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Perspective

Simulation-optimization with machine learning for geothermal reservoir recovery: Current status and future prospects

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Abstract:
In geothermal reservoir management, combined simulation-optimization is a practical approach to achieve the optimal well placement and operation that maximizes energy recovery and reservoir longevity. The use of machine learning models is often essential to make simulation-optimization computational feasible. Tools from machine learning can be used to construct data-driven and often physics-free approximations of the numerical model response, with computational times often several orders of magnitude smaller than those required by reservoir numerical models. In this short perspective, we explain the background and current status of machine learning based combined simulation-optimization in geothermal reservoir management, and discuss several key issues that will likely form future directions.

Maximum yet sustainable energy recovery from geothermal reservoirs depends on the optimal placement, depth and operation of injection and production wells (Akın et al., 2010; Ijeje et al., 2019). Scenario-analysis using numerical models of coupled fluid flow, heat and mass transport can be used to predict the performance of a geothermal reservoir over time under various injection-production scenarios, and the results can be employed to choose the best scenario among them. In this context, previous studies have employed numerical models such as TOUGH2 (Transport of Unsaturated Groundwater and Heat), COMSOL® Multiphysics, Schlumberger Eclipse, and NUFT (Non-isothermal Unsaturated-saturated Flow and Transport), for modeling geothermal reservoirs with either water or CO_2 as the working fluid (Chen et al., 2022). However, scenario-analysis does not guarantee optimal solutions. To overcome this limitation, combined simulation-optimization (CSO) can be used to derive explicitly the optimal resource exploitation strategies (Biagi et al., 2015). In CSO, a model of the geothermal reservoir is employed to assess the effect of various well placement and operation alternatives on energy recovery and reservoir longevity, and an optimization algorithm performs a systematic search for improved alternatives using one or multiple objective functions based on model outputs. Common objective functions include maximizing the net present value (Rajabi et al., 2021), maximizing power/heat production (Song et al., 2021), minimizing thermal drawdown (Samin et al., 2019), and maximizing the coefficient of performance (Babaei et al., 2022). Examples of previously used optimization algorithms in geothermal CSO include genetic algorithm (Samin et al., 2019; Song et al., 2021), simulated annealing (Akın et al., 2010) and particle swarm optimization (Schulte et al., 2020). CSO has been applied to a variety of reservoir types, spanning from carbonate reservoirs (Akın et al., 2010) to hot sedimentary aquifers (Blank et al., 2021).

Most previous geothermal CSO studies (Biagi et al., 2015) adopt a deterministic approach to reservoir simulation. However, factors such as geological uncertainty, reservoir heterogeneity, inevitably result in model predictive uncertainty,

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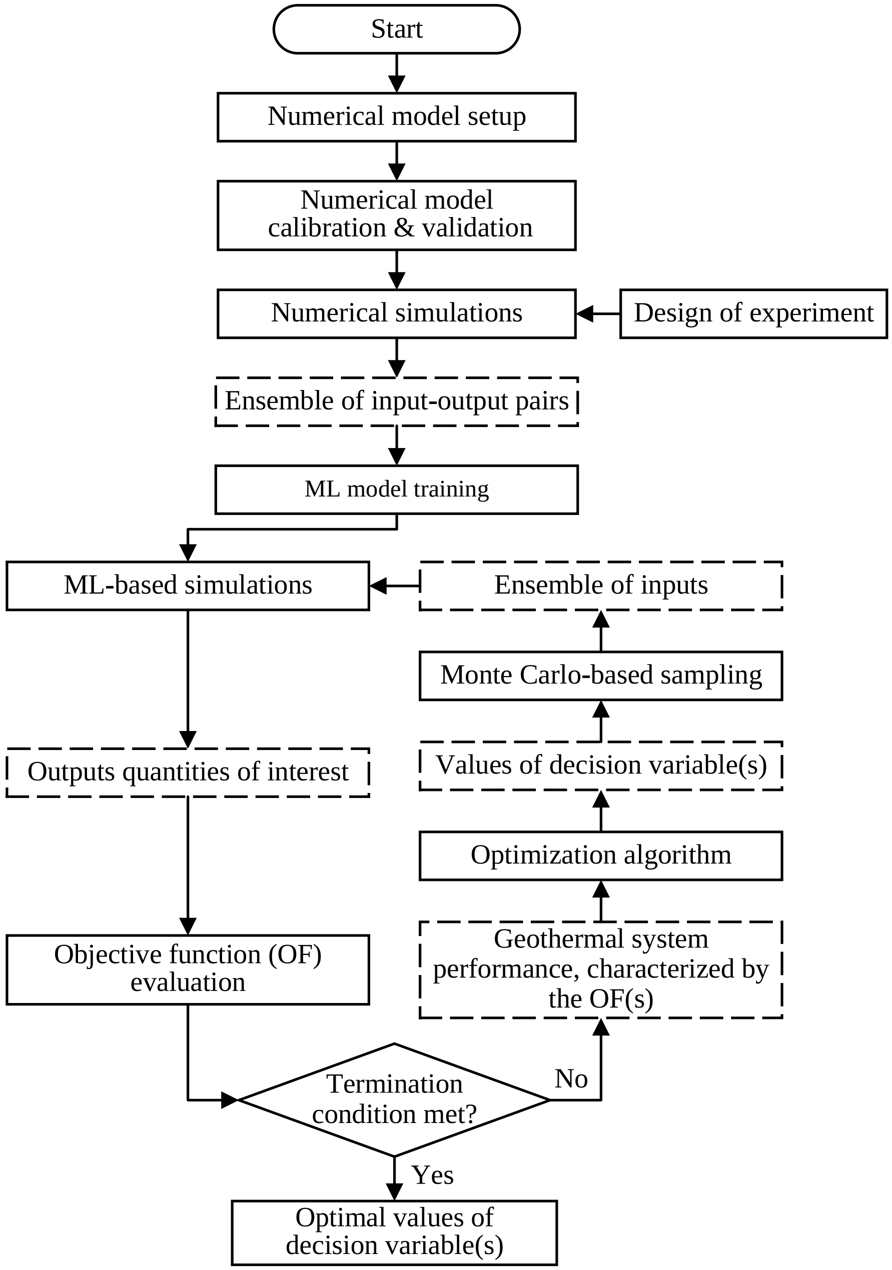

Fig. 1. Flowchart of ML-based CSO for optimal geothermal reservoir energy recovery.

which if ignored, may cause different real-world outcomes compared to what is expected from simulating a specific reservoir exploitation strategy (Schulte et al., 2020). Hence, deterministic CSO carries the risk of solution non-optimality, and stochastic CSO offers a naturally better choice. But then there is the problem of computational time, because numerical geothermal reservoir models are computationally expensive (Chen et al., 2020), and stochastic CSO often involves the use of uncertainty propagation techniques such as Monte Carlo simulation, which require large numbers of model simulations to achieve the desired accuracy (Rajabi et al., 2021). Therefore, it is crucial to find techniques that can drastically reduce the computational time of stochastic CSO. This is where machine learning (ML) comes to the rescue!

Tools from ML can be used to construct data-driven (often physics-free) approximations of the numerical model response, with computational times often several orders of magnitude smaller than those required by the reservoir numerical model. Note that, due to the high costs and physical limitations of reservoir exploration and field-scale injection/production experiments, it is generally unfeasible to satisfactorily train a ML model using solely field data from a geothermal reservoir. In practice, large ensembles of numerical model input-output pairs (performed over the range of operating conditions) are often employed to train ML models for geothermal reservoir simulation. Hence the use of ML models does not replace the requirement for developing a numerical model in the first place. The benefit of ML models lies in permitting the use of uncertainty propagation and stochastic/meta-heuristic optimization techniques that require a large number of system response evaluations. ML models of particular interest in previous geothermal CSO studies include neural networks as multilayer perceptron (Akın et al., 2010; Rajabi et al., 2021), and hybrid convolution-recurrent neural networks (Wang et al., 2022a), random forests (Wang et al., 2022b), multiple regression (Song et al., 2021) and multivariate adaptive regression splines (Chen et al., 2015). These ML models have been employed to relate control variables (e.g., injection flow rate and fluid temperature) and uncertain reservoir parameters (e.g., reservoir permeability), to state variables such as the flow rates, temperatures, and pressures at particular observation points (most commonly the production wells), as time series or at steady-state/specific time points.

The landscape of ML-based geothermal CSO is continuously evolving. A flowchart of Ml-based CSO is presented in Fig. 1. Here several key issues that will likely form future directions are discussed:

1) In geothermal reservoir simulation, the input and output spaces are both high dimensional and nonlinearly related to each other. Dimensions of the input/output vectors are usually lowered to pave the way for construction of ML models, as common ML models often struggle at scaling to high dimensional problems. However, this often comes at the cost of reduced accuracy and generalization ability, and losing important insight about the true behavior of the system. Hence one of the most important avenues for future research is to work toward developing geothermal CSO algorithms based on state-of-the-art ML models that are capable of handling high dimensional problems. Deep neural networks offer considerable potential in this regard.
2) Integration of power plant and geothermal reservoir production economics in ML-based CSO has been less explored in past research. But it can highly benefit the development of more efficient geothermal energy extraction systems, and hence will likely be better addressed in future work.
3) It is well known that the formulation of the objective function(s) and constraint(s) highly affects the choice of optimal values for the control variables in geothermal CSO. However, there is no unique choice or criterion for selecting the best formulation, and hence there is much need for systematic analysis of differ formulations, as well as innovative approaches for incorporating issues such as market and reservoir structural uncertainty in CSO formulation.

Conflict of interest

The authors declare no competing interest.

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