

Welcome!

The program will begin soon.
You will not hear audio until we begin.

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Data Driven Discovery of Physics for Reservoir Surveillance with Application to PTA

Dr. Sathish Sankaran

Xecta Digital Labs



<https://www.linkedin.com/in/sathishsankaran/>

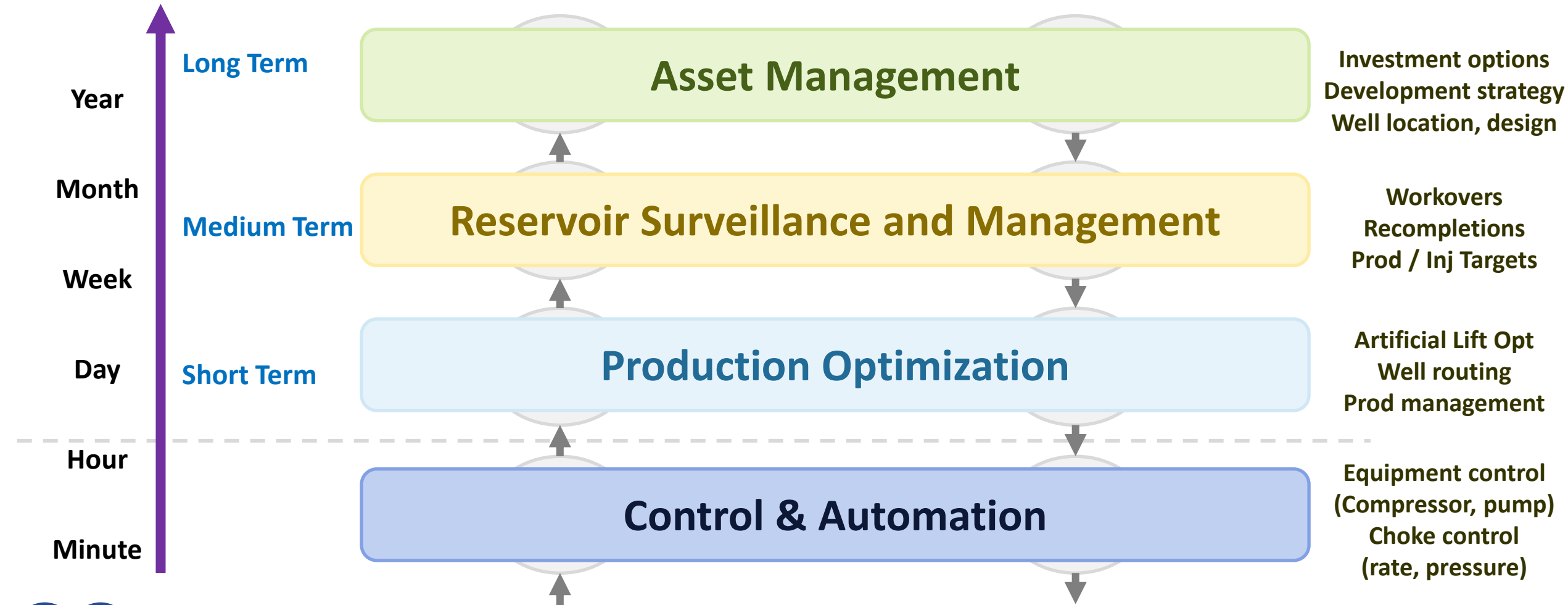


Linkedin

Towards Integrated Optimization

Multi Level Control Hierarchy

Typical Decisions

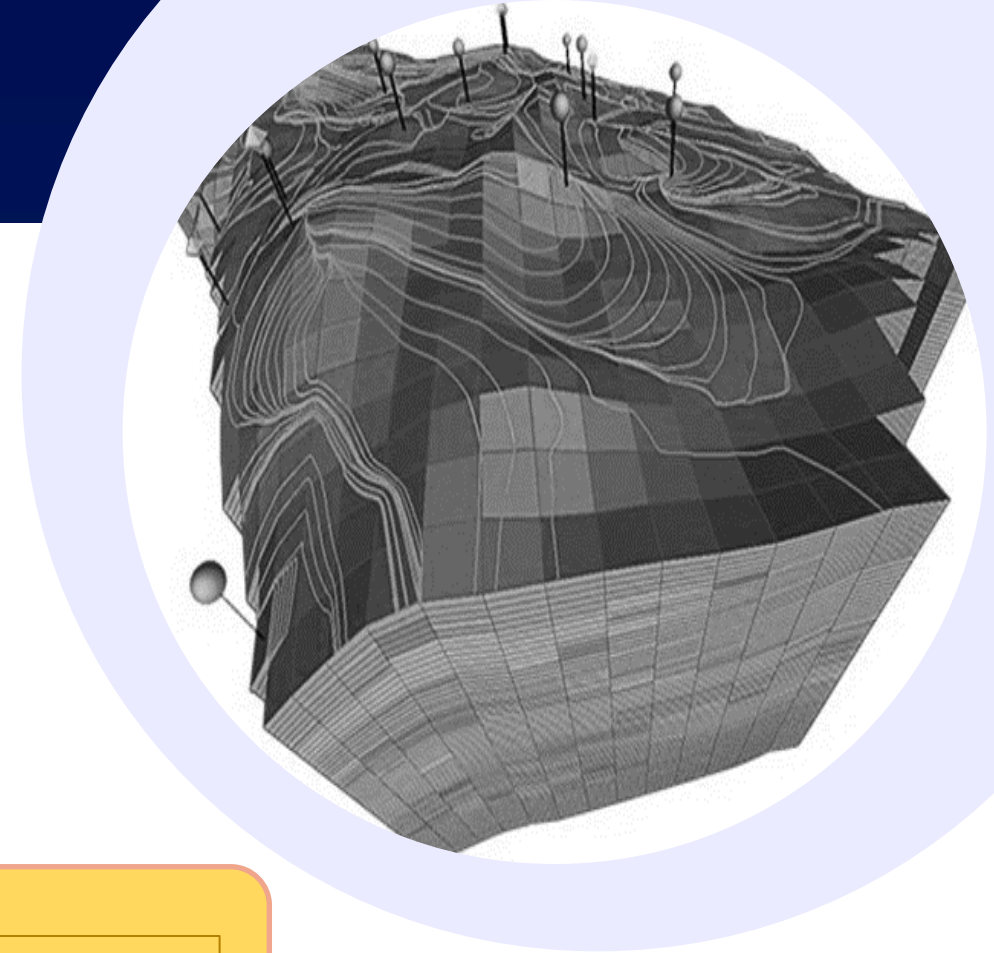


Reference: Adapted from Sankaran et al (2009)

Reservoir Surveillance

Definition:

Collect information to understand reservoir performance with fewest assumptions and enable robust response to changing subsurface, surface or economic conditions



Automate
Interpretable
Sustainability

Rates, Pressures

Data Volumes

Reservoir Performance $\rightarrow f(\text{Wells, Controls, Properties})$

Models

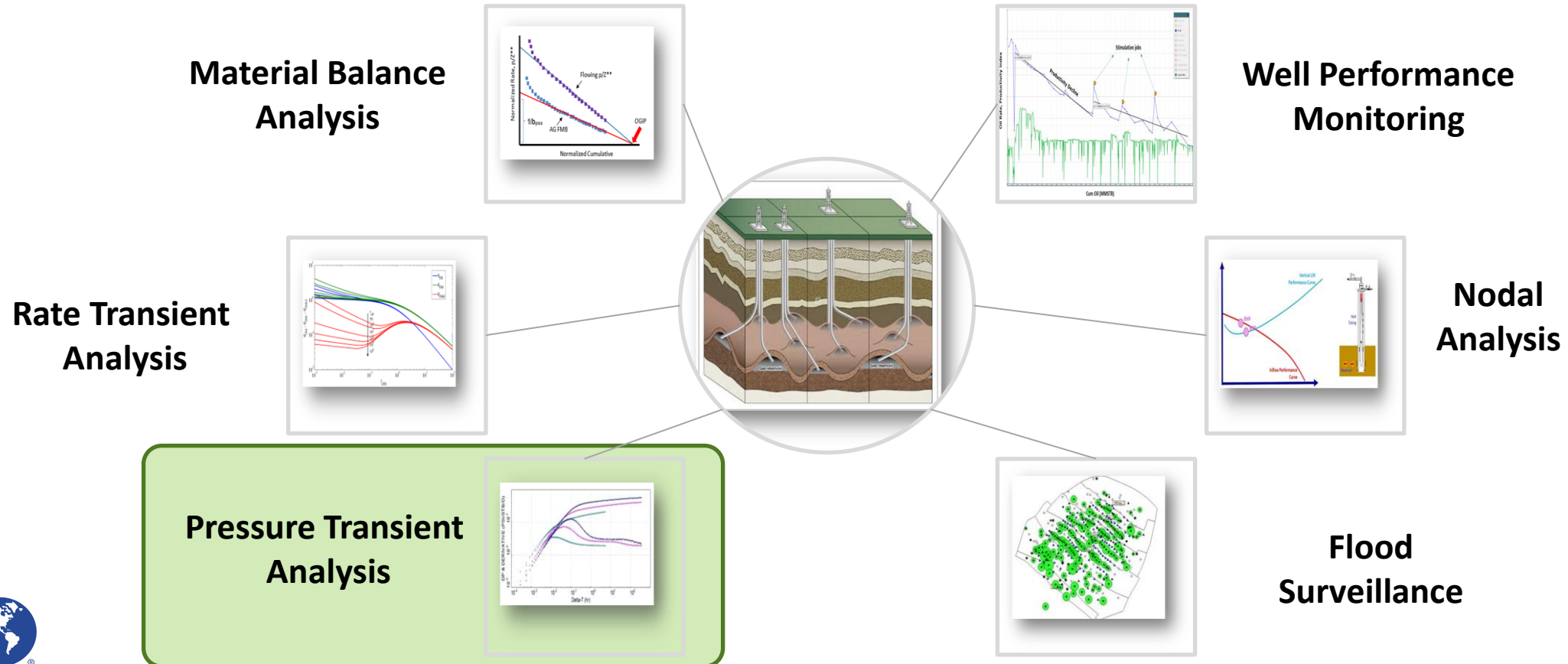
Full physics
Data-driven
Hybrid

Fluid/Rock parameters

Unknown
Uncertain
Complex
Time Varying

Reservoir Surveillance

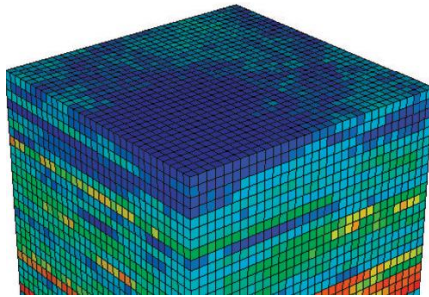
- **Objectives:**
 - Early understanding of reservoir / well performance
 - Identify under-performing elements (reservoir, well etc.) for remediation



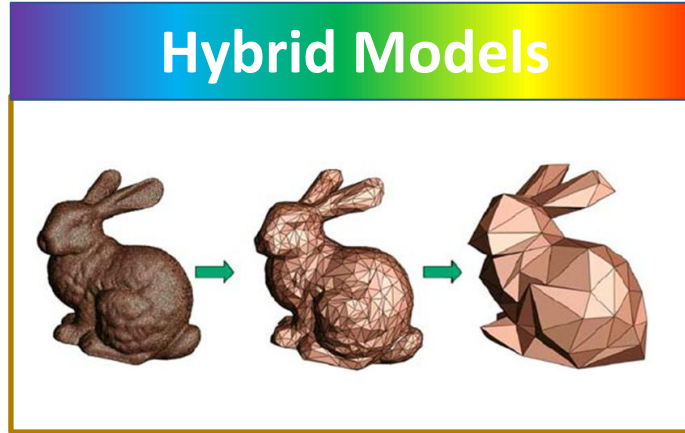
Hybrid Reservoir Modeling

Physics-constrained, data-driven modeling

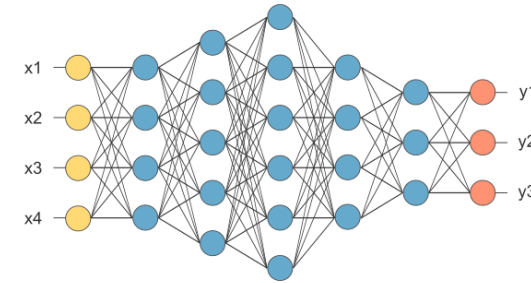
Full Physics



Hybrid Models



Data-Driven



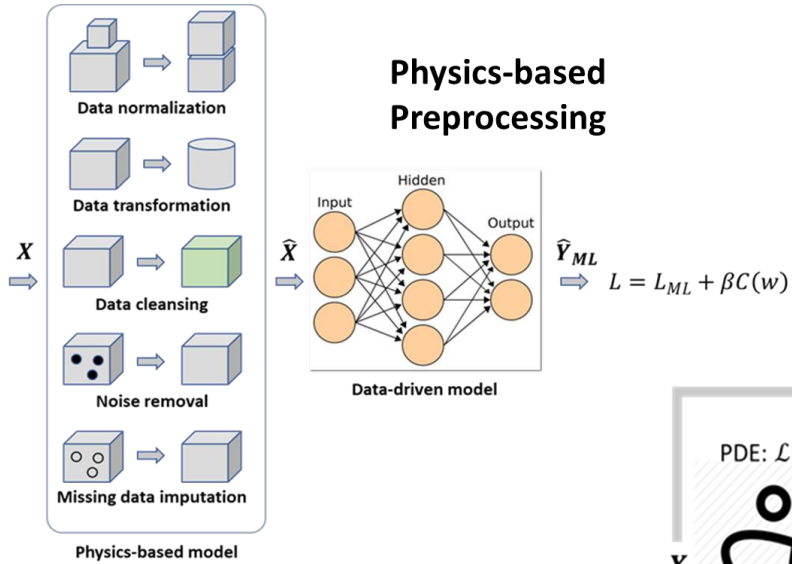
Conventionals

- Automate shutin analysis (SPE 196122)
- Estimate average reservoir pressure (SPE 209300)
- Track varying well productivity index (SPE 196122, SPE 209300)
- Virtual meter for flow rates (SPE 209300)
- Forecasting and flood optimization (SPE 203390, SPE 206238)

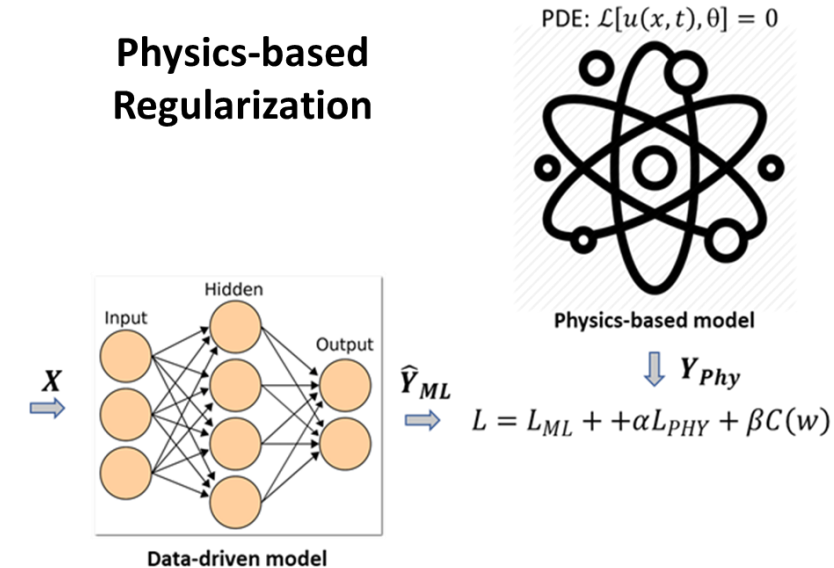
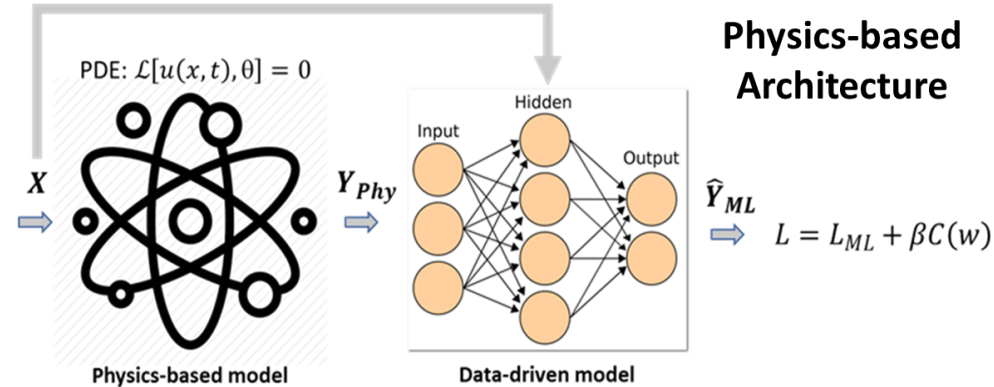
Unconventionals

- Hybrid bottomhole pressure (URTeC 5261)
- Transient well performance (URTeC 5023)
- Reduced-physics forecasting (URTeC 5023, 3723189, 371899)
- Production optimization (IPTC 22493, URTeC)
- Parent-child interference (SPE 195813)

Hybrid Reservoir Modeling

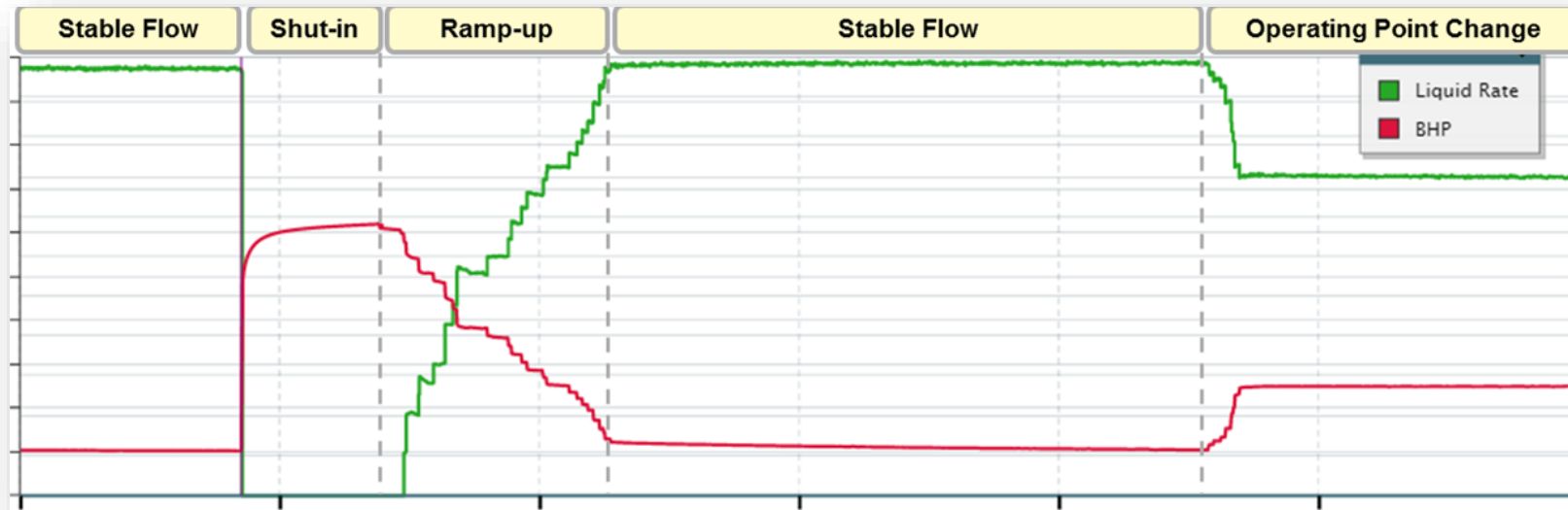


Reference: URTeC 5261



Tracking Well Performance

- Can we extract well diagnostics from routine production operations?



Shut-in

Well test start/stop

Artificial lift start/stop

Well restart

Stable flow

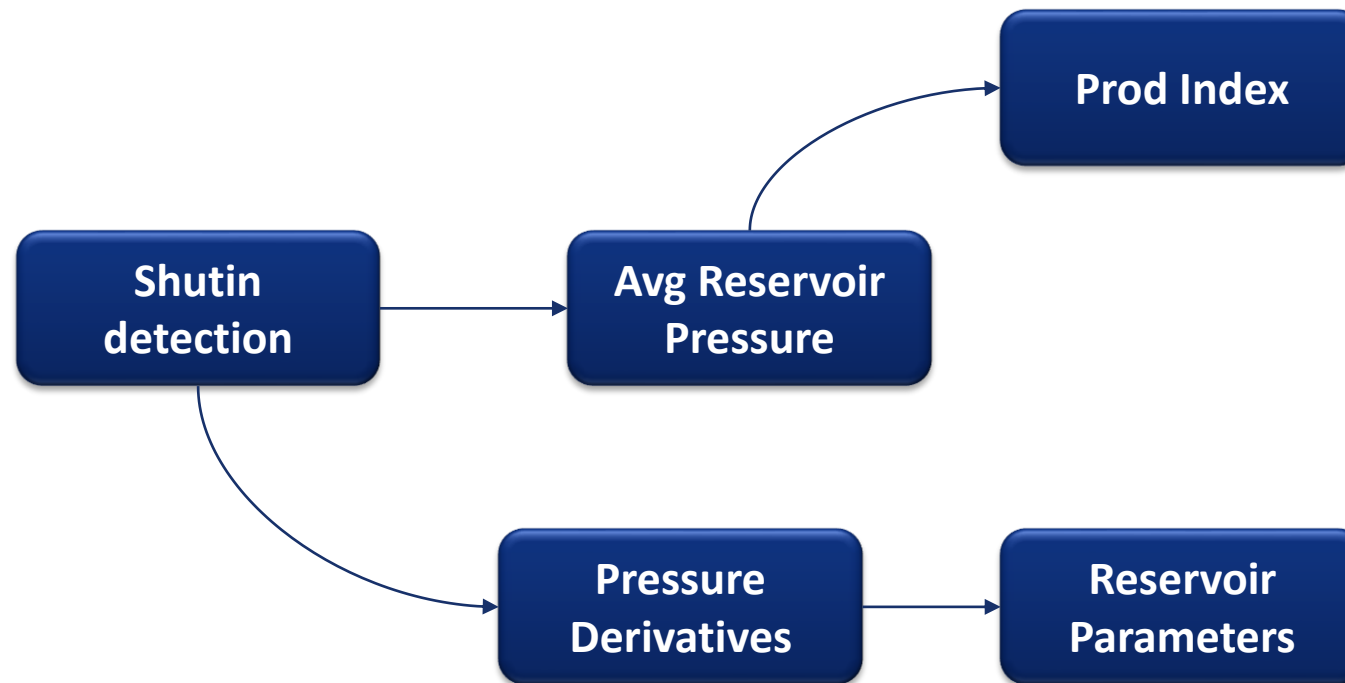
Choke change

Setpoint change

Flowline alignment

Pressure Transient Analysis

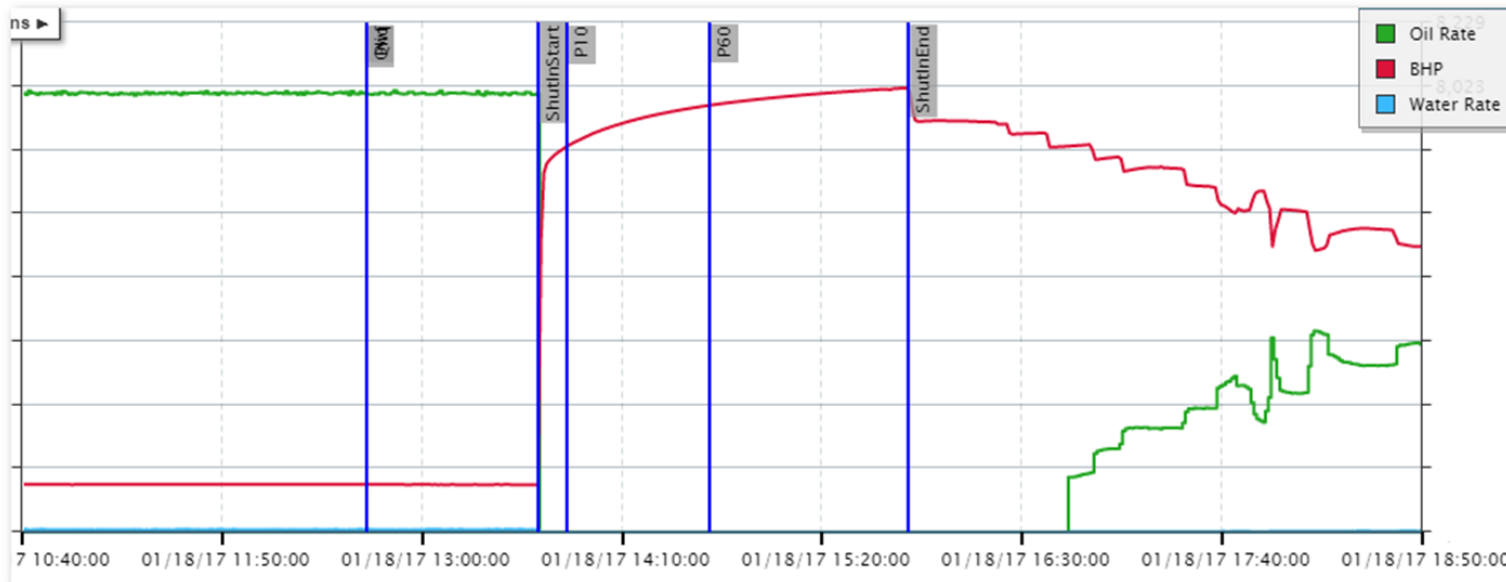
- Can we extract well diagnostics from routine production operations?
 - Estimate shutin pressure, average reservoir pressure, productivity index, pressure derivatives and other reservoir parameters



Pressure Transient Analysis

- **Productivity Index from Shutin**

- Quantify impact and analyze planned and unplanned shut-ins for well performance



Reference: Sankaran et al (2017)

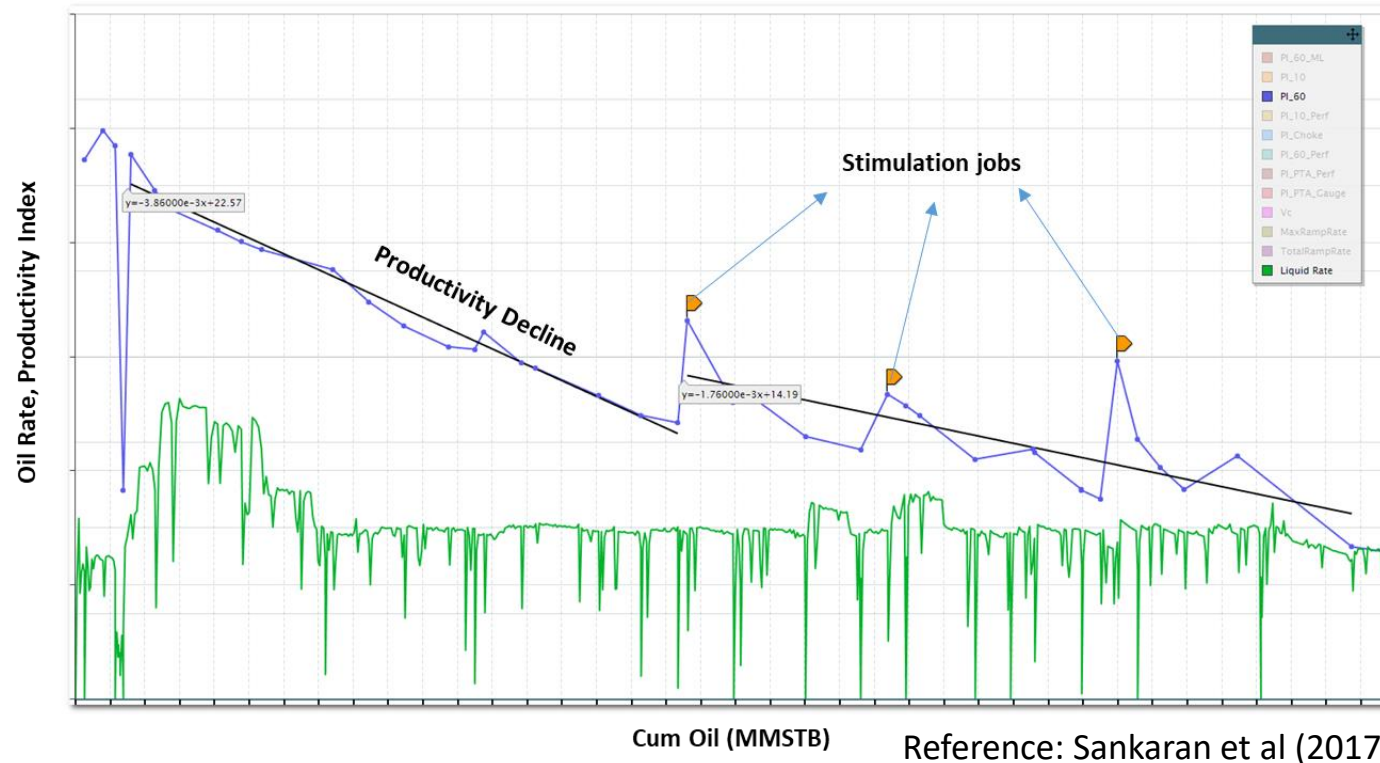
$$PI_x = \frac{q}{P_x - P_{wf}}$$

$$x = \left\{ \begin{array}{l} 1 \text{ hr} \\ 48 \text{ hr} \\ \text{Shutin end} \\ \text{Avg reservoir} \\ \text{etc.} \end{array} \right\}$$

Pressure Transient Analysis

- **Productivity Index from Shutin**

- Quantify impact and analyze planned and unplanned shut-ins for well performance
- Estimate shutin pressure, average reservoir pressure, productivity index, pressure derivatives and other reservoir parameters

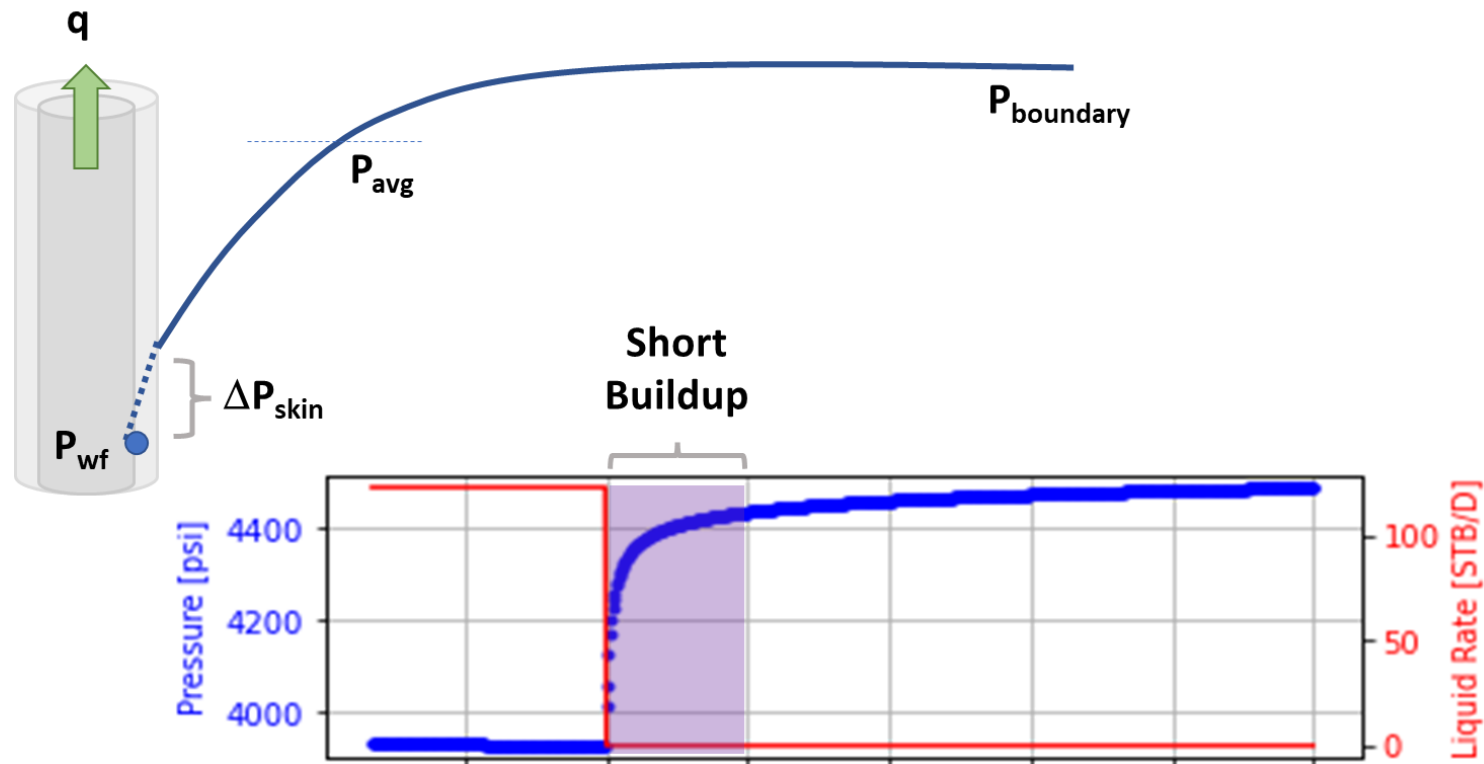


$$PI_{1hr} = \frac{q}{P_{1hr} - P_{wf}}$$

Pressure Transient Analysis

- **Average Reservoir Pressure**

- Estimate from short pressure transient (buildup) data
- Applications: IPR, OHIP estimation, material balance analysis, reservoir simulation, etc.



Pressure Transient Analysis

- **Average Reservoir Pressure**

- Estimate from short pressure transient (buildup) data
- Applications: IPR, OHIP estimation, material balance analysis, reservoir simulation, etc.

Known Well Drainage Configuration

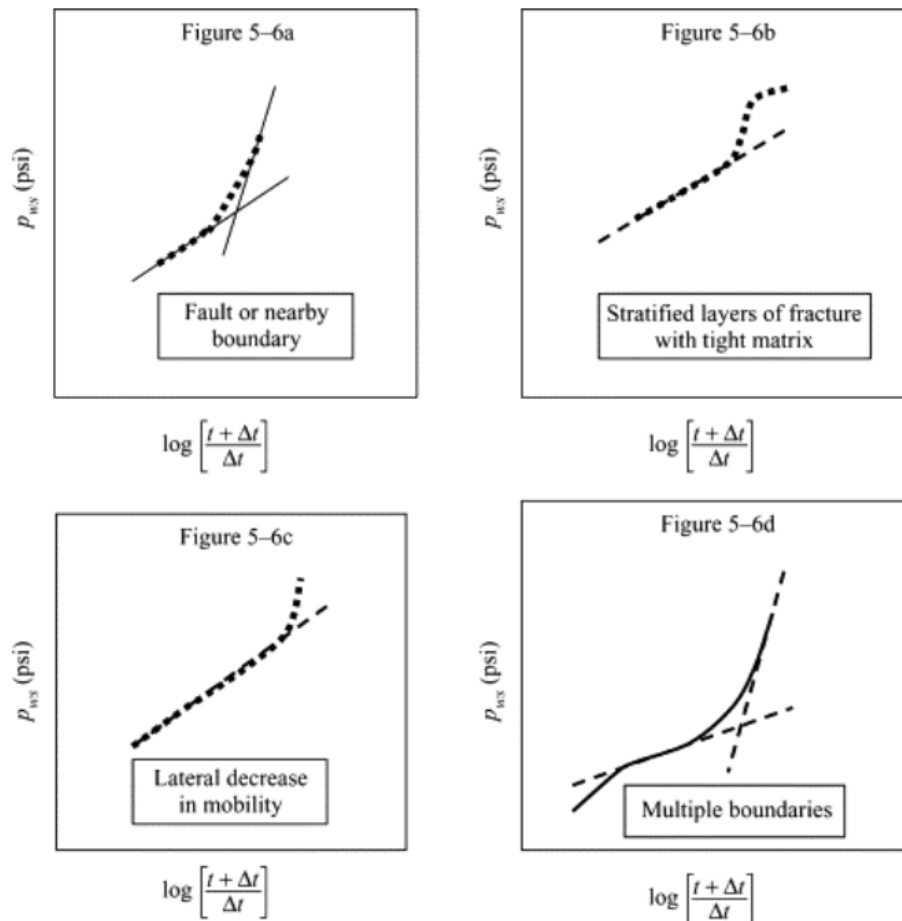
Miller et al (1950)
Mathews et al (MBH, 1954)
Horner (Horner time, 1967)
Ramey & Cobb
Dietz (1967)
Odeh & Al-Hussainy (1971)

Unknown Well Drainage Configuration

Muskat (1937)
Mead (Hyperbola, 1981)
Kabir & Hasan (Rectangular hyperbola, 1983)
Kuchuk (Inverse time, 1999)
Chacon (2004)
Crump & Hite (Modified Muskat, 2008)

Known Drainage Configuration

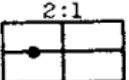
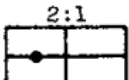
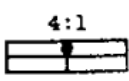
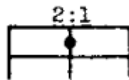
Average Reservoir Pressure



Horner plot – Chaudhry (2004)

TABLE 3 – DETERMINATION OF AVERAGE PRESSURE

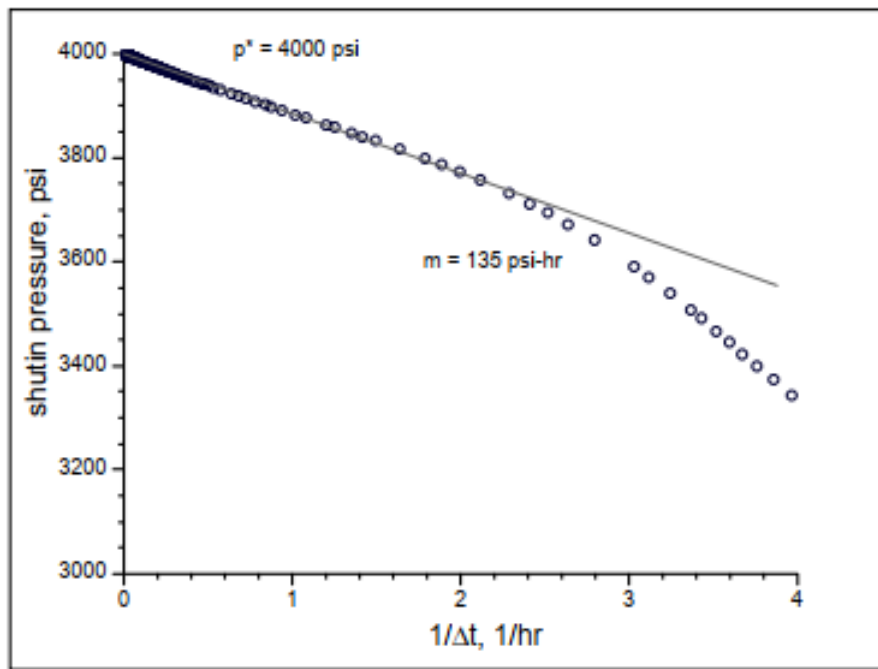
Well	p^* psia	$\frac{q\mu}{4\pi kh}$ atm	$\frac{q}{\text{at res. cond.}}$ cc/sec	$\frac{kh}{\mu}$ darcy-cm/cp	$f v_j$ cc x 10 ⁻¹¹	C atm ⁻¹	Total Production tank bbl
1	3877	1.594	86	4.29	1.76	2 x 10 ⁻⁴	4490
2	3858	.1870	74	31.5	1.49	2 x 10 ⁻⁴	5640
3	3932	3.051	63	1.643	1.28	2 x 10 ⁻⁴	1930
4	3787	2.047	330	12.83	6.77	2 x 10 ⁻⁴	10,800

Well	i sec x 10 ⁻⁶	$\frac{kt}{f\mu cA}$	Model	$\frac{p^* - \bar{p}}{q\mu/4\pi kh}$	$\bar{p}^* - \bar{p}$ psi	$\bar{p}$ psia	v_j/v_t	Volumetric Avg. Press.
1	9.94	1.21		1.76	41	3836	.156	
2	14.77	15.6		4.27	12	3846	.132	
3	5.96	.383		.11	5	3927	.113	
4	6.17	.585		1.90	57	3730	.599	
								3784

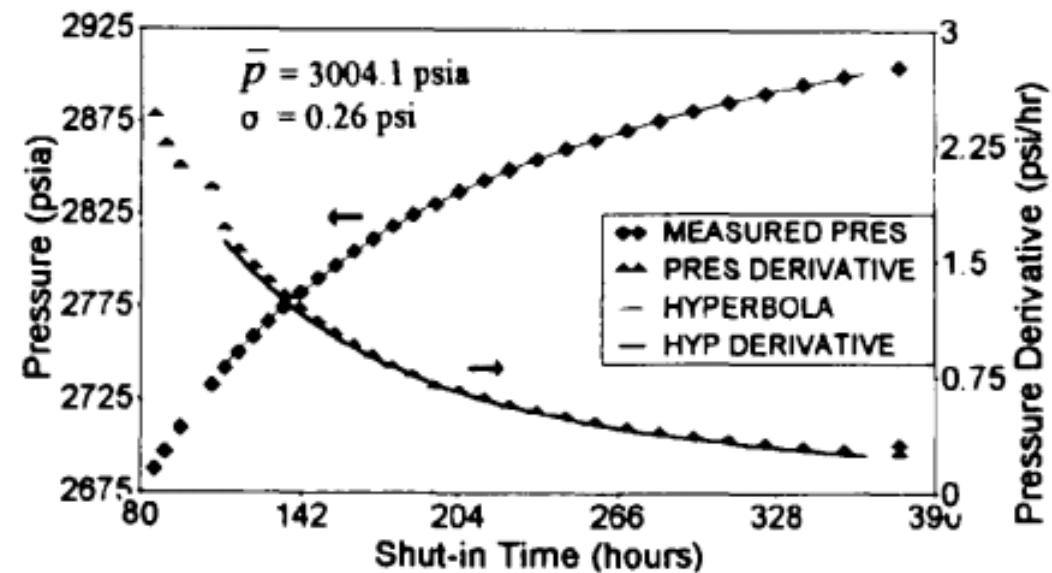
MBH (1954)

Unknown Drainage Configuration

- Average Reservoir Pressure



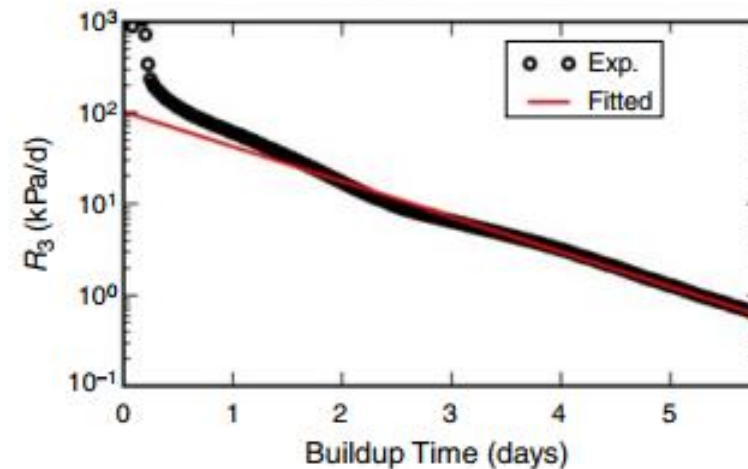
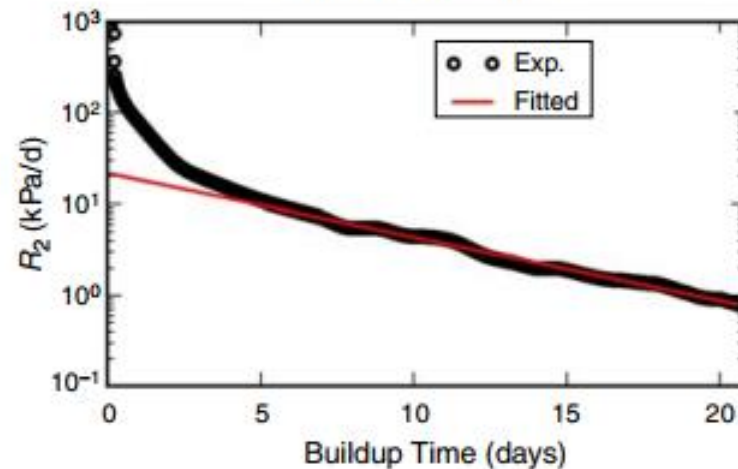
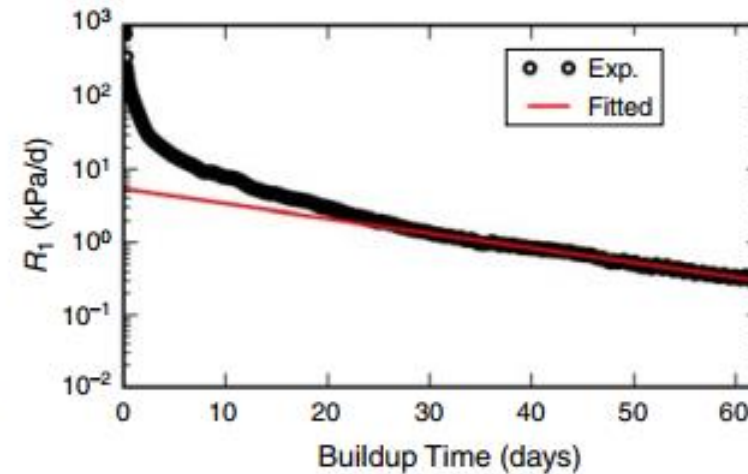
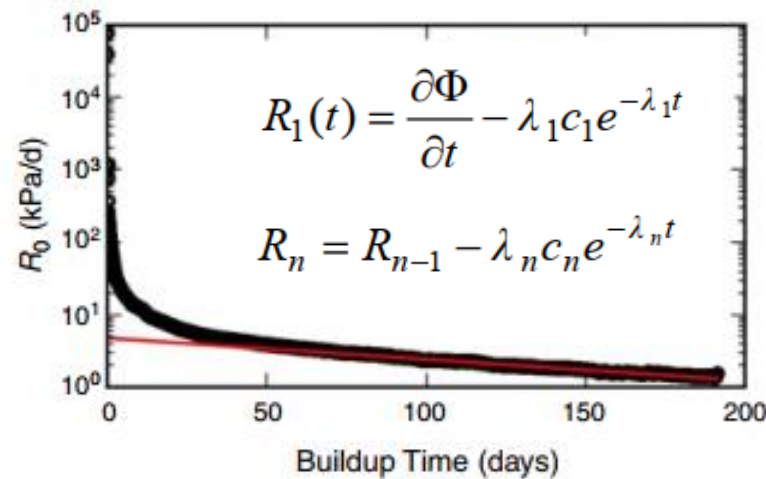
$$p_{ws} = a + \frac{b}{t} \quad \text{Kuchuk (1999)}$$



$$p_{ws} = a + \frac{b}{c + t} \quad \text{Kabir and Hasan (1996)}$$

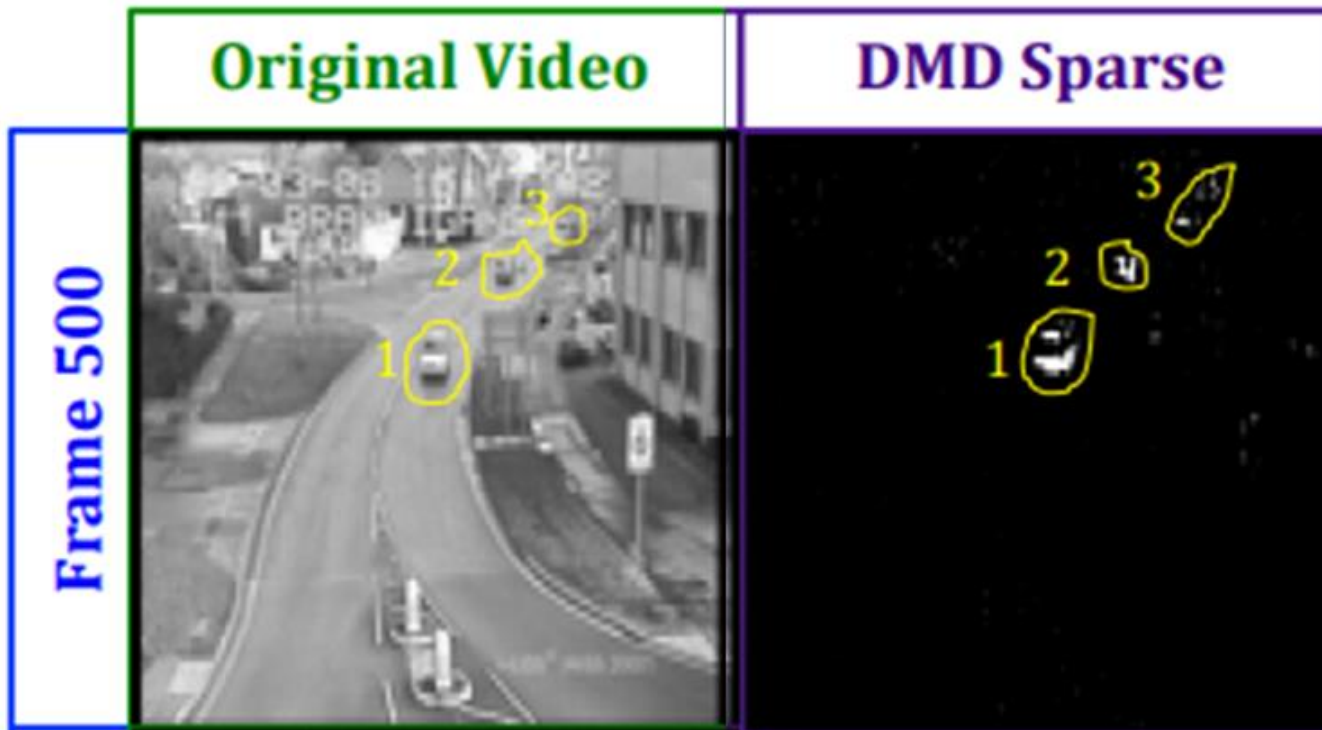
Unknown Drainage Configuration

- Average Reservoir Pressure



Crump and Hite (2006), Piccinini (2018)

Motivation



Background / foreground separation
in real time video

Reference: Grosek and Kutz (2014)

Can reservoir signal be expressed as a combination of various dynamics?

Unknown Drainage Configuration

- **Average Reservoir Pressure**

Eigenvalue expansion: $P(t, x, y, z) = P_{avg} - \sum_{i=1}^{\infty} c_i a_i(x, y, z) e^{-\lambda_i t}$

$$\frac{\partial P}{\partial t} = \frac{1}{\phi c_t} \nabla \cdot \left(\frac{K}{\mu} \cdot \nabla P \right)$$

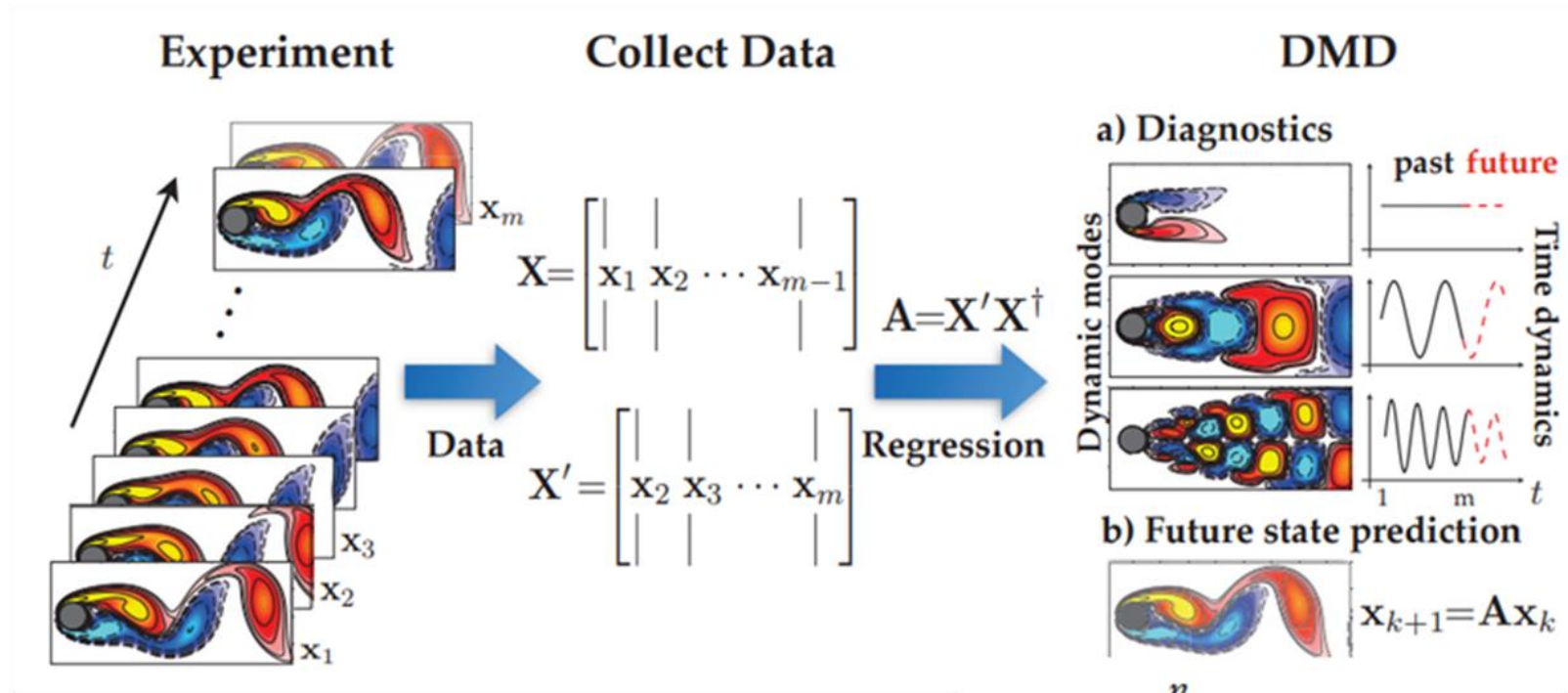
coefficients

eigenfunctions

eigenvalues

Reference: *Mikhailov and Ozisik (1984), Crump and Hite (2008)*

Dynamic Mode Decomposition (DMD)



Reference: Kutz et al. (2016)

$$\mathbf{x}(t) = \sum_{k=1}^n \phi_k \exp(\omega_k t) b_k$$

Variants: Exact DMD, Extended DMD, Optimized DMD, Compressive DMD, Multi-resolution DMD, Input-Output DMD, DMD with control, Ensemble DMD, Physics-constrained DMD

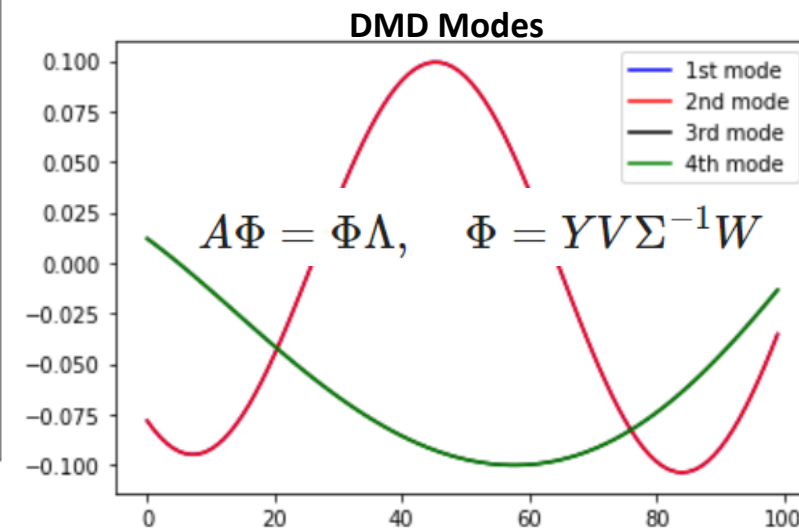
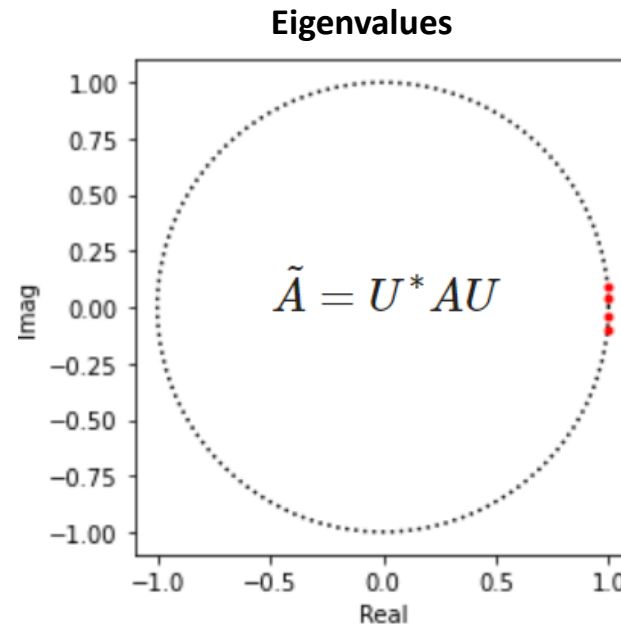
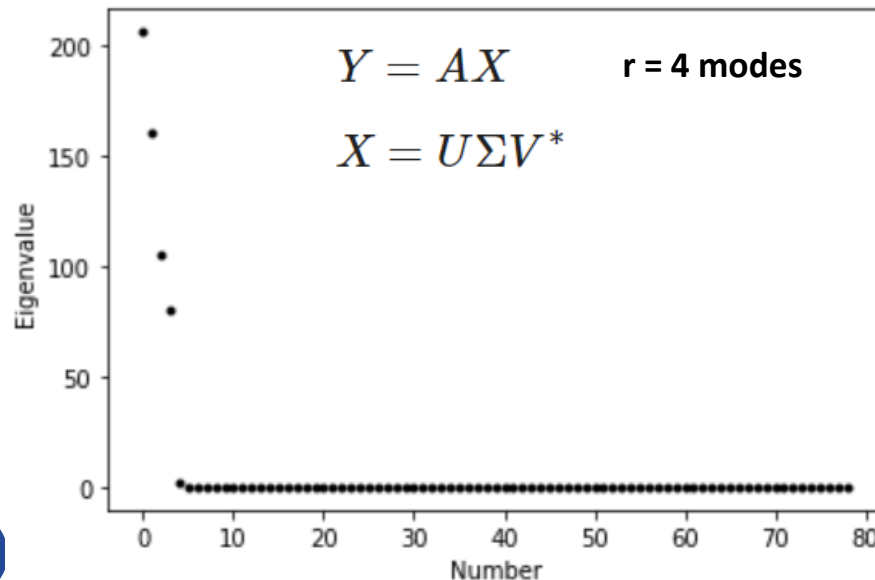
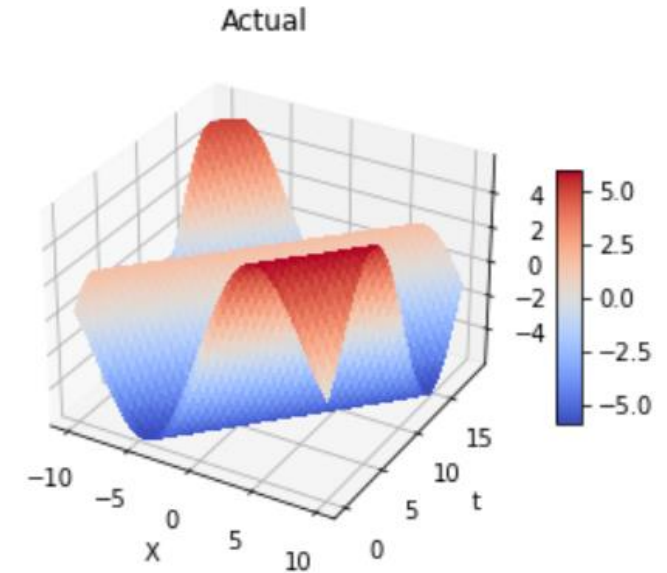
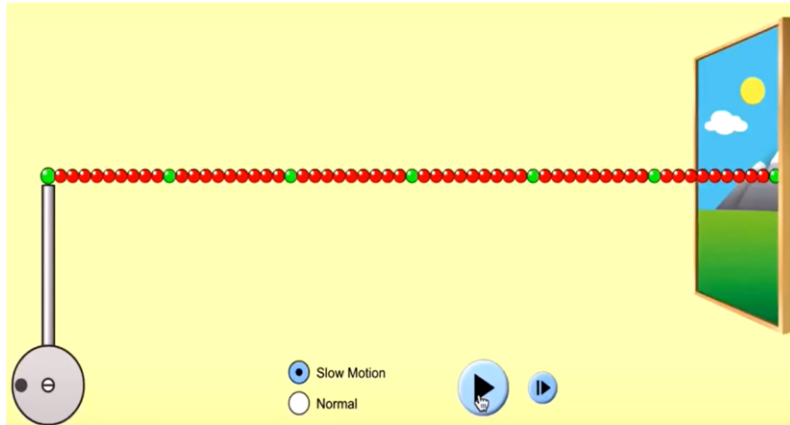
Applications: Fluid mechanics, neuroscience, epidemiology, video processing, robotics etc.

References: Tu et al. (2014), Sankaran et al. (2022)

DMD – Example

Traveling wave equation:

$$y = 1\sin(0.1x - 0.1t) + 2\sin(0.2x - 0.2t) + 4\sin(0.4x - 0.4t)$$

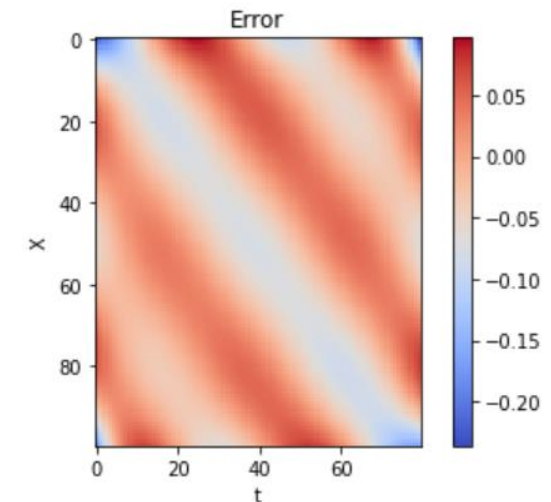
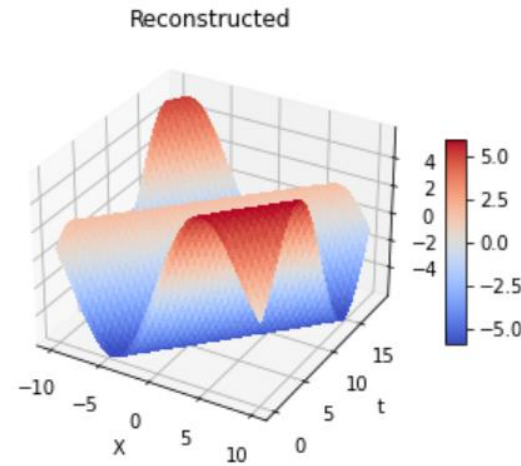
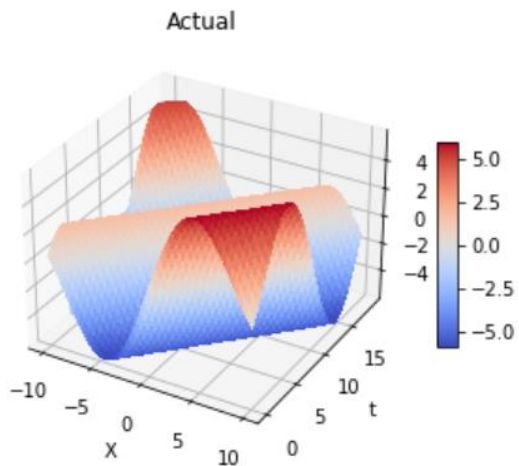
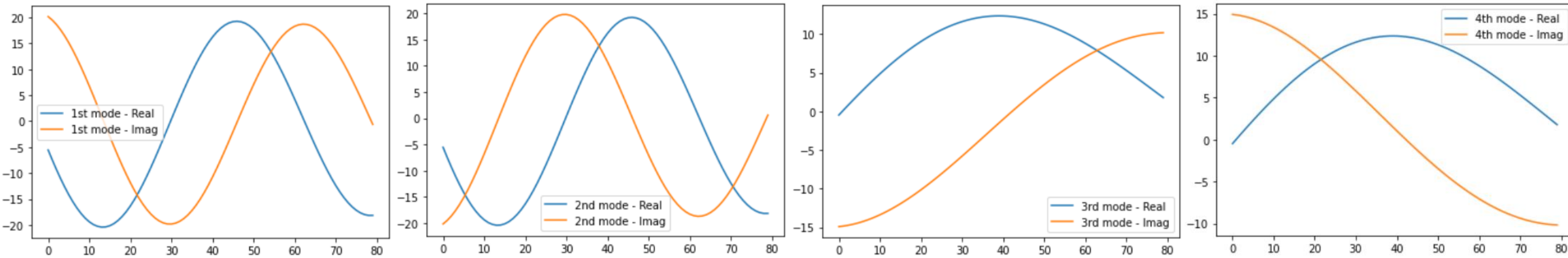


DMD – Example

Traveling wave equation:

$$y = 1\sin(0.1x - 0.1t) + 2\sin(0.2x - 0.2t) + 4\sin(0.4x - 0.4t)$$

Time Dynamics of DMD Modes



DMD + Time Delay Embedding

- **Average Reservoir Pressure**

- Reservoir diffusion

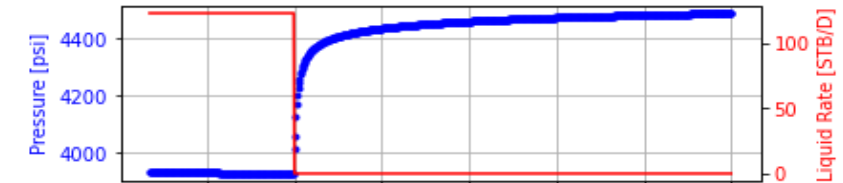
Eigenvalue expansion:

$$P(t, x, y, z) = P_{avg} - \sum_{i=1}^{\infty} c_i a_i(x, y, z) e^{-\lambda_i t}$$

coefficients

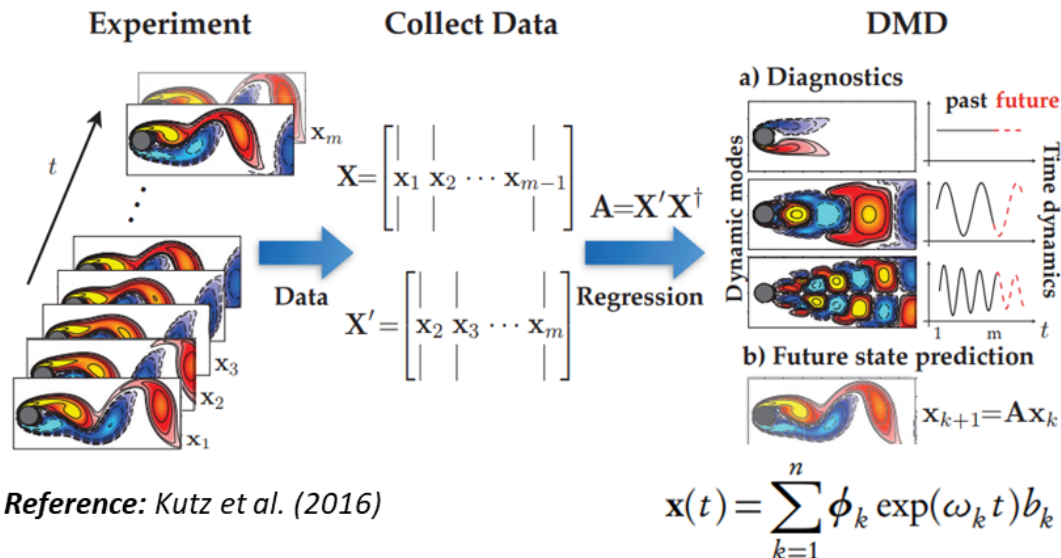
eigenfunctions

eigenvalues

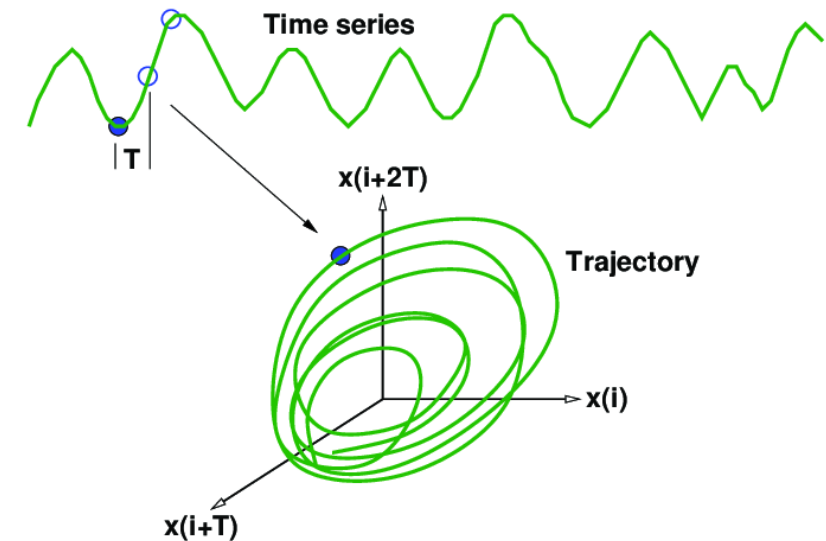


DMD with Time Delay Embedding

Dynamic Mode Decomposition (DMD)



Time Delay Embedding (TDE)



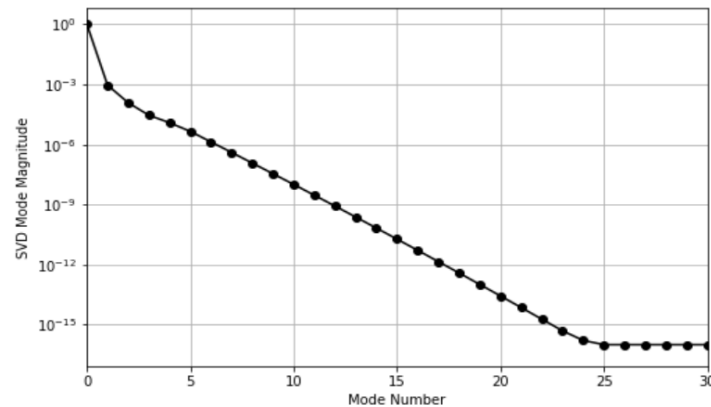
DMD + TDE – Validation With Physics

• Average Reservoir Pressure

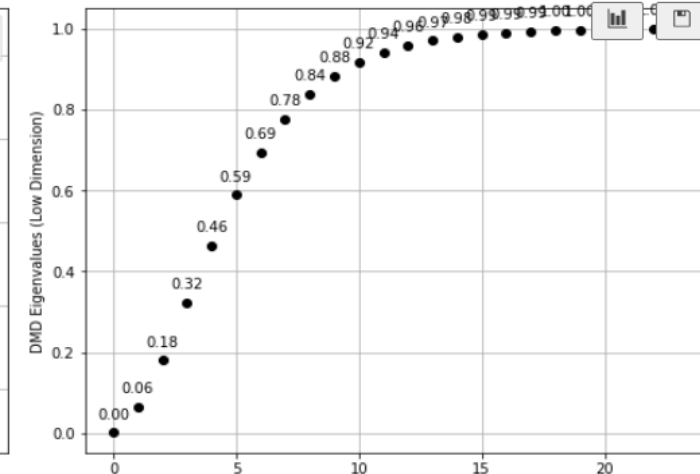
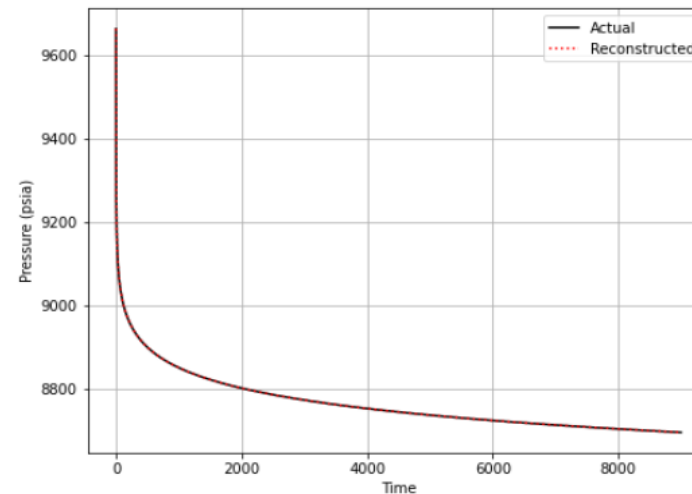
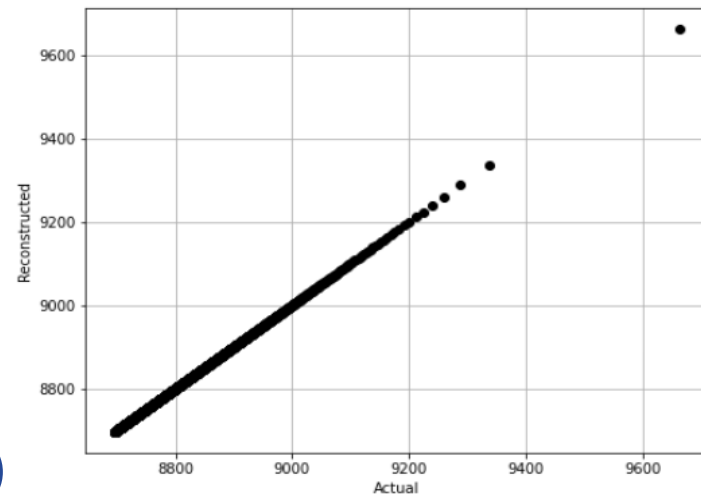
Line source:
$$P(t) = P_i + \frac{70.6 q B \mu}{k h} Ei \left(\frac{-948.1 \phi \mu c_t r_w^2}{k t} \right)$$

Reservoir and well properties

Initial Pressure	10000 psi
Permeability	100 md
Thickness	100 ft
Porosity	0.2
Total Compressibility	1.0E-6 psi ⁻¹
Well Radius	0.5 ft
Viscosity	1.0 cp
Formation Volume Factor	1.0 RB/STB
Constant Flow Rate	10000 STB/d



1000 TDEs
24 DMD modes



Hybrid Sparse Regression

- Average Reservoir Pressure

$$P(t, x, y, z) = P_{avg} - \sum_{i=1}^{\infty} c_i a_i(x, y, z) e^{-\lambda_i t}$$

Sparse Identification of Nonlinear Dynamics (SINDy)

Hybrid analytical, physics-based, non-linear candidate functions

- Radial (Horner)

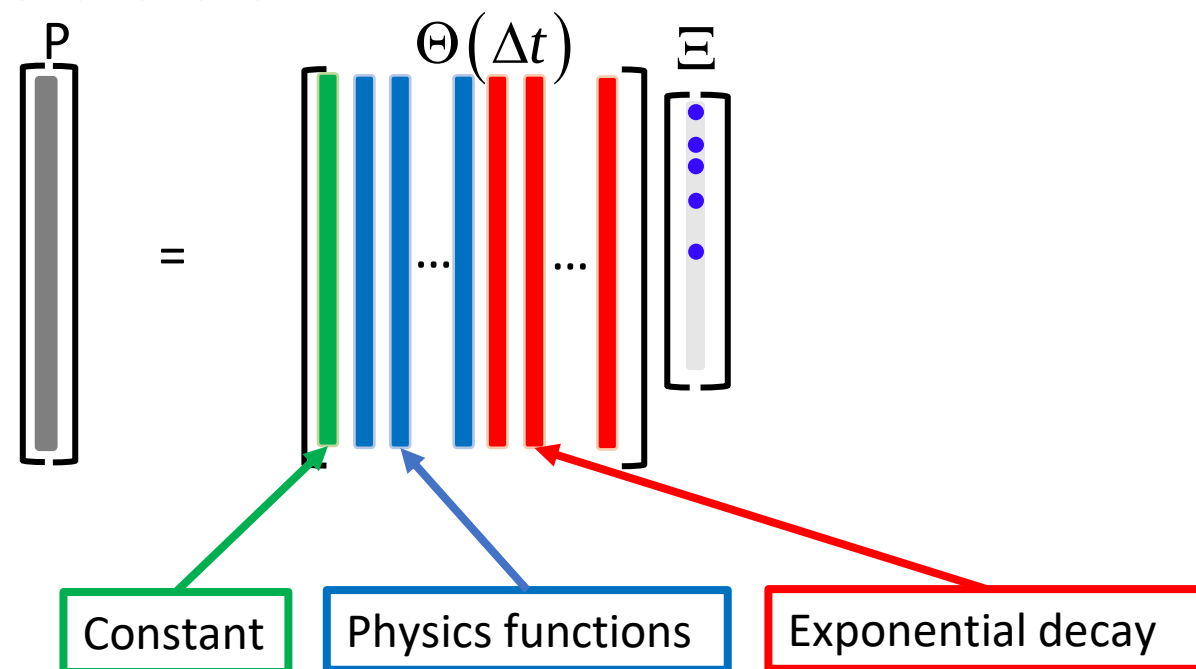
$$P(t) = P_{avg} - m \cdot \ln\left(\frac{t_p + \Delta t}{\Delta t}\right)$$

- Linear

$$P(t) = P_{avg} - m \cdot \Delta t^{\frac{1}{2}}$$

- Spherical

$$P(t) = P_{avg} - m \cdot \Delta t^{-\frac{1}{2}}$$



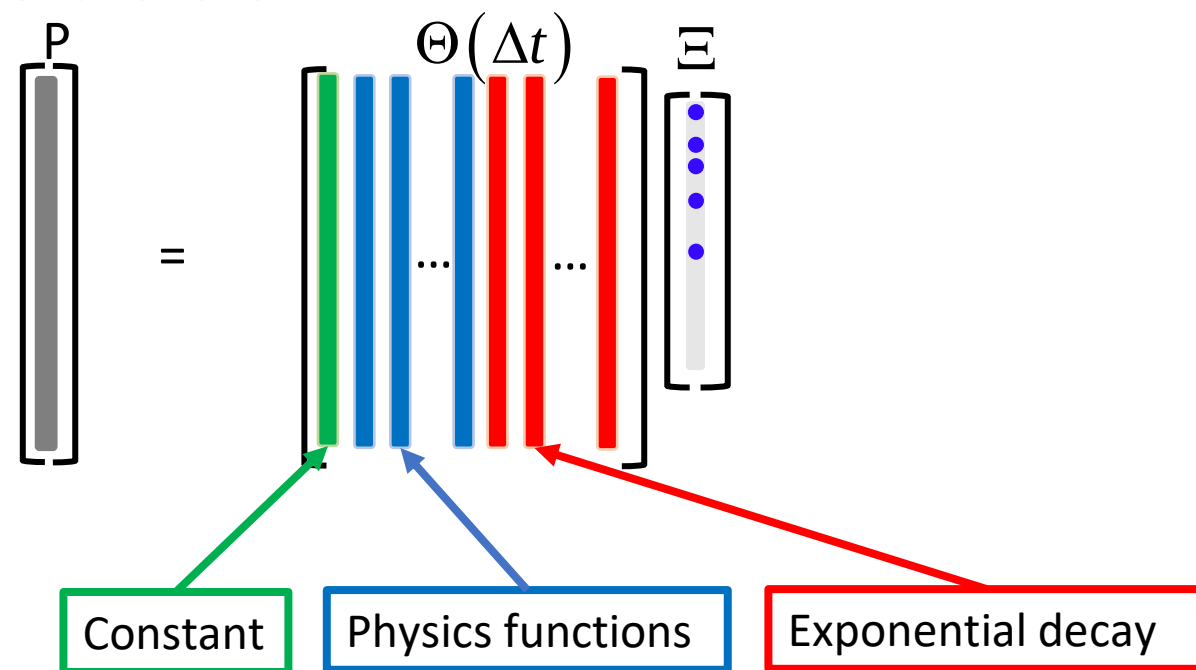
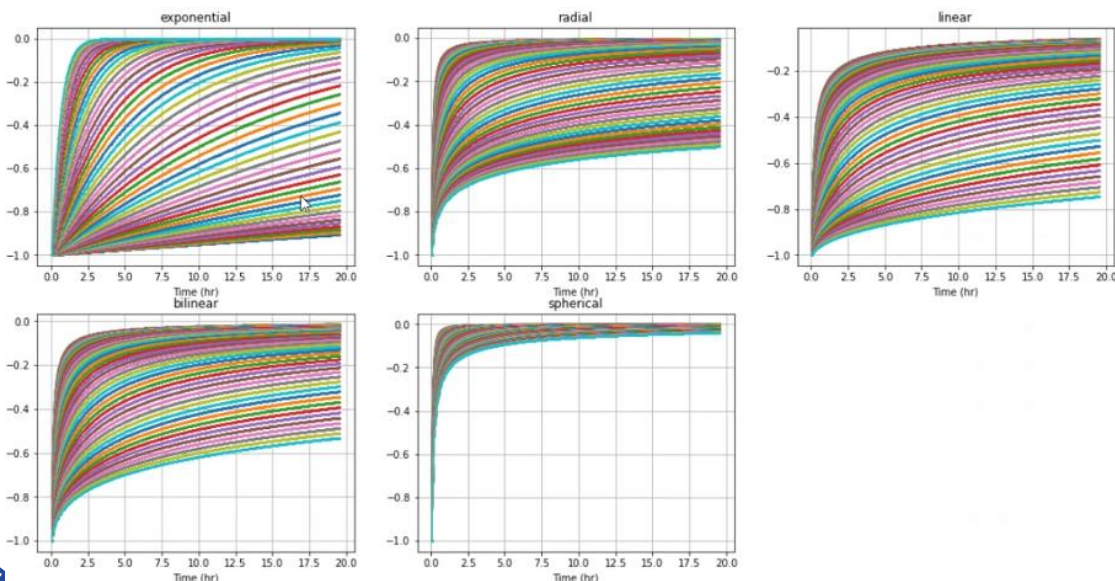
Hybrid Sparse Regression

- Average Reservoir Pressure

$$P(t, x, y, z) = P_{avg} - \sum_{i=1}^{\infty} c_i a_i(x, y, z) e^{-\lambda_i t}$$

Sparse Identification of Nonlinear Dynamics (SINDy)

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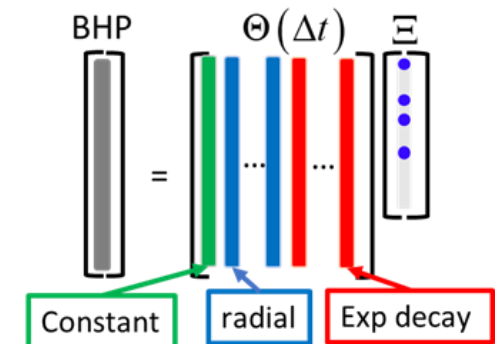
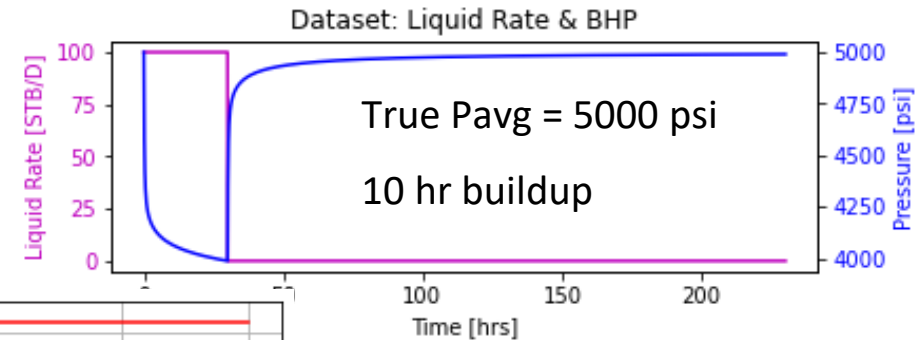
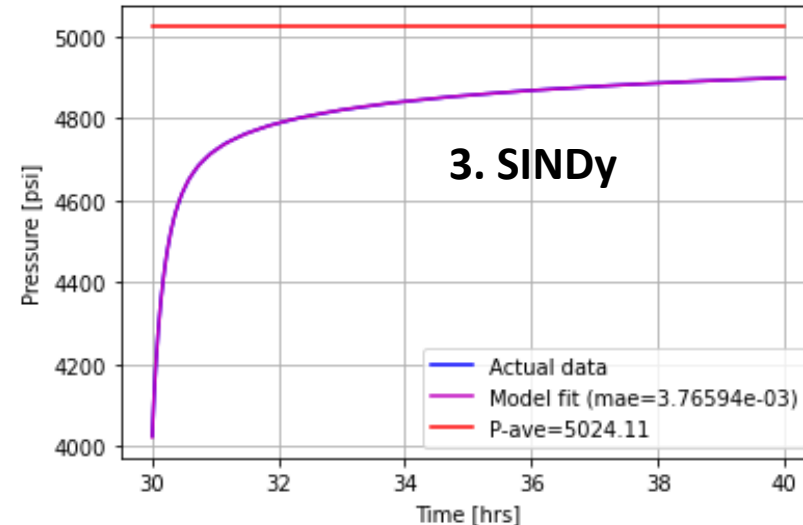
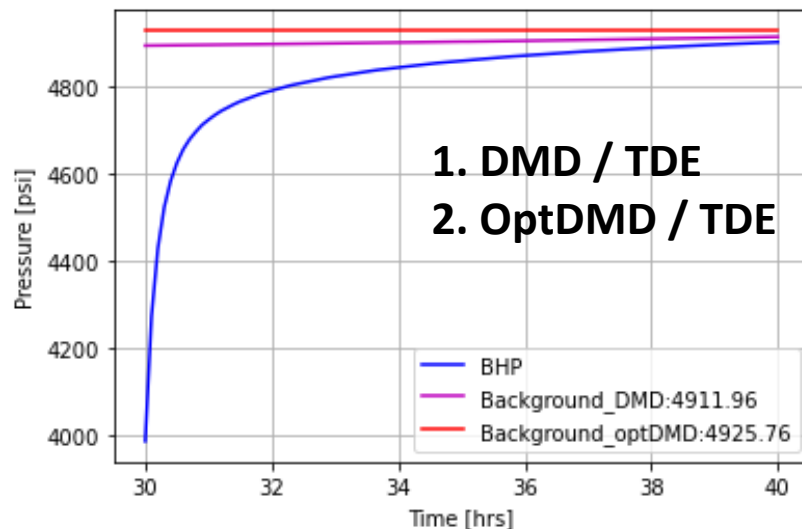
Case Studies

• Average Reservoir Pressure

Case 1 – IARF reservoir with wellbore storage

Method	Pavg (psi)	Error (%)
DMD / TDE	4911.96	1.76
OptDMD / TDE	4925.76	1.48
SINDy	5024.11	-0.48

Porosity	0.2
Permeability (mD)	20.0
Reservoir height (ft)	10.0
Flowrate (stb/day)	100.0
Viscosity (cp)	2.0
Initial reservoir pressure (psi)	5000.0
Formation volume factor (RB/STB)	1.0
Wellbore storage coefficient (bbl/psi)	0.001

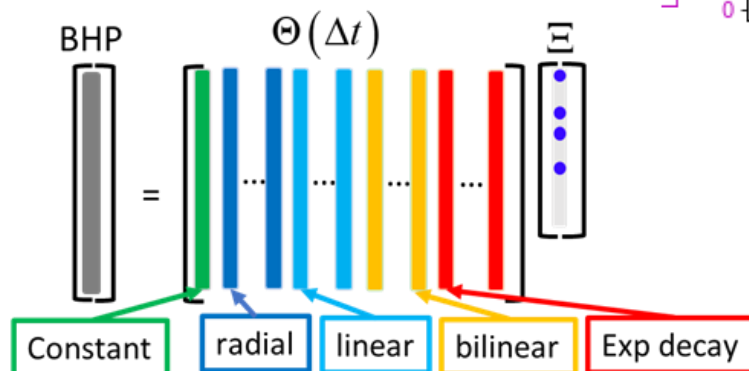
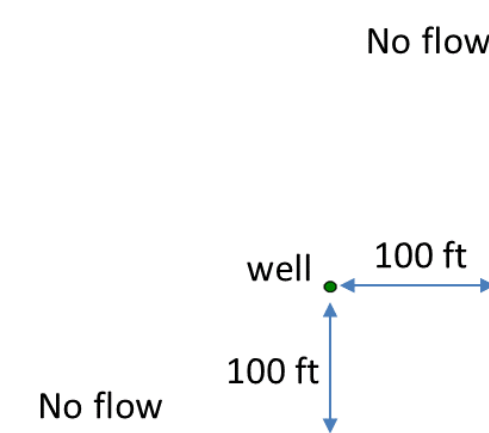
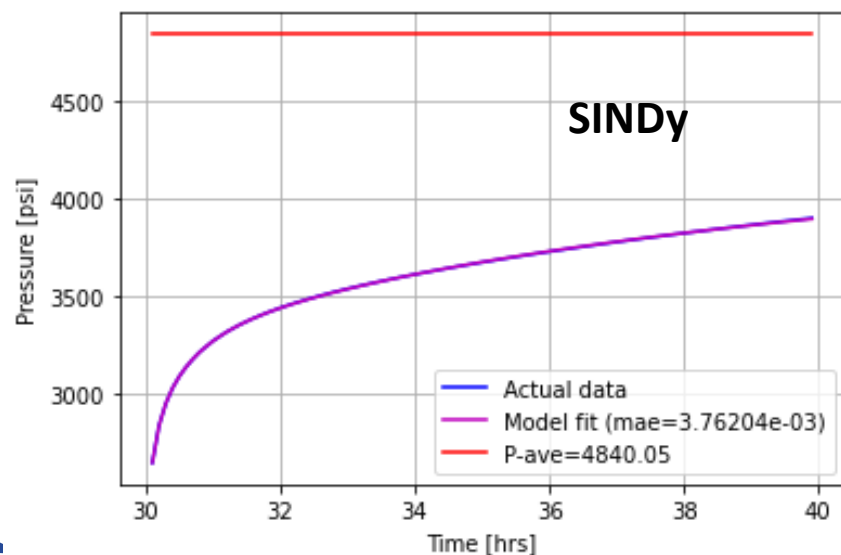


Case Studies

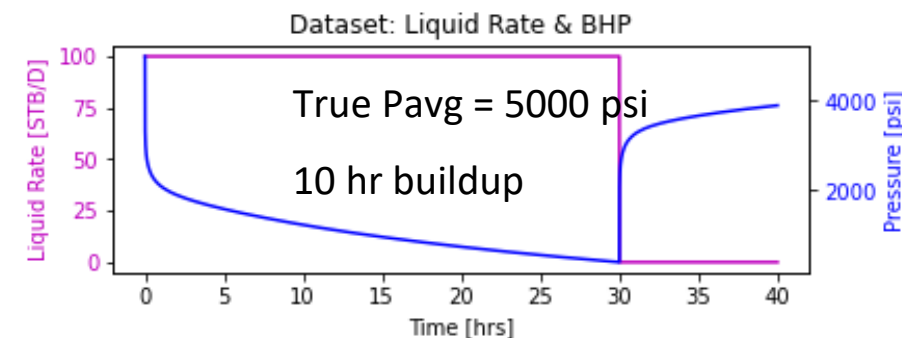
• Average Reservoir Pressure

Case 2 – Two perpendicular no-flow boundaries

Method	Pavg (psi)	Error (%)
Horner	4459.00	10.82
Kuchuk	4262.57	14.75
Crump	4270.15	14.60
SINDy	4840.05	3.20



Porosity	0.2
Permeability (mD)	10.0
Viscosity (cp)	2.0
Formation volume factor (RB/STB)	1.0
Total compressibility (1/psi)	5.0E-6
Flowrate (stb/day)	100.0
Initial reservoir pressure (psi)	5000.0
Reservoir height (ft)	10.0
Wellbore radius (ft)	0.32

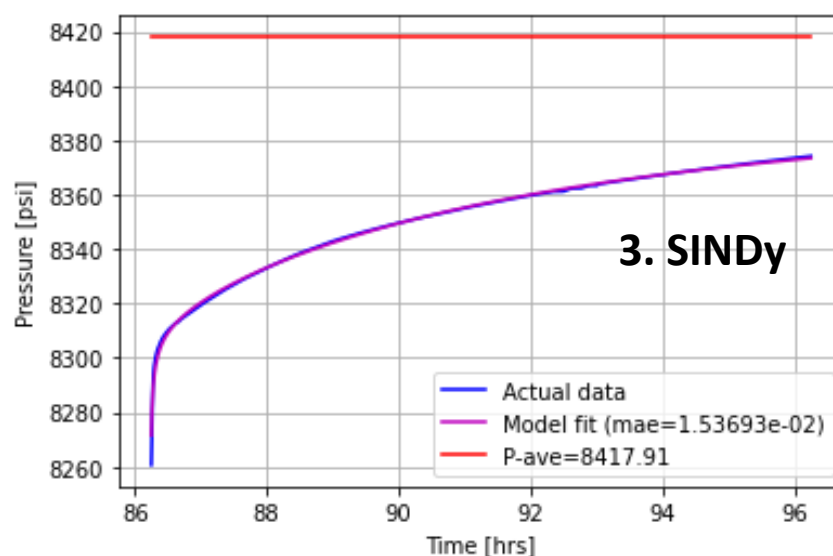
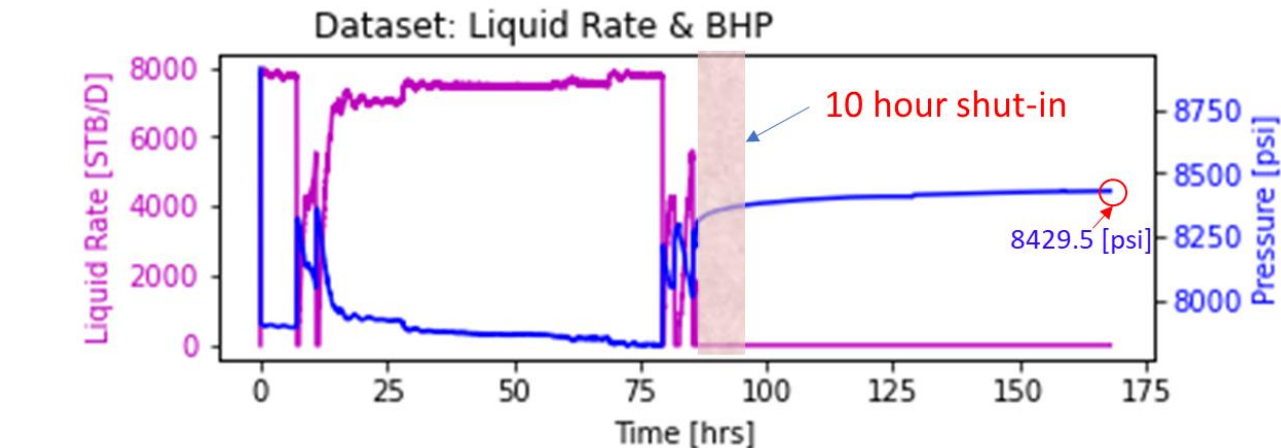
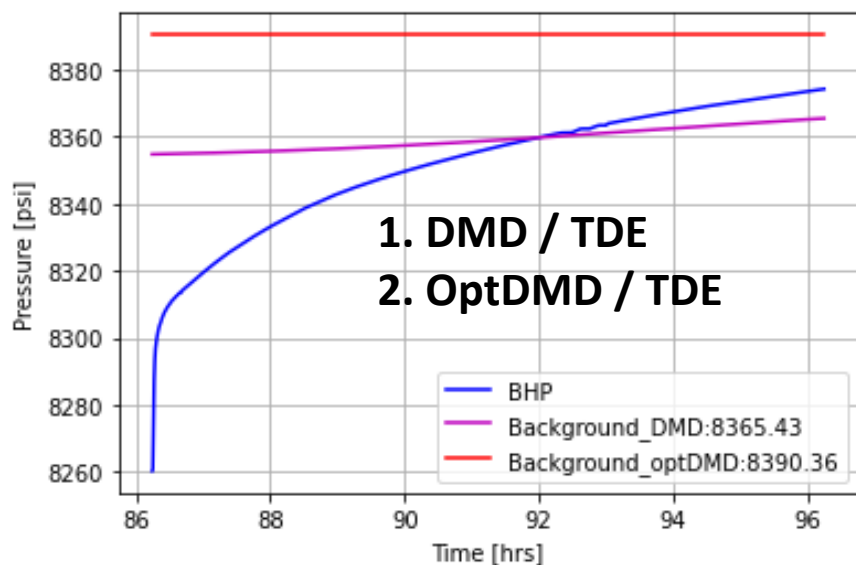


Case Studies

• Average Reservoir Pressure

Case 3 – Field A (Offshore Gulf of Mexico)

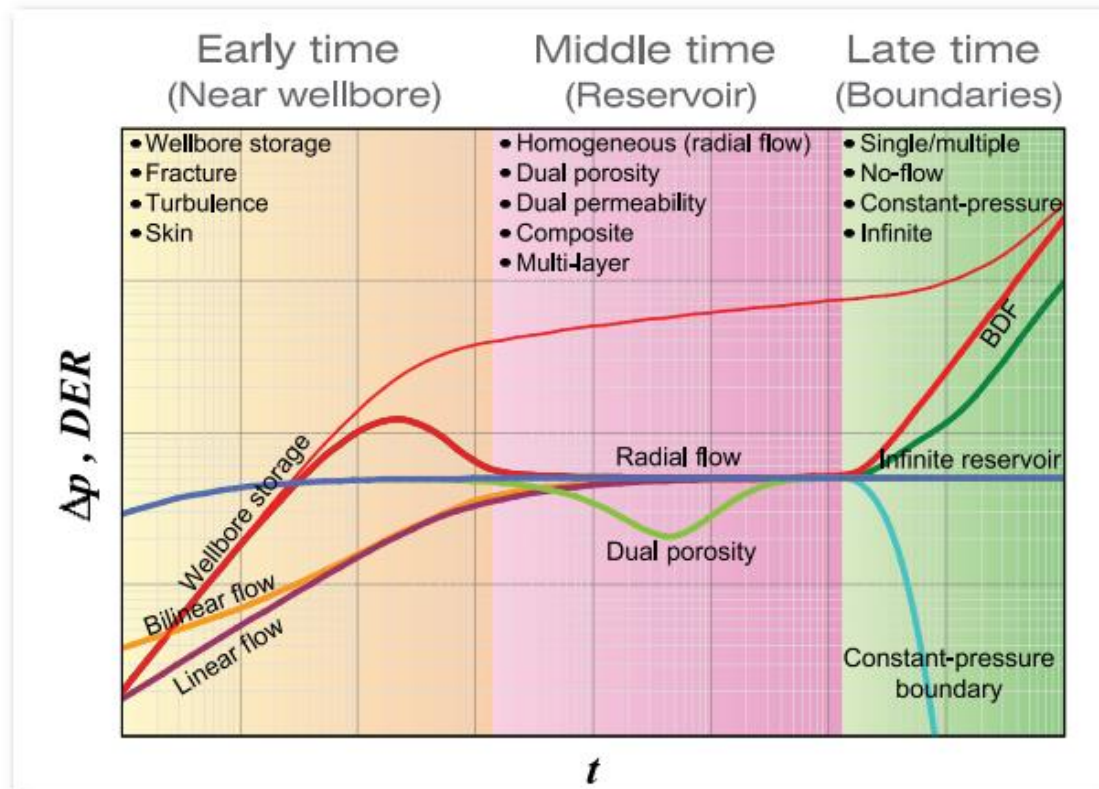
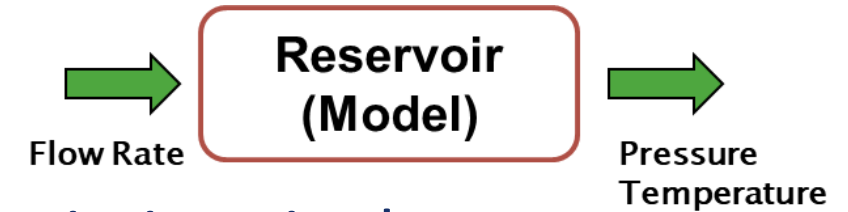
Method	Pavg (psi)	Error (%)
DMD / TDE	8365.43	0.76
OptDMD / TDE	8390.36	0.46
SINDy	8417.91	0.14



Pressure Transient Analysis

- **Productivity Index**

- Could we estimate PI without shutin?
- Build reservoir model from routine operational variations in data



Flow regime		Derivative Slope	Time Function*
Wellbore storage		1	t
Bilinear flow		1/4	$\sqrt[4]{t}$
Linear flow	fracture	1/2	$\sqrt{t}$
	horiz. well		
Spherical flow		-1/2	$1/\sqrt{t}$
Vertical radial flow in horizontal wells		0	$\log(t)$
Radial flow (∞ -acting)		0	$\log(t)$
Linear flow – Channel		1/2	$\sqrt{t}$
Boundary-Dominated Flow		1	t

Physics-Inspired ML Features

- **Productivity Index**

Develop hybrid models (physics + ML) describing relationships between well rate and BHP

Solve regression problem: $y^{(i)} = \theta^T x^{(i)}, i = 1, \dots, n$

Response variable: Pressure

$$y^{(i)} = \Delta p^{(i)}, i = 1, \dots, n$$

BHP Prediction
(virtual shut-in)

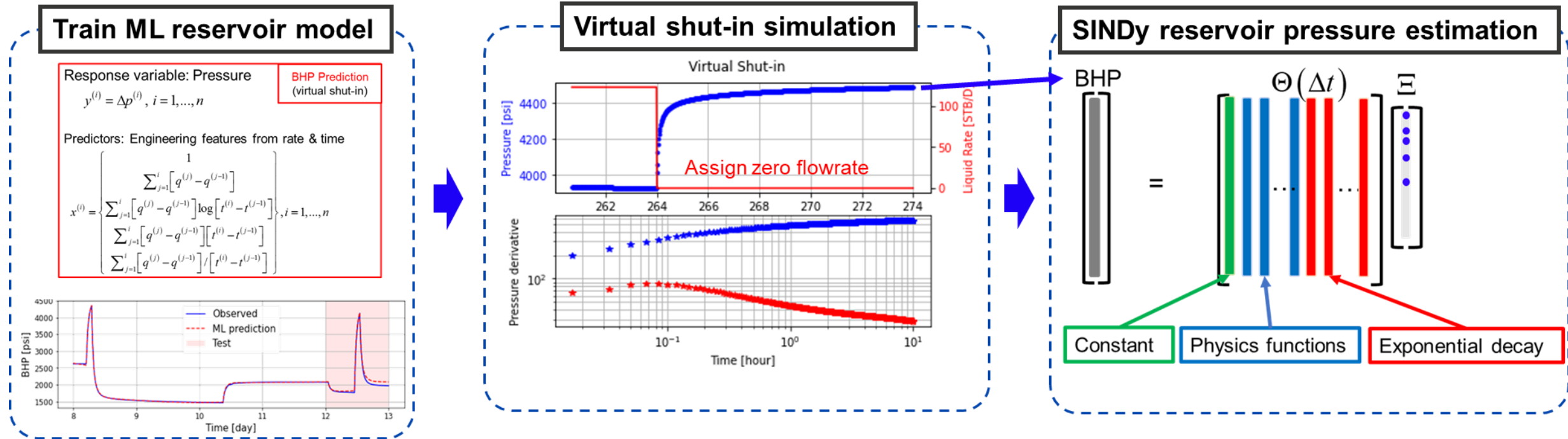
Predictors: Engineering features from rate & time

$$x^{(i)} = \left\{ \begin{array}{c} 1 \\ \sum_{j=1}^i [q^{(j)} - q^{(j-1)}] \\ \sum_{j=1}^i [q^{(j)} - q^{(j-1)}] \log [t^{(i)} - t^{(j-1)}] \\ \sum_{j=1}^i [q^{(j)} - q^{(j-1)}] [t^{(i)} - t^{(j-1)}] \\ \sum_{j=1}^i [q^{(j)} - q^{(j-1)}] / [t^{(i)} - t^{(j-1)}] \end{array} \right\}, i = 1, \dots, n$$

Reference: Tian et al (SPE 174034), Nagao et al (SPE-209300-MS)

Workflow Methodology

• Productivity Index

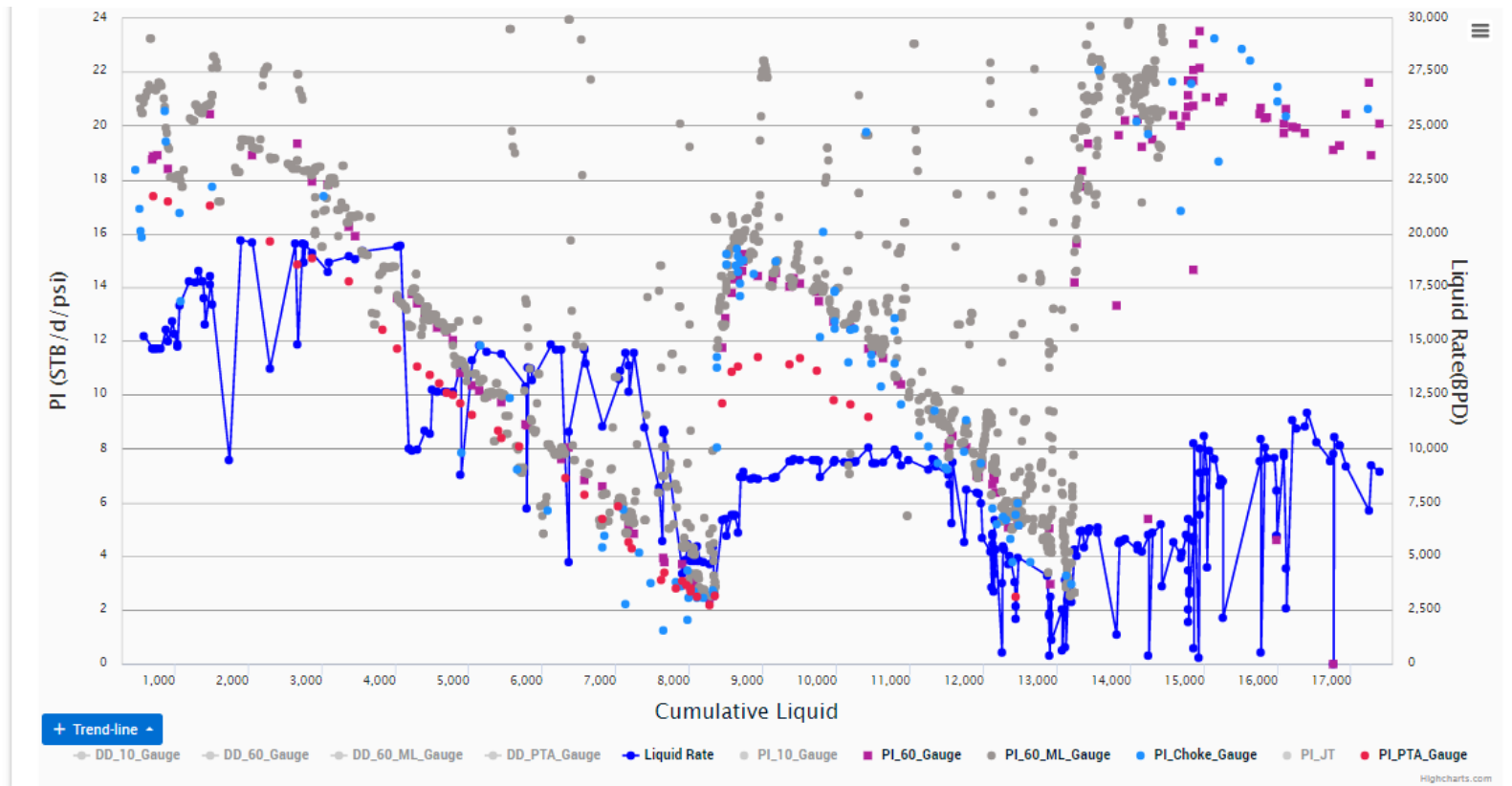


Reference: Tian and Horne (2015), Sankaran et al (2017)

Physics-Inspired ML Features

- **Productivity Index**

Develop hybrid models (physics + ML) describing relationships between well rate and BHP



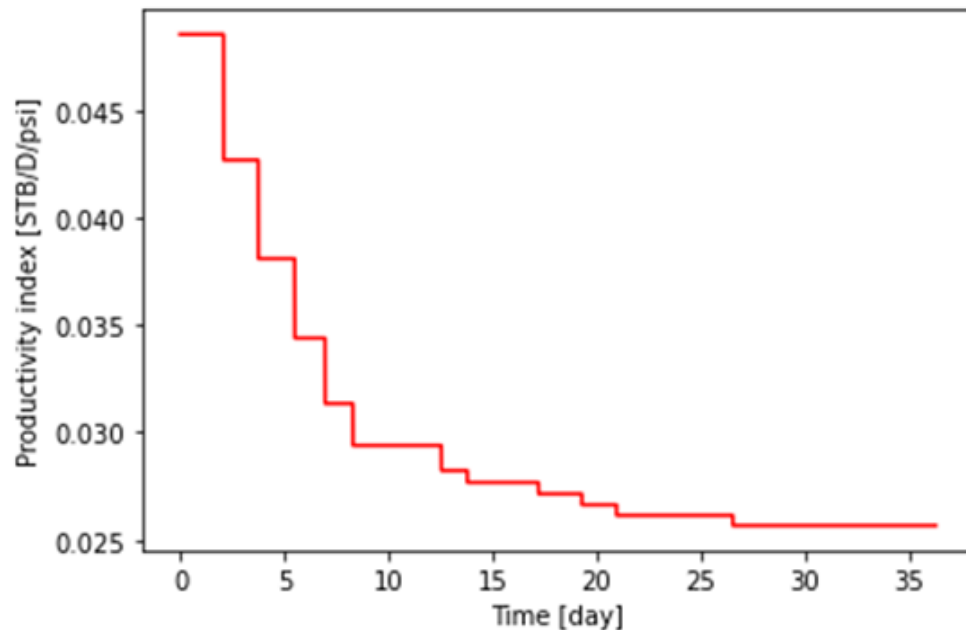
Reference: Sankaran et al (SPE 187222)

Case Studies

• Productivity Index

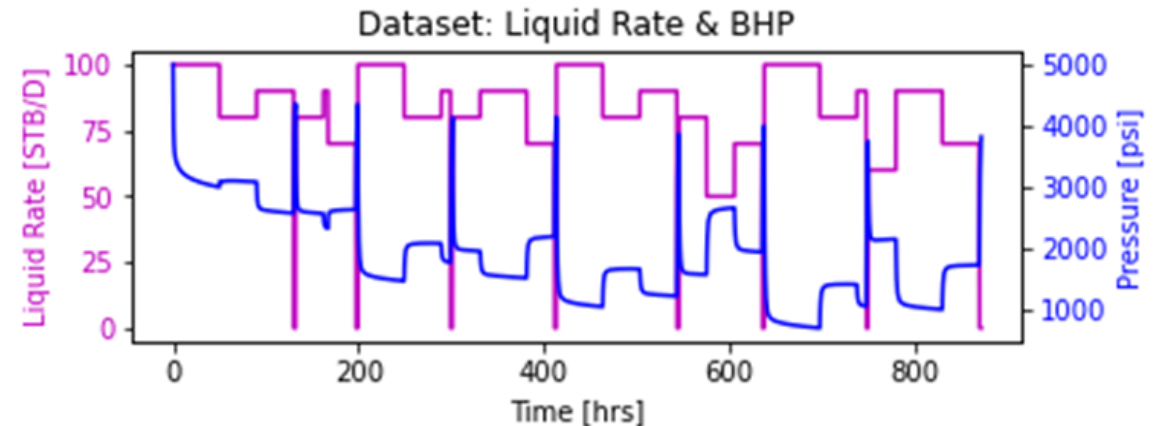
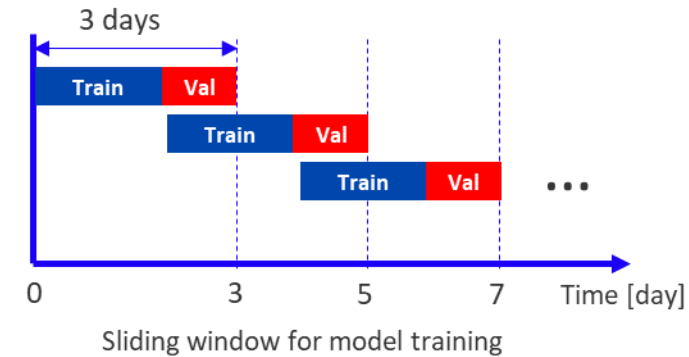
Case 4 – Declining well productivity

- Finite radial flow with closed boundary
- Variable skin, wellbore storage
- PI decline



Reservoir and well properties

perm	20 md
h	10 ft
poro	0.2
Ct	5E-6 1/psi
r_w	0.32
viscosity	2 cp
Pi	5000 psi
B	1 RB/STB
r_e	1000 ft
C	0.001 STB/psi

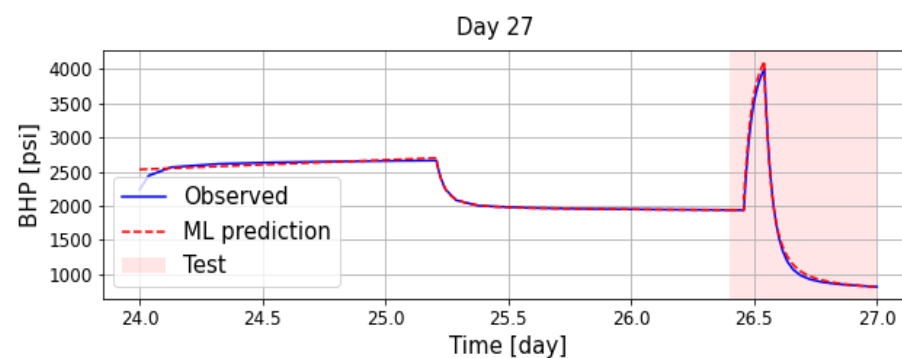
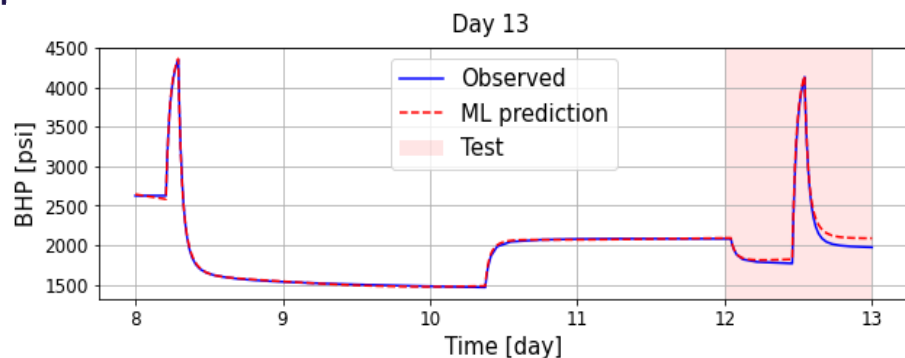


Reference: Nagao et al (SPE-209300-MS)

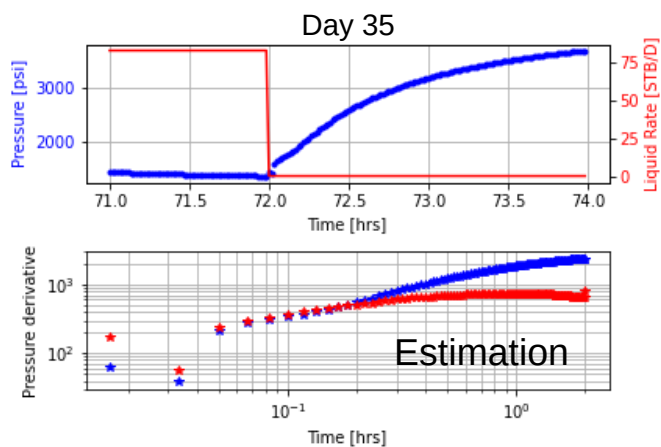
Case Studies

- Productivity Index

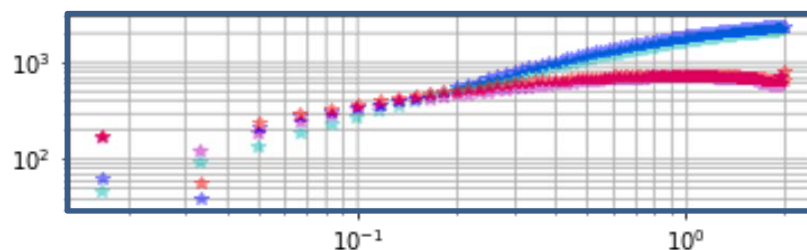
BHP prediction results for selected time frames



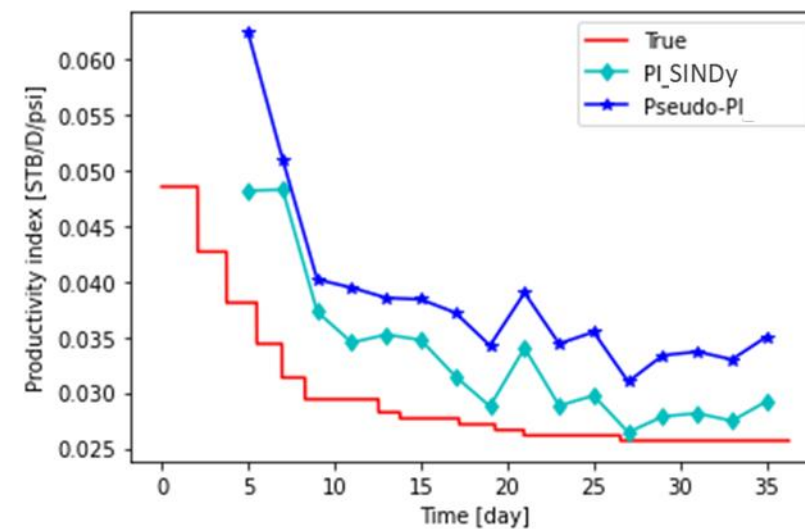
Virtual shut-in results



True vs Calculated Pressure Derivatives

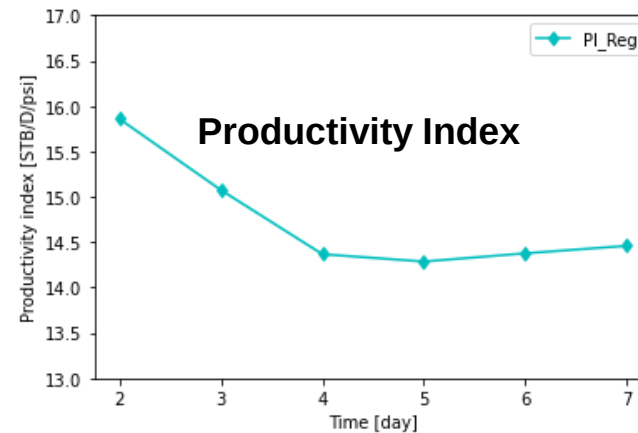
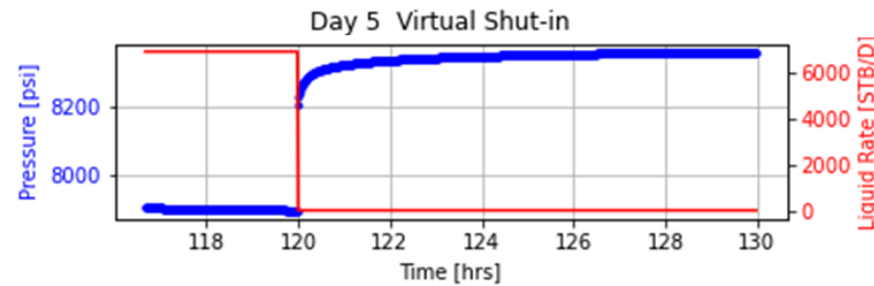
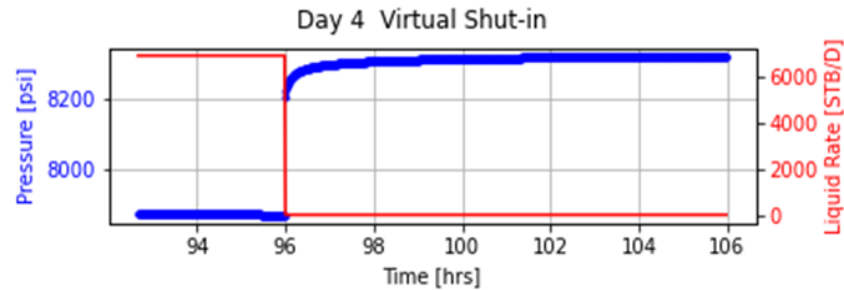
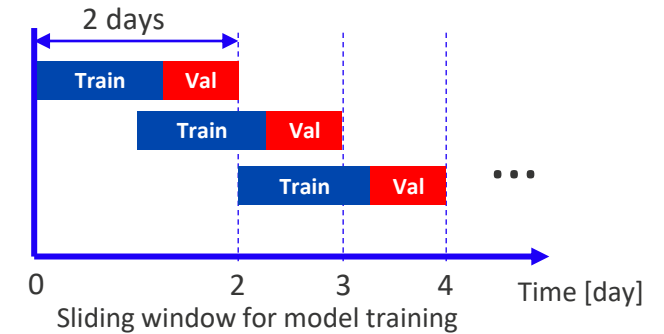
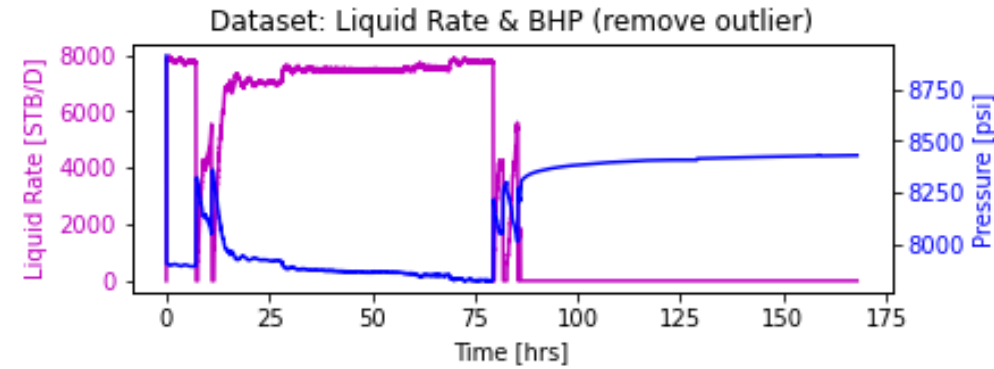


Productivity Index



Case Studies

- **Productivity Index**
Case 5 – Field Application



Reference: Nagao et al (SPE-209300-MS)

Virtual Metering

- Estimate rates from pressure

$$y^{(i)} = \theta^T x^{(i)}, i = 1, \dots, n$$

Response variables: Rate

$$y^{(i)} = \Delta q^{(i)}, i = 1, \dots, n$$

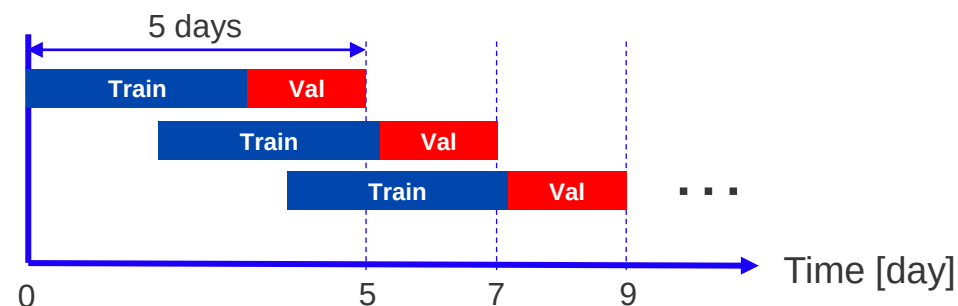
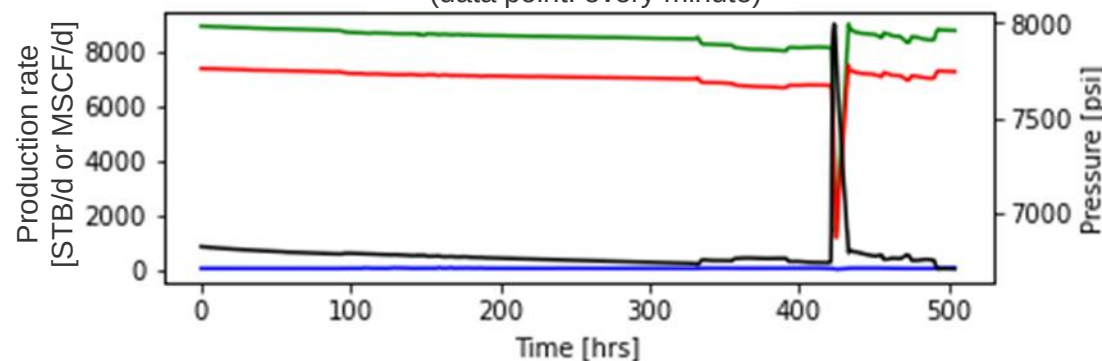
Rate Prediction
(virtual metering)

Predictors: Engineering features from BHP & time

$$x^{(i)} = \begin{Bmatrix} 1 \\ \sum_{j=1}^i [p^{(j)} - p^{(j-1)}] \\ \sum_{j=1}^i [p^{(j)} - p^{(j-1)}] \log[t^{(i)} - t^{(j-1)}] \\ \sum_{j=1}^i [p^{(j)} - p^{(j-1)}] [t^{(i)} - t^{(j-1)}] \\ \sum_{j=1}^i [p^{(j)} - p^{(j-1)}] / [t^{(i)} - t^{(j-1)}] \end{Bmatrix}, i = 1, \dots, n$$

Field data: multiphase flow rate and BHP

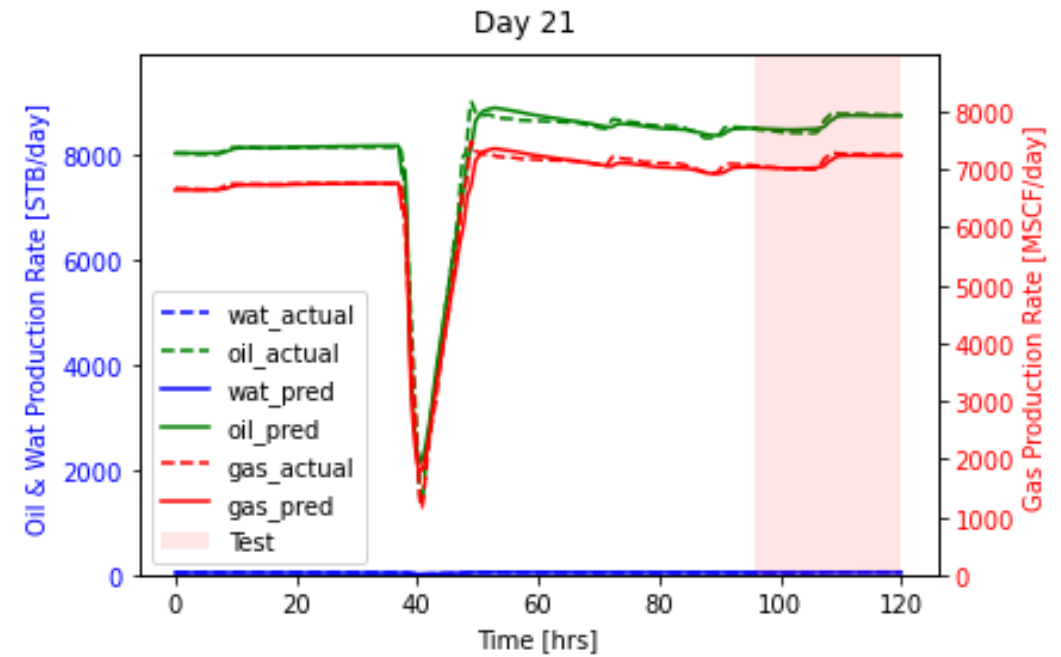
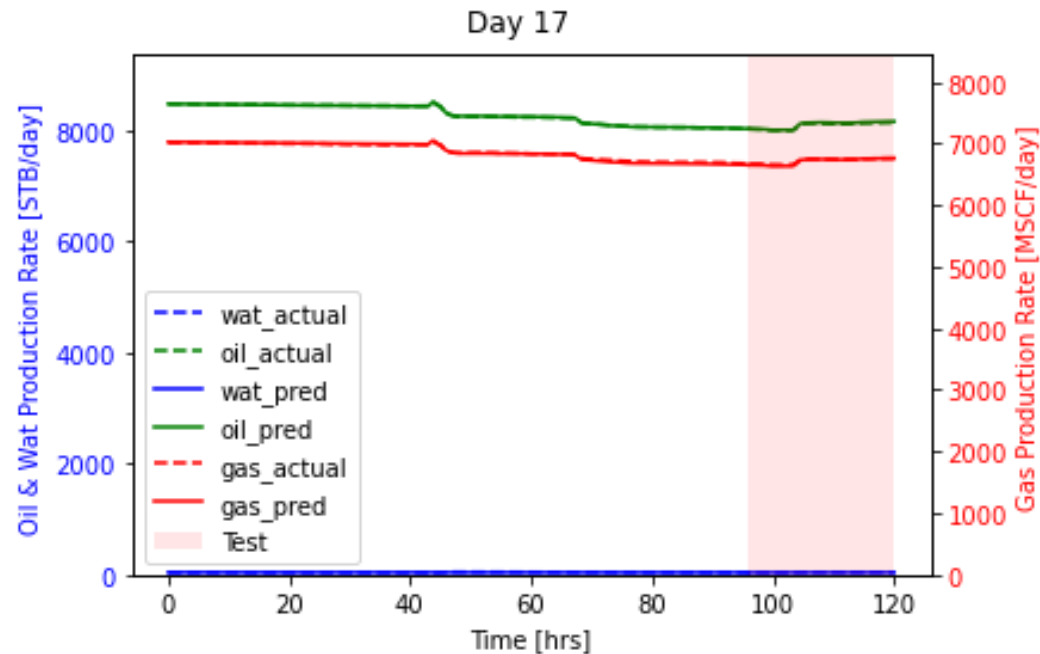
(data point: every minute)



Reference: Nagao et al (SPE-209300-MS)

Case Studies

- **Virtual Metering**
Case 6 – Field application



Summary

- **Hybrid models enable field-scale automation**
 - Balances speed, fidelity, physical consistency and interpretability for field optimization
- **Data-driven discovery of reservoir physics could lead to better interpretations for traditional workflows or new understanding**

Knowledge is of two kinds. We know a subject ourselves, or we know where we can find information upon it.

Samuel Johnson (1709 – 1784)

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