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Literature Review

AI-Based Smart Proxy Models for Accurate Oil Rate Prediction and Efficient Pipeline Monitoring

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Abstract

This research develops an advanced AI-based smart proxy model to significantly enhance the prediction of oil rates and the monitoring of crucial operational parameters such as temperature and pressure in oil field pipeline management. By integrating real-time data from Multiphase Flow Meters (MPFM) with sophisticated simulation outputs, the study introduces a dual-model approach that overcomes the limitations of traditional methods, improving both efficiency and cost-effectiveness. Model 1 employs high-precision real-time MPFM data to provide accurate oil rate predictions. By focusing on critical control points within expansive pipeline networks, this model strategically reduces dependency on extensive MPFM deployment, achieving substantial cost reductions while maintaining rigorous measurement standards. The incorporation of real-time data ensures immediate responsiveness to operational changes, facilitating accurate and reliable insights essential for effective pipeline management. Model 2 utilizes an AI-driven smart proxy to refine the outputs of conventional flow simulators such as OLGA. This model addresses computational challenges including high runtime and numerical convergence issues by selecting the most reliable and accurate simulation outputs. It provides rapid and dependable insights into flow dynamics, supporting timely operational decisions and proactive management that enhance the safety and efficiency of pipeline networks. The integration of Model 1 and Model 2 ensures localized precision and extends analytical capabilities across the entire pipeline network, significantly enhancing predictive accuracy. This harmonized approach not only sets new standards for flow assurance and pipeline management but also illustrates the transformative impact of AI on operational strategies in the hydrocarbon sector.

Introduction

The energy sector is fundamentally dependent on hydrocarbons, primarily sourced from oil and gas reserves within the Earth. Given the finite nature of these reserves, optimizing their extraction and utilization is crucial for ensuring energy security and enhancing operational efficiency [1]. The extraction of hydrocarbons involves complex processes, as these resources are obtained through wellbores drilled into underground reservoirs followed by their transportation through surface facilities designed to separate and process the oil, gas, and water before they reach their final industrial destinations [2]. This process presents significant technical challenges due to the dynamic nature of the involved fluids under varying pressure and temperature conditions [3]. One of the critical aspects of hydrocarbon extraction is the management of multiphase flow, which refers to the concurrent flow of gas, oil, and water through the production infrastructure. During extraction, the pressure in the reservoir naturally declines as fluids are withdrawn. This decline affects the wellbore, where fluid travels from the reservoir bottom to the wellhead, often leading to the liberation of gas from the oil phase if the pressure drops below the bubble point. This phenomenon can occur at various points along the flow path, including in the reservoir, wellbore, or pipelines. The presence of water further complicates this scenario, adding to the complexity of fluid management and separation. Accurate modeling of these multiphase flows is essential not only for the design and

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operation of wells and surface facilities but also for maintaining efficiency and safety. Moreover, optimizing these processes is crucial for mitigating safety risks and environmental impacts, such as leakage, which can have severe consequences for both operational integrity and ecological sustainability [4].

Traditionally, simulations for managing multiphase flow have relied on the black oil model, which simplifies fluid handling by categorizing the fluids into three primary phases: oil, water, and gas. This model assumes that the composition of these fluids remains constant along the flow path, an assumption that often fails under varying operational conditions [5]. The simplifications introduced by this model can lead to suboptimal designs and operational inefficiencies. Consequently, there has been a shift towards more sophisticated compositional modeling techniques that allow fluid composition to dynamically adjust in response to environmental factors, providing a more accurate representation of fluid behavior within the production system [6]. However, even with the advent of new approaches and sophisticated multiphase flow software, numerous assumptions and simplifications are still inherent in these models. These limitations highlight the need for more accurate and faster methods to better capture the complexities of multiphase flow dynamics and improve predictive capabilities. Recognizing the limitations of traditional multiphase flow models and the significant costs associated with advanced equipment such as multiphase flow meters for accurately determining parameters like oil rates, this research aims to develop an innovative pipeline model utilizing an AI-based smart proxy approach. This new model seeks to enhance accuracy, cost-efficiency, and speed in the extraction of results for the measurement and prediction of multiphase flow characteristics [7]. The primary objective is to enhance the predictive capabilities and operational efficiencies of traditional fluid flow simulators, such as the OLGA model, by incorporating advanced AI methodologies. This integration seeks to streamline computational processes, reduce model run times, and lower costs associated with traditional methods while maintaining or improving predictive accuracy.

The remainder of this paper is structured as follows: the next section reviews relevant literature on multiphase flow modeling and AI applications in oil field management. This is followed by a detailed description of the methodology employed in developing the AI-based smart proxy models. The subsequent sections present the results of applying these models to a case study, followed by a discussion of the findings and their implications for the hydrocarbon industry. The paper concludes with a summary of key contributions and suggestions for future research.

Literature review

Multiphase flow in oil and gas production

Multiphase flow, involving the simultaneous movement of oil, gas, and water, is a fundamental and complex phenomenon in oil and gas production [8]. Accurate modeling and prediction of multiphase flow are crucial for optimizing extraction processes, ensuring operational integrity, and minimizing environmental impacts [9]. Effective management of multiphase flow behavior significantly enhances the efficiency and safety of reservoir operations and surface facilities, ultimately leading to improved resource utilization and economic benefits. This complexity arises from the interaction of different fluid phases, liquid (oil and water), and gas within the production system. The behavior of these phases under varying pressure and temperature conditions presents significant challenges. Accurate modeling of multiphase flow involves predicting the distribution and movement of each phase, which is influenced by numerous factors including fluid properties, flow rates, and pipeline geometry. These factors interact in complex ways under varying operational conditions such as changes in pressure and temperature. Fluid properties like viscosity and density affect how each phase moves and interacts within the pipeline, while flow rates determine the velocity and mixing of the phases. Pipeline geometry, including diameter, length, and orientation, also plays a crucial role in shaping flow patterns and phase distribution. Effective modeling must account for these variables to accurately predict the behavior of multiphase flow in production systems [10].

When multiple phases flow concurrently, the interface between these phases can adopt various configurations, referred to as flow patterns. These patterns are crucial for understanding the dynamics of multiphase flow and can significantly influence the operational efficiency and safety of production processes. Flow patterns, such as stratified, annular, and slug flow, determine the distribution and interaction of the phases within the pipeline, impacting pressure drops, phase separation, and overall flow stability. Understanding these patterns is essential for optimizing production strategies and ensuring the safe operation of facilities [11]. The specific flow pattern observed in two-phase flow is highly dependent on variables such as pressure, flow rate, and channel geometry, making it a critical aspect of multiphase flow dynamics [12]. The hydrodynamics and flow mechanisms vary considerably with each flow pattern, significantly affecting factors like pressure drop and phase fraction distribution. Accurately predicting these parameters necessitates a clear understanding of the prevailing flow pattern under given flow conditions. Some common examples of flow patterns include bubble, slug, churn, and annular flow, each presenting unique characteristics and challenges in modeling and analysis. In vertical pipelines, the influence of gravity on the phases is minimized, leading to flow patterns dominated by the interplay between buoyancy and viscous forces. In horizontal pipelines, gravity plays a significant role, causing stratification where the heavier liquid phase tends to settle at the bottom while the lighter gas phase flows above it. This leads to flow regimes such as stratified flow, where distinct layers of liquid and gas are formed. Inclined pipelines, depending on the angle, exhibit a combination of behaviors seen in both horizontal and vertical orientations. The angle of inclination affects the flow regime transitions, resulting in complex patterns like inclined stratified flow or inclined annular flow. Factors such as pressure, flow rate, and channel geometry also play critical roles in determining flow patterns. For instance, high flow rates may cause a transition from bubble to churn flow, while variations in pressure can

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influence the distribution and velocity of each phase. Accurate prediction of these patterns is essential for optimizing the design and operation of wells and pipelines, as each flow regime affects pressure drops, phase separation, and overall flow dynamics differently [13].

Modeling techniques in multiphase flow

Given the intricate nature of multiphase flow, empirical correlations, which are based on experimental results from specific cases, are commonly utilized to address these challenges in both wellbores and pipelines. However, the application of these correlations is limited, as they often lack generalizability across a broad spectrum of conditions. These correlations can be tailored to specific flow regimes or designed to be independent of flow regimes [14]. Among the notable empirical correlations for wellbores, the Hagedorn and Brown correlation (Hagedorn, et al. 1965) is widely used for oil wells, while the Orkiszewski correlation (Orkiszewski, 1967) represents a pioneering effort specifically developed for gas wells. In pipelines, the Lockhart-Martinelli correlation (Lockhart & Martinelli, 1949) provides methods for calculating the pressure drop when two phases flow concurrently, crucial for the design and operation of long-distance oil and gas pipelines. Additionally, the Chisholm correlation (Chisholm, 1973) considers phase interactions under high-velocity conditions typical in gas transmission pipelines. Further contributions in this field include the correlations developed by Duns, et al. (1963), Beggs, et al. (1973), and Mukherjee, et al. (1983) for multiphase flow in vertical and inclined pipes, reflecting the evolving complexity and specificity required in such analyses [15].

An alternative approach to modeling multiphase flow involves the use of homogeneous models. These models assume that the fluid properties of the mixture can represent the individual phases, allowing the application of single-phase flow equations to the multiphase system. Homogeneous models often incorporate adjustments for slip velocity, accounting for the velocity differences between the phases. Such models equipped with slip adjustments are referred to as drift-flux models, highlighting their ability to reflect the dynamics of multiphase flow more accurately (Shi, et al. 2005). The Taitel-Dukler model (Taitel & Dukler 1976) for pipelines provides a robust framework for predicting flow regime transitions, integrating the concept of slip velocity effectively. However, homogeneous models have limitations due to their simplified assumptions and inability to capture the complex interactions between different phases accurately. Therefore, more advanced methods, such as the mechanistic model, are often preferred for their ability to provide a more detailed and accurate representation of multiphase flow dynamics [16].

Mechanistic models represent a sophisticated approach to multiphase flow modeling, grounded in fundamental physical laws and an in-depth understanding of the physics characterizing each flow pattern [17]. These models significantly enhance the ability to predict key parameters such as pressure and phase fraction profiles within pipes, particularly in scenarios that are difficult to replicate in laboratory settings or where reliable empirical correlations fail to exist (Petalas, et al. 2000). The methodology underlying mechanistic modeling involves first identifying the different flow regimes present within a system. Once these regimes are established, distinct models are applied to each regime to predict specific flow characteristics, such as liquid holdup and pressure drop. This approach was notably advanced by Taitel, et al. (1976, 1980), who described the physical mechanisms dictating transitions between various flow patterns, laying foundational work that has been expanded upon in subsequent studies. Following the pioneering contributions of Taitel, et al. numerous studies have presented comprehensive mechanistic models. Notable among these are the works of Ozon, et al. (1987), Hasan and Kabir (1988), and Ansari, et al. (1994), which focus on two-phase flow in vertical pipes. Conversely, research by Xiao, et al. (1990) and Kaya, et al. (2001) introduced models with limited applicability, specifically to certain pipe inclinations. More generalized studies, such as those by Petalas, et al. (2000) and Gomez, et al. (2000), have broadened the scope to include comprehensive mechanistic modeling of multiphase flow in wellbores. In pipeline systems, similar complexities arise as in wellbores, necessitating the adoption of mechanistic models that are equally grounded in the fundamental principles of physics. These models are particularly important for predicting flow behavior over the extensive lengths and varying conditions characteristic of pipelines. As in wellbores, different flow regimes within pipelines require distinct modeling approaches to accurately predict parameters like pressure drops and phase fraction profiles under various operational conditions. The importance of these models extends to the detailed analysis of flow pattern transitions, which are crucial for ensuring operational safety and efficiency in pipeline systems. For example, studies by Sun, et al. (2009) and Zhang, et al. (2012) have extended the groundwork laid by Taitel, et al. adapting it to the unique challenges presented by horizontal and inclined pipeline systems. These adaptations allow for a nuanced understanding of how flow patterns like slug or annular flows develop and transform under different pipeline inclinations and pressure conditions [18].

Another critical aspect of multiphase flow is the modeling of heat transfer. During oil production, the temperature at the sand face typically matches that of the surrounding formation. However, significant temperature variations can occur during production, especially with substantial drawdown at the bottomhole. According to the Joule-Thomson effect, this drawdown increases the temperature of the oil phase and decreases the temperature of the gas phase. As fluids ascend, their temperatures change due to heat exchange with the surrounding geological formations. In pipelines, similar thermal dynamics are observed. The temperature of the fluids adjusts as they travel, influencing viscosity and density, which affect flow rates and pressure drops [19]. This thermal behavior is complex due to varying environmental conditions and different thermal properties of pipeline materials. Accurate modeling of heat transfer dynamics in pipelines is essential, involving the calculation of temperature profiles and their impact on fluid properties and flow dynamics. Advanced thermal models that account for environmental

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context, pipeline material properties, and fluid characteristics are critical. These models help design pipelines that manage heat exchange effectively, ensuring operational efficiency and integrity. Integrating these thermal models with hydraulic models provides a comprehensive simulation of multiphase flow, enabling precise control and optimization of oil and gas transport processes [20].

Numerous studies have explored the dynamics of heat transfer between wellbore fluids and surrounding formations, beginning with Ramey's seminal work in 1962. He introduced a theoretical model to estimate wellbore fluid temperatures based on depth and production duration, though it was limited by assumptions of single-phase flow and neglecting kinetic energy and friction effects. Ramey also developed a general formula for calculating the overall heat transfer coefficient, considering the well radius as a linesource. Building on Ramey's model, Satter, et al. (1965) incorporated multiphase flow, accounting for kinetic energy and Joule-Thomson expansion. Alves, et al. (1992) expanded this further by predicting temperature distribution across all inclination angles. Hasan, et al. (1994) refined these models, discarding the line-source assumption for steady-state, two-phase flow. In pipelines, heat transfer considerations are equally crucial due to long transport distances and varying environmental conditions. Modern pipeline models adapt and expand wellbore heat transfer models to include multiphase flow, friction, and kinetic energy, which were initially overlooked. These enhancements enable more accurate predictions of temperature profiles along pipelines, essential for managing fluid properties and ensuring operational integrity and efficiency. Integrating advanced thermal models with comprehensive flow dynamics simulations is essential. Such robust systems ensure optimal operation across diverse geographical and climatic conditions, adapting to environmental interactions effectively. This holistic approach to modeling heat transfer and flow dynamics is crucial for developing resilient and efficient hydrocarbon transportation systems [21].

Accurately computing mixture properties is crucial for modeling pressure and temperature profiles in wellbores and pipelines. This process involves estimating the in-situ volume fractions of each phase. For gas-liquid flows, methodologies vary; in three-phase flows (gas, oil, water), combining liquid phases simplifies calculations, providing satisfactory accuracy (Wang, 1996). Modern models adapted from both wellbores and pipelines incorporate multiphase flow dynamics, friction, and kinetic energy to ensure precise pressure and temperature predictions. In pipeline systems, including extensive networks, advanced thermal models integrated with hydraulic simulations enhance operational efficiency and safety. These models must account for varying environmental conditions, complex geometries, and fluid interactions to optimize hydrocarbon transportation. This comprehensive approach ensures robust, reliable, and efficient pipeline operations, addressing the complexities of flow dynamics and thermal interactions to maintain system integrity and performance across diverse environments [22].

Overview of OLGA for dynamic multiphase flow simulation

The OLGA dynamic multiphase flow simulator is a comprehensive tool designed for simulating transient flow in multiphase systems, providing critical insights for maximizing production and minimizing risks associated with oil and gas operations. It is widely recognized as an industry-standard tool for dynamic multiphase flow simulation, offering a range of features and benefits tailored to the needs of both offshore and onshore developments. The development of OLGA began in the late 70s and early 80s, focusing on transient flow phenomena in the petroleum industry. Designing a pipeline in OLGA involves several parameters. The length of the pipeline determines the distance over which flow behavior is simulated. The diameter is crucial for determining flow characteristics, pressure drop, and flow rates. Roughness affects frictional losses and flow resistance within the pipeline, while the material influences structural integrity, corrosion resistance, and thermal properties. Building an OLGA model involves defining pipeline geometry and network topology, specifying fluid properties, setting boundary and initial conditions, and selecting numerical parameters to control simulation accuracy and efficiency [23].

The software can simulate various types of boundary conditions, including constant flow rate, constant pressure, and time-varying flow rates. Pipeline sectioning in OLGA improves accuracy by accounting for detailed pipeline geometry and environmental conditions, but it increases computational complexity. The pipeline system is divided into sections, with sequential calculations performed for each section to ensure detailed and accurate simulations. OLGA's ability to model dynamic multiphase flow with detailed input data and conservation equations makes it an indispensable tool for effective pipeline management and optimization in the oil and gas industry. Its comprehensive approach allows for precise modeling of various operational scenarios, enabling better decision-making and enhanced operational efficiency. Additionally, specifying the expected flow regime whether single-phase, two-phase, or multiphase is essential for accurate simulation. Operational scenarios such as startup, shutdown, and flow rate changes, along with additional constraints like friction factors and heat transfer coefficients, should also be included. OLGA employs nine conservation equations, continuity (mass conservation), momentum (axial, radial, vertical), and energy to simulate fluid flow behavior. The software models the pipeline as a series of connected segments, considering how terrain topography impacts pressure profiles, liquid holdup, and flow patterns [24].

AI-based smart proxy models in the oil and gas industry

Smart Proxy Models represent a significant advancement in the application of Artificial Intelligence (AI) and Machine Learning (ML) to numerical simulations, particularly in the oil and gas industry. These models are designed to replicate the behavior of comprehensive numerical simulation models with high accuracy, maintaining the original simulation's physics and space-time resolution. Unlike traditional proxy models that might simplify the underlying physics or use predefined functional forms, Smart Proxy Models leverage data from numerical simulations to learn and accurately mimic the intricate behaviors of fluid flow in hydrocarbon reservoirs. One of the key benefits of Smart Proxy Models is their ability to deliver highly accurate numerical simulation results without the need to modify the underlying mathematical equations, reduce the number of cells and time steps, or deploy numerous numerical simulations. This approach allows for the most realistic application of AI and ML in developing proxy models for numerical simulations, offering significant advantages in terms of computational efficiency and accuracy. The primary application of Smart Proxy Models in the oil and gas industry is in Numerical Reservoir Simulation (NRS). These models help in making reliable reservoir management decisions by examining various operational scenarios quickly and accurately. For instance, in a study conducted on a prolific mature field, a Smart Proxy Model was developed to optimize oil production while minimizing water-cut. The model enabled thousands of simulations runs in seconds, facilitating extensive sensitivity analyses and uncertainty quantification that would otherwise take months using traditional methods. A notable case study with the Abu Dhabi National Oil Company (ADNOC) utilized a well-based Smart Proxy Model to rank wells based on their probability of success in a rate relaxation program. This model identified wells that could potentially increase oil production with minimal water production, thereby enabling more informed decision-making in reservoir management. Similarly, in CO_2 sequestration projects, cell-based Smart Proxy Models have been employed to perform rapid sensitivity analysis and uncertainty quantification, crucial for optimizing CO_2 injection strategies [25].

Beyond upstream applications, Smart Proxy Models are also highly beneficial for midstream projects, especially in the design and management of complex pipeline networks. These models can simulate various pipeline configurations and operational scenarios quickly and accurately, supporting efficient and cost-effective pipeline network design and operation. By providing rapid and reliable insights, Smart Proxy Models enhance safety, reliability, and operational efficiency in the transportation of hydrocarbons. Ultimately, Smart Proxy Models represent a transformative technology in the oil and gas industry, leveraging AI and ML to enhance the capabilities of numerical reservoir simulations and other complex engineering tasks. Their ability to maintain the integrity of the original simulation's physics while significantly reducing computational time and resources offers substantial improvements in efficiency, accuracy, and cost-effectiveness.

Methodology

Overview

This section outlines the methodology employed in developing and validating the AI-based Smart Proxy Models for real-time oil rate prediction and pipeline monitoring. The dual-model approach integrates highprecision real-time data from Multiphase Flow Meters (MPFM) with AI-driven refinements of conventional flow simulators, specifically targeting improvements in predictive accuracy and operational efficiency.

Data collection

The data collection process for this study involved gathering comprehensive field data from an offshore oil field located in the Caspian Sea. This field began production in 1978 and is characterized by shallow water depths ranging from 8 to 42 meters. The field's hydrocarbon reservoirs, primarily within Pliocene-aged Red Series sandstones, exhibit favorable porosity and permeability, which are essential for efficient hydrocarbon extraction. The dataset for this study includes intricate details on the pipeline network of this field, essential for advanced modeling and optimization strategies. Specific measurements such as pipeline diameters, lengths, angles, and roughness are detailed alongside dynamic flow parameters like oil flow rates, Gas-Oil Ratios (GOR), and water cuts from each platform. The dataset encompasses daily measurements spanning different distinct attributes, with data collected from 272 wells assessed between the years 2021 and 2023. This extensive data collection effort was critical for developing the AI-based smart proxy model. The dataset included real-time high-accuracy data from MPFM, capturing oil rates every two hours from 94 distinct days. This real-time data integration ensured that the model could provide precise estimations essential for effective management of the pipeline networks. In this research, the field has two main pipeline networks. The first network comprises 8 pipelines connected to 6 platforms serving as mass sources. In contrast, the second network consists of 14 pipelines linked to 13 platforms acting as mass sources. The main flow of oil occurs within the second network, making it the primary pipeline network. The schematic of these two main pipeline networks is illustrated in Figure 1.

Data preprocessing

In the development of our AI-based smart proxy models, meticulous data preprocessing is essential to ensure the accuracy and applicability of the models in pipeline management. This process begins with the careful selection and cleaning of collected data, with a focus on stabilizing scattered two-hour interval measurements from Multiphase Flow Meters (MPFM) into more reliable daily data points. Such preprocessing is critical for managing extensive pipeline networks and achieving accurate predictive models. The handling of data from OLGA software, a fundamental tool for simulating multiphase flow in pipelines, forms a significant part of our preprocessing efforts. Outputs from OLGA are prone to numerical convergence problems and other computational issues, requiring rigorous review and validation. Domain experts play a crucial role in this phase, using their deep operational knowledge and engineering judgment to filter out any anomalies such as those caused by insufficient numerical resolution or improper simulation node selection that could compromise the model's integrity. These experts ensure that only the most accurate and reliable data are used for model training. Anomalies due to numerical dispersion or inadequately configured simulation nodes are particularly scrutinized. The identified discrepancies are corrected or

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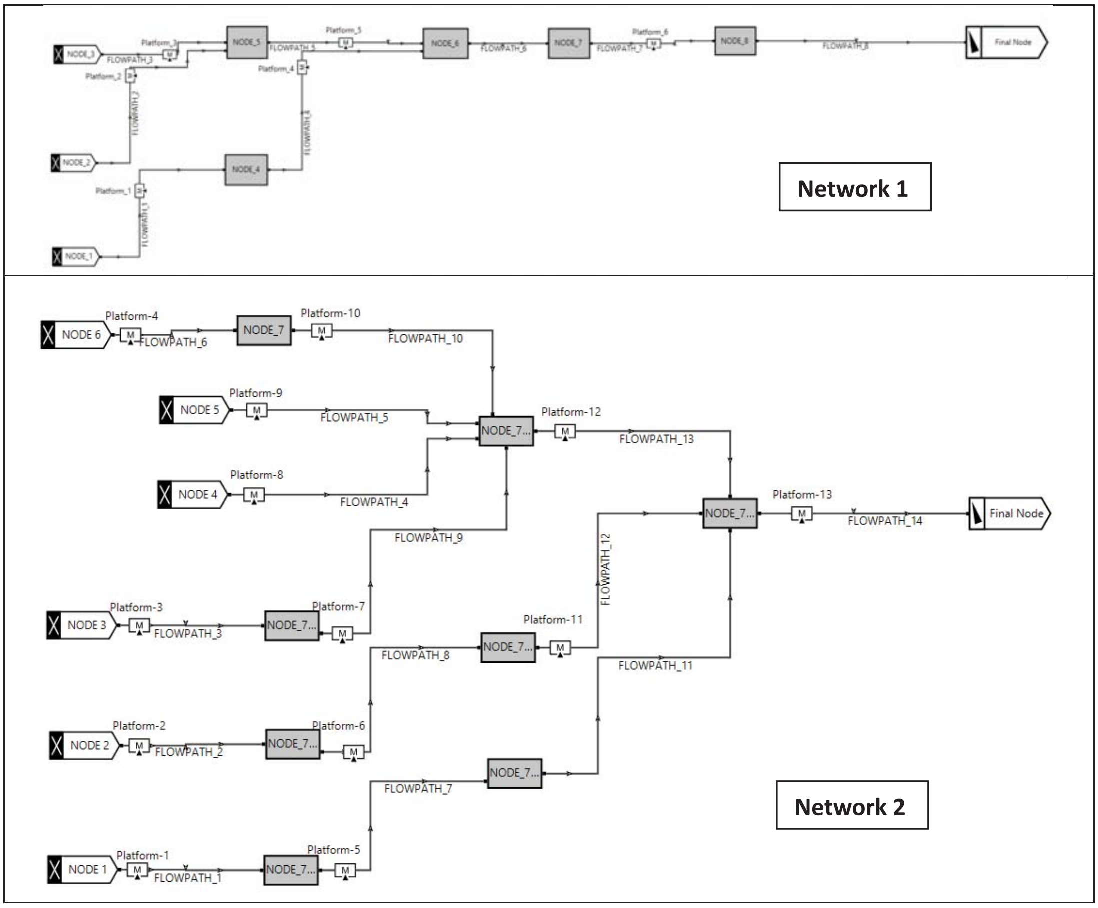

Figure 1: Pipeline Networks.

removed, with a special focus on maintaining the authenticity of operational conditions. This involves optimizing the number of nodes in the pipeline simulations and running multiple simulations to select configurations that yield the most precise results without imposing unnecessary computational burdens. Continuing into the model execution phase, vigilant monitoring is crucial to identify and address any issues such as numerical dispersion, warnings, or errors that could affect the model's performance and accuracy. Optimization strategies, including refining the segmentation of the pipeline network and implementing adaptive time-stepping methods, enhance model stability and computational efficiency. These measures prevent the artificial smoothing of sharp fronts and ensure the model accurately captures the physical behaviors of the flow. For missing data, typically resulting from instrumental failures or transmission errors, our approach involves 'data patching' where domain experts by using an AI approach replace missing or unreliable data points with estimates derived from a thorough analysis of adjacent data and operational conditions. This method ensures that the patched values reflect realistic operational scenarios, maintaining the continuity and accuracy of our datasets. After each simulation run, domain experts conduct rigorous validations of the outputs against empirical data and operational records. This validation confirms the model's accuracy and its utility in facilitating informed decision-making for pipeline management. Through this expert-guided approach, the accuracy of data inputs is ensured, and the foundation for our AI models is solidified, thereby providing the robustness required for effective real-world application and setting new standards in pipeline management and operational efficiency.

Figure 2 presents a schematic illustrating the typical real pipeline topology alongside a segmented representation within the OLGA software. This segmentation is crucial, as it allows for more accurate resolution of numerical issues within OLGA, ensuring that the model handles complex flow dynamics effectively and enhances the stability of simulations.

Data selection

Feature engineering and input data selection are critical steps in developing AI-based smart proxy models. It is essential to identify inherent correlations and relationships within the data to enhance the model's predictive capabilities. This involves selecting relevant features that significantly impact the target variables, such as pressure, temperature, and oil rate. Feature engineering involves transforming the raw data into meaningful inputs for the AI model. This process includes selecting Key Performance Indicators (KPIs) that are closely linked to the output variables. KPIs help in identifying potential correlations and refining the input features. The selected features are then validated through rigorous testing

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and integration into the model to ensure their predictive power and relevance. Also, in AI techniques, especially in AI-based smart proxy models, understanding the tier concept is crucial. According to Shahab Mohaghegh's book, the tier concept helps in structuring the data by recognizing different levels of influence and interaction between various parameters. In pipeline simulations using OLGA software, different nodes represent specific segments along the pipeline where measurements are taken, or predictions are needed. In the context of using neural networks, these tiers are selected based on the weights of each input to the output at the target node, with the model determining the internal connections of each tier. For example, predicting parameters such as temperature, pressure, or flow rate at a specific node may require data from tier 1, tier 2, or tier 3, indicating how many nodes along the pipeline can affect the target prediction node. For some parameters, tier 1 data may be sufficient, while others may require additional tiers depending on the parameter's complexity and the fluid dynamics involved. Figure 3 provides a clear schematic example of a typical pipeline with four nodes, effectively demonstrating this concept.

Model development

The methodology for developing the AI-powered smart proxy models involved two specialized models tailored to distinct operational needs, ensuring enhanced predictive accuracy and efficiency within complex multiphase flow environments in pipeline networks.

Model 1: High-precision AI model using actual measured data: Model 1 was designed to integrate real-time data from Multiphase Flow Meters (MPFM) to provide accurate oil rate predictions. This approach reduces the dependency on extensive MPFM deployments by strategically focusing on critical control points within the pipeline networks. Although the two-hour data recorded from MPFM is highly accurate, it needed to be aligned with the daily resolution of the input data. Therefore, the scattered two-hour interval measurements from MPFM were averaged to produce stable and reliable daily data points. This averaging process was crucial for achieving high precision in predictions, which is essential for effective day-to-day pipeline management. By doing so, Model 1 ensures precise monitoring and control, thereby enhancing the overall efficiency and reliability of pipeline operations.

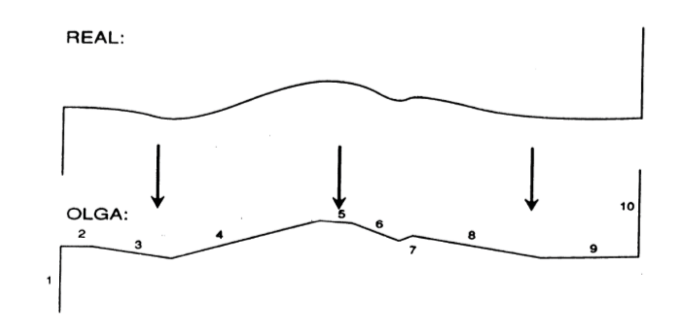

Figure 2: Pipeline Networks.

Figure 3: Pipeline Schematic with 4 Nodes.

Model 2: Enhanced AI-driven simulation for comprehensive pipeline analysis: Model 2 utilized an AI-based smart proxy model to enhance the outputs from traditional transient flow simulators like OLGA. This model addressed issues such as high runtime and numerical convergence problems by selecting the most reliable and accurate simulation outputs, validated by domain experts. The integration of these reliable outputs into the AI model ensured rapid and dependable insights into the pipeline networks' flow conditions.

Model integration and validation

The integration of Models 1 and 2 created a robust predictive framework that leveraged the strengths of both real-time measurements and advanced simulations. Model 1 provided high precision and immediate responsiveness at critical control points, while Model 2 expanded the scope of predictive analytics across the entire network. The data were categorized into different sets for training, calibration, validation, and blind data sets. The training set included a substantial portion of the data used to train the AI models and identify patterns. The calibration set was used to fine-tune the models, ensuring they accurately captured the nuances of the data. The validation set was employed to test the model's performance and ensure they could generalize to new, unseen data. Additionally, blind data sets, which the AI models had never seen before deployment, were used to evaluate the constructed AI models. This final evaluation step ensured the robustness and reliability of the models in real-world scenarios. The validation process involved rigorous testing of the AI models using the collected and preprocessed data. The models were evaluated for their predictive accuracy in estimating oil rates, temperature, and pressure within the pipeline networks. The results demonstrated significant improvements in computational efficiency and accuracy compared to traditional methods.

Results

Two distinct AI-based smart proxy models were developed, each with unique architectures tailored to specific purposes. These variations included differences in the number of neurons, hidden layers, and other hyperparameters. For Model 1, advanced AI software called "Improve," developed by Intelligent Solutions, Inc. (ISI), was utilized to create an Artificial Neural Network (ANN) specifically designed for predicting oil rates. Conversely, Model 2 was constructed using Python-based coding to develop the ANN model, aiming to predict temperature, pressure, and oil rate along the pipeline.

Model 1: High-precision AI model using actual measured data

For Model 1, the objective was to predict oil rates based on accurate production data from Multiphase Flow Meters (MPFM), which were set up at the final node in Network 2.

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The dataset consisted of production records over 94 distinct days spanning three years from 2021 to 2023. Initially, fuzzy clustering techniques were employed to categorize the MPFM oil rate data into three main clusters: poor, average, and good. This approach assigns membership values to each data point, indicating the degree to which it belongs to each cluster rather than strictly categorizing them into discrete groups. These clusters provided a clear understanding of the data distribution and variability, which was essential for the subsequent training and validation phases. The results of this clustering are illustrated in Figure 4.

For constructing an AI-based smart proxy model, the dataset was partitioned into four distinct groups: training, calibration, validation, and blind data. To ensure the integrity of the blind testing procedure, 12 data points were randomly selected and isolated from the model training process. The training set, comprising 70% of the remaining data after omitting the blind data, was used to develop the foundational predictive capabilities of the model. The calibration set, representing 15% of the data, was utilized to finetune the model parameters, optimizing performance. The validation set, including the remaining 15% of the data, was applied to evaluate the model's performance on unseen data. The blind data set, consisting of data points not seen by the model during training, was used to assess the model's predictive accuracy post-training. The schematic representation of the ANN model is presented in Figure 5.

During this phase, the ANN model was executed using input data selected based on the available data described in the data collection section, following the Key Performance Indicator (KPI) method. This strategic approach enabled a comprehensive assessment of the importance and relevance of input data for predicting the output. The KPI method provided initial guidance, which was further refined through model application to determine its effectiveness. Additionally, this approach facilitated the automatic selection of the optimal number of epochs by analyzing training and validation errors, thereby enhancing the model's efficiency and accuracy.

The coefficient of determination (R^2) values for the training, calibration, and validation phases were approximately 0.997, 0.823, and 0.832, respectively, as shown in Figure 6 with the optimized epoch number. The optimized epoch number was determined through an iterative process that analyzed the training and validation errors to find the point where the model's performance was maximized without overfitting. These high R^2 values indicate a strong correlation between the predicted and actual data, demonstrating the effectiveness of the ANN model in capturing the underlying patterns and making accurate predictions.

The final validation step involved using the 12 blind data points to rigorously test the model's efficacy. The model predicted these data points without any parameter modifications, achieving a prediction error rate of approximately 1% and an R^2 value of around 0.87, as detailed in Table 1 and visually represented in Figure 7. These metrics underscore the model's high predictive accuracy and reliability,

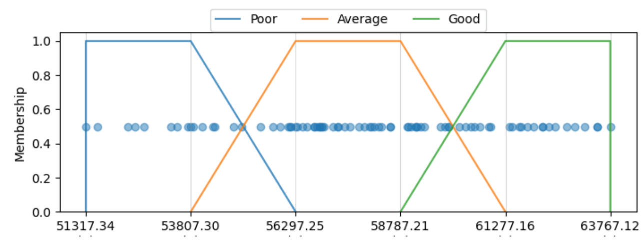

Figure 4: Fuzzy Clustering of MPFM Oil Rate Data.

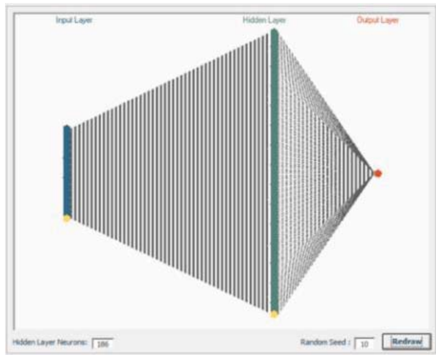

Figure 5: Schematic Representation of the ANN Model.

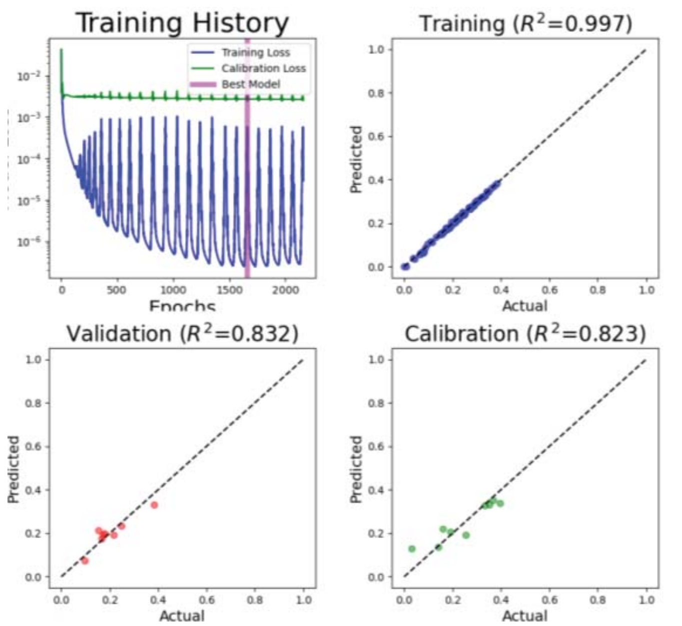

Figure 6: R^2 Values for Training, Calibration, and Validation Phases of the ANN Model.

highlighting its potential as a cost-effective alternative to the highly expensive MPFM methods.

Model 2: Enhanced AI-driven simulation for comprehensive pipeline analysis

Model 2 was developed using a Python platform to construct an ANN model that integrates traditional OLGA simulation outputs with carefully curated operational data, validated by domain experts. This innovative approach addresses common limitations of conventional simulation methods, such as long runtimes and numerical convergence issues. The aim of Model

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Table 1: Error Metrics and R^2 Values for AI Model Predictions on Blind Data.

Actual Oil Flow Rate (STB/d)	Predicted Oil Flow Rate (STB/d)	Difference	Error (%)
56343	56364	21	0.04 %
56692	57220	529	0.93 %
57815	57469	346	0.60 %
59183	59453	270	0.46 %
58019	58204	185	0.32 %
56974	58204	1230	2.16 %
57367	57825	457	0.80 %
57136	57497	361	0.63 %
56366	56459	93	0.17 %
56142	57235	1093	1.95 %
59155	58757	398	0.67 %
54374	54654	280	0.52 %
Average Error			0.77%

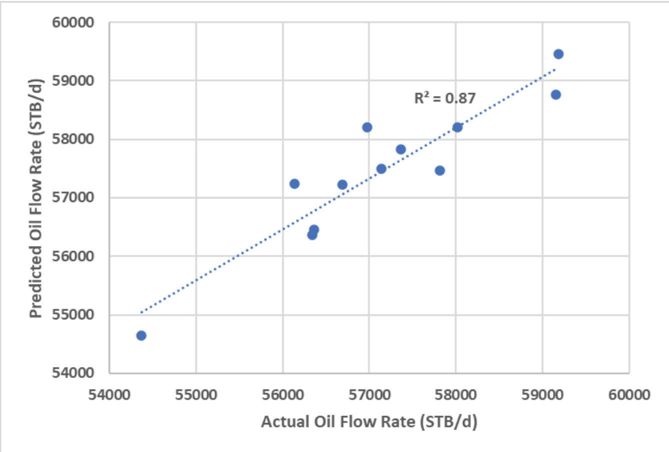

Figure 7: Predictive Accuracy of the AI Model on Blind Data.

2 was to predict temperature, pressure, and oil flow rate along the pipeline, providing a comprehensive analysis of the pipeline's operational parameters.

Model 2's development focused on a detailed analysis of a single pipeline within a network. This specific pipeline, selected from Network 1, carries oil through Platform 1 to Flow path 1, making it the nominated pipeline for this study. The primary objective was to conduct sensitivity and uncertainty analyses to understand the OLGA model's responses to various parameters. The data were categorized into four main groups: general input data, PVT properties, OLGA output data, and AI model target variables.

General input data included pipeline characteristics such as pipe diameter and pipe angle, as well as production data like oil rate, Gas-Oil Ratio (GOR), and water rate. PVT properties cover the physical properties of the fluids involved, including the densities and viscosities of oil, gas, and water. OLGA output data comprised calculated data from the OLGA model, such as flow regime and velocity. In cases where direct prediction of target variables was not feasible, OLGA output data were used as new input features. These predicted features then served as inputs for predicting the final target variables. Finally, AI model target variables were the parameters that the AI model was designed to predict, such as temperature, pressure, and oil rate.

The initial phase focused on predicting temperature distribution along the pipeline using general input data, with temperature-sensitive PVT data introduced later. This approach ensured comprehensive data usage for accurate temperature predictions, optimizing the AI proxy model's development.

Among the 60 different single-pipeline OLGA models constructed with various input parameters to cover several scenarios, 70% of the data were utilized for training and 30% for calibration, validation, and blind testing. Given the substantial volume of output data, traditional statistical metrics such as R^2 and Mean Squared Error (MSE) were often found to be inadequate for fully assessing model performance. As highlighted by recent studies, including those by Matejka Research, identical statistical metrics can result from distinctly different data patterns, which can lead to incorrect decisions [26]. The importance of visualizing model outputs to gain comprehensive insights was thus underscored by this phenomenon. Therefore, in this study, the results of the blind data versus pipeline length were visualized to highlight errors and better understand the model's performance. Through this visualization approach, deviations and anomalies that might not be apparent through statistical metrics alone were identified and interpreted. By focusing on graphical representations, a more nuanced evaluation of the model's predictive accuracy and robustness was ensured, leading to more reliable and actionable insights.

Parameters such as neuron count and epoch size were optimized to enhance prediction accuracy. High accuracy in temperature predictions was demonstrated across various scenarios. The model was run for 24 hours, and the results for four blind test data points taken at different times, and case numbers are illustrated in Figure 8. These four blind test data points are provided as examples among all blind test results to showcase the model's performance across different conditions.

In the next phase, the model initially struggled with pressure predictions because the input data were not adequately representative of accurate pressure prediction. To improve accuracy, feature engineering was employed to include gas enthalpy as a key input alongside the previously predicted temperature. After examining various parameters and constructing different ANN models, this parameter was selected as crucial. This approach significantly boosted the model's performance, as demonstrated by the accurate results. The predicted pressure for a specific case showed substantial improvement after incorporating gas enthalpy. The model was run for 24 hours, and Figure 9 presents the results for four blind test data points taken at different times and case numbers as examples.

The final phase focused on predicting oil rates by integrating PVT data alongside the previously predicted temperature and pressure. With temperature and pressure already predicted,

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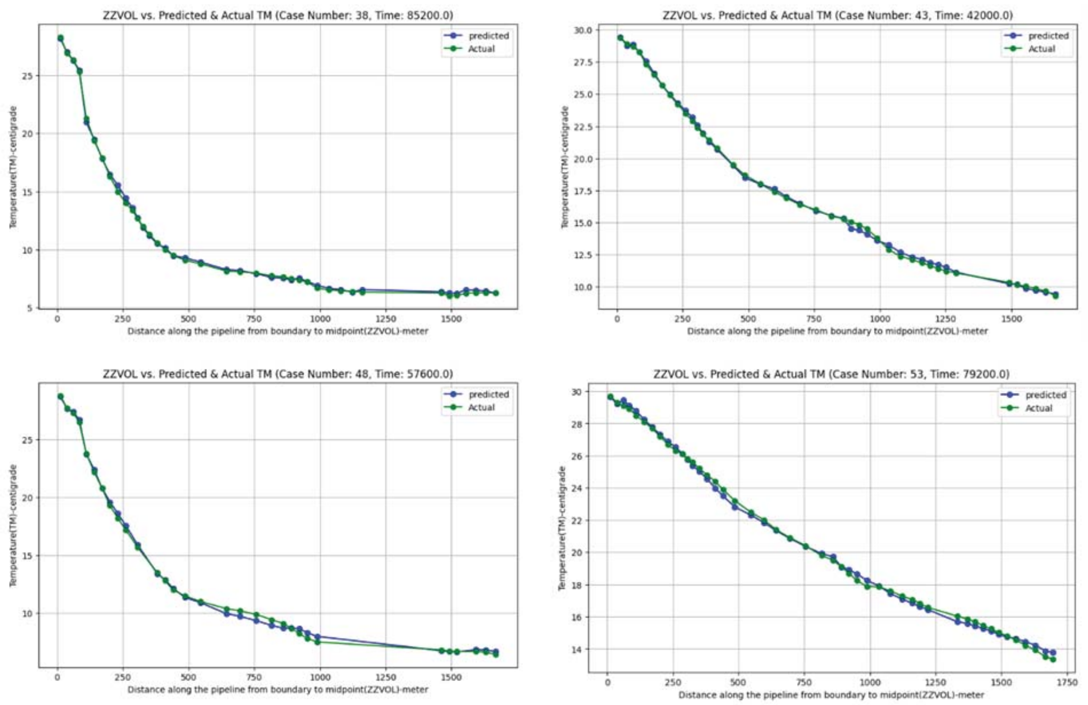

Figure 8: Temperature Predictions for Blind Test Data across Various Scenarios.

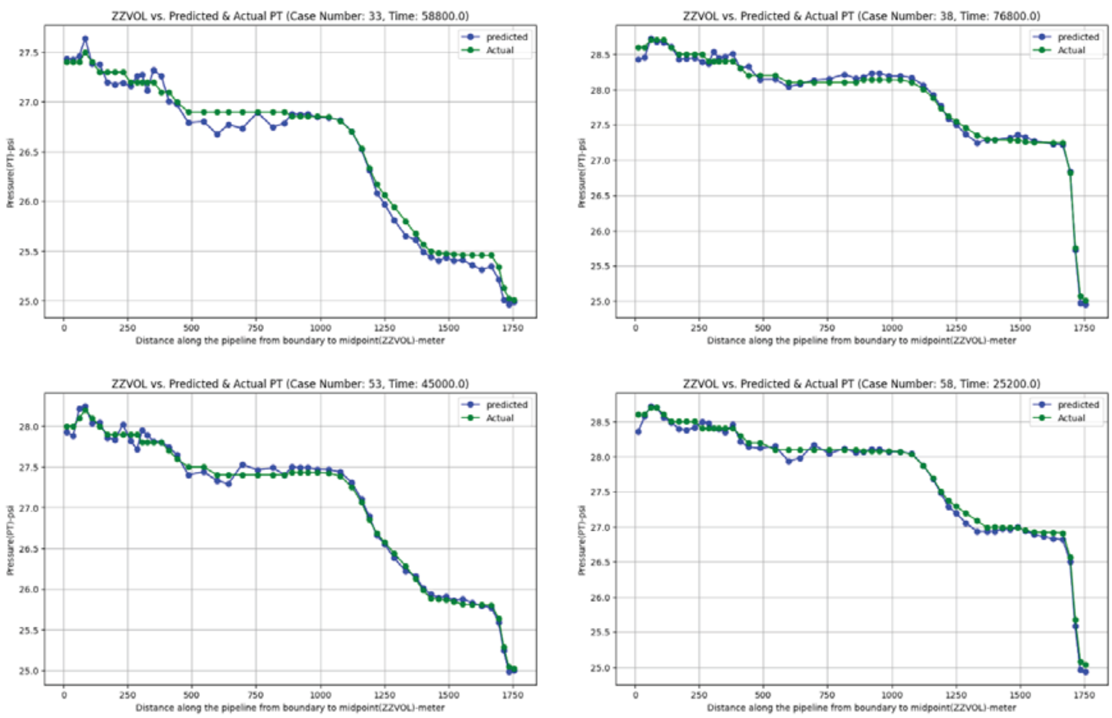

Figure 9: Pressure Predictions for Blind Test Data across Various Scenarios.

we utilized the PVT table, which relates each PVT parameter to specific temperature and pressure conditions. This detailed relationship allowed the model to accurately use PVT input data for predicting oil rates. Despite optimizing hyperparameters, the accuracy for oil rate predictions was lower than that for temperature and pressure, as shown in Figure 10.

Discussion and recommendations

Implementing AI-based smart proxy models in real oil field operations presents considerable challenges, particularly concerning data quality and system integration. High-quality, consistent data are essential, as these models depend heavily

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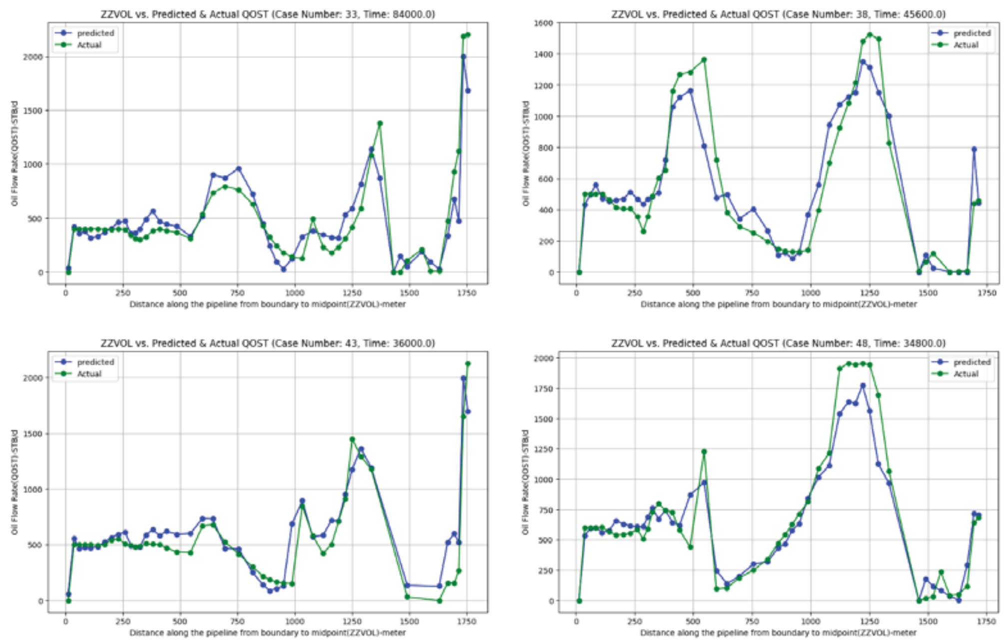

Figure 10: Oil flow rate Predictions for Blind Test Data across Various Scenarios.

on accurate inputs for training and operation. However, field data often contain gaps, noise, and inaccuracies due to equipment malfunctions or suboptimal data collection practices. Addressing these issues necessitates robust data preprocessing techniques to ensure model reliability. Another significant challenge is the integration of AI models with existing pipeline monitoring systems, such as Supervisory Control and Data Acquisition (SCADA) systems. These systems are not typically designed for seamless integration with AI, which requires custom solutions like middleware or Application Programming Interfaces (APIs) to enable real-time data sharing and analysis. Additionally, computational constraints and the need for real-time processing capabilities can limit the models' effectiveness. Implementing edge computing solutions to process data closer to the source can reduce latency and improve operational responsiveness, which is crucial for timely decision-making. Overcoming these challenges requires a comprehensive approach, including continuous model refinement, system upgrades, and the training of personnel in AI-enhanced operations. This ensures that the AI models enhance, rather than disrupt, oil field productivity and safety. By addressing data quality issues through advanced preprocessing and investing in integration and computational infrastructure, the deployment of AI models can be made more reliable and effective. The integration of AI-based smart proxy models holds significant potential to enhance predictive accuracy and operational efficiency within the oil and gas industry. This study demonstrates how substantial cost savings and accuracy improvements can support their widespread adoption. Continuous integration of real-time data ensures that models remain accurate and responsive, providing reliable insights for effective pipeline management. An incremental implementation strategy, starting with individual pipelines and expanding to complex networks, can increase reliability and enable comprehensive system predictions. Furthermore, refining feature engineering processes by capturing relevant parameters accurately and structuring data effectively can boost predictive capabilities. Involving domain experts in model validation and refinement is essential to ensure the predictions remain accurate and contextually relevant across different operational conditions. Traditional statistical metrics such as R^2 and Mean Squared Error (MSE) can sometimes obscure deeper insights; therefore, visualizing model outputs helps highlight errors and understand model performance, allowing for a nuanced evaluation of predictive accuracy and robustness. By following these recommendations, the industry can achieve significant improvements in operational efficiency, cost reduction, and predictive accuracy. This will facilitate better decision-making and more effective management of hydrocarbon transportation infrastructures, setting new standards for pipeline management and flow assurance.

Conclusion

This research demonstrates the significant advancements achievable through the integration of AI-based smart proxy models for oil rate prediction and pipeline monitoring in the oil and gas industry. By leveraging MPFM and refining traditional simulation outputs, the dual-model approach showcased substantial improvements in predictive accuracy, computational efficiency, operational effectiveness, and cost management.

Model 1, which employed high-precision real-time MPFM data, demonstrated a strong correlation between predicted and actual oil rates, underscoring the model's reliability and precision. This approach reduces dependency on extensive MPFM deployments by focusing on critical control points within the pipeline network, thereby achieving significant cost savings without compromising measurement accuracy. Model 2, which integrated traditional OLGA simulation outputs with

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AI enhancements, addressed common issues such as high runtimes and numerical convergence problems. This model provided rapid and reliable insights into pipeline flow dynamics, significantly enhancing the efficiency of operational decision-making processes. The ability to utilize OLGA output data as new input features when direct prediction was not feasible further highlighted the model's versatility and robustness. The dual model approach not only enhanced localized precision through Model 1 but also extended analytical capabilities across the entire pipeline network through Model 2. This harmonized approach facilitates more informed and proactive management of pipeline operations, improving safety, reliability, and efficiency. The integration of real-time measurements and advanced simulations sets new standards for flow assurance and pipeline management.

Beyond oil rate prediction, the methodologies developed in this study have potential applications in other areas of the oil and gas industry, such as midstream projects and complex pipeline network design. The models' ability to simulate various pipeline configurations and operational scenarios quickly and accurately supports efficient and cost-effective pipeline network design and operation.

This research successfully demonstrates the development and application of an AI-based dual-model approach for improving oil rate prediction and operational efficiency in pipeline management. The models have proven their effectiveness based on the comprehensive dataset derived from the mentioned oil field. Critically, the design of these models is not limited to specific datasets or field conditions. Their flexibility and modular architecture allow for easy adaptation and application to any other oil and gas field. This scalability ensures that the approach can be universally applied, making it a valuable tool for the broader industry. Through the intelligent integration of real-time data and advanced simulation techniques, the models are trained to detect actual operational anomalies with high precision. After proper training and calibration against empirical data, these models can reliably identify discrepancies such as oil leakages by comparing actual and predicted results. Any significant variations in pressure and oil rates are promptly flagged as potential indications of leakage. This capability is especially critical in offshore pipeline operations, where rapid detection and response to such anomalies are challenging yet vital for environmental protection and operational safety. Moreover, the models excel in operational environments demanding quick responses, such as offshore settings, where environmental considerations are paramount. The speed and accuracy of our AI-based smart proxy models make them not only practical but also indispensable tools in the quest to enhance pipeline safety and efficiency while minimizing environmental risks.

In summary, the approach detailed in this study sets new benchmarks for predictive accuracy and operational responsiveness in the oil and gas industry. It underscores the potential of AI-driven technologies to transform pipeline management across diverse environments, offering a robust solution to one of the industry's most pressing challenges.

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