.33x10^{-3}$**	**0.9494**
BPB	**0.40**	**0.75**	**0.27**	**$1.429x10^{-3}$**	**0.9460**
55P01A	**0.46**	**0.60**	**0.40**	**$1x10^{-3}$**	**0.9921**

Using Saaty scale of piecewise comparison, preference table between different criteria is constructed using table 1.

The pairwise comparison based on Saaty scale of preference (or importance) between different evaluating parameters is shown in table 7. Using the total sum of each column in table 7, each cell can be normalized as shown in table 8. Each cell in table 6 is divided by the corresponding total sum of that column.

Table 7. Preference table

	PDF	CDF	Reliability	Failure rate	Availability
PDF	1	2	1/2	2	1/5
CDF	1/2	1	1/5	1/2	1/5
Reliability	2	2	1	2	1/2
Failure Rate	1/2	2	1/2	1	1/5
Availability	5	5	2	5	1
	9	12	4.2	10.5	2.1

Table 8. Normalized pairwise table of criteria preference

	PDF	CDF	Reliability	Failure rate	Availability	Eigenvalue (λ)
PDF	0.1111	0.1667	0.1191	0.1905	0.0952	0.6826
CDF	0.0556	0.0833	0.0476	0.0476	0.0952	0.3293
Reliability	0.2222	0.1667	0.2381	0.1905	0.2381	1.0556
Failure Rate	0.0556	0.1667	0.1191	0.0952	0.0952	0.5318
Availability	0.5556	0.4167	0.4762	0.4761	0.4762	2.4008

The Eigenvalues were obtained by summing the values of each row in the table.

$$\boldsymbol{W} = \frac{\mathbf{1}}{\mathbf{5}}\begin{pmatrix} 0.6826 \\ 0.3293 \\ 1.0556 \\ 0.5318 \\ 2.4008 \end{pmatrix} = \begin{pmatrix} 0.13652 \\ 0.06586 \\ 0.21112 \\ 0.10636 \\ 0.48016 \end{pmatrix}$$

$$\boldsymbol{\lambda_{max}} = \begin{pmatrix} 0.13652 \\ 0.06586 \\ 0.21112 \\ 0.10636 \\ 0.48016 \end{pmatrix} (9\ 12\ 4.2\ 10.5\ 2.1)$$

$$\boldsymbol{\lambda_{max}} = 9 * 0.1365 + 12 * 0.06586 + 4.2 * 0.2111 + 10.5 * 0.10636 + 2.1 * 0.48016$$

$$\boldsymbol{\lambda_{max}} = 5.0305.$$

Inconsistency index is given as (Saaty, 1987; Saaty, 2008)
The consistency index (CI),

$$\boldsymbol{CI} = \frac{\lambda_{max} - n}{n - 1} \tag{15}$$

$$\boldsymbol{CI} = \frac{\lambda_{max} - n}{n - 1} = \frac{5.0305 - 5}{5 - 1} = 0.007639 \tag{16}$$

To compute the Consistency ratio, Saaty introduced the use of random consistence index (RI) table as shown in table 9.

Table 9. Random Consistency Index (*RI*)

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

For 5x5 matrix, the RI=1.12, then the consistence ratio is given as,

$$\boldsymbol{C}R = \frac{CI}{1.12}\text{x}100 \tag{17}$$

$$\boldsymbol{C}R = \frac{0.007639}{1.12}\text{x}100 \tag{18}$$

If the value of ***CR*** is smaller or equal to 10%, the inconsistency is acceptable otherwise is not accepted.

Using the eigenvalues in table 8, the values are arranged in order of their magnitude which gives the priority vector in table 10.

Table 10. Priority vector of criteria for evaluating equipment maintenance activities

	Priority Vector
Availability	**48.02%**
Reliability	**21.11%**
PDF	**13.65%**
Failure Rate	**10.64%**
CDF	**6.59%**

For each criterion in table 10, AHP method is applied to prioritize equipment maintenance activities based on that selected criterion.

Table 11. Equipment priority vector using PDF as a criterion

	Priority vector
55P01A	53.43%
BPA	18.89%
BPB	16.27%
EMLP01	6.96%
EMLP02	4.45%

Table 12. Equipment Priority vector using CDF as a criterion

	Priority vector
55P01A	43.17%
BPA	27.07%
BPB	17.65%
EMLP01	7.58%
EMLP02	4.54%

Table 13. Equipment Priority vector for reliability

	Priority vector
55P01A	47.75%
BPA	26.04%
BPB	15.12%
EMLP01	7.56%
EMLP02	3.53%

Table 14. Equipment Priority vector for MTBF

	Priority vector
55P01A	50.78%
BPA	22.22%
BPB	15.99%
EMLP01	6.98%
EMLP02	4.02%

Table 15. Equipment Priority vector for availability

	Priority vector
55P01A	53.42%
EMLP02	16.48%
BPA	12.92%
BPB	9.91%
EMLP01	7.29%

Using priority tables 16-14, the overall table for prioritizing equipment maintenance is derived that provides the best trade-off between the criteria. The combined weight determines if a piece of equipment desire urgent attention or characterized as having the best trade-offs or reliability.

Table 16. Overall priority table for maintenance of equipment

	Availability	Reliability	PDF	MTBF	CDF		Composite Weight
Weight	**48.02%**	**21.11%**	**13.65%**	**10.64%**	**6.59%**		
55P01A	53.42%	47.75%	53.43%	50.78%	43.1%	248.48	**49.69%**
EMLP02	16.48%	3.53%	4.45%	4.02%	4.58%	33.06%	**6.61%**
BPA	12.92%	26.04%	18.89%	22.22%	27.07%	107.14%	**21.43%**
BPB	9.91%	15.12%	16.27%	15.99%	17.65%	74.94%	**14.99%**
EMLP01	7.29%	7.65%	6.96%	6.98%	7.58%	36.46%	**7.291%**

Table 16 provides the final table of priority based on the Analytic Hierarchical Process computations. In this work, we focus on equipment with the worst maintenance records to prioritize budget and human resources to improve their effectiveness. The Electric Mainline Pump, (EMLP01), Electric Mainline Pump (EMLP02), and Booster Pump B (BPB) have the worst maintenance performance records of the year. Using this analysis, strategies can be made to allocate maintenance resource to improve the reliability of this equipment.

In AHP, the last eigenvalues of the normalized comparison matrix give the decision vector for prioritizing how maintenance can be carried out on equipment. But the quality of decision is evaluated by the consistency ratio, random consistency index and consistency index. Consistency ratio of less than 10% implies that the inconsistencies in the decision can be ignored. Since judgment is subjective, in this case, CR of >10% requires that the judgment be re-visited.

Applying quality control measures to decision making within the framework of AHP provides reliable methods for making decisions in equipment maintenance practices.

5. Conclusion

The AHP method of prioritizing maintenance schedule is presented, and the priority vector is derived for some selected equipment, as shown in table 4.3. Analytic Hierarchy Process (AHP) is one of multi-Criteria decision-making method that was initially developed by Prof. Thomas L. Saaty. In short, it is a method to derive ratio scales from paired comparisons. The inputs are obtained from pump station equipment from subjective opinions such as satisfaction, feelings and preference. AHP allow some small inconsistency in judgment because human is not always consistent. The ratio scales are derived from the principal Eigenvectors and the consistency index. The Eigenvector values of the pair comparison matrix provide the basis for prioritizing activities by quantitatively reducing options into a set of list of items arranged in order of importance.

As indicated in the findings, the quality of the decisions in AHP can be evaluated using standard metrics as consistency ratio, random consistency index and consistency index. These parameters are obtained from the eigenvalues or priority vector.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that no competing interests exist. The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

References

Abbassi, R., Bhandari, J., Khan Faisal, Garaniya, V., and Chai, S.(2016). Developing a quantitative risk-based methodology for maintenance schedule using Bayesian Network. *Chemical engineering Transactions, 48, 235-240.*

Ahmed, R., and Kamaruddin, S.(2012). An Overview of time-based and condition-based maintenance in industrial application. *Computer and Industrial Engineering, 63,135-149.*

Ahmad, R., Kamaruddin, S., Azid, I., & Almanar, I. (2011). Maintenance management decision model for preventive maintenance strategy on production equipment. *Journal of Industrial Engineering, International*, *7*(13), 22-34.

Ambituuni, A., Hopkins, P., Amezaga, J.M., Werner, D., and Wood, JM (2015). Risk assessment of a Petroleum Product Pipeline in Nigeria: The realities of managing problems of the theft/sabotage. *Safety Engineering VI, 151, 49-60*.

Arunraj, N. S., & Maiti, J. (2007). Risk-based maintenance—Techniques and applications. *Journal of hazardous materials*, *142*(3), 653-661.

Bebbington, M., Lai, C. D., & Zitikis, R. (2007). A flexible Weibull extension. *Reliability Engineering & System Safety*, *92*(6), 719-726.

Bernasconi, M., Choirat, C., & Seri, R. (2010). The analytic hierarchy process and the theory of measurement. *Management Science, 56*(4), 699-711.

Dey, P.K., Ogunlana, S.O., and Naksuksakul, S.(2004). Risk-based maintenance model for Offshore Oil and Gas Pipelines: A case study. *Journal of Quality in Maintenance Engineering, 10(3), 169-183*.

de Jonge, Teunter, R., and Tinga, T.(2017). The influence of practical factors on the benefits of condition-based maintenance over time-based maintenance. Reprint submitted to Elsevier.

Ebeling, C. E. (1997). Reliability and maintainability engineering. The United States of America: McGraw-Hill Companies, INC.

Florian, M. and Sorensen, J.D.(2017). Risk-based planning of operation and maintenance for offshore wind farms. *Energy Procedia, 137,261-272*.

Ghodrati, B. (2005). Reliability and operating environment based spare parts planning. PhD Thesis, Lulea University of Technology, Lulea, Sweden.

Godians, S.O. and Ramachandra, RS (2018). Application of Risk management Tools in Maintenance Operation of Swedish Industries- a Survey analysis. MSc thesis in Production, *Chalmers University of Technology*.

Higgins, R and Mobley, K.(2001). Maintenance engineering handbook (6th ed.) McGraw-Hill Professional.

Igbal, H., Tasfamariam, S., Haider, H., and Sadiq, R. (2016). Inspection and maintenance of Oil and Gas Pipeline: A review of policies. *In structure and infrastructure Engineering*.

Joz´wiak, I. J. (1997). An introduction to the studies of the reliability of systems using the Weibull proportional hazards model. Microelectronics Reliability, 37(6), 915–918.

Kolte, T.S. and Dabade, U.A.(2017). Machine operational availability improvement by implementing effective preventive maintenance strategies- A review and case study. *International Journal of Engineering Research and Technology*, *10(1), 700-708*.

Leoni, L., Toroody, A.B., De-Carlos, F., and Paltrinieri, N.(2018). Developing a risk-based maintenance model for a natural gas regulating and metering station using Bayesian Network. *Journal of Loss Prevention in the process industries (2018).*

Liao, Y., Liu, H., Yuan, J., Xu, Y., Zhou, W., and Zhou, C.(2019). A Holistic Approach to the Maintenance schedule for HV Cables. *IEEE Access, 7, 118975-11895*.

Kawa, A., & Koczkodaj, W. W. (2015). Supplier evaluation process by pairwise comparisons. *Mathematical Problems in Engineering*, *2015*.

Kezunovic, M., & Natti, S. (2006, August). Risk-based maintenance approach: A case of circuit breaker condition based monitoring. In *3rd International CIGRE workshop on Liberalization and Modernization of power systems, Irkutsk, Russia*.

Mili, R., Bassetto, S., and Siadat, A., and Tollenaere, M. (2009). Dynamic risk management unveils productivity improvements. *Journal of loss prevention in the process industries, 22, 25-34*.

Mohamed, A., & Saad, S. (2016). Fuzzy analytical hierarchy process for the selection of maintenance policies within petroleum industry.

Nielsen, J.S., and Sorensen, J.D.(2017). Computational framework for risk-based planning of inspections, maintenance and condition monitoring using discrete Bayesian networks. *Structure and Infrastructure Engineering, 14(8), 1082-1094*.

Nnadi, U., El-Hassan, Z., Smyth, D., & Mooney, J. (2007). Lack of proper safety management systems in Nigeria oil and gas pipelines. *Delta*.

Ogunwolu, L., Popoola, O. P., & Ibeh, S. C. (2015). A Decision Support Model and Analysis for Aircraft Maintenance Planning. *International Journal of Mathematical Sciences and Optimization: Theory and Applications*, *2015*, 16-32.

Ratnayake, RMC and Antosz, K.(2017). Development of a risk-based maintenance analysis with Fuzzy logic. *Procedia Engineering, 182, 602-610*.

Sadiq, R. and Tesfamariam, S. (2009). Environmental decision-making under uncertainty using intuitionistic fuzzy analytic hierarchy process (IF-AHP). *Stochastic Environmental Research and Risk Assessment, 23, 75-91*.

Saaty, T. (1980). The analytic hierarchy process (AHP) for decision making. In *Kobe, Japan* (pp. 1-69).

Saaty R. W. (1987). The Analytic Hierarchy Process-What It Is and How It Is *Pergamon Journals Ltd*, Vol. 9, No. 3-5, Pp. 161-176,

Saaty, T.L. (2008) 'Decision making with the analytic hierarchy process', Int. J. Services Sciences, Vol. 1, No. 1, pp.83–98.

Telford, S., Mazhar, MI, and Howard, I.(2011). Condition Based Maintenance (CBM) in the Oil and Gas Industry. *Proceeding of the International Conference on Industrial Engineering and Operations Management, Kuala Lumpur, Malaysia, January 22-24, 1152-1159*.

Usman, M.A., and Ngene, S.E.(2012). An Innovative Approach to Managing the Integrity of Oil and Gas Pipelines: Pipeline Integrity Management System. *Petroleum & Coal, 54(1), 1-8*.

Vivian, R.W. (2013). Ending the myth of the St Petersburg paradox. *SAJEMS NS16,347-364*.

Yang, L., Zhao, Y., Peng, R., and Ma, X. (2018). Hybrid preventive maintenance of competing failures under random environment. *Reliability Engineering and System Safety, 174, 130-140*.