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Redefining offset well analysis and knowledge capture using artificial intelligence techniques

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Abstract

Throughout the wellbore construction process vast amounts of data are generated and stored from various sources in efforts to improve operational efficiency, support informed decision-making and assist to control costs. Data types span across numerous silos such as geological, mechanical, well design and fluid properties. The amount of data can be overwhelming, with thorough analysis being a time intensive endeavor.

As part of asset appraisal and planning, the identification of relevant offset wells is paramount to informed development and service design. Within the wellbore construction fluids design of service, the identification of offset wells is of paramount importance, helping to identify operational risks, past lessons learned and best practice.

Considering the amount of data that is stored during a drilling operation, the multiple offset criteria and number of wells drilled, the identification of offset wells alone can be a time-consuming challenge.

Recent advances in embedding models, vector databases, computational efficiency and new ways to connect older technologies with new machine learning techniques, opens new avenues to work and process complex oil & gas data for efficient search. This allows the new offset well analysis tool to access offset wells based on user defined criteria and weight the relevance of the search beyond simple longitude and latitude distance. Today, searches can be conducted based on fluid criteria, well shape or design, bottom hole assembly design search criteria along with all the other parameters. The criteria for search engines can be utilized as singular search or plural depending on engineering design of the well requirements and combined using user-defined importance system.

Introduction

Historically, the identification and subsequent analysis of offset wells have primarily relied on the proximity between the planned well and existing surrounding wells. Selveindran et al., 2020 described this process, of utilizing drilling and exploration experience in a particular location to design and plan new wells. These traditional methods were guided by the collective expertise and knowledge of involved parties, who would assess similarity profiles based on geographic distance. While effective for many years, this approach exhibited notable limitations. For example, personnel often had to reach out to colleagues working on wells in adjacent states simply because they had heard of challenges or techniques that could inform current operations. Such anecdotal exchanges were necessary to supplement the data available, highlighting the shortcomings of proximity-based selection alone.

When offset well information is properly identified, classified, and incorporated into decision-making, it becomes a critical resource. This data can enhance operational safety, boost performance, reduce costs, and improve environmental outcomes. The true value of offset well data is realized only when it is comprehensively managed and systematically integrated into the analysis process.

The use of digital data and artificial intelligence in offset well analysis is not a new concept. Mikhail et al., 2015 discusses the vital importance of offset analysis as part of the well delivery process on the Norwegian Continental Shelf and the vastness of the data collected both in the public and private domain. The paper also goes on to outline the potential use of Artificial Neural Networks and cognitive systems in offset well analysis along with the requirement to search using natural language. It not only highlights how the use of such technologies would reduce time taken to get results but also provides more accurate input for planning. Today we find ourselves with widely available technology that can be utilized for such purposes.

Large efforts have been made in recent years to digitize business workflows. This has changed the way we have stored our data and developed tools that connect siloed data stores that allow us to leverage the latest developments in Artificial Intelligence and Data Science.

Advancements in Offset Well Analysis

The proposed methodology for offset well analysis moves beyond traditional latitude and longitude criteria. The new approach considers a broader set of well attributes, by leveraging advancements in data processing, matching, and vectorization. Enhanced data aggregation is achieved through the integration of sophisticated artificial intelligence technologies throughout the stages of data handling and extraction. This system employs a weighting mechanism - referred to as user importance metrics - where users assign different importance levels (weights) to various factors such as well design, fluid systems and parameters, and geographic distance. The algorithm then identifies the offset wells that best aligns with the user-defined criteria.

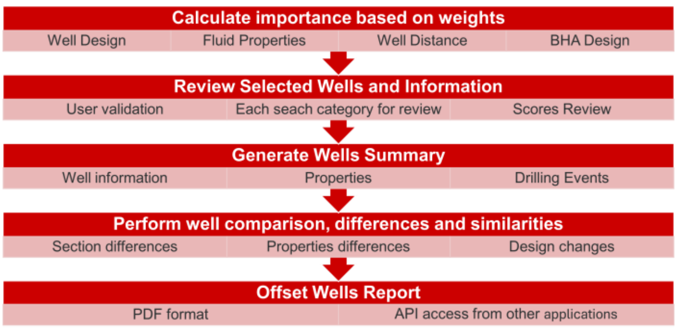

Figure 1 Methodology of the offset well analysis and knowledge capture using artificial intelligence techniques

Weighted Scoring in Offset Well Selection

Evaluation scores within offset well analysis clearly demonstrate how varying weights influence the identification of wells most suited to the specified parameters. For instance, in a simple scenario, the system is directed to locate offset wells using three criteria: drilling fluid, well design, and traditional distance. Each criterion receives a user-assigned weight, reflecting its relative importance in the selection process. This weighted approach provides a transparent breakdown of how each factor contributes to the final identification of suitable offset wells, offering users a tailored and data-driven solution for well planning and analysis.

Complementary to our AI driven, multi criteria ranking, structured historical analysis has been shown to improve design and trajectory planning by correlating inclination/azimuth, mud weight systems, and event history across nearby offsets (Omer et al., 2023).

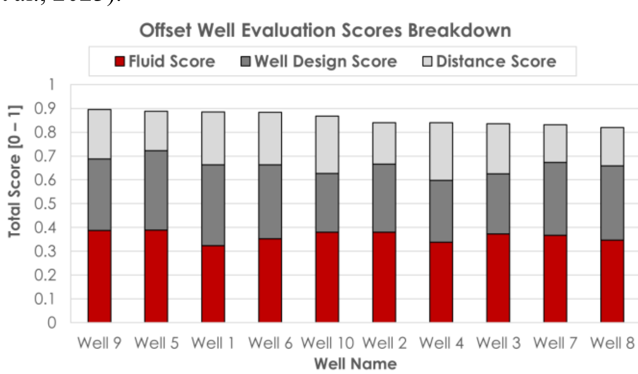

Figure 2 Example of scoring the relevancy of the end of well summary known as recap based on the selected categories.

Accelerated Offset Well Search and AI-Driven Reporting

Efficient Database Search Using Vector Space Encoding

The database search process leverages information encoded in a custom-designed vector space, enabling rapid identification of relevant offset wells in less than five seconds. This speed is achieved through parallel processing of parameters and the use of pre-established scoring systems within the databases. These computational advancements allow for immediate retrieval of wells using their unique IDs, facilitating further data processing and analysis.

In practice, teams that paired offset design attributes (inclination, azimuth) with structured event datasets reported clearer identification of safe mud weight windows and trajectory choices that avoided orientations parallel to weak bedding planes (Omer et al., 2023).

Advanced Computational Techniques for Rapid Analysis

By encoding well attributes - such as design specifications, drilling fluid properties, and geographic data - into a numerical vector space, the system supports swift and precise comparisons. The parallel processing architecture allows multiple search criteria to be evaluated simultaneously, significantly reducing the time needed to review large datasets for suitable offset wells.

Integration with Large Language Models for Reporting

Once the system identifies relevant wells, their database IDs allow for seamless access to detailed records. These records are then processed by large language models (LLMs), which synthesize and summarize technical data into coherent and comprehensive reports. This integration of vector-based search and AI-powered reporting streamlines workflows, making critical information both quickly accessible and effectively communicated for decision-making.

Benefits of Automated Scoring and Ranking

Automating the scoring and ranking of wells according to user-defined criteria minimizes human bias and error, increases consistency, and improves the overall quality of analysis. The modular design of the vector space and scoring systems also allows for straightforward expansion as new attributes and data sources can be added without extensive re-engineering, ensuring adaptability to evolving operational needs.

Comparative Evaluation of AI and Human-Generated Reports

In evaluating reports produced by artificial intelligence systems versus those generated by humans, the analysis focused on key categories: consistency, coherence, fluency, relevance, coverage, and overall performance. Definitions of these categories clarify their roles in assessing report quality. Recent studies show that LLM-generated reports outperform human reports in consistency, coverage, and relevance, providing a more reliable foundation for decision-making (Kowalchuk et al., 2025).

Performance Insights from Data Analysis

Based on an analysis of over 60 different end-of-well reports, AI-generated reports demonstrated significantly higher scores in consistency, relevance, and coverage. These improvements reflect enhanced data retention and knowledge capture for both current and future projects. The superior performance in these areas is attributed to the advanced short-term memory capabilities of LLMs and other AI components, a direct result of their underlying design.

Comparative Evaluation of AI-Generated and Human-Generated Reports

Key Evaluation Categories

In assessing reports produced by artificial intelligence systems versus those generated by humans, the analysis centered on the key evaluation categories mentioned above as per their definitions:

- Coherence – logical flow, structure, ease to follow
- Consistency – alignment with the source document, no contradictions
- Fluency – grammatical correctness, readability
- Relevance – pertinence to the topic, avoidance of tangents
- Coverage – completeness, inclusion of all key points
- Overall – holistic assessment of quality

Each category reflects distinct aspects of report quality and effectiveness, with definitions provided to clarify their roles in the evaluation process.

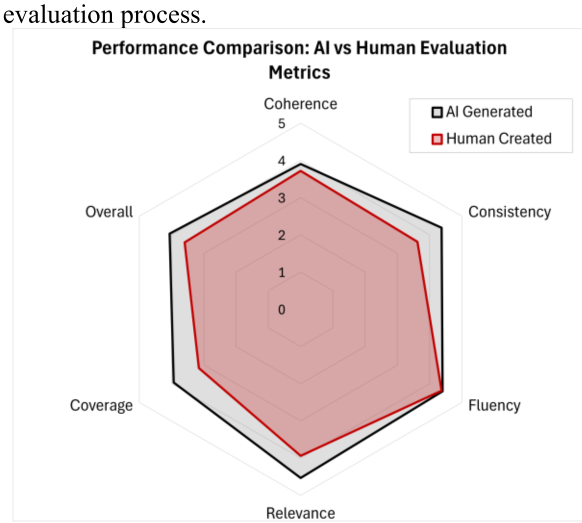

Figure 3 Performance analysis of information summarization between Human and Artificial Intelligence.

Performance Insights from Data Analysis

Data analysis spanning over 60 different end-of-well reports revealed clear advantages in favor of AI-generated reports, particularly in the areas of consistency, relevance, and coverage. These higher scores indicate improved data retention and more effective knowledge capture for both ongoing and future projects.

Superior performance in these categories can be attributed to the architecture of LLMs and other AI components, which possess enhanced short-term memory capabilities compared to humans. This advantage stems from the inherent design of AI systems, allowing them to efficiently process and retain information for report generation.

Importance of Coverage in Report Generation

Coverage - the extent to which information from databases, notes, and various sources is included in the report - is a critical factor. Comprehensive coverage ensures that all necessary details are captured, which is essential for the creation of drilling programs, drilling fluids programs, and other technical documents.

Analysis of data extracted from multiple wells demonstrates that, in general, AI systems are more capable and effective in summarizing information and extracting relevant details. While final decision-making remains the responsibility of trained personnel, AI-generated reports provide a more informative foundation and greater confidence that all pertinent data is incorporated in both reporting and analysis.

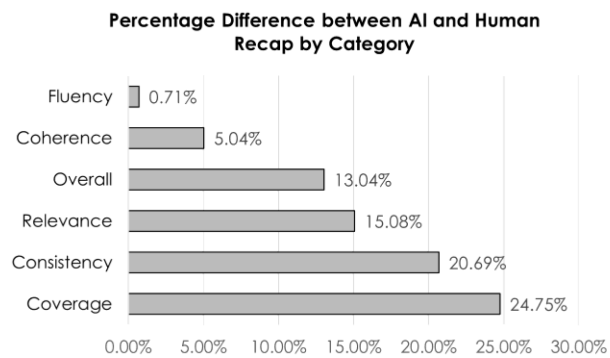

Figure 4 Percentage difference between human and artificial intelligence.

AI System Performance and Industry Impact

Superior Summary Generation and Speed

The general performance of the AI-driven system in generating accurate and comprehensive summaries far surpasses what even experienced subject matter experts (SMEs) can accomplish. One of the most significant advantages is the rapid report generation time: producing a single report typically takes less than 10 seconds. This enables faster response times when making critical decisions and leads to improved overall outcomes, largely due to the superior coverage and consistency of information captured by the AI system.

Consistent Efficiency Across Multiple Wells

As illustrated in Figure 4, the average time required for the AI system to generate a report (indicated in red) remains consistent across different wells, ranging from 4.5 to 10 seconds, with a maximum observed value of 12.5 seconds. The slight variation in generation times correlates with the volume of information to be processed - processing 60 reports naturally takes longer than processing just 10, highlighting the system's efficiency when handling large datasets.

Criteria	AI System	Human SMEs
Average Generation Time per Report	4.5 – 10 seconds (max 12.5s)	30 minutes – several hours
Consistency	High, uniform across datasets	Variable, depends on individual
Coverage of Information	Comprehensive, all sources included	May omit details due to oversight or fatigue
Scalability	Effortlessly processes large datasets	Limited by human capacity
Adaptability	Quickly integrates ne w data sources and criteria	Requires significant retraining or onboarding

Table 1 AI comparison to human subject matter expert for data analysis and report generation.

Scalability and Adaptability

Another notable benefit of this AI system is its rapid scalability: it can easily incorporate new data sources, apply advanced search algorithms, customize search criteria, and leverage prompt engineering techniques to refine output, all with minimal manual intervention. LLM-based workflows have demonstrated rapid scalability and adaptability in offset well analysis, enabling integration of new data sources and criteria with minimal manual intervention (Kowalchuk et al., 2025).

Enhanced Well Selection and Knowledge Management

The system is also engineered to identify the most suitable wells for analysis, with adjustable parameters based on specific user requirements. This represents a significant shift from traditional offset well evaluation methods, which typically prioritizes geographic proximity without always capturing the most relevant or accurate information. Previously, Oil & Gas companies relied on transferring knowledge through personnel rotation to compensate for these limitations. Today, however, the integration of AI allows for the creation of centralized, accessible knowledge hubs, fundamentally changing knowledge management in the industry. This is made possible through advanced artificial intelligence systems, robust encoding, and cutting-edge retrieval techniques, ensuring that decision makers have fast, reliable access to complete and actionable data.

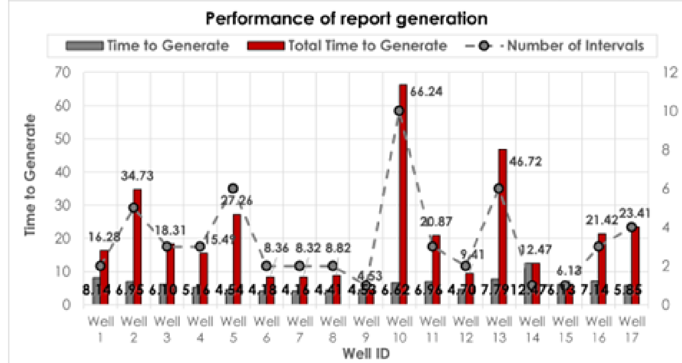

Figure 5 Performance of Artificial Intelligence system to generate summary of the well interval and full well.

Conclusion

The evolution of offset well identification and analysis is a clear reflection of a larger transformation taking place in the oil and gas industry. This transformation is being propelled by the convergence of advanced data management, artificial intelligence, and modern computational methods. In contrast to traditional practices that relied heavily on geographic proximity and anecdotal knowledge, the demands of today's increasingly complex operations require more sophisticated approaches.

Advancements in Methodology

By integrating vector-based search, user-defined weighting systems, and large language model-driven reporting, the methodology presented here marks a significant advancement in both analytical precision and operational efficiency. The system is capable of rapidly processing large volumes of heterogeneous well data, ranking offset wells through transparent and configurable scoring mechanisms, and automatically generating coherent, high-coverage reports. This fundamentally alters the role of digital technologies in well planning workflows.

Comparative Benefits of AI-Generated Reports

Comparative analyses highlight the advantages of these developments: AI-generated summaries consistently surpass human-produced reports in consistency, relevance, and coverage. As a result, decision-makers gain access to a more reliable foundation for making informed choices, while the risk of oversight is substantially reduced.

Scalability, Adaptability, and Knowledge Management

Beyond immediate improvements in time savings and accuracy, the scalability and adaptability of AI-driven systems empower organizations to construct centralized repositories of actionable knowledge. These resources transcend individual experience and personnel movement, enabling teams to identify the most suitable wells for analysis using criteria that are aligned with specific operational objectives, rather than relying solely on traditional distance-based heuristics.

Looking Ahead: A New Paradigm for Well Planning

Ultimately, the integration of artificial intelligence into offset well analysis is more than a simple technological upgrade — it represents a reimagining of how data is captured, interpreted, and applied throughout the well lifecycle. By embracing these advancements, operators can boost decision quality, streamline workflows, mitigate operational risks, and lay the groundwork for more intelligent and adaptive well planning practices in the future.

Nomenclature

AI = Artificial Intelligence
LLM(s) = Large Language Model(s)
SME(s) = Subject Matter Expert(s)

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