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The program will begin soon.

You will not hear audio until we begin.

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Flow Network Based Hybrid Models for Reservoir Applications

Dr. Zhenyu Guo
Xecta Digital Labs

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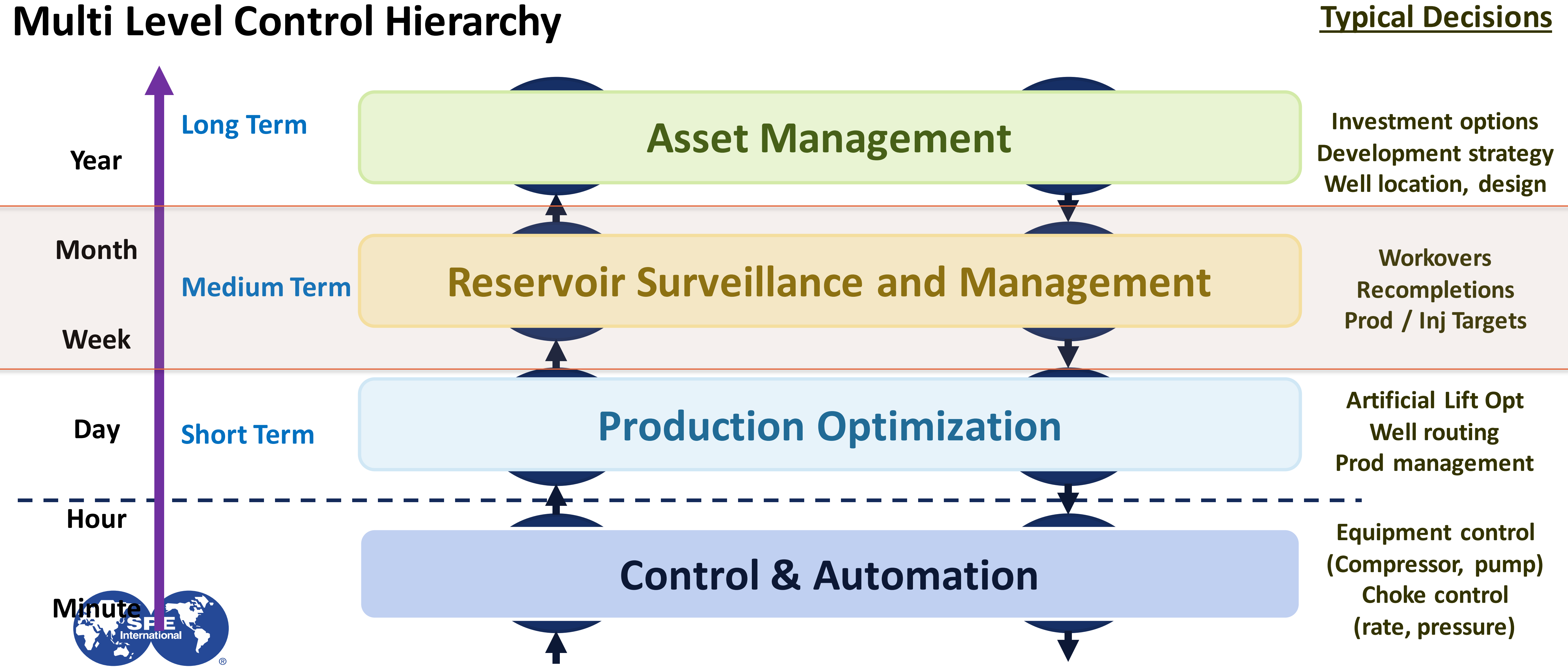
Outline

- Background
- Closed Loop Reservoir Management – Applications
- RGNet – Overview
- Hybrid Modeling – Combining Physics and AI/ML
- Case Studies
- Summary

Towards Integrated Optimization

Multi Level Control Hierarchy

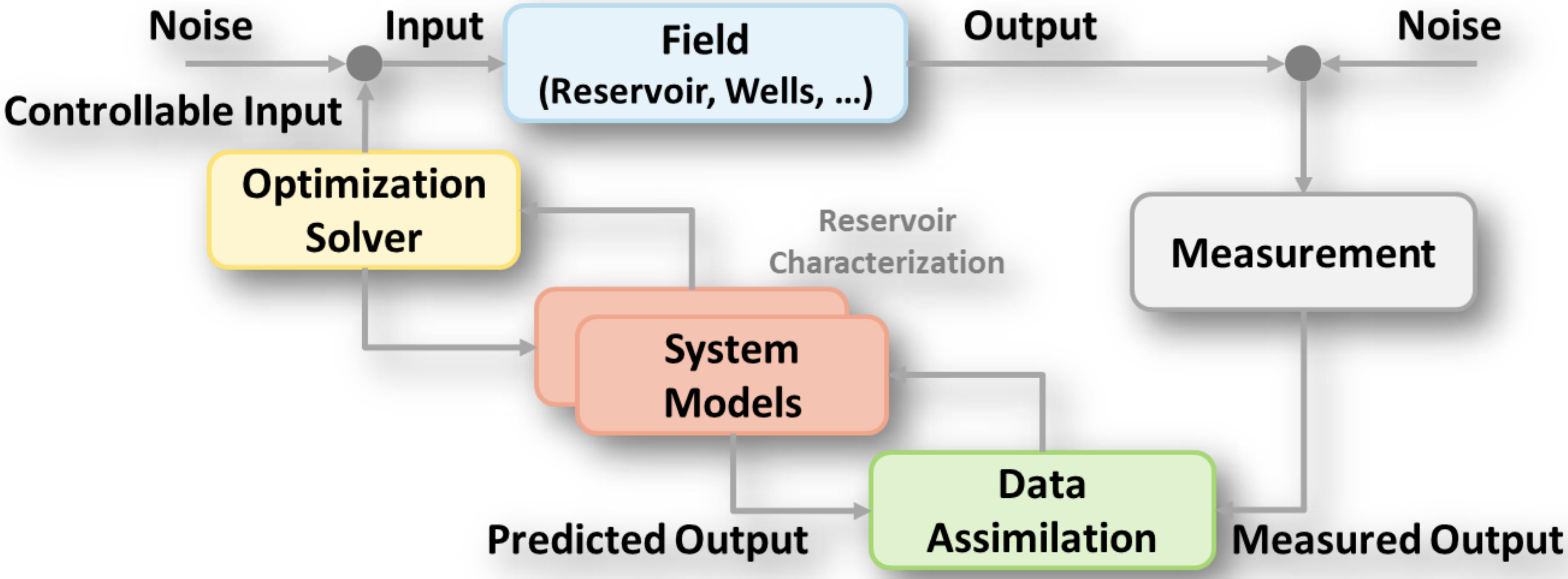


Reference: Adapted from Sankaran et al (2009)

Closed-Loop Reservoir Management

Objective

Build a robust and scalable reservoir model only from routine field measurements for closed loop reservoir management (CLRM): Data Assimilation (History Matching), Forecasting, Production Optimization, etc.



Concept of CLRM (Jansen et al. 2008)

Problem Statement

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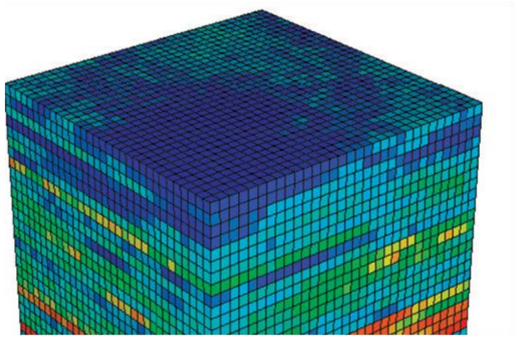
Build a robust and scalable reservoir model from routine field measurements for closed loop reservoir management

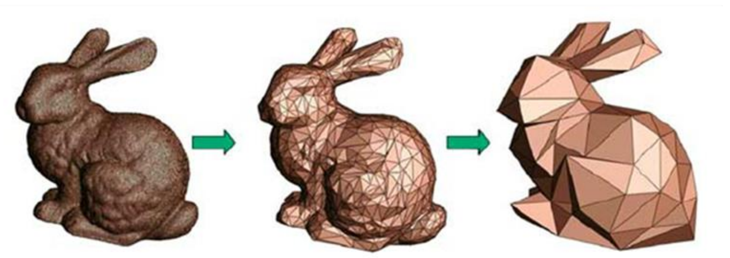
- Connected reservoir volume, Well connectivity analysis, Forecasting
- Production control optimization, Flood optimization, Integrated subsurface & surface network optimization

Physics-constrained, data-driven modeling

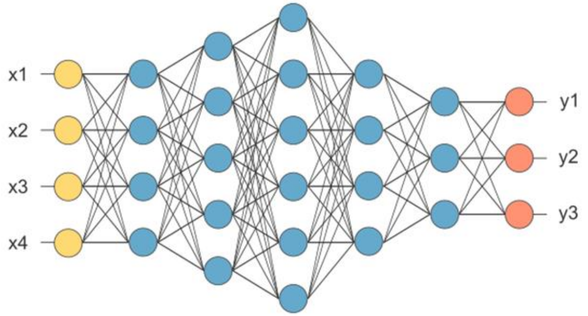
Full Physics



Hybrid Models



Data-Driven



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Natural signals are massively compressible (e.g. audio, video, image)

Reservoir Graph Network (RGNet)

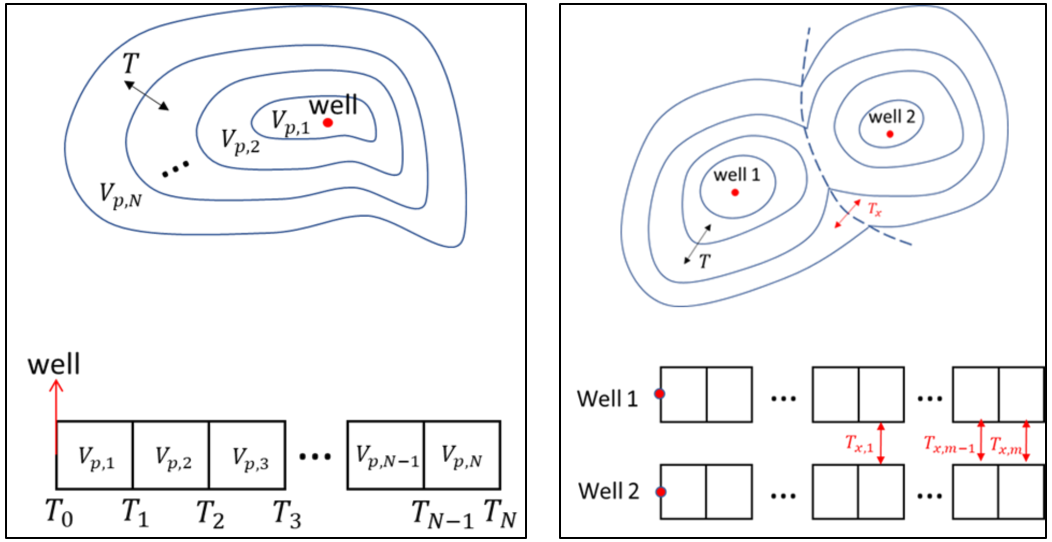
RGNet – Flow network based reduced physics model for practical reservoir management

Concept / Methodology

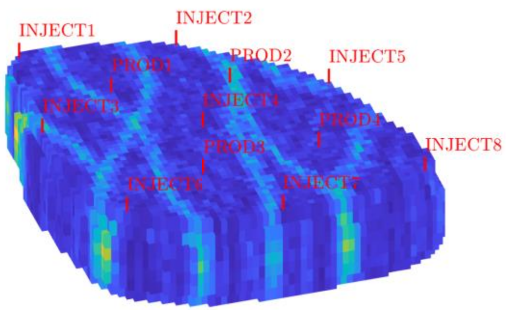
- Diffusive Time of Flight (DTOF)
- Transform fluid flow 3D diffusivity equation to 1D DTOF coords

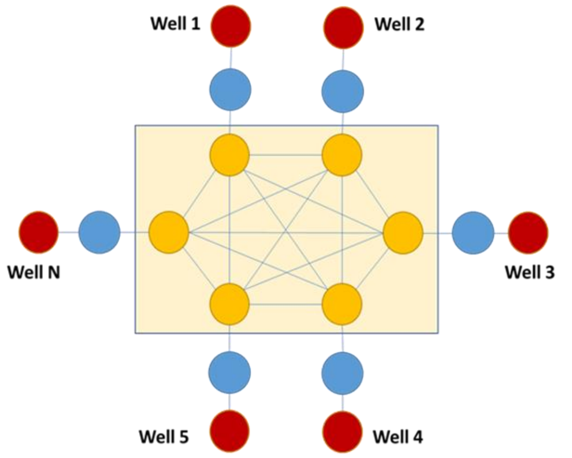
Key Differentiators

- Geometry-free approach (no dependence on geological model)
- Non-intrusive model built with routine measurements
- Incorporate any physics or multi-physics
- Parsimonious parameterization
- Rapid model execution (~1000x speedup)
- Physically insightful and interpretable results



RGNet Model





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RGNet Workflow

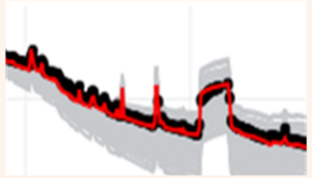
History Matching Parameter Definition

Prior Models

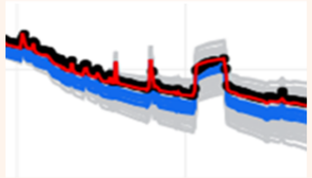
Assisted History Matching

Posterior Models

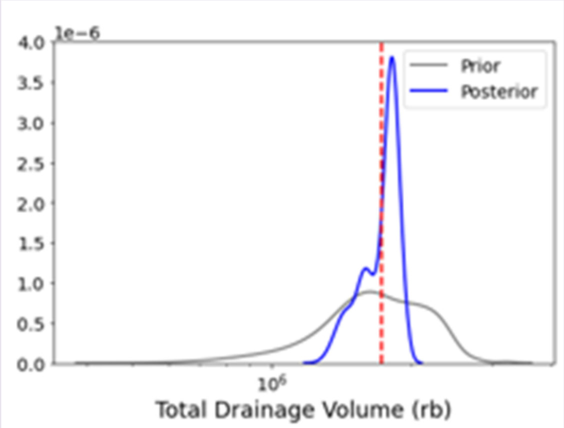
Multi–Model Uncertainty Runs



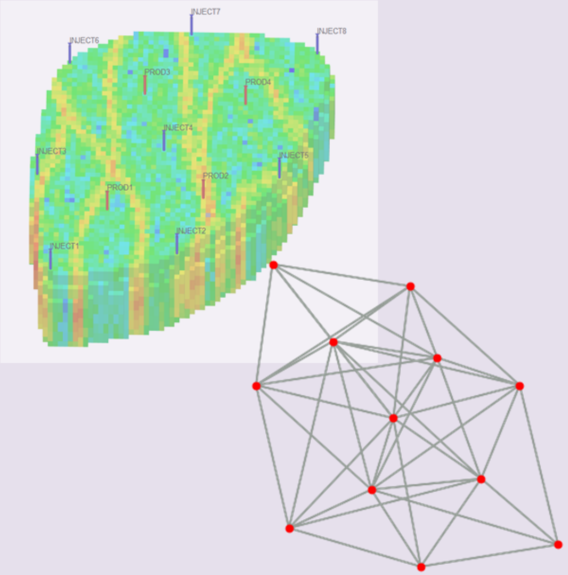
History Matched Model(s) Selection



Connected Volume

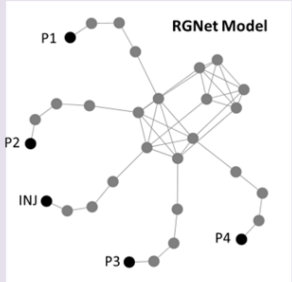


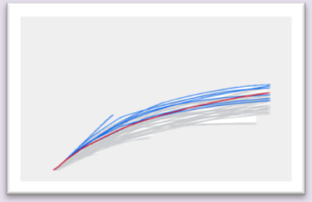
Reservoir Connectivity



Forecasting

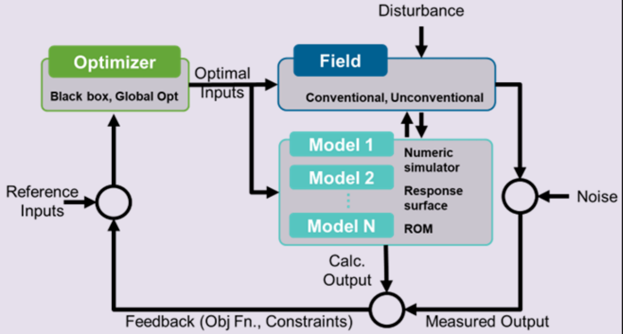
Future Well Controls





Optimization

Well Production Control (BHP, Injection Rates)



Example 1 – SPE 10

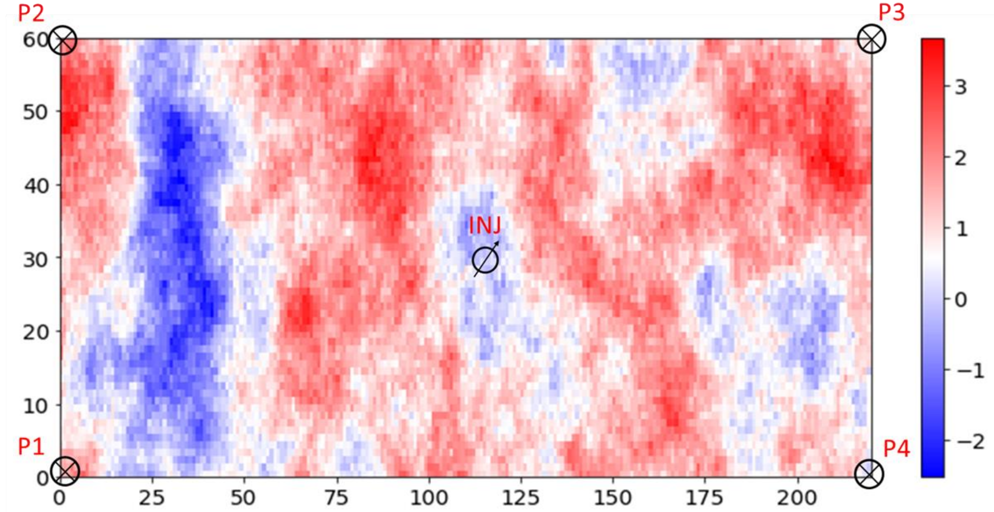
Reference: SPE 203390

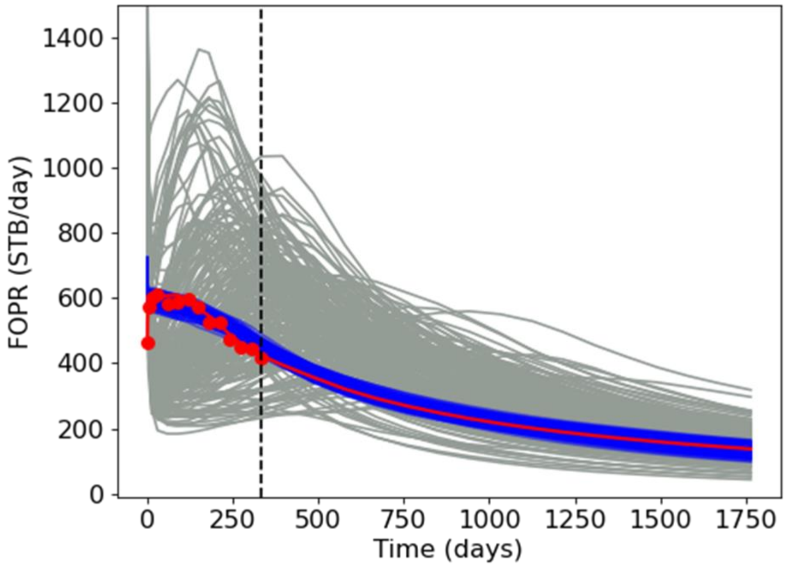
Forecasting based on reservoir graph network (RGNet) model

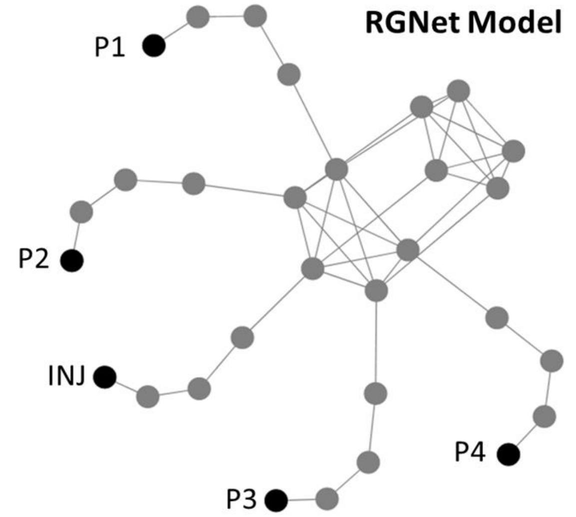
- 5-spot pattern flood (SPE10 mod)

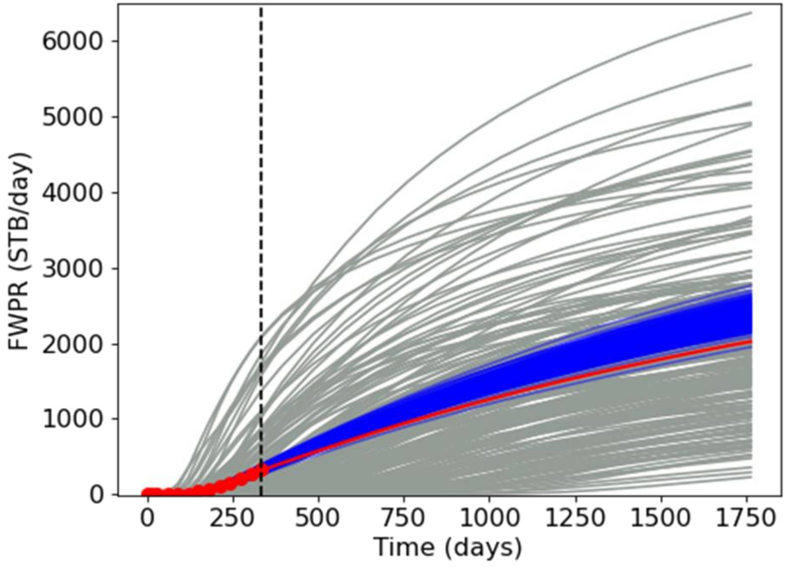
	3D Simulation	RGNet
Grid Blocks	132,000	30
No. Cores	6	1
Simulation time (secs)	570	0.2
Speed Factor	1X	2850X

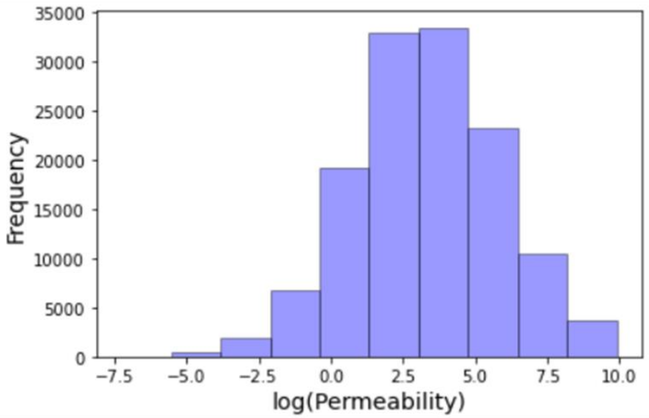
  - HM – 1600 runs, 200 model evals, 56 secs











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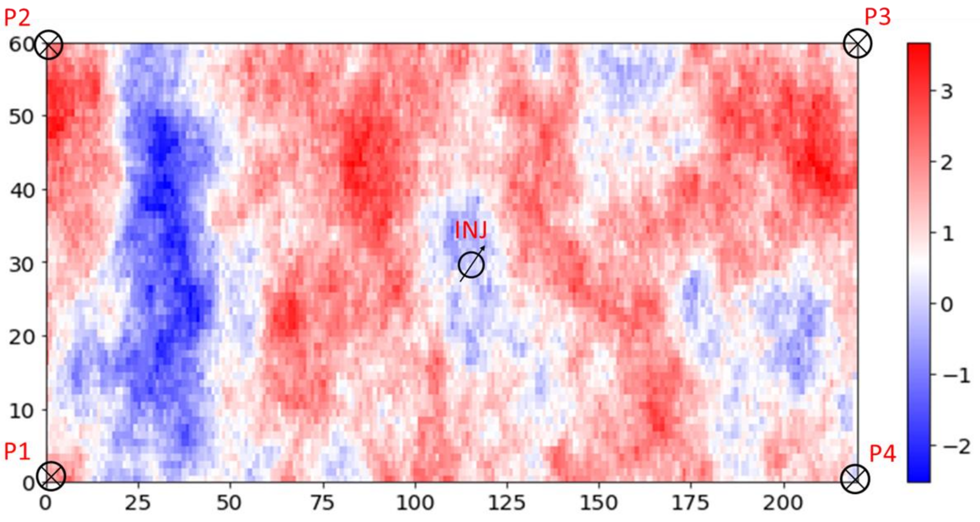

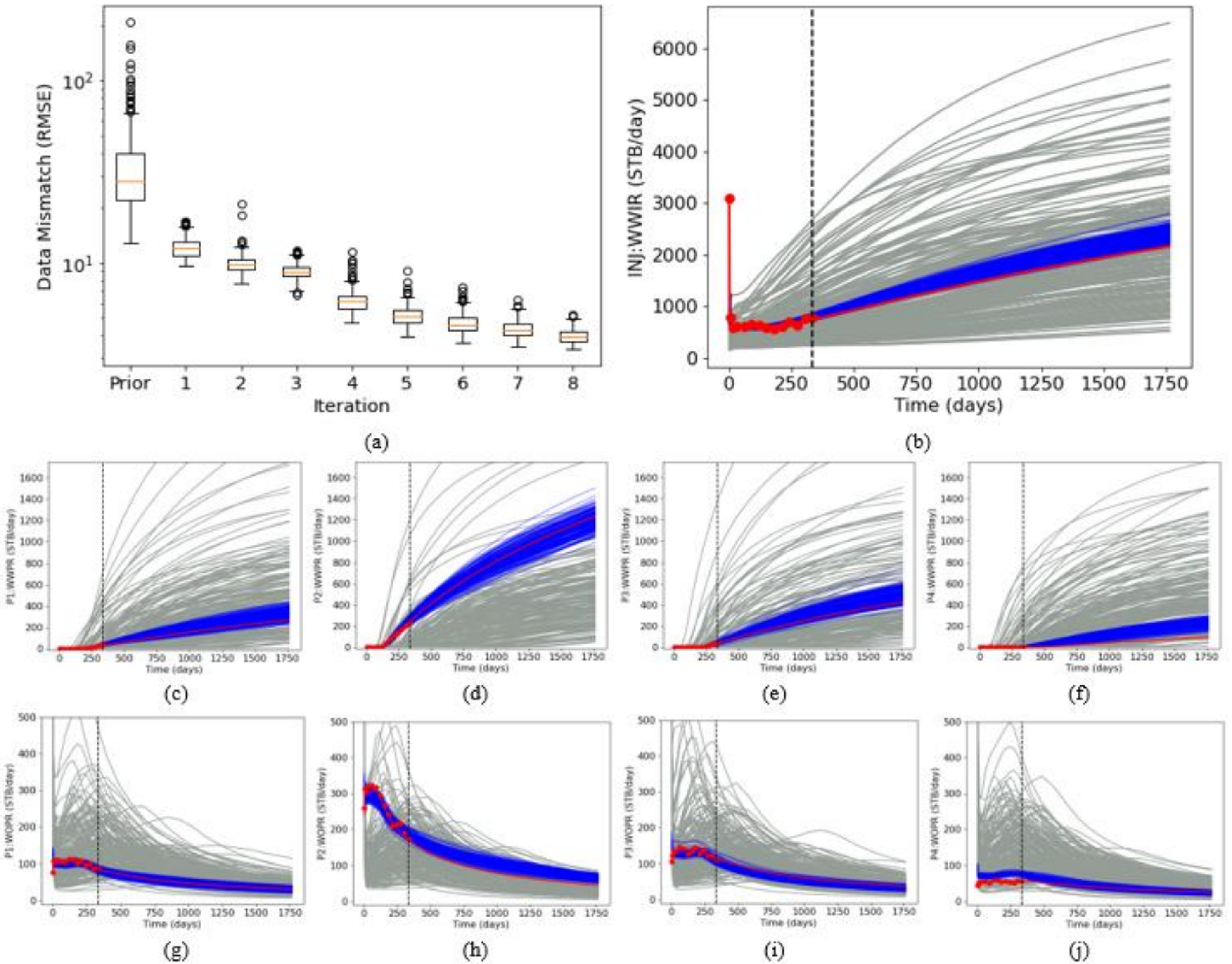

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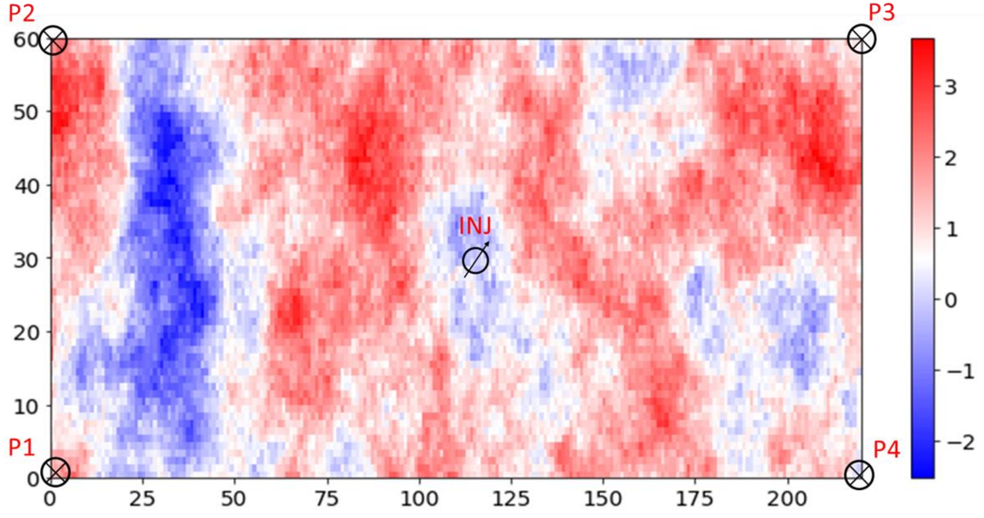
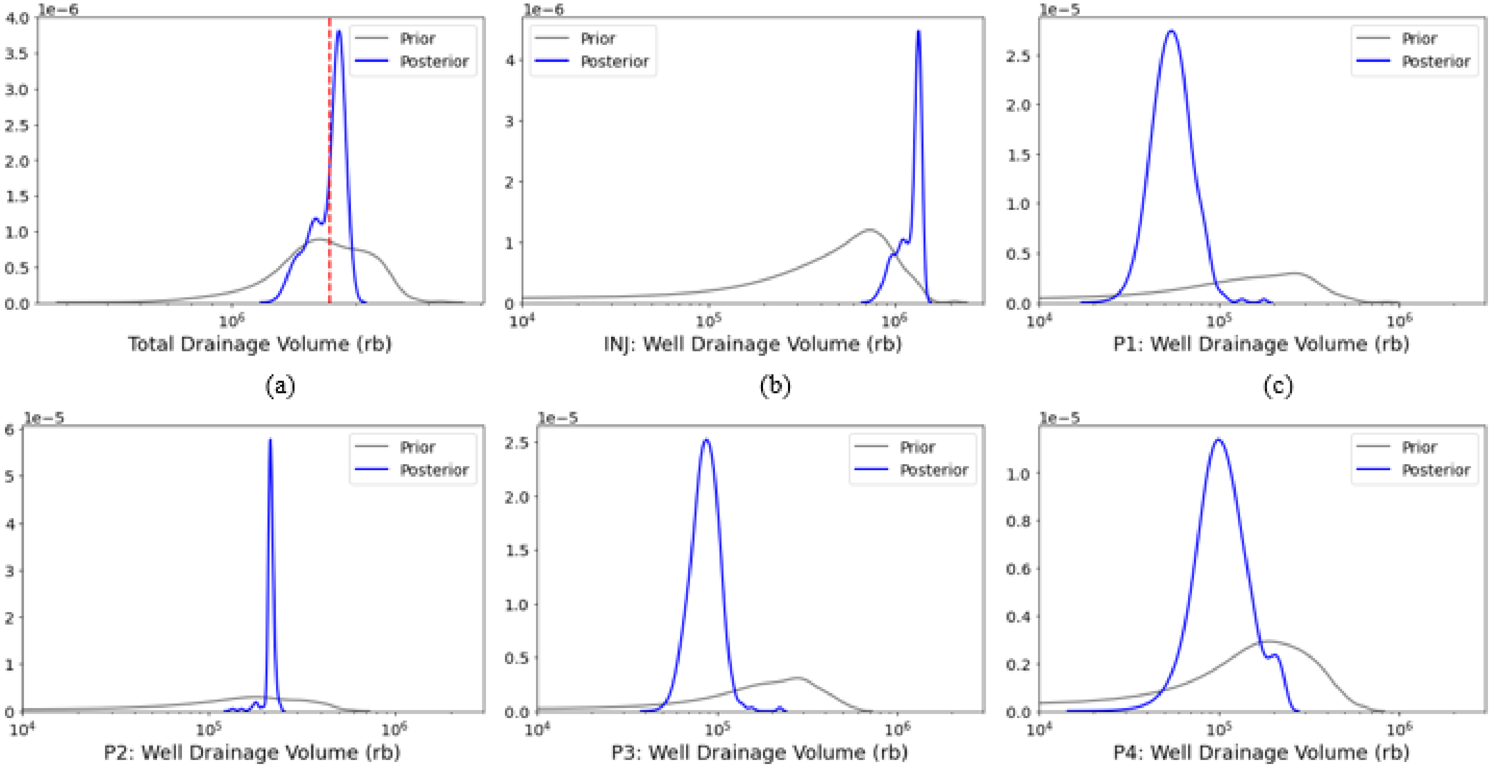
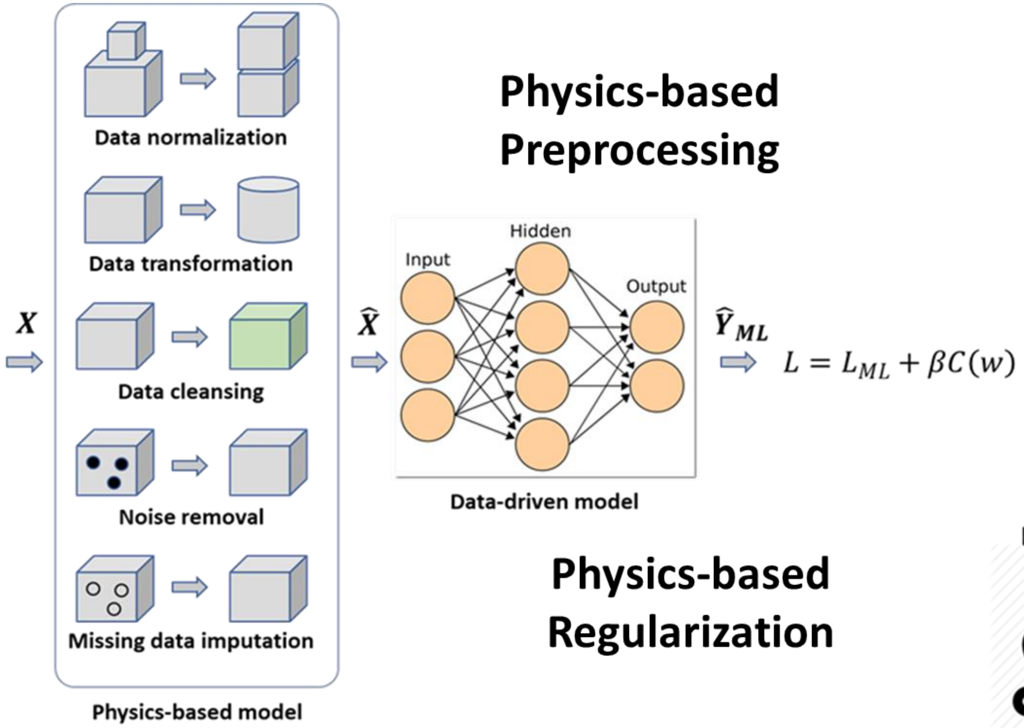




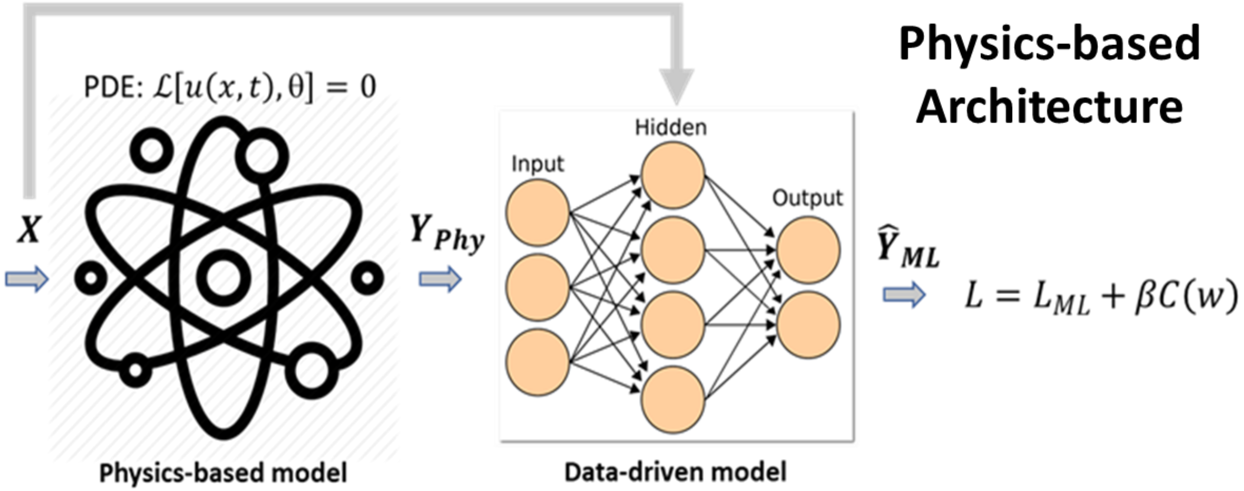
(a) (b) (c) (d) (e) (f)

Merging Physics and AI/ML

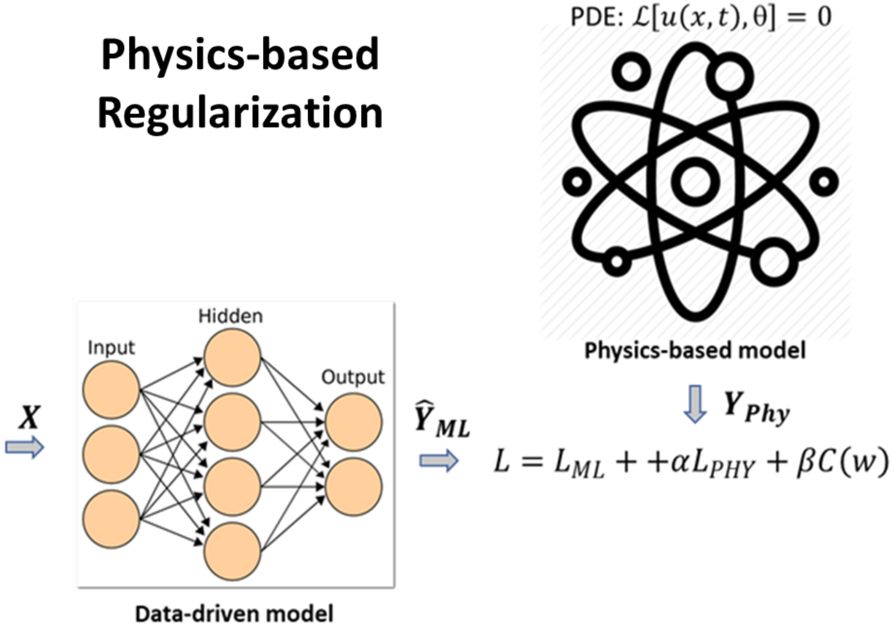
Physics-based Preprocessing



Physics-based Architecture



Physics-based Regularization



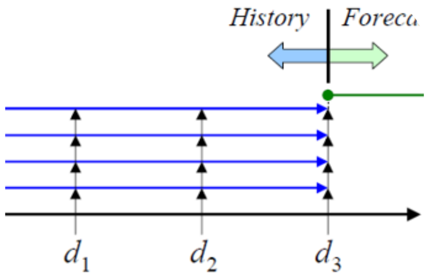
What do we cover?

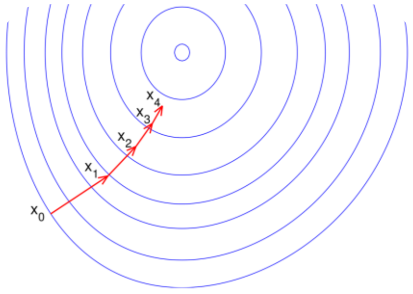
1. SVR-DGN: ML-Enhanced History-Matching Algorithm
2. Sparsity-Constrained History Matching
3. Hybrid-RGNet: Improve forecast accuracy by adding ML to RGNet

Reference: URTeC 5261

History Matching Approaches

Ensemble Smoother with
Multi-Data Assimilation
(Bayes Theorem)



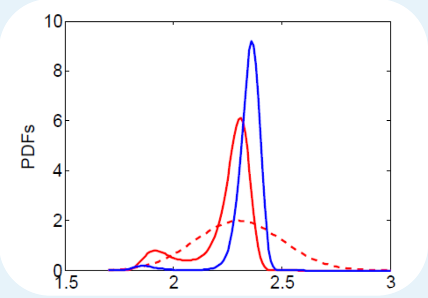


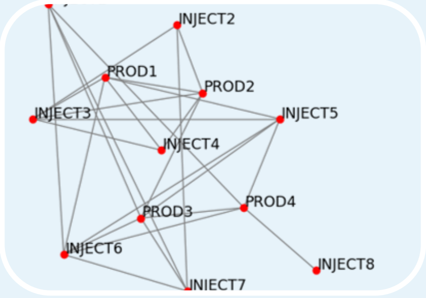
Data Mismatch Sensitivity
to Model Parameters

ES-MDA

Adjoint

Support Vector
Regression + Distributed
Gaussian Newton





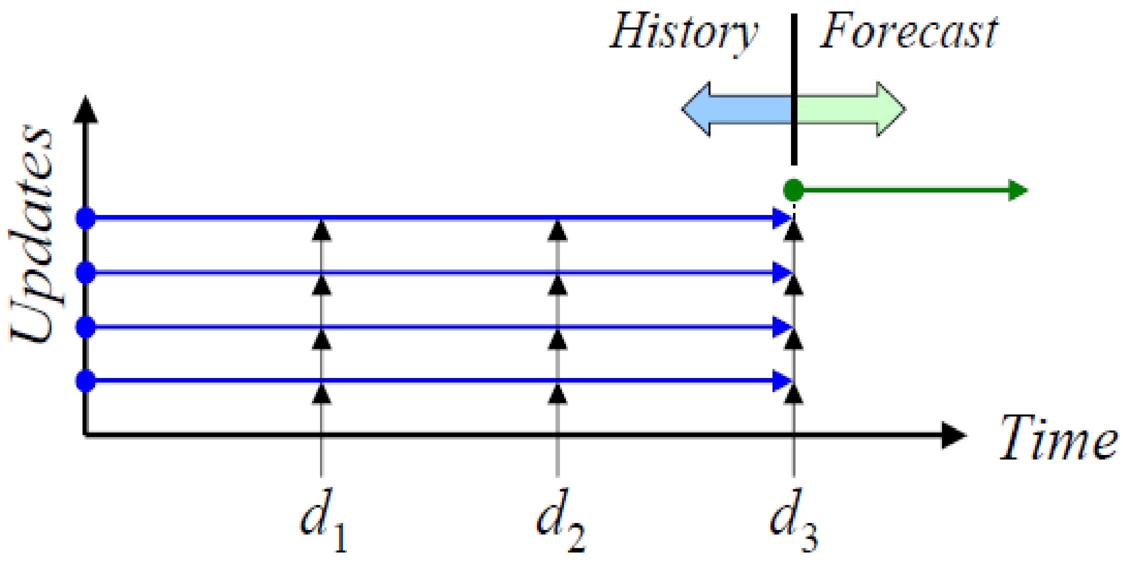
Sparsity-Constrained
Data Mismatch

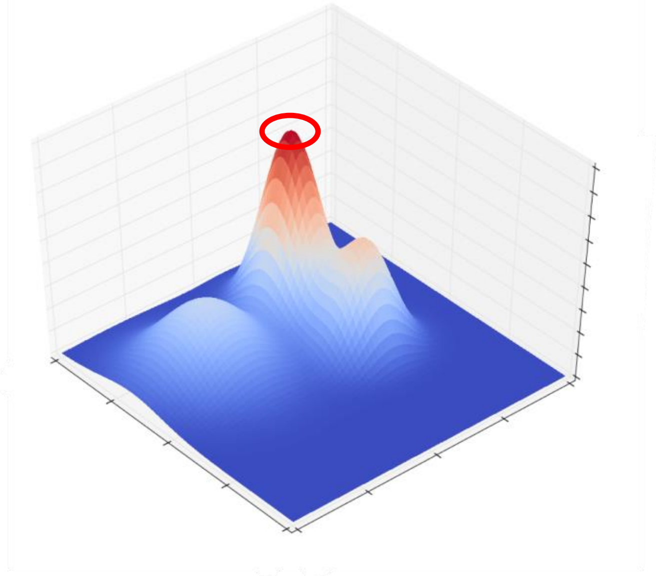
SVR-DGN

Sparse

ES-MDA

- **ES-MDA** (Emerick and Reynolds, 2011): ensemble-based assisted history-matching algorithm
- **Assumption**: Generate correct posterior distribution given Gaussian prior distribution and linear problem
- **Potential caveat**: Tend to yield a single-mode solution while ignoring other modes

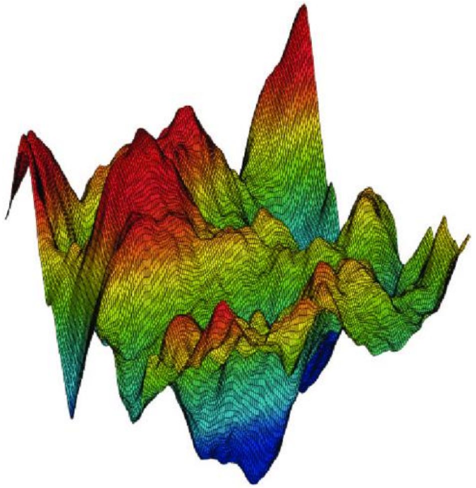




Multi-modal distribution (Bernstein, 2020)

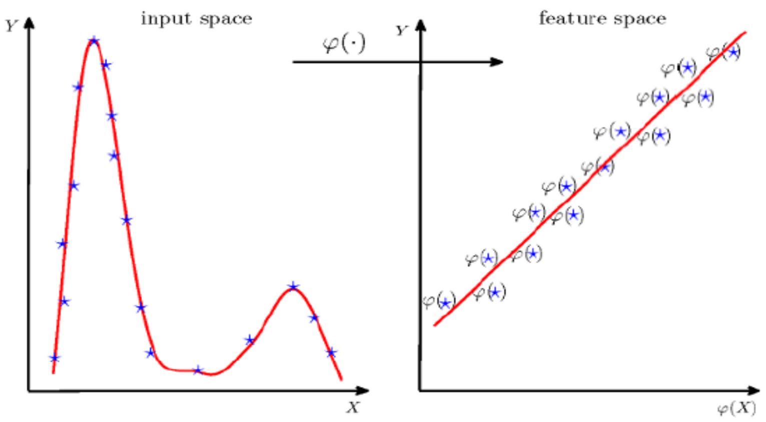
Hybrid Approach: SVR-DGN

- ML-enhanced history matching workflow (Guo et al 2018)
- **Features**
  - Intend to find multiple history-matched models in different basins
  - Combine ML to increase efficiency of history matching



2D problem with multi-modes

Support vector regression



Generate initial ensemble m_{ens}

Reservoir simulation in parallel: predict $y(m)$ for m in m_{ens}

SVR: train/update proxy for $y(m)$ and output $\nabla y(m)$ for m in m_{ens}

- SVR accuracy is improved as more training data are included

Gauss-Newton TR in parallel: propose new models and update m_{ens} and Δ_{ens} (trust-region size)

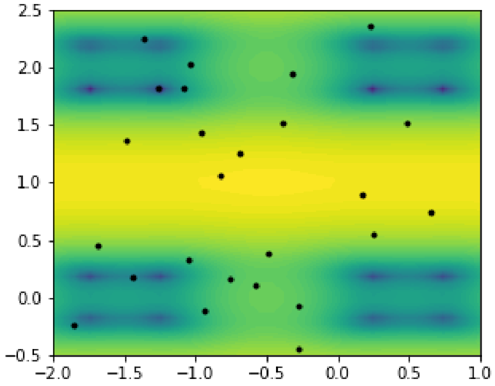
- Stop updating m_i if $\Delta_i < \Delta_{Min}$
- Stop if all models are converged or *MaxIter* is reached

ES-MDA vs SVR-DGN

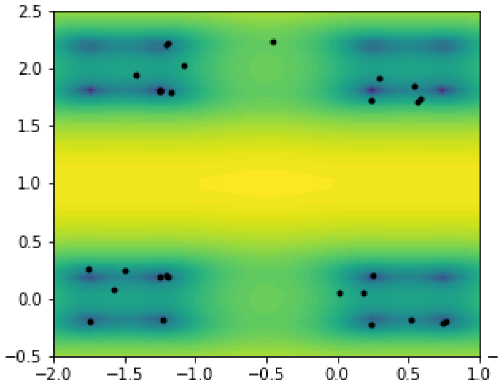
	ESMDA	SVR-DGN
Explicit Obj to incorporate additional regularization	No	Yes
Capability to find solutions @ different local basins	No	Yes
Utilization of optimization algorithm	No	Yes
Model robustness/diversity	Medium	High
Allow more iterations to improve match quality	No	Yes
Computational cost	Relatively low	Relatively high

Example 2: Synthetic 2D Example

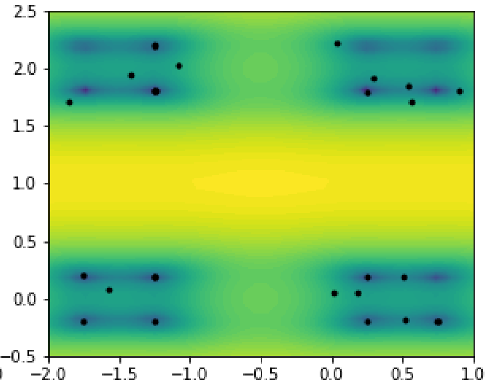
Test SVR-DGN: 5 iterations with 30 samples



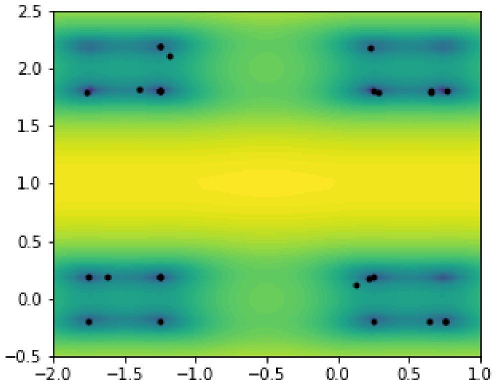
- Iter 0



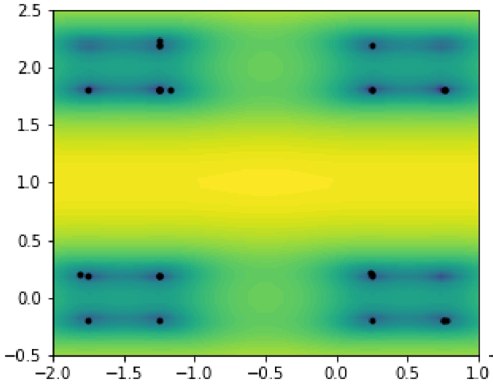
- Iter 1



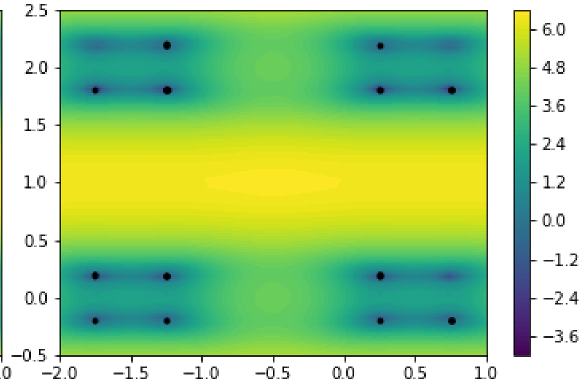
- Iter 2



Iter 3

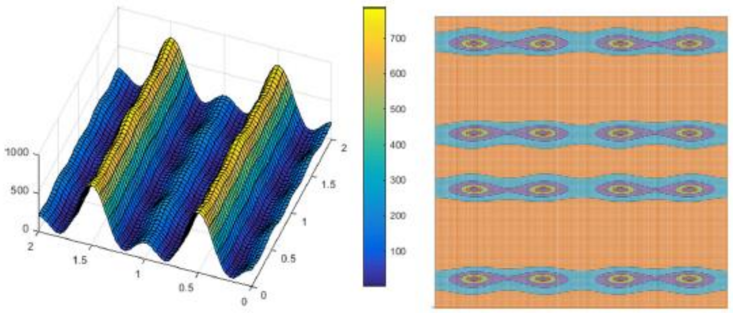


- Iter 4



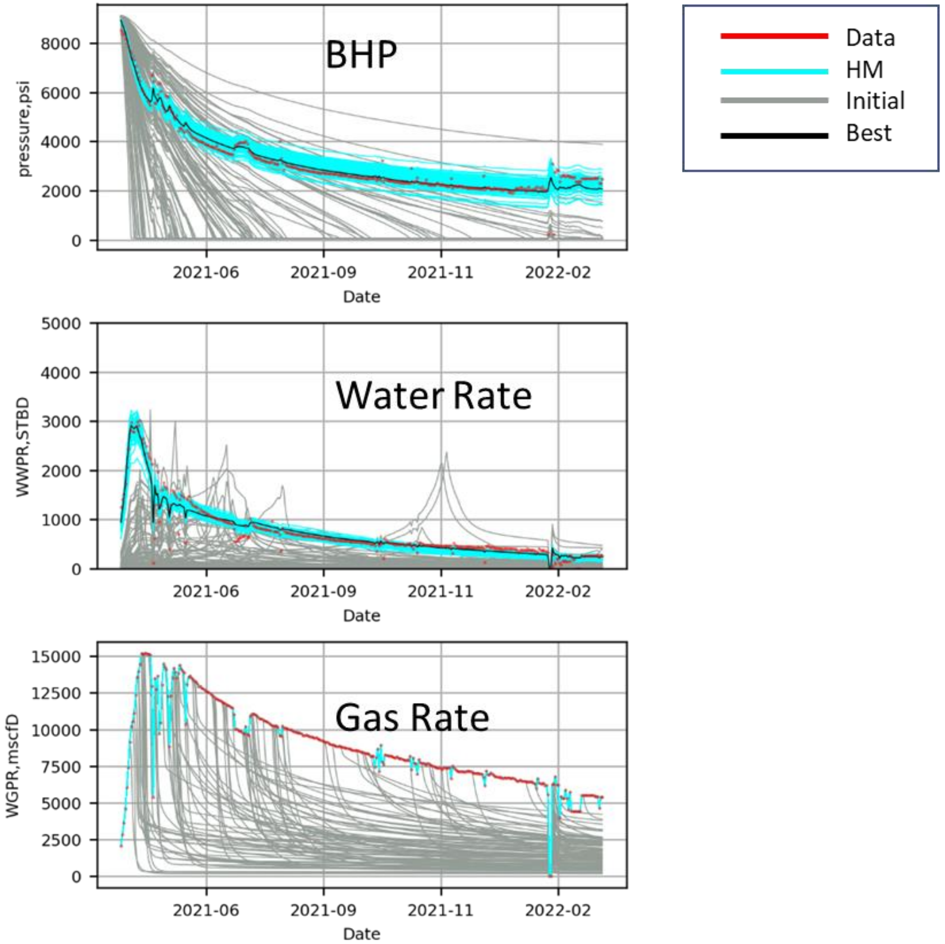
- Iter 5

Testing function with multiple solutions

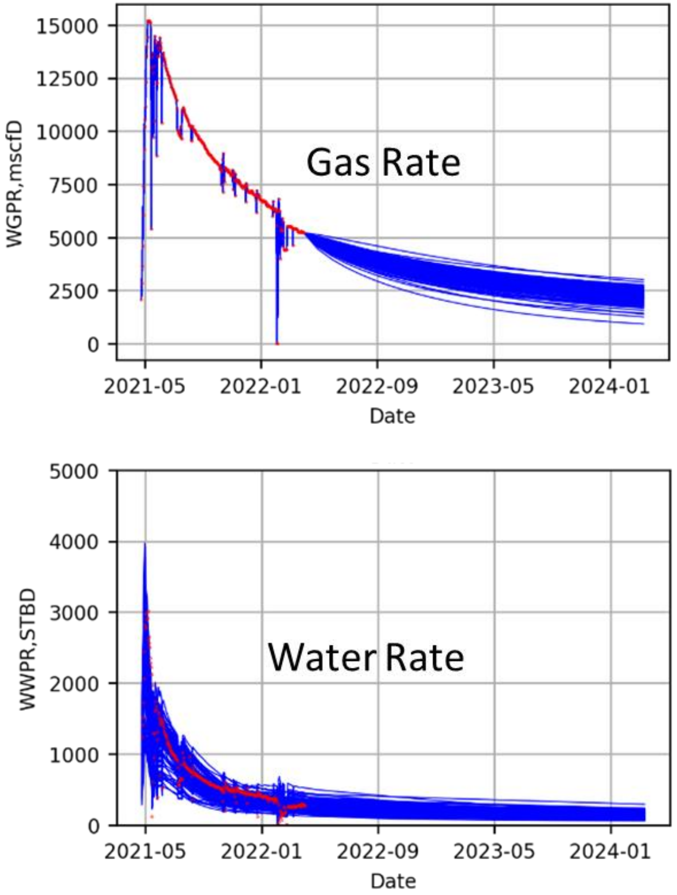


Example 3: Unconventional Gas (North America)

History Matching (ES-MDA)



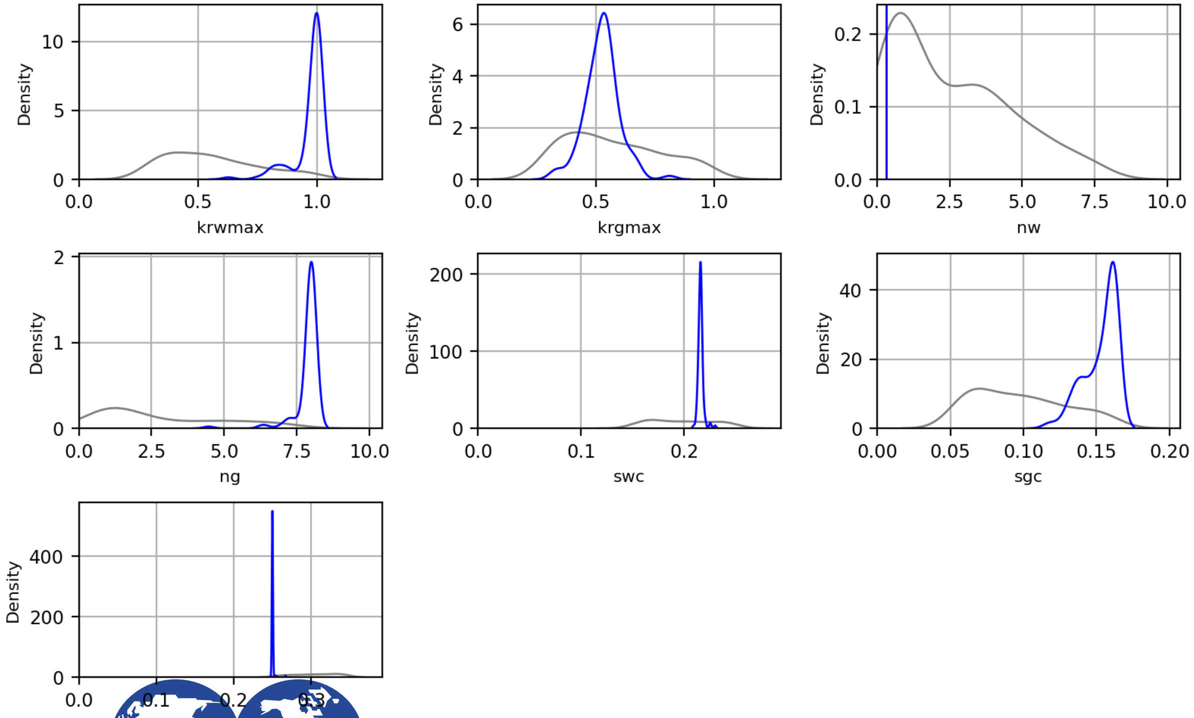
Forecast



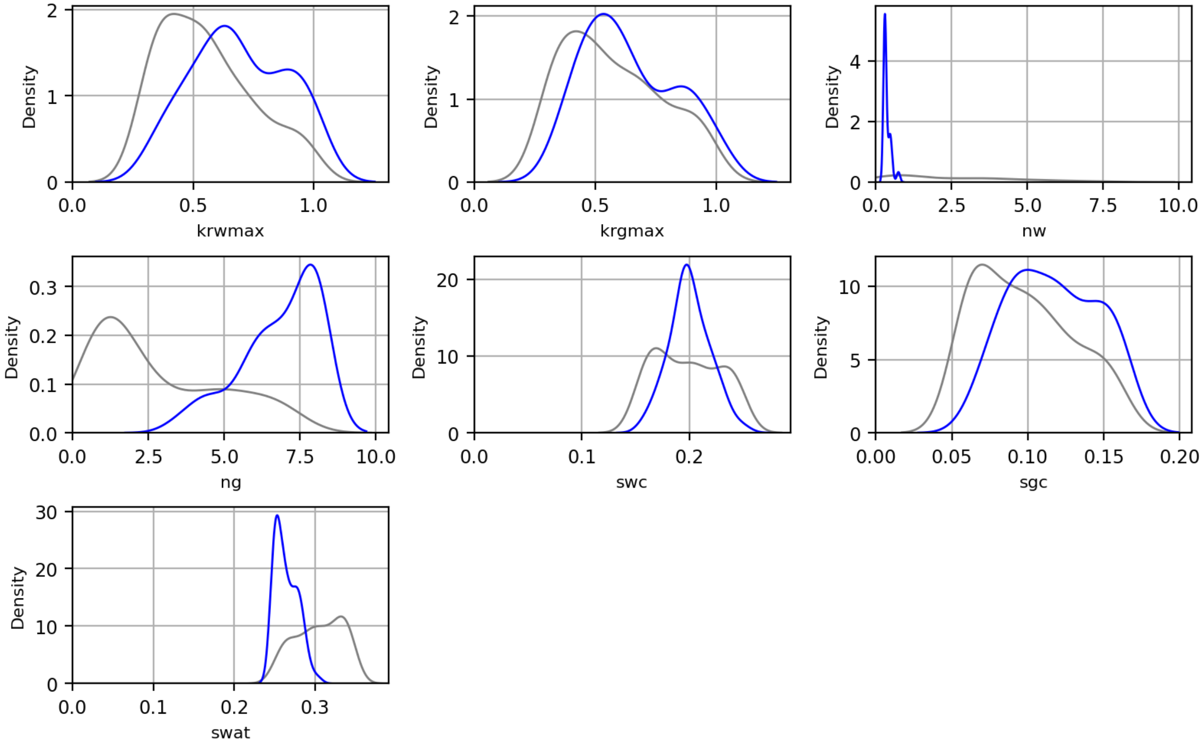
Example 3: Unconventional Gas (North America)

- **ESMDA shows ensemble collapse**
- **SVR-DGN generates more diverse distribution with same quality of match**

ESMDA



SVR-DGN

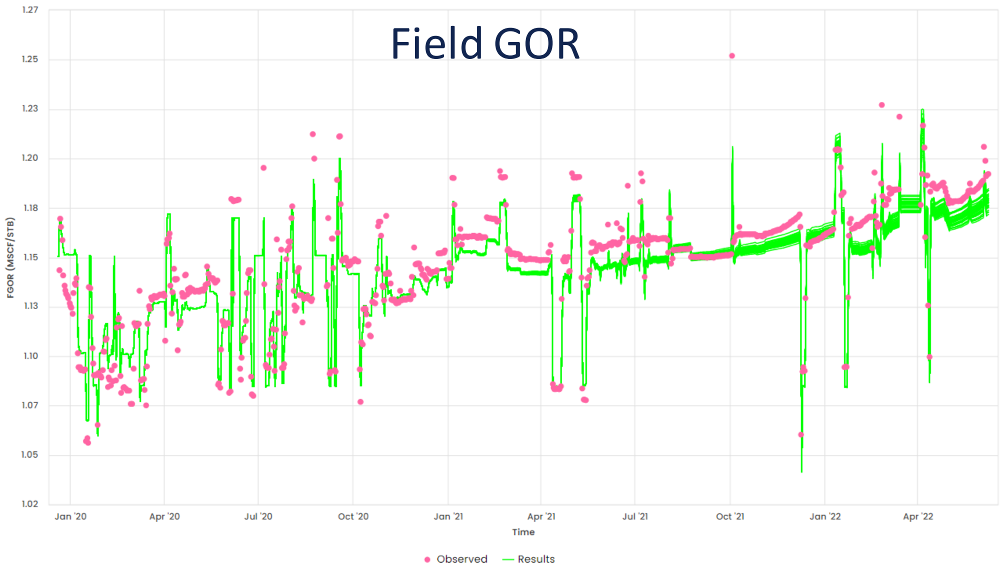


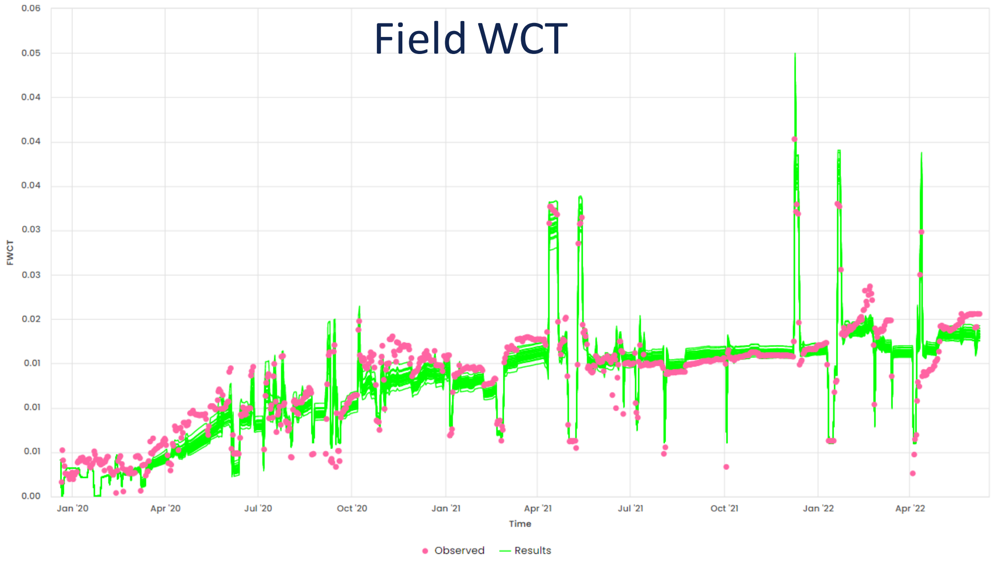
Example 4: Deep Water Asset

- **Objective**: Connected volume, reservoir connectivity analysis, uncertainty analysis and forecasting

- **History matching**
  - Water and gas injection rate control (WIR/GIR)
  - Oil production rate control (OPR)
  - Match on BHP, WCT, GOR

Total 15 wells (6 producers, 6 water injectors, 3 gas injectors)
Hyperparameters $N_{inner} = 2$, $N_{outer} = 1$
PVT, SCAL Single region, R_{si} matched to produced GOR for wells
History matching algorithm Support Vector Regression – Distributed Gauss Newton (SVR-DGN)
Initial pressure defined at common datum depth
Mobile water access for 2P1, 2P4 grid cells





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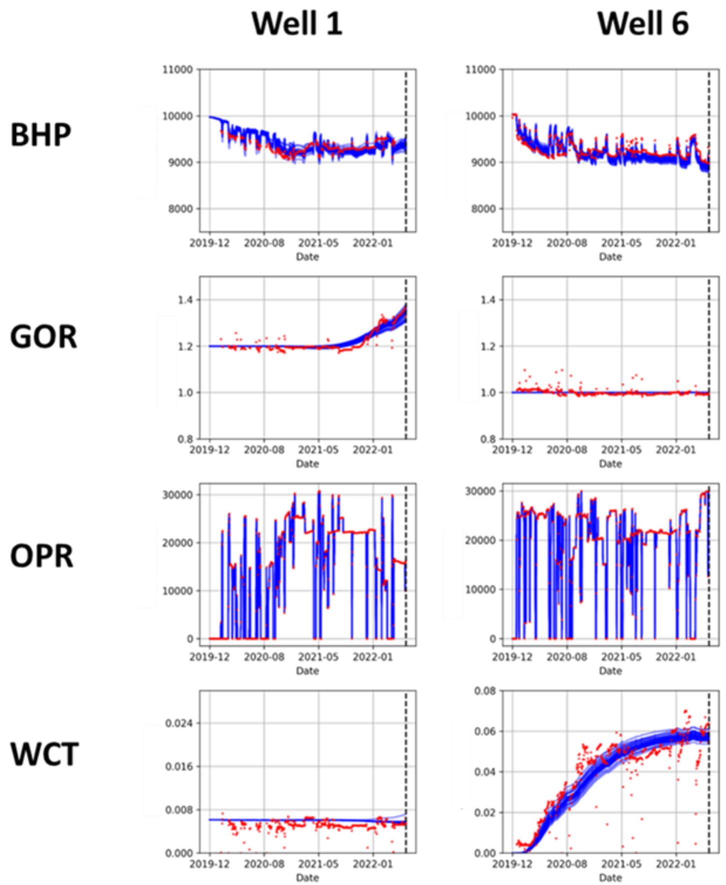
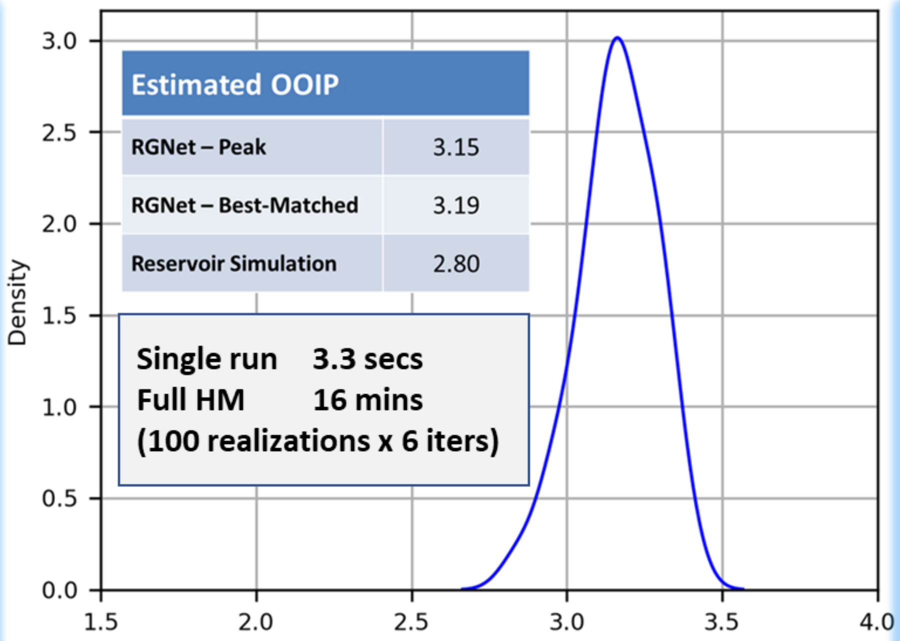




Estimated OOIP	
RGNet – Peak	3.15
RGNet – Best-Matched	3.19
Reservoir Simulation	2.80

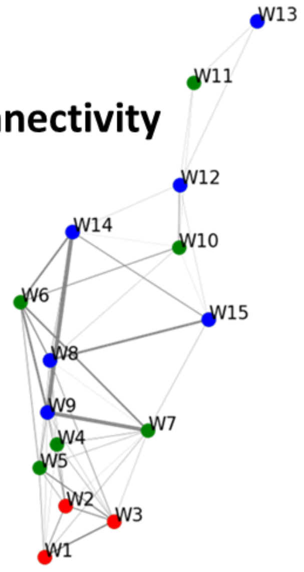
Single run 3.3 secs
Full HM 16 mins
(100 realizations x 6 iters)

6 producers, 6 water injectors, 3 gas injectors
Staged history matching – SVR + DGN
Rate control – match on BHP, WCT, GOR

MedAPE	HM	Forecast
Res Sim	1.6%	13.6%
RGNet	1.4%	8.6%

Blind validation (~8 months)

P50 connectivity



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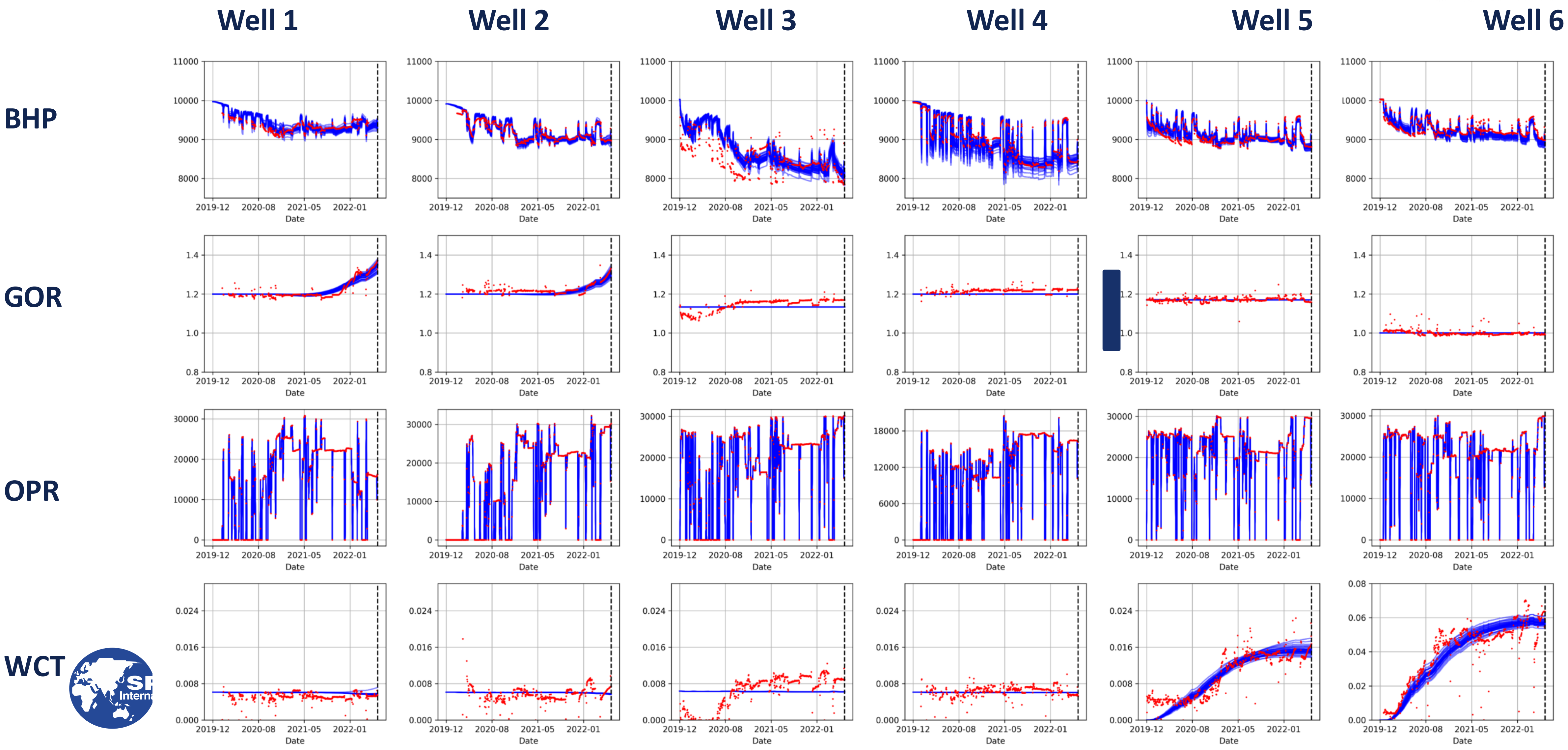

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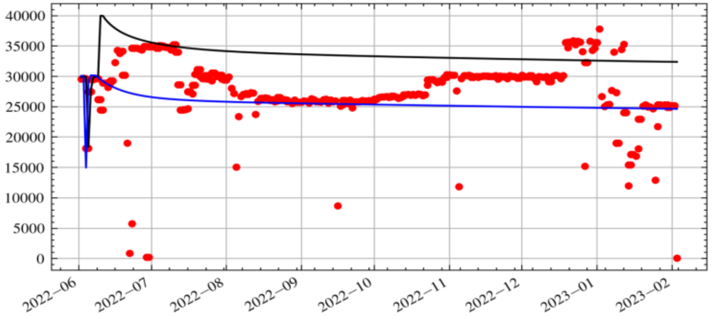
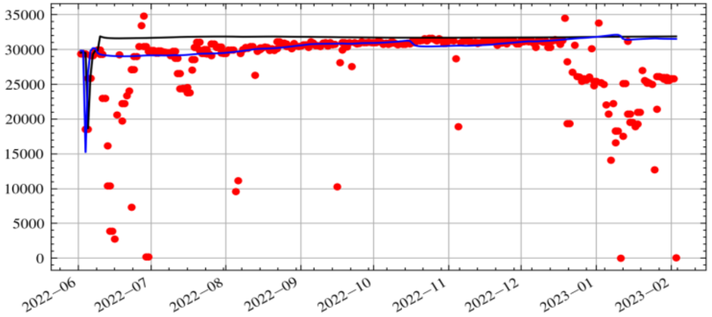
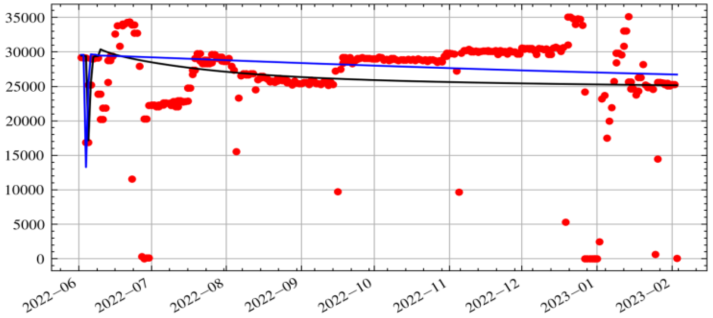
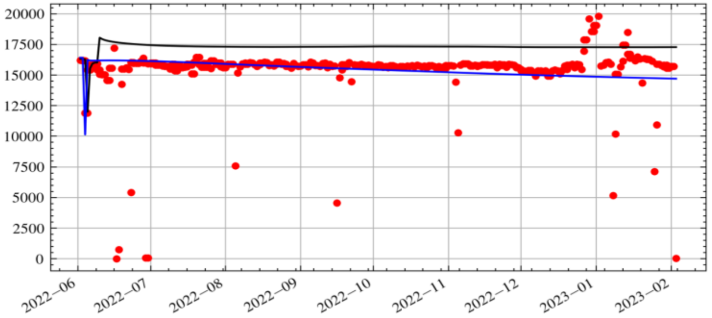
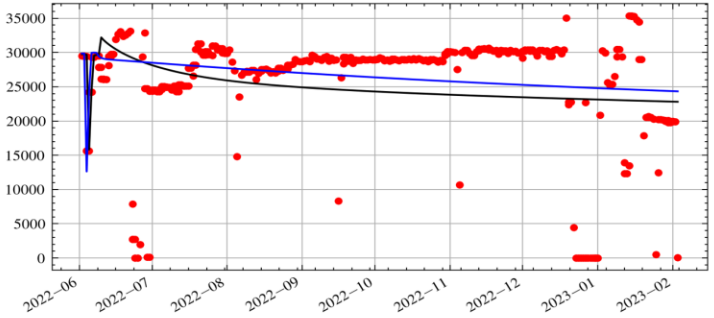






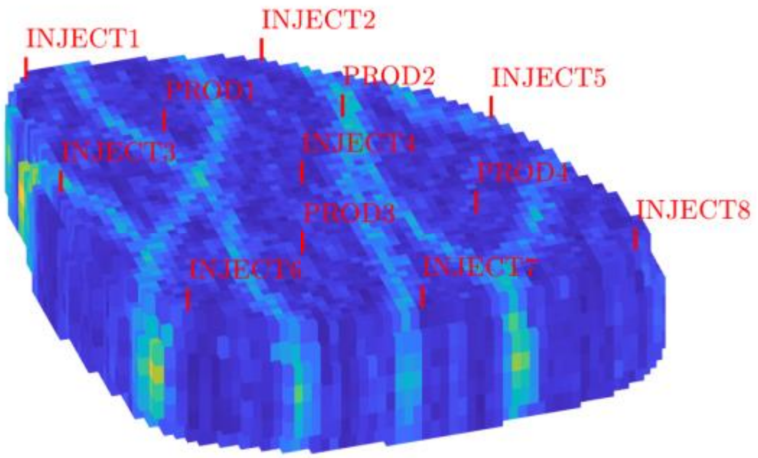




Data
Reference Model
RGNet Results

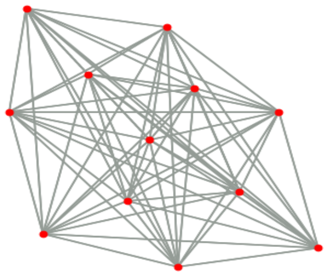
Sparsity-Constrained History Matching

- Original: Connect all the wells
- Improved: Connect wells based on distance and prior knowledge
- Further: Decide connections dynamically by matching data?



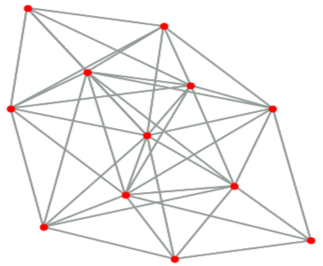
Egg model

Existing Connection Method



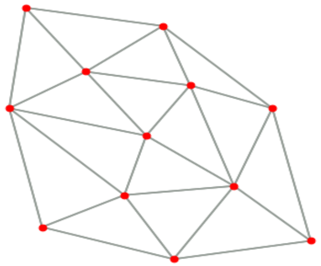
Dense connection

1. All well-pairs are considered



Max-min distance

2. Find threshold distance (TD) and connect wells with distance < TD

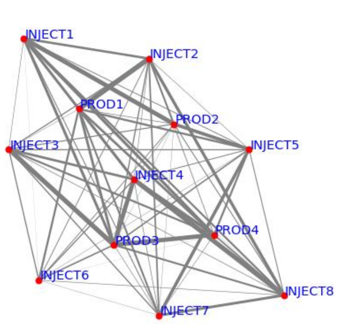


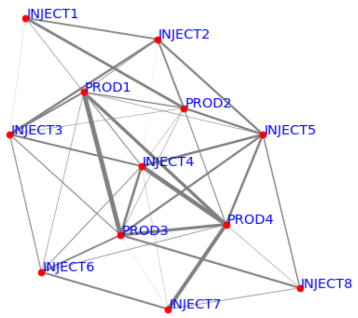
Delaunay triangulation

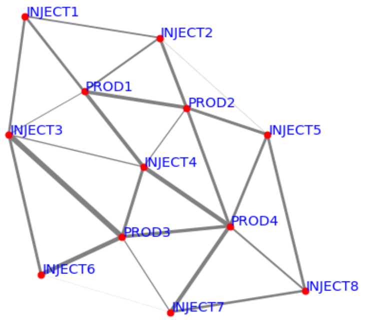
3. Connect nearest neighbors

4. enforce user-defined connectivity or constraints

Connectivity Visualization Based-On Line Thickness



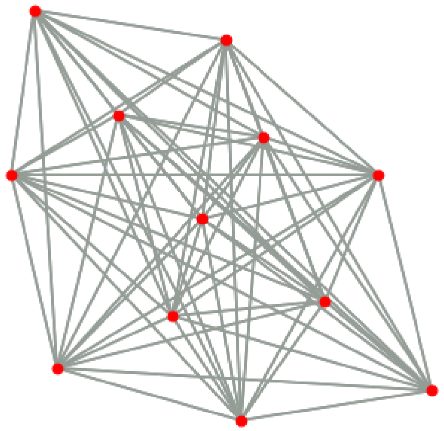




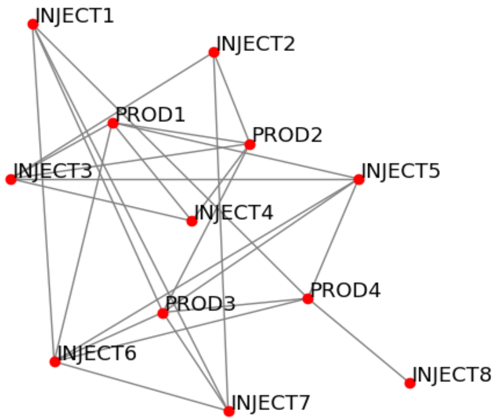
Sparsity-Constrained History Matching

- Sparsity-constrained optimization with SVR-DGN
  - Add regularization term to enforce sparsity
  - Simultaneously determine well connections and match data

$$\textbf{minimize } O(m) = \frac{1}{2}\underbrace{(d_{sim} - d_{obs})^2}_{\textbf{data mismatch}} + \frac{1}{2}\underbrace{\lambda \cdot T_x^2}_{\textbf{sparsity}}$$

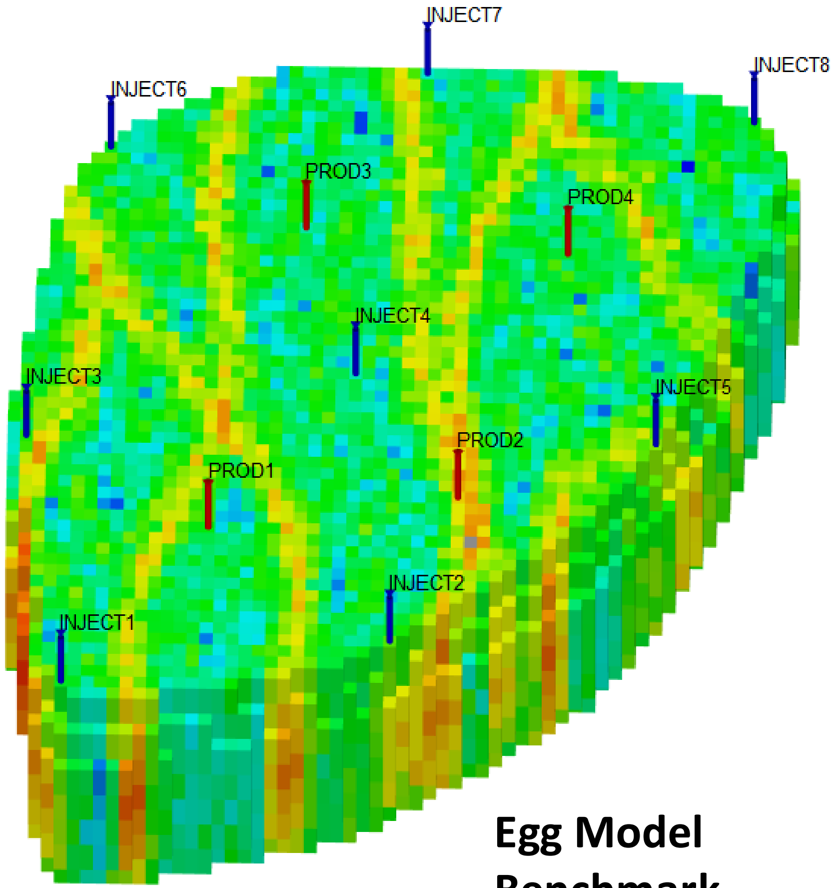


Initial Connection

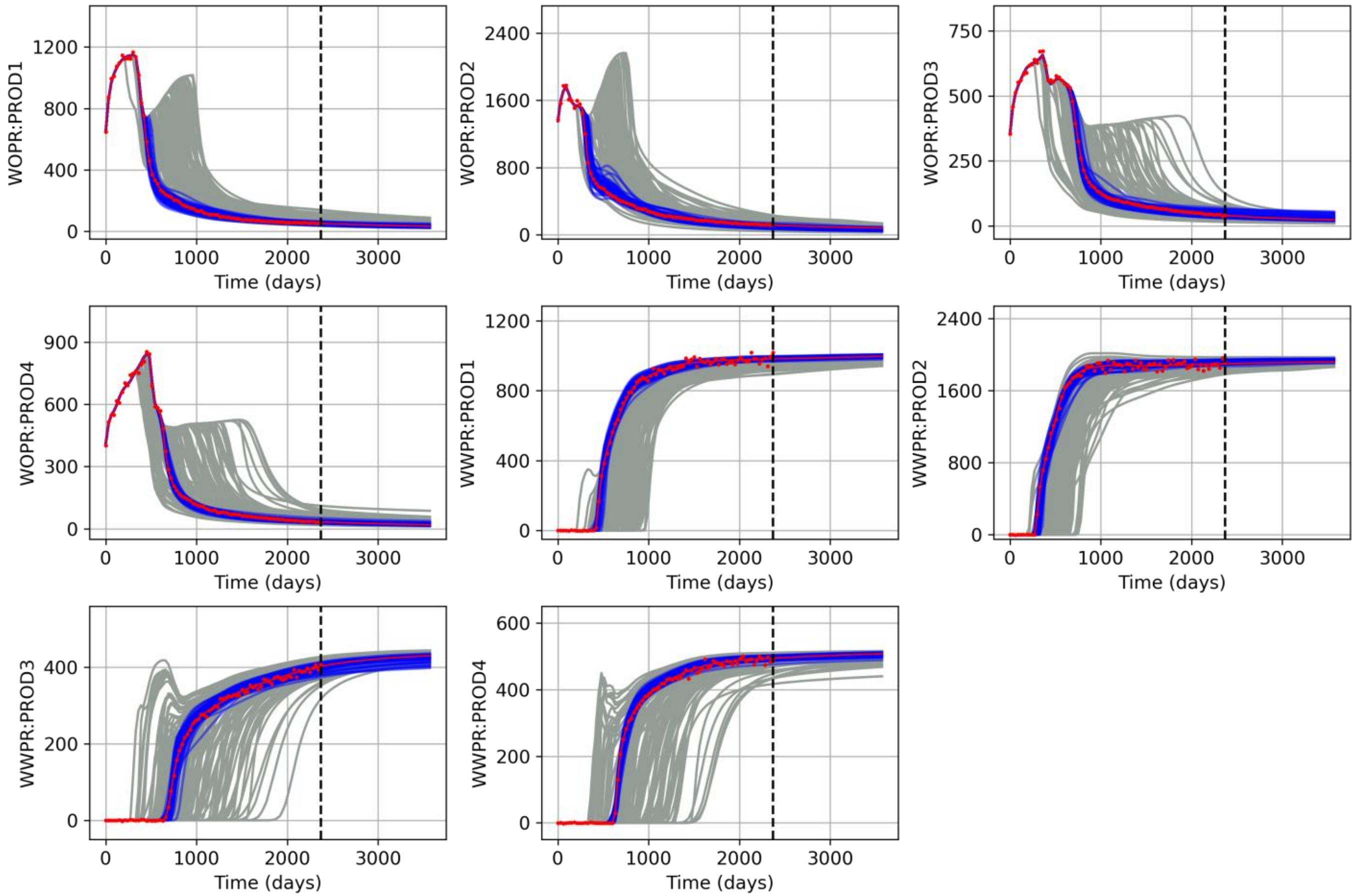


HM Connection (sparse)

Example 5: Sparsity Analysis

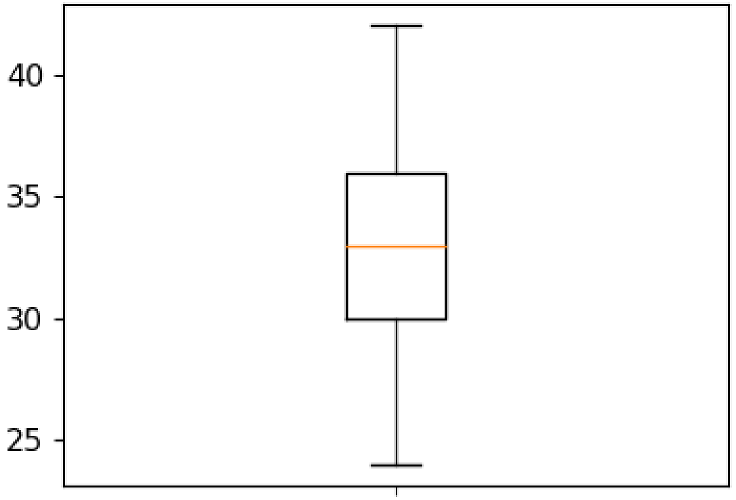


Egg Model Benchmark

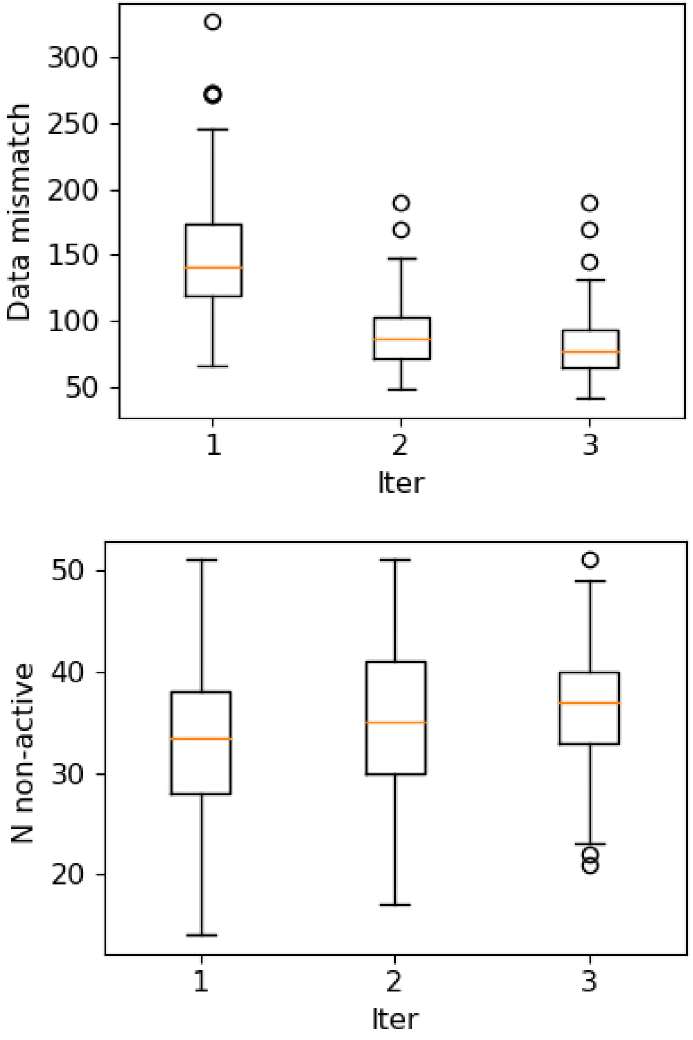


Example 5: Sparsity Analysis

- 8 injectors and 4 producers
- Full connection number = $\frac{12\times11}{2} = 66$
- ~50% of connections are disconnected after history matching



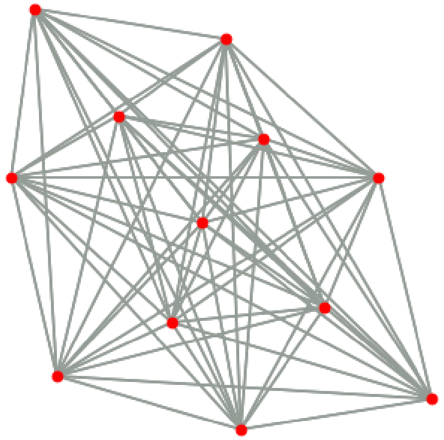
Distribution of non-active connections

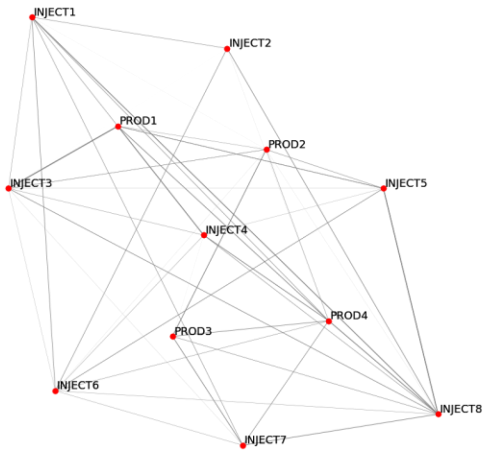


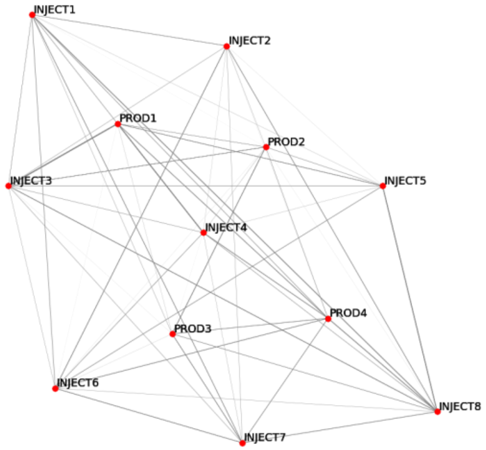
Data mismatch goes down and # inactive connections goes up with iterations

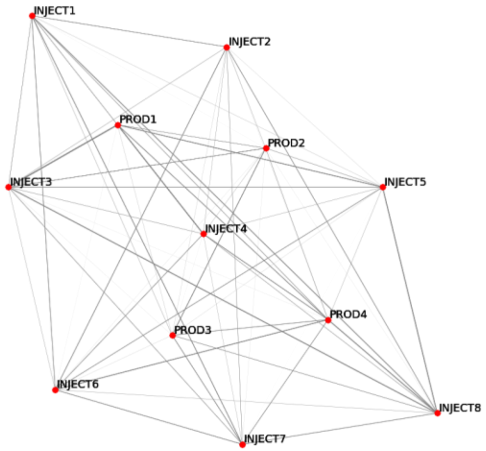
Example 5: Sparsity Analysis

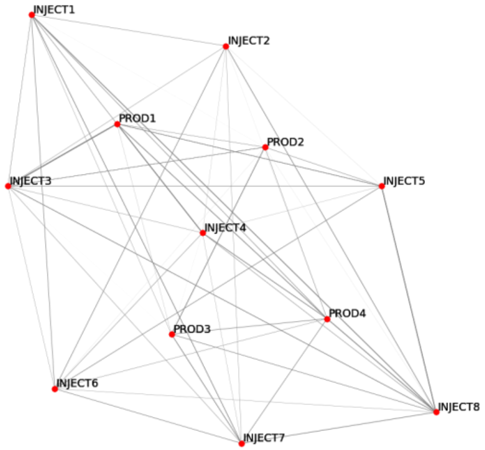
Well connection uncertainty

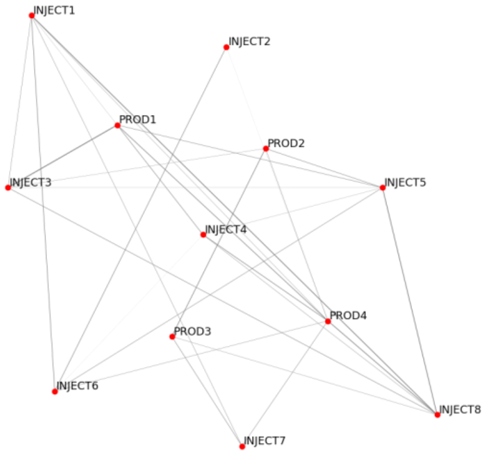






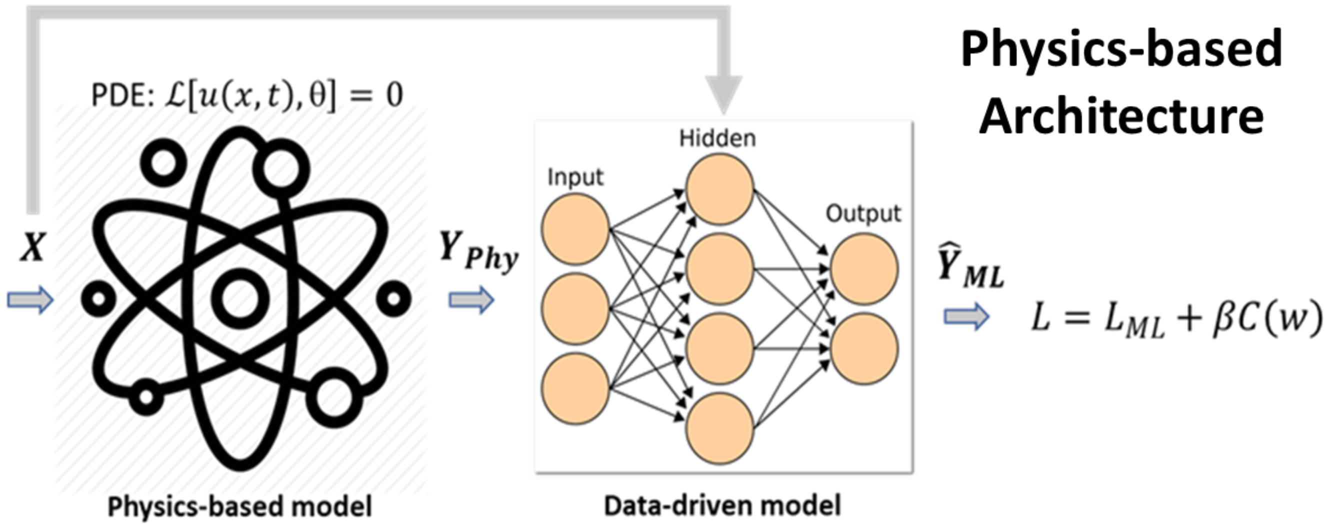






PIML + RGNet

- Use physics-based ML to improve RGNet HM/forecast performance
  - Train ML model to predict difference between model response and data
  - During forecast period, apply the difference to correct the forecast



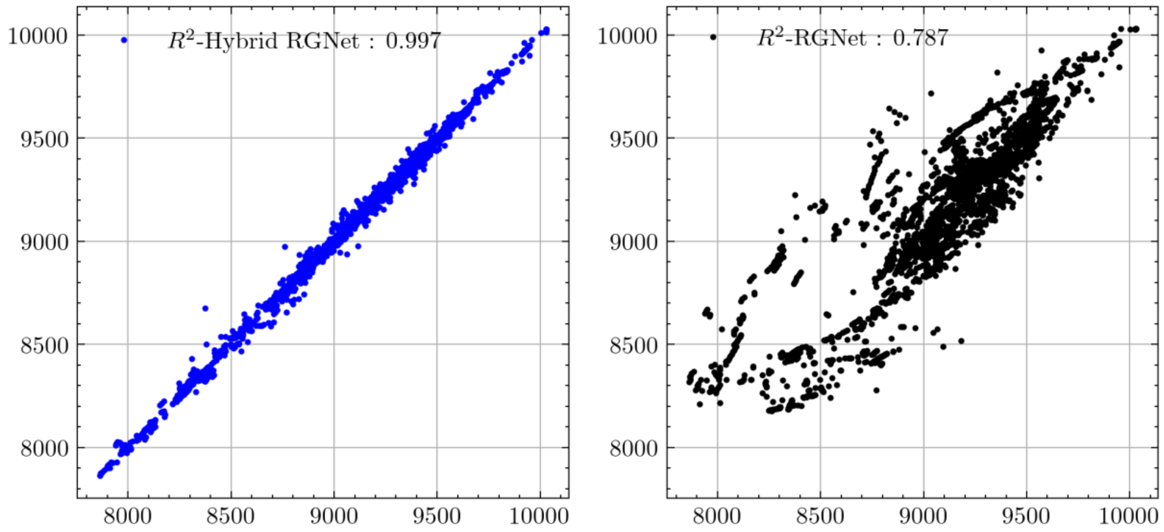
Physics-based Architecture

Example 6: Deep Water Asset

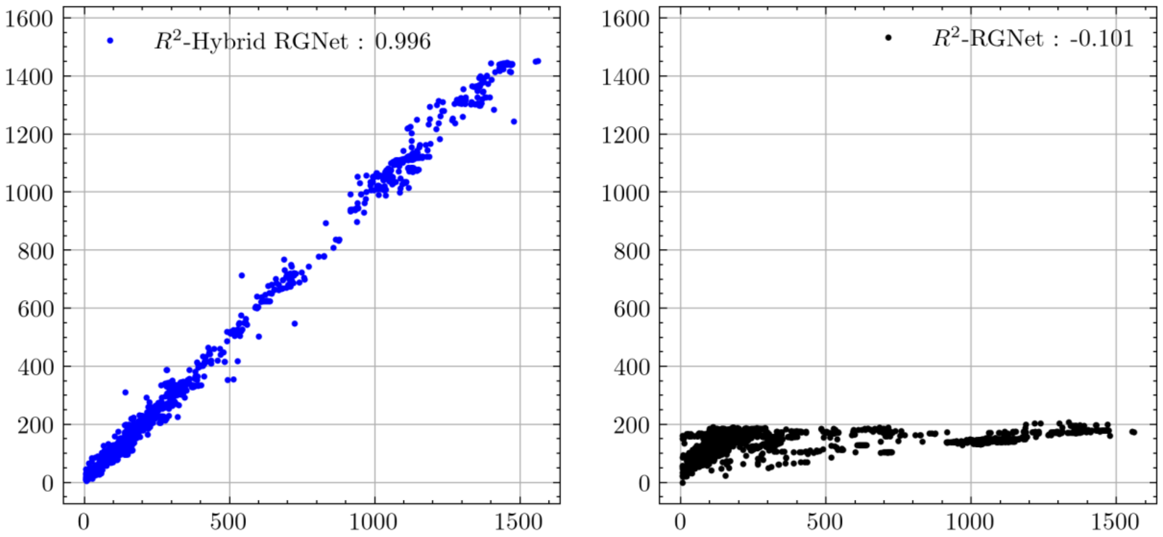
- Same example as Example 4.
- Intentionally remove mobile water in RGNet to test hybrid version.
- Training is based on history-matching period (75% of full history)

Training Error:

WBHP



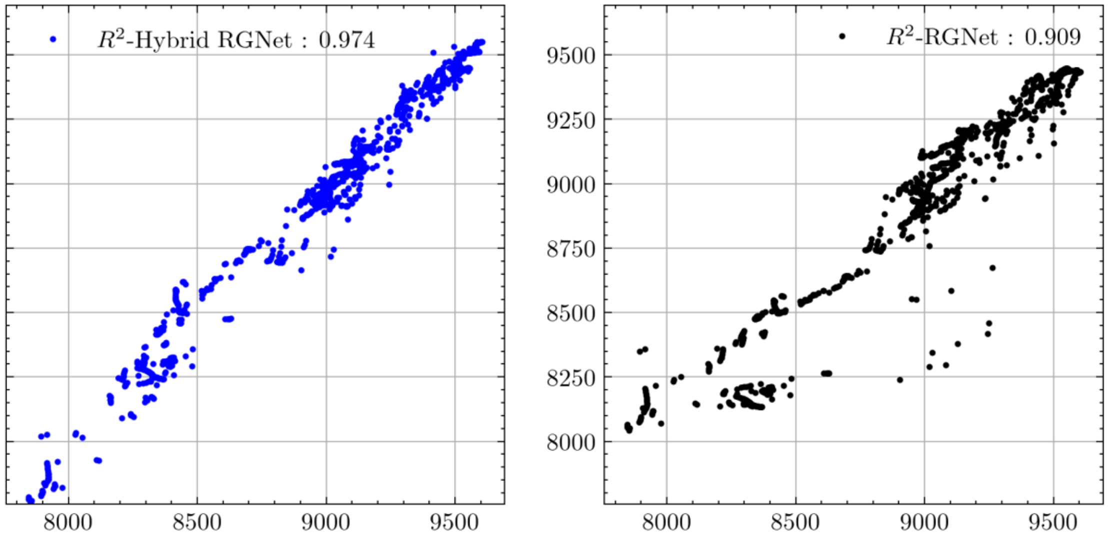
WWPR: Mobile water is removed in RGNet



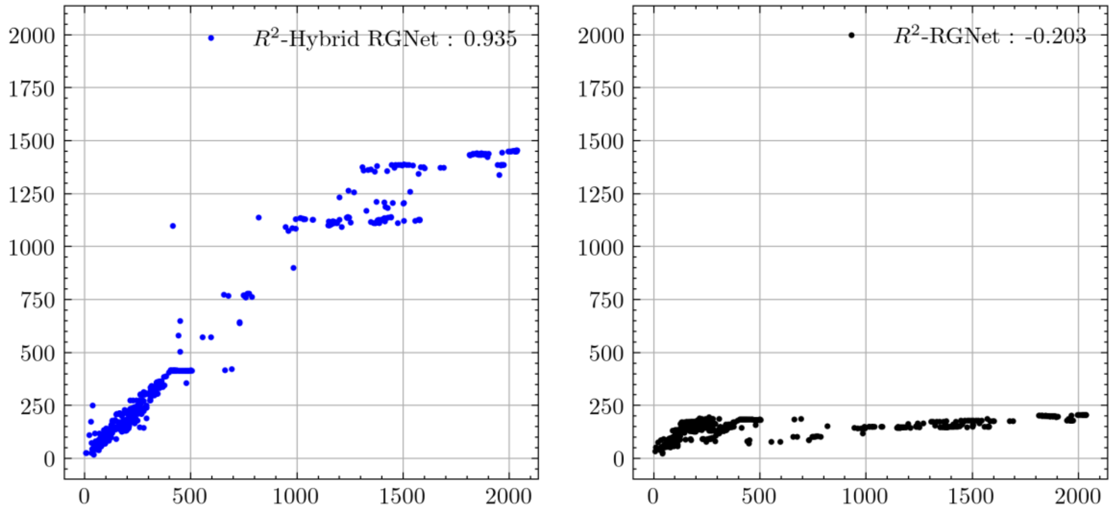
Example 6: Deep Water Asset

Testing Error:

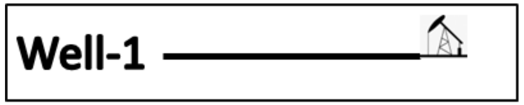
WBHP

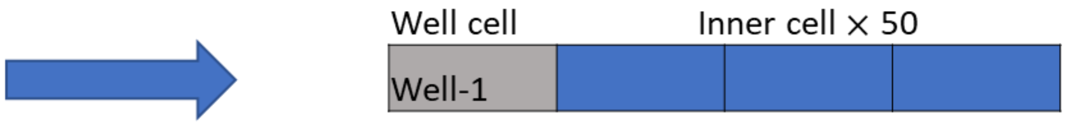


WWPR: Mobile water is removed in RGNet

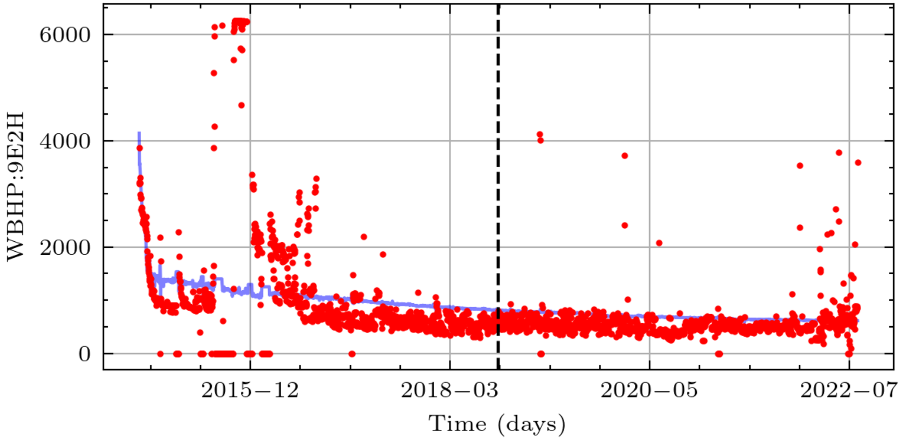


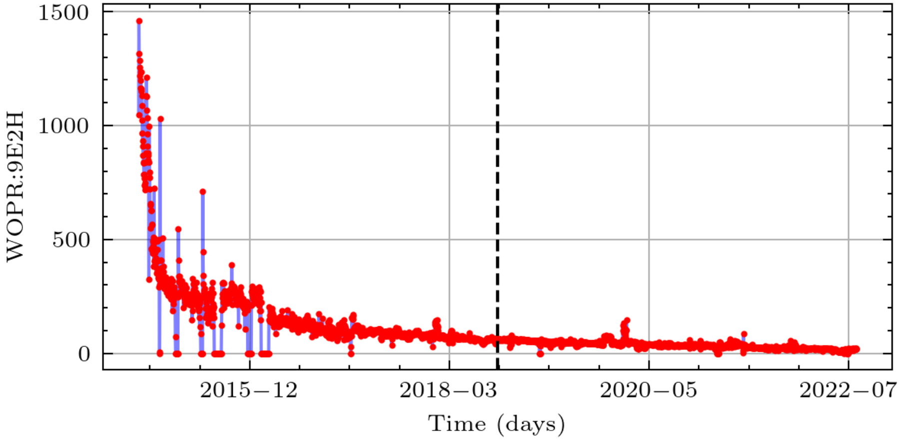
Example 7: Permian Unconv Oil Well





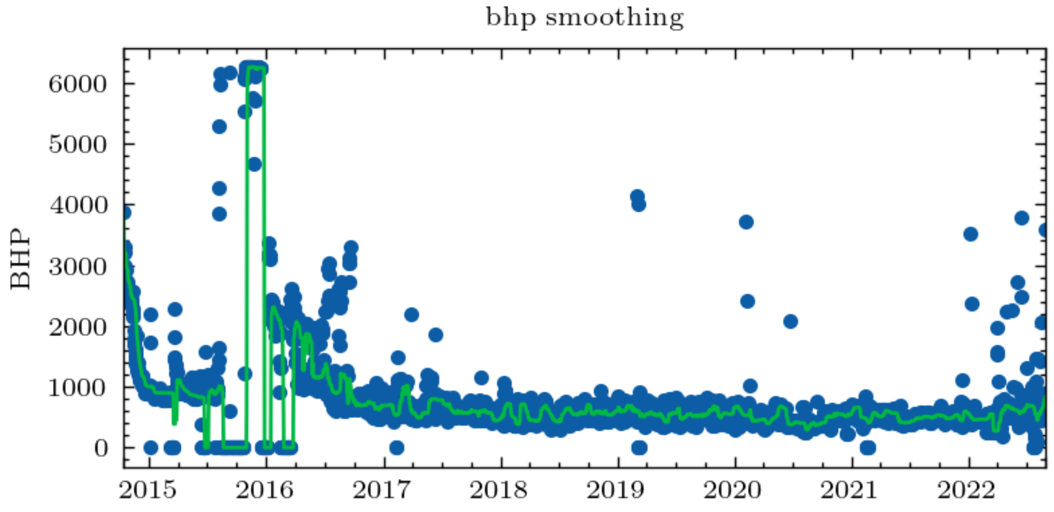
- Best Matched Model
  - Oil rate as well control
  - Match BHP
  - History of 8 years; match 4 years and predict rest.



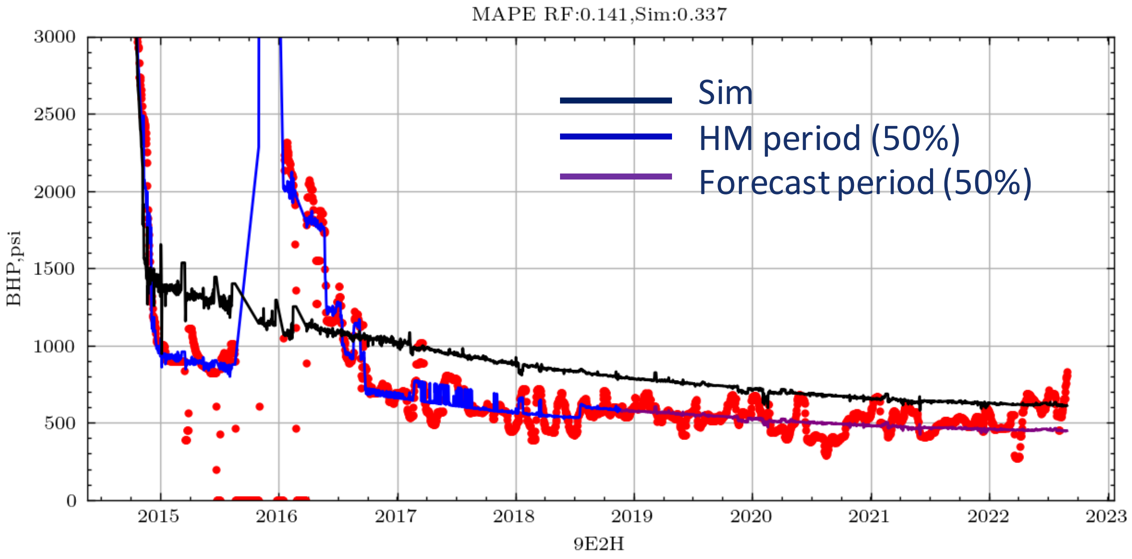


Example 7: Permian Unconv Oil Well

- **Data smoothing: 20 days' rolling median**



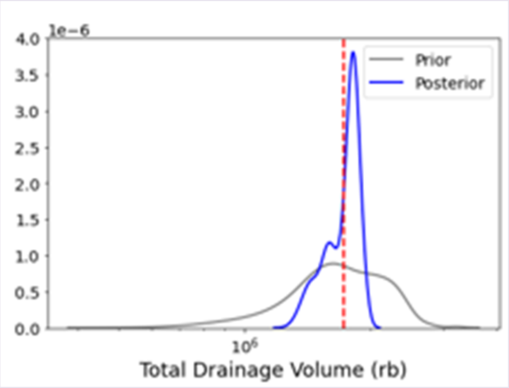
- **ML-enhanced Forecast**



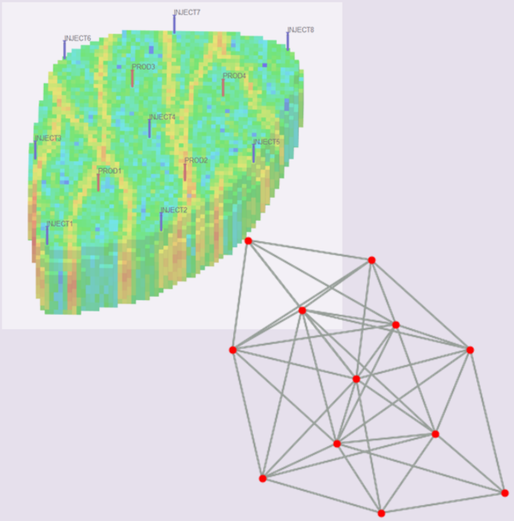
Summary

- Flow network-based hybrid reservoir models enable Closed Loop Reservoir Management
- Combining ML with RGNet enhances both accuracy and performance:
  - ML-enhanced history-matching algorithm (SVR-DGN)
  - Sparsity-constrained history-matching to decide connection and connectivity together
  - Physics-informed ML to enhance RGNet prediction accuracy

Connected Volume

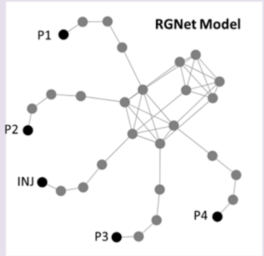


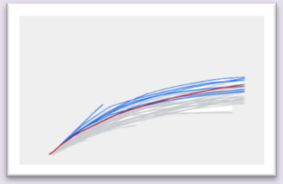
Reservoir Connectivity



Forecasting

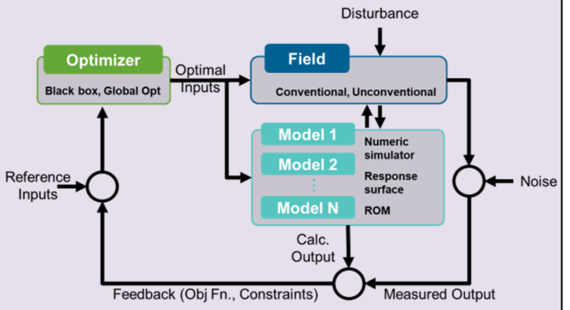
Future Well Controls





Optimization

Well Production Control
(BHP, Injection Rates)



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