



The Future of Wellbore Placement: Advances in Geosteering, Autonomous Drilling, and Real-Time Subsurface Intelligence

Engr. Dr. Ekeinde, Evelyn Bose

Department of Petroleum and Gas Engineering, Federal University Otuoke, Bayelsa State, Nigeria

Correspondence: ekindeee@fuotuoike.edu.ng

ABSTRACT :

Artificial Intelligence (AI), autonomous directional drilling solutions, deep electromagnetic (EM) sensing, and high-speed telemetry are converging in unprecedented ways, revolutionizing the science and art of wellbore placement. This review brings together the current knowledge on geosteering, logging while-drilling (LWD) tools, rotary steerable systems (RSS) and machine learning tools (ML) for reservoir navigation to uncover deficiencies in the research field and highlight these areas that need further investigation. Add stimulus a, then a b, then a c, then a d, and then a e, all the while hoping each one will enable us to better ionize the next group and ten years would pass without such a single, unified, constantly learning decision making framework, where you could have coherently integrated the near-bit petrophysical measurements, ultra deep azimuthal resistivity inversions, geological uncertainty quantification and the real-time autonomous steering into a single operational framework. This review traces the evolution from manual based steering by stratigraphy (SBS) to semi-automated geosteering systems then to fully closed-loop autonomous geosteering systems as simulated in recent operations. The advantages gained from key technologies such as ultra-deep azimuthal resistivity (UDAR) tools (DOI>30m), wired drill pipe telemetry, development of digital twin models and hybrid AI- physics based steering algorithms are embraced and evaluated. There are theoretical and methodological differences between academic research and industry practice that are explored ethical, environmental and geopolitical aspects are included. Alignment with six United Nations Sustainable Development Goals (SDGs 7, 8, 9, 12, 13, and 17) demonstrates the societal urgency of solving outstanding problems in reservoir navigation. The review concludes with a proposed multi-physics data-fusion roadmap for next-generation autonomous wellbore placement systems.

Keywords: wellbore placement; geosteering; rotary steerable systems; logging-while-drilling; ultra-deep azimuthal resistivity; autonomous drilling; machine learning

Introduction

The geometric placement of a wellbore relative to a producing reservoir horizon is arguably the single most consequential decision in the economics of any horizontal or deviated well. A misplacement of only a few feet in a thin, structurally complex pay zone can translate into a productivity differential of tens of thousands of barrels over a well's lifetime. Wellbore placement encompassing the real-time, decision-informed steering of a drill bit to remain within a defined geological target has therefore attracted sustained multidisciplinary investment from geoscience, petroleum engineering, computer science, and automation research communities.

Historically, wellbore placement was achieved through geologically calibrated directional drilling workflows in which a geosteering specialist would correlate Measurements-While-Drilling (MWD) or Logging-While-Drilling (LWD) logs against offset well signatures and pre-drill geological models to infer the wellbore's stratigraphic position (Meehan, 1994, as cited in Brantson et al., 2025). This stratigraphic-based steering (SBS) model has been effective in relatively simple geological situations but, as the name suggests, it is a model that is reactive rather than anticipating structural or fluids changes before the bit. The reactive paradigm not only produces a systematic time lag between deviation and steering correction, but is also extremely expensive in the case of thin targets or structurally complex reservoirs.

This restriction has been met with a conceptualization and a technological solution in three measurable types. The initial phase (roughly 1990-2005) developed a basic sensor suite (gamma ray, resistivity and neutron-density) that could be placed in the bottomhole assembly (BHA) to provide formation analysis data in real time. The second phase (2005-2018) brought in Azimuthal resistivity technologies that have finite depth of investigation, which allowed for detection by proximity to boundary and moved geosteering from the reactive to partially proactive regime. The third, still maturing, phase (2018 - present) relies on the combination of AI/ML algorithms, UDAR (ultra-deep electromagnetic sensing), wired drill pipe (WDP) high bandwidth telemetry and closed loop steering Autonomous systems. This third pillar – represented by the industry's first fully autonomous horizontal well landing, by the LOGIX platform developed by Halliburton (Halliburton, 2024) and the SLB's autonomous geesteering system, Neuro™ (SLB, 2024) has given clear evidence that for the first time, the theoretical maximum for such precision in the wellbore has been reached in field operations.

In spite of the above progress, the published literature shows that there is a critical and un-resolved gap between integration of the complete data pipeline

from near-bit petrophysics and multi-layer inversions from UDAR to stochastic integration of geological uncertainty, and to real-time UAI steering decisions into a continually self-updating, learning operational system. While there are many benefits to dividing and conquering a problem across multiple components (such as adding an ML component to a formation boundary, or using an inversion program to interpret resistivity acquired in a well), academic submissions tend to optimize that specific part and it is non-trivial to implement every part of an application in an academic setting and see how it performs. To fill this latter gap, this review compiles the vast amount of technical literature on the subject and outlines the architectural needs for the next-generation of integrated wellbore placement systems.

The Wellbore Placement Problem

Reservoirs as Dynamic Geological Surfaces

The wellbore placement problem is really a problem in geometry as the geosteerer must navigate a drill bit through the cemented, lithologic, gas-oil contact (GOC), oil-water contact (OWC), and geomechanically hazardous zones and maximize contact with a productive reservoir interval, given a pre-drill model of the subsurface structure. The "sweet spot" or productive interval (PI) is the zone of overhanging rock formations (structural closure) that is filled with reservoir rock (porosity, permeability, and absent is the zone of residual hydrocarbons) and contains fluids suitable for production (hydrocarbon saturation above residual).

The difficulty is that the geological models which can be used in advance of drilling are always incomplete. This positional ambiguity in the target's depth at any lateral location along the planned well path comes from the inability to resolve the structure at depth (typically 3D resolution of seismic is ~10-20 m in depth). This uncertainty is exacerbated by the fact that facies changes, cementation heterogeneity or sub-seismic faulting may make the pre-drill model invalid within meters of entering the bit. Thus, the purpose of real-time LWD measurements here is to continuously improve the local geological model and inform any adjustments to the model for prediction of the trajectory - a closed loop estimation-control problem.

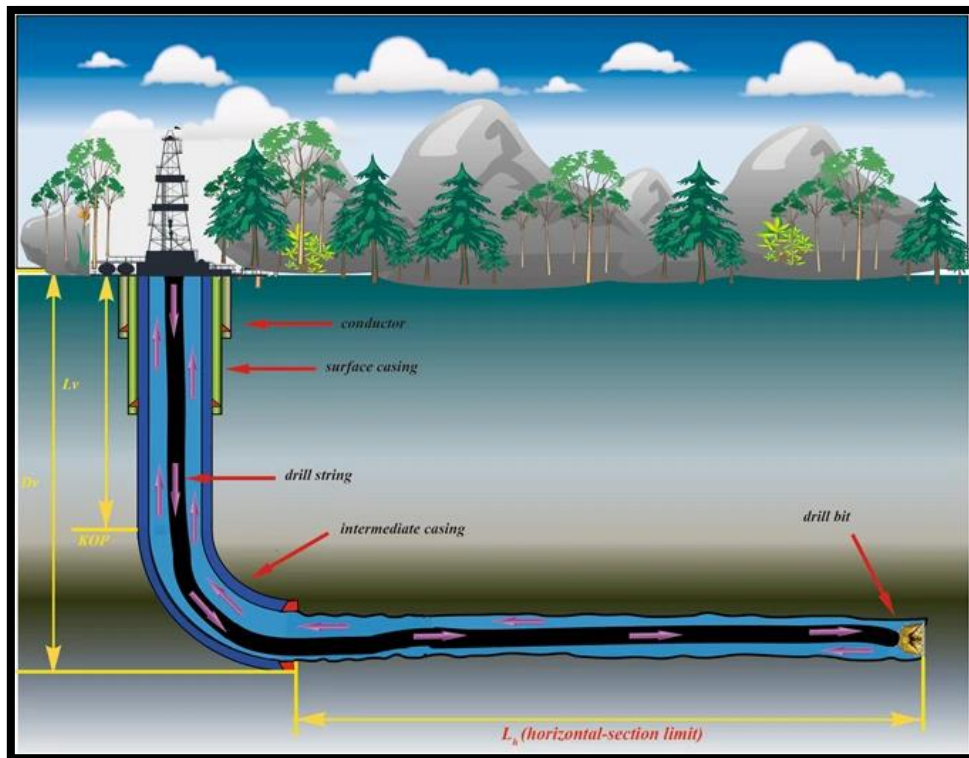


Figure 1. Representative extended-reach horizontal wellbore trajectory is presented; build section, kick-off point (KOP), casing programme (conductor, surface and intermediate casing) and the horizontal section of the well where reservoir contact length (RCL) has been maximised. This geometry follows the objective function vomainashion formulated in the following equation: (1) (Li, Gao, & Chen, 2017)

The objective function to place the wellbore can mathematically be described as the maximization of the Reservoir Contact Length (RCL) with tolerance for significant Tortuosity Index (TI) and weighted by Pay Quality Index (PQI) and directional constraints (Maximum Dogleg Severity, DLS):

$$\text{Maximize: } \int_{RCL} PQI(s) ds - \lambda \cdot TI$$

$$\text{subject to: } DLS(s) \leq DLS_{max} \quad \forall s \quad \dots (Eq. 1)$$

The Steering Lag Problem and Its Consequences

One-dimensional constraint that is fundamental to any downhole directional system is the separation between the sensors set (measuring formation properties) and the bit (actual changing direction). A typical bit-to-sensor offset in conventional LWD/BHA setup is 6 - 25 m and causes a systematic positioning error called steering lag. The geosteerer will only detect the LWD signature of the structural change when the formation top drops down unexpectedly or some defect kicks in and opens up the reservoir which displaces the bit. The correction steering impulse will then have to counteract the momentum of the trajectory which will use more footage than desired to restore the position to the target. However, near-bit sensor systems (such as the Halliburton-based NeoSteer) reduce the offset to only 1-2m, but add added mechanical complexity and lower density of sensors (Akinleye et al., 2024).

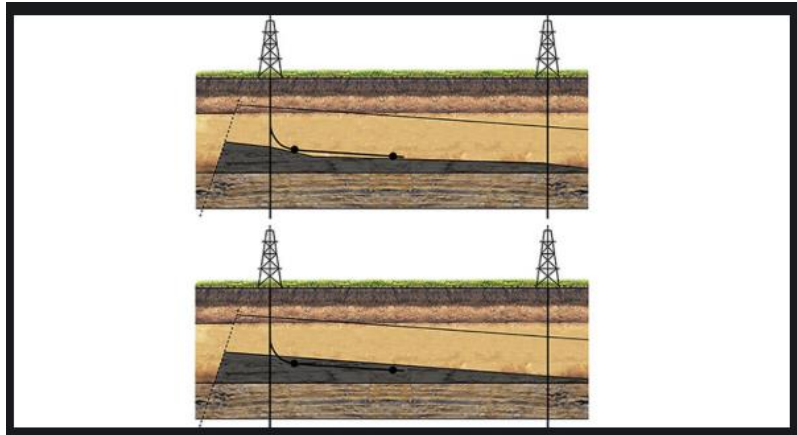


Figure 2. Normalized interpretation of a wellbore trajectory with a wide bit-to-sensor offset (Top) and near-bit sensing (Bottom) which leads to better identification at a closer time to the target edge limits, and to a smaller earlier corrective adjustment in that wellbore, minimizing excursion into off-target formation, the steering-lag effect discussed in this section. (Miszewski, 2026)

Logging-While-Drilling and Measurement-While-Drilling Technologies

Sensor Suite Evolution and Capabilities

LWD tools have gone beyond the simple gamma ray resistivity to become extremely sophisticated multi-physics measurement systems. The “typical” modern LWD (Logging while Drilling) package consists of three subsystems: (1) a gamma-ray sensor for lithologic discrimination and determination of shale volume, (2) a multi-frequency propagation resistivity array for the detection of formation fluids and porosity-resistivity transform relationships, and (3) a compensated neutron-density sensor for porosity estimation and fluid-type discrimination. Each sensor delivers a certain depth of investigation profile of the formation which can then be combined into a cross-sectional view of rock & fluid properties near the wellbore (Akinleye et al., 2024).

Acoustic LWD tools (such as SLB's Sonic Scope) provide added compressional and shear slowness values necessary for geomechanics characterization, including most notably the mechanical earth model (1D MEM) needed for wellbore stability calculation. Nuclear Magnetic Resonance (NMR) LWD tools deliver formation-fluid mobility directly related to completion design in order to make decisions on a per-interval basis regarding amount of perforation and stimulation intensity. In specific BHA configurations, the application of the traditional density-porosity sources is replaced with NMR; this was achieved in some cases in Abu Dhabi, with documented benefit (Sedik et al., 2022) for this very-high-cost environment of lost-in-hole, where radioactive-source risk is a primary concern.

Figure 3. Representative correlation between a lithostratigraphic column and a multi-curve LWD/wireline log suite (gamma ray, resistivity image, and porosity-sensitive curves), of the type used to tie real-time formation measurements to the pre-drill geological framework during LWD-based formation evaluation. (Stueland et al., 2011)

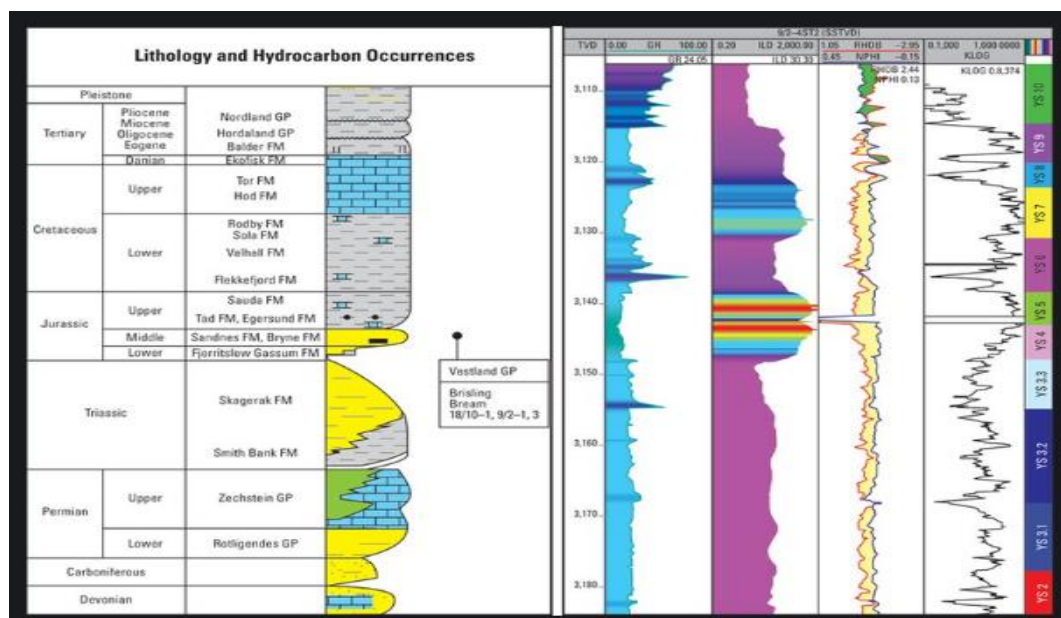


Table 1 provides a structured comparison of major LWD tool categories, their DOI characteristics, primary sensing modalities, and representative commercial systems.

Table 1. Comparative Summary of LWD Tool Categories and Their Key Characteristics in Wellbore Placement Operations

Tool Category	Depth of Investigation	Key Sensors	Primary Application	Real-Time Telemetry	Representative Systems
Conventional LWD	0.1-0.5 m	GR, Resistivity, Neutron-Density	Formation evaluation, litho-correlation	Mud pulse / EM	ARC, VISION (SLB)
Azimuthal Resistivity LWD	5-7 m	Tilted coil arrays, axial T/R	Reactive geosteering, boundary detection	Mud pulse /wired pipe	Peri Scope 15, AziTrak (Halliburton)
Ultra-Deep EM LWD	30-60+ m	Multi-component low-freq. coils	Proactive geosteering, reservoir mapping	Wired drill pipe / high-speed EM	Iri Sphere, Bright Star (Baker Hughes)
Near-Bit LWD/MWD	<0.5 m (at bit)	Near-bit GR, accelerometers, incl./azi.	Real-time bit-position control	Mud pulse	NeoSteer, Neo Mag (Halliburton)
Acoustic/Sonic LWD	0.3-1.0 m	Monopole/dipole acoustic	Geomechanics, formation strength	Mud pulse	Sonic Scope (SLB)

Table 1. LWD tool categories from conventional gamma-ray resistivity to ultra-deep EM systems, with depth-of-investigation ranges, sensor types, and representative commercial systems.

Near-Bit Measurement Systems

The development of near-bit LWD/MWD systems represents one of the most operationally impactful instrumentation advances in recent years. By relocating gamma-ray and inclination-azimuth sensors to positions within 0.5-2 m of the drill bit, near-bit systems effectively eliminate the dominant source of steering lag. The SVM-GWO (Support Vector Machine-Grey Wolf Optimizer) ML model validated with real-world LWD data from the Dora Martin-1H Well in the Eagle Ford Shale demonstrated 84% accuracy in formation classification from near-bit sensor inputs, confirming the viability of ML-enhanced near-bit steering (Brantson et al., 2025). The physical integration of inclinometers, azimuthal gamma-ray sensors, and directional accelerometers directly above the bit, combined with rapid downlink capability, enables the geosteering engineer to observe and respond to formation changes in near-real time a capability that fundamentally alters the economics of thin-bed horizontal drilling.

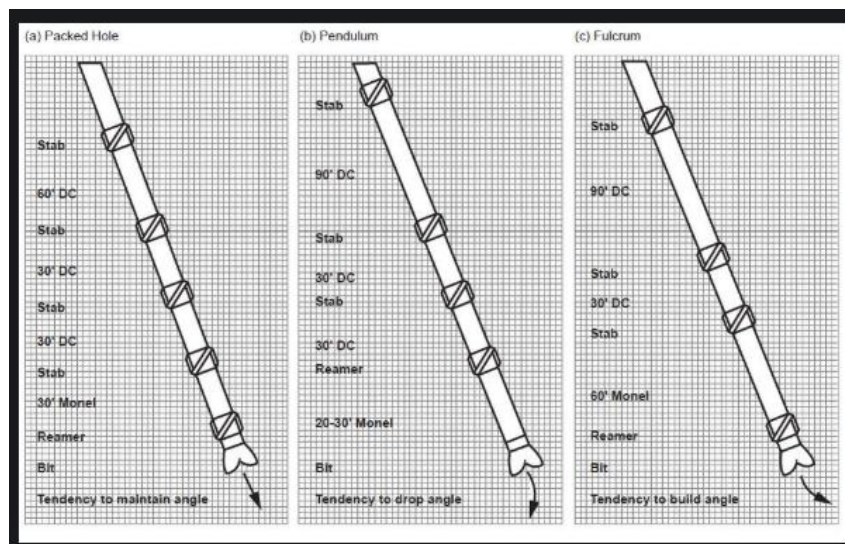


Figure 4. Representative rotary bottom-hole assembly (BHA) configurations used to control wellbore inclination during directional drilling packed-hole (angle-maintaining), pendulum (angle-dropping), and fulcrum (angle-building) arrangements. Stabilizer placement and spacing relative to the bit govern the build/drop tendency and, together with sensor sub placement, define the bit-to-sensor offset that drives steering lag. (Rotary Bottom Hole Assembly in Directional Drilling, 2021)

Engineering Principles and Performance Frontiers

Steering Architectures: Push-the-Bit vs. Point-the-Bit

Rotary steerable systems (RSS) have transformed directional drilling by enabling continuous drill string rotation during directional build, eliminating the slide-rotate alternation that characterizes mud-motor (positive displacement motor, PDM) assemblies (Li et al., 2023). There are two main architectures for deviations within the borehole, called push-the-bit, and point-the-bit, which represent a physics of generation of borehole deviations that is quite different. Push the bit RSS (SLB's PowerDrive Orbit) applies eccentric force to the side of the borehole wall which biases the trajectory of the bit. Point-the-bit RSS (such as Baker Hughes's AutoTrak G3) are a type of eccentric or offset mandrel in the tool collar that provides angular bias but no lateral thrust.



Figure 5. Illustrative point-the-bit rotary steerable system (RSS) assembly in which an internal eccentric mechanism causes bit deflection as a result of its motion about its own axis to generate a controlled deflection angle; allowing direction to be changed during drill string rotation. Deploying ROTAY with Directional Wells, 2017. (Rotary Steerable System in Directional Wells).

Andrade et al. (2021) proposed mathematical models for prediction of RSS performance using Newton's third law, beam bending analysis, and rate-of-penetration (ROP) modeling techniques, and validated them by the 2D and 3D case studies. Their analysis shows that the quality of the wellbores drilled in these systems tends to be better (lower tortuosity index, smoother caliper profile), but with higher complexity in both manufacturing and operating a steerable-motor well when compared to a rotary-steerable well (RSL) (Offshore Magazine, 2020a). In contrast, push-the-bit systems have a simpler mechanical design, fewer failure points and a premium which, though higher than the correspondingly designed point-the-bit systems, is still far less expensive. A comparison between mud-motor and RSS-based directional drilling methods (Askari et al., 2025), a direct one, confirms this tradeoff. The top box-and-whisker plots for the major categories of steering systems are shown in Table 2, a quick summary of performance parameters.

Table 2. Comparative Performance Characteristics of Rotary Steerable Systems and Conventional Mud Motor Assemblies

RSS Type	Steering Mechanism	Max DLS (°/100 ft)	Wellbore Quality	Cost (Relative)	Best Application
Push-the-bit RSS	Side-force pads	8-12	Good (smooth)	Moderate	Intermediate sections, high ROP
Point-the-bit RSS	Eccentric ring / mandrel	10-18	Excellent (minimal tortuosity)	High	ERD, high dogleg, precision landing
Hybrid RSS	Push + point combined	12-20	Excellent	High	Complex 3D trajectories
Autonomous RSS (AI-driven)	AI/ML closed-loop	Adaptive	Superior	Very High	Autonomous geosteering, real-time adjustment
Mud Motor (conventional)	Bent housing + slide	6-15	Poor (tortuosity)	Low	Simple directional wells, budget-constrained

Table 2. The different architecture types of the plane and their relative cost, maximum dogleg severity (DLS), wellbore quality and optimum application envelope are compared on the basis of the steering mechanism.

Wellbore Quality and Its Impact on Well Economics

Wellbore quality is a drilling aesthetic not just quantitative or qualitative measure, recognized to have documented cascading effects on completions efficiency, production sustainability and economics of well lifecycles defined signifying the “tortuosity index” (TI) for wellbores. When running casing

and liner, a tortuous hole poses high torque and drag issues and may make it difficult to initiate hydraulic fractures at the desired openings during the hole's lifetime; and when casing is in production, high torque and downhole drag cause early casing wear-out. Case histories from the North Sea demonstrate that RSS-drilled wells exhibit markedly superior casing-run performance compared to steerable-motor-drilled offsets, with one Magnus RSS deployment achieving 33% faster well delivery than planned while meeting all directional objectives for the first time in the field (Offshore Magazine, 2020b).

The cost-benefit relationship between RSS day-rate premiums (typically 3-4× higher than PDM+MWD, as reported by the U.S. Department of Energy's National Energy Technology Laboratory [NETL, 2011]) and improved well economics is now well established for offshore programs but remains sub-optimal for lower-margin onshore applications. Research into lower-cost RSS architectures reducing subassembly count by roughly 50% (34 vs. 70) and cutting servicing costs by approximately 75% compared to prior-generation tools (NETL, 2011) offers a pathway to broader terrestrial adoption, particularly relevant to developing-nation E&P programs such as those in the Niger Delta basin. Delta basin.

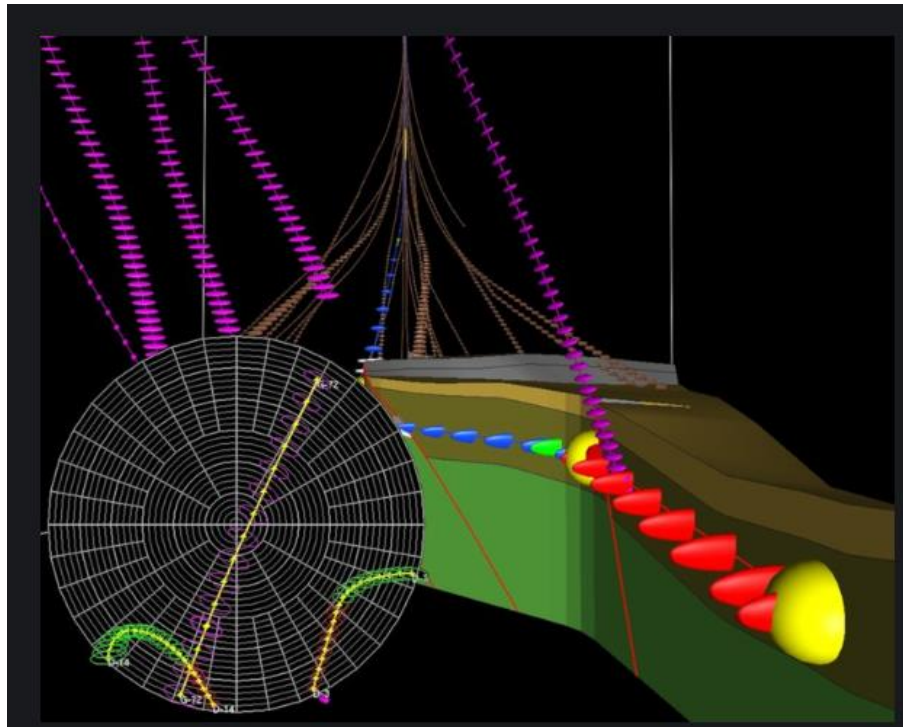


Figure 6. Three-dimensional visualization of a multi-well trajectory set, illustrating the spatial complexity that the Tortuosity Index (TI) is designed to quantify. Excessive doglegs and directional oscillation of the type shown increase torque-and-drag, complicate casing/liner running, and impair completion efficiency the wellbore-quality concerns discussed in Section 4.2. (White, 2021)

Geosteering Methodologies

Stratigraphic-Based Steering (SBS)

Stratigraphic-based steering (SBS) remains the dominant geosteering methodology in North American unconventional plays, where the lateral uniformity of shale formations makes stratigraphic correlation from offset well logs a reliable proxy for local depth-to-target. In SBS, the geosteering specialist projects all horizontal MWD/LWD logs onto the true vertical thickness (TVT) domain of a reference well, correlating the verticalized log set to the "type well" signature to infer local formation dip and the wellbore's position within the target zone (TZ). A statistical analysis of 131 expert geosteers competing in the Geosteering World Cup (GWC) 2020 spanning six continents in both conventional and unconventional simulation environments revealed that the quality of structural interpretation does not deterministically predict the quality of the resulting wellbore placement: expert drillers with superior geological interpretation nevertheless produced inferior well-positioning outcomes relative to peers who employed simpler but more decisive steering heuristics (Tadje et al., 2021).

This finding has profound implications for the design of ML-assisted geosteering systems. It suggests that the value of additional geological information saturates quickly as cognitive and communicative bottlenecks between the geologist, geosteering engineer, and directional driller constrain the speed of the human decision-making loop. Automation of this inter-disciplinary communication as demonstrated in Halliburton's LOGIX deployment in Ecuador, where automated geosteering target changes were transmitted to the directional drilling platform without human intervention in under a minute (Halliburton, 2024) directly addresses this bottleneck.

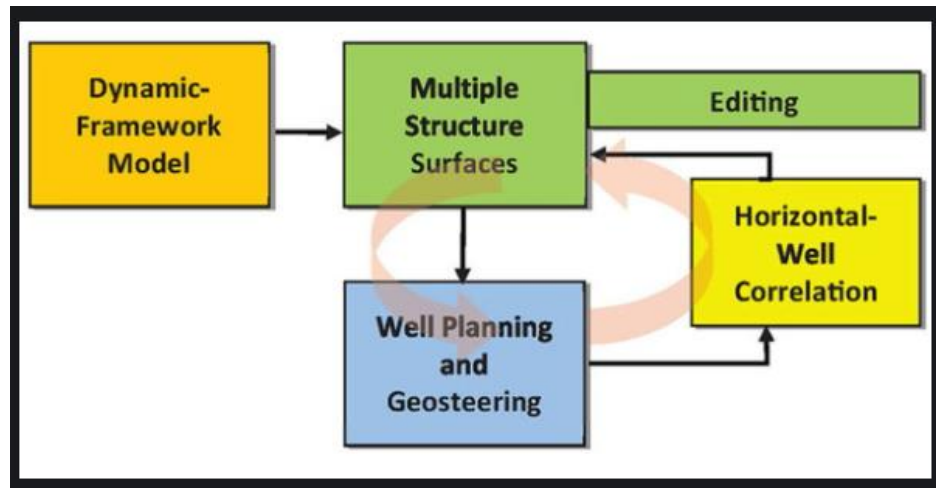


Figure 7. Iterative geosteering workflow linking a dynamic structural framework model, multiple candidate structure surfaces, horizontal-well correlation against offset/typewell logs, and well-planning updates, with continuous editing of the structural interpretation as new data arrive the correlation loop underlying stratigraphic-based steering (SBS). (Al-Maskeen et al., 2013)

Real-Time Geological Modeling and Well Placement Decision Loops

Modern geosteering workflows integrate multiple real-time data streams LWD curves, azimuthal images, depth-of-investigation resistivity inversions, offset well correlations into a continuously updated earth model from which steering decisions are derived. The automated workflow presented by ExxonMobil and Halliburton colleagues (El-Mawla et al., 2025) successfully combined: (1) automated well-to-well LWD correlation algorithms using offset log data; (2) AI-driven analysis of LWD azimuthal images for automated dip-picking, replacing subjective manual interpretation; and (3) boundary-mapping automation using deep and ultra-deep resistivity inversion data to define precise distance-to-bed-boundary in real time. The integrated system fed directly into directional drilling automation platforms, achieving reduced wellbore placement deviations, improved borehole tortuosity, maximized reservoir contact, and significant time savings relative to manual workflows (El-Mawla et al., 2025).

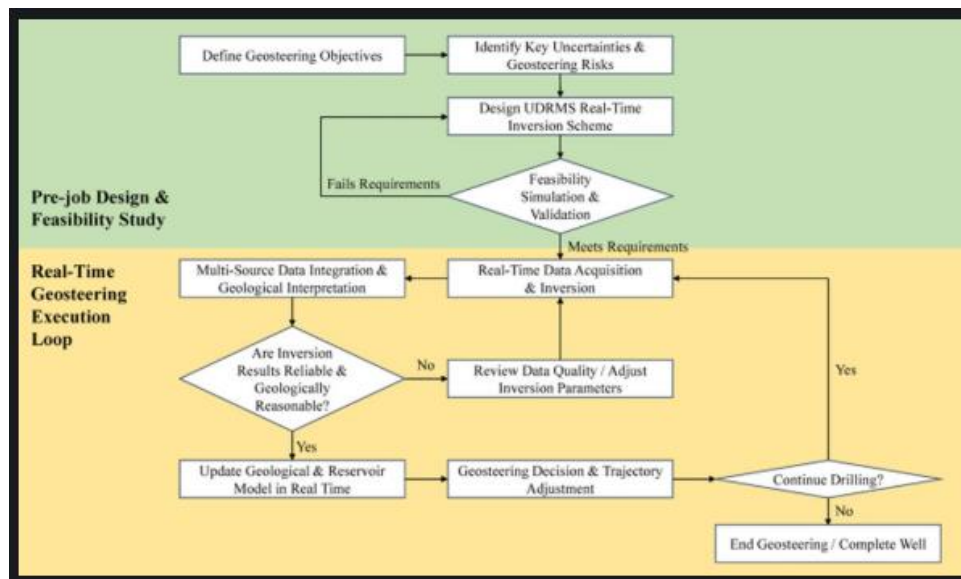


Figure 8. Generalized ultra-deep resistivity mapping/geosteering workflow, comprising a pre-job design and feasibility-simulation phase followed by a real-time execution loop in which inversion results are continuously reviewed for reliability, the geological model is updated, and trajectory adjustments are issued before drilling continues. This closed-loop structure mirrors the automated correlation-to-steering-command pipeline described by El-Mawla et al. (2025) and Hu et al., (2026)

Expanding the Geosteering Horizon

Azimuthal Resistivity Evolution: From Reactive to Proactive Sensing

The evolution of EM LWD resistivity technology can be partitioned into three generations defined by their depth of investigation. First-generation conventional LWD resistivity tools (DOI: 0.1-0.5 m) provided near-wellbore lithology discrimination but no directional sensitivity to formation

boundaries. Second-generation azimuthal resistivity tools (e.g., PeriScope, AziTrak, ADR, BWPR, AMR) with DOI of 5-7 m and 1D boundary inversion building on the foundational azimuthal deep-reading resistivity tool design of Bittar et al. (2007) and the deep directional electromagnetic measurement concepts of Omeragic et al. (2005), and validated for well-placement and reservoir-characterization improvement by Constable et al. (2012) drove the transition from reactive to proactive geosteering allowing detection of the approaching formation boundary before bit contact. Third-generation ultra-deep azimuthal resistivity (UDAR) tools (Stage III, 2016-present), operating at lower frequencies (2-100 kHz) with longer transmitter-receiver spacings (>10 m), achieve detection depths exceeding 30–60 m and employ full-tensor field measurements for anisotropy characterization and reservoir-scale geological mapping (Zhang et al., 2025).

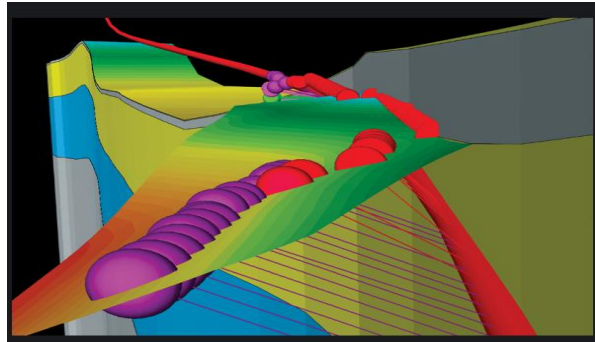


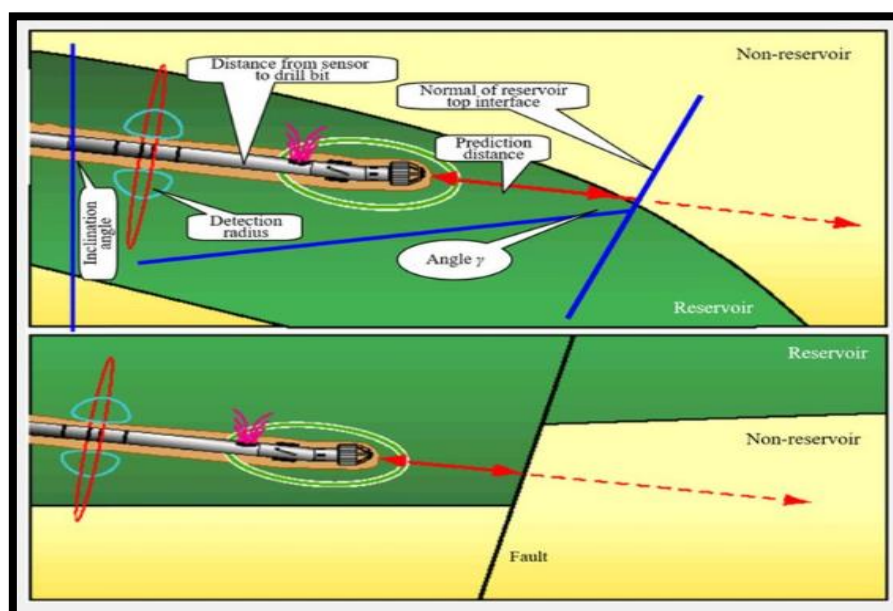
Figure 9. Three-dimensional visualization of an azimuthal deep-resistivity boundary detection response of the type generated by third-generation UDAR tools (e.g., AziTrak, PeriScope), showing the tool's directional sensitivity to a resistivity contrast surrounding the wellbore. Such full-tensor, multi-component measurements underpin the 3D inversion capability described by Baker Hughes, (2026)

Clegg and Rodriguez (2022) demonstrated that 3D inversion of ultra-deep EM LWD data in contrast to the conventional pseudo-2D stitched-1D inversion canvas reveals lateral resistivity variations in all directions around the wellbore, providing a genuinely volumetric understanding of reservoir geometry and fluid distribution. Their synthetic and field examples from the Norwegian Continental Shelf show that 3D inversion enables the detection of sub-seismic faults, lateral facies changes, and fluid-contact tilts that are systematically invisible to 1D processing workflows, building on finite-element forward-modeling schemes such as the 2.5D formulation of Rodriguez-Rozas and Pardo (2018) that make full 3D LWD resistivity inversion computationally tractable. This has direct implications for completing wells optimally: identifying which lateral intervals to perforate and which to isolate based on water saturation mapping ahead of the bit.

Ultra-Deep Look-Ahead Technology

A frontier class of EM LWD services including Halliburton's IriSphere and Baker Hughes's BrightStar achieves look-ahead capability, detecting geological structures directly ahead of the drill bit at distances exceeding 30 m (Yuan et al., 2025), a capability that field trials of the latest generation of advanced UDAR tools confirm translates directly into improved well-placement efficiency (El-Khamry et al., 2025) and, via ultra-high-definition inversion of the resulting deep azimuthal resistivity data, sharper delineation of the reservoir boundary itself (Vianna, 2025). This look-ahead sensing paradigm is a paradigm shift from an after-the-fault scenario, where the driller uses the look-around channel to notice the faulted or dipping horizon and subsequently changes the trajectory to avoid it, to a before-the-fault scenario, where the driller uses the look-ahead channel to predict, ahead of time, that a horizon is faulted or dipping, and adjust the trajectory accordingly. For the mature water flooded fields, where the position of the oil water contact (OWC) varies with the dominant range of reservoir heterogeneities, the look-ahead UDAR capability was shown as essential in an extended-reach case history in an offshore field in Abu Dhabi which allowed the geosteerer to stay 6-ft away from the roof of the reservoir while continuing to map various water encroachment zones that would have impacted production if cut through. (Khemissa et al., 2022.)

Figure 10. Look-ahead detection geometry for ultra-deep EM LWD sensing: A radical approach to the problem of bit penetration resolving the reservoir top (or fault offset: lower panel) already before penetration, and to attribute it's lowest part as a reservoir top (or fault offset)



The combination of ultra-deep EM inversions (both 1D and Gauss-Newton 3D) and azimuthal density, gamma ray and electrical image logs provides a holistic interpretation approach that was introduced by Riofrio et al (2023) at SPE Offshore Europe. When 2D EM inversion was further enhanced to also invert for anisotropy, 3D EM inversion becomes more capable to separate isotropic intervals from

anisotropic intervals with a system allowing to differentiate isotropic and anisotropic intervals within a well significantly deeper than from the borehole wall. The authors believe it should be the new paradigm for data-integration in any horizontal well in reservoirs that have non-trivial lateral heterogeneity.

The same job benefits further by Halliburton colleagues using portable X-ray fluorescence (XRF) spectrometry of the drilling cuttings to achieve elemental geochemical profiles, which correlated so well with the LWD gamma-ray and resistivity logs that the R^2 was >0.85 and enabled steering decisions to be made in real-time, identifying intervals of thin shale layers and pyrite rich cemented intervals. The reported results comprised a 20% decrease in non-productive time (NPT) and 15% increase in wellbore placement precision (ADIPEC Proceedings, 2024) metrics representing drilling cost savings and production optimization.

Artificial Intelligence and Machine Learning in Wellbore Placement ***ML Algorithms in Formation Classification and Steering***

Applications for machine learning in wellbore placement are divided by operational model into: (1) formation classification and formation boundary detection based on LWD sensor inputs; (2) trajectory optimization based on a geological model, direction, etc.; and (3) autonomous closed-loop geosteering where both classification and trajectory optimization are combined. A SVM-based study of formation classification by Brantson et al (2025) is prototypical of the first category, with formation classification accuracy of 84% from the features including formation density, porosity, gamma-ray, and synthetic rock density on the real LWD data from the Eagle Ford Shale. Using SVM-GWO architecture, it was established that the hyper-parameters optimization can significantly influence the generalization capability of the ML classifiers applied to imbalanced datasets contaminated by noise in LWDs. The SVM-GWO architecture showed that a ML classifiers hyper-parameter optimization using a Grey Wolf Optimizer can significantly enhance the generalization performance of the considered classifiers applied to imbalanced, noise-contaminated LWDs.

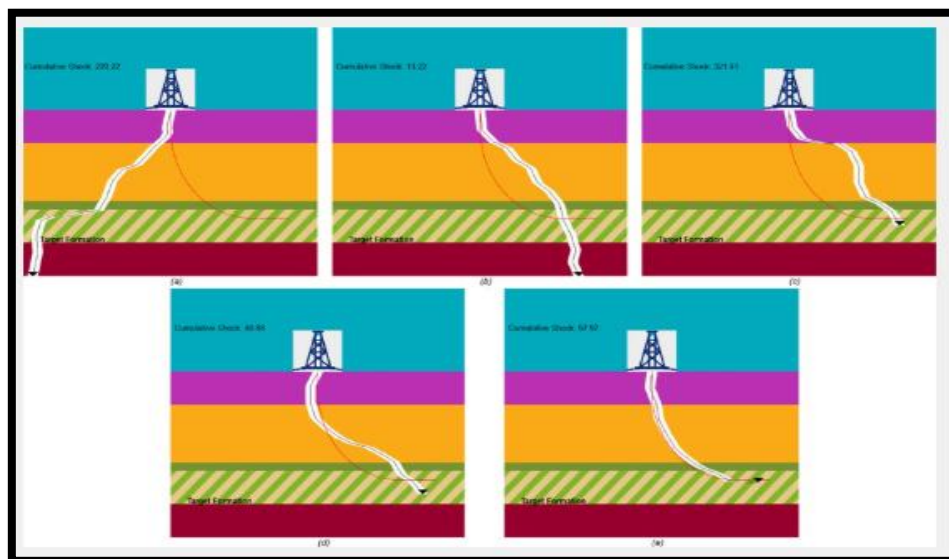


Figure 11. Here an illustrative example for a trajectory-optimization category application of ML is shown as examples of converging wellbore (blue dashed lines) toward the target formation (green hatched interval) at successive incremental footage checkpoints on the sequential trajectory.

The second class, trajectory optimization using ML, was developed by Mansouri et al., 2020 (see Brantson et al., 2025) and involved the application of Akima interpolation to smooth updates to well positions and testing under a variety of simulated geologic variations. The third most advanced instance of this third operational class is revolutionizing the modeling of velocity shapes in real time, as shown in the Ecuador first-autonomous-well campaign conducted by Halliburton (2024), where the ML system consumes velocity outputs from the formation classification product, calculates the trajectory corrections achievable within the RSS capability envelope, and then pushes the new velocity targets to a platform for well path automation within seconds without the need for human interaction.

The Human Factor, Training, and Automation Boundaries

Tadger et al. (2021) have analysed in detail the Geosteering World Cup (GWC) 2020 dataset to obtain the most statistically robust empirical evidence of the human cognitive limits of geosteering decision making. The discovery that the quality of geesteering did not increase with geologic interpretation undermines the industry's emphasis on nurturing human geesteering skills, which is not a sound allocation of resources, in the interest of focusing on geologic interpretation. The overall finding that geosteering quality was not reliably linked to the geologic interpretation calls into question the industry emphasis on investing highly in human geesteering skill building and skills-underdevelopment in process automation and decision support systems to the

interest of geologic interpretation. It also provides the design goal for ML assisted Geosteering, namely, the system should improve the performance of the expert, human geosteerer, particularly in the situations of high geological uncertainty and rapid structural change, the most critical situations for the performance of the expert, human geosteerer data.

As this occurs, a key ethical and organizational question comes to mind. There is a risk of full automation of geosteering introducing a new paradigm that takes away the role of experienced geosteering personnel. This is going to be a journey for the industry to undertake, shifting domain knowledge from humans to more sophisticated supervisory roles, model governance, and the role of geologic interpretation. Automation, in this case a geologist-geosteering engineer team, did not take over from the humans for the purposes of the Ecuador campaign (Halliburton, 2024) with 87.4% of the footage being autonomous.

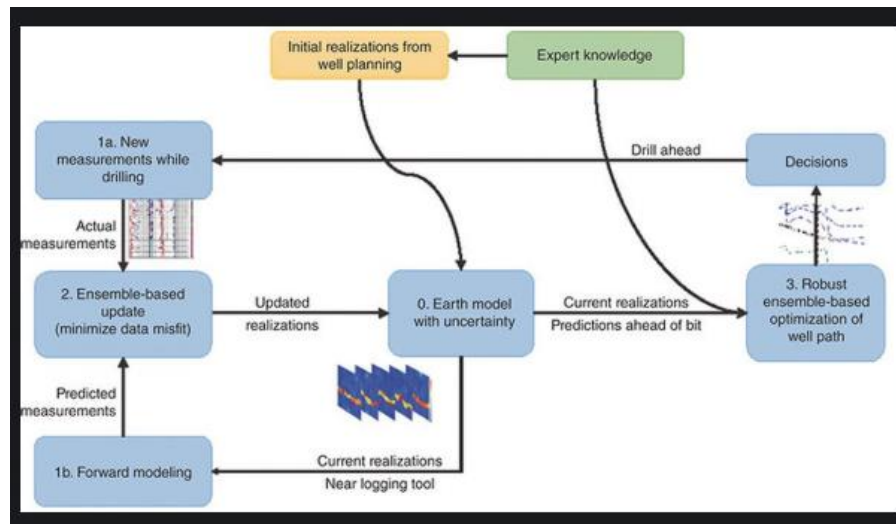


Figure 12. Initial realizations of the ensemble based, uncertainty aware geosteering architecture: populated earth model with uncertainty due to the initial realization of the wells, and uncertainty due to the expert knowledge; new LWD measurements as drilling progresses result in an ensemble-based model update; subsequent predictions in front of the bit are fed into the robust ensemble-based trajectory optimization; and decisions from the resulting optimization are fed back to the earth model as the drilling progresses. The concept is similar to the Halliburton LOGIX platform (Halliburton, 2024), which is based on AI-enabled autonomous geosteering, and SLB's Neuro™ system (SLB, 2024)

Telemetry, Digital Twins, and the Connected Wellbore The Bandwidth Bottleneck

Even at its very core, placing intelligence in the wellbore system is constrained by the data transmission bandwidth between downhole sensors and in the decision-making at the surface. Conventional mud-pulse telemetry (MPT), which encodes LWD data as pressure oscillations in the drilling fluid column, transmits at rates of 0.5–12 bits per second grossly insufficient for the continuous, high-resolution multi-sensor data streams that modern LWD arrays generate. Electromagnetic (EM) telemetry provides somewhat higher bandwidth (~12-24 bps) at shallow depths but degrades significantly in high-resistivity formations. Wired drill pipe (WDP) technology which embeds coaxial signal conductors within the drill string body, building on the intelligent-well telemetry drill-pipe concept first demonstrated by Jellison et al. (2003) achieves transmission rates of 57,600 bps or greater, enabling continuous transmission of high-resolution LWD data and bidirectional communication for RSS downlinks.

The practical impact of WDP on wellbore placement quality is well documented, and mirrors the gains reported for purpose-built real-time monitoring system architectures for geosteering well construction more broadly (Liang et al., 2012). Higher bandwidth enables: (1) continuous multi-channel LWD data streaming at full formation sampling resolution; (2) azimuthal image transmission for real-time dip analysis; (3) rapid (~1-second) RSS downlink confirmation; and (4) multi-parameter optimization loops that would be impossible with MPT's sequential, low-rate transmissions. The commercialization of WDP by Baker Hughes (IntelliServ®) and Halliburton (Intellipipe) has steadily expanded the operational envelope of WDP, though cost remains a barrier for routine deployment in lower-value wells.

Digital Twin Models for Wellbore Placement

A digital twin in the context of wellbore placement is a real-time, physics-based computational replica of the drill string, BHA, and formation environment that runs in parallel with the physical drilling operation, continuously updated with sensor measurements and used to predict the system's near-future behavior. The virtual drilling model developed by Brantson et al. (2025) included a full RSS simulation component, formation model, and an ML performance interface with known outcomes enabling drilling teams to practice complex drilling scenarios and in open water deployment, identify potential drilling hazards and set up and test their ML model performance.

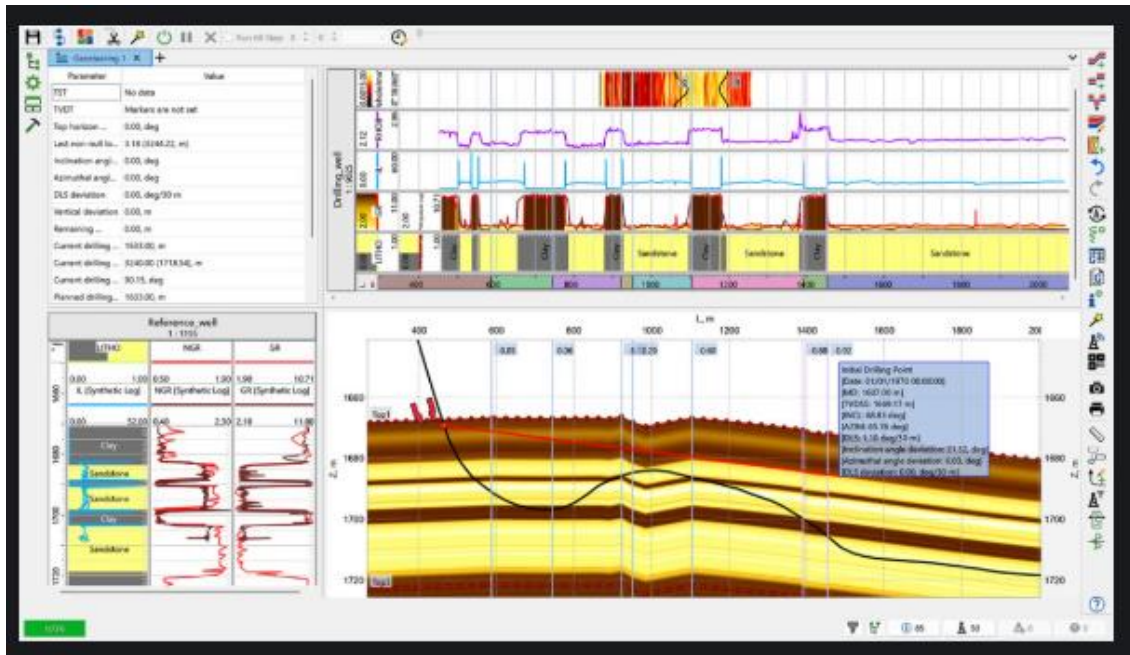


Figure 13. A real-time geosteering monitoring display of a digital twin that fuses a reference-well log display, live LWD curves and picked formation-boundary, and a structural cross section of the actual wellbore path in real time compared to a formation window.

In the Ecuador autonomous drilling campaign (Halliburton, 2024): Prior to sending geosteering commands, the ML's geosteering target changes have been compared against the predicted success of the required trajectory changes based on real-time BHA tool performance readings (torque, drag, vibration, and stick-slip state) recorded by the digital twin. This validation step an AI system validating its own decisions against a physics model is one of the valid architectures that the autonomous systems engineering community would recognize as the human-out-of-the-loop sequence of safety.

Methodological Debates, Stakeholder Perspectives, and Ethical Dimensions

Academic vs. Industry Priorities in Wellbore Placement Research

There is a constant conflict between the two approaches to research priorities (algorithmically sophisticated methods that are physically interpretable and publicly reproducible) versus deployment priorities (operational reliability, tool survivability, and cost reduction per barrel) in the published literature. Academic ML models that scope to geosteering with models such as SVM-GWO (Brantson et al., 2025) or formation boundaries trained using random forest and neural network classifiers often rely on curated, clean LWD data from a single formation, which poses a challenge for the model to be applicable in the noisier, multi-facies, structurally more complex sort of conditions found in commercial operations. In contrast to academic literature, the knowledge, experience and empirical findings embedded in industry systems are vast and are rarely represented in publications and studies, resulting in a particularly wide knowledge gap.

The difference brings methodological implications for the design of future systems for autonomous wellbore placement. The lack of Open, Representative, LWD-like Benchmark Datasets comparable to the ImageNet Dataset that sparked computer vision research significantly slows down the entire training, model testing and productionizing process for academic ML Models. Industry-academic consortia for sharing data, like International Ocean Discovery Program (IODP) data model in marine geoscience, is a timely structural need for the community of researchers aiming for wellbore placement.

Environmental and Geopolitical Dimensions

The accuracy of the placement of wells has environmental consequences. An out-of-control horizontal well is a costly problem in terms of how much drill footage is lost, how much more drilling fluid and cement is used, how much more cuttings has to be disposed of, and how much more of the aquifer-proximal formations are intersected with quantifiable environmental costs. On the other hand, with an optimized well location, that has maximum contact with the reservoir, the most it can produce from one well is achieved, which in turn means fewer wells being placed to develop a specific reservoir volume of production. The reservoir efficiency argument is key to the contribution of advanced wellbore placement technologies to SDG 13 (Climate Action) and SDG 12 (Responsible Consumption and Production).

The geopolitical factor is also important. Geosteering whether done autonomously or using AI—and the environmental data necessary to derive this information are currently focused in a limited number of key companies in the oilfield services sector, including SLB, Halliburton, Baker Hughes and Weatherford, this research indicates, and in particular in higher-value, offshore and unconventional plays across North America, Europe, and the Middle East. Other E&P industries in the developing world, such as the Niger Delta in West Africa, the onshore basins of South America, or the various reservoirs of the Southeast Asian region are continuing to be slow off the mark in terms of technology diffusion, and cost, local technical capacity and proprietary software ecosystems remain barriers. Addressing this asymmetry is directly relevant to SDG 17 (Partnerships for the Goals) and represents both an ethical

imperative and an untapped commercial opportunity for the services sector.

Table 3. Alignment of Advanced Wellbore Placement Technologies with United Nations Sustainable Development Goals (SDGs)

SDG	Goal Title	Mechanism of Contribution	Relevant Metric
SDG 7	Affordable and Clean Energy	Optimized wellbore placement maximizes hydrocarbon recovery from existing reservoirs, reducing energy price volatility and supporting the transition to cleaner combustion fuels	Recovery factor improvement: 15-30%
SDG 8	Decent Work and Economic Growth	Automated geosteering creates new skilled roles in data science and AI-driven drilling, while cost reductions support E&P investment	NPT reduction: 20-35%
SDG 9	Industry, Innovation, and Infrastructure	Integration of AI, digital twins, and real-time sensing advances industrial infrastructure for sustainable resource extraction	Autonomous drilling efficiency: 87% footage without intervention
SDG 12	Responsible Consumption and Production	Precise well placement reduces unnecessary re-drilling, sidetrack footage, and wasteful material use	Sidetrack reduction: up to 40%
SDG 13	Climate Action	Reduced NPT and optimized reservoir contact lower per-barrel carbon intensity and methane emissions from misplaced wells	CO ₂ e reduction per well: 10-20%
SDG 17	Partnerships for the Goals	Open-data initiatives and cross-industry AI collaboration accelerate technology diffusion to developing nations	Technology transfer to emerging E&P nations

Table 3. Mapping of wellbore placement technology advances to relevant UN SDGs, with mechanistic descriptions of how each technology driver contributes to each goal and representative outcome metrics.

Geological Risk and the Limits of Automation

Fully autonomous geosteering, as demonstrated in the Ecuador case and the SLB Neuro platform, achieves performance excellence in structurally predictable reservoirs. However, the geological risk profile of autonomous systems degrades in scenarios involving sub-seismic faulting, karst dissolution features (common in Middle Eastern and Southeast Asian carbonates), highly variable fluvial channel-belt reservoirs, or frontier exploration wells where no analogous offset data exists for model training. In these environments, the statistical foundations of ML steering algorithms are undermined by distributional shift the real-world geology differs systematically from the training distribution and human geological reasoning may be the only available corrective mechanism. This implies that autonomous wellbore placement systems require architectures that monitor their own epistemic uncertainty in real time, triggering a transparent handover to human control when confidence metrics fall below operationally defined thresholds. Such uncertainty-aware autonomous systems remain an active and largely open research challenge.

Toward a Next-Generation Integrated Wellbore Placement Architecture The Multi-Physics Data Fusion Framework

The foregoing synthesis leads to a clear architectural prescription for the next-generation wellbore placement system: a continuously learning, uncertainty-aware, multi-physics data fusion framework in which the geological model and the steering control law are jointly optimized in real time. This framework has five key elements:

- **Real-Time Formation Classification Engine:** A multi-model ensemble framework that integrates CNN-based image analysis methods for obtaining LWD images, gradient-boosted classifiers for prediction of log-curve cadre images, and physics-informed neural network (PINN) methods for forward modelling of resistivity images, to provide probabilistic formation-class prediction with calibrated uncertainty estimates at half-meter increments along the drilling hole.
- **Stochastic Geological Model Updater:** Propagation of uncertainties associated with sensor measurements, structural model, and petrophysical through a Bayesian ensemble-model framework to update a 3D geological model on a regular basis as drilling proceeds. New uncertainty-quantified representation is being used and replaces the current deterministic geomodel used in commercial platforms that is better suited for steering decisions that weigh risk.
- **Physics-Constrained Trajectory Optimizer:** A real-time model predictive control (MPC) algorithm, which requests the digital twin RSS performance model, calculating an optimized future trajectory as a solution of the objective function in Equation 1 that is constrained by both the direction and mechanical requirements. The structure of MPC is naturally a receding horizon which allows incorporating the updated geological information at each timestep.
- **Epistemic Uncertainty Monitor:** A meta leaning mechanism that monitors and screens the OOD distance between running samples by the

sensor and the training samples of all ML components, which sets in different escalation policies (automatic alert, advisory mode, mandatory human authority) accordingly to the breach of uncertainty thresholds. This part is the most important one for human-machine safe control relationship management.

- **High-Bandwidth Telemetry Integration Layer:** A telemetry pipeline for wired drill pipe normally transmitting all LWD pressure and temperature data to the surface, but also able to send commands back down the pipe. To cap it all, there is an architecture for Cloud computing integration for offloading for inversion workload on-demand.

Priority Research Directions

Based on the identified research gaps in the current literature, the following lines of research, representing the highest priority scholarly investments to the community for the next five years (2025-2030) are identified: Open-access LWD benchmark dataset for diverse geological environments (carbonate, clastic, fractured, HPHT) to enable community-wide comparison of ML model accuracy; Rigorous test, field trials, and validation across various geosteering environments to assess the accuracy of 3D inversion from UDX, relating them to the associated geologic data from closely spaced wells; Human factors research into the design of interfaces for decision workflows involving collaborative use of AI with humans in geosteering, including those for the calibration of level of trust, situation awareness, and management of alarms etc.; Estimate in advance the environmental impact of wellbore placement precision on per-barrel carbon intensity; Techno-economic modeling for advanced technology adoption of wellbore placement in unknown frontier E&P basins and assess community impact.

Conclusions

In this paper, the review summarized the current state of development of wellbore placement technology, which involves LWD sensor systems, rotary steerable architecture, geosteering methodologies, ultra-deep electromagnetic sensing, and autonomous drilling using AI/ML systems. Based on review of the evidence, the following conclusions are drawn:

- The wellbore placement is now in new world changing technological third stage that incorporates AI, ultra-deep EM sensing, wired drill pipe telemetry and closed-loop autonomous steering. The Ecuador and SLB deployments in 2024 are examples of proven use of autonomous geosteering in a field setting for structurally predictable reservoirs.
- There is a critical integration gap that needs to be resolved: an uncertainty-aware framework which coherently integrates near-bit sensing, UDAR multi-layer inversions, uncertain geological modelling and physics-based autonomous steering is missing from a fully operational architecture with continuous learning.
- The human factor is still affective in HGU environments. The system needs to have architectures that are uncertain in nature, tracking the autonomous entity's epistemic belief, and pointing to the need of principled human authority escalation such that ML models are not used outside their epistemic envelope.
- Advanced wellbore tech help drive SDG contributions of improved recovery factor and reduced NPT, skills development, waste reduction, CI reduction and tech diffusion into developing E&P nations exclusively through the lens of a benefit to SDG 7, 8, 9, 12, 13, and 17.

The research roadmap suggested herein centred on a Bayesian geological model updating, model-predictive control trajectory optimization and epistemic uncertainty monitoring framework for data fusion spanning multiple physics - provides a seamless path for realizing the capacity of autonomous placement of wells to the entire spectrum of geological environments around the world for petroleum development.

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