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AI-driven Maintenance Support for Downhole Tools and Electronics Operated in Dynamic Drilling Environments

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ABSTRACT Downhole tools are complex electro-mechanical systems that perform critical functions in drilling operations. The electronics within these systems provide vital support, such as control, navigation and front-end data analysis from sensors. Due to the extremely challenging operating conditions, namely high pressure, temperature and vibrational forces, electronics can be subjected to complex failure modes and incur operational downtime. A novel Artificial Intelligence (AI)-driven Condition Based Maintenance (CBM) support system is presented, combining Bottom Hole Assembly (BHA) data with Big Data Analytics (BDA). The key objective of this system is to reduce maintenance costs along with an overall improvement of fleet reliability. As evidenced within the literature review, the application of AI methods to downhole tool maintenance is underrepresented in terms of oil and gas application. We review the BHA electronics failure modes and propose a methodology for BHA-Printed Component Board Assemblies (PCBA) CBM. We compare the results of a Random Forest Classifier (RFC) and a XGBoost Classifier trained on BHA electronics memory data cumulated during 208 missions over a 6 months period, achieving an accuracy of 90 % for predicting PCBA failure. These results are extended into a commercial analysis examining various scenarios of infield failure costs and fleet reliability levels. The findings of this paper demonstrate the value of the BHA-PCBA CBM framework by providing accurate prognosis of operational equipment health leading to reduced costs, minimised Non-Productive Time (NPT) and increased operational reliability.

INDEX TERMS Bottom hole assembly, oil drilling, printed component board assembly, dynamic environments, failure modes, condition based maintenance, diagnostics, prognostics, machine learning, artificial intelligence.

ABBREVIATIONS

AI	Artificial Intelligence	LWD	Logging While Drilling
AMO	Assemble, Maintain and Overhaul	MTBF	Mean Time Between Failure
BDA	Big Data Analytics	MTTF	Mean Time To Failure
BHA	Bottom Hole Assembly	MTTR	Mean Time To Repair
CBM	Condition Based Maintenance	MWD	Measuring While Drilling
ESP	Electrical Submersible Pump	NPT	Non-Productive Time
FMMEA	Failure Mode Mechanisms and Effect Analysis	PCBA	Printed Component Board Assembly
HTTP	High Temperature High Pressure	PHM	Prognostics and Health Management
		RFC	Random Forest Classifier
		ROP	Rate Of Penetration
		RSS	Rotary Steering System
		RUL	Remaining Useful Life
		SOIC	Small Outline Integrated Circuit
		WOB	Weight On Bit

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I. INTRODUCTION

Despite a global trend of decarbonisation, oil and gas resources remain one of the central energy sources for the coming decades. Albeit there is ambiguity associated with the absolute values of oil and gas contribution due to factors such as global environmental policy, fluctuations in oil price and uncertainties in exploration. Global energy demand is predicted to grow, led by non-Organisation for Economic Cooperation and Development (OCED) states increasing their consumption by 70 % compared to a 15 % increase in OCED states until 2050 [1]. With globally improving living standards, energy demand is projected to grow as a result of rising consumerism and industrial manufacturing of goods and services [2]. The global share of renewables is expected to increase significantly compared to the current energy mix in the coming decade, with an annual growth of 3 % to 6 % [1], [2]. Though, oil is expected to reach peak demand in the near future, an average annual growth of approx. 0.7 % is estimated over the next 1-5 years. The gas-share, dominated by shale gas, supported by the global extension of the Liquefied-Natural-Gas (LNG) infrastructure, will continue to grow with a prospected annual average from 0.9 % to 1.7 % [2], [3]. An oil demand between 70 Mb/d and 130 Mb/d is estimated for 2040 compared to the current demand of 99.2 Mb/d reported in 2018 [4]. Gas consumption is expected to reach 4000 BCM in 2035 and up to 5500 BCM in 2040 [2], [5]. Based on these forecasts, the exploitation of existing oil and gas resources is not sufficient to meet the estimated demand. Therefore, multi trillion USD of investments into oil and gas infrastructure, and the exploration and development of existing resources and new reserves are required over the next two decades [2], [6], [7].

The costs associated with the exploration and development of new oil and gas reserves are constantly rising, as conventional and unconventional hydrocarbon resources become increasingly remote and challenging to access, whilst at the same time environmental regulations are more restrictive, i.e. with respect to environmental safety [8]. Moreover, to continue to access new reserves complex wellbore geometries are required which can only be achieved using advanced downhole tools.

In the context of this paper, we refer to downhole tools for deep drilling as a group of tools acting as a part of the drill string with enhanced functionality. The Bottom Hole Assembly (BHA) constitutes a multifunctional assembly of interchangeable tools for steering, formation-measurements, power-supply and communications. The drivers of this technical capability relate to the need to improve drilling efficiency through a more detailed understanding of the ambient geological formations. Therefore, the growing complexity of downhole tools has resulted in an ever-increasing count of Printed Component Board Assemblies (PCBA), larger memory storage and faster processors.

In order to reach hydrocarbon deposits, downhole tools are exposed to dynamic and harsh environments during drilling. These environments are commonly referred to

as High-Temperature-High-Pressure (HTHP) environments. The BHA and its internal electronics are subjected to ambient temperatures in the well bore exceeding 200 °C and extreme pressure regimes [9]. Bending and high levels of vibrational stress are induced into the BHA during drilling, further accelerating fatigue of the BHA and its components [8].

Therefore, to address the aforementioned economical, technical, and environmental challenges, whilst enabling reliable access to energy, industry and academia are looking into new performance and maintenance optimisation strategies. A key priority relates to how to monitor, operate, and Assemble, Maintain and Overhaul (AMO) oil and gas assets in order to improve fleet availability and performance. Within complex drill strings and downhole tools, the ambient conditions lead to component or sub-system failures which in turn lead to Non-Productive Time (NPT), threatening the economic viability of drilling operations. The proportion of drilling costs of the total well costs are considerable [10], with even higher costs offshore [11]; NPT can cost up to \$1m per day [12]. 15 % of total annual drilling costs are due to NPT caused by downhole tool failure – more precisely failed subcomponents of the BHA [13]. Hence, there is a need to ensure the economic viability of these drilling operations with a reduction of NPT caused by downhole tool failures via novel condition monitoring and maintenance strategies. Relying on modern technology enablers, such as digital infrastructure, embedded systems, and electronics, the industry is – now more than ever before – promoting the development of new big data driven reliability frameworks, such as Prognostics and Health Management (PHM).

BHA systems can experience a multitude of failures. In this paper we concentrate on the mitigation of electronic failures for the following reasons:

- Electronic assemblies are present in the majority of all downhole tools.
- Due to the multi-component nature of downhole tool electronics, e.g. PCBA, above average failure rates are registered for these assemblies, placing them as a pre-dominant failure cause.
- The complexity of electronic assemblies requires elaborate and costly maintenance.
- The prediction of electronic related failures is time demanding and insufficient with current methods.

Current BHA electronics maintenance strategies greatly rely on reliability testing. Though, due to the large number of subsystems and their individual components, coupled with the harsh operating conditions, traditional maintenance strategies based on offline reliability analysis are often not able to match the encountered, real world, operational lifecycles of downhole tools.

The need for modern operating and maintenance strategies has already been identified by other industry sectors, e.g. the aviation industry adopts PHM strategies to improve the reliability for their products and the reduction of maintenance costs which have risen significantly over the past years [14]. Industries operating in environments comparable to the oil

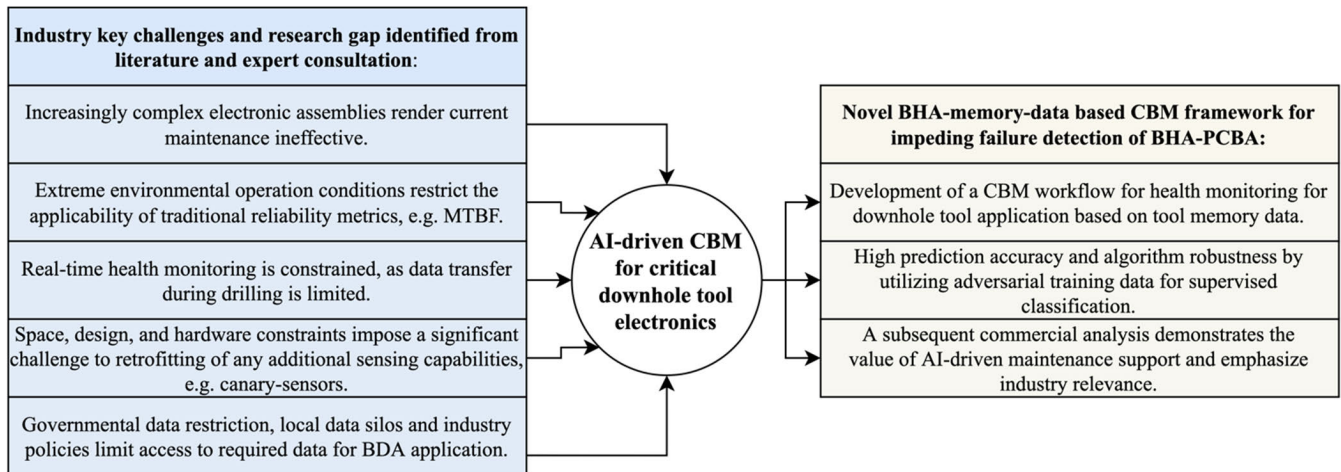


FIGURE 1. An overview of the challenges and benefits of AI-driven CBM for critical downhole tool electronics. The identified key challenges hinder the implementation of novel maintenance strategies for downhole tool electronics (left). AI-driven maintenance support for downhole tool can address these challenges and significantly improve current strategies for BHA-electronics failure detection (right).

and gas industry presently equipping their offshore assets with PHM capabilities [15]–[17]. Various sectors of the oil and gas industry began adapting new operational support and maintenance strategies, e.g., [18]–[20]. Moreover, especially in terms of electronics reliability several data-driven PHM frameworks have been developed, e.g., [21]–[23]. These adaptations tend to be of hybrid nature, combining current expert driven approaches with data-centric engineering [24]. However, as we have identified in an in-depth literature review, until very recently modern Big Data Analytics (BDA) based strategies have been exclusively used for *Reservoir Modelling* and *Surface & Completion* tasks. Downhole tool electronics have been widely excluded. This is due to the high level of specialisation of these tools, extended development cycles, space constraints, hardware constraints, real-time monitoring data bandwidth limitations, insufficient digital infrastructure, and the harsh dynamic environment.

Recognizing the central challenges associated with downhole tool maintenance, in this paper we design a Artificial Intelligence (AI)-driven implementation for CBM of downhole tool electronics (Fig. 1). We present an integrated maintenance framework designed as a retrofittable health management solution. Within this framework, we introduce a machine learning solution for Condition-Based Maintenance (CBM) of BHA-PCBA. Subsequently we assess the performance of the model and discuss the results based on a risk-cost model.

The paper is organized as follows. Section II – *BHA: Overview and Selected Failure Modes* reviews the working principle of the BHA and the operational challenges encountered when drilling for oil and gas. We then discuss BHA electronics and identify predominant failure modes. In Section III – *Maintenance: A Transformation towards Modern Maintenance Concepts* we contrast traditional oil and gas industry maintenance standards for downhole electronics with modern BDA driven maintenance concepts,

i.e. PHM. In Section IV – *BDA: An Oil and Gas Industry Review* we perform an in-depth analysis of the evolution and application of BDA within the oil and gas industry. The focus lies on the lifecycle management and reliability strategies for downhole tools. In this context Section V – *A BHA-PCBA CBM Framework* assesses the value and type of data available from BHAs for data-driven maintenance strategies. An outline of a BDA based holistic PHM approach for downhole electronics is presented. Moreover, the methodology for a deployable BHA-PCBA CBM framework extends the aspects of maintenance support for downhole tool electronics. Subsequently, results and a business case are discussed in Section VI – *Results*. The primary findings and possible future work are summarized in the Section VII – *Conclusion*.

II. BHA: OVERVIEW AND SELECTED FAILURE MODES

A. BOTTOM HOLE ASSEMBLY (BHA)

The BHA provides measurement, steering and communication capabilities; it supplies power to the downhole tools and allows a precise control of the wellbore trajectory, while surveying the surrounding formation. Multiple interchangeable tools are assembled, based on the requirements of the drilling operation (Fig. 2). The Rotary Steering System (RSS), has been developed to allow drill-bit steering and subsequently to control the well path. Two technologies are established today: *push-the-bit* in the desired direction by the extension of hydraulic pads; *point-the-bit* by bending the shaft above the drill bit [25]. Measurement While Drilling (MWD) tools determine the position and orientation of the drill string. Common measurements are inclination, azimuth and rotational speed of the drill string. Logging While Drilling (LWD) tools measure the characteristics of the surrounding formation, such as resistivity, porosity or formation pressure. A turbine is used to drive a generator which supplies power to the BHA modules. Utilizing the drilling mud, which is pumped through the drill string, the mud motor follows the

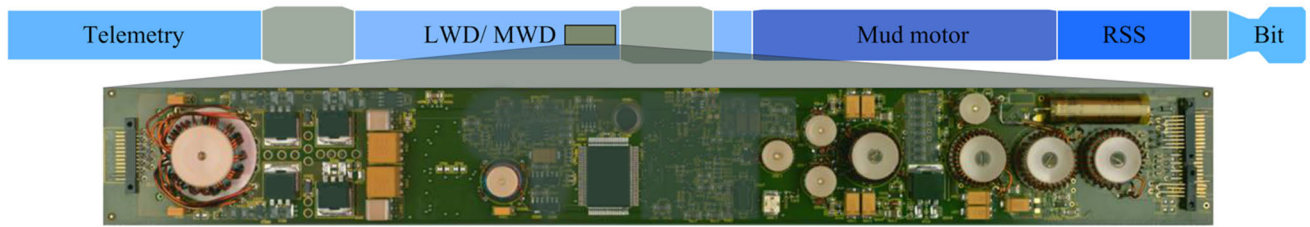


FIGURE 2. Schematic diagram of a BHA and an example of a common PCBA typically found in downhole tools.

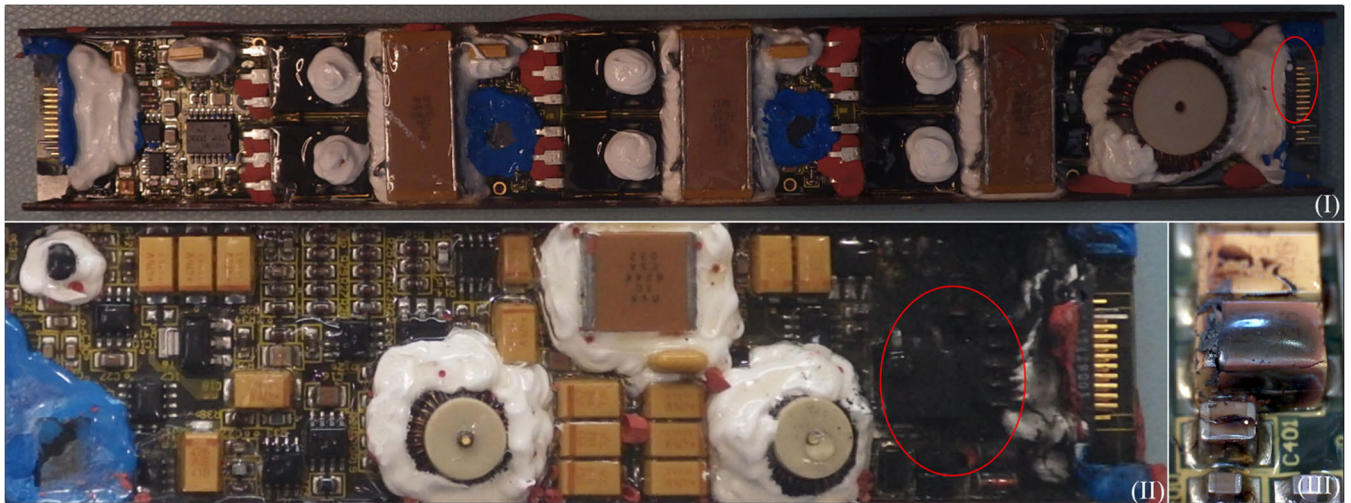


FIGURE 3. BHA-PCBA (I) Connector damage, (II) Semiconductor Failure, (III) Capacitor failure.

principles of a progressive cavity displacement pump. The mud motor is used to drive the drill bit if required. The telemetry unit is usually located at the top of the BHA. This module serves as communication link between the BHA and the surface. Via mud pulse telemetry, data is sent to and received from the surface. This is the only reliable technique for communication to greater drilling depths and is standard throughout the oil and gas industry [26]. However, data transfer rates are slow at 10 bit/s [27]. Assembled, the BHA commonly exceeds a length of 30 feet. The following section will give a brief overview of typical BHA failure modes of the built-in electronic assemblies.

B. ELECTRONICS FAILURE MODES

PCBAs hold multiple electrical and electro-mechanical components such as capacitors, semiconductors or resistors (Fig. 2). The PCBA and its components can be subjected to a diverse range of failure modes, due to the challenging operating conditions, namely high pressure, temperature, vibration and shocks.

In order to mitigate these failure modes and avoid accelerated aging of BHA-PCBA electronics, various techniques have been established. Electronics are kept under atmospheric pressure by the means of pressure barrels.

Thermal effects are opposed through the use of flasks, heat sinks, and thermal paste improving heat dissipation and delaying the increase of the electronics temperature during drilling. However, heat produced by the electronic components themselves will eventually exceed the ambient temperature which significantly affects the durability and performance of the electronics. Sealing components are an established strategy to suppress vibrational stress. The sealing component acts as a damper against vibrations. Further factors that should be considered are the component orientation, the number of components, the type of the electronic packaging, the soldering type, and the board geometry. In addition, the PCBA placement and the orientation within the housing of the BHA modules are decisive factors in order to suppress effects of vibrations.

Typical PCBA failures can be functional, software related, physical, or a combination of the three. Fig. 3 presents connector damage, a semiconductor failure and a capacitor failure. Connection damages can be due to mechanical load, e.g. excessive vibrations. Semiconductor and capacitor failures can be caused by shorted circuits or overheating Carter-Journet *et al.* [8] report various additional factors, e.g. non steady power supply and drill string Rotations Per Minute (RPM) affecting the reliability of these components.

However, high temperature is identified as a common cause for electrical component failure [28]. Beckwith [27] reports that the failure rate of downhole electronics is doubled with every 10 °C increase in ambient temperature. High temperature reduces the strength of connections and components. Furthermore, integrated circuits are subjected to electromigration which eventually can lead to a failure of the entire circuit. Moreover, lateral, axial, and torsional vibrations predominantly impact PCBA reliability [29]. In this context a case study conducted by Reckmann *et al.* [11] identifies lateral vibrations to be the principal factor contributing to the PCBA degradation, accounting for up to 29 % of vibration related MWD tool failures. Various other component and packaging related failures are documented in [12].

Concentrating on mechanical induced failures, high PCBA failure rates are associated with Small Outline Integrated Circuit (SOIC) packages. The schematics of a typical SOIC package are illustrated in Fig. 4. Wire bonds form the primary interconnects between the circuit chip (integrated circuit) and the metal lead frame in semiconductors. Wire bonding is an interconnection technique where two metallic materials – a wire and a bond pad – are bonded using one of three available methods: thermo-compression, ultrasonic, or thermostatic bonding [30]. Due to the uncertainties arising from the random nature of vibration loadings as well as temperature fluctuations, wire bond connections are susceptible to fatigue failure. This is a result of various thermo-mechanical damage mechanisms during the operational component life. However, during the lifecycle of a product several failure mechanisms may be activated on one single component by different environmental and operational parameters acting alone or in combination at various stress levels. A component failure occurs due to one predominant mechanism [31]. SOIC failure arises at the wedge bond, i.e. interface between the lead frame and the copper/ gold wire. As the temperature changes, bimetal bonds experience shear stresses as a result

of differential thermal expansion between the wire, bond, lead frame, and mould compound causing a heel crack as illustrated in Fig. 4. A more detailed investigation based on Failure Mode Mechanisms and Effect Analysis (FMMEA) of wire bond is beyond the scope of this analysis; however, the interested reader can refer to Pecht [31]. The maintenance strategies within the oil and gas sector are outlined in the following Section – III.

III. MAINTENANCE: A TRANSFORMATION TOWARDS MODERN STRATEGIES

Maintenance strategies have evolved from purely reactive strategies – a *run to failure* paradigm, often followed by long in-between shutdowns, potential safety and environmental risks as well as economical losses – towards proactive strategies such as preventive or time-based strategies on system and component level. If degradation of components is understood and systems are statically operated preventive maintenance has proven to be a functioning method. However, it may cause an early exchange of components [32]. Hence, the economic efficiency of this approach heavily depends on a well-established maintenance scheme closely correlating to the true times of system or component failure. Another disadvantage is the rigid setup of these approaches which do not readily adapt to dynamic operational patterns. Along the lines of preventive maintenance various metrics have been established, such as reliability- and hazard-functions as well as the Mean Time To Failure (MMTF), Mean Time To Repair (MTTR), or Mean Time Between Failure (MTBF) [33].

As in other industries a MTBF approach is widely used throughout the oil and gas industry to determine the statistical downhole tool reliability since the 1980s. However, as Reckmann *et al.* [11] state, this approach is skewed if applied as a metric for downhole tool reliability. The environmental and operational parameters are not consistent within the wellbore and therefore do not fulfil the assumption behind the MTBF approach. Furthermore, Brehme and Travis [10] demonstrate that despite an improvement of downhole tool reliability since the introduction of these metrics, every third BHA continues to remain the cause for NPT. In addition to insufficient reliability metrics in the oil and gas industry, no concise definition of a *failure* has been issued throughout the industry. The authors in [34] support this, reporting a wide variety of terms that are considered to be a tool failure. These aspects make MTBF – a solely statistical reliability-based measure – an overall ill-defined metric for assessing the true reliability of downhole tools or to determine the optimal time to perform maintenance. Moreover, with the ongoing automation of oil and gas industry assets, the technical and operational complexity evolves, questioning the capability of current strategies to meet stringent maintenance requirements in the future.

As emphasized before, assuring reliability of downhole tool electronics is challenging. The main reasons are the high number of individual components, and the diverse range of failure modes. Moreover, deriving reliability metrics

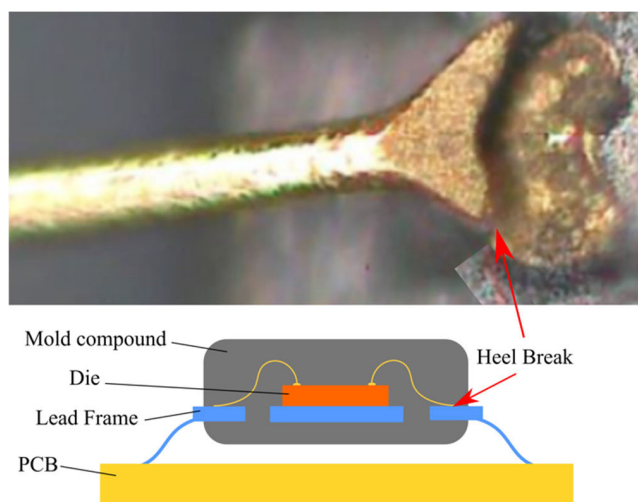


FIGURE 4. Typical SOIC package (bottom); Heel breakage (top).

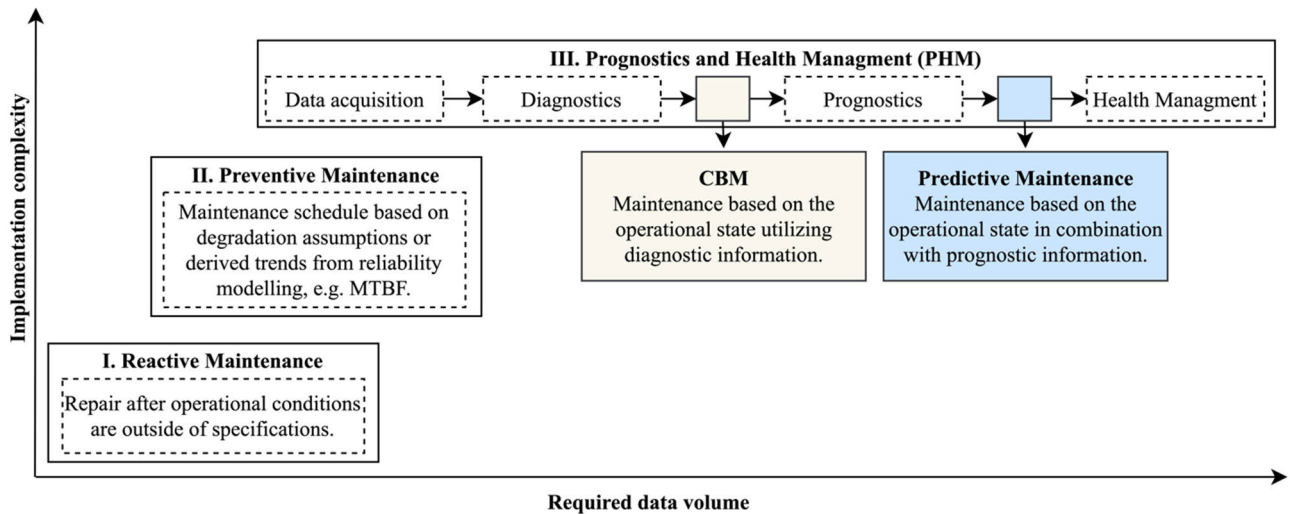


FIGURE 5. Qualitative comparison of PHM and its subdomains with traditional maintenance strategies.

via traditional reliability analysis and tools like FMMEA requires significant efforts, is time demanding, and costly. The complexity of the tools imposes arduous procedures to adequately reproduce failures and perform root cause analyses. Simultaneously, the required time for AMO services of downhole tool electronics increases – concurrently reducing fleet availability. Ultimately, an increased fleet volume is required to serve the same customer base and inability to find failure root causes leads to bulk removal of parts.

The nature of the multi-component electro-mechanical BHA systems renders traditional maintenance approaches inefficient. Hence, there is a requirement for a dynamic and adjustable downhole tool electronic lifecycle management, operational, and maintenance support. As in other sectors, e.g. the aviation [35] or the automotive industry [36], the oil and gas industry actively commences the research of novel strategies to derive suitable metrics for downhole tool reliability and maintenance scheduling [37]. As illustrated in Fig. 5 novel maintenance strategies emerged from traditional approaches [38], [39]. PHM aims to provide a holistic solution from the systems design stage onwards [40]. Prognostics focuses on the prediction of a systems future state, based on its preceded and current states, to forecast the system degradation trajectory respectively the Remaining Useful Life (RUL) [41]. Health management adapts the results of the prognostic approach and supports the maintenance decision making process to ensure the system integrity [42]. This can be either human guided or automated [40]. The key driver for the development of this technology is the reduction and optimisation of maintenance intervals and associated costs as well as the mitigation of system downtime [43]. PHM prioritises the state prediction of individual system deviations over population based statistical knowledge and expands the initial concept of diagnostic fault detection, isolation and identification of the fault type [44].

The detection of a faulty condition is associated with an evaluation of the degradation state, the system impact and a prediction of the systems RUL depending on future fault propagation [41]. To assess the current state of health as well as the future state three different approaches are commonly distinguished.

Model-based approaches translate the physical nature of the designated system into a deterministic mathematical representation to depict the degradation [42]. This approach outperforms other methodologies in terms of accuracy and precision, though requires domain specific expert knowledge and an extensive study of failure modes on a subcomponent or even material level relying on tools like FMMEA [45]. Physical models are also restricted by underlying assumptions which aim to analytically capture the system interdependencies [38]. Contrary, *data-driven approaches* are preferred, if a physical model cannot be obtained [14]. They rely on big data, e.g. operational data, timeseries data, failure data, and reports to assess the system or component state [46]. AI-driven maintenance strategies can detect underlying interrelations and degradation trends that traditional methods might not be able to depict adequately [45]. Albeit a relative slow-paced transformation in the oil and gas industry, the extension of the required digital infrastructure, embedding intelligence and increasing reliance on enabling technologies supports the future implementation of BDA based approaches. Coevally, BDA enabled real-time operational and offline maintenance support has the great potential to further ensure oil and gas fleet reliability and availability. BDA incorporates various techniques such as statistical analysis or AI to manage and derive information from big data [47]. Different aspects need to be considered in the scope of big data: volume, veracity, variety, velocity and value [48]. Commonly BDA contains multiple data formats requiring different methodologies to derive meaningful insights.

Furthermore, the data needs to be assessed in regard to its volume and type as well as quality, reliability and information value. If fused – physical models and data-driven techniques – a *hybrid approach* can compensate for the limitations of each individual approach.

PHM is associated with two different maintenance strategies. CBM arose from the need to individualise and tailor preventive maintenance to the requirements of systems and components. It utilizes diagnostic information as the state of the supervised system is constantly monitored. This enables apposite maintenance. Exemplarily, Zhan *et al.* [49] are investigating how CBM can improve MWD and LWD tool reliability as a real time health management strategy in comparison to traditional maintenance approaches. Predictive maintenance expands the diagnostic concept, providing a future state estimation for the system or component to determine the optimal time for maintenance.

The adoption of BDA for operational and maintenance support in the oil and gas industry is reviewed in the following Section – IV. In Section - V the suggested framework is extended towards AI-driven BHA-PCBA CBM support.

IV. BDA: AN OIL AND GAS INDUSTRY REVIEW

To determine the state of the art for BDA based applications the authors of this paper have conducted a thorough study of research published in the relevant field. Using a key word search, publications in various literature data bases have been analysed [50]–[54].

As Fig. 6 shows, utilization of big data driven applications has increased throughout the oil and gas industry over the past two decades. However, in this context the dominant focus is *Reservoir modelling & Characterization*, e.g. [55]–[57] and *Completion & Production* related applications, e.g. [58]–[61].

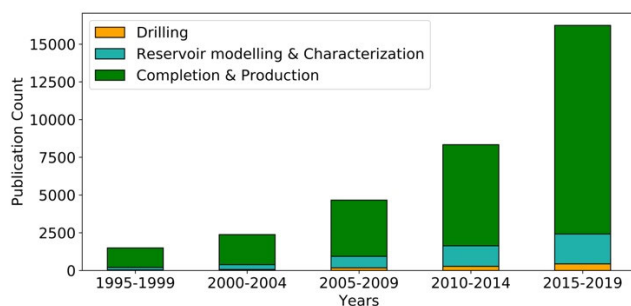


FIGURE 6. Application of BDA throughout the oil and gas industry classified into three major subdisciplines.

Only recently academia and industry have turned their interest towards the application of BDA based methodologies in the context of deep drilling [8]. Many AI-driven, drilling related applications focus on performance optimization during drilling. Conventional drilling performance metrics such as Weight On Bit (WOB), Rate Of Penetration (ROP), or torque have been used to identify issues during the drilling processes. Lashari *et al.* [62] present an approach

using a Feed Forward Neural Network to identify bit balling based on such features. The Neural Network is trained on time series data to predict the ROP which is then compared to the measured ROP during drilling. If the experienced ROP deviates from the model's prediction this can be used as an indicator for bit balling. Another example utilizing machine learning for ROP prediction is presented in [63]. A Long-Short-Term-Memory Neural Network model is deployed, utilizing additional features for training – the type of the drill bit, formation properties, and the rheological properties of the drilling mud are explored to improve model accuracy. Alternatively, a recent case study by Rashidi *et al.* [64] demonstrates how a bagged ensemble Decision Tree based on surface measurements, such as WOB, RPM, torque and depth predicts ROP. However, Decision Trees are sensitive to the type of data they are trained on and prone to overfit. This has been verified by findings in [65]. Therefore, the authors utilized a Random Forest Regressor which is less prone to overfitting and obtained the best performance, compared to various machine learning algorithms such as Support Vector Machines, K-Nearest Neighbours and an Artificial Neural Networks. Singh *et al.* [66] developed a deployable real-time solution for ROP prediction, evaluating the performance of eight different algorithms. The algorithms were trained on a dataset containing 50 wells. In addition to the above-mentioned features, additional features like flow rate and formation property indicators were used to further improve the performance of the models. Another example of applied machine learning for ROP estimation is presented in [67].

In order to improve interpretability and increase the ROP prediction accuracy the authors suggest a hybrid approach using a combination of physical models and machine learning. Further examples of machine learning for ROP prediction can be found in [68], [69].

Referring to Fig. 7, a more detailed analysis of BDA for oil and gas industry assets shows an increasing interest in the application of these methods for downhole tools. This is further supported by the findings displayed in Fig. 8. Though, only a small proportion of relevant publications considers BDA in the context of CBM and predictive maintenance for downhole tools. BDA driven applications for downhole tools only amount for a small fraction throughout the industry, i.e.

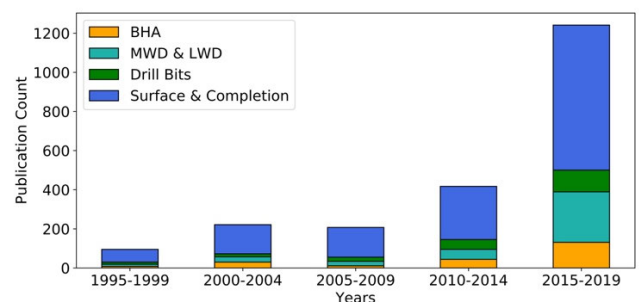


FIGURE 7. Application of BDA for different downhole tools and general Surface & Completion related applications.

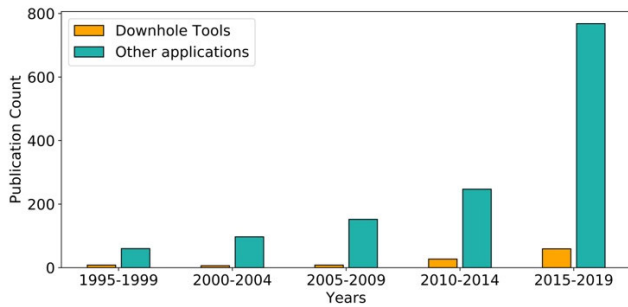


FIGURE 8. BDA in CBM and predictive maintenance categorized into Downhole Tool related applications and other oil and gas relevant sectors.

from 2015 to 2019 only 8.4 % of all relevant publications. However, recent trends relating to increasing economical and operational challenges as outlined above, suggest significant future investments into BDA related applications in the oil and gas industry. This acts as a key driver for the dissemination of data driven PHM for downhole tools.

AI for CBM or predictive maintenance of artificial lift systems is an active field of research. Artificial lift systems are used to maximize production from the well after the initial pressure has depleted. Sherif *et al.* [70] applied Principal Component Analysis to identify deviation from nominal operation conditions of Electrical Submersible Pumps (ESP). The promising results of this approach to identify impending ESP failures coincides with findings in [71]. A Support Vector Machine based approach is developed by Guo *et al.* [72], demonstrating an alternative application for the prediction of ESP failures. Another system to prolong oil production is known as beam or rod pumping. Traditionally the working conditions of these pumps are assessed by the use of dynamometer cards. The authors in [73] use a Convolutional Neural Network for classification of the operating stages of rod pumps. These Neural Networks are predestined for image classification, achieving over 90 % forecast accuracy of rod pump failure during field deployment. A different approach for rod pump CBM is presented by Bangert and Sharaf [74], identifying Decision Trees to be well suited for classifying the operational state of rod pumps. Further examples can be found in [75]–[79].

Likewise, data driven CBM or predictive maintenance are of increasing interest in other sectors of the oil and gas industry. Offshore assets, such as platforms, generators, or turbines are the focus of multiple AI-driven CBM applications, e.g. [80]–[82]. The detection, analysis and prediction of corrosion of offshore structures with state-of-the-art AI algorithms is another active area of research presented in [83] and [84].

Contrary to the exemplary application scenarios outlined above, research related to downhole tools such as RSS, MWD or LWD only accounts for a small portion in BDA-driven CBM or predictive maintenance applications. We have identified multiple reasons explaining this lack in research. Besides the constraints imposed by the harsh and uncertain environment downhole tools are operated under, the challenges associated with a data-driven maintenance approach need to

be understood. Restrictions in terms of hardware availability and a lack in big data availability have – so far – impeded the broad application of data-driven maintenance strategies. While latter one is by far the more pressing issue, hardware constraints in downhole tools have proven to be a major hurdle. Bybee [28] discusses various reasons which prevent the installation of additional sensing capabilities required for more elaborate data-driven maintenance applications, such as: space constraints, long lasting development cycles and hardware availability. Furthermore, any computational process needs to be designed to use as little power as possible to avoid any additional heat dissipation from the electronic components. Hence, the computational resources for downhole data processing, e.g. high-volume data sampling, are limited. Therefore, Carter-Journet *et al.* [8] state the need for improved electronics resilience in combination with extended functional capabilities to be able to satisfy the above stated requirements. With the advancements in enabling sensors and electronics, more data is becoming available, however, limited access to this data still represents a significant challenge for the implementation of data-driven maintenance for downhole tools. The industry has begun to adopt modern digital infrastructures to streamline and centralize data from drilling operations. However, the global scale of drilling operations, the volume, veracity, variety, velocity, and value of the data along the manifold value chain represent another considerable challenge for data aggregation and management.

Already in 1999, Aldred [13] stress the importance of a holistic data approach in order to minimize unplanned downtime due to tool failure and a subsequently improved tool reliability. The authors highlight the importance of data consistency and availability considering increasingly complex well geometries and harsh drilling environments. In [10], BHA reliability was improved by implementing a streamlined approach to capture tool data and failure reports in order to reduce the number of *systematic* downhole tool failures. However, maintaining such an approach on a global scale and throughout many departments participating in the development, maintenance and operation of the tools requires considerable efforts. Garvey *et al.* [85] highlights the need for complete and concise history data throughout the entire life of a downhole tool, essential for robust lifetime prediction. Reckmann *et al.* [86] discusses the importance of high quality/high frequency data for detection of tool failures and a complementary tool database capturing the tool history from various data sources. In [12] and [87] case studies of the challenges the oil and gas industry is facing in centralizing and streamlining drilling data are listed.

Though, reviewing recent literature various examples for BDA downhole tool maintenance approaches can be found. Brehme and Travis [10] explore the idea of a *total BHA reliability* methodology in order to improve the decision making for BHA maintenance. Garvey *et al.* [88] develop, as one of the first, a data-driven model to determine the stress level a BHA has been exposed to. Using lateral vibration run-to-failure data, cumulative stress-time functions are calculated.

This resembles the encountered stress history of the BHA and reflects various stress scenarios. Subsequently, approximation functions are used to determine the stress history of an operating BHA. This new curve is then compared to the stress-time type curves using kernel regression. Via a similarity measure a RUL prediction for the operating BHA is derived. The authors achieved an accuracy range of 2 %-20 % of the total tool lifetime. This prognostic approach supports the decision-making process for future BHA maintenance. The authors refine their methodology in [85] to address the issue of a complete BHA stress history data availability. A health state estimation model is deriving the stress time curves based only on parts of the data rather than a complete history. The overall life of the BHA is estimated based on these results which simplifies the deployment and distribution of the data. Reckmann *et al.* [86] define the requirements for an offline RUL estimation model supporting the operator's decision whether to rerun a downhole tool. In order to reduce NPT, Lahmadi *et al.* [89] present an approach to estimate the RUL of composite drill pipes. Failure of drill pipes often results in long downtime as recovery is difficult. Based on the RUL prediction of a Recursive Neural Network, maintenance scheduling can be improved, and subsequently NPT reduced. Zhan *et al.* [12] developed a model for anomaly detection for RSS modules using a Nonparametric Fuzzy Inference system, based on field data, such as RPM, electrical current of the RSS module, and the pump pressure in order to improve maintenance decision making. Using failure data from BHA-PCBA, Zhan and Zhao [29] elaborate a method for the development of a cumulative stress model for RUL

forecasting and maintenance decision making based on a hybrid approach, combining data driven methods and physics of failure. Zhan and Ahmad [90] discuss a retrofittable health management solution for real-time BHA-PCBA prognostics for downhole tools. The authors introduce canary sensors, which can be integrated into the PCBA, to record different types of downhole tool vibration. Based on pre-defined stress levels a cumulative stress score is attained from the sensor data. A data driven degradation model relates these sensor failure times and returns a RUL forecast. The authors Reckmann *et al.* [11] establish a relation between drilling dynamics and MWD tool failures. Based on downhole vibration data, failure probabilities using a Binary Logistic Regression approach are obtained reflecting the cumulative stress a MWD has been subjected to. However, the authors state that every MWD tool is considered as new during the start of a run. This assumption is critical as it introduces significant bias, because the complete stress history of the tool is no longer considered. An additional data driven method for the assessment of the health state of a LWD neutron generator is presented by Mosallam *et al.* [91]. The LWD memory data is downloaded after each run. Relevant data is selected based on expert knowledge. A robust health state indicator is constructed using three input features, namely: the output of the neutron detector, the drawn current, and voltage. A Decision Tree Classifier is applied, determining a healthy or non-healthy operating state of the neutron pulse generator during the run. Further evaluation of data-driven maintenance methods for downhole tools are presented in [92]–[94]. Relevant applications are listed in Table 1.

TABLE 1. Overview – Data-driven maintenance applications for downhole tools.

Authors	Year	Ref No.	Tool	Methodology
J. Brehme and T. Travis	2008	[10]	BHA	Establishing a reliable tool database to aid operational and maintenance decisions and reduce BHA failure.
D. Garvey, J. Baumann, J. Lehr, and J. Hines	2009	[88]	BHA	BD based cumulative vibrational stress profiles, reflecting degradation trends; RUL forecast based on similarity measure with the stress profiles.
H. Reckmann, P. Jogi, F. T. Kpetphoto, S. Chandrasekaran, and J. D. Macpherson	2010	[11]	MWD	Identifying significant features from drilling field data relating to MWD failures.
D. Garvey, M. John, and J. Baumann	2010	[85]	BHA	Extending approach developed in [88] requiring less data.
S. Zhan, J. Rodiek, L. E. Heuermann-Kuehn, and J. Baumann	2011	[12]	RSS	Anomaly detection using Nonparametric Fuzzy Inference System and Sequential Probability Ratio Test to identify possible degradation trends utilizing surface data.
K. Carter-Journet, A. Kale, D. Zhang, E. Pradeep, T. Falgout, and L. E. Heuermann-Kuehn	2014	[89]	BHA-PCBA	Bayesian based failure models utilizing field data for lifetime prediction.
A. Kale, K. Carter-Journet, T. A. Falgout, L. E. Heuermann-Kuehn, and D. Zurcher	2014	[90]	BHA-PCBA	Field data based cumulative degradation model in combination with outlier detection for RUL estimation.
S. Zhan and I. Ahmad	2015	[91]	BHA-PCBA	Retrofittable health management solution - canary sensors used for RUL estimation.
A. Kale, D. Zhang, A. David, L. Heuermann-Kuehn, and O. Fanini	2015	[92]	RSS	CBM framework utilizing field data and failure analysis.
A. Mosallam, L. Laval, F. B. Youssef, J. Fulton, and D. Viassolo	2018	[93]	LWD	Fault classification using decision trees.
H. Reckmann, A. Hohl, H. Oueslati, and O. Akimov	2018	[86]	BHA	Framework for holistic downhole tool data aggregation process to derive informed fleet reliability information aiming to improve adaptiveness and performance of tools while reducing NPT.

TABLE 2. The advantages and disadvantages of different downhole tool data sources.

Data type	Field data	Post run data	Maintenance data
Advantages	* Real time	* Tool memory data	* Detailed failure analyses
	* Availability	* Field reports	* Cost data
	* Support onsite decisions	* Event log	* Inspection & task details
Disadvantages	* Low sampling rate	* Availability	* Low sampling rate
	* Sparse data	* Data often not stored	* Textual data
	* Additional effort to collect and store in system	* Advanced expertise needed for analysis	* No concise standard in terms of language & format
	* Quantity & quality changes with market conditions	* Ignored as no immediate payoff	* Quality of data depends upon the regions
		* Quantity & quality changes with market conditions	* Challenging to isolate personnel skill level and competency factors from data

The above highlighted challenges are addressed in the following Section – V. An AI-driven BHA-PCBA CBM framework is introduced under consideration of the general PHM framework previously introduced in Section – III.

V. A BHA-PCBA CBM FRAMEWORK

As discussed in the previous Section – IV, BDA for downhole tool electronics is an underrepresented area of research in respect to modern maintenance strategies, such as PHM. The main reasons are the lack of available data, harsh environmental operating conditions, and hardware constraints. Based on data collected during drilling missions, we present a failure agnostic CBM framework for downhole electronics. Subsection A provides a synopsis of the various downhole tool data sources. Subsection B relates the BHA-PCBA CBM framework to PHM. Subsection C details a methodology for predicting PCBA failures.

A. DOWNHOLE TOOL DATA SOURCES

Prior to a drilling operation, service-customers specify the requirements for geological formation data (type of data and sampling rate). Hereinafter, the service provider designs the BHA based on these mission requirements. There are a multitude of mission possibilities and therefore 100s of types of BHAs to meet these mission requirements. Data transmission bandwidth is utilized to operate the BHA and transmit formation data for the customer. Spare bandwidth may not be available to transmit tool health data while drilling.

Table 2 provides an overview of the advantages and disadvantages of various data sources. Field data is acquired during drilling. It serves as the predominant source for real time operational decision making and contains information such as tool azimuth and inclination. The data received from downhole tools during drilling is truncated, due to slow data transfer rates. After completion of a run, high resolution downhole tool memory data is available on the surface and manually downloaded. This may contain various sensor measurements as well as tool performance-diagnostic information and event logs. Field hands might enter supplementary notes. In practice this data is often not readily available, as it is only occasionally downloaded during the follow-up maintenance.

Furthermore, an insufficient digital infrastructure or data regulations imposed by local authorities often only allows local access to this data. Maintenance data is typically obtained during AMO. It can provide detailed insights of BHA failure root causes. However, it is often subjective, and formats may vary widely. Like post run data aggregating complete maintenance reports and converting those to a practical format is due the lack in standardization expensive and time demanding.

B. PHM INTEGRATION

The focus for the integration of modern health monitoring strategies is dependent on AI, to be more precise machine learning. Following the guiding principles of the IEEE standard for PHM of electronic systems [95], Fig. 9 displays a holistic concept of PHM integration for improved BHA-PCBA monitoring, operational support and maintenance optimization. From post-run data and field data, diagnostic information is extracted containing data from a multitude of internal BHA sensing sources (e.g. vibrational stress, temperature) as well as binary, digital control data stored within the tool memory. This collected data serves as training data for the offline training phase of the presented CBM framework. Once deployed, newly collected data of the same format acts as input to the online CBM framework to predict PCBA failure assisting the operational maintenance decision making. In a second stage data from all sources is aggregated for predictive maintenance to derive a RUL forecast, including the estimate from the BHA-PCBA CBM framework. This in turn supports improved mission planning and health management.

C. BHA-PCBA CBM METHODOLOGY

Due to bandwidth limitations the resolution of surface data is not high enough to monitor and predict PCBA failure. Hence it is desirable to predict a PCBA failure before the BHA is sent out for a drilling mission, e.g. during AMO, as this gives access to high resolution data stored within the tool.

From a machine learning perspective, we treat the problem of support for maintenance decision-making as a classification problem. In other words, we assume the training dataset consist of n i.i.d data points, denoted as $D = (x_n, y_n)$;

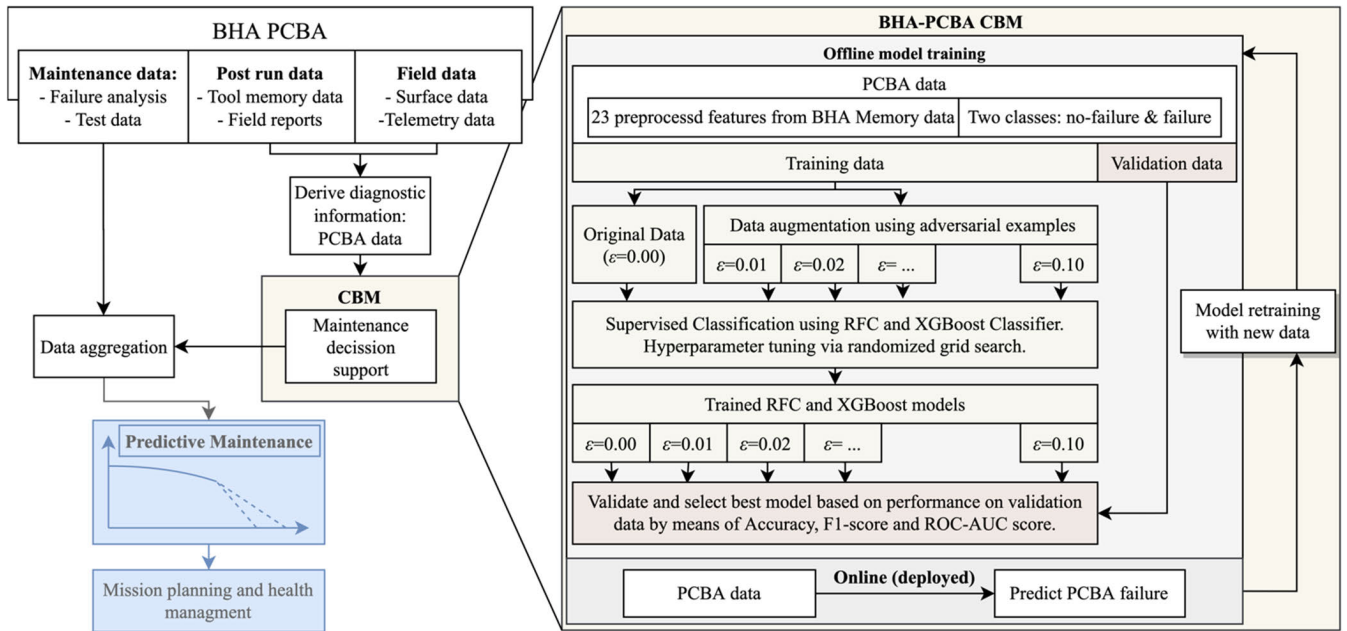


FIGURE 9. (Left) PHM integration. (Right) BHA-PCBA CBM framework.

where x represents the input feature space vector comprising of 23 dimensions (features), while y , the label, is assumed to be one of k classes, that is $y \in (1, \dots, k)$. The problem of predicting maintenance is treated here as a two-class problem, $k = 2$. One class represents the case when a PCBA needs replacement (*failure*), while the other class indicates the PCBA is fit for rerun (*no-failure*). In addition to a hard decision – *failure/ no-failure* – we also evaluate how confident the algorithm is in the prediction by means of a probability output $p(y = k|x)$. For maintenance decision-making purposes, it is essential to evaluate the algorithm’s capability, safety margins and reliability by quantifying how uncertain it is in a prediction. Therefore, we consider an algorithm to be confident in a prediction if it outputs the probability of a sample belonging to one of the classes greater or equal to a user specified threshold, denoted here by a maintenance decision threshold (TH_m). Translated into an engineering context a recommendation to carry out replacement of the PCBA is recommended in all cases where the probability of *failure* is greater or equal to TH_m , or vice-versa, no maintenance is suggested if probability of *no-failure* is greater or equal to TH_m . Depending on operational circumstances TH_m can vary in accordance with the acceptable level of prediction uncertainty.

We explore two algorithms which are embedded in a sequence of data processing components that are carried out in a hierarchical manner. This offline model training phase is schematically outlined in Fig. 9 (right). An algorithm is trained individually using this pipeline, followed by a comprehensive evaluation of its performance.

Each algorithm is evaluated based on specific classification scoring metrics. A comprehensive explanation of the metrics

used in classification settings can be found in [96]. Some metrics are scoring qualitatively, others are quantifying the probabilistic outputs. Qualitative measures take the predicted class label as input depending on the decision threshold TH_m . Probabilistic scores, on the contrary, are calculated based on the output probability associated with its respective class prediction. The discrete results of the prediction of the algorithm are therefore assessed by means of accuracy and F1 score. Subsequently the ROC-AUC score is used to assess how certain the algorithm is in its prediction, acting as a measure for class separability based on the predicted class probabilities. For uncertainty evaluation purposes we plot the combined class accuracy as a function of TH_m . Plots are obtained by filtering out test examples, according to $p(y = k|x) \geq TH_m$, corresponding to the confidence threshold in the interval $0.5 \leq TH_m \leq 1$ and plotting the accuracy on both classes for this threshold.

The section further discusses the individual steps during offline training as presented in Fig. 9 (right) as well the two presented algorithms.

1) DATA AUGMENTATION

To mitigate for out-of-distribution examples and increase robustness to outliers and thus, in turn, increase generalisation ability of the algorithms we introduce adversarial examples in the training dataset as described in [97] and [98]. Adversarial examples are carefully designed to be *similar* to a genuine training example but are misclassified by the algorithm. Given an input x with target y , we follow a similar approach to [97] where we make use of the fast gradient sign method to define an adversarial example as $x' = x + \epsilon \text{sign}(\nabla_x l(\theta, x, y))$;

where ε is a small perturbation value, $l(\theta, x, y)$ is the loss function with respect to the model parameters θ , input x and target y . In order to obtain the gradient of the loss function, $\nabla_x l(\theta, x, y)$ we employ a Ridge Classifier [99]. Intuitively, an adversarial sample introduces noise in the direction of the gradient and thus increases the loss of the Ridge Classifier. We thus augment the original training dataset by treating (x', y) as additional training samples. We investigate model performance for a range of perturbation factors in the interval, $\varepsilon = [0.00, 0.10]$. The motivation behind the use of multiple values is two folded: (1) to investigate the effect of ε on model performance and (2) to determine a suitable value for our application. The newly generated datasets are further referred to as adversarial training datasets. Results are depicted for selected perturbation factors in Section – VI.

2) CLASSIFICATION ALGORITHMS

Supervised learning in the form of classification is an important constituent in machine learning and can thus be solved via a plethora of methods ranging from parametric/non-parametric models, either based on a frequentist or Bayesian inference. Traditionally, simple parametric models, i.e. a model that absorbs information from available data in its parameters, have been used for such purposes due to ease of interpretability. However, in complex datasets such models lack in expressive power, and more often than not generalise poorly [100]. Note, we consider here non-parametric learning, a model whose number of parameters grow with the size of the training set.

This paper explores two non-parametric ensemble models, based on frequentist assumptions namely: Random Forest Classifier (RFC) and XGBoost Classifier. Ensemble methods are learning algorithms that first construct a set number of classifiers and then estimate a sample's class by a taking a weighted vote of their predictions. It has long been observed that ensemble methods improve predictive performance over single based algorithms [101]. Broadly, there are two classes of ensembles: (1) randomisation-based approaches where each decision tree is trained in parallel without any interaction e.g. Random Forest, and (2) boosting-based approaches where the ensemble members are trained sequentially e.g. AdaBoost or XGBoost [102]. While ensemble learning can be implemented with any learning algorithm, ensembles of decision trees, be it Random Forest or XGBoost, are popular due to computational advantages of decision trees i.e. fast training and testing. A decision tree classifies instances by sorting them down the tree from the root to the leaf node which provides the classification of the instance. This work considers decision trees with *gini index* as the loss function (1) to measure the quality of a split, given by subtracting the sum of the squared probabilities (p_i) of each class ($k = 2$) from one.

$$I_G = 1 - \sum_{i=1}^k p_i^2 \quad (1)$$

Ensembles of decision trees are known to achieve state-of-the-art performance on numerous supervised learning problems as demonstrated in [103].

The RFC is used here as a method for approximating discrete-value target functions, in which the learned function is represented by a collection of randomly generated decision trees. The randomness is introduced via bootstrapping, referred to as bagging [104], where each decision tree is trained on a different subset of the training data whilst randomly subsampling the set of candidate splits at each node. For further details on the implementation of the algorithm refer to [102].

In contrast to bagging techniques like the RFC, in which trees are grown to their maximum extent in parallel, boosting makes use of trees with fewer splits [105]. Trees are built sequentially such that each subsequent tree aims to reduce the errors of the previous tree. Each decision tree learns from its predecessors and updates the residual errors [106]. XGBoost has an option to penalize complex models through both L1 and L2 regularization and thus preventing overfitting. Additionally, it can also deal with sparse dataset and can make use of multiple cores on the CPU, accelerating the training process.

The above-mentioned algorithms require careful hyperparameter tuning. We adopt, instead of the common grid search, a random search approach where a random uniform distribution was considered for each algorithm's hyperparameters. Our choice for selecting such tuning technique is motivated by the fact that empirically and theoretically randomly chosen trials, no matter the distribution they are chosen from, are more efficient for hyperparameter optimisation than trials on a grid [107]. In addition, we couple the randomised grid search with a Stratified Cross-Validation (SKF) technique in order to accommodate for the high imbalance in the two classes – a low number of *failure* instances compared to *no-failure instances*. The SKF incorporates folds that are made by preserving the percentage of samples for each class and thus allowing the algorithm to train on balanced folds in order to prevent overfitting on one of the two classes.

VI. RESULTS

The following section describes and examines the results based on a BHA memory dataset set provided for this research.

A. MODEL ACCURACY

As prior discussed, various data is collected during drilling containing information regarding the formation, tool health and event logs. For the purpose of this study, memory data and field data (number of attempts and mission status) has been aggregated. The data was collected following the tool's arrival in a maintenance workshop after a mission. Memory data was collected after 208 missions over a 6-month period. All the missions are from a specific type of BHA. Out of 208 missions, 189 missions were recorded for one customer. Further 19 mission were recorded for another customer. BHA tool

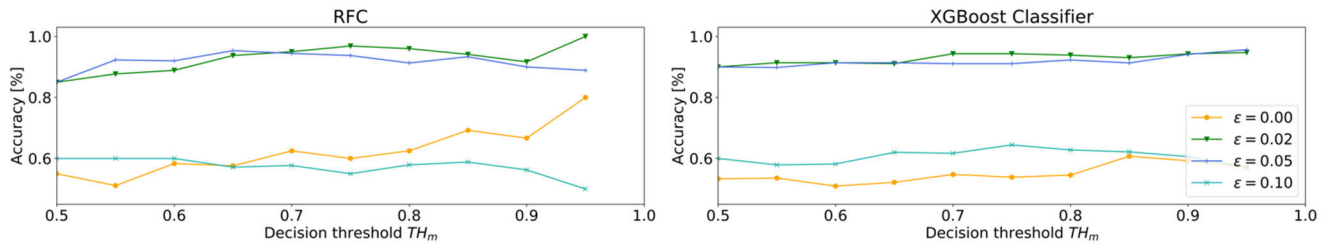


FIGURE 10. Accuracy score depending on decision threshold TH_m for RFC and XGBoost Classifier.

health data from the first customer was used to train the model. Tool health data from the second customer was used to validate the models.

All post run data and field data has been post-processed. Post-processing of the post run data, i.e. the event log provides the number of attempts of various BHA components to successfully or unsuccessfully establish an internal communication link. This internal communication network is resembled by various nodes. An accumulation of unsuccessful attempts or delays in communication at these nodes indicates malfunctioning behaviour of the BHA-PCBA which we aim to predict. The aggregated BHA-PCBA dataset is split into a training dataset and a validation set. The training data is augmented using adversarial training. Various perturbation factors have been studied, namely the original training data ($\varepsilon = 0.00$) and the following augmented data sets $\varepsilon = 0.02$, $\varepsilon = 0.05$ and $\varepsilon = 0.10$. A visualization of the effects of augmentation is depicted using heatmaps can be found in the Appendix.

The RFC and XGBoost Classifier are trained in turn on each of the 4 training sets. The randomized grid search based hyperparameter selection for the RFC trained on the augmented dataset $\varepsilon = 0.02$ suggests 200 parallel trees (the number of estimators) with a maximum depth of 50 as optimal model parameters. Trained on the same dataset, the XGBoost Classifier uses 100 sequential trees with a maximum depth of 5 per tree. The results for the standard decision threshold $TH_m = 0.5$ are depicted in Table 3. With reference to the aforementioned table, one can see the XGBoost Classifier performing slightly better than the RFC. In fact, using perturbation factors of $\varepsilon = 0.02$ and $\varepsilon = 0.05$ we obtained an accuracy of 90 %. From our assessment an increase in perturbation above $\varepsilon = 0.05$ does not equate to an improvement in accuracy. On the contrary, the performance of the algorithms decreases. We hypothesise that high perturbation introduces spurious correlations between features which in turn introduces a correlation bias, i.e. causes instability in the decision tree based algorithms [108].

B. MAINTENANCE THRESHOLD INTERPRETATION

As downhole tool failures can be very costly, the operational and maintenance support provided by the BHA-PCBA CBM framework needs to be adjusted according to risk exposure of the operation. Hence, a more cautious prediction shifts the priority towards the mitigation of all BHA-PCBA failures

TABLE 3. Performance comparison of two machine learning algorithms using different scoring functions.

Classifier	Dataset	Accuracy	F1	Roc-Auc
RFC	$\varepsilon = 0.00$	0.55	0.47	0.59
	$\varepsilon = 0.02$	0.85	0.82	0.96
	$\varepsilon = 0.05$	0.85	0.83	0.94
	$\varepsilon = 0.10$	0.60	0.45	0.62
XGBoost	$\varepsilon = 0.00$	0.53	0.39	0.61
	$\varepsilon = 0.02$	0.90	0.89	0.96
	$\varepsilon = 0.10$	0.60	0.37	0.65

during drilling which comes at the cost of over-maintenance. Therefore, if the maintenance decision threshold TH_m is increased, the algorithms predictions are treated more conservative. The predictions for both classes are filtered according to the criterion explained in Section – V-C. All predicted probabilities below TH_m are discarded/ not considered and subsequently treated as suspensions. Fig. 10 depicts the model accuracy as TH_m increases. This trend can be observed in particular for the RFC Classifiers trained on the augmented sets $\varepsilon = 0.02$ and $\varepsilon = 0.05$.

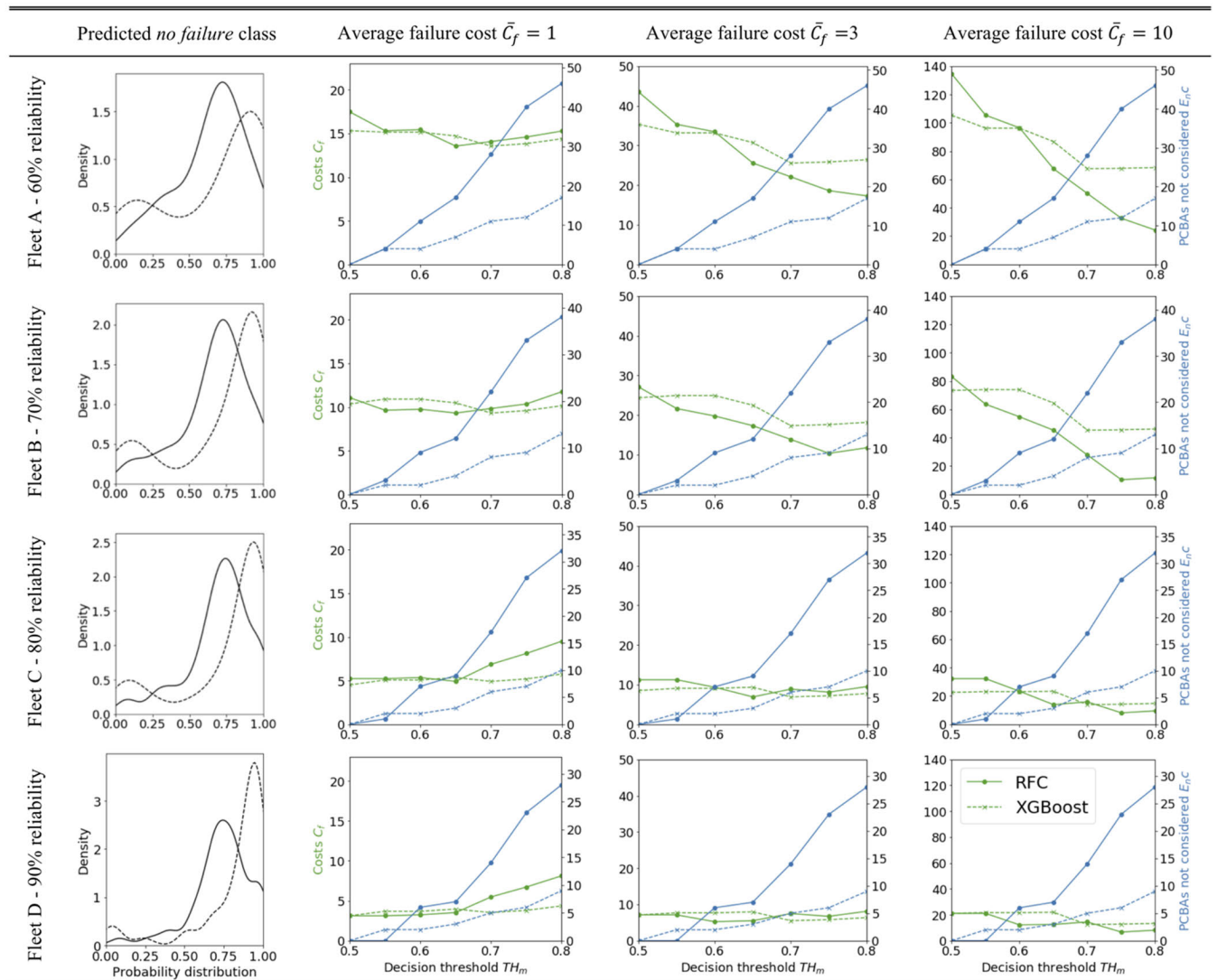
As the forecast certainty depends on the decision threshold TH_m and in turn on the separability of the predicted probabilities for the no-failure and failure class, the ROC-AUC score is used to select the best model for the consecutive analysis. Referring to Table 3, one can see that performance for the RFC and XGBoost Classifier is improved if trained on set $\varepsilon = 0.02$. Therefore, the following analysis is performed on the algorithms trained on set $\varepsilon = 0.02$.

Table 4 shows exemplary the results for maintenance decision making, using the proposed BHA-PCBA-CBM

TABLE 4. Maintenance support for BHA-PCBA for three scenarios with different levels of acceptable risk – results RFC $\varepsilon = 0.02$.

Operational Risk		Low	Medium	High
TH_m - no failure		0.5	0.6	0.7
BHA j - PCBA 1	0.82	●	●	●
BHA j - PCBA 2	0.68	●	●	×
BHA j - PCBA 3	0.95	●	●	●
BHA j - PCBA 4	0.59	●	×	×
...
BHA j - PCBA i	0.64	●	●	×
Run recommended		Yes	No	No

TABLE 5. Business case – Predictions based on models trained on the augmented dataset $\epsilon = 0.02$.



framework for RFC. Therefore, three scenarios of different operational risk are considered. In a high-risk scenario the operator might demand a higher prediction accuracy due to the increased severity of a failure. Under such circumstances an operator considers a BHA-PCBA only fit for rerun, if the algorithm predicts *no-failure* with a probability higher than $TH_m = 0.7$. If the model's predictions fall below the specified threshold TH_m , then the BHA-PCBA is suspended and maintenance is recommended. Contrarily, in a low risk application, e.g. $TH_m = 0.5$, the above predictions would have met the decision threshold criteria and the BHA-PCBA would be considered fit for a rerun.

In order to better understand how TH_m should be interpreted we explore the relevance of the proposed approach by an example of a maintenance business case. Maintenance cost is inevitably linked to tool design and its reliability, parts cost, labour cost, maintenance strategy and personnel competency.

In this example tool design and reliability are given for a fleet under consideration. Personal competency is not considered. A simplified cost model is introduced. This cost model accounts for parts costs (average PCBA replacement cost), labour costs (average cost of maintaining a tool without parts) and infield failure costs. The total costs of failure are calculated based on below equations:

$$C_f = \bar{C}_f F_{ni} \tag{2}$$

In (2) the total infield failure costs C_f are calculated by the average failure cost \bar{C}_f , depending on the severity of the failure, and the total number of failures F_{ni} which have not been correctly identified by the model.

$$C_m = (\bar{C}_p + \bar{C}_l) (F_i + F_{fi} + E_{nc}) \tag{3}$$

The total maintenance costs C_m are calculated according to (3). \bar{C}_p represent the average part cost and \bar{C}_l the average

labour cost; F_i the total number of correctly classified *failures* and F_{fi} the total number of falsely classified *failures*; E_{nc} is the total number of PCBAs not considered. As elaborated above, they are discarded because the prediction for a *failure* or *no-failure* lies below the decision threshold TH_m .

$$C_t = C_m + C_f \quad (4)$$

Subsequently the overall costs C_t are calculated as in (4). In Table 5 we consider 12 scenarios to evaluate the efficiency of the proposed approach. The scenarios are created by assuming three average failure costs $\bar{C}_f = 1, 3$ and 10 . Here 1 – a low impact failure – represents a scenario where a failure does not impact the business significantly and 10 – a high impact failure – represent a scenario where failure can lead to loss of business. *Fleet A, B, C* and *D* can be assumed to represent various reliability levels of a fleet. An outdated fleet can have a low level of reliability, e.g. *Fleet A*. Contrary, a lightly used, proactively maintained, younger fleet can have a high level of reliability, e.g. *Fleet D*. Fleet reliability for this example is modelled as the percentage of *no-failures* and *failures*; e.g. 90 % fleet reliability equates to 90 % *no-failures* and 10 % *failures* in the scrutinized test dataset. The reliability levels chosen here are not necessarily representative for a real fleet but rather serve as a mathematical exercise to select the optimal threshold TH_m in the context of the proposed BHA-PCBA CBM framework.

The results indicate that it is not necessary to have one superior approach for all scenarios. A variety of solutions should be deployed. Consequently, a choice is made based on the fleet reliability, available data, BDA infrastructure, and the business case. Various conclusions can be drawn from the analysis of the above stated business case. In general, the XGBoost Classifier returns a better distinction between *no-failure* and *failure* classes compared to RFC. However, for a high failure cost scenario, over-maintenance will further mitigate costs as the results for RFC indicate. If the failure costs increase relative to the maintenance costs, selecting a higher threshold TH_m can considerably reduce costs. The impact of a higher TH_m is heavily depended on the fleet reliability and decreases as the fleet reliability increases. Two root causes are identified for lower expenses at higher TH_m . Firstly, as the number of PCBAs increases for which predictions are not considered due to a non-meaningful forecast, the amount of misclassified entities declines. Simultaneously referring to Fig. 10 the model accuracy increases. Secondly, a misclassified failure tends to have a lower *no-failure* probability and therefore will rather be considered as a PCBA requiring maintenance if the threshold TH_m increases. Therefore, possible non identified infield failures can be mitigated. This trend gains significance as the fleet reliability decreases and failures become more costly. However, predictions for fleets with a high reliability and low impact failures indicate the best threshold being $TH_m = 0.5$.

VII. CONCLUSION

Industries are shifting from classical reliability paradigms towards BDA driven PHM to meet the requirements of increasingly complex systems. Likewise, as a review of relevant literature indicates, that the oil and gas industry recognizes this trend and is adopting modern health management strategies by implementing the required digital and physical infrastructure. However, due to the intricate nature of downhole drilling systems and the dynamic operating environment coupled with a competitive market and prolonged tool design and development cycles, current drilling systems require retrofittable health management solutions. Therefore, modern BDA is a promising enabler to further improve on health management strategies for modern downhole tool generations. A goal of BDA based health management is to provide cost effective and reliable products and services.

This paper presents a thorough review of BDA health management strategies for downhole drilling tools. PCBAs are identified as one of the major critical subsystems in BHA systems due to their high failure rates and diverse failure modes. In this context, we identified one predominant failure cause as being the SOIC on the PCBA. The main failure mode mechanism is caused by cracks in the heel of wire bond interconnects due to their susceptibility to fatigue as a result of thermomechanical mismatch. Though determining failure precursors for individual electrical components is challenging, time intensive and costly. Therefore, we introduce a failure mode agnostic BDA driven health management framework to be deployed in-field and during AMO for maintenance optimization and operational support. We present an AI-pipeline, called BHA-PCBA CBM framework to estimate the probability of PCBA failures trained on readily available BHA memory data. To increase robustness to outliers and prevent overfitting, we augment the data in a first instance by introducing adversarial samples. Adversarial examples can be interpreted as a computationally efficient solution to introduce additional training data around the perturbation-neighbourhood ε of the observed training examples. Subsequently, we analyse the performance of two algorithms, RFC and XGBoost Classifier. We find that a perturbation value of $\varepsilon = 0.02$ or $\varepsilon = 0.05$ serves as the best augmentation subset to differentiate between *failures* and *no-failures* with a high accuracy of 90 %. Furthermore, increasing the class decision threshold can help to reduce costs in high risk applications. The selection of an algorithm and its parameters depend upon the business needs. A tailored solution can be selected based on the need to increase revenue (lower NPT, lower number of failures, higher reliability) or to improve margins (lower AMO costs). Moreover, the fleet health and reliability constitute as a central factor in algorithm and parameter selection.

This paper demonstrated the use of AI to support maintenance decision-making based on operational data. However, future work is required. In particular, as more data becomes available, we aim to improve algorithm robustness,

optimize the selection of the perturbation factor ε , and implement multiclass classification for failure mode distinction. Furthermore, we intend to improve the algorithms' confidence in a prediction by implementing re-calibration methods such as isotonic regression.

APPENDIX

See Fig. 11.

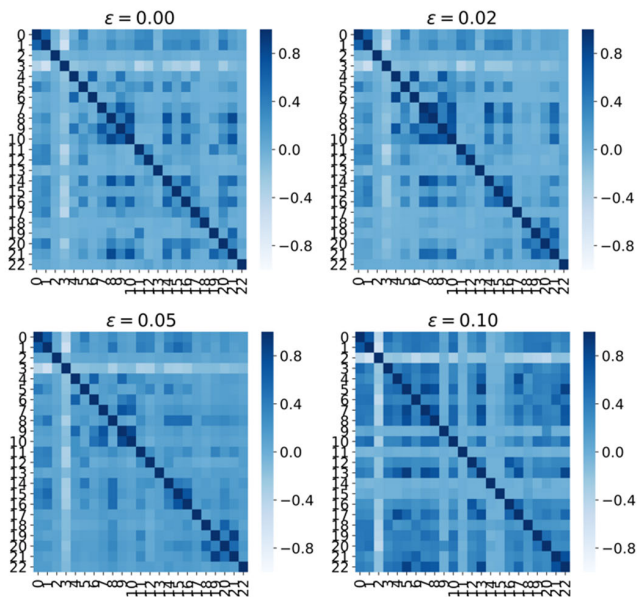


FIGURE 11. The correlation heatmap shows the correlation of each feature pair. The original data $\varepsilon = 0.00$ (top-left) and the augmented datasets are depicted.

REFERENCES

- [1] E. Sendich, *International Energy Outlook 2019 with projections to 2050*. Washington, DC, USA: U.S. Energy Information Administration, 2019.
- [2] BP Energy Economics, *BP Energy Outlook 2019 Edition*. London, U.K.: BP, 2019.
- [3] *World Energy Outlook 2019*. OECD, Paris, France, 2019. [Online]. Available: <https://www.iea.org/reports/world-energy-outlook-2019>
- [4] *Oil 2018: Analysis and Forecasts to 2023*. OECD, Paris, France, 2018. [Online]. Available: <https://www.iea.org/reports/oil-2018>
- [5] *Global Gas & LNG Outlook to 2035*, McKinsey, Bengaluru, Karnataka, 2018.
- [6] D. Calvetti, *Oil & Gas Industry: 2019 Trends*. Buenos Aires, Argentina: KPMG Argentina, 2019.
- [7] G. Biscardini, "Oil and gas trends 2019—Building growth strategies on shifting sands," in *Proc. 22nd Annu. Global CEO Surv. Trends*, London, U.K., 2019, p. 22.
- [8] K. Carter-Journet, A. A. Kale, T. Falgout, and L. Heuermann-Kuehn, "Drilling optimization: Utilizing lifetime prediction to improve drilling performance and reduce downtime," in *Proc. SPE Deepwater Drilling Completions Conf.*, 2014, pp. 1–14, doi: [10.2118/170270-MS](https://doi.org/10.2118/170270-MS).
- [9] I. Ahmad, O. Akimov, P. Bond, P. Cairns, N. Eide, T. Gregg, T. Heimes, A. Nwosu, and F. Wiese, "Reliable technology for drilling operations in a high-pressure/high-temperature environment," in *Proc. IADC/SPE Drilling Conf. Exhib.*, 2014, pp. 1–16, doi: [10.2118/167972-MS](https://doi.org/10.2118/167972-MS).
- [10] J. Brehme and T. Travis, "Total BHA Reliability—An improved method to measure success," in *Proc. IADC/SPE Drilling Conf.*, 2008, pp. 1–10, doi: [10.2118/112644-MS](https://doi.org/10.2118/112644-MS).
- [11] H. Reckmann, P. Jogi, F. T. Kpetehoto, S. Chandrasekaran, and J. D. Macpherson, "MWD failure rates due to drilling dynamics," in *Proc. IADC/SPE Drilling Conf. Exhib.*, 2010, pp. 1–10, doi: [10.2118/127413-MS](https://doi.org/10.2118/127413-MS).
- [12] S. Zhan, J. Rodiek, L. E. Heuermann-Kuehn, and J. Baumann, "Prognostics health management for a directional drilling system," in *Proc. Prognostics Syst. Health Manage. Conf.*, May 2011, pp. 1–7, doi: [10.1109/phm.2011.5939543](https://doi.org/10.1109/phm.2011.5939543).
- [13] W. Aldred, "Managing drilling risk," *Oilfield Rev.*, vol. 11, no. 2, pp. 2–19, 1999.
- [14] V. D. Nguyen, "A review: Prognostics and health management in automotive and aerospace," *Int. J. Prognostics Health Manage.*, vol. 10, pp. 11–14, May 2019.
- [15] F. Dinmohammadi, D. Flynn, C. Bailey, M. Pecht, C. Yin, P. Rajaguru, and V. Robu, "Predicting damage and life expectancy of subsea power cables in offshore renewable energy applications," *IEEE Access*, vol. 7, pp. 54658–54669, 2019, doi: [10.1109/access.2019.2911260](https://doi.org/10.1109/access.2019.2911260).
- [16] W. Tang, D. Flynn, K. Brown, R. Valentin, and X. Zhao, "The design of a fusion prognostic model and health management system for subsea power cables," in *Proc. OCEANS MTS/IEEE SEATTLE*, Oct. 2019, pp. 1–6, doi: [10.23919/oceans40490.2019.8962816](https://doi.org/10.23919/oceans40490.2019.8962816).
- [17] A. Stetco, F. Dinmohammadi, X. Zhao, V. Robu, D. Flynn, M. Barnes, J. Keane, and G. Nenadic, "Machine learning methods for wind turbine condition monitoring: A review," *Renew. Energy*, vol. 133, pp. 620–635, Apr. 2019, doi: [10.1016/j.renene.2018.10.047](https://doi.org/10.1016/j.renene.2018.10.047).
- [18] H. Devold, T. Graven, and S. O. Halvorsrá, "Digitalization of oil and gas facilities reduce cost and improve maintenance operations," in *Proc. Offshore Technol. Conf.*, Houston, TX, USA, 2017, pp. 1–16, doi: [10.4043/27788-MS](https://doi.org/10.4043/27788-MS).
- [19] F. Laborie, M. Biermann, A. Camp, and M. Sivertsen, "Prerequisites for performance-based contracts: Digitalization and data sharing changes business models in E&P supply chain," in *Proc. SPE Norway One Day Seminar*, Bergen, Norway, 2019, pp. 1–7, doi: [10.2118/195602-MS](https://doi.org/10.2118/195602-MS).
- [20] S. O. Settemsdal, "Highly scalable digitalization platform for oil and gas operations enables total asset visibility for predictive, condition-based fleet management across single and multiple sites," in *Proc. Abu Dhabi Int. Petroleum Exhib. Conf.*, Abu Dhabi, United Arab Emirates, 2019, pp. 1–11, doi: [10.2118/197820-MS](https://doi.org/10.2118/197820-MS).
- [21] D. Kwon, M. H. Azarian, and M. Pecht, "Remaining-life prediction of solder joints using RF impedance analysis and Gaussian process regression," *IEEE Trans. Compon., Packag., Manuf. Technol.*, vol. 5, no. 11, pp. 1602–1609, Nov. 2015, pp. 1602–1609, doi: [10.1109/tcpmt.2015.2477098](https://doi.org/10.1109/tcpmt.2015.2477098).
- [22] S. Kumar, N. M. Vichare, E. Dolev, and M. Pecht, "A health indicator method for degradation detection of electronic products," *Microelectron. Rel.*, vol. 52, no. 2, pp. 439–445, Feb. 2012, doi: [10.1016/j.microrel.2011.09.030](https://doi.org/10.1016/j.microrel.2011.09.030).
- [23] Z. Liu, Z. Jia, C.-M. Vong, S. Bu, J. Han, and X. Tang, "Capturing high-discriminative fault features for electronics-rich analog system via deep learning," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1213–1226, Jun. 2017, doi: [10.1109/tii.2017.2690940](https://doi.org/10.1109/tii.2017.2690940).
- [24] K. Moir, O. Niculita, and W. Milligan, "Prognostics and health management in the oil & gas industry—a step change," in *Proc. PHM Soc. Eur. Conf.*, vol. 4, no. 1, 2018, pp. 1–18.
- [25] S. Menand, C. Simon, L. Gerbaud, M. Ben Hamida, H. J. Denoix, B. Cuillier, J. Gaombalet, Y. Amghar, and H. Sinarde, "PDC bit steerability modeling and testing for Push-the-bit and Point-the-bit RSS," in *Proc. IADC/SPE Drilling Conf. Exhib.*, 2012, pp. 1–12, doi: [10.2118/151283-MS](https://doi.org/10.2118/151283-MS).
- [26] S. M. Mwachaka, A. Wu, and Q. Fu, "A review of mud pulse telemetry signal impairments modeling and suppression methods," *J. Petroleum Exploration Prod. Technol.*, vol. 9, no. 1, pp. 779–792, Mar. 2019, doi: [10.1007/s13202-018-0483-y](https://doi.org/10.1007/s13202-018-0483-y).
- [27] R. Beckwith, "Downhole electronic components: Achieving performance reliability," *J. Petroleum Technol.*, vol. 65, no. 08, pp. 42–57, Aug. 2013, doi: [10.2118/0813-0042-JPT](https://doi.org/10.2118/0813-0042-JPT).
- [28] K. Bybee, "Reliable electronics for high-temperature downhole applications," *J. Petroleum Technol.*, vol. 52, no. 7, pp. 56–57, Jul. 2000, doi: [10.2118/0700-0056-jpt](https://doi.org/10.2118/0700-0056-jpt).
- [29] S. Zhan and J. Zhao, "Advanced prognostic technique for improving the drilling performance of downhole tools," in *Proc. 1st Int. Conf. Rel. Syst. Eng. (ICRSE)*, Oct. 2015, pp. 1–9, doi: [10.1109/icrse.2015.7366418](https://doi.org/10.1109/icrse.2015.7366418).
- [30] P. S. Chauhan, A. Choubey, Z. Zhong, and M. Pecht, "Copper wire bonding," in *Copper Wire Bonding*. New York, NY, USA: Springer, 2014, pp. 1–9.
- [31] M. Pecht, "Prognostics and health management of electronics," in *Encyclopedia of Structural Health Monitoring*. Hoboken, NJ, USA: Wiley, 2009.

- [32] M. A. K. Malik, "Reliable preventive maintenance scheduling," *AIIE Trans.*, vol. 11, no. 3, pp. 221–228, Sep. 1979, doi: [10.1080/0569557908974463](https://doi.org/10.1080/0569557908974463).
- [33] P. A. Tobias and D. Trindade, *Applied Reliability*. Boca Raton, FL, USA: CRC Press, 2011.
- [34] F. Ng, "Recommendations for MWD tool reliability statistics," in *Proc. SPE Annu. Tech. Conf. Exhib.*, doi: [10.2523/19862-MS](https://doi.org/10.2523/19862-MS).
- [35] P. Korvesis, "Machine learning for predictive maintenance in aviation," Ph.D. dissertation, École Polytechn., University Paris-Saclay, Essonne, France, 2017.
- [36] R. Prytz, "Machine learning methods for vehicle predictive maintenance using off-board and on-board data," Ph.D. dissertation, School Inf. Technol., Halmstad University Press, New York, NY, USA, 2014.
- [37] Y. Ren, N. Wang, J. Jiang, J. Zhu, G. Song, and X. Chen, "The application of downhole vibration factor in drilling tool reliability big data Analytics—A review," *ASCE-ASME J. Risk Uncert. Engrg. Sys B, Mech. Engrg.*, vol. 5, no. 1, Mar. 2019, Art. no. 010801, doi: [10.1115/1.4040407](https://doi.org/10.1115/1.4040407).
- [38] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, and D. Siegel, "Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications," *Mech. Syst. Signal Process.*, vol. 42, nos. 1–2, pp. 314–334, Jan. 2014, doi: [10.1016/j.ymssp.2013.06.004](https://doi.org/10.1016/j.ymssp.2013.06.004).
- [39] H. Meng and Y.-F. Li, "A review on prognostics and health management (PHM) methods of lithium-ion batteries," *Renew. Sustain. Energy Rev.*, vol. 116, Dec. 2019, Art. no. 109405, doi: [10.1016/j.rser.2019.109405](https://doi.org/10.1016/j.rser.2019.109405).
- [40] K. Goebel, M. J. Daigle, A. Saxena, I. Roychoudhury, S. Sankararaman, and J. R. Celaya, "Prognostics: The science of making predictions," Tech. Rep., 2017.
- [41] S. Uckun, K. Goebel, and P. J. F. Lucas, "Standardizing research methods for prognostics," in *Proc. Int. Conf. Prognostics Health Manage.*, Oct. 2008, pp. 1–10, doi: [10.1109/phm.2008.4711437](https://doi.org/10.1109/phm.2008.4711437).
- [42] K. Javed, R. Gouriveau, and N. Zerhouni, "State of the art and taxonomy of prognostics approaches, trends of prognostics applications and open issues towards maturity at different technology readiness levels," *Mech. Syst. Signal Process.*, vol. 94, pp. 214–236, Sep. 2017, doi: [10.1016/j.ymssp.2017.01.050](https://doi.org/10.1016/j.ymssp.2017.01.050).
- [43] I. Roychoudhury, A. Saxena, J. R. Celaya, and K. Goebel, "Distilling the verification process for prognostics algorithms," in *Proc. Annu. Conf. Prognostics Health Manage. Soc.*, New Orleans, LA, USA, Oct. 2013.
- [44] S. Yang, D. Xiang, A. Bryant, P. Mawby, L. Ran, and P. Tavner, "Condition monitoring for device reliability in power electronic converters: A review," *IEEE Trans. Power Electron.*, vol. 25, no. 11, pp. 2734–2752, Nov. 2010, doi: [10.1109/tpe.2010.2049377](https://doi.org/10.1109/tpe.2010.2049377).
- [45] H. M. Elattar, H. K. Elminir, and A. M. Riad, "Prognostics: A literature review," *Complex Intell. Syst.*, vol. 2, no. 2, pp. 125–154, Jun. 2016, doi: [10.1007/s40747-016-0019-3](https://doi.org/10.1007/s40747-016-0019-3).
- [46] O. E. Dragomir, R. Gouriveau, N. Zerhouni, and F. Dragomir, "Framework for a distributed and hybrid prognostic system," *IFAC Proc. Volumes*, vol. 40, no. 18, pp. 431–436, Sep. 2007, doi: [10.3182/20070927-4-ro-3905.00072](https://doi.org/10.3182/20070927-4-ro-3905.00072).
- [47] *IEEE Smart Grid Big Data Analytics—Machine Learning and Artificial Intelligence in the Smart Grid Working Group, Big Data Analytics in the Smart Grid*, IEEE Smart Grid, Piscataway, NJ, USA, 2017.
- [48] S. Sagiroglu, R. Terzi, Y. Canbay, and I. Colak, "Big data issues in smart grid systems," in *Proc. IEEE Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Nov. 2016, pp. 1007–1012, doi: [10.1109/icrera.2016.7884486](https://doi.org/10.1109/icrera.2016.7884486).
- [49] S. Zhan, I. Ahmad, L. E. Heuermann-Kuehn, and J. Baumann, "Integrated PoF and CBM strategies for improving electronics reliability performance of downhole MWD and LWD tools," in *Proc. SPE Annu. Tech. Conf. Exhib.*, 2010, pp. 1–9, doi: [10.2118/132665-MS](https://doi.org/10.2118/132665-MS).
- [50] Google. Accessed: Mar. 22, 2020. [Online]. Available: <https://scholar.google.com/>
- [51] OnePetro. Accessed: Mar. 22, 2020. [Online]. Available: <https://www.onepetro.org/>
- [52] Elsevier. Accessed: Mar. 22, 2020. [Online]. Available: <https://www.elsevier.com/>
- [53] Scopus. Accessed: Mar. 22, 2020. [Online]. Available: <https://www.scopus.com/>
- [54] Web-of-Knowledge. Accessed: Mar. 22, 2020. [Online]. Available: <https://www.webofknowledge.com/>
- [55] B. S. Bageri, F. A. Anifowose, and A. Abdulaheem, "Artificial intelligence based estimation of water saturation using electrical measurements data in a carbonate reservoir," in *Proc. SPE Middle East Oil Gas Show Conf.*, 2015, pp. 1–17, doi: [10.2118/172564-MS](https://doi.org/10.2118/172564-MS).
- [56] T. D. Jobe, A. Research Center, E. Vital-Brazil, M. Khait, I. Research, and D. University of Technology, "Geological feature prediction using image-based machine learning," *Petrophysics SPWLA J. Formation Eval. Reservoir Description*, vol. 59, no. 6, pp. 750–760, 2018.
- [57] D. Ferraretti, G. Gamberoni, and E. Lamma, "Unsupervised and supervised learning in cascade for petroleum geology," *Expert Syst. Appl.*, vol. 39, no. 10, pp. 9504–9514, Aug. 2012, doi: [10.1016/j.eswa.2012.02.104](https://doi.org/10.1016/j.eswa.2012.02.104).
- [58] C. Chan, "An expert decision support system for monitoring and diagnosis of petroleum production and separation processes," *Expert Syst. Appl.*, vol. 29, no. 1, pp. 131–143, Jul. 2005, doi: [10.1016/j.eswa.2005.01.009](https://doi.org/10.1016/j.eswa.2005.01.009).
- [59] C. I. Noshi, A. I. Assem, and J. J. Schubert, "The role of big data analytics in exploration and production: A review of benefits and applications," in *Proc. SPE Int. Heavy Oil Conf. Exhib.*, 2018, pp. 1–14, doi: [10.2118/193776-MS](https://doi.org/10.2118/193776-MS).
- [60] J. Xiao and X. Sun, "Big data analytics drive EOR projects," in *Proc. SPE Offshore Eur. Conf. Exhib.*, 2017, pp. 1–9, doi: [10.2118/186159-MS](https://doi.org/10.2118/186159-MS).
- [61] M. Neuroth, P. MacConnell, F. Stronach, and P. Vamplew, "Improved modelling and control of oil and gas transport facility operations using artificial intelligence," in *Applications and Innovations in Intelligent Systems*. Cham, Switzerland: Springer, 2000, pp. 119–136.
- [62] S. E. Z. Lashari, A. Takbiri-Borujeni, E. Fathi, T. Sun, R. Rahmani, and M. Khazaeli, "Drilling performance monitoring and optimization: A data-driven approach," *J. Petroleum Exploration Prod. Technol.*, vol. 9, no. 4, pp. 2747–2756, Dec. 2019, doi: [10.1007/s13202-019-0657-2](https://doi.org/10.1007/s13202-019-0657-2).
- [63] J. Han, Y. Sun, and S. Zhang, "A data driven approach of ROP prediction and drilling performance estimation," in *Proc. Int. Petroleum Technol. Conf.*, 2019, pp. 1–5, doi: [10.2523/19430-MS](https://doi.org/10.2523/19430-MS).
- [64] M. Rashidi, A. Asadi, A. Abbasi, and E. Asadi, "Machine learning's application in estimation of the drilling rate of penetration—A case study from a wellbore in Iran," in *Proc. ARMA-CUPB Geothermal Int. Conf.*, 2019, pp. 1–4.
- [65] C. I. Noshi and J. J. Schubert, "Application of data science and machine learning algorithms for ROP prediction: Turning data into knowledge," in *Proc. Offshore Technol. Conf.*, 2019, pp. 1–10, doi: [10.4043/29288-MS](https://doi.org/10.4043/29288-MS).
- [66] K. Singh, S. S. Yalamarty, M. Kamyab, and C. Cheatham, "Cloud-based ROP prediction and optimization in real-time using supervised machine learning," in *Proc. 7th Unconventional Resour. Technol. Conf.*, 2019, pp. 3067–3078, doi: [10.15530/urtec-2019-343](https://doi.org/10.15530/urtec-2019-343).
- [67] C. Hegde, C. Soares, and K. E. Gray, "Rate of penetration (ROP) modeling using hybrid models: D eterministic and machine learning," in *Proc. Unconventional Resour. Technol. Conf.*, Houston, TX, USA, Jul. 2018, pp. 3220–3238, doi: [10.15530/urtec-2018-2896522](https://doi.org/10.15530/urtec-2018-2896522).
- [68] C. Hegde, S. Wallace, and K. Gray, "Using trees, bagging, and random forests to predict rate of penetration during drilling," in *Proc. SPE Middle East Intell. Oil Gas Conf. Exhib.*, 2015, pp. 1–12, doi: [10.2118/176792-MS](https://doi.org/10.2118/176792-MS).
- [69] C. Hegde, M. Pyrcz, H. Millwater, H. Daigle, and K. Gray, "Fully coupled end-to-end drilling optimization model using machine learning," *J. Petroleum Sci. Eng.*, vol. 186, Mar. 2020, Art. no. 106681, doi: [10.1016/j.petrol.2019.106681](https://doi.org/10.1016/j.petrol.2019.106681).
- [70] S. Sherif, O. Adenike, E. Obehi, A. Funso, and B. Eyiutoyo, "Predictive data analytics for effective electric submersible pump management," in *Proc. SPE Nigeria Annu. Int. Conf. Exhib.*, 2019, pp. 1–13, doi: [10.2118/198759-MS](https://doi.org/10.2118/198759-MS).
- [71] M. Abdelaziz, R. Lastra, and J. J. Xiao, "ESP data analytics: Predicting failures for improved production performance," in *Proc. Abu Dhabi Int. Petroleum Exhib. Conf.*, 2017, pp. 1–17, doi: [10.2118/188513-MS](https://doi.org/10.2118/188513-MS).
- [72] D. Guo, C. S. Raghavendra, K.-T. Yao, M. Harding, A. Anvar, and A. Patel, "Data driven approach to failure prediction for electrical submersible pump systems," in *Proc. SPE Western Regional Meeting*, 2015, pp. 1–6, doi: [10.2118/174062-MS](https://doi.org/10.2118/174062-MS).
- [73] X. Wang, Y. He, F. Li, X. Dou, Z. Wang, H. Xu, and L. Fu, "A working condition diagnosis model of sucker rod pumping wells based on big data deep learning," in *Proc. Int. Petroleum Technol. Conf.*, 2019, pp. 1–10, doi: [10.2523/iptc-19242-MS](https://doi.org/10.2523/iptc-19242-MS).
- [74] P. Bangert and S. Sharaf, "Predictive maintenance for rod pumps," in *Proc. SPE Western Regional Meeting*, 2019, pp. 1–12, doi: [10.2118/195295-MS](https://doi.org/10.2118/195295-MS).
- [75] S. Liu, C. S. Raghavendra, Y. Liu, K.-T. Yao, O. Balogun, L. Olabinjo, R. Soma, J. Ivanhoe, B. Smith, B. B. Seren, T. L. Lenz, D. C. C. Gunasekaran, and I. Ershaghi, "Automatic early fault detection for rod pump systems," in *Proc. SPE Annu. Tech. Conf. Exhib.*, 2011, pp. 1–11, doi: [10.2118/146038-MS](https://doi.org/10.2118/146038-MS).

- [76] C. S. Raghavenda, Y. Liu, A. Wu, L. Olabinjo, O. Balogun, I. Ershaghi, J. Zheng, D. Guo, and K.-T. Yao, "Global model for failure prediction for rod pump artificial lift systems," in *Proc. SPE Western Regional AAPG Pacific Sect. Meeting Joint Tech. Conf.*, 2013, pp. 1–10, doi: [10.2118/165374-MS](https://doi.org/10.2118/165374-MS).
- [77] D. K. Gold and T. Treiber, "Implementation of automated expert diagnostics to provide enhanced rod pump surveillance at S. Belridge field, CA," in *Proc. SPE Annu. Tech. Conf. Exhib.*, 2001, pp. 1–10, doi: [10.2118/71527-MS](https://doi.org/10.2118/71527-MS).
- [78] S. Gupta, L. Saputelli, and M. Nikolaou, "Applying big data analytics to detect, diagnose, and prevent impending failures in electric submersible pumps," in *Proc. SPE Annu. Tech. Conf. Exhib.*, 2016, pp. 1–15, doi: [10.2118/181510-MS](https://doi.org/10.2118/181510-MS).
- [79] E. R. Martinez, W. J. Moreno, V. J. Castillo, and J. A. Moreno, "Rod pumping expert system," in *Proc. Petroleum Comput. Conf.*, 1993, pp. 1–8, doi: [10.2118/26246-MS](https://doi.org/10.2118/26246-MS).
- [80] S. Cho, H.-B. Jun, J.-H. Shin, H.-J. Hwang, and C. Ha, "A study on the development of prognosis system for offshore plant equipment," in *Proc. 25th Int. Ocean Polar Eng. Conf.*, 2015, pp. 1–7.
- [81] P. Lu, H. Liu, C. Serratella, and X. Wang, "Assessment of data-driven, machine learning techniques for machinery prognostics of offshore assets," in *Proc. Offshore Technol. Conf.*, 2017, pp. 1–21, doi: [10.4043/27577-MS](https://doi.org/10.4043/27577-MS).
- [82] U. T. Tygesen, K. Worden, T. Rogers, G. Manson, and E. J. Cross, "State-of-the-art and future directions for predictive modelling of offshore structure dynamics using machine learning," in *Dynamics of Civil Structures*, vol. 2. New York, NY, USA: Springer, 2019, pp. 223–233.
- [83] W. Nash, T. Drummond, and N. Birbilis, "Deep learning AI for corrosion detection," in *Corrosion*. May 2019, pp. 1–11.
- [84] C. C. Ejimuda and C. M. Ejimuda, "Using deep learning and computer vision techniques to improve facility corrosion risk management systems," in *Proc. SPE Western Regional Meeting*, 2018, pp. 1–9, doi: [10.2118/190036-MS](https://doi.org/10.2118/190036-MS).
- [85] D. R. Garvey, M. John, and J. Baumann, "Nonparametric life consumption modeling of high end drilling tools," in *Proc. Annu. Rel. Maintainability Symp. (RAMS)*, Jan. 2010, pp. 1–6, doi: [10.1109/rams.2010.5448034](https://doi.org/10.1109/rams.2010.5448034).
- [86] H. Reckmann, A. Hohl, H. Oueslati, and O. Akimov, "Step change in BHA reliability and performance due to utilization of downhole drilling dynamics services," in *Proc. IADC/SPE Asia Pacific Drilling Technol. Conf. Exhib.*, 2018, pp. 1–19, doi: [10.2118/191096-MS](https://doi.org/10.2118/191096-MS).
- [87] B. Alotaibi, W. B. Contreras Otlavora, and M. S. Nefai, "Bottom-hole assembly management system (BHAMS)," in *Proc. SPE Saudi Arabia Sect. Tech. Symp. Exhib.*, 2014, pp. 1–11, doi: [10.2118/172175-MS](https://doi.org/10.2118/172175-MS).
- [88] D. Garvey, J. Baumann, J. Lehr, and J. W. Hines, "Pattern recognition based remaining useful life estimation of bottom hole assembly tools," in *Proc. SPE/IADC Drilling Conf. Exhib.*, 2009, pp. 1–8, doi: [10.2118/118769-MS](https://doi.org/10.2118/118769-MS).
- [89] A. Lahmadi, L. Terrissa, and N. Zerhouni, "A data-driven method for estimating the remaining useful life of a composite drill pipe," in *Proc. Int. Conf. Adv. Syst. Electric Technol. (IC_ASET)*, Mar. 2018, pp. 192–195, doi: [10.1109/aset.2018.8379857](https://doi.org/10.1109/aset.2018.8379857).
- [90] S. Zhan and I. Ahmad, "Real-time prognostic on downhole printed circuit board assembly of measurement-while-drilling/logging-while-drilling," U.S. Patent 9 051 814 B2, 2015.
- [91] A. Mosallam, L. Laval, F. B. Youssef, J. Fulton, and D. Viassolo, "Data-driven fault detection for neutron generator subsystem in multifunction logging-while-drilling service," in *Proc. PHM Soc. Eur. Conf.*, 2018, pp. 1–4.
- [92] A. Kale, D. Zhang, A. David, L. Heuermann-Kuehn, and O. Fanini, "Methodology for optimizing operational performance and life management of drilling systems using real time-data and predictive analytics," in *Proc. SPE Digit. Energy Conf. Exhib.*, 2015, pp. 1–16, doi: [10.2118/173419-MS](https://doi.org/10.2118/173419-MS).
- [93] K. Carter-Journet, A. Kale, D. Zhang, E. Pradeep, T. Falgout, and L. Heuermann-Kuehn, "Estimating probability of failure for drilling tools with life prediction," in *Proc. SPE Asia Pacific Oil Gas Conf. Exhib.*, 2014, pp. 1–17, doi: [10.2118/171517-MS](https://doi.org/10.2118/171517-MS).
- [94] A. A. Kale, K. Carter-Journet, T. A. Falgout, L. E. Heuermann-Kuehn, and D. Zurcher, *A Probabilistic Approach for Reliability and Life Prediction of Electronics in Drilling and Valuation Tools*. Houston, TX, USA: Baker Hughes, 2014.
- [95] *IEEE Standard Framework for Prognostics and Health Management of Electronic Systems*, 17431645 IEEE, Standard 1856-2017 Dec. 2017.
- [96] C. Ferri, J. Hernández-Orallo, and R. Modroui, "An experimental comparison of performance measures for classification," *Pattern Recognit. Lett.*, vol. 30, no. 1, pp. 27–38, Jan. 2009, doi: [10.1016/j.patrec.2008.08.010](https://doi.org/10.1016/j.patrec.2008.08.010).
- [97] I. J. Goodfellow, J. Shlens, and C. Szegedy, "Explaining and harnessing adversarial examples," 2014, *arXiv:1412.6572*. [Online]. Available: <http://arxiv.org/abs/1412.6572>
- [98] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus, "Intriguing properties of neural networks," 2013, *arXiv:1312.6199*. [Online]. Available: <http://arxiv.org/abs/1312.6199>
- [99] A. E. Hoerl and R. W. Kennard, "Ridge regression: Biased estimation for nonorthogonal problems," *Technometrics*, vol. 12, no. 1, pp. 55–67, 1970, doi: [10.2307/1271436](https://doi.org/10.2307/1271436).
- [100] C. E. Rasmussen, "Gaussian processes in machine learning," in *Summer School Machine Learning*. Cham, Switzerland: Springer, 2003, pp. 63–71.
- [101] T. G. Dietterich, "Ensemble methods in machine learning," in *Proc. Int. Workshop Multiple Classifier Syst.*, 2000, pp. 1–15, doi: [10.1007/3-540-45014-9_1](https://doi.org/10.1007/3-540-45014-9_1).
- [102] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.
- [103] R. Caruana and A. Niculescu-Mizil, "An empirical comparison of supervised learning algorithms," in *Proc. 23rd Int. Conf. Mach. Learn. (ICML)*, 2006, pp. 161–168, doi: [10.1145/1143844.1143865](https://doi.org/10.1145/1143844.1143865).
- [104] L. Breiman, "Bagging predictors," *Mach. Learn.*, vol. 24, no. 2, pp. 123–140, Aug. 1996.
- [105] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2016, pp. 785–794, doi: [10.1145/2939672.2939785](https://doi.org/10.1145/2939672.2939785).
- [106] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *J. Comput. Syst. Sci.*, vol. 55, no. 1, pp. 119–139, Aug. 1997, doi: [10.1006/jcss.1997.1504](https://doi.org/10.1006/jcss.1997.1504).
- [107] J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," *J. Mach. Learn. Res.*, vol. 13, pp. 281–305, Feb. 2012.
- [108] L. Toloäi and T. Lengauer, "Classification with correlated features: Unreliability of feature ranking and solutions," *Bioinformatics*, vol. 27, no. 14, pp. 1986–1994, Jul. 2011, doi: [10.1093/bioinformatics/btr300](https://doi.org/10.1093/bioinformatics/btr300).



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