AI-Enhanced Well-Steering: Open Workflow Implementation with Latent Space Geomodeling and Uncertainty Quantification

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Introduction

Applied Problem Statement:

In real-time drilling operations, such as for hydrocarbon extraction, geothermal wells, or infrastructure tunneling, engineers must continuously adjust the well trajectory to remain within a targeted geological zone **[1]**. This process, known as **geosteering**, is complicated by uncertainty in the geology ahead of the drill bit.

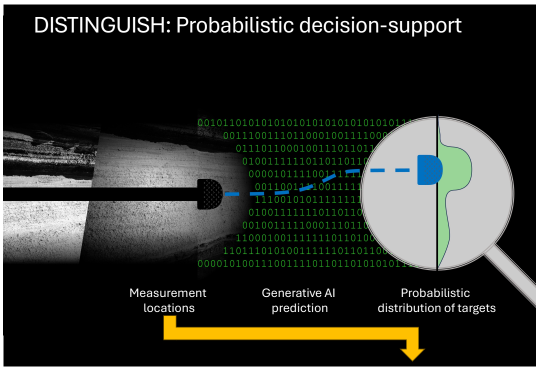
Domain Challenge:

Most current logging tools cannot measure subsurface properties in front of the drill bit. Typical ultra-deep electromagnetic (**EM**) Logging-While-Drilling (LWD) measurements still provide only localized and indirect information, which requires processing and interpretation to enhance geological understanding. Typical current workflows do not systematically integrate data into models during drilling **[2]**, resulting in potentially suboptimal steering decisions under uncertainty.

Goal:

We develop an AI-enhanced, data-assimilation-based geosteering workflow that integrates real-time sensor data with latent-space geomodels to improve decision-making under uncertainty through robust optimization.

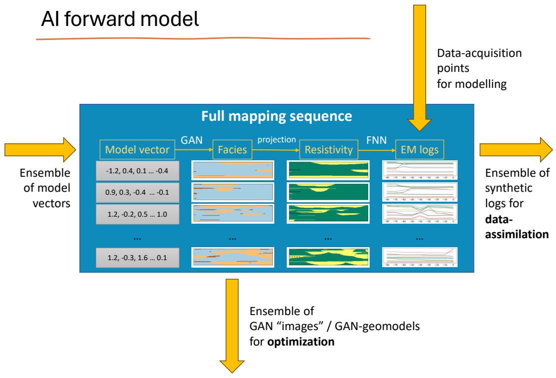
DISTINGUISH: Probabilistic decision-support



Key contributions

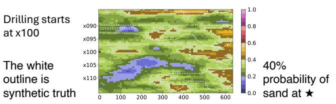
- **Latent-Space Geomodeling:** Offline-trained Generative Adversarial Networks (GANs) generate plausible geological realizations consistent with field knowledge.
- **Simulator-Trained EM Model:** A Forward Neural Network (FNN) emulates ultra-deep LWD EM tool responses, enabling the assimilation of modern real-time observations.
- **Ensemble-Based Model Updating:** An ensemble of latent vectors is incrementally updated as new data arrives, refining posterior geological uncertainty.
- **Decision Support via Dynamic Programming:** A Discrete Dynamic Programming (DDP) method selects steering actions that optimize global well placement under uncertainty.
- **Generative Drilling Workflow Benchmark:** A modular prototype is demonstrated on a specially prepared 3D geomodel benchmark tailored for geosteering, establishing a performance reference for future improvements.
- **Interactive Web-Based Demonstration:** An interactive app showcases the real-time behavior of the prototype and illustrates the key concepts of the workflow.

AI forward model



Prior ensemble

The prior consists of **250 model vectors** sampled from a Gaussian distribution perturbed towards the synthetic truth. It translates to an ensemble of GAN-geomodels with a large uncertainty in facies:

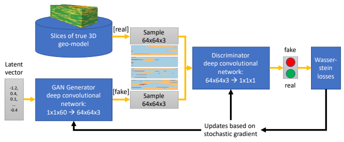


Offline GAN training

The GAN's generator (g_θ) and discriminator (D) are trained in an adversarial min-max game. The generator learns to produce realistic geomodel patches—resembling samples from the training **3D geomodels**—from **latent vectors** drawn from a multivariate Gaussian distribution.

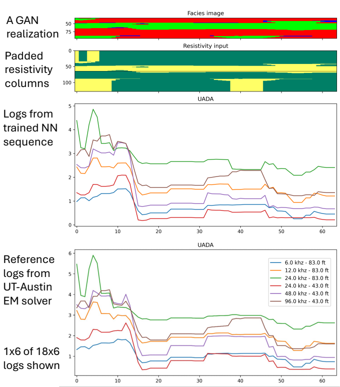
Thanks to its multi-scale convolutional architecture, small perturbations in the latent vectors yield smooth variations in the generated output. The GAN is trained using the Wasserstein loss:

$$L(D, g_\theta) = \mathbb{E}_{x\sim\mathbb{P}_r}[\log D(x)] + \mathbb{E}_{x\sim\mathbb{P}_\theta}[\log(1 - D(x))]$$



Offline FNN EM model training

A Forward Neural Network (FNN) approximates a 1D electromagnetic solver for an ultra-deep EM logging tool. It takes a column of 128 horizontal and vertical resistivities, including tool position, and predicts 18 measurements under 6 configurations. The FNN is trained to match synthetic logs **[4]** simulated by a high-fidelity 1D model **[5]** for columns from 3D geomodels.

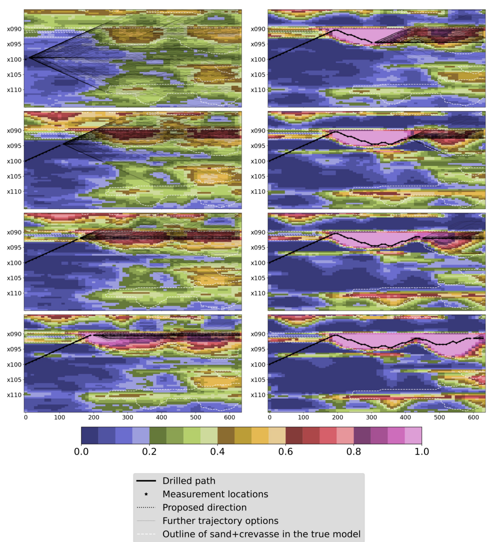


Global optimization with DDP

- Find **full best trajectory** for each realization using DDP
- Take the robust decision only for **the next segment**:
  - Consider allowed alternatives **(up/down/straight/stop)**
  - Choose the alternative giving **the best predicted value on average**

Numerical example

The figure shows sequential steps applying the workflow.

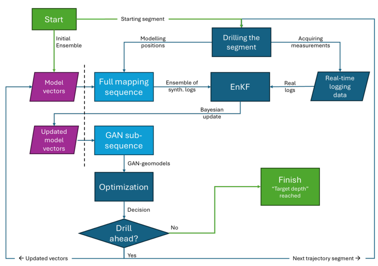


EnKF

As new measurements arrive, a non-localized Ensemble Kalman Filter (EnKF) assimilates them sequentially. The statistical misfit between predicted and observed logs drives Bayesian updates of the latent vectors, as defined by the **full mapping sequence** from latent space to predictions.

The update of latent vectors propagates through the **GAN sub-sequence**, resulting in global modifications to the geomodels and enabling probabilistic look-ahead predictions for optimization **[1]**.

Full workflow



Reproducibility

- Distinguish open-source portal: https://github.com/geosteering-no
- Open workflow demo with ultra-deep EM tool: https://github.com/geosteering-no/DISTINGUISH-WF

References

[1] Alyaev S, Fossum K, Djecta HE, Tveranger J, Elsheikh A. **DISTINGUISH Workflow: A New Paradigm of Dynamic Well Placement Using Generative Machine Learning.** In ECMOR 2024 / arXiv:2503.08509

[2] Rammay MH, Alyaev S, Larsen DS, Bratvold RB, Saint C. **Strategic geosteering workflow with uncertainty quantification and deep learning: Initial test on the Goliat Field data.** Geophysics 2024

[3] Alyaev S, Tveranger J, Fossum K, Elsheikh AH. **Probabilistic forecasting for geosteering in fluvial successions using a generative adversarial network.** First Break 2021 / arXiv:2207.01374

[4] Alyaev S, Shahriari M, Pardo D, Omella ÁJ, Larsen DS, Jahani N, Suter E. **Modeling extra-deep electromagnetic logs using a deep neural network.** Geophysics 2021

[5] Pardo D, Matuszyk PJ, Puzyrev V, Torres-Verdin C, Nam MJ, Calo VM. **Modeling of resistivity and acoustic borehole logging measurements using finite element methods.** Elsevier 2021