Predictive Risk Modeling of High-Probability Methane Leak Events in Oil and Gas Networks

Semiu Temidayo Fasasi [1*], Oluwapelumi Joseph Adebowale [2], Abdulmaliq Abdulsalam [3], Zamathula Queen Sikhakhane Nwokediegwu [4]

[1] Independent Researcher, Nigeria
[2] Independent Researcher, USA
[3] Independent Researcher, Durban, South Africa
[4] Department of Chemical and Petroleum Engineering, University of Lagos, Nigeria

* Corresponding Author: **Semiu Temidayo Fasasi**

Article Info

P-ISSN: 3051-3502
E-ISSN: 3051-3510
Volume: 02
Issue: 01
January - June 2021
Received: 10-12-2020
Accepted: 12-01-2021
Published: 06-02-2021
Page No: 40-46

Abstract
Methane emissions from oil and gas infrastructure represent a significant environmental and safety challenge due to their potent greenhouse gas effects and operational hazards. This paper proposes a theoretical framework for predictive risk modeling aimed at identifying and prioritizing high-probability methane leak events within complex pipeline networks. By integrating risk theory, probabilistic modeling techniques, and detailed leak dynamics, the framework systematically quantifies leak likelihood through weighted risk factors derived from infrastructure attributes, operational history, and environmental conditions. The model architecture encompasses data inputs, probabilistic computation, and output metrics to support dynamic temporal and spatial risk mapping, enabling proactive risk governance and resource allocation. Analytical considerations address critical modeling assumptions, risk thresholding strategies, and theoretical performance evaluation metrics. The proposed framework advances both theoretical understanding and practical risk management by facilitating early detection, prioritization, and informed decision-making without reliance on empirical case studies or simulations. Finally, the study outlines future research directions, including multi-risk integration, real-time adaptive modeling, and automated mitigation, highlighting the framework's potential to enhance methane leak management in pursuit of environmental sustainability and operational safety in oil and gas networks.

DOI: https://doi.org/10.54660/IJMER.2021.2.1.40-46

Keywords: Methane Leak Prediction, Risk Modeling, Oil And Gas Infrastructure, Probabilistic Risk Assessment, Temporal-Spatial Risk Mapping, Predictive Analytics

1. Introduction
1.1 Background
Methane is a potent greenhouse gas with a global warming potential significantly greater than that of carbon dioxide over a 20-year period. It plays a critical role in short-term climate forcing due to its high radiative efficiency and relatively short atmospheric lifetime. A major anthropogenic source of methane is the oil and gas sector, where it is both a product and a by-product of extraction, processing, and transportation activities (Dean *et al*., 2018, Balcombe *et al*., 2017). Leaks can occur at various stages of the supply chain, including upstream production sites, midstream compressor stations, and downstream pipelines. These leaks contribute not only to environmental degradation but also represent economic losses and operational inefficiencies (Kroeger *et al*., 2017, Whiting and Chanton, 2001). In recent years, the environmental implications of methane emissions have garnered increasing attention from global regulatory agencies.

International climate agreements and national policies are placing stricter limits on methane emissions, prompting oil and gas operators to adopt more robust emission reduction strategies (Molnár, 2018). Regulatory compliance now includes enhanced leak detection and repair mandates, emission reporting requirements, and financial penalties for non-compliance. This regulatory landscape underscores the urgent need for advanced tools that can anticipate and manage leak risks more systematically and effectively (Hemes *et al*., 2018, Alvarez *et al*., 2012).

Beyond regulatory compliance, methane leaks also pose significant safety and reputational risks. High-concentration releases can lead to fire and explosion hazards, threatening worker safety and nearby communities. Additionally, uncontrolled emissions damage the public trust and investor confidence in energy companies (Chernov and Sornette, 2020). Traditional inspection-based leak management approaches often miss transient or intermittent leaks and are resource-intensive. These realities point to a growing need for predictive tools that can support continuous monitoring and targeted interventions, thereby reducing the likelihood and impact of high-risk leak events (Chernov and Sornette, 2019, Kumar and Gupta, 2021).

1.2 Motivation for Predictive Risk Modeling

Conventional approaches to methane leak management have largely relied on routine inspections, sensor-based monitoring, or operator reports, methods that are inherently reactive (Niu, 2017, Behbahani, 2006). While these techniques are effective at identifying existing leaks, they offer limited foresight into where or when leaks are likely to occur (Kumar, 2016). This reactive posture can result in delayed responses, prolonged emissions, and missed opportunities for preventive maintenance. In contrast, a predictive framework provides foresight by identifying risk conditions that precede leak events, enabling preemptive actions that reduce both emissions and safety hazards (Huntley, 2005, Aldhafeeri *et al*., 2020).

Predictive analytics, particularly in industrial systems, has proven valuable for anticipating equipment failures, optimizing maintenance schedules, and improving operational resilience. Applying similar principles to methane leak risk modeling allows organizations to shift from a compliance-driven mindset to a risk-based strategy (Perumallaplli, 2021). By analyzing historical data, infrastructure characteristics, and operational patterns, predictive models can estimate the probability of leak events with greater precision. This capability supports better decision-making regarding resource allocation, inspection prioritization, and technology deployment (Adekunle *et al*., 2021, Lee *et al*., 2020).

Despite the promise of predictive methodologies, several limitations persist in current practice. Existing risk assessment tools often lack the granularity to differentiate between low- and high-probability leak scenarios. Additionally, many tools fail to integrate temporal and spatial factors, which are critical for understanding how risks evolve across a network (Pech *et al*., 2021). There is also a lack of standardized frameworks that account for uncertainties in sensor data, infrastructure age, and environmental conditions. These gaps highlight the need for a theoretically grounded approach to predictive risk modeling that is tailored specifically to the unique attributes of methane leak behavior in oil and gas networks (Li *et al*., 2017).

1.3 Objectives

This paper presents a theoretical framework for predictive risk modeling aimed at identifying high-probability methane leak events within oil and gas networks. The primary objective is to conceptualize a model that can quantify leak likelihood based on identifiable risk factors and their interactions. Unlike empirical studies that rely heavily on case-specific data, this work focuses on the development of a generalized theoretical structure that can be adapted across various operational contexts. The model integrates concepts from probabilistic risk assessment, system reliability theory, and network analytics to address both the frequency and potential impact of leak events.

A key contribution of this study is the introduction of a structured approach to feature selection and risk scoring, grounded in existing knowledge of methane leak mechanisms. The framework incorporates both static and dynamic factors, such as pipeline age, material properties, proximity to junctions, and temporal trends in leak occurrences, to capture the complex nature of risk evolution. In doing so, it provides a foundation for prioritizing inspection and mitigation efforts based on predictive risk profiles, rather than historical incidents alone. This forward-looking methodology supports more strategic deployment of limited resources and enhances operational readiness.

Moreover, the proposed model holds interdisciplinary relevance, offering insights not only for industrial risk managers and environmental scientists but also for systems engineers and policy makers. By formalizing the logic and structure of predictive risk modeling in the methane context, this paper contributes to the growing body of literature on environmental systems engineering and operational safety. It aims to catalyze further theoretical and applied research in predictive analytics for climate-critical sectors, ultimately supporting more intelligent and sustainable infrastructure management.

2. Theoretical Foundations of Risk Modeling

2.1 Risk Theory in Industrial Systems

Risk within complex engineered systems is fundamentally a function of the likelihood of an adverse event occurring and the magnitude of its potential consequences (Adekunle *et al*., 2021, Lee *et al*., 2020). In industrial contexts such as oil and gas networks, risk assessment serves as a critical tool for anticipating failures, safeguarding assets, and protecting human and environmental health (Adeleke *et al*., 2021, ADEWOYIN *et al*., 2021). Theoretical frameworks often conceptualize risk as the product of probability and impact, enabling quantification and prioritization of hazards. This allows organizations to allocate resources effectively toward risk mitigation and safety improvements. By systematically characterizing risks, decision-makers can balance operational performance against acceptable safety thresholds (Oluoha *et al*., 2021, ONIFADE *et al*., 2021).

A core element of risk theory involves hazard identification, which is the process of recognizing potential sources of harm within a system. In engineered systems, hazards can range from material degradation and mechanical failures to external events such as natural disasters. The identification phase establishes the foundation for subsequent analyses by mapping out where and how failures may manifest (ADEWOYIN *et al*., 2020a, EYINADE *et al*., 2020). Risk matrices are commonly employed tools in this regard, visually correlating the likelihood of an event with its severity to categorize risk levels. This structured approach facilitates communication across multidisciplinary teams and supports regulatory compliance (Odedeyi *et al*., 2020, OGUNNOWO *et al*., 2020).

Failure modeling further enhances risk characterization by exploring the mechanisms and pathways through which system components degrade or malfunction (Gorjian *et al*., 2010). Techniques such as fault tree analysis and failure mode effects analysis systematically dissect failure chains, revealing critical vulnerabilities and dependencies (Xing, 2020, Aslansefat *et al*., 2020). In the context of oil and gas infrastructure, modeling failures enables the anticipation of leak initiation points and escalation scenarios. By integrating these concepts, risk theory provides a comprehensive lens to examine how component-level events aggregate into system-level risks, informing proactive safety management strategies (Okuh *et al*., Adewoyin *et al*., 2020b).

2.2 Probabilistic Modeling Approaches

Probabilistic modeling techniques play an essential role in capturing the uncertainty and complexity inherent in industrial risk assessment. These methods allow analysts to quantify the likelihood of events whose occurrences are stochastic in nature, such as methane leaks in oil and gas networks (Gbabo *et al*., Ogunnowo). Among the most widely applied approaches are Bayesian networks, Poisson processes, and Markov models, each offering unique advantages depending on the data availability and system characteristics. Bayesian networks, for example, utilize graphical models to represent probabilistic dependencies among variables, enabling dynamic updating of risk estimates as new information becomes available (Okuh *et al*., Okuh *et al*.).

The Poisson process is particularly suited to modeling the occurrence of discrete events over time, making it relevant for leak event prediction, where failures can be considered random but with definable average rates. It provides a mathematically tractable framework to estimate the probability of a given number of leaks occurring within a specific interval (Kurtoglu and Tumer, 2008, Baldick *et al*., 2008). Markov models, on the other hand, are powerful for representing systems with memoryless transition probabilities between discrete states. They can simulate progression from safe conditions to leak initiation and eventual detection or repair, thus modeling temporal dynamics and state-dependent risks (Gbabo *et al*.).

In pipeline networks, these probabilistic tools collectively facilitate a more nuanced understanding of risk propagation and event likelihood. By accommodating data uncertainty, sensor inaccuracies, and complex interdependencies, probabilistic models support predictive analytics that are both flexible and robust. They enable operators to move beyond deterministic assessments, integrating spatial and temporal variability into risk forecasts. This is critical for tailoring inspection schedules and maintenance activities to changing operational conditions and infrastructure health (Lambert, 1975).

2.3 Methane Leak Dynamics and Risk Propagation

Methane leaks in oil and gas systems arise from multiple physical and operational factors, including material defects, corrosion, mechanical stresses, and operational errors. Leak initiation often begins at points of mechanical weakness, such as welds, joints, or valves, where structural integrity is compromised. Once a leak starts, its progression is influenced by pressure differentials, gas flow rates, and network topology. The interplay between these factors determines the rate of methane release, the spatial dispersion of the leak plume, and the potential escalation of risk to adjacent infrastructure or environments (Kiriliuk, 2021, Ahmed and Salehi, 2021).

The dynamics of leak propagation are inherently linked to the characteristics of the infrastructure. Older pipelines with aging materials or those exposed to corrosive environments exhibit a higher propensity for failure. Similarly, sections of the network that experience frequent pressure fluctuations or operational transients are more susceptible to leak development. The topology of the pipeline system, branching configurations, proximity to compressors, and valve placement, also affects how leaks spread and how risk concentrates at critical nodes. This spatial heterogeneity necessitates a modeling approach that accounts for localized vulnerabilities as well as network-wide interactions (Khalid *et al*., 2020).

Risk propagation in methane leak events is not only a function of physical dispersion but also of detection and response capabilities. Leaks that go undetected can escalate, increasing environmental and safety hazards. Conversely, rapid detection and mitigation can contain risk escalation. Therefore, predictive models must integrate leak dynamics with operational parameters such as sensor coverage, inspection frequency, and repair times. This integration enables the estimation of not just where leaks may occur, but also how risk evolves over time and space, supporting more effective risk prioritization and resource allocation (Collacott, 2012, Dusseault *et al*., 2014).

3. Predictive Framework Development

3.1 Model Architecture and Component Layers

The conceptual architecture of the predictive risk model for methane leaks is structured to systematically integrate diverse data inputs and transform them into actionable risk metrics. At its foundation, the model relies on a comprehensive set of data sources, including historical leak records, maintenance logs, sensor outputs, and infrastructure metadata. Historical data provide empirical context by capturing past leak occurrences, their locations, and severities, enabling the model to learn patterns indicative of risk. Maintenance records add insights about asset condition and intervention histories, while sensor data contribute real-time or near-real-time indicators of operational anomalies and environmental changes (Inderwildi *et al*., 2020, Agbede *et al*., 2021).

Central to the architecture is the definition and quantification of risk factors that influence leak probability. These factors encompass physical attributes such as pipeline material, age, diameter, and pressure, as well as operational variables including throughput rates and exposure to external stresses. The model processes these inputs using probabilistic algorithms to compute likelihood scores for potential leak events. This computation may involve weighting individual risk factors according to their relative importance, combining them into composite risk indices that reflect overall vulnerability at specific network points (Hsu *et al*., 2020).

The final output layer of the model translates computed probabilities into meaningful risk metrics, such as risk scores or alert levels, which can be used to guide operational decisions. These outputs are designed to be intuitive for stakeholders, facilitating prioritization of inspection efforts, allocation of maintenance resources, and targeted deployment of leak mitigation technologies. By modularizing the framework into input, processing, and output layers, the architecture ensures scalability and adaptability to different data availability scenarios and network complexities.

3.2 Feature Selection and Variable Importance

Identifying the most predictive features for high-probability methane leaks is a critical step in constructing an effective risk model. Feature selection begins with a review of domain knowledge and empirical evidence to isolate variables that influence leak occurrence. Pipeline material, for example, is a well-established predictor since certain alloys and coatings exhibit differing susceptibility to corrosion and mechanical fatigue. Similarly, proximity to compressors and high-pressure stations is significant due to increased mechanical stress and vibration in these zones, which can accelerate pipeline degradation.

Beyond physical infrastructure, operational history plays a vital role in feature identification. Records of previous leak incidents, repair frequency, and inspection outcomes serve as indicators of latent weaknesses and recurrent risk hotspots. Environmental factors such as soil type, temperature fluctuations, and seismic activity may also be relevant, depending on the network's geographical context. These variables contribute to a multifaceted risk profile that captures both intrinsic and extrinsic factors influencing leak likelihood.

Once candidate features are identified, the model assigns weights reflecting their relative importance. Weighting is informed by statistical analyses, expert judgment, and risk theory, aiming to balance sensitivity and specificity in leak prediction. Features with strong correlations to leak events receive higher weights, while those with marginal or indirect influence are down-weighted or excluded to prevent model overfitting. This rigorous feature selection and weighting process enhances the model's predictive accuracy and interpretability, ensuring that the risk scores generated reflect meaningful differences in leak probability.

3.3 Temporal and Spatial Risk Mapping

Effective risk modeling of methane leaks requires capturing variations across both time and the spatial dimensions of the pipeline network. Temporally, risk levels fluctuate due to factors such as seasonal temperature changes, operational cycles, and maintenance schedules. Incorporating time into the model allows for dynamic risk assessment that can anticipate periods of heightened vulnerability, enabling proactive interventions. For example, aging pipelines may exhibit increased risk during temperature extremes when material brittleness or expansion-contraction stresses peak.

Spatially, pipelines are distributed across diverse terrains and network configurations, creating heterogeneous risk landscapes. Mapping risk across network nodes and segments identifies "hotspots" where leak probability is elevated due to converging risk factors such as high pressure, material fatigue, or historical incident clustering. These spatial risk maps support targeted inspection strategies, concentrating resources on segments most likely to experience failure, thus improving efficiency and reducing overall system risk.

Combining temporal and spatial dimensions, the framework introduces predictive "leak anticipation windows", defined timeframes and locations where risk surpasses critical thresholds. This integration supports continuous monitoring and alert generation tailored to evolving network conditions. By aligning risk metrics with operational planning horizons, temporal-spatial risk mapping empowers decision-makers to transition from reactive to predictive maintenance regimes, enhancing safety and environmental stewardship across oil and gas infrastructure.

4. Analytical Considerations and Model Evaluation

4.1 Assumptions and Model Boundaries

Every predictive risk model is founded upon a set of explicit and implicit assumptions that define its applicability and reliability. One fundamental assumption is the stationarity of risk factors, meaning that the relationships between predictors and leak probabilities remain consistent over time. While this simplifies modeling by treating risk factors as stable, it may not fully capture evolving infrastructure conditions or emerging operational practices. Recognizing this assumption is vital because temporal shifts in technology, maintenance regimes, or environmental conditions can alter risk profiles, potentially reducing the model's predictive accuracy if unaccounted for.

Another critical assumption concerns data completeness and quality. The model presumes access to sufficiently detailed and accurate datasets, including leak histories, maintenance records, and sensor outputs. In reality, gaps or inconsistencies in data collection can introduce bias or uncertainty into risk estimates. For instance, undetected leaks or incomplete inspection logs may lead to an underestimation of risk in certain network segments. Addressing these limitations requires rigorous data management practices and potentially the integration of uncertainty quantification methods within the model to mitigate the impact of imperfect information.

The boundaries of the model are also defined by the level of abstraction employed. This framework emphasizes theoretical rigor by focusing on generalized relationships rather than site-specific empirical calibration. While this enhances adaptability across different oil and gas networks, it inherently limits precise predictive accuracy for individual installations. The model does not attempt to replace detailed engineering assessments but rather to provide a strategic risk prioritization tool grounded in sound theoretical principles. This balance between generalizability and specificity must be carefully managed to ensure the model remains both relevant and reliable.

4.2 Risk Thresholding and Classification

Distinguishing high-risk zones or events from low-risk ones is essential for translating probabilistic risk scores into actionable decisions. The model employs thresholding techniques that partition continuous risk outputs into discrete categories, such as low, medium, and high risk. Setting these thresholds involves statistical and domain-informed methods designed to optimize operational relevance and minimize erroneous classifications. For example, risk quantiles can be used to define categories based on the distribution of computed scores, with the top percentile often designated as high risk, warranting immediate attention.

Confidence intervals represent another approach to thresholding, where risk scores exceeding a predetermined statistical confidence level are classified as high risk. This method incorporates uncertainty explicitly, allowing decision-makers to gauge the reliability of risk classifications and balance false positives against missed detections. In contexts where safety is paramount, more conservative thresholds may be selected to prioritize early intervention even at the expense of increased false alarms.

Linking risk classifications to decision tiers facilitates structured responses within operational frameworks. High-risk designations might trigger immediate inspections or repairs, while medium-risk categories could prompt increased monitoring or preventative maintenance. Low-risk zones may be scheduled for routine checks at standard intervals. This tiered system ensures that limited resources are focused where they yield the greatest risk reduction benefits, enabling a cost-effective and safety-oriented approach to methane leak management.

4.3 Validation Concepts and Performance Metrics

Evaluating the theoretical performance of the predictive risk model requires carefully selected metrics that reflect its reliability and utility in guiding decision-making. Accuracy, defined as the proportion of correct risk classifications, is a fundamental metric but can be insufficient in imbalanced risk contexts where high-risk events are rare. Complementary metrics such as the false positive rate (incorrectly identifying low-risk zones as high risk) and false negative rate (failing to detect actual high-risk zones) provide a more nuanced assessment of model performance, emphasizing the trade-offs inherent in threshold selection.

Expected Value of Information (EVoI) is an advanced concept relevant to model evaluation, quantifying the benefit derived from using the model's predictions in decision-making compared to decisions made without such information. A model with high EVoI improves outcomes by reducing the cost of undetected leaks or unnecessary interventions. Assessing EVoI theoretically involves scenario analyses and cost-benefit frameworks, which help justify investment in predictive modeling capabilities.

Additionally, theoretical reliability bounds can be established using probabilistic sensitivity analyses, which explore how uncertainties in input data and model parameters propagate through risk estimates. These bounds inform confidence in predictions and identify conditions under which the model's outputs remain robust. While empirical validation requires data, these theoretical validation concepts emphasize model soundness and guide future empirical studies by highlighting critical factors affecting predictive performance.

5. Conclusion

5.1 Summary of Contributions

This paper has introduced a novel theoretical framework for predictive risk modeling aimed at identifying and prioritizing high-probability methane leak events in oil and gas networks. The proposed approach synthesizes key elements from risk theory, probabilistic modeling, and infrastructure dynamics to construct a comprehensive risk assessment tool. Unlike traditional methods that rely predominantly on reactive detection and empirical case studies, this framework emphasizes the proactive anticipation of leak events by integrating multifaceted risk factors and temporal-spatial considerations. Through rigorous feature selection and weighted risk scoring, the model facilitates more precise risk differentiation across complex pipeline systems.

Moreover, the modular architecture of the framework ensures adaptability across diverse operational contexts, allowing it to incorporate varying levels of data availability and infrastructure complexity. By formalizing leak dynamics alongside probabilistic dependencies and operational parameters, the framework establishes a theoretically sound basis for translating complex data into actionable risk metrics. This positions the model as a foundational tool to guide inspection prioritization and resource allocation in methane leak management, advancing both academic understanding and practical risk governance in energy infrastructure.

Collectively, these contributions address critical gaps in existing risk assessment methodologies by offering a structured, predictive perspective that balances theoretical rigor with operational relevance. The framework lays the groundwork for enhanced safety, environmental stewardship, and economic efficiency, reflecting a meaningful step forward in methane emissions mitigation strategies within the oil and gas sector.

5.2 Theoretical and Practical Implications

From a theoretical standpoint, this model enriches the body of knowledge in environmental systems modeling and operational risk theory by demonstrating how complex industrial risks can be probabilistically quantified and dynamically mapped. It highlights the importance of integrating static infrastructure attributes with evolving temporal factors, thereby extending traditional risk models that often treat these dimensions separately. This holistic perspective underscores the interplay between physical system characteristics and operational dynamics, providing a robust conceptual lens for future research on complex networked systems under uncertainty.

Practically, the framework offers tangible benefits for proactive risk governance. By translating predictive risk scores into decision-making tools, operators can move beyond compliance-driven maintenance toward risk-informed inspection scheduling, enabling more efficient and effective deployment of limited resources. This facilitates early identification of potential leak hotspots, reducing environmental impact and operational downtime. Furthermore, the model supports strategic infrastructure investment by pinpointing segments with elevated risk profiles, informing asset renewal and reinforcement priorities in alignment with sustainability goals and regulatory expectations. Overall, the proposed framework bridges the gap between theoretical risk quantification and practical implementation, empowering stakeholders across disciplines to anticipate, prioritize, and mitigate methane leak risks more systematically. It exemplifies how rigorous modeling approaches can directly inform policy, operational management, and long-term infrastructure resilience in climate-critical industrial sectors.

5.3 Future Research Directions

Several avenues exist to extend and enhance the proposed predictive risk modeling framework. One promising direction is the incorporation of multi-risk interactions, recognizing that methane leaks may co-occur or be influenced by correlated hazards such as corrosion, equipment fatigue, or external environmental stressors. Developing models that account for these complex dependencies would provide a more comprehensive risk profile and improve predictive accuracy.

Another important enhancement involves integrating real-time adaptive components into the framework. By leveraging streaming sensor data and machine learning algorithms, the model could dynamically update risk estimates in response to changing operational conditions and detected anomalies. Such adaptive capabilities would enable continuous risk monitoring and more timely interventions, moving closer to fully autonomous leak detection and prevention systems.

Lastly, future research could explore the integration of predictive risk modeling with automated mitigation technologies, such as smart valves and rapid-response containment systems. Theoretical work on coordinating prediction with automated control actions would deepen understanding of how predictive analytics can optimize both risk anticipation and immediate response. These advancements hold the potential to transform methane leak management into a more resilient, intelligent, and environmentally responsible practice, aligning with evolving industry and societal priorities.

6. References

1. Adekunle BI, Chukwuma-Eke EC, Balogun ED, Ogunsola KO. A predictive modeling approach to optimizing business operations: A case study on reducing operational inefficiencies through machine learning. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(4):791-799.
2. Adeleke AK, Igunma TO, Nwokediegwu ZS. Modeling advanced numerical control systems to enhance precision in next-generation coordinate measuring machine. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(4):638-649.
3. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. Advances in Thermofluid Simulation for Heat Transfer Optimization in Compact Mechanical Devices. [Publisher details incomplete]. 2020.
4. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. A Conceptual Framework for Dynamic Mechanical Analysis in High-Performance Material Selection. [Publisher details incomplete]. 2020.
5. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. Advances in CFD-Driven Design for Fluid-Particle Separation and Filtration Systems in Engineering Applications. [Publisher details incomplete]. 2021.
6. Agbede OO, Akhigbe EE, Ajayi AJ, Egbuhuzor NS. Assessing economic risks and returns of energy transitions with quantitative financial approaches. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(4):552-566.
7. Ahmed S, Salehi S. Failure mechanisms of the wellbore mechanical barrier systems: Implications for well integrity. Journal of Energy Resources Technology. 2021;143(7):073007.
8. Aldhafeeri T, Tran M-K, Vrolyk R, Pope M, Fowler M. A review of methane gas detection sensors: Recent developments and future perspectives. Inventions. 2020;5(3):28.
9. Alvarez RA, Pacala SW, Winebrake JJ, Chameides WL, Hamburg SP. Greater focus needed on methane leakage from natural gas infrastructure. Proceedings of the National Academy of Sciences of the United States of America. 2012;109(17):6435-6440.
10. Aslansefat K, Kabir S, Gheraibia Y, Papadopoulos Y. Dynamic fault tree analysis: state-of-the-art in modeling, analysis, and tools. Reliability Management and Engineering. 2020:73-112.
11. Balcombe P, Anderson K, Speirs J, Brandon N, Hawkes A. The natural gas supply chain: the importance of methane and carbon dioxide emissions. ACS Sustainable Chemistry & Engineering. 2017;5(1):3-20.
12. Baldick R, Chowdhury B, Dobson I, Dong Z, Gou B, Hawkins D, Huang H, Joung M, Kirschen D, Li F. Initial review of methods for cascading failure analysis in electric power transmission systems IEEE PES CAMS task force on understanding, prediction, mitigation and restoration of cascading failures. 2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century. 2008:1-8.
13. Behbahani AR. Need for Robust Sensors for Inherently Fail-Safe Gas Turbine Engine Controls, Monitoring, and Prognostics (Postprint). [Publisher details incomplete]. 2006.
14. Chernov D, Sornette D. Specific features of risk management in the industrial and agricultural sectors. Critical Risks of Different Economic Sectors: Based on the Analysis of More Than 500 Incidents, Accidents and Disasters. Springer; 2019:73-112.
15. Chernov D, Sornette D. Critical risks of different economic sectors. Based on the Analysis of More Than 500. Springer; 2020.
16. Collacott R. Mechanical fault diagnosis and condition monitoring. Springer Science & Business Media; 2012.
17. Dean JF, Middelburg JJ, Röckmann T, Aerts R, Blauw LG, Egger M, Jetten MS, de Jong AE, Meisel OH, Rasigraf O. Methane feedbacks to the global climate system in a warmer world. Reviews of Geophysics. 2018;56(1):207-250.
18. Dusseault MB, Jackson RE, Macdonald D. Towards a road map for mitigating the rates and occurrences of long-term wellbore leakage. [Publisher details incomplete]. 2014.
19. Eyinade W, Ezeilo OJ, Ogundeji IA. A Treasury Management Model for Predicting Liquidity Risk in Dynamic Emerging Market Energy Sectors. [Publisher details incomplete]. 2020.
20. Gbabo EY, Okenwa OK, Chima PE. Constructing AI-Enabled Compliance Automation Models for Real-Time Regulatory Reporting in Energy Systems. [Publisher details incomplete].
21. Gbabo EY, Okenwa OK, Chima PE. Integrating CDM Regulations into Role-Based Compliance Models for Energy Infrastructure Projects. [Publisher details incomplete].
22. Gorjian N, Ma L, Mittinty M, Yarlagadda P, Sun Y. A review on degradation models in reliability analysis. Engineering Asset Lifecycle Management: Proceedings of the 4th World Congress on Engineering Asset Management (WCEAM 2009), 28-30 September 2009. Springer; 2010:369-384.
23. Hemes KS, Chamberlain SD, Eichelmann E, Knox SH, Baldocchi DD. A biogeochemical compromise: The high methane cost of sequestering carbon in restored wetlands. Geophysical Research Letters. 2018;45(12):6081-6091.
24. Hsu A, Khoo W, Goyal N, Wainstein M. Next-generation digital ecosystem for climate data mining and knowledge discovery: a review of digital data collection technologies. Frontiers in Big Data. 2020;3:29.
25. Huntley SL. Early detection and monitoring of fuel

leaks. Cranfield University (United Kingdom); 2005.
26. Inderwildi O, Zhang C, Wang X, Kraft M. The impact of intelligent cyber-physical systems on the decarbonization of energy. Energy & Environmental Science. 2020;13(3):744-771.
27. Khalid HU, Ismail MC, Nosbi N. Permeation damage of polymer liner in oil and gas pipelines: A review. Polymers. 2020;12(10):2307.
28. Kiriliuk S. Reduction potentials and abatement costs for methane emissions associated with compromised wellbore sealing systems in Russian oil wells. Technische Universität Wien; 2021.
29. Kroeger KD, Crooks S, Moseman-Valtierra S, Tang J. Restoring tides to reduce methane emissions in impounded wetlands: A new and potent Blue Carbon climate change intervention. Scientific Reports. 2017;7:11914.
30. Kumar A. Model based operation of industrial steam methane reformers using large scale sensor data. [Publisher details incomplete]. 2016.
31. Kumar N, Gupta H. Methane: Risk assessment, environmental, and health hazard. Hazardous Gases. Elsevier; 2021:247-258.
32. Kurtoglu T, Tumer IY. A graph-based fault identification and propagation framework for functional design of complex systems. [Publisher details incomplete]. 2008.
33. Lambert HE. Fault trees for decision-making in systems analysis. University of California, Berkeley; 1975.
34. Lee J, Ni J, Singh J, Jiang B, Azamfar M, Feng J. Intelligent maintenance systems and predictive manufacturing. Journal of Manufacturing Science and Engineering. 2020;142(11):110805.
35. Li Z, Wang Y, Wang K-S. Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. Advances in Manufacturing. 2017;5(4):377-387.
36. Molnár A. Leaking towards climate change: The role of natural gas supply chains in global warming. Corvinus Journal of International Affairs. 2018;3(1):4-12.
37. Niu G. Data-driven technology for engineering systems health management. Springer Singapore; 2017:10.978-981.
38. Odedeyi PB, Abou-El-Hossein K, Oyekunle F, Adeleke AK. Effects of machining parameters on Tool wear progression in End milling of AISI 316. Progress in Canadian Mechanical Engineering. 2020;3.
39. Ogunnowo EO. A Conceptual Framework for Digital Twin Deployment in Real-Time Monitoring of Mechanical Systems. [Publisher details incomplete].
40. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. Systematic Review of Non-Destructive Testing Methods for Predictive Failure Analysis in Mechanical Systems. [Publisher details incomplete]. 2020.
41. Okuh CO, Nwulu EO, Ogu E, Ifechukwude P, Egbumokei IND, Digitemie WN. Creating a Sustainability-Focused Digital Transformation Model for Improved Environmental and Operational Outcomes in Energy Operations. [Publisher details incomplete].
42. Okuh CO, Nwulu EO, Ogu E, Ifechukwude P, Egbumokei IND, Digitemie WN. An Integrated Lean Six Sigma Model for Cost Optimization in Multinational Energy Operations. [Publisher details incomplete].
43. Oluoha O, Odeshina A, Reis O, Okpeke F, Attipoe V, Orieno O. Development of a Compliance-Driven Identity Governance Model for Enhancing Enterprise Information Security. Iconic Research and Engineering Journals. 2021;4(12):310-324.
44. Onifade AY, Ogeawuchi JC, Abayomi A, Agboola O, George O. Advances in Multi-Channel Attribution Modeling for Enhancing Marketing ROI in Emerging Economies. Iconic Research and Engineering Journals. 2021;5(6):360-376.
45. Pech M, Vrchota J, Bednář J. Predictive maintenance and intelligent sensors in smart factory. Sensors. 2021;21(4):1470.
46. Perumallaplli R. Predictive maintenance in cloud infrastructure: A machine learning framework. Available at SSRN 5228213. 2021.
47. WhITING GJ, Chanton JP. Greenhouse carbon balance of wetlands: methane emission versus carbon sequestration. Tellus B: Chemical and Physical Meteorology. 2001;53(5):521-528.
48. Xing L. Cascading failures in Internet of Things: Review and perspectives on reliability and resilience. IEEE Internet of Things Journal. 2020;8(1):44-64.