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Deep Learning History Matching for Real Time Production Forecasting

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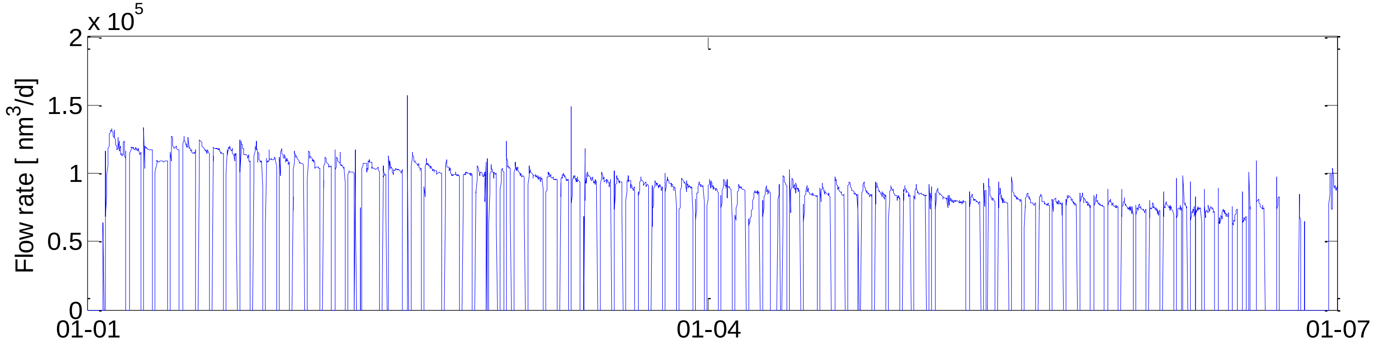
Introduction

- **Mature assets production issues**
  - e.g. liquid loading, scaling
  - Reliable prediction of production rates

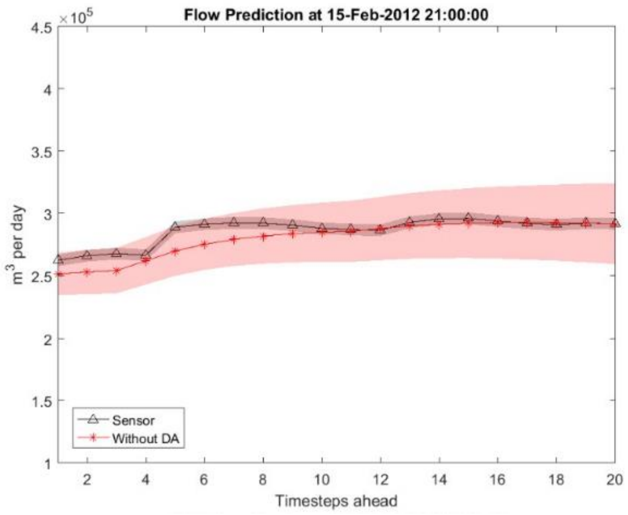


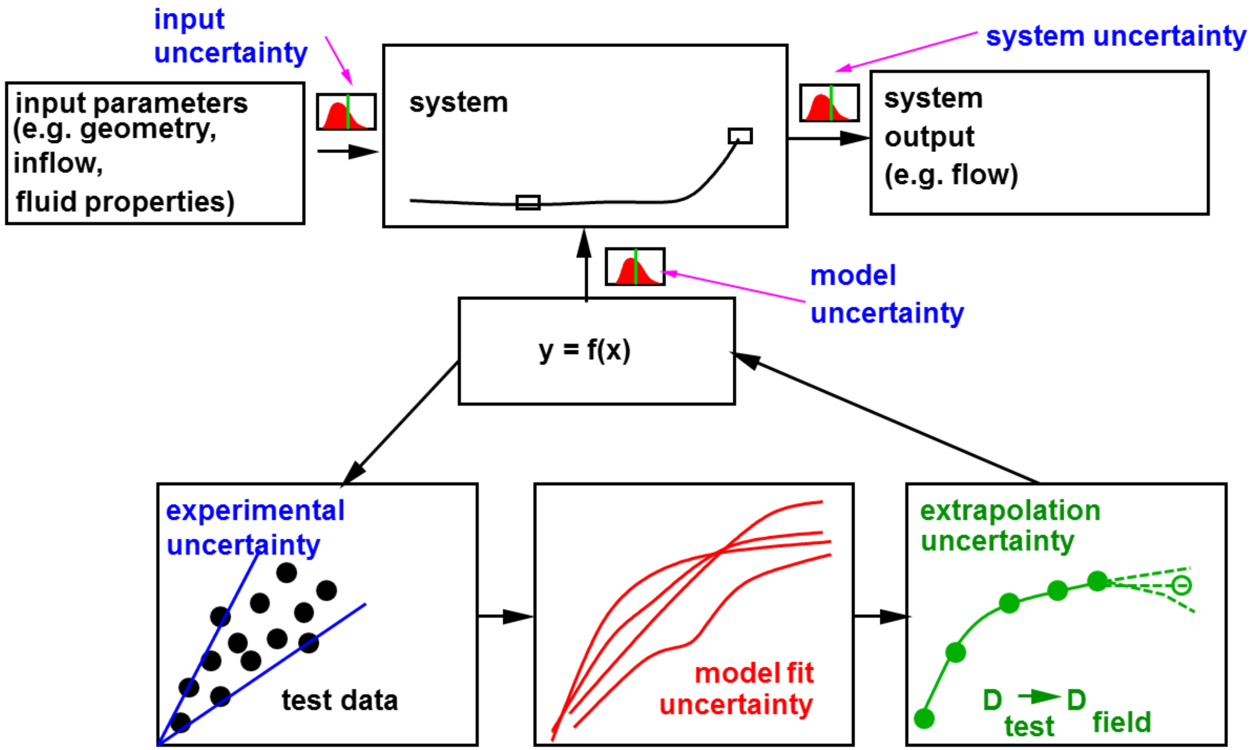
- **Availability of more and more data**
  - Development of cost effective sensors
  - Mature asset = Lots of historical data in different formats

- Clear need for **predictive models** to **improve operation**
  - Accurate and robust
  - Computationally efficient
  - Requires less manual calibration and tuning

Uncertainties and Forecasts

- Employing forward model for forecast
  - Physics-based model
  - Data-driven
- Uncertainties and errors inherent in
  - Measurements; irreducible
  - Models (parameters); reducible



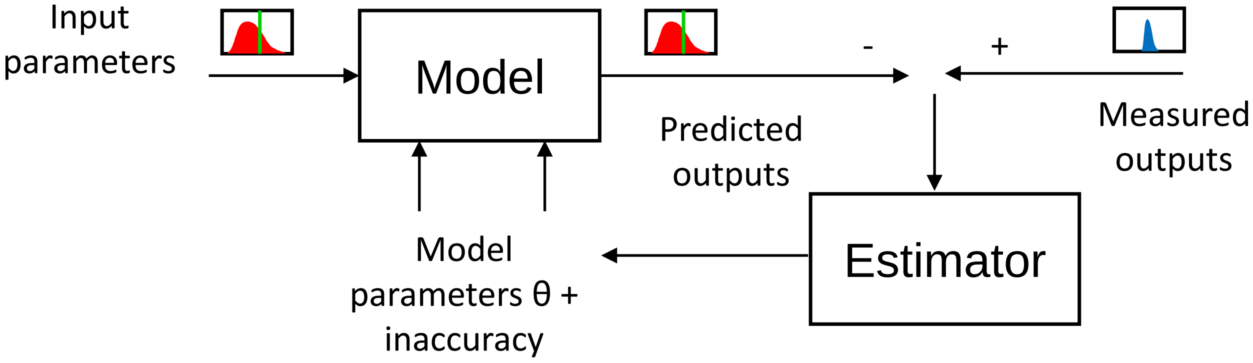


Objective

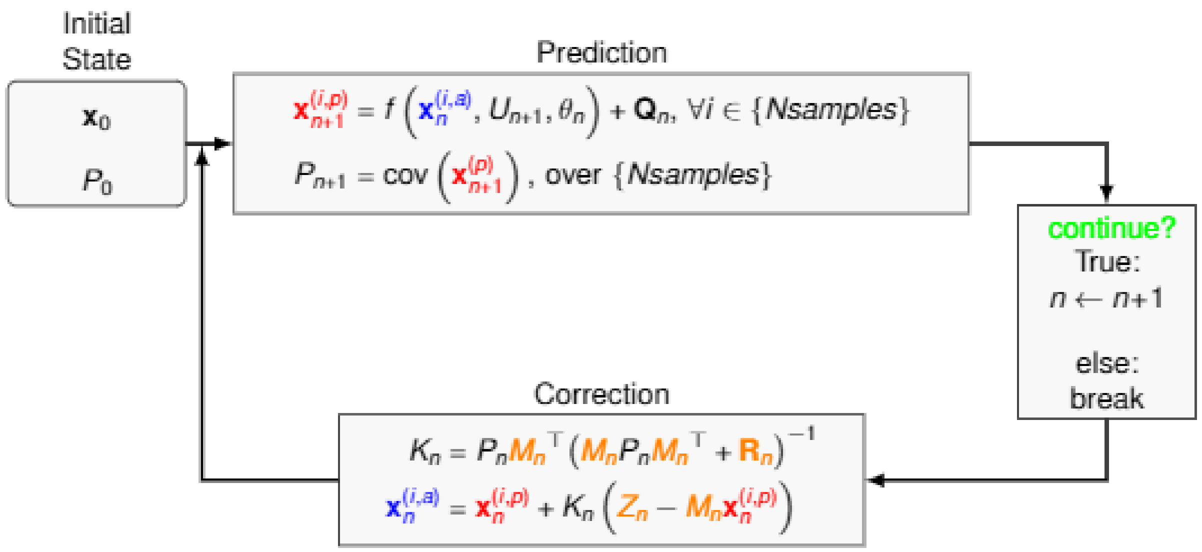
- Goal: Workflow development for production forecast updated with measurements
  - Cheap, robust and reliable production forecast model
  - Requires less manual calibration

- Most importantly to answer the question: Can this method help in improving forecasts from the forward models?

- KPI for workflow effectiveness



Methodology – Ensemble Kalman Filter



- The EnKF algorithm is essentially a predictor-corrector method. The prediction model in the figure is f.
- The algorithm first starts to predict the state of the system, given assumed values of the model parameters (i.e. the prior state).
- When data at the same timestep of the prediction are available, a correction is made (weighted least squares). We then have the posterior state, which we use for the predictions in the next timestep.

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Forward model – Stacked LSTMs

Layer (type)	Output Shape	Param #
gaussian_noise_1 (GaussianNo	(None, 36, 6)	0
lstm_1 (LSTM)	(None, 36, 5)	240
lstm_2 (LSTM)	(None, 36, 5)	220
lstm_3 (LSTM)	(None, 36, 5)	220
lstm_4 (LSTM)	(None, 36, 5)	220
lstm_5 (LSTM)	(None, 36, 5)	220
lstm_6 (LSTM)	(None, 5)	220
p_re_lu_1 (PReLU)	(None, 5)	5
dense_1 (Dense)	(None, 5)	30
dense_2 (Dense)	(None, 1)	6

Total params: 1,381
Trainable params: 1,381
Non-trainable params: 0

- Stacked LSTM as the forward model, with the following parameters
  - Production rate; Q
  - Tubing head pressure, Well head temperature; θ,
  - Choke opening; U
  - Model weight and bias parameter, W,

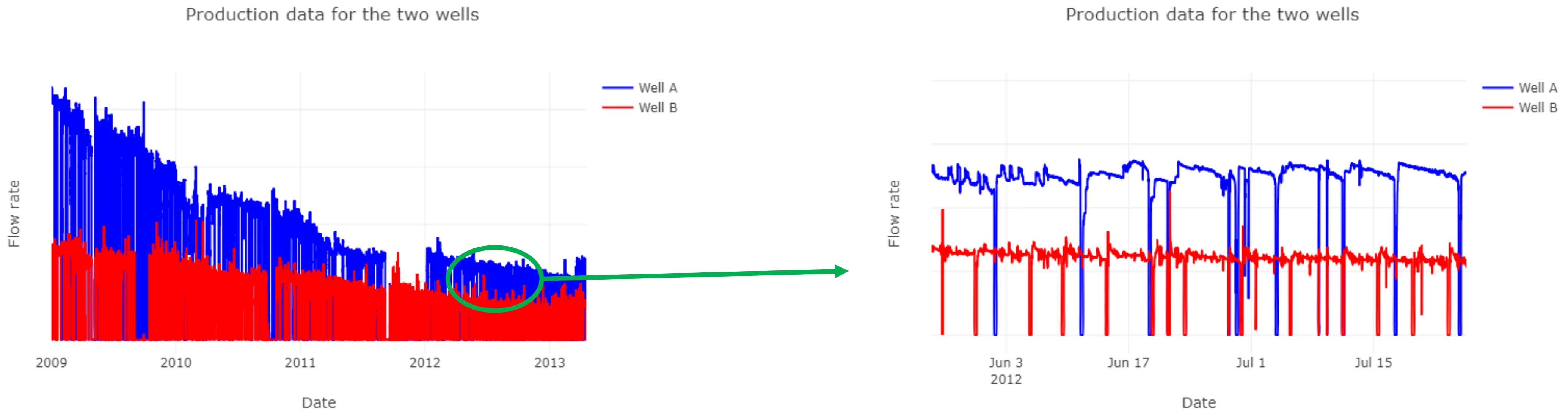
$$Q_{n+1} = f_{D-LSTM}\begin{pmatrix} Q_{n,n-1,\ldots,n-35} \\ \theta_{n,n-1,\ldots,n-35} \\ U_{n+1,n,\ldots,n-34} \\ W \end{pmatrix}$$

- The state space representation of the system is then given by

$$x_{n+1} = \begin{pmatrix} Q_{n+1} \\ W_{n+1} \end{pmatrix} = f(x_n, U_{n+1}) = \begin{pmatrix} f_{D-LSTM}(Q_n, \theta_n, U_{n+1}) + W_n \\ W_n \end{pmatrix}$$

Dataset

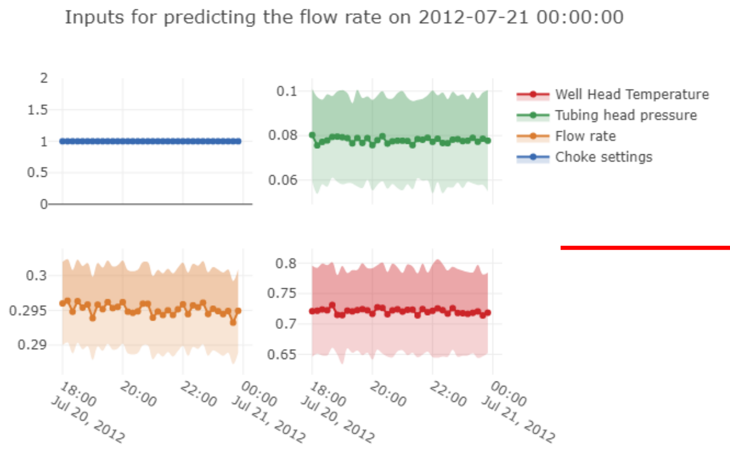
- Figure shows the entire production dataset for two mature wells in the North Sea from 2009 to mid 2013.
- Dataset contains the Production rate, Tubing head pressures, Well head temperatures, and Choke settings for the period.
- Can clearly see a decline in production rates due to salt formation for smaller time scales.

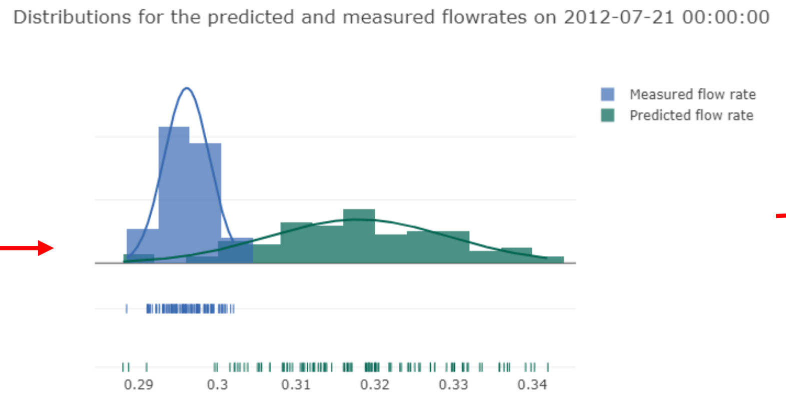


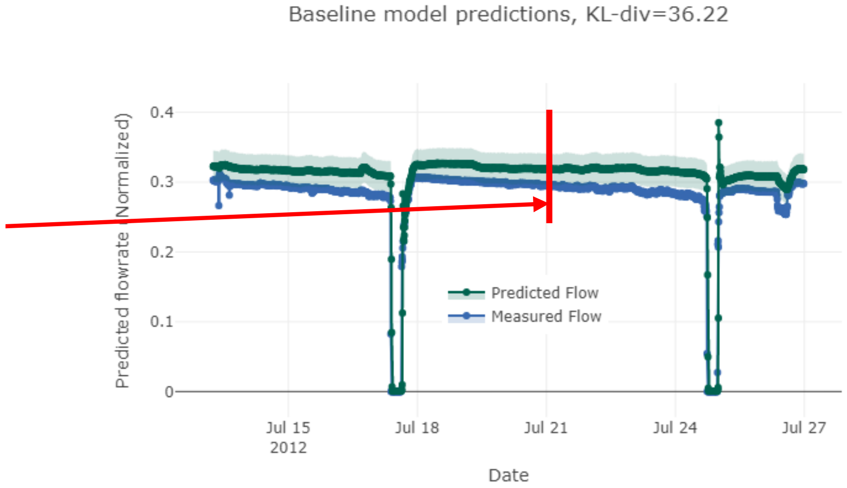
Uncertainties in dataset

- Add noise to the inputs scaled using the typical sensor sensitivities for each input variables.
- Determine the distribution of the forecasts using Monte Carlo. This provides the baseline case.

Normalized Variable	Scaled Standard deviation
Flow rate	0.003
Tubing Head Pressure Sensor 1	0.01
Tubing Head Pressure Sensor 2	0.01
Tubing Head Pressure Sensor 3	0.01
Temperature	0.04
Choke settings (valve opening)	0 (Assumed perfect)







Overview of cases

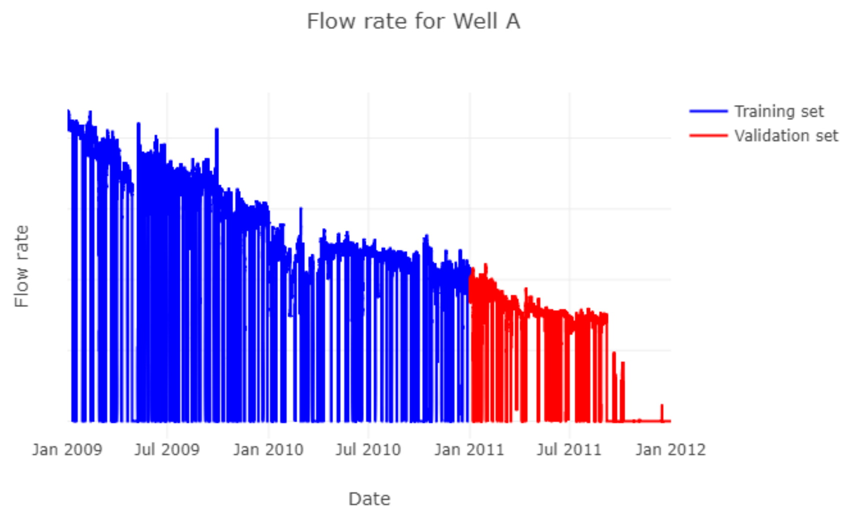
- Workflow was tested on two cases
  - Mature gas asset in North Sea, suffering from salt precipitation

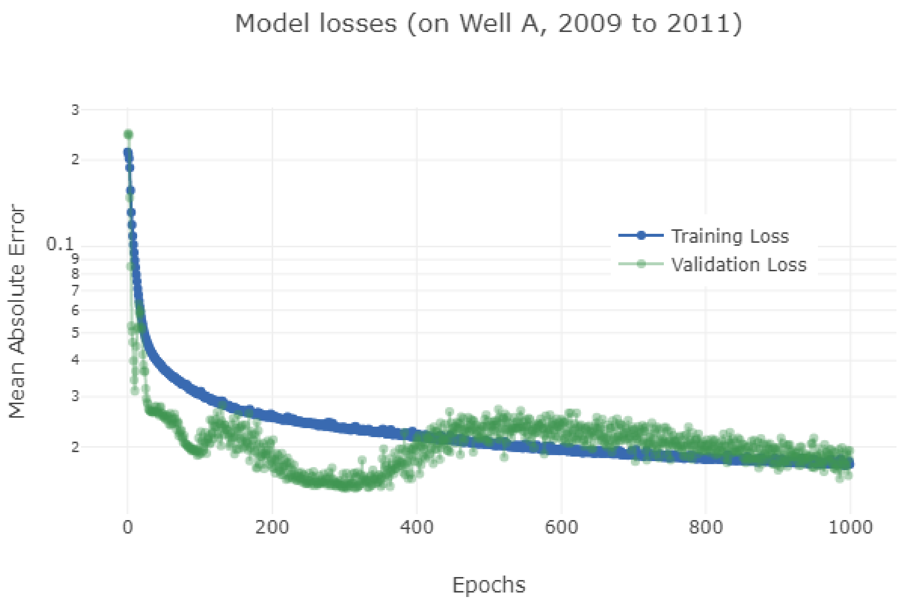
- Case I.
  - Training the forward model on Well A
  - Forecasting the production of Well A

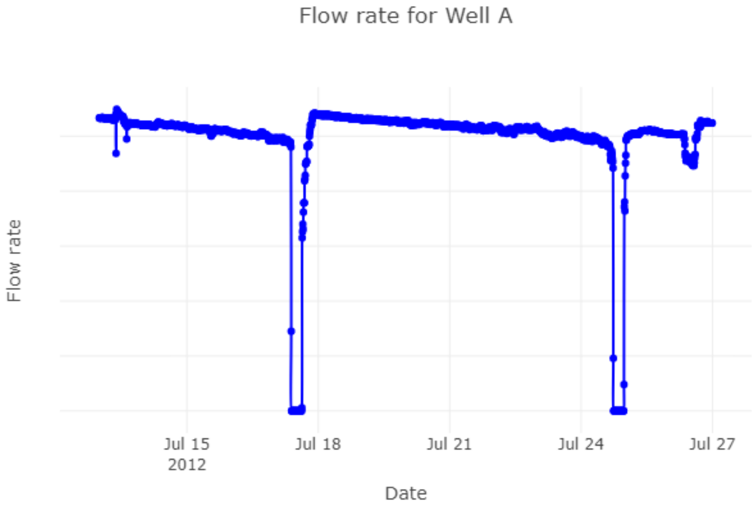
- Case II.
  - Training the forward model on Well A
  - Forecasting the production of Well B

Case I: Train Well A, Test Well A

- The training is performed on Well A dataset from 2009 to 2011
- Testing is performed on Well A in the period of Jul 13 - 27, 2012
- Initial model parameters (bias) uncertainties estimated in the training phase

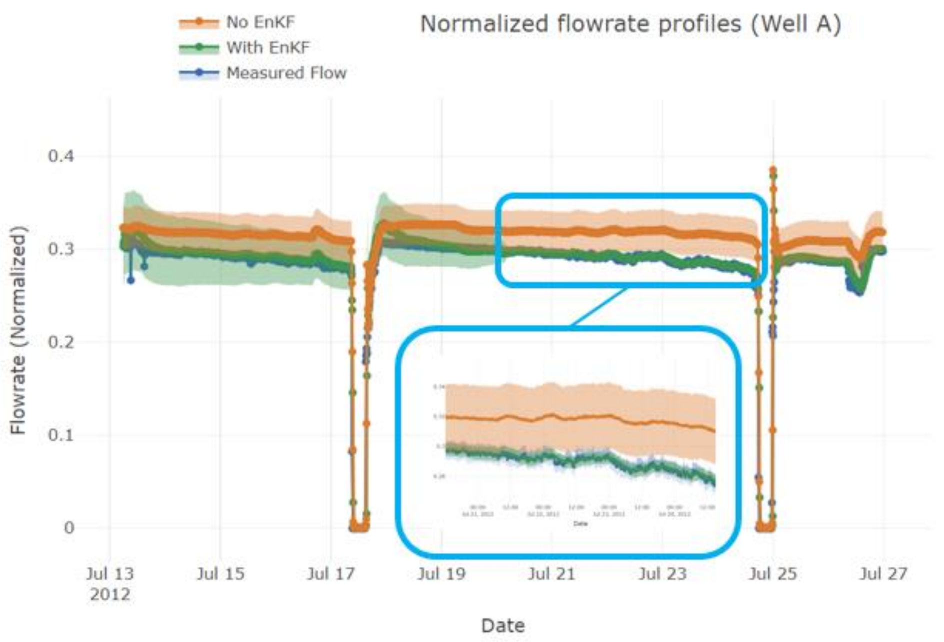


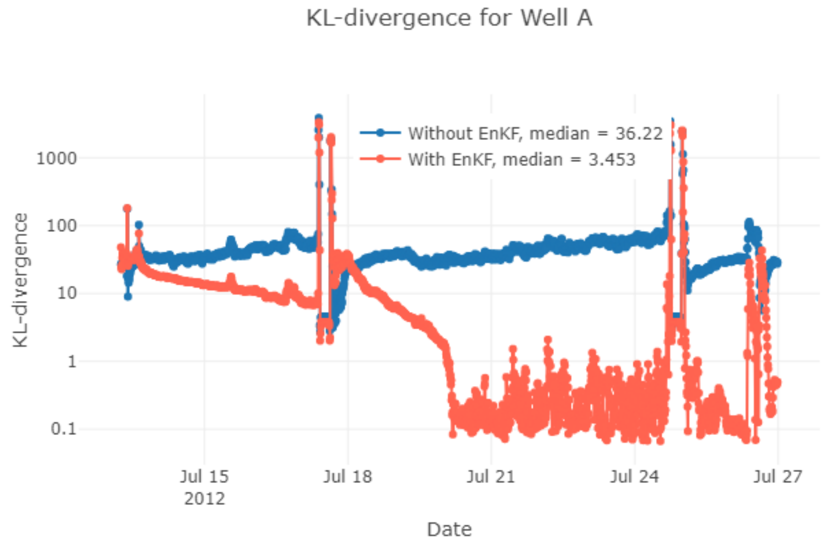




Results: Case I

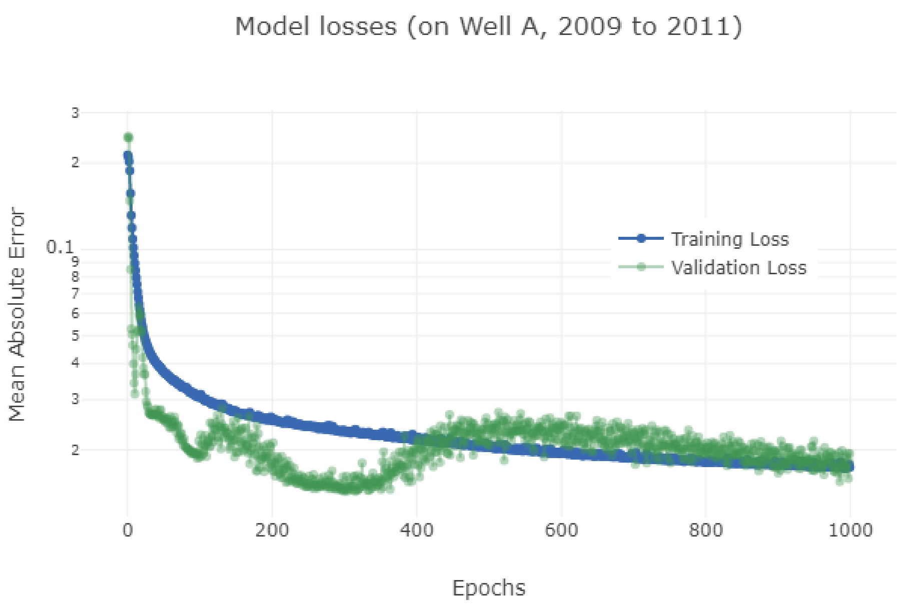
- Prediction results show that local bias errors are corrected.
- Better Kullback-Liebler divergence compared with baseline model.

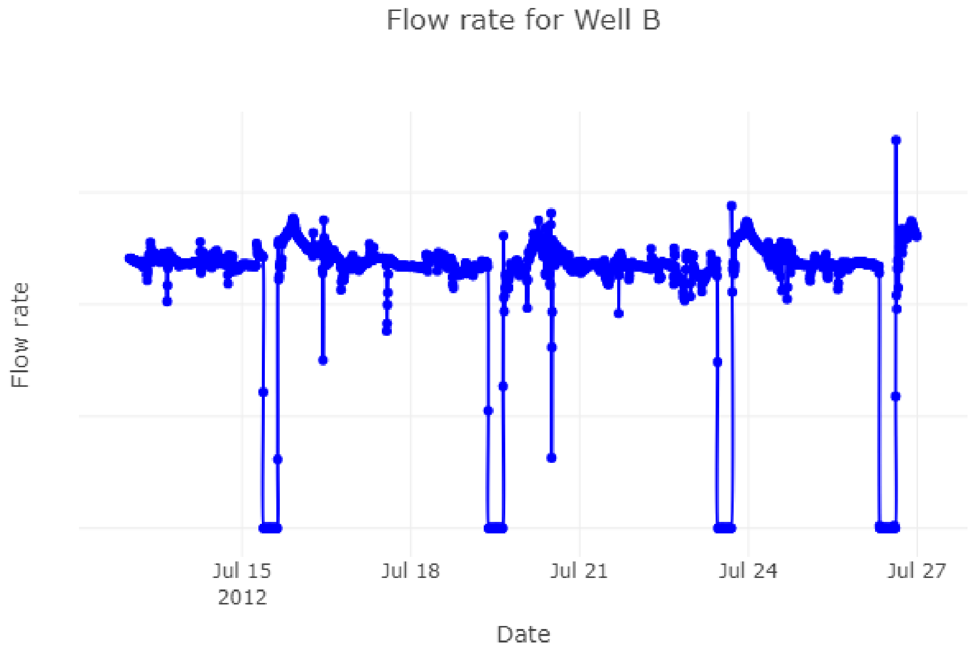




Case II: Train Well A, Test Well B

- Reuse the model trained from dataset of Well A
  - Avoid (sometimes computationally expensive) retraining of forward model
- Test dataset (same period) on Well B data





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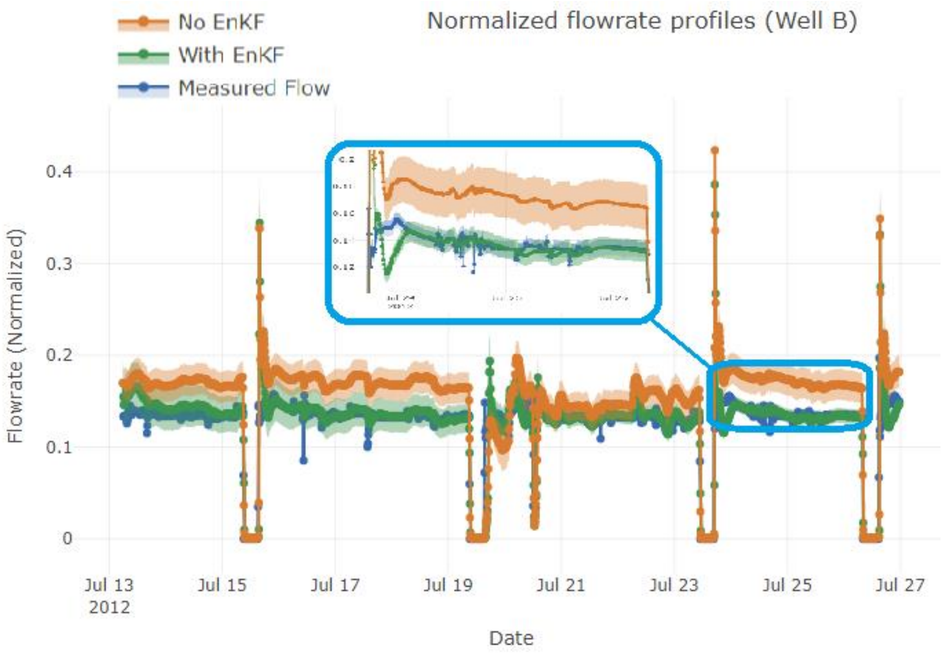
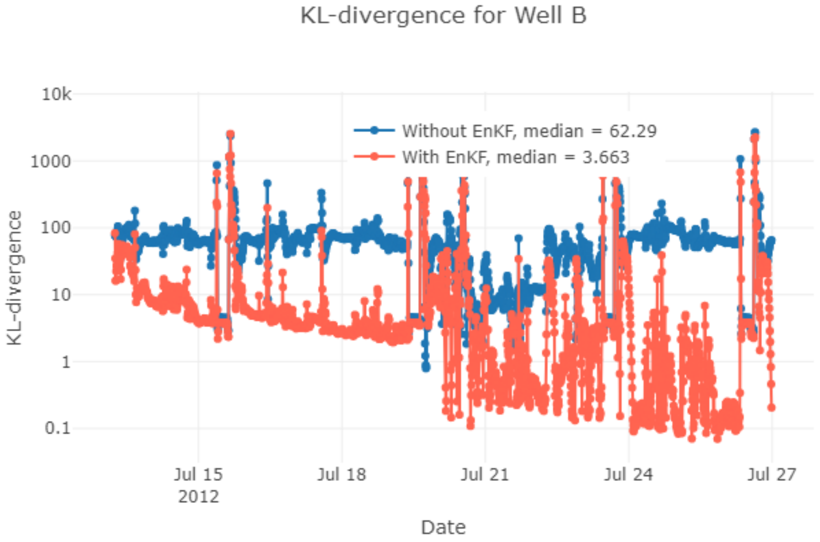
Results: Case II (1/2)

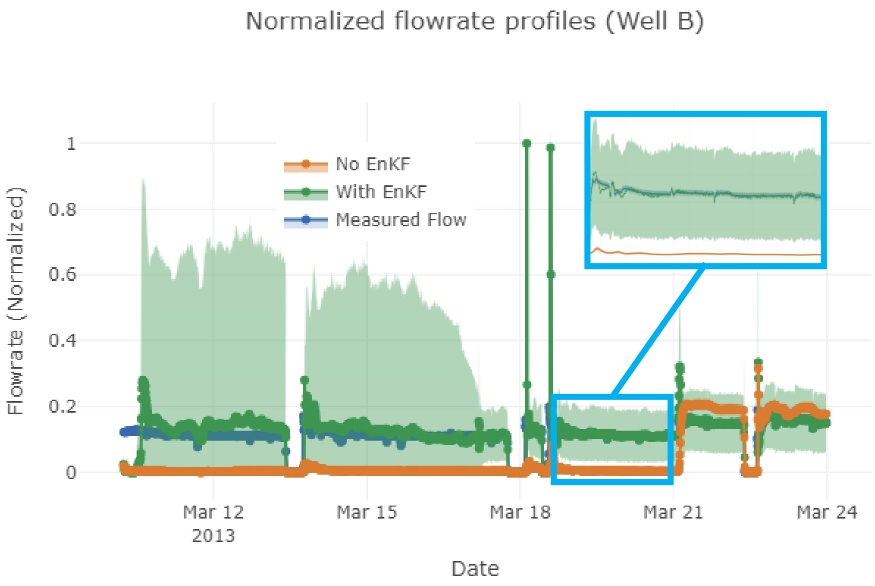
- Figure shows localized bias errors have been corrected. Moreover, uncertainties with the forecasts are also reduced.

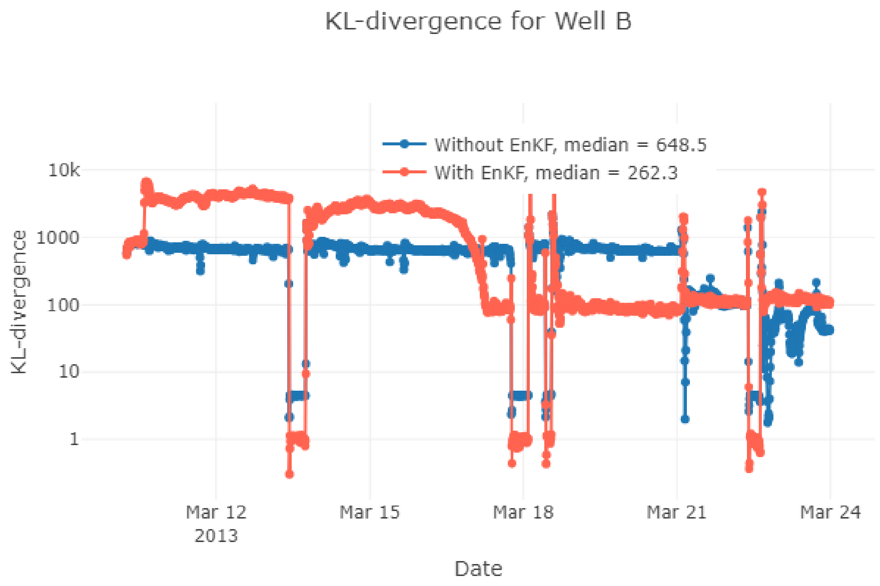




Results: Case II (2/2)

- Test also on a separate test period (March 10-24 2012) for Well B dataset.
- In the mean sense, the forecasts have been improved. Shows clearly that once the filter has settled, uncertainties are still relatively high. KL-divergence potentially can indicate need for retraining.





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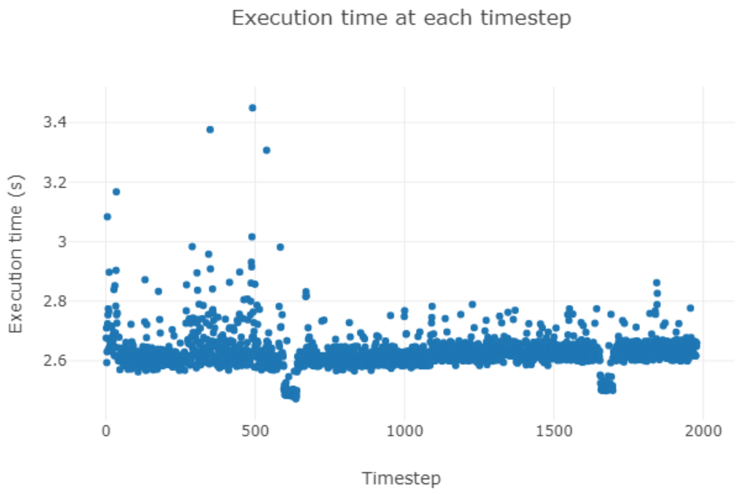
Results: Case I-II (Timings)

- Training performed on GTX1080 gpu, approximately ~ **5 hr**

- For performance testing, the model was deployed in a laptop with core i7-4810MQ with 16 GB ram.

- Each timestep takes about **3 seconds** (including data assimilation). Which means that the algorithm can be deployed in a real-time production optimization framework.

Processor:	Intel(R) Core(TM) i7-4810MQ CPU @ 2.80GHz 2.80 GHz
Installed memory (RAM):	16.0 GB
System type:	64-bit Operating System, x64-based processor



Conclusions

- Cheap and accurate models for production predictions, including the uncertainties in data
- Reduce the prediction uncertainties by incorporating new measurements/observations
- No retraining required, as long as the production trends are similar
- Generic workflow which could also be used as an operation support system (KPI, alarms,…)

Way forward

- Implementing the workflow in real-time (robust auto-tuned live forecast)

- Apply methodology to predict performance of other components in the production
  - Compressor, turbine performance degradation prediction

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