GRC 2020 VIRTUAL ANNUAL MEETING & EXPO

October 18-23, 2020

grc2020.mygeoenergynow.org

#GRCAM2020

Using Machine Learning to Predict Future Temperature Outputs in Geothermal Systems

Dmitry Duplyakin[1]
Drew L. Siler[2]
Henry Johnston[1]
Koenraad Beckers[1,3]
Michael Martin[1]

[1] National Renewable Energy Laboratory
[2] U.S. Geological Survey
[3] Heateon, Belgium

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

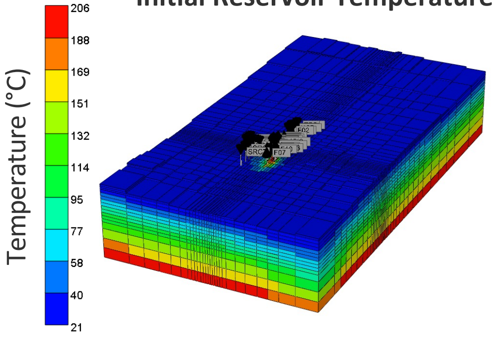
- Timeseries Forecasting
- Forecasting with additional channels
- Multi-well modeling for Brady reservoir

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

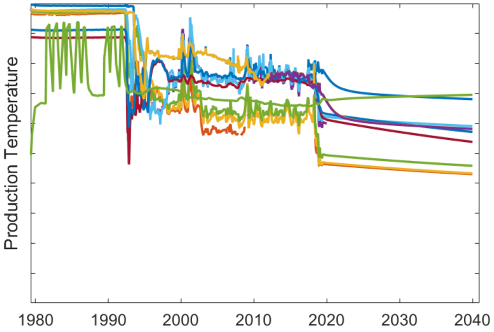
Simulations & Data

- 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

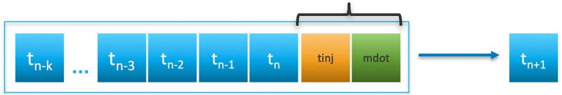


ML

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

Analytical Model (Song, et al., 2018)

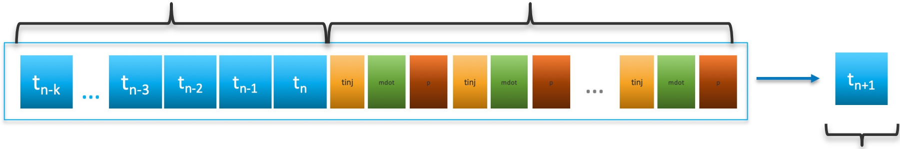
2 channels added to producer's *temperature* sequences: injection *temperature* and *mass flow*



Brady

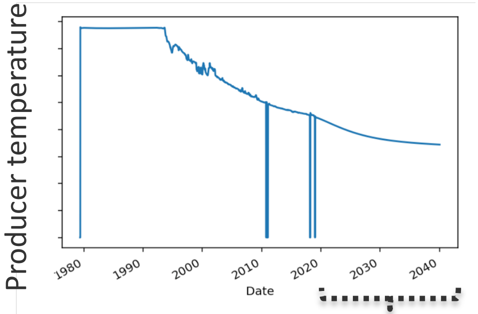
Producer's *temperature* in the past and now

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

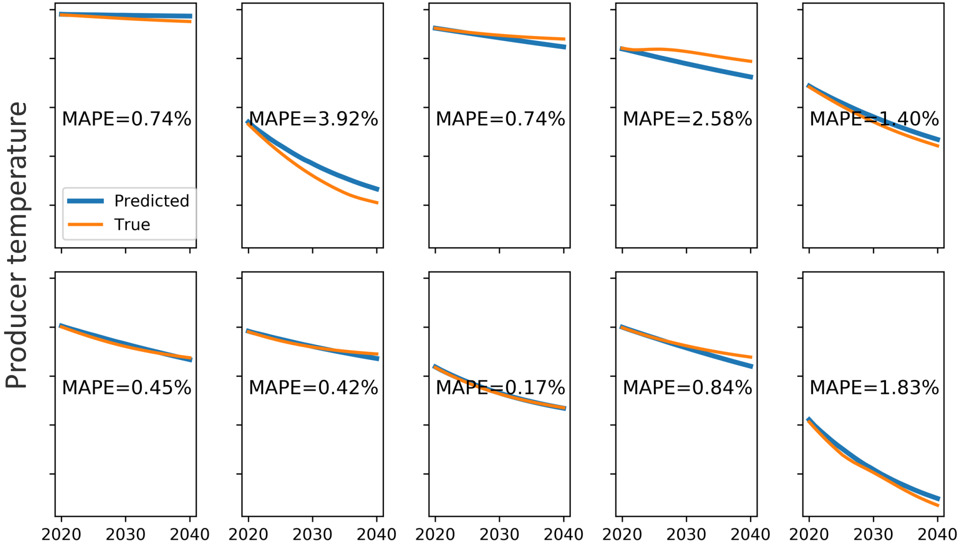
See which model generalizes best

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

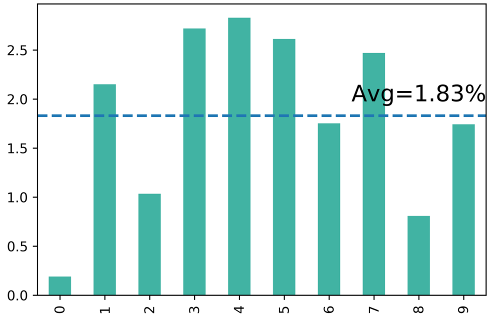
Evaluation Metric:
MAPE – Mean Absolute Percentage Error

Evaluation of Prediction Quality

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



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



Summary of Learning Experiments

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

Future Work:

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

References

- *Song, Xianzhi, Yu Shi, Gensheng Li, Ruiyue Yang, Gaosheng Wang, Rui Zheng, Jiacheng Li, and Zehao Lyu. "Numerical simulation of heat extraction performance in enhanced geothermal system with multilateral wells." Applied energy 218 (2018): 325-337.*
- *Nwachukwu, Chiazor. "Machine learning solutions for reservoir characterization, management, and optimization." PhD diss., 2018.*
- *Ruliandi, Dimas. "Geothermal power plant system performance prediction using artificial neural networks." In 2015 IEEE Conference on Technologies for Sustainability (SusTech), pp. 216-223. IEEE, 2015.*
- *Prieto, M. M., E. Montanes, and O. Menendez. "Power plant condenser performance forecasting using a non-fully connected artificial neural network." Energy 26, no. 1 (2001): 65-79.*
- *Brownlee, Jason. Deep learning for time series forecasting: Predict the future with MLPs, CNNs and LSTMs in Python. Machine Learning Mastery, 2018.*

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Geothermal Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

Acknowledgements We would like to thank John Akerley and John Murphy (Ormat Technologies Inc.) for their collaboration and important contributions to this study.