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Maintenance in Marginal Oilfield Production Facilities: A Review

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Abstract

Natural decline in various mainstream oilfield reserves and the high investment capital in upstream exploration and project development have promoted attention towards smaller oilfields referred to as Marginal fields. This provides operators the opportunity to commence exploration and production with minimum requirements of design, installation, and operations. Although the low Capital Expenditure (CAPEX) requirement favors the start-up of marginal oilfield operations, several operators are not able to sustain the field's operations due to the high Operational Expenditure (OPEX), particularly arising from facilities' maintenance. The aim of this paper is to review the maintenance strategies adopted in marginal oilfields, assess their effectiveness, and provide a pointer towards efficient and viable maintenance strategies for the sustainability of marginal oilfields. The study showed that time-based preventive maintenance is predominant in the oil industry, which constitutes up to 40% of net operational expenses. In other cases, reactive maintenance is adopted, which often results in an unplanned shutdown, known to be responsible for nearly half of the overall losses of an oil facility. A paradigm shift in maintenance to Reliability Centered Maintenance (RCM) was explored for marginal oilfield, with a comprehensive review of various maintenance strategies, ranging from maintenance optimization strategies, Heuristics and Metaheuristics, Artificial Intelligence (AI), and Data Mining techniques. It was observed that the application of AI best addresses the proposed RCM for marginal oilfields. This was drawn from the recorded limitations of the other concepts from verifiable similar works, where different AI techniques and Data analytics methods have been successfully applied to aid RCM.

Keywords

Marginal Oilfield, Reliability Centered Maintenance, Artificial Intelligence, Data Mining, Early Production Facilities

1. Introduction

The oil and gas sector plays a dominant role in a producing country's economy. It makes up most of the export earnings and contributes significantly to the Gross Domestic Product (GDP) [1]. In recent decades, the mainstream oil exploration and production fields around the world have been reaching maturation stage with natural decline in production. This has promoted attention towards smaller oil fields that are normally or initially considered unattractive [2]. Such fields are referred to as Marginal Oilfields. Furthermore, due to the high investment capital associated with the development of oil and gas upstream facilities in recent regime of dwindling oil prices, many indigenous operators are attracted to the development of marginal oilfields. This provides the opportunity to commence exploration and production activities from minimum requirements of design, operations, and maintenance, while maintaining quality and safety requirements [3].

In 2001, the Nigerian government instituted the marginal oilfield program, and in 2003, twenty-four (24) oilfields were awarded to 31 indigenous operators [2] [4]. In June 2020, The Department of Petroleum Resources (DPR) commenced another marginal field bid round program with 57 marginal fields on offer for investors, aimed at deepening indigenous participation in the Nigerian oil and gas industry [5]. Thus, oil and gas exploration and production through marginal field development is here to stay.

Development of marginal oilfield is said to be more viable with a Phased development approach rather than the traditional Engineering Procurement and Construction (EPC) approach [6]. The phased approach enables the operator a sequential development of the field, a "one-step-at-a-time" approach, which saves the commitment of high CAPEX early in the field development. Although the low CAPEX requirement favors start-up of marginal field operations, many operators are not able to sustain the field's operations due to the high Operational Expenditure (OPEX), particularly arising from the maintenance of the facilities.

In the simplest way, maintenance can be defined as the act of keeping something in proper functional condition. As such, it involves activities performed to ensure that an asset or piece of equipment continues to meet its intended function [7]. Thus, like any other asset or plant, maintenance is key to the performance of the marginal field operations to guarantee uptime, productivity, reliability, safety, regulatory statutory compliance, environmental preservation etc.

Unlike bigger operators, every downtime experienced in a marginal field result in high commercial implication, this is because a marginal field operator usually start-up operation by producing from one field asset. Thus, it is imperative to sustain production uptime as much as possible by ensuring the facility is always kept healthy. This is where an efficient maintenance strategy becomes critical to oil and gas marginal field operations.

In view of the increasing interest of the oil and gas sector towards marginal field development, particularly in Nigeria, it is, therefore, necessary to review the maintenance strategies that are currently being adopted. The aim of the review is to highlight the effectiveness of current maintenance schemes and provide a pointer for further research work towards efficient and viable maintenance strategies for marginal oilfield facilities.

2. Evolution and Types of Maintenance Techniques

Maintenance is said to have evolved through three generations; the first generation solely reliant on run-to-failure (R-2-F) otherwise referred to as Corrective Maintenance (CM). The second generation came-up with significant improvements over the CM technique, with the practice of prevention of breakdown, this is known as Preventive based Maintenance (PM). This was followed by the third generation where Predictive maintenance techniques became widely deployed [8].

Maintenance techniques and their classification have been widely reviewed by many authors. [9] with inference from [10], presented a broad classification for maintenance into Unplanned and Planned maintenance. Unplanned maintenance involves emergency and breakdown and, while planned maintenance includes predictive, preventive, corrective, and improvement maintenance. The study also identified Shutdown Maintenance (SM) as a subset of the planned maintenance techniques.

[11] built on the maintenance classification presented by [12] [13] and further classified maintenance techniques into Reactive (or breakdown), Proactive and Aggressive maintenance. Proactive techniques included preventive and predictive maintenance, while aggressive maintenance includes Total Productive Maintenance (TPM).

According to [14], a scientific approach to PM was introduced in 1950 through the discipline of operations research, using various analytical techniques such as statistics, mathematical programming, and artificial intelligence. This resulted in the classification of maintenance techniques into comprehensive-based and specific-based techniques. The comprehensive-based technique is also referred to as maintenance concept technique, which is described as the framework or approach an organization adopts for maintenance. In this approach, installation-specific maintenance techniques are developed based on the requirement of the organization/facility [15]. Examples include RCM, TPM, and Risk-based maintenance (RBM). Specific-based technique on the other hand considers a specific maintenance technique that has a unique principle in addressing maintenance problems. Examples of these are CM, PMs, Condition-based maintenance (CBM) and Predictive maintenance (PdM). Thus, the specific-based maintenance forms the basis for various maintenance strategies, they are discussed below.

1) *Corrective Maintenance* (*CM*)

Corrective maintenance also referred to as Reactive maintenance, Run-to-Failure (R2F) or unplanned maintenance is simply waiting for an equipment or its component to breakdown before fixing it. While this might appear cost effective as though the lifetime of the component or equipment is fully utilized in some cases, the cost of downtime resulting from the breakdown might be catastrophic [7]. Corrective maintenance includes remedial maintenance (R2F), differed maintenance and shutdown corrective maintenance [9].

2) *Preventive Maintenance* (*PM*)

Preventive maintenance can be said to be traditional maintenance strategy that is widely used in the industry. It represents the second generation of maintenance [16]. This approach is essentially planning inspections and maintenance activities on a time interval or machine-run basis, with the aim of preventing unexpected failures. Whilst this is an improvement on the first-generation approach of "break before fix", it does not fully guarantee avoidance of catastrophic failures. Although this practice tends to be beneficial in terms of increased component/equipment life-cycle closer to meeting the design-life, the frequency of maintenance activities carried out translates to high maintenance cost and can also be labor intensive. PM includes routine maintenance, opportunity maintenance, running maintenance, window maintenance, and shutdown preventive maintenance, also known as Turnaround Maintenance [10].

3) *Predictive Maintenance* (*PdM*)

The outweighing cons of CM and PM strategies challenged the emergence of Predictive maintenance (PdM), which offers the ability to maximize the useful life of a component/equipment while guaranteeing uptime at the same time. PdM involves techniques that measures and detects the systems degradation right from the early stages of the defect, thereby providing the opportunity to address such defects before growing into failures. Hence, rather than carrying out frequent inspection or maintenance on the equipment, which in some cases contributes to deterioration, PdM aims to perform maintenance based on the actual condition of equipment. When properly orchestrated, PdM method can prevent catastrophic equipment failures [7].

4) *Condition Based Maintenance* (*CBM*)

While condition-based maintenance is very similar to PdM, the primary difference is in the way by which the requirement for maintenance is measured. In fact, CBM was initially called "predictive maintenance" when it was first introduced by the Rio Grande Railway Company in the late 1940s [17]. It involves real-time measurement of the systems condition which triggers a need for maintenance once the measured parameters fall out of acceptable limits. While predictive maintenance also involves measurement of real-time parameters, it is considered as a more precise technique because it includes precise formulas in addition to the condition measurement to predict future maintenance requirement. It does not wait until measured parameters falls out of limit [18].

In recent times, industrial view to maintenance considers the comprehensive-based approach, where organizations develop maintenance strategies in-line with their operational needs. An elaborate review of maintenance management and techniques was presented by [19], which identified additional comprehensive based maintenance such as Effective Centered Maintenance (ECM), Maintenance outsourcing and Strategic Maintenance Management (SMM). Their study highlighted RCM as an integrated approach to maintenance that bridges the gap between Reliability and Maintainability. In the same view, [20] described RCM as an approach to adopt to optimize maintenance activities and resources of a facility.

5) *Reliability Centered Maintenance* (*RCM*)

An historic review of RCM revealed that the concept has been presented in theory as far back as 1969, by renowned scientists Nowlan and Heap [21]. In their first publication, they described the relationship between the frequency of performing maintenance and reliability, showing that majority of failures—up to 89% has a failure distribution not related to age whereas many maintenance strategies till date practices the opposite in the form of time-based maintenance. In the same perspective, a British military scientist in 1940, Conrad H. W. discovered that the flying time for a submarine bomber was extended by more than 60% simply by reducing maintenance [21].

Reliability Centered Maintenance provides a bespoke approach to maintenance. The approach is from the view that all the equipment in a facility are not of equal importance to the operation and safety of the facility. Moreover, from the equipment design point of view, equipment differs in design and operation which most times determine the level of degradation, and subsequently the rate or frequency of failure. Thus, RCM considers these factors in structuring a maintenance program by defining a specific maintenance need for a plant or facility. It is therefore said to be "a process used to determine the maintenance requirement of any physical asset in its operating context", according to [7]. In essence, RCM involves a systematic mix of specific-based maintenance techniques to achieve an optimal maintenance structure. Thereby, it identifies equipment which should be run-to-fail (CM), those requiring preventive/scheduled maintenance, and more substantially, promotes the practice of condition based and predictive maintenance.

[17] presented an ideal mix of an RCM program, as shown below.

- <10% Reactive;
- 25% to 35% Preventive;
- 45% to 55% Predictive.

[22] highlighted the attribute of RCM as an integrated approach that capita-

lizes on the collective strengths of several maintenance techniques applied optimally together rather than independently, thereby maximizing facility and equipment reliability and at the same time minimizing life-cycle cost. Furthermore, [22] also identified the components of RCM as reactive or CM, PM, CBM, and in addition, Proactive maintenance. A framework for RCM as adapted from [7] [22] is presented in **Figure 1**.

According to [23], RCM is said to be a systematic process of analyzing engineered systems to understand the following:

- System functions and the impact of functional failures;
- Equipment failure modes and causes that can result in functional failures;
- Optimal maintenance strategy for managing potential failures, such as to prevent the failures from occurring or to detect potential failures before it occurs, and;
- Spare holding requirements.

Thus, in achieving a successful RCM, the following techniques are to be considered:

- Failure Mode Effect Analysis (FMEA);
- Failure Mode Effect Critical Analysis (FMECA);
- Fault Tree Analysis (FTA), Event Tree Analysis (ETA) or Logical Tree Analysis;
- Risk-based decision-making tools such as risk-matrix.

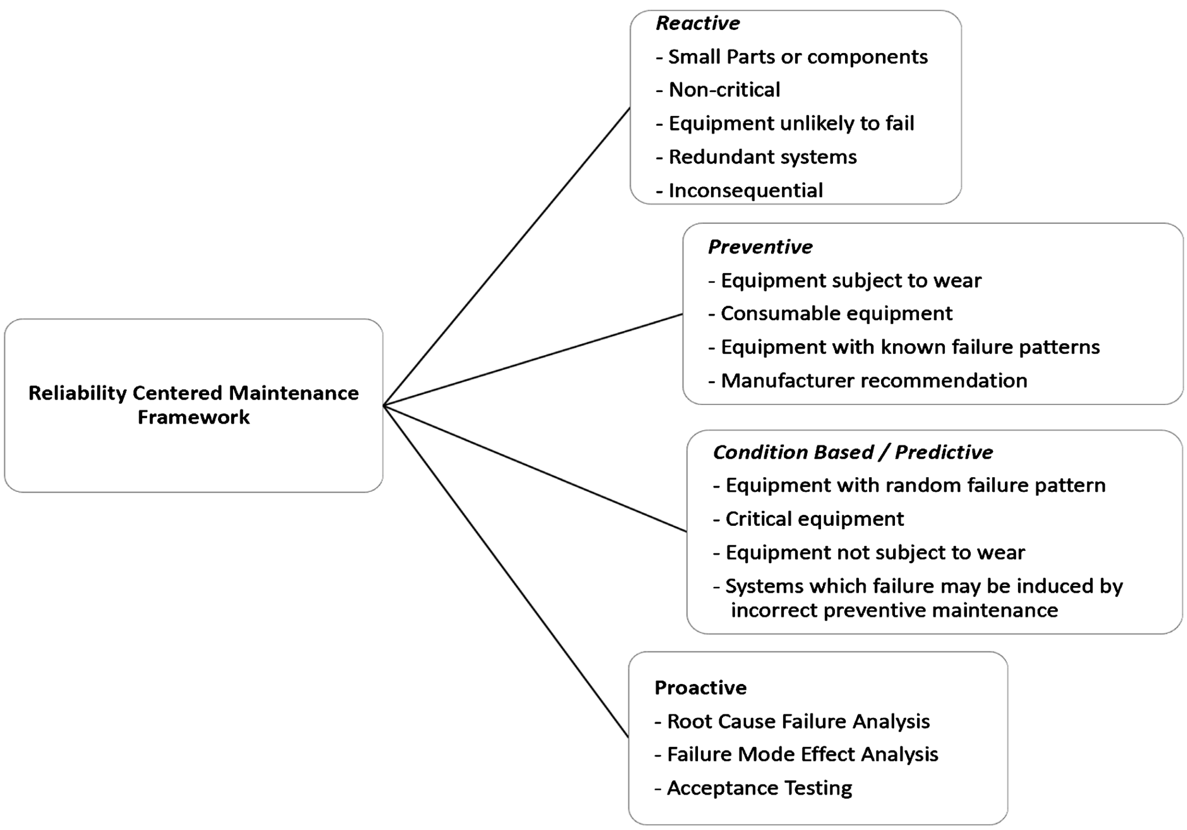

Figure 1. Typical RCM framework. Adapted from Sullivan *et al.,* (2010) and Afefy (2010).

3. Maintenance Techniques Applicable to Marginal Oilfield Production Facilities

1) *Overview of Maintenance in the Oil and Gas Industry*

Maintenance is very key to the healthy operations of any plant or facility. In the oil and gas industry where an hour downtime can result in loss up to hundreds of thousands of dollars, it is critical to ensure that the equipment are reliable and available at all times. Unplanned downtime does not only affect the revenue, an equipment break down may also have potential impact on interrelated equipment, leading to process slowdown and shutdowns [4].

According to [24], estimated downtime in the oil and gas industry ranges from 5% to 10%, higher than other industrial average of 3% to 5%, in the United States. In the same reference, the life expectancy of facilities in the upstream oil and gas industry is stated to be lower than the estimated 65% in other industries. These Key Performance Indicators (KPIs) showed that improvement is required in the reliability and maintenance of oil and gas processes, equipment, and facilities.

Maintenance in the oil and gas industry have been predominantly Preventive and time-based. According to [24], 90% of the oil and gas companies practice time-based "intrusive" preventive maintenance (PM), while 5% to 20% are left in the reactive maintenance category. In the same reference, 90% of equipment or component failures are random and not based on operating time parameters. Furthermore, routine/periodic check on equipment is said to support early failures in equipment rather than improving the reliability according to [25]; in a study aimed at optimizing maintenance strategy for large rotating equipment.

The term "intrusive" in the time-based preventive maintenance was elaborated by [26] in their description of Zero Shutdown (Zero S/D) PM philosophy. It was highlighted that for most PMs in the oil and gas industry, the facility is required to be shut down for the PM activities to take place. This mostly results in loss of revenue when not planned properly. In addition, the reliance on PM also encourages deferment of PM activities to meet shutdown schedules, which results in degradation of equipment in the facility, and subsequently breakdown, mandating reactive measures.

As summarized by [21], unplanned (Reactive) and scheduled maintenance constitutes up to 40% of net operational expenses in the oil and gas industry, while unplanned plant shutdown accounts for nearly half of the overall losses of an oil facility. This has paved way for continuous effort towards improving the maintenance in the industry, particularly towards reliability centered maintenance.

2) *Maintenance Techniques in Marginal Oilfield Operations*

The success of marginal oilfield operations relies significantly on efficient management and control of the operating expenses (OPEX). As previously mentioned, unplanned plant shutdown accounts for nearly half of the overall losses of an oil facility. These unplanned shutdowns usually result from unexpected equipment breakdown due to poor maintenance strategy or culture [21]. At the time of this review and to the best knowledge of the authors, no work was sighted in literature on the topic of marginal field facilities maintenance, particularly for an Early Production Facility (EPF)[1]. Several articles reviewed and cited in this study showed that typical maintenance strategy adopted in the oil and gas industry is predominantly time-based (scheduled) preventive maintenance.

A cue of the Nigerian oil and gas industry maintenance can be taken from the industry regulatory guide, [27]—Mineral Oils (safety) Regulations, which provides guidance for the Nigerian oil and Gas development, safety, operations, and maintenance. The recommendations in the guide for maintenance are entirely schedule-based preventive maintenance which mandates operators to perform certain inspection, testing and certification of equipment on a time-based approach. This has been the practice in most of the marginal field operations.

In recent years, the DPR have started encouraging a Risk-Based Maintenance approach, which recognizes the downsides of routine/scheduled maintenance on certain equipment, thereby purports a risk-based methodology for equipment inspection and maintenance [28]. It is therefore necessary to explore the application of RCM to marginal oilfield facilities maintenance.

4. Advances in Maintenance Techniques

1) *Optimization Strategies/Techniques in Maintenance*

[19] in their literature review of maintenance management presented a classification for maintenance optimization techniques into qualitative and quantitative models. Techniques such as Total Productive Maintenance (TPM) and RCM are in the category of qualitative modelling, while the quantitative approach involves deterministic/stochastic models. These include Bayesian approach, mixed integer linear programming, multiple criteria decisions making (MCDM), Fuzzy linguistic approaches, Galbraith's information processing model, Simulation and Markovian probabilistic models, Analytic Hierarchy Process (AHP), etc.

The classification of maintenance mathematical optimization models as quantitative approach is supported by [29] who defined maintenance optimization model as a mathematical model used to quantify costs benefits of maintenance in order to obtain an optimal balance. While the field of the quantitative maintenance optimization techniques rapidly evolved over the years due to advancement in computing, researchers have expressed several applicability limitations of the concepts as captured by [30]. These limitations include difficulty in interpretation, focus on mathematical discipline rather than practical application, bewilderment in the application of various models to specific maintenance problems, etc. To solve many of these challenges, [30] presented a general classification framework for maintenance optimization models with focus on the objectives and criteria for the optimization model.

[31] also presented a review and analysis of the publications in the domain of

[1]Data presented by [2] on marginal oilfield operations in Nigeria showed that the most common type of production facility utilized is the Early Production Facilities (EPF).

maintenance optimization with an exhaustive list of main contributors in literature. In their conclusion, it was also noted that gaps existed in the application of quantitative optimization to maintenance policies such as CM, PM, RCM, etc. In the recent decade, researchers have significantly extended studies towards the practical application of maintenance optimization techniques. [32] in their study for a new stochastic model for preventive maintenance and maintenance optimization, presented a literature review of the field, also highlighted those that provided practical approaches to maintenance optimization, such as the work of [33]. An extensive review of maintenance optimization is also presented by [34], for further reference.

Moreover, in a bid to close the gap between academics and industrial maintenance optimization, [35] presented a case study for obtaining an optimal balance between PM and CM policy for an automotive company. The solution proposed was based on reliability and the application of maintenance optimization model that integrates the optimized decision into a Computerized Maintenance Management System (CMMS). The major limitation highlighted in this study was lack of data and the inability to filter time data per equipment component required in identifying failure modes and information.

An improvement in the data limitation for maintenance optimization grew in the field of condition-based maintenance (CBM) where real time data are available for optimization models. [36] presented a review of CBM optimization for stochastically deteriorating system, stating that the field had only recently received increased attention. Unlike time-based maintenance (TBM) modelling which primarily relies on historical failure data, CBM combines data driven reliability models with real-time sensor-data to develop strategies for condition monitoring and maintenance, thereby reducing unnecessary maintenance actions and eliminating risks associated with preventive maintenance [36].

Maintenance optimization model of assets can either be a single-unit/component or a multi-unit/component system [34]. A single-component system is described as a system with no sub-unit, where maintenance intervention is applied solely to the unit. A multi-unit on the other hand consists of multiple units or subsystems where deterioration occurs differently within the sub-units. Therefore, maintenance intervention is carried out individually for each unit.

A typical example of a single-unit CBM optimization model for a discrete-state deterioration system is presented by [37]. The aim was to find an optimal replacement schedule of a system that is periodically inspected and operated in a controlled environment, using Markov deterioration. The authors demonstrated that the optimal replacement policy showed control-limit behavior in line with the system's condition and its operating environment.

[37] in their study highlighted that the literatures in CBM optimization modelling have majorly focused on single-unit system due to the difficulties and complexity of probabilistic analysis for multi-component systems. [34] [38] described the dependencies involved in multi-component systems modelling. It is

also acknowledged in their reviews that the application of CBM optimization is lagging in practice.

Ostensibly, the maintenance policy in the context of this study refers to a multi-component system's maintenance as it considers marginal oilfield facility. Due to the dimensionality and complexity of multi-unit systems optimization modelling, maintenance optimization is said to shift towards the application of heuristics techniques [38]. This is complimented by the rise in the study and application of Artificial Intelligence (AI) to aid maintenance functions.

2) *Heuristics and Metaheuristic Optimization Techniques*

Heuristics and metaheuristics optimization techniques were introduced in 1945 by G. Polya and attained proper development in the early 70's when they were applied to solving specific problems in different fields of science [39]. The emergence of heuristics arose from the need to overcome some certain limitations of conventional optimization techniques, such as passing-over of local optimal solution, risk of convergence, constraints handling, and numerical difficulties [39].

[40] provided a brief history of Heuristics evolution. During the initial period of their introduction, only mathematical heuristics concepts were attempted, which were not robust enough to solve problems involving large scale multi-component or combinatorial optimization problems. Thereafter, heuristics brought about the introduction of Expert Systems in the early 80's, still with limitations in handling complex problems. In the following decades from the early 1990's, heuristics techniques developed into the application of techniques which imitates physical phenomenon, nature and biological evolution, and mathematical algorithms in solving complex optimization problems. These are referred to as "Modern Heuristics" techniques.

According to [41] "A heuristic algorithm is one that is designed to solve a problem in a faster and more efficient fashion than traditional methods by sacrificing optimality, accuracy, precision, or completeness, for speed". Thus, they provide better computational performance than conventional optimization techniques. Although heuristics techniques are not able determine a perfect or an accurate solution, they are likely to produce a set of quality approximations to the exact solution very quickly [39].

Heuristics Optimization

The term heuristic is said to have its derivation from a Greek verb "heuriskein" which means "to find" [42]. Furthermore, heuristics are experienced-based optimization methods that rely on the expertise of the solver [43]. Thus, general heuristics finds its application fundamentally as search methods [44]. [39] highlighted the two main types of heuristics search strategies cited in literature, namely: Uninformed or blind search and Informed search strategies. A review of these search methods is presented by [45].

However, due to the limitations of numerical inefficiency of the above search strategies, especially when dealing with high dimensional problems amongst others, substantial research work has been devoted to the domain of heuristics optimization. This have significantly proliferated the identification of new heuristics techniques that have successfully overcome the above limitations. These techniques are known as metaheuristics.

Metaheuristics Methods

Similarly, to heuristics, metaheuristics are also experienced-based family of searching algorithms introduced at the mid-1980's that can solve complex optimization problems by utilizing a set of several conventional heuristics [39]. As the "meta" in the names applies, which means "beyond, in upper level" metaheuristic is said to be a high-level heuristic technique that guide other heuristics in attaining a better evolution in the search space [42] [46]. Although, metaheuristics algorithms can only provide approximations to the exact solution, rather than finding the global optimal solution, they are found very attractive in application because they do not require any special knowledge of the optimization problem [39]. Thus, they can be applied to any form of optimization problem, and they are also able to work with an abstract level description of the problem [42].

A comprehensive history of metaheuristics is provided by [47]. A few examples are presented in **Table 1**. Classification of metaheuristics techniques have also been presented in literature by many authors. An all-inclusive version of the classification can be seen in [48]. Examples of metaheuristics algorithms pseudo-codes are presented in [49].

Hybridization of metaheuristics with other field such as Operations Research (OR) and Artificial Intelligence (AI) have also been studied widely in literature, an overview of such is presented by [50] [51].

3) *Application of Heuristics in Domain of RCM for Oil and Gas Facility*

Metaheuristics are widely applied across various fields and industries. Several studies were seen in literature on the application of metaheuristics in the domain of Reliability Centered Maintenance. An example is the work of [52] where the authors aimed at optimizing the overall machine utilization with respect to total cost of maintenance and work delays of a system under RCM. Five different metaheuristics were adapted for the study; differential evolution (DE), genetic algorithm (GA), water wave optimization (WWO), particle swarm optimization (PSO), and biogeography-based optimization (BBO). Out of all the algorithms, WWO was said to produce the best performance based on computational experiments on a variety of real-world scenarios.

[53] also proposed reliability-based heuristic model for optimization of the replacement age for industrial equipment. The model was applied to two operational cases; one to decrease corrective replacement rate and the other to reduce preventive replacement ratio. While there are several studies in the literature on the application of heuristics to maintenance problem, none was cited on the maintenance of marginal field oil and gas facility, to the best of the authors knowledge.

Table 1. Examples of metaheuristics optimization algorithms.

Metaheuristics Optimization Methods	Further Reading
• Simulated Annealing • Tabu Search • Evolution Strategy • Genetic Algorithm • Differential Evolution • Immune Algorithm • Particle Swarm Optimization • Ant Colony Optimization • Honeybee Colony Optimization • Swarm Intelligence • Group Search Optimization • Cuckoo search • Grey wolf Optimization • Harmony search algorithm • Inversive weed optimization algorithm • Teaching learning-based optimization • Artificial immune system algorithm • Firefly algorithm • Krill herd algorithm • Crisscross optimization algorithm • Line-up competition algorithm • Exchange market algorithm • Fuzzy Systems • Pareto Multi-objective Optimization • Trust Tech Methods • Greedy Random Adaptive Search Procedure (GRASP)	[39] [41] [43] [48]

Moreover, within the domain of RCM, the study carried out by [20] presented a maintenance optimization procedure for an oil and gas storage depot, using Artificial Intelligent (AI) model. The maintenance procedure investigated in their study is similar to that of the marginal field oil and gas facility in view. Thus, it is essential to review the application of Artificial intelligence to oil and gas facilities' maintenance.

4) *Application of AI to Oil and Gas Industry Maintenance*

The concept of Artificial Intelligence (AI) has been available for a very long time, tracing back to a British Mathematician in the year 1950, who raised the curiosity of the "thinking ability" of machines [54]. Since then, the concept has been evolving, albeit constrained in the 1970s due to limitations in the implementation complex AI algorithms. Furthermore, the field of AI has experienced substantial progression from the 1990s till date because of rapid development in computerization [54]. Over the years, AI has been widely applied in every area of life and fields, as such, the oil and gas sector being the core of the energy industry has also benefited enormously from the concept. Several advancements have been made in the areas of exploration and production engineering with the application of AI, in what researchers have termed AI oilfields—an advanced version of the digital oilfield [55].

Due to the amount of data now readily available and data analysis involved in the implementation of RCM, particularly condition-based maintenance (CBM) and Predictive maintenance (PdM), the concept of AI has been considerably embraced to enhance the RCM strategy [21].

One of the earliest methods of AI applied to maintenance was the Experts Systems (ES), tracing back to the 1960s, where it finds application in automated diagnosis systems [56]. Thereafter, this programming technique has been evolving and still finds application in today's effective maintenance and management. [57] described the expert systems as a knowledge intensive software that can perform tasks which normally requires human expertise. Since the basis of this technique significantly relies on knowledge, it is also referred to as Knowledge-Based system (KBS). Although the two terms are used interchangeably, [58] described the subtle difference in the terms. KBS being the architecture of the system itself, while "expert system" represents the specific task the system is applying expert knowledge to resolve.

The general architecture of the expert system is shown in **Figure 2** below. Essentially, all expert systems are knowledge-based systems. The KBS system comprises of two core components, the Knowledge base—which represents the

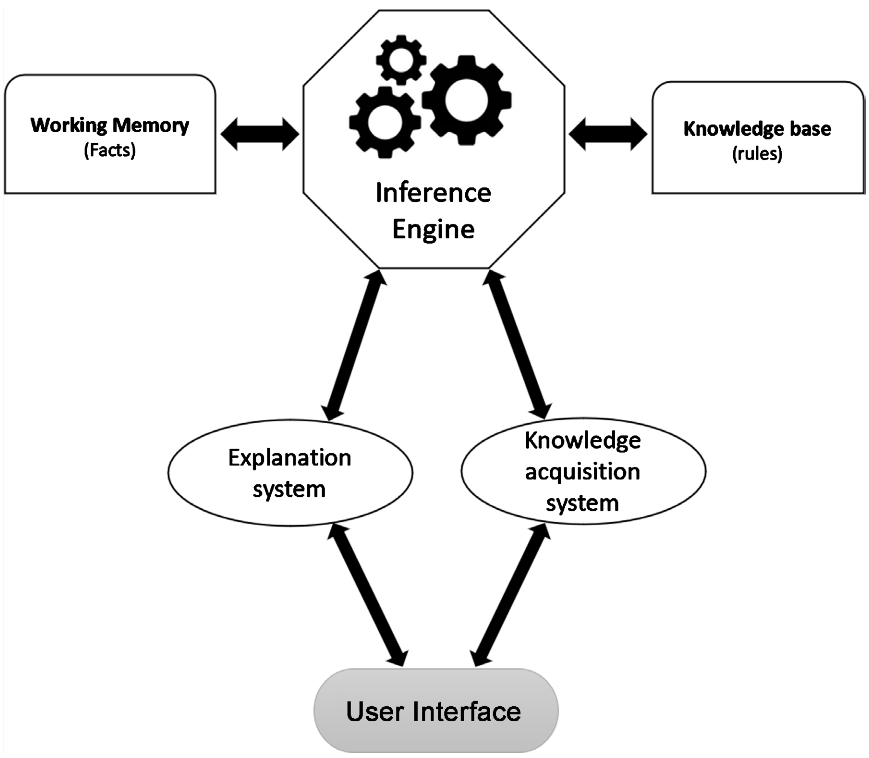

Figure 2. General architecture of an expert system (Adapted from Tolun *et al.*, 2016).

storehouse of raw knowledge from human experts, and the inference engine which performs the intelligence function of the KBS.

Another AI application that has been very prominent in recent years in the digitalization of industries is Machine Learning (ML) based AI. Following the emergence of the Industrial Forth Revolution also popularly referred to as the Industry 4.0 or simply I4.0; the proliferation of research in the domain of digital industry has blossomed significantly [59].

Machine learning is made up of algorithms and they are categorized into three different types, namely: supervised, unsupervised, and reinforced learning. Comprehensive details of the classification can be found in the work of [60]. While various algorithms have been developed for the ML AI approach, the data-driven methods that have been applied to CBM and PdM includes, Artificial Neural Network (ANN), Support Vector Machines (SVM), Random Forest (RF), Logistics Regression (LR), Decision Tree (DT), Regression Tree (RT), Vector Space Model (VSM), etc. A lot more methods are available in literature, one of the main challenges is in selecting the most appropriate, simple, yet efficient method. VSM, LR, DT and RF are known to require huge amount of data in solving problems.

A successful ML aided maintenance regime heavily depends on the deployment of sophisticated technologies. Five different technologies have been identified by [61] as the key driver for PdM. These include sensors, network, augmented intelligence, and augmented behavior, in their respective implementation sequence. At the center of this chain, technology integration is where ML comes into play, by execution of algorithm-based models that uses historical data to predict failure [60]. While the concept has proven to offer tremendous benefits to industrial maintenance, the application in the marginal oil and gas fields might be limited due to the conservative nature of technologies deployed in such operations. A lot of the marginal fields are manually operated and usually equipped with pneumatic control systems, thereby limiting the scope of ML application to the maintenance activities.

The combination of expert systems with machine learning techniques is also practicable, and this is referred to as connectionist expert system. An example of this was presented in [57], which described a connectionist expert system based on ANN. Unlike a conventional KBS, the neuron network serves as the knowledge base for the expert system that performs the classification task, see **Figure 3**. The main advantage of the ANN based connectionist expert system is the underlining learning algorithm which allows it to generate expert systems automatically from training examples [57].

A substantial number of studies have been published in the application of AI for oil and gas operations and maintenance. An example of this is presented by [62] in the application of AI for predictive operation and maintenance of crude oil and gas gathering systems. The authors proposed an AI based model using brute-force search algorithm to develop a schedule of batch operating cycle of

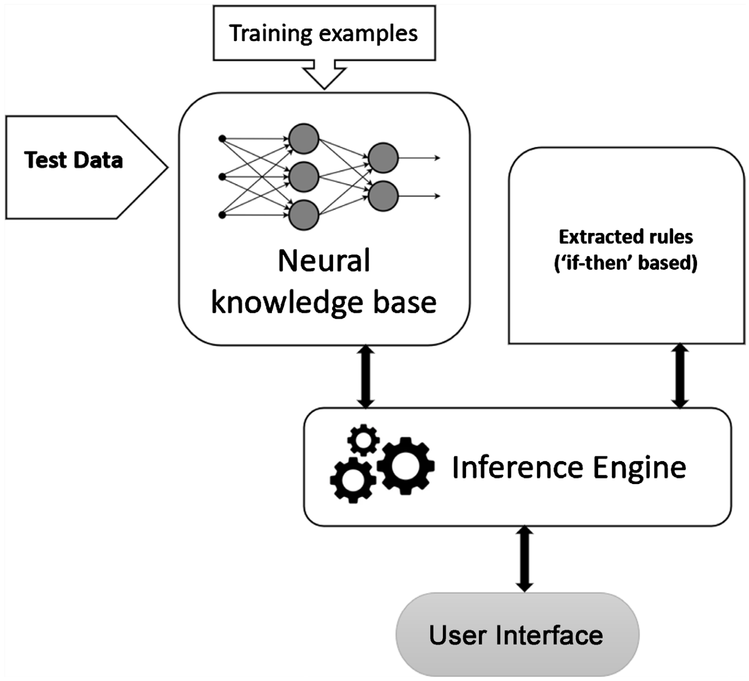

Figure 3. Artificial neural network based connectionist expert system (Adapted from Tolun *et al.,* 2016).

transporting produced fluids in a sequence that facilitates the removal of stationary solids deposits, wax/paraffins, etc., from the flowlines without human input.

In the domain of RCM however, a study that particularly catches attention is the work carried out by [20] in applying AI-based model for the optimization of maintenance in a petroleum storage depot. The study aimed at implementing an Expert System AI-based model to RCM of petroleum depot, using a plant in Zimbabwe as a case study. The equipment at the depot was first analyzed using Nowlan and Heap risk analysis to identify the critical equipment of the depot operations. Thereafter, Ishikawa diagrams and Failure Mode Effect Critical Analysis (FMECA) were used to analyze potential failure modes in the system.

The FMECA analysis showed that the equipment with the highest Risk Priority Number (RPN) were the pumps. A Jess Java-rule engine was thereafter used to develop an expert system-based diagnosis software for the pumps. The key benefits realized from the study was a shift of maintenance practice from reactive based to a proactive approach. The expert system also provided gains in maintenance cost reduction normally experienced in engaging specialist/ human experts in the diagnosis of the critical equipment, which at times results in longer downtime due to the time it takes to bring the experts to the field.

A similar work [20] was carried out by [63] where an efficient and timely diagnosis mechanism was developed for pumps' failures, using a knowledge acquisition system combined with a fuzzy rule-based inference system for the AI model development.

In another research work, [64] presented a study on the application of AI for

Just-In-Time Maintenance (JIT) in a typical oil and gas facility. The authors introduced the term "Dynamic Perspective Maintenance (DPM)", which is said to be a paradigm shift from traditional static maintenance. DPM is a time-variable-strategy that utilizes scalable-AI model which can absorb configuration variation of equipment that are digitally connected. The application of DPM facilitates rapid migration to the I4.0 era and has the potential of reducing maintenance cost of assets up to 20%. One of the objectives of the study is to develop a model that predicts future failure modes from the diagnosis of developing abnormal conditions, using near-real-time assessment of the equipment. In achieving this, the authors attempted the problem with different AI ML techniques, both supervised and unsupervised. The application of the supervised techniques for real-time series database with reliable maintenance records required high level of data cleansing. Hence, the authors attempted unsupervised cluster-based approach using the k-Means clustering algorithm, this produced 98% prediction accuracy and only 2% outlier fraction. Case studies were presented to JIT maintenance of Instrument Air compressor (IA) package and Pipeline Integrity Management System (PIMS). In the IA package application, a yield of 15% - 20% cost savings in life cycle maintenance was estimated.

Thus, it is verifiable that AI have been successfully applied for various purposes within the domain of oil and gas facilities maintenance. Key benefits were attributed to optimized maintenance strategy and cost reduction, particularly in RCM applications. However, there are some limitations to the implementation of RCM. Due to the emphasis the technique places on condition-based monitoring or predictive maintenance, it may be challenging to implement in facilities or equipment that does not have data readily available or capabilities for real-time data gathering.

5) *Data Treatment and Analytics*

[64] stated that one of the biggest challenges on making Industry 4.0 (I4.0) feasible is mining meaningful database for the intended application. [65] described data mining as the process of mining information and knowledge from large database or information repositories. [66] noted that many research effort is focused on data mining built on input data that is assumed quality, that is, the notion that data that is well distributed with no missing or incorrect values. This usually results to poor quality outputs, low performance, and disguise of useful pattern that are hidden in the data.

Developments in the application of information and database technologies is facilitated by the emergence of Knowledge Discovery in Database (KDD), which involves an iterative sequence of four (4) steps, namely: problem definition, data preparation (data pre-processing), data mining and post data mining [66]. The first step is essential defining the goal of knowledge discovery project which must be clearly identified and verified as actionable. The second step involves techniques used in analyzing the raw data and transforming it to quality data. The third step involves the application of intelligent methods to extract data patterns, and lastly, post data mining, which involves evaluation of data pattern, model deployment, maintenance, and knowledge presentation. The second and third step is considered most crucial, which is further reviewed below.

Data Pre-Processing

Data pre-processing techniques are used to analyze and transform raw data into quality data required for efficient data mining. These include data collection, data reduction, data integration, data cleaning, data transformation and data discretization [66]. Data preparation is considered a crucial research topic as it usually take-up 80% of the data engineering effort, consuming more time than data mining. It can be as challenging—if not more than the mining step [67]. Extensive literature on the importance of data preparation is presented by [66].

A review of techniques that have been published in literature towards data preparation is also capture in the work of [66]. Different pre-processing strategies are used depending on the properties of the data in context. These strategies include supervised ML techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM) and deep learning. According to [68], Cluster analysis (such as k-means cluster) is one of the most widely used unsupervised ML technique for exploratory data analysis in identifying hidden patterns. Also, in the domain of predictive maintenance (PdM), clustering analysis offers high flexibility and effectiveness in handling multi-dimensional data.

Data Mining

Data mining involves the application of intelligent methods to extract data patterns from datasets. Depending on the interest of the data mining, patterns explored in the data includes classification rules or trees, clustering, dependency, regression, sequence modelling, etc. [66]. A variety of data mining techniques have been explored substantially in literature; these techniques can be classified based on the following perspective: the knowledge to be discovered, the available dataset to be mined and the techniques to be utilized in the mining [65]. Such classifications of data mining techniques include data visualization, generalization, characterization, pattern matching, classification, association, clustering, evolution, and meta-rule guided mining [65] [69]. Other techniques which are used for knowledge mining from different kinds of databases include global information system, rational, transactional, object oriented, spatial, and active databases [69].

An extensive review of research works spanning across a decade (2000-2011) in Data Mining Techniques (DMT) and their applications was carried out by [69]. The authors surveyed and classified DMT into nine (9) categories and presented exhaustive examples of each.

[70] described the concept of data mining for maintenance applications. It was stated that data mining technique depends largely on the purpose for mining the data. For instance, when data are unclassified and with the purpose of knowledge discovery, unsupervised methods such as cluster analysis are appropriate. Whereas when the maintenance task is predictive, supervised learning methods such as decision trees are utilized.

5. Conclusions

The literature review provided an in-depth dive into the field of maintenance, particularly relating to the upstream sector of the oil and gas industry. It was established that the maintenance policies adopted in the industry are predominantly corrective and preventive maintenance. Whereas, as seen from the works of many authors, it is highly recommended to adopt RCM for several benefits, these include maintenance cost reduction, extension of equipment useful life, reduction of random failures and unplanned shutdown, etc.

More so, in Nigeria where most marginal field operators rely heavily on the regulator's (DPR—now: Nigerian Upstream Petroleum Regulatory Commission, NUPRC, and Nigerian Midstream and Downstream Petroleum Regulatory Authority, NMDPRA) guides and recommendations for facility maintenance, which is framed largely on time-based preventive maintenance, recent developments in the regulatory recommendations now promote the adoption of risk-based maintenance strategies such as RCM.

Furthermore, from the comprehensive review of various maintenance strategies that have been developed or extensively studied in literature, ranging from maintenance optimization strategies, heuristics and metaheuristics, artificial intelligence, and data mining applications, it was deduced that the application of AI best addresses the proposed RCM for the marginal oilfield facility. This was drawn from the recorded limitations of the other concepts and verifiable similar works as reviewed, where different AI techniques and Data analytics methods have been successfully applied to aid RCM.

The following knowledge gaps with opportunities for future studies are hereby identified:

- To the best of the author's knowledge, no work was sighted in the direction of addressing the maintenance of an oil and gas marginal field EPF.
- Also, the authors did not come across any work that has been carried out in the direction of applying AI for RCM of a marginal field production facility, even more so in Nigeria.

Thus, there is an opportunity to study the application of RCM in the context of marginal oilfield production facility maintenance. This also extends to examining appropriate AI and data analytics techniques that can be deployed to aid the RCM of a marginal oilfield EPF, especially in Nigeria where development of such fields is on an exponential rise.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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