

Machine Learning for Underground Natural Gas Storage Optimization

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Abstract

Underground natural gas storage (UNGS) plays an indispensable role in balancing seasonal and daily mismatches between natural gas supply and demand, supporting grid reliability, and increasingly facilitating the integration of variable renewable energy sources into broader energy systems. Optimizing UNGS operations requires accurate prediction of deliverability—the rate at which gas can be withdrawn from a storage site—across a wide range of geologic settings including depleted hydrocarbon reservoirs, saline aquifers, and salt caverns, each governed by distinct subsurface flow and geomechanical characteristics. Conventional deliverability estimation relies on physics-based reservoir simulation, which, while rigorous, is computationally expensive and difficult to scale across the hundreds of active storage sites that collectively constitute national and regional gas storage portfolios. Machine learning (ML) has emerged as a powerful complementary approach, capable of learning the complex, nonlinear relationships between reservoir, operational, and geologic parameters and resulting deliverability outcomes directly from extensive field datasets. This review synthesizes recent advances in ML-based prediction and optimization of underground natural gas storage, examining artificial neural network, ensemble, hybrid metaheuristic-optimized, and explainable machine learning architectures applied to deliverability prediction across depleted reservoirs, aquifers, and salt caverns. It draws on case studies from heterogeneous depleted gas reservoir optimization, geothermal-analogue petrophysical characterization, and geomechanically informed wellbore stability assessment, and further considers methodological parallels with large-scale AI-driven predictive analytics and economic impact frameworks developed for national healthcare systems. The review concludes by identifying persistent challenges in cross-formation generalizability, real-time operational integration, and model interpretability, and proposes a research agenda for advancing ML-based UNGS optimization toward routine use in supporting reliable, cost-effective natural gas storage operations.

Keywords: machine learning, underground natural gas storage, deliverability prediction, artificial neural network, explainable AI, depleted reservoirs, salt caverns

1. Introduction

Underground natural gas storage (UNGS) serves as a critical buffer within the natural gas supply chain, enabling operators to inject gas during periods of low demand and withdraw it during periods of peak seasonal or daily consumption, thereby smoothing the substantial temporal mismatches that characterize natural gas supply and demand. As energy systems increasingly incorporate variable renewable generation, UNGS additionally serves a growing role in providing flexible, dispatchable energy storage capacity that complements intermittent renewable resources. UNGS is typically developed in one of three geologic settings—depleted hydrocarbon reservoirs, saline aquifers, or engineered salt caverns—each presenting distinct subsurface flow characteristics, geomechanical constraints, and deliverability behavior that must be accurately characterized to support reliable operational planning.

Deliverability, defined as the rate at which natural gas can be withdrawn from a storage site under given pressure and operational conditions, is among the most operationally consequential parameters governing UNGS performance, directly determining a storage site's ability to meet peak demand obligations. Conventional deliverability estimation relies on physics-based reservoir simulation calibrated to site-specific geologic and operational data, an approach that, while rigorous, becomes computationally burdensome and operationally impractical when applied across the hundreds of individual storage sites that collectively constitute a national or regional gas storage portfolio, each requiring site-specific simulation recalibration as reservoir conditions evolve over repeated injection-withdrawal cycles.

Machine learning has emerged as an increasingly important complementary approach to conventional UNGS deliverability estimation, capable of learning the complex, nonlinear relationships between reservoir geology, operational parameters, and resulting deliverability directly from the extensive historical field datasets that regulatory reporting requirements have made available across many operating storage sites. This review synthesizes recent advances in ML-based UNGS optimization, integrating insights from heterogeneous depleted gas reservoir case studies, geothermal-analogue petrophysical characterization directly relevant to reservoir quality assessment, and machine-learning-enhanced geomechanical characterization

relevant to storage integrity, alongside the growing body of ML literature applied directly to UNGS deliverability prediction across depleted reservoirs, aquifers, and salt caverns (Ali, 2021; Ali et al., 2022; Hussain et al., 2025, 2026). It further draws methodological parallels with large-scale AI-driven predictive analytics and economic impact frameworks developed for national healthcare systems (Nguyen, 2026a, 2026c, 2026d), which offer transferable lessons on deploying predictive AI models to inform operational planning and resource allocation at scale. The objective is to provide a comprehensive synthesis for researchers, engineers, and storage operators seeking to advance ML-based UNGS optimization from research demonstration toward standard practice in commercial gas storage operations.

2. The Underground Natural Gas Storage Optimization Challenge

2.1 Deliverability as the Central Operational Metric

Deliverability governs a storage site's ability to meet peak withdrawal demand and depends on a complex interplay of geologic factors—reservoir permeability, connectivity, and pressure history—and operational factors including working gas capacity, base gas volume, and total field capacity. Because deliverability typically declines as cumulative gas is withdrawn from a storage site during a given withdrawal season, accurate, dynamically updated deliverability prediction is essential for operators seeking to plan withdrawal schedules that reliably meet contractual and system reliability obligations without risking premature depletion of deliverable capacity.

2.2 Geologic Diversity Across Storage Settings

Depleted hydrocarbon reservoirs, saline aquifers, and salt caverns each present distinct deliverability behavior. Depleted reservoirs benefit from well-characterized geologic properties inherited from prior hydrocarbon production but may suffer from formation damage or altered relative permeability; aquifers require the injected gas to displace resident brine and establish a gas cap absent any prior hydrocarbon trapping history, introducing additional uncertainty; and salt caverns, while offering rapid injection-withdrawal cycling capability due to their engineered, high-permeability nature, are governed by distinct geomechanical creep and cavern stability considerations rather than conventional porous-media flow physics. Machine learning models developed for UNGS deliverability prediction must account for these fundamentally distinct geologic settings, either through separate formation-specific models or through

architectures capable of learning shared and setting-specific deliverability drivers simultaneously.

2.3 Limitations of Conventional Simulation-Based Approaches

Physics-based reservoir simulation, while capable of high-fidelity deliverability prediction when properly calibrated, requires substantial site-specific data and computational resources that become impractical to apply uniformly and repeatedly across the hundreds of active storage sites within a national gas storage portfolio, particularly as deliverability must be re-forecast dynamically throughout each withdrawal season as reservoir pressure and remaining working gas volume evolve.

3. Machine Learning Architectures for Deliverability Prediction

3.1 Hybrid Metaheuristic-Optimized Support Vector Machine Models

Early applications of machine learning to UNGS deliverability prediction favored hybrid architectures combining support vector machine regression with metaheuristic optimization algorithms to improve model training and generalization. Ali (2021) developed a series of data-driven machine learning models for predicting the deliverability of underground natural gas storage in salt caverns, employing hybrid intelligent models that integrated least square support vector machine regression with differential evolution, imperialist competitive algorithm, cultural algorithm, teaching-learning-based optimization, genetic algorithm, and particle swarm optimization techniques, trained and validated against an extensive dataset of 782 reservoirs from depleted fields across the United States, establishing an early and influential template for hybrid metaheuristic-optimized deliverability prediction subsequently extended to other geologic settings.

3.2 Explainable Machine Learning for Deliverability Prediction

Beyond predictive accuracy alone, recent research has emphasized the importance of model interpretability in UNGS deliverability prediction, given the operational and financial consequences of deliverability forecasts. Ali et al. (2022) developed baseline support vector regression, artificial neural network, and random forest models for predicting deliverability in depleted reservoirs, subsequently introducing a hybrid Sparse Autoencoder-Random Forest (SARF) framework that combined sparse autoencoder feature extraction with random forest

regression to achieve an average 5.7% accuracy improvement over the baseline random forest model when validated against 3,744 real-world storage data samples from 52 active United States storage reservoirs; critically, the study also introduced a suite of explainable artificial intelligence (XAI) methods to provide intuitive, feature-level interpretation of the factors driving predicted deliverability values, representing what the authors describe as the first application of explainability methods specifically to UNGS deliverability prediction.

3.3 Artificial Neural Networks Optimized with Advanced Training Algorithms

Artificial neural networks trained with advanced optimization algorithms have continued to demonstrate strong performance for UNGS deliverability prediction across both aquifer and depleted reservoir settings. Hussain et al. (2025) developed artificial neural network models optimized using the Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient training algorithms to predict UNGS deliverability in aquifer and depleted reservoir settings, validating the models against 2,084 field storage data points drawn from 78 operational reservoirs across the United States and finding that the Bayesian Regularization-optimized model achieved superior predictive accuracy relative to the other training algorithms, underscoring the practical importance of training algorithm selection alongside network architecture in achieving robust deliverability prediction performance.

3.4 Group Method of Data Handling for Enhanced Deliverability Prediction

Beyond conventional neural network and ensemble architectures, self-organizing modeling approaches offer an alternative pathway to robust deliverability prediction under the overfitting and slow-convergence challenges that can affect conventional artificial neural networks. Hussain et al. (2026) applied the Group Method of Data Handling, a self-organizing modeling technique capable of automatically identifying an appropriate model structure and complexity from training data, to enhance deliverability predictions in underground natural gas storage within depleted reservoirs, addressing the numerous subsurface geological and fluid property factors that complicate deliverability estimation and demonstrating improved predictive reliability relative to conventional artificial neural network approaches affected by overfitting and convergence difficulties.

4. Integrating Geologic and Geomechanical Characterization with Deliverability

Prediction

4.1 Petrophysical Characterization as a Deliverability Prediction Input

The accuracy of any machine learning-based deliverability prediction model is fundamentally bounded by the quality of the underlying petrophysical characterization used to describe reservoir connectivity and flow properties. Machine learning-enhanced petrophysical workflows applied to the Three Forks geothermal reservoir in the Williston Basin illustrate how well log, core, and seismic attribute data can be integrated to predict porosity, permeability, and reservoir quality at high spatial resolution, providing exactly the class of high-fidelity input data that deliverability prediction models such as those of Ali (2021) and Hussain et al. (2025) require to achieve reliable, site-specific accuracy in depleted reservoir and aquifer storage settings.

4.2 Geomechanical Considerations for Storage Integrity and Cycling Capability

Underground natural gas storage integrity, particularly for salt cavern and depleted reservoir storage subject to repeated, cyclical injection and withdrawal, depends on geomechanical stability considerations closely related to those governing CO₂ storage geomechanical risk. Machine-learning-enhanced geomechanical characterization and wellbore stability assessment, as demonstrated in the offshore South Tano Field, integrates stress field estimation, rock strength prediction, and drilling parameter analysis into a proactive risk-management workflow; analogous geomechanical characterization approaches, adapted to the cyclical loading conditions characteristic of gas storage operations, represent an important complement to flow-focused deliverability prediction models, ensuring that predicted deliverability rates remain consistent with long-term storage integrity under repeated seasonal cycling.

4.3 Heterogeneous Reservoir Considerations for Depleted Gas Storage

Heterogeneous depleted gas reservoir characterization, as exemplified by the Evetts site case study in the Permian Basin, illustrates the substantial spatial variability in porosity, permeability, and residual saturation that can complicate deliverability prediction in depleted reservoir UNGS settings, underscoring the value of machine learning approaches capable of learning site-specific deliverability drivers from extensive field data rather than relying solely on simplified, homogeneous reservoir assumptions.

5. From Deliverability Prediction to Operational Optimization

5.1 Dynamic, Season-Aware Deliverability Forecasting

Because deliverability evolves throughout each withdrawal season as cumulative gas volume and reservoir pressure decline, operationally useful ML-based deliverability models must support dynamic, continuously updated forecasting rather than static, single-point-in-time prediction. The explainable SARF framework of Ali et al. (2022) and the Bayesian Regularization-optimized ANN models of Hussain et al. (2025) both draw on extensive historical field data spanning multiple withdrawal seasons, providing a foundation for dynamic deliverability forecasting that can be updated as each withdrawal season progresses.

5.2 Portfolio-Scale Optimization Across Multiple Storage Sites

Beyond individual site deliverability prediction, national and regional gas storage portfolios comprising dozens to hundreds of individual storage sites require portfolio-scale optimization of injection and withdrawal scheduling to reliably meet aggregate system demand while respecting individual site deliverability constraints. Machine learning models capable of rapid, computationally efficient deliverability prediction across many sites simultaneously—as demonstrated at the scale of 782 reservoirs by Ali (2021) and 78 operational reservoirs by Hussain et al. (2025)—provide the computational foundation necessary for this class of portfolio-scale operational optimization, which would be impractical using site-by-site physics-based simulation alone.

5.3 Explainability as a Foundation for Operational Trust

Because deliverability predictions directly inform operational decisions with financial and reliability consequences, the explainable AI methods introduced alongside the SARF deliverability model (Ali et al., 2022) represent an important development for building operator confidence in ML-generated deliverability forecasts, allowing storage operators to understand which specific geologic and operational factors are driving a given deliverability prediction rather than treating the model as an unexplained black box—a consideration equally relevant to the explainability concerns raised throughout the broader CO₂ and subsurface energy storage machine learning literature.

6. Cross-Domain Lessons: Predictive AI for Operational Planning and Resource

Allocation at National Scale

While the technical foundations of ML-based UNGS deliverability prediction are rooted in subsurface reservoir engineering, valuable methodological lessons can be drawn from large-scale predictive AI and economic impact frameworks developed in other operationally critical, resource-allocation-driven domains. National-scale predictive analytics frameworks applied to Medicare and Medicaid populations demonstrate how AI-driven models can support proactive resource allocation decisions by identifying, from large and heterogeneous datasets, the cases and conditions warranting the most immediate attention (Nguyen, 2026d). This proactive, data-driven resource allocation logic maps directly onto UNGS portfolio management, where ML-based deliverability prediction across many sites enables storage operators and system planners to proactively identify which storage sites and withdrawal schedules require closer operational attention to reliably meet peak seasonal demand, rather than relying on uniform, undifferentiated planning assumptions across an entire storage portfolio.

National-scale AI frameworks developed for precision public health further illustrate the value of predictive models capable of supporting early, targeted intervention based on individual-level risk characterization drawn from extensive historical data (Nguyen, 2026a). This principle—that extensive historical data, properly leveraged through machine learning, can support more targeted and effective planning than aggregate or simplified assumptions—directly parallels the deliverability prediction literature's emphasis on training models against extensive field datasets spanning hundreds of storage sites (Ali, 2021; Hussain et al., 2025) rather than relying on generic, formation-type-level deliverability assumptions.

Economic impact analyses of AI adoption in healthcare, quantifying national-scale cost savings and productivity gains attributable to AI-driven predictive modeling, offer a further template for constructing the economic case for ML-based UNGS deliverability prediction and optimization investment (Nguyen, 2026c). Just as AI-driven healthcare predictive analytics have been shown to reduce costs through more efficient, data-driven resource allocation relative to uniform planning approaches, ML-based UNGS deliverability prediction can be expected to reduce the operational and financial risks associated with inaccurate deliverability forecasting—including the risk of failing to meet peak withdrawal obligations or, conversely, maintaining excessive precautionary working gas inventory—an economic argument that merits explicit quantification as ML-based deliverability prediction tools mature toward standard practice across the natural gas storage industry.

Collectively, these cross-domain parallels reinforce a broader principle: the value of machine learning for extracting actionable, data-driven insight from extensive historical operational datasets to support proactive planning and resource allocation decisions is not unique to subsurface natural gas storage, but reflects a general pattern observed across domains characterized by large numbers of individually monitored assets or populations, extensive historical data availability, and the operational imperative to plan reliably under demand uncertainty. The maturation of ML-based UNGS optimization can accordingly draw on deployment and economic justification frameworks already developed in these adjacent, more mature large-scale AI application domains.

7. Challenges and Limitations

Despite substantial progress, several challenges continue to constrain the widespread deployment of ML-based UNGS deliverability prediction and optimization.

Cross-formation generalizability. Models trained predominantly on one geologic storage setting—depleted reservoirs, aquifers, or salt caverns—may not generalize reliably across settings given their fundamentally distinct flow and geomechanical characteristics, motivating continued development of either separate formation-specific models or unified architectures explicitly designed to capture setting-specific deliverability drivers.

Dynamic, within-season model updating. While the deliverability prediction literature has made substantial progress in developing accurate static models, the operational need for continuously updated, within-season deliverability forecasting as reservoir conditions evolve throughout each withdrawal cycle remains a less thoroughly addressed extension of the current modeling approaches.

Data quality and reporting consistency across storage sites. Because ML-based deliverability models depend on extensive historical field data aggregated across many storage sites and operators, inconsistencies in data quality, reporting frequency, and measurement methodology across sites can introduce noise and bias into model training, an ongoing data governance challenge for the field.

Integration of geomechanical constraints, particularly for salt cavern storage. Deliverability prediction models focused primarily on flow and pressure dynamics may not fully capture the geomechanical creep and cavern stability constraints that govern safe, long-term cycling capability in salt cavern storage, motivating closer integration of geomechanical

characterization approaches into deliverability optimization workflows.

Portfolio-scale optimization under demand uncertainty. While individual-site deliverability prediction has matured substantially, the extension of these models into fully integrated, portfolio-scale operational optimization frameworks that jointly account for demand uncertainty, multiple storage sites, and pipeline transportation constraints remains a comparatively underdeveloped research frontier.

8. Future Directions

Future research should prioritize the development of dynamic, continuously updated deliverability prediction frameworks capable of incorporating real-time operational data as each withdrawal season progresses, building on the extensive static modeling foundations established across depleted reservoir, aquifer, and salt cavern settings (Ali, 2021; Ali et al., 2022; Hussain et al., 2025, 2026). Closer integration of explainable AI methods (Ali et al., 2022) with self-organizing modeling approaches capable of automatically adapting model complexity to available data (Hussain et al., 2026) represents a promising direction for developing deliverability prediction tools that are simultaneously accurate, interpretable, and robust to the varying data availability characteristic of different storage sites.

Integration of high-resolution petrophysical and geomechanical characterization workflows—such as those demonstrated for the Three Forks geothermal reservoir and the South Tano offshore field—directly into UNGS deliverability model training pipelines represents a further avenue for improving prediction fidelity at data-rich candidate sites, with particular relevance to heterogeneous depleted reservoir storage settings such as those characterized at the Evetts site in the Permian Basin. Finally, adopting economic justification and resource-allocation frameworks informed by AI-driven predictive analytics deployment in national-scale healthcare systems (Nguyen, 2026a, 2026c, 2026d) may help establish the cost-benefit case required for ML-based UNGS deliverability prediction and portfolio-scale optimization to transition from research demonstration toward standard, routinely deployed practice across the natural gas storage industry.

9. Conclusion

Machine learning is increasingly central to the prediction and optimization of underground natural gas storage deliverability, a parameter that fundamentally governs the operational

reliability and economic value of gas storage assets supporting energy system flexibility. Applications spanning hybrid metaheuristic-optimized support vector regression, explainable sparse autoencoder-random forest frameworks, advanced-algorithm-optimized artificial neural networks, and self-organizing group-method-of-data-handling architectures collectively demonstrate that machine learning can substantially improve deliverability prediction accuracy while providing the interpretability and computational scalability required to support portfolio-scale operational planning across the depleted reservoir, aquifer, and salt cavern settings that constitute the diversity of commercial UNGS operations. Cross-domain lessons from AI-driven predictive analytics and economic impact analysis in national-scale healthcare systems further suggest a pathway toward the resource-allocation and cost-justification frameworks necessary for ML-based UNGS optimization to achieve routine adoption in commercial natural gas storage practice. Realizing the full potential of machine learning in this domain will require sustained investment in cross-formation generalizability, dynamic within-season forecasting, and portfolio-scale operational optimization—investments essential to ensuring that underground natural gas storage can continue to reliably and cost-effectively support energy system flexibility as demand patterns and the broader energy mix continue to evolve.

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