Deliverable report 1

AI and IAGEN+ Application Use Case

Energy Optimization in the Oil Industry: Predictive Analysis of Well Performance in Vaca Muerta

I. Introduction

Vaca Muerta, located in the Neuquén basin of Argentina, emerges as one of the the most significant shale gas and shale oil formations in the world. Its Recoverable reserves are estimated at 8.7 trillion cubic meters of natural gas and 16 billion barrels of oil and condensate, a volume sufficient to satisfy the energy needs of all of Argentina for more than a century.

This formation stands as the second largest shale gas reserve in the world. world and the fourth largest shale oil producer. The mining and energy sector, boosted in largely due to Vaca Muerta, constitutes a considerable portion of the Gross Domestic Product Argentina's Gross (GDP) . The increase in energy exports from Vaca Muerta is contributing to Argentina's trade surplus and helping to stabilize the exchange rate. Oil production in Neuquén, the main province where Vaca Muerta is located, represented about 68% of the total Argentine in 2024, which led to a significant reduction in imports of gas .

The high quality of the Vaca Muerta shale has contributed to the decrease in operating costs and improved efficiency through production incentives and tax exemptions. The number of fracking wells in Vaca Muerta has experienced a notable increase, indicating intense extraction activity. Production Total shale in Vaca Muerta has increased by 150% since 2020, reaching 740,000 barrels of oil per day. By the end of 2024, oil production of Vaca Muerta increased tenfold compared to 2014, becoming the main driver of Argentina's growing hydrocarbon yield. The exploitation of this vast reserve requires large investments in infrastructure, technology and highly specialized personnel. The geological and operational complexity inherent in the Shale hydrocarbon extraction requires the use of advanced technologies to maximize well efficiency and profitability.

II. Presentation of the opportunity in context

One of the main challenges in the exploitation of Vaca Muerta lies in the variability in well production, directly attributable to heterogeneity geological nature of the formation. This heterogeneity is manifested in the diversity of the porosity, permeability and hydrocarbon content along the length of the formation, which inevitably impacts initial and final production rates.
on the long-term decline curves of each well.

Accurately predicting this variability represents a significant obstacle for researchers. traditional methods such as stochastic analysis and empirical experience, often They fail to accurately predict long-term productivity and fail to capture the inherent complexity of shale wells.

Accurately determining the future performance of a well is critical to decision making. of financial and operational decisions.

On the obsolescence of traditional methods

Decline curve analysis (DCA), for example, is based on historical production data and assumes consistent decline patterns, a assumption that may not be valid for the complexity of shale wells. Material balance equations (MBE) require detailed knowledge of the reservoir properties and fluid behavior, information that may be difficult to obtain accurately in shale formations.

Numerical simulations, while offering a more sophisticated approach, can be computationally intensive and highly dependent on the accuracy of the input parameters, which often requires a considerable investment of time and resources. Although sophisticated, the approach of numerical simulations requires resource- and time-consuming, as they are computationally intensive and depend on precise input parameters.

Traditional methods, such as numerical simulations, despite their sophistication, often present challenges due to their dependence on parameters of precise input and its significant computational demand. Incorporate interaction The complex nature of geological factors, operating parameters, and external influences on well performance is generally difficult with these methods, which may require a considerable investment of time and resources.

Generative Artificial Intelligence (GENI) and the evolution towards AI agents present a significant opportunity to improve the prediction of performance of wells using advanced models that analyze large volumes of historical, operational, and geophysical data. “Classical” AI-based approaches, including machine learning and deep learning, have demonstrated a superior accuracy in predicting oil prices and oil performance wells by capturing complex time dependencies and nonlinear relationships in large data sets.

For example, LSTM networks, a type of deep learning model, have demonstrated the ability to outperform traditional time series models such as ARIMA and Exponential Smoothing in predicting oil prices and production rates. Other studies have found that hybrid AI models that combining CNN and LSTM can achieve higher accuracy in predicting oil well production compared to individual models. Also the Machine learning techniques such as Random Forest have also proven to be effective. effective in predicting oil production rates with high accuracy.

If we add or complement this predictive logic with capabilities of the With IAGEN and AI agents, it is possible to transform well performance evaluation and reduce uncertainty in decision-making.

III. Application of “classical AI” + IAGEN in the Specific Activity

Approaches based on “classical AI”, including machine learning and deep learning, have demonstrated superior accuracy in predicting the oil prices and well performance by capturing complex temporal dependencies and nonlinear relationships in large data sets. However, it is the integration of these techniques with Generative Artificial Intelligence (GENAI) that presents an even more significant opportunity. This combination can transform Radically improve well performance evaluation and drastically reduce the uncertainty in decision-making.

Generative Artificial Intelligence (GENAI) is a branch of artificial intelligence that focuses on creating new content, such as models, images, code, or text, from existing data. This technology uses advanced algorithms to analyze large amounts of information, identify patterns and generate new content and original that is often indistinguishable from that created by humans.

Simplified structure of the stages of using IAGEN for predictive analysis well performance.

- Data collection

Key data (production, pressure, temperature) is collected from IoT sensors, databases historical and operational reports.

What is it for?: It provides the information base necessary to understand the past and current well behavior.

- Data cleaning and preparation

Errors are corrected, missing data is completed, and formats are standardized.

What is it for?: It ensures that models learn from reliable and comparable data, improving the accuracy of predictions.

- Training generative models

Generative AI algorithms (such as LSTM or GANs) trained with historical well performance data are used.

What is it used for?: It allows the system to learn complex patterns and relate variables to anticipate future well behavior.

- Simulation of future scenarios

Different operating conditions are tested (e.g. changes in water injection or pressure).

What is it for?: It allows you to predict how the well will respond to changes, helping in strategic decision-making.

- Analysis and generation of recommendations

Model predictions are interpreted to suggest operational improvements or detect possible failures in advance.

What is it for?: Optimizes production, reduces risks, and improves well efficiency.

Real-time monitoring and feedback

Predictions are compared with actual performance and the model is updated. constantly.

What is it for?: Ensures that the model continues to learn and adapt to conditions changing reservoir.

Detailed description of How to apply classical AI plus IAGEN

Generative Adversarial Networks (GANs) are a type of artificial intelligence that focuses on generating new data, such as images, music, or even synthetic data. They work with two neural networks that compete with each other: one generates the data and the other another evaluates them. Unlike models like ChatGPT or Gemini, which specialize In processing and generating text, GANs focus on creating multimedia content or data structured. While ChatGPT and Gemini understand and respond in human language, GANs create new things, such as realistic photos of people who don't exist or original music.

We can combine GANs with classical AI (supervised machine learning algorithms such as LSTM and Random Forest) to analyze historical patterns and generate accurate predictions. The generative capabilities of these models allow us to create hypothetical and novel but possible scenarios, rather than simply extrapolating past trends. This is particularly valuable for capturing non-linear behaviors and unexpected changes in production that the models Traditional predictive AI alone could be overlooked. In short, classical AI provides the analytical and predictive foundation, while IAGEN expands the possibilities by generating scenarios and synthetic data that enrich and complement the analysis.

Historical Records Analysis with IAGEN

Using data and information linked to historical records requires a prior process of preprocessing to ensure its quality and usefulness. This includes cleaning data to handle missing values and outliers, normalization to scale data to a common range and feature engineering to create new ones relevant variables from existing ones. The quality and completeness of the data Historical data have a direct impact on the accuracy and reliability of predictive models.

To train IAGEN models, detailed historical data from the wells. This data includes information on oil, gas, and water production, pressures in the well, fluid composition, geological characteristics of the ground (such as depth and porosity) and operational data such as frequency of pumping and injection rates.

For example: consistent information is obtained on the log of a well during the last five years. This record reflects parameters and data linked to how much oil and gas was produced daily, the pressure inside the well at different depths, whether the fluid was more oil or more water, and how the pump or water injection was adjusted. All of this data makes up a very valuable set of information. valuable. By feeding this dataset into an IAGEN model, the model learns to recognize patterns from a good iteration of “no code” instructions.

The IAGEN is key, as it can be used to establish relevant correlations without there is a need to start from scratch to train a predictive model with classic AI. In this way, under a "no code" format (without programming) it could learn that when water injection pressure increases, oil production also tends to increase a few days later, with a series of variables and nuances that can unfold in a visualization dashboard or report. With this knowledge, the model can predict how the well will behave in the future if certain changes are made operatives.

Generative Modeling

Let's look at a hypothetical scenario of applying Generative Neural Networks -GANs-. An oil company is exploring a new field in Vaca Muerta. Currently, the company has limited seismic data and logs from existing wells, which creates uncertainty. To improve reservoir characterization, the company could use a Generative Adversarial Network (GAN). In this approach, the generator creates synthetic 3D models of the reservoir by varying key factors such as the porosity, permeability, and geological structure. The discriminator compares these synthetic models with the available real data, identifying differences and offering feedback. Through this iterative process, synthetic models become increasingly accurate and realistic. Eventually, the company obtains multiple plausible scenarios of the deposit, allowing to simulate different production conditions, reduce geological uncertainties and optimize strategy drilling and development.

Long Short-Term Memory (LSTM) networks are a specialized type of network recurrent neural network that stands out for its ability to analyze and learn from data are organized in sequences, like time series. Unlike other models that can forget past information, LSTMs are designed to retain long-term relevant information, making them ideal for modeling processes that evolve over time. In the context of oil well performance, where production data, pressure and other parameters vary continuously, LSTMs They offer a powerful tool to predict future trends and optimize decision-making. of decisions.

Real-Time Prediction

Integration with IoT sensorsThe Internet of Things (IoT) refers to a network of physical objects, or "things," that are equipped with sensors, software, and other technologies in order to connect and exchange data with other devices and systems over the Internet. In the oil industry, IoT sensors deployed in Wells play a key role in collecting real-time data on various parameters, such as pressure, temperature and flow rate.

This integration of IoT technology provides a solid foundation for the application of Generative Artificial Intelligence (GENAI) in predictive analytics. By leveraging real-time data from IoT sensors, GENAI can generate models and more accurate simulations, enabling more informed decision making and efficient optimization of well operations. deployed in the wells allows continuous monitoring of key parameters such as pressure, temperature and flow rates.

In short: real-time data streams are fed into IAGEN models trained to provide updated predictions of the performance of the production. Models can dynamically adjust their forecasts based on the latest sensor readings, providing timely information for adjustments and operational interventions.

This real-time prediction capability enables proactive decision making. and the optimization of well operations. The combination of historical data analysis, generative modeling, and real-time prediction within IAGEN determines a paradigm shift to understand and forecast the performance of wells, leaving behind the static nature of traditional methods. In addition, the ability of GANs to generate realistic synthetic data and LSTMs to Capturing temporal dependencies suggests that IAGEN can effectively address the challenges posed by data scarcity.

Finally, while integration with IoT sensors to obtain real-time data represents a growing trend and a long-term goal for the industry Oil and gas in Vaca Muerta, its widespread implementation faces challenges significant. While there is clear potential for continuous optimization through AI-driven monitoring and control, adoption of these technologies is inconsistent. nor immediate.

In the reality of Vaca Muerta, digitalization varies considerably between the different companies and operations. Some leading companies have begun to investing in IoT sensors and advanced data analysis systems, but many other still rely on more traditional methods. The infrastructure needed to support complete digitalization, including robust network connectivity and data storage and processing systems, may be limited in some areas of training.

In addition, the transition to digitalization requires significant investments and Changes in organizational culture. Companies must train their staff, adapt their operational processes and overcome resistance to change. The availability of Technical staff specializing in IoT and data analysis can also be a factor limiting.

Therefore, while digitalization and IAGEN have enormous potential to transform the industry in Vaca Muerta, it is crucial to recognize that its implementation It is a gradual and complex process.

IV. AI Agents and Agentic Workflows. The Evolution of Generative AI.

1. Concept of IAGEN agents

In recent years, generative artificial intelligence (GAI) has revolutionized the way we interact with technology, enabling the development of systems capable of generating content, answering complex questions and assisting with tasks high-demand cognitive skills. From this capacity, a new architecture emerges Technological: IAGen-powered agents. These agents are not simple conversational interfaces, but autonomous systems that can interpret instructions, make decisions, execute tasks and learn from their interactions with the around.

An IAGen agent combines large language models with components additional features such as external tools, memory, planning and autonomous execution. This allows them to operate in complex environments, with the ability to break down Step-by-step objectives, coordinate multiple actions, interact with digital systems (such as databases, APIs or documents) and adapt to changes in context in real-time. These qualities distinguish them from traditional chatbots and open up a range of more sophisticated and customizable applications.

At the organizational level, these agents are being used to automate processes, generate data analysis, assist in decision making and improve the user experience, both internally and externally. For example, they can assume human resources, legal, financial or logistical tasks, and even those linked to the technical areas of production processes, acting as intelligent assistants that collaborate with human teams. This ability to integrate knowledge and execute tasks autonomously transforms the way organizations can scale your operations without losing quality or control.

In addition, agentic workflows—structures where multiple agents collaborate with each other to solve complex problems—allow responsibilities to be distributed between different agent profiles, each with specific functions. This generates Hybrid work environments where humans and agents coexist, optimizing times, costs, and results. The ability to connect agents with tools such as Google Drive, CRMs or document management platforms further expands its capabilities.

The development of IAGen-powered agents represents a crucial step towards a new era of intelligent automation.

Among the benefits of authentic workflows driven by business models generative artificial intelligence, the possibility of automating processes is found complete, end-to-end production systems, and even add value from the leveraging the skills of language models based on these technologies.

However, its implementation also poses technical, ethical and legal challenges, from responsible design to human oversight. Therefore, understanding your architecture, its operational logic and potential impacts are essential for its effective and safe adoption in diverse professional contexts.

2. IAGEN agents applicable to predictive analysis of well performance

Adopting an AI agent paradigm with no-code and low-code approaches presents a significant opportunity to overcome the limitations of traditional methods and accelerate the adoption of artificial intelligence in the petroleum industry. By simplifying the development and implementation of AI solutions, access to these is democratized technologies, allowing professionals without deep technical training to create and customize agents tailored to your specific needs.

This logic reduces the costs associated with custom software development, speeds up the experimentation and iteration, and allows you to more easily adapt to changes in operational and reservoir conditions. By complementing predictive models and generative AI agents already described can automate workflows complex, from real-time data collection and analysis to generating recommendations and making proactive decisions, thus maximizing efficiency and productivity.

Furthermore, the use of no-code and low-code platforms for creating AI agents (CITE OUR BOOK) allows for greater flexibility and scalability. These tools typically offer intuitive interfaces and pre-built components that can be assembled and customized without the need to write code from scratch. This accelerates development and fundamentally facilitates integration with existing systems and adapting to new data sources or operational requirements. By reducing the dependence on specialized developers and allow greater participation of experts in the field, a culture of innovation and collaboration is fostered, where Technical knowledge and industry experience combine to create AI solutions that are more effective, less expensive, and increase the capacity of optimization in different tasks. In short, we must move towards an approach hybrid that combines analytical and predictive methods with the ability to automation and adaptation of AI agents.

3. Description of the agentic workflow for the implementation of IAGEN in the Predictive analysis of well performance in Vaca Muerta. Key stages.

- Initially, multi-source data collection is carried out, extracting information from IoT sensors installed in the wells (for real-time production, pressure and temperature data), historical databases (containing production logs, well tests and geological studies) and operational reports (such as maintenance and intervention records). The variety and Data coverage is critical for model training robust.
- Once collected, the data undergoes a cleaning and Normalization. This involves handling missing values using imputation techniques, identifying and treating outliers, and normalizing or standardization of data to ensure consistency and compatibility for model training. Data quality assessment is a critical step in this process.
- The next stage involves training the generative model. Appropriate generative AI models (such as GANs, LSTMs, or hybrid architectures) are selected based on the specific prediction task and the

data characteristics. These models are trained using the data preprocessed historical data, optimizing hyperparameters and validating the model performance with previously unseen data.

- With the trained model, the scenarios are simulated. generative models to simulate various future production scenarios, by introducing different operating parameters (such as changes in injection rates or adjustments in choke size) or external factors (such as a possible decrease in reservoir pressure). Multiple plausible outcomes are generated to assess uncertainty.

- Analysis of simulation results and real-time predictions allows for the generation of practical recommendations to optimize operations. wells. Knowledge is provided on possible improvements in the production, cost reduction opportunities and early warnings on possible problems.
- Finally, continuous monitoring of the actual performance of the well is carried out in compared to predictions from IAGEN-powered AI agents, using real-time data streams. Models are retrained or periodically adjusted with new data to improve their accuracy and adapt to changing reservoir conditions and operational modifications. Implementing feedback loops ensures that the model remains relevant and effective over time.

The iterative nature of this workflow, which involves monitoring continuous and dynamic adjustment, allows for constant improvement and adaptation of predictive models. The integration of data from multiple sources and the use of Simulation scenarios within IAGEN provide a more comprehensive approach holistic and prospective for well management compared to the traditional methods.

4. Hypothetical Example of Application in Vaca Muerta

In a specific well within Vaca Muerta that was experiencing fluctuations in its production, five years of detailed historical data were collected. This data included daily oil and gas production rates, wellhead pressure, downhole pressure, gas lift injection rates and relevant geological parameters.

An LSTM-based IAGEN model was trained on this data to identify production decline patterns associated with operating configurations specific and the behavior of the reservoir. The model detected a correlation between periods of low gas lift injection pressure and subsequent drops in production, as well as patterns indicating a possible water breakthrough.

Based on this knowledge, IAGEN recommended adjusting the injection pressure of gas lift within a specific range and implement a management strategy more proactive water. For the next six months, with the recommended adjustments implemented, the oil production of the well increased by 18%, which demonstrates the practical impact of IAGEN on well performance optimization. This specific example illustrates the ability of IAGEN to identify non-linear relationships. obvious insights within complex well data and translate these insights into practical recommendations that lead to significant improvements in production.

V. Expanded development of specific technologies and models. Examples of use additional.

- Generative Neural Networks (GANs)

Generative Neural Networks (GANs) constitute a class of models of deep learning composed of two neural networks: a generator and a discriminator . The generator aims to create synthetic data that is indistinguishable from the real data, while the discriminator attempts to distinguish between the real data and the generated data. These two networks are trained in an adversarial manner; the generator seeks to deceive the discriminator by generating increasingly realistic samples, and the discriminator strives to improve its ability to identify samples false. This iterative process continues until the generator is able to produce data that the discriminator can no longer differentiate from real data. The architecture GANs typically involve deep convolutional neural networks for image-like data (such as reservoir models or seismic data) and recurrent networks for sequential data (such as production time series). The process Training involves the iterative updating of the networks' weights generator and discriminator based on its performance in this adversarial game.

GANs find diverse applications in the oil and gas industry. In it Reservoir modeling is used to generate realistic 3D models of underground reservoirs, based on limited well data or seismic information. In the interpretation of seismic data, can generate synthetic seismic data for facilitate the interpretation of underground structures and the detection of faults. Also They are used to improve well log data, generating synthetic logs to complete existing data or create augmented data sets for training other predictive models. While not explicitly detailed in the provided fragments, GANs also have potential for the creation of Virtual twins of oil and gas assets for simulation and maintenance predictive .

Use Case	Description
Modeling of Deposits	Generates realistic 3D models of deposits, improving geological understanding and accuracy of the simulation.
Interpretation of Seismic Data	Create synthetic seismic data for improve the clarity and precision of the underground imaging and detection of faults.
Data Improvement Well Logs	Generates synthetic well logs to increase the real data limited, improving characterization of deposits and training of other AI models.
Prediction of Production	It can be used to generate probabilistic forecasts of the future production from wells in various scenarios.
Detection of Anomalies	GANs can be trained with data normal operations and then used

	to identify deviations or anomalies that could indicate failures in the teams.

GANs offer a powerful approach to generating high-quality synthetic data. in the oil and gas industry, addressing the common challenge of data sets limited or proprietary. Their ability to learn complex distributions and create realistic samples makes them invaluable for tasks such as reservoir modeling and seismic interpretation, where obtaining extensive real-world data can be difficult or expensive. The adversarial training process of GANs can lead to generated data that is more robust and realistic compared to other models generative, making them particularly suitable for applications that require high fidelity, such as creating virtual twins or enhancing ensembles of critical data.

- Deep Learning Models (LSTM)

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) designed to mitigate the problem of memory fading. gradient, which allows them to learn long-term dependencies in data sequential. They incorporate a memory cell and gating mechanisms (input, forget, and output gates) that regulate the flow of information through the network. The architecture of LSTMs is composed of interconnected LSTM units, organized in layers, capable of processing time series data of various types lengths. Bidirectional LSTMs have the ability to process sequences both forward and backward, allowing them to capture the context of both past as well as future.

LSTMs find a wide range of applications in the petroleum and gas industry.
Gas. They are used to predict future oil, gas, and water production.
based on historical production data and operating parameters. It is also
They apply to predictive maintenance, predicting failures in critical equipment such as pumps, compressors, and other assets based on sensor data and historical maintenance records. LSTMs are useful for anomaly detection,
identifying unusual patterns in production data or meter readings
equipment sensors that could indicate operational problems or potential failures.
In addition, they are used in predicting the flow of water and sand, forecasting the changes in water and sand production in wells over time. Although less directly focused on well performance, LSTMs are also
used in financial time series analysis, predicting fluctuations and
oil price trends.

Use Case	Description
Production Prediction	Predicts the rates of future production of oil, gas and water using historical data and parameters operatives.
Predictive Maintenance	Predicts equipment failures critics like bombs and compressors based on

	sensor data.
Anomaly Detection	Identify unusual patterns in operational data that may indicate problems or possible equipment failures.
Flow Prediction Water and Sand	Predicts changes in the production of water and sand in oil and gas wells.
Optimization of Well Operations	It can be used to analyze operating parameters and predict configurations optimal to maximize the production.

LSTMs are highly effective in analyzing the dependent nature of the well performance data time, making them a valuable tool for predicting future production trends and identifying possible operational problems. Its ability to remember long sequences of data allows them to capture the gradual decline in production and the impact of interventions over time. The successful application of LSTMs in various forecasting tasks within the oil and gas industry, including production, maintenance and anomaly detection, highlights its versatility and potential for a widespread use in operations optimization.

- Natural Language Processing (NLP)

Natural Language Processing (NLP) is a field of artificial intelligence which focuses on training computers to understand, interpret and generate information human language. In the oil and gas industry, NLP finds various applications. It is used to extract key information from technical reports, logs, and other sources. maintenance, operating procedures and geological studies, facilitating the Identification of data relevant to well performance, well status equipment and potential risks. NLP is also used in the analysis of feelings, evaluating opinions expressed in reports, customer comments or social media data related to the sector's operations or companies. In addition, it is used to build knowledge bases from non-textual data. structured, improving information retrieval and decision-making. The development of chatbots and virtual assistants powered by NLP allows us to provide Real-time assistance to field workers for troubleshooting, providing guidance and answering questions about equipment or procedures. Finally, NLP plays an important role in improving regulatory compliance, analyzing regulatory documents and internal reports to ensure adherence to safety and environmental standards. NLP has the potential to Unlock valuable insights hidden in the vast amounts of unstructured text data generated in the oil and gas industry, providing insights that might be overlooked with traditional analysis methods of data. The use of NLP for tasks such as regulatory compliance and data management security highlights its potential to improve operational integrity and reduce risks in a highly regulated and safety-critical industry.

VI. Direct Benefits in Operational and Strategic Terms

1. Recovery Factor Optimization

IAGEN has the ability to identify optimal operating parameters, such as injection rates, throttle settings and parameters artificial lift, which maximizes hydrocarbon recovery from wells in Vaca Muerta. By simulating different operating strategies, IAGEN can predict its impact on the final recovery factor and recommend the most effective approaches. This may result in a significant increase in the total amount of oil and gas extracted from the deposit throughout its useful life.

2. Reduction of Operational Costs

IAGEN's predictive capabilities allow maintenance scheduling proactively, minimizing unplanned downtime and costs associated with emergency repairs. Optimized resource allocation based on IAGEN production forecasts can reduce consumption of energy, chemical use and other operating expenses. The detection Early detection of equipment anomalies and potential failures can prevent costly catastrophic breakdowns and extend the life of critical assets.

3. Improvement in Operational Safety

IAGEN can predict potential safety risks, such as pipeline leaks, faults in abnormal equipment or pressure conditions, allowing interventions timely and prevent accidents. Real-time monitoring and analysis of operational data can provide early warnings of unsafe conditions, which allows operators to take corrective measures. NLP applications within IAGEN can analyze safety reports and identify recurring problems or potential risks that need to be addressed. The direct benefits of IAGEN in terms of recovery optimization, cost reduction and improvement of the security create a compelling business case for adoption in the industry oil and gas in Vaca Muerta. The proactive nature of IAGEN, which allows the prediction and prevention instead of reaction, represents a significant shift in the operating philosophy that can generate substantial long-term advantages.

4. Measurable Impact

The application of IAGEN in predictive analysis of well performance in Vaca Muerta offers a measurable impact in several key areas. A 25% increase in accuracy of predictions, compared to traditional methods, translates into more reliable forecasts for production planning and financial projections. This improvement in accuracy allows companies to make operational and strategic decisions with greater confidence. In addition, a 30% reduction in monitoring costs, a result of IAGEN's capacity to automate data analysis and predict problems before they require remediation intensive manual supervision or costly interventions. Finally, it is experienced a 15% reduction in well evaluation times, thanks to the capacity of IAGEN to process and analyze large data sets quickly, which accelerates decision-making on drilling and completion activities.
These quantifiable benefits highlight IAGEN's tangible value proposition for oil and gas operations in Vaca Muerta, suggesting a solid return on investment investment for companies that adopt this technology.

5. Comparison with Traditional Methods

Feature	Traditional Methods DCA, MBE, (e.g., Numerical Simulation)	IAGEN (Based on AI Generative)
Data Management	Mostly data structured, limitations with large volumes and data no linear.	Excellent handling of large volumes of structured and unstructured data structured, capacity to identify patterns complexes.
Adaptability	Requires settings significant manuals to adapt to new conditions or data.	HE adapts dynamically to new data and conditions changing through the continuous learning.
Precision	It may be limited by assumptions simplified and difficult to capture relationships non-linear.	Greater precision in the prediction thanks to the ability to learn complex relationships and trigger forecasts probabilistic.
Scalability	You may face challenges of scalability with	Highly scalable, capable of process

	large sets of data and simulations complex.	large sets of data of manner efficient.
Evaluation Time	The simulations numerical can be computationally intensive and consume a long time.	Reduce significantly he evaluation time thanks to processing fast and to the analysis automated.
Nature of the Prediction	Predictions deterministic based on models physicists either empirical.	Predictions probabilistic that consider the uncertainty and generate multiple scenarios futures.
Ability to Capture Heterogeneity	Difficulty modeling with precision the heterogeneity geological and its impact in production.	Can learn patterns related complexes with the heterogeneity and improve the accuracy of the prediction.

Traditional models rely on empirical approximations and simulations deterministic, while IAGEN offers a dynamic, data-driven approach in real-time and continuous learning.

Traditional methods are often based on simplified assumptions that may not be valid for complex deposits such as Vaca Muerta. They may have Difficulties in handling large volumes of data and non-linear relationships complex. Their accuracy may be limited, especially for long-term predictions. term or under changing operating conditions.

In contrast, IAGEN offers a dynamic, data-driven approach that can adapt to the specific characteristics of each well and the reservoir in general. It can learn complex patterns from historical data and generate forecasts. probabilistic, providing a more complete understanding of the possible future results. The limitations of traditional methods for capturing the The complexities of unconventional deposits such as Vaca Muerta are a important driver for the adoption of AI-based solutions such as IAGEN. The IAGEN's ability to learn from data and adapt to conditions changing suggests a higher degree of robustness and accuracy compared to the Traditional methods that rely on fixed assumptions and may not be able to capture the dynamic nature of well performance.

VII. Challenges and Strategies to Overcome Them

The implementation of IAGEN in the petroleum industry faces several barriers.

a. One of them is the limitations of data infrastructure, which require a robust infrastructure for the storage, processing and management of large volumes of historical, operational and real-time data.
b. Fragmented data sources and legacy systems can complicate Data integration. Ensuring data quality and consistency is crucial to the reliability of IAGEN models.

c. Another important barrier is resistance to organizational change, which can arise from a lack of understanding or trust in IAGEN and technologies AI among oil and gas industry personnel. The staff shortage Qualified with experience in both AI and oil and gas operations may make implementation difficult.

d. Finally, regulatory compliance requires adaptation to the regulations of Security and protection of data relevant to the oil and gas industry and the use of AI technologies. The risks of cybersecurity associated with AI systems and data , as well as the Ethical considerations related to the use of AI in decision-making .

Strategies for Effective Integration

To achieve effective IAGEN integration, several options can be implemented: strategies.

- The use of scalable cloud platforms for storage, Model processing and deployment can address limitations of infrastructure and provide the necessary computing resources.
- Cloud platforms offer flexibility and cost-effectiveness for managing large data sets and running complex AI models.
- It is recommended to explore “on-premise” or local AI Agent models.
- Short-term investment in AI agent implementation equipment: requires investment in proof of concept and pilot testing. The focus here is that the training of talent to implement, since it is verified a cost reduction trend in systems that allow automation “no code” and “low code”. For the first stage, it is also recommended to use teams with experience in designing and implementing AI agents. By

Finally, it is key to form an “in-house” team for support and appropriation of an agentic culture that redefines interaction human-machine.

- Staff training through comprehensive training programs on the principles and applications of AI in the oil and gas industry can help overcome organizational resistance and develop expertise necessary.
- Training existing staff and attracting new talent with AI skills are crucial for successful integration.
- Establish strategic alliances with companies specialized in AI and Research institutions can provide access to technologies cutting edge, experience and best practices to implement IAGEN effectively. Collaborations can help overcome the gap in knowledge in AI and accelerate the adoption process.
- Successful implementation of IAGEN requires a multifaceted approach that address not only the technological challenges but also the aspects organizational and regulatory.
- Invest in staff training and forge strategic alliances with experts in AI are crucial steps for oil and gas companies to develop internal capabilities and leverage external knowledge for integration effective.
- Address cybersecurity risks and ensure compliance with Relevant regulations are essential to build confidence and ensure the responsible and sustainable deployment of AI technologies in the industry oil and gas.

VIII. Conclusion

The application of IAGEN in predictive analysis of well performance in Vaca Muerta represents a significant advance in energy optimization for the oil industry. By harnessing the power of generative AI, companies can achieve substantial improvements in operational efficiency, reduce costs associated with unplanned downtime and inefficient resource allocation, and improve the security of your operations. The knowledge derived from IAGEN allows more informed strategic decision-making, leading to maximization profitability and optimized exploitation of valuable energy resources within the Vaca Muerta formation. Looking ahead, continued development and Integration of AI technologies such as IAGEN will be crucial for the industry of oil and gas in Argentina remains competitive, sustainable and efficient in a rapidly evolving global energy landscape.

Sources cited

1. www.thinkbrg.com, access: February 2, 2025, https://www.thinkbrg.com/thinkset/the-key-to-making-argentina-an-energy-transition-powerhouse/#:~:text=Accordingly%2C%20it%20is%20often%20considered,needs%20for%20over%20a%20century.

2. Cow Dead - Wikipedia, access: February 2, 2025, https://en.wikipedia.org/wiki/Vaca_Muerta

3. Argentina's crude oil and natural gas production near record highs..., access: March 18, 2025, https://www.eia.gov/todayinenergy/detail.php?id=63924

4. Credit FAQ: Renewed Interest In Argentina's Vaca Muerta Shale | S&P Global Ratings, access: February 2, 2025, https://www.spglobal.com/ratings/en/research/articles/250117-credit-faq-renewed-interest-in-argentina-s-vaca-muerta-shale-13381062

Machine Translated by Google

5. Vaca Muerta: Argentina on the global energy stage - Tecpetrol, accessed: February 2, 2025, ~~https://www.tecpetrol.com/en/news/2025/techint-group-at-ceraweek~~

6. Argentina oil and gas sector: Vaca Muerta shale can drive near-term growth and fuel medium-term opportunities - Deloitte, access: February 2, 2025, https://www2.deloitte.com/us/en/insights/economy/americas/vaca-muerta-argentina-energy-sector-boom.html

7. Argentina's Vaca Muerta: 10 Years of Fracking and Local... - NACLA |, accessed: February 2, 2025, https://nacla.org/argentina-vaca-muerta-fracking-resistance

8. Argentina's Vaca Muerta Fuels Oil Production Surge - Brazil Energy Insight, access: February 2, 2025, https://brazilenergyinsight.com/2025/03/13/argentinas-vaca-muerta-fuels-oil-production-surge/

9. Vaca Muerta production prompts Argentina's largest energy trade surplus in nearly 20 years, access: February 2 2025, https://worldoil.com/news/2025/1/23/vaca-muerta-production-prompts-argentina-s-largest-energy-trade-surplus-in-nearly-20-years/

10. www.ssdynamics.com, access: February 2, 2025, https://www.ssdynamics.com/guide-oil-production-forecasting-methods-and-analysis/#:~:text=These%20methods%20include%20decline%20curve,short%2Dterm%20oil%20pr ~~production%20forecasting.~~

11. The Ultimate Guide to Oil Production Forecasting: Methods and ..., access: February 2, 2025, https://www.ssdynamics.com/guide-oil-production-forecasting-methods-and-analysis/

12. (PDF) Knowledge-Based Machine Learning Approaches to Predict ..., access: February 2, 2025, https://www.researchgate.net/publication/378704647_Knowledge-Based_Machine_Learning_Approaches_to_Predict_Oil_Production_Rate_in_the_Oil_Reservoir

13. A Data-Driven Oil Production Prediction Method Based on the Gradient Boosting

Decision Tree Regression - Tech Science Press, accessed: February 2, 2025, https://www.techscience.com/CMES/v134n3/49751/html

14. Productivity Prediction Methods of Multi-Fractured Horizontal Wells in Low-Permeability Reservoirs: Progress and Challenges - Frontiers, accessed: February 2, 2025, https://www.frontiersin.org/journals/energy-research/articles/10.3389/fenrg.2022.861333/full

15. Time-Series Well Performance Prediction Based on Convolutional ..., access: February 2, 2025, https://www.mdpi.com/1996-1073/16/1/499

16. A Two-Stage Prediction Framework for Oil and Gas Well Production ..., access: February 5, 2025, https://pubs.acs.org/doi/10.1021/acs.energyfuels.4c04762

17. Comparative Analysis of LSTM and Traditional Time Series Models ..., access: February 5, 2025, https://www.preprints.org/manuscript/202410.2355

18. Comparative Analysis of LSTM and Traditional Time Series Models on Oil Price Data, access: February 5, 2025, https://www.researchgate.net/publication/385091883_Comparative_Analysis_of_LSTM_and_Traditional_Time_Series_Models_on_Oil_Price_Data

19. Oil Production Rate Forecasting by SA-LSTM Model in Tight Reservoirs - GeoScienceWorld, access: February 5, 2025, https://pubs.geoscienceworld.org/gsw/lithosphere/article/2024/1/lithosphere_2023_197/632785/Oil-Production-Rate-Forecasting-by-SA-LSTM-Model

20. Time-series well performance prediction based on Long Short-Term Memory (LSTM) neural network model | Request PDF - ResearchGate, accessed: February 5, 2025, https://www.researchgate.net/publication/337191923_Time-series_well_performance_prediction_based_on_Long_Short-Term_Memory_LSTM_neural_network_model

21. Time-series well performance prediction based on Long Short-Term ..., access: February 5, 2025, https://ui.adsabs.harvard.edu/abs/2020JPSE..18606682S/abstract

22. Adaptive Production Forecasting Using a Long Short-Term Memory..., access:

February 5, 2025,
https://jpt.spe.org/adaptive-production-forecasting-using-a-long-short-term-memory-net
work

23. Performance of long short-term memory networks in predicting athlete injury risk, Accessed: February 5, 2025, https://journals.sagepub.com/doi/full/10.3233/JCM-247563

24. Performance Analysis of Long Short-Term Memory Predictive Neural ..., access: February 5, 2025, https://www.mdpi.com/2227-7390/11/6/1432

25. Optimization of Oil Well Production Prediction Model Based on Inter ..., access: February 5, 2025, https://www.mdpi.com/2079-9292/14/5/1004

26. A Well Production Prediction Method of Tight Reservoirs Based on a Hybrid Neural Network, accessed: February 5, 2025, https://www.mdpi.com/1996-1073/16/6/2904

27. Machine Learning Approach for the Prediction of Age-Specific Probability of SCA3 and DRPLA by Survival Curve Analysis - PMC, accessed: February 5, 2025, https://pmc.ncbi.nlm.nih.gov/articles/PMC10159758/

28. Drilling Down: How AI is Changing the Future of Oil and Gas, accessed: February 5, 2025, https://www.sandtech.com/insight/drilling-down-how-ai-is-changing-the-future-of-oil-an
d-gas/

29. Digital transformation in oil and gas—how energy companies can fix ..., access: February 5, 2025,
https://www.kearney.com/industry/energy/article/digital-transformation-in-oil-and-gas-
how-energy-companies-can-fix-legacy-data-for-the-best-ai-advantage

30. AI in Oil and Gas: Preventing Equipment Failures Before They Cost Millions, access: February 5, 2025,
https://energiesmedia.com/ai-in-oil-and-gas-preventing-equipment-failures-before-they-
cost-millions/

31. AI in Oil and Gas: 7 Best Practices for Data Readiness - IPT Global, accessed: February

5, 2025,
https://iptglobal.com/blog/ai-in-oil-and-gas-7-best-practices-for-data-readiness/
32. AI spells opportunity and manageable risk for the oil and gas industry, access: March 18, 2025,
https://www.dnv.com/article/ai-spells-opportunity-and-manageable-risk-for-the-oil-and-gas-industry/
33. Generative AI in Oil & Gas Market Trends | Market Research Future, accessed: March 18, 2025,
https://www.marketresearchfuture.com/reports/generative-ai-in-oil-gas-market/market-trends
34. Oil & Gas: the Future with Generative AI - - Datategy, accessed: March 18, 2025,
https://www.dacategy.net/2024/01/05/oil-gas-the-future-with-generative-ai/
35. arxiv.org, accessed March 18, 2025, https://arxiv.org/abs/1802.05622
36. Simulation Enhancement GAN for Efficient Reservoir Simulation at Fine Scales - Bohrium, access: March 18, 2025,
https://bohrium.dp.tech/paper/arxiv/d34e0eed3c2884c4c598964b3d22ff33f83427fa27ae6edf2bef3004ac6086b0
37. Generative Artificial Intelligence for Subsurface Modeling and ..., access: March 18, 2025,
https://jpt.spe.org/twa/generative-artificial-intelligence-for-subsurface-modeling-and-his Tory matching
38. Conditioning of Generative Adversarial Networks for Pore and ..., access: March 18, 2025, https://www.earthdoc.org/content/papers/10.3997/2214-4609.201800774
39. (PDF) Leveraging Generative Adversarial Networks (GANs) to ..., access: March 18, 2025,
https://www.researchgate.net/publication/375744189_Leveraging_Generative_Adversarial_Networks_GANs_to_Enhance_Well_Logging_Data_Interpretation_for_Sustainable_Near-Field_Exploration

40. Simulation Enhancement GAN for Efficient Reservoir Simulation at Fine Scales - POT ADS, access: March 18, 2025, https://ui.adsabs.harvard.edu/abs/2024MatGe.tmp....7L/abstract

41. Utilizing GANs for Synthetic Well Logging Data Generation: a Step Towards Revolutionizing Near-Field Exploration | Earthdoc, accessed: March 18, 2025, https://www.earthdoc.org/content/papers/10.3997/2214-4609.202471016

42. AI-Driven Reservoir Management: GANs and GMM for Enhanced Control | earthdoc, access: March 18, 2025, https://www.earthdoc.org/content/papers/10.3997/2214-4609.202437004

43. Conditioning of three-dimensional generative adversarial networks for pore and reservoir-scale models - arXiv, access: March 18, 2025, https://arxiv.org/pdf/1802.05622

44. GAN–supervised Seismic Data Reconstruction: An Enhanced–Learning for Improved Generalization - arXiv, access: March 18, 2025, https://arxiv.org/html/2311.10910v2

45. Generating Paired Seismic Training Data with Cycle-Consistent Adversarial Networks, accessed March 18, 2025, https://www.mdpi.com/2072-4292/15/1/265

46. (PDF) A new approach for seismic inversion with GAN algorithm - ResearchGate, access: March 18, 2025, https://www.researchgate.net/publication/389813686_A_new_approach_for_seismic_inversion_with_GAN_algorithm

47. (PDF) Tools, Technologies and Frameworks for Digital Twins in the Oil and Gas Industry: An In-Depth Analysis - ResearchGate, accessed: March 20, 2025, https://www.researchgate.net/publication/384709701_Tools_Technologies_and_Frameworks_for_Digital_Twins_in_the_Oil_and_Gas_Industry_An_In-Depth_Analysis

48. Advancing Predictive Maintenance in the Oil and Gas Industry: A ..., access: March

20, 2025,
https://www.researchgate.net/publication/384302277_Advancing_Predictive_Maintenance_in_the_Oil_and_Gas_Industry_A_Generative_AI_Approach_with_GANs_and_LLMs_for_Sustainable_Development

49. LSTM for Production: Part 2 - JPT - SPE, accessed: March 20, 2025,
https://jpt.spe.org/twa/lstm-for-production-part-2

50. What is LSTM - Long Short Term Memory? - GeeksforGeeks, access: March 20, 2025,
https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/

51. An early warning system for oil wells based on improved long short-term memory network - Frontiers, access: March 20, 2025,
https://www.frontiersin.org/journals/earth-science/articles/10.3389/feart.2024.1508776/epub

52. Reservoir Production Prediction Model Based on a Stacked LSTM Network and Transfer Learning - PMC - PubMed Central, accessed: March 20, 2025,
https://pmc.ncbi.nlm.nih.gov/articles/PMC8697399/

53. Forecasting Water Production from Oil and Gas Wells Using Machine Learning Models, a Case Study from the Paradox Basin, Utah - AAPG Search and Discovery, access: March 20, 2025,
https://www.searchanddiscovery.com/documents/2024/42593bakelli/ndx_bakelli.pdf

54. Artificial intelligence for predictive maintenance in oil and gas operations - World Journal of Advanced Research and Reviews, accessed: March 20, 2025,
https://wjarr.com/sites/default/files/WJARR-2024-2721.pdf

55. Predictive Maintenance of Oil and Gas Equipment using Recurrent Neural Network, access: March 20, 2025,
https://www.researchgate.net/publication/368096367_Predictive_Maintenance_of_Oil_and_Gas_Equipment_using_Recurrent_Neural_Network

56. Predictive maintenance in the energy and utilities industries: Evaluating LSTM, GAN,

TimeGPT, and vector databases - Zemoso Technologies, accessed: March 20, 2025, https://www.zemosolabs.com/blog/predictive-maintenance-in-the-energy-and-utilities-industries-evaluating-lstm-gan-timegpt-and-vector-databases

57. Predicting Failure Rate of Oil & Gas Equipment Using ML - RIT Digital Institutional Repository, access: March 20, 2025, https://repository.rit.edu/cgi/viewcontent.cgi?article=12517&context=theses

58. Predictive_Maintenance using LSTM - Kaggle, accessed: March 20, 2025, https://www.kaggle.com/code/vamshikreddy/predictive-maintenance-using-lstm

59. Are GANs still relevant? [D] : r/MachineLearning - Reddit, accessed: March 20, 2025, https://www.reddit.com/r/MachineLearning/comments/1bb34gj/are_gans_still_relevant_d/

60. Oil Price Forecasting Using Conditional Generative Adversarial Networks (GANs) with Sentiment Analysis | by M Alruqimi | Medium, accessed: March 20, 2025, https://medium.com/@m.alruqimi/oil-price-forecasting-using-conditional-generative-adversarial-networks-gans-with-sentiment-9616998c82d2

61. How Generative AI Can Fuel Oil and Gas Data Analytics | Publicis Sapient, access: March 18, 2025, https://www.publicissapient.com/insights/maintenance-co-pilot

62. Generative AI in Oil and Gas: Optimize Production, Safety, and Sustainability | SoftServe, access: March 20, 2025, https://www.softserveinc.com/en-us/generative-ai/energy

63. Generative AI: The next frontier in energy & utilities and oil and gas innovation | Infosys BPM, access: March 23, 2025, https://www.infosysbpm.com/blogs/generative-ai/generative-ai-the-next-frontier-in-energy-and-utilities-and-oil-and-gas-innovation.html

64. Generative AI for Oil & Gas - C3 AI, accessed: March 23, 2025, https://c3.ai/generative-ai-for-oil-and-gas/

65. The oil industry adopts generative AI to optimize its operations - energynews, access: March 23, 2025,

https://energynews.pro/en/the-oil-industry-adopts-generative-ai-to-optimize-its-operations/

66. wjarr.com, access: March 23, 2025, https://wjarr.com/sites/default/files/WJARR-2023-1423.pdf

67. Predictive Analytics in Oil and Gas: Applications & Advantages - Appinventiv, access: March 18, 2025, https://appinventiv.com/blog/predictive-analytics-in-oil-and-gas/

68. AI in Oil and Gas Industry- Benefit, Use Cases, and Examples, accessed: March 23, 2025, https://oyelabs.com/ai-in-oil-and-gas-industry-use-cases-and-examples/

69. AI in Oil and Gas: Future Trends & Use Cases - Moon Technolabs, accessed: March 23, 2025, https://www.moontechnolabs.com/blog/ai-in-oil-and-gas/

70. Apply AI in Oil and Gas Industry With Automation Power - Bacancy Technology, Accessed: March 18, 2025, https://www.bacancytechnology.com/blog/ai-in-oil-and-gas

71. Worker Safety is a Pressing Issue in the Oil and Gas Industry; AI is Here to Help - Avathon, access: March 23, 2025, https://avathon.com/blog/worker-safety-is-a-pressing-issue-in-the-oil-and-gas-industry-ai-is-here-to-help/

72. Harnessing AI for Improved Safety and Efficiency in the Oil and Gas ..., access: March 23, 2025, https://www.aiquris.com/knowledgehub/harnessing-ai-for-enhanced-safety-and-efficiency-in-the-oil-and-gas-industry

73. AI's Role in Oil and Gas Exploration | DW Energy Group, accessed: March 23, 2025, https://www.dwenergygroup.com/ais-role-in-oil-and-gas-exploration/

74. How Can AI Revolutionize Risk Management in Oil & Gas? - - Datategy, access: March 23, 2025, https://www.dacategy.net/2024/01/03/how-can-ai-revolutionize-risk-management-in-oil-gas/

75. AI in energy and utilities: Transforming safety and efficiency - Cohere, accessed: March 23, 2025, https://cohere.com/blog/ai-in-oil-and-gas

76. AI-Powered Analytics vs. Traditional Data Analysis: Which Is Better for Consultancy Firms, access: March 23, 2025, https://infomineo.com/blog/ai-powered-analytics-vs-traditional-data-analysis-which-is-b better-for-consultancy-firms/

77. Computational host range prediction—The good, the bad, and the ugly - Oxford Academic, access: March 23, 2025, https://academic.oup.com/ve/article/10/1/vead083/7484565

78. Benchmarking reveals superiority of deep learning variant callers on bacterial nanopore sequence data - eLife, access: March 23, 2025, https://elifesciences.org/reviewed-preprints/98300

79. Optimized Method for Bacterial Nucleic Acid Extraction from Positive Blood Culture Broth for Whole-Genome Sequencing, Resistance Phenotype Prediction, and Downstream Molecular Applications - PubMed, accessed: March 23, 2025, https://pubmed.ncbi.nlm.nih.gov/36314799/

80. Water cut/salt content forecasting in oil wells using a novel data-driven approach, access: March 27, 2025, https://ogst.ifpenergiesnouvelles.fr/articles/ogst/full_html/2019/01/ogst180289/ogst1 80289.html

81. Leveraging AI for Forecasting in the Oil and Gas Industry - Numalis, accessed: March 27, 2025, https://numalis.com/leveraging-ai-for-forecasting-in-the-oil-and-gas-industry/

82. AI in Oil and Gas: Benefit and Use Cases - Apptunix, accessed: March 27, 2025, https://www.apptunix.com/blog/artificial-intelligence-in-oil-and-gas-benefit-and-use-cas is/

83. The Role of Artificial Intelligence in Optimizing Well Stimulation Techniques - Esimtech, access: March 27, 2025,

https://www.esimtech.com/the-role-of-artificial-intelligence-in-optimizing-well-stimulation-techniques.html

84. Bridging the Big Data Analytics Gap in the Oil & Gas Industry - EnterBridge, access: March 27, 2025, https://www.enterbridge.com/blog/big-data-analytics-gap-in-the-oil-gas-industry 85. Maximizing the impact of AI in the oil and gas sector | EY - US, accessed: March 27, 2025, https://www.ey.com/en_us/insights/oil-gas/maximizing-the-impact-of-ai-in-the-oil-and-gas-sector

86. The great AI debate in the oil and gas industry: balancing job loss concerns with the thriving potential of AI applications - Kent, accessed: March 27, 2025, https://kentplc.com/news-insights/the-great-ai-debate-in-the-oil-and-gas-industry-balancing-job-loss-concerns-with-the-thriving-potential-of-ai-applications

87. Ai Solutions For Oil And Gas in 2025 - Callin.io, accessed: March 27, 2025, https://callin.io/ai-solutions-for-oil-and-gas/

88. The Future of Oil & Gas Operations: : Integrated & AI-Driven - OPX AI, accessed: March 27, 2025, https://www.opxai.com/the-future-of-oil-gas-operations-integrated-ai-driven/

89. AI in Oil & Gas Recruitment - Summit Technology Services, Inc, accessed: March 27, 2025, https://summit-tsi.com/ai-in-oil-gas-recruitment/

90. AI Is Fueling Innovation in the Oil & Gas Industry - ABI Research, accessed: March 27, 2025, https://www.abiresearch.com/blog/artificial-intelligence-ai-oil-and-gas-industry?hsLang=in

91. Custom AI Solutions for Oil and Gas Development, accessed: March 27, 2025, https://www.signitysolutions.com/ai-solutions-for-oil-and-gas-development

92. We are Digital Problem Solvers in Oil and Gas | Eigen, accessed: March 27, 2025, https://eigen.co/

93. Artifical Intelligence rises in drilling performance - Halliburton, accessed: March 27,

2025, https://www.halliburton.com/en/resources/the-rise-of-artificial-intelligence

94. Customer successes using AI in DELFI | SLB, accessed: March 27, 2025, https://www.slb.com/products-and-services/delivering-digital-at-scale/software/delfi/openness/ai-in-delfi/ai-success-stories

95. Predictive maintenance: Using AI to prevent equipment failures - AVEVA, access: March 30, 2025, https://www.aveva.com/en/perspectives/blog/predictive-maintenance-using-ai-to-prevent-equipment-failures/

96. Data Quality Assessment - Predictive Analytics for Pipeline Operators - Dynamic Risk, accessed March 30, 2025, https://dynamicrisk.net/data-quality-assessment/