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SUBPRO Zero

High-Dimensional State Estimation with Commercial Process Simulators Using a Variant of the Unscented Kalman Filter

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Motivation

- Process Simulators
  - Can make it easier to model complex processes
  - Can be more trustworthy
  - Access to the simulators internals can be limited
- We want to use one for state estimation

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State Estimators

Extended Kalman Filter (EKF)

Needs the Jacobian

Unscented Kalman Filter (UKF)

Can be unstable with many states

Cubature Kalman Filter (CKF)

Without the central point

Moving Horizon Estimator (MHE)

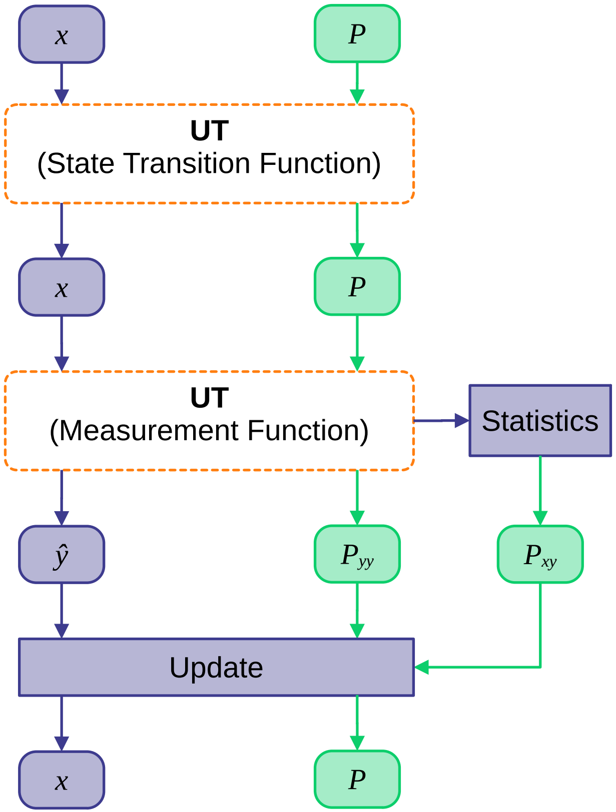
Needs the model equations directly

Particle Filter (PF)

Computationally Expensive

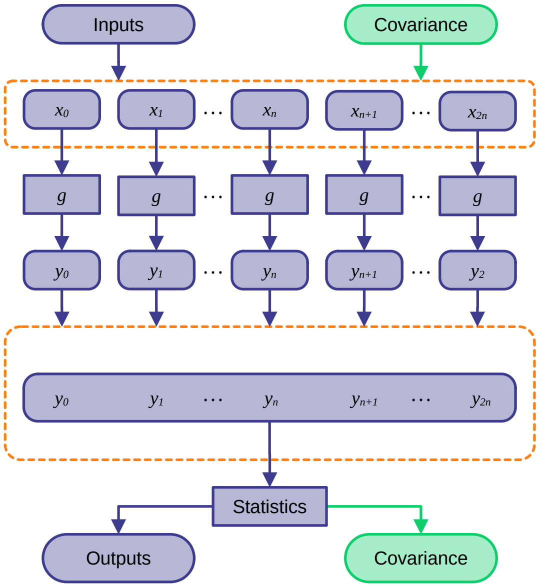
Unscented Kalman Filter (UKF)

- Compared to the Extended Kalman Filter
  - Does not require the Jacobian
  - Uses instead the Unscented Transformation (UT)
- Can be used with a black-box model
- We use the UKF due to a recent innovation with the UT



Unscented Transformation (UT)

- Based on approximating the result of a nonlinear function
- Propagates sigmapoints
  - Selected from the probability distribution
- Weights
  - Determined by the probability distribution and number of states
  - The central point can be negative



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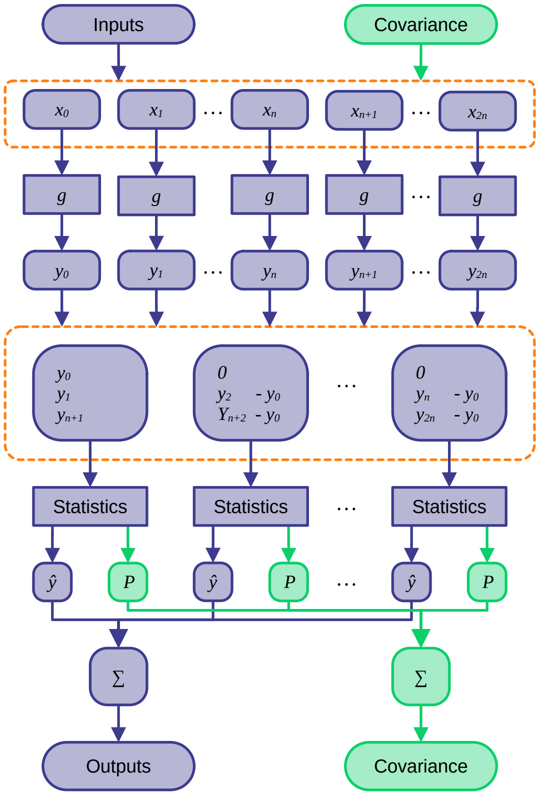
High-Dimensional Unscented Transformation (HD-UT)

- A reformulation of the UT
  - Splits the sigmapoints
  - A single split retains the central point
  - Recombines the results to get the mean and covariance
- Effects
  - Arbitrary number of states
  - Optimal weights



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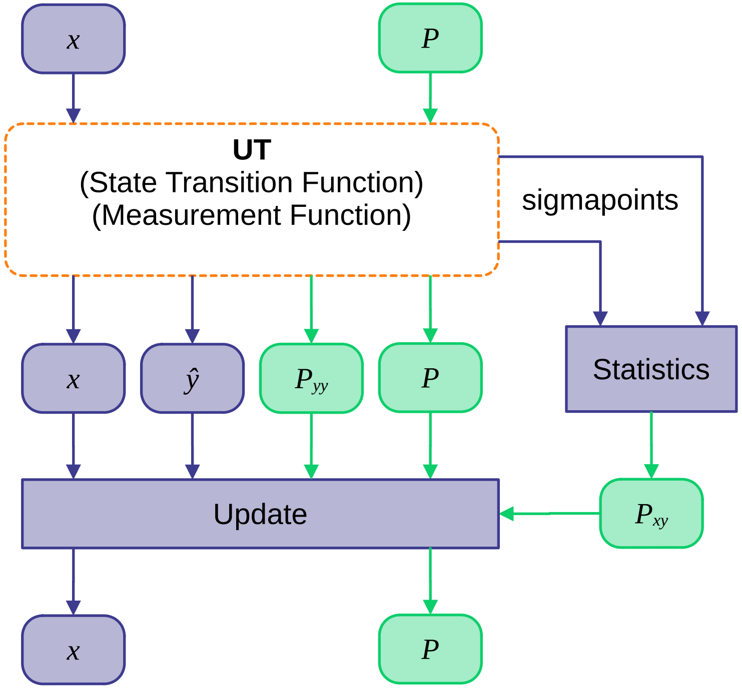
Unscented Kalman Filter (UKF)

- For use with Process Simulators
  - Returns states and measurements simultaneously
- We skip the second UT
  - Which is optional, but increases accuracy



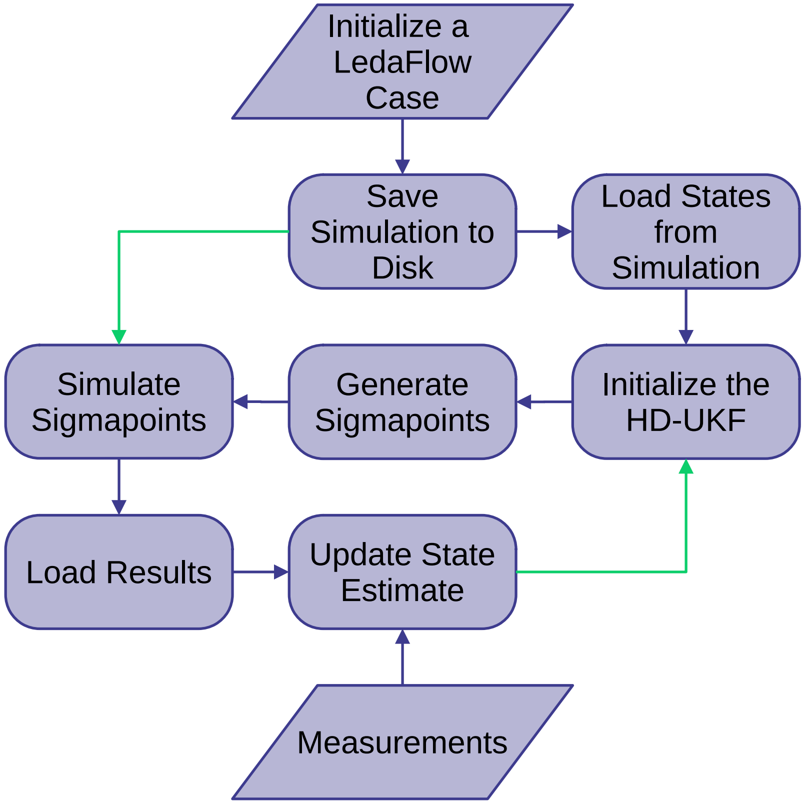
States

- Process Simulator Downside
  - For State Estimation
  - The state Expression is fixed
- Kalman Filter assumptions
  - Gaussian Distribution
  - Unconstrained values

- Fractions violate these
  - All must be within [0,1]
  - All must sum to 1
  - DOF = # of Fractions – 1
- We use a logratio transformation
  - Which reduces the number of variables
  - $z_i = \log \frac{x_i}{x_1} \forall i = 2 \ldots n$

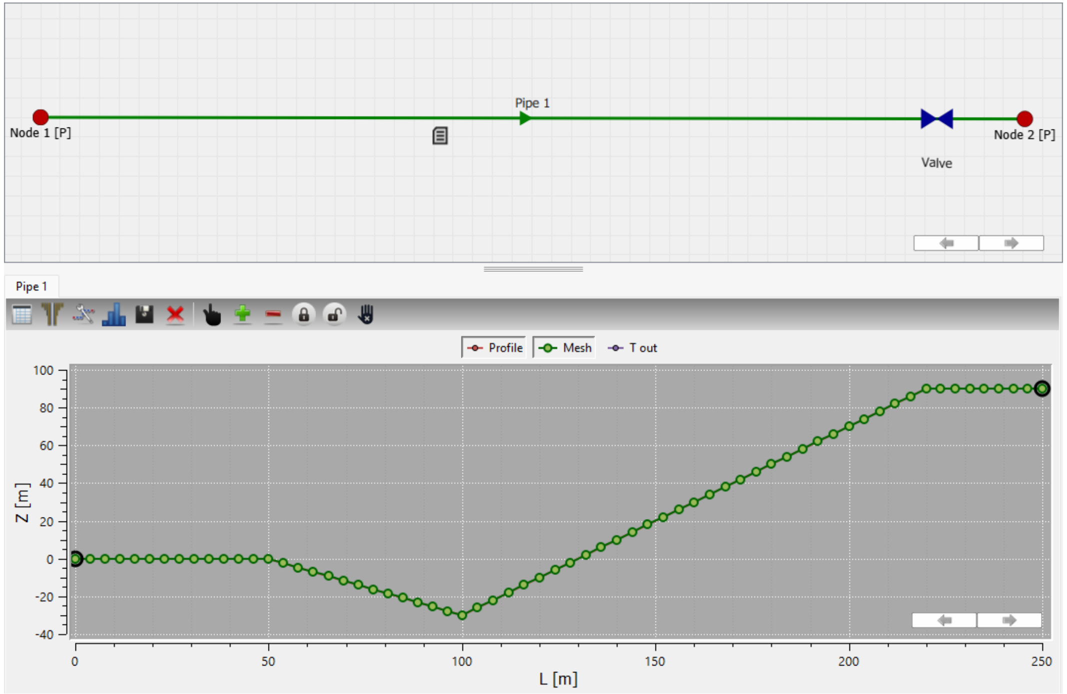
Implementation

- We have implemented the method for a case in LedaFlow
  - Which is an Oil & Gas simulator
- The number of states depend on the number of phases
  - 2 phases: 9 states,
  - 3 phases: 13 states,
  - Which scales with the number of nodes



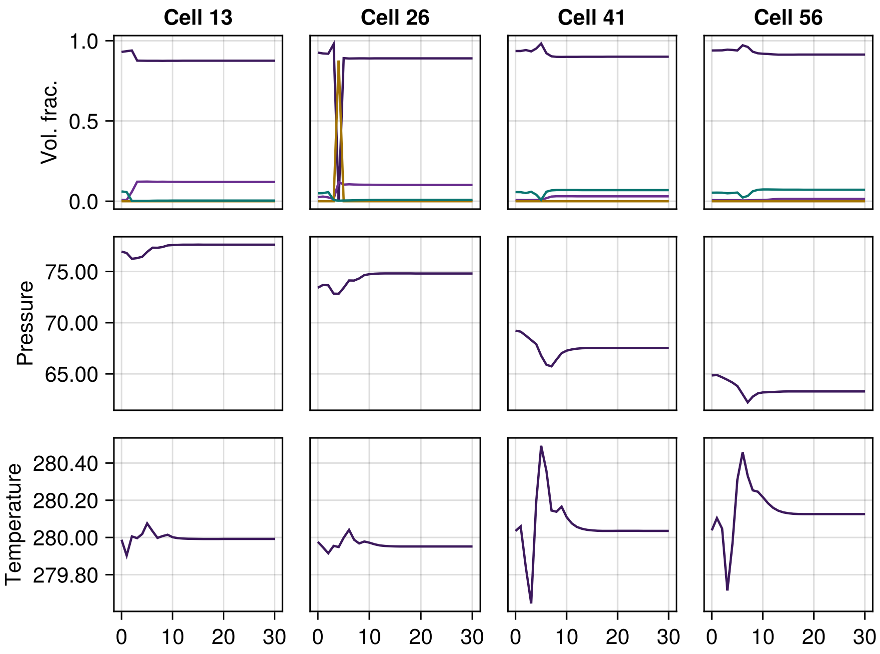
LedaFlow Case

- Simple Riser
  - Two Phases
  - Valve with a fixed opening
  - Pressure specified boundary conditions
- Measurement
  - Pressure in the bottom



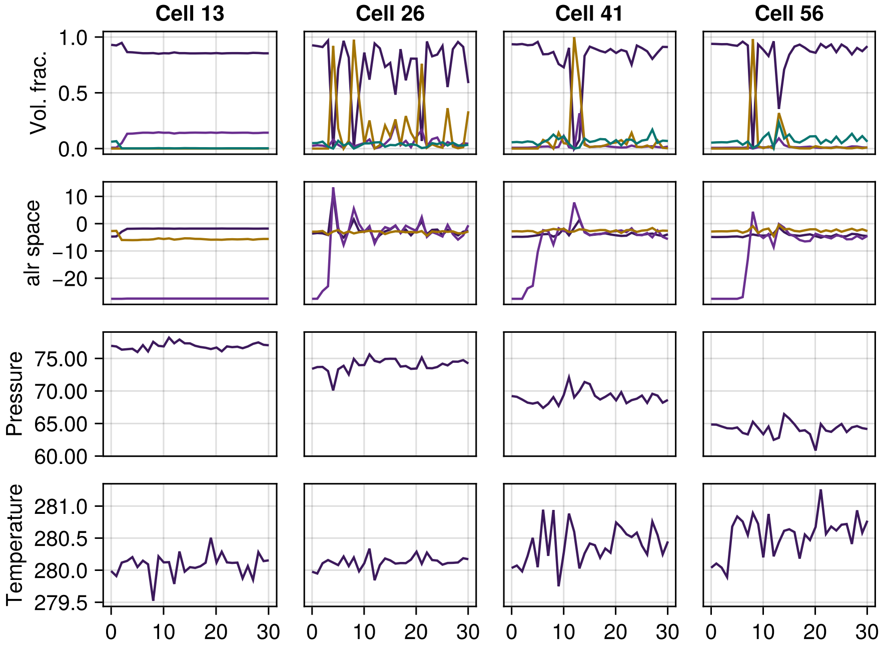
LedaFlow Case

- Dynamics
  - Initialized with the steady-state pre-processor
  - Reaches a different steady-state
- State Estimator
  - Also initialized with the steady-state pre-processor
  - Without noise



LedaFlow Case

- These are the Results
  - We measure the pressure next to cell 26
- The pressure & temperature
  - More accurate near cell 26
- Volume fractions
  - Oscillates



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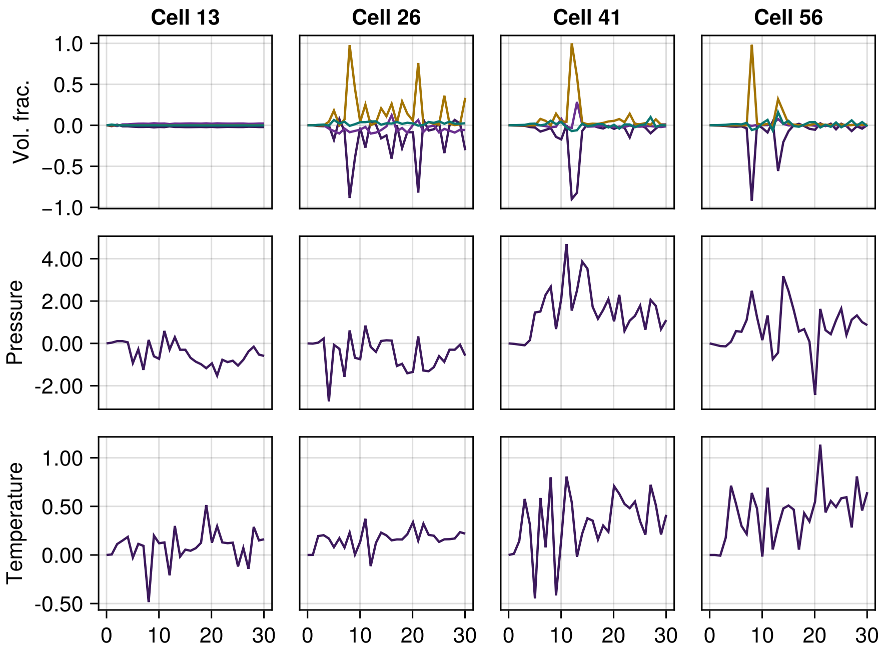

Conclusion & Future Work

- The Estimator Works
- The current implementation struggles with the volume fractions
- Add more measurements
- Check the performance of different measurements
- Implement the ILR transformation
- Test it on different process simulators

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