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REVIEWPAPER

Machine Learning Techniques for Natural Gas Exploration, Production and Distribution: A Review

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***Abstract*—Machine learning (ML) technology is increasingly becoming an important tool in the natural gas industry, providing advancements in areas such as exploration, production, reservoir characterization, and pipeline transportation. Unfortunately, the classical methods have certain shortcomings, which include the employment of complicated non-linear models and high computational cost as well as large-scale reservoir simulation problem. To address the aforementioned challenges, various ML models, including but not limited to support vector machines (SVMs), random forests (RF), linear regression (LR), extreme gradient boosting (XGBoost), artificial neural networks (ANNs), and other types of deep learning techniques, have been applied in forecasting, prediction, fault diagnosis, and optimization applications. The review paper will give an insight into the application of machine learning techniques in natural gas exploration and production process and pipeline transport. It will highlight the capabilities of ML techniques to analyze and deal with big data, improve prediction accuracy, facilitate intelligence-based decision making and increase operational efficiency in the natural gas industry. Furthermore, it will discuss some limitations of ML approaches in the field. Finally, future research directions are presented highlighting the need for ML in creating intelligent, reliable, and automated natural gas systems for sustainable industrial operations.**

Keywords*— *Natural Gas Reservoir Analysis, Production Forecasting, Pipeline Monitoring Systems, Predictive Analytics, Reservoir Simulation, Fault Detection, Intelligent Energy Systems.

I. INTRODUCTION

Natural gas exploration and production are critical components of the global energy sector, with increasing demand for efficient and sustainable resource utilization. An unusual and potentially different energy source is shale gas. One of the key technologies in shale gas formation that controls shale gas output is hydra fracturing [1]. Optimizing fracturing parameters and successfully obtaining shale gas from split reservoirs requires forecasting shale gas output based on geology and breaking reservoir characteristics. Due to a variety of intricate and interrelated factors, including geological and fractured reservoir features, predicting gas output in shale gas reservoirs has long been challenging.

Reservoir characteristics like absorption and desorption flows, reservoir complexity, and fracture permeability fluctuation all affect reservoir performance modeling [2]. Although it is difficult to get property data, several studies have tried to estimate and simulate the productivity of shale gas deposits using decline curve and ML approaches. The main challenges in shale gas extraction include well spacing, the optimal stage duration, the rate of pressure exertion, and the number of clusters for each phase engaged.

By examining the relationship and pattern recognition between productivity and variables comprising reservoir characteristics, fluid cracking records, and chemical attributes, machine learning techniques have been applied to evaluate the effects of shale gas generation [3]. The whole production of shale deposits has been predicted using exploratory data analysis (EDA) and supervised learning algorithms including regression analysis, SVM, and gradient boosting tree machines (GBM).

The use and improvement of ML methods for estimating transient supply and equilibrium capacity. The strengths, weaknesses, and optimizations techniques of the various methods can be analyzed in order to discern existing and upcoming trends in ML-based forecasting. Particular importance is attributed to the incorporation of ML and physical limitations for better prediction accuracy and interpretability [4]. There is an increasing application of ML technologies in the field of natural gas exploration during seismic interpretation and reservoir characterization [5]. The above methods enhance the exploration process while minimizing uncertainties associated with finding possible gas deposits.

A. Structured of the paper

This paper's structure is as follows: Section II describes the background of the natural gas industry and machine learning. Section III discusses ML applications, Section IV outlines challenges and limitations, Section V reviews related literature, and Section VI conclusion and future research.

II. BACKGROUND ON NATURAL GAS INDUSTRY AND ML TECHNIQUES

The natural gas industry involves exploration, production, and distribution, where machine learning techniques enhance prediction, optimization, monitoring, and decision-making processes efficiently.

A. Pipeline Optimization in Natural Gas Systems

Studies have demonstrated that streamlining pipeline operations may greatly reduce the cost of pipeline networks and enhance their operating features. The most effective ways to run natural gas transmission pipes are found using optimization techniques [6]. Over the past several decades, many optimization approaches have been thoroughly developed. There are two types of pipeline optimization methods: stochastic (evolutionary) and classical (deterministic). Dynamic programming, generalized gradient, and linear programming are commonly used classical techniques in pipeline optimization. However, these techniques have limitations such as high computational time, difficulty in handling nonlinear problems, and dependence on initial values.

Fig. 1. Natural gas pipeline optimization factors

Fig.1 illustrates the major parameters used for natural gas pipeline optimization, including gas throughput, net profit, compressor location, power consumption, total cost, line pack, fuel consumption, greenhouse gas emissions, and pipeline routes.

B. *Traditional Reservoir Simulation Approaches*

One of the best methods for combining information and knowledge from many fields, including geology, petrophysics, geophysics, reservoir, and production engineering, to simulate fluid flow in a reservoir is reservoir simulation. In order to enhance geological understanding and provide forecasting capabilities, the reservoir simulation model is history matched using production and pressure information from the asset [7]. The simulation process includes developing a reservoir model, history matching, and performing prediction simulations. Traditional reservoir simulation methods have several limitations such as high computational time, dependence on initial values, difficulty in handling nonlinear problems, and requiring substantial computational resources and complex mathematical procedures.

C. *Fundamentals of Machine Learning Techniques*

Various machine learning models and algorithms are widely used in the natural gas industry for prediction, classification, regression, and reservoir analysis. Different supervised learning algorithms are commonly applied based on the nature of the reservoir data and forecasting requirements.

- **Support Vector Machine (SVM):** A popular and effective supervised learning algorithm applied in various fields. SVM techniques use a kernel function to translate the initial input data samples to a higher-dimensional space in order to handle nonlinear information. SVM is capable of handling nonlinear feature connections and high-dimensional issues with huge characteristic fields.
- **Random Forest (RF):** It is an expanded version of bagging that adds random attribute selection to decision tree training. It is trained by choosing a subset of the original data at random and using many models that have been trained on that subset for classification as well as regression. It is simpler to use, quicker to teach, and convertible to a parallel approach.
- **Linear Regression (LR):** Linear regression is a widely used analytical method in mathematical statistics for determining the numerical association among two or more parameters. A helpful multimodal statistics method for determining the relevance of every independent variable for the factor that depends is multiple linear regression (MLR).
- **Extreme gradient boosting (XGBoost):** ML algorithm built around the fusion idea. Gradient boosting is implemented methodically and effectively, using either a tree or a linear model as the initial learners [8]. Its advantages include adding regularization to simplify the learned model and prevent overfitting. It supports parallel processing and has high computational efficiency.

D. *Productivity Prediction and Benefits of Data-Driven Methods*

Because natural gas wells have large inter-well variations and poor control reserves, productivity forecasting is an essential component of reservoir construction. Empirical analytic techniques can guide well output and offer insights into gas-well profitability. These days, the oil industry uses statistically driven ML techniques [9]. The efficiency principle is satisfied in real field manufacturing when ML and well productivity prediction are combined.

III. APPLICATION OF MACHINE LEARNING IN NATURAL GAS EXPLORATION, PRODUCTION, AND DISTRIBUTION

ML has emerged as a powerful strategy in the natural gas industry for analyzing large volumes of operational data, identifying complex patterns, improving process reliability, and supporting intelligent system management.

A. *Geological Data Analysis and Formation Identification:*

The use of ML algorithms to interpret the massive volumes of data produced by the gas sector during operations has grown in significance. In the gas business has been acknowledged as a potential technique. ML techniques enable accurate and real-time prediction of lithology changes and geological formations using drilling and well-log data. These approaches improve subsurface characterization, optimize drilling activities, reduce operational costs, and assist in hydrocarbon exploration and reservoir analysis.

B. *Production Forecasting and Performance Analysis*

Machine learning techniques analyze operational and geological parameters to forecast natural gas production, improve performance evaluation, enhance decision-making, and optimize resource utilization.

- **Feature Analysis for Natural Gas Production:** The bar chart with stacking shows the correlation coefficients between a number of geophysical features and the objective variable. The goal variable and hook-load have the most positive association. Furthermore, there are relatively high positive correlations between bit depth, torque, and equivalent circulation density, demonstrating strong predicted associations with the target.

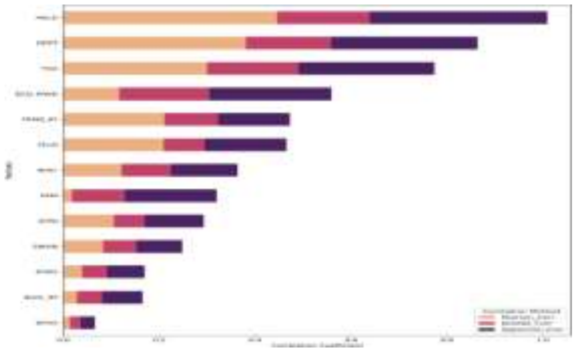

Fig. 2. Feature correlation analysis for geological formation prediction.

In Fig. 2, geological feature analysis results are presented, showing the highest positive correlation between the target variable and Hook-load, followed by bit depth, torque, and equivalent circulating density.

- **Role of Geological Parameters in Production Prediction:** Bit depth, equivalent circulation density, hook-load, and torque are examples of variables that exhibit clear class order, indicating their efficacy in distinguishing distinct creation tops. RPM exhibits a limited capacity for differentiation due to significant overlap across many categories.
- **Machine Learning Models for Production Prediction:** SVM, RF, K-nearest neighbor (KNN), and multilayer perceptron (MLP) are applied in order to control the linear and nonlinear dependencies in the dataset. Random Forest helps avoid overfitting [10], although SVM and MLP are able to deal with the nonlinear relationships very efficiently. The use of a comprehensive algorithm ensures accurate predictions.

C. *Reservoir Analyzation and Production Optimization*

Method of SHAP values is one of those that was developed in the sphere of machine learning to clarify the "black box models". This approach, which is grounded in theory of games, provides both local and global explanations by using margin-based effects of a characteristics to the system's output. The foundation of the SHAP value technique is the development of an additive explanation model in which each characteristic is seen as a contributor. The starting time of wells (STW) is the initial factor influencing gas output, according to the XGBoost model. The catcher well inclination angle, completion duration, shut-in piping sizing, and fluid-gas ratio (GLR) [11]. Positively SHAP valued represented positive correlation with respect to gas production, while negatively valued represented negative correlations. Increase in time spent on opening wells and higher gas/liquid ratios had positive impact on gas production.

D. *Intelligent Pipeline Monitoring and Distribution Systems:*

ML techniques have been successfully used in various aspects of natural gas pipelines and distributions like predictions, fault diagnosis, corrosion evaluation, gas production forecasts, and pipeline surveillance. Examples of machine learning algorithms that are popularly used for improving oil and gas processes include ANN, SVM, RF, DL, LSTM, and neuro-fuzzy models. ANNs have been used in predicting the width of craters in underground gas pipelines, corrosion defect depth, gas phase contamination removal, and reservoir engineering problems [12]. Other deep learning techniques that have yielded high precision for prediction purposes include LSTM, GRU, and DCNN + LSTM. Furthermore, Neuro-Fuzzy and ANFIS models have been used for predicting rupture pressures as well as fault identification in pipeline systems [13]. ML techniques are useful in managing complicated nonlinear relations, improving predictions, mitigating operational risks, and facilitating monitoring.

IV. CHALLENGES AND LIMITATIONS FOR NATURAL GAS INDUSTRY

The adoption of ML technologies in natural gas exploration, manufacturing, and transportation comes with numerous advantages, but a few hurdles persist[14]. The major issues concerning data quality, model performance, computational difficulty, interpretability, and operational risks are provided below:

A. *Data Quality and Availability:*

- The quality and quantity of the data set utilized have a major impact on how well ML systems execute. In the case of the natural gas sector, there are issues arising in relation to the incompleteness, inconsistency, and heterogeneity of the data set obtained from various sources including sensors, wells, reserves, and pipelines[15]. Additionally, real-time processing and storage needs contribute to the difficulty of implementing an ML system in an industrial environment.

B. *Model Performance and Generalization*

Conventional ML techniques like SVM, XGBoost, Light Gradient Boosting Machine (LightGBM), ANNs, and Bidirectional Long Short-Term Memory (BiLSTM) might not be as robust in different operation scenarios. The prediction accuracy of these algorithms might be influenced by any variations in gas composition, reservoir features, and temperature and pressure values. Thus, the development of generalizable models is still a challenge.

C. *Forecasting and Computational Challenges:*

Many machine-learning-based forecasting models have difficulties handling non-linear and non-stationary data, thus affecting the prediction accuracy. Therefore, hybrid and ensemble forecasting models are gradually becoming popular in the field [16]. Furthermore, complex models that use deep learning often require a lot of processing power and big training sets, which increases compute expenses and increases training times.

D. *Model Interpretability and Reliability*

Many ML and deep learning algorithms are black boxes in nature because their internal workings cannot be understood easily by anyone. Such a characteristic is a hindrance in the usability of such algorithms in practice [17]. Moreover, both mathematical and empirical models use simplifying assumptions that can cause them to miss certain relationships and work with poor data quality.

E. *Cybersecurity, Ethical, and Workforce Challenges*

However, there are increasing apprehensions about cybersecurity and data privacy in regard to the use of AI and ML in natural gas industry. It is important to protect data and AI models from any kind of cyberattack for guaranteeing safety and reliability of operations. Additionally, there are certain ethical issues associated with the use of AI technology[18]. Additionally, the lack of knowledgeable individuals who have knowledge in artificial intelligence as well as natural gas systems is another problem.

V. LITERATURE REVIEW

The literature review studies the application of ML in exploring, producing, and distributing natural gas, focusing on prediction accuracy, efficiency, prediction methods, obstacles, and constraints.

Saeed et al. (2025) came out with a Transformer-Based Spatio-Temporal Framework (TSTF) to predict the consumption of natural gas (RLNG) for power generation in Pakistan. This model is an adaptation of large-scale inverters because the behaviour of natural gas demand is extremely complicated, non-linear, and irregular. The method blends Chebyshev graph convolution networks (ChebyNet) to capture geographical linkages and a variety of heads of analysis to capture multiscale periodic demand dynamics. The proposed model outperforms the existing models like LSTM and GRU and provides practical implications in the context of optimizing the operational process of the power sector, while also dealing with climatic volatility[19].

Li et al. (2025) suggested using SCADA data to identify leak abnormalities in natural gas pipelines using a masked transformer detection algorithm. They circumvent the limitations of a typical neural network modelling lengthy time-series data by combining an encoder-only Transformer with a masked method to collect sparse leak labels. Real natural gas pipeline data validated accurate detection of anomalies from leaks and better performance than other models[20].

Su and Zhao. (2024) suggested a hybrid model for predicting natural gas spot prices by fusing deep learning (DL) with denoising technology based on compressed sensing. The original natural gas spot price data is preprocessed using compressed sensing denoising to obtain pure data, which is subsequently input into a deep learning model to provide precise prediction outcomes. The suggested method enhances natural gas price forecasting and offers insightful information for risk reduction, cost optimization, sustainable development, and well-informed decision-making[21].

Zuo et al. (2024) suggested a hybrid leak detection technique for pipelines used to collect natural gas under various operating conditions (MOCs). A reconstruction- and prediction-one-dimensional convolutional long short-term memory autoencoder (RP-1dConvLSTM-AE) is used for improved feature acquisition from multidimensional time-series information following anomaly reduction and longer-short sequence generation to improve data quality. To identify leaks under various operating settings, a multifaceted judging technique using a one-class support vector machine (OCSVM) was created. The efficacy of the suggested approach was shown by empirical results utilizing actual SCADA data[22].

Sonkar et al. (2022) developed a ML based method for deploying UAVs fitted with a gas sensor and LiDAR payload to identify and estimate natural gas leaks. To gather leakage data at various loitering heights and leakage pressures, two experiments were carried out in actual air conditions. The data was subjected to both ANN and Reduced Support Vector Machine (RSVM), with the ANN model offering quicker and more precise leakage identification than RSVM. The study showed that compared to manual inspection, UAV-based leak detection is quicker and less expensive[23].

Zhao et al. (2022) created a sophisticated multi-sensing system that uses acoustic emission (AE), differential pressure (DP), and near-infrared (NIR) technology to assess gas-liquid flow. A least absolute shrinkage and selection operator (LASSO) machine learning model was utilized to calculate the liquid phase volume % using the gathered characteristics as input, and the optimal fuse result was discovered. Experimental results showed validated prediction accuracy and efficient measurement of flow rates of the gas-liquid flow[24].

TABLE I. Summary of thery Of The Study on Machine Learning Techniques In The Natural Gas Industry

Authors	Study on	Contributions	Advantages	Limitations	Recommendations
Saeed et al. (2025)	Natural gas consumption forecasting using TSTF	Developed a Transformer-Based Spatio-Temporal Framework integrating ChebyNet and multi-head attention	Captures spatial and temporal dependencies and improves forecasting performance	Focused on RLNG consumption in a specific power sector	Extend the framework to other natural gas systems and regions
Li et al. (2025)	Pipeline leak anomaly detection	Proposed a masked Transformer model using SCADA data	Improves long-time series modeling and leak detection capability	Relies on the availability of SCADA data	Develop more generalized leak detection systems
Su and Zhao (2024)	Natural gas spot price prediction	Combined compressed sensing denoising with deep learning	Improves forecasting accuracy and supports decision-making	Performance may depend on data quality	Integrate additional economic and environmental factors
Zuo et al. (2024)	Leak detection under multiple operating conditions	Proposed RP-1dConvLSTM-AE with OCSVM	Enhances feature learning and detects leaks under different conditions	Requires high-quality multivariate time-series data	Improve real-time implementation capability
Sonkar et al. (2022)	UAV-based natural gas leakage detection	Applied ANN and RSVM using UAV, gas sensors, and LiDAR	Faster and cost-effective alternative to manual inspection	Performance may be affected by atmospheric conditions	Develop autonomous large-scale monitoring systems
Zhao et al. (2022)	Gas-liquid flow measurement	Developed a multisensor system with a LASSO model	Improves flow measurement accuracy	Requires integration of multiple sensors	Extend the framework to industrial-scale applications

VI. Conclusion And Future Work

In the natural gas sector, machine learning techniques are increasingly playing a crucial role, contributing to more accurate predictions, efficient operations, and decision-making. The \ML models such as SVM, Random Forest (RF), Linear Regression (LR), XGBoost, ANN, deep learning techniques have demonstrated promising results in the fields of natural gas exploration, production prediction, reservoir analysis, demand forecasting, and pipeline distribution management. The following approaches can deal with large volumes of operational data, discover complicated nonlinear correlations, reduce risk factors, and improve monitoring and forecasting processes. There are several factors that restrain their broad use, however, such as data quality challenges, computational complexity, cybersecurity issues, uncertainty handling, and the non-interpretability of some of the higher models. More reliable and efficient hybrid models, involving advanced technologies, and better ways to deal with uncertainties in complex industrial environment are the areas requiring further study. A forecasting tool needs to take into account a number of different operating conditions and time horizon such as weekly, monthly and year forecasting for strategic and operational planning. Furthermore, the inclusion of the analysis of key facilities (gas sources, consumers and storage systems) will improve the applicability of the model and decision support. Overall, machine learning has great potential to power intelligent, automated, reliable and data-driven natural gas operations in the future.

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