



Hybrid Machine Learning Virtual Flow Metering

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Agenda



- Importance of well flow metering
- Multiphase flow metering methods
- Virtual Flow Metering (VFM)
- Hybrid Machine Learning (ML) VFM
- Project case study
- Summary
- Q & A



Importance of Well Flow Metering



- Production allocation and revenue
 - How much is produced from which well
- Reservoir characterization
 - Reservoir depletion and remaining life, improved oil recovery options
- Flow assurance
 - Slugging, corrosion/erosion, chemical injection, hydrates
- Operations
 - Daily production goals, well control, safe operations



Multiphase Flow Metering



- In-line flow meters
- Separation flow meters
- Virtual flow meters

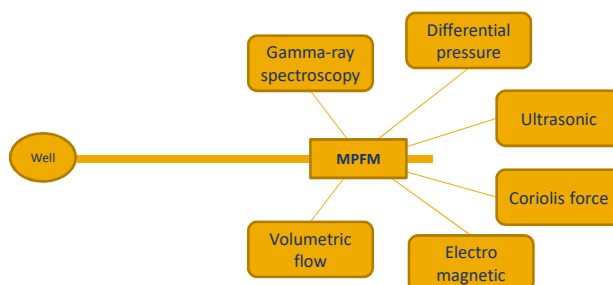


NFOGM: Norwegian Society for Oil and Gas Measurement

In-line Flow Meters



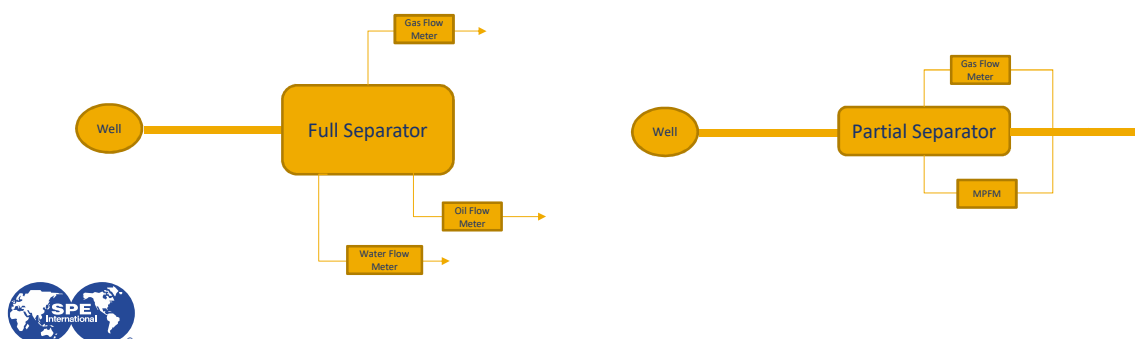
- Direct measurement in the multiphase line without sampling or phase separation
- Measure gas volume fraction (GVF), volumetric flowrate, water-cut, density
- Require pressure and temperature measurements and some fluid properties
- Correlate raw measurements to standard phase flow rates



Separation Flow Meters



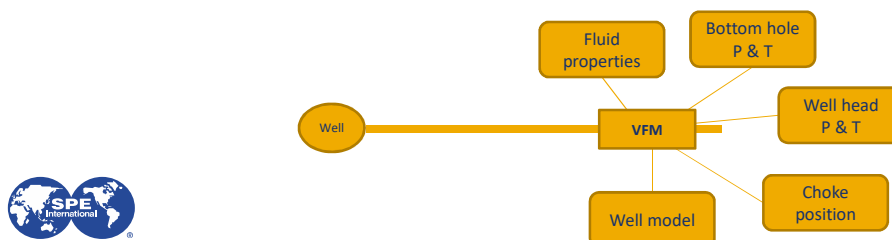
- Full or partial separation of phases before direct measurement using single-phase or multiphase flow meters
- Test separator is common example of full separation flow metering of wells



Virtual Flow Meters



- Use existing sensors to infer phase flow rates
- No direct measurements are performed
- Can be classified into two groups:
 - **Signal processing systems:** estimate flow based on statistical processing or pattern recognition
 - **Process simulation (or model-based) systems:** estimate flow using process models with estimated or measured fluid properties.



Model-based VFM



Simulate multiphase flow in pipes to determine phase flow rates

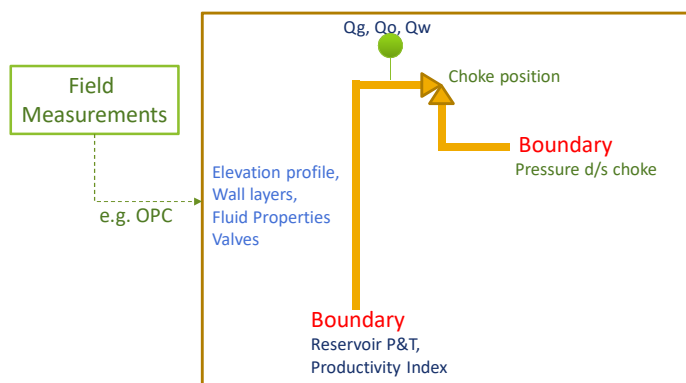
- Steady State models
 - First-principle based models that provide steady state multiphase flow results
- Dynamic models
 - First-principle based models that provide dynamic or transient multiphase flow results



Dynamic Model-based VFM: Basics



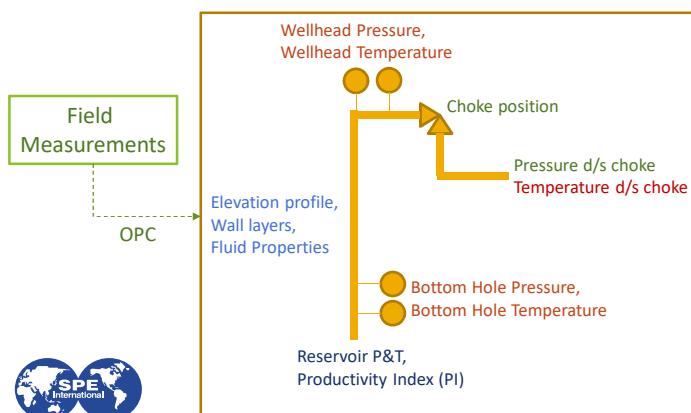
Simulate well hydrodynamics in real-time using available field measurements to set boundary conditions and valve positions



Dynamic Model-based VFM: Calibration



Model must be maintained true to field and calibrated.



- Fluid properties are important!
- Commonly calibrated:
 - Choke bias
 - Ambient temperature
 - Heat Transfer Coefficients
 - Wall roughness
 - Reservoir P&T / PI
- Difficult to estimate:
 - Gas-to-Oil Ratio (GOR)
 - Water-Cut (WC)

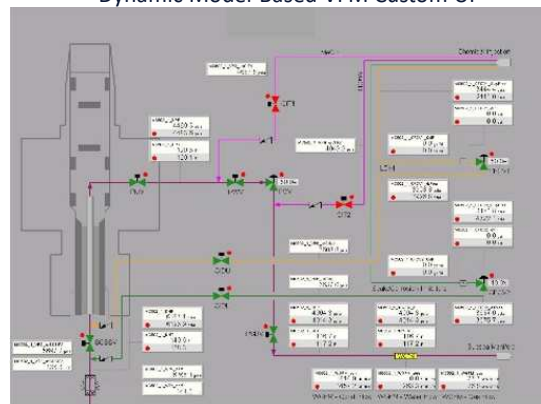
Dynamic Model-based VFM: Basics



Simulate well hydrodynamics in real-time using available field measurements to set boundary conditions and valve positions

- Provide real-time window into the process
- Provide planning and predictive capability
- High fidelity dynamic models of flow process
- Synchronized with the field process

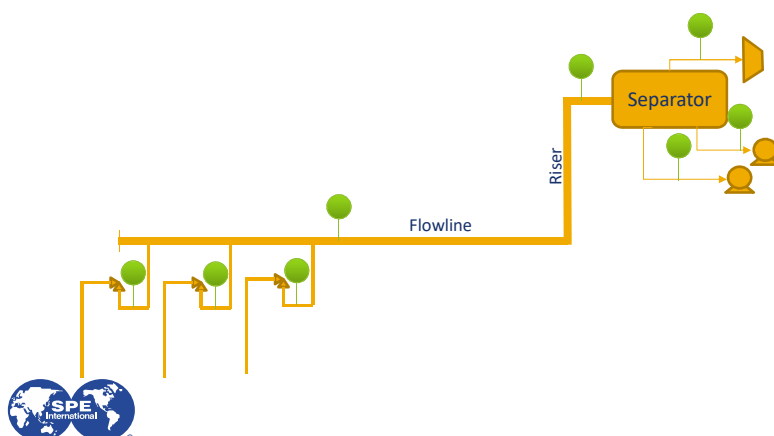
Dynamic Model-Based VFM Custom UI



Dynamic Model-based Production Management Systems



VFM as part of a production management system



Process state at all locations

P & T Profiles along flowlines

Liquid holdup in flowlines

Phase flow in flowlines & wells

Inhibitor rates and holdup

Hydrate monitoring

Leak detection

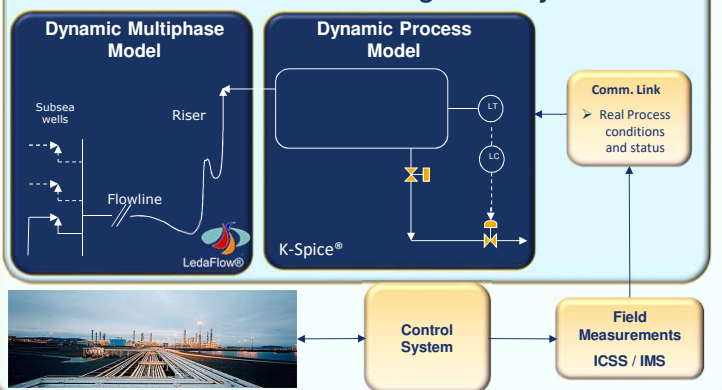
Corrosion & erosion

Equipment performance

KDI Dynamic Model-based Production Management Systems



Online Production Management System



Real-time Simulator

Planning/What-if Simulator

Predictive/LookAhead Simulator

Performance Monitoring

Virtual Flow Metering

Hydrate monitoring

Leak/Blockage detection

Corrosion & erosion Monitoring

Process Optimization

Multiphase Flow Metering Methods Pros & Cons



In-line Metering

- Best direct flow measurement option available currently
- 2% to 20% error
- Costly
- Must be kept calibrated
- May fail over time



Separator Metering

- Conventional
- 1% to 5% error
- Production deferment
- May not be practical for some wells (low flow or flow assurance issues)
- Operational disruption

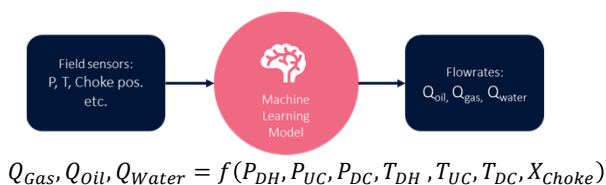
Virtual Metering

- Cost-effective
- 2% to 20% error
- Model must be maintained and calibrated
- Uncertainty in model inputs (GOR/WC)
- Simulator downtime

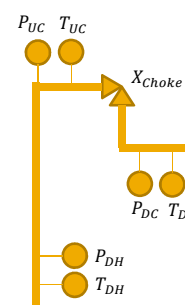
Machine Learning VFM Drivers



Machine Learning is very good at finding relationships between inputs and outputs



- Robust → no model convergence issues
- Simple and fast calculation → no high-end hardware required; model speed is a non-issue
- Easy to deploy → No need for frequent model monitoring or calibration
- Scalability → No issues going from 10 to 1,000 ML models on the same hardware
- Can estimate GOR or Water-cut



Machine Learning requires large **quantities of quality** data

Machine Learning VFM Challenges



Challenges for ML Flow Metering using field data:

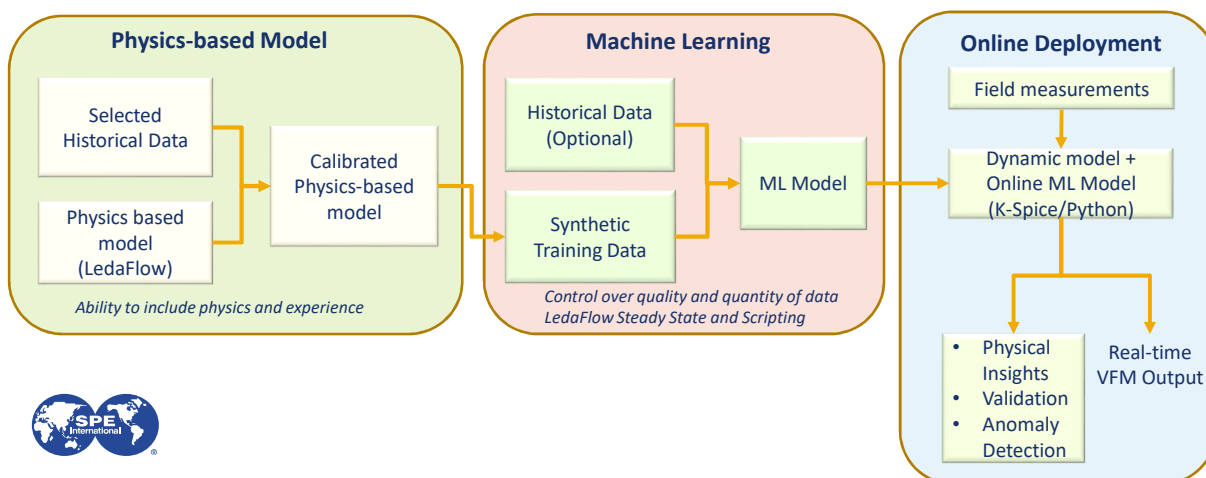
- **Quantity** of field data is not always available
 - Green field; little historical data
 - Faulty/missing measurements
- **Quality** field of data is not always available
 - Data at all possible choke openings, flow rates, expected GORs and water-cuts



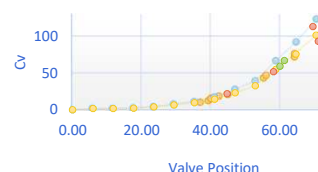
Hybrid Machine Learning VFM



Physics-based models (Synthetic data) + Machine learning



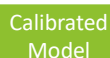
Hybrid ML VFM for Oil well; Measurement data available over 3 years



- Choke Cv curve
- HTC
- Roughness/friction factors



$$Q_{Gas}, Q_{oil}, Q_{Water} = f(P_{DH}, P_{UC}, P_{DC}, T_{DH}, T_{UC}, T_{DC}, X_{choke})$$

$$\begin{aligned} P_{DC} &= \{1000 \dots 9000\} \text{ psig, Np} \\ Q_{oil} &= \{0 \dots 20,000\} \text{ sbpd, Nq} \\ GOR &= \{400 \dots 800\} \text{ scf/sbbl, Ng} \\ WC &= \{0 \dots 100\} \%, Nw \\ X_{choke} &= \{0 \dots 100\} \%, Nx \\ T_{DH} &= \{200 \dots 300\} \text{ F, Nt} \end{aligned}$$


Synthetic Data

Run LedaFlow Steady State using automated scripting

$$Q_{Gas}, Q_{Oil}, Q_{Water}, P_{DH}, P_{UC}, P_{DC}, T_{DH}, T_{UC}, T_{DC}, X_{Choke}$$
[illegible]

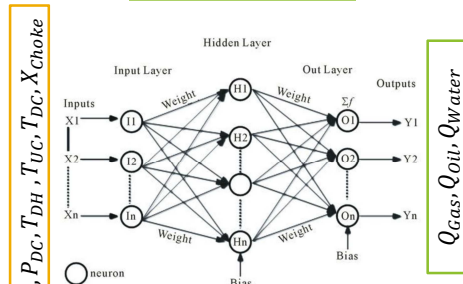
Total number of data points =
 $N_p * N_q * N_g * N_w * N_x * N_t$



Case Study: Hybrid ML VFM Machine Learning



Machine learning



Can apply physical insights by combining inputs; but not necessary

$$\sqrt{P_{UC} - P_{DC}}$$

$$\Delta P = P_{DH} - P_{UC}$$

$$\Delta T = T_{DH} - T_{UC}$$



- Some details on ANN training
 - Activation function = ReLU
 - Adam optimizer
 - Loss function = mean squared error
- Available ML tuning parameters
 - number of hidden layers
 - Number of nodes in a hidden layer
 - Learning rate
 - Batch size
 - Epochs
- If expected accuracy against test data not achieved, then tune or generate more training data and re-train
- Select the best ML model

Case Study: Hybrid VFM ML VFM Accuracy

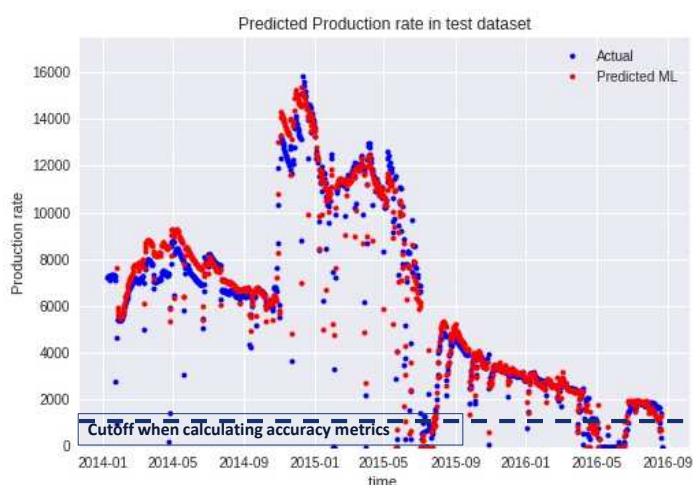


Comparison against field measured data

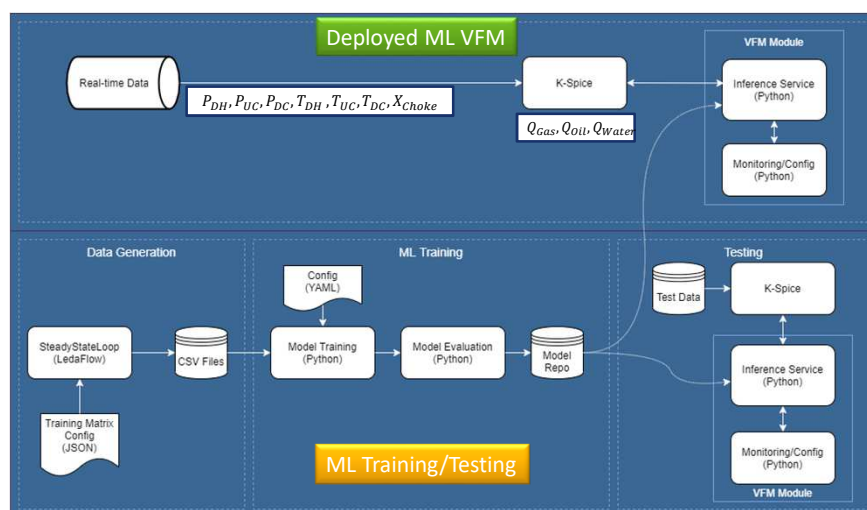
Red dots: ML-predictions
Blue dots: Real measurements

Key accuracy metrics:

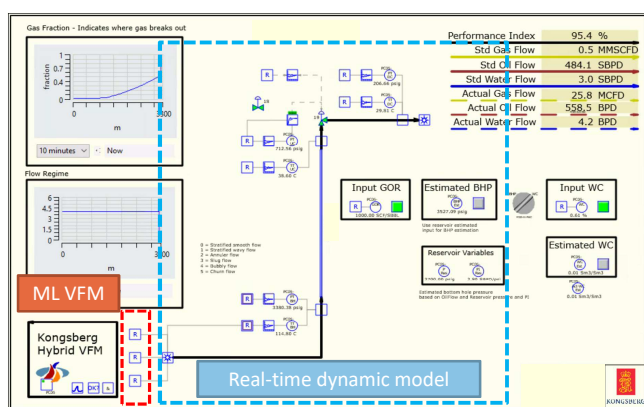
Mean absolute error: 450
Mean absolute %-error: 5 %
Cumulative error: 2 %



Case Study: Hybrid VFM Online Deployment

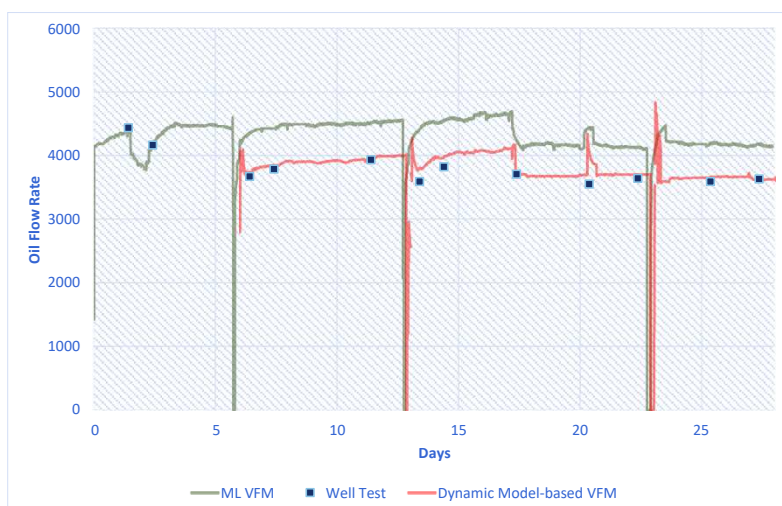


Case Study: Hybrid VFM



- **ML VFM + dynamic model**
 - ML VFM provides inlet flow boundary conditions; no need for manual input of GOR or Water-cut
 - Dynamic model provides flow assurance insights
 - VFM decoupled from dynamic model issues; always available
 - ML VFM can be used as inputs to pipeline management systems
 - Deviation from measurements indicate real issues: flowline blockage; choke erosion/blockage etc.

Case Study: Hybrid VFM Comparison & Insights



Summary



- ML VFM is type of signal processing/pattern recognition virtual metering
- Hybrid ML VFM provides best of both worlds approach (ML + dynamic models)
- ML VFM computation effort is front-loaded; instant estimations
- Robust; no dynamic model convergence or calibration issues
- Confidence and accuracy by validating results in a physics-based model
- Increased knowledge about the wells to be monitored when combined with dynamic model; anomaly detection possible (flowline/choke blockage)
- Implements seamlessly into a production management system
- Subject matter expertise required to develop good hybrid ML models



Q & A



Thank you!

