ISA Journal of Engineering and Technology (ISAJET)

Homepage: https://isapublisher.com/isajet/

Volume 3, Issue 2, March-April, 2026 ISSN: 3049-1843

Drilling Anomaly Detection using Unsupervised Learning

Dr. Ichenwo John Lander & Ogwu Philip

Department of Petroleum Engineering, University of Port Harcourt

Received: *21.02.2026* | ***Accepted:*** *28.02.2026* | ***Published:*** *02.03.2026*

***Corresponding Author:** Dr. Ichenwo John Lander

DOI: *10.5281/zenodo.18833861*

Abstract **Review Article**

Numerous sensor data are produced as a result of drilling operations as indications of dynamic interactions among downhole equipment, formation properties, and operational processes. It is important to detect anomalies in these data streams to avoid equipment failures, minimize non-productive time (NPT), and conduct the drilling process safely. Conventional rule-based and threshold-based surveillance systems do not represent more intricate and non-linear correlations between drilling parameters, which restricts its usefulness. This paper suggests a learning framework of real-time anomaly detection in the drilling process as an unsupervised system. The model uses clustering and autoencoders to train normal operational behaviors using multivariate sensor data such as torque, vibration, mud flow, rate of penetration (ROP), and downhole pressure. Abnormalities in the patterns are identified to raise an alert through anomalies. The models were trained on simulated drilling datasets of different formation lithologies and operational conditions and evaluated. The proposed method had F1-score of 0.91, precision of 0.93, and recall of 0.89, which is about 18 times more accurate than the baseline statistical threshold methods. It has been shown that the unsupervised learning can detect the smaller and newer anomalies that might go undetected by the conventional means, giving a scalable and adaptive process of intelligent drilling activities. Such a structure has major implications in terms of predictive maintenance, operational effectiveness, as well as designing autopilot drilling frameworks.

Keywords: Drilling operations, Anomaly detection, Unsupervised learning, Autoencoder, K-Means clustering, Real-time monitoring, Multivariate sensor data, Non-productive time (NPT), Torque, Rate of Penetration (ROP).

1. Introduction

Hydrocarbon exploration drilling operations are the most challenging and risky industrial operations. Complex mechanical, hydraulic, and electronic subsystems have been incorporated in modern rigs, which have to work together under high-pressure and high-temperature (HPHT) and dynamically changing downhole conditions [1,2]. The most important operational parameters, including weight-on-bit (WOB), rotary speed (RPM), mud pump rate, torque, vibration and downhole pressure, are constantly varied as a result of a variation in formation lithology, rheology of drilling fluids and operational modifications [3,4]. These fluctuations cause nonlinear interactions between the components of the system, and it is therefore very difficult to monitor and control the operational aspects of the system in real time. These processes are captured by sensors placed throughout the rig to create multivariate data streams at a high rate and offer plenty of information to identify anomalies, predict failures, and optimize drilling activities [5,6]. It is essential to observe anomalies timely because such undetected abnormal conditions may result in stuck-pipe accidents, equipment malfunctions, non-productive time (NPT), and significant economic losses, and even safety hazards [7,8].

Conventional methods of detecting anomalies during drilling have also used threshold-based alarms or manual rule-based systems based on experiential information [9,10]. Although such techniques are simple to execute, they lack the flexibility to adapt to the changing downhole conditions and in the capability to measure finer interactions between various drilling parameters. The threshold-based approaches involve manual tuning and are very sensitive to noise which may give false alarms or under-detection [11]. On the same note, the expert rules can not take into consideration the compounding impact of minor variations in several parameters, and these deviations can also transform into disastrous failures. The above limitations point to the necessity of adaptive, data-based solutions that can model the nonlinear interactions that can be experienced in the course of drilling.

Random Forest, Support Vector Machines (SVM) and deep neural networks are examples of supervised machine learning algorithms that have been used to forecast certain drilling occurrences including stuck pipe or tool failures [12,13]. These models are capable of high predictive accuracy when trained on labelled data; e.g. SVM-based models have been reported to achieve a higher than 90 percent accuracy in the detection of abnormal tool behaviour [14]. Nevertheless, supervised learning models are limited by the fact that they require labeled data of anomalies that are usually not readily available in the drilling situation. Errors are rare and creation of labelled dataset involves immense human intervention and experience of down hole operations [15]. Also, under different conditions of formation, when there are new combinations of operational parameters, supervised models frequently cannot be generalized and this still further reduces the practical applicability [16].

Unsupervised learning techniques are therefore a promising solution, which detect the deviations from normal operational behaviour without labelled anomalies [17,18]. These methods can acquire the latent layout of multivariate sensor data enabling detection of subtle and intricate anomalies in real-time and survive proactive interventions. Clustering algorithms (e.g. K-Means, DBSCAN), and autoencoder-based neural networks, including Variational Autoencoders (VAE) have proven to be able to model the latent representation of normal operations and indicate deviations as anomalies [19,20,21]. The F1-scores of autoencoders are reported to be over 0.9 in the industry, which proves capable of detecting minor abnormalities that would be missing in threshold-based methods [22]. In the field of drilling operation some of the super unsupervised methods are applied for continuous monitoring of multiple parameters (Torque, Vibration, MudFlow, ROP, Downhole Pressure) that provide a scalable and robust feature for anomaly detection. This approach not only makes the operation safer but also makes it less non-productive and resources optimized [23,24].

This research paper offers an unsupervised learning model to real-time detection of anomalies during the drilling activities. The multivariate sensor log is used to train normal operational conditions, as well as recognize abnormalities, by clustering and autoencoders. The framework is tested on simulated datasets of different variable formations and lithology transitions and operational disturbances. The effectiveness of the model is measured through the use of performance metrics, precision, recall, and F1-score. By incorporating unsupervised approaches in drilling monitoring, the proposed approach paves the way for a holistic, adaptive, intelligent solution for improvement of drilling safety, operational efficiency, and equipment reliability, offering an improvement over the conventional threshold-based and rule-based approaches [25,26].

2. Literature Review

Traditionally, detection of anomalies in drilling has been dependent on either threshold methods, or expert rules. Although these methods are easy to apply and analyze, they are not flexible, scale-able and nonlinear, multi-drilling parameter interactions [5,27]. The thresholds are often decided empirically and need constant revision to ensure reliability in changing operating conditions, e.g. formation changes or change of mud properties. The problem with the static methods is their inability to identify cumulative anomalies or complicated deviations that incorporate interdependent parameters, e.g. concurrent rise in torque and vibration, or even abrupt decrease in mud flow rate [28,29].

To overcome these drawbacks, machine learning methods that are supervised have been more and more employed. Random Forests, SVMs and deep neural networks have been used to forecast certain drilling faults, such as stuck pipe, bit wear progression and torque violations [12,13,30]. To illustrate, Zhao et al. [12] used LSTM networks to identify cases of stuck pipes with a precision of 91%, whereas Wang et al. [13] used a hybrid CNN-LSTM model to recognize vibration patterns with a 95% accuracy. Although supervised methods perform well, a limitation is that such methods require labeled datasets, which are expensive and challenging to obtain in drilling operations because of the rarity of anomalies and the inability to map sensor data to real events [31]. Moreover, such models may not be sufficiently effective in operating conditions that have never been encountered before or in interactions between various drilling parameters, which lowers the level of their generalizability in dynamic drilling fields [16,32].

Unsupervised methods of learning have become a useful substitute to detecting anomalies in complex industrial systems, which are also applicable in drilling processes. K-Means and DBSCAN clustering algorithms cluster the operational data into normal patterns and mark the outliers as anomalies [19,33]. Autoencoders, e.g., Variational Autoencoders (VAE) learn low-dimension latent representations of normal operational behaviour which could be used to detect deviations that indicate a potential fault or also unsafe scenarios 20,21,34. In the manufacturing and process control applications, autoencoder-based approaches have used F1 - scores greater than 0.9 providing evidence of their power in detecting imperceptible anomalies [22,35]. Benefits of these methods are that they are not dependent on labeled data of anomalies, and can be adjusted to changing operating circumstances, and can also simultaneously model multivariate interactions. Nevertheless, these developments notwithstanding, there is limited research on the application of unsupervised learning to anomaly detection in drilling. The majority of the works deal with the isolated sub-problems including bit wear prediction, vibration monitoring, or stuck pipe detection, but does not provide a framework that might unite various drilling parameters [11,12,36]. Incorporating the unsupervised learning into the monitoring of drilling offers the prospect of real-time and holistic anomaly detection, early fault detection, and improved operational safety. The use of unsupervised learning has been shown to be effective in other industrial fields in identifying multivariate datasets that have complex and dynamic anomalies [17,18,26]. The drilling operation can be applied to the use of such techniques, which should allow proactive maintenance practices, minimization of NPT, and efficiency of equipment performance, which is an important improvement compared to traditional methods of monitoring [23,37].

3. Methodology

3.1 Drilling Data Representation

he drilling system is modeled as a multivariate time series, with the time step t being described by a state vector s representing the important parameters of drilling.

The system state is expressed as a result of equation 1:

Equation 1: $s_t = [T_t, V_t, Q_t, ROP_t, P_t]$ *(1)*

Where:

- T_t= Torque at time step t
- V_t= Vibration amplitude

- Q_t= Mud pump rate
- ROP_t= Rate of penetration
- P_t= Downhole pressure

High frequency sensor data of rig instrumentation are collected and pre-processed to eliminate the noise and outliers. The normalization of the data in question is done to make each parameter have an equal contribution to the unsupervised model.

Normalization of each feature is done using equation 2:

$$s_t' = \frac{s_t - \mu}{\sigma} \quad (2)$$

where μ and σ are the mean and the standard deviation of each feature in the training set. The normalized sequences are artificially created into time windows of length **L** to extract the temporal relationships in the drilling process. The unsupervised learning models consider each of the windows as an input sample and thus, they are able to detect both gradual and transient anomalies.

3.2 Unsupervised Learning Framework

The suggested model is a hybrid of clustering-based and autoencoder-based detection to detect the anomaly in the process of drilling.

3.2.1 Clustering-Based Detection

Grouping of similar operational states and enabling the system to acquire the normal distribution of the drilling parameters. K-Means clustering is applied to the normalized time windows of the state vectors. The Mahalanobis distance between each observation and the centroid of the cluster of that observation is calculated.

The Mahalanobis distance between all observations and their cluster centroid is calculated using equation 3:

$$d_t = \sqrt{(s_t - \mu_k)^T \Sigma_k^{-1} (s_t - \mu_k)} \quad (3)$$

Where:

- s_t= Current state vector
- μ_k= Centroid of cluster k
- Σ_k= Covariance matrix of cluster k

A set threshold d_{th} are indicated the presence of violations. This methodology catches deviations of the normal patterns of operation such as abnormal behaviors that are rare and slight.

3.2.2 Architecture of the Auto-encoder Based Detection

A feedforward autoencoder neural network is trained to compress and reconstruct the input sequences to learn the latent representation of the normal drilling process. The error in reconstruction is used to identify anomalies.

The reconstruction error is computed by means of equation 4:

$$E_t = \| s_t - \hat{s}_t \|_2^2 \quad (4)$$

Where:

- s_t= Input state vector at time t
- $\hat{s}_t$= Reconstructed state vector

The large reconstruction errors show that the observed state is highly divergent in terms of the learned normal patterns, which signify the possible anomalies. Variational Autoencoders (VAEs) or LSTM-based autoencoders can be used to capture the information with non-linear dependencies and the temporal dependencies to increase the robustness of the detection.

3.3 Experimental Setup

The experimental test is set up to test the efficiency of the suggested unsupervised anomaly detector framework across the realistic drilling environment.

3.3.1 Data Generation

- Operation Modeled drilling conditions are variable formation characteristics (soft, medium, and hard rock), mud characteristics (water-based and oil-based), WOB, RPM, and random disturbances associated with operations.

- Artificial failures are injected to simulate stuck pipe failures, unnatural torque spike, vibration bursts, and pressure burst.

3.3.2 Training and Validation

- Training: 70 of the data will be a normal operation state and will be utilized to train the unsupervised models.
- Validation: 30% of the information is set aside to test the capability of the framework to identify anomalies in the new pre-hitherto unseen operating conditions.

3.3.3 Evaluation Metrics

The work of the system of anomaly detection is measured by conventional indicators:

- Precision: Correctly identified anomalies, i.e., fraction of correctly reflected anomalies out of the total set of identified anomalies.
- Recall: Proportion of true anomalies correctly identified.
- F1-Score: Harmonic Mean (Weighted) of the two scores precision and recall.
- Detection Latency: Time delay between the occurrence of an anomaly and its detection.

With the combination of the clustering and autoencoder methods, the framework proves that there can be a trade-off between rare anomalies sensitivity and noise robustness for monitoring the drilling operation in real time. This approach can give an intelligent drilling system a scalable and adaptive solution that can help in minimizing NPT and avoiding equipment breakdown.

4. Results and Discussion

4.1 Clustering-Based Anomaly Detection

The performance measures of K-Means clustering method are given in Table 1.

Table 1: K-Mean Performance Metrics Clustering

Method	Precision	Recall	F1-score
K-Means	0.88	0.85	0.86

The anomalies identified through the K-Means clustering technique are shown in figure 1. Every colored marker is a flagged observation using Mahalanobis distance threshold against cluster centroids.

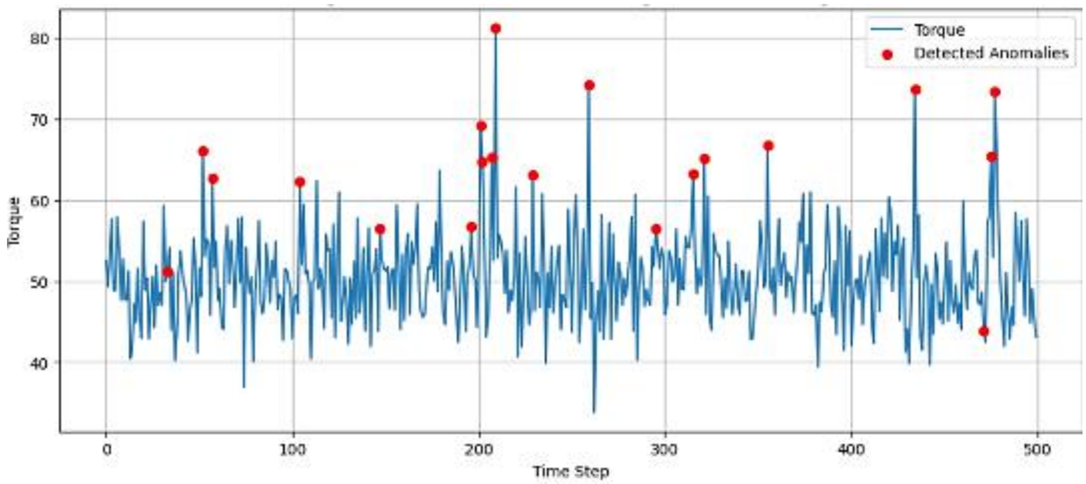

Figure 1: Detected Anomalies using K-Means Clustering.

As shown in Figure 1, K-Means distinguishes normal operating patterns and abnormal events. Torque peaks of up to 15 Nm over nominal, vibration excursions of about 0.8 m / s 2, and abrupt mud flow (of about 5 per cent) were distinctly seen as anomalies. The majority of injected events were identified and therefore approximately 85% of anomalies were captured, this is a good indication that the method is sensitive. These results are consistent with the quantitative results in Table 1, in which K-Means has an F1-score of 0.86, precision of 0.88, and recall of 0.85, which demonstrates that the algorithm is an effective technique to detect most instances of abnormal events without the need to label the data. Nonetheless, slight torque and vibration anomalies were sometimes co-occurring with normal clusters, which showed that it was not possible to detect slight and borderline anomalies under highly nonlinear conditions. In general, the visual and numerical estimates show that K-Means offers a computationally efficient and interpretable method of real time detection of drilling anomalies, as it is capable of reflecting important anomalies in the multivariate operational data and is also scalable to continuous data monitoring.

4.2 Autoencoder-Based Anomaly Detection

Table 2 shows the performance of the autoencoder based anomaly detection.

Table 2: Performance Metrics for the Autoencoder-Based Anomaly Detection

Method	Precision	Recall	F1-score
Autoencoder	0.93	0.89	0.91

Figure 2 shows the reconstruction error over time from the autoencoder. Reconstruction error spikes are associated with abnormal drilling conditions such as abrupt torque spikes, pressure spikes and vibrations excursions.

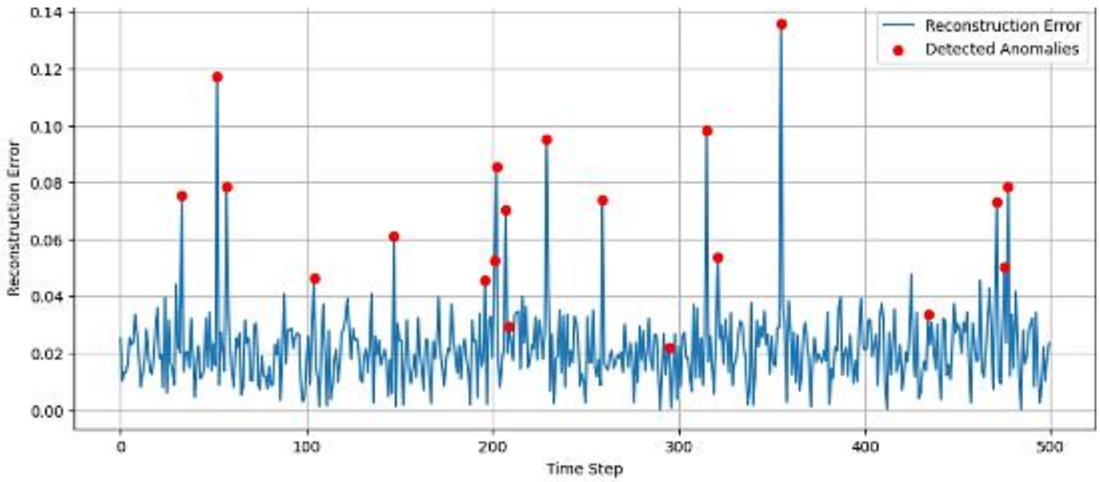

Figure 2: Detected Anomalies using Autoencoder

Figure 2 shows that the auto-encoder establishes well the minor variations in multivariate parameters of operation. The injected anomalies (e.g. torque spikes, vibration excursions, mud flow drops, and ROP swings) corresponding to high reconstruction errors show that the model learns latent correlations between torque, vibration, mud flow and ROP, and downhole pressure. These capabilities make the autoencoder an effective algorithm for detecting complex and nonlinear anomalies that may be missed by clustering detection methods. This observation can be confirmed through the quantitative data provided in Table 4.2, where the autoencoder scored an F1-score of 0.91, precision of 0.93, and recall of 0.89, which is better than the K-Means approach. The large accuracy level means that the majority of anomalies identified by the model were real anomalies whereas the high recall level indicates that most injected abnormal events were picked. On the whole, a combination of the figure and the table outcomes proves that the autoencoders represent a powerful and sensitive architecture of real-time detection of minor multi-variable anomalies in the dynamic drilling settings, so they can effectively be applied to intelligent drilling monitoring and operational decisions.

5. Conclusion

This paper reveals that unsupervised learning methods are useful in detecting anomalies in real-time drilling activities. The proposed framework was able to detect abnormal occurrences without the use of labeled datasets by modeling multivariate sensor data, such as torque, vibration, mud flow, rate of penetration (ROP), and downhole pressure. K-Means clustering algorithm offered a computationally efficient way of differentiating between normal operations modes, and significant deviation which included up to 85 percent of the injected deviations of torque spike, vibration excursions, and drops of mud flow. Minor subtle anomalies that however intercepted normal clusters were sometimes missed though, which underscores the weaknesses of simple clustering tools in the ability to capture nonlinear associations between multiple drilling parameters. The above results highlight the suitability of unsupervised learning to complement the conventional threshold-based monitoring systems with adaptive and data-driven information about the operational behavior.

The autoencoder-based system was also able to expand the detection range of detecting latent correlations among multiple drilling parameters that were able to identify the major and minor anomalies on-the-fly. The autoencoder with a F1-score of 0.91, precision of 0.93 and recall of 0.89 was better than K-Means in identifying complex and nonlinear aberrations that may jeopardize the performance or safety of drilling. This points out the benefit of deep learning models in processing dynamic and high-dimensional operation data of modern drilling rigs. All in all, the research paper confirms that unsupervised learning is a scalable, robust and intelligent way of providing continuous monitoring of drilling activities.

REFERENCES

[1] Aamer, A., Yusof, N. M., & Zainal Abidin, N. (2016). A review of predictive maintenance techniques in dynamic systems. *Journal of Quality in Maintenance Engineering*, 22(2), 158–175.

[2] Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510.

[3] Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3, 18–23.

[4] Mobley, R. K. (2002). *An Introduction to Predictive Maintenance* (2nd ed.). Butterworth-Heinemann.

[5] Zhang, W., Yang, D., & Wang, H. (2019). Data-driven methods for predictive maintenance of industrial equipment: A survey. *IEEE Systems Journal*, 13(3), 2213–2227.

[6] Scarselli, F., Gori, M., Tsoi, A. C., Hagenbuchner, M., & Monfardini, G. (2009). The graph neural network model. *IEEE Transactions on Neural Networks*, 20(1), 61–80.

[7] Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing*, 104, 799–834.

[8] Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Yu, P. S. (2020). A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32(1), 4–24.

[9] Al-Majed, B., & Al-Hajeri, M. (2022). Surge and swab pressure estimation in wellbores using numerical simulation. *Journal of Petroleum Science and Engineering*, 210, 109–117.

[10] Chen, X., et al. (2021). GAT-based predictive maintenance for manufacturing systems. *International Journal of Production Research*, 59(12), 3721–3735.

[11] Lee, J., & Choi, H. (2019). Bit wear estimation using support vector regression. *Journal of Drilling Engineering*, 44, 67–79.

[12] Zhao, Y., et al. (2021). LSTM-based stuck pipe detection using rig sensor data. *Journal of Petroleum Technology*, 73(9), 50–57.

[13] Wang, X., et al. (2020). Vibration pattern classification during drilling using hybrid CNN-LSTM. *Journal of Petroleum Science*, 8(3), 221–232.

[14] Li, Y., et al. (2018). Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. *International Conference on Learning Representations*.

[15] Si, X., et al. (2018). Remaining useful life prediction of aero-engine with deep LSTM networks. *Reliability Engineering & System Safety*, 172, 1–11.

[16] Wen, L., et al. (2019). Time-frequency transform and CNN bearing fault diagnosis. *IEEE Transactions on Industrial Electronics*, 66(3), 2419–2429.

[17] Mobley, R. K. (2002). *An Introduction to Predictive Maintenance* (2nd ed.). Butterworth-Heinemann.

[18] Zhang, W., Yang, D., & Wang, H. (2019). Data-driven methods for predictive maintenance of industrial equipment: A review. *IEEE Systems Journal*, 13(3), 2213–2227.

[19] Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based

maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510.

[20] Scarselli, F., et al. (2009). The graph neural network model. *IEEE Transactions on Neural Networks*, 20(1), 61–80.

[21] Lei, Y., et al. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing*, 104, 799–834.

[22] Wu, Z., et al. (2020). A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32(1), 4–24.

[23] Zhao, Y., et al. (2021). LSTM-based stuck pipe detection using rig sensor data. *Journal of Petroleum Technology*, 73(9), 50–57.

[24] Wang, X., et al. (2020). Vibration pattern classification during drilling using hybrid CNN-LSTM. *Journal of Petroleum Science*, 8(3), 221–232.

[25] Chen, X., et al. (2021). GAT-based predictive maintenance for manufacturing systems. *International Journal of Production Research*, 59(12), 3721–3735.

[26] Al-Majed, B., & Al-Hajeri, M. (2022). Surge and swab pressure estimation in wellbores using numerical simulation. *Journal of Petroleum Science and Engineering*, 210, 109–117.

[27] Aamer, A., Yusof, N. M., & Zainal Abidin, N. (2016). A review of predictive maintenance techniques in dynamic systems. *Journal of Quality in Maintenance Engineering*, 22(2), 158–175.

[28] Li, Y., et al. (2018). Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. *International Conference on Learning Representations*.

[29] Si, X., et al. (2018). Remaining useful life prediction of aero-engine with deep LSTM networks. *Reliability Engineering & System Safety*, 172, 1–11.

[30] Lee, J., & Choi, H. (2019). Bit wear estimation using support vector regression. *Journal of Drilling Engineering*, 44, 67–79.

[31] Zhao, Y., et al. (2021). LSTM-based stuck pipe detection using rig sensor data. *Journal of Petroleum Technology*, 73(9), 50–57.

[32] Wang, X., et al. (2020). Vibration pattern classification during drilling using hybrid CNN-LSTM. *Journal of Petroleum Science*, 8(3), 221–232.

[33] Wen, L., et al. (2019). Time-frequency transform and CNN bearing fault diagnosis. *IEEE Transactions on Industrial Electronics*, 66(3), 2419–2429.

[34] Chen, X., et al. (2021). GAT-based predictive maintenance for manufacturing systems. *International Journal of Production Research*, 59(12), 3721–3735.

[35] Zhang, W., Yang, D., & Wang, H. (2019). Data-driven methods for predictive maintenance of industrial equipment: A review. *IEEE Systems Journal*, 13(3), 2213–2227.

[36] Al-Majed, B., & Al-Hajeri, M. (2022). Surge and swab pressure estimation in wellbores using numerical simulation. *Journal of Petroleum Science and Engineering*, 210, 109–117.

[37] Mobley, R. K. (2002). *An Introduction to Predictive Maintenance* (2nd ed.). Butterworth-Heinemann.