HOW TO DESIGN THE MOST PRODUCTIVE GEOTHERMAL WELL?

Development of Decision-making ML Algorithm for Finding Optimum Well Parameters in Enhanced Geothermal Systems

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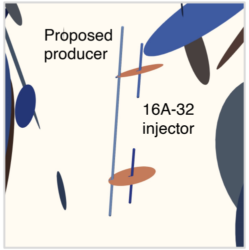
INTRODUCTION

- Finding the optimum design for Enhanced Geothermal Systems' production well can be tedious – hundreds of parameters may be involved at once
- A decision-making algorithm was developed to help geothermal operators find the optimum production well parameters that can deliver maximum output over the life of the field, while accounting for parasitic losses
- Since geothermal operators may have **different appetite to risk vs reward,** the algorithm that can quantify risk aversion for well placement recommendations.
- Datasets generated based on Utah FORGE field using GeoDT program (Frash, 2022) was used to develop and train the ML model and optimizer



METHODS

EXPLORATORY DATA ANALYSIS

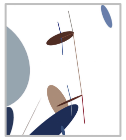
Explore dataset to rank parameters and test utility function design using **Pearson's coefficient and range bucketing**

PROXY MODEL TRAINING

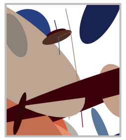
Train using Light Gradient Boosting algorithm across **>44,000 combinations of reservoir realization vectors and decision vectors**

WELL PLACEMENT OPTIMIZER

Optimize using Dual Annealing algorithm on 100,000 realizations to get **optimum well placement across risk factors**



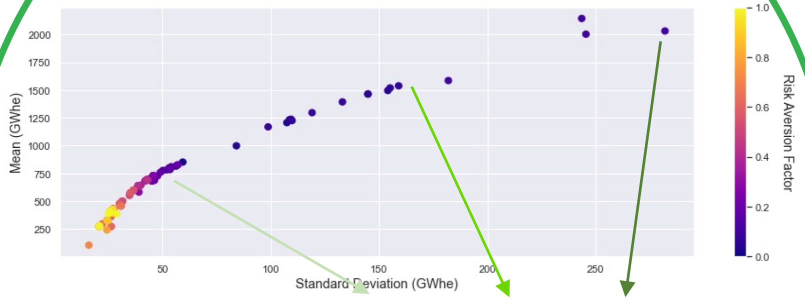
Decision vector 1 realization 1 . . .



Decision vector 1 realization 100,000

WELL PARAMETERS RISK VS REWARD EFFICIENCY CURVE

The optimum well placement parameters vary with risk aversion; parameters have different distribution types.

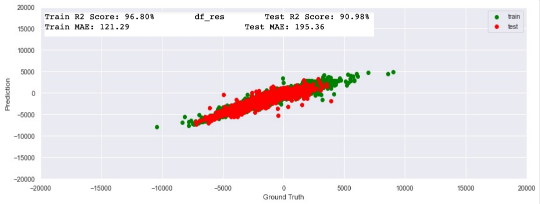


Power output (GWe)	**750**	**1500**	**2000**
Std Deviation (Gwhe)	**28**	**50**	**260**
w_spacing (m)	498.47	673	698
w_intervals	5	6	6
w_phase	1.5	0.00	0.00
w_proportion (deg)	0.98	0.87	0.80
w_skew (deg)	0.02	0.16	-0.18
w_toe (deg)	-0.0307	-0.053	-0.028
Tinj (°C)	84.06	83.00	88
Qinj (m^3/s)	0.0126	4.49 e-02	4.4 e-02

PROXY MODEL TRAINING

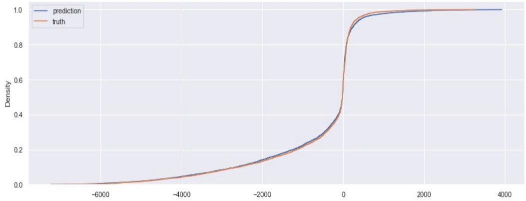
PROXY MODEL SCORES

High R^2 Score: 96.8% for training set, 90.98% for test set



POWER OUTPUT DISTRIBUTION

Consistent distribution of power output result



CONCLUSION

1. **Risk aversion can be quantified into utility function** so that geothermal operators can decide on the most optimum well placement parameters based on their risk tolerance
2. **Optimum well parameters are generally consistent** with GeoDT high-performance scenarios (Frash, 2022)
3. **Adding 1-2 more wells to the producer-injector pair can greatly increase the power output**, however cost will also increase
4. Similar decision-making algorithm **can be developed to find the most optimum configuration of other energy sources**, such as for solar panel density or wind turbine placement

REFERENCES

Frash, L.P., 2022, Optimized Enhanced Geothermal Development Strategies with GeoDT and Fracture Caging**.** Proceedings of 47th Workshop on Geothermal Reservoir Engineering Stanford University, Stanford, California, February 7-9, 2022.