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Application of Analytical Hierarchical Process in Equipment Maintenance Scheduling and Decision-Making Process in Oil/Gas

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Operational efficiency and reliability of equipment directly impact production and revenue streams. 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 of equipment. The culture of maintenance evolves considerably from run to failure and corrective to preventive maintenance practices. These set of activities are expensive and significantly affect the cost of sales and operating expenditure especially in Oil and Gas sector. With the need to optimize operating cost, use of data in prioritizing equipment maintenance becomes necessary. This paper provides a novel approach for prioritizing critical equipment maintenance activities using Analytical Hierarchical Process (AH). A family of Weibull distribution function are use 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 $\gamma \in \{0.5,1,2\}$ are considered, which affects the shape of the distribution functions. The results show that multi-criterion

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AHP-approach supports subjective decision making by providing quantitative weighted ranking of equipment based on priority. The result indicates that equipment with best values has lowest priority ranking.

Keywords: 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 [1, 2]; 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 [3,1,4]. 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 [5]. 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 [6].

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 [7]. 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 [8]. 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 [9]. 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 [9]. Earlier maintenance practices were based on corrective actions where equipment or systems are given attention only when there is a failure [9]. 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 [10,9]. 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 [9].

Variants of preventive maintenance have been developed to optimize resources allocation and improve overall maintenance efficiency [11]. This is one of the industrial practices of increasing operational availability of existing equipment to increase productivity [10]. Time-based and condition-based maintenance were among the most reviewed topics [12,13,14]. 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 Fig. 1 [12].

Fig. 1. shows a typical curve for the equipment life cycle. The cycle can be divided into burn-in, useful life, and wear-out [15]. 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 Fig. 2. To begin time-based maintenance, data analysis of the failure trend is carried out to statistically investigate the failure characteristics of the equipment [12]. 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 [12]. 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 [16,17]. 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 [18].

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 [19].

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.

1.1 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 [20].

Risk-based maintenance process approaches maintenance practice by identifying hazards associated equipment or systems and estimating risks [21]. 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 [22].

Overall equipment effectiveness can be measured using criteria [23].

$$Availability = \frac{PPT - DT}{PPT} \text{x}100 \quad (1)$$

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

$$Quality\ rate = \frac{PA - DA}{PA} \text{x}100 \quad (3)$$

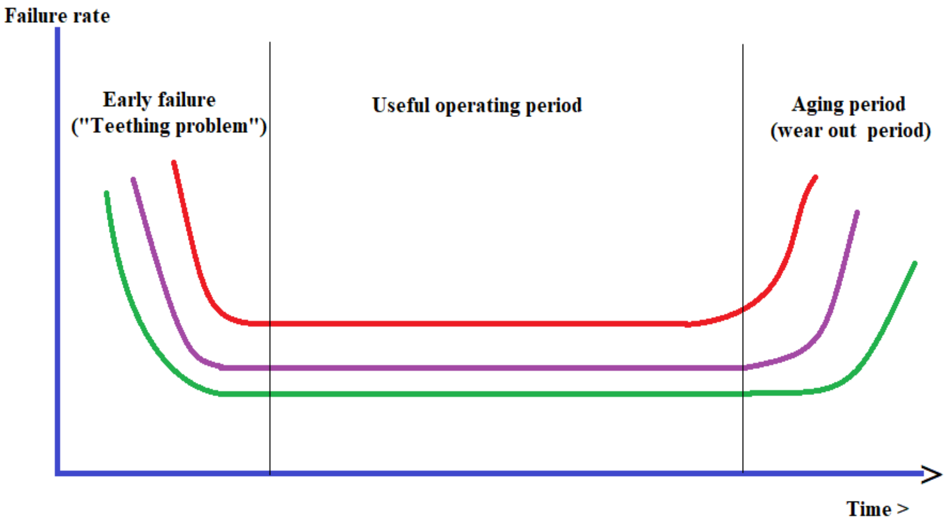

Fig.1. Equipment life-cycle curve

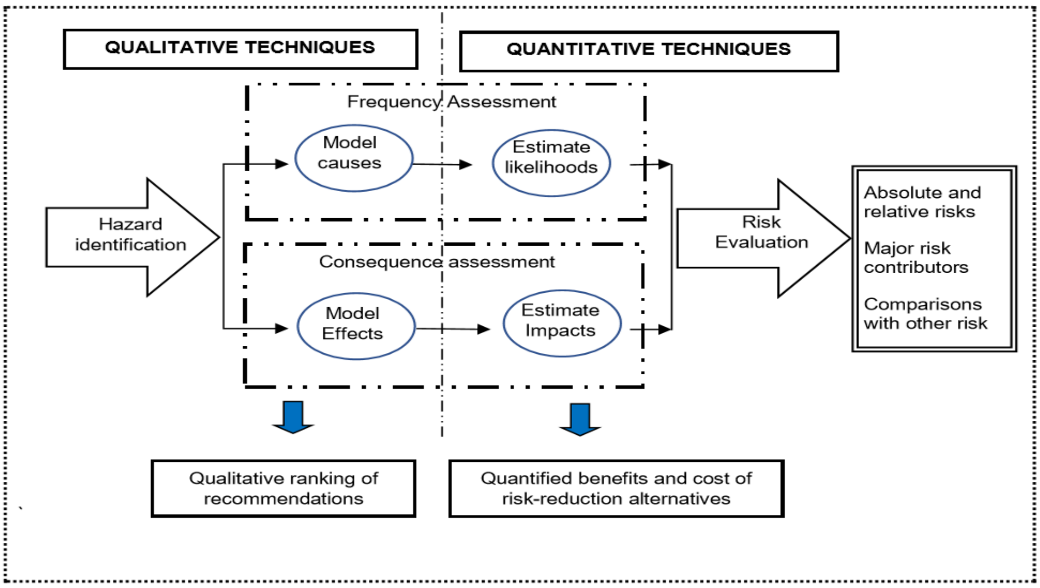

Fig. 2. Process in Risk assessment (Godians and Ramachandra, 2018)

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 [24].

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 [25]. 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 [25]. Fig. 3 shows a pictorial representation of the algorithm for risk-based maintenance using the Bayesian network.

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 [26]. Computational frameworks for maintenance risk planning of inspections and repairs using discrete Bayesian Network were developed for Offshore Oil and Gas infrastructures [27]. 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 [28] 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 [28].

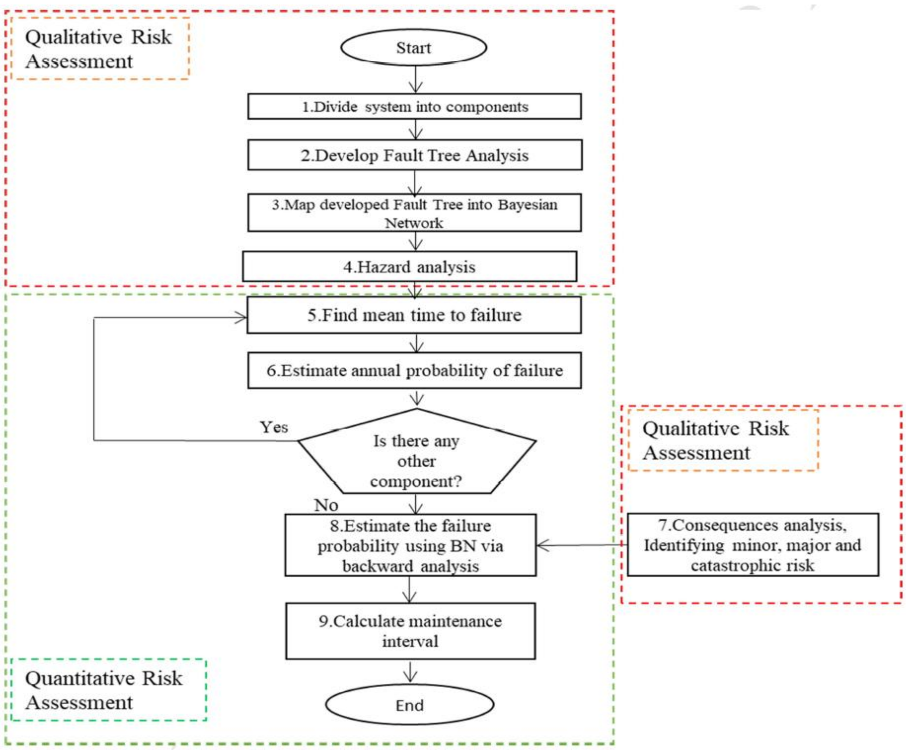

Fig. 3. Bayesian Network for modeling risk and uncertainty in risk-based maintenance in Gas pipelines and metering station (Leoni et al., 2018)

2. MATERIALS AND METHODS

In this section, we consider five (5) criteria for evaluating and prioritizing equipment maintenance. The parameters are Weibull Continuous Distribution Function (CDF), Weibull Probability Density Function, Reliability function, failure rate and equipment availability [29].

The priority mapping between different criteria in AHP is shown in Fig.4. Pairwise matrix and priority vector for the parameters in Fig.4 are derive using Saaty scale as shown in Table 1.

Using the Weibull function, the following distribution function and other parameters are derived.

The probability density function is defined as;

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

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

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\gamma}} \quad (2)$$

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

$$R(t) = e^{-\left(\frac{t}{\alpha}\right)^{\gamma}} \quad (3)$$

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

$$\text{MTBF} = \text{Mean life} = \frac{\text{Total Time}}{\text{No. of Failures}} = \frac{1}{\lambda} \quad (4)$$

where λ is the failure rate of equipment or component.

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

$$\text{MTTR} = \frac{\text{Maintenance Time}}{\text{No. of Repairs}} \quad (5)$$

The **availability** of equipment is given as

$$\textbf{Availability} = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} = \frac{\text{Uptime}}{\text{Uptime} + \text{down time}} \quad (6)$$

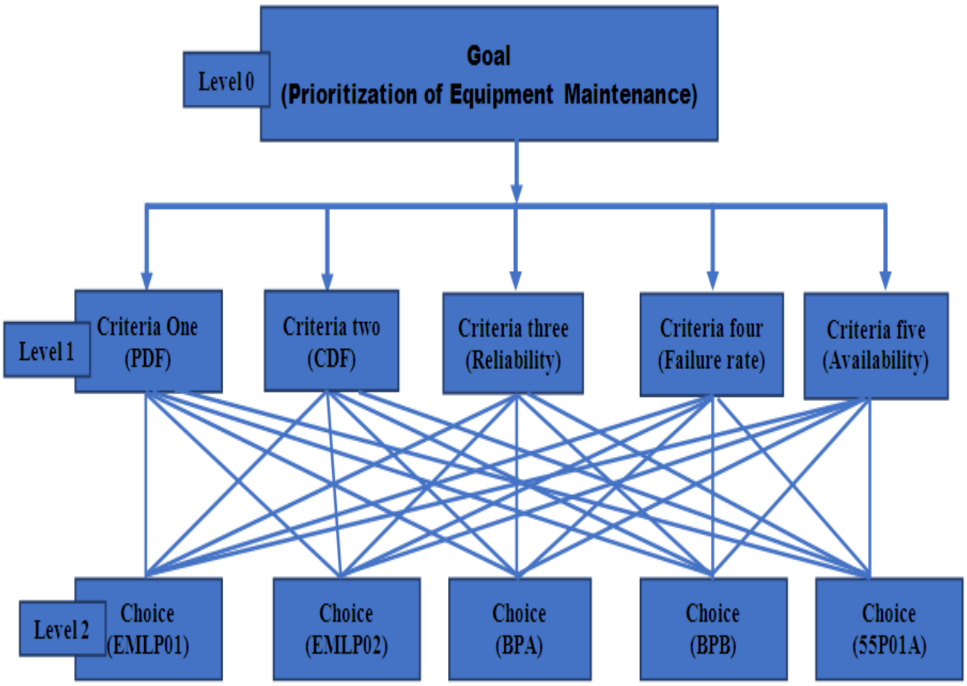

Fig. 4. Criteria mapping in maintenance prioritization using AHP

Table 1. The fundamental scale of importance [20]

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.

3. RESULTS AND DISCUSSIONS

3.1 Decision Making Criteria

In this section, we derive priority matrix and compute the weighted matrix using 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, Nigeria. Nine critical equipment were selected and information from their maintenance records covering the period of January to December 2019 were used to calculate the failure rate, mean-time between failure, and reliability of the equipment. Table 2 shows the list of critical maintenance equipment and their common faults [30]. Table 3 and Table 4 contain the estimates of the MTBF and MTTR were estimated from the data obtained to determine equipment availability and Weibull distribution functions using Eq. (1-6). The Weibull distributions are calculated using Eq.1-3 and presented in Table 5.

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.

Figs. 5-7 show the plots of Weibull cumulative distribution function with respective to operating hours at value of shape characteristics. The distribution function is an increase function showing the characteristics of different equipment at different MTBF. Equipment with lower MTBF exhibits higher Weilbull cumulative distribution function (CDF). This indicates that MTBF is proportional to CDF.

Figs.8-13 show the plots of Weibull probability density function (PDF) at different values of shape parameters. In Fig.8 and Fig.9, the plots decay with increasing time at different values of MTBF while in Fig.10, the PDF exhibits oscillation like behavior. The function increases with time to a maximum value before decaying with respect to time. Equipment with lowest MTBF has the highest value at maximum. In each case of the PDFs, the higher the MTBF, the more quickly the function decays as a function of time.

Figs.11-12 show the plots of equipment reliability function at different values of gamma shape parameter with time. The plots validate the fact that the higher the MTBF of an equipment, the higher the reliability. The reliability curve decays gradually with time at MTBF =1000 hrs. having the highest reliability function value at any given time. The reliability plots indicate that equipment useful life cycle reduces with number of operating hours.

The three (3) Weilbull parameters describes different aspect of equipment behavior at different value of shape parameter. The parameter affects the shape of the plots not significantly except for Fig.10 where the function oscillates at some points.

3.2 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, the values of CDF, PDF, reliability, failure rate and availability are calculated at 1000 operating hours and the shape parameter is taken to be 1. Table 6 presents the values of each of the parameters [31].

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.

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	-	-	-

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	-	-	-

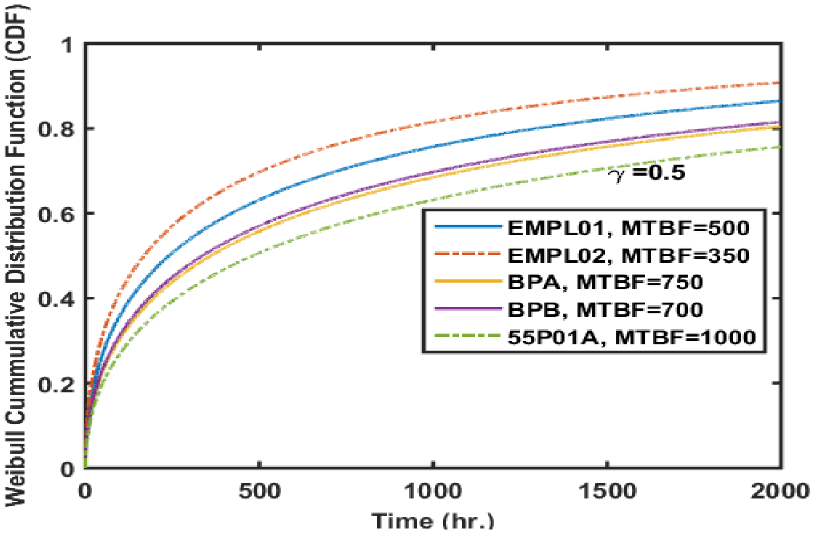

Fig. 5. CDF of selected equipment as a function of time at $\gamma = 0.5$

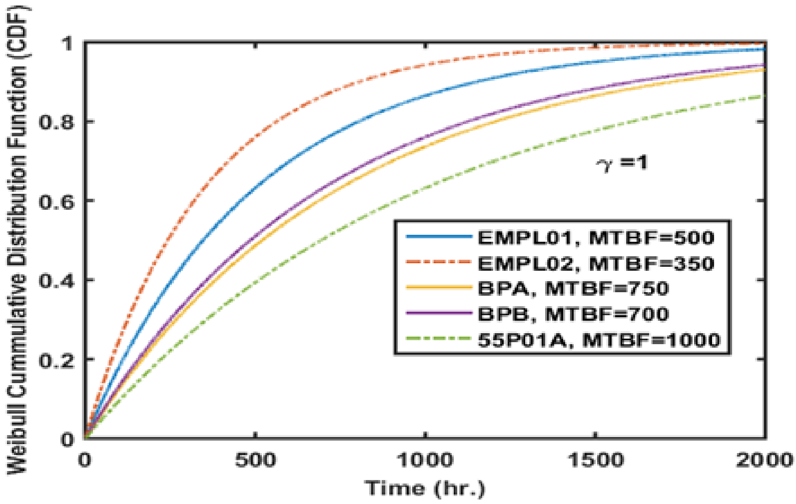

Fig. 6. CDF of selected equipment as a function of time at $\gamma = 1$

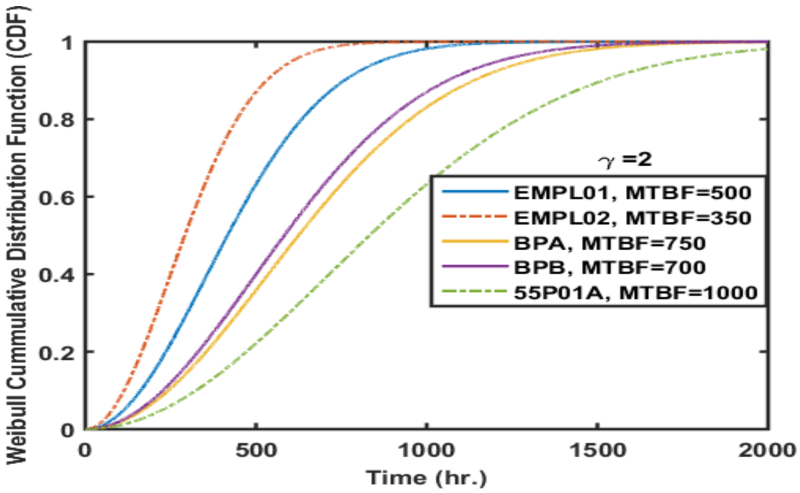

Fig. 7. CDF of selected equipment as a function of time at $\gamma = 2$

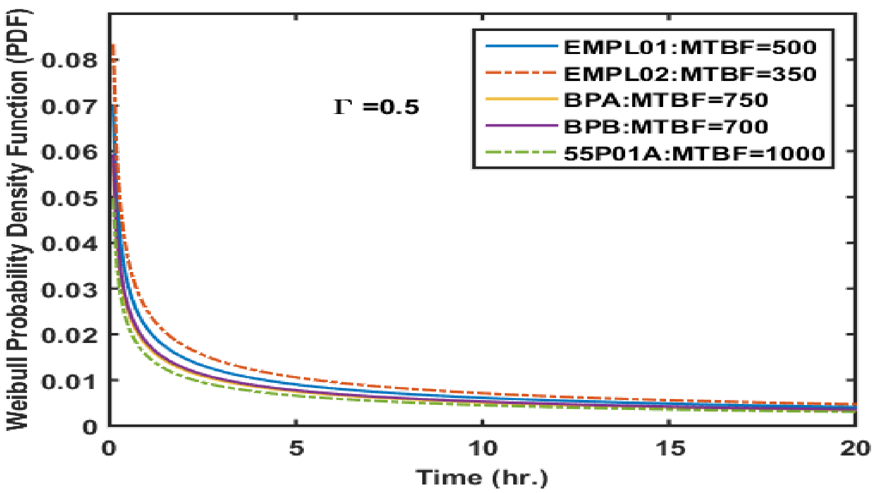

Fig. 8. PDF of selected equipment as a function of time at $\Gamma = 0.5$

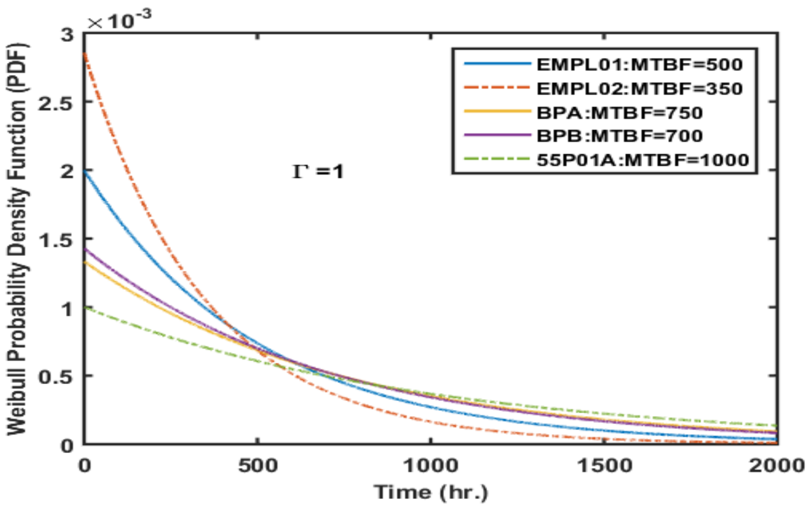

Fig. 9. PDF of selected equipment as a function of time at $\Gamma = 1$

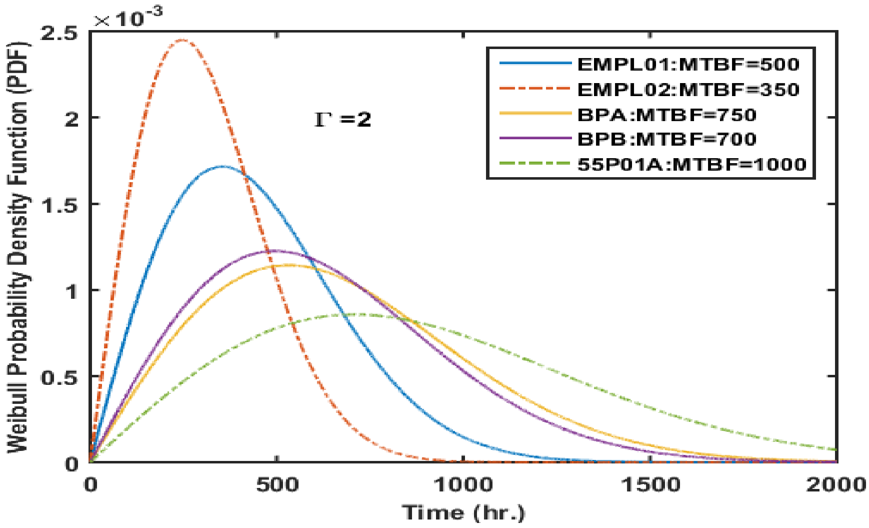

Fig.10. PDF of selected equipment as a function of time at $\Gamma = 2$

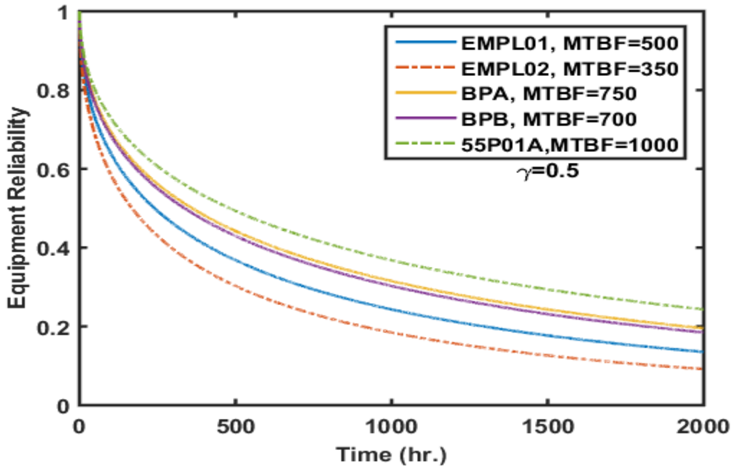

Fig. 11. Equipment reliability of selected equipment as a function of time at $\gamma = 0.5$

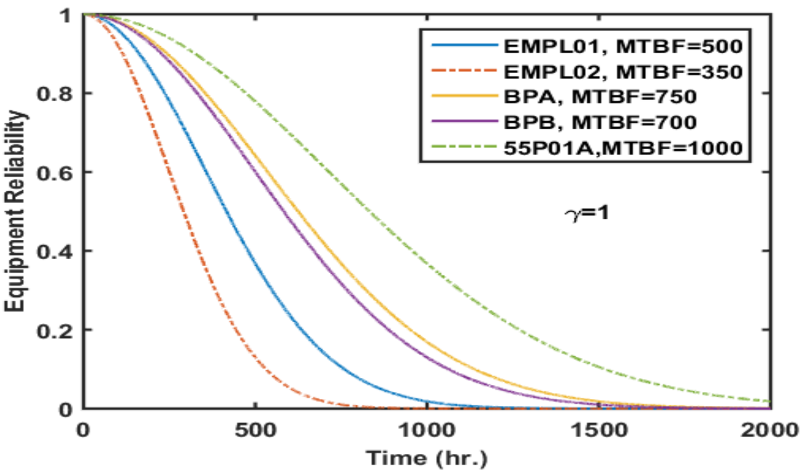

Fig.12. Equipment reliability of selected equipment as a function of time at $\gamma = 1$

Table 6. Different values of criteria

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

Table 7. Preference (Priority or pairwise) 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

Using Saaty scale of piecewise comparison in Table 1, preference table between different criteria is constructed. The table allow values to be assigned when comparing two parameters based on the scale. Table 7 shows the priority or preference table which is a vector. The cell of each column is normalized by total sum of each of the corresponding column. Table 8 shows the normalized Table 7.

The Eigenvalues were obtained by summing the values of each row in the table. The maximum eigenvalue is obtained by multiplying Eq. (7) with the sum of each column of Table 7.

$$\boldsymbol{W} = \frac{\mathbf{1}}{\mathbf{5}}\begin{pmatrix}0.6826\\0.3293\\1.0556\\0.5318\\2.4008\end{pmatrix} = \begin{pmatrix}0.13652\\0.06586\\0.21112\\0.10636\\0.48016\end{pmatrix} \tag{7}$$

$$\boldsymbol{\lambda_{max}} = \begin{pmatrix}0.13652\\0.06586\\0.21112\\0.10636\\0.48016\end{pmatrix}(9\ 12\ 4.2\ 10.5\ 2.1) \tag{8}$$

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

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

Using Inconsistency index proposed by Saarty,

The consistency index (CI),

$$\boldsymbol{CI} = \frac{\lambda_{max} - n}{n-1} \tag{10}$$

$$\boldsymbol{CI} = \frac{\lambda_{max} - n}{n-1} = \frac{5.0305 - 5}{5-1} = 0.007639 \tag{11}$$

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

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

$$\boldsymbol{CR} = \frac{CI}{1.12}\text{x}100 \tag{12}$$

$$\boldsymbol{CR} = \frac{0.007639}{1.12}\text{x}100 \tag{13}$$

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 five parameters are ranked in order of their magnitude percentage which gives the priority vector in Table 10.

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

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

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%

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%

Table 16. Overall priority table for scheduling Equipment

	Availability	Reliability	PDF	MTBF	CDF		Composite 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%

Using priority Tables 16-14, the overall ranking of equipment maintenance is derived. This gives best trade-off between the criteria.

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 or composite weight 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 or least composite weight. Using this analysis, strategies can be made to allocate maintenance resource to improve the reliability of this equipment [32].

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 [33-34]. 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.

4. CONCLUSION

In this work, multi-criterion AHP decision making method has been used to prioritize maintenance scheduling. The process is tested using equipment maintenance data of five equipment. The priority vector of some selected equipment was calculated and ranked. The result indicated that subjective decision making can be parameterized to arrive at best possible solution [35]. The use of AHP allows equipment performance to be ranked and selected for maintenance based on composite weight. The ranking provides quantitative means of justifying subjective decision making.

DISCLAIMER

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.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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