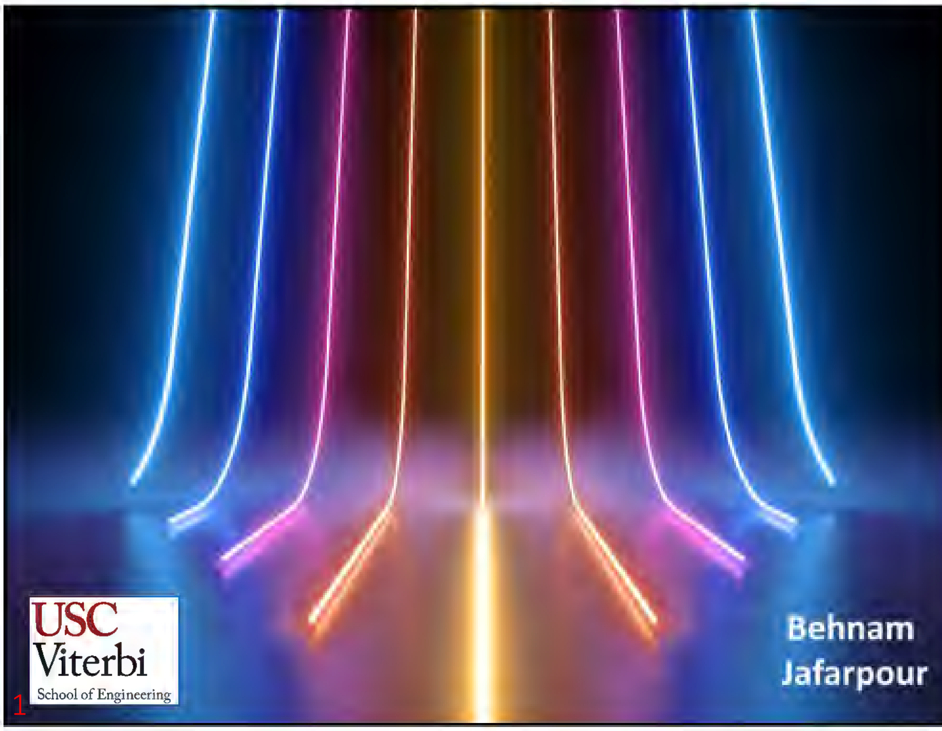

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SUMMIT

Sep 30 – Oct 1 2021

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USC-Energi Simulation Center for Advanced Reservoir Characterization and Forecasting

Dynamic Characterization Research

Behnam Jafarpour

USC Viterbi School of Engineering

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Center for Advanced Reservoir Characterization & Forecasting

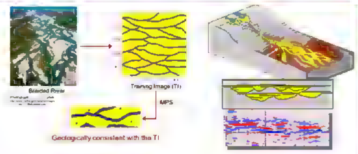
Annual Energi Simulation Summit (Online), September 31-October 1, 2021

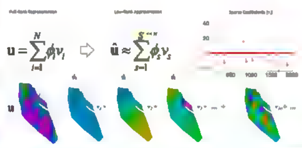
2 Creating a more sustainable energy future through simulation research

2

(i) Description and Characterization of Complex Geosystems

Describing Complex Geosystems ⇨

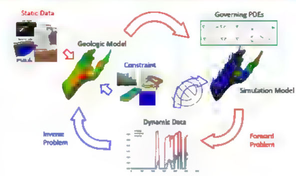


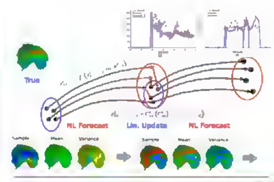


⇦ Compact/Sparse Representations

(ii) Dynamic Model Updating and Uncertainty Quantification

Integrating Dynamic Data into GeoModels ⇨

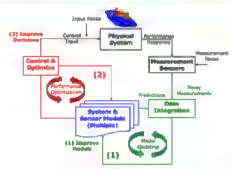


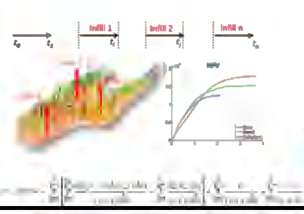


⇦ Quantifying and Reducing Uncertainty

(iii) Field Development Optimization

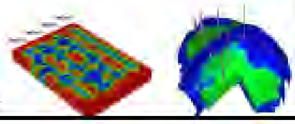
Optimizing Subsurface Resource Recovery





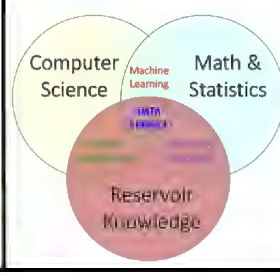
Unconventional

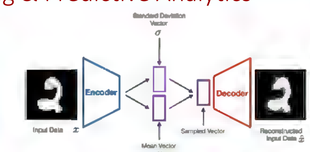
GCS

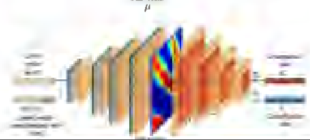


(iv) Data Science for Prediction and Decision Support

Machine Learning & Predictive Analytics







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'a foundation for the future'

USC Viterbi School of Engineering

Advanced Reservoir Characterization and Forecasting

Dynamic Neural Network Models for Prediction and Optimization of Geothermal Energy Production

Behnam Jafarpour

Annual Energi Simulation Summit
Sep 31-Oct 1, 2021
Online Webinar

Creating a more sustainable energy future through simulation research

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Research Thrust Areas

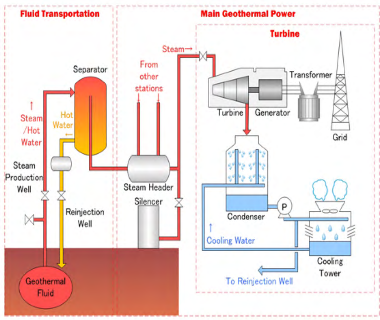
Power Plant:

Fault prediction/diagnosis and model predictive control for efficient automation of power plant operations

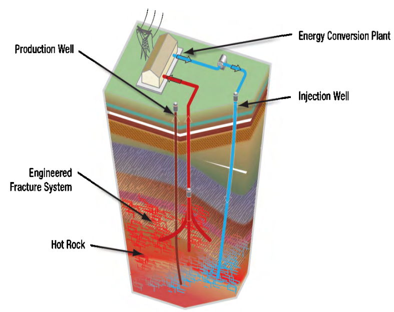
Reservoir/Resource:

Customized predictive analytics and closed-loop control for geothermal reservoirs

Power Plant



Reservoir/Resource



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USC-Cyrq Energy Inc. Collaboration

USC Team

→ **Behnam Jafarpour, PI** (Professor, CHE/ECE/CEE)

Deep learning for subsurface energy systems

→ **Robert Young** (Associate Professor of Chemical Engineering Practice)

Process modeling and control

→ **Anyue Jiang** (PhD Student, Chemical Engineering)

Recurrent neural networks for multi-physics data

→ **Zhen Qin** (PhD Student, Petroleum Engineering)

Optimization and control with recurrent neural networks

→ **Yingxiang (Sam) Liu** (PhD Student, Electrical and Computer Engineering)

Anomaly detection and predictive control based on neural network models

→ **Wei Ling** (PhD Student, Chemical Engineering)

Dynamic deep neural network models for power plant operations

Cyrq Energy Inc. Team

→ **Trenton Cladouhos** (PhD)

VP of Resource

→ **Jalal Zia** (PhD)

VP of Engineering

→ **Dave Faulder**

Director of Reservoir Engineering

→ **Michael Swyer**

Senior Geoscientist

→ **Ian Spanswick**

President (O2RC Solutions)

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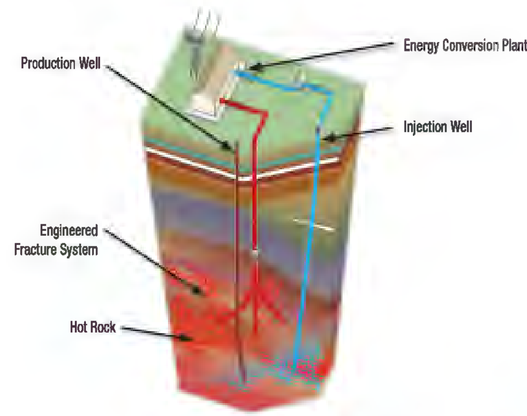
Reservoir/Resource



Reservoir/Resource:

Customized predictive analytics and closed-loop control for geothermal reservoirs

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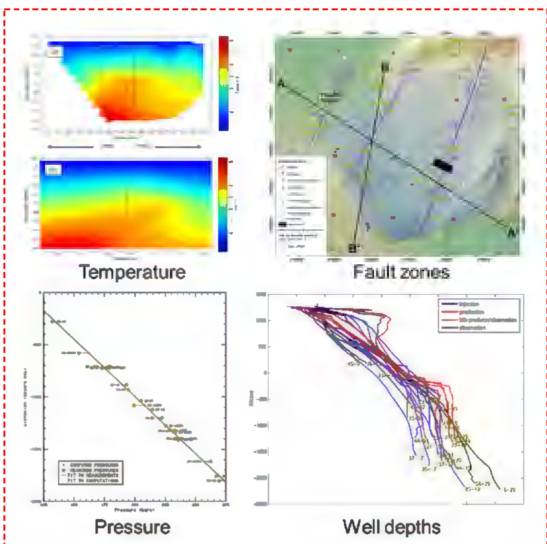
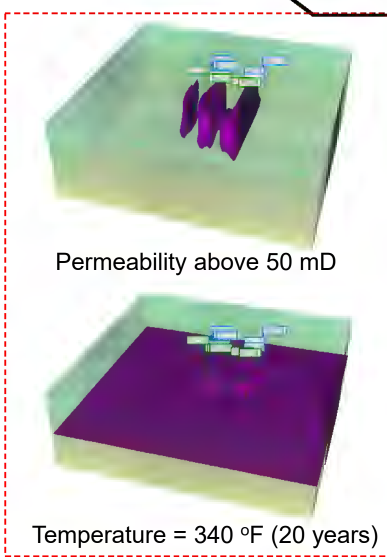
Field Data and Simulation Model





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Simulation & Deep Learning Model

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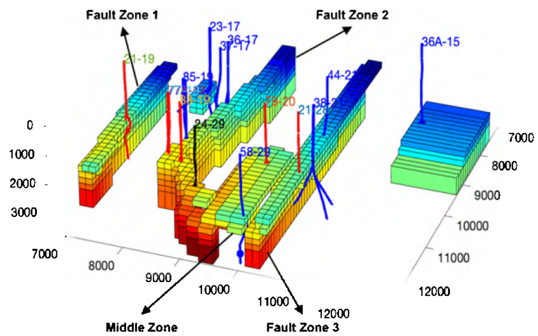
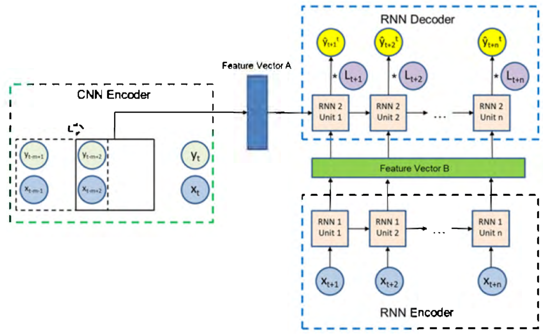
Simulation Model



Deep Learning Model



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Short-Term and Long-Term Predictions

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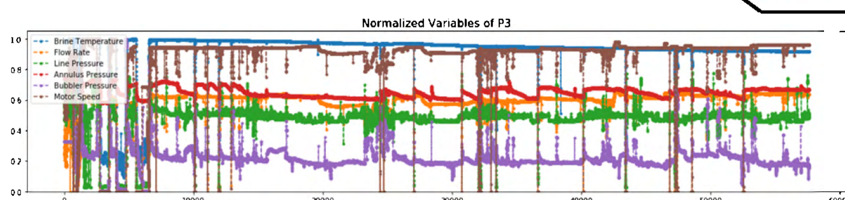
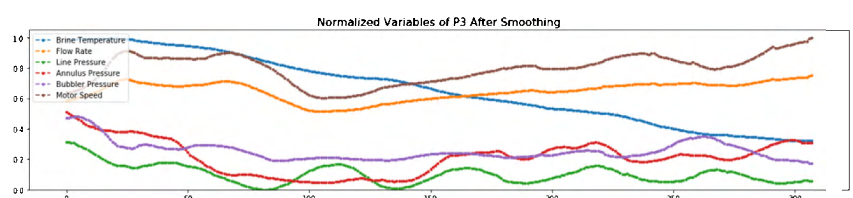
Raw hourly data for short-term prediction



Smoothed weekly data for long-term prediction



High frequency data → Long sequences

Low frequency feature → Possible long-term predictions

Variability introduced by shut-in → Steps that should be ignored

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Short-Term Predictions

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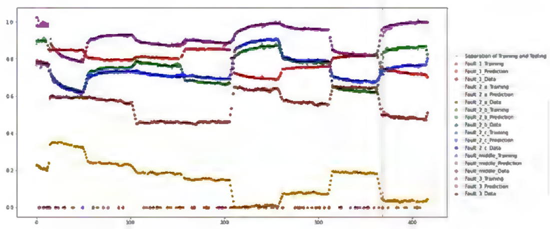
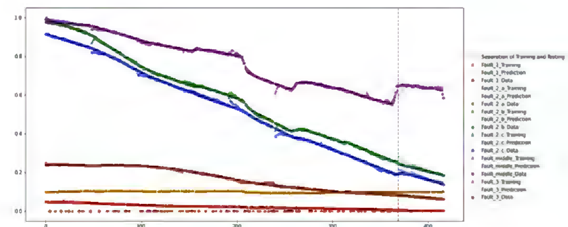
Short Term Predictions (Using historical data)

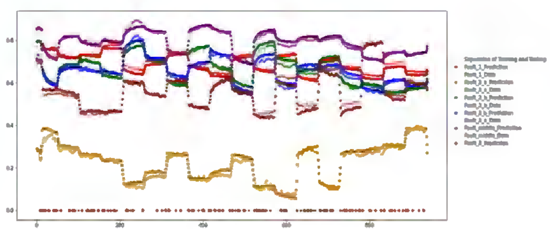
Producer BHP

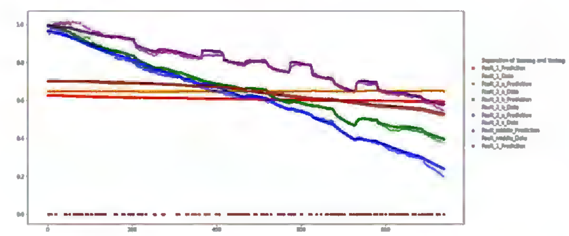


Producer Enthalpy



Long-Term Predictions (using ensemble of simulated historical data)





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Field Performance Optimization

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Objective Functions:

→ Net Power Generated,

→ Min-max Temperature changes,

→ Min-Average Temperature changes

$$E_{\text{net}} = \sum_{t}^{T} E_{\text{gross}}(\text{kWh}) - E_{\text{pumps}}(\text{kWh})$$

$$J(\mathbf{u}) := \frac{1}{t}\sum_{\tau}^{t} \max \Delta \boldsymbol{T}(\tau, \mathbf{u})$$

$$J(\mathbf{u}) := \frac{1}{Nt} \cdot \sum_{p}^{N} \sum_{\tau}^{t} (\Delta \boldsymbol{T}(\tau, \mathbf{u}))$$

Control Variables:

→ Injection/Production Rate

Constraints:

→ Total production rate

→ Mass balance (Production = Injection)

→ Upper and lower bounds

$$\min_{\mathbf{u}} J(t, \mathbf{u})$$

s. t.

$$\Sigma_p^N \mathbf{u}_{prod,p} = \mathbf{Q}_{prod}$$

$$\Sigma_p^N \mathbf{u}_{prod,p} = \Sigma_i^M \mathbf{u}_{inj,i}$$

$$\mathbf{LB} \le \mathbf{u} \le \mathbf{UB}$$

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Objective Function

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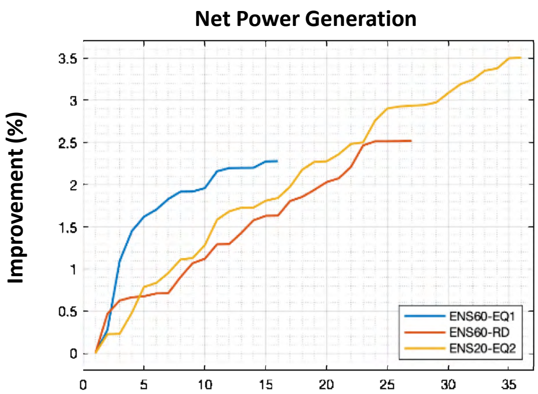
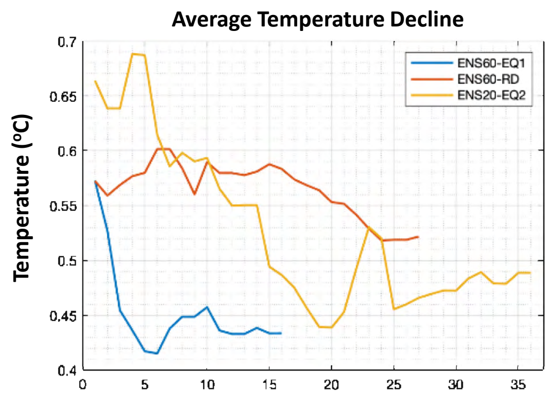
Max Net Power: $\max J(\mathbf{u}) := \sum_{\tau}^{t} \mathrm{E_{gross}}(\mathrm{kWh}) - \mathrm{E_{pump}}(\mathrm{kWh})$

Min Avg dT: $\min J(\mathbf{u}) := \frac{1}{Nt} \cdot \sum_{p}^{N} \sum_{\tau}^{t} (\Delta \boldsymbol{T}(\tau, \mathbf{u}))$





Maximizing Net Power Generation → improved temperature decline (sustainable production)

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Proxy-Based Optimization

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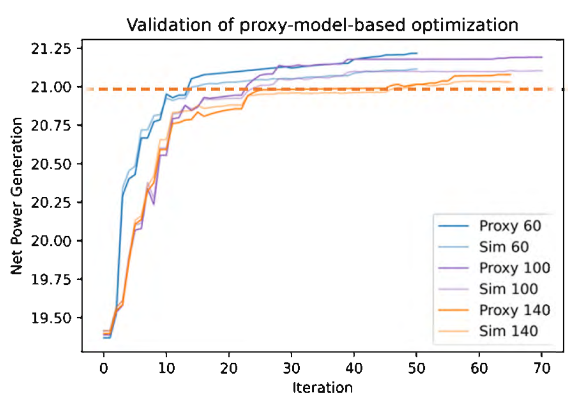
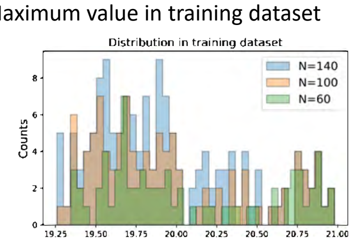
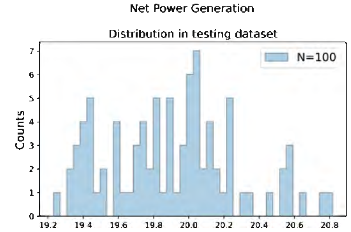


Maximum value in training dataset



Training dataset



Testing dataset

Net Power Generation

Comments:

→ Monitor: Acceptable prediction during optimization

→ Extrapolation: Optimal value higher than the maximum value in training dataset.

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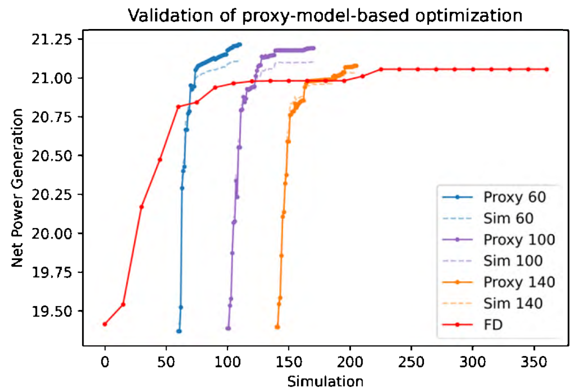
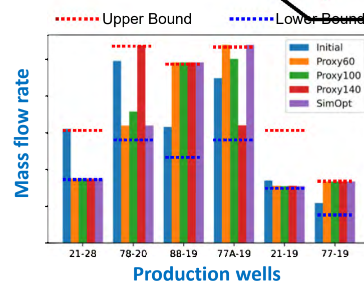
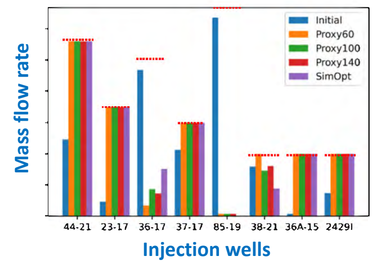
Proxy-Based Optimization







Comments:

→ Validation: simulation-based optimization

→ Controls & objective: converge to same values.

→ Computational cost: Proxy: 60~140. Sim: 360

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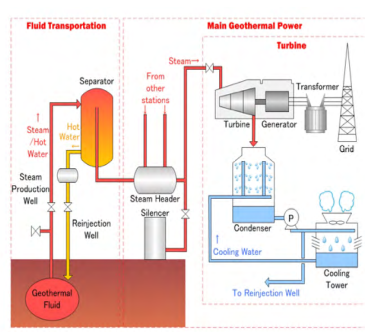
Power Plant

Power Plant



Power Plant:

Fault prediction/diagnosis and model predictive control for efficient automation of power plant operations

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Predictive Model

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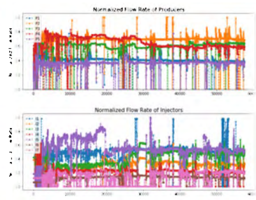

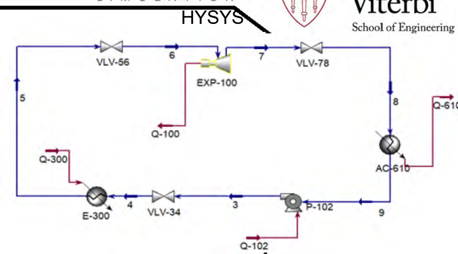

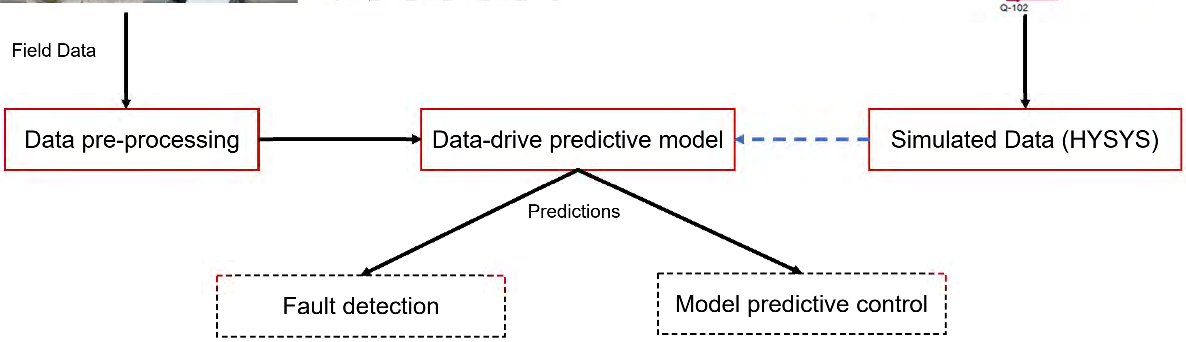

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Dynamic Neural Network Model

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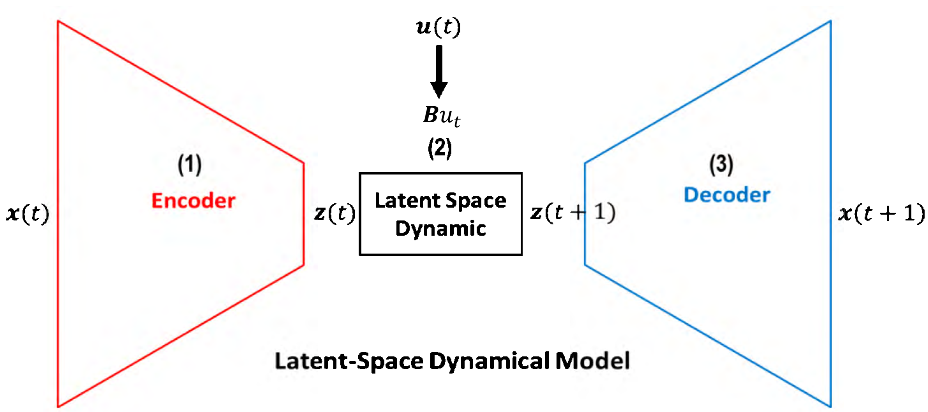
(i) **Encoder** captures data patterns to enable dimensionality reduction and latent-space representation

(ii) **Latent-space dynamical model** to compactly describe the evolution of the latent states

(iii) **Decoder** to map the resulting predictions in the latent space back to the original data space



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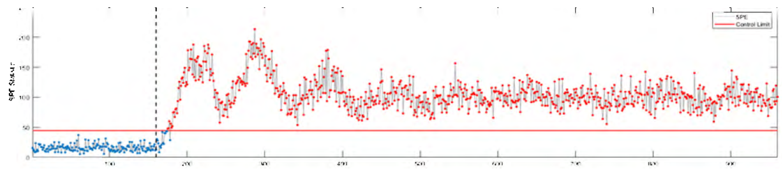
Fault Detection: Monitoring Index and Limits

Statistical Monitoring Index

→ Squared Prediction Error (SPE) statistic, rooted in Principal Component Analysis

$$\text{SPE} = \|\tilde{\mathbf{x}}\|^2 \qquad \tilde{\mathbf{x}}\text{: DNN prediction error}$$



Control Limit

→ The sample is considered normal if its SPE is below a certain threshold δ_α^2

→ δ_α^2 is the upper limit of SPE with a confidence level of α in a χ^2 distribution

$$\delta_\alpha^2 = g\chi_{h;\alpha}^2 \quad \text{where} \quad g = \frac{\theta_2}{\theta_1} \quad , \quad h = \frac{\theta_1^2}{\theta_2} \quad , \theta_i = \sum_{j=l+1}^{m} \lambda_j^i$$

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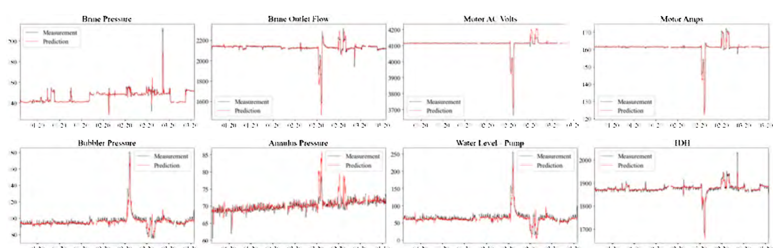
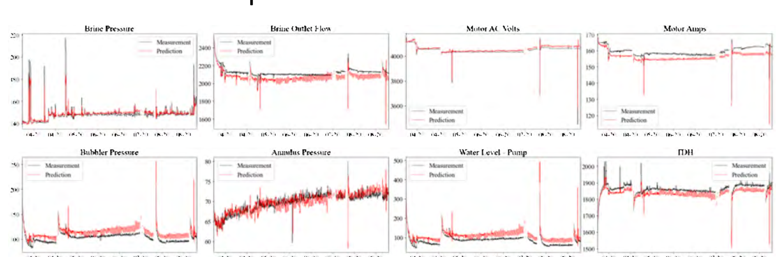
Validation with Pump Data

Pump data: Before maintenance



Pump data: After maintenance



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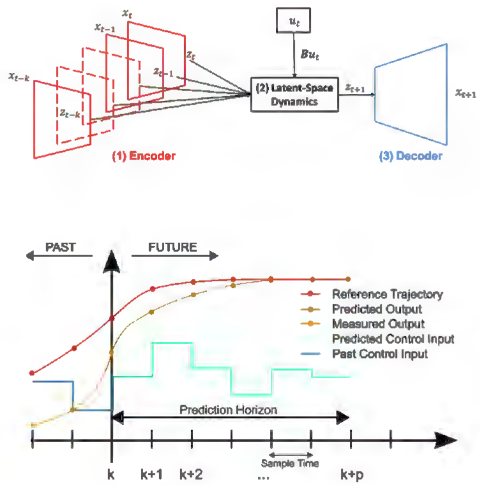
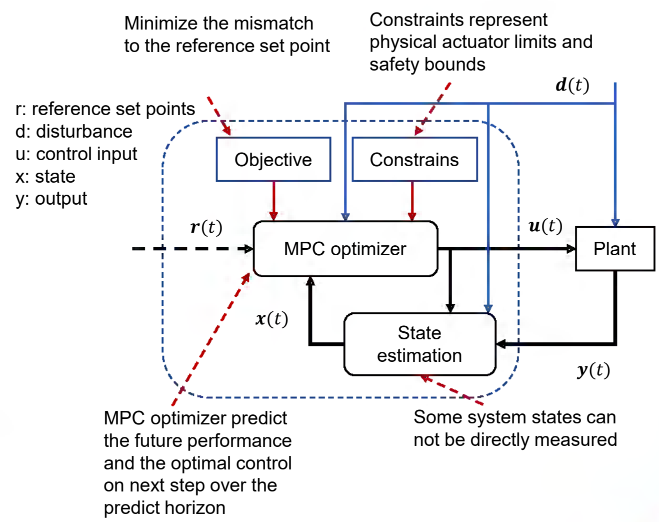
Model Predictive Control (MPC)

Objective: Using the DNN model for Model Predictive Control (MPC)



MPC Example



MPC Diagram

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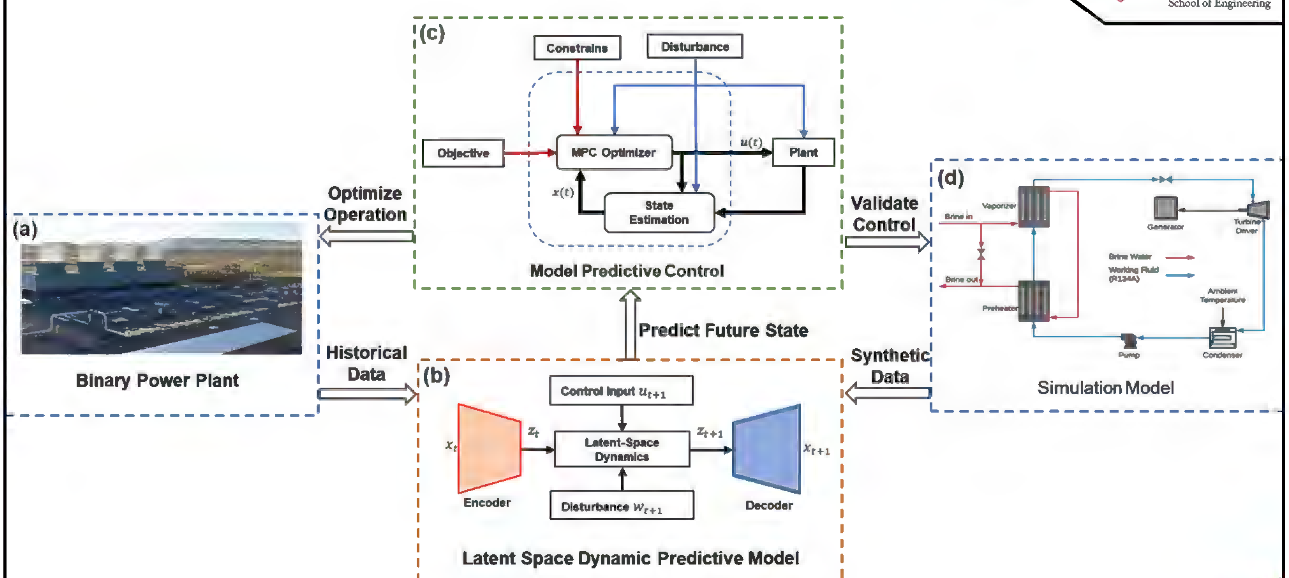
Overall Workflow



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Examples

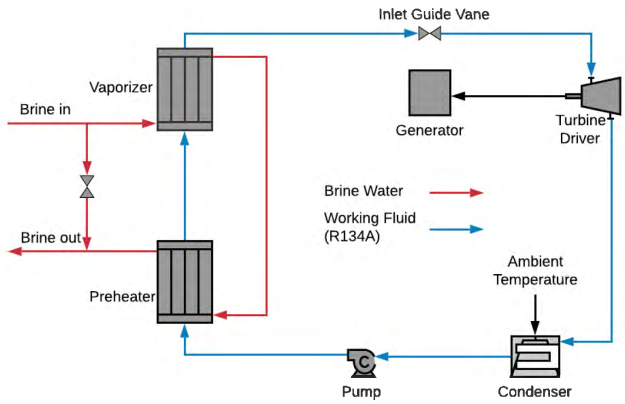
Organic Rankine Cycle Power Plant

Measurements: 23 variables

Control variables:
- Condenser fan speed
- Inlet guide vanes (IGV) set point
- Working fluid pump speed

Disturbances:
- Ambient temperature
- Inlet brine variable

Organic Rankine Cycle Diagram



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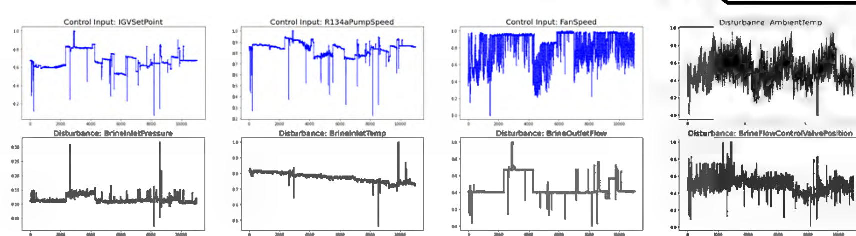
Predictive Model

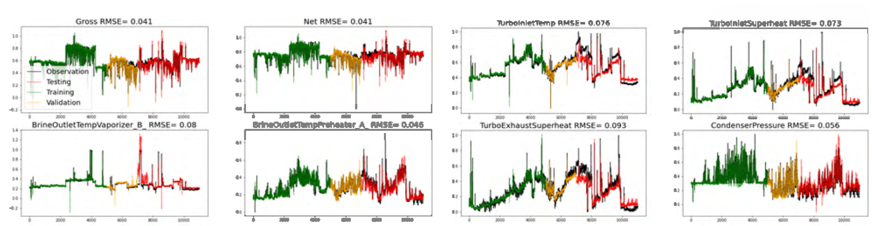
- Data resolution: hourly
- Training: 5000 samples
- Validation: 1000 samples
- Testing: 3000 samples



Control and disturbances

Model:
- Past samples $k = 3$,
- Latent variable $n_z = 6$,
- Prediction horizon $p = 12$

RMSE = 0.07



12 step ahead prediction for 23 variables

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Preliminary Results

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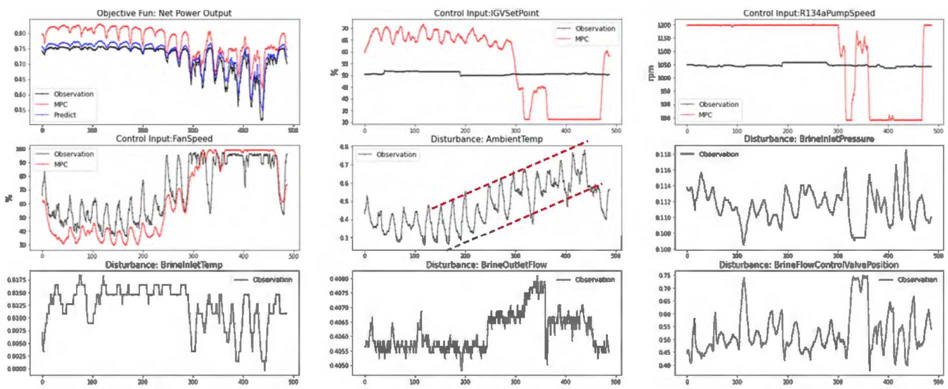
Average improvement in **net power production** is **4.0%**



MPC tries to **increase pump speed, open the IGV**, and **decrease condenser fan speed** when the **ambient temperature** is **relatively low**.

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Preliminary Conclusions

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Developed and applied deep learning-based prediction models for:

1) Energy production prediction and optimization (Reservoir)
2) Fault detection and MPC application (Power Plant)

General observations:

→ Deep learning models are easy to develop and deploy for field applications

→ Short-term predictions with historical field data are generally acceptable

→ May need additional data or constraints to enable long-term predictions

→ Extrapolation (prediction out of training range) is challenging, need for physics

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Acknowledgement

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