3-1-2019

The Application of Downhole Vibration Factor in Drilling Tool Reliability Big Data Analytics - A Review

Yali Ren
Georgia Institute of Technology

Ning Wang
University of Houston

Jinwei Jiang
University of Houston

Junxiao Zhu
University of Houston

Gangbing Song
University of Houston

See next page for additional authors

Authors
Yali Ren, Ning Wang, Jinwei Jiang, Junxiao Zhu, Gangbing Song, and Xuemin Chen

Yali Ren
Department of Computer Science,
Georgia Institute of Technology,
North Avenue,
Atlanta, GA 30332
e-mail: yren78@gatech.edu

Ning Wang
Department of Electrical and
Computer Engineering,
University of Houston,
Engineering Bldg 1,
4726 Calhou Road,
Houston, TX 77204
e-mail: nwang@uh.edu

Jinwei Jiang
Department of Mechanical Engineering,
University of Houston,
Engineering Bldg 1,
4726 Calhoun Road,
Houston, TX 77204
e-mail: jjiang7@uh.edu

Junxiao Zhu
Department of Mechanical Engineering,
University of Houston,
Engineering Bldg 1,
4726 Calhoun Road,
Houston, TX 77204
e-mail: jzhu10@uh.edu

Gangbing Song[1]
Department of Mechanical Engineering,
University of Houston,
Engineering Building 2,
4726 Calhoun Road,
Houston, TX 77204
e-mail: gsong@uh.edu

Xuemin Chen
Department of Engineering,
Texas Southern University, Houston,
Leonard H. O. Spearman Technology Building,
3100 Cleburne Avenue,
Houston, TX 77004
e-mail: chenxm@tsu.edu

The Application of Downhole Vibration Factor in Drilling Tool Reliability Big Data Analytics—A Review

In the challenging downhole environment, drilling tools are normally subject to high temperature, severe vibration, and other harsh operation conditions. The drilling activities generate massive field data, namely field reliability big data (FRBD), which includes downhole operation, environment, failure, degradation, and dynamic data. Field reliability big data has large size, high variety, and extreme complexity. FRBD presents abundant opportunities and great challenges for drilling tool reliability analytics. Consequently, as one of the key factors to affect drilling tool reliability, the downhole vibration factor plays an essential role in the reliability analytics based on FRBD. This paper reviews the important parameters of downhole drilling operations, examines the mode, physical and reliability impact of downhole vibration, and presents the features of reliability big data analytics. Specifically, this paper explores the application of vibration factor in reliability big data analytics covering tool lifetime/failure prediction, prognostics/diagnostics, condition monitoring (CM), and maintenance planning and optimization. Furthermore, the authors highlight the future research about how to better apply the downhole vibration factor in reliability big data analytics to further improve tool reliability and optimize maintenance planning. [DOI: 10.1115/1.4040407]

Keywords: downhole drilling vibration, field reliability big data (FRBD), lifetime prediction, prognostics/diagnostics, condition-based maintenance

1 Introduction

With drilling technology advancement, oil and gas drilling activities more frequently occur in the rock layer of thousands of meters depth and severe downhole conditions [1]. The challenging downhole environment includes temperature exceeding 200 °C, shock and vibration levels surpassing 15 g, pressure beyond 207 MPa, strong abrasive formation, horizontal path instead of conventional vertical bore hole, and others [2,3]. Figure 1 illustrates several typical features of drilling activities. The harsh downhole conditions are around or beyond operating tools' design specification constraints, and severely damage even the sturdiest and most reliable components, such as printed circuit board

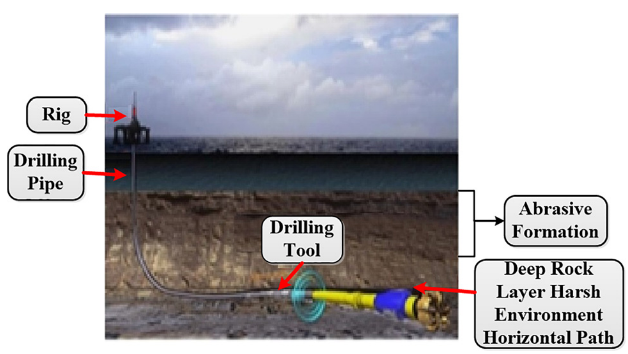

Fig. 1 Illustration of drilling activity [3]

[1]Corresponding author.
Manuscript received September 1, 2017; final manuscript received May 23, 2018; published online August 14, 2018. Assoc. Editor: Faisal Khan.

assemblies parts in logging-while-drilling (LWD) and measurement-while-drilling (MWD) tools [2,4,5]. This phenomenon leads to the increased tool failure rate, system downtime, nonproductive time, higher maintenance and repair costs, and lowered operation reliability for both drilling operators and service providers [3,4,6]. Consequently, the analysis, evaluation, and prediction of drilling tool failure and operation reliability in the complicated downhole conditions, as well as the methodology for optimizing maintenance plan and reducing lifecycle cost, has become an emerging research topic in reliability engineering field [2,4,7].

Drilling tool failure and operation reliability are affected by combination and interaction of multiple downhole operation, environment and dynamic factors in a complicated and uncertain way [4,8]. These factors include drilling, operating, circulation hours, drilled depth, temperature, vibration, shock, pressure, face angle, torque, rotation speed, current, voltage, power cycle, well deviation, orientation, inclination, humility, flow rate, gamma radiation, viscosity, sand content, weight on bit (WOB), mud type, mud weight, PH of mud, contaminants, noise levels, and others [8]. Due to the system and human factor limitation, the interactive impact of multiple parameters to different drilling tools cannot be accurately measured [3,4]. However, the previous research reveals that downhole vibration is one important factor to weaken tool robustness, reduce tool reliability and life expectancy [2,4,5,7,9]. In addition, downhole vibration can also cause excessive stabilizer wear, well trajectory deterioration, high-frequency noise, lower rate of penetration (ROP), decreased measurement accuracy, and other serious issues [10]. Therefore, the research about drilling tool vibration signal detection, monitoring, measurement, data acquisition, and analysis has significance for drilling optimization, efficiency, and reliability improvement [10–12].

Increasingly, modern electronic development enables drilling tools to be designed with automatic signal and data tracking, collection, measurements, storage, and transmission functions for effective data analytics, conditional monitoring, and drilling control [4,13–15]. A large variety of downhole drilling operation, environment, and dynamic data is captured, measured, and collected by multiple sophisticated sensors, transmitted to surface equipment, and instantaneously streamed to the data center for processing via surface acquisition systems. Drilling downhole data are multivariate and of high dimension. Various variables are tracked and information is recorded at small time intervals, which provides periodic snapshots of downhole environments, drilling performance, and cumulative tool usage [16]. Surface equipment can process, decode, and interpret the downhole data or signals to analyze the real time downhole drilling operation status [7,13]. Unquestionably, drilling downhole data are available for tracking, analyzing, and predicting tool operational reliability, failure and lifetime, determining tool warranty-cost, and optimizing drilling process [17].

For global drilling operators or service providers, downhole data from worldwide geographic drilling operations will constantly accumulate and increase in sizes in surface equipment, and eventually form massively large dataset named as field reliability big data (FRBD), which is far beyond the storage and processing capability of a single server [17]. FRBD is stored, transmitted, and processed by multiple distributed servers, then extracted, transformed, and overloaded to various enterprise databases or warehouses for data query, collection, and advanced analytics. FRBD has large size at Terabytes (TBs) or Petabytes (PBs) level [17]. It also contains ample covariate and time-varying information, and meaningful tool reliability information [17]. Thus, FRBD provides a valuable data source for implementing a series of data analytics methods and technologies, such as machine learning, pattern recognition, and business intelligence for a wide range of reliability big data analytics topics. These topics include tool reliability assessment, modeling, prediction, failure analysis, reliability in tool design, development, testing, maintenance planning, and lifecycle cost analysis [18]. As a consequence, more and more research efforts have been put on reliability big data analytics methodologies of drilling tools [2,6,17]. To the best knowledge of the authors, as a critical factor to affect operation reliability, the detailed role of vibration factor in drilling tool reliability big data analytics has not been systematically explored by any academic article. Therefore, this literature review will focus on the unexplored impacts, applications, and research of downhole vibration in the reliability analytics based on FRBD.

The rest of this paper is organized as follows: Section 2 discusses the drilling tool downhole vibration modes, impacts and related research. Section 3 summarizes the features and advantages of FRBD compared to traditional reliability data analytics. Section 4 reviews the methodologies, models, techniques, and applications of vibration factor in drilling tool reliability big data analytics emphasizing in lifetime and failure prediction, prognostics and diagnostics, condition monitoring (CM), and maintenance optimization. Sections 3 and 4 include two types of methods and algorithms: those generally applying on big dataset and not being suitable for regular dataset, and those working well with both regular and big datasets. The first type mainly includes cloud computing, deep artificial neural network (ANN) and deep learning, which may generate poor generalization with small or regular dataset. Future research is summarized in Sec. 5, and Concluding remarks are drawn in Sec. 6.

2 Drilling Tool Downhole Vibration

Since drilling is the process of cutting rock by chipping or crushing, vibrations are almost unavoidable [19]. The downhole vibration is measured, monitored, and recorded in tool electronics sensors placed in the drilling assembly, and reported as root-mean-square in the unit of acceleration with gravity so that the field technicians could comprehend it and analyze the underground condition [4,20]. The vibration in an average drilling run is more than 8000 shuttle launches [21]. As is shown in Fig. 2, three principle vibration modes, which include lateral vibration, axial vibration, and torsional vibration, commonly exist in drilling downhole operation.

Lateral vibration is transverse to the drilling tool axis, and normally occurs when the drilling string moves laterally to its ration axis [22]. Lateral vibration is related to the bending of the drilling axis and the resonant behaviors at some critical rotary speed as well [9]. Lateral vibration is typically responsible for the highest frequency dynamics (normally 50 Hz and above, or below 0.02 s period) [23]. The influencing factors of drilling lateral vibration include the fossa dynamics, the axial alternating force, the drill bit displacement, the shaft lining, and the drill string construction [20]. Drilling tools have two types of lateral vibrations: left/right lateral motions known as Lateral Acceleration, and off-center rotation known as Whirl (forward whirling and backward whirling), which is excited because of wellbore contact in low strength formations [9,10]. Lateral acceleration is the most destructive vibration mode being responsible for 75% of drill string failures and requiring immediate attention and control [9,24,25]. Whirl is

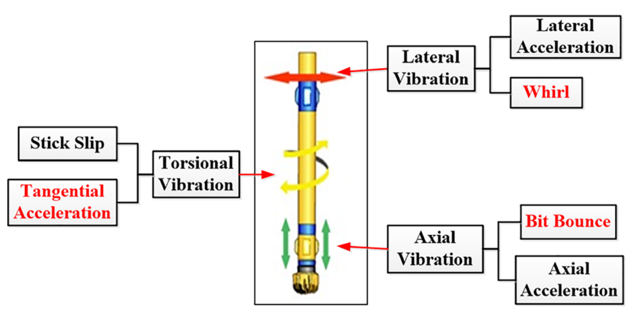

Fig. 2 Three main modes of downhole vibration [9]

a stable phenomenon, which can be identified with ROP increase, a high steady torque, or the absence of stick-slip [9]. The mud plays an important role as a nonlinear damping medium to stabilize the bottom hole assembly (BHA) lateral vibrations [10]. However, constant exposure to lateral vibrations can cause high-frequency bending moment fluctuations associated with large vibration amplitude in BHA, premature BHA components fatigue failure, wellbore washout, wear of stabilizers, and serious damage to the drilling electronics and tool body [4,10]. Lateral vibration is not transmitted up the drilling string and hardly detected at the surface [9].

Axial vibration is parallel to the drilling tool axis, and occurs when the drill string moves along its rotation axis [9,22]. Axial vibration is more prevalent when tricone bits are applied for drilling [9]. Axial vibrational can be discovered in the order of 3–20 HZ frequency [23]. Low-frequency (3–7 HZ) axial vibration is generally associated with bouncing motions, and higher frequencies (greater than 15 HZ) are relevant to the BHA resonances or the interaction of the teeth or the cutters with the formation [26]. Axial vibration is commonly generated by lithology changes or fractures when a new cutting pattern is initiated by the bit [9]. Axial vibration excited by the bit and formation interaction leads to bit bounce, which causes cutting tooth wear and bearing failure and manifests the most severe sign of axial vibration [10,27]. Axial vibration together with a roller cone bit could indicate a bit or cone issue, while axial vibration with polycrystalline diamond compact bit could reveal bit balling or severely worn cutting structures [9]. Axial vibration can result in drill bits damage, buckling fatigue, low ROP, accelerated bearing, seal, stabilizers and top-drive wear, broken tooth cutters, and LWD/MWD tool failures [9,27]. Axial vibration commonly exists in vertical wells when drilling hard formations, which can manifest as WOB fluctuations with relatively stable downhole torque values and be detected at surface [10,23]. Axial vibration becomes more crucial to implement downhole axial generator tools or drill hard formations.

Torsional vibration, also called slick-slip vibration, is the alternating phenomenon of rotational acceleration and deceleration [9]. Torsional vibration is found in the frequency of 0.1 Hz–5 Hz [19]. Torsional vibration exists in the rotary path of drilling string axis, and can be observed as the variation in downhole rotation per minute [4,9,28]. Torsional vibration is always throughout the drilling process, and occurs as a result of the twisting of the drill string by the interaction from the BHA and the wellbore, or from the drill bits and the formation [9]. Torsional vibration also commonly appears when polycrystalline diamond compact bits are used without depth of cut control, and it is often formation-dependent due to lithology changes [9]. During the "stick" phase, the drill bit and/or drill string rotation ceases, both radial and axial accelerations are significantly reduced, close to zero or even negative, sufficient torque builds up and WOB gets lowered slightly, which causes the drill string rotation to resume in the "slip" phase [9,23]. Another possible reason for torsional vibration is that the motor continues to run the drill string while the bit is stuck downhole [4]. Consequently, the torsional energy accumulated in the drill string will be released once the drill bit is free, causing the BHA to rotate in the undesired opposite direction [4]. Torsional vibration has a remarkable effect on all downhole measurements [23]. Torsional vibration causes irregular downhole rotation, material fatigue, physical damage of the drilling tool and electronics, and slows down the drilling process [4,29]. Torsional vibration can be detected at surface by the fluctuation of the power to maintain a constant rotation rate [30].

Normally, the biggest risk for vibration damage comes from heavier components [5]. Additionally, combined with other downhole parameters, downhole vibration is an amplifier of many possible reliability issues, and can produce more complicated and damaging impact to drilling tools [31]. For example, the vibration factor is especially dangerous and has more detrimental effect on tool failure and reliability in high-temperature and high-pressure downhole environment [21,31]. The destructive impact of vibration will be more severe with increased rotation per minute, which causes the tool components to degrade and fail faster [2]. In addition, when large amplitude vibrations encounter resonance in drilling operation, myriad damaging effects can happen, leading to erratic downhole torque, poor bit performance, excessive drilling component wear, MWD/LWD, top drive and other rig equipment failures [9]. As a result, modeling and simulating vibration using downhole vibration data, extracting its natural frequencies, and analyzing the drilling tool dynamic behaviors are important for failure detection, analysis, and prevention [10]. Numerous research efforts have been put on the vibration signal detection, simulation, monitoring, transmission, modeling, testing, analysis, mitigation, and control in the last few decades [10,12,19,20,24,25,27–30,52].

3 Reliability Big Data Analytics

3.1 Big Data Features and Technology. Big data is massive, unstructured, and complex data set that is difficult to be handled by traditional data processing system [53]. Big data has the large size, which can surpass Gigabytes (GBs) and reach TBs or PBs in size, high Velocity to meet demand or real-time requirement, and high Variety, which includes various data types, formats, nature sources (i.e., audio, video, website, etc.), forms (i.e., structured, semi-structured and unstructured), uses, and ways of analysis [54]. In addition, big data can have great Variability, which can hamper data processing and management, varied Veracity due to data inconsistency, incompleteness, ambiguity, latency, deception and approximations, and Horizontal Scalability to join multiple datasets [53–55].

Big data systematic framework requires innovative data generation, acquisition, transmission, storage, search, sharing, sampling, large-scale processing mechanisms, and analytics solutions [54]. Big data often resides on the platforms with broadly varying computational and network capabilities, and data volume operated by modern applications grows at a tremendous speed requiring TBs or PBs space [56]. Therefore, big data posts privacy issue and other intriguing challenges for the parallel and distributed computing platforms [56]. Consequently, several solutions including non-relational database, in-memory database, distributed systems, and massive parallel processing database with high performance and platform scalability have been adopted for big data [55]. MapReduce and Hadoop are respective examples of parallel processing model and frameworks to perform big data analytics with efficiency, reliability, scalability, and manageability [54].

The goal of big data analytics is to handle and analyze enormous data, extract useful information and meaningful knowledge, and gain valuable insights to support effective decision-making from rapid growth large datasets [55]. Big data environment requires magnetic, agile, deep analysis skills that differ from those of the traditional enterprise data warehouse environment [55]. Several applicable methods play important roles in big data analytics, which include A/B testing, machine learning (i.e., supervised learning, unsupervised learning and reinforcement learning), natural language processing, cloud computing, business intelligence, advanced databases, data visualization and visual discovery techniques, etc. [53–57]. Supervised learning techniques include some classical models: partial least squares, linear regression and penalized regression for linear regression; support vector machines, multivariate adaptive regression splines, and ANNs for nonlinear regression; and bagging tree, boosted tree, and random forest in regression trees [57]. Classification and regression tree is one widely used decision tree learning techniques to construct the exploratory data analytics and predictive models [57,58]. Data mining techniques comprise association rules, clustering, classification, pattern discovery, regression analysis, neural networks, cluster analysis, genetic algorithms, decision trees, etc. [59]. Big data analytics normally allows relaxed accuracy constraints on the quantitative output, which can influence algorithm design [56]. Randomized algorithms project input data into sketching

Table 1 Comparison of Traditional Reliability Data and FRBD [16,17,60]

Traditional reliability data	FRBD
Experiments and accelerated life testing	Operation, environment, failure, degradation, and dynamic
Aggregated data on the population units	Individual unit usage data
Regular dataset (<= GBs)	Large dataset (>= TBs or PBs)
Include intended usage data only	Include intended and unintended in-field usage data for better reliability analysis.
Lack covariate information	Have ample and dynamic covariate information
Enables reactive maintenance and inspection on population units	Enables proactive preventive maintenance and inspection on the individual unit.
Failure and censoring time can be binned into intervals when no covariate exists	Can be divided into in small subdataset for analysis by proper binning of observations.
Not suitable to be stratified	Can be stratified in logical, manipulated, and homogeneous subgroups for better modeling.
Fewer risk of excessive sampling	Risk of excessive sampling at a too high frequency exists
Difficult for long-term reliability assessment	Better for long-term reliability prediction
Less cost for data retrieval, storage, manipulation, aggregation, and analysis	More cost from sensors, data retrieval, acquisition, storage, manipulation, aggregation, complex system, and analysis.

approximations of reduced size before applying the expensive computing kernels and project back at the cost of provable bounds for accuracy loss [56].

3.2 Field Reliability Big Data. Traditional reliability analytics is mainly conducted through the analysis of population data from life testing experiments [60]. Traditional reliability analytics uses empirical, probabilistic, or statistical methods including probability distribution, statistical inference, Bayesian statistics, Weibull regression analysis, accelerated failure-time model, proportional/nonproportional hazard model, etc. [16] With the increase in field data storage capabilities and collection methods, TBs or PBs multidimensional field data named as FRBD has been available, which include operation, environment, failure, degradation, and time-varying dynamic data. FRBD can indicate system operating conditions and health status, and enable analysis and computation of wear, damage accumulation, life-limit, proactive inspection, and restoration in reliability big data context [60]. The comparison of traditional reliability data and FRBD is listed in Table 1.

3.3 Reliability Analytics Based on Field Reliability Big Data. Reliability big data analytics is collecting, processing, and analyzing enormous FRBD through observation, measurement, and experiments with the below purposes:

- To check, interpret, and extrapolate the field operation, failure, maintenance, and cost data.
- To diagnose and infer reasons for tool failure mode, effect, root cause, and corrective action.
- To predict and forecast tool field failure probability, equipment lifetime, reliability, and financial needs.
- To recommend measures to minimize in-service failures and prevent unplanned maintenance.
- To estimate cost of failure and cost of maintenance and discover measures to reduce life cycle cost (LCC).
- To assist design, testing, operation, maintenance, and warranty decision-making [17].

Although reliability big data analytics could utilize some traditional reliability data analytics and general big data analytics methods, only a few research efforts have been specifically made to classify the entire reliability big data analytics or how to utilize FRBD to improve reliability analytics and prediction for products and systems [16,17,60]. The biggest challenge is how to use FRBD to develop proper models for various applications effectively [17]. Generally, two modeling efforts are involved: regression like model relating the response to dynamic covariates, and a dynamic covariate model when predictions or other inferences are desired [17]. Meeker and Hong provide a strategic perspective on the potential impact of FRBD in reliability with a natural extension from traditional reliability methods and propose the ideas to enhance the impact of the statistical and reliability analysis based on FRBD [17,60]. Additionally, drilling industry has utilized FRBD to perform reliability analytics and prediction to improve drilling reliability, efficiencies, proactive, and reactive reliability decision-making [1,2,6,7,13,61–63].

4 Reliability Big Data Analytics With Downhole Vibration Factor

Downhole vibration factor has been applied in drilling tool reliability evaluation, analysis and predictions, which can enhance design reliability, failure monitoring and prevention, reliability and lifetime prediction, maintenance planning and optimization, as well as lifecycle cost reduction [60].

4.1 Fundamental Concepts for Reliability Analytics. Several important concepts for reliability big data analytics include reliability, availability, maintainability, mean time between/to failures (MTBF/MTTF), mean time to repair, failure (hazard) rate, censored data, failure probability distribution, mission profile, equivalent circulation hour (ECH) [18,64].

Reliability is the probability that an item will perform a specific function without failure under required conditions for a specified period of time [18]. Availability is the probability that a product is operable and in a committable state without failure or undergoing repair [18]. Maintainability is the probability that a failed product is repaired within a given amount of time [18]. Meantime between/to failures (MTBF/MTTF) is the average time to failure (TTF) for a nonrepairable/repairable system [18]. High MTBF/MTTF normally indicates a system with high reliability. Failure (hazard) rate (λ, lambda) is the frequency that a component fails per unit of time, and is reciprocal to MTBF/MTTF [18]. A drilling tool's lifecycle failure rate normally follows bath tube curve.[2] Typically, the more severe downhole vibration is, the lower MTBF and the higher failure rate the drilling tool has. Analyzing the correlation between vibration value, MTBF and failure rate from FRBD will assist drilling company to predict specific tool reliability in different downhole environment, and set up applicable MTBF and failure rate for each future drilling activities.

Failure data is categorized into four different types [18]:

- Exact failure time data, in which the exact failure time is clearly known;
- Right-censored data, in which it is only known that the failure happened or would have happened after a specific time,

[2] https://en.wikipedia.org/wiki/Bathtub_curve

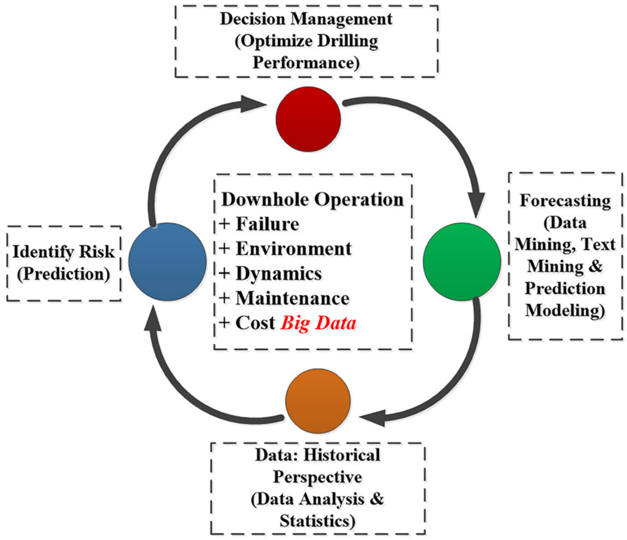

Fig. 3 Field reliability big data driven lifetime and failure prediction process [2]

and the common scenario is that an item is still functioning when the test ends;

- Left-censored data, in which it is only known that the failure happened before a particular time, and the common scenario is the item is not checked prior to being tested but is periodically examined and a failure is discovered at the first examination;
- Interval-censored data, in which it is only known that the failure happened between two different times.

Common failure probability distributions for reliability analysis include Weibull, exponential, lognormal, normal and other distributions. Weibull distribution is one fundamental reliability distribution and it is widely used in tool failure, maintenance, and lifecycle analysis. Exponential distribution is applicable when the tool passes "infant mortality" stage and has nearly constant failure rate [18]. Lognormal distribution is suitable to model TTF and sometimes time to repair for electronic and mechanical products [18]. Normal distribute can be applied at the tool wear-out phase with an increasing failure rate [18]. Maximum likelihood approach is commonly used in parameters estimation, extrapolation, and statistical predication [17].

Mission Profile is the specific technical description of the operating conditions of a drilling task, which always include the downhole temperature, stress, vibration, torque, flow rate, electricity, well deviation, etc. Analyzing and evaluating vibration data in FRBD provides better opportunity to measure and visualize drilling tool actual usage information for reliability target generation and prediction. Drilling tool life extension can be obtained by derating the mission (e.g., lowering drilling rotational speed to reduce the impact from vibration-induced damages) [4].

Equivalent circulation hour is developed to consider the factors affecting the reliability of tools for maintenance recommendation [6]. ECH essentially adjusts a tool's running time based on multiple factors including actual usage, environmental conditions, downtime, transportation, etc. [6] ECH adjustment standard is determined by engineering analysis, environmental testing, accelerated testing, and diagnostics/prognostics about various factors' contribution to tool age and degradation [6]. Generally, a tool that operates in extremely high vibration has greater ECH than actual running hours as tools experience more wear in more severe vibration than in normal conditions. Sensor data (e.g., vibration sensor, actuator pressures, and pressure transducer readings) has been utilized to track environmental conditions, identify the part degradation, and damage, calibrate ECH and trigger appropriate level of preventive maintenance (PM) [6].

4.2 Life Time/Failure Prediction. Due to the availability of information-rich FRBD for failed and surviving units, the restrictions of simulating actual operating environment with physics-based methods, and the accuracy issue of predicting field reliability using the laboratory test data, FRBD-driven methodologies for TTF modeling and reliability prediction have gained momentum [4,16,17,65]. Lifetime and failure prediction provides a cutting-edge way to recognize the precursors of costly field failures by using statistical modeling, data mining, machine learning, and other advanced analytics methods [2]. Efficiently predicting failure and the remaining life of the wearing component is crucial to

Table 2 Applications of tool life time/failure prediction using FRBD with vibration factor

Author	Application	Methods	Pros/Cons
Sutherland et al. [71]	Electronic motor life distribution	Data mining, statistical approaches	Easy to implement./Sensitive to variation or noise.
Chi et al. [72]	Predicting the fatigue life of drill string	Computerized model, analytical method	Rigorously coupling the axial and torsional vibration./May not be suitable for various downhole drilling operation.
Yan et al. [73]	On-line assessment and performance prediction of remaining tool life in drilling operations.	Hybrid method, logistic regression analysis, Autoregressive moving average model	A feasible method to detect tool wear and predicting tool remaining life./Needs more validations from application.
Wu et al. [74]	Develops an integrated decision support system for failure/lifetime prediction, PM of rotational tools	ANN, Cost matrix	Be effective in machine remaining life prediction./Be complex to implement.
Pham et al. [75]	Proposes the hybrid model to estimate/forecast the machine state.	Hybrid model, ARMA, GARCH	Gets verified in empirical results./Needs more validation from practice.
Hong et al. [17,76]	Field failure prediction based on failure-time data and dynamic covariate with unit-to-unit variability for individual units.	Accelerated failure time model, multivariate time series, and cumulative exposure model.	Presents a general framework for prediction using failure time data.
Carter-Journet et al. [2–4]	Drilling tool failure and lifetime prediction.	Parameter estimation, statistical analysis, Bayesian math	Improves life time prediction performance./Be complex to implement.
Frenzel et al. [77]	Drilling optimization with predicting and resolving drilling dysfunctions and failures in real-time.	Drill string modeling, optimization system	Has efficiency in mitigating drilling dysfunction.

Table 3 Applications of tool prognostics/diagnostics using FRBD with vibration factor

Author	Application	Methods	Pros/Cons
Vlok et al. [84]	Determine the optimal replacement policy for reliability critical components.	Weibull proportional hazards model	Gets validated using data from operation plant
Mishra et al. [85]	Discusses a generic process for lifetime consumption monitoring of electronics.	Physics-of-failure based stress, damage models	Testing result correlates well with empirical results.
Vlok et al. [86]	Utilize historic failure data and diagnostic measurements to estimate residual life and determine PM.	Proportional intensity Models	Easy to justify and benchmark
Sun et al. [87]	Mechanical system hazard estimation with accelerated life test and CM data.	Proportional covariate model	Reduces the number of accelerated life tests and is easy to implement.
Zhang et al. [83]	Use of eigenvector analysis for machinery condition prognosis; Pump CM as an example	Eigenvector analysis, Principal component, Multivariate analysis	Get validated using pump data during flow fluctuation.
Saxena et al. [88]	Identifies near optimal design parameters of diagnostic systems for monitoring mechanical systems.	Genetic algorithms, ANN, Hybrid techniques	Effective and powerful./Additional constraint of available computational time. May not suitable for some complex system.
Chen et al. [89]	Investigate the intelligent processing of mechanical component health data to improve prognostics and diagnostics.	Artificial intelligence, data analysis, data mining, statistics	Improves equipment management./Higher computation requirement.
Zhao et al. [90]	Assessing the operation and product reliability of directional drilling systems	Dynamic factor model	Improves KPI reliability assessment in directional drilling system.

prevent costly downhole in-service failures, eliminate unnecessary maintenance, improve reliability and drilling performance, reduce downtimes and failure risk, schedule timely maintenance, lessen maintenance and failure costs, and enhance dexterity to the decision-making [2,4]. FRBD driven lifetime and failure prediction has the following iterative process in Fig. 3.

Vibration combined with other downhole factors such as temperature, shock, and resonance have a damaging impact on drilling tool failure and lifetime [4,21,47,66–68]. Table 2 lists research efforts on applying vibration factor in reliability modeling and predictions based on FRBD by statistical modeling, Bayesian method, data mining, Monte Carlo simulation, advanced computing, and analytics methods [17,69,70].

4.3 Prognostics/Diagnostics. 99% tool failures are preceded by certain conditions, signs, or special indications, which include abnormal vibration [11,78]. Diagnostics can be used to pinpoint sources of failure, detect and isolate specific faults, and identify fault severity and effect for making proper repair, trending specific failures, and performing effective reliability estimation [6,79] Prognosis is an estimation of time to failure and risk for existing or potential failure modes, which utilizes physics principles, present and past conditions, and data techniques to predict the future condition and reliability, hidden damages, and remaining life [79,80]. Prognostics can prevent unexpected failures, assist maintenance, repair and replacement decision-making, and save maintenance costs [11,81]. Prognostics health management is the discipline consisting of methods and technologies to assess the product reliability in its actual life cycle conditions so as to determine the failure probability and mitigate system risk, which is especially useful for sensitive and complex system health monitoring [11,82]. Prognostics health management highly relies on the sensor technology to obtain long-term accurate information for anomaly detection, fault isolation, and fast failure prediction [11].

Several existing prognostic models can be roughly allocated into four categories: physical model, signal-based model, reliability-based model, and hybrid model, all of which utilize regression or extrapolation techniques to forecast the future based on the historical and current conditions [83]. Reliability-based model is reasonably well advanced for maintenance prediction [83]. With enhanced modeling capabilities from big data, FRBD can be used in prognostics to provide improved short-term and long-term predictions of the remaining life of a system [17]. As an example, downhole vibration data from sensors can indicate the onset of abnormal wear or damage, and changes in degradation rate [17]. The existing and potential applications of using FRBD with vibration for prognostics/diagnostics and reliability analysis are listed in Table 3.

4.4 Condition Monitoring. Condition monitoring is a process to continuously monitor certain signals with some types of sensors and appropriate indicators to indicate the equipment condition in diagnostics/fault detection and identify the issues of machinery system [91,92]. Build-in and multifunctions sensor technology and strategies, sensor data (e.g., vibration, thermograph, temperature, pressure, voltage, acoustic emission data), process monitoring, and signal-detection algorithms can be used to detect unusual system degradation, undesirable system states, unsafe operating conditions, and precursors to system failure [17]. Then, corresponding preventive measures can be used to protect a system by reducing load to safe levels or shutting the system down [17]. Reliability estimation from condition data generates a time series of reliability evaluations concerning operation time, which will be projected into the future for prediction or prognosis [16]. Condition monitoring systems support prognostic/diagnostic models, the detection of potential failures, and the prediction of

Table 4 Applications of health and reliability assessment using FRBD with vibration monitoring

Author	Application	Methods	Pros/Cons
Ocak et al. [93]	Fault detection and diagnosis scheme for rolling element bearings.	Hidden Markov modeling	Proven to have high accuracy
Zhang et al. [16]	Reliability analysis/prediction with degradation CM data	Recursive Bayesian analysis	Enables reliability analysis and prediction using degradation data
Han et al. [94]	CM fault diagnosis system for induction motors based on motor vibration signals.	Fault diagnosis system, Pattern recognition, and genetic algorithm	Test validates system performance./High computational requirement.
Heidarbeigi et al. [52]	Develops a neural network simulator built for prediction of faults in gearbox.	Back propagation learning, Multi-layer ANN	Has adaptability to different architectures./Consumes computing resources and needs long training time.
Zarei et al. [50]	Fault diagnose and detect bearing defects of induction motors	Intelligent method based on ANN	Performance is validated./Consumes computing resources and needs long training time.
Abu-Mahfouz et al. [95]	Presents an effective drill wear feature identification scheme based on robust clustering techniques.	Robust clustering techniques, Fourier transform, statistics	Clustering results can be used to design classifiers.
Kumar et al. [96]	Detection and classification for the degree or magnitude of effect for tool wears and faults in drilling process.	Support vector machine, ANN, Bayes classifier	Has feasibility and the performance is validated.

operation reliability at an early stage in order to minimize downtime and maintenance costs [11].

Vibration monitoring, which can be carried out on-line through periodical or continuous practice, is the most popular CM technique in machine health and reliability assessment, especially for rotating equipment [11,83]. International Organization for Standardization (ISO) standard adopts the root-mean-square value of vibration signals to differentiate machine health conditions (ISO 10816 1998). Multivariate analysis can be applied in the monitored vibration signal to extract features and identify machine health information and reliability presentation [83]. Table 4 lists existing examples of vibration monitoring in the analysis of FRBD.

4.5 Maintenance Planning and Optimization. The combination of conditional monitoring, diagnostics, and prognostics leads to condition-based maintenance (CBM), time and cost reduction, and increased availability [6,80]. Condition-based maintenance is one form of PM that performs a real-time assessment of equipment conditions, calculates, and recommends maintenance actions based on the information collected through condition monitoring process to maximize the effectiveness of PM decision-making. CBM focuses on the system failure prognostic and remaining useful life estimation/prediction approach with historical and real-time data instead of predetermined failure time limit approach to determine appropriate maintenance [11,96]. Maintenance plants can incorporate risk-informed CBM decision into reliability constraint and spare part forecasting for tool maintenance or replacement [3]. CBM available input can include historical and real-time field data of the monitored parameters (e.g., vibration, temperature, sound, heat, noise levels, etc.), effect data (e.g., field failure, malfunction, degradation, etc.), prognostic information, and maintenance historical data from the shop [97]. CBM data can be classified into three types: value type, waveform type, and multidimensional type [81]. Vibration and acoustic data are examples of waveform type data, which have noise effects or unwanted signal that should be minimized or eliminated [11]. CBM desired output can be recommended maintenance actions (system restart, lube oil change, lower pressure, etc.), the optimal time and cost for each action, the remaining useful life, failure threshold, and utility function after each action as functions of time, cost, and safety [97]. CBM plays a crucial role in the oil and gas drilling facilities due to the criticality and capital-intensive investments of the oil and gas drilling activities, which can cause possibly unaffordable financial and severe environmental consequences from unexpected failures [97,98]. Some critical drilling equipment employs diverse monitoring sensors and means to detect early deterioration and predict failures for CBM application [97].

The complexity of CBM data analysis and modeling heavily relies on condition data type, volume, and complexity [11]. The high frequency of real-time data calls for an appropriate big data infrastructure and system architecture [97]. With the era of big data, CBM requires large data samples, high data collection cost, complex data cleaning process, real-time and data-rich environments for prognostic-based decision support [11,97,99]. FRBD poses great opportunities to CBM data processing, analysis and modeling, knowledge discovery and provision of CBM recommendations [97]. FRBD enables prognostic-based decision support for CBM to cope with several challenges such as highly dynamic and real-time information, to predict the equipment health state and update maintenance-related recommendations continuously [97]. Machine learning, data mining, decision support methods, artificial intelligence algorithms, regression, and extrapolation are used for handling large volume of real-time condition data and providing maintenance recommendations based on tool health predictions [97]. An example of oil and gas drilling tool life management and CBM work flow is shown in Fig. 4.

Another important maintenance concept is reliability centered maintenance (RCM), which is defined by Electric Power Research Institute (EPRI) as a systematic consideration of system functions, the way functions fail, and a priority-based consideration of safety and economics that identifies applicable and effective PM tasks [100]. The objective of RCM is to reduce maintenance and LCC, by focusing on the critical functions of the system, and removing maintenance actions, which are not strictly necessary [100]. Developing the optimal drilling tool RCM policies requires modeling and analysis of FRBD, equipment quality, job and waiting time, transportation and cost factors and algorithm of predicting

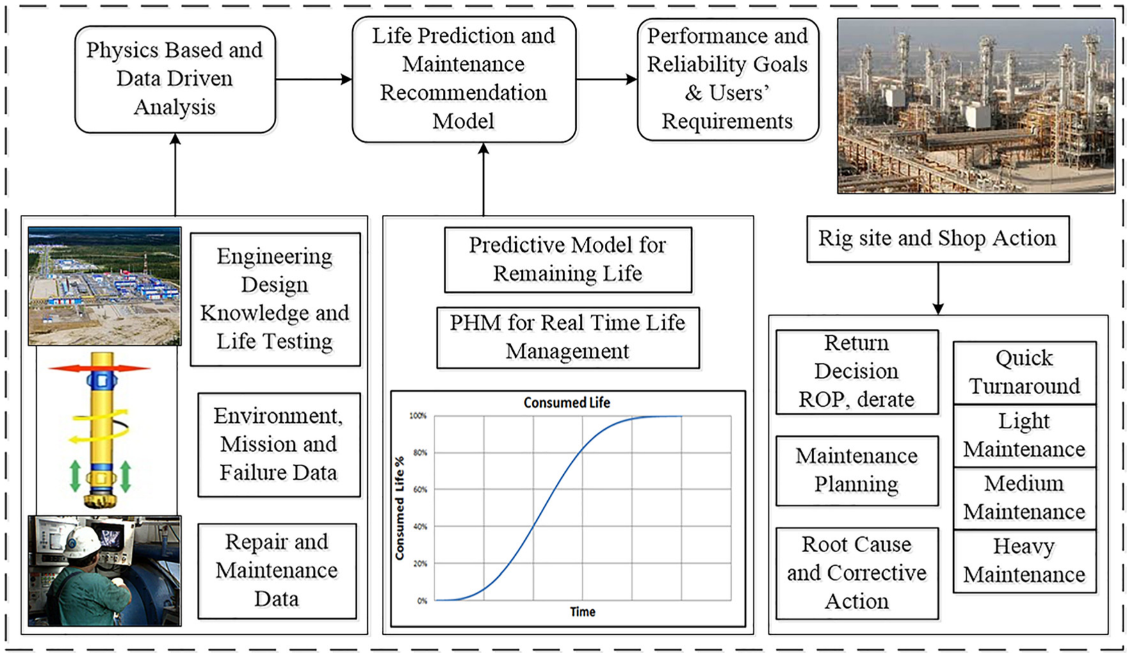

Fig. 4 Drilling tool life management and CBM work flow [2,4]

Table 5 Applications of maintenance planning and optimization using FRBD with vibration factor

Author	Application	Methods	Pros/Cons
Liu et al. [101]	Integrate data collection and vibration analysis of hydropower turbine to assess equipment conditions and support maintenance effectively.	Advanced vibration analysis algorithms, System dynamics identification, CBM	Has potentials to improve maintenance decision-making
Orhan et al. [35]	Detecting bearing defects on machines as a PM strategy	Spectral analysis, Statistical analysis	Easy to understand. Get validated by Rolling element bearing cases
Heng et al. [102]	Predict machinery failure and estimate survival probabilities for CBM.	ANN, CBM, Kaplan–Meier estimator	Can predict with more accuracy./ Consumes computing resources and needs long training time.
Niu et al. [103]	Uses RCM and employs data fusion strategy to improve CM and health prognostics.	RCM, Data fusion technology	Performance can be obtained with good generality
Cho et al. [6]	Review the tradeoffs of R&M costs and failure cost; Optimize the repair and maintenance cycles to minimize LCC	RCM, Cost Tradeoffs	Optimizes R&M cost and cost of failure
Kale et al. [4,7]	Utilizes predictive life models and real-time data to optimize operation and maintenance decision-making.	Predictive analytics, CBM	Improves the maintenance prediction performance./Complex to implement

performance and consumed life as the function of usage, failure, and maintenance history [4,6,97]. As a crucial drilling tool operational factor, vibration factor has been applied in the analytics of FRBD for maintenance optimization, which is listed in Table 5.

5 Future Work

Although FRBD obtained from field usage has tremendous value in reliability analysis and prediction, reliability big data analytics including vibration factor by itself cannot solve all drilling tool reliability issues especially when the accuracy of extrapolation is highly demanded [17,60]. Future research is summarized as below:

(1) Most analytics based on FRBD focuses on individual reliability characteristics or failure criteria, while drilling tools have more than one failure modes simultaneously caused by vibration together with other downhole factors. Therefore, it is necessary to link and analyze downhole vibration data with multiple downhole factors, coupled failure modes, and physics-based models of drilling tools interactively, emphasizing on the failure mode with greater cost impact [36]. Model and predict the system reliability

according to the interaction of hardware and software reliability instead of isolating them [60]. Detailed knowledge about the physics of failure and certain expert opinions are critical to justify the extrapolation and provide proper degree of precision assurance for reliability prediction based on FRBD with vibration factor [17].

(2) Collect, analyze, and integrate FRBD including vibration from the early stages of product design in an integrated reliability design environment [60]. Combine information from different sources such as data from product design, laboratory experiment, accelerating life test, manufacturing quality, field operation, maintenance workshop, and engineering knowledge to enable reliability analytics to be performed in a broader scale and produce an enhanced influence from product design. Especially, degradation data caused by downhole vibration have valuable dynamic covariate information to improve reliability predictions on severe vibrations, whirl, or bump events [16,63]. Autocorrelation in the covariate process can be modeled to reduce analytical time and improve efficiency [16].

(3) Nowadays, although several advanced statistical and analytical methods and algorithms have been discovered for prognostic-based decision support for CBM implementation, most solutions cannot adequately support proactive maintenance decision-making with vibration factor [97]. In addition, there is limited research on the deep learning application in reliability analysis on high-dimensional FRBD with respect to vibration [104]. One future research will focus on the utilization, examination, and incorporation of additional statistical modeling, machine learning, ANN, decision methods, especially deep learning in drilling tool lifetime prediction, maintenance recommendation, and economic replacement time decision support using FRBD with vibration factor.

(4) Common approaches to apply vibration factor in drilling tool reliability big data analytics lack the adequate consideration of data quality issues and integrity measurement. Moreover, human errors are can be discovered in each phase of reliability big data analytics [105]. Generally, big data analytics allows looser accuracy constraints on the quantitative output [56]. Thus, the estimated failure distribution cannot fit the recorded failure point or reflect reliability reality well due to data quality issues [106]. More research is required to keep the FRBD analytics with vibration factor updated with the cutting-edge data quality and integrity management, human error reduction, and noise reduction techniques [16].

6 Conclusion

Oil and gas drilling tools can experience fluctuating and extreme downhole parameters in operation process, which increases failure rate and reduces operational reliability significantly. Downhole vibration factor adversely affects tool operation reliability, system availability, failure rate, maintenance activity, etc. Meanwhile, complicated drilling activities generate heterogeneous and information-rich data (FRBD) with abundant tool operation, environment, real-time dynamics and system health information, unprecedented complexity, distinctive scale, temporal dimensional and data type varieties, which creates broad opportunities for the reliability big data analysis. Improving drilling reliability and reducing operation cost propels the advancement of reliability analysis and prediction based on FRBD with vibration factor.

This paper reviews drilling tool downhole crucial factors, the modes, impacts, monitoring, measurement, modeling, analysis, and control methods of downhole vibration, and the features and analytical techniques of FRBD. Furthermore, this paper specifically explores the existing and potential methodologies, models, and application for vibration factor in drilling tool reliability big data analytics including lifetime and failure prediction, prognostics and diagnostics, condition monitoring, and maintenance planning and optimization. Finally, the paper proposes the future trends about the application of downhole vibration factor in reliability big data analytics of drilling tools.

References

[1] Ze, H., Xiaohui, X., Liang, G., Ping, C., Junlan, L., and Qiang, Z., 2014, "Research on the System of down-Hole Engineering Parameters Measure While Drilling," Open Pet. Eng. J., **7**(1), pp. 149–153.

[2] Carter-Journet, K., Kale, A. A., Falgout, T., and Heuermann-Kuehn, L., 2014, "Drilling Optimization: Utilizing Lifetime Prediction to Improve Drilling Performance and Reduce Downtime," SPE Deepwater Drilling and Completions Conference, Galveston, TX, Sept. 10–11, SPE Paper No. SPE-170270-MS.

[3] Carter-Journet, K., Kale, A., Zhang, D., Pradeep, E., Falgout, T., and Heuermann-Kuehn, L., 2014, "Estimating Probability of Failure for Drilling Tools With Life Prediction," SPE Asia Pacific Oil & Gas Conference and Exhibition, Adelaide, Australia, Oct. 14–16, SPE Paper No. SPE-171517-MS.

[4] Kale, A. A., Carter-Journet, K., Falgout, T. A., Heuermann-Kuehn, L., and Zurcher, D., 2014, "A Probabilistic Approach for Reliability and Life Prediction of Electronics in Drilling and Evaluation Tools," Annual Conference of the Prognostic and Health Management Society, Fort Worth, TX, Sept. 29–Oct. 02

[5] Beckwith, R., 2013, "Downhole Electronic Components: Achieving Performance Reliability," J. Pet. Technol., **65**(8), pp. 42–57.

[6] Cho, J. J., Phillips, R. G., and Rice, K. D., 2013, "Improving Service Reliability for Drilling and Evaluation Operations Using an Optimized RCM Strategy," Offshore Technology Conference (OTC), Rio de Janeiro, Brazil, Oct. 29–31, Paper No. OTC-24295-MS.

[7] Kale, A. A., Zhang, D., David, A., Heuermann-Kuehn, L., and Fanini, O., 2015, "Methodology for Optimizing Operational Performance and Life Management of Drilling Systems Using Real Time-Data and Predictive Analytics," SPE Digital Energy Conference and Exhibition, The Woodlands, TX, Mar. 3–5, SPE Paper No. SPE-173419-MS.

[8] Carpenter, C., 2015, "Efficient Drilling of Ultra-HP/HT Wells in the Gulf of Thailand," J. Pet. Technol., **67**(4), pp. 123–126.

[9] Zhan, S., Ahmad, I., Heuermann-Kuehn, L. E., and Baumann, J., 2010, "Integrated PoF and CBM Strategies for Improving Electronics Reliability Performance of Downhole MWD and LWD Tools," SPE Annual Technical Conference and Exhibition, Florence, Italy, Sept. 19–22, SPE Paper No. SPE-132665-MS.

[10] Ghasemloonia, A., Rideout, D. G., and Butt, S. D., 2015, "A Review of Drillstring Vibration Modeling and Suppression Methods," J. Pet. Sci. Eng., **131**, pp. 150–164.

[11] Ahmad, R., and Kamaruddin, S., 2012, "An Overview of Time-Based and Condition-Based Maintenance in Industrial Application," Comput. Ind. Eng., **63**(1), pp. 135–149.

[12] Baumgartner, T., and van Oort, E., 2014, "Pure and Coupled Drill String Vibration Pattern Recognition in High Frequency Downhole Data," SPE Annual Technical Conference and Exhibition, Amsterdam, The Netherlands, Oct. 27–29, SPE Paper No. SPE-170955-MS.

[13] Pritchard, D. M., York, P., and Roye, J., 2016, "Achieving Savings Through Reliability Using Real Time Data," Offshore Technology Conference, Houston, TX, May 2–5, Paper No. OTC-26935-MS.

[14] Qilong, X., Ruihe, W., Feng, S., Leilei, H., and Laiju, H., 2014, "Continuous Measurement-While-Drilling Utilizing Strap-down Multi-Model Surveying System," IEEE Trans. Instrum. Meas., **63**(3), pp. 650–657.

[15] de Almeida, I. N., Jr Antunes, P. D., Gonzalez, F. O., Yamachita, R. A., Nascimento, A., and Goncalves, J. L., 2015, "A Review of Telemetry Data Transmission in Unconventional Petroleum Environments Focused on Information Density and Reliability," J. Software Eng. Appl., **8**(9), p. 455.

[16] Zhang, S., Ma, L., Sun, Y., and Mathew, J., 2007, "Asset Health Reliability Estimation Based on Condition Data," World Congress on Engineering Asset Management, Harrogate, England, pp. 2195–2204.

[17] Meeker, W. Q., and Hong, Y., 2014, "Reliability Meets Big Data: Opportunities and Challenges," Qual. Eng., **26**(1), pp. 102–116.

[18] Benbow, D. W., and Broome, H. W., 2012, *The Certified Reliability Engineer Handbook*, ASQ Quality Press, Milwaukee, WI.

[19] Dong, G., and Chen, P., 2016, "A Review of the Evaluation, Control, and Application Technologies for Drill String Vibrations and Shocks in Oil and Gas Well," Shock Vib., **2016**, p. 34

[20] Ge, L., Hu, P., Hu, Z., Chen, P., Yang, Q., Wang, Z., and Liao, J., 2014, "Study on Storable down-Hole Drilling String Vibration Testing System," Open Pet. Eng. J., **7**(1), pp. 154–157.

[21] Florence, F., Iversen, F., and Macpherson, J., 2013, "Drillers' Notes," IEEE Instrum. Meas. Mag., **16**(5), pp. 43–56.

[22] Albdiry, M. T., and Almensory, M. F., 2016, "Failure Analysis of Drillstring in Petroleum Industry: A Review," Eng. Failure Anal., **65**, pp. 74–85.

[23] Baumgartner, T., and Oort, E. V., 2015, "Maximizing Drilling Sensor Value Through Optimized Frequency Selection and Data Processing," SPE Annual Technical Conference and Exhibition, Houston, TX, Sept. 28–30, SPE Paper No. SPE-174986-MS.

[24] Sotomayor, G. P., Placido, J. C., and Cunha, J. C., 1997, "Drill String Vibration: How to Identify and Suppress," Latin American and Caribbean Petroleum Engineering Conference, Rio de Janeiro, Brazil, Aug. 30–Sept. 3, SPE Paper No. SPE-39002-MS.
[25] Kriesels, P. C., Keultjes, W. J., Dumont, P., Huneidi, I., Owoeye, O. O., and Hartmann, R. A., 1999, "Cost Savings Through an Integrated Approach to Drillstring Vibration Control," SPE/IADC Middle East Drilling Technology. Conference, Abu Dhabi, United Arab Emirates, Nov. 8–10, SPE Paper No. SPE-57555-MS, pp. 139–150.
[26] Macpherson, J. D., Paul, P., Behounek, M., and Harmer, R., 2015, "A Framework for Transparency in Drilling Mechanics and Dynamics Measurements," SPE Annual Technical Conference and Exhibition, Houston, TX, Sept. 28–30, SPE Paper No. SPE-174874-MS.
[27] Li, Z., and Guo, B., 2007, "Analysis of Longitudinal Vibration of Drill String in Air and Gas Drilling," Rocky Mountain Oil & Gas Technology Symposium, Denver, CO, Apr. 16–18, SPE Paper No. SPE-107697-MS.
[28] Chen, S. L., Blackwood, K., and Lamine, E., 1999, "Field Investigation of the Effects of Stick-Slip, Lateral, and Whirl Vibrations on Roller Cone Bit Performance," SPE Annual Technical Conference and Exhibition, Houston,TX, Oct. 3–6, SPE Paper No. SPE-56439-MS.
[29] Dareing, D. W., and Vonderhejde, M. A., 1997, "Effect of Torsion on Stability, Dynamic Forces, and Vibration Characteristics in Drillstrings," ASME J. Energy Resour. Technol., **119**(1), p. 11.
[30] Wu, X., Karuppiah, V., Nagaraj, M., Partin, U. T., Machado, M., Franco, M., and Duvvuru, H. K., 2012, "Identifying the Root Cause of Drilling Vibration and Stick-Slip Enables Fit-for-Purpose Solutions," IADC/SPE Drilling Conference and Exhibition, San Diego, CA, Mar. 6–8, SPE Paper No. SPE-151347-MS.
[31] Ahmad, I., Akimov, O., Bond, P., Cairns, P., Eide, N., Gregg, T., Heimes, T., Nwosu, A., and Wiese, F., 2014, "Reliable Technology for Drilling Operations in a High-Pressure/High-Temperature Environment," IADC/SPE Drilling Conference and Exhibition, Fort Worth, TX, Mar. 4–6, SPE Paper No. SPE-167972-MS.
[32] Mirani, A., and Samuel, R., 2016, "Mitigating Vibration Induced Drillstring Failures Using Data Analytics: Workflow and Case Study," IADC/SPE Drilling Conference and Exhibition, Fort Worth, TX, Mar. 1–3, SPE Paper No. SPE-178849-MS.
[33] Heinisch, D., Oueslati, H., Popp, T. M., Meyer-Heye, B., Schepelmann, C., and Reckmann, H., 2016, "Testing and Characterization of Shock and Vibration Loads to Enhance Drilling Tool Reliability and Efficiency," Abu Dhabi International Petroleum Exhibition & Conference, Abu Dhabi, United Arab Emirates, Nov. 7–10, SPE Paper No. SPE-183037-MS.
[34] Al-Ghamd, A. M., and Mba, D., 2006, "A Comparative Experimental Study on the Use of Acoustic Emission and Vibration Analysis for Bearing Defect Identification and Estimation of Defect Size," Mech. Syst. Signal Process., **20**(7), pp. 1537–1571.
[35] Orhan, S., Aktürk, N., and Celik, V., 2006, "Vibration Monitoring for Defect Diagnosis of Rolling Element Bearings as a Predictive Maintenance Tool: Comprehensive Case Studies," Ndt E Int., **39**(4), pp. 293–198.
[36] Jain, J. R., Oueslati, H., Hohl, A., Reckmann, H., Ledgerwood, L. W., III Tergeist, M., and Ostermeyer, G. P., 2014, "High-Frequency Torsional Dynamics of Drilling Systems: An Analysis of the Bit-System Interaction," IADC/SPE Drilling Conference and Exhibition, Fort Worth, TX, Mar. 4–6, SPE Paper No. SPE-167968-MS.
[37] Ghasemloonia, A., Rideout, D. G., and Butt, S. D., 2014, "Analysis of Multi-Mode Nonlinear Coupled Axial-Transverse Drillstring Vibration in Vibration Assisted Rotary Drilling," J. Pet. Sci. Eng., **116**, pp. 36–49.
[38] Kapitaniak, M., Hamaneh, V. V., Chávez, J. P., Nandakumar, K., and Wiercigroch, M., 2015, "Unveiling Complexity of Drill–String Vibrations: Experiments and Modelling," Int. J. Mech. Sci., **101–102**, pp. 324–337.
[39] Kreuzer, E., and Steidl, M., 2012, "Controlling Torsional Vibrations of Drill Strings Via Decomposition of Traveling Waves," Arch. Appl. Mech., **82**(4), p. 515.
[40] Agostini, C. E., and Nicoletti, R., 2014, *Dynamic Modeling and Vibration Analysis of Oilwell Drillstring During Backreaming Operation. In Topics in Modal Analysis I*, Vol. 7, Springer International Publishing, Cham, Switzerland, pp. 123–131.
[41] Gulyaev, V. I., Lugovoi, P. Z., and Borshch, E. I., 2013, "Self-Excited Vibrations of a Drillstring Bit," Int. Appl. Mech., **49**(3), pp. 350–359.
[42] Tang, L., and Zhu, X., 2015, "Effects of the Difference Between the Static and the Kinetic Friction Coefficients on a Drill String Vibration Linear Approach," Arabian J. Sci. Eng., **40**(12), pp. 3723–3729.
[43] Bowler, A. I., Logesparan, L., Sugiura, J., Jeffryes, B. P., Harmer, R. J., and Ignova, M., 2014, "Continuous High-Frequency Measurements of the Drilling Process Provide New Insights Into Drilling System Response and Transitions Between Vibration Modes," SPE Annual Technical Conference and Exhibition, Amsterdam, The Netherlands, Oct. 29, SPE Paper no. SPE-170713-PA.
[44] Ledgerwood, L. W., Hoffmann, O. J., Jain, J. R., El Hakam, C., Herbig, C., and Spencer, R., 2010, "Downhole Vibration Measurement, Monitoring, and Modeling Reveal Stick/Slip as a Primary Cause of PDC-Bit Damage in Today," SPE Annual Technical Conference and Exhibition, Florence, Italy, Sept. 19–22, SPE Paper No. SPE-134488-MS.
[45] Khorshidian, H., Mozaffari, M., and Butt, S. D., 2012, "The Role of Natural Vibrations in Penetration Mechanism of a Single PDC Cutter," 46th U.S. Rock Mechanics/Geomechanics Symposium, Chicago, IL, June 24–27, Paper No. ARMA-2012-402.
[46] Sahebkar, S. M., Ghazavi, M. R., Khadem, S. E., and Ghayesh, M. H., 2011, "Nonlinear Vibration Analysis of an Axially Moving Drillstring System With Time Dependent Axial Load and Axial Velocity in Inclined Well," Mech. Mach. Theory, **46**(5), pp. 743–760.
[47] Wassell, M., and Stroehlein, B., 2010, "Method of Establishing Vibration Limits and Determining Accumulative Vibration Damage in Drilling Tools," SPE Annual Technical Conference and Exhibition, Florence, Italy, Sept. 19–22, SPE Paper No. SPE-135410-MS.
[48] Samuel, R., 2013, "Modeling and Analysis of Drillstring Vibration in Riserless Environment," ASME J. Energy Resour. Technol., **135**(1), p. 013101.
[49] Jones, S., and Sugiura, J., 2017, "Drilling Dynamics Data Recorders Now Cost-Effective for Every Operator-Compact Embedded Sensors in Bit and BHA Capture Small Data to Make the Right Decisions Fast," SPE/IADC Drilling Conference and Exhibition, The Hague, The Netherlands, Mar. 14–16, SPE Paper No. SPE-184738-MS.
[50] Zarei, J., Tajeddini, M. A., and Karimi, H. R., 2014, "Vibration Analysis for Bearing Fault Detection and Classification Using an Intelligent Filter," Mechatronics., **24**(2), pp. 151–157.
[51] Karabay, S., and Uzman, I., 2009, "Importance of Early Detection of Maintenance Problems in Rotating Machines in Management of Plants: Case Studies From Wire and Tyre Plants," Eng. Failure Anal., **16**(1), pp. 212–224.
[52] Heidarbeigi, K., Ahmadi, H., Omid, M., and Tabatabaeefar, A., 2010, "Evolving an Artificial Neural Network Classifier for Condition Monitoring of Massy Ferguson Tractor Gearbox," Int. J. Appl. Eng. Res., **5**(12), pp. 2097–2107.
[53] Chen, M., Mao, S., and Liu, Y., 2014, "Big Data: A Survey," Mobile Networks Appl., **19**(2), pp. 171–209.
[54] Hu, H., Wen, Y., Chua, T. S., and Li, X., 2014, "Toward Scalable Systems for Big Data Analytics: A Technology Tutorial," IEEE Access, **2**, pp. 652–687.
[55] Elgendy, N., and Elragal, A., 2014, "Big Data Analytics: A Literature Review Paper," Industrial Conference on Data Mining, Petersburg, VA, July 16–20, pp. 214–227.
[56] Kambatla, K., Kollias, G., Kumar, V., and Grama, A., 2014, "Trends in Big Data Analytics," J. Parallel Distrib. Comput., **74**(7), pp. 2561–2573.
[57] Xiao, C., 2015, "Using Machine Learning for Exploratory Data Analysis and Predictive Models on Large Datasets," Master's thesis, University of Stavanger, Stavanger, Norway.
[58] Loh, W. Y., 2011, "Classification and Regression Trees," Wiley Interdiscip. Rev.: Data Min. Knowl. Discovery, **1**(1), pp. 14–23.
[59] Liao, S. H., Chu, P. H., and Hsiao, P. Y., 2012, "Data Mining Techniques and Applications–a Decade Review From 2000 to 2011," Expert Syst. Appl., **39**(12), pp. 11303–11311.
[60] Parker, P. A., 2014, "Discussion of "Reliability Meets Big Data: Opportunities and Challenges," Qual. Eng., **26**(1), pp. 117–120.
[61] McCubrey, R., Johnson, A., Adsit, R., Veeningen, D., and Pixton, D., 2013, "System Reliability and Metrics for the High-Speed Networked Drillstring Telemetry and along String Evaluation," SPE/IADC Drilling Conference, Amsterdam, The Netherlands, Mar. 5–7, SPE Paper No. SPE-163570-MS.
[62] Lines, L. A., Mauldin, C. L., Hill, J. W., and Aiello, R. A., 2014, "Advanced Drilling Dynamics Sensor Allows Real-Time Drilling Optimization, Damage Prevention and Condition Monitoring of RSS and LWD BHAs," SPE Annual Technical Conference and Exhibition, 7, Amsterdam, The Netherlands, Oct. 27–29, SPE Paper No. SPE-170586-MS.
[63] Sugiura, J., Samuel, R., Oppelt, J., Ostermeyer, G. P., Hedengren, J., and Pastusek, P., 2015, "Drilling Modeling and Simulation: Current State and Future Goals," SPE/IADC Drilling Conference and Exhibition, London, Mar. 17–19, SPE Paper No. SPE-173045-MS.
[64] Finkelstein, M., 2009, "Virtual Age of Non-Repairable Objects," Reliab. Eng. Syst. Saf., **94**(2), pp. 666–669.
[65] Vaca-Trigo, I., and Meeker, W. Q., 2009, "A Statistical Model for Linking Field and Laboratory Exposure Results for a Model Coating," Service Life Prediction Polymeric Mater., pp. 29–43.
[66] Mirgkizoudi, M., Liu, C., and Riches, S., 2010, "Reliability Testing of Electronic Packages in Harsh Environments," 12th Electronics Packaging Technology Conference (EPTC), Singapore, Dec. 8–10, pp. 224–230.
[67] Lall, P., Choudhary, P., Gupte, S., Suhling, J., and Hofmeister, J, 2007, "Statistical and Built-in Reliability Test for Feature Extraction and Health Monitoring of Electronics Under Shock Loads," 57th Electronic Components and Technology Conference (ECTC'07), Reno, NV, May 29–June 1, pp. 1161–1178.
[68] White, M., 2008, "Physics-of-Failure Based Modeling and Lifetime Evaluation. Microelectronics Reliability," Jet Propulsion Laboratory, National Aeronautics and Space Administration, Washington, DC.
[69] Li, M., and Meeker, W. Q., 2014, "Application of Bayesian Methods in Reliability Data Analyses," J. Qual. Technol., **46**(1), p. 1.
[70] Corbetta, M., Sbarufatti, C., Manes, A., and Giglio, M., 2015, "Real-Time Prognosis of Crack Growth Evolution Using Sequential Monte Carlo Methods and Statistical Model Parameters," IEEE Trans. Reliab., **64**(2), pp. 736–753.
[71] Sutherland, H., Repoff, T., House, M., and Flickinger, G., 2003, "Prognostics, A New Look at Statistical Life Prediction for Condition-Based Maintenance," IEEE Aerospace Conference, Big Sky, MT, Mar. 8–15, pp. 3131–3136.
[72] Chi, A. I., Zhang, J., Ge, W., and Guo, B., 2006, "Prediction of Fatigue Life of Drillstring Under Axial-Torsional Combined Vibrations," SPE Gas Technology Symposium, Calgary, AB, Canada, May 15–17, SPE Paper No. SPE-99356-MS.

[73] Yan, J., and Lee, J., 2007, "A Hybrid Method for On-Line Performance Assessment and Life Prediction in Drilling Operations," IEEE International Conference on Automation and Logistics, Jinan, China, Aug. 18–21, pp. 2500–2505.
[74] Wu, S. J., Gebraeel, N., Lawley, M. A., and Yih, Y., 2007, "A Neural Network Integrated Decision Support System for Condition-Based Optimal Predictive Maintenance Policy," IEEE Trans. Syst., Man, Cybern.-Part A: Syst. Humans., **37**(2), pp. 226–236.
[75] Pham, H. T., and Yang, B. S., 2010, "Estimation and Forecasting of Machine Health Condition Using ARMA/GARCH Model," Mech. Syst. Signal Process., **24**(2), pp. 546–558.
[76] Hong, Y., and Meeker, W. Q., 2013, "Field-Failure Predictions Based on Failure-Time Data With Dynamic Covariate Information," Technometrics., **55**(2), pp. 135–149.
[77] Frenzel, M., Wassell, M., and Brown, C., 2014, "Case Histories of Real-Time Drilling Optimization Combining Drill String Modeling, Surface Measurements and Downhole Measurements," IADC/SPE Drilling Conference and Exhibition, Fort Worth, TX, Mar. 4–6, SPE Paper No. SPE-167960-MS.
[78] Bloch, H., and Geitner, F., 1999, *Machinery Failure Analysis and Troubleshooting* (Practical Machinery Management for Process Plants, Vol. 2), Elsevier, Waltham, MA.
[79] Ly, C., Tom, K., Byington, C. S., Patrick, R., and Vachtsevanos, G. J., 2009, "Fault Diagnosis and Failure Prognosis for Engineering Systems: A Global Perspective," IEEE International Conference on Automation Science and Engineering (CASE 2009), Bangalore, India, Aug. 22–25, pp. 108–115.
[80] Luo, J., Namburu, M., Pattipati, K., Qiao, L., Kawamoto, M., and Chigusa, S. A., 2003, "Model-Based Prognostic Techniques [Maintenance Applications]," IEEE Systems Readiness Technology Conference (AUTOTESTCON 2003), Anaheim, CA, Sept. 22–25, pp. 330–340.
[81] Jardine, A. K., Lin, D., and Banjevic, D., 2006, "A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance," Mech. Systems Signal Process., **20**(7), pp. 1483–1510.
[82] Cheng, S., Azarian, M. H., and Pecht, M. G., 2010, "Sensor Systems for Prognostics and Health Management," Sensors, **10**(6), pp. 5774–5797.
[83] Zhang, S., Hodkiewicz, M., Ma, L., and Mathew, J., 2006, "Machinery Condition Prognosis Using Multivariate Analysis," *Engineering Asset Management*, Springer, London, pp. 847–854.
[84] Vlok, P. J., Coetzee, J. L., Banjevic, D., Jardine, A. K., and Makis, V., 2002, "Optimal Component Replacement Decisions Using Vibration Monitoring and the Proportional-Hazards Model," J. Oper. Res. Soc., **53**(2), pp. 193–202.
[85] Mishra, S., Ganesan, S., Pecht, M., and Xie, J., 2004, "Life Consumption Monitoring for Electronics Prognostics," Aerospace Conference, Big Sky, MT, Mar. 6–13, pp. 3455–3467.
[86] Vlok, P. J., Wnek, M., and Zygmunt, M., 2004, "Utilising Statistical Residual Life Estimates of Bearings to Quantify the Influence of Preventive Maintenance Actions," Mech. Syst. Signal Process., **18**(4), pp. 833–847.
[87] Sun, Y., Ma, L., Mathew, J., Wang, W., and Zhang, S., 2006, "Mechanical Systems Hazard Estimation Using Condition Monitoring," Mech. Syst. Signal Process., **20**(5), pp. 1189–1201.
[88] Saxena, A., and Saad, A., 2007, "Evolving an Artificial Neural Network Classifier for Condition Monitoring of Rotating Mechanical Systems," Appl. Soft Comput., **7**(1), p. 441
[89] Chen, S. L., Craig, M., Callan, R., Powrie, H., and Wood, R., 2008, "Use of Artificial Intelligence Methods for Advanced Bearing Health Diagnostics and Prognostics,"Aerospace Conference, Big Sky, MT, Mar. 1–8, pp. 1–9.
[90] Zhao, X., and Ensor, K. B., 2012, "Dynamic Factor Model on Directional Drilling System," IEEE Conference on Prognostics and System Health Management (PHM), Beijing, China, May 23–25, pp. 1–7.
[91] Peng, Y., Dong, M., and Zuo, M. J., 2010, "Current Status of Machine Prognostics in Condition-Based Maintenance: A Review," Int. J. Adv. Manuf. Technol., **50**(1–4), pp. 297–313.
[92] Campos, J., 2009, "Development in the Application of ICT in Condition Monitoring and Maintenance," Comput. Ind., **60**(1), pp. 1–20.
[93] Ocak, H., and Loparo, K. A., 2005, "HMM-Based Fault Detection and Diagnosis Scheme for Rolling Element Bearings," ASME J. Vib. Acoust., **127**(4), pp. 299–306.
[94] Han, T., Yang, B. S., and Yin, Z. J., 2007, "Feature-Based Fault Diagnosis System of Induction Motors Using Vibration Signal," J. Qual. Maint. Eng., **13**(2), p. 163.
[95] Abu-Mahfouz, I., and Banerjee, A., 2014, "Drill Wear Feature Identification Under Varying Cutting Conditions Using Vibration and Cutting Force Signals and Data Mining Techniques," Procedia Comput. Sci., **36**, pp. 556–563.
[96] Kumar, A., Ramkumar, J., Verma, N. K., and Dixit, S., 2014, "Detection and Classification for Faults in Drilling Process Using Vibration Analysis," IEEE Conference on Prognostics and Health Management (PHM), Cheney, WA, June 22–25, pp. 1–6.
[97] Bousdekis, A., Magoutas, B., Apostolou, D., and Mentzas, G., 2016, "Review, Analysis and Synthesis of Prognostic-Based Decision Support Methods for Condition Based Maintenance," J. Intell. Manuf., pp. 1–4.
[98] Telford, S., Mazhar, M. I., and Howard, I., 2011, "Condition Based Maintenance (CBM) in the Oil and Gas Industry: An Overview of Methods and Techniques," International Conference on Industrial Engineering and Operations Management, Kuala Lumpur, Malaysia Jan. 22–24, pp. 1152–1159.
[99] Kothamasu, R., Huang, S. H., and VerDuin, W. H., 2009, "System Health Monitoring and Prognostics—A Review of Current Paradigms and Practices," *In Handbook of Maintenance Management and Engineering*, Springer, London, pp. 337–362.
[100] Rausand, M., 1998, "Reliability Centered Maintenance," Reliab. Eng. Syst. Saf., **60**(2), pp. 121–132.
[101] Liu, S., and Wang, S., 2006, "Machine Health Monitoring and Prognostication Via Vibration Information," Sixth International Conference on Intelligent Systems Design and Applications (ISDA'06), Jinan, China, Oct. 16–18, pp. 879–886.
[102] Heng, A., Tan, A. C., Mathew, J., Montgomery, N., Banjevic, D., and Jardine, A. K., 2009, "Intelligent Condition-Based Prediction of Machinery Reliability," Mech. Syst. Signal Process., **23**(5), pp. 1600–1614.
[103] Niu, G., Yang, B. S., and Pecht, M., 2010, "Development of an Optimized Condition-Based Maintenance System by Data Fusion and Reliability-Centered Maintenance," Reliab. Eng. Syst. Saf., **95**(7), pp. 786–796.
[104] Li, C., Sánchez, R. V., Zurita, G., Cerrada, M., and Cabrera, D., 2016, "Fault Diagnosis for Rotating Machinery Using Vibration Measurement Deep Statistical Feature Learning," Sensors, **16**(6), p. 895.
[105] Li, Y., Cho, J. J., and Ren, Y., 2014, "How Can the Petroleum Industry Benefit From Human Reliability Analysis?," IADC/SPE Drilling Conference and Exhibition, Fort Worth, TX, Mar. 4–6, SPE Paper No. SPE-167983-MS.
[106] Gitzel, R., Turring, S., and Maczey, S., 2015, "A Data Quality Dashboard for Reliability Data," IEEE 17th Conference on Business Informatics (CBI), Lisbon, Portugal, July 13–16, pp. 90–97.