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# AI-POWERED FORECASTING AND OPTIMIZATION IN OIL AND GAS PIPELINE OPERATIONS WITH RESEARCH TOOLS, TRENDS AND OPPORTUNITIES

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***Abstract*—**The oil and gas pipeline industry is one of the sectors that moving towards using AI for enhancing equipment reliability, safety of operations and maintenance effectiveness in complex transmission networks' operation. The paper presents a complete summary of predictive and preventive maintenance measures in pipeline systems with the focus on AI-guided predictive analytics used in asset integrity management. The condition-based and risk-based maintenance models, time series prediction, classification, regression and anomaly detection algorithms that are used in failure forecasting and leak detection. Advanced sensing devices, such as smart sensors embedded in SCADA, and distributed monitoring systems, aid in real-time data capture and make it possible to make intelligent decisions. The mechanisms of corrosion and leakage in $CO_2$ pipelines are given special consideration as thermodynamic and environmental factors exacerbate operational risks in $CO_2$ pipelines. New trends like digital twins, edge computing, hybrid energy optimization, sustainability-driven metrics, etc. are analyzed as well. Although there has been a great improvement, the issues of the heterogeneity of data, model generalization, interpretability, and cybersecurity continue to be a major limitation to scalable AI implementation in high-stakes oil and gas environments.

***Keywords*—**Artificial Intelligence (AI), Oil and Gas Pipelines; Predictive Maintenance, Preventive Maintenance, Leak Detection and Corrosion Monitoring**.**

## I. Introduction

The oil and gas (O&G) sector is a complex and dangerous industry whose equipment reliability, environmental performance, and efficiency are of prime importance. The contemporary pipeline networks are thousands of kilometres with varying terrains that connect the upstream production system, the midstream transmission system and the downstream distribution system [1]. These massive resources are subjected to operational pressures, corrosion, external forces and environmental risks and are therefore prone to failure [2]. The failure of equipment, or the bursting of the pipes may lead to serious economic losses, environmental pollution, and safety risks. As a result, pipeline integrity is a strategic issue of both the operators and regulators in the long term.

Common methods of managing pipeline risks are based on regular inspection, diagnostics by rules, and the Integrity Management Programs (IMPs) that have to be controlled by industrial regulations and standards. Though these measures offer orderly supervision, they fail to work with time as infrastructure grows older and the operation complexity rises [3][4] Moreover, the regulatory bodies are not free to undertake independent safety culture and compliance, which hinders preemptive reduction of risks. The precision and dependability of traditional risk assessment tools highly rely on present pointers and fixed evaluation frameworks that might fail to adequately articulate nonlinear frameworks of the systems and dynamic risk development.

As the energy infrastructure and digital technologies develop quickly, predictive modelling based on Artificial Intelligence (AI) has become a disruptive approach to the management of pipelines [5]. Modern pipeline systems create huge datasets out of Supervisory Control and Data Acquisition (SCADA) systems, inline inspection (ILI) tools, IoT sensors, acoustic monitoring tools, and surveillance platforms during their lifecycle [6][7]. The sophisticated AI methods, such as machine learning (ML), deep learning (DL), hybrid physics-informed models, computer vision, and data-driven optimization, allow detecting anomalies in real time, predicting corrosion rate, locating leaks, flow optimization, and Remaining Useful Life (RUL), to name a few [8]. These capabilities change the reactive maintenance of pipelines to the predictive and condition-based approaches.

### *A. Structure of the Paper*

The remainder of this paper is organized as follows: Section II presents an overview of oil and gas pipeline systems, maintenance strategies, and AI-driven predictive approaches. Section III discusses AI applications and sensing technologies in pipeline operations, while Section IV outlines emerging trends, challenges, and future perspectives. Section V highlights the summary of the literature review, and Section VI presents the key findings of the study and suggestions for further study.

## II. Overview of Oil and Gas Pipeline Systems.

The stability of the equipment is the key to smooth operations, productivity maximization, and cost reduction in the oil and gas sector. With the growing pressure on the sector to improve operational efficiencies whilst not compromising on safety and environmental requirements, it is important to note that the importance of having effective maintenance strategies is more important. The consequences of equipment failures are not only high downtime and loss of money but also risks to the personnel and environmental integrity. That is why the introduction of effective measures to promote the reliability of equipment is a key to the long-term successful existence of the oil and gas business. The crude oil supply chain is illustrated in Figure 1, where the units of production are connected to the storage facilities and pump stations by the collecting lines [9].

The production-to-consumer process is complete as the crude oil is given through the transmission pipelines to the refineries and subsequently the refined products are channeled to the marketing terminals and service stations.

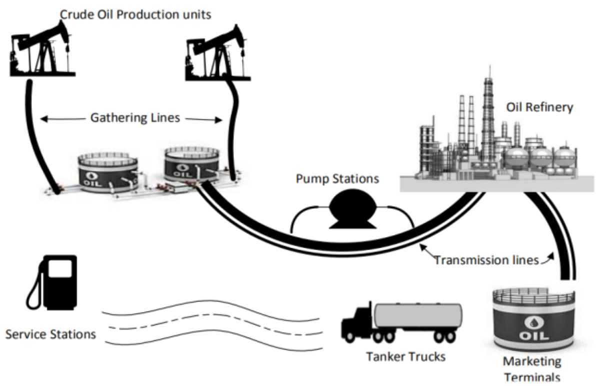


Fig. 1. Oil and Gas Pipeline System: Oil Pipeline System

In the context of the oil and gas industry, predictive modelling is aimed at improving equipment efficiency in terms of failure prediction and efficient maintenance plans. Such a strategy is essential in enhancing efficiency and minimizing expenses incurred in the operation and safety of the industry. Through maximum data generated through multiple means, predictive modelling enables organizations to make sensible decisions and apply proactive maintenance actions. The supply chain of natural gas as provided in Figure 2 commences with the gas wells and flow of gas through gathering systems to compressor station, processing station and storage tanks [10]. The refined gas is then passed through high-pressure transmission lines and supplied to power generation plants, domestic consumers, and commercial properties to be used as final products.

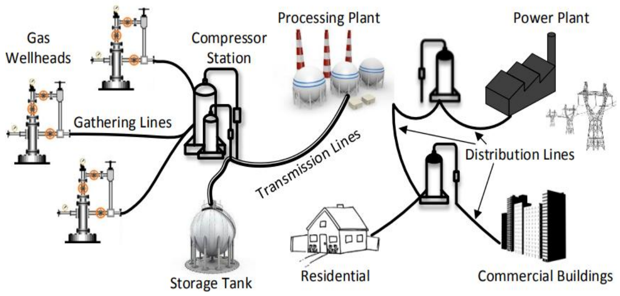


Fig. 2. Oil And Gas Pipeline System: Gas Pipeline System

## A. Predictive vs. Preventive Maintenance

Here are predictive and preventive maintenance based on AI used for oil & gas operations are described below:

### 1) Predictive Maintenance

Condition-based maintenance (CBM), another name for predictive maintenance, is based on routine or real-time pipeline state monitoring to assist in maintenance decision-making. The method presumes that pipelines are gradually corroded and that condition monitoring allows them to be brought to a timely intervention before they fail disastrously. CBM can either be an in-service monitoring at the time of operation or an off-line monitoring at times of shutdown. Decision in maintenance can either be diagnostic (finding out the cause of failures) or prognostic (anticipating future failures) [11]. It is especially helpful because prognostic methods allow planning of the work in the most efficient manner, minimize unanticipated breakdowns, and enhance the utilization of assets. CBM is very critical in ensuring the establishment of the best inspection intervals [12]. The scheduling of traditional inspections used to be dependent on the calendar dates or specific periods of operation. But nowadays, reliability models, probabilistic evaluations and cost optimization methods are combined to find the optimal frequency of inspection. This constraint gave way to the risk-based maintenance strategies.

### 2) Preventive Maintenance

Preventive maintenance (PM) refers to planned repair or replacement procedures that are carried out in advance to prevent failure. These are policies which are based on scheduled interventions at a certain time, age or usage.

#### a) Age-Based Policies

The policies of age-based maintenance include the replacement or repair of the pipeline components by the age limit. The decisions with regards to maintenance are made when the unit hits a certain age or when the unit fails before it does. Imperfect maintenance is also a frequent practice in most instances, during which the system is reinstated to a partially better condition instead of a like-new condition [13]. As age-based policies are commonly used in conventional engineering systems, they are less common in pipeline-related policies because of their decentralized nature and different environmental conditions.

#### b) Time-in-Service-Based Policies

Time-in-service policies plan maintenance after a set period of time without respect to failure history. Periodic preventive maintenance is under this category. Although reduced maintenance times enhance reliability and availability, the maintenance costs increase. The variables used in the decision are typically the maintenance interval, the reference age, and the number of repairs. In the case of pipelines, periodic tests are occasionally implemented on certain sections, using cost optimization and operational limitations. Failure/ Repair Limit Policies.

#### c) Failure/Repair Limit Policies

These policies blend between imperfect and perfect maintenance policies. Maintenance is carried out until a specified number of failures or repairs are achieved in which full replacement is done. Hybrid preventive maintenance plans have also been made through integrating the age based, time based and repairing-limit requirements to improve reliability as at the same time reducing downtime and cost. Nevertheless, the traditional preventative policies are not widely used within the pipeline systems because of the possible serious outcomes of failure.

## B. Artificial intelligence for predictive maintenance.

In order to enhance business operations and decision-making, the oil and gas sector uses these strategies to forecast equipment failure [14]. Predictive analytics enables businesses to be proactive and make data-driven choices by quickly processing vast amounts of data that are gathered from several sources, including sensors and historical records. AI has the ability to completely transform maintenance methods, and its further advancement undoubtedly has an impact on how the O&G industry evolves in the future. This is due to persistent problems with AI techniques and tools, including overtraining, coincidence effects, and overfitting. Predictive analytics has recently become a transformational capacity, and platforms are seeking to include these methods to predict future patterns and likely consequences. As demonstrated in Figure 3, clustering, prediction, and classification are the best uses of predictive analytics in the oil and gas sector. To anticipate equipment failure and maximize maintenance schedules, a range of algorithms is utilized, and occasionally combinations of algorithms are included:

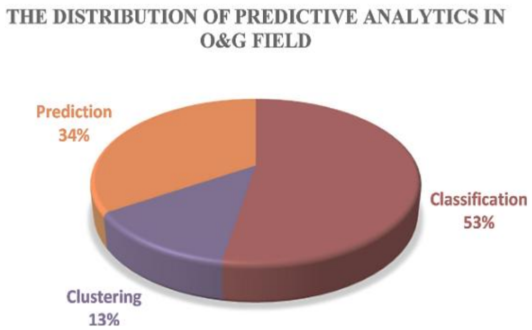


Fig. 3. Distribution of the Predictive Analytics Model in the O&G Field

*1) Time-Series Forecasting Algorithms*

- **Autoregressive Integrated Moving Average (ARIMA):** Forecasts based on previous time-series data are made using ARIMA models. With the use of patterns and seasonality in equipment performance data, this model can forecast future values.
- **Exponential Smoothing (ETS):** Makes predictions using time-series data by applying smoothing techniques. They are helpful for predicting maintenance requirements since they level out previous findings.
- **Long Short-Term Memory (LSTM):** A particular kind of recurrent neural network (RNN). Because LSTM networks are good at identifying long-term relationships in time-series data, they may be used to forecast equipment breakdowns from consecutive sensor readings.

*2) Classification Algorithms*

- **Support Vector Machines (SVM):** Data may be categorized using this model into "failure" or "no failure." They are helpful in spotting trends before equipment malfunctions.
- **Decision Trees (DT) and Random Forests (RF):** Effectively identify the conditions that result in maintenance events by classifying data according to decision criteria.
- **Gradient Boosting Machines (GBM):** A model that is formed by the combination of many weak models in a way to form a strong predictive model. They are helpful in identifying failure occurrences by analyzing the consequences of feature interactions.

*3) Anomaly Detection Algorithms*

- **Isolation Forest:** The model may be used to identify anomalous patterns that may indicate impending equipment failure since it separates the dataset's outliers.
- **Autoencoders:** Autoencoders are neural network models that are taught to learn a low-dimensional representation of data and are recognized for anomalous behaviour that may be a sign of failures.

*4) Regression Algorithms*

- **Linear Regression (LR):** It is the most widely used model and deals with dependent versus independent variables. This model is able to forecast the time of equipment wear, or failure rate according to different workable parameters.
- **Polynomial Regression:** The data may be fitted to more complex models that more properly represent non-linear patterns using this kind of transformation, which is LR employing polynomial features.

The model uses sensor data from specific machines to predict the asset's lifespan. According to the results, XGBoost has been effectively employed to forecast asset maintenance, and the model's classification accuracy has risen by 6.43% when compared to the RF method [15]. In the oil & gas sector, predictive analytics algorithms for preventative maintenance are evolving and showing promise. Predictive analytics continues to make significant contributions to improvements in asset management and operational efficiency through the integration of cutting-edge technology, data utilization, and a focus on sustainability and safety.

*C. Inspection and Maintenance Policies for O&G Pipelines*

Oil and gas (O&G) pipelines are ranked among the safest and most effective in transportation of petroleum products, as its accident rates are relatively low, but the aging infrastructure, environments, operational stresses, and degradation of material of the pipeline have great impacts on the integrity of pipelines and proper management of these pipelines can only be achieved through effective inspection and maintenance measures to maintain a safe and reliable operation. Examples of external causes of the failure of the pipelines include interference by third parties, equipment failures, natural hazards, extreme temperatures, and improper installation, whereas examples of internal causes include corrosion, erosion, material flaws, weld cracks, fatigue, and damage caused by vibration. Corrosion and mechanical damage are the most common worldwide. Despite the fact that some risks are minimized by advances in materials and manufacturing technologies, maintenance decision-making is critical to improving reliability and reducing economic and environmental impacts. In this regard, the policies and guidelines of pipeline inspection and maintenance can broadly be divided into corrective, preventive, predictive (condition-based), and proactive (risk-based) strategies, each being characterized by time of implementation, procedure, and the degree of risk behavior.

## III. Applications and Tools of AI in Pipeline Operations

The importance of AI-based tools and sensor devices in improving pipeline inspection, leakage detection, and valuation of corrosion with the help of the sophisticated data analysis and forecasting. It highlights the combination of intelligent sensing and the big data model, as well as the ML intelligence cooperative to realize proactive integrity control better, and significantly enhance the operational safety of gas pipelines, oil pipelines, and $CO_2$ pipeline networks.

*A. In-Line Inspection Sensor Technologies.*

Remote sensing is a general term that refers to the vast array of technological tools used to collect data on objects or areas from a distance. For pipeline surveillance, remote sensing can be satellite, aerial and ground-based sensors [16]. These technologies can sense the alteration of the environment (e.g., a leak, spill or other anomalies) that could be detected by pipeline infrastructure.

*1) Satellite-Based Pipeline Monitoring*

Pipeline monitoring via satellite is emerging as a valid and efficient alternative. Satellites with sophisticated sensors are able to gather data and pictures with excellent resolution across large regions [17]. This is a very useful ability for the remote or inaccessible pipeline surveillance. Satellites can spot temperature anomalies, shifts in vegetation health and changes to surface features that may indicate possible pipeline issues.

*2) Benefits of Satellite-Based Monitoring*

There are a number of benefits of using satellite in the monitoring of the pipeline:

- **Wide Coverage:** Satellites are able to track large pipeline systems in various geographical regions and terrains.
- **High-Resolution Data:** High-resolution photos taken by contemporary satellites enable the identification of even the smallest irregularities.
- **Frequent Updates:** Satellites can deliver frequent reports, guaranteeing ongoing pipeline integrity monitoring.

*3) Airborne Remote Sensing for Pipeline Monitoring*

In addition to satellites, airborne platforms, such as drones and manned aircraft are being exploited for pipeline monitoring using remote sensing [18][19]. These systems contain several kinds of sensors, for example infrared cameras, LiDAR and multispectral cameras that can identify leaks, corrosion or damage to the casing in the pipeline network.

*4) Advantages of Airborne Remote Sensing*

Airborne remote sensing provides an elastic and much more detailed method of pipeline surveillance:

- **High Mobility:** Drones and aircraft are capable of landing within only a few seconds in a specific location, and therefore, they can be used in targeted inspections.
- **Detailed Surveys:** Physical conditions such as corrosion, cracks and other defects of pipelines can be captured in airborne systems with detailed information on the physical condition of the pipes.
- **Cost-Effective:** In the case of smaller pipeline sections, drones can be used as a cost-efficient method for satellite imagery.

*B. Leakage and Corrosion Mechanisms in $CO_2$ Pipelines.*

$CO_2$ pipeline leakage is a complex and high-risk problem, especially with intensive development of carbon capture, utilization and storage (CCUS) infrastructure; because dense or supercritical $CO_2$ has different thermodynamic characteristics from conventional hydrocarbon fluids, such as rapid depressurization, phase changes and physically forming dry ice once suspended. The processes of leakage are caused by internal degradation, as well as external damage. Impurities like water, $H_2S$, $SO_2$, $O_2$, and other contaminants that exist in the $CO_2$ stream are very influential, especially with regard to internal corrosion. Even small quantities of water may generate carbonic acid which results in acidic conditions that enhance general corrosion, localized pitting, stress corrosion cracking and corrosion fatigue in cyclic pressurization [20]. Although rather pure, dry $CO_2$ is not as aggressive, the combined presence of oxidants, sulfur compounds, high temperature, and flow turbulence greatly contributes to the increased rate of electrochemical and gas-phase corrosion reaction, resulting in instability corrosion products, scale spallation, and continuous exposure of fresh steel surfaces. These mechanisms are thermodynamically and kinetically driven and the rate of degradation is determined by interacting chemical, thermal, as well as hydrodynamic processes and not individual species influence. Soil corrosion, microbial corrosion, coating defects, and cathodic protection system limitations are external corrosion issues that affect pipelines especially underground or submerged pipes (as shown in Figure 4). Buckling underground movement, overpressure events, thermal expansion, and third-party interference are also mechanical factors that increase structural weakness, particularly when corrosion damage has been made in advance.

Traditional types of leak detection systems, such as the SCADA-based monitoring, negative pressure wave and in-line inspection devices, can be limited to detect early forms of anomalies in supercritical $CO_2$ pipelines because of the low-level acoustic and pressure indicators, the management of $CO_2$ transport systems is best ensured in case the level of impurities, operational conditions, and environmental exposure are integrated with using predictive analytics and sophisticated real-time monitoring as well as data-driven modelling solutions to provide the opportunity to conduct proactive maintenance and predict a failure in time.

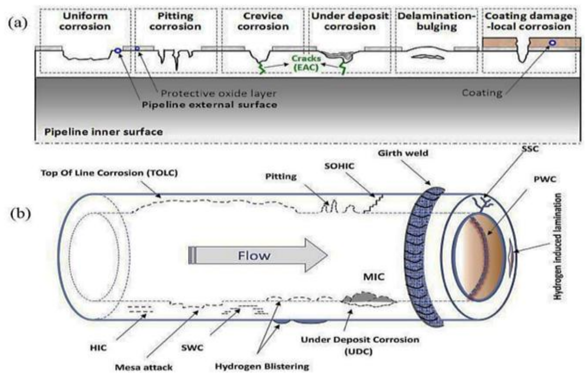


Fig. 4. The Corrosion Forms of Oil and Gas Pipelines (a) External Corrosion (b) Internal Corrosion

*C. AI-Based Leak Detection in Pipeline Systems.*

Leak detection using AI has emerged as an essential development in contemporary pipeline systems carrying oil, gas, water, hydrogen, and supercritical $CO_2$ to overcome numerous shortcomings of conventional methods used in monitoring systems like SCADA systems, pressure threshold detectors, and statistical methods of detecting changes. The traditional methods tend to have a problem with late detection, noise, and high false alarms, especially when operating under transient conditions. By comparison, ML and DL architectures process vast amounts of past data and present sensor data to detect subtle anomalies in terms of leakage. Acoustic leak localization and detection in gas and oil pipelines have been highly effective using both active acoustic emission and passive vibration-based monitoring. CNN, SVM, KNN, and Transformer-based models have also demonstrated good performance in leak detection and localization. ML models such as autoencoders and LSTM networks, and decision trees are used on pressure, flow, and accelerator data in water distribution systems with highly dynamic variations in flow and pressure that lessen the sensitivity and uncertainty. Similarly, there are specialized challenges that accompany the $CO_2$ and hydrogen transport pipelines owing to super-critical state, enhanced diffusivity as well as impurity-induced corrosion physics -requiring predictive and highly sensitive AI solutions capable of handling distributed temperature sensing (DTS), vibration or flow anomalies within complex thermodynamic constraints. Despite the observation that AI-based leak detection achieves significant enhancements regarding procedural accuracy and time-on-task, most research is conducted on wind-tunnel validation case studies in simplified setups, and therefore, the question of scaling up and real-world generalization remains a challenge.

## IV. Emerging Trends and Future Perspectives in AI For Pipeline Operations.

The O&G pipeline operations directed at the cyber-physical integration, digital twins, edge analytics, hybrid energy optimization, and sustainability-focused decision-making. It also provides high-level future directions and challenges including automation, model generalization, data governance cybersecurity, interpretability, and importance of healthy human-AI partnership in high stake environments.

### A. Emerging Trends and Future Perspectives

The optimization landscape of oil and gas industry is quickly changing today through cyber-physical systems (CPS), edge computing, sustainability-drive innovations. Semi-autonomous capabilities are achievable through distributed sensor networks, digital twins and edge-based analytics such that the remote assets can self-monitor and minimally change the operational parameters with regard to human intervention. "Digital platforms are now integrated in the coupling of real-time data gathering, AI-driven decision engines and reservoir simulation to improve drilling performance, production forecasting and maintenance scheduling."[21]. Hybrid energy systems too are increasingly becoming popular, in which intelligent algorithms actively regulate the balance between traditional power generation and renewable energy and energy storage aiming to minimize the costs of operations and carbon emissions [22]. ML-based enhanced oil recovery (EOR) modelling, digital core analysis, and real-time pressure-flow optimization are also being highly used in reservoir and production management, especially in complex oil and gas formations like tight oil and fractured carbonates to enhance efficiency of recovery [23].

#### 1) Future Perspectives

In the future, the future of AI in oil and gas defined by greater automation, scalable adoption of digital, and workforce change. The operation risks are likely to be minimized because of autonomous drilling systems, smart well completions, and AI-aided optimization of the production process, which enhance precision and cost-effectiveness. Predictive analytics and limited-data learning techniques more broadly implemented to improve the flexibility of models in a wide range of geological conditions and solve the existing generalization problem [24]. Non-technical barriers however, require overcoming these barriers like data governance, cross-disciplinary collaboration, cybersecurity, and organizational readiness in order to achieve widespread adoption [25][26]. It also reshapes the skills needed by petroleum engineers, who gain and grow to require more data science and systems modelling skills, as well as AI-based decision support. In the decade to come, the industry probably move toward the fully integrated, low-carbon, and digitally optimized business, in which AI is no longer a support system but a key element of the strategic planning, risk reduction, and sustainable energy creation.

### B. Challenges and Limitations of AI in Oil and Gas Industries

Implementation of artificial intelligence (AI) in the oil and gas industry (OGI) is a huge opportunity, but comes with incessant technical and operational issues. It is a very dynamic and complex industry with a high-stakes environment where decisions are directly influenced by safety, production efficiency and environmental performance [27][28]. While ML and AI systems are capable of analyzing vast volumes of sensor data, wellbores, drilling systems, and production facilities, there are a few structural constraints. Key challenges include:

- There are problems with data heterogeneity and integration since operational data have different sources and formats, as well as different stakeholders.
- Data quality and validation problems, including missing, noisy, or inconsistent sensor data.
- Little model generalization, in which models developed in one geological field or asset frequently do not perform well in reported reservoirs or conditions of operation. The implementation and retraining costs are high, in general, as often the ML models need new datasets and recalibration to work with new projects.
- Infrastructure limitations, especially in remote fields, where real-time data transfer and computing capabilities could be poor.

Along with technical problems, the implementation of AI in oil and gas processes presents possible risks and restrictions to work. Although predictive analytics and pattern recognition systems powered with AI may help to increase safety by identifying equipment abnormalities, protocols, and warning signs of failure, such phenomena as high pressure, high temperature, heavy machinery, and corrosive conditions are inherent to the work of an oilfield [29]. The excessive use of AI systems without a human component on its oversight can introduce the vulnerability of decision-making, particularly in cases where the models fail to recognize abnormal conditions or when they work beyond the boundaries of their training parameters [30].

## V. Literature Review

Recent innovations in predictive modelling of oil and gas pipelines that are driven by AI are also highlighted in the studies summarized in Table I and include risk assessment, corrosion prediction, leak detection, hybrid flow modelling, and advanced control strategies. All these articles show how ML, DL, and optimization algorithms in combination with system dynamics are being integrated to improve pipeline safety, reliability, and operational efficiency.

Xue (2025) PE gas pipeline system risk assessment using Principal Component Analysis (PCA) and System Dynamics Modelling (SDM) mainly focuses on analyzing the failure mechanism of PE pipelines. By integrating urban gas pipeline detection results and pipeline patrol records, risk assessment indicators are constructed based on basic pipeline characteristics and surrounding environmental factors. Principal Component Analysis (PCA) is used to extract the principal components that affect gas pipeline risks, and then a System Dynamics Model (SD model) is applied to build causal feedback loops to predict the temporal evolution of pipeline failure probabilities [31].

Fu et al. (2025) developed a model that uses the Sparrow Search Algorithm-optimized Light Gradient Boosting Machine (SSA-LightGBM) to estimate the average corrosion rate. Using Stochastic Perturbation Data Augmentation (SPDA), the initial dataset was increased from 60 to 300 samples in order to improve model accuracy. Following training, the optimized SSA-LightGBM model underwent a thorough performance evaluation using error analysis and stability assessment. According to the stability index, it demonstrates that the SSA-LightGBM model achieves exceptional stability and precision [32].

Nuthalapati et al. (2024) suggest the Deep Learning-assisted Gas Pipeline Leakage Detection System (DLGPLDS) using infrared cameras to accurately detect the leak location. A system of infrared cameras is suggested for use in gas plants, transportation, and manufacturing to track the undetectable leaks of methane gas in real-time. This research recommends using a histogram equalization procedure to remove the background noise effectively. The leaking of invisible gas may be successfully identified by this knowledge-based infrared camera system. This novel approach uses CNNs to categorize infrared camera images into groups based on whether or not they contain natural gas leaks [33].

Cui, Wang and Dong (2024) propose a corrosion rate prediction model with high precision and, using this model as a basis, provide an accurate evaluation of the pipeline's remaining life to enhance the dependability and operational safety of gas and oil pipelines. First, the corrosion rate of gas and oil pipelines is accurately predicted using the MFO-LSSVM model. The suggested LS-MFO model combines the MFO and LSSVM to improve prediction accuracy, particularly in complex scenarios. Following that, a hybrid Long Short-Term Memory (LSTM) and Deep Neural Networks (DNN) is employed to estimate the remaining life of the pipelines, accounting for time-dependent as well as nonlinear nature of corrosion rate [34].

Song et al. (2023) employ a hybrid modelling approach, combining mechanistic models with data-driven AI models. To tackle the problem of soft flow monitoring in multiphase pipelines, develop a hybrid model by combining an LSTM neural network with a genetic algorithm-optimized Simpson formula for mechanistic modelling using a unique fusion technique. Additionally, oil-gas-water multiphase pipelines may be operated and maintained intelligently and efficiently with a hybrid model that combines Random Forest (RF), Gradient Boosting Trees (XGBoost), and Artificial Neural Networks (ANN) [35].

Zhang and Dubljevic (2022) The target tracking model predictive controller is intended for a pipeline system with boundary control actuation implementation. For the nonlinear coupled hyperbolic partial differential equations (PDEs) that characterize the system of interest, the operational stable state of interest acts as the linearization point. Without requiring model reduction or spatial discretization, the boundary-controlled system is converted into an in-domain representation for the Cayley-Tustin temporal discretization transform. By creating a model predictive controller for the discrete-time pipeline model, stability and continuous set-point target tracking are achieved [36]

TABLE I. SUMMARY OF RECENT STUDIES ON PREDICTIVE MODELING IN OIL AND GAS PIPELINE.

| Reference | Study On | Approach | Key Findings | Challenges / Limitations | Future Work |
|---|---|---|---|---|---|
| Xue (2025) | PE Gas Pipeline Risk Assessment | Integrated urban gas inspection data and patrol records; applied Principal Component Analysis (PCA) to extract major risk factors; developed System Dynamics Model (SDM) with causal feedback loops for temporal risk evolution prediction | Identified principal risk factors influencing PE pipelines; SD model effectively predicted temporal evolution of failure probabilities | Dependence on quality and completeness of inspection data; SD model assumptions may oversimplify real-world nonlinear interactions | Integration with real-time monitoring systems and AI-based dynamic updating models |
| Fu et al. (2025) | Corrosion Rate Prediction | Sparrow Search Algorithm (SSA)-optimized LightGBM (SSA-LightGBM); dataset expanded via Stochastic Perturbation Data Augmentation (SPDA) | Achieved high prediction accuracy and strong stability index; improved performance over baseline models | Small original dataset (only 60 samples); potential overfitting despite augmentation | Application to larger real-world datasets and integration with online monitoring systems |
| Nuthalapati et al. (2024) | Gas Pipeline Leakage Detection | Deep Learning-assisted Gas Pipeline Leakage Detection System (DLGPLDS); Infrared cameras; Histogram Equalization for noise removal; CNN-based classification | Accurate real-time methane leak detection; effective background noise reduction; successful classification of leak/non-leak images | Dependence on camera positioning and environmental conditions (temperature, lighting); high equipment cost | Deployment in large-scale industrial environments and integration with automated alert systems |
| Cui, Wang & Dong (2024) | Corrosion Rate & Remaining Life Prediction | MFO-LSSVM for corrosion rate prediction; LSTM + DNN for Remaining Useful Life (RUL) estimation | High-precision corrosion prediction under complex environments; improved RUL estimation capturing nonlinear and time-dependent behavior | Computational complexity; requirement of high-quality time-series data | Real-time deployment and hybrid physics-AI corrosion modeling |
| Song et al. (2023) | Multiphase Pipeline Flow Measurement & O&M Optimization | Hybrid model combining Genetic Algorithm-optimized mechanistic model (Simpson formula) + LSTM; Hybrid ensemble (RF, XGBoost, ANN) for intelligent O&M | Improved soft sensing accuracy; enhanced intelligent operation and maintenance of multiphase pipelines | Complexity in integrating mechanistic and AI models; computational cost | Development of adaptive hybrid frameworks and real-time industrial validation |
| Zhang & Dubljevic (2022) | Model Predictive Control for Pipeline Systems | Nonlinear PDE-based pipeline modeling; boundary transformation; Cayley-Tustin time discretization; Model Predictive Control (MPC) | Stabilised and tracked set-points consistently without the need for model reduction or spatial discretisation. | Model linearization limits applicability under highly nonlinear operating conditions; high mathematical complexity | Extension to fully nonlinear MPC and integration with AI-based adaptive control systems |

## VI. CONCLUSION AND FUTURE WORK

Artificial Intelligence (AI) integration of the oil and gas pipeline processes is a revolutionary change toward the use of intelligent data in the management of assets. The use of predictive analytics, advanced sensing systems, and condition-based maintenance models would ensure that the pipeline operators are able to achieve expected standards of reliability, safety, performance efficiency. AI algorithms that anticipate early failures include time-series forecasting, categorization, anomaly detection, and regression, optimal inspection schedules and proactive leak detection. Implementation of smart sensors, SCADA-implemented systems, and digital monitoring systems also enhances real-time integrity management in oil, gas, and

 

$CO_2$ networks. Yet, challenges such as data heterogeneity, model generalization, interpretability, infrastructure constraints, and cybersecurity risk need to be approached with due consideration. In a safety-critical environment, the need to have a balanced human-AI collaboration is critical. In general, AI is developing into an enabling strategy of sustainable, resilient, and digitally optimized pipeline processes.

The research areas to be conducted in the future are explainable models of AI, edge-based deployment that is scalable, and cross-field model generalization. The use of digital twins, federated learning, and effective cybersecurity systems will make the process more reliable. Also, the adaptability of complex and changing pipeline environments may be enhanced with the use of sustainability metrics and limited-data learning techniques.

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