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Trends of Intelligent Transformation in Geothermal Development

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ABSTRACT

As the global shift toward clean energy accelerates, smart geothermal systems are becoming a leading example of integrating geothermal development with advanced digital technologies. This trend is driving the industry toward more intelligent and low-carbon practices, marking a shift from experience-based to data-driven approaches. This paper focuses on the core technological framework of smart geothermal systems—intelligent characterization, intelligent prediction, and intelligent optimization—and reviews recent advances and challenges. Intelligent characterization integrates multi-source data and artificial intelligence to enable precise modeling and dynamic inversion of geothermal reservoirs, overcoming the limitations of traditional methods. Intelligent prediction, based on digital twins and multi-physics simulation, supports accurate forecasting of production trends and production decision-making. Intelligent optimization uses real-time data and closed-loop feedback to continuously refine development strategies, enhancing efficiency and sustainability. Addressing issues such as data scarcity and rigid models will require closer integration of AI and domain knowledge. The hybrid approach combining data-driven and physics-based methods is key to building accurate reservoir models and rapidly optimizing production strategies. Together, these elements form the foundation for the intelligent transformation of geothermal development.

1 INTRODUCTION

As the global energy structure shifts toward cleaner and low-carbon systems, geothermal energy has emerged as a stable and sustainable renewable resource. However, the strong heterogeneity of geothermal reservoirs poses significant challenges. Conventional approaches to geological exploration, numerical simulation, and optimization often suffer from low data utilization, high computational costs, and dependence on empirical judgments, making it difficult to achieve precise reservoir development. To overcome these limitations, smart geothermal field technologies have become a key direction for innovation. This integrated framework encompasses three core components: (1) Intelligent inversion, which leverages real-time monitoring data and artificial intelligence (AI) algorithms to address the inefficiency and ill-posedness of traditional history matching, enabling accurate reservoir characterization. (2) Intelligent prediction, which combines data-driven models with physical principles to overcome the computational constraints of purely numerical simulations, allowing efficient forecasting of reservoir dynamics and production performance. (3) Intelligent optimization, which employs AI algorithms and surrogate models to optimize injection–production parameters and well configurations, improving energy recovery and economic returns throughout the system's lifecycle. This review systematically examines recent progress in intelligent inversion, prediction, and optimization. It highlights key methodologies (e.g., AI algorithms, dimensionality-reduction techniques, and physics-informed models), summarizes representative applications, identifies current challenges, and outlines future directions to support technological advancement and engineering implementation in smart geothermal fields.

2 INVERSION OF GEOTHERMAL RESERVOIR PARAMETERS

Usually, the geothermal reservoir has strong heterogeneity, and geological exploration methods are difficult to fully reflect its distribution characteristics. To further deepen the understanding of underground reservoirs, real - time monitoring of parameters such as fluid pressure, temperature, and flow rate is required at geothermal production sites to provide data support for characterizing geothermal reservoirs. After obtaining the change information of geothermal production indicators during the geothermal extraction process, the geological model can be calibrated through the history matching method. That is, the on - site monitoring data is compared with the prediction results of the established quantitative relationship model. If there is a deviation, the reasons are analyzed and the model parameters are adjusted. For example, if the production temperature predicted by the model does not match the actual monitored value, parameters such as fracture density may need to be adjusted to make the model more accurately reflect the actual situation. However, history matching is a typical ill-posed inverse problem with multiple possible solutions. Traditional history matching relies on trial-and-error, manually tuning parameters to achieve an acceptable match, without standardized guidelines—making the process heavily dependent on the engineer's experience and judgment. This often results in randomness, subjectivity, and inefficiency. Reservoir inversion based on real-time monitoring data and artificial intelligence can ensure accuracy while significantly reducing manual effort and computation time.

Intelligent model does not require complex equation discretization and iterative solution. Replacing the numerical model with it can significantly improve the fitting speed. Suzuki et al. (2022, 2024) applied multiple AI algorithms to relate temperature–pressure distributions to reservoir permeability, developing a data-driven geothermal reservoir modeling method. Bao et al. (2023) integrated field temperature–pressure data with a coupled thermal–hydraulic–solid mechanics model and deep learning–based inversion to characterize the heterogeneous flow field of the Utah FORGE EGS site. Ullah et al. (2024) combined a bidirectional gated recurrent unit (BiGRU) to capture nonlinear relationships with Bayesian particle swarm optimization (PSO) for automatic hyperparameter tuning, achieving efficient geothermal reservoir modeling.

Given that history matching often involves high-dimensional geological parameters, direct calculations can sometimes be difficult to handle. Dimensionality reduction techniques have thus become an important research focus. The methods project the high-dimensional problem into a low-dimensional space while preserving essential features. Common techniques include principal component analysis (PCA), Karhunen–Loève (K–L) decomposition, and discrete cosine transform (DCT). Dimensionality reduction can also transform non-Gaussian parameters into Gaussian latent variables, meeting the statistical requirements of certain methods such as ES-MDA. Wu et al. (2021) proposed an Enhanced Geothermal System (EGS) inversion framework (Figure 1) that combines PCA for dimensionality reduction with ES-MDA to estimate the spatial distribution of fracture apertures. Chen et al. (2025) proposed a deep-learning–based joint inversion framework using a convolutional variational autoencoder (CVAE) to parameterize non-Gaussian fracture media into quasi-Gaussian low-dimensional latent variables. These were then updated via ES-MDA using multiple datasets—including hydraulic tomography (HT) and thermal tracer tomography (TT)—to achieve high-fidelity characterization of fracture media. The inversion results for fracture distribution are shown in Figure 2.

The intelligent inversion of geothermal reservoirs will focus on breaking through the bottlenecks of insufficient data and limited physical interpretability, with mechanism-data fusion and well-seismic data constraints as core directions to further improve the accuracy and reliability of reservoir characterization.

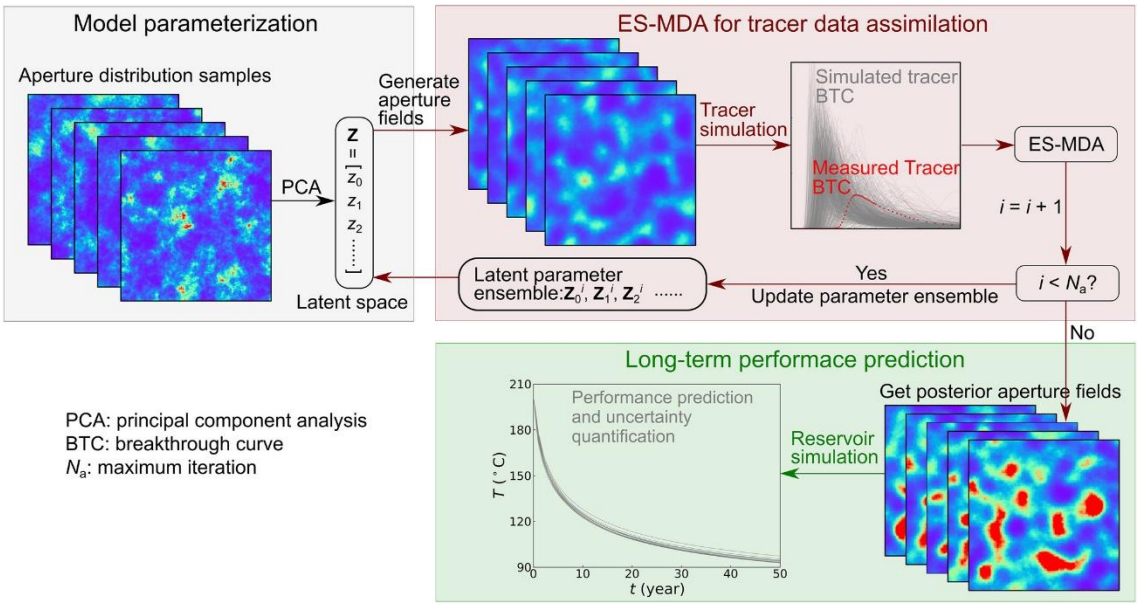


Figure 1. Inverse framework for single fracture aperture distribution (Wu et al., 2021).

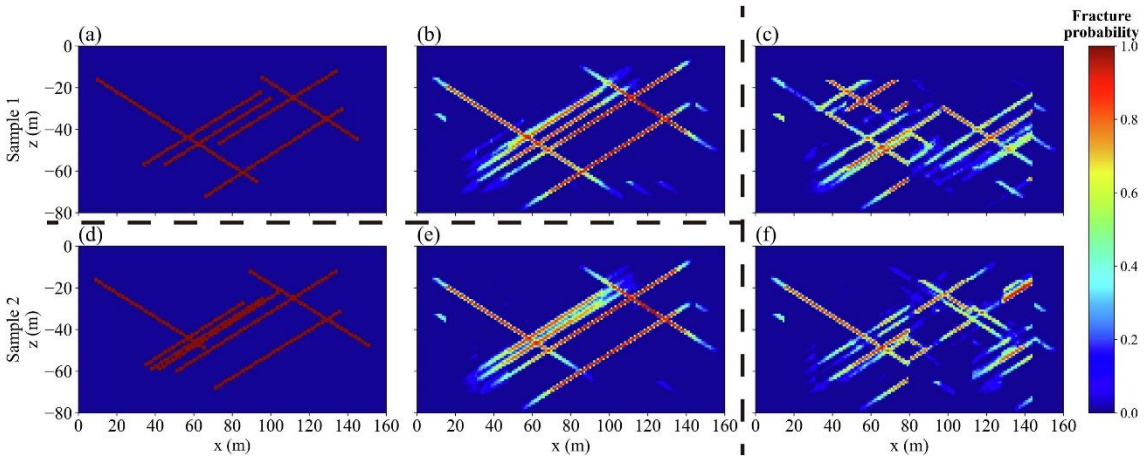


Figure 2. The inversion results for fracture distribution (Chen et al., 2025).

3 INTELLIGENT PREDICTION OF GEOTHERMAL SYSTEM

During geothermal energy exploitation, complex Thermal–Hydraulic–Mechanical–Chemical (THMC) coupled multi-physics processes are involved. The Effective management of geothermal resources requires a detailed understanding of reservoir conditions and spatial heterogeneity within the geothermal system. Numerical simulation has long been the primary approach for investigating geothermal reservoir development. Although such methods provide stable and physically interpretable results, they are often constrained by complex mesh generation and high computational cost. With the rapid advancement of artificial intelligence (AI) and machine learning (ML) technologies, intelligent prediction of geothermal reservoir performance has attracted increasing attention. Data-driven intelligent models can learn from production data and establish highly nonlinear mappings between operating parameters and reservoir responses, achieving remarkable prediction accuracy. Aydin et al. (2020) developed an artificial neural network (ANN) model to estimate reservoir pressure and temperature based on wellhead production data. Peng et al. (2022) employed a deep convolutional generative adversarial network (DCGAN) to capture the relationship between fracture distributions and reservoir pressure, demonstrating that generative adversarial networks (GANs) can efficiently predict geothermal production dynamics. Shi et al. (2021) proposed a hybrid approach combining a long short-term memory (LSTM) neural network with a multilayer perceptron (MLP) for geothermal production forecasting, where the incorporation of injection mass flow rate, reservoir temperature, and horizontal well spacing as constraints significantly enhanced prediction accuracy and stability. Wang et al. (2023) constructed a hybrid convolutional–recurrent neural network in which a convolutional neural network (CNN) captures the spatial features of reservoir property fields, while an LSTM network approximates the sequence-to-sequence temporal mapping. This model effectively predicts production responses (rate and temperature) under varying permeability and injection–

production schemes, thus facilitating production optimization. Jiang et al. (2023) introduced a multi-scale recurrent neural network (RNN) model for extrapolating geothermal production time-series data, where the conventional RNN component captures short-term nonlinear behaviors and the fully connected neural network (FCNN) component learns the long-term declining trend of heat production. Li et al. (2024) developed a hybrid neural network framework that uses an ANN to identify nonlinear correlations between static constraints and thermal breakthrough time, and a bidirectional gated recurrent unit (BiGRU) to forecast temporal variations in production temperature, evaluating 22 influential factors in total.

However, in practical geothermal reservoir development, challenges such as non-uniqueness of solutions and limited data availability are frequently encountered. Data-driven methods are highly sensitive to data quality; the quantity and reliability of input data directly determine the accuracy of production forecasting. Moreover, these methods require a well-defined and explicit mapping between input and output variables, which often cannot be guaranteed in complex geothermal systems. Consequently, purely data-driven intelligent approaches have struggled to gain wide application in real engineering practice. Nevertheless, even limited datasets often embed rich underlying physical principles. By effectively integrating deep learning techniques with physics-informed data, it becomes possible to develop hybrid intelligence frameworks that are jointly driven by physical mechanisms and data observations. Raissi et al. (2017) proposed the Physics-Informed Neural Network (PINN), in which governing physical equations are incorporated as constraints within the loss function, serving as regularization terms during backpropagation training. PINNs can achieve high-accuracy and highly generalizable models with sparse training data, and their mesh-free nature helps mitigate the “curse of dimensionality” commonly encountered when solving high-dimensional partial differential equations. Ishitsuka et al. (2023) applied PINNs to predict the spatial distributions of temperature, pressure, and permeability in two-dimensional geothermal systems, demonstrating the applicability of PINNs to geothermal reservoir analysis. Similarly, Xie et al. (2025) combined PINNs with a wellbore heat transfer model to predict wellbore temperature profiles under various drilling conditions and operational parameters, validating the feasibility of using PINNs for dynamic and real-time temperature prediction in geothermal wells.

Research on mechanism–data-driven methods in the geothermal field is still in its early stages. Most existing studies introduce physics-based constraints into the loss function, without fundamentally modifying the architecture of neural networks. Chuang et al. (2022) pointed out that Physics-Informed Neural Networks (PINNs) suffer from limitations in terms of computational efficiency and convergence. Some researchers have therefore developed new neural network architectures to approximate the differential equations governing subsurface flow systems. Zhen et al. (2024) proposed physics-guided recurrent neural network models (phy-RNN and phy-GRU) to address long-term prediction and extrapolation tasks during geothermal reservoir production, and successfully applied them to field data. Yan et al. (2024) introduced a novel Physics-Informed Machine Learning (PIML) framework incorporating an improved Hyperbolic-ReLU (HyperReLU) activation function to robustly predict the temperature of produced geothermal fluids. In summary, future research should systematically investigate theoretical foundations of mechanism–data integration methods and develop efficient, robust, and transferable geothermal dynamic simulation models. Such advances will enable accurate characterization and optimized development of complex geothermal reservoirs in engineering practice, providing reliable technical support for the efficient utilization of deep geothermal resources.

Overall, physics-informed intelligent prediction methods show strong potential for capturing key reservoir characteristics, mitigating data sparsity, and improving forecasting accuracy. However, current models still exhibit limited generalization under complex geological structures, insufficient representation of multi-scale coupled processes and the characterization of geological uncertainties Future research should advance the theoretical foundations of physical constraints, network architecture design and training strategies to deliver more robust and reliable predictive tools that can support large-scale geothermal resource development.

4 INTELLIGENT OPTIMIZATION OF GEOTHERMAL SYSTEM

Geothermal system optimization aims to maximize energy extraction and economic returns over the life cycle of the reservoir by adjusting operational parameters such as injection rates, production rates, and well placement. However, the strong heterogeneity and complex thermo-hydro-mechanical-chemical (THMC) coupling effects in subsurface reservoirs make it difficult to accurately predict system behavior under different operational strategies, which leads to significant uncertainty in optimization outcomes. Traditional optimization methods rely heavily on numerical simulation and manual scenario analysis. Engineers typically define a limited set of operational schemes based on experience, then use reservoir simulators to evaluate each scenario and select the best-performing option. This approach is computationally prohibitive due to the high cost of full-physics simulations, Moreover, its limited search space often fails to identify truly optimal solutions. Furthermore, the

process is heavily dependent on the engineer's intuition and prior knowledge, introducing subjectivity and potentially missing more efficient operational strategies.

Geothermal system optimization aims to maximize heat extraction and economic returns throughout the reservoir lifecycle by adjusting operational parameters such as injection rate, production rate, and well placement. However, the strong heterogeneity and complex thermo–hydro–mechanical–chemical (THMC) coupling in subsurface reservoirs make it challenging to predict system behavior under varying operational strategies, thereby introducing significant uncertainty into optimization outcomes.

Traditional optimization approaches rely heavily on full-physics numerical simulations and manual scenario analyses, which are computationally expensive and limited in search scope. Engineers often define a few operational schemes based on prior experience, evaluate them using simulators, and select the best-performing option—often missing more efficient strategies due to subjectivity and incomplete parameter exploration.

In this context, artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools for geothermal optimization. Samin et al. (2019) developed a hybrid numerical design approach that integrates a multi-objective genetic algorithm with finite element thermo-hydraulic simulation, significantly improving both thermal power output and cost-effectiveness of doublet enhanced geothermal systems (EGS). Song et al. (2021) employed multi-objective optimization (MOO) to simultaneously adjust injection temperature, flow rate, and production pressure, achieving a 36.23% reduction in water loss and delaying thermal breakthrough by 1.1 years.

Machine learning has also accelerated real-time decision-making. Chen et al. (2024) proposed an ML-accelerated optimization framework that reduces computational costs by one to two orders of magnitude while maintaining high accuracy. Similarly, Chen et al. (2024)developed a surrogate-assisted level-based learning evolutionary search (SLLES) algorithm for high-dimensional geothermal well control problems, achieving a robust balance between exploration and exploitation. Zhao et al. (2025) further combined the particle swarm optimization (PSO), genetic algorithm (GA), backpropagation neural network (BPNN) (PSO-GA-BPNN), and the Analytic Hierarchy Process (AHP) methods to establish a comprehensive hybrid optimization framework, identifying optimal design parameters for power generation efficiency.

Hybrid intelligent optimization represents the current state-of-the-art approach, combining physics-based numerical modeling with data-driven methods. These hybrid frameworks preserve the interpretability and generalizability of physical models while leveraging ML efficiency. Zhao et al. (2025) demonstrated that physics-informed neural networks (PINNs) can rapidly predict geothermal reservoir behavior consistent with physical laws. Raissi et al. (2019) originally proposed PINNs as a deep learning framework for solving PDEs under physical constraints. To address the challenge of computational cost and limited data, Chen et al. (2025) introduced a multi-fidelity surrogate model that integrates coarse and fine-scale models, achieving efficient optimization of geothermal systems. Yan et al. (2024) further developed a physics-informed machine learning (PIML) framework capable of mapping nonlinear relationships between fracture permeability fields and production temperature, demonstrating excellent transferability across different reservoirs.

The next frontier in geothermal optimization is real-time adaptive control. Digital twin technologies enable continuous feedback between operational data and simulation models. Butean et al. (2024) demonstrated that digital-twin-driven optimization dynamically adjusts pressure and flow rate to maximize heat pump efficiency, achieving minimal energy losses. (Smirnov et al., 2021) implemented digital twin simulators for hybrid geothermal–renewable systems, significantly enhancing overall energy utilization. Buster et al. (2021) introduced GOOML—a machine-learning-based operational optimization framework—which integrates thermodynamic modeling with AI-driven decision support, achieving high accuracy across several commercial geothermal plants.

However, implementing real-time optimization still faces challenges, including computational resource limitations, sensor latency, robustness under varying field conditions, and multi-objective trade-offs. Future research should therefore emphasize tightly coupled physics-informed ML frameworks capable of performing robust, real-time, multi-objective optimization under uncertainty.

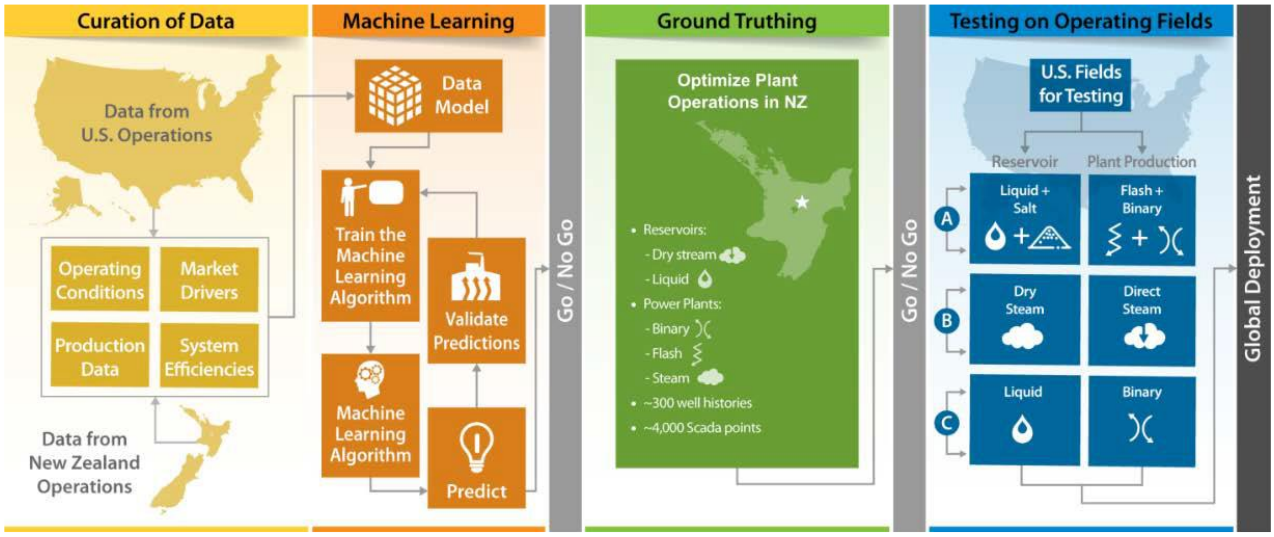


Figure 3: General Overview of GOOML Project Flow (Siratovich et al., 2020).

5 CONCLUSION

Smart geothermal field technologies integrate artificial intelligence with geothermal engineering principles to address the fundamental limitations of traditional methods in reservoir characterization, dynamic prediction, and system optimization. This paradigm shift—from experience-driven to intelligence-driven geothermal development—is vital for achieving large-scale, high-quality utilization of geothermal resources.

In intelligent inversion, AI-based reservoir inversion techniques have significantly improved the efficiency of history matching by replacing complex numerical models. Intelligent dimensionality-reduction methods further address the challenges of high-dimensional geological parameters and poor adaptability to non-Gaussian statistics. However, current approaches still face limitations such as insufficient data and weak physical interpretability. Future research should focus on mechanism–data integration and the incorporation of well and seismic data constraints to enhance the reliability of inversion results.

Physics-informed intelligent prediction methods have substantially enhanced geothermal reservoir forecasting by embedding governing equations into learning frameworks. The approaches capture key geothermal reservoir characteristics that are difficult to represent using traditional data-driven models, thereby significantly enhancing prediction capabilities. However, current intelligent prediction methods still face challenges, including limited generalization under complex geological heterogeneity, insufficient representation of multi-scale coupled processes, and inadequate characterization of geological uncertainty. Future research should emphasize the development of mechanism–data fusion architectures, improved physical constraints, and more efficient training strategies and integrating multi-source observational data to support accurate characterization and predictive development of geothermal reservoirs.

In intelligent optimization, AI algorithms and surrogate models substantially reduce the computational burden of conventional optimization workflows. Multi-objective and physics-informed optimization frameworks enhance both energy efficiency and economic performance, while digital-twin technologies are pushing optimization toward real-time adaptive control. Nevertheless, challenges remain in handling sensor delays, multi-objective trade-offs, and complex operating conditions. Further development of tightly coupled physics-informed machine-learning frameworks is needed to achieve real-time, multi-objective optimization under uncertainty and ensure efficient operation throughout the geothermal system's lifecycle.

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