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Quantifying and integrating decision-making for geothermal well life-cycle risk under geological uncertainty: A review

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Abstract

As global energy systems shift toward low-carbon models, deep geothermal energy is an important clean resource with stable output and high potential. Commercial development, however, remains constrained by heavy upfront capital costs and geological uncertainty. Well construction and surface facilities typically account for 50 to 75 percent of total project investment, and extreme downhole conditions, such as high temperatures, abrasive formations, and complex fracture networks, readily trigger incidents causing substantial non-productive time (NPT) and cost overruns. Managing risk while improving cost efficiency across the full well life cycle is therefore a central industry challenge. This paper reviews recent progress and frameworks for integrated decision-making and risk control in geothermal wells. In siting, target-area selection has evolved from qualitative expert judgment toward spatial decision systems combining multi-criteria evaluation (MCE) with machine learning; with well-field co-optimization, these reduce blind early siting and sunk costs. In construction, where mechanistic and numerical models are hard to parameterize and computationally costly, data-driven algorithms now support real-time rate-of-penetration (ROP) prediction, transient bottom-hole thermal management, and incident early warning. In investment appraisal, probabilistic simulation, value-of-information (VOI) theory, and life-cycle assessment (LCA) have moved evaluation beyond deterministic single-well cost estimates toward multi-objective optimization of levelized cost, long-term thermal revenue, and carbon footprint.

Keywords: Geothermal well; geological uncertainty; Decision-making; Risk management; Techno-economic evaluation

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1. Introduction

As the global energy mix transitions toward low-carbon, sustainable sources, geothermal energy is becoming an important part of the future clean-energy system because of its large reserves and its stable, clean output [1,2]. Geothermal wells are the key conduit for developing this resource, and their core function is to transport heat from deep formations to the surface. Yet despite the vast thermal potential stored at depth, large-scale commercial development still faces major obstacles. The most fundamental bottlenecks are the very high upfront capital intensity and the extreme uncertainty of subsurface geological conditions [3,4]. Early-stage investment risk in deep geothermal projects is high, and well construction together with supporting works often accounts for 50 to 75 percent of total project investment [5]. Compared with conventional oil and gas wells, geothermal wells are not only more expensive to build; a siting or well-design error also leads directly to very high sunk costs [6].

The high cost and high risk of geothermal wells stem from their complex subsurface environment and long-term operating conditions. Geothermal reservoirs usually occur in crystalline rock that is very hot, hard, and abrasive, and that is cut by well-developed natural faults and fracture networks [7–9]. These conditions place severe demands on wellbore integrity, casing service life, and downhole monitoring components, and they shorten the service life of downhole tools [10,11]. In highly fractured and underpressured formations, geothermal wells are also prone to lost circulation and stuck-pipe incidents. The resulting non-productive time (NPT) is the leading cause of cost overruns and schedule delays in geothermal projects [12]. Faced with these highly nonlinear and dynamic conditions, traditional trial-and-error methods based on coarse experience, and purely physics-based numerical models with high computational cost, can no longer meet the need for real-time response and precise risk control in the field.

As in the broader field of engineering management, decision-making for geothermal wells is also shifting from subjective qualitative experience toward quantitative, data-driven analysis to address these challenges and maximize return on investment [13–16]. Early studies often borrowed mature practices from the oil and gas industry, but the complex geology of geothermal reservoirs means that conventional oil and gas theory and technology cannot simply be transferred without adaptation [17–19]. Current research therefore focuses on developing intelligent decision-support systems for geothermal wells that integrate geographic information systems (GIS), operations-research algorithms, machine learning, and big-data analytics into platforms spanning planning, construction, and operation [20]. In the siting stage, deep fusion of multi-source geoscience data within spatial decision systems greatly reduces the subjectivity of early site selection. During construction, intelligent algorithms provide strong computational support and precise quantitative analysis for real-time rate of penetration (ROP) prediction, active management of transient bottom-hole thermodynamics, and anomaly warning under complex conditions. At the project level, value of information (VOI) theory, Monte Carlo simulation, and multi-objective evolutionary algorithms allow decision-makers to balance siting risk, construction cost, and long-term economic and environmental benefits under geological uncertainty.

Recent commercial enhanced geothermal system (EGS) projects further demonstrate the engineering value of AI-augmented, data-driven spatial decision-making. Using its proprietary AI-driven subsurface interpretation technology, Fervo Energy identified a new play concept for thermal sedimentary basins and optimized its drilling program accordingly, encountering a very high-temperature resource above 291 degrees Celsius at a depth of about 11,200 feet in the Project Blanford appraisal well in Utah [21]. At its Cape Station project in the same state, Fervo combined public data from the neighboring DOE FORGE and Blundell sites with high-resolution 2022 gravity and magnetotelluric (MT) surveys to build a three-dimensional geological-temperature model, updated iteratively while drilling, that guided the placement and landing depth of four Frisco horizontal wells; drilling results showed close agreement between predicted and measured lithology and temperature, with measured values meeting or exceeding predictions, and the campaign achieved a 100 percent drilling success rate [22,23]. The adjacent DOE FORGE program, which supplied much of the de-risking data for Cape Station, embedded machine learning into subsurface decisions more systematically, covering machine-learning estimation of the stress field trained on experimental data, unsupervised clustering to identify reservoir mechanical layers, and optimization of injection and production well geometry based on microseismicity and discrete fracture networks. Together these provide a transferable analytical framework for reservoir characterization and well design in hard-rock EGS [24–26]. These cases show that integrating multi-source geological and geophysical data into three-dimensional modeling and intelligent interpretation is moving EGS siting and drilling or stimulation decisions from experience-based judgment toward quantitative, reproducible support. However, existing reviews tend to focus on a single stage or a single technique, such as geothermal prospectivity mapping [27], uncertainty and risk evaluation during exploration [19], machine learning applications in drilling [28], and data analytics for above-ground operations [29], or they survey representative applications of artificial intelligence across the geothermal life cycle [20]. How geological uncertainty propagates among siting, drilling, and investment decisions, and how the applicability and validation level of decision methods differ across these stages, have not yet been reviewed systematically. Because the three stages rely on the same incomplete subsurface information and constrain one another, improving any single stage in isolation can hardly reduce overall project risk, which motivates the present review.

Accordingly, the basic hypothesis of this review is that geological uncertainty is the common thread running through geothermal well siting, drilling, and investment decisions, and that integrating decision methods through the propagation and updating of this uncertainty across stages reduces life-cycle risk more effectively than optimizing any single stage in isolation. Building on this hypothesis, the objectives of this review are to synthesize the decision methods of the three stages systematically, to compare their data requirements, applicability, and level of field validation, and to clarify how uncertainty is transferred between stages. To this end, this paper reviews the decision framework from early siting and planning, through well construction, to project investment appraisal. It first examines the core techniques of the siting stage, including GIS- and machine-learning-enhanced target-area selection, construction of well-location conceptual models, and selection of well-system types and operating modes. It then reviews real-time engineering decisions made

during construction, including ROP optimization, bottom-hole temperature evolution and management, and real-time monitoring of lost circulation and stuck-pipe incidents. Finally, it examines investment decisions from a life-cycle perspective, discussing probabilistic modeling of well time and cost, extraction of the value of geological data under uncertainty, and techno-economic evaluation based on multi-objective algorithms, so as to inform future low-cost, efficient geothermal development. The overall structure is shown in Fig. 1. The scope of this review centers on integrated decision-making under geological uncertainty and covers the complete life cycle from siting and layout, through drilling, to investment appraisal.

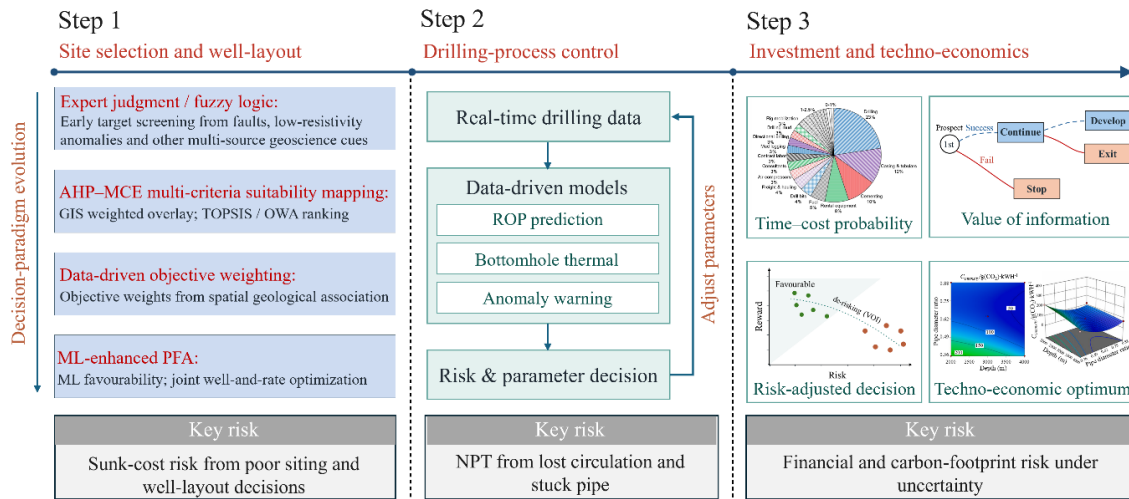


Fig. 1. Structure of this review.

The siting, drilling, and investment stages of geothermal wells are not independent of one another. Geological uncertainty in temperature, permeability, and fracture distribution runs through all three stages, propagating from one stage to the next and being updated as new information is acquired. In the siting stage, geological uncertainty appears as uncertainty in the resource favorability and geological risk of target areas; GIS-based multi-criteria evaluation (MCE), machine-learning-enhanced PFA, and geophysical inversion combined with conceptual models produce a three-dimensional subsurface model that still carries uncertainty. In the drilling stage, this uncertainty does not disappear but turns into engineering risk: the heterogeneity of hard rock causes ROP fluctuation, high temperature raises the bottom-hole circulating temperature and causes thermal damage to downhole tools, and fractured, underpressured formations trigger lost circulation and stuck pipe, all of which ultimately appear as NPT and schedule variation. At the same time, the real-time inflow of logging-while-drilling and surface drilling data continuously reduces this uncertainty, so data-driven prediction of ROP and bottom-hole temperature and anomaly warning are essentially online updates of the subsurface state. In the investment stage, the geological and engineering uncertainty accumulated over the first two stages finally becomes economic uncertainty, under which conflicting objectives must be balanced through multi-objective optimization. The three stages thus form a feedback loop: the siting conceptual model provides the prior, pre-drilling geophysical surveys and while-drilling observations provide new information, and their fusion continually revises judgments on well location, well spacing, make-up well deployment, and financial reserves.

VOI theory is used to weigh whether reducing uncertainty justifies the cost of further exploration, and the outcome of the first exploration well also updates the expected success of nearby well locations. This review therefore treats siting, drilling, and investment as a unified, coupled decision process with geological uncertainty as its main thread, rather than as three separate stages.

To ensure systematic and reproducible coverage, the literature was collected following a systematic search and screening procedure (Fig. 2). Three databases were searched, namely Web of Science, Scopus, and EI Compendex. The database search covered 2010 to 2026; earlier classical models and methodological works were added through backward citation tracking of the included studies. The search strings combined geothermal-well terms, such as "geothermal well", "geothermal drilling", and "enhanced geothermal system", with decision-related terms covering the siting, drilling, and investment stages, such as "site selection", "well placement", "rate of penetration", "lost circulation", "stuck pipe", "well cost", "value of information", "life cycle assessment", and "multi-objective optimization", as well as "machine learning" and "decision-making". The initial search returned 2512 records, including 1042 from Web of Science, 876 from Scopus, and 594 from EI Compendex. After 671 records were removed by keyword and time-window filtering, the titles and abstracts of the remaining 1841 records were screened, and 353 articles were retained for full-text assessment. At the full-text stage, a study was included if it addressed geothermal wells, or drilling problems directly transferable to geothermal wells, and proposed, applied, or evaluated quantitative decision, prediction, or optimization methods for at least one stage: siting and layout, drilling, or investment and techno-economic evaluation. On this basis, 24 articles without accessible full text, 62 duplicate publications, 122 out-of-scope studies, and 33 other review articles were excluded, and 112 studies were finally included in this review. In addition, a small number of company press releases, industry news reports, and preprints were cited to reflect recent progress in commercial geothermal development; as these sources are not peer reviewed, they are used only to illustrate engineering practice.

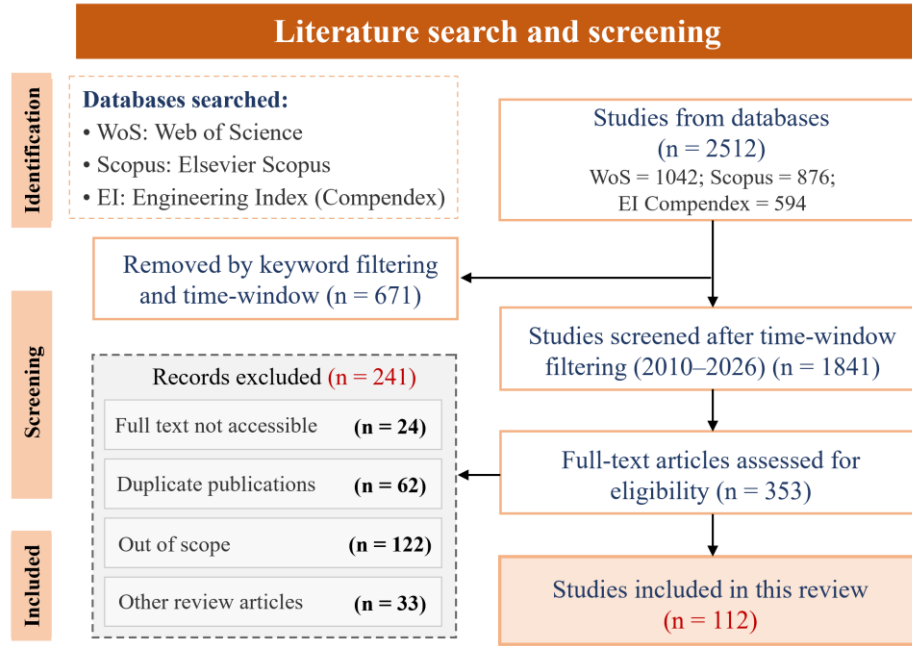


Fig. 2. Literature search and screening process.

2. Siting and layout decisions for geothermal wells

Well siting and system layout are among the high-risk, low-tolerance stages of the geothermal life cycle. Deep geological structures are highly heterogeneous in space, subsurface reservoir features are largely invisible, and well construction with supporting works usually accounts for 50 to 75 percent of total project investment [30,31]. Because of this high upfront capital intensity, a siting or well-network error leads directly to very high sunk costs.

2.1 Identification and selection of geothermal target areas

Identifying and evaluating geothermal target areas is a complex, interdisciplinary spatial decision task. Its core is the deep fusion and interpretation of multi-source exploration data, including geological structure, geophysical anomalies, and geochemical signatures [32,33]. Traditional qualitative judgment by experts is prone to subjective bias. To bridge the gap between decision-makers' domain knowledge and complex spatial-analysis tools, GIS-based spatial decision-support systems minimize human error and provide a scientific basis for combining exploration results from different disciplines [34,35]. To remove subjectivity from indicator weighting, current research uses data-driven models such as weights of evidence and evidential belief functions, which determine weights objectively by quantifying the spatial association between known geothermal sites and geological features [36,37]. In early siting, GIS platforms apply knowledge-driven models such as Boolean logic and fuzzy mathematics to integrate fault distribution, low-resistivity anomalies, and surface fluid features, guiding precise well placement [38]. Fuzzy-logic methods, in particular, handle boundary uncertainty in multi-source data effectively and often outperform Boolean overlay models in the accuracy and flexibility of target

prediction [39,40]. MCE that combines the analytic hierarchy process (AHP) with GIS weighted overlay is widely used to generate geothermal suitability maps, clearly separating highly suitable from unsuitable areas and reducing the risk of siting errors [41,42].

Operations-research algorithms have been added to the GIS framework to refine multi-criteria evaluation. Cambazoğlu et al. [43] used the TOPSIS method, which ranks potential areas by their proximity to an ideal solution, to order geothermal potential areas rigorously, while Kiavarz and Jelokhani-Niaraki [44] applied ordered weighted averaging (OWA) to let decision-makers move flexibly between risk-averse and risk-seeking strategies and thereby balance the number of well sites against prediction accuracy (Fig. 3). For validation, Abdel Zaher et al. [45] used ArcGIS to overlay weighted layers of fault distance, Bouguer gravity anomaly, seismicity, Curie-point depth, and heat flow, producing a national geothermal favorability map for Egypt. Noorollahi et al. [35] applied similar weighted-overlay and spatial-distance techniques in northeastern Japan; more than 97 percent of existing production wells fell within the first-priority areas predicted by the GIS model, confirming the model's reliability. In more complex settings, GIS models combine subsurface three-dimensional fault models with surface social, economic, and environmental constraints such as population density, district-heating networks, and nature reserves to assess overall project accessibility and development potential [4,34,46,47].

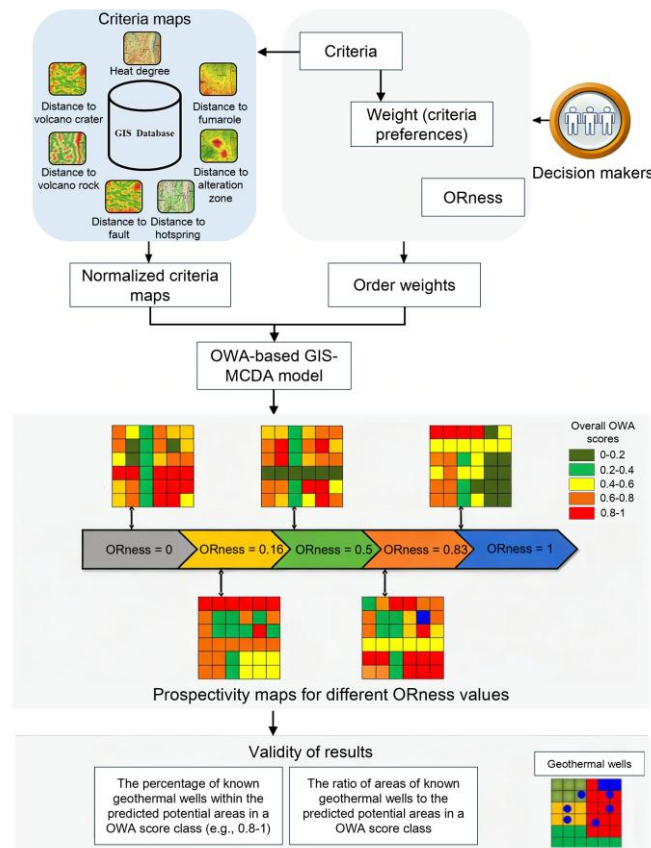


Fig. 3. Geothermal siting decisions using a GIS-based OWA method.

As the technology has matured, GIS-based predictive models have grown from tools for locating thermal

anomalies into Play Fairway Analysis (PFA) frameworks that combine geological, geophysical, and other attributes [48]. Drawing on big data, Li et al. [27] extended the traditional model with machine-learning-enhanced PFA, using unsupervised learning and clustering to process sparse or incomplete datasets and to reveal hidden geological features that are difficult to detect by visual inspection. In case studies of Texas and the Brady geothermal field, Tende et al. [49] showed that machine-learning-enhanced PFA, through coupled analysis of fracture-zone density, sedimentary contacts, and surface temperature, isolated the hidden features that govern geothermal resource formation and markedly improved the accuracy and success rate of deep-system target prediction. Table 1 summarizes the spatial decision models used for geothermal target selection and their main features.

Table 1. Spatial decision-analysis models for geothermal well target areas.

Category	Model	Role and features	Data/input requirements	Weighting and objectivity	Main limitations	Applicable conditions	References
Basic spatial decision	SDSS	Bridges the gap between expert knowledge and complex analysis tools; integrates multi-dimensional geoscience data (geology, geophysics, geochemistry) and reduces human error.	Multi-dimensional geoscience layers (geology, geophysics, geochemistry)	Integration platform; assigns no weights itself and depends on the embedded analysis methods	Results depend on the quality of the integrated models and data	Early integrated decisions that fuse multidisciplinary data and reduce human error	[34,35]
Knowledge-driven	Boolean logic, fuzzy mathematics	Integrate faults and low-resistivity anomalies in early exploration. Fuzzy logic handles boundary uncertainty in multi-source data more flexibly and precisely than Boolean logic.	Layers of faults, low-resistivity anomalies, and surface fluid features	Expert-defined rules; relatively high subjectivity	Sensitive to thresholds and rules; uncertainty hard to quantify	Early reconnaissance with sparse data and well-understood mechanisms	[38]
Classical multi-criteria	AHP, MCE	Assign subjective weights from expert experience to generate suitability maps and delineate priority drilling areas.	Multi-source factor layers plus expert judgment matrices	Subjective weights assigned by experts	Subjective weights; correlations among factors not addressed	Suitability mapping at small to medium scales	[41,42,45,49]

Data-driven	WofE, EBF	Quantify the spatial association between known geothermal sites and geological features to set weights objectively and remove subjectivity.	Known geothermal occurrences and geological factors; sufficient, spatially unbiased samples required	Weights determined objectively from spatial statistical associations	Depends on known occurrences; limited in underexplored areas	Areas with many known geothermal occurrences	[36,37]
Advanced operations research	TOPSIS	Rank potential areas rigorously using proximity to an ideal solution.	Indicators of pre-evaluated candidate areas	Objective ranking that depends on prior weights	Depends on the quality of prior indicators and weights	Priority ranking of candidate areas	[43]
	OWA	Let decision-makers move flexibly between risk-averse and risk-seeking drilling strategies.	Indicators of pre-evaluated candidate areas	Adjustable risk attitude (pessimistic to optimistic)	Depends on the quality of prior indicators and weights	Ranking under different risk attitudes	[44]
Complex-constraint evaluation	Integrated-constraint model	Overlay subsurface three-dimensional fault models with surface constraints to assess overall project accessibility.	Subsurface three-dimensional fault models plus surface social, economic, and environmental constraint layers	Mainly overlay of hard constraints	Requires high-quality three-dimensional geological models and multi-source constraint data	Assessment of overall project accessibility and development potential	[4,46,47]
AI and big data	ML-enhanced	Combine PCA and NMFk unsupervised learning with	Multi-source heterogeneous	Data-driven; reduces manual	Requires label quality and	Regional-scale prospects with	[50–52]

PFA	clustering to process incomplete data and reveal hidden geological features.	data, including sparse or incomplete records	weighting	computing power; limited interpretability and transferability	relatively rich data; mining of hidden features
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These spatial decision methods differ in data requirements, objectivity, and applicable conditions. Knowledge-driven models such as Boolean logic and fuzzy mathematics, together with classical multi-criteria evaluation, are simple to compute and highly interpretable, which suits early regional reconnaissance with sparse data, but their indicator weights rely on subjective expert judgment and their results are prone to human bias. Data-driven models determine weights objectively from the spatial statistical association between known geothermal occurrences and geological factors, but they require sufficient and spatially unbiased known samples, which are often unavailable in underexplored areas. Machine-learning-enhanced PFA can extract features from multi-source, heterogeneous, and sparse data and suits regional-scale evaluation where data are relatively rich, but it places higher demands on label quality, feature engineering, and computing power, and its interpretability and transferability across geological domains remain difficult. In terms of geothermal system type, high-temperature volcanic-magmatic systems rely more on geophysical and geochemical factors such as MT, Curie-point depth, and surface heat flow, whereas sedimentary-basin systems and EGS place more weight on structural and fracture connectivity and on characterizing the temperature field, so several methods usually need to be combined in practice. Moreover, most of these models are validated by the proportion of known production wells falling within high-favorability zones, which is essentially a retrospective test, and their predictive ability in entirely new areas remains to be examined.

2.2 Conceptual modeling and spatial layout of well locations

Once a target area is selected, the focus of siting shifts to precise targeting of individual wells and the spatial layout of the well network. Traditional siting often falls into the trap of chasing, or even stacking, geophysical anomalies. Siting must instead rest on an integrated conceptual model of the geothermal resource that is physically self-consistent. Integrating surface geology, fluid geochemistry, and MT data to predict the natural-state isotherm distribution guides targeting effectively and reduces the risk of unproductive investment [53,54]. For MT data, the key is not the center of a shallow low-resistivity anomaly but the three-dimensional form of the resistivity structure: locating the undulating base of the conductive clay cap reliably maps the true extent of the high-temperature reservoir [32]. This dynamic conceptual-model approach has been applied successfully in the field. Gudmundsson and Mortensen [55], developing the Krafla high-temperature field in Iceland, continually refined the reservoir conceptual model by combining local fault structure, MT anomalies, and surface CO₂ emission anomalies. Guided by this model, a directional well trajectory penetrated the shallow volcanic gas zone and reached a deep, highly permeable superheated fracture system. To find optimal targets in three dimensions, geophysical and geological modeling have been merged further into siting. Elbalawy et al. [56] combined three-dimensional seismic attribute interpretation with a geothermal-fairway analysis model to quantify the three main geological risks of heat source, reservoir fracture permeability, and cap rock in three-dimensional space; this model narrowed a 350-square-kilometer exploration area to four specific target zones with high favorability and low risk, providing a scientific basis for precise well placement.

For multi-well systems, optimizing well layout and spacing is a key decision that determines the productive

life of the resource. Because reservoirs are strongly heterogeneous and groundwater flow creates complex thermal plumes, relying on a single geological model or empirical spacing readily causes premature thermal breakthrough or low circulation efficiency during operation [57–60]. Fig. 4 shows a simulation-optimization framework for well layout. For deep EGS, Schulte et al. [61] built a surrogate model based on design of experiments and combined it with a multi-objective particle-swarm algorithm to co-optimize across a library of three-dimensional models spanning eighteen geological-uncertainty scenarios. Incorporating geological uncertainty into siting allowed the technical trade-off between maximizing heat extraction and minimizing pumping energy to be balanced, yielding optimal injection-production spacing and layout suited to complex geology. Layout is equally important for controlling thermal breakthrough in shallow multi-well systems [58]. Park et al. [60] developed a simulation-optimization model combining a genetic algorithm with FEFLOW and showed that a single maximum-spacing strategy is often uneconomic within the limited space of urban settings; by co-optimizing well positions and injection-production flow rates, the best balance between installation cost and system performance can be found while meeting environmental thermal constraints. For larger, denser well networks, Halilovic et al. [62] introduced a gradient-based optimization method constrained by an adjoint partial differential equation. Compared with traditional discrete siting, this method continuously and simultaneously optimizes the precise three-dimensional coordinates of dozens of pumping and reinjection wells based on local hydrogeological conditions such as natural groundwater temperature and flow velocity.

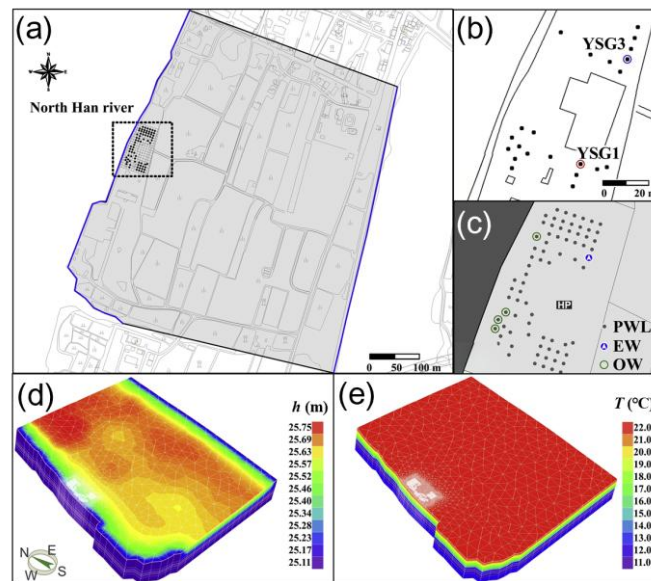


Fig. 4. Workflow for geothermal well-network layout and spacing optimization based on numerical simulation and optimization algorithms: (a) site map; (b) existing well layout; (c) layout after optimization, showing extraction wells, observation wells (OW), potential injection well locations (PWL), and heat pumps (HP); (d) initial hydraulic-head distribution; (e) temperature distribution [60].

During planning, three-dimensional well placement and well boundaries are also subject to considerable subsurface uncertainty and strict thermodynamic constraints. To avoid the heavy computational cost of high-fidelity computational fluid dynamics (CFD) models, combining efficient machine-learning surrogate models

with stochastic optimization has become a promising alternative to numerical simulation for evaluating optimal layout and placement constraints. Chen et al. [63] built an efficient optimization framework that couples a multivariate adaptive regression splines (MARS) surrogate model with the BOBYQA algorithm; under fault uncertainty, it jointly optimized well placement and injection-production rates and reduced the optimization time from hours per CFD run to a few seconds. To address spatial uncertainty in formation properties, Khan et al. [64] used deep learning to build a chained multi-output model predicting target depth and formation features and fed its predictions into an enhanced firefly algorithm that searched continuous three-dimensional space to find well coordinates with the lowest construction cost and best formation conditions. On the physical boundary of the well, Wang et al. [5] combined Monte Carlo simulation with sensitivity analysis to quantify the probabilistic effect of various parameters on bottom-hole temperature; this framework allows operators to evaluate the maximum safe extension length of a horizontal geothermal well before deploying expensive tools. This siting framework, built on conceptual models and multi-dimensional optimization, avoids the technical and financial risk of unproductive investment and lays the groundwork for construction and long-term thermal management.

2.3 Selection of drilling technology and equipment

Because geothermal reservoirs are typically hard, abrasive, and extremely hot, transferring conventional oil and gas drilling technology without adaptation often results in low ROP and severe equipment wear [65]. Serious lost circulation and stuck-pipe problems caused by deep fault zones are also leading causes of increased NPT and cost overruns. An empirical analysis of several geothermal wells by Lowry et al. [66] quantified this: managing lost circulation consumed nearly 20 percent of effective drilling time on average and raised the cost per foot by more than 60 percent. Under such conditions, and especially when lost-circulation materials such as cellulose used in conventional drilling degrade quickly in the high temperatures of geothermal reservoirs [67], operators must make a complex trade-off among cost, efficiency, and safety, weighing higher upfront equipment investment against reduced reservoir-damage risk. Building a system-level, automated technology-matching matrix helps decision-makers reduce subjective bias across many technology combinations and quantify the expected value of each engineering strategy under specific conditions [68,69].

For practical implementation, Nwanwe and Teodoriu [70] developed a drilling-technology selection system that takes formation pressure, rock strength, expected cost, and time as inputs and evaluates 81 technology combinations quantitatively. For fragile reservoirs prone to severe induced formation damage or differential sticking, the model tends to recommend underbalanced or managed-pressure drilling; although these raise upfront equipment rental costs, their combined safety and efficiency benefits in real-time wellbore-pressure feedback, loss prevention, and reservoir protection far outweigh those of conventional drilling. Fig. 5 shows the decision system for selecting geothermal drilling technology and equipment.

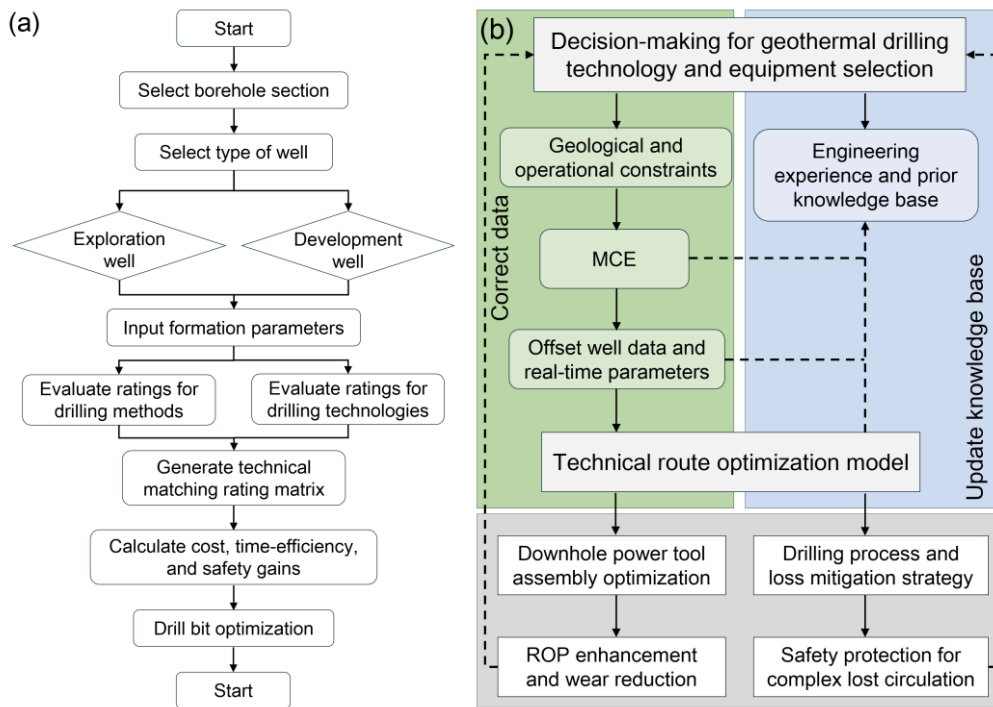


Fig. 5. Automated decision system for selecting geothermal drilling technology and equipment: (a) operating flow of a matrix selector matching drilling methods and power tools to formation properties [70]; (b) logical framework for technology selection [71].

For tool selection in hot, hard-rock formations, the decision analysis by Amer et al. [71] showed that turbodrills offer better high-temperature stability than conventional rotary steerable systems and thus avoid the safety hazards and high costs of downhole electronics failing at high temperature. Field data support this reasoning. In highly abrasive, deep, hot, hard-rock formations offshore Saudi Arabia, coupling a turbodrill with an impregnated diamond bit and an automatic anti-stall clutch avoided the thermal damage to the rubber stator of conventional positive-displacement motors and overcame the frequent sticking seen in hard rock; this combination raised drilling efficiency by 38 percent while cutting the frequency of tripping by more than 50 percent [72]. When devising strategies for severe losses, Winn et al. [12] found that the field typically follows a stepwise, cost-based approach: operators first try low-cost, readily available lost-circulation materials, and if these fail and non-degradable materials risk permanently damaging reservoir permeability, they turn to more aggressive strategies such as aerated mud or even drilling with total losses, so as to safeguard thermal output while improving overall safety and cost efficiency.

3. Decisions during the drilling process

The engineering risks faced during drilling are, to a large extent, a continuation of the geological uncertainty left over from the siting stage: uncertainty in temperature, permeability, and fracture distribution appears here as ROP fluctuation, bottom-hole thermal damage, lost circulation, and stuck pipe, and it is updated

in real time with while-drilling data. During drilling, traditional physical and thermodynamic numerical models are theoretically rigorous but computationally expensive; a single simulation often takes hours and cannot meet the need for real-time response to changing field conditions [28,73]. In recent years, the rapid growth of logging-while-drilling and surface parameter data has allowed data-driven artificial-intelligence algorithms to take the lead in real-time drilling decisions [29]. Machine learning can process large volumes of high-dimensional, nonlinear data with very low latency and can offer new insight for parameter optimization and incident prevention in dynamic, complex subsurface environments [18].

3.1 Real-time ROP prediction and drilling-parameter optimization

ROP directly determines the economic viability and duration of well construction. Traditional multiple-regression models based on physical and empirical formulas often fit poorly in complex geothermal reservoirs. The classical Bourgoyne and Young (BY) model gives the general ROP prediction equation [74]:

$$ROP = \exp \left(a_1 + \sum_{j=2}^8 a_j x_j \right) \quad (1)$$

where ROP is the penetration rate (ft/h), a_1 to a_8 are regression constants, with a_1 mainly representing the effect of formation strength, and x_2 to x_8 are normalized functions describing normal compaction, undercompaction, bottom-hole differential pressure, bit weight and bit diameter, rotary speed, tooth wear, and bit hydraulics, respectively. Applying it to geothermal construction requires multiple-regression analysis of large drilling datasets to solve for eight independent regression constants. These constants are strongly region-dependent, often vary sharply with lithology changes or increasing depth, and can produce physically unrealistic negative values when data are limited, which severely limits generalization and real-time decision efficiency in heterogeneous hard rock. Maurer's perfect-cleaning model offers an alternative [75]:

$$ROP = K \cdot \frac{N(W - W_0)^2}{D_B^2 S^2} \quad (2)$$

where K is a proportionality constant whose value depends on the unit system, N is rotary speed (r/min), W is weight on bit (lbf), W_0 is the threshold weight on bit (lbf), D_B is bit diameter (in.), and S is rock compressive strength (psi), with ROP in ft/h. In practice, however, the powdered cuttings produced when hard rock breaks accumulate easily, so the bottom hole is rarely perfectly cleaned. Repeated regrinding of cuttings beneath the bit wastes a large share of mechanical energy, and the actual ROP is far below the theoretical prediction. The Hareland and Rampersad model instead works from the force geometry of a single cutter [76]:

$$ROP = \frac{14.14 \cdot N_s \cdot N}{D_B} \left[\frac{d_s^2}{4} \cos^{-1} \left(1 - \frac{4W_{mech}}{N_s d_s^2 \pi \sigma_c} \right) - \left(\frac{d_s}{2} - \frac{W_{mech}}{N_s d_s \pi \sigma_c} \right) \sqrt{\frac{W_{mech}}{N_s \pi \sigma_c} \left(d_s - \frac{W_{mech}}{N_s \pi \sigma_c} \right)} \right] \quad (3)$$

where N_s is the number of cutters, d_s is cutter diameter, W_{mech} is the mechanical weight on bit, and σ_c is the dynamic compressive strength of rock under confining pressure. Because the formula is highly complex and still requires empirical lithology-correction coefficients to compensate for variables such as rock strain rate and bottom-hole hydraulics that theory cannot capture, physical models often fail when applied to the extreme formations of geothermal drilling, since their physical parameters cannot be set precisely [77].

Data-driven models show clear advantages in overcoming the computational bottleneck of classical physical models and in capturing ROP trends in complex formations [78]. The best choice of algorithm, however, depends heavily on dataset size. Geothermal exploration typically has limited data, under which conventional artificial neural networks (ANNs) tend to overfit and are computationally costly; shallow tree-based ensemble models then usually generalize more robustly and run more efficiently than ANNs. When drilling data are abundant, deep learning and complex neural architectures surpass shallow models [79,80]. Prediction frameworks must be developed for the specific geothermal setting. Ben Aoun and Madarász [81] used a random-forest regression model to evaluate geothermal drilling at the Utah FORGE site, explaining 84 percent of field ROP variability with very low absolute error. Deep geothermal projects, however, often lack offset-well history for training. To overcome this, Diaz et al. [82] used drilling data from a shallower section of the same 4,200-meter well in South Korea to predict ROP in the next section (Fig. 6). Cumulative-data training combined with a square-root resampling strategy reduced the network's mean absolute percentage error to 15.6 percent. In the field, data-driven optimization has translated into notable performance: in the Sugarloaf appraisal well of its Cape Station project in Utah, Fervo Energy reached a true vertical depth of 15,765 feet in only 16 drilling days, 79 percent faster than the U.S. Department of Energy benchmark for ultra-deep geothermal wells, achieving an average ROP of 95 feet per hour, an instantaneous ROP above 300 feet per hour beyond 15,000 feet, and a maximum footage of 3,290 feet on a single bit [83].

Most current work performs passive prediction and lacks active optimization. Many studies treat weight on bit and rotary speed only as static features to fit ROP in the forward direction, without solving the inverse problem of finding the parameter combination that balances rate and safety. Without coupling predictive models to real-time optimization algorithms, intelligent assistance remains at the level of foreseeing outcomes and does not yet form a closed loop that can directly guide field control [28]. In this direction, recently proposed multimodal intelligent agents based on large language models (LLMs) offer a new route toward closed-loop decision-making; they are envisioned to perceive logging-while-drilling data in real time, predict bit trajectory through internal reasoning, and suggest adjustments to weight on bit and rotary speed [84,85]. Such concepts of autonomously adjusting drilling parameters, however, come mostly from conceptual frameworks and offline

studies in the oil and gas sector and have not yet been validated in geothermal field operations. Given scarce downhole data, model hallucination, and concerns about real-time reliability, they are currently better suited as aids to field decisions than as autonomous systems that issue downhole commands directly.

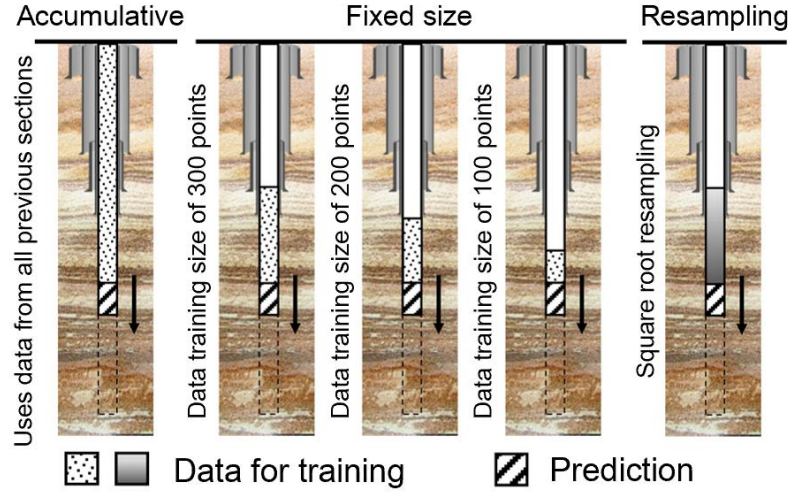


Fig. 6. Three schemes for selecting training data in geothermal ROP prediction: cumulative data, fixed sample size, and square-root resampling [82].

3.2 Bottom-hole temperature prediction and active thermal management

Typical hot dry rock reservoirs lie between 3 and 6 kilometers deep and are defined as dense, impermeable, high-temperature rock above 150 degrees Celsius that contains almost no natural fluid [7–9]. Under some extreme conditions, such as magmatic systems in volcanic areas, temperatures within 7 kilometers can exceed 650 degrees Celsius. At the Krafla high-temperature field in Iceland, conventional production temperatures reach about 350 degrees Celsius; during drilling of the IDDP-1 deep well, the magma encountered exceeded 900 degrees Celsius and measured wellhead fluid temperatures topped 450 degrees Celsius [86,87]. Knowing the bottom-hole circulating temperature accurately and in real time is therefore vital for maximizing the service life of the bit and downhole electronics [88]. Analytical models such as those of Ramey [89] and Hasan and Kabir [90] are limited by steady-state heat-transfer assumptions and ignore additional downhole heat sources. To overcome these limits, current research builds fully transient hydro-thermodynamic numerical models using finite-difference or finite-volume methods for the complex environment of deep geothermal wells. For the significant mechanical heat generated in hard-rock drilling, Li et al. [91] developed a fully transient temperature model that treats bit rock-breaking, drill-string rotational friction, and viscous dissipation as dynamic heat sources and tracks the expanding heat-transfer boundary caused by drilling fluid. To move closer to the extreme thermal environment of real deep wells, Xiao et al. [10] abandoned the assumption of constant fluid properties and treated the density, specific heat, viscosity, and thermal conductivity of the drilling fluid and tubulars as nonlinear functions of downhole temperature and pressure, coupled with a complex multi-layer casing structure;

Yang et al. [92] applied an analytical model to temperature control and prediction at ultra-high-temperature wells such as OM-41C in Kenya. For extreme multiphase conditions in deep reservoirs, such as high-pressure steam phase change or non-condensable gas influx, physical models become far larger: the non-isothermal two-phase flow model of Xu et al. [93] must simultaneously solve gas-liquid mass and momentum conservation with interphase slip together with multiple transient energy-conservation equations for the formation-wellbore system. Although such models rigorously reveal heat conduction and convection between wellbore and formation, they are time-consuming and adapt poorly to sudden changes in parameters such as flow rate and inlet temperature, making them unsuitable for real-time thermal management in the field.

Data-driven models can overcome this limitation because they analyze large datasets rapidly and adapt to emerging data patterns, which suits real-time applications [73]. For precise transient thermal management, Khaled et al. [73] used a long short-term memory (LSTM) deep-learning model to predict transient changes in bottom-hole circulating temperature (BHCT). Its gated memory mechanism captured the transient thermodynamic behavior well, keeping the mean absolute error below 1.5 degrees Celsius across various dynamic scenarios and providing a basis for quick engineering decisions. To turn such complex predictions into intuitive field guidance, Khaled et al. [94] introduced Drilling Heat Maps to geothermal work: a two- and three-dimensional visualization tool combining surface data with hydro-thermodynamic simulation that gives operators intuitive optimal operating points for active temperature management, optimizing drilling efficiency while avoiding thermal damage to downhole tools. Purely data-driven models, however, depend heavily on large training sets that are hard to obtain in complex geothermal drilling. Yuan et al. [95] therefore embedded fluid-dynamics partial differential equations for mass, momentum, and energy conservation directly into the loss function of a physics-informed neural network (PINN), overcoming the physical distortion that ANNs suffer with small samples. For more efficient field use, current research combines PINNs with traditional heat-transfer models in real-time frameworks; Xie et al. [96] used a PINN to invert the static pre-drilling wellbore-formation initial temperature field accurately (Fig. 7) and then combined it with a transient heat-transfer model to predict bottom-hole temperature dynamically under complex conditions such as pump and drilling stoppages, providing a robust basis for high-temperature drilling-fluid optimization and active thermal management.

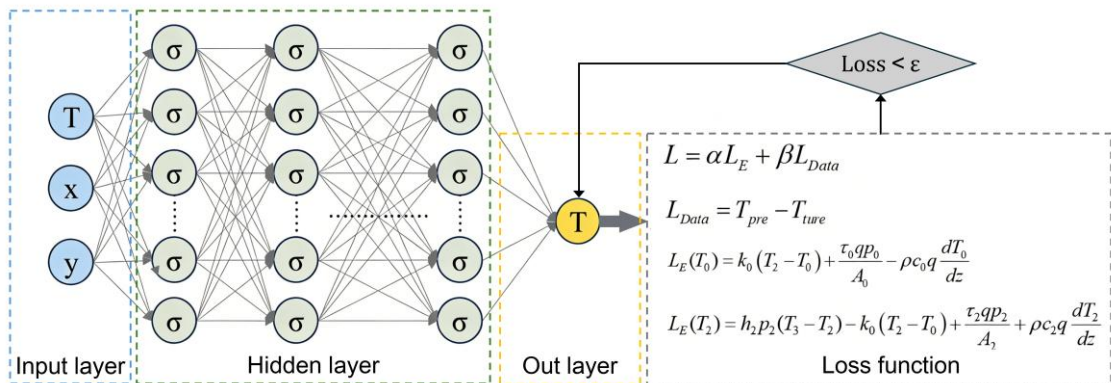


Fig. 7. PINN modeling framework for thermal management in geothermal drilling. The governing-equation (physics) losses $L_E(T_0)$ and $L_E(T_2)$ are evaluated on the drilling-fluid temperatures inside the drill string (T_0) and in the annulus (T_2), respectively [96].

3.3 Drilling anomaly early-warning systems

The natural fracture zones that pervade geothermal reservoirs readily trigger serious lost circulation and stuck-pipe events, which are the core causes of increased NPT and cost overruns [97,98]. Oil and gas practice has relied mainly on classical physics-based models, such as torque-and-drag models for predicting stuck pipe and equivalent circulating density (ECD) models or threshold-based statistical logs for monitoring losses [99,100]. These deterministic models usually depend on only a few dominant variables and struggle to represent the complex conditions of geothermal hard-rock formations [101]; they also lack self-learning and adaptive ability. When a physical model deviates, anomaly identification still depends heavily on the observation and experience of the drilling supervisor or domain experts, a traditional mode that readily misses faint precursors and tends to lag [102,103]. Developing intelligent warning systems that convert while-drilling time-series data into forward-looking risk probabilities is therefore key to reducing construction risk.

Several practical studies have addressed different anomaly types in geothermal drilling. For lost-circulation warning, Kiran et al. [17] used real-time mud-logging data from Utah FORGE, applied change-point analysis to extract the slope of the ROP curve as an additional feature, and combined it with an incremental-learning framework to raise the prediction accuracy of random-forest and gradient-boosting algorithms by 5 to 7 percent. For stuck-pipe warning, Bayan and Zulkarnain [101] combined statistics and machine learning on data from the Darajat field in Indonesia and confirmed that hook load, torque, and standpipe pressure are the most significant predictors. Sarwono et al. [100] modeled North Sumatra geothermal data with an ANN and achieved 84 percent accuracy and 74 percent recall in stuck-pipe prediction. For time-series warning, Aspiras et al. [102] studied New Zealand geothermal drilling data and, rather than looking back over the whole well, used a two-hour rolling window to forward-simulate incident probability one hour ahead; automated time-series feature engineering combined with machine learning outperformed traditional methods that rely on manual feature extraction by domain experts. Table 2 summarizes current warning models for lost circulation, stuck pipe, and high-temperature thermal damage.

Table 2. Summary of early-warning systems for drilling anomalies in geothermal wells.

Anomaly type	Key monitored features	Algorithms and architecture	Geothermal setting and data size	Uncertainty/imbalance handling	Validation strategy and performance	References
Lost circulation	ROP slope, ECD, outlet-flow fluctuation	K-nearest neighbors (KNN), decision tree (DT), random forest (RF), gradient boosting (GB)	Utah FORGE, USA (hard-rock EGS); wells 21-31 and 58-32; logging and mud-logging data from two wells	SMOTE with window filtering; incremental learning	80:20 random split checked with different random seeds; RF/GB accuracy about 86.7%, 5% to 7% above baseline models	[17]
Stuck pipe	Hook load, torque, SPP	PCA dimensionality reduction, discriminant analysis, logistic regression, back-propagation neural network (BPNN)	Darajat field, Indonesia (49 wells in the field); 32 stuck-pipe events in 16 wells, 2007-2019	PCA dimensionality reduction	Binary classification workflow; correct classification about 88.5% for well DRJ 43	[101]
Stuck pipe	Hook load, torque, SPP	Multilayer perceptron (MLP), SMOTE oversampling	North Sumatra field, Indonesia; five wells on pad T	SMOTE oversampling	Train/test split; 84% accuracy and 74% recall	[100]
Stuck pipe	Automated time-series features from the TSFRESH	XGBoost, AdaBoost, DT, support vector machine	Geothermal wells in New Zealand; time-series data at about 720 points per hour	Forward rolling simulation	Two-hour rolling window predicting one hour ahead; outperforms the manual-feature	[102]

	library				baseline	
High-temperature damage	Depth, horizontal length, flow rate, inlet temperature, mud density	LSTM, XGBoost, stacked ensemble	Generic deep and ultra-deep high-enthalpy geothermal wells; more than 400 numerical simulations and over 132,000 data points	Bayesian optimization; stacked ensemble	Training and testing on synthetic data; MAE below 1 °C under constant parameters	[73]
High-temperature damage	Wellbore temperature, bottom-hole pressure, nonlinear fluid properties	PINN	Xiong'an area, China (well SNLG87-29); small sample of about 3,000 collocation points	Physical equations embedded in the loss function to alleviate small-sample distortion	Compared with the finite-difference method; high inversion and prediction accuracy	[95]

These studies share several limitations. First, samples are generally scarce and highly site-specific: most studies rely on only a few wells in a single geothermal field, and incidents are rare events with severe class imbalance, so oversampling such as SMOTE is often needed, and models transferred across wells or fields are prone to distribution shift. Second, algorithm choice depends closely on data volume: shallow tree-based ensembles are more robust with small samples and require little computing power, whereas deep time-series models such as LSTM need larger datasets, and PINNs alleviate small-sample distortion through physical equations at the cost of heavier training and tuning. In addition, many methods are transferred directly from oil and gas drilling without independent validation under hard-rock, high-temperature geothermal conditions, and they mostly use simple random splits rather than leave-well-out cross-validation, with small test sets. Overall, these models remain largely at the stage of offline case studies or retrospective validation, and no long-term operation as a real-time warning system in a geothermal field has yet been reported; their transferability under small samples, class imbalance, and site differences remains the main bottleneck for engineering application.

The influence of small samples and transferability on model selection and credibility deserves particular attention. With small samples, high-capacity deep networks readily overfit and produce overconfident predictions, whereas methods with stronger inductive biases are usually more robust; among them, PINNs impose conservation equations as soft constraints, in effect replacing part of the data requirement with physical priors, and offer a feasible way to alleviate small-sample distortion. Site specificity means that models trained on a few wells in a single field often learn the geological and operational fingerprint of that site rather than general patterns, so their performance degrades markedly when they are transferred to new wells or fields; transfer learning and domain adaptation, progressive training with cumulative offset-well data and square-root resampling, and uncertainty quantification for extrapolation regions are all feasible remedies. Furthermore, lost circulation and stuck pipe are rare events with severe class imbalance, and evaluation by overall accuracy alone masks missed detections of the minority class, so imbalance-sensitive metrics such as recall, precision, F1, and PR-AUC are more appropriate, and oversampling methods such as SMOTE should be used with caution because they may generate unrealistic samples from high-dimensional time-series features. Drilling is also a nonstationary process in which distribution shift occurs with lithology changes, increasing depth, and abrupt changes in operating conditions; static offline models gradually lose accuracy as drilling proceeds and need continuous updating through incremental or online learning and drift detection. In short, whether intelligent drilling models can be deployed reliably depends on whether they combine generalization with a faithful characterization of uncertainty under small samples, class imbalance, and distribution shift, rather than on high accuracy on a particular dataset, a point that has also received attention in machine learning studies in related fields [104–107].

Intelligent monitoring during geothermal drilling remains largely at the stage of passive warning for a single anomaly and has not yet formed the global, autonomous decision capability needed for complex deep conditions. Future work could proceed in two directions. First, PINN-based frameworks tailored to the extreme geothermal environment, embedding fluid and thermodynamic PDEs directly in the loss function, would reduce

the heavy reliance of pure data-driven models on training samples. Second, as artificial intelligence and LLMs develop, drilling decision support may evolve from passive warning toward reasoning-capable assistance, for example through multi-agent frameworks that integrate geological interpretation, thermal management, and drilling control to process while-drilling signals in real time and suggest optimized values for parameters such as weight on bit and rotary speed. This direction, however, is still exploratory and requires extensive validation in safety, explainability, suppression of model hallucination, real-time reliability, cybersecurity, and responsibility allocation; until then, such systems can serve only as aids to human decisions in the field, and any command involving downhole execution should still be reviewed by engineers.

4. Investment decisions for geothermal wells

The geological and engineering uncertainty accumulated during siting and drilling, and updated with data, ultimately enters investment decisions as economic uncertainty. Geothermal projects are capital-intensive in their early stages [3,4]. Because subsurface conditions such as temperature, permeability, and fault distribution are invisible early on, investors face substantial financial risk [19]. Risk is generally tied to the probability of success and its economic consequences, while uncertainty reflects the inability to value specific geological parameters precisely. Building sound cost-and-time evaluation models and quantifying how geological uncertainty affects final economic returns are therefore the core basis for go or no-go decisions and for setting investment strategy [13].

4.1 Probabilistic time-cost modeling and expected net present value

Construction and supporting works for deep geothermal wells usually exceed half of total project investment, and total well cost rises nonlinearly with target depth. Early cost estimates typically used deterministic methods to relate single-well cost to depth [108]. Using data from tens of thousands of oil and gas wells drilled between 1976 and 2003, Augustine et al. [109] developed a depth-dependent well-cost index that normalized historical geothermal well costs to a dollar baseline and correlated cost with depth across periods. In recent years, however, geothermal well costs have risen more slowly than oil and gas costs, so an index built solely on oil and gas wells no longer fully applies to geothermal drilling. Table 3 compares the key differences between the two in cost modeling and life-cycle intervention [110,111]. Using data from 42 actual geothermal wells drilled between 2008 and 2013, Lukawski et al. [111] rebuilt the geothermal well-cost relationship:

$$C_{geo} = 1.72 \times 10^{-7} \times (MD)^2 + 2.3 \times 10^{-3} \times MD - 0.62 \quad (4)$$

where C_{geo} is the total geothermal well cost (million U.S. dollars, 2012 dollars) and MD is the measured depth of the well (m).

Table 3. Comparison of conventional oil and gas wells and deep geothermal wells in cost modeling and economic evaluation.

Dimension	Conventional oil and gas drilling	Deep geothermal drilling
Base data and sample size	Extensive historical data allow high-confidence prior distributions to be fitted.	Detailed cost history is scarce; modeling usually rests on a few dozen recent wells.
Learning curve and cost decline	Learning effects are strong; average cost of development wells within a block is about 8 percent below exploration wells.	Few wells per field and strong heterogeneity greatly limit cost savings from learning.
Cost probability distribution	Costs are relatively concentrated with a narrow uncertainty range, usually normal or lognormal.	Strongly right-skewed, with a long right tail representing costly extreme incidents.
Time-cost prediction	Traditional risk analysis; delay and cost increase are usually a simple linear relationship.	Customized probabilistic simulation can capture nonlinear time-cost coupling.
Life-cycle intervention	NPV models are driven mainly by market price swings and reservoir decline.	Expected NPV can guide integrated interventions such as deploying make-up wells.

These early studies gave useful average-cost predictions, but with limited data at the time, such deterministic methods could not estimate the uncertainty around the average or handle the NPT arising from complex subsurface conditions. To characterize this uncertainty, Lukawski et al. [30] introduced Monte Carlo simulation into predictive cost models and, by fitting construction data from hundreds of wells, quantified the total-cost probability distribution for deep wells between 8,000 and 15,000 feet (Fig. 8). Deep wells not only carry higher cost uncertainty but also show a more pronounced right skew. To predict time and cost jointly, Yost et al. [31] adapted a tunneling decision-aid system from civil engineering to EGS well construction. The system considers not only the direct effect of different geological grades on ROP but also the probability distribution of sudden incidents, generating reliable time-cost scatter plots through Markov-chain simulation and letting managers set more resilient financial reserves before construction. Probabilistic prediction is also expanding from construction cost to whole-life economic analysis. Addressing reservoir-structure uncertainty, Goumas et al. [112] used Monte Carlo sampling and treated key physical quantities that directly drive cost, such as well depth, as core random variables; the method produced an NPV probability distribution and quantified the probability of investment failure. Patterson et al. [113] used expected NPV to assess how fracture distribution affects project profit; the model can guide field intervention directly, for example by evaluating whether expected profit can cover the high cost of deploying make-up wells and thereby setting the best strategy against thermal decline. Recent commercial projects confirm these patterns. Through repeated drilling at Cape Station, Fervo cut the fastest single-well drilling time to 21 days, about 70 percent less than its first horizontal well drilled at Project Red in 2022, and the drilling cost of the first four horizontal wells fell from 9.4 million to 4.8 million U.S. dollars per well [114]. A reserves report by the independent assessor DeGolyer and

MacNaughton further indicated that the proprietary EGS design can achieve a heat-recovery rate of 50 to 60 percent, about three times that of conventional geothermal technology [115]. This shows that the engineering learning curve can compress both the uncertainty range of the cost distribution and the right-skewed tail caused by costly incidents.

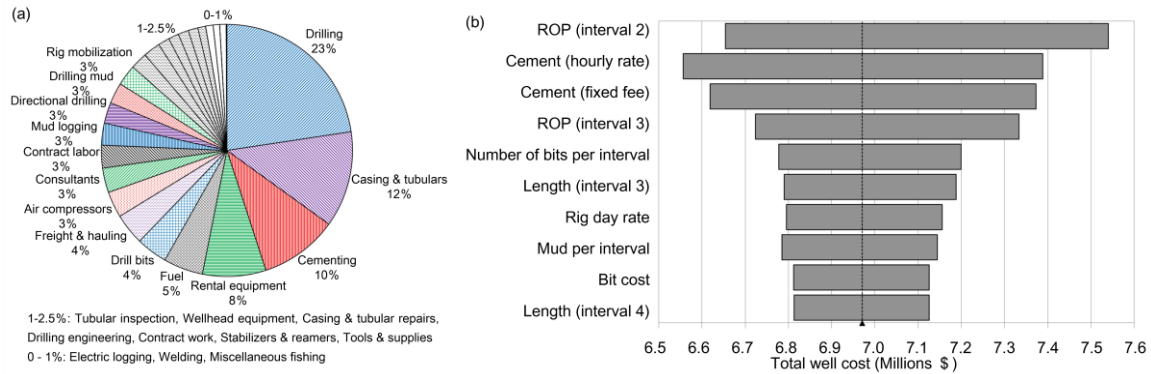


Fig. 8. Investment breakdown and risk assessment for an 8,000-foot EGS well: (a) average cost contribution of each operation; (b) sensitivity ranking of the dominant risk factors driving total-cost uncertainty, where Interval denotes different well-section runs [30].

4.2 Risk quantification and value-of-information (VOI) analysis under geological uncertainty

Efficiently acquiring key subsurface information within budget, and thereby reducing the drilling failure rate, is the central problem of the exploration stage; its foundation is quantifying exploration risk. Starting from a single geological interpretation, geostatistics and decision analysis systematically convert geological parameters that are inherently subjective and uncertain, such as permeability, temperature, and reservoir volume, into measurable financial-risk indicators [19]. With financial risk defined, deciding whether to spend heavily on new data requires VOI theory. Experience from oil and gas exploration shows that reducing uncertainty does not by itself create financial value; new information creates real value only when it has the potential to change the decision-maker's chosen course of action [116]. Following this logic, an exploration activity should be undertaken only when the increase in expected monetary value it brings clearly exceeds its acquisition cost [13].

In practice, because geophysical inversion is non-unique and samples the subsurface only indirectly, forward simulation is needed to quantify how reliably geophysical data distinguish geothermal targets [117,118]. Trainor-Guitton et al. [119] evaluated the VOI of MT data by integrating multiple possible interpretations of the geothermal clay cap from three-dimensional MT inversion and quantifying how far these data could revise production expectations, thereby avoiding unproductive well placement. As data sources multiplied, Trainor-Guitton and Rosado [120] used kernel density estimation to smooth the data distribution and assessed the relative reliability and economic value of different data types, such as fault slip, stress, and heat flow, in indicating geothermal anomalies across geological domains. For costly three-dimensional seismic surveys, the analysis by Muzi et al. [121] showed that in large geothermal prospects involving multiple planned wells, three-

dimensional seismic greatly reduces subsurface risk and its economic gain far exceeds acquisition cost; but when used only to evaluate EGS stimulation of a single developed well, its VOI often cannot cover the high cost.

Decision analysis is also widely used for the complex spatial trade-offs of exploration and appraisal. Schneider et al. [122] examined the trade-off in choosing an exploration well location: drilling at the structural crest to maximize the chance of discovery, or drilling downdip to confirm reserves large enough for commercial development. By building a decision tree based on expected monetary value, decision-makers can quantify the trade-off of a downdip location between a lower success rate and a larger commercial resource. The zone-based portfolio analysis of van Unen et al. [123] introduced a distance-controlled conditional-probability model, showing that when formation properties are spatially correlated, the success of the first exploration well greatly updates the success probability of nearby subsequent wells. This dynamic decision-tree framework, which extends VOI from a single well to a whole asset portfolio, raises average expected profit and lowers overall risk, and it is especially suited to undeveloped areas with high geological uncertainty but strong spatial correlation.

4.3 Techno-economic decisions based on life-cycle assessment (LCA) and multi-objective optimization

A geothermal well is not an isolated upfront project; its core design parameters, such as target depth, well spacing, and trajectory, directly determine performance over a life cycle spanning decades [124]. The materials and equipment used in construction and completion often dominate the project's long-term environmental burden across several dimensions [125]. As the energy transition raises expectations, investment objectives are shifting from simply lowering single-well construction cost toward a life-cycle win-win in both economics and environment [126]. Traditional economic evaluation, moreover, tends to focus on initial construction cost, whereas life-cycle cost studies of infrastructure show that the long-term optimal option cannot be identified from initial investment alone [127,128]. In addition, single-objective optimization cannot reconcile competing goals: widening well spacing and deepening wells raise net power generation but multiply construction cost and circulation resistance.

Because earlier economic evaluations failed to include the external costs of environmental and social impacts, Cook et al. [129], in an environmental life-cycle cost study of EGS, used methods such as ReCiPe to convert environmental externalities from construction, casing and cementing, and later operation, including CO₂ and H₂S emissions, into monetary value. They confirmed that although deep wells are extremely capital-intensive upfront, over the full life cycle the levelized cost of electricity (LCOE) of EGS remains highly competitive. Raos et al. [130] likewise confirmed that variation in well-construction capital expenditure is the most visible factor controlling project LCOE. LCA studies of specific operations further confirm that a well's physical parameters and material use largely determine early environmental burden. Sigurjónsson et al. [131] showed that for deep projects, construction and completion account for a very high share of greenhouse-gas emissions and water footprint; in the deep EGS project at Vendenheim, France, the steel used in casing alone

contributed as much as 50 percent of the life-cycle climate-change impact. To cut this burden at the source, an LCA of the Hellisheidi plant in Iceland by Karlsdottir et al. [125] showed that changing engineering decisions, such as using electric rather than diesel drilling rigs when deploying make-up wells, markedly reduces cumulative non-renewable energy demand and carbon emissions. When the perspective widens from equipment and materials for a single well to macro-scale system planning, the overall scale of well deployment also governs long-term economics. In a district-heating setting, Pratiwi and Trutnevyte [132] used decision trees to analyze thousands of decision paths and found that matching the scale of well development to total surface heat demand is central to the competitiveness of the levelized cost of heat (LCOH).

When construction, environmental, and reservoir-rock objectives conflict, multi-objective evolutionary algorithms become a powerful tool for finding the best design. For the depth and borehole geometry of deep geothermal wells, Xia et al. [133] built a multi-objective optimization model combined with LCA that revealed a clear trade-off: an aggressive strategy pursuing ever-greater depth raises thermodynamic output and lowers LCOE but markedly increases carbon emissions during construction and later pumping-power consumption (Fig. 9). Using the NSGA-II algorithm, they found Pareto-optimal well parameters that balance economic cost against carbon footprint. Xu et al. [134] extended multi-objective optimization to mechanical damage in the subsurface reservoir. For long-term production from hot dry rock, they took minimizing flow resistance, maximizing net power generation, and maximizing economic benefit as three objectives, and after combining TOPSIS and VIKOR found that the optimal design accounting for rock-damage evolution raised net power generation and economic benefit by 45.84 and 21.35 percent, respectively, over the baseline. More importantly, as the expected production period lengthened, the core deployment parameters of the optimal design became more conservative automatically, in line with the rock-fracturing pattern. This framework, which integrates subsurface rock mechanics, well placement, and surface economic thermodynamics, closes the loop of life-cycle assessment for geothermal wells. Closed-loop geothermal systems have already reached engineering practice: Eavor achieved the world's first commercial closed-loop system connected to the grid at Geretsried, Germany, with a design capacity of 8.2 MWe and 64 MWth and no need for reservoir permeability or fluid reinjection [135]. By mid-2026, however, only 6 of the loops were complete, 2 of which were blocked by cuttings and could not be cleared, so the actual electrical output was only about 0.5 to 1 MWe, far below design, and the project revealed budget overruns; the operator subsequently decided to exit operation [136,137]. This shows that well-system selection requires careful trade-offs among geological adaptability, long-term operational reliability, and life-cycle economics.

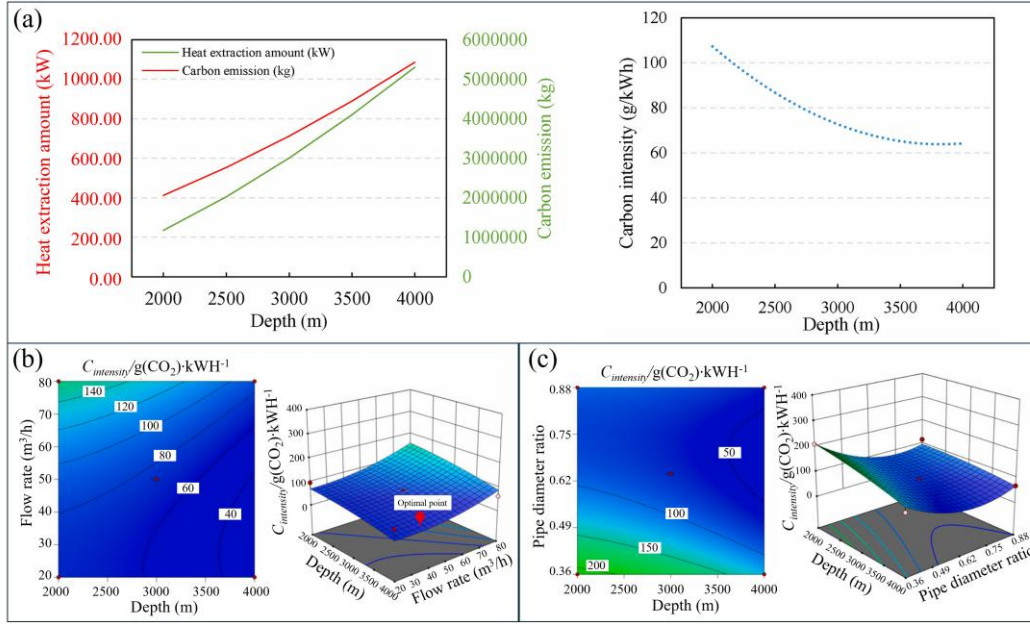


Fig. 9. Carbon-emission assessment and multi-dimensional decision response for key geothermal well parameters: (a) single-factor carbon-intensity trend with well depth; (b) depth-flow coupled response surface; (c) depth-to-diameter-ratio coupled response surface [133]. As depth increases from 2,000 to 4,000 meters, both heat extraction and carbon emission rise, but the higher geothermal gradient at depth improves thermal efficiency, so heat extraction rises faster than emissions. Carbon intensity therefore falls, from 108.42 g/kWh at 2,000 meters to 63.27 g/kWh at 4,000 meters, indicating that deeper development offers a more carbon-efficient solution. In multi-parameter decisions, the interaction between depth and circulation flow strengthens with depth, and the flow range giving the lowest carbon intensity is 20 to 50 cubic meters per hour. When the diameter ratio is near 0.62, increasing depth drives a clear decline in carbon intensity.

Existing techno-economic evaluations often focus in isolation on lowering single-well construction cost or on a single policy incentive, without considering the life-cycle environmental externalities of geothermal wells or the dynamic interaction with the regional energy mix. To address this, future LCOE or LCOH optimization should not consider only the technical trade-off between depth and thermal output; it must also combine the embodied carbon of the whole well process, such as emissions from steel casing, cement manufacture, and supporting equipment, with the carbon footprint of the regional grid. Coupling this macro-scale economics-carbon model with machine-learning spatial prediction would allow regional extension to areas of high geological uncertainty. Integrating subsurface siting risk, life-cycle carbon footprint, and regional carbon markets in this way would substantially improve the market competitiveness and financial viability of deep geothermal energy.

Investment decision methods differ markedly in data dependence, in the questions they can answer, and in their applicable conditions, and the literature contains conclusions that are condition-dependent or even contradictory. Deterministic cost-depth functions [108,109,111] are simple to compute and suit early feasibility

screening, but they cannot capture the uncertainty around the mean or NPT. The cost index built from oil and gas well data [109] was later found to be no longer fully applicable to geothermal wells because the cost trends of the two diverged, so a geothermal-specific model had to be refitted [110,111], a typical lesson in method transfer. Probabilistic simulation using Monte Carlo methods or Markov chains [30,31,112] can capture the right-skewed tail of deep-well cost and the coupling between time and cost, and suits cases with sufficient analog-well data, large depths, and high uncertainty, but its conclusions depend heavily on reliable prior distributions and are easily distorted when samples are scarce. VOI and decision-tree methods [13,116,119,122,123] suit judging, before large capital commitments, whether new information is worth acquiring, but their value is highly case-dependent: Muzi et al. [121] showed that the VOI of three-dimensional seismic surveys in multi-well prospects far exceeds their acquisition cost, whereas such surveys are often not worthwhile when used only to evaluate EGS stimulation of a single developed well, and Schneider et al. [122] revealed the trade-off for exploration wells between maximizing the chance of discovery at the structural crest and confirming commercial reserves down dip. LCA and multi-objective optimization [125,129,131,133,134] suit multi-objective trade-offs at regional and life-cycle scales under carbon constraints, but they require extensive inventory data and computing resources, and the choice among Pareto solutions depends on decision-makers' preferences. Their conclusions are also condition-dependent; for example, Xia et al. [133] found that deepening wells lowers the carbon intensity per kilowatt-hour but raises embodied carbon and pumping consumption, so no single optimum exists. There is also an apparent contradiction regarding the learning curve: conventional experience suggests that learning effects are limited in a single geothermal field because of few wells and strong heterogeneity, yet at Cape Station, repeated drilling reduced the drilling cost of Fervo's first four horizontal wells from 9.4 million to 4.8 million U.S. dollars per well and shortened the fastest drilling time to 21 days [114], indicating that within a sufficiently large single project, learning effects can still markedly narrow the uncertainty range of cost.

From the perspective of validation maturity, the methods reviewed here can be grouped into three categories (Table 4). By stage, drilling has the most field validation, but its physical models and incident-warning methods are also largely transferred directly from oil and gas drilling; siting methods have mostly been validated with geothermal data or case simulations, and few have been tested against actual drilling results; and no investment decision method has yet been verified in the field, with cost data from commercial projects so far usable only for retrospective calibration. This distribution shows that most methods remain in the second and third categories, and that the gap between algorithm research and engineering application lies mainly in the lack of independent field validation in geothermal settings.

Table 4. Classification of geothermal well decision methods by validation maturity.

Stage	Validated in geothermal fields	Geothermal adaptation (validated with data or case studies)	Transferred from oil and gas or conceptual
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Siting and layout	Noorollahi et al. [35] (Japan, prediction of production-well locations); Gudmundsson and Mortensen [55] (directional drilling at Krafla, Iceland); Fercho et al. [22], Norbeck et al. [23], and Fervo [21] (geological and temperature models tested by drilling at Cape Station and Blanford)	Schulte et al. [61]; Park et al. [60]; Halilovic et al. [62]; Chen et al. [63]; Khan et al. [64]; Wang et al. [5]; Li et al. [27]; Faulds et al. [50]; Siler et al. [52]; Tende et al. [49]; Mustafa et al. [25]; Ning et al. [26]	Methods at this stage derive mainly from geoscience mapping and operations research; no obvious direct transfer from oil and gas is found
Drilling	Ben Aoun and Madarász [81] (Utah FORGE); Diaz et al. [82] (4,200 m well, South Korea); Kiran et al. [17]; Bayan and Zulkarnain [101]; Sarwono et al. [100]; Aspiras et al. [102]; Fervo [83] (commercial drilling decisions)	Khaled et al. [73]; Yuan et al. [95]	Classical ROP models: Bourgoyne and Young [74], Maurer [75], Hareland and Rampersad [76]; tool and technique selection: Nwanwe and Teodoriu [70], Pilisi et al. [69], Nour et al. [68]; oil and gas incident warning: Salminen et al. [99], Brankovic et al. [103]; analytical wellbore heat transfer: Ramey [89], Hasan and Kabir [90]; concept of LLM-based multi-agent autonomous drilling: Chen et al. [84], Li et al. [85]
Investment and life cycle	No investment decision method has yet been verified in the field; commercial cost data such as Fervo [114] can currently be used only for retrospective calibration	Lukawski et al. [30]; Yost et al. [31]; Trainor-Guitton et al. [117,119]; Trainor-Guitton and Rosado [120]; Muzi et al. [121]; van Unen et al. [123]; Cook et al. [129]; Sigurjónsson et al. [131]; Karlsdottir et al. [125]; Raos et al. [130]; Pratiwi and	Oil and gas cost index: Augustine et al. [109]; theoretical basis of VOI and decision analysis: Bratvold et al. [116], Schneider et al. [122]

5. Conclusions and outlook

Against the backdrop of the global energy transition, the high cost and extreme geological risk of geothermal well development have driven a change in engineering management. This paper has reviewed the decision framework across the full geothermal well workflow, with the following main conclusions.

- (1) In the siting stage, target-area selection has moved from qualitative overlay with expert-assigned weights to spatial decision methods that combine GIS, weights of evidence, and machine-learning-enhanced PFA, reducing the subjectivity of manual weighting. For targeting and layout, studies generally use the geological conceptual model as a constraint and apply surrogate models and evolutionary algorithms to co-optimize injection-production locations, spacing, and operating parameters, balancing heat extraction, pumping energy, and thermal-breakthrough risk while cutting numerical simulations that once took hours down to seconds.
- (2) In the drilling stage, data-driven models are replacing mechanistic formulas that are strongly region-dependent and hard to fit, and numerical models that are computationally expensive. Ensemble tree models such as random forest and gradient boosting, together with ANNs, are used for real-time ROP prediction and can combine cumulative training with resampling to handle limited offset data; time-series deep-learning models such as LSTM predict transient bottom-hole circulating temperature to inform drilling-fluid optimization and active thermal management; and machine-learning models combining rolling windows with automated feature engineering identify precursors of lost circulation and stuck pipe for real-time warning. In addition, PINNs embed mass, momentum, and energy conservation in the loss function, easing the physical distortion of pure data models under small-sample conditions.
- (3) In the investment stage, methods have progressed from deterministic single-well cost functions to probabilistic, multi-objective decisions. Monte Carlo simulation and Markov chains describe the right-skewed cost distribution of deep wells and the long right tail caused by incidents, informing pre-construction financial reserves; VOI theory uses the potential of new information to change an existing decision as the criterion for data acquisition; and LCA combined with multi-objective evolutionary algorithms extends the objective from single-well construction cost to a trade-off among LCOE, thermal revenue, and carbon footprint, where a design accounting for rock-damage evolution raised net power generation and economic benefit by 45.84 and 21.35 percent, respectively. Commercial practice shows that the learning curve from repeated drilling can compress cost uncertainty, while operating problems with closed-loop systems show that well-system selection must balance geological adaptability against long-term reliability.

Geological uncertainty is the main thread running through the three stages. It propagates from siting to drilling and then to investment and is continually updated with new information. In the siting stage it appears as uncertainty in resource favorability and target risk; in the drilling stage it turns into engineering risks such as ROP fluctuation, thermal damage, and NPT; and in the investment stage it translates into economic uncertainty, including the right-skewed cost tail, the NPV distribution, LCOE or LCOH, and carbon footprint. Geophysical and while-drilling data continually update the subsurface model, VOI theory judges the economic value of acquiring information on this basis, and decisions on well location, well spacing, make-up wells, and financial reserves are revised accordingly. Reducing geothermal development risk therefore depends not on optimizing any single stage in isolation but on building a decision system that spans the whole workflow, follows geological uncertainty as its main thread, and supports information-driven updating.

5.1 Outlook

Although intelligent tools have greatly improved decision efficiency in geothermal well development, deeper and more extreme reservoirs and the complexity of the wider energy market call for further research in several directions. First, given the scarcity of effective downhole data under extreme geothermal conditions, future bottom-hole temperature models could strengthen PINN development, embedding fluid and thermodynamic PDEs directly in the model to avoid physical distortion with small samples and to provide robust predictions for wellbore thermal management and drilling-parameter optimization. Second, as general-purpose artificial intelligence advances, anomaly warning may extend toward LLM-based multi-agent collaborative decision-making, in which agents with different specialties jointly process real-time while-drilling signals and offer intervention suggestions to help reduce NPT. Autonomously issuing engineering commands, however, is still a prospective idea; its field implementation is constrained by safety, explainability, real-time reliability, and responsibility allocation, and in the near term it should remain subject to human review. Third, future techno-economic decisions should avoid an isolated single-well view and build a system that couples subsurface siting risk, life-cycle carbon footprint, and regional carbon markets, combining engineering iteration with innovative financial hedging tools and machine-learning spatial prediction to reshape the long-term financial viability and market competitiveness of geothermal projects under high geological uncertainty.

Finally, for the intelligent methods above to truly serve low-cost, efficient geothermal development, research must move beyond algorithmic accuracy and confront the engineering and institutional constraints of real deployment. The first is sensor reliability: downhole high temperatures and pressures often exceed the tolerance of conventional electronics and MWD/LWD tools, and sensor drift, failure, and data loss directly erode the input quality of data-driven models, which is the primary bottleneck under extreme conditions. The second is data interoperability: mud-logging, logging-while-drilling, and surface systems often use heterogeneous formats and sampling rates, and the lack of unified data standards and real-time interfaces hinders multi-source data fusion and online inference. The third is computing infrastructure: real-time decisions require low-latency edge or on-site computing, whereas training complex numerical and deep models relies on back-

end high-performance computing, so an architectural trade-off is needed between on-site timeliness and offline high fidelity. Closely related is continuous model maintenance: distribution shift requires online updating and version management, together with mechanisms to monitor and roll back model degradation. Economic feasibility cannot be ignored either: sensor retrofits, data platforms, and computing investment are additional costs in themselves, and deployment should be justified by quantifiable reductions in NPT and cost rather than by assuming positive returns. In addition, the field decision chain depends heavily on the experience and trust of drilling supervisors, so model interpretability and human-machine interfaces directly affect adoption, and automated decisions involving downhole safety must comply with industry safety regulations and clarify responsibility when algorithms fail. These factors are closely related to the scarcity of effective downhole data and to the need to integrate subsurface, environmental, and financial considerations emphasized throughout this review, and they should be treated as unavoidable prerequisites for future research on intelligent geothermal decision-making.

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