



Geothermal Operational Optimization with Machine Learning

ASME ES2021

NREL/PR-6A20-79934

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This report has been prepared under grant DE-EE-0008766 and is provided to the U.S. Department of Energy Geothermal Technologies Office. This report may contain information that is confidential in nature and should not be disclosed outside of the U.S. Department of Energy.

Geothermal Operational Optimization with Machine Learning



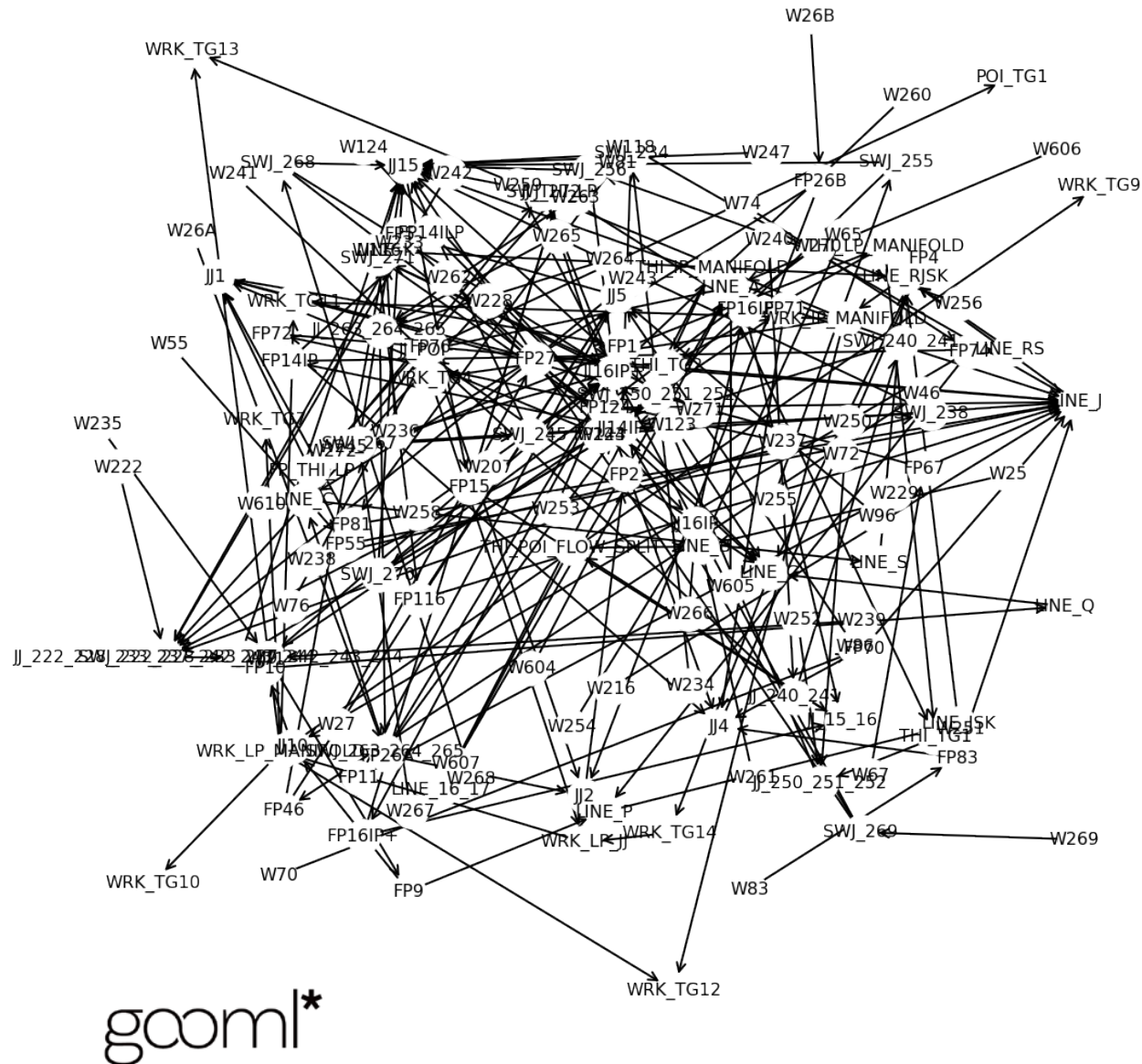
Wairakei Steamfield



How Engineers See it

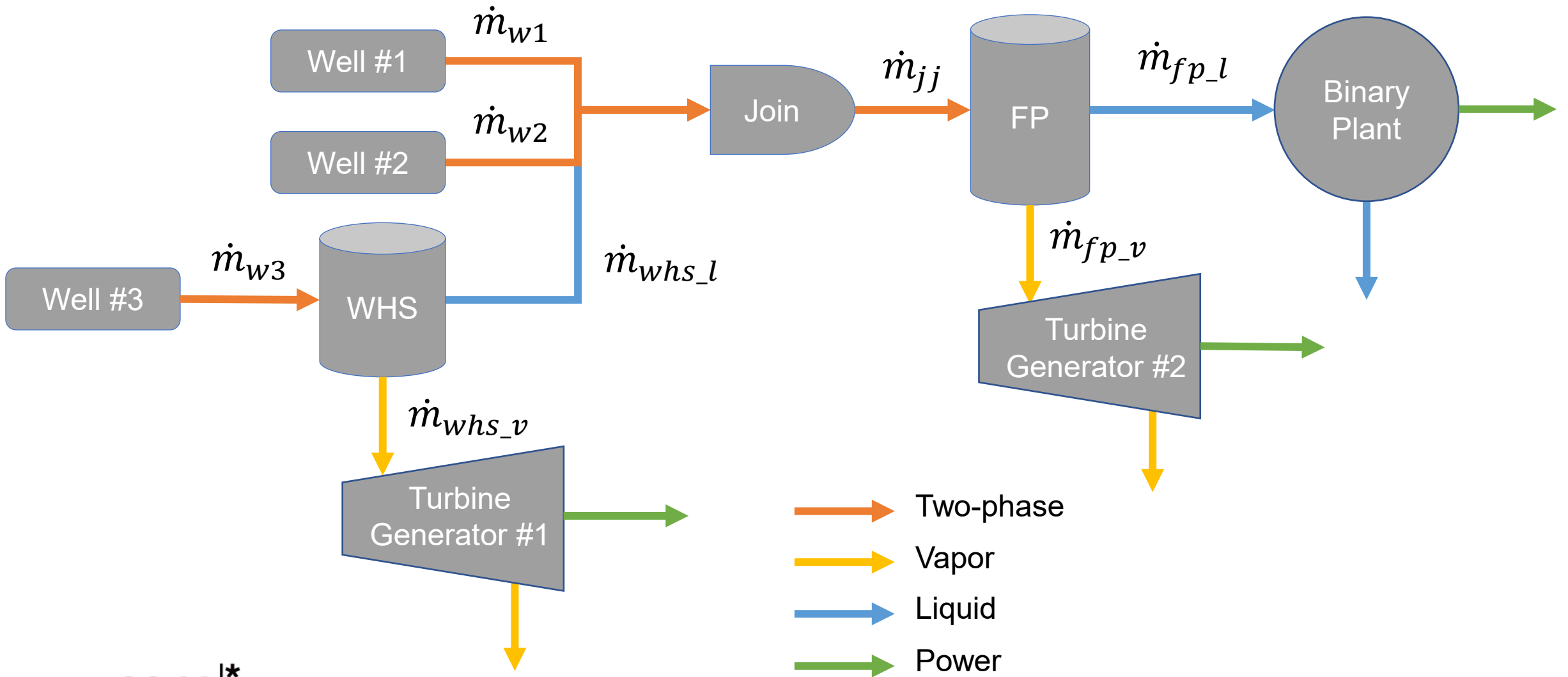


How Python Sees It



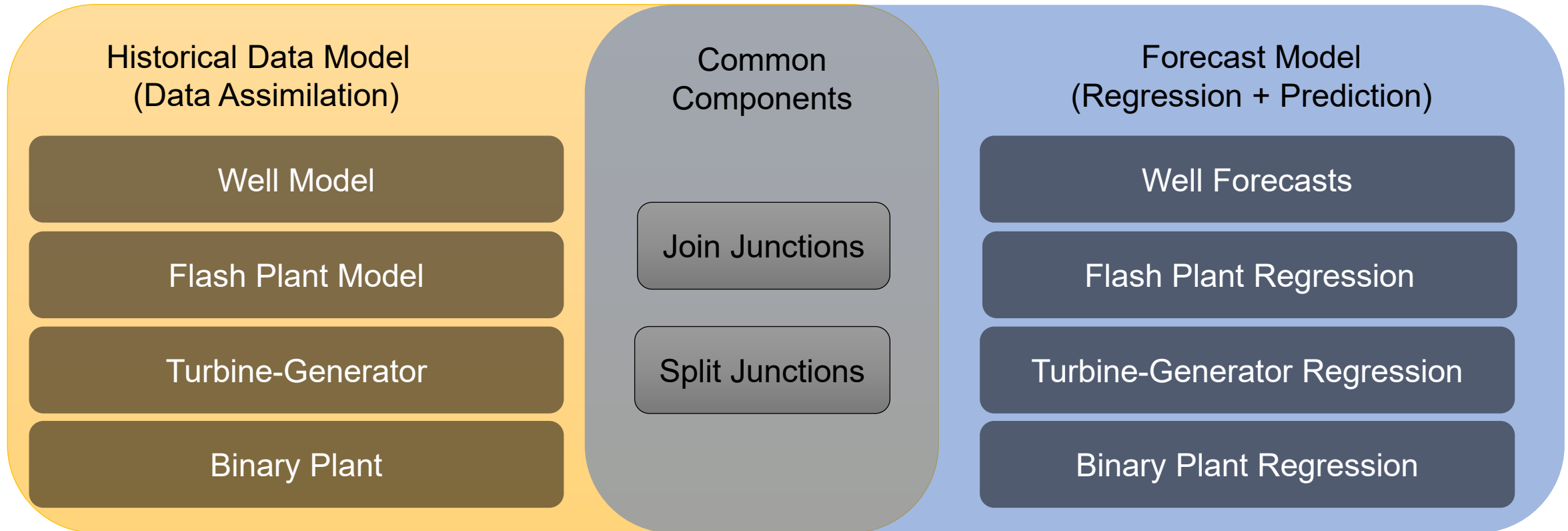
- 20+ component models
 - wells, turbines, weir boxes, join junctions, flash plants, wellhead separators, etc...
- 3 system frameworks
 - historical, forecast, and uncertainty
- 175 interconnected components in the Wairakei model:
 - 67 wells
 - 29 flash plants
 - 11 turbine-generators
 - 68 junctions / manifolds

Simplified System Network



Model Development and Architecture

GOOML component models fall into two system frameworks:



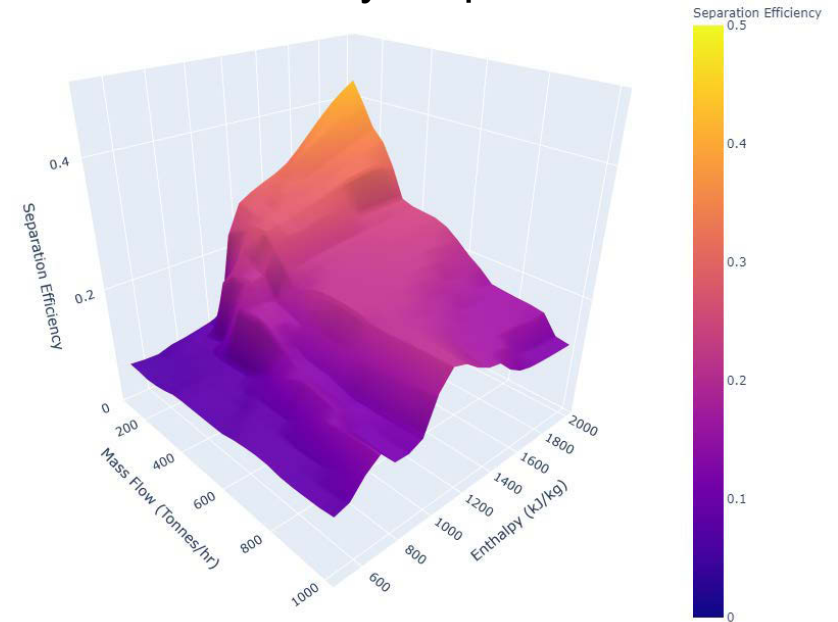
Flash Plant Modeling



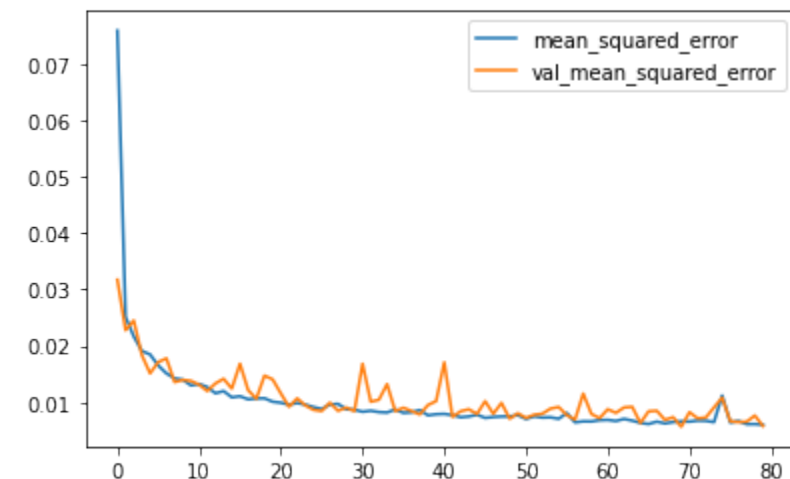
Flash Plant Modeling

- Based on a TensorFlow feed-forward neural network
- Physics-informed features using “traditional” semi-empiric relations:
 - Pressure drop
 - Residence time
 - Cyclone design number
 - Theoretical flash fraction
 - etc...

Saliency Map

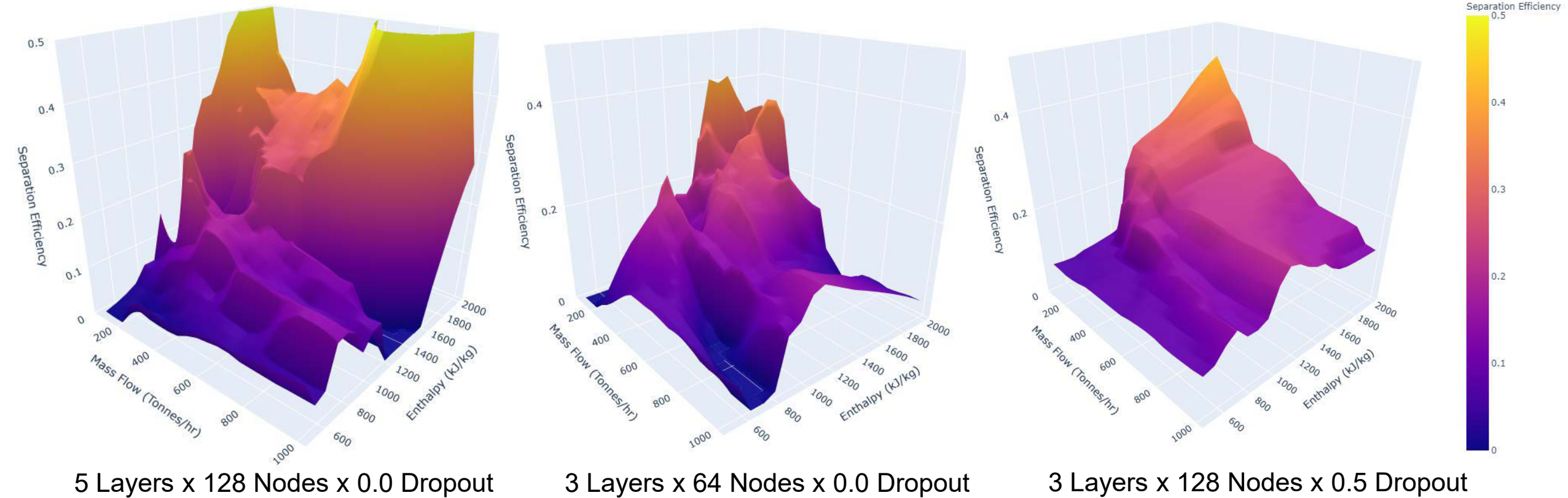


Training Loss



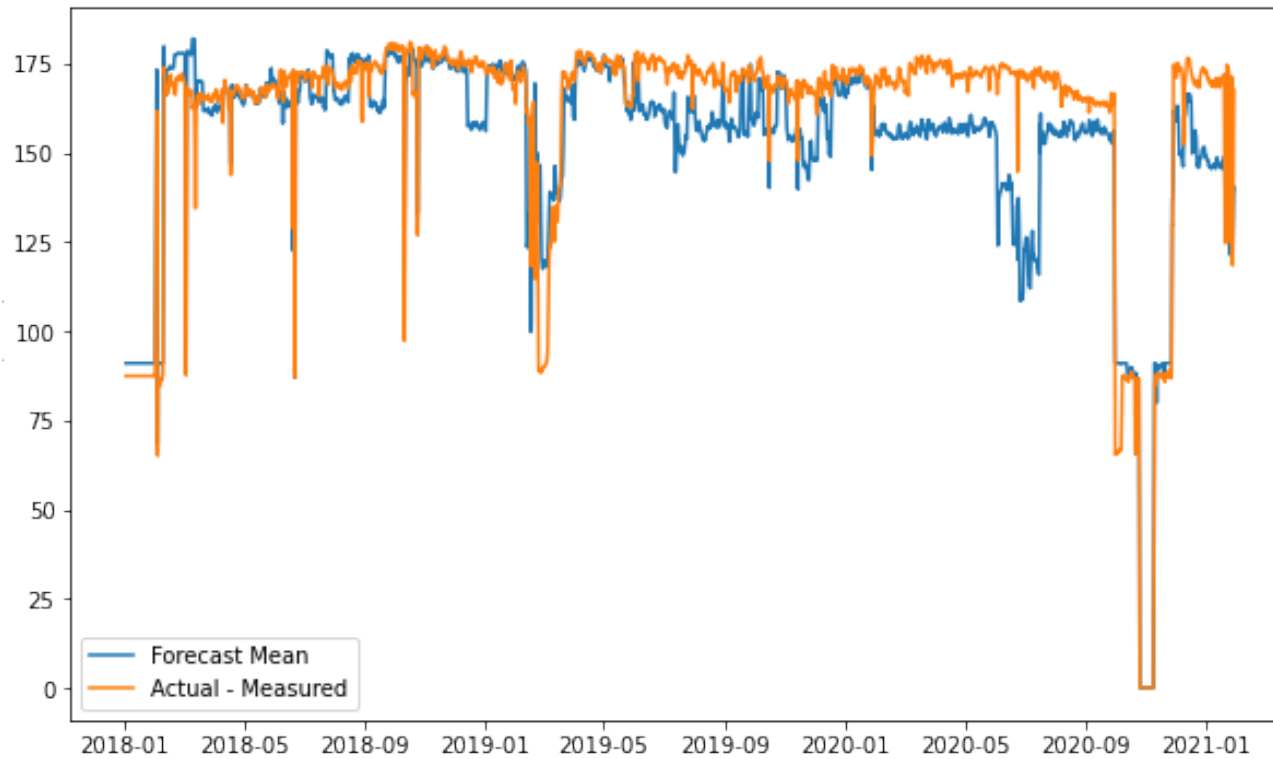
Flash Plant Modeling

- Saliency maps show how the model architecture affects overfitting

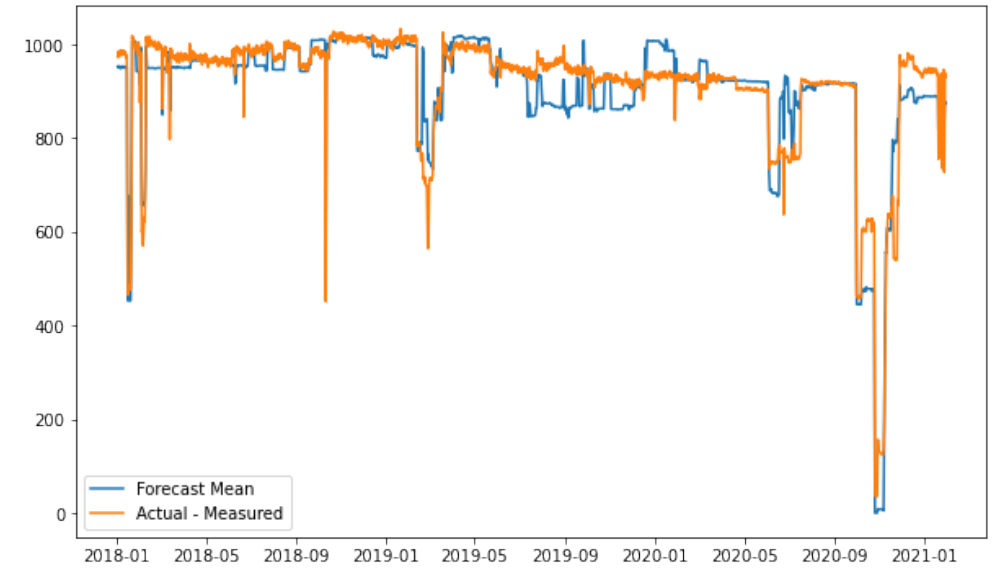


Hindcast Validation

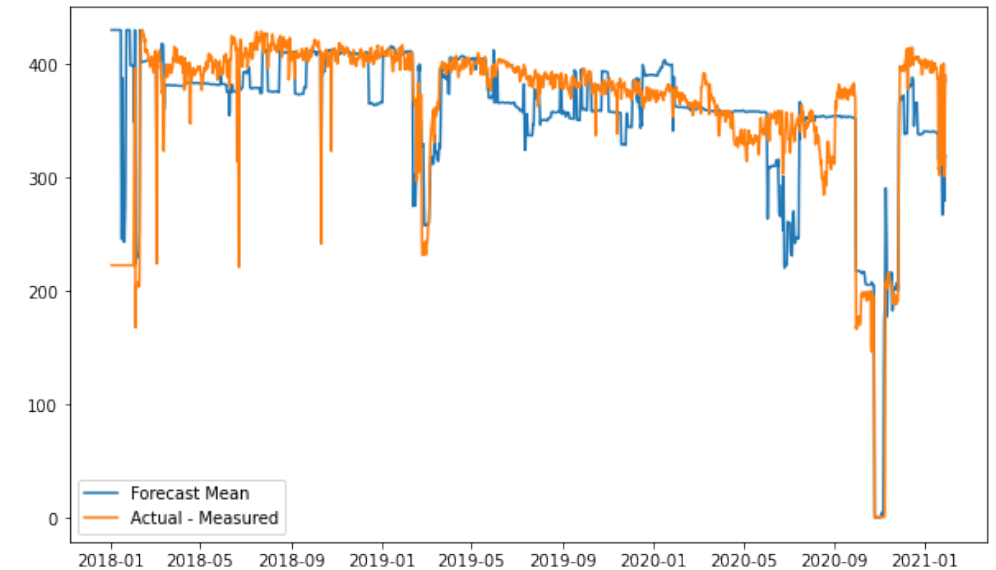
Power Generation



Intermediate-Pressure Steam

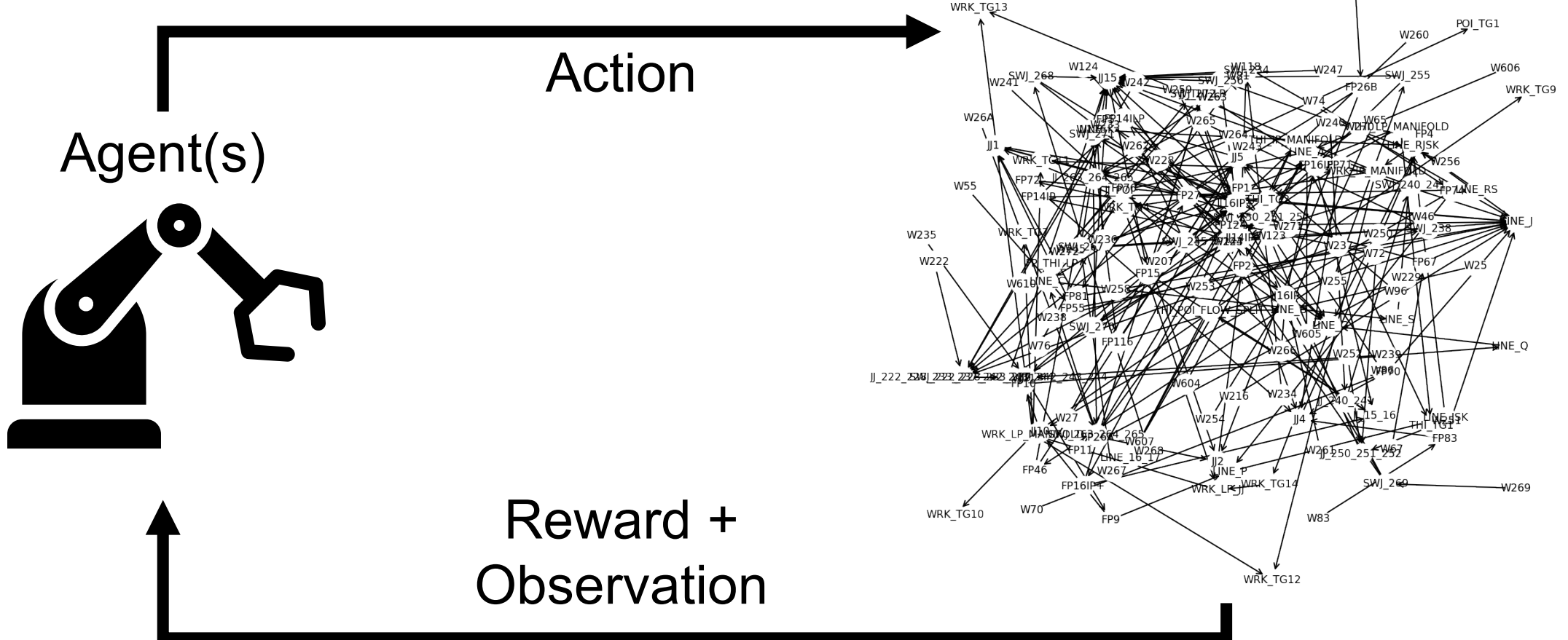


Low-Pressure Steam



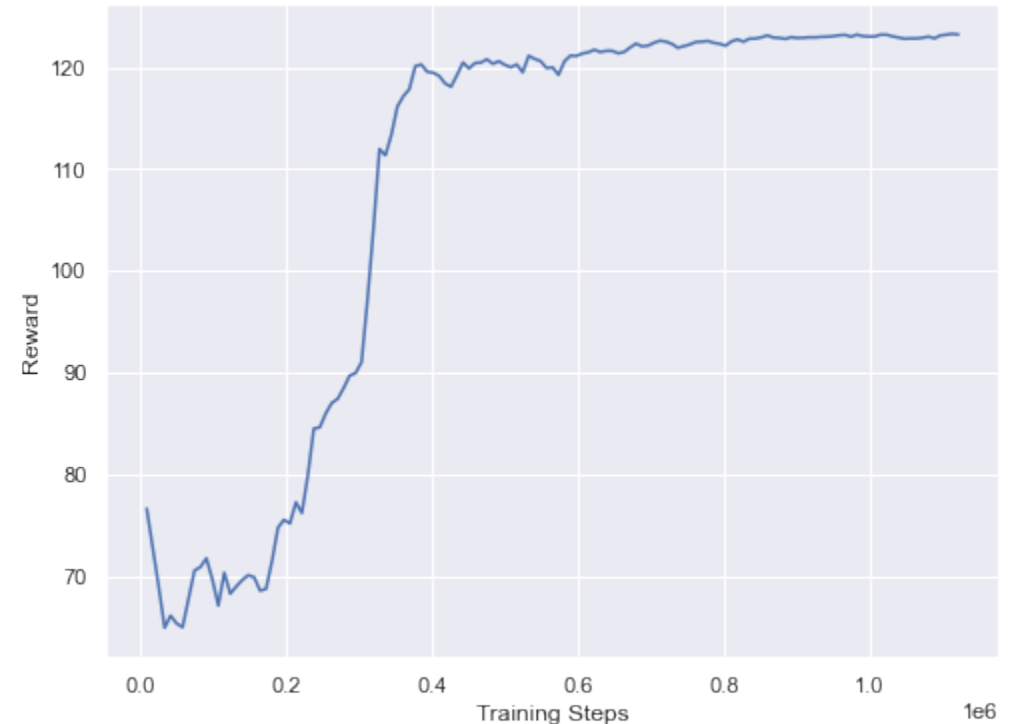
System-Level Reinforcement Learning

GOOML Environment

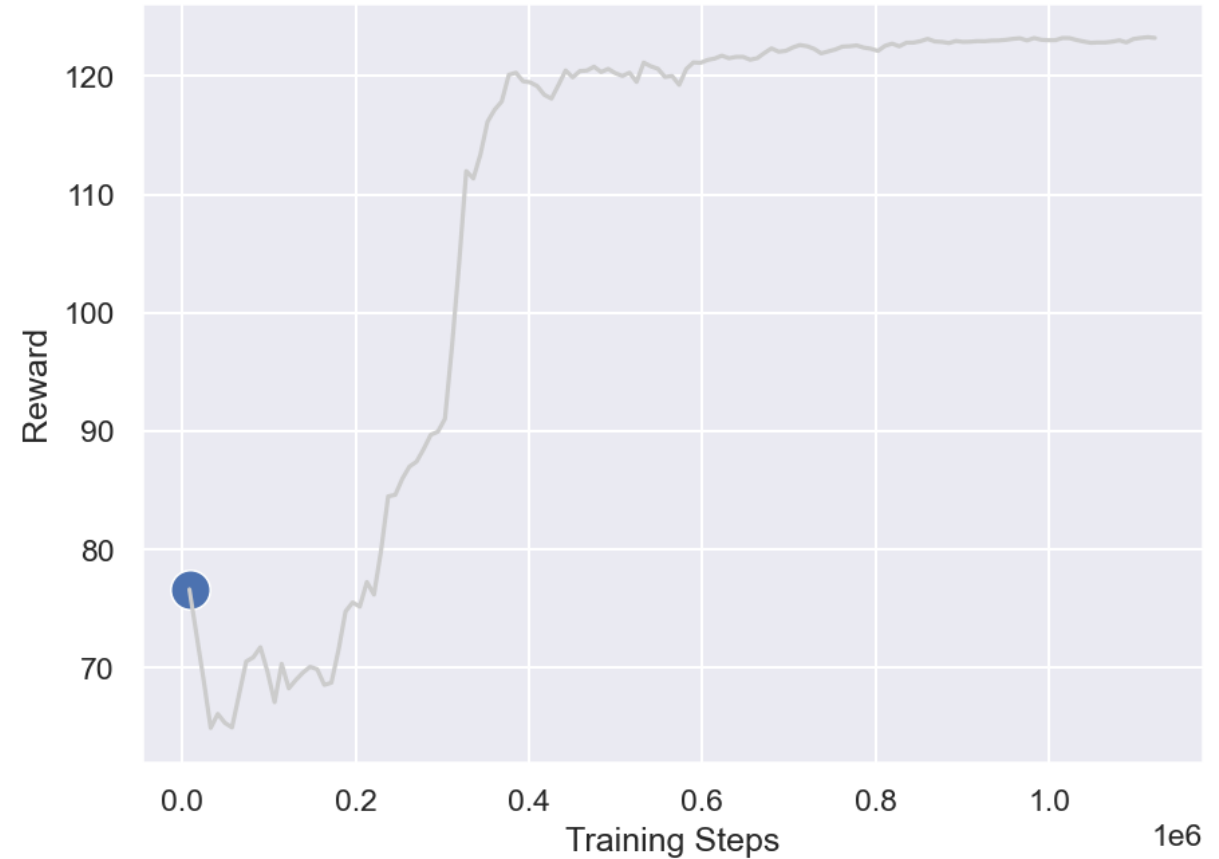
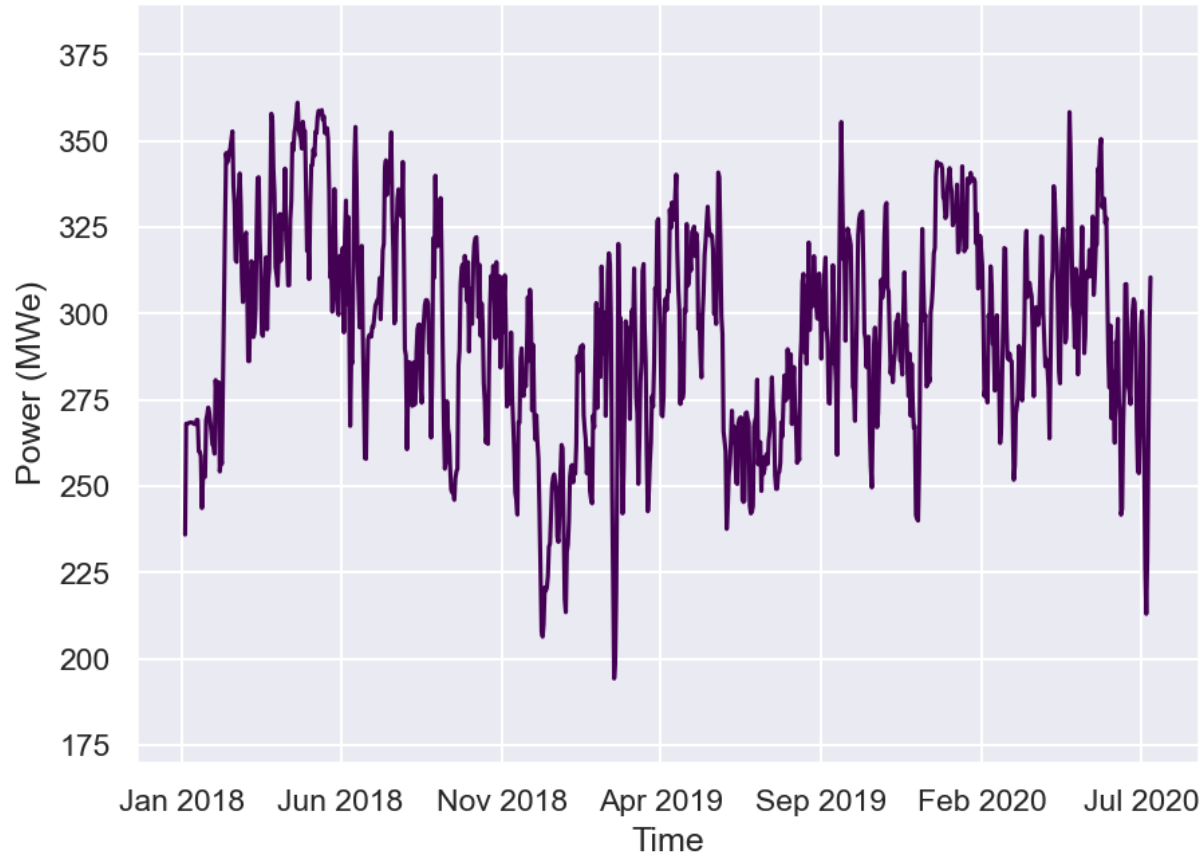


Reinforcement Learning Experiment

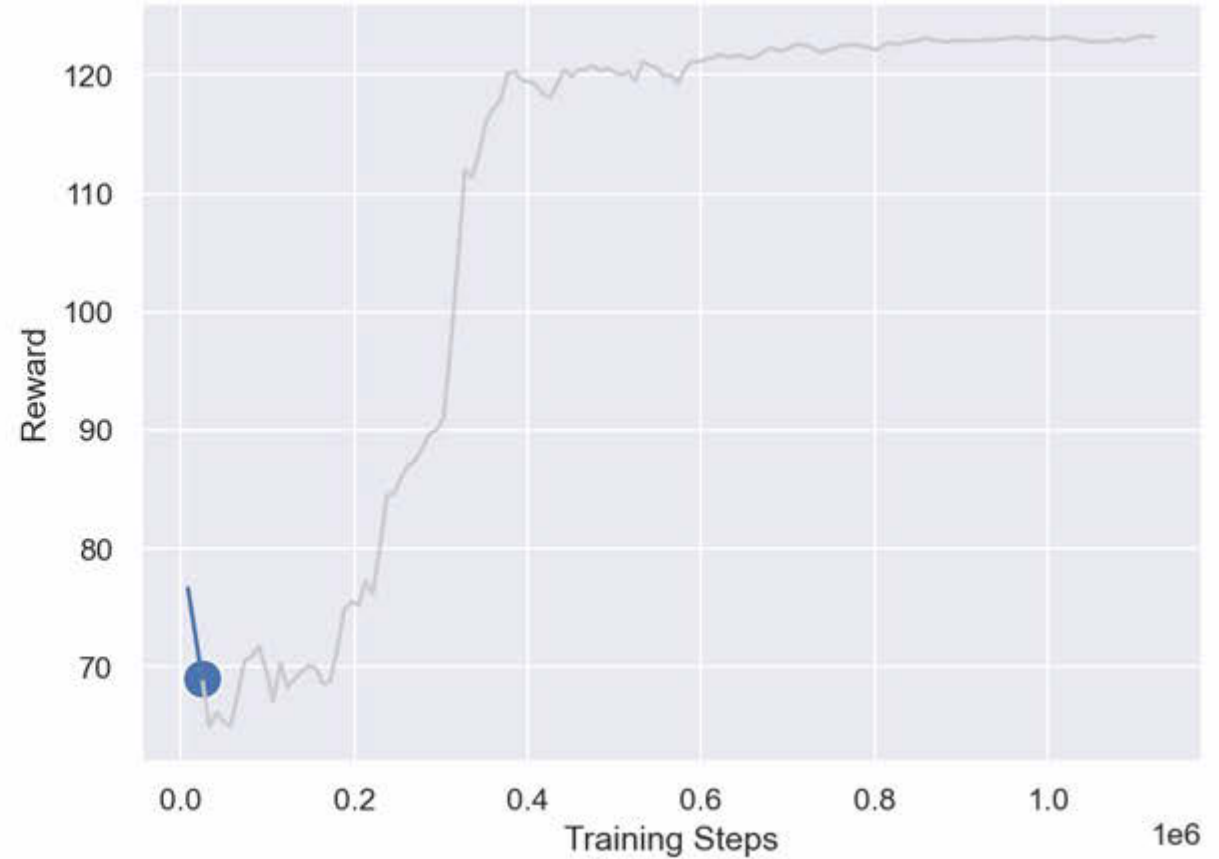
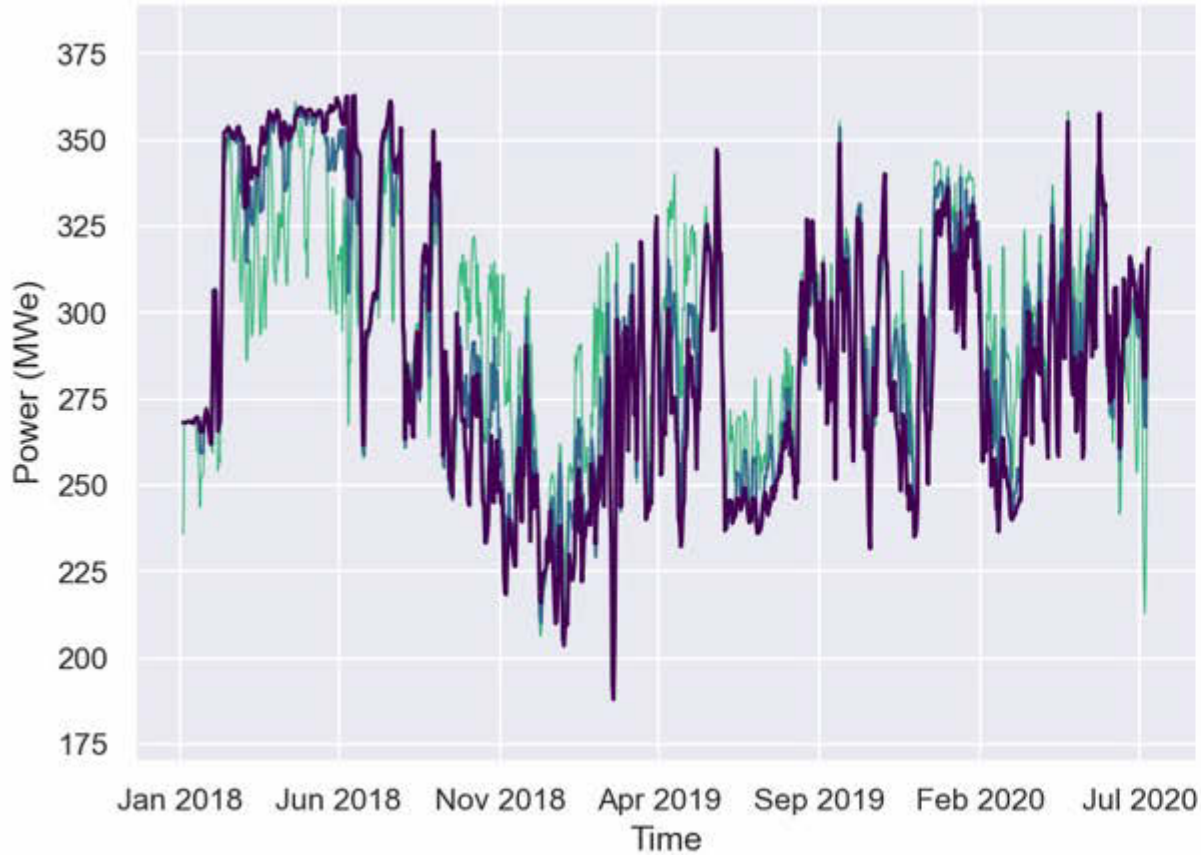
- Agent Controls:
 - IP Pressure (+/- 2 bar)
 - LP Pressure (+/- 1 bar)
 - Control Well Pressure (+/- 2 bar)
- Reward:
 - Based on power
 - Relative to the “baseline” scenario
- Results:
 - Added 20 MWe* to the system!
 - *could be pushing the environment to un-acceptable operating conditions.



Reinforcement Learning Experiment



Reinforcement Learning Experiment



High Level Conclusions *

The GOOML framework is a powerful tool for geothermal analysis

- Forecasts:
 - The GOOML system can forecast future operational scenarios
- Operations:
 - Reinforcement learning agents can act as operation suggestion engines

Looking Forward

- Additional research:
 - Steamfield design optimization
 - Reinforcement learning validation
- Additional steam field models:
 - NTGA Kawerau (model built, being validated)
 - ORMAT McGinness Hills (model built, being validated)
- Open-source software
 - Coming soon!

Good
gooml*

to you all!