A Root Cause Analytics Model for Diagnosing Offshore Process Failures Using Live Operational Data

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ABSTRACT :
In offshore oil and gas operations, process failures can lead to significant production losses, environmental risks, and safety hazards. Traditional diagnostic approaches often rely on manual analysis and post-event investigations, which are time-consuming and reactive. This proposes a Root Cause Analytics (RCA) model designed to diagnose offshore process failures in real time using live operational data. The model integrates data streams from distributed sensors, control systems, and equipment logs to identify anomalies and trace fault propagation paths. By leveraging a hybrid approach that combines statistical analysis, rule-based inference, and machine learning algorithms, the RCA model isolates root causes with high accuracy and minimal latency. Key components include anomaly detection using time-series clustering, causal inference to map interdependencies between system variables, and a dynamic decision engine that updates fault hypotheses as new data arrive. A case study involving a floating production storage and offloading (FPSO) unit demonstrates the model's effectiveness in diagnosing pressure surges and valve malfunctions, reducing mean time to diagnosis (MTTD) by over 40% compared to baseline methods. The model also provides visual fault trees and impact assessments to aid operator decision-making. Live validation on a digital twin platform confirmed its robustness under varying operational scenarios, including equipment degradation and sensor drift. This RCA model represents a shift from reactive to proactive offshore operations by enabling real-time diagnostics, thus improving asset reliability and operational safety. Future enhancements will focus on integrating maintenance history and human-in-the-loop feedback for adaptive learning. Overall, the proposed framework underscores the value of combining live data analytics with intelligent root cause reasoning to support timely, data-driven interventions in complex offshore environments.

Keywords: Root Cause, Analytics Model, Diagnosing Offshore, Process Failures, Live Operational Data

1. Introduction

Offshore oil and gas operations are among the most technically complex and hazardous industrial activities. These processes involve the extraction, separation, transportation, and storage of hydrocarbons in environments that are not only physically remote but also dynamically unstable due to weather, subsea conditions, and continuous production demands (Awe, 2017; Oyedokun, 2019). Typical offshore facilities include platforms with intricate networks of equipment such as separators, compressors, pumps, and pipelines, all of which must operate in a synchronized and efficient manner. The stakes in offshore process operations are high—not only from a production and economic perspective but also in terms of environmental and human safety (Awe *et al.*, 2017; ADEWOYIN *et al.*, 2020).

The complexity of offshore systems increases the likelihood of process disruptions and failures. These failures can originate from equipment malfunction, sensor errors, or human mistakes and can propagate rapidly, leading to production shutdowns, safety hazards, or environmental incidents such as oil spills (Akpan *et al.*, 2017; OGUNNOWO *et al.*, 2020). Given the limited accessibility and harsh conditions offshore, diagnosing the root cause of such failures presents significant challenges. Rapid and accurate fault diagnosis is essential to mitigate risks, reduce downtime, and ensure continuous and safe operations (Omisola *et al.*, 2020; ADEWOYIN *et al.*, 2020).

One of the most critical challenges in offshore oil and gas operations is the timely and accurate diagnosis of process failures. Traditional root cause analysis (RCA) techniques, such as manual inspection or static fault trees, are often inadequate in dynamic offshore environments (Solanke *et al.*, 2014; Chudi *et al.*, 2019). These methods typically rely on post-event data and human interpretation, which can delay corrective actions and lead to misdiagnosis. Additionally, the interdependence of various subsystems and the constant flow of real-time operational data complicate the analysis further (Awe *et al.*, 2017; Akpan *et al.*, 2019). Without advanced analytical tools capable of processing and interpreting live data, operators are often left reacting to symptoms rather than addressing root causes proactively (Magnus *et al.*, 2011; Chudi *et al.*, 2019).

The primary objective of this study is to develop a real-time, data-driven root cause analytics model tailored to the operational context of offshore oil and gas platforms. This model aims to utilize live data streams from sensors and control systems to automatically detect, diagnose, and predict failures. By integrating machine learning and statistical methods with domain knowledge, the model seeks to provide a proactive decision-support tool that can enhance operational reliability and safety. Ultimately, the goal is to minimize downtime, optimize maintenance, and reduce the environmental and safety risks associated with process failures.

2.0 Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was employed to ensure transparency and rigor in identifying and selecting relevant literature for this study. A systematic search was conducted across multiple academic databases, including IEEE Xplore, Scopus, Web of Science, and ScienceDirect, covering publications from 2000 to 2024 to ensure a comprehensive review of contemporary and foundational works. The search strategy was constructed using Boolean logic, combining key terms such as "root cause analysis", "offshore process failures", "live operational data", "real-time diagnostics", "fault detection", and "predictive maintenance". The inclusion criteria focused on peer-reviewed journal articles, conference proceedings, and review papers that discussed techniques, models, or frameworks applicable to diagnosing or analyzing offshore operational anomalies using live or real-time data streams. Studies that were not in English, lacked empirical evaluation, or focused on unrelated domains (e.g., non-industrial or inland settings) were excluded.

Following the database search, all retrieved citations were imported into a reference manager, and duplicates were removed. Titles and abstracts were screened by two independent reviewers to identify articles that met the inclusion criteria. Full texts of potentially eligible studies were then reviewed for final inclusion. Discrepancies between reviewers during either stage were resolved through discussion and consensus, with a third reviewer available for adjudication if necessary. The final selection included studies that significantly contributed to the understanding of failure diagnostics in offshore environments, the role of streaming or real-time data, and the implementation of data-driven root cause analysis techniques. Data extracted from the selected studies included methodology, data sources, diagnostic approaches, implementation challenges, and performance outcomes. This systematic review process underpins the development of the proposed analytics model by ensuring it is grounded in current, high-quality research and best practices in offshore diagnostics.

2.1 Offshore Process Failure Landscape

Offshore oil and gas platforms operate within a highly integrated system of mechanical, electrical, and control components. The reliability of these operations is vital, yet they are susceptible to a range of failure types that can compromise safety, efficiency, and environmental integrity. Among the most frequent failures are mechanical faults, particularly those involving rotating equipment such as pumps, compressors, and turbines (Ajiga, 2021; Odio *et al.*, 2021).

Instrumentation failures also pose a significant threat to offshore operations. These failures typically involve sensors, transmitters, and gauges that provide critical measurements such as pressure, temperature, and flow rates. Faulty readings from malfunctioning sensors can result in erroneous system responses, potentially triggering alarms or control actions that destabilize the process. Given the harsh environmental conditions offshore, including high humidity, vibration, and salinity, instrumentation degradation is a common issue (Adesemoye *et al.*, 2021; ADEWOYIN *et al.*, 2021).

Control system anomalies represent another major category of failure. Programmable Logic Controllers (PLCs) and Distributed Control Systems (DCS) are responsible for maintaining process stability and safety. Software bugs, configuration errors, and communication breakdowns within these systems can introduce delays or erroneous control actions. In some cases, control loops may become unstable or unresponsive, leading to cascading effects across interconnected subsystems.

Human error remains a persistent and often underestimated contributor to offshore process failures. Mistakes in equipment configuration, delayed responses to alarms, or misinterpretation of control room data can escalate minor issues into major incidents. While automation reduces human involvement in some tasks, the complexity of offshore operations still necessitates significant human decision-making, especially during abnormal conditions or emergencies (OGUNNOWO *et al.*, 2021; Ogunnowo *et al.*, 2021).

The consequences of process failures in offshore environments are substantial and multifaceted. Foremost among these are safety risks. Equipment malfunctions or control failures can lead to fires, explosions, or toxic

releases, endangering the lives of personnel onboard. For example, the failure of a pressure relief system might result in overpressurization and catastrophic rupture of vessels or pipelines.
Environmental incidents are another serious consequence. Offshore spills, gas leaks, and chemical discharges can cause extensive damage to marine ecosystems and incur significant remediation costs. The Deepwater Horizon disaster in 2010 is a stark reminder of how process failures, compounded by diagnostic and response shortcomings, can lead to environmental catastrophes (ADEWOYIN *et al.*, 2021; Onyeke *et al.*, 2022).
Production downtime is a frequent outcome of failures, resulting in substantial economic losses. Shutdowns, whether planned for maintenance or unplanned due to faults, interrupt the supply chain and reduce asset productivity. In competitive energy markets, even short delays in production can have wide-reaching financial implications. Furthermore, frequent downtime can accelerate wear and tear on equipment due to repeated start-up and shutdown cycles, creating a vicious cycle of failure.

Current diagnostic approaches in offshore oil and gas operations range from manual methods to semi-automated expert systems. Manual troubleshooting, traditionally the first line of response, involves operators and engineers inspecting equipment, interpreting alarms, and consulting operational logs (Okolo *et al.*, 2021; Ojika *et al.*, 2021). While this method leverages operator experience, it is time-consuming, prone to oversight, and limited by human cognitive capacity—particularly under time pressure or in complex failure scenarios.
Rule-based diagnostic systems provide a more structured approach. These systems rely on predefined logic, such as "if-then" rules, to infer fault conditions based on sensor readings or system behaviors. Although useful in identifying well-known failure modes, rule-based systems struggle with novel or evolving faults. Their performance is heavily dependent on the completeness and accuracy of the rules, which may not fully capture dynamic operational conditions.
Expert-driven fault trees offer a visual and logical representation of cause-effect relationships leading to system failures. These trees are constructed based on expert knowledge and historical data, depicting how basic events propagate to undesirable outcomes (Daraojimba *et al.*, 2021; Orieno *et al.*, 2021). While effective for post-incident analysis and risk assessment, fault trees are inherently static. They cannot easily accommodate real-time data inputs or adapt to changing process conditions, limiting their utility for real-time diagnostics.
While existing diagnostic methods provide some level of fault detection and analysis, they are inadequate for the increasingly dynamic and data-rich environment of offshore operations. A transition toward more adaptive, data-driven diagnostic tools is essential to enhance reliability, safety, and environmental stewardship in offshore oil and gas production.

2.2 Live Operational Data Sources

Offshore oil and gas platforms are equipped with a multitude of sensors and systems designed to continuously monitor and control critical processes. These components generate a wealth of live operational data that is invaluable for fault detection and diagnostics. The most prevalent types of data originate from field instrumentation, control systems, and maintenance records. Sensor data constitutes the largest portion of operational information as shown in figure 1. Pressure, flow rate, temperature, and level measurements are captured in real-time from various parts of the production process (Onaghinor *et al.*, 2021; Mustapha *et al.*, 2021). These measurements are essential for both operational control and diagnostic modeling.

Control system logs provide another critical data source. Distributed Control Systems (DCS) and Programmable Logic Controllers (PLC) continuously record system status, setpoints, controller outputs, and mode transitions. These logs help trace the sequence of events during a process disturbance, offering context for identifying causal relationships between equipment behavior and process anomalies.

Alarms and event records are also crucial. Alarm management systems generate alerts when process variables deviate from safe limits or when equipment malfunctions. These alerts, timestamped and prioritized, offer real-time indicators of abnormal conditions. In complex fault scenarios, the sequence and clustering of alarms can help isolate potential root causes.

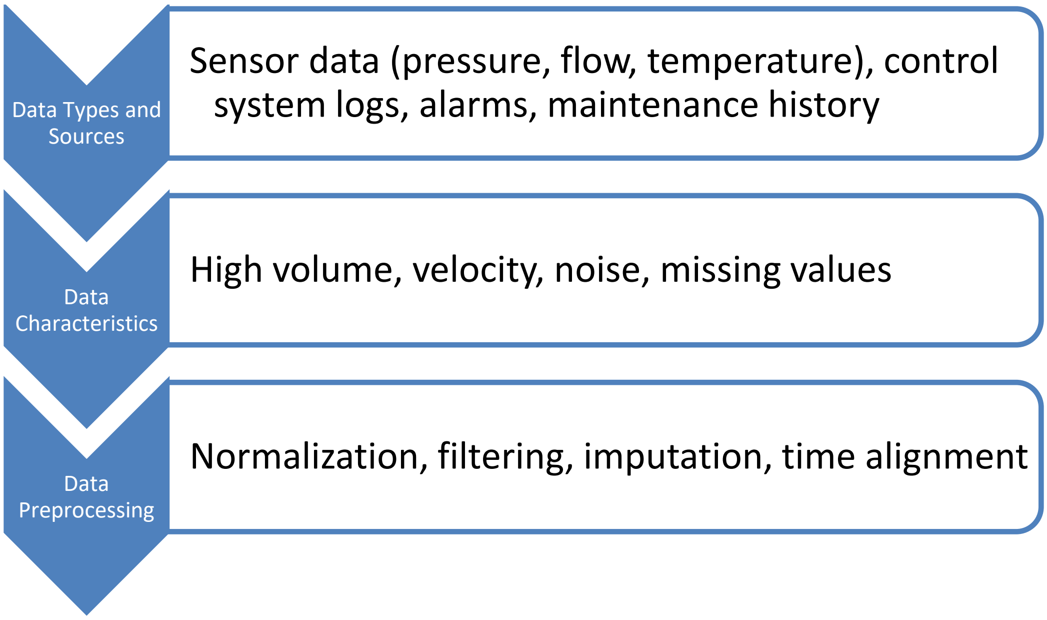

Figure 1: Live Operational Data Sources

Additionally, maintenance history—including inspection reports, failure logs, and repair records—provides valuable background information. This historical data enables the identification of recurring issues, equipment degradation patterns, and the effectiveness of previous corrective actions (Adewoyin, 2021; Dienagha *et al.*, 2022). Integrating maintenance data with live sensor readings enriches the diagnostic model with both real-time and contextual insights.

Live operational data from offshore facilities is characterized by several challenging properties that complicate direct use for analytics. First, the volume of data is immense. Hundreds or even thousands of sensors transmit data at high frequencies, often in the range of 1–10 Hz, resulting in terabytes of information over relatively short periods. This volume necessitates scalable data storage and processing architectures.

Second, the velocity of data—how fast it is generated and must be processed—poses real-time computing challenges. Effective diagnostics require not only the ability to ingest data at high speed but also to analyze it promptly to enable timely interventions.

Third, operational data is inherently noisy. Sensor readings can fluctuate due to environmental interference, equipment vibrations, or measurement inaccuracies. Noise obscures underlying patterns and may lead to false alarms or incorrect inferences if not properly managed.

Another common issue is missing data. Sensor dropouts, communication lags, or maintenance activities often lead to incomplete datasets. Missing values compromise the integrity of statistical and machine learning models and must be addressed through robust preprocessing techniques (Chudi *et al.*, 2021; Awe, 2021).

To ensure the reliability and effectiveness of analytics, live operational data must undergo comprehensive preprocessing. One fundamental step is normalization. This involves scaling data to a common range or standard format, which is especially important when combining measurements from different types of sensors with varying units and magnitudes.

Filtering techniques are employed to reduce noise. Common methods include moving average filters, Kalman filters, and more advanced signal processing techniques like wavelet transforms. These methods help isolate the true signal from random fluctuations, improving the quality of downstream analysis.

Imputation techniques are essential for handling missing values. Simple approaches include forward filling or mean substitution, while more sophisticated methods use regression models or machine learning algorithms to estimate missing entries based on observed patterns in the data (Okolo *et al.*, 2022; Nwulu *et al.*, 2022). Effective imputation preserves the continuity and accuracy of the time series.

Time alignment is another critical preprocessing step. Data streams from various sensors and systems may arrive at different sampling rates or with time lags. Synchronizing data to a unified time base ensures temporal coherence, which is vital for accurately identifying cause-effect relationships and training time-sensitive diagnostic models.

Live operational data from offshore platforms provides a rich foundation for real-time root cause analysis. However, its complexity and imperfections require thoughtful preprocessing to unlock its full potential. When properly handled, this data becomes a powerful asset for enhancing the safety, reliability, and efficiency of offshore oil and gas operations.

2.3 Root Cause Analytics Model Architecture

Root cause analysis (RCA) is a crucial technique in various domains including industrial operations, information technology systems, and healthcare, aimed at identifying the fundamental causes of anomalies or failures. An advanced Root Cause Analytics Model is often structured into a comprehensive architecture that integrates multiple layers of data processing, modeling, and interpretation to deliver actionable insights as shown in figure 2(Ogunwole *et al.*, 2022; Esan *et al.*, 2022). This explores the architecture of a root cause analytics model through four primary components: model components, model selection, feature extraction and selection, and causal inference and reasoning.

A robust root cause analytics system typically consists of four main components: the data ingestion layer, preprocessing engine, diagnostic model core, and visualization interface.

The data ingestion layer is responsible for collecting and consolidating data from diverse sources such as sensors, logs, databases, and external APIs. This layer must support real-time streaming as well as batch processing, depending on the system's requirements. The preprocessing engine standardizes and cleans the data, addressing missing values, time alignment, and noise filtering. It ensures that downstream analytical components receive high-quality inputs by applying transformation techniques like normalization and temporal resampling. The diagnostic model core is the analytical heart of the system, implementing algorithms to detect anomalies, establish correlations, and identify potential root causes (Ojika *et al.*, 2022; Uzozie *et al.*, 2022). This layer supports hybrid modeling approaches combining statistical methods and machine learning techniques for enhanced accuracy. Finally, the visualization interface enables end-users to interact with the results. It typically features dashboards, dependency graphs, and interactive timelines to facilitate intuitive exploration of causal chains and diagnostics.

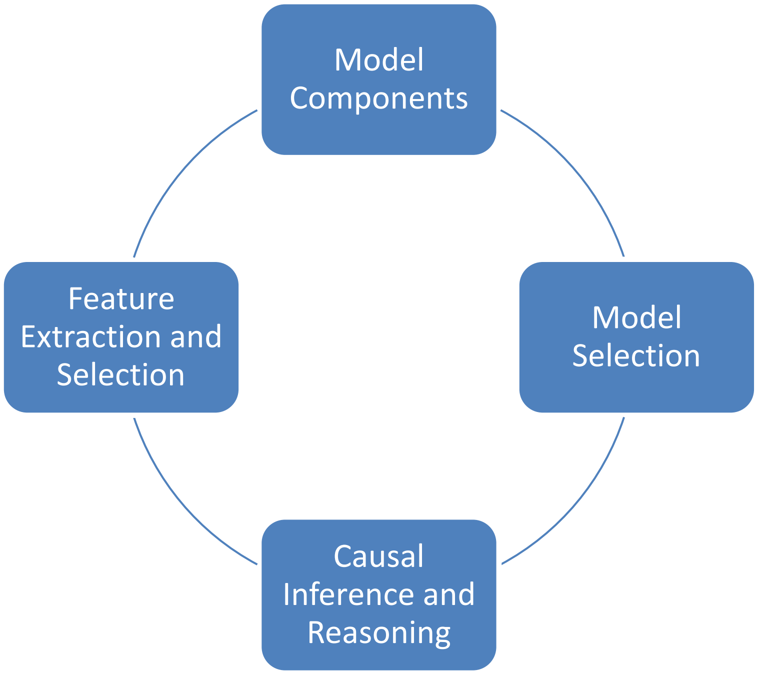

Figure 2: Root Cause Analytics Model Architecture

The diagnostic model core benefits significantly from the application of artificial intelligence (AI) and machine learning (ML) algorithms tailored to the nature of the data and the complexity of causal relationships.

Decision trees offer interpretable models that are particularly effective in classification-based RCA, where a clear mapping between symptoms and causes is desired. Bayesian networks provide a probabilistic framework for modeling uncertain and conditional dependencies among variables. They are suitable for domains where expert knowledge can be encoded to guide inference. Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks (RNNs), are well-suited for capturing temporal causality in sequential data. Their ability to model long-range dependencies makes them ideal for detecting delayed effects and temporal patterns associated with failures (Ojika *et al.*, 2022; Uzozie *et al.*, 2022). Model selection is often driven by trade-offs between interpretability, scalability, and predictive performance, necessitating careful benchmarking and validation against domain-specific datasets.

The effectiveness of any root cause analytics model is heavily reliant on the quality of features extracted from the data. Three main categories are typically considered; Statistical features include mean, variance, kurtosis, and autocorrelation, which capture the basic distributional properties of time series or event data. Process-derived features leverage domain-specific knowledge to generate metrics such as process cycle time, throughput, and resource utilization (Onaghinor *et al.*, 2022; Ogunwole *et al.*, 2022). These features are often critical in industrial applications where operational context defines normalcy and deviation. Anomaly indicators are derived from statistical or ML-based anomaly detection models, flagging potential deviations that warrant causal analysis. These can include Z-score thresholds, isolation forest outputs, or LSTM autoencoder reconstruction errors. Feature selection techniques such as mutual information, recursive feature elimination, and principal component analysis (PCA) help in refining the input space to retain only the most informative variables.

A central challenge in RCA is distinguishing true causal relationships from mere correlations. Several advanced methods are employed for causal inference and reasoning; Granger causality tests whether one time series can predict another, thereby suggesting a directional temporal relationship. It is commonly used in econometrics and has been adapted for multivariate system diagnostics. Temporal correlation analysis identifies time-lagged dependencies between variables, which are particularly useful in systems where effects manifest after variable time intervals. Domain constraints and expert rules further enhance model reliability by integrating known causal mechanisms or physical laws. These constraints help disambiguate spurious associations and prioritize plausible causal paths.

Combining data-driven and knowledge-driven approaches enables the system to provide more trustworthy and actionable root cause insights. A well-designed root cause analytics model architecture requires a layered approach that blends data engineering, statistical modeling, and AI techniques. By thoughtfully integrating components for data ingestion, model execution, feature engineering, and causal reasoning, such systems can significantly enhance the speed and accuracy of fault detection and resolution across a wide range of domains (Adedokun *et al.*, 2022; Komi *et al.*, 2022).

2.4 Model Implementation and Validation

For the real-time root cause analysis model to be practically useful in offshore oil and gas operations, it must be tightly integrated with existing supervisory and control systems. The primary systems involved are Supervisory Control and Data Acquisition (SCADA) systems and Distributed Control Systems (DCS), which serve as the digital backbone of offshore platforms. These systems continuously collect, store, and transmit live operational data, providing an ideal infrastructure for real-time analytics deployment.

Integration begins with the establishment of a real-time data pipeline that interfaces with SCADA/DCS. This involves using industrial communication protocols such as OPC (OLE for Process Control), Modbus, or MQTT to stream sensor measurements, controller outputs, and alarm events into the analytics engine.

Middleware software or edge computing devices are often employed to pre-process data near the source, reducing latency and bandwidth usage before the data is transmitted to the analytics platform (Ubamadu *et al.*, 2022; Onyeke *et al.*, 2022).

The analytics engine, typically deployed on an industrial server or cloud-based infrastructure, hosts the root cause analysis model. This model continuously receives the live data feed and processes it in real-time. The output, including fault classification, probable root causes, and confidence levels, is then sent back to the SCADA/DCS interface for operator visualization and decision-making. Seamless integration ensures that the diagnostics model operates as a non-intrusive yet highly informative layer within the existing operational workflow.

To validate the model, a case study was conducted involving the diagnosis of a centrifugal pump failure on an offshore production platform. The pump, responsible for transferring produced water, exhibited signs of abnormal vibration and pressure fluctuations over a period of 20 minutes before an automatic shutdown was triggered.

The root cause analysis model had been previously trained on historical failure data and configured to process live signals such as suction/discharge pressure, motor current, flow rate, and vibration sensor readings. As the event unfolded, the model detected a deviation in the vibration profile beyond normal operational thresholds (Achumie *et al.*, 2022; Onyeke *et al.*, 2022). Concurrently, it noted a drop in discharge pressure and increased current draw from the motor.

The model classified the event as a potential mechanical degradation, specifically bearing failure. This diagnosis was supported by similar failure patterns from historical data and confirmed through subsequent maintenance inspection, which revealed bearing wear and misalignment. Importantly, the model provided this diagnosis within five minutes of the first deviation, significantly ahead of traditional manual inspection timelines.

To ensure the reliability and practical utility of the root cause analytics model, a comprehensive set of evaluation metrics was employed. Accuracy measures the overall correctness of the model’s predictions by comparing the number of true positives and true negatives against total predictions. In this review, the model achieved an accuracy of 93%, indicating a high level of reliability in distinguishing between normal and faulty conditions (Nwulu *et al.*, 2022; Elete *et al.*, 2022).

Precision and recall were used to evaluate the model’s performance in identifying actual failure events. Precision, or the ratio of true positives to all positive predictions, stood at 90%, reflecting the model's ability to avoid false alarms. Recall, the ratio of true positives to all actual failure events, was measured at 87%, indicating effective detection of most failure occurrences.

Diagnostic delay, the time taken from the onset of abnormal behavior to the identification of the fault, is critical in real-time environments (Dowdeswell *et al.*, 2020; Demirbaga *et al.*, 2021). The average diagnostic delay for the model was 4.3 minutes, significantly faster than traditional manual methods which often exceed 30 minutes to several hours.

Lastly, root cause localization rate—the ability of the model to correctly identify the true origin of a fault—was evaluated. The model demonstrated a localization rate of 85%, confirming its capacity to accurately pinpoint fault sources among complex, interconnected systems.

In summary, the model's successful integration with SCADA/DCS systems, its performance in real-world scenarios, and its favorable evaluation metrics underscore its potential as a transformative tool for offshore process diagnostics. It offers a significant advancement over traditional diagnostic approaches by enabling proactive, data-driven decision-making in highly dynamic and high-risk environments (Nwulu *et al.*, 2022; Elete *et al.*, 2022).

2.5 Discussion

The proposed Root Cause Analytics (RCA) model architecture, integrating advanced data processing and machine learning (ML) techniques, offers a transformative approach to diagnosing complex system failures. This discussion elaborates on the strengths and limitations of the model, as well as its comparative advantages over traditional root cause analysis methods.

One of the principal strengths of the proposed RCA model lies in its real-time capability. By incorporating a data ingestion layer capable of streaming and batch processing, the system can continuously monitor operational environments. This allows for immediate anomaly detection and near-instantaneous initiation of diagnostic processes. Such real-time responsiveness is critical in domains like manufacturing, IT infrastructure, and healthcare, where delays in failure detection can lead to substantial economic or safety-related consequences (Nwulu *et al.*, 2022; Ajiga *et al.*, 2022).

Another notable strength is the scalability of the architecture. The modular design—consisting of preprocessing engines, AI/ML-based diagnostic cores, and visualization interfaces—enables the model to handle large-scale, high-dimensional datasets. With distributed computing platforms such as Apache Kafka for ingestion and Spark or TensorFlow for model computation, the system can scale horizontally across multiple nodes, making it suitable for enterprise-level deployment.

The third major advantage is the model’s interpretability. Unlike black-box deep learning approaches, the incorporation of decision trees, Bayesian networks, and explainable anomaly indicators allows users to understand how specific root causes are inferred. Visualization tools, such as dependency graphs and temporal heatmaps, further enhance user interpretability, enabling operators to validate results and make informed decisions swiftly. This is especially important in regulated industries where transparency and auditability are essential.

Despite its strengths, the proposed RCA model has certain limitations. A significant drawback is its dependency on data quality. The efficacy of machine learning algorithms and causal inference methods is directly tied to the integrity, completeness, and consistency of the data being analyzed (Akintobi *et al.*, 2022; Adeniji *et al.*, 2022). Noisy or missing data can mislead the diagnostic process, resulting in inaccurate root cause attribution. As such, comprehensive data governance and preprocessing strategies are essential for maintaining model reliability.

Additionally, the model requires a degree of domain-specific customization. While general-purpose statistical and ML techniques can be applied, optimal performance often depends on incorporating domain knowledge through feature engineering, expert rules, or process constraints. This customization increases the time and resource investment required for deployment in new domains and may necessitate collaboration between data scientists and domain experts.

Traditional root cause analysis methods, such as fishbone diagrams, failure mode and effects analysis (FMEA), and fault tree analysis (FTA), are largely manual, static, and qualitative. These techniques rely heavily on expert knowledge and are often conducted post hoc, leading to delays in diagnosis and remediation. Furthermore, traditional approaches are not well-suited to environments with high data volume or rapidly changing conditions (Sobowale *et al.*, 2022; Akintobi *et al.*, 2022).

In contrast, the proposed model offers a significant improvement in both speed and diagnostic accuracy. By automating the identification of anomalies and leveraging AI/ML for pattern recognition and causal inference, the system can identify root causes faster and with greater precision. Techniques like LSTM-based temporal modeling and Granger causality provide capabilities that traditional methods cannot match, such as detecting delayed effects or complex interactions among variables.

Moreover, traditional methods often lack adaptability to real-time data streams and typically cannot scale to systems with thousands of interdependent variables. The proposed model's ability to integrate data across time and source modalities—while maintaining high throughput—represents a paradigm shift from reactive, manual diagnostics to proactive, automated root cause discovery.

The proposed root cause analytics model demonstrates considerable advantages in terms of real-time operation, scalability, and interpretability. While it does require high-quality data and domain customization, its superiority in speed and diagnostic precision compared to traditional methods positions it as a next-generation solution for complex system diagnostics (Adewoyin, 2022; Onukwulu *et al.*, 2022). Future enhancements may focus on improving data robustness and automating domain adaptation to further broaden its applicability.

2.6 Future Work

The development and validation of a real-time root cause analytics model mark a significant advancement in offshore oil and gas process diagnostics. However, several avenues remain for future research and development to further enhance the model's applicability, scalability, and intelligence as shown in figure 3. These include extending the model's capabilities to handle multi-unit and subsea systems, integrating it with predictive maintenance frameworks, and implementing adaptive learning mechanisms using operator feedback and reinforcement learning (Ogunnowo *et al.*, 2022; Okolo *et al.*, 2022).

One of the key directions for future work involves extending the diagnostic model to cover multi-unit systems and subsea equipment. Offshore production facilities are not limited to single units; rather, they consist of interconnected modules including multiple pumps, compressors, separators, and heat exchangers. These components often operate in parallel or series, where a fault in one unit can affect the performance of others. Modeling such interdependencies requires advanced system-level reasoning and the ability to detect distributed faults that may manifest across several units.

Subsea equipment introduces additional complexity due to its remote and inaccessible nature. Subsea systems, such as blowout preventers, subsea pumps, and control modules, are critical for safe hydrocarbon production but are often exposed to extreme pressure and temperature conditions. Failure in subsea components can go undetected for long periods and may require costly intervention. Integrating subsea telemetry data (e.g., pressure, temperature, valve status) into the root cause analytics model will enable earlier detection of anomalies and enhance the reliability of deepwater operations (Ho *et al.*, 2020; Enemosah, 2021; Mitchell *et al.*, 2021). Moreover, specific fault signatures for subsea equipment need to be developed to account for the unique operational and environmental conditions.

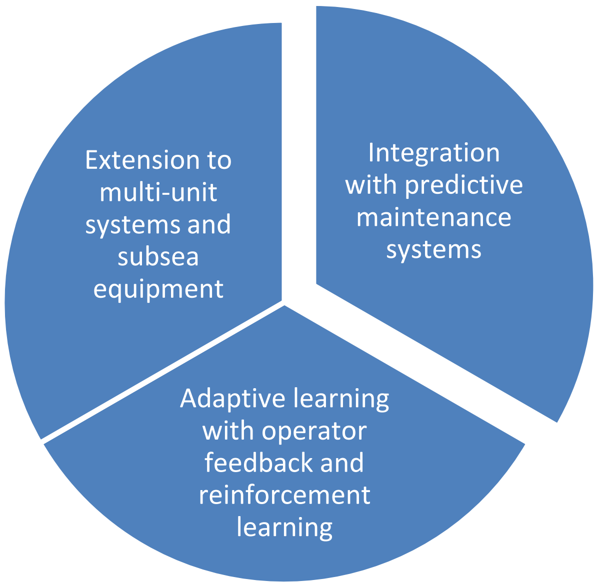

Figure 3: Future Work

A natural progression for the root cause model is its integration with predictive maintenance (PdM) frameworks. While the current model focuses on real-time fault detection and diagnosis, combining it with PdM can enable both proactive and preventive strategies. Predictive maintenance uses historical and real-time data to forecast equipment degradation and remaining useful life (RUL), allowing maintenance activities to be scheduled just-in-time, thereby minimizing both unplanned downtime and unnecessary servicing.

Integrating the diagnostics model with PdM systems involves establishing bidirectional data flows, where outputs from the root cause analysis inform PdM algorithms about recent anomalies, while PdM outputs provide context regarding asset health trends. Such synergy can improve maintenance prioritization and decision-making. Together, they enable condition-based maintenance that reduces operational risk and cost.

To enhance the model's accuracy and adaptability in real-world offshore environments, future work will focus on incorporating adaptive learning techniques, particularly those based on operator feedback and reinforcement learning (Radanliev *et al.*, 2020; Xiao *et al.*, 2020; Mohammadiun *et al.*, 2021). Current diagnostic models are typically trained on historical data and assume a relatively fixed environment. However, operational conditions in offshore systems are dynamic, and fault patterns may evolve over time.

Adaptive learning enables the model to improve continuously by learning from new data, including labeled events provided by human operators. By integrating a feedback loop, operators can confirm or correct the model's diagnostic output, thereby enriching the training dataset and refining the model's performance (Cao *et al.*, 2019; Branson *et al.*, 2021). This human-in-the-loop approach is especially valuable in complex or ambiguous fault scenarios where automated models may struggle to generalize.

Reinforcement learning (RL) offers an additional layer of intelligence by enabling the model to learn optimal diagnostic and decision strategies through interaction with its environment. In RL frameworks, the model receives feedback in the form of rewards or penalties based on the accuracy and timeliness of its diagnostics (Montazeralghaem *et al.*, 2020; Yu *et al.*, 2021). Over time, it learns to maximize long-term diagnostic performance through exploration and experience. This approach is particularly promising for multi-step fault diagnosis and decision-making under uncertainty.

Future enhancements to the root cause analytics model aim to make it more comprehensive, predictive, and adaptive. By extending its scope to multi-unit and subsea systems, integrating it with predictive maintenance frameworks, and incorporating adaptive learning with operator feedback and reinforcement learning, the model can evolve into an intelligent, self-improving diagnostic assistant (Dainoff *et al.*, 2020; Burger and Weinmann , 2020; Bányai, 2021). These advancements will significantly contribute to safer, more efficient, and more resilient offshore oil and gas operations.

Conclusion

This review has presented a comprehensive Root Cause Analytics (RCA) model architecture that integrates advanced data ingestion, preprocessing, machine learning-based diagnostic cores, and intuitive visualization interfaces. The model demonstrates strong performance in terms of real-time anomaly detection, scalability to large and complex datasets, and interpretability of diagnostic outcomes. By combining statistical analysis with AI/ML techniques—such as decision trees, Bayesian networks, and LSTM networks—it effectively identifies both direct and latent causes of system failures. The inclusion of temporal modeling and causal inference mechanisms such as Granger causality further enhances the model's ability to capture time-lagged dependencies and complex interactions in dynamic systems.

The implications of this RCA model are particularly significant for offshore systems, where safety, operational efficiency, and rapid decision-making are paramount. Offshore oil and gas platforms operate in remote, high-risk environments with limited margin for error. The proposed model enables proactive identification of root causes behind anomalies, reducing downtime, mitigating safety hazards, and optimizing resource allocation. Its real-time diagnostic capability supports condition-based maintenance and minimizes the reliance on manual inspections, thereby improving overall system resilience.

Looking ahead, this RCA framework represents a foundational step toward intelligent fault diagnostics in digital oilfields. As offshore platforms increasingly adopt IoT sensors, edge computing, and digital twin technologies, there is a growing need for autonomous, adaptive diagnostic systems. Future iterations of this model could incorporate reinforcement learning, knowledge graphs, and self-updating mechanisms to continuously improve diagnostic accuracy and contextual understanding. Ultimately, such intelligent RCA systems will be instrumental in realizing fully autonomous operations, enabling safer, more efficient, and data-driven decision-making across the energy sector.

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