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Geosteering Real-Time Geosteering Optimization Using Deep Learning Algorithms Integration of Deep Reinforcement Learning in Real-time Well Trajectory Adjustment to Maximize Reservoir Contact and Productivity

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Abstract

Geosteering is a critical process in directional drilling, aimed at optimizing well trajectories to maximize reservoir contact and productivity. Traditional geosteering techniques often struggle with challenges such as uncertainty in geological formations, real-time decision-making, and the need for constant adjustment of well trajectories. Recent advancements in artificial intelligence (AI), particularly deep learning and deep reinforcement learning (DRL), present promising solutions to these challenges by enabling real-time optimization of drilling operations. This review explores the integration of DRL algorithms into geosteering systems, focusing on their potential to optimize well trajectory adjustments dynamically and autonomously. Deep reinforcement learning, a subset of machine learning, allows for the development of intelligent systems capable of learning from the environment and making decisions based on real-time data inputs. In the context of geosteering, DRL can continuously adjust well trajectories by processing information from downhole sensors, such as measurements while drilling (MWD) and logging while drilling (LWD), as well as seismic and geological data. By utilizing DRL, drilling systems can maximize reservoir contact, minimize non-productive time, and reduce the risk of deviating from target zones. This review also highlights the integration of DRL with other advanced technologies, such as real-time sensor networks and automated control systems, for seamless operation. Through case studies and real-world applications, the review examines the impact of DRL-based geosteering on drilling efficiency, cost reduction, and reservoir performance. Additionally, it addresses the challenges of implementing DRL models, such as the need for high-quality data and computational complexity, and offers insights into future advancements and scalability in the oil and gas industry. The integration of deep reinforcement learning in real-time geosteering represents a significant step toward more efficient, adaptive, and intelligent drilling practices.

Keywords: Geosteering, Deep Learning Algorithms, Reinforcement Learning, Trajectory Adjustment

1. Introduction

Geosteering is a critical process in oil and gas exploration, specifically in the drilling phase of reservoir development (Onita and Ochulor, 2024) [35]. It refers to the practice of adjusting the trajectory of a wellbore in real-time to navigate through subsurface geological formations. The primary objective of geosteering is to maintain the well within the targeted reservoir zone, maximizing production while minimizing drilling risks and costs (Egbumokei *et al*., 2024). In traditional geosteering, decisions about well trajectory adjustments are often based on real-time sensor data and geological models, with human intervention playing a crucial role (Onukwulu *et al*., 2024). However, this approach can be limited by the complexity of geological formations, the variability of subsurface conditions, and the inability to fully process large volumes of data in real-time. As oil and gas companies continue to target increasingly complex reservoirs, optimizing well trajectories has become more critical than ever to ensure economic efficiency and successful reservoir management (Oladipo *et al*., 2023) [34].

Real-time well trajectory optimization plays an essential role in modern geosteering operations. The ability to adjust a well's path based on real-time data enables drillers to respond promptly to changes in geological conditions, thus enhancing the likelihood of staying within the reservoir's productive zone (Basiru *et al*., 2023). Effective optimization minimizes the risks of wellbore instability, reservoir damage, and wasted resources, ensuring that the well is drilled in the most productive manner possible. Given the complexity of subsurface formations, real-time optimization is necessary for achieving better reservoir contact, reducing non-productive time (NPT), and increasing the overall efficiency of drilling operations (Johnson *et al*., 2024).

The integration of artificial intelligence (AI), particularly deep learning and deep reinforcement learning (DRL), offers significant improvements in geosteering capabilities (Weldegeorgis *et al*., 2024) [53]. Deep learning, a subset of machine learning, can recognize complex patterns in large datasets, such as the data obtained from drilling sensors and seismic surveys. DRL, a more advanced form of machine learning, enables autonomous decision-making by training agents to take actions that maximize rewards over time, based on real-time inputs. When applied to geosteering, DRL algorithms have the potential to optimize well trajectory adjustments dynamically by learning from real-time data, geological conditions, and operational constraints. These AI-powered techniques provide higher accuracy, adaptability, and predictive power, overcoming many of the limitations associated with traditional geosteering methods (Onukwulu *et al*., 2024).

The objective of this review is to examine the integration of DRL algorithms in optimizing real-time well trajectories in geosteering. It will explore how deep learning and DRL can be applied to address the challenges of uncertainty and variability in subsurface geology, the need for continuous wellbore adjustments, and the demands for cost efficiency and productivity maximization. Furthermore, this review will assess how these AI techniques can be integrated with existing drilling technologies, sensor networks, and automation systems to create a more efficient, responsive, and intelligent geosteering process. By investigating the potential benefits and challenges of DRL in geosteering optimization, the review will highlight the future prospects of AI in revolutionizing oil and gas exploration practices.

2. Background

Geosteering as a discipline emerged to address the complexities of drilling within targeted reservoir zones (Daramola *et al*., 2023) [7]. Traditionally, directional drilling is employed to steer the wellbore through subsurface formations. However, as reservoirs become more intricate and deeper, drilling precision becomes paramount, and real-time well trajectory adjustments are required to ensure optimal well placement. Conventional geosteering techniques often rely heavily on human expertise, using real-time data from measurement while drilling (MWD) and logging while drilling (LWD) sensors. While these methods are effective, they are limited by the speed of human decision-making and the complexities of real-time geological interpretation (Onita *et al*., 2023).

The advent of AI and machine learning, particularly deep learning, has opened new opportunities for improving geosteering. Machine learning algorithms can quickly process and analyze vast amounts of sensor data, recognizing patterns and predicting optimal well trajectories in real time. DRL, a branch of machine learning, can take this a step further by enabling systems to autonomously adjust the well trajectory, learning from past data and continuously optimizing well placement decisions to maximize productivity. As the oil and gas industry increasingly embraces digitalization and automation, AI-driven geosteering presents an opportunity to reduce operational costs, improve drilling accuracy, and boost the overall efficiency of exploration projects. However, this integration requires overcoming several technical challenges, including data quality, model robustness, and computational demands (Farooq *et al*., 2024). Despite these challenges, the potential benefits of using deep learning and DRL in geosteering are substantial, with the promise of creating more precise, efficient, and autonomous drilling systems.

2.1 Methodology

The PRISMA methodology for the exploration of real-time geosteering optimization through deep learning algorithms, particularly the integration of deep reinforcement learning (DRL) for well trajectory adjustment, follows a structured process to ensure comprehensive evaluation and transparency of findings. This methodology encompasses a systematic approach to identify, select, and assess relevant studies, ultimately synthesizing evidence on how DRL can optimize geosteering operations and enhance reservoir contact and productivity in oil and gas exploration.

The first step involves a comprehensive literature search across multiple electronic databases such as Scopus, IEEE Xplore, and ScienceDirect. This search is designed to capture studies from peer-reviewed journals, conference proceedings, and industry reports published in English within the last decade, focusing on topics related to geosteering, well trajectory optimization, and the application of deep learning and DRL techniques. A set of predefined keywords, such as "geosteering," "real-time well trajectory," "deep reinforcement learning," and "machine learning in drilling," is used to ensure the inclusion of relevant research.

The next phase involves applying inclusion and exclusion criteria to select studies. Relevant articles are those that address the integration of AI or machine learning models, particularly DRL, into real-time geosteering and trajectory optimization. Studies discussing the practical applications, challenges, and case studies of DRL in oil and gas exploration are prioritized. Excluded are studies that do not directly relate to real-time decision-making in geosteering or those that focus on other AI techniques without an emphasis on deep learning or DRL.

Following study selection, data extraction focuses on gathering information such as the type of deep learning or DRL models used, the methodologies employed for real-time trajectory adjustment, key findings on well optimization, and the impact on reservoir contact and productivity. Additionally, relevant data concerning the integration of these models with sensor networks, downhole measurements, and the effectiveness of these algorithms in various geological settings are extracted.

The data synthesis process involves qualitative analysis of the extracted data. This is followed by a thematic synthesis where common themes regarding the effectiveness of DRL in geosteering optimization, the operational improvements, and the challenges faced during implementation are identified. The findings are grouped based on factors like model performance, computational efficiency, and real-time adaptability to various subsurface conditions.

Throughout the process, risk of bias is assessed by evaluating the methodological quality of the included studies. Potential sources of bias, such as the small sample size of case studies or overfitting in AI models, are considered and discussed. This ensures that the findings are robust and reliable, contributing to a clearer understanding of the role and future potential of DRL in real-time geosteering optimization.

Finally, the methodology includes a discussion of the limitations of the current body of literature, such as gaps in data availability, the need for more extensive field trials, and the challenges associated with computational complexity and integration with existing drilling technologies. These limitations are considered in the context of future research directions, ensuring that the findings are presented with an eye toward further innovation in AI-driven geosteering solutions.

2.2 Geosteering and its Challenges

Geosteering refers to the process of adjusting the trajectory of a wellbore in real-time during the drilling process to optimize its placement within a targeted subsurface reservoir. This technique is crucial in ensuring the well remains within the productive zones of a reservoir, where hydrocarbons are most concentrated (Johnson *et al*., 2024). By adjusting the well's trajectory, geosteering helps enhance reservoir contact, minimize drilling risks, and maximize the overall productivity of oil and gas operations. The primary goal of geosteering is to drill a well that maximizes recovery while minimizing costs and non-productive time (NPT).

However, geosteering faces numerous challenges, particularly in real-time well trajectory adjustment. The complexities of subsurface conditions often introduce significant uncertainties, making accurate well placement difficult. Reservoir heterogeneity, with variations in rock type, porosity, and permeability, can affect the migration of hydrocarbons, making it harder to predict the best path for the well (Ekemezie and Digitemie, 2024). Moreover, geological anomalies, such as fault lines, fractures, and unexpected fluid movement, may result in wellbore instability, leading to costly operational delays and potential well failures. Wellbore stability is a critical concern, as improper trajectory adjustments can lead to the loss of drilling equipment or reduced well productivity. Therefore, ensuring cost efficiency and accurate decision-making during geosteering requires addressing these uncertainties and managing complex geological conditions in real-time (Onukwulu *et al*., 2022).

Historically, geosteering relied heavily on manual processes and operator expertise. Conventional approaches involved real-time data acquisition through tools such as measurement-while-drilling (MWD) and logging-while-drilling (LWD) sensors. Operators would interpret this data and manually adjust the well trajectory based on their knowledge of the formation and expected subsurface behavior. Additionally, pre-programmed models were often used to predict the well's path, guiding drilling engineers to adjust the trajectory based on geological interpretations and predetermined assumptions about the reservoir's characteristics. While these conventional techniques have been effective to some extent, they present several limitations. One of the major drawbacks is the reliance on human decision-making, which can introduce subjectivity, errors, and delays, especially when faced with complex or rapidly changing conditions (Fredson *et al*., 2021) [23]. The accuracy of well trajectory adjustments is often limited by the operator's ability to process large amounts of real-time data and make decisions quickly. Additionally, traditional models often lack the flexibility needed to adapt to unpredictable subsurface conditions. This results in suboptimal well placement, leading to reduced reservoir contact and potentially missed opportunities for higher production. Furthermore, manual geosteering approaches can be costly due to the time and labor-intensive processes involved, especially when adjustments need to be made frequently to respond to unforeseen challenges.

The limitations of traditional geosteering techniques have led to the increasing adoption of artificial intelligence (AI) and machine learning (ML) in oil and gas operations. AI refers to the use of algorithms and computational models that simulate human intelligence to perform tasks such as problem-solving, decision-making, and pattern recognition. Deep learning, a subset of machine learning, is particularly well-suited for geosteering applications due to its ability to analyze complex datasets and identify non-linear relationships in the data. Machine learning has a rich history in the oil and gas industry, particularly in seismic data processing, reservoir modeling, and predictive maintenance (Johnson *et al*., 2024). Over the past two decades, advancements in ML have significantly improved decision-making processes in drilling operations. Machine learning algorithms, such as neural networks, decision trees, and support vector machines, are capable of processing vast amounts of real-time data from MWD and LWD sensors, allowing for more accurate and timely well trajectory adjustments. These models are trained on historical drilling data, enabling them to predict optimal well paths by recognizing patterns in geological formations and well performance.

In geosteering, the integration of deep learning algorithms offers several advantages over traditional techniques. Deep neural networks can automatically learn complex relationships in large, high-dimensional datasets, allowing for real-time, data-driven decision-making. This ability to adapt to new, unseen geological conditions in real-time enhances the accuracy and reliability of well trajectory adjustments. Furthermore, AI models can continuously improve by learning from new data, which makes them more adaptable to changing reservoir conditions compared to static, pre-programmed models (Onukwulu *et al*., 2021).

As AI technology has evolved, deep reinforcement learning (DRL) has emerged as a promising tool for real-time well trajectory optimization. DRL algorithms allow systems to autonomously adjust well paths by learning optimal decision-making strategies over time through trial and error, guided by a reward system that maximizes reservoir contact and productivity. DRL's ability to make continuous adjustments based on real-time feedback has the potential to revolutionize geosteering, enabling more accurate and efficient well placement, reducing human error, and improving overall drilling performance. The adoption of AI and deep learning techniques represents a significant advancement in geosteering. These technologies provide a more reliable, efficient, and accurate approach to well trajectory optimization, offering solutions to many of the challenges faced in traditional geosteering practices. As AI continues to evolve, it is poised to reshape the landscape of oil and gas exploration, enabling more precise, cost-effective, and sustainable drilling operations.

2.3 Deep Reinforcement Learning (DRL) in Geosteering

Deep Reinforcement Learning (DRL) is an advanced subset of machine learning that combines reinforcement learning (RL) with deep learning techniques to address complex decision-making problems in dynamic environments (Basiru *et al*., 2023). The fundamental principles of DRL revolve around the interaction between an "agent" and its "environment." The agent is tasked with taking actions that will maximize cumulative rewards over time, based on feedback received from the environment.

In a DRL setup, the environment represents the system or problem domain in which the agent operates. The agent perceives the state of the environment, which includes information about the system at a given time, and then takes an action that influences the environment. After taking an action, the agent receives a "reward," which serves as feedback that guides future decision-making. The objective is for the agent to learn a policy that maps states to actions in a way that maximizes the long-term reward. Key DRL algorithms include Q-learning, Deep Q-Networks (DQN), and policy gradient methods. Q-learning is one of the foundational RL algorithms that estimates the optimal action-value function (Q-function) to determine the best actions to take in a given state. DQNs extend Q-learning by leveraging deep neural networks to approximate the Q-function, allowing it to handle high-dimensional state spaces, such as those encountered in real-time geosteering. Policy gradient methods, on the other hand, directly optimize the policy by updating the parameters of a neural network, allowing the agent to continuously refine its actions based on the reward signals it receives (Johnson *et al*., 2024).

Geosteering is the process of adjusting the trajectory of a wellbore in real-time to optimize reservoir contact, and the application of DRL in this context presents a significant advancement over traditional methods. In conventional geosteering, operators manually adjust the well path based on real-time data, such as measurement-while-drilling (MWD) and logging-while-drilling (LWD) sensors. However, these decisions are often constrained by human interpretation and can be slow or inaccurate. DRL can simulate and optimize well trajectory adjustments by treating the geosteering process as a sequential decision-making problem. In this context, the agent (drilling system) makes decisions about adjusting the well path, based on the state of the environment, which includes the geological data, well parameters, and feedback from the drilling operation (Basiru *et al*., 2023). By continuously receiving real-time data and rewards based on the success of the well trajectory (such as improved reservoir contact and productivity), the DRL agent learns to optimize the well's path in a dynamic and adaptive manner. Training DRL models for geosteering involves using large datasets that include geological characteristics, such as rock type, porosity, permeability, and fault structures, along with real-time well data, including pressure, temperature, and drilling rates. The model is trained to predict optimal trajectory adjustments that maximize reservoir contact, taking into account factors such as wellbore stability, operational constraints, and geological uncertainties. The training process involves running simulations or using real-world drilling data, where the model iteratively improves its decision-making capability by adjusting well parameters based on the rewards (or penalties) associated with the outcome of its actions.

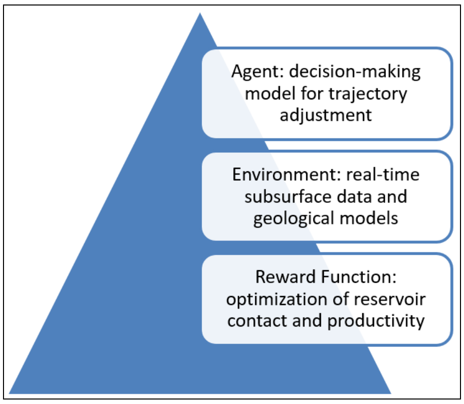

Fig 1: Components of DRL in geosteering

The integration of DRL in geosteering offers several significant benefits for real-time well trajectory optimization. First, DRL enables dynamic and adaptive decision-making. Unlike traditional methods, where well trajectory adjustments are based on predefined models or human intervention, DRL agents continuously learn from real-time data and adjust their decisions in response to changes in the geological environment (Onukwulu *et al*., 2023). This allows for more flexible and accurate well placement, even in the face of unpredictable subsurface conditions. Second, DRL enhances the ability to maximize reservoir contact and well productivity. By optimizing the trajectory of the well in real-time, DRL models can ensure that the wellbore stays within the most productive zones of the reservoir, thereby improving hydrocarbon recovery rates. The agent's continual learning process allows it to navigate complex formations more effectively, ensuring better reservoir management. Finally, DRL can help reduce operational costs and non-productive time (NPT). With the ability to make more accurate and timely decisions, DRL agents minimize the need for costly corrective measures that often arise from inaccurate well placement. Additionally, by improving wellbore stability and reducing the number of unnecessary adjustments, DRL can streamline drilling operations, ultimately leading to cost savings and improved operational efficiency (Ekemezie and Digitemie, 2024). The application of DRL in geosteering holds great promise for optimizing real-time well trajectory adjustments. By integrating deep learning with reinforcement learning, DRL provides a powerful tool for navigating the complex and dynamic environment of oil and gas drilling, maximizing reservoir contact, improving productivity, and reducing costs. As the technology continues to evolve, its potential to revolutionize geosteering and enhance drilling operations is immense (Fredson *et al*., 2022) [24].

2.3 Integration of DRL into Geosteering Systems

Effective geosteering relies heavily on the collection and integration of real-time data from various downhole sensors. Measurement-while-drilling (MWD) and logging-while-drilling (LWD) technologies provide essential information on wellbore parameters such as pressure, temperature, and geological formations. In addition to these sensors, seismic surveys and other advanced monitoring techniques allow for the continuous gathering of data on subsurface conditions (Basiru *et al*., 2022) [4]. This comprehensive data collection enables a more accurate and dynamic understanding of the reservoir's properties and behavior, crucial for optimizing wellbore placement and trajectory. For Deep Reinforcement Learning (DRL) systems to be effective, they must incorporate real-time feedback from these sensors to continuously adapt and improve their decision-making processes. By feeding real-time data into DRL models, the system is able to adjust the well trajectory on an ongoing basis, responding to changing reservoir conditions. This integration facilitates an autonomous and adaptive control system that ensures the most efficient drilling path is maintained (Onukwulu *et al*., 2024; Egbumokei *et al*., 2024). Continuous learning from real-time data also allows the DRL model to refine its predictions and improve accuracy, reducing the need for human intervention and mitigating risks associated with poorly optimized drilling paths.

Training DRL models for geosteering requires creating a robust and representative environment that mimics real-world conditions. This is typically done by leveraging historical drilling data combined with simulated reservoir models. Historical data offers valuable insights into previous drilling operations, well trajectory adjustments, and the corresponding outcomes in terms of productivity and reservoir contact (Onukwulu *et al*., 2022). These real-world examples serve as the foundation for training the DRL model, which learns to make optimal decisions based on the patterns and relationships found in the data. Simulated reservoir models, which replicate the complex subsurface environment, play a critical role in ensuring the DRL model's accuracy and generalization. These models allow for testing and refining the DRL system under a variety of conditions without the need for costly and time-consuming real-world experimentation. However, the challenge lies in ensuring that the model is robust and can generalize effectively to real-world situations. This involves validating the model against diverse geological scenarios and ensuring it remains adaptable when facing new, previously unseen reservoir conditions. Model validation is crucial to guarantee the reliability of DRL-based decision-making systems in operational settings, particularly given the uncertainty and variability inherent in subsurface environments (Egbumokei *et al*., 2024; Onukwulu *et al*., 2024).

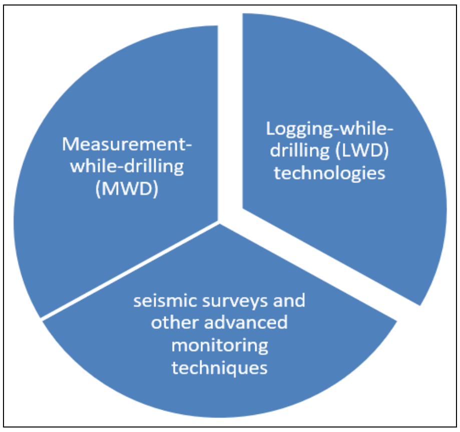

Fig 2: Downhole sensors of integration of DRL into geosteering systems

Integrating DRL into existing geosteering platforms for real-time decision-making is a transformative approach to optimizing well trajectory adjustments. Once the DRL model is trained and validated, it can be incorporated into the geosteering system to automatically adjust the well path during drilling operations (Egbumokei *et al*., 2024). This real-time integration involves continuously feeding updated sensor data into the DRL model, which then processes the data and makes adjustments to the well trajectory in real-time (Johnson *et al*., 2024). Automated control systems are critical for implementing DRL recommendations during the drilling process. These systems receive the DRL model's recommendations, such as changes in the well's direction or depth, and execute them automatically. This real-time feedback loop allows for immediate adjustments to be made, ensuring that the well remains on the optimal path based on dynamic subsurface conditions (Ekemezie and Digitemie, 2024). In addition to improving accuracy, this integration reduces human error and operational delays associated with manual adjustments, leading to more efficient and cost-effective drilling operations. Moreover, real-time application of DRL systems enables faster adaptation to unforeseen challenges, such as encountering fault zones, porosity changes, or pressure anomalies. The ability to continuously optimize well trajectories in response to these challenges ensures better reservoir contact, maximizes hydrocarbon recovery, and enhances overall operational efficiency. As a result, automated DRL systems significantly improve decision-making, reduce non-productive time (NPT), and lower operational costs. Integrating DRL into geosteering systems marks a significant advancement in drilling technology. By incorporating real-time sensor data, simulating geological conditions for training, and enabling automated well trajectory adjustments, DRL offers a more adaptive, efficient, and accurate approach to geosteering. As the technology continues to mature, the potential for enhancing the accuracy and productivity of oil and gas operations will only grow, reducing risks and improving overall drilling performance.

2.4 Case Studies and Applications

Deep Reinforcement Learning (DRL) has gained significant attention for its potential to optimize geosteering and well trajectory adjustments in real-time. Several real-world examples demonstrate its successful application in the oil and gas industry, particularly in maximizing reservoir contact, improving drilling efficiency, and reducing operational risks (Johnson *et al*., 2024). One notable case study involves the integration of DRL models in the geosteering operations of a major offshore oil field. By using a combination of seismic data, downhole measurements, and historical drilling information, the DRL system was able to continuously adjust well trajectories to maintain optimal reservoir contact. This dynamic decision-making process resulted in significant improvements in the field's productivity, with increased hydrocarbon recovery rates compared to traditional geosteering methods. Furthermore, the model's real-time optimization capabilities allowed for faster reaction to unexpected geological challenges, such as encountering faults or rapid pressure changes, thereby reducing the frequency of costly re-drilling and non-productive time (NPT).

Another successful implementation occurred in a shale gas field, where DRL algorithms were applied to optimize horizontal drilling paths in complex geological formations (Onukwulu *et al*., 2024). The DRL system, after training on a combination of wellbore data and geological simulations, provided real-time trajectory adjustments based on continuous sensor feedback. As a result, the operation experienced a marked reduction in drilling time and associated costs, while improving the overall well productivity. The key performance improvement in this case was the ability to consistently drill closer to the target reservoir zone, enhancing both well placement and production rates (Onukwulu *et al*., 2021; Digitemie and Ekemezie, 2024). These case studies exemplify the potential of DRL to improve reservoir contact and drilling efficiency while mitigating risks, such as wellbore instability and equipment failure, that often arise in conventional geosteering techniques.

Despite its promising applications, the implementation of DRL in geosteering is not without its challenges (Onita *et al*., 2023). One major difficulty lies in the quality and completeness of the data required to train DRL models effectively. For DRL systems to function optimally, they rely on high-quality real-time data from various sensors, such as MWD, LWD, and seismic surveys. However, in practice, data acquisition can be hindered by sensor malfunctions, limited data coverage, or inconsistent measurements. This leads to incomplete or noisy datasets, which can adversely affect the model's ability to learn and make accurate decisions. Ensuring the availability of reliable, high-quality data is therefore crucial for the success of DRL in geosteering applications (Onukwulu *et al*., 2021). Another challenge encountered during DRL integration is the computational complexity involved in processing large datasets and making real-time trajectory adjustments. DRL models require substantial computational power to process the input data, simulate possible outcomes, and adjust well trajectories accordingly. This can lead to delays in decision-making, especially when operating in deep or offshore wells where communication latency and computational resources are limited. Overcoming these challenges requires the development of more efficient algorithms and hardware, capable of processing complex data faster and with greater accuracy. Furthermore, while DRL has shown promise in enhancing geosteering operations, lessons learned from initial trial applications indicate that integration with existing geosteering systems can be complex. Many traditional systems were not designed to accommodate real-time machine learning-based decisions. Consequently, engineers have had to work closely with data scientists to ensure smooth integration and data flow between the DRL model and the geosteering platform (Farooq *et al*., 2024). This collaboration has revealed the importance of robust, flexible systems that can easily integrate machine learning techniques and adapt to changes in operational requirements.

Despite the early successes, there remain several areas for improvement in the integration of DRL for geosteering (Johnson *et al*., 2024). One significant area is the need for enhanced model robustness to deal with the unpredictability of subsurface conditions. DRL models should be designed to handle the inherent uncertainties in the geological environment, such as unexpected faults, porosity changes, or pressure anomalies, which can significantly affect the drilling process. Additionally, further research is needed to improve the generalization of DRL models across diverse geological settings, ensuring that they are adaptable and resilient to a wide range of subsurface conditions (Eyo-Udo *et al*., 2024) [20]. Moreover, as DRL systems become more widespread, there is a growing need for standardized protocols and regulatory guidelines to ensure safety and operational efficiency. Implementing clear standards for data collection, system integration, and model validation will be crucial to driving broader adoption of DRL-based geosteering solutions. While the successful implementation of DRL in geosteering has led to notable improvements in reservoir contact, drilling efficiency, and risk reduction, challenges related to data quality, computational complexity, and system integration remain. By addressing these issues and refining DRL models, the oil and gas industry can further harness the potential of machine learning to optimize well trajectories and enhance the overall efficiency of drilling operations (Basiru *et al*., 2023).

2.5 Future Directions and Research

The field of Deep Reinforcement Learning (DRL) has made significant strides in optimizing real-time well trajectory adjustments, particularly in geosteering applications. However, there is still ample room for improvements and innovations that could elevate the effectiveness of DRL models in complex drilling environments. One promising area of advancement is the application of transfer learning in DRL for geosteering. Transfer learning involves training models on one domain and then transferring the learned knowledge to a different but related domain. This approach could significantly reduce the amount of data required to train models for different reservoir types or geological conditions, improving efficiency and minimizing the need for extensive retraining (Onukwulu *et al*., 2024).

Additionally, the use of multi-agent systems is an emerging avenue of research that can enhance DRL in geosteering. Multi-agent systems involve multiple independent agents, each with its decision-making model, which can interact and collaborate to optimize drilling operations. This concept is particularly beneficial in complex reservoirs where multiple wells are drilled simultaneously, and interactions between well trajectories must be carefully managed (Onukwulu *et al*., 2021). By incorporating multi-agent DRL models, drilling systems could optimize trajectories not only in individual wells but also across a network of wells to ensure maximum reservoir contact and efficiency. This type of approach could allow for a more collaborative decision-making process between wells, potentially increasing the overall productivity of a drilling operation.

Moreover, integrating more complex geological and environmental factors into DRL models is essential for advancing the capabilities of geosteering (Anaba *et al*., 2023) [1]. Current DRL models primarily focus on wellbore stability and trajectory optimization but often fail to incorporate deeper geological nuances, such as fault lines, reservoir heterogeneity, and subsurface pressure variations. Including these factors could lead to more robust and accurate trajectory predictions, reducing the risk of wellbore instability and improving reservoir access (Digitemie and Ekemezie, 2024). These improvements would be crucial for operating in more challenging and unpredictable environments, such as deepwater or unconventional resources.

As DRL-based geosteering systems continue to demonstrate their potential in pilot projects, a significant challenge will be scaling these technologies for widespread industrial use (Johnson *et al*., 2024). While DRL has shown success in small-scale operations, applying these models to large-scale drilling projects will require additional research into system efficiency, computational speed, and real-time decision-making capabilities (Egbumokei *et al*., 2024). Scaling DRL-based geosteering systems will demand faster processing of larger datasets, robust integration with existing drilling infrastructure, and seamless collaboration between machine learning models and engineering teams (Onukwulu *et al*., 2023). One of the critical issues in scaling DRL models is commercial viability. While these models show great promise in improving drilling efficiency, their widespread adoption in the oil and gas industry depends on their cost-effectiveness. To transition from experimental setups to mainstream commercial applications, DRL-based geosteering systems must prove that they can deliver substantial operational savings, reduce non-productive time, and improve overall drilling performance. For this to happen, significant investment in technology infrastructure will be needed, alongside strategic partnerships between machine learning developers, drilling contractors, and oil and gas operators. A successful commercialization strategy will also need to address challenges such as workforce training, system integration, and long-term maintenance.

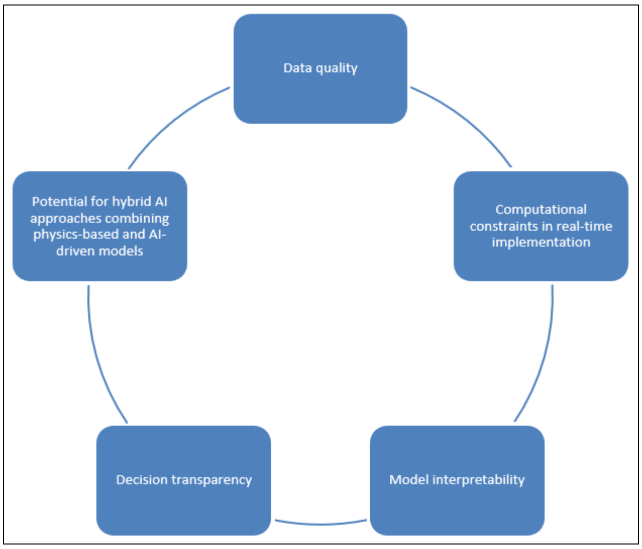

Fig 3: Challenges of integration of deep reinforcement learning

The future of DRL in geosteering lies in its integration with other advanced technologies. One promising direction is the combination of DRL with real-time seismic imaging to provide more comprehensive and accurate subsurface data (Uchendu *et al*., 2024) [52]. Seismic data plays a crucial role in understanding the geological environment, but traditional seismic surveys are limited by their time-lag and resolution. By integrating real-time seismic imaging with DRL, geosteering systems could have access to updated and precise subsurface models, allowing them to adjust well trajectories with a higher degree of accuracy (Iriogbe *et al*., 2024) [25]. Another key technology that could significantly enhance DRL-based geosteering is Internet of Things (IoT) sensors. These sensors collect real-time data on wellbore conditions, pressure, temperature, and other environmental factors. When combined with DRL models, IoT sensors could provide a continuous feedback loop that allows the system to adjust drilling decisions in real-time based on up-to-the-minute information. Moreover, cloud computing can be used to handle the large computational load required by DRL models, enabling faster data processing, storage, and model training. Cloud-based platforms can also enhance collaboration among various stakeholders, providing a centralized location for monitoring, optimization, and decision support. The integration of DRL into geosteering systems holds enormous potential for improving well trajectory optimization and maximizing reservoir productivity. The future of DRL in this field will likely involve advancements such as transfer learning, multi-agent systems, and the incorporation of more complex geological factors (Digitemie and Ekemezie, 2024). Scaling DRL for large-scale applications and ensuring its commercial viability will require significant research, while the collaboration with other cutting-edge technologies like real-time seismic imaging, IoT, and cloud computing will unlock new capabilities for intelligent decision-making. As the technology matures, the oil and gas industry are poised to benefit from smarter, more efficient, and cost-effective geosteering operations (Egbumokei *et al*., 2024).

3. Conclusion

In summary, Deep Reinforcement Learning (DRL) has emerged as a transformative tool in optimizing well trajectory and maximizing reservoir productivity in geosteering. Through its dynamic and adaptive decision-making capabilities, DRL allows for real-time adjustments to well trajectories, improving reservoir contact and ensuring more efficient drilling. By continuously learning from real-time feedback, DRL-based systems have the potential to overcome many of the challenges associated with traditional geosteering methods, such as wellbore instability, reservoir uncertainties, and limited adaptability. The integration of DRL into geosteering operations promises to enhance productivity, reduce non-productive time, and lower operational costs, marking a significant advancement in the field.

The future impact of AI-powered geosteering in the oil and gas industry is profound. As DRL systems evolve, they will increasingly influence large-scale drilling operations by offering more precise, data-driven decision-making. These systems will likely become central to next-generation drilling platforms, where automation and machine learning models work in concert to optimize not only individual wells but entire drilling campaigns. The potential for improving efficiency and reducing risks will be critical as the industry seeks to access more challenging resources, such as deepwater and unconventional reservoirs. Furthermore, the ability to predict and adapt to subsurface conditions in real-time will make drilling operations safer and more sustainable.

Final thoughts on the continued evolution of real-time optimization techniques in the energy sector highlight an exciting future ahead. As AI, machine learning, and other advanced technologies continue to advance, the oil and gas industry will experience a shift towards increasingly automated and data-driven operations. The integration of DRL into geosteering is just one example of how technology is reshaping the energy sector, offering unprecedented levels of efficiency and operational control. The continued development and refinement of these techniques will pave the way for smarter, more sustainable, and cost-effective energy exploration and production.

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