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An efficient optimization of well placement and control for a geothermal prospect under geological uncertainty

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HIGHLIGHTS

- An efficient optimization framework is developed for a realistic geothermal site.
- Optimization under various geological uncertainties leads to different results.
- Permeability of formation where wells are perforated is most sensitive for optimization.
- Water circulation is the primary heat transfer method during production.

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ABSTRACT

This study applies an efficient optimization technique based on a multivariate adaptive regression spline (MARS) technique to determine the optimal design and engineering of a potential geothermal production operation at a prospect near Superstition Mountain in Southern California, USA. The faster MARS-based statistical model is used as a surrogate for higher-fidelity physical models within the intensive optimization process. Its use allows for the exploration of the impacts of specific engineering design parameters in the context of geologic uncertainty as a means to both understand and maximize profitability of the production operation. The MARS model is initially developed from a training dataset generated by a finite set of computationally complex hydrothermal models applied to the prospect. Its application reveals that the optimal engineering design variables can differ considerably assuming different choices of hydrothermal flow properties, which, in turn, indicates the importance of reducing the uncertainty of key geologic properties. The major uncertainty sources in the natural-system are identified and ranked first by an efficient MARS-enabled total order sensitivity quantification, which is then used to assist evaluating the effect of geological uncertainties on optimized results. At the Southern California prospect, this parameter sensitivity analysis suggests that groundwater circulation through high permeable structures, rather than heat conduction through impermeable granite, is the primary heat transfer method during geothermal extraction. Reservoir histories simulated using optimal parameters with different constraints are analyzed and compared to investigate the longevity and maximum profit of the geothermal resources. The comparison shows that the longevity and profit are very likely to be overestimated by optimizations without appropriate constraints on natural conditions. In addition to geothermal energy production, this optimization approach can also be used to manage other geologic resource operations, such as hydrocarbon production or CO_2 sequestration, under uncertain reservoir conditions.

1. Introduction

Reinjection of geothermal fluids into geothermal reservoirs has been demonstrated as an essential practice for increasing the productive lifetime of reservoirs and recovery of thermal energy. Reinjection helps to maintain pressure in the geothermal reservoirs, slow down production declines in response to pressure drawdown [1], and, as a result, extent the period of time over which useful thermal energy can be recovered. The development and management of geothermal fields is complicated and expensive and maximum potential geothermal energy recovery depends on optimal well location and operation [2,3]. Simulation-based optimization methods can address these problems by utilizing production and

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economic models to evolve favorable production designs and strategies through the minimization of one or more quantitative physical or economic objective functions. Often, these approaches may require a large number of intensive forward model simulations, which may quickly become impractical because of their substantial computational burden. As an alternative, a simpler and approximate "surrogate model" may be constructed as a means to provide a faster simulation of the physical system, which may potentially benefit an optimization or sensitivity-based analysis that would otherwise requires thousands or more of iterative geothermal production simulations. Surrogate or "response surface" models that relate input variables to output responses are developed through the use of statistical models that are fitted by training datasets generated by a finite set of more complex physical simulation models. Surrogate-based optimization approaches have been extensively studied and advanced in the past decade in various application fields [4–11]. Widely used surrogate model techniques in hydrology include polynomial regression, kriging, radial basis functions, sparse grid interpolation, support vector machines, and artificial neural networks [12–14]. Here, we consider the multivariate adaptive regression spline (MARS) technique as developed by Friedman [15] more than two decades ago and routinely used in automatic engineering design [16]. MARS is a nonparametric regression technique that adaptively develops local models in local regions for flexible regression modeling of high dimensional data. Each local model is represented by a basis function and an associated coefficient to be determined. Comparative studies have shown that MARS is superior to other high dimensional regression methods (e.g. polynomials) in accuracy and reduction in computational cost of fitting process [4,17].

Optimal development and management of a geothermal reservoir will call for an accurate understanding of reservoir behavior under both natural and engineered conditions. However, for geothermal optimization problems, there are a variety of uncertainties associated with the rock properties and structural features of the formation that may significantly affect the optimized results. Assessment of these effects on optimal well placement and control will assist development and management of a geothermal reservoir.

This study couples a complex hydrothermal simulation model and a MARS-based surrogate model to investigate the effects of geological uncertainties (fault size, geological unit permeability) on optimal well placement and control (re-injection well location, production rate) in a geothermal prospect near Superstition Mountain in Southern California, USA. Comparative optimization cases are implemented using prior and posterior probability distributions of geological parameters, which are adapted from a previous study on a MARS-based Bayesian inversion [18] to represent maximal and reduced geological uncertainties respectively. To evaluate the influence of uncertainties of individual geological properties on optimal results, additional optimization experiments are designed and conducted by sequentially fixing the uncertain geological parameters during optimizing process.

2. MARS-based optimization framework

The MARS-based optimization framework consists of several steps that include: Conceptual design and parametric definition of the hydrothermal flow system of interest, including ranges in uncertain geological properties and operational parameters to be optimized; Development of physical hydrothermal flow models for this system; Construction and validation of a MARS surrogate model through the generation and processing of training data drawn from these steps; and Application of the MARS surrogate models in the optimization process to minimize objective functions. As illustrated in Fig. 1, these steps involve the MARS-based optimization proceeds as follows:

1. Conceptual Design of the Surrogate: The conceptual model design leads to a series of M uncertain parameters with associated ranges or probability distribution functions (PDFs), including unknown geological properties and operational parameters to be included in surrogate model. Using a Latin Hypercube (LH) method [19], these are sampled N times to yield a set of N training sample vectors. In this study all parameters are assumed to have a uniform-type of PDF.
2. Training Data Generation: These N sample vectors, each with M components, are used as inputs to develop N hydrothermal flow models for the system. Here, we utilize the NUFT (Nonisothermal Unsaturated–saturated Flow and Transport) model [20] that considers both initialization (run 1 million year to steady state) and production simulation (run to 1000 years of extraction from the initial natural state). The results of each simulation are used to construct individual model responses, in this case, representing an evaluation of the objective function to be minimized in the optimization process.
3. MARS Model Development: In MARS algorithm, local models are adaptively developed in local regions for flexible regression modeling of high dimensional data. The model can be written as $\hat{f}(\mathbf{x}) = \sum_{i=1}^{k} a_i B_i(\mathbf{x})$, where $\mathbf{x} \in \mathcal{R}^m$, and $\mathcal{R}^m$ is the m-dimensional space. k and a_i are the number and coefficients of associated basis functions $B_i(\mathbf{x}) = \prod_{j=1}^{J_i}[S_{ji} \cdot (x_{v(j,i)} - t_{ji})]_+$, $i = 1, 2, 3, \ldots,$ where $(\cdot)_+ = \max(0, \cdot)$, J_i is the interaction order of basis B_i, that is, the number of variables included in the basis function, $S_{ji} = \pm 1$ is the sign indicators, $v(j,i)$ is the index of the design variable x which is split on knots t_{ji}. a_i and $B_i(x)$ can evaluated after the number of locations of knots is adaptively chosen based on the response function changes. The N pairs of sample input vector versus response (objective function) are used to construct a MARS model, as shown in shaded portion of Fig. 1. A MARS model that is fitted well does not necessarily mean it is good for predic-

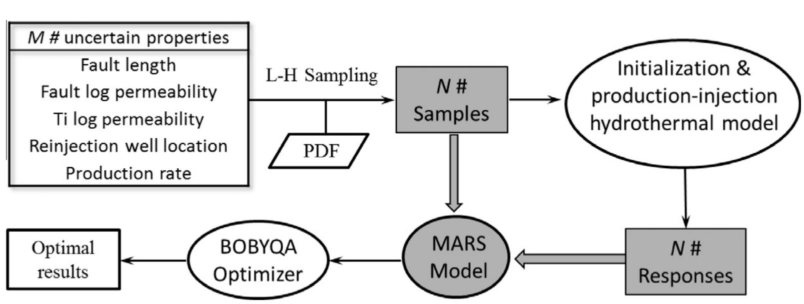

Fig. 1. Schematic diagram of the MARS-based optimization framework. The gray shaded part shows that MARS models are trained by dataset generated from the physical models.