**Abstract**

The present disclosure provides methods and systems for monitoring a drilling system, including methods and systems for estimating the life consumption of downhole drilling tools. The system employs a plurality of sensors that provide sensor signals related to the status of components in the drilling system. The sensor signals are analyzed using Functional Principal Component Analysis (FPCA) to give estimations for one or more performance metrics, including the life consumption of downhole drilling tools.

**Diagram**

1. Collecting a first set of sensor signals
2. Constructing a model using Functional Principal Component Analysis (FPCA) based on the first set of sensor signals, wherein the model is used to estimate one or more performance metrics of a component in the downhole drilling tool.
3. Collecting a second set of sensor signals.
4. Revising the model based on the second set of sensor signals.
5. Estimating the one or more performance metrics of the component in the downhole drilling tool using the revised model.
Figure 2

Fraction of variance explained by No. of PC for function $\text{tr}_r s_{\text{p},m}$

$k = 3$, FVE = 98.33% (final choice)
collecting a first set of sensor signals

constructing a model using Functional Principal Component Analysis (FPCA) based on the first set of sensor signals, wherein the model is used to estimate one or more performance metrics of a component in the downhole drilling tool

collecting a second set of sensor signals

revising the model based on the second set of sensor signals

estimating the one or more performance metrics of the component in the downhole drilling tool using the revised model

Figure 4
SYSTEM AND METHOD FOR MONITORING DRILLING SYSTEMS

TECHNICAL FIELD

[0001] The present disclosure relates to systems and methods for monitoring drilling systems for oil and gas exploration, particularly systems and methods for real-time estimation of life consumption and life span of downhole drilling tools.

BACKGROUND

[0002] The drilling system used in the modern petroleum and gas explorations complex electro-mechanical systems. It includes both surface equipment as well as downhole drilling tools. A drilling assembly is a downhole drilling tool that breaks and traverses the earth formation. A drilling assembly includes a drill bit and a drill collar. It may also include a downhole motor, a rotary steerable system, telemetry transmitters, as well as measurement-while-drilling (MWD) and logging-while-drilling (LWD) instruments. Although MWD refers to the measurement of the movement and location of the drilling assembly while the drilling continues and LWD focuses more on the measurement of formation properties, they are used interchangeably in this disclosure.

[0003] Properties of the earth formation measured in the drilling process typically include resistivity, density, porosity, permeability, acoustic properties, nuclear-magnetic resonance properties, corrosive properties of the fluids or formation, and salt or saline contents. Parameters of the drilling assembly measured typically include velocity, vibration, bending moment, etc. Downhole vibrations can be further categorized into axial vibration (e.g., bit bounce), which is along the drill string axis; lateral vibration (e.g., whirl), which is transverse to the drill string axis; and torsional vibration (e.g., stick slip), which is in the rotary path about the drill string axis. The MWD/LWD instruments also monitor drilling operating parameters including weight-on-bit (WOB), drilling fluid flow rate, pressure, temperature, rate of penetration, azimuth, tool face, drill bit rotation, etc.

[0004] Alternative to or complimentary to the MWD/LWD instruments, wireline logging may be used to examine the earth formation. Typically, after the drill string is removed from the borehole, a sonde is lowered to the bottom of the region of interest and subsequently pulled upward. On the upward trip, the sonde measures the properties of the formation along its path.

[0005] Sensors are employed to obtain measurements in both the MWD/LWD instruments and the wireline logging approach. Other electronic components include active components, such as printed circuit board assemblies (PCBA) and transistors, or passive components, such as resistors and capacitors. PCBAs are used throughout a drilling assembly. For example, a PCBA can be used in the operation of the power supply, temperature sensors, pressure transducers, the battery, etc. The master memory board, the read out board, the transmitter or a receiver board, and the accelerometer board are among PCBAs commonly used in a downhole environment.

[0006] A PCBA can be coupled to various sensors in a drilling assembly by any known methods. In some embodiments, sensors may be integrated in the PCBA, e.g., on a master memory board. Sensors can be measurement sensors that monitor real-time conditions during a drilling process. In other embodiments, sensors may be prognostic sensors. Prognostic sensors are subject to more severe conditions than in a typical drilling operation (e.g., higher temperature or pressure) so that they fail at an accelerated rate. They can be used to estimate the time of failure of another component.

[0007] Other than monitoring the condition of a PCBA, sensors can be mounted on any other suitable components in a drilling assembly. For example, they can be attached to a drill bit to monitor its movement or temperature. Sensors can also be mounted along the borehole, for example, to monitor the pressure or flow rate of the drilling mud along the path. Sensors (e.g., RFID) can even be put into the fluid in the drilling system and be dispersed into the earth formation.

[0008] A processor usually is a part of the PCBA. It is configured to receive, store, or execute data such as computer codes or sensor signals. For example, a processor can be coupled to a program module which supplies executable instructions and a recording medium that stores various results of calculations performed by the processor. Sensor signals are the input to the processor.

[0009] In addition to the drilling assembly, a drilling system also includes downhole drilling tools such as drill pipes, casing, and packers that divide the borehole into different sections. The drilling system further includes surface equipment or subsystems a drilling mud circulation system (mud pumps, flow meters, etc.), a drilling platform and its associated hardware (valves, manifolds, generators, pumps, etc.), as well as additional monitoring and control systems on the surface.

[0010] Any downtime in a drilling system for repair and maintenance can be costly. Modern oil and gas explorations in deeper wells and harder to reach locations further increase the failure rate as well as the overall cost of the drilling operation. For example, directional drilling systems face considerably severe operating environments, with bottom hole temperatures in excess of 200° C., high lateral and axial vibrations of 15 g, RMS (Root Mean Square), and pressures exceeding 250000 PSI while drilling profiles requiring up to 15/100 ft. Therefore, it becomes more desirable to implement cost-effective maintenance strategies, for example, longer on-stream time, less frequent equipment replacements, and smaller inventory of replacement parts. To achieve these goals would require closer monitoring of the status of downhole drilling tools and better understanding of the environment in which they operate. The present disclosure provides methods and apparatus for monitoring a drilling system, including methods and apparatus for predicting the degradation trend and the useful lifetime of downhole drilling tools.

SUMMARY

[0011] The present disclosure provides a method for monitoring a drilling system. The method comprises a step of collecting a first set of sensor signals. The sensor signals are from sensors deployed throughout the drilling system, including downhole drilling tools, which includes mechanical and electronic parts. Sensor signals reflect one or more conditions of the component in the downhole drilling tool, such as temperature, pressure, and vibrations. The method also involves a step of constructing a model using Functional Principal Component Analysis (FPCA) based on the first set of sensor signals. The sensor signals are used to determine model parameters.

[0012] Furthermore, after collecting a second set of sensor signals, the model is updated using the second set of sensor
signals by adjusting the model parameters. The model is used in estimating one or more performance metrics of the components in the drilling system, including life consumption and remaining useful life. Accordingly, the operator can obtain real time estimates of the life consumption of the drilling tools.

The present disclosure also provides a system for monitoring a downhole drilling tool. The system comprises a drilling assembly and a plurality of sensors disposed about the drilling assembly, wherein the sensors provide sensor signals associated with the drilling assembly. The system also includes one or more computers which has a processor, a non-transitory machine readable medium communicably coupled to the processor, and a set of processor-executable instructions embodied in the non-transitory machine readable medium. The instructions are configured to implement a method for monitoring a downhole drilling tool described herein.

The present disclosure further provides a drilling system. The drilling system includes a downhole drilling tool and a plurality of sensors disposed about the downhole drilling tool, wherein the plurality of sensors traverse an underground formation with the downhole drilling tool and generate sensor signals that reflect a condition of one or more components of the downhole drilling tool. The drilling system also includes a computer configured to implement a method for monitoring a downhole drilling tool described herein.

BRIEF DESCRIPTION OF THE DRAWINGS

The teachings of the present invention can be readily understood by considering the following detailed description in conjunction with the accompanying drawings.

FIG. 1 shows a test data set used in validating the FPCA model of the current disclosure.

FIG. 2 illustrates Fraction of Variance Exampled (FVE) in response to the number of principal components selected.

FIG. 3 shows the life consumption estimation in comparison with the true life consumption.

FIG. 4 illustrates a method of the current disclosure.

DETAILED DESCRIPTION

Reference will now be made in detail to embodiments of the present disclosure, examples of which are illustrated in the accompanying drawings. It is noted that wherever practicable, similar or like reference numbers may be used in the drawings and may indicate similar or like elements.

The drawings depict embodiments of the present disclosure for purposes of illustration only. One skilled in the art would readily recognize from the following description that alternative embodiments exist without departing from the general principles of the present disclosure.

According to one aspect of the current disclosure, sensors are deployed throughout a drilling system including downhole drilling tools, which further comprises a drilling assembly, drill pipes, casing, and packers. The sensors can be attached to the surface of or reside inside the body of parts such as the drill bit, the drill string, the downhole motor, a drilling pipe, the drilling collar, the downhole battery, and the downhole alternator. They are also employed in electronic components such as the MWD/LWD instruments.

According to another aspect of the current disclosure, the sensors measure one or more performance metrics of the downhole drilling tool, such as vibration, pressure, temperature, the weight on bit (WOB), RPM, and transmit the sensor signals to a computer system for storage and analysis. The measurement sensor signals report the status of a downhole component. The prognostic sensor signals may not directly reflect the status (e.g., temperature, vibration) of a downhole component but may be correlated to the status of a component that the sensor is not directly associated with. For example, a prognostic sensor may be used to predict the life time of a PCBA board. To do so, a correlation can be first made in a controlled environment (e.g., a lab) wherein the sensor is subject to a temperature higher (e.g., 20°C. higher) than the PCBA is subject to. The prognostic sensor may fail at an accelerated rate than the PCBA, from which an accelerated factor can be obtained. With this correlation of life span, in a downhole environment, the status of a prognostic sensor can be used to estimate the status of another component, such as a PCBA.

According to a further aspect of the current disclosure, sensors are installed on the components of a drilling system that are on the surface. For example, in a managed pressure drilling system, the rotating control device (RCD) is a subsystem that employs high pressure seals, bearings, manifolds, and pumps. Sensors are deployed on the RCD to monitor the vibration or the noise level of the bearings and high pressure seals. Flow meters, pressure sensors, vibration detectors, temperature sensors are installed on the mud circulation pumps.

According to a further aspect of the current disclosure, the sensor signals are used to predict or estimate a performance metric of the downhole drilling tool or surface equipment or subsystems. The metrics may include failure probability, life consumption, and remaining useful life. The sensor signals can be used in performing cumulative damage analysis, degradation analysis, and life cycle management.

The information obtained from the sensors can be used to optimize the drilling and exploration performance, to avoid Non-Productive Time (NPT) on the rig site, and to reduce the repair and maintenance expense.

According to still one aspect of the current disclosure, Functional Data Analysis (FDA) is used to estimate the performance metrics, e.g., life consumption, of a drilling tool. The Functional Principal Component Analysis (FPCA) models is constructed for sensor signals and provides a collection of computational tools to handle the collected degradation trends from different failure components of the same type. The resulting unit-specific FPC scores capture pattern changes in the sensor signal on an individual unit, and these scores can be adjusted when new sensor signals are collected. In this case, a sensor signal associated with a drilling tool that fails over time is also referred to as a degradation signal as it reflects the trend of degradation of the drilling tool.

The first step in conducting a FDA analysis is to build a FPCA model. In this regard, a degradation signal can be described by a smooth curve contaminated by random errors. Consider one signal first. Let $x_i(t)$ be the $i$th measurement of signal on unit $j$ at time $t$, with the end of the time interval $T$.

$$x_i(t_j) - R_i(t_j) + \epsilon_i \text{ for } t = 1,2, \ldots, n_j, 0 \leq t \leq T. \tag{1}$$

wherein $R_i(t_j)$ is the uncontaminated signal and $\epsilon_i$ is an independent identically distributed (i.i.d.) random error.
following the normal distribution $N(0, \sigma^2)$. According to Karhunen-Loève theorem, a stochastic process can be represented by an infinite linear combination of orthogonal functions:

$$R_{j}(t_{0}) = M(t_{0}) + \sum_{j=1}^{\infty} \theta_{j} \xi_{j}(t_{0}) = M(t_{0}) + \sum_{j=1}^{\infty} \theta_{j} \xi_{j}(t_{0}),$$

(2)

[0029] where $M(t_{0})$ is the grand mean curve of the signal across all units, $\xi_{j}(t_{0})$ is the value of the $j$th eigenfunction at $t_{0}$, the number of eigenvalues $N$, to be included can be determined based on the explained proportion of functional variation, and $\theta_{j}$ are the unit-specific FPCA scores. The set of orthonormal eigenfunctions $\xi_{j}(t)$ account for the basic functions about the expansion of the signal which approximates the signal as closely as possible. Particularly, these functions need to satisfy:

$$f_{j}^{(d)} \xi_{j}(t)(d\tau) - f_{j}^{(d)} \xi_{j}(t)(d\tau) = 0, \quad j = 1, 2, \ldots, n_{j}.$$

(3)

[0030] These eigenfunctions can be estimated in a non-parametrical manner. $R_{j}(t)$ is one of its independent realisations of the stochastic signal $R(t)$. The relationship of eigenvalues and eigenfunctions can be found by using the Fredholm integral equation on the covariance $C_{j}(u, v)$ of $R(t)$:

$$f_{j}^{(d)} C_{j}(u, v)(d\tau) = -\int_{0}^{T} \xi_{j}(u, \tau) \mathrm{d} \tau.$$

(4)

[0031] Then, the orthogonal expression of $C_{j}(u, v)$ in terms of the resulting eigenfunctions and eigenvalues is:

$$C_{j}(u, v) = \sum_{j=1}^{\infty} \lambda_{j} \xi_{j}(u) \xi_{j}(v), \quad 0 \leq u, v \leq T,$$

(5)

[0032] The functional scores $\theta_{j}$ of unit $j$ can be calculated by:

$$\theta_{j} = f_{j}^{(d)} \xi_{j}(u) \xi_{j}(v)(d\tau).$$

(6)

[0033] Considering other model parameters, Eq. (1) becomes:

$$X_{j}(t_{0}) = M(t_{0}) + \sum_{j=1}^{\infty} \xi_{j}(t_{0}) + e_{j}, \quad i = 1, 2, \ldots, n_{j}.$$  

(7)

[0034] Once the model is constructed, parameters in the model are estimated, including the grand mean function, the FPCA function scores, etc. Estimation of Grand Mean Function $M_{j}(t_{0})$

[0035] The grand mean smoother across all available training degradation signals $X^{T} = [X_{1}(t_{1}), \ldots, X_{n}(t_{n})]^T$ can be captured by Locally Weighted Scatterplot Smoothing (LOWESS) technique. The prominent advantage of LOWESS is to model a process without relying on physical knowledge about the process. Gaussian kernel has been widely used to compromise the performance and computational cost. The local approximation can be fitted by the local linear kernel regression with the coefficients $[\alpha_{0}, \alpha_{1}]$ estimated by:

$$\min \left\{ \sum_{i=1}^{n} \sum_{i'=1}^{n} W_{ij} \left[ \|X_{j}(t_{0}) - (\alpha_{0} + \alpha_{1} t_{0}) \|^{2} \right] \right\}.$$  

(8)

[0036] where

$$w_{ij} = \left( \frac{t_{0} - t_{i}}{h_{ij}} \right)^{2}, \quad W(x, y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^{2}}{2}}$$

is the Gaussian kernel function, and the bandwidth $h_{ij}$ can be determined by the cross-validation. The estimated coefficients depending on time $t$ are:

$$[\hat{\alpha}_{0}, \hat{\alpha}_{1}] = (T^{TW})^{-1} T^{W} X,$$

(9)

[0037] wherein

$$T = \begin{pmatrix} 1 & \cdots & 1 & \cdots & 1 \end{pmatrix}^{T},$$

and

$$W = \text{diag}(w_{11}, w_{12}, \ldots, w_{nm}).$$

[0038] Estimation of Functional Scores

[0039] To explain the major variation of a sensor signal, the significant eigenvalues can be found based on the covariance of the signals. Let $K_{j}(u, v) = \text{cov}(X(u), X(v))$ be the covariance of the collected stochastic signals. The coefficients $[B_{0}, B_{1}, B_{2}]$ depending on the query moments $u, v$ can be solved through the optimization:

$$\min \sum_{j=1}^{n} \sum_{i=1}^{m} \left( \frac{X_{j}(t_{0}) - \dot{X}_{j}(t_{0})}{h_{ij}} \right)^{2} + \text{min} \sum_{j=1}^{n} \sum_{i=1}^{m} \left[ R_{j}(t_{0}) - \dot{R}_{j}(t_{0}) \right]^{2},$$

(10)

[0040] where $h_{0}$ and $h_{1}$ are respective bandwidths, and $R_{j}(t_{0})$ is the raw covariance estimated by:

$$K_{j}(u, v) = \text{cov}(X(u), X(v)).$$

(11)

[0041] Since $K_{j}(u, v) = C_{j}(u, v) + \sigma_{j}^{2} I_{(u>v)}$, in which $I_{(u>v)} = 1$ when $u>v$, 0 otherwise. In case of the intense signal data, each eigenvalue $\lambda_{j}$ can be estimated by performing numerical integration:

$$\hat{\lambda}_{j} = \int_{0}^{T} \int_{0}^{T} \xi_{j}(u) \xi_{j}(v) W(u, v) \mathrm{d} u \mathrm{d} v.$$  

(12)

[0042] The FPCA scores for each unit $j$ can be calculated by:

$$\hat{\theta}_{j} = \int_{0}^{T} \left[ X_{j}(t_{0}) - \hat{M}_{j}(t_{0}) \right] \xi_{j}(u) \xi_{j}(v) \mathrm{d} u \mathrm{d} v.$$  

(13)

[0043] The FPCA scores estimated from Eq. (13) would be biased for sparse signal readings contaminated by measurement errors. An effective alternative method to correct this problem is called Principal Analysis by Conditional Expect-
Let \( \hat{\theta}_{j_s} \) be the \( s \)th FPCA score of unit \( j \) given \( n \) observations \( X=[X(t_1), \ldots, X(t_n)]^T \) collected so far. The conditional expectation of \( \hat{\theta}_{j_s} \) is:

\[
\hat{\theta}_{j_s} = \frac{1}{n} \sum_{i=1}^{n} \hat{\theta}_{j_s}(t_i),
\]

wherein the functional scores \( \hat{\theta}_{j_s}(t_i) \) are evaluated at all collected measured moments \( n \). The covariance matrix of FPCA scores \( \hat{\theta}_{j_s}(t_i) \) can be expressed as:

\[
\text{cov}(\hat{\theta}_{j_s}(t_i), \hat{\theta}_{j_s}(t_j)) = \frac{1}{n} \sum_{i=1}^{n} \left( \hat{\theta}_{j_s}(t_i) - \bar{\hat{\theta}}_{j_s} \right) \left( \hat{\theta}_{j_s}(t_j) - \bar{\hat{\theta}}_{j_s} \right),
\]

where \( \bar{\hat{\theta}}_{j_s} = \frac{1}{n} \sum_{i=1}^{n} \hat{\theta}_{j_s}(t_i) \).

Given estimation of all the model parameters, the sensor signal \( X(t) \) at time \( t \) can be predicted by:

\[
\hat{X}(t) = \hat{M}_t(\hat{X}(t)) = \hat{M}_t(\hat{X}(t)) + \epsilon, \tag{16}
\]

where \( \hat{M}_t(\hat{X}(t)) = \sum_{i=1}^{n} \hat{\theta}_{j_s}(t_i) \).

Moreover, it is proved that the asymptotic point-wise Standard Deviation (STD) of \( \hat{X}(t) \) is:

\[
\text{STD}(\hat{X}(t)) = \frac{1}{n} \sum_{i=1}^{n} \text{STD}(\hat{\theta}_{j_s}(t_i)), \tag{17}
\]

where \( \text{STD}(\hat{\theta}_{j_s}(t_i)) = \frac{1}{n} \sum_{i=1}^{n} \left( \hat{\theta}_{j_s}(t_i) - \bar{\hat{\theta}}_{j_s} \right)^2 \).

The confidence interval of \( X(t) \) can be known at desired significant level \( a \) as:

\[
\left[ \hat{X}(t), \hat{X}(t) + 2 \text{STD}(\hat{X}(t)) \right]. \tag{18}
\]

where \( z_{1-a} \) is the \( 1-a/2 \) percentile of the standard normal distribution.

The FPCA model has been validated. In one example, degradation profiles of turbofan engines of the same type due to wear and tear were based on the usage patterns (four different combinations of operational conditions and fault modes). The damage degree of these engines may vary from one another as different engines often undergo different operating conditions. Fifteen engines under the same combination of operational condition (Sea Level) and fault mode (HPC degradation) were selected. For each engine, sensor readings were collected from 26 sensor channels and the sensor measuring the Low Pressure Turbine (LPT) outlet temperature was utilized to indicate degradation process. The training dataset include LPT readings from ten engines from inception of their operations to the moment that they failed. The data from the other five engines is treated as the test dataset.

Note that the same validation can be applied to a component in a downhole drilling tool, e.g., a drill bit. For example, sensor signals associated with multiple drill bits in their respective operations can be used as the training dataset to construct a FPCA model. The model thus constructed can be used in predicting the performance metric of a drill bit in operation using sensor signals as the test dataset. The test dataset in turn can be used to update the training dataset so that the model estimation becomes more accurate as more and more sensor signals become available.

As shown in FIG. 1, in the test dataset, different proportions of available measurements were use, i.e., 50%, 60%, 70% and 80% of the complete set of data from the start of the operation to the failure of the components. Estimations were made regarding the life consumption or remaining useful life after each available proportion of signals passes. The moment at which the degradation trend reaches the preset failure threshold (1430 unit temperature in this case) was recorded as the predicted failure time. Estimated life consumption from the time of analysis was performed were calculated to provide an estimated failure time.

In applying the FPCA model to predict failure moment, a traditional way is to use time information as the predictor and amplitude information as the response variable. That is to say, given a known response value (fix amplitude threshold), the predictor value (time) will be derived reversely from the model. Alternatively, amplitude can be used as the predictor and time information as the response variable. This transformed axis facilitates the mathematical calculation since it is convenient to fit the model given the fixed amplitude threshold value as predictor.

The FPCA model includes a grand mean function, several eigenfunctions, and Functional scores. In this example, the bandwidth chosen for the mean function is 5.9474, and the bandwidth values for the covariance function are (1.4795, 1.4795). From the training dataset, the first three eigenvalues are: \( \rho_1 = 78601, \rho_2 = 4327 \) and \( \rho_3 = 3046 \), which account for 98.33% of Functional Variation Explained (FVE).

Assuming 95% of FVE, the FPCA model for the LPT signal based on a transformed axis can be expressed as:

\[
t_j(X_j) = \hat{M}_t(X_j) + \sum_{i=1}^{3} \hat{\theta}_{j_s}(X_j) + e, \tag{19}
\]

The FPCA model obtained from the training dataset was used to predict the failure moments for each test units given the different available proportions of LPT signal readings which are used to obtain the unit-specific FPCA scores as addressed in Eq. (14). In the second stage, the failure moment at fixed LPT temperature amplitude threshold was predicted with 100(1-c)% confidence interval using Eqs. (16) and (18).

The reliability metric applied here is called Life Consumption (LC):

\[
\text{Life Consumption} = \frac{T(\text{Query})}{T(\text{Failure})}, \tag{35}
\]

where \( T(\text{Query}) \) stands for current query moment, and \( T(\text{Failure}) \) means the real or predicted failure time.

Another similar metric is remaining useful life, which is:

\[
\text{Remaining Useful Life} = T(\text{Failure}) - T(\text{Query}). \tag{36}
\]

Accordingly, compared with the true life consumption (\( \text{True}_{LC} \)) at query moment, the estimation error of the Estimated\_LC is calculated using the following equation:

\[
\text{LC Estimation Error} = \frac{\text{True}_{LC} - \text{Estimated}_{LC}}{\text{True}_{LC} \times 100\%}. \tag{37}
\]
The predicted life consumption errors are listed in Table 1 to demonstrate the performance of the FPCA model. Table 1 shows estimation errors using different amount of data, i.e., 50%, 60%, 70%, and 80% of the total signal readings through the whole life span of a monitored component. In other words, 50% means data from the beginning of the operation up to half of the life time of the drilling tool is used in the model. As shown, when the estimation is based on a larger set of data, the estimation error becomes smaller. When 80% of data was used, the estimation error is less than 5%. Confidence interval of LC estimation when 80% signal readings are collected is also shown on FIG. 3.

| Test unit 1 | 30.82% | 14.37% | 4.76% | 0.01% |
| Test unit 2 | 24.72% | 16.63% | 11.84% | 4.09% |
| Test unit 3 | 37.77% | 19.18% | 3.26% | 1.63% |
| Test unit 4 | 38.71% | 8.50% | 6.6% | 2.27% |
| Test unit 5 | 36.27% | 17.40% | 3.79% | 5.09% |

The FPCA model disclosed herein performs better in comparison with others, such as the Path Classification and Estimation Model (PCE), which combines the linear regression and kernel weighted average. Table 2 summarizes the percentage of estimation errors of the FPCA model and the PCE model. As shown, the FPCA model offered much higher estimation accuracy for all the five test components from 50% available signal proportion up to 80%.

| Test 1 | 71.54% | 30.82% | 14.37% | 4.76% | 0.01% | 15.79% | 4.09% |
| Test 2 | 50.13% | 24.12% | 16.63% | 11.84% | 4.18% | 4.09% |
| Test 3 | 45.73% | 35.77% | 19.18% | 4.10% | 3.26% | 4.09% |
| Test 4 | 71.52% | 38.71% | 8.5% | 6.6% | 5.15% | 2.27% |
| Test 5 | 1.93% | 36.27% | 9.37% | 17.4% | 11.41% | 0.01% | 15.65% | 5.09% |

Therefore, as shown in FIG. 4, the current disclosure method comprises the steps of collecting a first set of sensor signals (e.g., the training dataset) and constructing a model using Functional Principal Component Analysis (FPCA) based on the first set of sensor signals, wherein the model is used to estimate one or more performance metrics of a component in the downhole drilling tool. The method also comprises steps of collecting a second set of sensor signals (e.g., the test dataset) and revising the model based on the second set of sensor signals. The revised FPCA model is used to estimate one or more performance metrics of the component (e.g., failure probability, life consumption, etc.).

3. The method of claim 2, wherein the condition of the component in the drilling system is chosen from a temperature, a pressure, a vibration, a weight on bit, a noise level, or an RPM.

4. The method of claim 1, wherein the component in the drilling system is a printed circuit board assembly (PCBA).

5. The method of claim 1, wherein the performance metric is chosen from a failure probability, a life consumption, or a remaining useful life.

6. The method of claim 1, wherein the model comprises a plurality of model parameters, including a grand mean function, a plurality of eigenfunctions, and a plurality of FPCA function scores.

7. The method of claim 1, wherein the first set of sensor signals is used as a training dataset to construct the model.
8. The method of claim 1, wherein the second set of sensor signals comprises a test dataset.

9. The method of claim 7, wherein the first set of sensor signals comprises signal readings from the component in the downhole drilling tool from inception of an operation to failure of the component.

10. The method of claim 8, the first set of sensor signals comprises signal readings from the same component from more than one operations.

11. A system for monitoring a downhole drilling tool, comprising:
   a drilling assembly;
   a plurality of sensors disposed about the drilling assembly, wherein the sensors provide sensor signals associated with the drilling assembly;
   a processor;
   a non-transitory machine readable medium communicably coupled to the processor;
   a set of processor-executable instructions embodied in the non-transitory machine readable medium, the instructions being configured to implement a method, the method comprising:
   collecting a first set of sensor signals;
   constructing a model using Functional Principal Component Analysis (FPCA) based on the first set of sensor signals, wherein the model estimates a performance metric of a component in the downhole drilling assembly;
   collecting a second set of sensor signals;
   revising the model based on the second set of sensor signals; and
   estimating the performance metric of the component in the downhole drilling assembly using the revised model, wherein the sensor signals reflect at least one condition of the component in the downhole drilling assembly.

12. The system of claim 11, wherein the drilling assembly comprises a drill bit, a drilling collar, and a MWD/LWD instrument.

13. A drilling system, comprising:
   a downhole drilling tool;
   a plurality of sensors disposed about the downhole drilling tool, wherein the plurality of sensors traverse a underground formation with the downhole drilling tool and generate sensor signals that reflect a condition of one or more components of the downhole drilling tool;
   a computer configured to implement a method, the method comprising:
   collecting a first set of sensor signals;
   constructing a model using Functional Principal Component Analysis (FPCA) based on the first set of sensor signals, wherein the model estimates a performance metric of a component in the downhole drilling tool;
   collecting a second set of sensor signals;
   revising the model based on the second set of sensor signals; and
   estimating the performance metrics of the component in the downhole drilling tool using the revised model.

14. The drilling system of claim 13, wherein the component in the downhole drilling tool is chosen from a drill bit, a drill string, a downhole motor, a MWD/LWD instrument, a drilling pipe, a drilling collar, a battery, a sensor, or an alternator.

15. The drilling system of claim 14, wherein the condition of the component in the downhole drilling tool is chosen from a temperature, a pressure, a vibration, an a weight on bit (WOB), or an RPM.

16. The drilling system of claim 13, wherein the component in the downhole drilling tool is a printed circuit board assembly (PCBA).

17. The method of claim 13, wherein the performance metric is chosen from a failure probability, a life consumption, or a remaining useful life.

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