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Using Machine Learning to Predict Future Temperature Outputs in Geothermal Systems

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Problem

Optimization of a power plant's output requires the ability to ***predict*** output temperatures and pressures of production wells based on the inputs of injection wells, production mass flow rates, and the history of the field

Approach

Machine Learning (ML) techniques can capture nonlinear relationships between independent/dependent variables in geothermal systems

Investigation

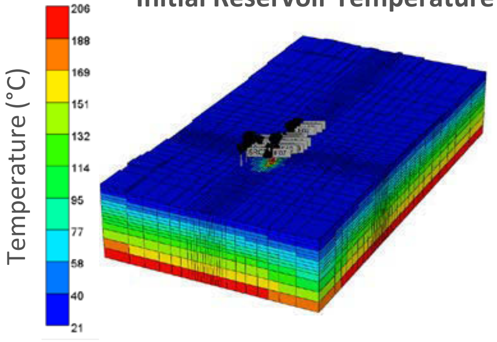
- Timeseries Forecasting
- Forecasting with additional channels
- Multi-well modeling for Brady reservoir

1-injector, 1-producer analytical model (Song, et al., 2018)

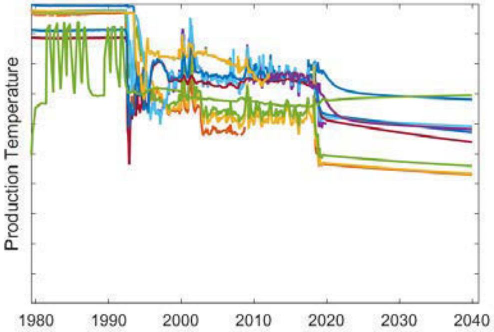
Simulations & Data

- 3D numerical thermo-hydraulic (TH) dual-porosity reservoir model developed for Brady Hot Springs in CMG STARS
- Model validated using historical data
- Future production temperature and pressure profiles simulated for various injection and production flow scenarios

Initial Reservoir Temperature



Example Temperatures Profiles

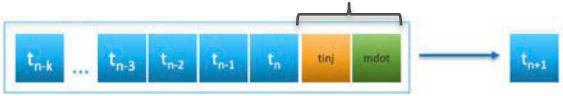


ML

- **MLP** (Multilayer Perceptron)
- **LSTM** (Long Short-Term Memory) networks
- **CNN** (Convolutional Neural Network)

Analytical Model (Song, et al., 2018)

2 channels added to producer's *temperature* sequences: injection *temperature* and *mass flow*



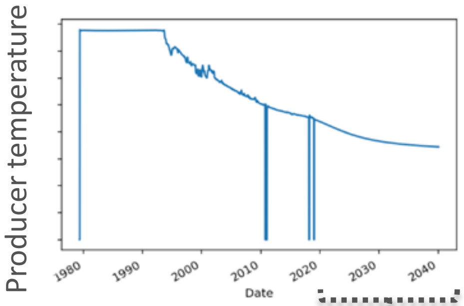
Brady

Producer's *temperature* in the past and now

Injectors' current *temperature*, *pressure*, *mass flow* (12 channels for 4 injectors)

Future value of producer's *temperature*

Learning Brady Reservoir's data



37 simulated scenarios (baseline + 36)

Training: 24 (65%)

Validation: 3 (10%)

Test: 10 (25%)

Vary
# of neurons
and
# of epochs

Train multiple models

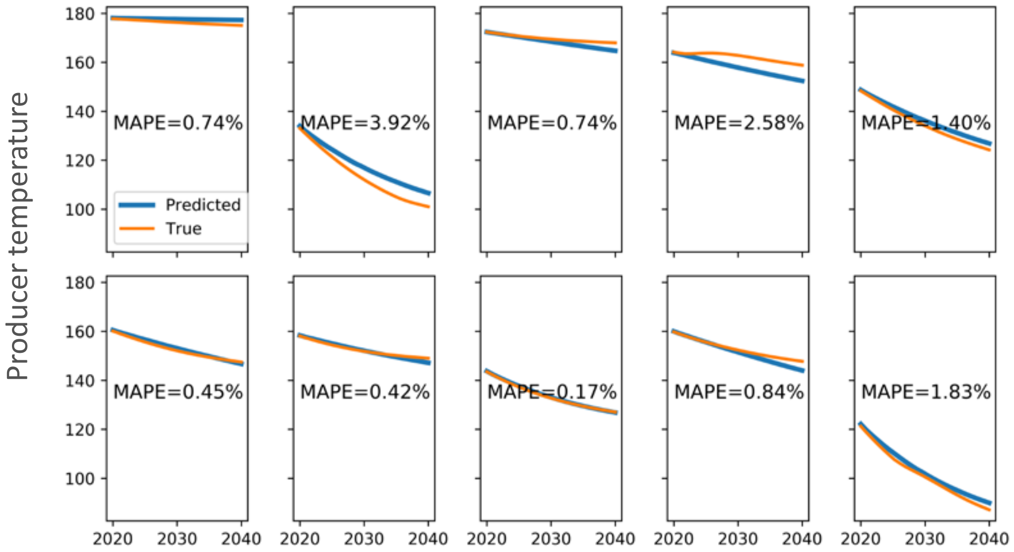
See which model generalizes best

Evaluate selected model's prediction accuracy/error on unseen data

<u>Evaluation Metric:</u>
MAPE – Mean Absolute Percentage Error

Evaluation of Prediction Quality

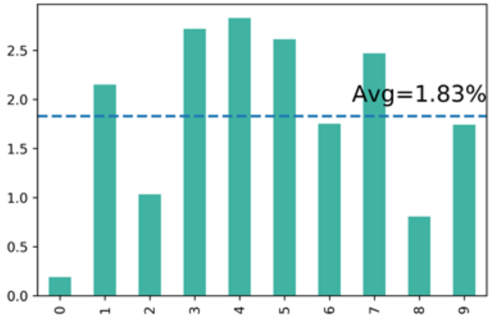
Examples of scenarios predicted from start to finish (2020-2040)



Summary of Learning Experiments

- Average MAPE: 1.8 - 6.5%
- Maximum MAPE: 3 - 16%
- Errors get smaller if we predict <20 years

MAPE for individual predicted scenarios (best trained MLP model is shown)



Future Work:

- Train multi-headed networks to predict several quantities
- Model exergy & energy
- Run & learn from simulations with additional constraints

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