CO_2-based geothermal systems using a hybrid CFD-ML framework

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Summary

Geothermal well optimization and modeling are fundamental to improving sustainable energy solutions. The purpose of this study is to present a hybrid Computational Fluid Dynamics (CFD) and Machine Learning (ML) framework for simulating and optimizing geothermal wells using CO_2 as the working fluid. As an effective greenhouse gas sequestering agent, CO_2 offers significant advantages, such as greenhouse gas sequestration potential and solubility in water. Due to CO_2's complex dynamics and the high length-to-radius ratios characteristic of geothermal wells, traditional CFD models have a difficult time being computationally efficient. In this study, a hybrid framework was developed to address these challenges by combining the accuracy of CFD simulations with the predictive and optimization capabilities of machine learning.

By integrating ML into a previously validated semi-dimensionless CFD framework, this research enhances prediction accuracy, reduces computational costs, and optimizes operational parameters. Injection rates, wellbore geometries, and tubing-to-annulus configurations can all be explored rapidly with this integration, thus enabling efficient optimization of geothermal systems.

Theory / Method / Workflow

The proposed framework combines semi-dimensionless CFD with ML models to address the computational inefficiency inherent to traditional simulations. CFD models that are semi-dimensionless solve governing equations in the longitudinal and transverse directions in dimensionless form, whereas models that are dimensioned solve the equations in the longitudinal and transverse directions in real units. Through the use of a representative one-meter segment of the wellbore, this approach reduces computational complexity without compromising accuracy.

ML models are trained with a comprehensive dataset generated by high-fidelity CFD simulations. In these models, supervised learning algorithms are used to predict temperature, and flow dynamics under various operating conditions. In addition to an accurate representation of CO_2's thermophysical behavior, dynamic property updates ensure an accurate representation of its phase transitions and heat transfer characteristics. In addition to speeding up the optimization process, the ML component provides rapid surrogate predictions for scenarios that would otherwise require extensive CFD simulations.

Figure 1: Illustration of the hybrid CFD-ML framework workflow

Results, Observations, Conclusions

In the hybrid framework, computational costs are significantly reduced while accuracy is maintained at a high level. Compared to fully dimensional models, simulations reduced runtime by up to 700 times for wells deeper than 2 kilometers. Prediction errors consistently fell below 5% for the models using ML, which agreed well with the results of CFD and experiments. Injection of CO_2 through annulus produced higher outlet temperatures and thermal efficiencies than injection through tubing, especially at lower flow rates and deeper wells. Optimization using machine learning showed that insulating the tubing and selecting the optimal injection parameters further enhanced energy recovery. Using CO_2 as a working fluid also contributes to greenhouse gas sequestration, which aligns with global sustainability goals.

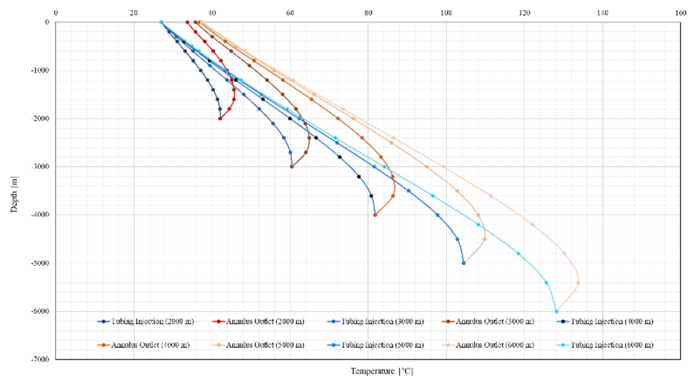

Figure 2: Variation of temperature according to well height from 2000 m to 10000 m

Novel/Additive Information

Semi-dimensionless CFD models for geothermal systems using CO_2 as a working fluid are integrated into this study for the first time. Using a hybrid approach, geothermal energy production can be optimized rapidly and accurately. In addition to enhancing energy recovery, the framework also contributes to reducing greenhouse gas emissions. To further enhance operational efficiency, the framework will be extended to multi-well systems and include real-time adaptive simulations.

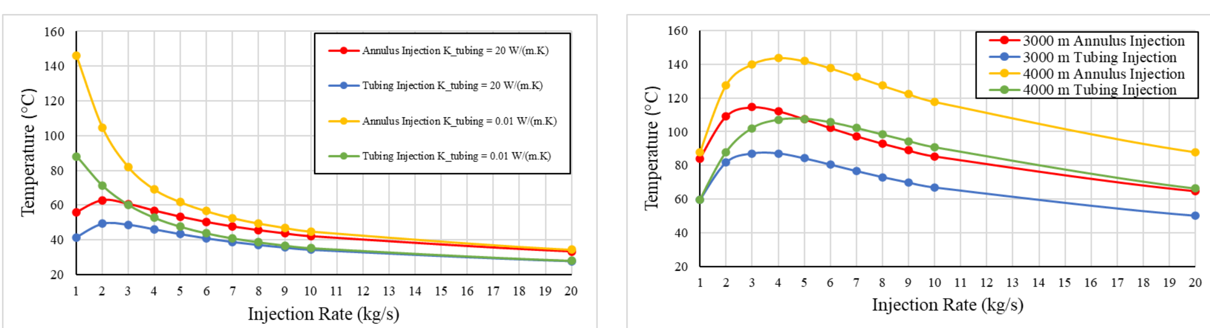

Figure 3: Variation of temperature according to injection mass rate for isolated tubing and different depth.

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